MACHINE LEARNING-BASED IDENTIFICATION OF KEY ELECTROMYOGRAPHY AND KINEMATIC FEATURES FOR CHRONIC NECK PAIN CLASSIFICATION

by

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ABSTRACT

In the realm of neck pain management, researchers and medical professionals are constantly exploring new methods. This includes better assessments of pain and related mobility issues, as well as enhancing treatment to improve the recovery of individuals with neck pain. This thesis centres on the utilisation of machine learning (ML) techniques to investigate how electromyography (EMG) and kinematic features can be used to classify people with or without chronic neck pain as this may ultimately guide improved assessment and management of patients with neck pain disorders and associated movement impairments.

Specifically, the objective of this research is to develop a deeper understanding of how EMG signals and kinematic measurements differ between people with and without chronic neck pain and how such data can be used for classification purposes. By analysing and identifying patterns within these data streams, valuable insights can potentially be gained to aid in the assessment, and treatment of neck pain conditions.

To achieve this goal, a comprehensive literature review of relevant studies on neck pain assessment and ML applications was conducted (Chapter 1). Various EMG and kinematic datasets were then collected from participants with and without chronic neck pain, and appropriate feature extraction techniques were applied. ML algorithms were then employed to classify groups with and without neck pain and then, identify key EMG and kinematic features (Chapter 2). These methodologies were examined across diverse tasks, including dynamic contractions of the neck (Chapter 3), static posture (Chapter 4), and gait (Chapter 5).

The results of this thesis showed, firstly, the ability of different ML algorithms to accurately classify people with chronic neck pain compared to healthy individuals across a wide variety of tasks. Secondly, the results identified and highlighted key EMG and kinematic characteristics that improved the performance of all algorithms. These characteristics provide insights into potential muscle activity as well as movement anomalies that are present in people with chronic neck pain. These findings offer a significant step forward in the understanding of the biomechanical and neuromuscular differences in individuals with neck pain compared to pain-free individuals. Additionally, the identified EMG and kinematic characteristics can potentially serve as a foundation for the development of targeted rehabilitation protocols, aiming to address the specific neuromuscular and movement abnormalities found in patients with chronic neck pain. Future research can delve deeper into the causal relationships between these identified characteristics and the presence of neck pain, potentially leading to preventive strategies and interventions.

Keywords: Neck pain, Electromyographic, Kinematics, Feature selection, Machine Learning.

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LIST OF ACRONYMS

AI	Artificial Intelligence
AS	Anterior Scalene
BC	Betweenness Centrality
BMI	Body Mass Index
CNP	Chronic Neck Pain
CNS	Central Nervous System
CPR	Centre for Precision Rehabilitation
EEG	Encephalography
EMG	Electromyography
FN	False Negative
FP	False Positive
IC	Intermuscular Coherence
IMU	Inertial Measure Unit
K-NN	K -Nearest Neighbour
LDA	Linear Discriminant Analysis
LOO	Leave One Out
MAV	Mean Absolute Value
MCU	Multi-Cervical Unit
MDF	Median Frequency
ML	Machine Learning
MNF	Mean Frequency
MNP	Mean Power
MU	Motor Unit

MVC	Maximal Voluntary Contraction
NCA	Neighbour Component Analysis
NDI	Neck Disability Index
NRS	Numerical Rating Scale
PKF	Peak Frequency
RMS	Root Mean Square
ROM	Range of Motion
SC	Splenius Capitis
SCM	Sternocleidomastoid
SD	Standard Deviation
SE	Spectral Entropy
SSI	Sigle Square Integral
ST	Strength
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TP	Total Power
UK	United Kingdom
VAR	Variance
WL	Waveform Length

LIST OF PUBLICATIONS

Journal Papers

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CHAPTER 1: INTRODUCTION

This initial chapter provides a comprehensive summary of the main topics that will be explored in this thesis. Initially, it presents an overview of fundamental considerations of neck pain and ML approaches. The core of this chapter then provides a thorough examination of significant contributions in the emerging intersection between neck pain and ML. The chapter concludes by delineating the objectives of the thesis and providing an overview of the comprehensive framework that guides the progression of the research.

1. Literature Review

The present literature review provides an in-depth analysis of neck pain and the role of ML techniques in the field. Beginning with an exploration of the definition, prevalence, and socio-economic impact of neck pain, the review presents the current limitations and challenges in the assessment and treatment of neck pain. In parallel, it offers a concise overview of ML, including fundamental principles, diverse types, and expansive applications in pain research. A key focus is the application of ML in creating innovative, objective, and efficient techniques that could help in the classification of neck pain.

1.1. Neck Pain

1.1.1. Definition

Pain is defined as 'an unpleasant sensory and emotional experience associated with, or resembling that associated with, actual or potential tissue damage' according to the revised guidelines by the International Association for the Study of Pain (Raja et al., 2020). Building upon this general definition, neck pain refers to a prevalent health condition characterised by discomfort in the anatomical region of the neck. This area typically spans from the bottom of the head to the top of the shoulders and may include the upper back (Bogduk, 2003; Dennison & Leal, 2011; Merskey & Bogduk, 1994). However, it is important to differentiate the primary site of pain (the neck) from areas where pain may radiate or spread due to underlying causes. The pain experienced in the neck may vary, ranging from mild to severe, and may be accompanied by a range of symptoms like stiffness, tingling, and numbness. Notably, while neck pain itself is confined to the cervical region, certain pathophysiological conditions causing neck pain can lead to symptoms in other areas, such as radiating pain to the arms.

The definition of neck pain varies widely in the literature. This discrepancy is, in part, attributable to the etiological bifurcation of neck pain into physical and psychosocial categories, thereby contributing to a multifaceted clinical presentation of neck pain. Because of the challenges in both describing and categorising neck pain, the term 'non-specific neck pain' is used for any symptomatic disorder of the cervical spine that lacks a pathoanatomical cause (Dennison & Leal, 2011). Non-specific neck pain frequently corresponds with muscle, joint or ligament-related factors and might be associated with issues such as poor ergonomics, stress, or prolonged muscle fatigue (Rao, 2002).

1.1.2. Classification

The classification of neck pain is an important aspect of diagnosing and treating this common condition, as it helps in understanding the underlying causes and determining the most effective treatment strategies. Classification provides a general framework for identifying subgroups of patients based on the primary goal of treatment, with the ultimate aim of matching individuals to specific interventions from which they are most likely to benefit (Childs et al., 2004).

Neck pain can be classified into different categories based on various factors such as the source of pain, the duration of the pain and treatment-based considerations. However, it is crucial to acknowledge that these classification systems have overlap and are not mutually exclusive. A single case of neck pain can fall into multiple categories simultaneously, reflecting the complex and multifaceted nature of this condition.

Treatment-based classification

The process of diagnosing non-specific neck pain on clinical grounds, involves identifying key symptoms and ruling out serious conditions or 'red flags'. The primary symptom is pain in the cervical region, often radiating to other areas such as the occiput, nuchal muscles, shoulders, and upper limbs. There can also be limitations in movement (e.g., flexion, extension, lateral flexion and rotation) which often increases with age and frequently does not align well with the intensity of the pain (Binder, 2007b).

The treatment-based classification system, grounded in the 2008 Neck Pain Clinical Practice Guidelines, is a well-established approach for the management of neck pain. This system effectively organizes neck pain into four primary categories: (1) neck pain with mobility deficits, (2) neck pain with movement coordination impairments, (3) neck pain with headache, and (4) neck pain with radiating pain (Blanpied et al., 2017). This categorization aids healthcare professionals in tailoring interventions to address the specific needs of individuals, enhancing the potential for positive treatment outcomes.

Classification by pain mechanisms

Classifications of pain based on mechanisms focus on organizing pain according to the neurophysiological processes that initiate and maintain it. This approach identifies three distinct types of pain, as outlined by (Butler, 2000):

- Neuropathic pain: based on the irritation or compression of specific nerve roots, resulting in symptoms that follow the nerve’s pathway. This type of pain often relates to conditions affecting the spinal nerves, such as herniated discs or spinal stenosis, such as cervical radiculopathy.
- Nociceptive pain: this type of pain occurs when tissue damage or potentially damaging stimuli activate nociceptors, which are sensory receptors for painful stimuli. In the context of neck pain, nociceptive pain is often due to mechanical or inflammatory conditions affecting muscles, ligaments, joints, or the cervical spine. Conditions such as whiplash-associated disorders, cervical spondylosis, and muscular strains typically fall under this category. The pain is usually well localized and often described as sharp, aching, or throbbing.
- Nociplastic pain: formerly known as central sensitization, involves alterations in the central nervous system's processing of pain without clear evidence of tissue damage (nociceptive pain) or nerve injury (neuropathic pain). It is characterized by increased sensitivity to pain and can manifest as widespread pain, fatigue, and emotional distress. In the neck, this might be seen in conditions like fibromyalgia,

where there's an enhanced pain response without clear mechanical or inflammatory causes.

The results of the only study carried out in the cervical area demonstrated that 43% of patients reported experiencing non-neuropathic pain, 7% had predominantly neuropathic pain, and a notable 50% encountered mixed pain. This distribution suggests a significant presence of mixed neuropathic-nociceptive pain, frequently attributed to degenerative conditions such as disc herniation or facet hypertrophy, which lead to foraminal stenosis (Cohen & Hooten, 2017).

Classification by cause

Neck pain can stem from a variety of causes, each with its unique mechanisms and implications for patient care. Among these causes are:

- Traumatic causes: it typically arises from sudden and forceful events such as car accidents, falls, sports injuries, or physical assaults. Whiplash is a classic example, where the rapid back-and-forth movement of the neck causes strain to the muscles and ligaments. Despite the association between physical exertion or trauma and neck pain, such history is identified as a causative factor in fewer than 15% of patients (Cohen & Hooten, 2017).
- Postural causes: they are increasingly prevalent due to modern lifestyles, particularly the extended use of computers and mobile devices. Poor ergonomic practices and prolonged periods of sitting or standing in improper positions contribute to strain and discomfort in the neck and shoulders. The phenomenon known as text neck syndrome, resulting from looking down at handheld devices for extended times, exemplifies how contemporary habits are contributing to a

rise in neck pain instances, underlining the importance of awareness and preventive measures in daily routines (Cuellar & Lanman, 2017).

- Degenerative causes: primarily involve the aging process and the wear and tear on the cervical spine. This includes cervical osteoarthritis, also known as spondylosis, where the cartilage between the vertebrae wears down, and degenerative disc disease, characterized by the deterioration of the intervertebral discs. These conditions lead to chronic pain due to the degeneration of joint cartilage, formation of bone spurs, and potential nerve impingement, significantly affecting mobility and quality of life (Binder, 2007a).
- Infectious/Inflammatory causes: these conditions cause pain through direct infection of the spinal tissues or as part of a systemic inflammatory response. Although these are serious conditions, they are relatively rare, contributing to less than 0.4% of neck pain cases (Bogduk, 2003).
- Referred pain: which is pain perceived in the neck but originating from another part of the body, such as shoulders, upper back or head. The exact mechanism of referred pain is not fully understood, but it is thought to involve complex interactions within the nervous system, causing the brain to perceive pain in a different location from its source. For instance, myocardial infarction, where the pain may radiate to the neck, jaw, or upper back.
- Biopsychosocial factors: this classification acknowledges the intricate interplay between biological, psychological, and social influences on neck pain. Unlike the more straightforward causes, biopsychosocial factors encompass a wide range of contributors that can initiate or exacerbate neck pain. Biological aspects include physiological and anatomical components such as genetic predisposition, underlying medical conditions. Psychological components involve the

individual's mental health status, emotional responses to pain, and perceptions of pain. Social factors reflect the role of the patient's environment and social interactions on their experience of neck pain. This includes workplace ergonomics, family and social support systems, among others (Cohen & Hooten, 2017).

Classification by duration

Classification by duration is a critical aspect of understanding and managing neck pain, as it helps to guide the prognosis, treatment strategies, and the potential for underlying causes. Neck pain can be categorized into three main durations: Acute neck pain typically lasts for a short period, often up to four weeks. Subacute neck pain extends beyond the initial four weeks but subsides before the twelve-week mark. However, when neck pain persists beyond twelve weeks, it enters the realm of chronicity. Chronic neck pain can be particularly debilitating, and can be recurrent or constant over months or even years (Binder, 2007a).

Within the scope of this thesis, the emphasis will be placed on chronic non-specific neck pain, a condition known for its prevalent yet often ambiguous characteristics that present a complex field for investigation within the extended domain of neck pain. Chronic neck pain is identified by persistent discomfort localized to the neck area, distinct from the various conditions that contribute to its onset, some of which may also cause symptoms in areas such as the arms. Importantly, chronic neck pain itself does not inherently include arm pain but may arise alongside underlying conditions that produce symptoms extending beyond the neck region. This differentiation is vital for understanding the unique challenges and complexities chronic neck pain entails, particularly in diagnosis and management. Unlike acute or subacute forms of neck pain, chronic neck pain embodies a comprehensive interaction of biological, psychological, and social factors, necessitating a nuanced approach to treatment and care.

1.1.3. Epidemiology

Neck pain, as a significant global health challenge, has gained increasing recognition due to its widespread prevalence and negative impact on quality of life. According to the Global Burden of Disease Study, neck pain is among the top five disorders in terms of years lived with disability, with a global point prevalence estimated at 4.9% as of 2017 (Disease et al., 2018). Furthermore, estimates suggest that up to 70% of adults will experience it at some point in their lives (Dennison & Leal, 2011; Lee et al., 2016).

Alarmingly, many individuals do not achieve complete pain resolution, leading to a chronic progression of the condition that pervades their entire lifespan (Chiu et al., 2005; Cote et al., 2009). Research suggests that between 50% and 85% of individuals who experience neck pain may report it again within one to five years. Specifically, approximately 30% of patients with neck pain are likely to develop chronic symptoms, and around 37% report persistent problems for at least twelve months. This highlights the high recurrence and chronicity rates of neck pain. These insights are essential in understanding the long-term impact of neck pain and the need for effective management strategies (Childs et al., 2008; Olson, 2016).

In terms of pain mechanism subgroups, studies have shown varying prevalence rates. Nociceptive pain arises from tissue damage or inflammation and is frequently reported. It represents the predominant type of chronic pain, covering conditions such as arthritis and the majority of spinal pain cases. Nonetheless, its prevalence exhibits significant variation across diverse populations and settings. This variability can be attributed to its expansive definition and the wide range of conditions that can induce it. Neuropathic pain, resulting from nerve damage, also has a significant presence. Estimates suggest that between 6.9% and 10.0% of the general population experience neuropathic pain, and it is expected to rise in the future (Dydyk & Givler, 2020). Nociplastic pain, which arises from altered pain processing without clear evidence of actual tissue or nerve damage, is increasingly recognized. Fitzcharles et al. describe nociplastic pain as distinct from nociceptive and neuropathic pain, often seen in conditions like fibromyalgia or tension-type headache, but the exact prevalence in neck pain cases is not specified (Fitzcharles et al., 2021).

In the context of the United Kingdom (UK), a specific aspect of neck pain that warrants attention is its association with work-related musculoskeletal disorders. According to a recent report by the (Health and Safety Executive, 2022), neck pain, along with disorders affecting the upper limb, accounts for 37% of all work-related musculoskeletal disorder cases. This category of disorders is responsible for 36% of working days lost, with an average of 14.9 days lost per case. These statistics highlight the significant impact of neck pain on the working population in the UK and underline the need for targeted interventions and strategies to address this prevalent condition in the occupational setting.

1.1.4. Impact

The economic impact of neck pain is multifaceted, considering both direct and indirect costs. Direct costs encompass medical expenses such as diagnostic tests, treatment modalities, hospital visits, and medication. In contrast, indirect costs primarily include productivity loss due to absenteeism, decreased work efficiency, and potential unemployment related to disability. A study by (Maniadakis & Gray, 2000) estimated the total cost of back and neck pain in the UK to be between 1% and 1.7% of the Gross Domestic Product, underscoring the profound economic implications of this condition.

In terms of disability-adjusted life years (DALYs), chronic neck pain is indeed a significant contributor. Disability-adjusted life years represent the total number of years lost due to ill-health, disability, or early death. Chronic neck pain, due to its long-lasting nature and potential for leading to disability, contributes significantly to the DALYs within populations, reflecting its substantial impact on public health. For instance, (Hoy et al., 2014) reported that neck pain ranks fourth highest in terms of disability as measured by years lived with disability, and 21st in terms of overall burden among all health conditions.

Additionally, chronic neck pain significantly affects quality of life, leading to functional limitations that restrict an individual's ability to perform daily activities, ranging from basic self-care tasks to professional responsibilities and social engagements. These limitations can profoundly impact life satisfaction and overall well-being, often resulting in decreased quality of life. Moreover, the condition extends its effects into the economic and social spheres, impairing interpersonal relationships and psychological wellbeing. The association between chronic pain and an increased risk of mental health disorders, such as depression and anxiety, creates a vicious cycle of physical and mental health decline, exacerbating social isolation. Oladeji et al. (2011) and Nolet et al. (2015) have both highlighted the interconnectedness of physical pain with psychological distress, underscoring chronic neck pain as not only a physical health issue but also a significant concern for mental health, further diminishing an individual's quality of life and emphasizing the need for a holistic approach to management and care (Nolet et al., 2015; Oladeji et al., 2011).

Collectively, the current literature underscores neck pain as a prevalent and debilitating condition with considerable economic and social consequences. This necessitates robust research efforts to develop more effective and efficient assessment and management strategies to mitigate the burden of neck pain on both individuals and societies.

1.1.5. Anatomy of the Neck

A comprehension of the anatomy of the neck is pivotal in understanding potential sources of pain. The composition of the neck is a complex anatomical structure and includes:

- Cervical vertebrae: consists of seven vertebrae with different shapes and sizes. They are categorised into two main groups: C1-C2 and C3-C7. The first group formed by Atlas (C1) and Axis (C2) are specialised on allowing movements like nodding and rotation apart from providing support and stability. The remaining five vertebrae are interconnected by facet joints, which guide and restrict motion within the cervical spine. These joints permit controlled flexion, extension, and rotation, contributing to the overall flexibility and stability of the neck. Their structure and function allow a broad range of motion while maintaining the structural integrity of the cervical spine. Additionally, these facet joints can become a source of pain due to various factors such as degeneration, inflammation, or injury (Binder, 2007a).

- Intervertebral discs: fibrocartilaginous cushions situated between the vertebrae in the cervical spine. They act as shock absorbers, permitting flexibility and movement while preventing the bones from rubbing against each other.
- Ligaments: fibrous bands of tissue that connect bones to other bones. In the neck, ligaments provide stability and help to limit movements that might cause injury, such as excessive twisting or bending.
- Spinal cord: located within the vertebral canal of the cervical spine, the spinal cord is a bundle of nerves that transmits messages between the brain and the rest of the body. In the cervical region, it controls signals to and from the arms and upper torso. Due to the small room between vertebrae, discs, ligaments and muscles, pain can emanate if these nerves become mechanically compressed, making it a significant source of discomfort (Binder, 2007b).
- Neck muscles: neck muscles are responsible for supporting the head and allowing movement in various directions. The muscles work together in a coordinated way to provide stability, enable movement, and also play a fundamental role in postural control. The neck comprises numerous muscles, some of the prominent ones being the sternocleidomastoid, scalenes, splenius capitis, splenius cervicis, longus capitis, and longus colli, among others. Within this context, this thesis focusses on four muscles with their detailed anatomical presentations provided in **Figure 1.1**:
  1. Sternocleidomastoid (SCM): Originating from the sternum and clavicle and attaching to the mastoid process of the temporal bone, the SCM is mainly responsible for neck flexion. When acting separately, it rotates the head to the opposite side.

2. Anterior Scalene (AS): Located deep on the side of the neck, the AS originates from the transverse processes of the cervical vertebrae and inserts into the first rib. Its main roles include aiding neck flexion and elevating the first rib during deep inhalation, but it is also active during neck flexion.
3. Splenius Capitis (SC): Positioned posteriorly in the neck, this muscle runs from the lower cervical and upper thoracic vertebrae up to the base of the skull. Its primary function is to extend the head and neck, and when only one side contracts, it helps in rotating the head to the same side.
4. Upper Trapezius (UT): A segment of the larger trapezius muscle, the UT section starts from the base of the skull and reaches down to the clavicle and acromion of the scapula. Its fundamental duties include elevating the scapula and aiding the neck in extension.

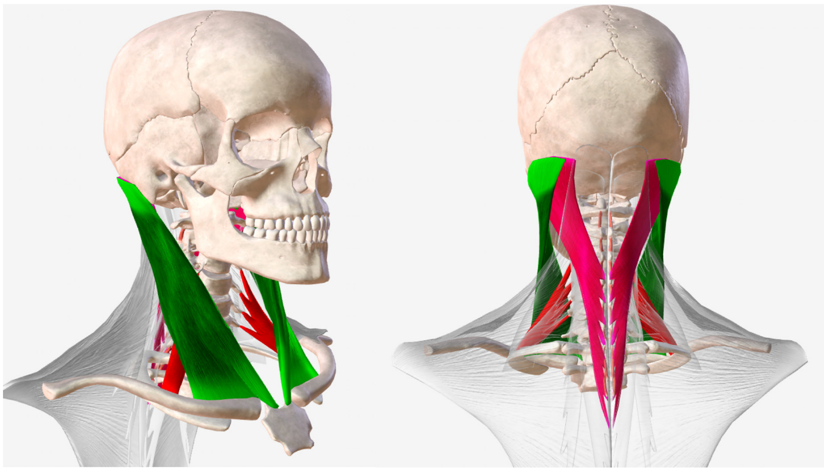

Figure 1.1. Anatomical illustration of the key neck muscles. This figure provides detailed depictions of the Sternocleidomastoid (SCM) in green, Anterior Scalene (AS) in red, Splenius Capitis (SC) in pink, and Upper Trapezius (UT) in grey muscles, highlighting their origins, insertions, and relative positions within the neck region. Source: BioDigital Human Software

1.1.6. Influence of Neck Pain on Motor Function

Neck pain can profoundly influence an individual's capacity to carry out a diverse range of daily activities. This impact spans from performing basic movements, such as dynamic actions or maintaining static postures, to more intricate tasks like coordinating head movements with changes in direction during running or balancing head posture when carrying objects. These challenges highlight the disturbance that neck pain can cause to the essential systems of head stability and postural control.

Different studies have demonstrated various ways in which neck pain affects motor functions, underscoring the complexity of its influence on daily life activities. For instance, (Sremakaew et al., 2021a) found that individuals with chronic idiopathic neck pain exhibited compromised gait speed and performance during tandem walk tasks and cognitive-motor dual tasks, indicating a significant impact of neck pain on the ability to perform complex motor activities. This suggests that the presence of neck pain can affect both the cognitive and physical aspects of motor function, limiting an individual's mobility and quality of life.

Similarly, (Gizzi et al., 2015) showed that experimental muscle pain leads to impaired synergistic modular control of neck muscles, which can affect posture and movement efficiency. This impairment in muscle coordination can lead to difficulties in performing precise movements, further exacerbating the impact of neck pain on motor function.

Research by (Baarbe et al., 2018) demonstrated that subclinical recurrent neck pain and its treatment have significant impacts on motor training-induced plasticity of the cerebellum and motor cortex. This indicates that neck pain not only affects motor function directly through physical mechanisms but also indirectly by altering brain areas responsible for motor control and learning.

As a further example, (Tsang et al., 2018) investigated the effects of combining ergonomic interventions and motor control exercises on muscle activity and kinematics in people with work-related neck-shoulder pain. Their findings suggest that targeted interventions can modify motor control and muscle activity, offering a potential pathway for rehabilitation and improvement in motor functions for individuals suffering from neck pain.

The preceding discussion illuminates the significant ways in which neck pain can disrupt everyday functions, affecting everything from basic posture maintenance to complex motor activities and cognitive-motor integration. This established context sets the stage for a focused analysis of particular tasks —cervical flexion, postural control, and gait— that are essential for daily living and heavily influenced by the condition of the cervical spine. Additionally, the tasks selected for this investigation are not only crucial for understanding the complex impact of neck pain on motor functions but are also chosen for their practicality. They are relatively easy to analyze and perform by individuals experiencing neck pain, making them ideal for both clinical assessments and therapeutic interventions. By investigating tasks that are fundamental yet accessible to those with neck pain, we aim to bridge the gap between theoretical knowledge and practical application, facilitating more effective strategies for managing and mitigating the impact of neck pain on daily life.

Impact on Specific Motor Tasks

- Cervical dynamic movements

Dynamic cervical movements are integral to our daily lives. From swiftly checking both ways when crossing the street, to shifting our gaze between the environment and our phones, or even guiding our direction as we walk, these subtle and seemingly insignificant motions are indispensable for our daily living (Tommasi et al., 2009).

The cervical spine performs a diverse range of movements, including flexion, extension, lateral flexion, and rotation. Flexion represents the forward bending of the head and neck. It mainly relies on the careful work of the deep neck flexors which guide the chin downward towards the chest. When circumstances demand stronger or swifter flexion, the superficial neck flexor, mainly the sternocleidomastoid, steps into action, lending a stronger contribution to the motion (Jung et al., 2023). In contrast, extension sees the head and neck arching backward. The superficial extensors, including the trapezius and the SC and cervicis, lead this movement, drawing the head to its rearward position. Supplementing this action are the deeper extensors like the semispinalis capitis, semispinalis cervicis and multifidus. They play a pivotal role by ensuring stability and support, acting as a well-coordinated safety net during extension (Jung et al., 2023). Lateral flexion involves a side-to-side tilt of the head, analogous to trying to touch the shoulder with one's ear without rotating the face. It is a harmonious interplay between certain muscles on one side contracting while others on the opposite side stretch. Muscles like the scalenes and the levator scapulae play a significant role in this sideways tilt (Jung et al., 2023). Lastly, rotation facilitates our ability to turn our head left or right. The primary muscles driving this movement are the SCM and the splenius muscles (Jung et al., 2023).

Given the broad spectrum of cervical movements, for the scope of this thesis, our emphasis will be on cervical flexion. The rationale behind this selection is twofold: First, its predominant role in various postures and activities, such as sitting, standing, and lying down. Second, its simplicity and ease of execution. Research indicates that individuals with neck pain may find cervical flexion movements to be less provocative compared to extension or rotation. For instance, (Cagnie et al., 2007) found that neck muscle strength, particularly in movements associated with cervical flexion, differs significantly between individuals with chronic neck pain and healthy controls, suggesting that flexion may be less likely to exacerbate pain. Additionally, (Peolsson et al., 2016) demonstrated the effectiveness of neck-specific exercises, which include cervical flexion, in improving outcomes for individuals with chronic whiplash-associated disorders.

However, this does not diminish the significance of cervical rotation or extension in daily life or their potential impact on individuals with neck pain. Future research should continue to explore the multifaceted nature of cervical movements and their implications for neck pain management.

For those with neck pain, these biomechanically simple but important motions can be affected. For instance, during tasks like the cranio-cervical flexion test that primarily involves a gentle nodding motion of the head, it has been observed that people with neck pain demonstrate reduced activation of the deep cervical flexor muscles, longus colli and longus capitis. This decreased activation is accompanied by an augmented activation of the superficial muscles, particularly the SCM and AS muscles (Falla et al., 2004e; Johnston et al., 2008). This adaptation suggests a modified motor strategy employed to accomplish the task (Falla et al., 2004e). Additionally, increased activity of superficial cervical flexor muscles has been also seen in people with neck pain during the dynamic movement of the upper limb (Falla et al., 2004a). Notably, these changes in muscle function are not exclusive of dynamic movements, irregular muscle patterns are also evident during isometric contractions. For example, research has indicated a decreased neuromuscular efficiency of the neck flexors, especially at lower contraction intensities (Falla et al., 2004b).

These changes in muscle activity also manifest in changes in cervical kinematics. One of the most frequently examined aspects is the range of motion (ROM) of the cervical spine. A multitude of studies have highlighted a reduced ROM during flexion-extension and rotation in individuals with neck pain (Rudolfsson et al., 2012). However, more recent research has presented findings that are not entirely consistent with these earlier observations (Lascurain-Aguirrebena et al., 2018a). This later study found no significant between-group differences in ROM in the primary axes of any tested neck movements (flexion, extension and rotation). Others studies have also identify differences in head speed, acceleration and smoothness during head movements in people with neck pain (Franov et al., 2022; Sjolander et al., 2008). For a more in-depth exploration of these findings, see next Section 1.1.7.

- Static and Dynamic Postural Control

Maintaining an upright static posture is fundamental to many everyday tasks and interactions. The alignment and stability of the cervical spine in posture are crucial not only for functionality but also for overall well-being. Posture reflects the equilibrium and interaction of various muscle groups and can indicate how the body compensates for imbalances or discomfort (Winter, 2005).

Understanding the mechanisms of head stability and postural control is crucial when examining the complexities of neck pain. Head stability, or the ability to maintain a steady head position and movement coordination, depends on sensory input from the cervical spine, the vestibular system, and muscular control (Treleaven, 2008). When neck pain disturbs these systems, it can lead to dizziness, and coordination issues.

Similarly, postural control involves the integration of sensory input from the visual system, and muscles/joints, along with proper musculoskeletal function and central nervous system processing. This allows the body to maintain an upright, balanced position (Horak, 2006). Neck pain can compromise postural control by altering sensory signals from the neck, disrupting muscular coordination, and creating a cycle of pain and instability. These disruptions manifest not only in obvious signs like postural sway but also in subtler aspects of head control during everyday movements.

It is important to highlight that although there is not a strong correlation between posture and neck pain, certain static postures, such as forward head posture, may be implicated in specific instances. Although research indicates that static posture is generally consistent among individuals with and without neck pain, a key difference arises in terms of postural endurance: those with neck pain often struggle to maintain an upright position during prolonged activities like computer work, gradually adopting a forward head posture (Falla et al., 2007; Szeto et al., 2002).

For those with neck pain, discomfort can lead to adaptive postures that may further strain the cervical muscles. Specifically, in tasks related to standing balance, vertical posture, and clinical balance tests, research has shown that individuals often exhibit reduced head stability, (Michaelson, 2003), increased postural sway (Michaelson, 2003; Sjöström et al., 2003), and increased muscle activity in the SCM and SC muscles (Sremakaew et al., 2021b). These physiological adaptations could be compensatory mechanisms the body employs to alleviate pain, but they unintentionally compromise postural biomechanics (Silva & Cruz, 2013).

Moreover, (Jull et al., 2002) underscored the efficacy of exercises designed to enhance dynamic postural control, demonstrating their potential to diminish neck pain and elevate functional outcomes. This finding implies that therapeutic strategies focusing on the dynamic components of postural control may offer significant benefits for individuals afflicted with neck pain. Complementarily, research conducted by (Yip et al., 2008) corroborates the idea that advancements in postural control can mitigate the intensity and disability resulting from neck pain. These studies collectively advocate for the incorporation of postural control improvements into intervention programs.

Such postural and biomechanical deviations can have long-term implications on the health of the cervical spine. While the relationship between posture and neck pain is a subject of ongoing debate, understanding these altered postural habits is crucial for developing comprehensive management strategies.

- Gait

Human walking is a rhythmic and consecutive process that represents one of the most fundamental human activities. Gait involves not only the lower limbs but also requires a collaborative effort from the entire body, including the cervical spine. The cervical region plays a pivotal role in stabilising and orienting the head, maintaining eye level with the horizon and aiding in effective environmental perception while walking (Courtine & Schieppati, 2003a).

If very common and straightforward tasks like static and dynamic actions are both challenging for people with neck pain, gait is not an exception. Changes in gait can be subtle but are often present. Notably, reduced proprioception, shortened step length, reduced gait speed and more asymmetrical gait have been documented for people with neck pain (Burton et al., 2023; Falla et al., 2017; Kirmizi et al., 2019; Poole et al., 2008; Sjöström et al., 2003). In clinical settings, slower gait velocity is often identified as a common feature among those with neck pain (Uthaikhup et al., 2014).

Furthermore, such disruptions are not limited to linear walking but also evident during more complex gait such as curved gait, turning, or dual task gait, where walking is combined with another cognitive or physical activity (Alsultan et al., 2019; Uthaikhup et al., 2014).

Despite the impact of neck pain on gait dynamics, research remains scattered on muscle activity during walking in individuals suffering from neck pain. This gap in the literature limits our understanding of the muscular compensations and adaptations that occur as a result of neck pain. Such studies could provide deeper insights into the muscular adaptations and compensations that occur due to neck pain during walking.

Given the consistent evidence of the negative impact of neck pain on measures of gait health (Burton et al., 2023), it is crucial to consider this condition in the evaluation of gait disorders. The interrelation between neck pain and gait disturbances highlights the importance of a holistic approach in patient care, acknowledging the role of the cervical spine in overall motor function and stability (Courtine & Schieppati, 2003a). Therefore, this thesis aimed to delve deeper into the examination of gait in individuals with neck pain in order to expand the understanding of how neck pain affects specific gait parameters. This investigation not only broadens the comprehension of the multifaceted effects of neck pain on locomotion but also emphasizes the need for integrating muscular and kinematic assessments within a comprehensive therapeutic framework.

Due to the impact of neck pain on physical performance, which spans from simple movements to more complex forms of movement, it is evident that this condition significantly impairs an individual's daily functioning and overall quality of life. Given that neck pain affects both dynamic activities and static postures, as well as changing the way a person walks, it presents a complex problem that necessitates a multifaceted approach for effective management. The multifaceted nature of this problem underscores the critical necessity for objective measures in assessing neck pain.

1.1.7. Objective Measures for Neck Pain

Traditionally, the assessment of neck pain largely relied on self-report questionnaires and physical examination. While they provide valuable insights into an individual's perception of their pain and disability, these methods are inherently subject to bias and do not capture the full spectrum of neck pain's impact on physical functioning. Over the last few decades, researchers have recognised the need for more objective methods to evaluate the impact of neck pain (and other musculoskeletal disorders). Consequently, objective measures have been increasingly employed to quantify neck function, offering a more accurate picture of the physical implications of this condition.

With the advancements in biomedical engineering, tools like EMG and motion capture systems have become increasingly valuable in providing a more objective and quantifiable evaluation of musculoskeletal disorders.

- Electromyography

EMG is the measurement of the electrical activity generated by the muscle fibres. In essence, it offers valuable insights into muscle activity and neuromuscular control. The body of literature supporting the use of EMG for understanding muscle activation patterns in musculoskeletal disorders is vast. The validity and reliability of EMG as a robust tool for assessing muscle activity are well-established ensuring consistent and accurate measurements across different muscles and conditions (Mohseni Bandpei et al., 2014; Silverman et al., 2021). Specially, in neck pain, EMG has shown exceptional reliability, with Intraclass Correlation Coefficients (ICC) ranging from 0.81 to 0.97 for the upper trapezius muscle during sitting (Kim et al., 2019).

Initial investigations using EMG methodology had already highlighted differences in force production, SCM relaxation times and efficiency (Barton & Hayes, 1996). As research progressed, the presence of these kind of adaptations has been confirmed by several publications, and at the same time, their understanding has been expanded as well. For instance, more recent studies have showed that people with neck pain demonstrate reduced EMG amplitude of SCM and SC muscles and delayed onset times in response to external perturbations (Boudreau & Falla, 2014). Furthering this, Lindstrom et al.

observed increased coactivation of the SCM and SC muscles during isometric neck contractions (Lindstrom et al., 2011). There are also evident changes in feed-forward control in both deep and superficial cervical flexor muscles, emphasising the intricate neuromuscular adaptations in neck pain individuals (Falla et al., 2004c) .

However, a notable limitation in the current body of literature is the lack of exploration into additional EMG attributes such as variance, waveform length or median frequency of the signals. From the time perspective analysis, numerous studies predominantly focus on amplitude features, such as the Root Mean Square (RMS), or averaged rectified values (also known as mean absolute value (MAV)). This is due to their relative ease of computation and their ability to provide an overview of muscle activity levels. The widespread use of established EMG features, while valuable, can create a bias against exploring alternative features, potentially hindering innovation in the field.

Nevertheless, numerous time-based EMG parameters have been effectively employed, offering new insights in diverse fields such as upper limb prosthetics, hand movement classification, and even facial recognition research. These studies commonly utilize a combination of features to capture the significant properties of EMG signals and distinguish between different muscle movements. Typically, this feature sets includes well-known metrics like the MAV and RMS, supplemented with variance, waveform length (WL), or the simple square integral among many others. This comprehensive approach ensures a robust representation of the signal's key characteristics. For instance, variance is noted as a beneficial metric to enhance the typical on-off activation patterns in EMG studies (Richards et al., 2014). Meanwhile, WL has been highlighted for its superior performance in classification tasks, offering a balance between accuracy, stability, and computational efficiency (Oskoei & Hu, 2008). In the context of neck pain, time-domain features such as RMS and MAV have been prominently utilized as metrics of comparison. These parameters, with a proven track record in EMG analysis, continue to be central in differentiating muscle activation patterns between healthy individuals and those with neck pain across different tasks (Falla et al., 2004c; Jull et al., 2004; Siegmund et al., 2007). However, no additional studies exploring diverse time-domain features for neck pain have been found.

On the other hand, from the frequency perfective, only few studies have explored additional attributes like the Mean Frequency (MNF) or Mean Power Frequency (MP) within neck pain populations (Falla et al., 2004d; Falla et al., 2004f; Falla et al., 2003). In particular, in Falla et al., 2003 investigation, it was found that individuals with neck pain show grater fatigability of SCM and AS muscles than the control subjects; this was evidenced by the notably higher initial values and steeper slopes observed in the MNF values (see **Figure 1.2**).

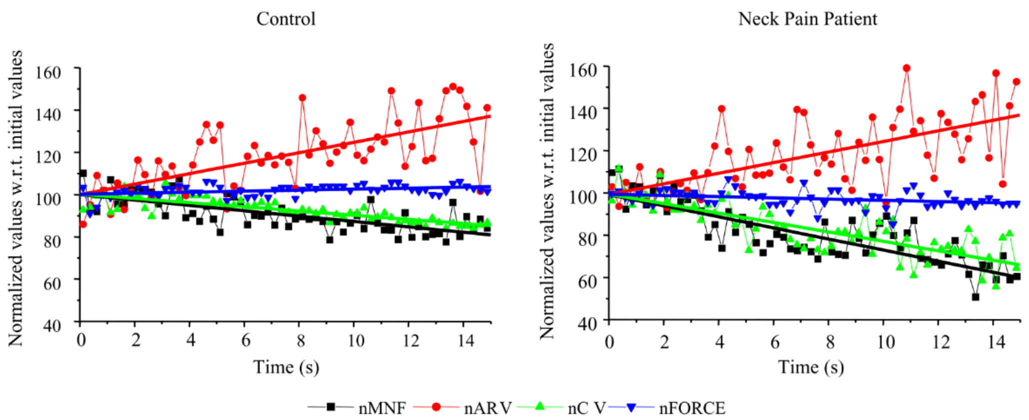

Figure 1.2. Sample plots showcasing fatigue in the SCM muscle for both a neck pain sufferer and a control individual when contracting at 50% of MVC. The EMG metrics in focus are average rectified value (ARV), conduction velocity (CV), and mean frequency (MNF). Each metric is normalised based on the regression line's intercept. Notably, a quicker shift in the MNF over time indicates more pronounced fatigue in the SCM muscle of the neck pain patient. Source: Falla et al., 2003.

Further insights into frequency domain analysis in neck pain are provided by a systematic review of difference EMG variables between people with and without neck pain (Castelein et al., 2015). This review encountered nine studies focusing on MP or Median Power Frequency (MDF) parameters. Among these, five studies, including those by (Andersen et al., 2014); (Elcadi et al., 2013); (Larsson et al., 2000);(Schulte et al., 2006); and (Sjogaard et al., 2010), found no significant differences between patients with neck pain and healthy controls during fatiguing tasks. However, the remaining studies presented significant yet conflicting results. (Larsson et al., 1999) reported lower MP values in patients, suggesting an accelerated fatigue development in their most painful muscles during specific tasks. Contrastingly, (Madeleine et al., 1999) found higher MP values in butchers with neck pain during work-simulated activities. (Falla & Farina, 2005)noted significant differences in MP during a hand-tapping task, with neck pain patients showing lower values in a specific endurance interval. Lastly, (Kallenberg et al., 2007) identified significant differences in MDF during an isometric shoulder girdle elevation task, concluding a less pronounced myoelectric response in patients compared to controls.

Given the established utility of conventional amplitude features like RMS and MAV, alongside the emerging significance of time-based parameters (such as variance and waveform length) and frequency domain insights (including the ones already studied, MNF and MP), a combined use of time and frequency features is deemed essential. This approach is not only motivated by the desire to capture the significant properties of EMG signals more accurately but also to overcome the limitations posed by relying solely on traditional measures. By integrating both time and frequency domain features, this thesis aims to provide a more comprehensive representation of muscular behaviour, thereby potentially uncovering more intricate patterns of muscle dysfunction associated with neck pain.

Moreover, this kind of feature combination from different domains has demonstrated significant utility in prior studies, for example, in classifying hand and leg movements (Toledo-Pérez et al., 2019) or in recognition of prehensile postures (Wang et al., 2013). By extrapolating from these studies, one might hypothesise that a comprehensive evaluation of EMG characteristics could offer deeper insights into the neuromuscular adaptations associated with neck pain.

- Motion analysis

Motion capture technologies, encompassing inertial, optical, or mechanical systems, have revolutionised biomechanical studies, allowing for precise measurement and analysis of human kinematics across multiple body parts simultaneously. Using high-resolution sensors and advanced algorithms, these systems capture detailed human movements, serving various applications from sports science to rehabilitation. They provide a comprehensive view of body dynamics, highlighting the interplay between different regions, and have significantly enhanced our understanding of human movement (Menache, 2011).

These systems' validity and reliability for precise measurement and analysis of human kinematics are supported by extensive calibration and validation efforts, ensuring high accuracy in capturing movements. A notable example is the study conducted by (Muyor et al., 2017), focusing on the measurement of spinal sagittal thoracic and lumbar curvatures, alongside sacral inclination in a standing posture. This research highlighted the motion capture system's outstanding test-retest reliability, with ICCs reaching 0.98. The findings also emphasized the system's minimal systematic biases and errors, showcasing its superior precision in evaluating spinal configurations compared to conventional radiographic methods.

Inertial motion capture systems also have proven their outstanding reliability and precision consistently. For instance, their application in assessing cervical ROM for flexion, extension, and lateral flexion yielded ICCs of 0.89 and 0.88, respectively. These results align closely with the reliability of other advanced electromagnetic and optical motion analysis systems in examining cervical spine dynamics. Further corroborating this high level of reliability, additional studies have mirrored these ICC values for flexion and extension (0.85) and lateral flexion (0.87), reinforcing the precision of motion capture technologies in biomechanical research (Lascurain-Aguirrebena et al., 2018b; Yoon et al., 2019).

Several studies have highlighted kinematics irregularities in people with neck pain across various tasks. Sjolander et al. investigated head kinematics, identifying distinct differences in individuals with neck pain during fast head rotations. These included a reduced peak velocity, a more limited ROM, and higher jerk index values during head rotations (Sjolander et al., 2008). Similarly, Tsang et al. observed decreased angular velocity and acceleration in neck flexion and extension during a reaching tasks among neck pain participants (Tsang et al., 2014). Notably, they found no differences in ROM and the authors suggested that the influence of neck pain on movement patterns may predominantly manifest in the modification of movement dynamics, such as speed and acceleration, rather than altering the overall extent or amplitude of spinal movement.

Despite the frequent use of ROM, as a measure in studies of neck pain, the literature presents an inconsistent picture regarding its relationship with individuals experiencing neck pain. This inconsistency is evidenced by studies reporting contrasting findings. For instance, (Rudolfsson et al., 2012) identified ROM restriction in individuals with neck pain, while (Sjolander et al., 2008) observed no significant differences in ROM between symptomatic and asymptomatic participants. Additionally, (Lascurain-Aguirrebena et al., 2018a) also discuss the variability in this relationship. Such divergent results indicate that the association between neck pain and ROM is not straightforward and may be influenced by various factors, including the methods used to measure ROM, the characteristics of the study population, and the specific nature of the neck pain experienced by individuals.

Similar incongruences can be observed in the case of the smoothness or jerk. In detail, the notion of jerk or the sudden change in motion, is also increasingly being recognised as a significant marker in the assessment of neck pain. The increase in jerk signifies a lack of smoothness and control in movement, a characteristic often observed in individuals with neck pain. However, findings regarding this characteristic are not consistent across various studies. A recent systematic review by Franov et al. highlighted this inconsistency, revealing conflicting results. For instance, one study within the review identified a decrease in the number of velocity peaks among patients with neck pain, which contrasts with findings from other research that reported either an increase or no significant change in different movement smoothness variables (Franov et al., 2022; Moghaddas et al., 2019).

In the case of gait, elderly individuals suffering from neck pain were found to have a slower walking pace and a longer stride compared to controls (Poole et al., 2008). Subsequently, in a study conducted by Falla et al. (Falla et al., 2017) with a younger population revealed not only decreased gait speed but also a shortened step length, and less trunk rotation during treadmill walking. Similarly, (Kirmizi et al., 2019) observed reduced gait speed in people with neck pain across different walking conditions (preferred walking, preferred walking with head rotation and walking at maximum speed). Given this body of evidence, complemented by the recent systematic review from Burton et al., it becomes clear that a reduced walking speed stands as a common feature in those presenting with neck pain (**Figure 1.3**) (Burton et al., 2023).

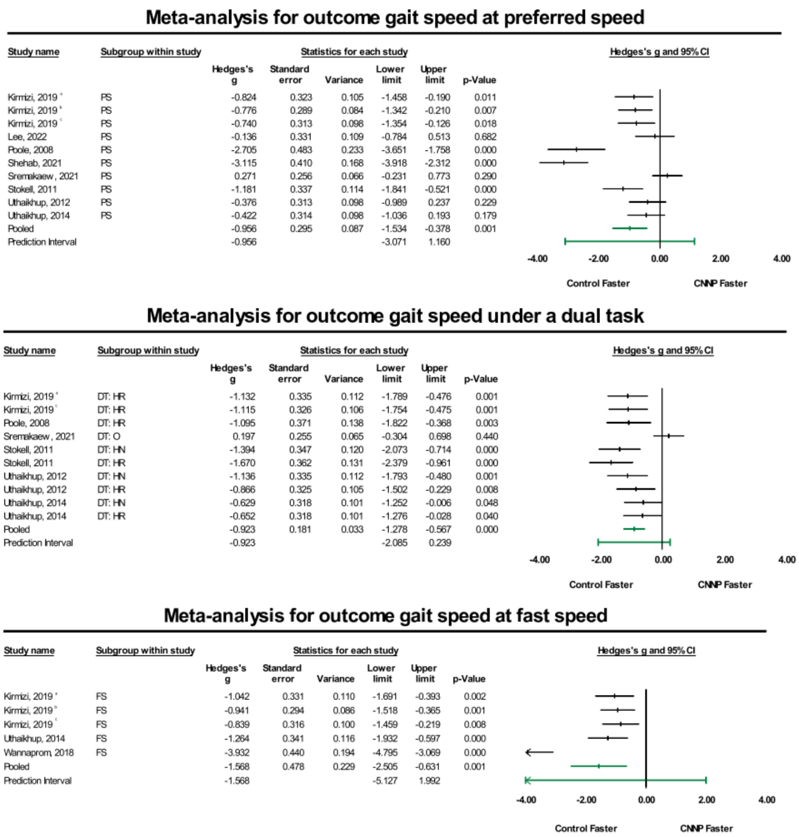

Figure 1.3. Meta-analysis forest plots representing the outcome of gait speed across the three evaluated walking conditions: preferred walking speed, dual task, and fast walking speed. PS: preferred speed, DT: dual task, HR: head rotation, HN: head nodding, O: Other motor dual task, FS: fast speed. Source: Burton et al., 2023.

Similar to the situation with the EMG parameters, kinematics characteristics have not been completely explored when assessing people with neck pain. There is a high prevalence of time-dependant variables such as speed, acceleration, or ROM in the literature. Frequency features in kinematic analysis have been analysed only in one study by Yang et al. during cervical circumduction. In this study, they introduced the calculation of Spectral Entropy (SE) and found significant differences between asymptomatic individuals and those with neck pain (Yang et al., 2014). This work not only suggests that SE and possibly other frequency features could serve as valuable indicators of kinematic changes but also raises important questions about the broader spectrum of frequency features that have not been explored. Therefore, there is a clear need for broader exploration of a variety of frequency features. This signifies investigating an entirely new, largely unexplored dimension that could potentially help us uncover additional kinematic adaptations associated with the presence of neck pain.

In summary, the traditional reliance on self-reported measures to evaluate neck pain is insufficient in painting the full picture of the condition's physical impact. The integration of advanced biomedical tools, namely EMG and motion capture systems, has allowed for more objective, reliable, and comprehensive assessments of physical impairments in people with neck pain. These technologies offer valuable insights into the altered muscle activation patterns and kinematic irregularities associated with neck pain. A wealth of research has proven the role of muscular dysfunction and modified movement, including gait, in people with neck pain, enriching our understanding of the condition's underlying pathophysiology mechanisms of the condition. Nevertheless, the scientific discourse emphasises the necessity for continued exploration into additional EMG and kinematic parameters. These parameters have the potential to reveal patterns that can effectively differentiate between groups and, in turn, serve as potential biomarkers.

A biomarker, or biological marker, is defined as a characteristic that is objectively measured and evaluated as an indicator of normal biological processes, pathogenic processes, or pharmacologic responses to a therapeutic intervention (Biomarkers Definitions Working, 2001). The identification of such biomarkers holds transformative potential for neck pain management. By identifying specific physiological or kinematic indicators of neck pain, clinicians can tailor treatments more accurately to individual patients. Studies in neck pain have shown that exercise programs targeting specific motor impairments identified through kinematic or EMG analysis can be more effective in reducing pain and improving function (Berg et al., 1994; Falla, 2012; Price et al., 2020). Thus, recognising a particular muscle activation pattern, for example, might lead to targeted physiotherapy exercises or interventions aimed at correcting those specific impairments.

1.2. Machine Learning Approaches

1.2.1. Definition and Impact

ML is a subset of artificial intelligence (AI) that allows systems to automatically learn and improve from experience without being explicitly programmed (Tack, 2019). This implies that the algorithms possess the capability to learn independently and make predictions or decisions without human intervention, deriving insights exclusively from the data they are provided with.

The learning process of ML algorithms can be broken down into several key steps: First, a model is trained using a dataset containing input-output pairs, known as training data. The model generates predictions based on the input data. The difference between these predictions and the actual output data (known as the error) is then calculated using a loss function. An optimisation algorithm, that adjusts the parameters of the model to minimise this error. This process is repeated many times, iteratively refining the model's parameters. Once the model is trained, it can make predictions on new, unseen data (test data). The end result is a model that can be applied to new data, encapsulating a complex interplay of statistical, computational, and domain-specific insights.

Based on the methodology by which algorithms interpret and learn from data, two primary categories of learning approaches can be identified:

- Supervised learning: In this approach the algorithm learns from labelled data. This means that both input (i.e., features of the data) and output (labels) are provided to the ML model during the training process. The goal is for the algorithm to discern a function or a mapping from the input to the output. It essentially "learns" from the training data so that it can apply this learned knowledge to unseen or test data. Common tasks for supervised learning include regression (predicting a continuous output) and classification (predicting a categorical output).
- Unsupervised learning: This involves training the algorithm on unlabelled data. The ML model receives data inputs but not explicit outputs. Instead, the algorithm must find structure in its input but itself, such as clustering or by finding associations and patterns. The goal here is to understand the underlying structure or distribution in the data in order to learn more about the data or to reduce its dimensionality.

It is worth noting that these are not the only categories of ML algorithms. There are also semi-supervised learning algorithms, which use a small amount of labelled data with a large amount of unlabelled data, or reinforcement learning algorithms, where an agent learns to make decisions by taking actions that maximise some notion of cumulative reward in an environment (Skansi, 2018).

Feature selection

In the pursuit of refining these models, feature selection emerges as a pivotal technique, particularly in scenarios where a vast number of features contrast with a relatively small dataset of training examples. In such contexts, it is trickily easy to craft a decision function that perfectly classifies the training data but fails significantly when applied to unseen test data. In order to avoid this, methodologies such as wrapper, filter, and embedded approaches are employed to pinpoint the most impactful features. This strategic selection not only simplifies the learning process but also enhances computational efficiency (for further details, see Section 2.3). Among the wrapper techniques, Recursive Feature Elimination is noteworthy for its methodical removal of the least significant features, as determined by the model's weights or coefficients. Similarly, Sequential Feature Selection stands out by dynamically adding or removing features based on their impact on the model's accuracy (Dash & Liu, 2003).

Filter methods, on the other hand, leverage statistical measures to sift through features, discarding those that offer minimal predictive value concerning the target outcome. Notably, Mutual Information and Chi-Squared tests are prominent for their effectiveness in this regard. Embedded methods, such as LASSO (Least Absolute Shrinkage and Selection Operator) and Decision Trees, represent another essential category. LASSO is celebrated for its ability to impose penalties on the magnitudes of coefficients, effectively nullifying some and thus executing feature selection. Conversely, Decision Trees inherently conduct feature selection by selecting the most informative features for data splitting at each node, showcasing their intrinsic value in model refinement. These methods, each with their unique advantages and applications, are instrumental in enhancing model performance by meticulously selecting relevant features, thereby preventing overfitting, reducing model complexity, and improving prediction accuracy.

Model tuning and validation

Hyperparameter tuning and validation techniques serves as another method to refine model performance, akin to feature selection. These techniques ensure that the model not only fits the training data well but also generalizes effectively to new, unseen data. Specifically, hyperparameter tuning involves finding the right combination of input values to optimize the performance of a ML model. Hyperparameter tuning, in particular, involves the careful selection of input values that fine-tune the model's performance. Hyperparameters, which are predetermined before the learning algorithm begins, are crucial in guiding the behavior of ML algorithms. They significantly affect the model's ability to adapt to new data. These settings range from those that shape the model’s architecture, to the extent of regularization enforced, and even to the model's learning pace (Li et al., 2017).

When dealing with small sample size databases, hyperparameter tuning present unique challenges. A model might be tuned too closely to the limited training data available, impairing its generalization to new data. Moreover, performance evaluations on small datasets have high variance. This means the results of hyperparameter tuning might not be representative of the model's true performance. In such scenarios, simpler models or those with fewer hyperparameters may be preferable, as they are less likely to overfit. Techniques like cross-validation become even more critical, as they help in making the most out of the limited data by assessing the model's performance more robustly.

Cross-validation is a method used to evaluate the generalizability of a model, especially those tailored for small datasets, by partitioning the original dataset into multiple small train-test splits to validate the model on each. This approach helps in utilizing the limited data more effectively, providing a more accurate estimation of the model's performance on unseen data. Its fundamental principle lies in evaluating a model on data points that were not part of the dataset used to train the model. Numerous studies have tested this methodology and recommend it as a crucial tool for robust model evaluation (Varoquaux, 2018).

Sample size determination

Determining the appropriate sample size in ML is indeed a complex issue, primarily because ML approaches are fundamentally data-driven and often do not start with a predefined hypothesis in the same way traditional statistical tests do. In statistical hypothesis testing, sample size calculations are typically based on desired power, significance level, and the expected effect size. However, in ML, the focus shifts towards objectives like ensuring the stability of feature selection, the generalizability of the model to unseen data, and the overall performance of the model (Mao et al., 2016).

One of the main challenges in sample size determination for ML is the absence of a prior hypothesis. This aspect makes traditional methods less directly applicable. The complexity of the ML model and the number of features significantly impact the required sample size. More complex models, such as deep neural networks with many parameters, typically require larger datasets to train effectively without overfitting. Similarly, a larger sample size can enhance the stability of feature selection, ensuring that the model consistently identifies important features across different data subsets. Additionally, ensuring that a model generalizes well to new, unseen data necessitates a sufficiently large and representative sample that captures the diversity and variability of the underlying population.

Multiple methods have been suggested for calculating the necessary sample size in ML research. One method includes applying established standards to determine the smallest sample size needed for ML model validation studies (Goldenholz et al., 2023; Rajput et al., 2023). A different strategy assesses how sample size influences the performance of classifiers and effect sizes, creating guidelines from these outcomes (Althubaiti, 2023). Additionally, it is essential to engage in open and realistic discussions regarding the appropriateness of the calculated sample size, considering factors such as research objective, data availability, project timeline, and cost (Balki et al., 2019). However, despite these methodologies, there remains a challenge in achieving a universally applicable formula due to the diversity of ML models and the specific contexts in which they are applied. Each model and use case may require a unique approach to sample size determination, influenced by the complexity of the model, the variability within the data, and the precision required for the study's outcomes.

Since ML is inherently data-driven, data serves as its essential foundation. The primary objective of ML is to develop methodologies that are versatile and can identify useful patterns within data, ideally without the need for extensive domain-specific knowledge. In recent times, data capture and collection have become increasingly accessible due to the arrival of modern devices such as smartphones, tablets, and wearable sensors, along with improved connectivity technologies like Wi-Fi and Bluetooth. As a result, the integration of ML approaches has emerged as an invaluable resource across various industries.

Even within the healthcare industry alone, there is a broad spectrum of studies that cover a diverse range of topics from gait analysis and lung mechanics, to diagnosing conditions like glaucoma, stroke, dementia and Alzheimer's disease (Bullock et al., 2020; Chan et al., 2002; Costa et al., 2016; Mannini et al., 2016; Niloofar Hezarjaribi; Su et al., 2020). In this line, the healthcare sector, is experiencing a paradigm shift as AI approaches are used to predict disease, optimise patient treatment plans, and enhance our overall understanding of human health (Mehta, 2023). By deciphering patterns and insights from vast datasets that are beyond human analytic capabilities, AI is helping to create personalised treatment strategies, anticipate disease spread, and improve patient outcomes (Obermeyer & Emanuel, 2016). For instance, DeepMind's AI, outperforming human radiologists in breast cancer detection, demonstrates the remarkable potential of AI to enhance diagnostic precision. This system reduced false positives by 5.7% and false negatives by 9.4% (McKinney et al., 2020).

1.2.2. Application in Pain Research

The application of ML techniques in pain research has opened new avenues for understanding the complex nature of pain. By harnessing the power of ML algorithms, researchers can identify patterns and make predictions that can aid in the management of pain.

Recalling the previously defined concept of pain and neck pain in Section 1.1, when this pain extends beyond three months, it is termed as chronic or persistent pain (Jenssen et al., 2021). These definitions lead us to two main challenges: Firstly, pain is an entirely personal experience, and secondly, chronic pain may bear physical as well as psychological ramifications, thus adding to its complexity. The situation becomes even more complicated when the pain lasts for extended periods and becomes increasingly challenging to manage.

In such contexts, conventional analytic methods, such as self-report questionnaires, often fall short due to their inherent limitations, including the reliance on patient recall and the potential for bias. These biases can significantly influence how a patient reports their experience, as their current emotional and physical state may affect their recollection and evaluation of symptoms. This phenomenon is thoroughly examined in the study by (Van den Bergh & Walentynowicz, 2016) which highlights the discrepancies between real-time and retrospective reports of symptoms. The investigation reveals that retrospective symptom reports are not only subject to inaccuracies due to memory decay but also to cognitive biases that can distort the reporting of past pain experiences. For instance, a patient's current mood can colour their recollection of pain intensity, leading to over- or under-reporting of symptoms. This underscores the necessity for employing more objective and real-time methods in assessing pain, to bypass the limitations presented by subjective self-assessments.

In a comprehensive systematic review conducted by (Jenssen et al., 2021), it was discovered that ML is predominantly used in pain research in the following ways:

- Classification/diagnosis of patients with chronic pain using structured health data
- Classification/diagnosis of patients with chronic pain using text and images
- Genomics approaches and pain biomarker identification
- Treatment
- Self-management
- Measurement of pain intensity

The authors of the review emphasised the high prevalence of classification and clustering techniques applied in pain research. Furthermore, they highlighted the extensive application of ML techniques in the context of low back pain and fibromyalgia, reflecting the substantial research interest and prevalence of these conditions in the field. Conversely, chronic neck pain was mentioned just once, indicating its status as one of the less studied conditions within the realm of ML applications in pain research.

Building upon this, (Matsangidou et al., 2021) conducted another systematic review focused specifically on the application of ML in pain medicine. This review reinforced the findings of Jenssen et al., highlighting the dominance of supervised classification and regression techniques in in addressing a range of issues related to pain, including but not limited to low back pain, shoulder pain, and spinal cord injuries. The reviewed studies primarily employed classical ML algorithms such as Support Vector Machines (SVM) and Random Forest (RF), alongside Bayesian techniques for classifying tasks by assigning predefined labels to data. Additionally, regression algorithms were commonly used to produce continuous numerical outputs, serving crucial roles in categorizing pain intensity and forecasting pain occurrence, its probability, variability, and response to treatment.

Furthermore, (Lotsch & Ultsch, 2018) presented findings from a broader investigation into the use of AI in pain research. Echoing the results of both Jenssen and Matsangidou, Lotsch emphasized the commonly used of similar ML algorithms, with a noteworthy addition of deep learning methodologies that have become very prominent after regression approaches. Consistent with Jenssen et al., the review identified low back pain, musculoskeletal discomfort, and osteoarthritis as the predominant pain types addressed through ML.

On the other hand, a recent systematic review by (Barrera-Garcia et al., 2023) highlights the critical role of feature selection across diverse scientific disciplines, including medicine, chemistry, biology, and the physical sciences. This comprehensive analysis surveyed numerous ML studies to identify trends in algorithm usage. Remarkably, the review revealed that the K-Nearest Neighbors (K-NN) classifier emerged as the most prevalent, appearing in a substantial 77% of the reviewed papers. This was closely followed by the Support Vector Machine (SVM) algorithm, which was noted for its presence in 17.4% of the studies. This finding underscores the widespread applicability and preference for K-NN in tackling feature selection problems across various scientific fields.

Referring again to Jessen's review, features such as displacements, speed, and smoothness were frequently employed to evaluate body dynamics. For instance, research conducted by (Olugbade et al., 2015) introduced feature optimization algorithms and ML techniques aimed at distinguishing between low and high pain intensities during physical activities, leveraging data on the displacement range of the arms, trunk, and neck. Similarly, (Qin et al., 2016) used speed and smoothness metrics from various body parts to create an ML-based system capable of continuously identifying pain-related behaviours through patient body movements. Additionally, (Golabchi et al., 2019) explored the use of EMG parameters such as RMS, variance, and energy to autonomously recognize abnormal muscle activity patterns during functional evaluations of individuals with lower back pain.

In contrast, the domain of prosthetics control and rehabilitation engineering has seen extensive research dedicated to exploring a broader array of features for pattern recognition and detecting movement intentions. This effort aims to harness the nuanced patterns of EMG signals, thereby enhancing the functionality and precision of prosthetic devices and other assistive technologies. Researchers in this field employ a diverse combination of time and frequency domain features to achieve the highest possible accuracy in classification. Among the most prevalent in the time domain are RMS, MAV, WL, and Variance, while the frequency domain frequently utilizes features like MNF and MDF. Despite the critical role these features play in the successful actuation of prostheses and the advancement of myoelectric control systems, the literature often lacks a detailed explanation for the selection or preference for certain sets of features over others. Typically, the choice of features tends to vary significantly across studies.

In the present thesis, a similar approach will be adopted by utilizing some of these EMG features, which have not been previously tested in the context of neck pain research. This innovative application aims to uncover new insights and potentially improve the understanding of neck pain.

1.2.3. Application in Neck Pain

Currently, the integration of ML models into the exploration of neck pain remains relatively limited. Over the past four years, since the study of Jenssen et al., only a handful of studies have delved into this specific area (Ferrillo et al., 2023; Liew et al., 2022; Park et al., 2023; Paskali et al., 2022) and out of those, a mere two have analysed neck pain as a standalone condition. These studies have mainly been centred around different techniques such as ultrasound imagine analysis, medical reports or biomechanical variables.

For instance, the study conducted by Liew et al. (Liew et al., 2022) explored the utility of complex ML algorithms, such as gradient boosting and random forest, for predicting non-specific neck pain outcomes and for classifying neck pain status using biomechanical variables from a clinic registry database. Notably, the application of ML models has shown promise in improving the prediction performance over traditional logistic regression, possibly due to the capacity of ML to better handle non-linearity between predictors and outcomes (see **Figure 1.4**).

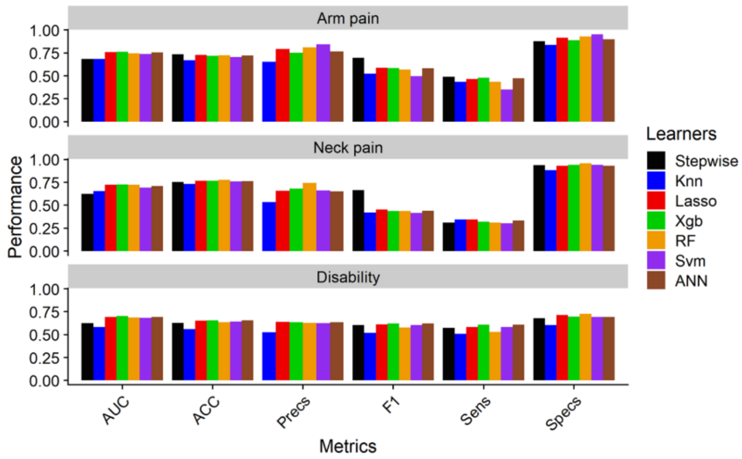

Figure 1.4. Comparative metrics for seven machine learning models predicting arm pain, neck pain, and disability outcomes. Key: AUC: area under the ROC curve; ACC: accuracy; Precs: precision; F1: F1 score; Sens: sensitivity; Specs: specificity. Models: Knn: K nearest neighbor; Lasso: least absolute shrinkage and selection operator; Xgb: extreme gradient boosting; RF: random forest; Svm: support vector machine; ANN: artificial neural networks. Source: Liew et al., 2022.

A more recent development is the application of ML in digital image analysis to quantify muscle stiffness associated with neck pain (Paskali et al., 2022). Using ultrasound elastography images, certain ML algorithms like the random forest, have been effective in distinguishing between patients with chronic neck pain and asymptomatic individuals. This approach could potentially lead to the identification of novel biomarkers for muscle dysfunction in neck pain, significantly improving our understanding of the condition.

While these innovations indicate the potential benefits of ML in neck pain research, it is important to acknowledge that the field is still in its early life. The benefit of ML in prognostic modelling may be dependent on factors like sample size, variable type, and the specific disease being investigated. As techniques continue to be refined and the understanding of these methods advances, the integration of ML models into neck pain research is expected to provide more sophisticated and accurate tools for prediction, classification, and comprehension of this prevalent condition.

1.2.4. Limitations in ML Approaches

While ML has immense potential, it is not without its limitations. It is essential to understand these limitations to apply ML models effectively and accurately interpret their results.

- Overfitting: One of the most common problems in ML, overfitting occurs when an ML model learns the training data too well (Hawkins, 2004). It captures not only the underlying patterns but also the noise or outliers in the data. As a result, while the model might perform exceptionally well on the training data, it performs poorly on unseen data (test data) because it is not generalised enough to handle new inputs. Techniques such as cross-validation, regularisation, and early stopping are commonly used to combat overfitting (Hastie T. et al., 2009).
- Curse of Dimensionality: As the number of features or dimensions in the dataset increases, the amount of data needed to ensure the ML model can learn effectively grows exponentially, a phenomenon known as the "curse of dimensionality" (Shany et al., 2015). High-dimensional datasets can lead to overfitting, increased computational cost, and decreased model interpretability.
- Generalisability: This term denotes the ML model's ability to correctly apply to new, unseen examples that differ from the training data. As training data often represents only a small fraction of all possible scenarios, generalisation is a central goal in pattern recognition (Bishop, 2006). To achieve that, ML models, particularly deep learning models, often require massive amounts of data to train effectively and provide accurate results for effective performance in real-world applications (Halevy et al., 2009).
- Bias in Data: The training datasets are the source from which ML models extract and learn information. If the training data contains biases, the models will learn

and perpetuate these biases, leading to unfair or unethical outcomes. This is a significant concern in fields such as facial recognition and hiring, where biased data can lead to discriminatory practices. Thus, it becomes imperative to guarantee the integrity and quality of the data to prevent such undesirable outcomes. (Buolamwini & Gebru, 2018).

- Interpretability and Transparency: ML models, especially complex ones like deep neural networks, are often termed as "black boxes" because their inner workings can be hard to interpret. This lack of transparency can be problematic in many applications where understanding why a particular decision was made is important, like in the healthcare sector (Castelvecchi, 2016).

These limitations highlight the need for careful model selection, data analysis, and validation in ML applications. Despite these challenges, ongoing research and development in the field continue to advance our ability to harness the full potential of ML.

1.3. Purpose of the Thesis

The purpose of the thesis is to investigate physical features associated with the presence of chronic non-specific neck pain by extracting and analysing associated biomechanical and EMG indicators through the application of ML techniques. In this way, the thesis aims to enrich the understanding of this condition and the associated neuromuscular and kinematic disturbances. The thesis recognises non-specific neck pain as a prevalent and debilitating health condition with substantial economic, social, and individual impacts. It emphasises the need for robust research efforts to develop more effective and efficient assessment and management strategies for neck pain.

By integrating ML approaches into the study of chronic non-specific neck pain, the thesis aims to employ the power of data analysis and pattern recognition to uncover new insights and improve classification approaches. The use of completely objective measures, such as EMG and motion capture systems, in assessing neck pain is highlighted as a vehicle to obtain more accurate and comprehensive information about the physical impact of this condition.

Overall, the primary aim is to determine if ML algorithms can effectively differentiate between individuals with and without chronic non-specific neck pain during various tasks. Additionally, this research seeks to identify the specific muscle activity and kinematic features that are most significant for this differentiation process.

Building on the hypothesis that existing literature has already shown distinct physiological differences between individuals with and without neck pain across different functional activities, it is anticipated that ML algorithms will possess a strong capability to effectively separate these groups for each task analysed. This expectation is based on the subtle variances in muscle activation and movement dynamics offer a measurable foundation for ML models to facilitate precise classification, enhancing our comprehension of neck pain and improving diagnostic and therapeutic approaches.

1.3.1. Aim and Objectives

The primary aim of this thesis is to enhance the understanding of neuromuscular and kinematic disturbances in people with chronic non-specific neck pain by leveraging ML approaches.

Objectives:

1. To investigate the potential of ML algorithms in differentiating individuals with chronic non-specific neck pain from those without neck pain during various tasks.
2. To identify and analyse the most significant muscle activity and kinematic features that play a pivotal role in the differentiation process.

1.3.2. Specific Aims of the Studies

The thesis encompasses three main studies, each addressing the overall objective aim of the thesis. Each study focuses on a specific task: dynamic task (repeated neck flexion), a static task (using the phone over a specific period of time), and gait analysis (including rectilinear, curvilinear, and dual-task gait). All these studies aim to distinguish people with chronic non-specific neck pain from healthy controls using ML algorithms trained with features derived from EMG and/or kinematics. The specific aims of these studies are described below and illustrated in **Figure 1.5**:

I. Study 1: Dynamic Task Classification

   The aim of this study is to accurately distinguish individuals into groups with chronic non-specific neck pain and healthy controls during dynamic neck movement, specifically focusing on three consecutive neck flexion movements. By employing ML algorithms, the study aims to identify the most informative subset of EMG features that enable effective classification and provide insights into the distinctive patterns associated with the presence of neck pain during dynamic tasks.

II. Study 2: Static Task Classification

This study aims to differentiate individuals with and without chronic non-specific neck pain based on features derived from a static task involving extended phone use. Using ML algorithms, the study seeks to identify the key EMG and kinematics features that contribute to accurate classification and shed light on the specific effects of the presence of neck pain on muscle activation, and control of posture during static tasks.

III. Study 3: Gait Task Classification

The aim of this study is to categorise individuals into groups experiencing chronic non-specific neck pain versus healthy controls by analysing features extracted from various types of gaits, including rectilinear, curvilinear, and dual-task gait. Through the utilisation of ML algorithms, the study aims to identify the most relevant EMG and kinematics subset of features that distinguish between individuals with chronic non-specific neck pain and healthy individuals during different gait patterns.

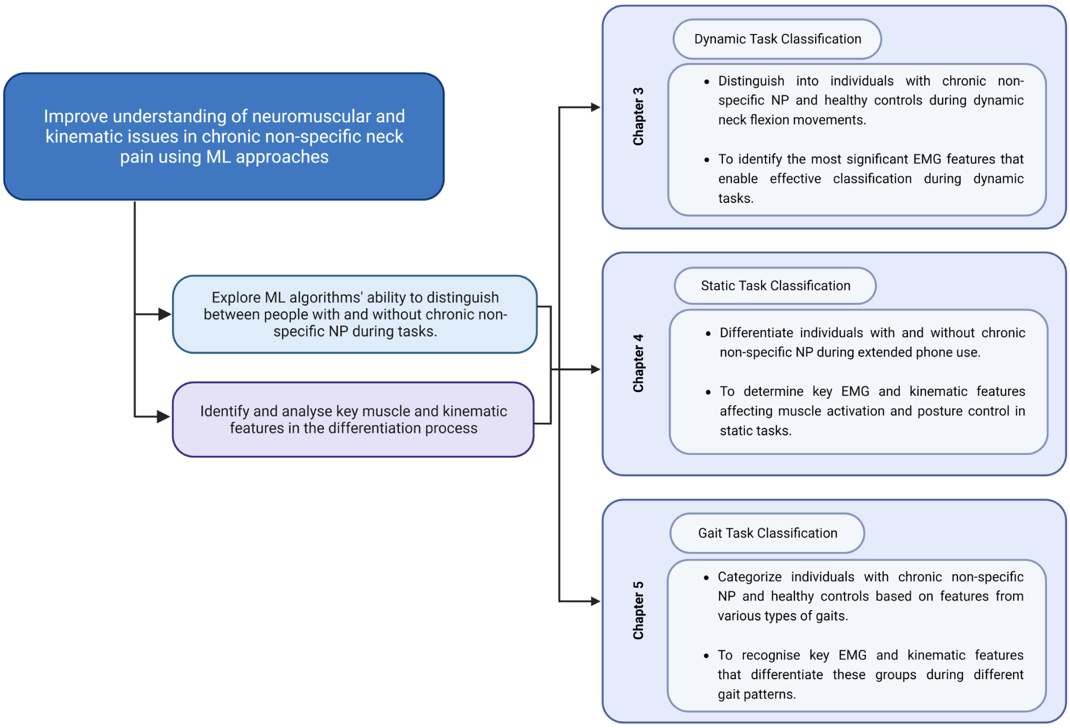

Figure 1.5. Flowchart of aims and objectives of the thesis linked to the relevant chapter. ML: machine learning, NP: neck pain.

CHAPTER 2: METHODOLOGY

This second chapter outlines the framework employed to conduct the research and achieve the objectives presented in the previous chapter. This chapter starts with a description of the data collection process, featuring participant selection and measurement systems. Subsequently, the conditioning and extraction of features is discussed, with a focus on time and frequency domain analysis. Post extraction, the chapter navigates through feature selection using Neighbourhood Component Analysis (NCA). The three supervised algorithms implemented, their training methodologies, and performance evaluations are also described. The final section offers a comprehensive exploration of how functional muscle networks were created and integrated into the analysis.

A. THE PROPOSED MACHINE LEARNING APPROACH

2. Machine Learning Framework

To evaluate the classification between individuals with chronic non-specific neck pain and those without, and to determine the optimal subset of features, this thesis proposes the pipeline illustrated in **Figure 2.1**. The framework initially incorporates data collection, during which data is gathered from both asymptomatic participants and those experiencing chronic neck pain. This is followed by data conditioning, where the acquired data is filtered and examined to ensure its quality and usability. Subsequently, various features are calculated and then examined by three ML models. Ultimately, a specific set of features is chosen by a feature selection model. These selected features are then used by the same classifiers to compare the performance of the ML models, as well as to evaluate the relevance of the selected features. Following, each step of the pipeline will be outlined.

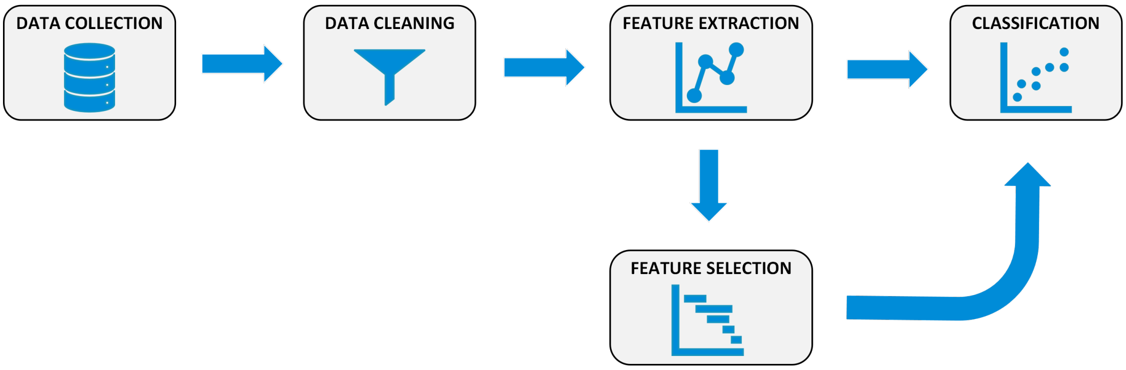

Figure 2.1. Flowchart of the methodology proposed

2.1. Data Collection

Data collection, a vital pillar of any research study, is a complex and detailed endeavour that aims to compile essential information from specific sources. This rigorous procedure requires a precise definition, including a thorough delineation of the particular sources to be examined, the methods to be employed, and the exact metrics to be applied. In the following sections, these topics are examined more deeply, identifying participants and discussing in detail the systems utilised, particularly EMG and motion capture methodologies.

2.1.1. Participants

For the comprehensive research contained within this thesis, a diverse pool of participants was recruited, including both healthy individuals and those afflicted with chronic non-specific neck pain. All the studies presented in the current thesis followed the same criteria related to inclusion/exclusion and participant information provided.

Specifically, individuals with chronic non-specific neck pain could participate in the study provided if they met the following conditions: their average pain intensity, experienced over the previous month, exceeded 3 on a 10-point Numerical Rating Scale (NRS), where 0 signified no pain and 10 represented the most severe pain conceivable (Boonstra et al., 2016; Kamper et al., 2015); and they had a record of neck pain persisting for over three months. Additionally, neck pain participants were excluded if they had a history of specific neck pathologies such as cervical radiculopathy, spinal stenosis, or tumours.

On the other hand, asymptomatic volunteers were accepted if they had no record of neck pain requiring professional medical attention within the last two years. Individuals were not considered for the study if they had undergone spinal surgery in the past, had a rheumatological condition, had an ongoing or chronic respiratory condition, or were involved in an active compensation claim related to an injury.

All participants received both written and oral details outlining the procedures of each study. Prior to participation, written informed consent was obtained from each individual. To eliminate potential bias, no predictions or suggestions about the expected results were revealed. Ethical approval for all research projects presented in this thesis was granted by the Ethics Committee of the University of Birmingham (UK) and conducted according to the principles of the Declaration of Helsinki. Experimental sessions were conducted in a controlled environment within the laboratory facilities of the Centre for Precision Rehabilitation for Spinal Pain (CPR Spine).

2.1.2. Measurement Systems

To execute the research encapsulated within this thesis, it was employed a variety of systems for the efficient and accurate collection of muscle activity and kinematics data.

- Surface electromyography

As mentioned in Section 1.1.7, EMG serves as a powerful tool for measuring and recording muscle activity. Within this field, Surface EMG (sEMG), in particular, plays a unique role. As indicated by its name, sEMG involves carefully positioning electrodes right on the skin's surface above the muscle of interest. These sensitive electrodes are designed to capture the nuanced electrical activity produced by muscle fibers as they contract and relax. sEMG is easy to use with minimal to no discomfort for the person under examination, making it a widely preferred tool in various clinical and research environments.

For the present studies carried on this thesis, sEMG with bipolar electrodes was used to record the electrical activity of different neck muscles (further specific details are presented in the individual chapters). In order to obtain high quality signals from the different experiments the following protocol was followed (Merletti et al., 2016):

1. Muscle palpation: This process involved identifying the specific locations of the muscles by manually palpating them and applying slight pressure. After determining the most suitable points for sensor placement, these areas were marked with a pen to ensure precision in subsequent steps. Following the SENIAM recommendations, bipolar surface electrodes were then positioned at these marked points (Merletti & Hermens, 2000).
2. Skin preparation: The skin was cleaned exfoliated with an abrasive paste and finally cleaned with water and dried to remove any remaining residue. If hair was present in the area, it was shaved off initially.
3. Sensor attachment: Both electrodes and their associated sensors were placed over the cleaned skin using adhesive stickers and tape. This was done to secure them firmly in place and prevent movement artifacts that could interfere with the accuracy of the readings.
4. Signal verification: The final step was to ensure the correct functioning of the sEMG signals. This process began by validating the connections between the electrodes, sensors, and the computer. Additionally, it was checked the signal to noise ratio to ensure the accuracy of the data, and examined any power line interference that might affect the readings. Subsequently, the participants were asked to execute simple head movements. By observing these movements, it becomes evident that the relevant muscles are activated at the appropriate times.

- Motion analysis systems

To record kinematic data during different tasks, two different systems were used:

- Optical motion capture system

Optical motion tracking systems have been widely used in gait research and for clinical proposes (Simon, 2004). Sophisticated and intricate movements can be effectively recorded using three-dimensional tracking systems that utilise infrared cameras and reflective markers. After strategic placement of reflective markers on key anatomical landmarks, the infrared cameras positioned around the space capture the positions of each marker. Once movement commences, cameras record the marker positions many times per second, and by combining the perspectives of multiple cameras, a three-dimensional representation of motion is reconstructed, providing comprehensive data on the subject's movement. Despite requiring visibility of markers and a controlled environment, these systems capture subtle motion information. This enables the calculation of aspects such as velocity, acceleration, and angular measurements in different planes, making them indispensable tools in fields like biomechanics, animation, and sports science (Menache, 2011).

The kinematics analysis, in motion capture systems, is typically done by the software included within the system. This software is capable of translating the raw data coming from the markers into body kinematics, gait events and kinematic features of joint and body segments.

However, this kind of systems have some drawbacks such as high expense, complex setup, limited to the laboratory conditions and necessitates an extensive training. Despite its unparalleled detail and accuracy, the system's dependence on visible markers and a controlled environment restricts its applicability to laboratory settings, compounded by its high cost, complexity of setup, and the extensive training required for operation. Commercial systems, while excelling in studio settings, often falter in everyday environments due to issues like unreliable global transformations and common drift seen in purely inertial setups. On the other hand, the high quality of motion capture systems is counterbalanced by their notorious complexity and cost, which limits accessibility. There have been efforts aimed at developing these systems from commodity components to reduce setup costs and make motion capture more consumer-friendly (Wang, 2011). Moreover, traditional systems require controlled lighting and specific settings to function correctly, a constraint that severely limits the capture of outdoor or large-area motions. Additionally, the accuracy and precision of motion capture systems, critical to their utility, can be significantly affected by various factors, including camera setup, marker size, and the use of lens filters. A study by (Windolf et al., 2008) highlighted the variability in system performance, underscoring the need for meticulous configuration to ensure the reliability of captured data.

In general, the utilization of this kind of systems in gait analysis is supported by their unparalleled high accuracy and resolution, capability to provide detailed kinematic data, and non-invasive nature of measurement. These systems are acclaimed for their exceptional spatial and temporal resolution, which is pivotal in the precise measurement of movement. Such accuracy is indispensable for detecting subtle gait abnormalities or changes in gait patterns over time, elements crucial for both clinical assessments and research endeavours. This precision in capturing the minutiae of movement facilitates the identification of even the most nuanced alterations in gait, which can be instrumental in diagnosing and monitoring various conditions (Saboune & Charpillet, 2005) Furthermore, optical motion capture systems excel in delivering detailed three-dimensional kinematic data, encompassing a comprehensive analysis of the entire gait cycle. This includes the measurement of joint angles, velocities, and accelerations—data crucial for a deep understanding of walking mechanics and pinpointing potential issues (Mihradi et al., 2011). Additionally, the non-invasive nature of these systems, which involves the simple placement of reflective markers on the skin or clothing of individuals, ensures that the natural gait is not disrupted.

- Inertial Measurement Unit

An Inertial Measurement Unit (IMU) is an electronic device that directly measure an object's orientation and angular velocity, using a combination of accelerometers, gyroscopes, and sometimes magnetometers. With advancements in electronics, these devices have become significantly smaller, allowing for easy placement on different surfaces. As a result, they are referred to as wearable sensors, as they can be placed on various body parts without producing any discomfort. They are commonly secured with an elastic band around the target limb or an adhesive sticker. By placing a combination of IMUs on the body, precise tracking of movement and orientation in space can be achieved simultaneously for different limbs and body parts.

For instance, IMUs have been demonstrated significant utility in gait analysis and in clinical practise, for example, in Parkinson' Disease (Caramia et al., 2018). Their straightforward implementation, user-friendly operation and low-cost, make them attractive alternatives to the more expensive and complex motion capture systems.

Notably, while IMUs offer significant advantages in terms of ease of use, affordability, and flexibility of application, they may not achieve the same level of precision in capturing extremely subtle movements as their optical counterparts. Despite their widespread adoption across various fields for motion analysis, the use of IMUs brings forward unique challenges that underscore the trade-offs between convenience and data fidelity.

The performance of IMUs faces challenges due to sensor limitations and environmental factors. Accelerometers and gyroscopes in IMUs show linearity within limited sensor ranges, leading to nonlinearity in extended ranges, which necessitates complex calibration for accuracy, especially in long-range applications (Zhang et al., 2022). Additionally, IMUs are susceptible to magnetic disturbances that can significantly impair their accuracy, particularly in precise joint angle measurements, often necessitating a recovery period in a magnetically neutral environment to return to baseline accuracy (Robert-Lachaine et al., 2017). This highlights the challenges in maintaining IMU reliability across varying conditions.

Although challenges exist, with adequate calibration, IMUs can achieve error margins of less than 1°, thereby offering a reliable means of assessing postural stability and sway under static conditions (Brodie et al., 2008). The efficacy of IMUs in measuring postural stability has been corroborated under both controlled static and dynamic conditions, validating their accuracy in capturing sensor orientation and angular velocity (Taylor et al., 2017). The capability of IMUs to facilitate the assessment of balance and stability beyond the confines of laboratory environments significantly enhances their utility. By enabling evaluations in more naturalistic settings, IMUs underscore their indispensability not just in clinical assessments but also in the broader research domain focused on postural control and balance disorders.

Further details regarding the specific systems used and their characteristics are explained in Chapters 3, 4, and 5.

2.2. Data Conditioning

In order to ensure the reliable measurement of muscle activity and body motion, it is necessary to decontaminate the signals from any unnecessary interference, often referred to as noise. Hence, conducting a preliminary analysis becomes crucial to enhance the processing, analysis, and interpretation of the data at later stages, thereby preventing the propagation of noise.

After the conclusion of data collection, the raw data is exported for an initial analysis phase. This phase involves two main processes: cleaning and transformation. These processes, along with subsequent analyses detailed in the remainder of the present chapter, were executed using custom scripts developed in MatLab 2019b, version 11.6 (MathWorks, Natick, MA, USA). Data analysis was performed with the MatLab's Statistical and Machine Learning Toolbox.

2.2.1. Data Cleaning

This is one of the most important steps during the pre-processing. Here, it is when it is needed to find and correct errors in the raw data like duplicates, outliers or missing values.

In the case of EMG, data cleaning consists mainly of noise reduction. EMG signals can be contaminated from different sources such as movement artifacts, electrical interference or skin impedance. Movement artifacts are unwanted disruptions in the data caused by the movement of the subject or the device (and its wires). Electrical interference refers to noise caused by usually power lines or other electronic equipment. In both cases, the noise can be often removed using filters such as a notch filter (for power line interferences, typically at 50-60Hz) or a bandpass filter to allow only the frequency of interest for EMG signals (often between 15 and 400Hz). Furthermore, in applications where EMG electrodes are placed near the neck, additional considerations must be made to mitigate potential contamination from electrocardiogram (ECG) signals, given their proximity to the heart. To address this, strategic electrode placement, differential amplification in a bipolar EMG configuration, and signal filtering with a 3rd order Butterworth bandpass filter between 15 and 400Hz are employed. These methods collectively ensure that ECG interference is minimized, enhancing the reliability and accuracy of the EMG data by focusing on muscle activity while excluding unrelated electrical signals. Skin impedance is the resistance of the skin to the electrical signal that is being recorded. As per the suggestions provided in Section 2.1.2, impedance can be effectively reduced by thoroughly cleaning and drying the skin prior to any recordings. This minimises the barriers for signal transmission, thereby enhancing the quality and accuracy of the EMG data captured (Clancy et al., 2016).

While IMUs may not experience as wide a range of noise interference as EMG, they are nonetheless vulnerable to certain types of noise disruptions. Two of these are zero frequency components and high-frequency noise. Zero frequency components or direct current bias are a constant offset present in the data which could produce unwanted linear trends. Those can be easily removed by using filters with detrending methods. High frequency noise refers to that noise which is not related to the human movement as most meaningful movements occur below 10Hz. Therefore, high-frequency components beyond this threshold are likely to be noise and not meaningful signal. To tackle this issue, a low-pass filter is often used (Winter, 2005).

2.2.2. Data transformation

This refers to the process of converting raw data into a format more suitable for furthers analysis. In general, it involves processes like scaling or normalisation in order to bring all the different variables to the same scale in order to provide a uniform set of attributes. For example, in EMG, normalisation is often done to facilitate comparisons across individuals or conditions. This is due to many factors such as muscle size, skin thickness and differences in muscle activation that can vary significantly between subjects. Therefore, EMG data is normalised to a reference contraction, usually a maximal voluntary contraction (MVC) performed by the individual (Burden, 2010).

MVC normalization plays a pivotal role in establishing baseline comparability for EMG data, enabling adjustments for individual differences in muscle strength and activation capacity. This technique facilitates the quantification of EMG amplitudes as a percentage of the MVC, thereby providing a more nuanced understanding of muscle activation levels across diverse tasks and conditions. Such a methodology, as elucidated by Burden (2010), significantly improves the comparability of EMG data by standardizing signals against a maximal voluntary contraction benchmark. This addresses the inherent variability observed in raw EMG signals, as documented by (De Luca, 1997) and (Hug, 2011), enhancing data comparability across different participants, muscle groups, and experimental settings.

The advantages of MVC normalization extend to the enhanced interpretability of muscle activation data, allowing for precise comparisons across varying muscles, individuals, and activities on a relative scale. Nevertheless, the efficacy of this technique is contingent upon the participant's ability to exert a true maximal effort. This may pose challenges in populations experiencing pain, injury, or neuromuscular disorders. Variations in maximal effort, driven by motivational factors, skill level, task comprehension, or fatigue, may introduce inconsistencies in the normalization process. Furthermore, the applicability of MVC normalization may be constrained by its specificity to the muscle under examination and the nature of the contraction performed, potentially limiting its utility across diverse research designs or muscle actions. This normalization presupposes a linear relationship between EMG amplitude and muscle force, a theory that might not universally apply, as suggested by (Alkner et al., 2000). Moreover, some individuals may find MVC trials uncomfortable, and factors like electrode placement accuracy and muscle fatigue could confound normalized EMG values, which aim to offer improved interpretability and comparability by representing muscle activation as a proportion of maximal capacity (Farina et al., 2002).

Despite these inherent challenges, MVC amplitude normalization markedly improves the clarity of EMG data interpretation. However, the deployment of this method necessitates a thoughtful consideration of its limitations and the research context at hand. Grasping these restraints is essential for the accurate analysis of muscle activation patterns, underscoring their significance in biomechanical and physiological studies.

On the other hand, normalisation is also fundamental aspect of ML analysis. Feeding the algorithm with normalised data not only simplifies the learning process but also significantly influences the results. For instance, if data is not normalised, the different scales of features can cause the algorithm to take longer to find this optimal set, thus affecting the speed of convergence and potentially slowing down the learning process. This is because differences in the range of feature values can lead to different gradients (vectors directing towards the fastest increase of a function), causing the algorithm to take longer to find the optimal solution. Moreover, certain ML models involve mathematical operations such as dot products or Euclidean distances, which can be also affected by features spanning different range of values (Kubat, 2017).

On top of that, without normalisation, some ML algorithms might accidentally assign more importance to features with higher values. By normalising, equal importance is allocated to each feature, thereby improving the model's capacity for accurate and unbiased predictions.

2.3. Feature Extraction

A feature is, in essence, a condensed abstraction or simplification of the raw data that can be afterward easily manageable and interpreted. It represents measurable properties of an individual or a phenomenon. The process of transforming raw data (after data conditioning) into features is known as features engineering or feature extraction (Guyon & Elisseeff, 2006). Engineering an effective set of features is a crucial component of ML, serving as a prerequisite for achieving a good performance in any learning task. In other words, a well-defined feature set can enhance the performance of any model.

When dealing with signals, features can be extracted in both time and frequency domains, which provide two different perspectives of the same signal. For this particular thesis, well-known features from EMG and kinematics in both domains were considered along with other features that are not as widely recognised or used in the literature of neck pain. The set of features extracted are described in the following sections.

2.3.1. Time Domain

Time domain features provide intuitive and straightforward information about changes in signals over time. In the present thesis is covered the following features:

- EMG

Time-domain features are statistical parameters derived directly from the pre-filtered EMG signals. These features do not involve any further transformations and provide valuable information about the characteristics of the raw EMG signals. Their calculation is predominantly based on the amplitude of the input signals, providing a straightforward analysis method (Clancy et al., 2016; Spiewak, 2018).

In Section 1.1.2., it was highlighted that numerous time-based EMG parameters have been effectively employed in various fields, including upper limb prosthetics, hand movement classification, and facial recognition research, offering new insights through the capture of significant properties of EMG signals. Notably, these studies have employed a combination of features such as the MAV, RMS, Variance, WL, and the SSI among others to capture the different signal's key characteristics. Given the success of these time-based features in enhancing signal analysis by capturing distinct muscle movements and facilitating improved classification tasks, our methodology incorporates a selection of these well-established time features. This approach is reinforced by the objective to provide a comprehensive analysis of EMG signals in the study of neck pain. By integrating these proven time-based parameters, along with exploring additional features not as widely recognized in the neck pain literature, this research aims to offer a better understanding of the complexities associated with neck pain, drawing upon the insights presented in previous studies.

The EMG time-domain features calculated in the present thesis are:

1. Mean Absolute Value (MAV): It is an essential feature in EMG signal analysis and represents the average rectified value of the EMG signal. It is often used to indicate the muscle contraction level (Spiewak, 2018). It reflects the average muscle contraction level, serving as an indicator of how active the muscle is during the recording period. Physiologically, MAV can be related to the recruitment of muscle fibers within the recorded muscle group, providing an indication of muscle activation levels during different tasks.
2. Root Mean Square (RMS): It is another key attribute that provides a measure of the power of the EMG signal and is a standard method to estimate the amplitude of the signal (Clancy et al., 2016). It correlates with the force generated by the muscle, as it considers both the amplitude and frequency components of the signal. RMS is particularly useful in estimating the strength of muscle contractions and can be indicative of muscle fatigue over time. he calculation method of RMS inherently places additional weight on higher amplitude fluctuations by squaring these values, thereby heightening its sensitivity to variations in contraction intensity. In contrast, the MAV presents a less sensitive yet more stable analysis, robust to sudden fluctuations or outliers, and provides a consistent overview of signal amplitude. This distinction makes RMS particularly

adept at capturing the dynamic aspects of muscle activity, whereas MAV offers a reliable measure of overall muscle engagement.

3. Variance (VAR): Represents the distribution of the EMG signal around its mean value. It gives an idea of how the signal is spread and may suggest the complexity or fluctuation in muscle activity (Phinyomark et al., 2009). High variance might indicate a more complex or fluctuating muscle activation pattern, possibly due to factors like muscle fatigue or non-uniform fiber recruitment. VAR is important for analyzing the uniformity of muscle activation and detecting changes in muscle behavior, which can have implications for assessing muscular health and function.
4. Waveform Length (WL): Denotes the cumulative length of the EMG waveform. It measures the rate of change of a signal, identifying levels of muscle contractions or muscle fatigue (Phinyomark et al., 2014). This feature is particularly useful for detecting changes in muscle activity that may occur with fatigue or during sustained contractions. An increase in WL indicates a more complex signal with frequent changes in amplitude and frequency, which could occur during rapid or variable muscle contractions. WL's physiological relevance is in its ability to track the rate and pattern of muscle contractions, offering insights into muscle endurance and fatigue.
5. Single Square Integral (SSI): It is the total power of the signal. It gives information about the global activity and energy of the muscle (Sijiang & Vuskovic, 2004). It is particularly valuable in applications requiring an assessment of the muscle's total exertion or energy output, such as in endurance training or rehabilitation monitoring. SSI is included for its capacity to aggregate signal power over time, offering insights into the sustained performance of the muscle.

The mathematical definitions for all features, from the time domain, are comprehensively outlined in **Table 2.1**.

- Kinematics

The time-domain features in kinematics rely mainly on position, velocity and acceleration, are not only straightforward to compute but also intuitive to interpret. To conduct a comprehensive analysis of the kinematics, it was opted for a complete selection of time-domain features, which encompass velocity, acceleration, jerk, and smoothness. In detail, the calculation of smoothness in the literature of neck pain can indeed vary significantly. Some studies interpret smoothness as the number of peaks in velocity, while others define it in terms of normalised jerk cost (Franov et al., 2022). For the present case, smoothness was calculated as the metric of time-integrated squared jerk. In this way, low values represents a smooth movement and high values an abrupt movement (Shahbazi et al., 2018). Additionally, it was incorporated an additional kinematic time-domain feature, named path length, which measures the total distance travelled by a given point. In essence, lower values of path length may show a more efficient performance, indicative of minimal travel distance and an absence of any disturbance during movement. In contrast, high values could denote problems during the execution of the trajectory (Shahbazi et al., 2018). Detailed mathematical definitions for all kinematic time-domain features are provided in **Table 2.1**.

Table 2.1. Mathematical definitions of time domain features.

Features	Mathematical definitions
EMG	

Mean Absolute Value (MAV)	$MAV = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert$, where x_i represents i^{th} sample of the EMG signal, and N denotes the total number of samples in a signal window.
Root Mean Square (RMS)	$RMS = \sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}}$
Variance (VAR)	$VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2$
Waveform Length (WL)	$WL = \sum_{i=1}^{N-1}\lvert x_{i+1} - x_i\rvert$
Simple Square Integral (SSI)	$SSI = \sum_{i=1}^{N} x_i^2$
Kinematics	
Velocity	$v = {}^{\Delta x}/_{\Delta t}$ where Δx represents the change in position and Δt is the change in time.
Acceleration	$a = \Delta v / \Delta t$
Jerk	$j = \Delta a / \Delta t$
Smoothness	$S = \int_{t_1}^{t_2} \sqrt{j^2}\, \partial t$ where t_1 represents the starting point of the observation period and t_2 the end point.
Path length	$PL = \int_{t_1}^{t_2} \sqrt{a^2}\, \partial t$

2.3.2. Frequency Domain

Every collected and analysed signal possesses a distinct frequency composition, known as the signal spectrum. In contrast to their time-domain counterparts, frequency-domain features require a more complex calculation, based on the Fourier Transform which decompose the original signal (in the time domain) into different frequency bands (Winter, 2005).

- EMG

In the field of muscular activity analysis, frequency features are commonly used to study muscle fatigue and Motor Unit (MU) recruitment. As highlighted in the previous section, this set of features is also commonly employed in EMG classification and recognition studies (Phinyomark et al., 2012a; Winter, 2005). The features obtained from the frequency domain are described as follows:

1. Mean Frequency (MNF): Among the most frequently used features, along with MDF, the MNF represents the arithmetic mean of the frequency components within the power spectrum of the signal (Phinyomark et al., 2012a). It is particularly useful for evaluating the overall frequency content of the muscle's electrical activity. MNF tends to decrease with muscle fatigue, reflecting a shift toward lower frequency components as muscle fatigue progresses. This occurs due to the physiological fact that slower-twitch muscle fibers, which operate at lower frequencies, become more dominant as fatigue sets in, replacing the faster-twitch fibers that operate at higher frequencies.
2. Median Frequency (MDF): Denotes the frequency value that bisects the spectrum into two equal-amplitude segments. Unlike MNF, MDF is less influenced by the presence of noise and outliers in the signal, making it a reliable indicator of muscle

fatigue. As fatigue develops, MDF decreases, indicating a shift towards lower frequency components, similar to MNF, but it offers a more stable measure over time (Phinyomark et al., 2012b). For instance, in the presence of high-frequency noise, MDF is less impacted compared to MNF, thus offering a more accurate reflection of changes in the frequency spectrum.

3. Peak Frequency (PKF): It is the frequency at which the maximum power occurs in the power spectrum. It provides an indication of the dominant frequency components in the signal (Phinyomark et al., 2012a). Changes in PKF can reflect alterations in MU recruitment strategies, such as when different fiber types (fast vs. slow twitch) become more active under varying conditions of muscle use or fatigue.
4. Mean Power (MP): Refers to the average power of the signal in the frequency domain. It is useful for estimating the overall energy content of the signal (Phinyomark et al., 2012a). MP provides a clear view of how power is spread out over the frequency spectrum of muscle activity, showing us the average level of activity at different frequencies. If MP increases, it suggests that muscle activation is becoming more consistent across a wider range of frequencies. On the other hand, if MP decreases, it may indicate that muscle activation is focusing on a narrower set of frequencies, which could be a sign of muscle fatigue or the muscle using a specific type of fiber more heavily. Understanding MP is crucial for analyzing how muscle activity is distributed and identifying changes that occur due to varying physical demands or during different phases of muscle fatigue.
5. Total Power (TP): Represents the sum of all spectral components' power. It represents the total energy content in the signal and is a key feature in comparing the energy distributions of different signals (Phinyomark et al., 2012a). TP

provides a complete view of the energy output by the muscle, reflecting the overall activity level and the sum total of electrical activity generated by muscle contractions. An increase in TP indicates higher muscle activity, potentially due to greater muscle fiber recruitment or increased contraction intensity. Conversely, a decrease in TP suggests reduced muscle activity, possibly because of fatigue or relaxation. TP is particularly useful for assessing the overall effort and capacity of the muscle during tasks.

6. Intermuscular Coherence (IC): Refers to a method of analysis to examine the frequency domain correlation between EMG signals from different muscles. Its helps in understanding the common neural input to different muscle pairs, providing insights into the coordination of multiple muscles (Tiran, 2013).

The mathematical formulations for all the EMG features derived from the frequency domain are presented in **Table 2.1**.

- Kinematics

Although frequency features have considerable potential, they have been relatively underplayed in previous kinematic studies. These features can be particularly impactful, most notably in studies involving cyclical or repetitive movements, such as the analysis of human gait. Recognising the potential contributions of these frequency features to enrich our understanding, the analysis includes the introduction of the following frequency features:

1. Spectral Entropy (SE): It measures the probability of occurrent of an event. Specifically, it can provide insights into the regularity and predictability of different frequency components. A lower entropy would indicate a more uniform,

repetitive movement like biking, while a higher entropy would indicate a more complex, variable movement like running (Bao & Intille, 2004).

2. Total Power (TP): Refers to the total energy of a signal in the frequency domain. It is a way of quantifying how much information is carried by a signal. Higher total energy values would typically suggest a more vigorous activity, while lower values might correspond to less intense or slower activities (Bao & Intille, 2004).

The mathematical formulations for the kinematic features derived from the frequency domain are presented in **Table 2.2**.

Table 2.2. Mathematical definitions of frequency domain features.

Features	Mathematical definitions
EMG	
Mean Frequency (MNF)	$MNF = \frac{\sum_{j=1}^{M} f_j \cdot P_j}{\sum_{j=1}^{M} P_j}$, where f_j represents a frequency value of the spectrum at a frequency bin j, P_j is the EMG power spectrum at a frequency bin j, and M is the length of the frequency bin.
Median frequency (MDF)	$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j$
Peak Frequency (PKF)	$PKF = \max(P_j),\ j = 1, \ldots, M.$
Mean power (MNP)	$MNP = \frac{\sum_{j=1}^{M} P_j}{M}$
Total power (TP)	$TP = \sum_{j=1}^{M} P_j$

Intermuscular Coherence (IC)	$$IC(f) = \frac{\lvert P_{xy}(f)\rvert^2}{P_{xx}(f)P_{yy}(f)}$$ where $P_{xy}\,(f)$ is the cross-power spectral density of the two time-domain signals $x(t)$ and $y(t)$ at a given frequency f and $P_{xx}\,(f)$, $P_{yy}(f)$ are the auto-power spectral densities of $x(t)$ and $y(t)$, respectively.
Kinematics	
Spectral Entropy (SE)	$$SE = -\sum_{j=1}^{M} P_j \log_2 P_j$$
Total Power (TP)	$$TP = \sum_{j=1}^{M} P_j$$

2.4. Feature Selection

Feature selection is a vital process in ML, serving to identify and choose a subset of significant features from a larger set for use in model creation. Its importance lies in its ability to improve the model's performance, prevent overfitting, lower computational expenses, effectively handle high-dimensional datasets and obtain new insights of the mechanisms that produced the data. The process of feature selection is applicable in various learning contexts, encompassing both supervised and unsupervised methodologies. It is noteworthy that the process of feature selection remains highly respectful of the original representation of the features. This implies that the process merely selects a meaningful subset from the whole, without any transformation or manipulation of the original variables. Therefore, it offers an added benefit of interpretability.

Despite the broad applicability of feature selection, the implementation is often more emphasised in supervised learning, specifically in the area of classification tasks (Novakovic et al., 2011). However, alongside feature selection, the concept of feature ranking (or importance) offers a complementary perspective. Unlike feature selection, which aims to identify a subset of features, feature ranking evaluates and orders all features according to their relevance or contribution to the model's performance. This ranking facilitates understanding of each feature's importance, without necessarily excluding data from the model development process.

Inside of feature selection, three main categories can be identified: filter, wrapper and embedded techniques. Filter techniques engage with the inherent statistical characteristics of the data to discern and select features. This involves an extensive exploration of each feature's relevance, guided by various statistical metrics, which leads to a selection of features that are considered significant for the model. In contrast, wrapper techniques adopt an alternative approach where they utilise a predictive model, such as a classifier, as the criteria for feature assessment. The effectiveness of features is evaluated based on the performance of this chosen model, thereby determining the optimal subset of features. Lastly, embedded techniques represent a combination between the filter and wrapper techniques. They perform feature selection as a part of the model construction process. This results in an intrinsic connection between the feature selection and the model, making them particularly efficient and specific to the chosen learning algorithm (Guyon et al., 2006).

Indeed, each category of feature selection has its own advantages and drawbacks, hence, the choice of method should rely on the specific objectives and nature of the data. The literature offers a diverse range of methods for feature selection (Saeys et al., 2007). Neighborhood Component Analysis (NCA) presents a valuable addition to the field with the potential to enhance data understanding and model performance.

NCA represents a novel approach within the embedded techniques category. NCA stands out by providing a mechanism for feature ranking within the context of feature selection. It optimizes a feature weighting vector, which inherently ranks features based on their impact on model accuracy. This dual capability distinguishes NCA from traditional feature selection methods by not only identifying relevant features but also quantifying their importance. Such a process is particularly advantageous in fields requiring precise interpretation of feature relevance, like the biomedical applications cited, including EMG analysis, Alzheimer's Disease research, and EEG studies techniques which already successfully implemented this technique (Jin & Deng, 2018; Malan & Sharma, 2019; Manit & Youngkong, 2011).

Moreover, the efficacy of NCA has been previously demonstrated, notably in the field of chronic neck pain detection. In the study conducted by (Biswas et al., 2022), researchers used NCA to design a biomarker for identifying chronic neck pain among participants through the analysis of EMG signals during curvilinear walking. By harnessing NCA to isolate the most impactful features from the EMG data, they achieved notable diagnostic precision. This accomplishment highlights NCA's effectiveness in the meticulous selection and processing of EMG features for the detection of neck pain, affirming its suitability and efficiency.

In conclusion, while traditional feature selection methods focus on choosing a subset of significant features, NCA extends this by also ranking features according to their importance. This dual function enhances model interpretability and efficacy, making NCA a powerful tool for feature selection and ranking in ML applications.

2.4.1. Neighbourhood Component Analysis

NCA is an innovative, non-parametric method proposed by (Goldberger et al., 2004). It is designed to analyse and interpret complex data by assessing relationships between individual elements. One of the defining characteristics of NCA is its ability to recognise and employ a specific mathematical relationship within the data. This relationship is known as a quadratic distance metric, and it is a way to precisely measure how close or far apart points are from one another.

By using this measurement, NCA can effectively categorise similar points together, transforming the quadratic distances into probabilities as **Figure 2.2** illustrates. The key idea is that a data point (reference point) selects another point as its neighbor with a certain probability, and NCA aims to maximize the expected number of correctly classified points based on these probabilities. This probabilistic approach enables NCA to classify similar points effectively, and it is especially robust in scenarios with complex and non-linear relationships between data points. Uniquely, NCA does not make assumptions on the class distributions, and it preserves all information during the dimensionality reduction process.

In detail, the algorithm assesses a weighting vector w that corresponds to the feature vector x_i by optimizing the nearest neighbor learning classifier within the NCA framework. Similar to the 1-nearest neighbor classifier, a reference sample point x_j is selected for the sample x_i from all samples. The probability Pij of x_j being chosen as a reference point for x_i is higher depending on the closeness of the distance between the two samples. This distance can be measured by a weighted distance D_w defined as:

$$D_w(x_i, x_j) = \sqrt{\sum_{m=1}^{M} w_m \cdot (x_{im} - x_{jm})^2}$$

where w_m is the assigned weight of the m^{th} feature. The relation between the probability P_{ij} and the weighted distance D_w is established by introducing a kernel function k, which returns large values for small D_w. The probability P_{ij} can be defined as:

$$P_{ij} = \frac{k(D_w(x_i, x_j))}{\sum_{k \neq i} k(D_w(x_i, x_j))}$$

indicating that the likelihood of selecting a point as a neighbor is inversely related to the weighted distance, emphasizing closer points have a higher chance of being selected as neighbors.

Through this process, NCA differentiates itself by focusing on feature weighting and ranking, rather than merely selecting features based on a threshold. Specifically, it generates a feature weighting vector, providing a ranking of all features based on not only their statistical distribution but also their discrimination power (see **Figure 2.2**). This ranking is integral to understanding NCA's approach: it prioritizes features according to their relevance and contribution to model performance, rather than selecting a subset for exclusion or inclusion based on predefined criteria. The NCA algorithm allows for the selection of the most significant features, those with a weight greater than 5% of the maximum weight, for example. This identification process is guided by the goal of maximising classification accuracy, which can be regulated through an optimal regulation parameter (Yang et al., 2012).

NCA had shown to outperform classical reduction methods, such as Principal Component Analysis (PCA) or other popular feature selection technique like ReliefF (Malan & Sharma, 2019). This is primarily attributed to NCA's ability to retain the entirety of information throughout the reduction process and its capability to operate without presupposing the data's distribution.

Consequently, NCA serves as an effective tool for exploratory data analysis and feature ranking (importance), in contrast to traditional feature selection methods. It excels by providing insights into the relative importance of each feature, thereby enhancing the understanding and interpretation of complex datasets. This makes it valuable for various ML and data science applications. This makes it valuable for various ML and data science applications.

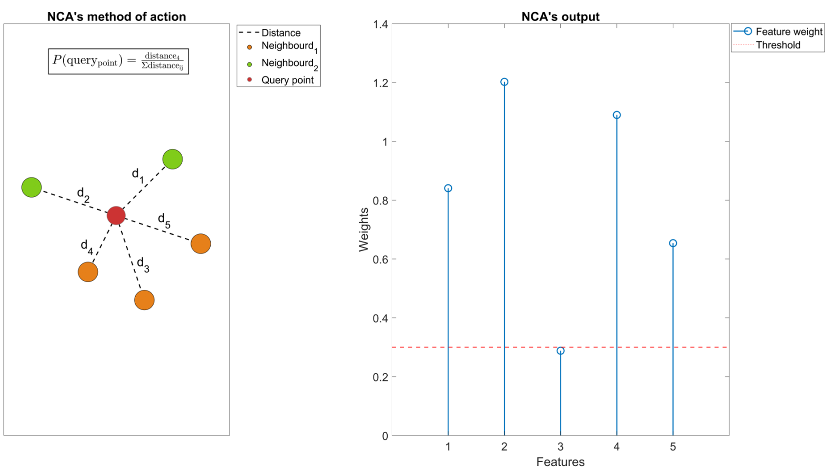

Figure 2.2. On the left, example of NCA's approach and on the right, NCA's features ranking.

In the context of the present research, the NCA approach is used to discern the most significant features in the discrimination between subjects with neck pain and healthy individuals. The rationale behind the employment of NCA pivots around two central objectives. The first aim tends to the improve the efficacy of the classification algorithms. The second objective seeks to identify the features that have a substantial impact on the classification process, thereby revealing potential markers that may be influenced by the task or pain-related factors.

2.5. Supervised Algorithms

As mentioned in Section 1.2.1, supervised algorithms operate on the principle of learning from provided labelled data to make predictions or decisions. In the context of the present thesis, three state-of-the-art supervised algorithms were selected for the classification, namely Linear Discriminant Analysis (LDA), K-Nearest Neighbour (K-NN), and Support Vector Machine (SVM). This decision was motivated by their differing data processing strategies, the intention to examine the performance efficacy of NCA and their proven effectiveness in the literature (Hayashi et al., 2015; Mokdad et al., 2020; Perumal & Sankar, 2016; Shi et al., 2018).

2.5.1. Linear Discriminant Analysis

LDA is a widely acknowledged parametric technique used extensively in the domain of ML and pattern recognition. Its operational principle is based on the concept of finding the optimal linear combination of features that best separates distinct classes in the data. By projecting the data onto a lower-dimensional space, it essentially constructs a separating boundary that maximises between-class variance while concurrently minimising the within-class variance. **Figure 2.3** illustrates a demonstration of a two classes-problem, showing the decision boundary selected by LDA.

LDA displays several qualities that are beneficial for real-time applications. Owing to its minimal computational demands, simplicity, and capacity to yield commendable results. However, one big downside is its linearity, which will lead to less satisfactory performance working with non-linear data. In this thesis, the LDA was specifically designed with an equal predictor covariance treatment among classes, which assumes homogeneity of variance-covariance matrices across groups, thereby simplifying the model structure. Additionally, gamma was set to 0.2 to adjust the decision boundary slightly, which can help in improving classification accuracy when dealing with datasets that do not strictly meet the LDA assumptions.

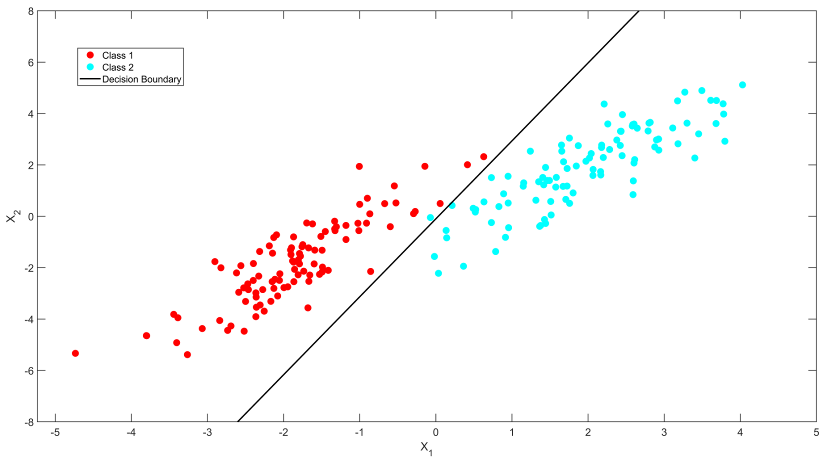

Figure 2.3. Example of a two-class separation problem using LDA

2.5.2. K-Nearest Neighbour

The K-NN algorithm is widely recognised as one of the most fundamental and frequently applied on classification techniques, particularly in the realm of action recognition (Choi et al., 2014; Ghasemzadeh et al., 2012; Zainuddin et al., 2016).

This non-parametric algorithm works by assigning a test sample to a class based on its proximity in feature space to the nearest training sample. Fundamentally, it starts by calculating the distance between the test sample and the pre-existing data contained within the training dataset. Following this, K-NN identifies the 'k' data points that are the closest to the test sample and classifies the new test sample by the predominant class within its surrounding area. **Figure 2.4** illustrates a visual representation of this procedure.

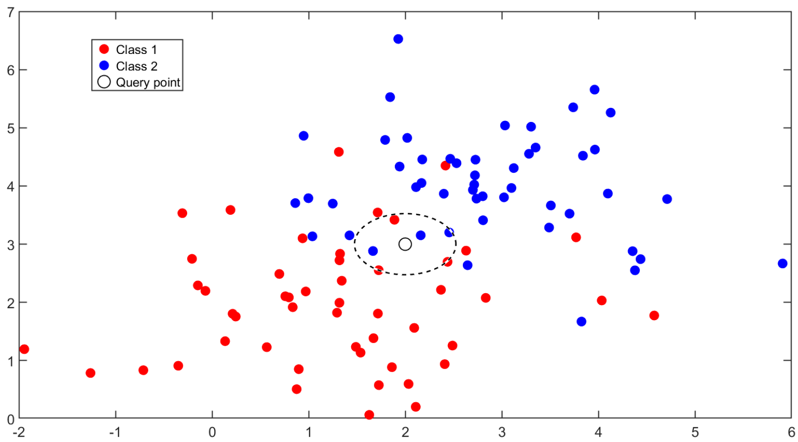

Figure 2.4. Example of a two-class separation problem using K-NN

In this thesis, Euclidean distance served as the metric for determining this proximity. To balance the risk of underfitting and overfitting, it was selected five (k = 5) as the number of nearest neighbors. It should be noted that there is no universally accepted protocol for determining the optimal k-value (Ghosh, 2006). As such, the experimental process involved evaluating a range of k-values (3, 5, and 7) before selecting the one that produced the best performance outcomes. The weight given to the neighbors was uniform, meaning all neighbors are weighted equally. This decision was made to maintain the simplicity of the model and ensure that the distance metric remains the primary determinant of the classification, without additional complexity introduced by varying the influence of individual neighbors based on their proximity.

2.5.3. Support Vector Machine

SVM is a potent, kernel-based classification algorithm that offers robust solutions to high-dimensional problems. It has shown remarkable results in multivariate scenarios, from the classification of human hand movements (Rabin et al., 2020) to gait classification of Parkinson's Disease (Caramia et al., 2018), and even prediction of Alzheimer's disease (Jin & Deng, 2018).

The key functionality of SVM revolves around constructing a hyperplane or set of hyperplanes in a high-dimensional space, which is used for classification, regression, or other tasks. The optimal hyperplane is determined by the data points, or "support vectors", that are closest to the class boundaries, and the goal of SVM is to maximise the margin around the separating hyperplane (Smola & Schölkopf, 2004).

SVM is capable of handling both linear and non-linear problems due to its kernel flexibility. For linearly separable data, a linear kernel function may be employed. However, when the problem involves non-linearly separable data, a Radial Basis Function (RBF) kernel or polynomial kernel can be used to project the data into a higher-dimensional space where linear separation is possible. In this thesis, the SVM was configured with a radial basis function kernel for all the present studies, emphasizing its adeptness at managing non-linear separability. This setup, with its default parameterization except for the specified kernel, was uniformly applied to enhance model consistency and comparability across studies. Exceptionally, for section 5.1, the configuration employed a linear kernel to address the specific data characteristics of that study section. Apart from the kernel functions, the rest of the parameters remained at their default settings, ensuring a standardized approach while allowing for the flexibility to tackle both linear and non-linear datasets effectively (Regularization parameter (C) = 1, Kernel Scale = 1, Cache Size = 1000). **Figure 2.5** shows a demonstration of two classes separation with RBF configuration.

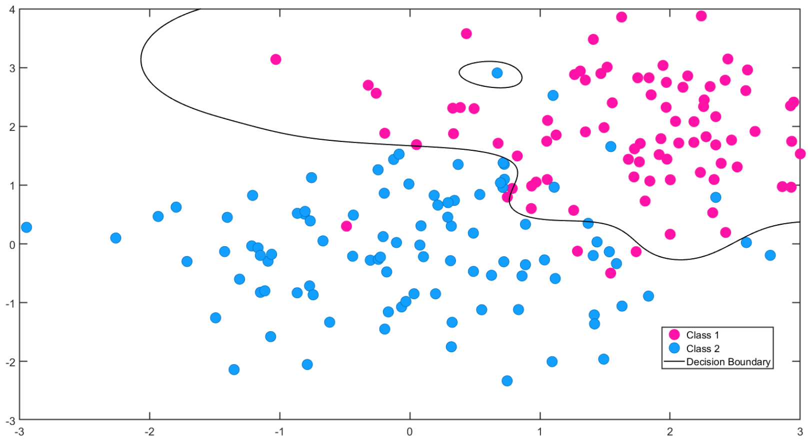

Figure 2.5. Example of two-class separation problem using SVM-RBF

2.5.4. Training process

In its simplest configuration, the model selection process involves two main data sets: a training set that is used for parameter estimation and a validation set that is used for adjusting a model to the training sample accurately. Simply comparing performances on the training data is not enough, as an overly complex model can fit the training examples perfectly but perform poorly on new data (poor generalisation). This is known as overfitting. The validation set helps detect overfitting by comparing the performance of different models. The best selected model's performance on the validation set gives an optimistic estimate of how it will perform on new data. To get a final assessment, a separate test set is needed, distinct from the training and validation sets (Guyon et al., 2006).

For datasets with limited size, a single split of the data into a training set and validation set may lead to a highly imprecise estimate of the generalisation error. A better approach is to divide the data into 'K' subsets, train the model on 'K-1' subsets, validate on the remaining subset, and repeat this process 'K' times with different splits between training and validation data. This technique is commonly known as K-fold cross-validation or Leave-One-Out cross-validation (LOO) when the ‘K’ subset is equal to one (Guyon et al., 2006). Because of database limitations, cross-validation techniques have been implemented for training all ML algorithms, aiming to ensure more reliable performance evaluations.

2.5.5. Performance evaluation

To verify the performance of the proposed ML methods, it was assessed the accuracy, sensitivity and specificity. Accuracy measures the classifier's capability to correctly differentiate data points, sensitivity indicates its ability to correctly classify data points belonging to the class under examination, and specificity measures its capability in distinguishing data points not belonging to the class under examination. These performance measures are valuable in determining whether the classifiers are performing better than random chance.

Their calculations rely on the counts of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), as illustrated in the following equations:

$$Accuracy = \frac{TP\ +\ TN}{TP\ +\ TN\ + FP\ + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificty = \frac{TN}{TN + FP}$$

Where TP represents the number of data points correctly assigned to the class under examination (positive class), while FP refers to the number of data points that are incorrectly assigned to the class under examination. TN represents the number of data points correctly assigned to the negative class, and FN represents the number of data points incorrectly assigned to the negative class.

Upon establishing a thorough understanding of these metrics, it is important to discuss what contributes an acceptable accuracy level for the current models employed in the neck pain classification. Unlike applications with higher stakes in misclassification (i.e., cancer diagnosis, heart disease prediction, or stroke risk assessment), the classification of neck pain presents a scenario where the risk of incorrect classification is less significant than it is for more severe conditions. This lower risk permits a more deliberate strategy in determining the criteria for "good" accuracy (Valdivia et al., 2021). This decision interlinks with different considerations:

1. Disease Prevalence: With the variable prevalence of neck pain, the model adjusts its focus between capturing as many true cases as possible (sensitivity) and avoiding the misclassification of those without the condition (specificity).
2. Severity and Impact: Given neck pain's generally non-life-threatening nature, the model seeks a balance. It aims to correctly identify sufferers for treatment while minimizing unnecessary concern or treatment for those incorrectly classified.
3. Cost Considerations: Financial aspects, such as the cost of unnecessary treatments for false positives, are manageable in the context of neck pain. This flexibility supports a preference for ensuring no cases of neck pain are missed.
4. Diagnostic Challenges: Since diagnosing neck pain typically does not involve invasive or expensive tests, the model can afford to prioritize accurately identifying true cases over minimizing false positives.
5. Treatment Efficacy: With effective treatments available, prioritizing the identification of all potential neck pain sufferers becomes feasible, reflecting an emphasis on maximizing patient care over the cost implications of false positives.

Considering these factors, it was determined a 70% accuracy threshold as indicative of "good" performance for the ML model. This standard represents a carefully considered balance, acknowledging the comparatively lower consequences of misclassification in this context (Kay et al., 2015).

B. Additional Analyses: An In-Depth Exploration of Coherence

2.6. Functional Muscle Network Analysis

The central nervous system (CNS) demonstrates an intricate and detailed functional organization to control complex motor tasks such as walking or balance. This complexity has attracted the attention of researchers, prompting extensive study in this area (Boonstra et al., 2015; Kerkman et al., 2020; Wojtara et al., 2014). To understand this coordination, researchers have looked deeper into the concept of muscle networks. Muscle networks refer to the way groups of muscles are functionally interconnected, often exhibiting synchronized activity patterns. Investigating these networks provides insights into how the CNS orchestrates movement.

IC analysis of paired EMG signals is a powerful tool for studying muscle networks (Hansen et al., 2005). It reveals the temporal synchronization between different muscle groups, indicating how these muscles co-activate over time to produce smooth and coordinated movements. This synchronization, captured through shared frequencies in EMG signals, provides empirical evidence of the underlying muscle synergies at work. Muscle synergies have been widely studied in various types of gaits, including treadmill walking and normal gait as well as postural stability (Barthelemy et al., 2010; Kerkman et al., 2018; van Asseldonk et al., 2014).

Recent advancements in muscle network analysis have expanded our understanding of how muscles interact during complex movements. By applying graph theory, researchers have revealed the modular and hierarchical nature of muscle synergies. This highlights how the CNS effectively simplifies the control of intricate motor functions (Kerkman et al., 2017; O' Reilly & Delis, 2022). Furthermore, muscle networks demonstrate the properties of small-world networks – high clustering and short path lengths. This architecture allows for both specialized and integrated communication across the musculoskeletal system, ensuring robustness and efficiency (O'Keeffe et al., 2021). Thus, muscle networks offer innovative means to explore the neural pathways that facilitate motor coordination, advancing understanding of motor function control.

2.6.1. Intermuscular Coherence and Connectivity Matrices

In the course of this thesis, it was introduced the IC, a well-established measure of functional synchronisation between different muscles (Dobie & Wilson, 1989; Miranda de Sá et al., 2002; Simpson et al., 2000), as a novel and promising frequency feature that could uncover new differences between healthy and neck pain individuals. By calculating coherence between groups of neck muscles, it is possible to quantify the level of connectivity strength at different frequency bands, spanning the entire spectrum from delta to high beta bands (Grosse et al., 2002). Notably, coherence in low frequencies (<5Hz) has been associated with force production, while the alpha band (8–12 Hz) is linked to involuntary force oscillations, and the beta band (12–25 Hz) is related to corticospinal projections (Castronovo et al., 2015).

The calculation of IC yields a connectivity strength value for each pair of EMG signals within a specified frequency band, resulting in a weighted adjacency matrix for each subject. To highlight only significant connections and filter out less relevant ones, a threshold is applied (Halliday et al., 1995). To ensure consistency across subjects, a proportional threshold is employed, maintaining the same connection density (Fornito, 2016). Upon obtaining the average coherence matrix for each group, the muscular connectivity can be visually illustrated in a graphical representation by applying graph theory. It basically interprets each muscle as a node within the network, while the functional connections, revealed by IC, are illustrated as edges connecting these nodes. **Figure 2.6**. illustrates an example of a four-node network, along with its corresponding adjacency matrix. As depicted in the figure, every connection in the network is symbolised by a square of yellow colour (value 1) in the adjacency matrix. This value simply indicates the presence (value 1) or absence (value 0) of a link between the nodes.

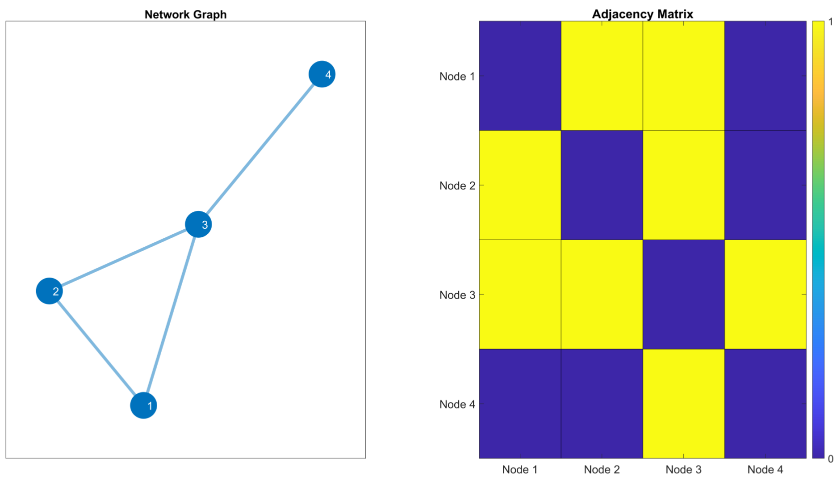

Figure 2.6. Example of four-node network (left) and its corresponding adjacency matrix (right)

2.6.2. Graph metrics

Graph theory is commonly used in EEG studies, where a larger number of signals are collected, resulting in networks with numerous connections and nodes. This permits the application of multiple metrics for comparison (Fornito, 2016). Nevertheless, in the context of this thesis, the data collection involves a smaller number of signals (limited by the number of neck muscles accessibility), leading to networks with a reduced number of connections and nodes. As a result, the analysis focuses on two key metrics: strength (ST) and betweenness centrality (BC). These metrics offer valuable insights into the network's characteristics, despite the limited data, enabling a focused investigation of the neural interactions in the context of the study.

On one hand, BC identifies key nodes in the network with high information traffic, and it is calculated as the ratio of shortest paths passing through a specific index node among all node pairs in the network. A higher BC value for a node indicates that it plays a more critical role in facilitating communication or interaction across the network. Physiologically, it reflects how certain muscles or groups of muscles may be pivotal to coordinating movements or transmitting neural information across the musculoskeletal system. On the other hand, ST represents the cumulative weights of links connected to a node, revealing the overall strength of connections between muscles. It reflects the muscle's influence or contribution to the collective muscle activity, with higher strength pointing towards a more prominent role in the neural control of movement (Mheich et al., 2020). All these network measures were computed using the Brain Connectivity Toolbox, a specialised tool for analysing functional connectivity and graph-based interactions between signals (Rubinov & Sporns, 2010).

CHAPTER 3: DYNAMIC TASK CLASSIFICATION

This chapter examines the exploration of potential EMG biomarkers related to cervical dynamic contractions in individuals with chronic non-specific neck pain. Utilising the methodology outlined in Chapter 2, the performance of various ML algorithms, the most significant features, and the complex muscle networks involved are investigated in detail.

3. Exploring EMG Biomarkers in people with Neck Pain during Neck Dynamic Contractions

3.1. Introduction

As highlighted in Chapter 1, numerous studies have demonstrated that individuals afflicted with neck pain often demonstrate significant alterations in muscle activity while executing functional tasks. Despite this understanding, the precise causes and consequential impact of these alterations remain ambiguous. Interestingly, there is a lack of comprehensive research or studies about this topic, particularly when looking at how neck pain relates to dynamic muscle contractions. While numerous studies have examined dynamic contractions of the neck muscles, only a limited number specifically aim to understand the relationship between these contractions and neck pain (Berg et al., 1994; Qu et al., 2019; Zaragoza-Rivera et al., 2020). Among the few studies available, one notable research found that people with neck pain present different membrane muscle fiber properties in the UT muscle and altered control strategies when compared to healthy individual during dynamic upper limb contractions (Falla & Farina, 2005).

The lack of extensive research on this topic highlights a significant opportunity for further study and learning. In the following sections, the propose is to further explore neck muscle activity during dynamic contractions in people with chronic neck pain, specially, neck flexions under load. It is expected that this task might reveal distinguishable differences between groups, enabling the classification of neck pain through ML algorithms. Furthermore, the aim is to extract the key features that contribute more to this classification. This study aims not only to deepen our understanding of changes in neck muscle activity in people with neck pain but also to unveil key insights that ML can offer in this context.

3.2. Methods

3.2.1. Participant recruitment

Twenty healthy participants and 20 people with chronic neck pain (CNP) were recruited for the study. The sample size was determined by taking an approximate average of the sample sizes used in previous studies that investigated similar populations and cervical muscles, specifically focusing on muscle activity and dynamic contractions (Castelein et al., 2015). This calculation yielded an average sample size of 15.8 for patients and 14.4 for control subjects from five different studies (Falla et al., 2004a; Falla & Farina, 2005; Helgadottir et al., 2011; Kallenberg et al., 2007; Zakharova-Luneva et al., 2012). Acknowledging its limitations, this method offers a rational baseline for conducting meaningful analysis within the constraints encountered in recruiting a larger cohort due to the specificity of the condition and exceptional circumstances such as a pandemic.

Participants with neck pain qualified for the study if they had an average neck pain intensity exceeding 3 on a NRS over the past four weeks, where 0 represents no pain and 10 signifies the worst pain conceivable. Furthermore, these participants had to have a neck pain history lasting over three months. Their perceived neck disability was assessed using the Neck Disability Index (NDI). In addition, detailed information regarding the location of the neck pain (Pain Side Location) and the side they perceived as most painful (Most Painful Side) were also acquired to investigate possible relationships with asymmetries in muscle networks analysis.

The study was conducted in a laboratory at the CPR Spine, under the approval of the University of Birmingham's Ethics Committee (ERN_19-1864), and in alignment with the Declaration of Helsinki. The inclusion/exclusion criteria and participant information provided adhere to the guidelines outlined in Section 2.1.

3.2.2. Experimental protocol

Participants were securely seated on a Multi-Cervical Unit (MCU, BTE Technologies, Inc, Hanover, MD), a weight-stack device that employs a mechanical pulley system, to perform the task. They were located with their back and legs firmly against the chair with straps, and their forearms resting comfortably on the chair's armrests. Following this, their heads were delicately attached to the MCU apparatus (see **Figure 3.1**). Subsequently, they executed six isometric maximal voluntary contractions (MVCs), split evenly between neck flexion and extension exercises, with a brief rest interval of three seconds separating each contraction. Throughout this stage, participants received encouraging verbal motivation to improve their performance.

Upon the completion of the MVCs, participants then conducted three successive neck flexion exercises, this time under load (1.38 kg). Three repetitions ensure participants could maintain optimal performance throughout, as the MVCs plus the familiarization time might contribute to early fatigue and reduce the exercises' effectiveness. This strategy was designed to preserve the quality of muscle contractions and protect participants from undue stress or strain, potentially leading to inaccurate results or an increased risk of injury.

The three flexions were synchronised with a digital metronome set to 35 beats per minute (bpm). The tempo determination was influenced by the study of (Connell et al., 2021), which employed a tempo of 60 bpm for more dynamic tasks in individuals with neck pain. This approach allowed participants to perform the exercise consistently, without experiencing undue fatigue or perceiving the pace as extremely easy. Participants can consistently perform the exercise without undue fatigue or the feeling of an overly relaxed pace. Participants usually began their movements after listening to the metronome beat for two to three cycles.

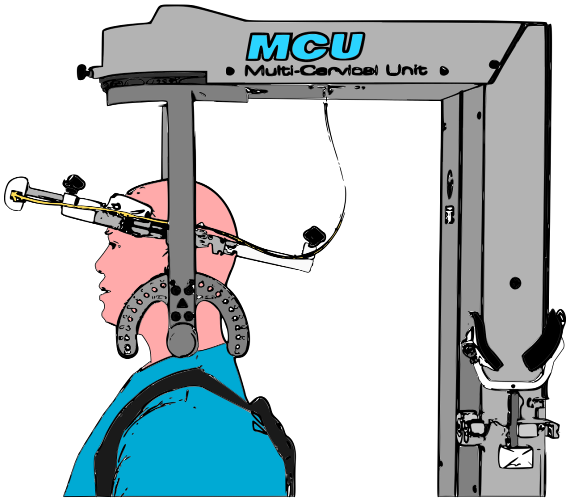

Figure 3.1. Multi-Cervical Unit (MCU). Source: Inkscape software.

3.2.3. Measurement systems

The Multi-Cervical Unit (BTE Technologies, Inc, Hanover, MD) was used to perform the cervical flexions. It has the capacity to secure the body and exclusively engage the muscles of the cervical region during a given exercise, making it ideal for carrying out a precise and safe cervical analysis, especially for individuals with neck pain (Pearson et al., 2009). Additionally, it offers a range of weight options to modulate the level of resistance applied to the movement. For the case of this study this weight was set to 1.38 kg for the participants. The choice of the weight was based on prior pilot tests conducted to estimate the appropriate resistance that challenges participants without causing undue strain, especially those with pain.

Surface bipolar EMG was recorded from UT, SC, AS and SCM bilaterally. Data acquisition was performed using a wireless measurement system (Ultium, Noraxon USA Inc., Sampling rate: 2000Hz, Resolution: 24 bits, Baseline noise: < 1 μV, CMRR: < -100dB) with dual-electrodes, positioned in alignment with SENIAM's guidelines

(Merletti & Hermens, 2000). All procedures detailed in Section 2.1.2 were meticulously followed.

3.2.4. Data analysis

To mitigate noise, the EMG data was filtered using a zero-lag, fourth-order Butterworth band-pass filter, implementing cut-off frequencies of 15 Hz and 400 Hz, in conjunction with a notch filter at a cut-off frequency of 50 Hz. For each recorded muscle, EMG data were normalised in relation to the participants' MVCs. Specifically, the normalisation of neck flexor muscles (SCM and AS) was executed with respect to the flexion MVCs, while normalisation of the neck extensor muscles was performed relative to the extension MVCs (UT and SC). This practice ensured comparability across different muscle groups and activities (Besomi et al., 2020). These tasks chosen for MVC normalization directly correspond to the primary functions of the targeted muscle groups. This ensures the normalization process accurately reflects the maximum activation potential these muscles can achieve during their most common actions. Consequently, this method facilitates a precise evaluation of muscle activation levels under conditions that closely resemble their natural function.

Following the procedure detailed in Chapter 2, after the completion of data extraction and conditioning, the extraction of features follows. All features described on **Table 2.1** and **Table 2.2** were extracted from the EMG data. In total, 88 features were extracted, encompassing 11 features per muscle. These features were then used as the input for the three algorithms described in previous section (LDA, K-NN, SVM) to classify between individuals with and without CNP. This input was processed both with and without the application of NCA in order to assess its utility and to extract the most relevant features.

The algorithms were trained employing the LOO cross-validation technique. In order to identify any potential differences in variables such as age, Body Mass Index (BMI), and muscle network parameters among the groups, an independent samples Student's t-test was employed. For the categorical variables related to pain location, a Chi-Square Goodness-of-Fit Test was used to test the uniformity of the distribution of responses. Prior to the analysis, the assumption of normality was verified using the Shapiro-Wilk test. Results were expressed as mean ± standard deviation, and a p-value of less than 0.05 was considered statistically significant.

3.3. Results

Table 3.1 provides a detailed overview of the participants' demographic characteristics. After the statistical analysis, no significant differences were identified between the groups in terms of these demographic characteristics, as supported by a p-value greater than 0.05. For the variable Pain Side Location, the Chi-Square statistic with p=0.82, indicating no significant difference for one side over the other. Similarly, for the variable Most Painful Side, the Chi-Square statistic with a p=0.21, also suggesting no significant difference for one side being more painful than the other.

The summarised results for each supervised model's overall accuracy, specificity, and sensitivity are presented in **Table 3.3**. This table illustrates the performance of each ML method in two scenarios: one using all features collectively, and another where only the features selected by NCA are applied. It is evident from all the cases that implementing the NCA algorithm enhances accuracy, specificity, and sensitivity, underscoring NCA's proficiency in detecting and eliminating extraneous or disruptive features that may hinder classifier performance.

The most notable classification performance by a 75% of accuracy when employing the SVM algorithm. This was closely followed by the K-NN algorithm with 72.5% of accuracy, and finally, the LDA algorithm exhibited a success rate of 67.5%. Another significant observation to make is the specificity exhibited by the K-NN algorithm, with a rate of 80%. This indicates its great capability to correctly identify negative instances which could be useful in scenarios where the accurate elimination of a condition or event is critical. To further elaborate, **Figure 3.2** provides insights into the number of features needed to reach these accuracy levels using the subset of features chosen by the NCA. Specifically, the SVM required nine features to achieve the 75% accuracy, while K-NN needed only three to attain 72.5%, and LDA required eight to reach 67.5%.

Table 3.1. Demographic characteristics of participants.

	Neck pain Mean ± SD	Control Mean ± SD	p-value*
Age (years)	26.85 ± 5.36	30.5 ± 7.41	0.065
BMI (kg/m^2)	22.896 ± 3.06	24.1255 ± 3.39	0.134
Gender (females %)	65	50	-
NDI (0-50)	24.3 ± 11.12	-	-
Average neck pain intensity (0–10)	4.05 ± 1.80	-	-

(*) Independent samples t-test, NDI: Neck Disability Index, SD: Standard deviation, BMI: Body Mass Index.

Table 3.2. Performance metrics for each classification algorithm reported as means (standard deviations) in percentage.

		All features	Selected features by NCA
K-NN	ACCU	47.50 (25.92)	72.50 (4.19)
	SPEC	47.36 (31.51)	80.00 (5.72)
	SENS	47.61 (22.74)	68.00 (5.69)
SVM	ACCU	47.50 (23.38)	75.00 (5.88)

	SPEC	47.36 (28.19)	72.72 (5.08)
	SENS	47.61 (21.06)	77.77 (7.11)
	ACCU	45.00 (14.25)	67.50 (4.28)
LDA	SPEC	44.44 (24.54)	70.58 (7.41)
	SENS	45.45 (12.38)	65.21 (3.68)

ACCU: accuracy, SPEC: specificity, SENS: sensitive.

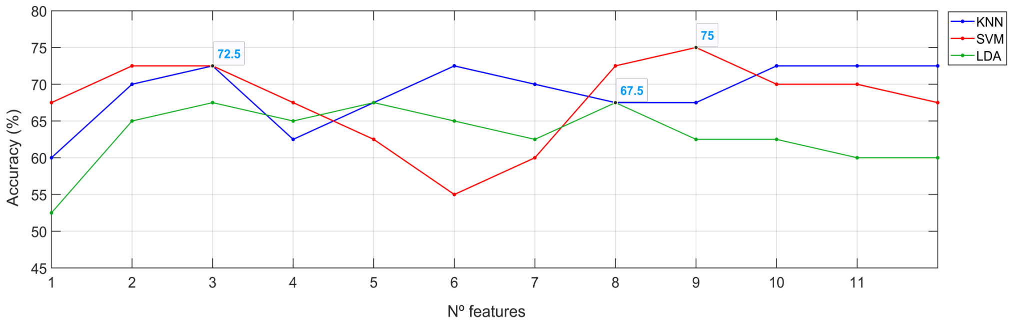

Figure 3.2. Accuracy versus the number of features selected by NCA. Features names corresponding to x-axis: SC Left MAV, SC Right MAV, SC Right RMS, UT Left WL, SCM Left MNF, AS Left MNF, SCM Right MDF, SC Left MDF, SC Right MDF, SCM Left PKF, AS Left PKF, IC.

The weight distribution of features as determined by the NCA is visually represented in a boxplot in **Figure 3.3**. This diagram illustrates not only the relative importance of each feature for the classification process, but it also identifies the neck muscle that encapsulate the most influential features. In this representation for the cervical flexion, clearly, the SC holds the heights weights, followed by the SCM and the UT. Conversely, the AS carries the least weight among them.

Table 3.3. presents the specific features that the NCA has selected, in addition to their corresponding weights. Overall, the SC with MAV and MDF and the UT with WL have the most significant influence on the classification process. Meanwhile, the muscles with lower weights like the AS muscles might play a less prominent role in the classification. Additionally, a mix of time-domain and frequency-domain features were selected which suggests that both domains are important for the classification and therefore, for differentiating muscle activity.

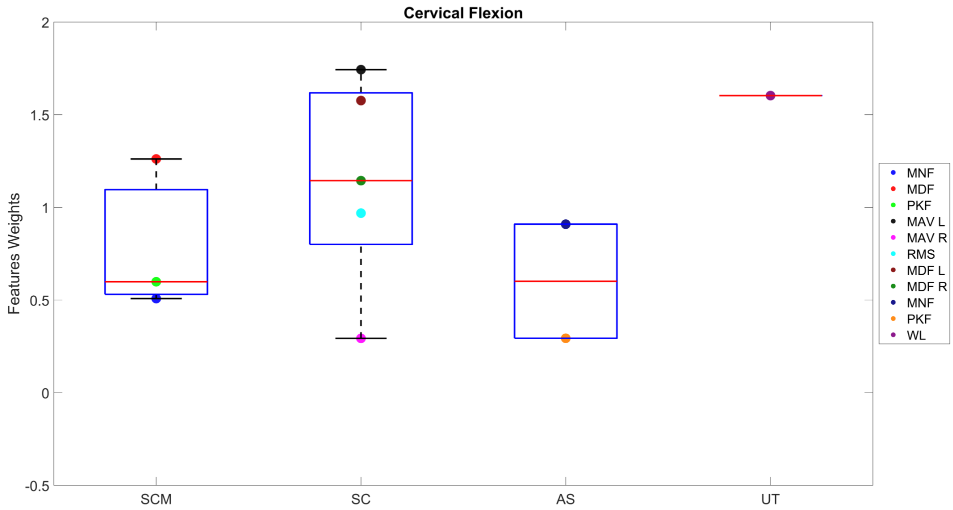

Figure 3.3. NCA weights of each neck muscle for cervical flexion. Mean Frequency (MNF), Median Frequency (MDF), Peak Frequency (PKF), Mean Absolute Value (MAV), Root Mean Square (RMS), Waveform Length (WL)

Table 3.3. Features selected by NCA.

Muscles	Features	Features Weights	*Mean (SD)*
SCM	MNF	0.507	0.789 (0.412)
	MDF	1.261	
	PKF	0.598	
SC	MAV Left side	1.743	1.145 (0.57)
	MAV Right side	0.293	
	RMS	0.968	
	MDF Left side	1.576	
	MDF Right side	1.144	
AS	MNF	0.909	0.601 (0.436)
	PKF	0.293	
UT	WL	1.603	-
	IC	0.698	-

Interestingly, IC was also selected as one of the key features for the classification. This observation underscores the importance of examining the structure of networks to assess the functional interactions among neck muscles. As previously stated in Section 2.6, every network measure was extracted from weighted coherence matrices and averaged across nodes for each group, condition, and frequency band. The BC and the ST were found to be significant in the delta band when comparing those with and without CNP. No meaningful differences were observed across the other frequency bands (**Table 3.4**).

Figure 3.4 illustrates the representation of the neck muscle networks in the delta band during cervical flexion. The size of the nodes corresponds to the degree, which is quantified by the number of connections or edges to other nodes, i.e., muscles. The magnitude of the connection is indicated by the size of the edge. From the figure, it can be observed that the muscle network of individuals with CNP shows thinner edges and fewer connections, mainly localised around SC and SCM muscles. On the other hand, the control group displayed a more symmetrical network, better distributed and with more connections.

Table 3.4. Network parameters of the cervical flexion task

	ST	BC
CNP	2.486 ± 0.458	0.013 ± 0.020
CONT	2.118 ± 0.389	0.033 ± 0.039
P-VALUE	0.01	0.03

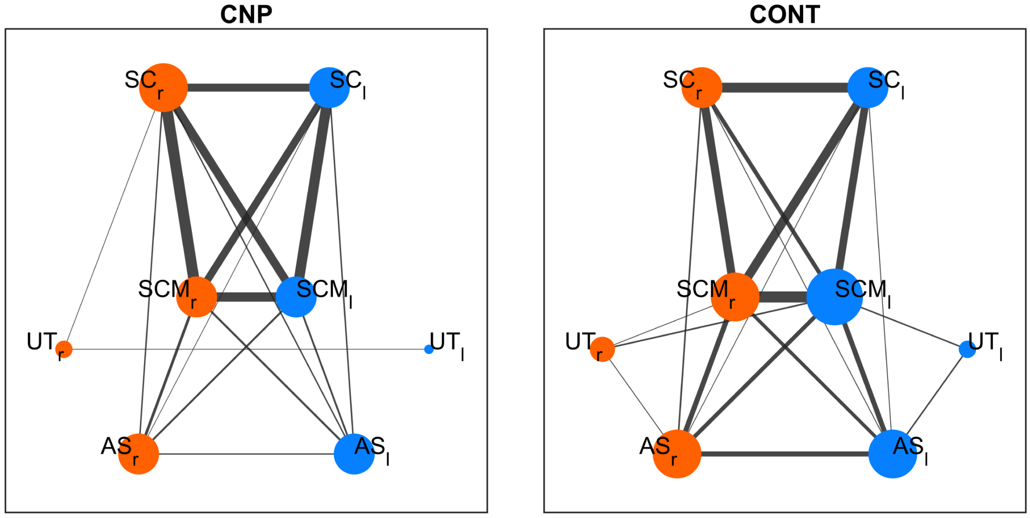

Figure 3.4. Functional networks of both groups at delta band (1-4 Hz) during dynamic contractions. Orange nodes represents left side muscles and blue nodes the right-side ones. CNP: chronic neck pain, CONT: Control group.

3.4. Discussion

The present study aimed to explore potential EMG biomarkers in people with CNP during dynamic contractions of the neck, particularly focusing on neck flexions under load. By employing three ML algorithms, the study pursued to identify the characteristics that help to differentiate individuals with CNP from healthy controls.

3.4.1. Performance of ML algorithms

The SVM stood out by achieving a 75% accuracy rate using nine specific features. Such a performance reinforces the findings from prior studies like (Toledo-Pérez et al., 2019), which highlighted SVM's strong performance in classifying EMG data. The inherent strength of SVM lies in its ability to find the optimal hyperplane that separates classes. Given the results, it is reasonable to infer that the dataset presented a clear margin of separation, which SVM exploited. Moreover, the need for a higher number of features suggests the complex and intricate nature of the problem's space, in which a larger feature set helps to refine the classification boundary.

The K-NN closely followed the SVM in performance, achieving an accuracy of 72.5% using just three distinct features. It also showed an 80% specificity rate, which underscores the algorithm's proficiency in accurately classifying negative instances. The remarkable performance of K-NN, even with a reduced number of features, suggests the possibility that the dataset may exhibit distinct groupings or localised clusters. Furthermore, this resilience to a reduced feature set suggests that the algorithm may exhibit robustness in the face of noise or irrelevant variables. This adaptability proves especially useful when dealing with data of inconsistent quality or navigating the intricacies of feature selection.

On the other hand, LDA achieved a 67.5% accuracy rate, utilising eight features. Even though it did not exceed the other two algorithms, LDA still made a valuable contribution to the study. Its slightly lower result could be indicative of the linear assumptions it adopts, which perhaps were not the most fitting for this dataset. Alternatively, another possibility is that the methodologies of the other two algorithms took better advantage of the inherent specificities of the data. This performance ranking mirrors findings in Dhindsa's study, where EMG signals were analysed to predict knee angle; in both investigations, SVM ranked highest, followed by K-NN, with LDA pursuing in third place (Dhindsa et al., 2019).

The detailed insights drawn from these algorithms indicates that the specific features employed are valuable for classifying aspects of CNP, which may guide future research in targeting these features for more effective management strategies. The findings also emphasise the importance of feature selection and the impact it has on the overall success rate, revealing an intricate balance between feature complexity and classification efficiency.

3.4.2. High impact features

The features with the most significant impact on classification were identified to be MAV and MDF from the SC muscle, and WL from the UT muscle. The significant role of these features emphasises the importance of various time and frequency domains for differentiating neuromuscular function.

SC with MAV and MDF measures represent the amplitude and frequency content of the muscle's activity. MDF and MAV in the SC muscles could reflect the presence of altered muscle coordination in individuals with CNP. The elevated MAV on the left side suggests an asymmetry in muscle activation, potentially indicative of a compensatory mechanism or dominance in muscle usage that could arise from chronic pain or avoidance of pain-inducing postures (Falla et al., 2004d; Hao et al., 2020). The fact that these measures are representative of both the amplitude and frequency content of muscle activity indicates that individuals with CNP might exhibit a continuous high activity and altered MU recruitment patterns, which could be a response to pain or an attempt to minimize movement that exacerbates pain (Cheng et al., 2015). Moreover, the MDF, can be associated with muscle fatigue. Its high relevance in the classification process might imply that individuals with CNP experience more rapid muscle fatigue, possibly due to constant tension or inefficient muscular support.

While SC is primarily considered an extensor and rotator of the head it also acts to stabilise the cervical spine and head. This stabilisation role might lead to identify differences in muscular activity during cervical flexion. Consistently, prior research has found increased activity of the SC relative to the semispinalis cervicis in individuals with CNP pain when local resistance was applied to the neck during isometric contractions (Schomacher et al., 2012). Furthermore, a study found that women with chronic tension-type headache demonstrated greater co-activation of the SC, an antagonist muscle, during cervical flexion contractions compared to healthy women (Fernandez-de-las-Penas et al., 2008).

The significance of the WL in the UT muscle might illustrate the complexity of the signal. This suggests that variations in the WL might correlate with alterations in muscle function or compensation patterns often seen in neck pain condition. For instance, previous studies have demonstrated that the trapezius showed muscle activity differences during dynamic tasks between participants with whiplash and healthy controls (Nederhand et al., 2000), as well as among individuals with CNP pain (Falla & Farina, 2005). Additionally, WL has been highlighted as one of the most successful and commonly used features in EMG signal classification (Phinyomark et al., 2014).

3.4.3. Muscle networks

The selection of IC as a key feature underscores the importance of understanding how different muscles interact each other. This observation aligns with emerging evidence that highlights the role of muscle networks in the coordination of complex movements (Kerkman et al., 2020). Pain-induced changes in these networks may alter the functional relationships between muscles (Liu et al., 2011).

The results showed fewer and more irregular connections in the muscle network of individuals with CNP, mainly localised around SC and SCM muscles, while the control group displayed a more symmetrical and better-distributed network. These findings may reflect a disruption in the normal functional connections between neck muscles in individuals with CNP. This change may be indicative of a protective mechanism to reduce strain on the affected painful region, but it might come at the cost of optimal movement and coordination. This aligns with modern theories on motor adaptations to pain, positing that the immediate response to pain is aimed at protecting the affected body part from further pain or injury (Falla et al., 2017; Hodges & Tucker, 2011).

Further, the network analysis also revealed significant findings on ST and BC metrics. The CNP group showed a higher ST value than the Control group, due to a stronger synchrony between SC and SCM muscles, as it can be seen on **Figure 3.4**. One potential explanation for this might be the co-activation between SC and SCM. Co-activation could be a compensatory mechanism, where both muscles activate simultaneously to provide stability or facilitate movement. On the other hand, The CNP group has a lower BC value compared to the control group. This may indicate that in individuals with CNP pain, the muscles are less likely to act as bridges or central connectors within the network, possibly due to alterations in the normal functional connections between muscles (Fornito, 2016). Finally, the exclusive significance within the delta band deserves particular attention, as it represents the most relevant frequency range for generating and controlling force. In previous studies significant coherence in the delta band was noted during tasks involving posture and gait, attributable to the robust common synaptic input found in this band (Dideriksen et al., 2018).

3.5. Conclusion

This first study provides valuable insights into potential EMG biomarkers of neck pain during dynamic contractions of the neck, specifically identifying key differences between individuals with CNP and healthy controls using SVM, K-NN, and LDA algorithms. The findings highlight not only the significance of specific features like MAV, MDF, and WL but also the importance of understanding IC and muscle network behaviour in CNP. The alterations in ST and BC within the delta band, further underline the complex neuromuscular adaptations occurring in CNP, emphasising the delta band's role in force generation and control. Although the study has some limitations concerning the small sample size and a relatively narrow set of muscles analysed, it introduces an innovative approach in understanding neck muscle activity through network analysis.

CHAPTER 4: STATIC TASK CLASSIFICATION

This chapter investigates the differences between individuals with and without CNP during prolonged stationary smartphone use. ML algorithms are employed to analyse critical EMG and kinematic characteristics for accurate classification. The focus lies on exploring the impact of neck pain on muscle activation and postural control during extended smartphone use. After a detailed description of the research methods and the presentation of results, an in-depth discussion interprets the significance of the findings. The overarching goal is to evaluate biomechanical challenges associated with prolonged smartphone use in the context of neck pain.

4. Exploring EMG and Kinematic Biomarkers in People with Neck Pain During Prolonged Smartphones Use

4.1. Introduction

With the widespread and prolonged use of smartphones, there is growing concern about associated health risks, particularly musculoskeletal disorders (Gustafsson et al., 2017). Smartphones have become ubiquitous in modern society, leading to significant shifts in how individuals communicate, work, and engage in leisure activities. This shift has prompted a growing focus on the potential health implications of prolonged smartphone use, with particular concern for neck pain. Recent studies suggest a high prevalence of neck pain among office workers who use smartphones for extended periods, reaching rates of 30.1%. Moreover, smartphone overuse has been associated with a six-fold increase in the likelihood of experiencing neck pain. This phenomenon is not limited to physical discomfort; studies indicate a link between excessive smartphone use and psychological distress such as anxiety, stress, and depression (Derakhshanrad et al., 2021). Furthermore, a review by (Korhan & Elghomatİ, 2019) highlights the prevalence of neck discomfort among smartphone users, with reported rates ranging from 32.5% to 85.6%.

Notably, neck pain has seen a rise in prevalence, especially in individuals who frequently use their smartphones in varied postures such as sitting, standing or walking (Maayah et al., 2023; Yoon et al., 2021). Research has demonstrated a notable correlation between excessive smartphone use and the onset of musculoskeletal pain in specific regions of the body. The incidence of such pain is particularly high, with the neck, shoulders, and upper back being the most frequently impacted areas. The continuous head flexion and non-neutral postures associated with extended smartphone use gradually contribute to poor posture, eventually leading to discomfort and pain (Ahmed et al., 2022; Mustafaoglu et al., 2021). Specifically, during smartphone usage, there is an increase in the muscle activity of the UT, cervical erector spinae, and neck extensor muscles, especially in individuals already experiencing neck pain. Furthermore, the research highlighted increased neck flexion angle, head tilt angle, and forward head shifting while using smartphones. Notably, individuals with neck pain were found to adopt a more flexed posture compared to those without pain. (Eitivipart et al., 2018; Ning et al., 2015) .

A prolonged head flexion posture stresses the cervical spine by dramatically increasing up to 60 pounds the weight that it holds. This posture provokes changes in proprioception, cervical curvature and muscles activity to accommodate the increased weight (Namwongsa et al., 2019). Common postures adopted when using a smartphone, include sitting with the head tilted forward, lying on one's back with the phone held overhead, and standing with the arms held up to maintain the device at eye level. Each of these postures can lead to an uneven distribution of cervical spine load and contribute to chronic posture-induced damage, leading to mechanical dysfunction and chronic pain (Chen & Chan, 2023). All these factors may contribute to chronic postured-induced damage, leading to mechanical dysfunction and chronic pain.

Given the limited exploration of smartphone usage in neck pain populations and the limited research using a broader range of EMG and kinematic features beyond simple head flexion and muscle amplitude, there is a need for the inclusion of a wider range of features and more in-depth analysis to understand their interactions. To address this gap, the study aims to employ ML techniques to identify key EMG and kinematic characteristics that could shed light into the specific issues related to prolonged smartphone usage and the resultant neck pain conditions.

4.2. Methods

4.2.1. Participant recruitment

The study involved a total of 40 participants, comprising 20 individuals without neck issues and another 20 participant who suffer from CNP. Those with CNP were included if, over the past month, they reported an average neck pain intensity of more than 3 on the NRS—a scale where 0 indicates no pain and 10 marks extreme pain. Additionally, participants were only considered if their experience of neck pain spanned over a duration of three months or more. Their perceived level of neck disability was evaluated using the

NDI. Compliance with inclusion/exclusion parameters and the provision of participant information were in accordance with guidelines specified in Section 2.1.

The research was carried out in a controlled setting at the CPR Spine laboratory, having obtained ethical clearance from the Ethics Committee at the University of Birmingham (ERN_19-1864) and in agreement with the ethical standards outlined in the Declaration of Helsinki. All participants provided written informed consent.

4.2.2. Experimental protocol

Participants were instructed to stand in a designated position and watch a two-and-a-half--minute YouTube video on a smartphone without shifting from the marked spot. The duration of the video and the standing position were chosen based on prior research (Lee et al., 2015; Ning et al., 2015). They were required to hold the phone with both hands, ensuring it remained in a vertical orientation while maintaining an upright stance, mirroring the methodologies used in the studies by(Ning et al., 2015; Yoon et al., 2021). No specific guidelines were provided regarding the positioning of their head, arms, or hands, allowing participants to adopt their natural posture. A visual representation of a participant engaged in this task can be seen in **Figure 4.1**.

All participants viewed the same video: a time-lapse of the Birmingham Energy Innovation Centre, using the same smartphone, a Samsung Galaxy A3 (2017). This particular video was selected because its dynamic content continuously captures and holds the viewer's attention, ensuring there is always something engaging happening on screen.

Figure 4.1. Smartphone Task Stance. Source: DALL·E, OpenAI.

4.2.3. Measurement systems

Bipolar sEMG was captured from the UT, SC, AS, and SCM bilaterally. The data was collected using a wireless system (Ultium EMG, Noraxon USA Inc., Sampling rate: 2000Hz, Resolution: 24 bits, Baseline noise: < 1 μV, CMRR: < -100dB) with dual-electrodes, positioned according to SENIAM's guidelines (Merletti & Hermens, 2000). All the steps outlined in Section 2.1.2 were followed meticulously.

Three-dimensional kinematic data were obtained using three IMUs (dimensions: 37.6 mm × 52.0 mm × 18.1 mm and weighing: 34 g) placed on forehead, neck (C7) and right lateral thigh. These sites are crucial for evaluating balance, lower limb dynamics, and upper back posture, providing a holistic view of body mechanics. The chosen IMUs are notable for their compact and lightweight construction, ensuring they do not disrupt natural movements, thereby enhancing the comfort of participants and the accuracy of the data collected. The deliberate decision to limit the study to just three sensors was driven by the goal to streamline the setup, minimizing the complexity while still capturing essential postural data. This approach tests the efficiency and effectiveness of using a minimal sensor array to accurately analyze posture and movement, demonstrating the potential for simplified yet robust assessment techniques in biomechanical research (Ghislieri et al., 2019). Data acquisition was performed using a wireless measurement system (myoMOTION Research Pro, Noraxon USA Inc., Sampling rate: 100Hz). Simultaneous collection of EMG and 3D kinematic data were synchronised using the myoSync (Noraxon USA Inc.,) device which sends out a sync pulse to all connected systems.

4.2.4. Data analysis

EMG data was filtered using a zero-lag, fourth-order Butterworth band-pass filter with cut-off frequencies set at 15 Hz and 400 Hz. On the other hand, kinematic data was filtered using a second-order Butterworth filter with a cut-off frequency at 6 Hz. Considering the reduced muscle activation intrinsic to this task, all EMG data were normalised relative to relative to a baseline established by the mean amplitude of reference EMG data, following the protocol previously established by (Yoon et al., 2021), who investigated the same task. Moreover, to mitigate potential interference, the initial and final 30 seconds of each recording were excluded, particularly to counteract abnormalities from abrupt motions or adjustments.

Following the methodology outlined in Chapter 2, once data extraction and conditioning were completed, the feature extraction process is initiated. Features delineated in **Table 2.1** and **Table 2.2** were extracted from the EMG and kinematic datasets. Specifically, from the EMG analysis, a total of 88 features were extracted and from the kinematics analysis, 63 features were extracted. Subsequently, these features were input into the three algorithms mentioned earlier (LDA, K-NN, SVM) for classification between subjects with CNP and those without. This data was analysed both in the presence and absence of NCA to evaluate its effectiveness and determine the most important features. A LOO cross-validation technique was used for training the algorithms. To determine any distinguishable differences in variables like age, BMI, and muscle network parameters across groups, the Student's t-test was calculated. A p-value below 0.05 was considered statistically significant.

4.3. Results

The demographic attributes of the participants are detailed in **Table 4.1**. As evidenced by a p-value exceeding 0.05, the evaluation showed no significant differences in these characteristics between the groups.

Table 4.1. Demographic characteristics of participants.

	Neck pain Mean ± SD	Control Mean ± SD	p-value*
Age (years)	26.85 ± 5.36	30.5 ± 7.41	0.065
BMI (kg/m^2)	22.896 ± 3.06	24.1255 ± 3.39	0.134
Gender (females %)	65	50	-
NDI (0-50)	24.3 ± 11.12	-	-
Average neck pain intensity (0–10)	4.05 ± 1.80	-	-

(*) Independent samples t-test, SD: NDI: Neck Disability Index, SD: Standard deviation, BMI: Body Mass Index.

4.3.1. EMG results

Table 4.2 provides a summary of the overall accuracy, specificity, and sensitivity for each supervised model. It gives a comparative account of how each ML method performs in two distinct situations: one where all the features are used together, and another where features identified by the NCA are used. A clear pattern emerges from all the algorithms

- the application of the NCA algorithm consistently improves accuracy, specificity, and sensitivity. This reinforces the effectiveness of the NCA in recognising and filtering out unnecessary or obstructive features, thereby enhancing the performance of the classifier.

SVM led in classification accuracy with 80%, followed by K-NN at 72.5% and LDA at 62.5%. Sensitivity was notably high for SVM and K-NN, at 87.5% and 84.61% respectively, indicating their reliability in reducing FN and thus enhancing accuracy. **Figure 4.2** details the number of features needed for these accuracy levels, based on a feature subset from NCA. Specifically, nineteen features were required for SVM to achieve 80%, K-NN needed twenty for 72.5%, and LDA used just five for 62.5%.

Table 4.2. Performance metrics of EMG analysis for each classification algorithm reported as means (standard deviations) in percentage.

		All features	Selected features by NCA
K-NN	ACCU	45.00 (15.30)	72.50 (7.73)
	SPEC	41.67 (27.38)	66.67 (11.03)
	SENS	46.42 (10.90)	84.61 (6.78)
SVM	ACCU	40.00 (20.53)	80.00 (10.66)
	SPEC	38.89 (23.64)	75.00 (12.87)
	SENS	40.90 (26.81)	87.50 (9.39)
LDA	ACCU	42.50 (10.45)	62.50 (7.36)
	SPEC	43.47 (10.83)	66.67 (7.08)
	SENS	41.17 (25.09)	60.00 (8.28)

ACCU: accuracy, SPEC: specificity, SENS: sensitive.

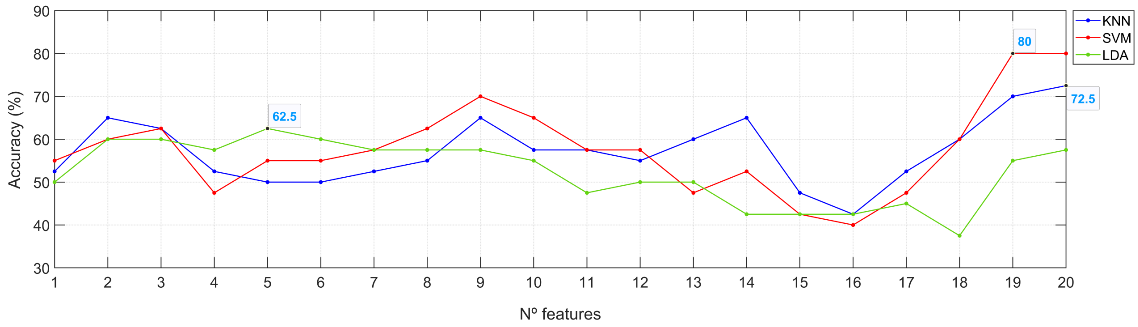

Figure 4.2. Accuracy versus the number of EMG features selected by NCA. Features names corresponding to x-axis: UT Right VAR, SCM Left MAV, UT Left RMS, UT Right RMS, UT Left WL, SCM Left SSI, SCM Left MNF, SCM Right MNF, SC Left MNF, SC Right MNF, SCM Left BP, AS Right BP, SC Left BP, SCM Left PKF, SCM Right PKF, AS Right PKF, SC Right PKF, UT Left PKF, UT Right PKF, IC.

Figure 4.3 illustrates the weight distribution of EMG features as identified by the NCA using a boxplot. This visualisation not only showcases the comparative significance of each feature in the classification task, but it also pinpoints the neck muscle encompassing these critical features. In the context of the phone use, it is evident that the SC dominates in terms of weight, followed by the SCM and then the UT. On the other hand, the AS holds the minimal weight in comparison to the others.

In **Table 4.3**, the features selected by the NCA and their respective weights for EMG are detailed. The SC muscle showcases the highest mean, signifying its primary role in the algorithm's classification, especially through frequency features like MNF, TP, and PKF. Following closely are the SCM and UT muscles, which present a mix of time and frequency features, though the frequency ones notably dominate. In the case of the UT, the WL feature stands out, carrying the maximum weight, which evidently impact the classification performance. Conversely, muscles with lower weights, like the AS, might have a lessened role in this context. While the feature collection spans both time and frequency domains, frequency features command a significant 75% accuracy, substantially greater than the time domain's 25%. Furthermore, the recurring prominence on the PKF feature across different neck muscles may indicate evolving neuromuscular strategies, possibly pointing to muscle fatigue from prolonged task engagement.

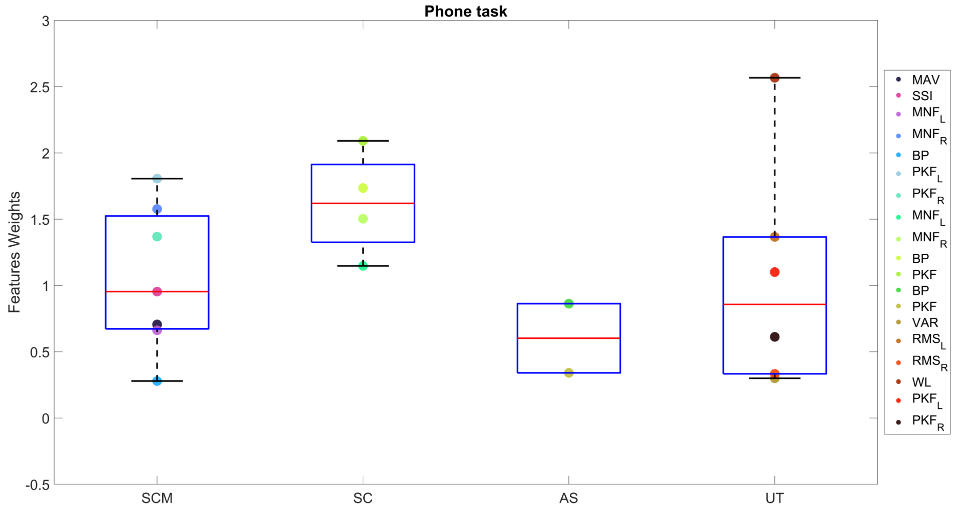

Figure 4.3. NCA weights of neck muscle activity during the phone task Mean Frequency (MNF), Median Frequency (MDF), Peak Frequency (PKF), Mean Absolute Value (MAV), Root Mean Square (RMS), Waveform Length (WL), Variance (VAR), Single Square Integral (SSI), Total Power (TP).

Table 4.3. EMG features selected by NCA

Muscles	Features	Features Weights	*Mean (SD)*
	MAV	0.7056	
	SSI	0.9531	
	MNF Left	0.6615	
SCM	MNF Right	1.5765	1.04 (0.55)
	TP	0.2784	
	PKF Left	1.8058	
	PKF Right	1.3682	
	MNF Left	1.1474	
SC	MNF Right	1.5030	1.61 (0.39)
	TP	1.7348	
	PKF	2.0910	
AS	TP	0.8624	0.601 (0.36)
	PKF	0.3403	
	RMS Left	1.3661	
UT	RMS Right	0.3329	1.04 (0.85)
	VAR	0.2995	

	WL	2.5668	
	PKF Left	1.1008	
	PKF Right	0.6119	
	IC	1.4282	-

IC emerged as a pivotal feature for classification, highlighting the importance of the synchrony between muscles to maintain a posture for a long time. As detailed in Section 2.6, network measures were derived from weighted coherence matrices and then averaged across each group, condition, and frequency band. However, BC and ST did not show any significance in any frequency band. **Table 4.4** presents BC and ST values for the delta band, revealing minimal differences between groups. Additionally, identifying clear graphical differences in the topography of their muscle networks proves challenging (see **Figure 4.4**). Both networks display a great number of connections and therefore, similar nodes' sizes.

Table 4.4. Network parameters of the static task

	ST	BC
CNP	1.665 ± 0.474	0.042 ± 0.034
CONT	1.670 ± 0.327	0.041 ± 0.047
P-value	0.97	0.90

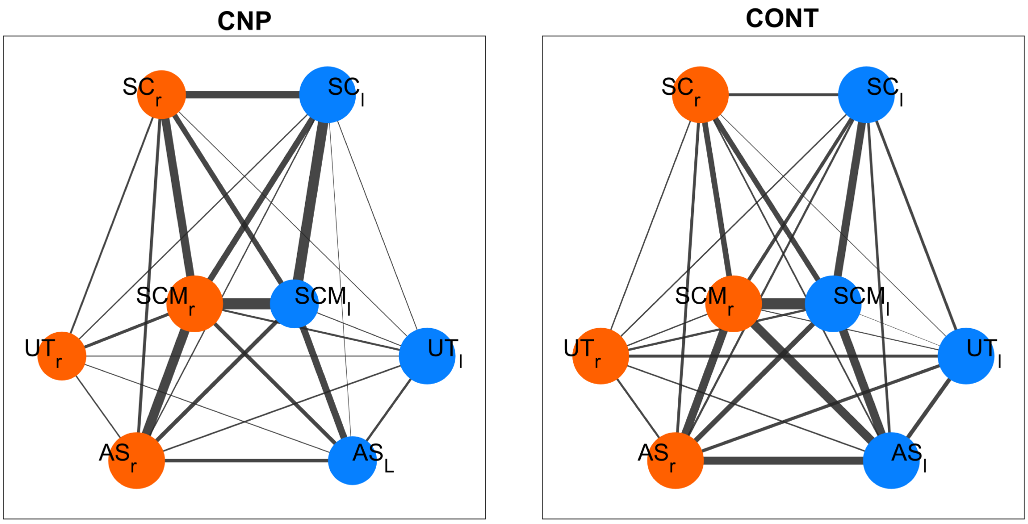

Figure 4.4. Functional networks of both groups at delta band (1-4 Hz) during static task. Orange nodes represents left side muscles and blue nodes the right-side ones. CNP: chronic neck pain, CONT: Control group.

4.3.2. Kinematic results

Table 4.5 offers a comparative analysis of the performance metrics - accuracy, specificity, and sensitivity - for each supervised model when trained using kinematic features. In line with the EMG analysis, the use of NCA optimisation enhances all three performance metrics. K-NN leads in accuracy at 75%, with SVM close behind at 72.5%, and LDA at 57.5%. For specificity, SVM excels with an 80% rate, mirroring its strong performance in EMG metrics, especially when compared to K-NN. This suggests SVM's heightened capability for correct negative case classification within the dataset. LDA, however, shows only a slight improvement when NCA-selected features are applied. **Figure 4.5** outlines the correlation between the number of features, as identified by NCA, and model accuracy. Specifically, K-NN utilises six features to near a 75% accuracy level. SVM, on the other hand, requires five features to reach 72.5% accuracy. LDA stands out for its efficiency, achieving a 57.5% accuracy rate with just a single selected feature.

Table 4.5. Performance metrics of Kinematic analysis for each classification algorithm reported as means (standard deviations) in percentage.

		All features	Selected features by NCA
	ACCU	45.00 (18.95)	75.00 (2.47)
K-NN	SPEC	45.00 (17.57)	65.38 (2.79)
	SENS	45.00 (27.54)	77.77 (3.69)
	ACCU	40.00 (10.45)	72.50 (6.40)
SVM	SPEC	40.90 (7.68)	80.00 (8.76)
	SENS	38.89 (36.13)	68.00 (5.14)
	ACCU	47.50 (18.95)	57.50 (9.90)
LDA	SPEC	47.62 (27.09)	56.52 (9.83)
	SENS	47.36 (27.10)	58.82 (10.36)

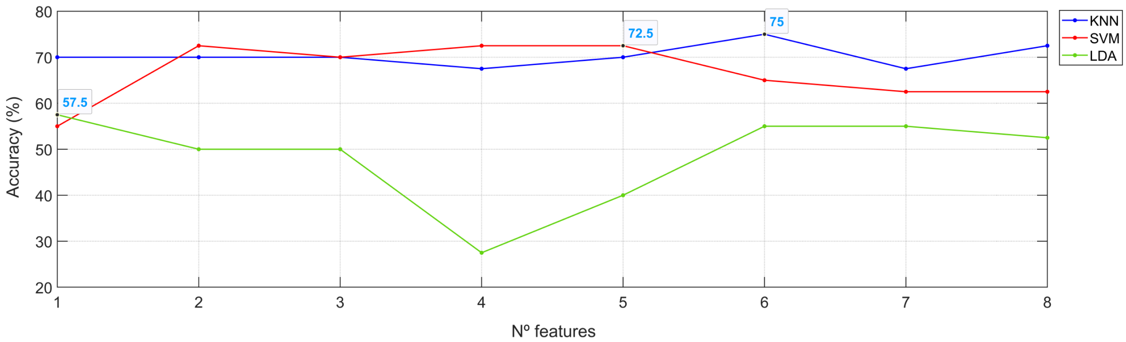

Figure 4.5. Accuracy versus the number of Kinematic features selected by NCA. Features names corresponding to x-axis: Min head acceleration, Mean head jerk, Max head jerk, Mean neck jerk, Min head smoothness, Min head power, Min neck power, Min right leg power.

In **Figure 4.6**, a boxplot illustrates the weight distribution of kinematic features as determined by the NCA. Notably, a significant number of features derived from the head, leading to a higher overall mean. This prominence underscores the head's crucial role in the classification task. Sequentially, the neck and right thigh follow, although with fewer selected features. Among the features, Jerk stands out as the most frequently selected, followed closely by Power. This accentuates the significance of both time and frequency domains in ensuring the algorithms' precision during the static task. Interestingly, and as expected for a static task, the right leg features were not considered relevant enough to be selected by the NCA. **Table 4.6** provides a detailed enumeration of kinematic features chosen by the NCA, accompanied by their corresponding weights. Notably, Acceleration of the head, Power of the neck, and Smoothness carry the most significant weights.

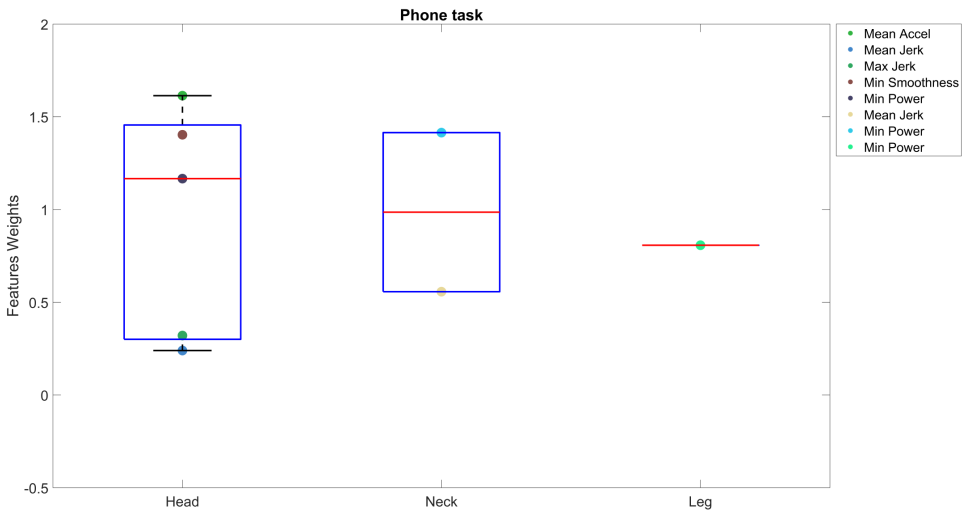

Figure 4.6. NCA weights of kinematic features for each IMU during the phone task

Table 4.6. Kinematic features selected by NCA

Body segments	Features	Features Weights	*Mean (SD)*
Head	Mean Acceleration	1.6140	0.948 (0.631)
	Mean Jerk	0.2398	
	Max Jerk	0.3207	
	Min Smoothness	1.4031	
	Min Power	1.1668	
Neck	Mean Jerk	0.5571	0.985 (0.606)
	Min Power	1.4148	
Leg	Min Power	0.8076	-

4.4. Discussion

The study effectively utilises ML algorithms to classify individuals either with or without CNP, based on crucial kinematic and EMG features observed during extended smartphone use. Additionally, the essential features for accurate classification are highlighted, providing insight into the biomechanical challenges linked to prolonged smartphone usage when neck pain is present.

4.4.1. Performance of ML algorithms

In the analysis of muscle activity, both SVM and K-NN displayed notable accuracy levels—80% for SVM and 72.5% for K-NN. Additionally, they demonstrated robust specificity values of 87.5% and 84.61%, respectively. High specificity suggests that these algorithms are effective in correctly identifying individuals without pain, minimising the risk of FP. Such results underscore the efficacy of these algorithms in discerning between groups with and without pain based on muscle activity. This ranking of performance in the ML algorithms mirrors Chapter 3 findings, with SVM at the forefront, closely followed by KNN, and LDA trailing behind. Interestingly, even though the same EMG features were analyzed in both chapters, the accuracy values reported in Chapter 3 were slightly lower compared to those observed in this study.

In the kinematic analysis, a similar trend was observed. Both SVM and K-NN showed high levels of accuracy rates, 72.5% and 75%, respectively. It is noteworthy that K-NN slightly outperformed SVM in this context. Nevertheless, SVM exhibited higher specificity, registering 80%, compared to K-NN's 77.77%.

In comparing the outcomes of both analyses, it is evident that across scenarios, all algorithms effectively distinguish between groups, with their performance further enhanced by the integration of NCA. Both K-NN and SVM consistently demonstrated their efficacy for this task, while LDA was somewhat less effective. While K-NN and SVM have flexibility in handling different data structures and patterns, LDA operates on the assumption that the classes are linearly separable. LDA's inherent strength is predicated on its ability to find the direction that maximises the separation between classes. However, in many real-world scenarios, especially in human research, the data distributions are complex and may not adhere to strict linear patterns (Rajput et al., 2012).

It is essential to underscore that the ML algorithms demonstrated robust performance even in scenarios where distinctions between groups are subtle. During the phone task, the movements are minimal and infrequent, often related to maintaining posture and balance. Such subtle movements may not always be readily detectable using rudimentary statistical analyses, which emphasises the ability of the ML techniques in this study.

4.4.2. High impact features

In the EMG analysis, the SC's features emerged as the most relevant for the classification task. This subset of features consists of MNF, PKF, and TP, all of which originate from the frequency domain. MNF is an indicator of the average frequency of the power spectrum of the EMG signal and is sensitive to muscle fiber type composition and muscle fatigue. PKF represents the frequency at which the maximum power of the EMG spectrum occurs, often associated with the firing properties of MU and changes in muscle fiber conduction velocity due to fatigue or other physiological conditions. TP reflects the sum of power across all frequencies and is indicative of the overall electrical activity within the muscle. Therefore, changes in MNF and PKF might be indicative of muscle fatigue or underlying neuromuscular changes. Higher MNF values could correspond to increased muscle fiber recruitment as a compensatory mechanism in cervical pathology or during prolonged postural tasks. Conversely, a decline in MNF might suggest muscle fatigue or diminished neuromuscular efficiency, which are common in CNP patients (Falla et al., 2003).

Remarkably, frequency features constituted 75% of the selected features. This underscores the significance of examining such features to explore into the physiological and functional attributes of muscles, including aspects like fatigue or degeneration. This is particularly crucial in the context of CNP, an area that remains not fully understood and thus, warrants further exploration.

The pivotal role of the SC in classification during a postural task is consistent with prior research. Studies have demonstrated that neck extensor muscles, particularly the SC, experience increased load as they compensate the weight of the head in a flexed position (Villanueva et al., 1997; Xie et al., 2016; Yoon et al., 2021). However, other factors such as neural drive (MU discharge rate and recruitment), or muscle fiber type distribution could also influence these spectral variables. For instance, the neural drive to the muscle can affect the frequency content of the EMG signal. A higher neural drive could result in a shift in the MNF and PKF towards lower frequencies, potentially affecting the classification task. Conversely, an increase might suggest enhanced neural drive or changes in muscle fiber composition towards faster twitch fiber. Additionally, the different type of muscle fibers present in the SC could also influence the frequency parameters, as different fiber types have distinct electrical characteristics. Importantly, variations in sodium-potassium pump activity and muscle membrane properties can also influence the action potentials, thus affecting the spectral variables (Fitts, 1994).

On the other hand, PKF emerges notably as the most frequently selected feature across various muscles, while WL in the UT takes priority as the highest weight in the classification. This distinction underscores the crucial interplay between frequency attributes and time-domain characteristics in the EMG signal analysis. The prominence of PKF suggests that the inherent frequency content of muscle activations provides invaluable insights, possibly relating to factors such as fatigue or neuromuscular coordination (Falla et al., 2003; McAuley et al., 1997). Its widespread selection across different muscles may indicate a universal relevance in characterising muscle behaviour during the examined tasks.

A noteworthy observation was the selection of the UT muscle's WL, which appeared concurrently with the RMS of the same muscle. Elevated WL and RMS could indicate higher muscle activity levels, which may be associated with compensatory strategies to mitigate pain or maintain head and neck posture, especially in scenarios of prolonged smartphone usage. The prominence of the UT in terms of time-domain feature selection underscores its potential significance in differentiating between the groups during the postural task. This aligns with previous literature, which has also highlighted the pivotal role of the UT muscle. Specifically, prior investigations, such as the one by (Vahedi et al., 2022) have documented increased UT muscle activity when individuals use smartphones while standing. Furthermore, elevated activity in the UT muscle has been observed in individuals with neck pain during smartphone usage in a seated position (Xie et al., 2016).

In line with the insights from Chapter 3, the emphasis on SC muscle features in both chapters underscores the muscle's critical role in neck posture and pain management across various tasks. Moreover, the focus on WL of the UT muscle highlights its relevance in diverse activities. This recurring emphasis suggests that changes in WL could serve as a dependable marker for shifts in muscle function or compensatory patterns in CNP. Moreover, the reiterated selection of the IC feature, as observed in Chapter 3, emphasizes the critical importance of muscle coordination in the comprehensive understanding of CNP. This expands upon Chapter 3's focus, pointing towards a more comprehensive EMG feature set for CNP classification.

Regarding the kinematic analysis, the most significant contributions emanated from the head features, with neck and leg features following in importance. Given the nature of the task, it stands to reason that the emphasis and relevance of the features predominantly centre on the head's kinematics. This is consistent with earlier research, which has indicated an increased head flexion during smartphone use (Yoon et al., 2021). Similarly, this pattern of head flexion is present in individuals with neck pain (Kim, 2015).

Furthermore, key attributes such as Acceleration, Power, and Smoothness were selected. This suggests the presence of fine-tuned head and neck movements to achieve optimal viewing angles during smartphone use. The prominence of Power, especially its minimum values across the head, neck, and legs, points to instances of stabilisation or decreased movement activity, likely for maintaining balance and comfort. The Smoothness metric underscores the emphasis on ensuring fluidity and stability in movements, perhaps as a response to abrupt shifts in acceleration. Interestingly, the selection of features such as acceleration and smoothness align with prior research examining head kinematics in individuals with neck pain (Franov et al., 2022; Tsang et al., 2014). Notably, Smoothness and Jerk have been highlighted as pivotal characteristics distinguishing those with neck pain (Moghaddas et al., 2019; Sjolander et al., 2008).

4.4.3. Muscle networks

Another informant feature selected during the EMG analysis was the IC. This might suggest the presence of muscle synergies involved in maintaining posture. Previous studies on muscle coherence and synergies in balance postures have demonstrated that coordinated muscle activity is crucial for stability. Any disruption in these synergies might compromise postural control (Boonstra et al., 2015; Wojtara et al., 2014).

From a statistical perspective, network metrics did not show significance in any frequency band. Additionally, there were not clear graphical differences in the muscle networks. This uniformity could either be due to the inherent limitations and sensitivity of the employed network metrics or to the task's insufficient complexity. Although IC emerged as a notable feature, the networks did not show any group-specific variations during standing. Interestingly, these results do not reveal the strong group-specific distinctions anticipated from Chapter 3's focus on muscle network disruptions in CNP. This suggests that the task may not have been complex enough to fully elicit those disruptions, or that the impact of CNP on muscle networks might be more evident in different types of tasks.

4.5. Conclusion

The exploration into kinematic and EMG biomarkers in people with CNP during smartphone use while standing has provided valuable insights. Through the application of three ML algorithms, particularly SVM and K-NN, this study achieved significant accuracy in discerning between individuals with CNP and asymptomatic participants.

Both algorithms proved their strength in distinguishing subtle differences in muscle activity and kinematics, even when movements are minimal.

From the EMG analysis, the prominence of features from the SC muscle and the frequent selection of PKF across various muscles underscore their significance in understanding muscle behavior during postural tasks with frequency analysis. In terms of kinematics, features from the head dominated the results. Significant attributes such as Acceleration, Power, and Smoothness might suggest efforts by participants to refine their viewing angles, maintain a stable posture, and execute fluid motions.

CHAPTER 5: GAIT TASK CLASSIFICATION

Content from this chapter has been published:

1. **Jiménez-Grande, D.**, Farokh Atashzar, S., Martinez-Valdes, E., De Nunzio, A., & Falla, D. (2021). Kinematic biomarkers of chronic neck pain measured during gait: A data-driven classification approach. Journal of biomechanics, 118, 110190. https://doi.org/10.1016/j.jbiomech.2020.110190

2. **Jiménez-Grande, D.**, Farokh Atashzar, S., Martinez-Valdes, E., & Falla, D. (2021). Muscle network topology analysis for the classification of chronic neck pain based on EMG biomarkers extracted during walking. PloS one, 16(6), e0252657. https://doi.org/10.1371/journal.pone.0252657

3. **Jiménez-Grande, D.**, Farokh Atashzar, S., Devecchi, V., Martinez-Valdes, E., & Falla, D. (2022). A machine learning approach for the identification of kinematic biomarkers of chronic neck pain during single- and dual-task gait. Gait & Posture, 96, 81–86. https://doi.org/10.1016/j.gaitpost.2022.05.015

This chapter aims to conduct a thorough investigation into the changes in EMG signals and kinematic profiles among individuals with CNP during different gait patterns. The focus initially lies on curvilinear and rectilinear gaits, covering their unique characteristics, the methods used for their study, the data obtained, and a subsequent interpretation of these findings. Afterwards, the chapter explores the dynamics of single and dual-task gaits. It outlines the research methods, presents the results gathered, and engages in a crucial discussion about their implications. The ultimate goal of this chapter is to provide a better understanding of how neck pain might affect biomechanics and muscular function under various gait conditions.

5. Exploring EMG and Kinematic Biomarkers in Neck Pain During Different Types of Gaits

Understanding the various types of gaits in individuals with neck pain is vitally important for both clinical and research settings. The manner in which a person walks, or their gait, can offer invaluable insights into the underlying biomechanical disturbances, compensatory mechanisms, and even the severity of their condition. For those with neck pain, subtle or pronounced alterations in gait might hint at a broader musculoskeletal impact or reflect adaptations to minimise discomfort. Differentiating between curvilinear and rectilinear gaits, as well as single- and dual-task gaits, could provide new insights about how neck pain may influence gait patterns. This understanding may shed light on the true extent to which this condition impacts individuals.

5.1. Curvilinear and Rectilinear Gait

5.1.1. Introduction

Walking typically appears to be a straightforward task for physically fit adults without neurological or musculoskeletal disorders. However, walking involves intricate interactions and coordination between different body segments and joints, especially during nonlinear trajectories that necessitate anticipatory adjustments. These adjustments typically initiate with the head and eyes aligning with the intended direction, followed by trunk reorientation, which is accompanied by directional changes in the centre of mass (Courtine & Schieppati, 2003a; Godi et al., 2019).

During walking, individuals often experience variations in their trajectory, resulting in a combination of what are termed as "curvilinear" and "rectilinear" gaits. In a daily scenario, on average, 30% of gait time is spent walking along curved paths (Segal et al., 2008). Research indicates noticeable changes in muscle activation patterns (Courtine et al., 2006; Duval et al., 2011), kinematics (Courtine & Schieppati, 2004), and cerebral activity (Wagner et al., 2008) when comparing curvilinear trajectories to rectilinear gait. This comparison suggests that walking along curved paths may place a greater computational burden on the CNS, an observation that could benefit from further exploration into the underlying mechanisms (Turcato et al., 2018).

Research has consistently shown that individuals with neck pain exhibit different movement patterns and muscle behaviours compared to asymptomatic controls. These changes encompass muscle activity differences such as increased co-activation, diminished specificity of activity, and delayed onset (Falla, 2004; Lindstrom et al., 2011; Schomacher et al., 2012). Similarly, in terms of gait disturbances, affected individuals often exhibit a narrower step width, shorter step length, and slower gait speed (Burton et al., 2023; Treleaven, 2008). In fact, these biomechanical differences might be not limited to the neck alone.

In this context, the objective is to explore a broader array of kinematic and EMG features that have not yet been extensively studied in the context of neck pain, particularly in curvilinear gait, which has also been somewhat overlooked in this condition. The aim is to deepen the understanding of biomechanical adaptations in both the muscular and kinematic realms experienced by individuals with neck pain, pinpointing key characteristics that could provide valuable insights.

5.1.2. Methods

- Participants recruitment

In this study, 20 asymptomatic individuals were compared with 20 individuals with nonspecific CNP. Both healthy and CNP participants were selected according to the inclusion and exclusion criteria, and participant information was distributed as stipulated in Section 2.1.

The study was conducted in a regulated environment at the CPR Spine lab, after obtaining ethical approval from the University of Birmingham's Ethics Committee (CM06/03/17-1) and aligned with the ethical guidelines set forth in the Declaration of Helsinki.

- Experimental protocol

All participants were asked to walk without shoes at a speed they chose, following a curved path with a 1-meter radius in alignment with (Courtine & Schieppati, 2004), moving in counterclockwise. Additionally, they walked a straight path of 6 meters, the maximum length feasible within the laboratory environment. They repeated this three times, taking a 2-minute break between each attempt. A trial was considered finished when the participant arrived at the final point. For the curved walk, the beginning and ending points were identical. The sequence in which the paths were taken was chosen at random (see **Figure 5.1**).

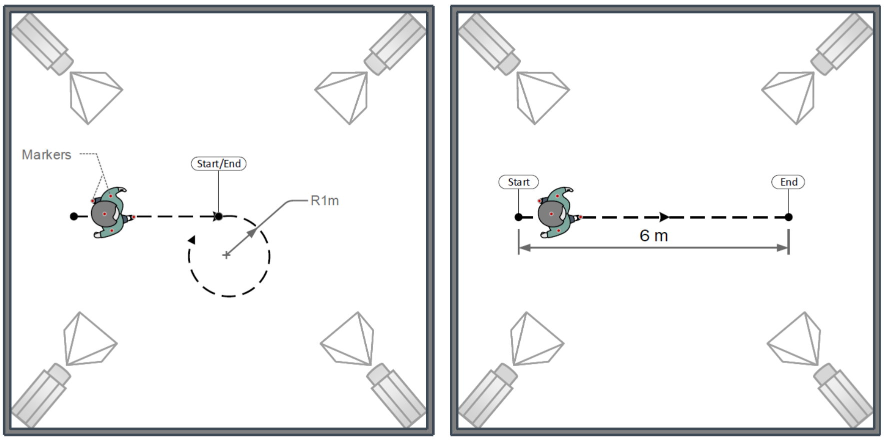

Figure 5.1. Experimental setup. Curvilinear task (left) and rectilinear task (right). Source: Microsoft Visio.

- Measurement systems

Gait dynamics were captured using an optoelectronic system (BTS Bioengineering, Italy). This system integrates eight infrared cameras, each boasting a resolution of 2.2 MPixels and operating at a sampling frequency of 100 Hz. These cameras were meticulously calibrated to monitor the three-dimensional trajectories of spherical passive reflective markers. For consistency and precision, twenty six markers were strategically positioned directly on the skin of the participants over the anatomical landmarks, following an adapted version Davis biomechanical model (Davis et al., 1991). This adaptation incorporates an in-depth analysis of the body's movements across the three fundamental axes—sagittal (anterior-posterior), coronal (medial-lateral), and longitudinal (vertical)—to examine the degrees of freedom at various joints (see Figure 5.2). To identify specific gait events, the BTS Smart Analyzer software was utilised. This software is designed to detect the initial foot contact and toe lift-off by monitoring two reflective markers situated on the heel and metatarsus respectively (Borghese et al., 1996).

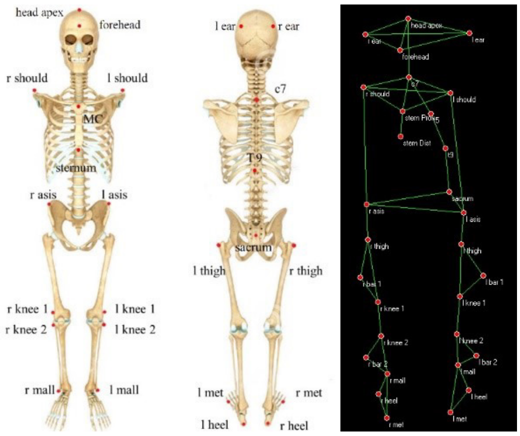

Figure 5.2. Biomechanical model

The sEMG data were captured from the UT, SC, and SCM on both sides of the body. A wireless EMG system (BTS FreeEMG, BTS S.p.A., Milan, Italy) was employed to gather the data. This system operates at a 1000Hz sampling rate with a 16-bit precision. Before attaching the electrodes to the skin, all the preparatory steps detailed in Section 2.1.2 were meticulously followed. Bipolar surface electrodes, measuring 16×12mm (BTS FreeEMG 300), were placed in adherence to the guidelines set by SENIAM, maintaining an inter-electrode gap of 2cm (Merletti & Hermens, 2000). The EMG readings were obtained from the BTS software known as EMG Analyzer.

This complete measurement system is ideal for the simultaneous analysis of kinematic and EMG data with the high precision required to investigate curvilinear and rectilinear gait. The optoelectronic system, with its meticulous marker placement and calibrated cameras, provides a detailed and accurate picture of three-dimensional movements. This precise kinematic data can then be seamlessly integrated with the sEMG data captured by the wireless EMG system. The high sampling rates of both systems ensure the capture of the nuanced interplay between muscle activity and limb movements during each gait cycle. This combined approach offers a comprehensive understanding of the biomechanical differences between curved and rectilinear walking patterns.

- Data analysis

The kinematic data was evaluated using a 3D reconstruction software, specifically the SMART Tracker and SMART Analyzer by BTS (Milan, Italy). Following this approach, movements of several body parts—such as the Head, Trunk, Pelvis, Hip, Knee, Ankle, and Foot—were tracked. Subsequent to this analysis, features as outlined in **Table 2.1** were extracted for each body segment across each trajectory. In total, 126 features were extracted. Furthermore, an additional dataset that combined data from both walking conditions was integrated, named combined (curvilinear and rectilinear).

The EMG data was filtered by using a zero-lag fourth-order Butterworth band-pass filter, set with cut-off frequencies at 10 and 500 Hz, and a notch filter with a 50 Hz cut-off frequency. For each muscle recording, the maximum EMG amplitude over a 0.5s interval was utilised to normalise the signals, following the approach recommended by (Kieliba et al., 2018). Similar to the observations in Chapter 4 regarding postural control, where muscle activation levels are not particularly high, gait also exhibits relatively moderate activation, underscoring the importance of this normalization technique to accurately reflect the subtleties of muscle engagement during such activities. Subsequently, the data was examined to extract the features described in **Table 2.1** and **Table 2.2**. In this process, a total of 88 features were extracted, signifying a comprehensive analysis of the EMG signals.

Both kinematic and EMG features were calculated from all participants within a single gait cycle and then averaged over various gait trials for each walking condition. To prevent datasets with more features than samples and sidestep the curse of dimensionality, these feature sets (EMG and Kinematic) were separately inputted into the supervised algorithms. As detailed in Chapter 2's methodology, three supervised algorithms with different learning approaches were used to classify between CNP and healthy individuals based on these attributes. Additionally, this data was assessed with and without the incorporation of NCA to gauge its utility and highlight the key features. A five-fold cross-validation method was chosen for algorithms training. Significant variations in factors like age, BMI, and muscle network parameters among the groups were identified using the Student's t-test, with a p-value less than 0.05 being considered statistically significant.

5.1.3. Results

The demographic details of the participants can be found in **Table 5.1**. No notable differences in demographic attributes were observed between the groups ($p > 0.05$).

Table 5.1. Demographic characteristics of participants.

	Neck pain Mean ± SD	Control Mean ± SD	p-value*

Age (years)	28.5 ± 9.0	26.3 ± 8.8	0.33
BMI (kg/m^2)	38.5 ± 5.6	38.4 ± 6.9	0.47
Gender (females %)	60	50	-
NDI (0-50)	11.5 ± 6.7	-	-
Average neck pain intensity (0–10)	4.1 ± 1.9	-	-

(*) Independent samples t-test, NDI: Neck Disability Index, SD: Standard deviation, BMI: Body Mass Index.

- Kinematic results

Table 5.2 summarises the results for overall accuracy, specificity, and sensitivity for each supervised model across different trajectories. This table presents the classification performance of each method using all the features combined, as well as when employing features selected by NCA for individual trajectories. A consistent improvement in accuracy, specificity, and sensitivity is evident when the NCA algorithm is applied, underscoring the algorithm's capacity to identify and eliminate irrelevant or noise-laden features that could adversely affect the classifiers. The highest classification performance of 90%, was achieved with the curvilinear trajectory using the K-NN algorithm. This underscores the superior predictive value of curvilinear walking over rectilinear, and the comparative advantage of K-NN over SVM and LDA in binary classification tasks.

Table 5.2. Performance metrics of kinematic analysis for each classification algorithm and each trajectory reported as means (standard deviations) in percentage.

		Curvilinear	Rectilinear	Combine
All features				
K-NN	ACCU	55.00 (16.84)	35.00 (18.95)	35.00 (18.14)
	SPEC	53.33 (14.80)	36.36 (24.89)	36.36 (18.60)
	SENS	53.57 (21.73)	33.33 (19.80)	33.33 (12.78)
SVM	ACCU	55.00 (6.84)	30.00 (14.25)	30.00 (17.65)
	SPEC	54.16 (21.73)	34.61 (18.94)	34.61 (18.42)
	SENS	56.25 (14.80)	21.42 (18.31)	21.42 (17.56)

LDA	ACCU	45.00 (22.36)	40.00 (20.53)	40.00 (16.53)
	SPEC	45.45 (27.38)	38.88 (24.64)	38.88 (14.62)
	SENS	44.44 (19.49)	40.90 (19.90)	40.90 (26.14)
Selected features by NCA				
K-NN	ACCU	90.00 (18.54)	67.50 (17.67)	70.00 (12.96)
	SPEC	100.00 (28.19)	68.42 (11.78)	68.18 (8.17)
	SENS	83.33 (16.24)	66.66 (35.35)	72.22 (14.25)
SVM	ACCU	82.50 (14.25)	55.00 (20.53)	62.50 (12.18)
	SPEC	80.95 (15.19)	44.00 (21.48)	61.11 (21.57)
	SENS	84.21 (23.28)	40.00 (29.36)	59.09 (12.80)
LDA	ACCU	82.50 (18.95)	60.00 (16.29)	60.00 (7.65)
	SPEC	84.21 (19.48)	52.17 (30.21)	57.89 (8.79)
	SENS	80.95 (19.48)	52.94 (22.05)	57.14 (6.85)

ACCU: accuracy, SPEC: specificity, SENS: sensitive.

Figure 5.3 displays the outcomes post NCA application. The horizontal axis represents all body segments, while the vertical axis indicates the feature weighting factors determined by the NCA algorithm. Features with a higher weight are more relevant for classification, whereas those with lower values are considered less significant and thus excluded from the dataset. The figure reveals that, across all trajectories, the body segments Hip, Ankle, and Foot exhibit the least discriminative potential.

The NCA algorithm identified a total of thirty one features relevant for the curvilinear trajectory, fifty for the rectilinear trajectory, and twenty nine for the combined condition, originating from the Head, Trunk, and Pelvis. Notably, none were identified from the Hip, Knee, Ankle, or Foot. To determine optimal classification performance with the fewest features, accuracy was plotted against the number of NCA-selected features in **Figure 5.4**. This graph reveals that the K-NN algorithm consistently yields the highest accuracy: eleven features for curvilinear gait, seven for rectilinear gait, and nine for the combined trajectory. Introducing more features generally led to worse performance in the classifier, implying that certain gait features may be unnecessary, not offering any added discriminatory value.

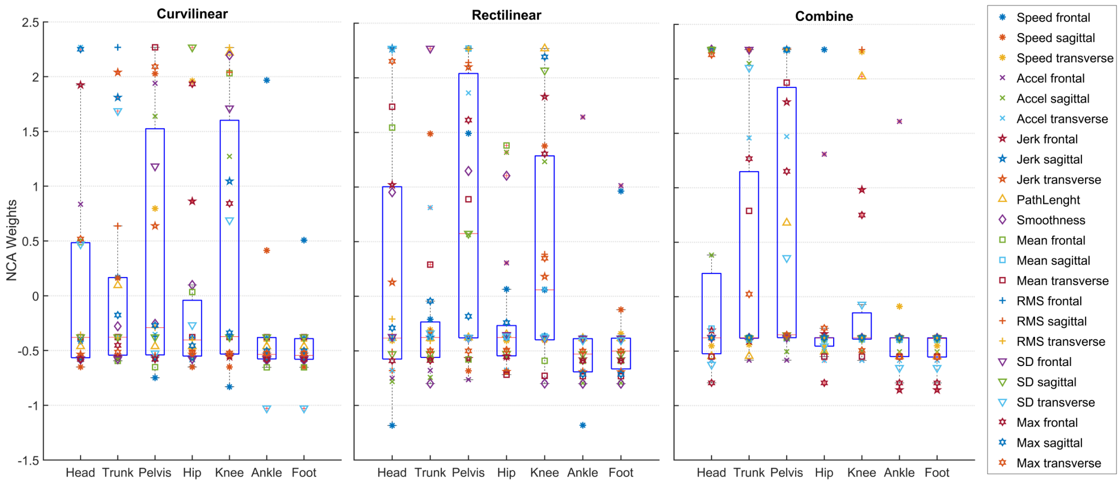

Figure 5.3. NCA weights for each body segment and trajectory.

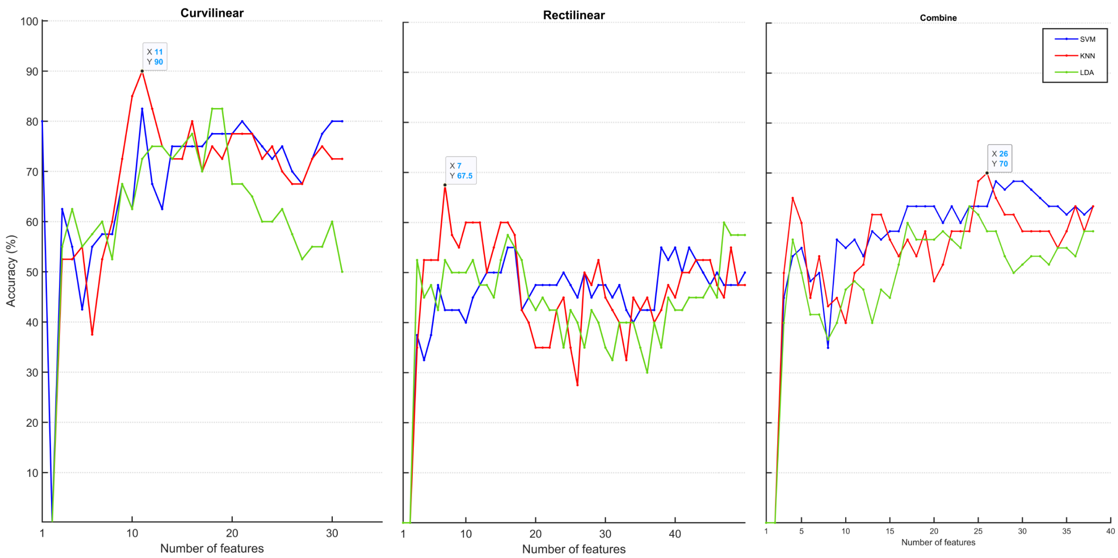

Figure 5.4. % Classification Accuracy vs. Number of Features Selected by NCA for Each Trajectory. The 40 features selected are: Mean jerk Rotation Head, Mean speed Tilt Trunk, Mean acceleration Tilt Trunk, Mean speed Tilt Pelvis, Mean jerk Tilt Pelvis, Mean jerk Rotation Pelvis, Mean Smoothness Pelvis, Mean speed Oblique Hip, Mean Smoothness Hip, Mean speed Rotation Knee, Mean jerk Oblique Knee, Mean Head Rotation, Mean Trunk Rotation, Mean Pelvic Tilt, Mean Hip Oblique, RMS Head Rotation, RMS Pelvic Oblique, RMS Pelvic Rotation, Max Head Oblique, Max Trunk Oblique, Max Ankle Plantar Flexion, SD Pelvic Oblique, Mean Path Length Head, Mean acceleration Rotation Pelvis, Mean Path Length Pelvis, Mean jerk Oblique Hip, Mean jerk Tilt Knee, Mean Pelvic Tilt, Mean Pelvic Rotation, Mean Hip Rotation, Mean Knee Valgus, Mean Knee Flexion Extension, Mean Knee

Rotation, RMS Knee Valgus, RMS Foot Inversion, Max Head Oblique, Max Knee Rotation, SD Head Oblique, SD Trunk Oblique, SD Hip Rotation

Table 5.3 displays the features, tracked from various body segments through NCA, that possess the highest discriminative capability, leading to optimal classification performance. For all three trajectories, these key features are linked to kinematic parameters and consistently involve the same three body segments: Head, Trunk, and Pelvis.

Table 5.3. Selected kinematic features by NCA for each type of gait

	Curvilinear		Rectilinear		Combine	
Body segments	Features	FW*	Features	FW	Features	FW
Head	Accel (frontal plane) Accel (transverse plane) Jerk (frontal plane)	0.925 0.638 1.529 1.03 (0.45)	Jerk (frontal plane) Jerk (sagittal plane) Jerk (transverse plane) Smoothness	0.789 1.033 0.558 1.388 0.79 (0.23)	Accel (sagittal plane) Jerk (sagittal plane) Smoothness	0.377 1.200 1.104 0.89 (0.45)
Trunk	Speed (sagittal plane) Jerk (sagittal plane) Jerk (transverse plane) Path length	0.708 1.566 1.468 0.213 0.98 (0.64)	Speed (frontal plane) Speed (sagittal plane) Accel (frontal plane)	0.597 1.712 0.041 0.93 (0.75)	Speed (sagittal plane) Accel (sagittal plane) Accel (transverse plan)	1.942 1.125 1.417 1.49 (0.41)
Pelvis	Speed	2.341	-	-	Accel	1.426

	(sagittal	1.153		(transverse	1.367
	plane)	1.659		plane)	0.786
	Speed	1.093		Jerk	1.19 (0.35)
	(transverse	1.56 (0.57)		(transverse	
	plane)			plane)	
	Accel			Path length	
	(frontal				
	plane)				
	Accel				
	(sagittal				
	plane)				

(*) FW: Feature weight (discriminative power).

- EMG results

The overall performance of each classifier across different gait trajectories, both before and after integrating NCA, can be found in **Table 5.4**. Especially, the SVM algorithm stands out in the curvilinear trajectory, reaching an accuracy of 85% post-NCA. Following the introduction of NCA, all the three algorithms exhibited a boost in their performance. In addition, they all demonstrated enhanced accuracy, specificity, and sensitivity when analysing curvilinear gait.

Table 5.4. Classification performance for each trajectory.

		Curvilinear	Rectilinear	Combine
All features				
K-NN	ACCU	62.00 (12.50)	35.00 (20.91)	37.00 (7.12)
	SPEC	61.90 (10.82)	35.00 (36.17)	37.50 (6.54)
	SENS	63.15 (20.83)	35.00 (24.72)	37.50 (8.49)
SVM	ACCU	45.00 (11.18)	32.50 (14.25)	56.25 (2.79)
	SPEC	45.00 (35.35)	31.57 (33.07)	56.41 (5.00)
	SENS	45.00 (7.45)	33.33 (23.00)	56.10 (3.21)
LDA	ACCU	65.00 (17.67)	42.50 (10.45)	47.50 (5.59)
	SPEC	65.00 (22.36)	42.85 (10.27)	47.36 (5.70)

	SENS	65.00 (15.16)	42.10 (12.60)	47.62 (5.52)
Selected features by NCA				
K-NN	ACCU	80.00 (9.32)	55.00 (6.00)	60.00 (5.49)
	SPEC	83.33 (9.56)	54.54 (6.02)	58.69 (5.39)
	SENS	78.94 (9.42)	55.55 (6.34)	61.76 (5.73)
SVM	ACCU	85.00 (13.69)	55.00 (18.54)	62.50 (2.79)
	SPEC	81.81 (9.37)	60.00 (30.69)	60.46 (2.35)
	SENS	88.88 (9.51)	54.17 (14.79)	62.50 (25.0)
LDA	ACCU	75.00 (9.76)	55.00 (13.69)	56.25 (10.80)
	SPEC	72.72 (12.36)	56.25 (12.47)	58.06 (12.10)
	SENS	77.77 (12.80)	55.00 (17.25)	55.10 (11.18)

The analysis conducted using the NCA algorithm is visualised in **Figure 5.5**. On the horizontal axis, the three pairs of neck muscles (SCM, SC, and UT) are represented, while the vertical axis captures the weightage of each feature determined by NCA. Distinct symbols, detailed in the accompanying legend, indicate each feature. This representation helps to understand the distribution and importance of the features. Those with greater weights are considered pivotal for classification, while lower-weighted features are seen as unnecessary and consequently removed from the dataset. When comparing the feature weights across trajectories, the SCM muscle in curvilinear gait stands out with the highest median, marked by a red line. This emphasises the significance of the SCM muscle in providing valuable features for CNP identification, subsequently enhancing classification accuracy.

Following the feature reduction based on their weightage, accuracy was plotted against the number of features to identify optimal classification performance for each algorithm across trajectories. **Figure 5.6** shows that for curved path gait, the SVM model achieves 85% accuracy using sixteen features. The K-NN model follows closely with 80% accuracy, requiring fifteen features, and LDA has an accuracy of 75% with seventeen features. The sixteen features associated with the best performance, signifying the highest discriminative capability, are detailed in **Table 5.5**. Importantly, The IC feature is a key factor in the classification results and could play a vital role in differentiating between the groups. SSI and WL also ranked high in terms of class separability. In detail, an equal distribution of features comes from both the time and frequency domains. Additionally, more than half of the selected features are associated with the SCM muscle. On the other hand, features assessed during the rectilinear gait or combined trajectories resulted in suboptimal classification, achieving accuracies of 55% and 62.50% respectively, when using the SVM algorithm.

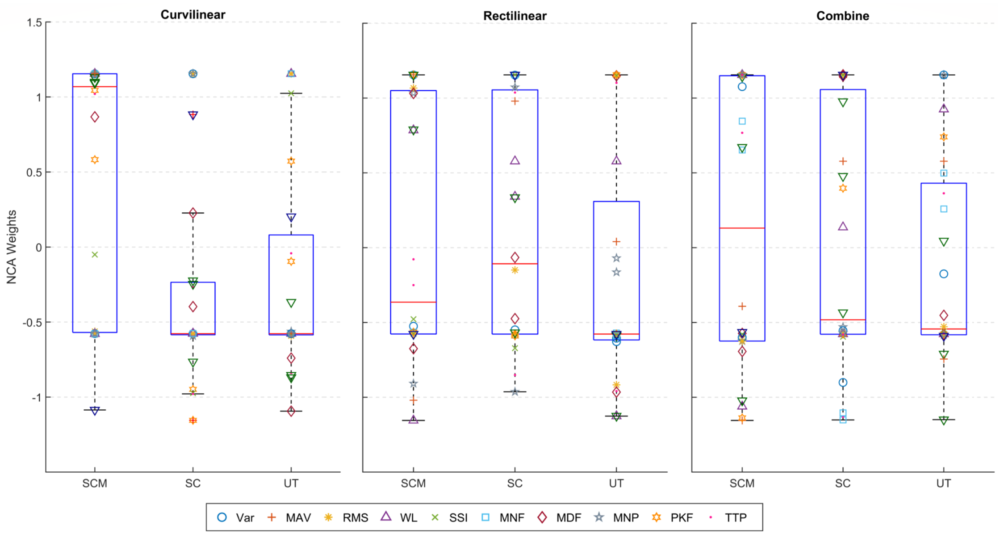

Figure 5.5. NCA weights of the features for each gait trajectory grouped by muscle. Variance (VAR), Mean Average Value (MAV), Root Mean Square (RMS), Waveform Length (WL), Single Square Integral (SSI), Mean Frequency (MNF), Median Frequency (MDF), Mean Power (MNP), Peak Frequency (PKF), Total Power (TP).

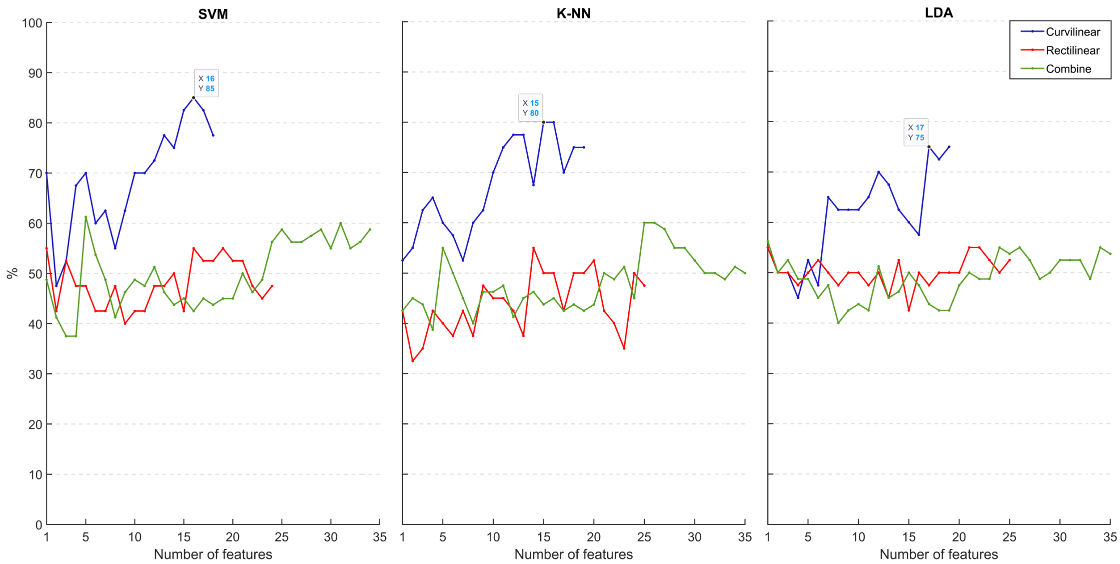

Figure 5.6. Dependence of % classification accuracy on the number of features selected by NCA. Features names corresponding to the x-axis: RMS SCM Right, WL SCM Right, SSI SCM Right, VAR SCM Left, WL SCM Left, MNF SCM Right, TP SCM Right, IC, MNF SCM Left, MDF SCM Left, BP SCM Left, Max SCM Left, TP SCM Left, MAV SC Right, MAV SC Left, WL SC Left, MNF SC Right, MDF SC Right, BP SC Right, TP SC Right, MDF SC Left, PKF SC Left, Total Power SC Left, MAV UT Right, WL UT Left, MNF UT Right, MDF UT Right, PKF UT Right, TP UT Right, MDF UT Left, TP UT Left.

Table 5.5. Selected EMG features by NCA.

		Curvilinear			Rectilinear		Combine		
Muscles	Side	Features	FW*	Mean (SD)	Features	FW	Features	FW	Mean (SD)
SCM	R	VAR	2.409	1.28 (0.80)	MAV	4.097	MAV	0.100	2.30 (1.97)
		MAV	1.022				RMS	2.918	
		SSI	0.524				WL	3.902	
		MNF	1.168				SSI	0.848	
		PKF	1.880						
	L	VAR	1.817	2.22 (0.66)	-	-	VAR	3.565	-
		SSI	2.992						
		PKF	1.113						
		MSC	0.852						
SC	L	VAR	0.881	1.47 (1.05)	-	-	-	-	-
		WL	2.692						
		MNF	1.103						
		PKF	2.616						
UT	R	MNF	1.046	1.04	-	-	-	-	-
		MDF	1.607						
	L	MAV	0.245	-	-	-	-	-	-

*FW: Feature weight (discriminative power), R: right, L: left, SD: standard deviation.

The networks' topology was studied to evaluate functional connections between neck muscles under various conditions and frequencies bands for both groups. Each network measure was derived from weighted coherence matrices and averaged per node for every group, setting, and frequency band. During curvilinear walking in the delta band, the BC displayed a significance difference (p = 0.021) between individuals with and without CNP. Interestingly, during rectilinear walking within the same frequency range, the BC differences were not statistically significant (p = 0.068). Moreover, the ST exhibited no significant discrepancies between groups, as indicated in **Table 5.6**. Other frequency bands did not show significant variances. **Figure 5.7** illustrates the indirect neck muscle connections in the delta band during both curvilinear and rectilinear walking. The size of each node represents its degree, representing the number of links to other nodes (muscles). The width of the edge corresponds to the connection's intensity. From the figure, it is evident that the muscle network of those with CNP have thinner edges and fewer connections, suggesting reduced muscle network connectivity during curved walking.

Table 5.6. Network parameters from curvilinear and rectilinear gait

		Curvilinear	Rectilinear	p-value
ST	CNP	0.901±0.06	0.913±0.04	P > 0.05
	Control	0.933±0.04	0.923±0.03	
BC	CNP	0.034±0.02	0.046±0.03	P < 0.05
	Control	0.015±0.06	0.029±0.02	

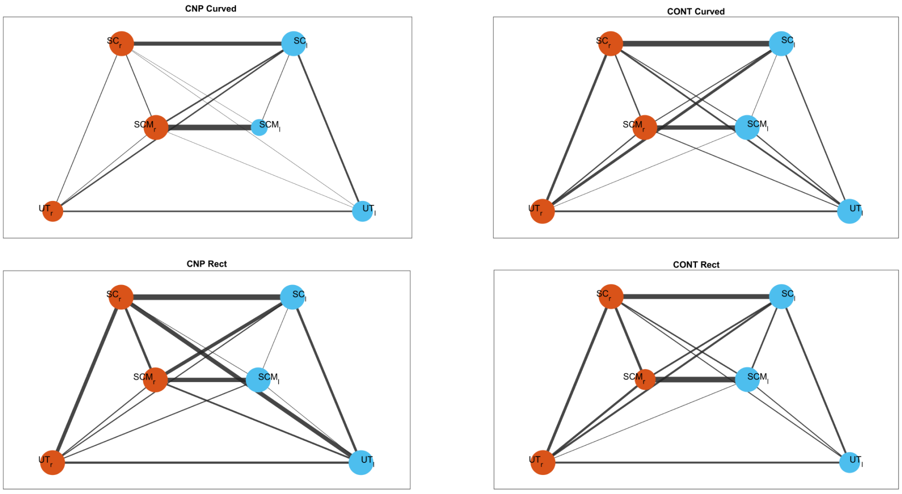

Figure 5.7. Functional networks of CNP and control groups during curvilinear and rectilinear task at delta band. Orange nodes represents left side muscles and blue nodes the right-side ones.

5.1.4. Discussion

This study explores an extensive array of kinematic and EMG features, including some that have not been previously examined in the context of neck pain. Importantly, the focus on curvilinear gait has yielded noteworthy findings. The research has expanded understanding of biomechanical changes in both the muscular and kinematic areas for people with CNP. Following, the implications of these results are discussed, organised into two separate sections: one focusing on kinematic findings and the other on EMG data.

- Kinematics

- *Gait characteristics*

Human movement produces different types of data, especially related to motion and forces, which can be useful for categorising people based on their unique walking styles (Horst et al., 2019). Previous research has examined gait patterns in populations with and without CNP, revealing distinct differences in movement dynamics between these groups

(Alsultan et al., 2019; Falla et al., 2017; Kirmizi et al., 2019). Nevertheless, the incorporation of ML methodologies remained unexplored. Incorporating such strategies could offer supplementary means to identify key characteristics in CNP individuals and increase the precision in recognising those predisposed to recurrent pain episodes. The results indicate that, in comparison to rectilinear and combined gait, curvilinear walking provides the most significant data. It obtained an accuracy, specificity, and sensitivity of 90%, 100%, and 83.33% in succession via the NCA-K-NN algorithmic procedures. In a holistic view, the combination of classifiers demonstrated enhanced performance during the curvilinear trajectory relative to rectilinear and combined gait. Previous literature has largely focused on the dynamics of linear gait in CNP populations (Alsultan et al., 2019; Falla et al., 2017; Kirmizi et al., 2019), identifying features such as reduced walking speeds, shorter step lengths, and limited trunk mobility. In contrast, other clinical populations, such as those with Parkinson's disease or post-stroke conditions, experience increased difficulties in walking along curved paths compared to linear ones (Godi et al., 2010; Guglielmetti et al., 2009). The research further emphasises that complex gait dynamics, requiring adjustments in multiple body segments, serve as the most effective metrics for evaluating gait in CNP populations. This enhances the ML model's ability to identify key features within this specific patient group.

- *Performance of approaches*

In terms of classification methods, the K-NN classifier outperformed others across all proposed trajectories, achieving an accuracy of 90% for curvilinear, 67.5% for rectilinear, and 70% for combined paths. This is in comparison to SVM, which scored 82.5% for curvilinear, 55% for rectilinear, and 62.50% for combined, and LDA with 82.5% curvilinear, 60% rectilinear, and 60% combined. The SVM classifier has gained recently significant attraction in musculoskeletal disorder classification due to its ability to capture intricate relationships (Hayashi et al., 2015). Its classification style, whether linear or non-linear, is dictated by its kernel function (Deisenroth et al., 2020).

For this research, it was employed the linear kernel function with SVM. It is noteworthy that both LDA and SVM, being linear classifiers, lagged behind KNN in performance. This variation from previous chapters, where SVM emerged as the superior classifier, may be attributed to the inherent characteristics of the K-NN algorithm, which excels in non-linear classification. K-NN's effectiveness in this context likely stems from its compatibility with the non-linear and non-stationary properties of the data, in contrast to the linear kernel configuration used for SVM. This highlights the importance of matching the algorithm's capabilities with the data's underlying patterns to achieve optimal classification performance. Additionally, the superior performance of K-NN may also be linked to its inherent non-linear classification capability, which more closely matches the non-linear and non-stationary features of the dataset. Across all the supervised models explored, the NCA demonstrated superior classification strength, even with a reduced feature set, by identifying the most relevant features effectively. Such enhanced classification aligns with past studies that have implemented NCA and observed improved outcomes (Manit & Youngkong, 2011; Raghu & Sriraam, 2018).

- *High impact features*

Kinematic attributes, including speed, acceleration, and jerk, particularly form the head, trunk, and pelvis, played a pivotal role in the precise categorisation of individuals with CNP versus those without symptoms during walking. This is consistent with previous work by (Sjolander et al., 2008), in which it was identified the jerk index as an innovative metric for objectively studying sensorimotor disruptions in CNP patients during voluntary head movements. The dominant presence of these kinematic variables points towards biomechanical deviations. These deviations could possibly come from involuntary adaptations like abrupt or lethargic motions to avoid pain, as earlier studies have indicated (Hodges & Falla, 2015; Hodges & Tucker, 2011). The incorporation of ML techniques adds a quantitative and objective dimension to the analysis of kinematic data, thereby mitigating some of the limitations associated with conventional statistical methods. These key variables selected might serve as biological markers to elucidate distinctions between groups, thereby supplementing clinical evaluations in the future.

- EMG

- *Gait characteristics*

Numerous studies have observed muscle activity differences between CNP patients and those without symptoms (Falla et al., 2004e; Jull et al., 2004). The results support these findings, highlighting the potential of EMG measures from the SCM and SC muscles to distinguish between the groups. This aligns with observations from previous chapters, where the relevance of the SC muscle in classification tasks was demonstrated, further emphasizing its significance in differentiating between individuals with and without CNP.

A key finding was the superior classification provided by the curvilinear gait. This suggests that the more commonly studied rectilinear gait might not capture these differences as effectively. Nonlinear walking, given its demand for detailed coordination across body segments and anticipatory actions, offers a more challenging task (Courtine

& Schieppati, 2003a, 2003b), possibly making it a better context for observing discrepancies in muscle activity.

- *Performance of approaches*

The SVM algorithm had the highest performance, with an accuracy of 85%, specificity of 81.81%, and sensitivity of 88.88% during curvilinear gait. K-NN and LDA also did well during curvilinear gait with accuracies of 80% and 75%. For rectilinear gait, all three classifiers had a 55% accuracy with similar specificity and sensitivity. Previous studies trained these classifiers with EMG data from limb muscles showed the same ranking: SVM outperformed, then K-NN, followed by LDA (Dhindsa et al., 2019; Mokdad et al., 2020). Some research even suggests K-NN typically outdoes LDA (Kim et al., 2011). The superior performance of all three algorithms when analysing curvilinear paths suggests that nonlinear gait provides more distinct features for classification. This enhanced discriminative power could be attributed to the heightened muscle activity and coordination required for more complex tasks, such as maintaining head position in the presence of increased shear forces. Moreover, the consistent performance ranking of SVM, K-NN, and LDA algorithms, as observed in this analysis of both gait patterns, mirrors the findings in previous Chapters 3 and 4.

- *High impact features*

Many studies have focused on the ideal feature selection for characterising EMG signals. In this study, the NCA streamlined the features based on their discrimination power. NCA consistently improved classification results with fewer features across all supervised models. **Table 5.5** shows more features selected from the SCM muscle, aligning with **Figure 5.5** that indicates a higher median weight for SCM in curvilinear gait than other muscles. This pattern of feature selection underscores the pivotal function of the SCM in neck mechanics during curvilinear motion. The SCM is a primary muscle facilitating neck rotation, a crucial action for orienting the head and guiding the body through the curved trajectory inherent to curvilinear gait (Bordoni et al., 2023). As the head initiates and leads the directional change, the SCM is engaged significantly, thereby becoming a dominant part in the classification.

The most relevant features for the classification were SSI and WL, both time-domain. This might suggest potential alterations in muscle recruitment and activation patterns in individuals with neck pain. SSI, representing the overall energy of the EMG signal, could reflect either increased muscle activation in a compensatory manner or decreased activation due to protective mechanisms or dysfunction. Similarly, WL's focus on signal complexity might indicate less coordinated or more frequent muscle contractions in response to pain or less simplified activation patterns stemming from fatigue or inhibition. Prior research has established that time-domain features are particularly effective in signal classification (Phinyomark et al., 2012a). Furthermore, previous studies recognise WL as a crucial feature in EMG identification (Phinyomark et al., 2014; Toledo-Pérez et al., 2019). Consistent with observations in Chapters 3 and 4, WL was once again selected as a significant feature, highlighting its persistent importance across different contexts and analyses in distinguishing between individuals with CNP and healthy controls.

PKF and VAR also showed significant discriminatory value. On one hand, PKF potentially hints at possible changes in muscle fiber composition or fatigue tendencies. A lower PKF is often linked to a shift towards slower muscle fiber types, a hallmark of fatigue or chronic pain adaptation. Additionally, PKF variations could reflect altered MU recruitment in response to pain or underlying muscle dysfunction. This is also supported by its significance during the prologue smartphone use task in Chapter 4. On the other hand, VAR might emphasise changes in muscle activity variability, likely coming from irregular muscle contractions.

- *Muscle networks*

IC was identified by NCA as a crucial feature, achieving notable accuracy in classification. This might indicate the presence of distinct muscle synergies in individuals with CNP and the appearance of task-specific synergies during curvilinear walking. Furthermore, the consistent identification of IC as a relevant feature across all chapters suggests that muscle coordination may be a crucial factor for differentiating participants with neck pain across different scenarios.

Network topology was employed to analyze the neural synchrony of these synergies, revealing graphical and statistical differences between CNP and control groups during curvilinear gait in the delta band (Hay & Wachowiak, 2017). These findings diverge from those presented in Chapter 4, which focused on a static postural task and did not demonstrate similar differences. In contrast, the results are in line with the observations in Chapter 3, where significant differences were also identified in muscle network behaviours during the dynamic cervical flexion task. This suggests that the differences in muscle coordination patterns between CNP sufferers and controls are more pronounced in dynamic movements, such as cervical flexions and curvilinear walking, than in static postures.

The differences identified in the muscle networks were predominantly observed within the delta frequency band. This frequency band, as evidenced by prior research, demonstrates significant coherence during activities such as posture maintenance and gait, indicative of a significant shared synaptic input that is pivotal for these motor tasks (Dideriksen et al., 2018). The delta band's critical involvement in the production and modulation of force uncovers its indispensable role in the intricate mechanisms of motor control and coordination (Farina & Negro, 2015). Moreover, the muscle networks metrics revealed that individuals with CNP showed higher BC values compared to the control, indicating that in CNP subjects, certain nodes have a dominant role in information flow within the network (Fornito, 2016).

5.1.5. Conclusions

This research revealed that that both kinematic data and surface EMG techniques contain valuable information that could be used to classify individuals with and without nonspecific CNP. Specifically, the kinematic data collected during walking suggests the feasibility of using biomarkers for an objective evaluation of movement impairments linked to CNP. Concurrently, the application of IC as a novel method in this study revealed unique task-specific synergies presence during curvilinear gait between the two groups, thereby enhancing the classification performance. As the research progresses, it becomes essential to determine whether these potential biomarkers and synergies can estimate those susceptible to recurrent neck pain episodes during remission periods.

5.2. Single- and Dual-task Gait

5.2.1. Introduction

Dual-task walking, defined as performing two discrete tasks simultaneously, is a critical component of functional walking essential for daily life (Baek et al., 2021). This often involves walking while concurrently engaging in a cognitive task, like talking with a friend, or a motor task, such as carrying a cup of coffee. The concept of dual-task interference arises from the observation that engaging in simultaneous tasks can impact gait performance, a phenomenon noted not only in healthy individuals but also in those with neurological disorders (Liu et al., 2017). The prevailing hypothesis suggests that simultaneous tasks compete for the brain's cortical resources, leading to modifications in gait (Montero-Odasso et al., 2012). These alterations, often exhibited as a slowing of gait, are indicative of the increased demands on cortical attention processes during walking, termed dual-task costs.

When comparing asymptomatic individuals with those suffering from CNP, kinematic differences during walking become more pronounced during complex activities, such as walking with continuous head rotations (Falla et al., 2017). Prior research reveals that those with CNP exhibit reduced walking speed during dual-task gait (Alsultan et al., 2019) and display decreased variability in trunk rotation in these demanding conditions (Falla et al., 2017). Motivated by the observed kinematic differences and the prevalence of such tasks in daily life, this study investigates the potential of ML algorithms to analyze kinematic data under these conditions. Specifically, the aim is to determine whether ML can effectively distinguish between individuals with and without CNP during dual-task gait.

IMU sensors have proven their reliability and effectiveness in the realm of human motion analysis (Hu et al., 2018). Considering the observed gait abnormalities in individuals with CNP, the present study aims to distinguish between regular and modified gaits using kinematic features from three IMU sensors. Earlier studies have highlighted the capability of IMU-derived motion metrics to spot gait changes in individuals with musculoskeletal disorders (Odonkor et al., 2020; Wang et al., 2021; Zugner et al., 2019). Yet, many gait investigations have focused solely on specific biomechanical parameters like gait speed, step length, and acceleration (Baghdadi et al., 2018; Odonkor et al., 2020), examining potentially insightful frequency features. Consequently, the study integrated both time and frequency-based kinematic attributes to discern differences between those with CNP and asymptomatic participants, evaluating their classifying potency.

This investigation used the methodology presented in Chapter 2 to identify the most discriminative gait features and body segments for the classification. Three supervised algorithms were employed to differentiate between people with CNP and asymptomatic individuals during both single- and dual-task gait. The aim of the present study is to highlight key gait anomalies in individuals with CNP, enabling easy detection using just three sensors, streamlining gait analysis in subsequent research.

5.2.2. Methods

- Participants recruitment

The study involved 18 asymptomatic participants and 21 individuals with CNP. Participant selection for both the healthy and CNP groups strictly followed the inclusion and exclusion guidelines, and details about the participants were shared in agreement with the specifications in Section 2.1.

The investigation took place in a controlled setting at the CPR Spine laboratory, having received ethical consent from the University of Birmingham's Ethics Committee (ERN_19-0564), and was in accordance with the ethical principles outlined in the Declaration of Helsinki.

- Experimental protocol

Participants performed both single-task and dual-task walking exercises, each along an 8m straight path at their chosen pace. In the dual-task exercise, participants were instructed to rotate their heads repetitively (from one side to the other) to their comfort level while walking. Each task was performed three times by every participant. These tasks are illustrated in **Figure 5.8**.

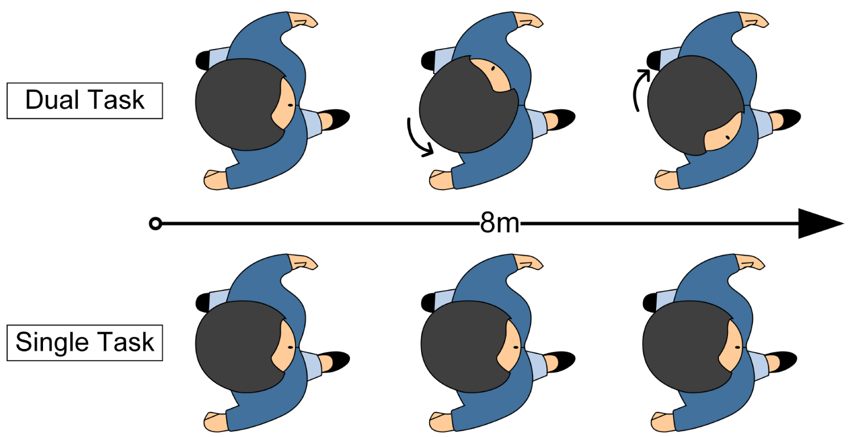

Figure 5.8. Tasks performed by the subjects. Source: Microsoft Visio.

- Measurement systems

A wireless IMU system (myoMOTION Research Pro, Noraxon USA) was used to capture the gait kinematics. Three IMUs, each measuring 37.6 mm x 52.0 mm x 18.1 mm and weighing 34g, were attached to the forehead, upper thoracic spine (T1), and lower thoracic spine (T12) using double-sided tape. The forehead sensor is essential for tracking head orientation and rotational movements, providing direct data on how head rotation tasks influence overall posture and gait. Meanwhile, the sensors placed on the upper and lower thoracic spine are strategically located to capture the compensatory adjustments and the core stability mechanisms engaged during the dual-task. This positioning allows for a comprehensive analysis of the spine's movement, essential for understanding the biomechanical adaptations that occur when the head is rotated during walking. This configuration ensures that all relevant aspects of dual-task gait dynamics are captured (Ghislieri et al., 2019). Another IMU was placed near the ankle on the right shank to help segment gait cycles from stationary phases. Recording at a 100 Hz sampling rate, these IMUs tracked acceleration and angular velocity on the three axes. Data processing used the Noraxon software (MyoRESEARCH 3.12) with a body model adjusted to individual participant measurements. Before each session, this model was calibrated to the anatomical stance. Additionally, an integrated Kalman filter refined the raw data automatically.

- Data analysis

The data were processed into individual gait cycles. To begin, linear trends of gravitational components were subtracted from accelerometer readings to remove zero frequency components (a method known as detrending) (Cole et al., 2014). A second-order Butterworth filter with a 6 Hz cut-off was then employed (Gjoreski & Gams, 2011; Sun & Hill, 1993; Winter et al., 1974). Gait cycles were identified as the period between two consecutive heel strikes of the same foot and then adjusted to yield 101 data points, representing 0–100% of the cycle's duration. The initial and final steps of each trial were excluded, and an average value was calculated for every participant (Chia Bejarano et al., 2017).

Post-processing, essential kinematic features from each gait cycle were extracted to characterise the observed patterns. These features covered both time and frequency domains: the time domain included variables like Velocity, Acceleration, Jerk, and smoothness, while the frequency domain comprised metrics such as Entropy, Energy, and Power derived from accelerometer data. Each of these features was computed for every sensor axis separately. Next, a norm vector was generated by combining these axes, a step that simplified the data while enhancing its robustness against rotation (Zhang et al., 2014). Frequency-based features were obtained using the Fast Fourier Transform, and normalisation was carried out using a hamming window (Dargie, 2009). The resulting feature vector incorporated the mean, peak, and lowest values of each feature. In total, 63 features were extracted through this process.

As detailed in Chapter 2, three supervised learning techniques (KNN, SVM, and LDA) were employed for the classification of participants with and without CNP based on their gait kinematic features. A LOO cross-validation scheme was adopted to train and validate all model. For enhancing algorithm performance and refining datasets, feature selection was carried out using NCA. The impact of NCA's feature selection was assessed by executing the three algorithms with and without its application.

5.2.3. Results

Table 5.7 provides the demographic information of the participants. Between the groups, there were not any significant distinctions in demographic features ($p > 0.05$).

Table 5.7. Participant demographic details.

	Neck pain Mean ± SD	Control Mean ± SD	p-value*
Age (years)	32.1 ± 8.6	30.1 ± 5.3	0.14
BMI (kg/m^2)	22.9 ± 3.5	22.95 ± 3.8	0.48
Gender (females %)	76%	50%	-
NDI (0-50)	15.6 ± 5.9	-	-
Average neck pain intensity (0–10)	5.4 ± 1.8	-	-

(*) Independent samples t-test, NDI: Neck Disability Index, SD: Standard deviation, BMI: Body Mass Index.

Initially, the classifiers were trained using all the gathered features, without any feature selection, to establish baseline performance and to evaluate the impact of the feature selection method. **Table 5.8** showcases the classification outcomes for every algorithm and task, both pre and post the use of NCA. The improvement in the performance metrics such as accuracy, specificity, and sensitivity post NCA's application highlights the algorithm's ability to identify key differentiating kinematic features. This in turn enables the classifiers to more effectively discriminate between the different groups.

In both scenarios, prior to and after applying NCA, the classification performance increased notably during the dual-task gait condition. The peak performance was observed in the dual-task gait using NCA-SVM algorithms with an accuracy of 86.85%. Following closely were K-NN and LDA, achieving accuracies of 84.22% and 81.60% respectively. A similar performance hierarchy was evident for single-task gait: SVM led with 76.30%, trailed by K-NN at 71.06%, and then LDA at 68.39%. Impressively, NCA-SVM showcased the greatest sensitivity at 92.85% and excellent specificity at 83.30%. This indicates that it was highly effective in correctly identifying a large majority of true

CNP cases, while also successfully identifying a substantial number of non-CNP instances. Given the potential consequences of misclassifying individuals with CNP, the emphasis on sensitivity in this context is particularly important.

Table 5.8. Performance metrics for each classification algorithm and each task reported as means (standard deviations) in percentage.

		Single-task	Dual-task
All features			
K-NN	ACCU	58.92 (12.46)	74.28 (16.23)
	SPEC	63.15 (19.49)	78.94 (13.31)
	SENS	55.00 (18.25)	70.00 (23.28)
SVM	ACCU	61.53 (10.41)	75.00 (28.94)
	SPEC	61.53 (8.84)	71.78 (34.25)
	SENS	61.53 (27.38)	68.42 (47.14)
LDA	ACCU	56.07 (21.50)	53.57 (8.65)
	SPEC	58.33 (42.66)	57.89 (7.07)
	SENS	53.33 (13.41)	50.00 (26.24)
Selected features by NCA			
K-NN	ACCU	74.28 (7.36)	82.14 (12.10)
	SPEC	78.94 (7.44)	85.00 (11.02)
	SENS	70.00 (8.05)	78.94 (13.97)
SVM	ACCU	79.64 (9.31)	87.14 (11.35)
	SPEC	80.95 (7.52)	83.33 (9.42)
	SENS	77.77 (12.36)	93.33 (13.67)
LDA	ACCU	66.42 (5.84)	79.64 (10.90)
	SPEC	66.66 (5.80)	74.07 (8.57)
	SENS	66.66 (6.51)	91.66 (17.67)

Figure 5.9 displays a boxplot detailing the feature weights determined by NCA during the validation phase. This visual representation highlights not just the features considered more or less important for classification, but also pinpoints which body segments contain the most pertinent features. From this illustration, it becomes evident that, across both tasks, the head is the body segment given the highest weighting, followed by the lower and upper thoracic spine areas. The NCA algorithm chose sixteen features for the single-task gait and eleven for the dual-task gait. Following tests on these feature sets aimed to identify the subset that yields the optimal classification performance using the fewest number of features. **Figure 5.10** plots the accuracy of each classifier against the number of features that NCA selected. In the single-task gait context, SVM reached an accuracy of 76.30% with five features, while K-NN registered 71.06% with four, and LDA achieved 68.39% using seven features. Conversely, for dual-task gait, the highest accuracies for SVM (86.85%), K-NN (84.22%), and LDA (81.60%) were all achieved by using nine features.

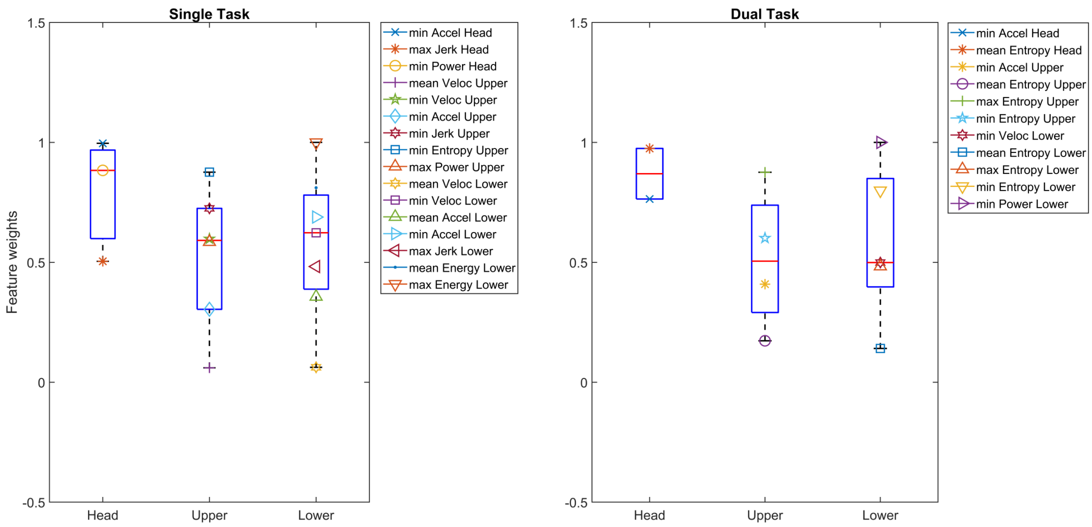

Figure 5.9. NCA weights for Single-task (Left) and Dual-task (Right) obtained from the validation set.

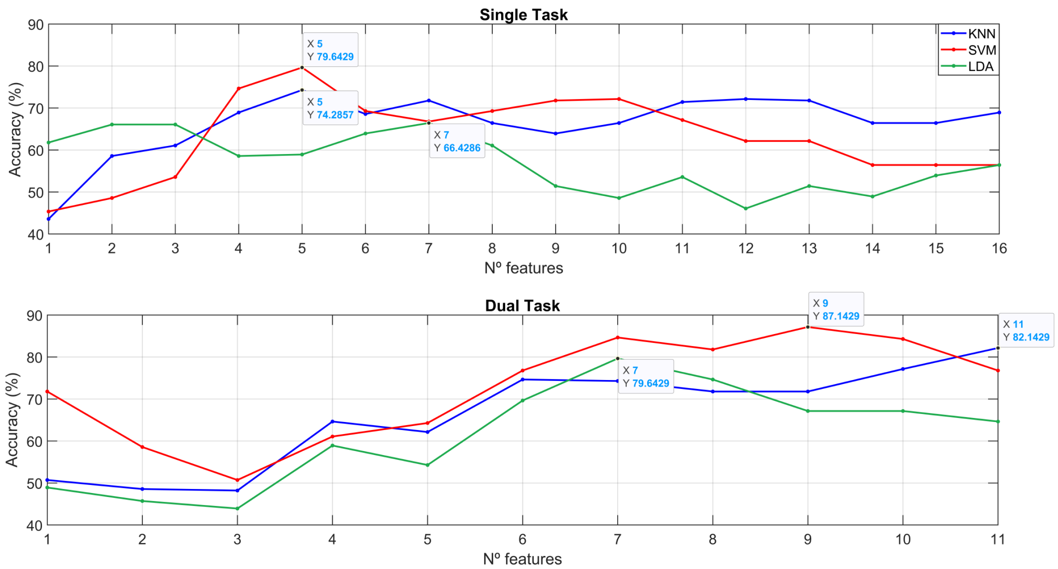

Figure 5.10. Accuracy versus the number of features for Single task (Up) and Dual task (Bottom). Features names corresponding to the x-axis for single-task: min Velocity Lower spine, min Acceleration Head, mean Acceleration Lower spine, min Acceleration Lower spine, min Acceleration Upper spine, max Jerk Head, min Jerk Upper spine, max Jerk Lower spine, min Entropy Upper spine, min Power Head, max Power Upper spine, mean Energy Lower spine, max Energy Lower spine. Features names corresponding to x-axis for dual-task: min Velocity Lower spine, min Acceleration Head, min Acceleration Upper spine, mean Entropy Head, mean Entropy Lower spine, max Entropy Lower spine, min Entropy Lower spine, mean Entropy Upper spine, maximum Entropy Upper spine, min Entropy Upper spine, min Power Lower spine.

Table 5.9 enumerates all the features chosen by NCA, along with their respective weights. A notable observation is that features with greater weights are predominantly frequency features in both tasks, highlighting the significance of frequency attributes for classification. In the dual-task gait, Entropy emerged as the dominant feature. Meanwhile, Acceleration and Velocity were the most represented for the single-task gait. The prominence of these features in the dual-task can be attributed to its inherent complexity. Given that participants from both groups might have executed the dual-task at a slower pace, distinctions in Speed, Acceleration, or Jerk were not as evident. This scenario accentuated the crucial role of frequency features in distinguishing between the groups.

Table 5.9. Kinematic features chosen by NCA

Single-task	Dual-task

Body segments	Features	FW*	Mean (SD)	Features	FW	Mean (SD)
Head	Min Accel	0.996	0.794 (0.257)	Min Accel	0.763	0.868 (0.149)
	Max Jerk	0.504		Mean Entropy	0.974	
	Min Power	0.883				
Upper spine	Mean Veloc	0.060	0.524 (0.295)	Min Accel	0.408	0.513 (0.297)
	Min Veloc	0.597		Mean Entropy	0.172	
	Min Accel	0.304		Max Entropy	0.875	
	Min Jerk	0.724		Min Entropy	0.600	
	Min Entropy	0.875				
	Max Power	0.585				
Lower spine	Mean Veloc	0.062	0.574 (0.308)	Min Veloc	0.499	0.584 (0.329)
	Min Veloc	0.623		Mean Entropy	0.140	
	Mean Accel	0.356		Max Entropy	0.483	
	Min Accel	0.688		Min Entropy	0.799	
	Max Jerk	0.482		Min Power	1.000	
	Mean Energy	0.810				
	Max Energy	1.000				

*FW: Feature weight (discriminative power)

5.2.4. Discussion

In this study, the efficiency of ML techniques in classifying individuals with and without CNP using IMU-informed gait characteristics across both single-task and dual-task gaits was showcased. Furthermore, the most pivotal features specific to each task that significantly influence classification were identified. The importance of a dual-task condition in testing motor abilities and, in turn, accentuating distinctions between groups was also highlighted.

- *Gait kinematics*

Wearable sensors have proven to be both convenient and effective in capturing gait kinematics, as evidenced by this study's findings. Numerous studies have explored gait anomalies in individuals affected by neurological conditions like Alzheimer's disease (Hsu et al., 2014), Parkinson's disease (Abdulhay et al., 2018; Yang et al., 2016), and Stroke (Mannini et al., 2016; Panwar et al., 2019). Responding to the demand for straightforward patient assessment, wearable sensors, when paired with ML models, have proven effective in evaluating the impact of neurological issues. This field has seen growing attention over recent years (Lotsch & Ultsch, 2018). However, such techniques have been less explored for individuals with musculoskeletal conditions.

Given that individuals with CNP might exhibit atypical gait behaviours (Falla et al., 2017; Sjolander et al., 2008), significant kinematic gait features using data from merely three wearable sensors, and analysed through ML methods were pinpointed. The findings indicate that a dual-task gait, involving an added motor task, yields a more precise classification than a single-task gait. This observation remained consistent both before and after the application of the feature selection technique (SVM: 76.30% before, 86.85% after). Essentially, this suggests a more distinct separation between groups. The complexity of the dual-task gait, due to its need for enhanced coordination and control, might be heightened when movement is constrained by pain. This fact underscores the potential of dual tasks to spotlight gait differences, particularly in CNP individuals compared to asymptomatic individuals. Additionally, these results are consistent with the previous section related to curvilinear and rectilinear gait, where it was found that curvilinear gait provided better differentiation between groups. It appears that engaging in challenging tasks could enhance the identification of differences between groups, further supporting the notion that complexity in task execution can illuminate the distinct characteristics of CNP gait. Previous studies support these findings, indicating that individuals with neck pain exhibit more noticeable gait irregularities during complex tasks compared to simpler ones (Uthaikhup et al., 2014). Interestingly, the head was the principal contributor to classification data across both tasks, suggesting that a single forehead sensor might be sufficient to determine gait quality and differentiate between groups.

- *Performance of approaches*

After employing the feature selection technique, there was a notable improvement in the classification accuracy across all classifiers. SVM stood out with the highest accuracy, specificity, and sensitivity figures (86.85%, 83.30%, and 92.85% respectively), achieved using just nine features. This implies reduced computational demand, quicker results, and more dependable classification. Of the three methods, the linear classifier LDA registered the least accuracy for both tasks, hinting that the dataset might not be easily separated linearly, especially given SVM's superior performance. In essence, the application of NCA leads to a streamlined process and enhanced accuracy for all models by emphasising the importance of only significant features through weighted information. These results align with the performance rankings observed in previous Chapters 3 and 4, as well as the EMG section in 5.1.4, where a similar pattern of SVM outperforming K-NN and LDA in classification tasks was demonstrated. This consistent ranking across different analyses further underscores the robustness of SVM in handling complex datasets and highlights the effectiveness of employing feature selection techniques like NCA to improve classification outcomes.

- *High impact features*

Employing NCA is key for isolating clear, pertinent features capable of distinguishing between individuals with and without CNP, thereby improving the effectiveness of the proposed ML classification approach. In the single-task gait scenario, time-domain features, especially Acceleration and Velocity, were dominant. Yet, frequency attributes like Energy, Entropy, and Power had more distinguishing capacity (represented by higher weights) in the NCA analysis. On the other hand, during the dual-task gait, there was a more pronounced presence of frequency features, though Acceleration and Velocity were still evident. These findings underscore that inertial signals from human gait encompass valuable frequency domain information. This observation aligns with existing research, suggesting that frequency attributes can significantly enhance the outcomes of gait analysis (San-Segundo et al., 2016). Particularly in the dual-task scenario, these frequency characteristics were pivotal. One possible explanation could be that the complexity of simultaneously performing two tasks promotes caution in movement among individuals, whether or not they have CNP, likely leading to a decrease in walking speed. As a result, variables related to speed may not exhibit significant differences between the two groups. The frequency characteristics, however, may capture subtle changes in muscle activation and coordination, offering valuable insights that speed-related metrics may overlook.

For instance, features such as entropy—which captures the predictability and complexity of movement patterns—and power—which quantifies the intensity and efficiency of energy costs during motion—are particularly insightful. In the context of dual-task gait, entropy changes might reflect irregular or abrupt movement patterns, suggesting a compromised ability to perform smooth and coordinated motions when individuals with neck pain are challenged with additional cognitive or motor tasks. Conversely, variations in power features may indicate an altered strategy in energy generation or utilization during movement, potentially pointing to a conservative expenditure of energy by individuals with neck pain to mitigate discomfort or to compensate for perceived instability.

5.2.5. Conclusions

This research introduces a classification model tailored for distinguishing individuals with CNP from those without symptoms using IMU-based gait kinematics, gathered via merely three wearable sensors during walking. By employing a feature selection method, the most pertinent features were identified, ML model's performance were enhanced, and the distinguishing capacity of frequency features for the classification were highlighted. These findings indicate that individuals with CNP exhibit distinct kinematic attributes in both the time and frequency domains. Furthermore, dual-task interference accentuates the gait variations observed in those with CNP.

CHAPTER 6: THESIS SUMMARY AND FUTURE WORK

This chapter consolidates the significant outcomes from the studies presented in the present thesis that employed different ML techniques to identify key EMG and kinematic features for CNP classification. These studies independently analysed kinematic and EMG attributes in diverse tasks, such as dynamic neck contractions, smartphone use, and gait analysis through ML approaches. By examining these diverse lines of investigation, this chapter aims to provide a comprehensive discussion of the primary findings, the limitations present in the research landscape and suggest future lines of investigation and improvement.

6. Overview of Major Findings

6.1. EMG Biomarkers During Dynamic Neck Contractions

The SVM algorithm proved particularly effective, achieving a 75% accuracy rate in distinguishing between individuals with CNP and healthy controls, using nine distinct features. Essential features like SC associated with MAV and MDF, and UT associated with WL, were selected, highlighting the crucial role of both time and frequency domains in understanding changes in neuromuscular function. Furthermore, the study elucidated the importance of IC by revealing statistically significant differences in network metrics such as ST and BC across the delta band. These findings highlight the intricate inter-muscular interactions present in people with CNP.

6.2. Kinematic and EMG Biomarkers During Prolonged Smartphone Use

SVM emerged as the most accurate in the EMG analysis with an 80% accuracy rate, closely followed by K-NN at 72.5%. The NCA notably enhanced the performance metrics across all models. Key muscles like SCM, SC, and UT, as well as frequency features like MNF, TP, and PKF, were identified as significant contributors for the differentiation between groups. Additionally, the IC was again selected as a relevant feature for the classification. However, the network metrics did not demonstrate significance between groups. When considering kinematics, K-NN led in accuracy at 75%, with head movements and features like jerk and power being critical for classification. Both SVM and K-NN excelled in sensitivity and specificity, making them particularly useful in identifying subtle yet essential differences in people with CNP.

6.3. Kinematic and EMG Features During Curvilinear and Rectilinear Gait

The study found that curvilinear gait provided the most relevant data for classifying CNP. In the kinematic analysis, the K-NN algorithm, enhanced with NCA, exhibited the highest classification performance with an accuracy of 90% for curvilinear walking. Features from the Head, Trunk, and Pelvis were the most influential for classification. In the EMG analysis, the SVM algorithm outperformed others in the curvilinear trajectory as well, achieving an accuracy of 85% after integrating NCA. The SCM muscle was found to be the most significant in curvilinear gait. Both kinematic and EMG classifiers performed better when fewer, more relevant features were selected, indicating that NCA effectively enhanced classification by identifying and focusing on the most critical features. Moreover, neck muscle networks analysis revealed significance values of BC and graphical differences between groups. This points towards a complex interplay of muscle coordination in people with CNP during more challenging gait types.

6.4. Kinematic Analysis During Single and Dual-task Gait Using IMU

The SVM classifier, especially after the implementation of the feature selection technique, exhibited superior performance in delineating differences between the CNP and control groups, proving its robustness in complex, dual-task scenarios (accuracy of 87.14%). In the realm of high-impact features, a distinct shift was observed; acceleration and velocity were pivotal in the single-task scenario, whereas, in the dual-task context, attributes rooted in the frequency domain, including energy, entropy, and power, came to the forefront. This differentiation amplifies our comprehension of the intricate dynamics at play in CNP, underscoring the need for multifaceted analytical approaches to capture the condition's complexity.

6.5. Limitations of the Studies

While the studies presented within this thesis provide significant insights into the use of ML to differentiate between individuals with CNP and those without symptoms, several limitations must be acknowledged:

- Sample size: The studies' conclusions are based on small sample sizes, which are not ideal for ML research. This limitation not only undermines the robustness and generalizability of the findings but also increases the susceptibility of the dataset to bias. Furthermore, a constrained sample size elevates the risk of overfitting, a condition where the model is excessively tailored to the training data, leading to poor performance on new, unseen data (Hastie T. et al., 2009). To counteract these limitations, it was employed the widely recognized technique of cross-validation across all studies. This approach enhances the accuracy of the model's performance evaluation and facilitates a more dependable interpretation of the results. Nonetheless, it is crucial to recognize that, despite these methodological safeguards, the small sample size continues to restrict the extendibility of our findings. Thus, the results should be interpreted with caution, and findings may require further validation with a larger dataset. Consequently, to achieve more reliable outcomes in ML research, the collection of larger and more diverse samples is imperative.

- Pain severity: In the studies conducted, participants with CNP reported experiencing only mild to moderate levels of pain intensity, averaging around 4 on a 10-point scale. Consequently, it remains an open question whether the findings can be generalised to individuals who experience more severe forms of CNP or those with distinct types of neck pain disorders such as those discussed in Chapter 1.

- Machine learning models: While the SVM and the K-NN performed well in these studies, there exists a wide array of ML algorithms with different approaches. Each algorithm comes with its own set of assumptions, strengths, and limitations that might offer diverse or even enhanced insights. For instance, Random Forest and Naive Bayes are other ML algorithms frequently used in healthcare settings showing high accuracy outcomes (Uddin et al., 2019).

- Feature extraction and selection: The studies heavily rely on NCA for feature selection. While NCA is effective, different feature selection methods might yield diverse insights. Comparing different feature selection approaches might offer new insights of features interactions and complex interplays that could be relevant for CNP detection.

- Muscle networks: Networks analysis usually involve a large set of sources such as EEG signals for brain networks or groups of individuals for social networks (Rubinov &

Sporns, 2010). Given that the present studies focused on a relatively limited number of muscles, the results should be interpreted with caution. However, this research marks the first application of network analysis to explore neck muscle activity, laying a foundational groundwork for future studies.

In summary, the studies provided valuable insights into how ML can be instrumental in exploring and elucidating the distinctions in muscle activity and kinematic in people with CNP. However, there are clear areas for improvement via future research. Increasing the sample size, including a wider range of tasks, exploring different ML models, and ensuring the findings are clinically relevant by investigating in-depth the features highlighted to assess their viability as future biomarkers. By addressing these issues, future research will be better positioned to offer more practical and effective solutions for individuals affected by CNP and the healthcare professionals who support them.

6.6. Comprehensive Summary of Contributions

ML algorithms such as SVM and K-NN, proved to be instrumental in understanding the intricate interplay of kinematic and EMG features in classifying CNP. Both kinematic and EMG features provide invaluable insights into the differences between individuals with CNP and those without symptoms. The specific tasks and the complexity introduced, such as curvilinear movement and dual-task scenarios, augment the classifiers' ability to differentiate between groups. The studies conducted highlights the value of meticulous feature selection in improving model accuracy and suggests that a synergistic approach—integrating ML with kinematic and EMG characteristics—offers a promising pathway for future investigation.

The contributions to the literature directly support these main ideas:

- Introducing a robust ML pipeline specialised in differentiating between two distinct subject groups, only based on kinematic and EMG features, across multiple tasks.

- Establishing that the experimental results presented in this thesis align coherently with existing scholarly research (Burton et al., 2023; Falla, 2004; Franov et al., 2022). Specifically, the results suggest that ML algorithms have the potential to identify neuromuscular control differences between individuals with CNP and healthy individuals. However, further validation is crucial to confirm the significance and nature of these differences.

- Identifying and emphasising previously unexplored key features in muscle activation (e.g., coherence, peak frequency) and kinematics (e.g., acceleration, jerk) that might serve as potential biomarkers for CNP. This work also facilitates the identification of the most relevant muscles or body segments during specific tasks. Interestingly, coherence emerged as a significant feature for classification in all the studies conducted. This is particularly noteworthy because previous research has already suggested coherence as a biomarker for motor neuron disease (Fisher et al., 2012). Another important observation is the interdependency of features for classification efficiency. In other words, a variable that may seem irrelevant when considered in isolation could substantially enhance performance when integrated with other features (Guyon et al., 2008).

- Demonstrating the superior performance of ML algorithms, notably SVM and K-NN. These algorithms are highly effective in non-linear classification, thereby highlighting the inherent non-linear tendencies within human data. Interestingly, it was found a common pattern in the performances of these algorithms across all the present studies. In every study, SVM or K-NN consistently outperformed LDA. This finding aligns with previous research where a similar ranking of performance was observed, as previously noted in Chapter 5 (Dhindsa et al., 2019; Fernandez Rojas, 2018; Mokdad et al., 2020).

- Showcasing the exceptional capability of the NCA algorithm in feature selection. The algorithm not only reduces noise within the dataset but also optimises dimensionality, universally improving the performance of all employed ML algorithms across multiple domains, from sEMG signal pattern recognition for prosthesis control (Manit & Youngkong, 2011) to motor imagery-based brain-computer interfaces that use EEG signals (Malan & Sharma, 2019), and even in the prediction of disease stages in mild cognitive impairment and Alzheimer's disease using magnetic resonance imaging data (Jin & Deng, 2018). This underscores NCA's versatile applicability across diverse conditions and types of data.

- Providing evidence that complex tasks, such as dual-task scenarios and curvilinear gait, offer greater discriminatory power in identifying individuals with and without CNP. This suggests that the exploration of more challenging tasks could be valuable, as they are more likely to stimulate specific neural or physiological pathways that are associated with the perception of pain, making them more easily detectable through ML methods.

- Analysing for the first-time neck muscle networks in people with CNP. The findings reveal that these topographical maps can offer invaluable insights into the unique muscle synergies activated during specific tasks. Importantly, these muscle synergies exhibit distinct differences in individuals with CNP when compared to healthy individuals, thereby opening new avenues for future research.

6.7. Future Lines of Work

The progression of this research into the intersections of ML, kinematics, and EMG in the context of CNP necessitates a focus on several key areas for future exploration. In this way, the limitations previously identified also guide the future directions for improvement.

- Expanding participant pool and diversity: The first step involves including a wider variety of participants. By ensuring diverse age, gender, and ethnic representation, the findings can be made more applicable to a broader population, giving a clearer picture of how neck pain affects physical performance. A broader dataset of participants would not only enable more effective generalisation of findings but also facilitate the application of advanced ML approaches, such as deep learning. Deep learning algorithms require vast and diverse datasets to train effectively, ensuring that the model captures the underlying patterns and relationships in the data comprehensively. Therefore, a deeper analysis with the use of highly advanced learning algorithms among with large datasets could yield more intricate insights and potentially uncover subtle patterns that might not be apparent with smaller datasets and simpler algorithms. In particular, automated systems that apply deep learning for medical imaging have shown encouraging results in accurately diagnosing and staging conditions like Alzheimer's disease, breast cancer, and lung cancer (Faust et al., 2018).

- Models' interpretability: As highlighted in Section 1.2.4, the lack of transparency can be problematic in contexts where understanding why a particular decision was made is important. Due to the need to clarify and comprehend the rationale behind decision-making, a new branch of study known as Explainable AI (XAI) has emerged (Schmidt & Biessmann, 2019). It employs techniques that describe the minimal changes needed in the input variables to change a model's prediction. Future research should integrate this approach to gain deeper insights into ML model performance and the significance of various features. Incorporating explainable AI could be particularly impactful in high-risk sectors like healthcare, aiding in the development of clinically actionable models.

- Improving feature selection: It would also be beneficial to use various feature selection methods. Moving beyond NCA could reveal more complex and insightful patterns essential for understanding and identifying CNP patterns. The current literature provides a wealth of options in this regard, given the extensive array of feature selection algorithms available (Dhal & Azad, 2021). In alignment with this, it would be highly recommended that future investigations take into account and test the relevant subset of features identified in the present thesis. A comparative analysis involving these groups of features and diverse selection methodologies, could offer additional validation and potentially evolve into recognised biomarkers for CNP. The confirmation of these groups of features as reliable biomarkers would mark a pivotal stride in the nuanced, data-driven, and personalised management of CNP, bridging the gap between technological innovation and enhanced patient care.

- Muscle networks: Advancing our understanding of muscle topology maps requires a multi-faceted approach. Future work should extend the analysis to include a larger and more diverse sample population, incorporate a more comprehensive set of muscles (nodes), and employ a broader array of parameters. Doing so will not only deepen our insights into the unique muscle synergies in individuals with CNP but also facilitate comparisons against healthy controls.

- Leveraging technology: As technology continues to advance, using wearable and smart tech for real-time data collection and analysis could be instrumental. However, the wearable and wireless technology used in the present thesis, even though it is advanced and modern, should still improve in order to be more accessible and easier to use for clinical environments. Integration challenges, cost-effectiveness, and user-friendliness remain critical areas for development.

To move forward, future studies should prioritize two critical areas: data acquisition and dissemination. The collection of larger, more comprehensive, and diverse datasets is paramount. Such datasets will not only enhance the robustness of analytical models but also facilitate a more profound understanding of the underlying mechanisms and the interplay of relevant variables. Furthermore, ensuring broad accessibility of these datasets to the wider research community is crucial. Open access to data encourages collaborative actions, accelerates the pace of innovation, and unlocks the potential for groundbreaking discoveries and novel methodologies.

For instance, to address the challenges associated with limited data size and the computational or time expenses of ML, researchers could adopt a strategy of sharing pretrained models. This would be especially valuable for teams or individuals facing constraints in data volume, which hampers their ability to conduct comprehensive algorithm validation. By utilizing models that have already been trained on larger datasets, these researchers can apply sophisticated ML techniques to their own, potentially smaller datasets. This collaborative approach not only mitigates the limitations posed by scarce data and resource-intensive training processes but also promotes a more collaborative scientific community.

On the other hand, integrating wearable devices like Fitbit and utilizing smartphones for markerless motion capture offer practical and less invasive methods for collecting data. These approaches make it easier and more affordable to gather a vast array of kinematic and physiological data from diverse populations, directly enhancing the research's depth and relevance. However, despite these advancements, there currently is not a device as universally recognized or commercially available as Fitbit specifically for measuring muscle activity over extended periods. Nonetheless, various innovative methods and devices, including the MAX30105 optical sensor and wearable force sensors, have been developed and validated for muscle activity monitoring in a numerous of settings, from everyday activities to targeted exercises and rehabilitation (Lukowicz et al., 2006; Sikora & Paszkiel, 2019). These developments reflect the growing field of muscle activity monitoring and point to a future where comprehensive, non-invasive muscle activity tracking becomes a closer reality, mirroring the advancements seen in kinematic data collection.

Additionally, employing data augmentation techniques, such as the Synthetic Minority Over-sampling Technique (SMOTE), can effectively enlarge small datasets, helping to build more robust ML models (Sreejith et al., 2020). When these strategies are paired with interpretable ML models, they not only could improve the accuracy of the models but also provide clearer insights into neck pain's underlying mechanisms. This innovative methodology provides a valuable solution for researchers facing challenges related to small or imbalanced datasets, whether these challenges stem from methodological constraints, limited access, or external factors such as the COVID-19 pandemic.

6.7.1. Future Research Directions

Based on the findings of the current thesis, this section presents recommendations for future neck pain research. These recommendations cover task selection, sensor placement, relevant features, and ML algorithms to promote more effective and accurate assessment strategies.

- Task Selection

The comparative analysis across dynamic neck contractions, prolonged smartphone use, and different gait patterns, reveals curvilinear and dual-task gait as highly discriminative tasks for CNP assessment. These tasks appear to offer richer insights into the neuromuscular alterations associated with CNP compared to simple rectilinear gait or static postures.

Curvilinear gait, which involves navigating turns and curves, requires greater coordination and muscular effort compared to walking in a straight line. This increased demand places additional stress on the neuromuscular system, thereby amplifying the manifestations of CNP and making these alterations more observable. The specific challenges of maintaining balance and posture during curvilinear motion might provoke compensatory strategies and muscle activations that are distinct in individuals with CNP.

Similarly, dual-task gait, which combines walking with a secondary cognitive or motor task, introduces an added layer of complexity. This complexity challenges the cognitive-motor integration further, potentially aggravating the symptoms of CNP and highlighting the condition's impact on overall movement efficiency. The simultaneous engagement in a cognitive or additional motor task while walking necessitates increased neuromuscular coordination and control, aspects that are often compromised in CNP sufferers. Consequently, dual-task gait serves as a powerful lens through which the subtle yet significant deviations in gait and posture associated with CNP can be detected.

Overall, these findings suggest that incorporating more complex and demanding tasks into the assessment of CNP can provide deeper insights into the condition's effects on neuromuscular function.

- Sensor Selection and Placement

The integration of EMG and kinematic systems has been shown to offer comprehensive insights into both the muscular and kinematic aspects of CNP. Optimal placements for EMG sensors include the SCM, SC and UT muscles, given their significance in highlighting differences between CNP patients and controls. Specially, the SCM and SC muscles have proven to be particularly valuable in the assessment and classification of CNP due to their direct involvement in neck movements and posture. Specially, SC demonstrated to compound relevant information to classify between participants and healthy individuals during cervical flexions and static tasks. This finding could serve as guide for clinicians to include these kinds of tasks in their assessments and evaluate the performance of SC during these tasks. In the same way, SCM provided to contained relevant information for the classification during the curvilinear gait. As this could be explained due to the role of the SCM for the rotation of the head and therefore for the gaze and performance of the curved trajectory, clinicians could also investigate this kind of task and muscle during their assessment which could give them more information about participant neck’s condition.

The AS muscle, on the other hand, did not emerge as significantly relevant for the classification tasks. This observation could be attributed to two main factors: firstly, the AS muscle may exhibit low activity or have a minimal role during the movements analyzed, making its contributions less detectable in the context of CNP. Secondly, being a deeper muscle, the AS's involvement and activity levels might not be fully captured by superficial EMG techniques. Further research should address this topic to have a more complete understanding of this muscle and its relationship with neck pain.

In kinematic analysis, the placement of markers on the head, trunk, and pelvis within motion capture systems is essential to capture the full range of gait dynamics comprehensively. Alternatively, data from Chapters 4 and 5 reveal that kinematic information from the head was particularly critical for classification tasks, suggesting that employing a single head-mounted IMU could effectively identify notable differences in gait patterns. This finding implies that utilizing just one sensor, specifically positioned on the head, may suffice to differentiate between individuals with and without CNP in clinical environments. Such a streamlined approach could greatly facilitate the diagnostic process, offering a practical and accurate method for CNP assessment. Consequently, future research is encouraged to explore and validate this simplified strategy.

- Relevant Features

Throughout the studies, a combination of time-domain and frequency-domain features, were used to find differences between the groups and in all studies both domain of features were present in the process of boosting the ML algorithms. This implies the benefit of employing a broad spectrum of analytical perspectives to detect distinctions. This approach emphasizes the significance of incorporating both types of features to capture a comprehensive picture of neuromuscular behavior.

Furthermore, WL and IC consistently emerged as the most frequently selected features in EMG analysis. This underscores their importance in differentiating CNP-related muscle activation patterns and suggests that WL and IC features could have potential to become markers in differentiating neck pain. Future studies should prioritize further investigation of these features. Specifically, IC demonstrated real potential not to only differentiate groups but also serving as a graphical tool. This new approach of IC can provide really informative representation of muscular coordination in an easy way to be understood by both patients and clinicians and find potential abnormalities in people with this condition.

In terms of kinematic features, traditional metrics like speed, acceleration, and smoothness have been complemented by the inclusion of frequency-based features such as entropy and power, particularly in the later chapters of the study. This evolution in feature selection reflects an expanding understanding of CNP's kinematic manifestations and suggests that these frequency-based kinematic features might offer additional layers of differentiation. Future research is encouraged to delve deeper into the potential of these kinematic features, exploring their capacity to contribute to a more nuanced and comprehensive analysis of CNP.

- ML Algorithms for CNP Classification

The consistent performance of SVM across various analyses positions it as the preferred algorithm for CNP classification tasks. Its kernel's configurational flexibility enables adaptation to various data characteristics or scenarios, substantially increasing its utility. This adaptability also solidifies its standing as a highly suitable option for nuanced classification challenges. The K-NN algorithm's notable success further positions it as a viable alternative for such classifications. Both algorithms have demonstrated commendable accuracy, but they also boast promising sensitivity and specificity values. These metrics are crucial in the medical diagnostic context, as they ensure not only the correct identification of CNP cases (sensitivity) but also the accurate exclusion of non-CNP cases (specificity). This combination of high accuracy, sensitivity, and specificity makes SVM and K-NN particularly well-suited for classification scenarios of this nature.

On the other hand, LDA underperformed, despite its demonstrated efficacy in various studies. This discrepancy, as highlighted in earlier chapters, may stem from its linear approach to classification, which is less effective for data types (such as human assessment) where linearity is uncommon. Thus, based on the evidence presented in this thesis, LDA is not recommended for classification tasks of this nature.

Incorporating these recommendations into future work will likely yield significant advancements in the diagnosis, monitoring, and treatment of neck pain. This section should not only serve as a coping stone to the current research findings but also as a bridge to future investigations, highlighting the potential for integrated approaches to neck pain assessment that exploit the strengths of various sensors, features, and ML techniques.

6.7.2. Advancing Neck Pain Management with Machine Learning

Integrating advanced technologies like EMG, kinematic analysis, and ML into the management of CNP signifies a pivotal advancement towards more objective and impactful treatment methodologies. This approach not only underscores the seamless adoption and benefits of these technologies but also their pivotal role in elucidating complex pain mechanisms, refining diagnostic precision, and facilitating personalized care strategies.

In this thesis, the application of ML algorithms has been instrumental in demonstrating the muscular and kinematic differences between healthy individuals and those suffering from CNP, building upon the foundation laid by previous research that utilized statistical analysis for similar comparisons. This advancement highlights ML's unique ability to not only replicate but also enhance the insights gained from traditional research methods, providing a deeper, data-driven understanding of CNP by reflecting the most relevant features for such differences. By using ML, this work underscores the variations in muscle function and movement patterns that characterize CNP, offering a more detailed perspective on the biomechanical intricacies of this condition.

Utilizing EMG and kinematic analysis in conjunction with ML offers an in-depth, data-driven view into the physiological and biomechanical facets of neck pain. This method has the potential to uncover the presence of multiple pain mechanisms within patients, an issue that might not be fully represented by questionnaires or patient reports due to the challenges in articulating such a subjective experience. ML's ability in analyzing vast datasets to identify patterns and correlations enables the detection of distinct pain mechanisms affecting an individual, guiding the development of focused treatment plans.

ML technology stands at the forefront of transforming the evaluation, diagnosis, and management of neck pain. Through the application of supervised learning techniques, healthcare providers can accelerate diagnoses, categorize patients based on underlying patterns, and pinpoint precise pain mechanisms essential for prompt and effective intervention.

Furthermore, ML enables the crafting of treatment strategies tailored to the varied nature of neck pain disorders and the specific needs of patients, significantly enhancing treatment outcomes (Khan et al., 2024).

These ML-driven methodologies promise highly personalized treatment plans that consider the unique characteristics of specific disorders and the detailed information of individual patients. By integrating specific data such as clinical histories, biomarkers, and imaging results, ML algorithms are equipped to create targeted treatment plans that address the fundamental causes of pain, thereby amplifying treatment efficacy. Advanced learning techniques facilitates earlier diagnosis, precise patient grouping, and the discovery of underlying mechanisms and patterns, crucial for initiating immediate and successful treatments (Lotsch & Ultsch, 2018; Matsangidou et al., 2021).

However, integrating advanced technologies like ML and AI into clinical settings, particularly for tools such as EMG and motion capture systems demands careful consideration. These tools require specialized equipment and a deep understanding for accurate use. Specifically, EMG sensors and motion capture systems must be precisely placed and calibrated to guarantee the collection of valid data. Despite the cost of these technologies becoming more manageable and their ease of use improving over time, adopting them in a healthcare environment still entails a notable upfront investment in both the technology itself and in staff training. Moreover, integrating these systems into daily clinical operations must be executed smoothly to avoid any disruption to routine patient care and to guarantee consistent data collection (Taribagil et al., 2023).

When introducing ML into healthcare practices, it is imperative to acknowledge and address the specific characteristics of these algorithms, prioritizing the clarity of the models to support informed decision-making by clinicians. Ensuring the transparency of these models and their reproducibility is critical for their successful adoption in medical settings. Researchers are tasked with the responsibility of thoroughly documenting data processing methods, the details of the models used, and the protocols for training and validation. This level of detail raises trust in AI-powered clinical decision-support systems and nurtures their acceptance among healthcare professionals, paving the way for their widespread use in various healthcare scenarios. Additionally, enhancements in XAI will improve the intelligibility of ML models, providing researchers and clinicians with a clearer understanding of how algorithmic decisions are made (Miotto et al., 2018). This understanding is essential for the practical and confident application of these technologies in patient care, ensuring that clinicians can implement these advanced tools effectively.

6.8. Concluding Remarks

The thesis aimed to evaluate the capabilities of ML algorithms for the assessment of biomechanical and EMG characteristics associated with CNP. Through ML data analysis, the research contributes to a more objective, data-driven methodology for differentiating individual with and without CNP.

I. Dynamic Task Classification: All ML algorithms effectively differentiated between subjects with and without CNP pain during dynamic neck movements. The study successfully identified key subset of EMG features like MAV, MDF, and WL, enabling effective classification and providing valuable insights into the unique neuromuscular patterns of individuals with this condition.

II. Static Task Classification: The ML algorithms were successful in differentiating between subjects with and without CNP during static task. The analysis identified critical EMG and kinematic variables that vary between individuals with CNP and healthy controls during prolonged phone usage. The EMG analysis highlighted the importance of features from the SC muscle and the frequent selection of PKF across various muscles. Kinematically, features like Acceleration, Power, and Smoothness specifically from the head dominated the results.

III. Gait Task Classification: When evaluating various types of gaits, the ML algorithms demonstrated a high degree of accuracy classifying people with and without CNP. The complexity of the gait tasks was crucial in identifying significant differences between the groups. The research unearthed unique muscle synergies during curvilinear gait and emphasised the role of frequency features for an effective classification during dual-task gait.

Overall, the research presented in this thesis not only marks a milestone in the study of neuromuscular and movement disturbances present in people with CNP by introducing innovative methodologies but also opens new avenues for future exploration of this condition. The work offers a robust, data-driven framework and different subsets of relevant features enhancing understanding of both the neuromuscular and kinematic dimensions.

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Chapter 1

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