STATIC FATIGUE DETECTION IN OFFICE SYNDROME USING sEMG AND MACHINE LEARNING

PARAMA PRATUMMAS

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วิทยาลัยนวัตกรรมด้านเทคโนโลยีและวิศวกรรมศาสตร์ มหาวิทยาลัยธุรกิจบัณฑิตย์

ปริญญา วิศวกรรมศาสตรมหาบัณฑิต สาขาวิชาวิศวกรรมคอมพิวเตอร์

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เสนอโดย นายปรมะ ประทุมมาศ

สาขาวิชา วิศวกรรมคอมพิวเตอร์

อาจารย์ที่ปรึกษาสารนิพนธ์ อาจารย์ ดร.ชัยพร เขมะภาตะพันธ์

ได้พิจารณาเห็นชอบโดยคณะกรรมการสอบสารนิพนธ์แล้ว

....ประธานกรรมการ

(รองศาสตราจารย์ ดร.ลัญฉกร วุฒิสิทธิกุลกิจ)

.... กรรมการและอาจารย์ที่ปรึกษาสารนิพนธ์

(อาจารย์ ดร.ชัยพร เขมะภาตะพันธ์)

....กรรมการ

(ผู้ช่วยศาสตราจารย์ ดร.มัชฌิกา อ่องแตง)

วิทยาลัยนวัตกรรมด้านเทคโนโลยีและวิศวกรรมศาสตร์รับรองแล้ว

....คณบดีวิทยาลัย นวัตกรรมด้านเทคโนโลยีและวิศวกรรมศาสตร์

(อาจารย์ ดร.ชัยพร เขมะภาตะพันธ์)

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Author Parama Pratummas
Thematic Paper Advisor Dr.Chaiyaporn Khemapatapan
Department Computer Engineering
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ABSTRACT

There are many people around the world getting illness from their workplace as a result of the office syndrome. The purpose of this study is to present the detection system that can identify the fatigue status as in the static position. One subject was recorded surface electromyography (sEMG) on the shoulder while working in the office in a sitting position. The information from the EMG sensor board linked to the surface electrodes was passed to the NodeMCU V2 ESP8266 and then sent to the Arduino IDE. The recorded samples were initially labeled as non-fatigue, but if the individual felt fatigue, they were reclassified as fatigue. These datasets were manipulated and prepared for data analysis by creating seven features (mean, integrated EMG, mean absolute value, mean absolute value1, mean absolute value2, simple square integral, and root mean square). By recursive feature elimination, these seven features were grouped into three: original dataset, feature set I (mean, integrated EMG, mean absolute value, simple square integral, and root mean square), and feature set II (integrated EMG, mean absolute value2, and simple square integral), and then put into six machine learning models (Logistic Regression, Support Vector Machine, Naive Bayes, k-nearest Neighbors, Decision Tree, and Multi-layer Perceptron) to compare the accuracy and performance. As a result, Multi-layer Perceptron was found to have the highest accuracy at 99.6690 percent with a fit time of 18.322849 seconds. Nevertheless, decision tree might be the machine learning model of choice in this research due to its nearly accuracy of 99.2482 percent and faster fit time at 0.027955 seconds.

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CHAPTER 1

INTRODUCTION

1.1 Background and Significance of the Problem

There is an essential reason why the prosperity of worker health, which encompasses a large portion of the entire population, is a crucial prosperity-related concern all over the world. The workplace clinical benefit system is an important venue for clinical benefit intervention among adults. Most experts forget that they put a lot of emphasis on their profession, which might lead to ailment movement over time. Muscle fatigue, particularly in the upper back, is unquestionably a common clinical concern in office situation (Ryu et al., 2016). A few medical issues, such as obesity, hypertension, excessive blood sugar, and abnormal lipid profile, have become more common among workers. These middle-class workers are more likely to have major heart and blood vessel disorders, as well as metabolic profile issues. Further investigation reveals that middle-class workers are at a higher risk of metabolic issues than non-middle-class workers (Kim & Oh, 2012).

The surface EMG signal is a special kind of electric phenomena that can be used to determine the difference in activity between individual muscle units. This is because the signal reflects the mobility and proliferation of muscle cells. The joining of the electricity of every filament creates the movement of the motor part. The expected coherence of movement covers with action potentials, and the quantity of these gatherings at last comprises the sEMG. SEMG signals are characterized by temperamental and unpredictable signs. The development of sEMG signals is the result of the accumulation of many features (CJ, 1997). There are various brain intentions that are sent to the cortical working environment during activity or development. They keep waking them up and keeping them energized. When it comes to over-consumption, the cerebrum creates defensive mechanisms in order to keep us from exceeding certain limits (Yan et al., 2004). When fatigue sets in, the central tactile framework is no longer reinforced, leading to a decrease in energy use, and a decrease in the number of motor nerve cells ending in redundancies.

Hence, as confirmed by most examinations, the typical frequency of recurring electrical side effects in the muscles diminishes with the onset of fatigue (Zhou et al., 2013). Many investigations have found that it is possible to notice muscle fatigue with sEMG. Chowdhury et al. documented the sEMG capacity of the major trapezius and sternocleidomastoid muscles beyond incredibly monotonous activity. Discrete wavelet transform (DWT) was used to measure neck and shoulder muscle fatigue and suggested that DWT necessarily predicts neck muscle fatigue during dynamic activity (Chowdhury et al., 2013). Chen et al used sEMG to anchor the movement of cervical muscle action upon fatigue. It was recommended that the sternocleidomastoid muscle and the adversary muscle be weakened during neck flexion preparation, and that the recurrence of sEMG signal be expanded with increasing exhaustion (Chen et al., 2010). Andersen et al looked at the EMG signals from the neck muscles to see which measures could help improve recovery from exercise. They found that horizontal extending, standing up, and planning to shrug the trapezius muscles all had positive effects (Andersen et al., 2008). Hostent et al stressed the importance of muscle fatigue in significant distance drivers using EMG signals. The results showed that muscle fatigue led to an expansion in muscle electrical activity and a decrease in muscle recurrence rates (Hostens & Ramon, 2005).

Machine learning includes assessments and procedures that allow computers to learn. Machine learning approaches cover key areas such as data retrieval, complex programming applications, and programming applications. Grouping multiple calculations together can provide multivariate, nonlinear, nonparametric feedback or explanations. Due to the unusual limitations of machine learning-based methods, it has been widely used in science and design. The basic explanation of machine learning is that the evaluation or performance of machines can conquer new data meters. Several calculations are guided. That is, he looks at the data he finds and soon makes predictions about new data based on historical data. Some are out of control, so you can create shapes without predictive data. Some are partially controlled and a combination of the two. This study focused on one of the most popular machine learning calculations: a controlled model. The training data we used was different from the controlled training. These preparation data are used to create estimation or evaluation constraints from the information variable (X) to the yield variable (Y). Given a nominal set of information, the correct answer or required return (number) is now known. Classification and regression procedures are two types of observable evolution that are widely used to advance preliminary models (El Bouchefry & de Souza, 2020).

There have been many studies here, but most focus on dynamic fatigue. In other words, entities must be made in different stages of development with different MVCs with different tasks. It is clear that such a space for exploration did not really exist. There are few studies on the control of static fatigue. Therefore, this study focuses on the problem of fatigue caused by office syndrome. In this study, we collected sEMG from the subjects' shoulder muscles for screening for fatigue relavant structures. We tried to find the best option for the function and compared it with different classification models, following the best model with the best accuracy and performance.

1.2 Research Question

Is there any static fatigue detection in office syndrome using surface electromyography (sEMG) and machine learning?

1.3 Research Objectives

1.3.1 To develop static fatigue detection in office syndrome using surface electromyography (sEMG) and machine learning

1.3.2 To discover the best fit for the features and compare different classification models to propose the best model with maximum accuracy and performance.

1.4 Conceptual Framework

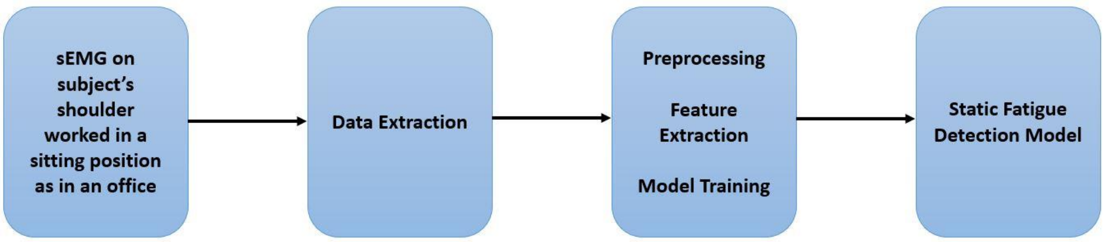

Figure 1.1 Conceptual Framework.

In the study, there was one subject who did not experience any real effort or enthusiasm recently. We used surface electromyography (sEMG) and machine learning to determine the location of static fatigue in office applications. Three additional surface electrodes were placed on the shoulder of the subject. The subject worked in a sitting position, such as in an office. Once the sensor was fixed and the signal stabilized, the subject's EMG signal and fatigue state (fatigue or non-fatigue) were recorded during the study. The study was stopped when the subjects showed an obvious fatigue for a few minutes. In this study, one subject was tested for 15 minutes. The information request system started receiving the information. We tried to find the best match for the items and compare different explanatory models to provide the best model with the best accuracy and performance. This information is then pre-processed, including the distribution and preparation of the sample. Therefore, a static fatigue recognition model has been developed, as shown in Figure 1.1.

1.5 Expected Benefits

1.5.1 To discover static fatigue detection in office syndrome using surface electromyography (sEMG) and machine learning.

1.5.2 To utilize internet of things (IoT) technology in the further process of knowledge gathering and apply to the medical device in the future.

1.5.3 To assist in the diagnosis of office syndrome accurately.

1.5.4 To minimize an error in the evaluation of office syndrome.

1.6 Delimitation

1.6.1 Use of surface electromyography (sEMG) and machine learning to investigate the locations of static fatigue proposed in office applications.

1.6.2 It was studied the development of static fatigue detection in the office using surface electromyography (sEMG) and machine learning.

1.6.3 The aim of the exploration was to facilitate the detection of static fatigue in an office environment using surface electromyography (sEMG) and machine learning and to compare different grouping models to find the best fit for the function and provide the best model with maximum accuracy and performance.

1.6.4 A subject who has not recently experienced any real effort or suffering participated in the study.

1.6.5 sEMG from NodeMCU V2 ESP8266 is recorded when it is placed with a surface electrode on the shoulder through a connected EMG touch panel. When the sensor was fixed and the signal was stable, the EMG signal and the subject's fatigue state (fatigue or non-fatigue) were recorded during the analysis. The analysis was stopped when the subjects reported an apparent discomfort within minutes. In this test, a subject was tested for 15 minutes. This IoT architecture is controlled by the Arduino IDE.

1.6.6 The signals are discarded and preprocessed to obtain different characteristics of the dataset. Six machine learning models (Logistic Regression, Support Vector Machine, Naive Bayes, k-closest Neighbors, Decision Tree, and Multi-layer Perceptron) were the mentioned models in this study. Mean, integrated EMG, mean absolute value, mean absolute value1, mean absolute value2, simple square integral, and root mean square of the original data set and the feature-selected information were prepared and tested to provide an assessment of the outcome of fatigue or non-fatigue.

1.6.7 The data search system started with the collection of information. This information is preprocessed using by Jupyter notebooks and Google colaboratory notebooks with python. Thusly, static fatigue identification model was proposed.

1.7 Definitions

1.7.1 Static Fatigue of Muscle

Muscle fatigue, described as a necessary or expected force or a mismatch in strength, is a common side effect of exercise or physical movement. This side effect occurs with many diseases and mostly unrelated diseases. From a physiological point of view, fatigue is associated with metabolic fatigue and the accumulation of side effects in the contractile muscles as reduced contractility. In addition, physiological and physical factors such as muscle fiber structure (slow jumps of fast muscle fiber), neuromuscular properties, storage of energy-rich metabolites, buffer thresholds, ion induction, and capillary and mitochondrial thickness can address muscle fatigue profiles. Thus, the fatigue factors are associated with changes in the muscles (peripheral fatigue) and the nervous system (central fatigue). Muscle fatigue has long been studied using a variety of activity models, conventions, and assessment strategies. There are several methods used to study muscle exhaustion (ultrasonography, acoustic myography, mechanical surface imaging). In addition, kinematic and energy assessments are recorded as signs of fatigue, taking into account speed, muscle contraction rate, joint points and movement. Another commonly used device is surface electromyography (sEMG), which provides a harmless assessment with surface electrodes. The basic limits of sEMG (adequacy and repeatability) are used primarily to assess the degree of muscle fatigue during static and dynamic contractions. A side effect of muscle fatigue during isometric stenosis is the extension of the sEMG root mean square (RMS) signal, which is resolved by recording additional motor units. Another side effect of muscle exhaustion during compression is that the average number of repetitions changes to a lower value over the entire power range. The average repetition threshold depends on changes in the rate of permeability of the muscle fibers and subsequent changes in the wavelength range of the expected activity of the motor unit. However, there are many variables that affect the nature of the EMG signal (the size of the tissue between the electrode and the outer muscle layer, the depth and area of the dynamic wires, the time and force of muscle contraction, and its terminal and diffuser properties). Therefore, the EMG translation is inaccurate and the boundaries of the symbols and markers must be correctly identified in order to correctly interpret the experimental results (Gawda et al., 2018).

1.7.2 Office Syndrome

As of now, the improvement of the general public is affected by absolute informatization in all circles of life, and creation is progressively portrayed by the broad utilization of data innovation. This has prompted a critical expansion in the portion of individuals engaged with business related to the utilization of computer innovation. It is realized that the most well-known devices of a cutting-edge office are data innovation and office hardware. In this manner, it tends to be expressed that as of now the work cycle in the not set in stone by long haul work at the computer, and crafted by office representatives ought to be considered as crafted by computer clients. The concentrated expansion in the quantity of office representatives is joined by an expansion in their responsibility and working hours, the support of exhaust by managers, which has prompted a critical spread of outer muscle illnesses among the functioning age populace. Simultaneously, pathologies of a spine and joints among office laborers are frequently went with torments in the outer muscle framework and lead to a present moment or consistent loss of working limit. The noticed wellbeing problems among the populace working in the workplace have arrived at such a scale that wellbeing experts started to utilize the term 'tedious strain injury' to decide a complicated arrangement of side effects as a word related pathology. Various investigations of specialists in ergonomics, word related security and biomechanics show that among the most undermining factors for the psychophysiological capacities of computer clients are static-unique burdens on the spine brought about by being in a dreary situation against the foundation of countless generalized exceptionally planned developments performed simply by the hand muscles. The examination of standardizing acts and reports that lay out wellbeing, clean and sterile prerequisites for the hardware of work environments of computer clients shows that the really regularizing record on work insurance of office laborers is "Rules of work security during activity of computers", which plainly expresses the requirement for directed breaks for rest enduring 10 minutes after every hour of work for computer administrators and 15 minutes like clockwork for representatives who use computers. In any case, both the references and that's what creators' own experience show, tragically, these breaks are either not utilized as expected or there are no such breaks by any stretch of the imagination, and office laborers, who typically work no less than 40 hours per week, remain more often than not during the functioning day sitting at the computer. The group of office laborers, including representatives, computer administrators, bookkeepers, secretaries, directors, and so forth, who effectively utilize computers throughout their expert obligations, are overwhelmingly predominant in office syndrome (Lazko et al., 2021).

1.7.3 Surface Electromyography

Electromyographic signals are increasingly fundamental in a variety of applications, such as prosthetic devices, the human-machine community, and rehabilitation devices. However, the distorted EMG signal is an important test in the subsequent expansion of the exhibition application. EMG flags collected by muscle electrodes are disturbed by screams that interfere with sound recording. Therefore, EMG signals must be distributed legitimately to eliminate arousal. Recurrence of panic-contaminating EMG signals may be low or high. Low reflection stress is usually caused by the balance of the speaker. This excitation can usually be prevented by using high frequency channels, and the high frequency sounds come from the nerve conduction. High repeatability occurs in computers and radio stations and can be eliminated by using low-pass channels. The high-pass channel is used to reject the low-frequency frequencies that occur in the area of the electrical panel. The frequency at which a channel is transmitted along with a broadcast channel is called the bandwidth. Frequencies that a channel cannot pass through are called stop bands. The concept of a low frequency channel is the opposite of a high frequency channel. That is, the frequencies above the threshold are removed and connected below. EMG transmission must reject high and low frequencies as they advance in specific frequency bands, which end up using specific channels called band channels. This bandwidth channel licenses specific groups that broadcast within an unspecified range of the client. In any case, it makes sense to receive a certain range of frequencies whose bandwidth is ideal for the type of study on EMG boards. There are many harmless methods to distinguish muscle fatigue, the main strategies being surface electromyography (sEMG) and mechanomyography (MMG). The EMG records the electrical signals of the muscles, and the MMG records the mechanical movements of the muscles. However, there are various strategies that are rarely used in clinical or fatigue studies, such as sonomyography (SMG) to recognize fatigue and prosthetic conditioning using ultrasound, characterization by near-infrared spectroscopy (NIRS) to measure hemoglobin retention. In additions, acoustic myograph (AMG) is to record muscle sounds, this is a special use of MMG. Each strategy identifies and studies one or more muscle side effects, symptoms, and characteristics. However, the best way to recognize muscle fatigue is superficial EMG (Yousif et al., 2019).

1.7.4 Machine Learning

Machine learning is the part of software that creates detailed plans that allow computers to "learn" directly without modification. It begins with human reasoning in the 1950s and focuses on achievable goals and applications, especially prediction and improvement. Computers "learn" from machine learning by "experimenting" with the presentation of tasks. Progressive "experience" generally refers to relevant information. Of course, there are no clear boundaries between machine learning and factual methodologies. The fact that certain strategies are considered "machine learning" or "facts" as anyone reports real contradictions and many calculations (e.g., least absolute shrinkage and selection operator (LASSO), step-by-step recovery) can be considered based. Together, despite their strategic similarities, machine learning is perceived as rational and fundamental. Machine learning with (extensive) degrees of freedom of distortion usually demonstrates predictive accuracy in speculative predictions targeting large, high-level datasets (i.e., containing many covariates). Regardless of the specific qualifications between the approaches, machine learning provides the basic equipment for professionals in the spread of disease. In particular, an evolving focus on 'big data' reflects the problems and information indicators for which machine learning calculations are successful, as well as the more commonly used measurable measurement techniques. This core paper provides a basic prologue to machine learning based on providing each user with a starting point for those wishing to integrate parametric and machine learning methods into epidemiological studies focused on the purpose of these strategies. General machine learning calculations are Linear Regression, Logistic Regression, Decision Tree, Support Vector Machine (SVM), Naive Bayes, k- Nearest Neighbors (kNN), K-Means, Random Forest, Dimensionality Reduction Algorithms, Gradient Boosting algorithms, GBM, XGBoost, LightGBM, and CatBoost (Bi et al., 2019).

CHAPTER 2

LITERATURE REVIEW

2.1 Office Syndrome

2.1.1 Background

Immovable work is becoming more and more common in large parts of the world as the concept of work has changed rapidly due to renaming. A few experts have suggested that delaying standing position - e.g., sitting in the long time in front of a computer all day - may cause postural instability and be considered a risk factor for work-related musculoskeletal disorders (WMSDs), leading to office workers' complaints as a result of office syndrome. Abnormal supported positions are more likely to cause changes in the head, shoulder, and spinal curvature, resulting in the action of the head forward, rounded shoulders, and rounded back, frontal inclination, and winged scapula. Such conditions are thought to bring about constant instability and degenerative changes in the joints of one member, and at the same time are linked to external muscle imbalances and pain (Yaghoubitajani et al., 2022).

2.1.2 Epidemiology

Considered research, neck and shoulder disorders, brain aches, progressive neck stiffness, and scapular dyskinesia may have a negative impact on normal functioning and daily functioning. In addition, most tests reported approximately 50.5 percent and 44.8% of the most common shoulder and back pain among office workers. Computer clients reported adverse effects of external muscle strains of 68% in the neck, 66% in the back, and 45% in the shoulder. In 2014, among the staff of the Iranian office, Nejati et al. distributed a high degree of office space consisting of front head, rounded shoulders, and back as 61.3%, 48.7%, and 78.3%, respectively. Meanwhile, Noroozi et al. pointed out that office workers have a lot of external muscle problems, as delays in sitting and working with computers are part of the reasons why these people experience external muscle problems that often increase the risk. In any case, a major study by looking at a close partner focuses on finding a link between computer use and high risk taking and shoulder pain. In this way, it is the reason why some people tend to promote office disruption. It has been previously stated that the growing capacity, regardless of its purpose, limits assistance between fixed and real work applications (Yaghoubitajani et al., 2022).

2.1.3 Risk Factors

Due to the adverse effects of external muscles that compel circulatory costs including deteriorating leave, poor work ethic, medical costs, disability, termination of employment, and absenteeism from office workers, issues such as lifestyle interventions, visible evidence of at-risk gatherings. Inefficiency, increased well-being, and early expectations in the workplace can be expected as amazing strengths to increase efficiency and reduce absenteeism. Other risk factors affecting efficiency and performance in the workplace may be associated with isolated, classical, social, and environmental factors, including noise, light, temperature, and the like, which often cause financial misfortune. In addition, the office position is expressed by correcting the upper trapezius and sternocleidomastoid following deep cervical and spinal flexibility, lower trapezius, and serratus for major muscle defects. It may cause correction of scapula muscle actuation, developmental patterns, and a few abnormalities in the upper appendage that all this time contribute to cervicothoracic and glenohumeral fractures. Moving like a scaffold between the shoulder and the cervix, the scapula plays an important role in providing support and strength to the neck and shoulders. Previous experiments have also shown an association between progressive NSP and scapular dyskinesis by altering scapular stiffness during scapular alignment in the rest area and also reported that neck pain may alter postural behavior during delayed sitting activities, for example, while using a computer. In addition, extended cervical and thoracic curvature and slumped posture are known to affect scapular alignment, shoulder muscle strength, and shoulder range of motion. Numerous trials have been determined to prevent muscle dexterity in the neck muscles, cervical tension, and abnormal head position associated with high EMG movement of the neck flexors, and have shown a close relationship between the action of the upper trapezius muscle, neck point, and depression during prolonged stay. Brandt et al. detailed power areas between sawn NSP power and trapezius muscle delicacy among occupants. Judging by the findings of the past, the anterior serratus and lower trapezius provide strength to the scapula and align with the proper scapular position to move as a basic shoulder joint and to balance the strength of the scapular turn. Therefore, a corrected scapula sound may cause or support a mechanical fracture that elevates the cervical spine and affects the recurrence of neck pain. Meanwhile, increased scapular volume can be found in both shoulder and neck pain due to neuromuscular lopsidedness between deep phasic muscles and shallow tonic (Yaghoubitajani et al., 2022).

2.1.4 Management

It is worth considering the dynamic management of the office environment among office workers. In this way, Cools et al. recommended an important recovery approach that focused on the actual requests of workplace employees, such as adjusting axioscapular muscle strength and scapular arrangement during exercise for the remaining points. Therefore, performing remedial procedures right from the bat in the recovery program, playing all mediation in a sitting or standing position, and maintaining a high level of physical training to re-neutralize are considered various mitigation strategies on a regular basis of neck pain. Although a few trials have investigated the production of workplace pleas for redress or to combat WMSDs as a global medical problem, affecting both managers and representatives, effective interventions still need to be justified. The office environment may transform muscle regeneration projects, which can be seen as one of the strongest improvements in a mid-range car system. In addition, changes in muscle actuation have been observed in office workers who experience persistent pain in the shoulder and neck and postural instability, respectively. In this society, postural dysfunction and corrected muscle stiffness are related to functional impairment and poor visual acuity. Due to the lack of testing for office-based computer clients, it seems common to check for side effects related to external muscles, including forward head circumference, round shoulders, and rounded back near office-related muscles' EMG-affected office disorders, neck and shoulder pain, vacations canceled for such persons. Although many studies have revealed the positive effects of directed and unhelpful interventions in the management of WMSD, a few studies have emphasized that controlled applications will likely be useful for maintenance and adherence, and therefore, in fact, contribute to the reduction of serious adverse effects. On the other hand, performance under management may be financial information and generally not an accessible asset in the workplace; however, few people like to exercise when it comes to their daily work schedule. As many countries as a whole have used solitary confinement during the global COVID-19 violence, office workers are encouraged to telephone and adhere to community-level guidelines. Over time, rules based on evidence of homework are lacking in the treatment of office syndrome (Yaghoubitajani et al., 2022).

2.2 Muscle Fatigue

2.2.1 Background

Fatigue is a subtle side effect that many people experience and is associated with many diseases. Often seen as a strange feeling of laziness, weakness and a feeling of exhaustion, fatigue is linked to a problem in doing a deliberate job. The accumulation of fatigue, in the unlikely event of a relapse, causes fatigue, chronic fatigue syndrome (CFS), overuse of exercise, and, surprisingly, endocrine disorders, fractures, natural diseases and health risks. There are a variety of strategies to order fatigue. As your name suggests, fatigue can be categorized into extreme fatigue and persistent fatigue. Severe fatigue may improve immediately at rest or lifestyle changes, while chronic fatigue is a condition that appears to be a fixed sleep that lasts four months but has not improved rest. Fatigue can also be referred to as mental fatigue, which refers to the mental or visual components of fatigue, as well as the actual fatigue, which leads to the introduction of the motor framework. Muscle fatigue is seen as a significant decrease in strength or strength buildup due to contractual action. It can start at different levels of the car road and is usually divided into central and peripheral sections. Peripheral fatigue is brought about by changes in neuromuscular or distant joints. Moderate fatigue begins in the central nervous system (CNS), which slows down brain motor. Muscle fatigue is a common occurrence that limits exercise and other difficult or delayed movements. In addition it is the ups and downs of daily life under a variety of stressful conditions, including emotional, physical and cardiovascular problems, as well as maturity and weakness (Wan et al., 2017).

2.2.2 Factors

The structure of the skeletal muscle strength depends on parallel components, and discomfort in any area above the cross-scaffolds can add to the development of muscle fatigue, including shock, particles, skeletal structures and strength. In particular, metabolic components and reactants are depleted during withdrawal, such as hydrogen ions (H +), lactate, inorganic phosphate (Pi), reactive oxygen species (ROS), heat shock protein (HSP) and orosomucoid (ORM), moreover have an impact muscle fatigue (Wan et al., 2017).

2.2.3 Diagnosis

Muscle fatigue is most noticeable in a healthy living person. Risk-free techniques that expose the site can now be used to evaluate the expected areas of the entire power creation framework in human trials. All stimulated muscle reactions are recorded using electromyography (EMG) electrodes inserted into the muscle. To date, there are no specific factors that are faithfully associated with any type of fatigue. Types of exercise (e.g., oxygen or anaerobic, short-term or long-term), type of exercise (e.g., increased or constant, isometric or non-isometric, focused or eccentric), and degree of fatigue and length all influence biomarker profile. As shown by the system and metabolic changes during muscle fatigue, three categories of biomarkers can be targeted: (1) ATP metabolism biomarkers, such as lactate, ammonia and hypoxanthine; (2) Oxidative stress (ROS) biomarkers, such as lipid peroxidation, protein peroxidation, and antioxidant power; and (3) Symptoms of inflammatory organisms, such as TNF-α, leukocyte, and interleukins (Wan et al., 2017).

2.2.4 Management

Poor exercise, prolonged fighting, preparation for war and a few related illnesses (e.g., stroke) can cause muscle fatigue, which can adversely affect sports success, military prowess and patient recovery. As of now, there are no official or official recommendations for the treatment of muscle fatigue. However, a few obscure drugs, such as synthetic substances (for example, amphetamine and caffeine), common substances (for example, American ginseng and rhodiola rosea) and dietary supplements (e.g., nutrients and minerals and creatine), have was used in the clinic or temporarily, and have shown a few implications for different trials (Wan et al., 2017).

2.3 Electromyography

2.3.1 Background

Electrical tests that produce bone tissue speak to the central EMG signal. EMG is used to test myoelectric signals using electrical measurements. These myoelectric signals are produced by motor neurons that are part of the central nervous system (CNS). Since EMG signals are due to neuromuscular movements, they can be used to analyze muscle damage, nerve damage, and muscle fractures caused by nerve and energy disorders. EMG signals are used to collect precise data or can be used even by a computer or a high level of deep-seated learning how to control complex automated applications. In addition, in some cases, EMG symptoms may be used to assess the movement and contraction of muscle growth (Gohel & Mehendale, 2020).

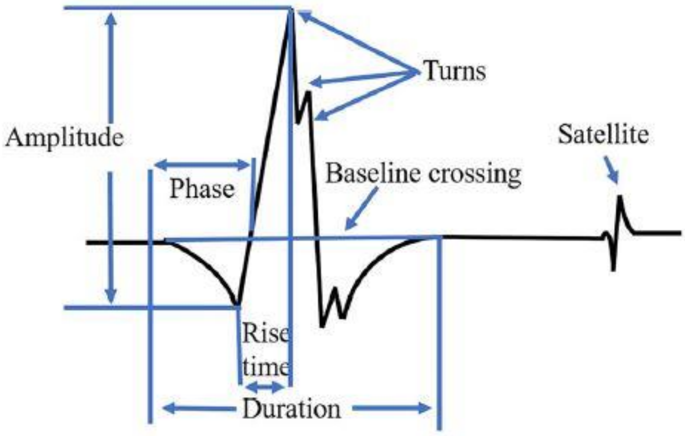

Figure 2.1 Basic temporal characteristics of the EMG signal.

Source: Gohel and Mehendale (2020)

Figure 2.1 shows the fundamental transient attributes of the EMG signal. The amplitude is the positive top to negative pinnacle voltage. Phase is the time term of the underlying negative cycle. The rise time is characterized as the time stretch among negative and positive pinnacles. There are three turns in the EMG signal. The duration is characterized as the all-out time between two negative cycles. A satellite is a little sign followed by the principal EMG signal (Gohel & Mehendale, 2020).

There are two main types of electrodes used to measure EMG signals - needle electrodes and surface terminals. Needle electrodes are divided into three subtypes: mono-polar terminals, single-fiber EMG electrodes, and concentric-EMG electrodes. The needle electrodes are approximately 1 mm^2 wide. The surface electrodes are 0.5-2.5-cm wide and due to their location are painless. The additional terminals operating at the level of the synthetic balance distinguish the transition between muscle skin and body skin by electrolytic conduction. The surface terminals are of two types: gelled EMG electrodes and dry EMG electrodes. There are 3 main types of electrograms, namely. Electroencephalogram (EEG), electrocardiogram (ECG), and EMG. The advantage of using EMG over ECG and EEG is that the ECG and EEG signals are less than 100 Hz while EMG signals cover access from 5 Hz to 2 kHz. EMG symptoms can be shown with a variety of examples (Gohel & Mehendale, 2020).

2.3.2 Surface Electromyography

Muscle strengthening has passed before the onset of electrophysiological events, from excitement of motor neurons in the spinal cord to an increase in the force of action on all T-tubules of muscle. This large number of times, in a way, adds to the age and distribution of electrical energy in the connective tissue, called the electromyogram. An electromyogram is often called an impedance signal, as it mixes the commitment of different units; Depending on the tension and the strength of the pressure, the number of powerful motor units can range from tens to hundreds (Rampichini et al., 2020).

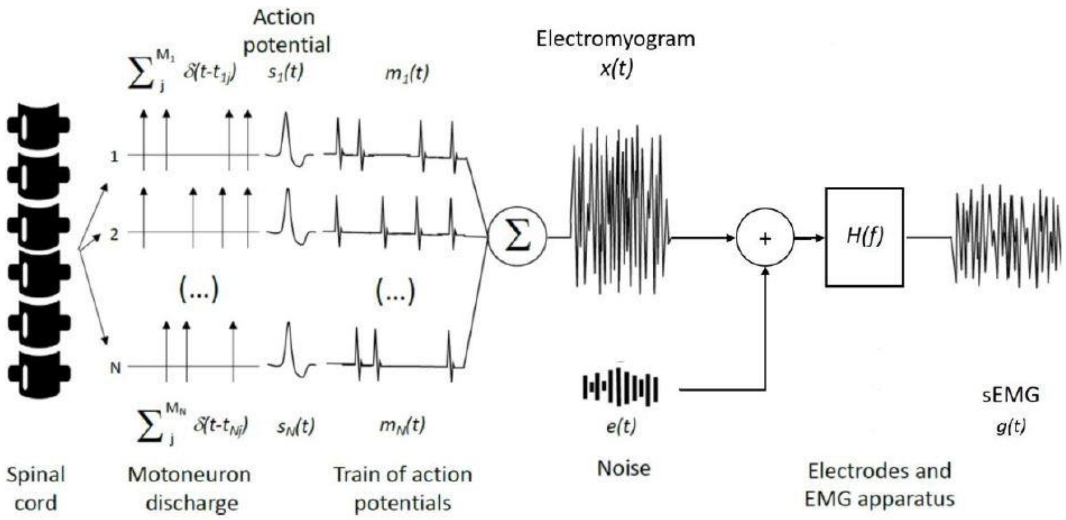

Figure 2.2 Generation of Electromyograms.

Source: Rampichini et al. (2020)

As schematically represented in Figure 2.2, the interference electromyography (EMG), $x(t)$, might be demonstrated as the number of trains of motor unit action potentials $m_i(t)$, each characterized as the time convolution between the release moments $\delta(t\text{-}t_{ij})$ and the waveform $s_i(t)$ of the action potential of each single unit as equation (1).

$$x(t) = \sum_i^N m_i(t) = \sum_i^N \sum_j^{M_i} \delta\left(t - t_{ij}\right) * S_i(t) \quad (1)$$

where N and M_i separately compare to the quantity of motor units enrolled and the all-out number of releases (j = 1, 2, 3, … , M_i) for the i-th motor unit. The level of EMG interference is accordingly

obviously subject to how frequently motor units release and on the quantity of motor units energized. Plainly, the level of interference increments with the compression level. Two primary sources describe $m_i(t)$: the release moment t_{ij} and the waveform addressing the motor unit action potential, $s_i(t)$. Being the sign emerging from the spinal line and deciding the beginning and recurrence of muscle excitation, the train of motivations describing the motor unit release moments is viewed as the brain drive to the muscle. The numerical and reasonable definitions for EMG don't be guaranteed to infer a central beginning for the release moments as frequently improperly considered; synaptic sources of info emerging from corticospinal pathways, spinal interneurons, and peripheral afferent input on the whole decide the net brain drive to muscles. Uniquely in contrast to the muscle brain drive, the waveform of motor unit action potential conveys no data from the spinal string. It is altogether characterized by peripheral factors, connected with physiological, physical and identification viewpoints. Physiological (e.g., conduction speed, intracellular activity likely spans) and physical (e.g., profundity and length of muscle filaments) perspectives are not under the immediate control of the experimenter. Then again, discovery viewpoints, as position and size of electrodes, ought to be carefully characterized by the muscle contemplated and the reason for the review. Taking into account the boundless inspecting of sEMG with several surface terminals, i.e., bipolar electrodes, here we accordingly center consideration around the impact of bipolar montages. The greatness of the bipolar montage move capacity might be drawn closer as equation (2).

$$|H(f)| \propto \sin^2(\pi f d) \quad (2)$$

with *d* being the middle-to-middle distance between terminals. In light of its high-pass separating reaction for spatial frequencies less than 1/2*d*, the bipolar montage is a straightforward method for constricting well known mode signals related with power line impedance and far-field potentials. Advantages of constriction of the last option factor are thoroughly thought out in examinations pointed toward assessing conduction speed however might be problematic when the aim is to appraise force from EMGs. Obviously, $|H(f)| = 0$ at the frequencies $f = n/d$, $n \in \mathbb{N}$. Taking into account the multiplicative impact of $H(f)$ on the EMG range), the bipolar montage drives accordingly to plunges in the recurrence range $G(f)$ of the recorded EMG. The electrode filter function $H(f)$ is especially significant when bipolar terminals are adjusted lined up with the basic muscle strands, by which existence are entwined. For this situation, the contention of the sine capacity can be revamped as $\pi fd/v$, with v relating to the action potential conduction speed. This connection among d and v could persuade endeavors to characterize the proper between terminal distance not prompting unearthly plunges and strategies for the assessment of conduction speed from dunks area in $G(f)$. The two prospects are doubtful however, given they are legitimate for the particular case electrodes and strands dwell in equal headings and in light of the fact that the conduction speed varies between motor units. In addition, the meaning of suitable between electrode distance in bipolar recording ought not be founded on the aversion of unearthly plunges and of spatial associating yet on whether and how much both influence the chance of extricating physiologically pertinent data from the electromyogram. Albeit brief distances might help weakening the discovery of undesired sources, non-designated muscles, it might bring about the location of signs unrepresentative of the entire, target muscles. Despite the selectivity-explicitness issue has been customarily recognized, gives an account of this matter are early. Subsequently, it tends to be expected that the bipolar EMG is both particular and explicit, inspecting solely from all filaments of the objective muscle (Rampichini et al., 2020).

2.4 Internet of Things

2.4.1 Background

The 21st century is seeing a high-speed computerized unrest. Internet of Things (IoT) is a new idea where certifiable actual elements can be somewhat controlled with the assistance of the Internet. IoT engineering contains an actual item network that is incorporated with sensors, electronic gadgets, and programming which permit them to assemble and move information through an IoT organization. These substances are likewise called shrewd articles since they can detect the climate and can be somewhat controlled through existing IoT network design by incorporating with the actual climate. IoT emphatically affects regular routines as it gives new answers for each part of society (Uppal et al., 2021).

2.4.2 IoT Framework

IoT is a peculiarity that outcomes in an occasion between the sensor, ongoing organization, and the server farms. In an IoT application, the discernment layer comprises of brilliant articles implanted with sensors that gather and cycle ongoing data of the physical and computerized universes. These sensors help in the estimation of the actual assets and screen the progressions in the actual climate. There is a requirement for memory in the doorway to get the sensor information that the sensors ship off the entryways. In some cases, these sensors create a lot of information that need a hearty and elite presentation wireless sensor network (WSN) that moves this information to the objective entryway on time. A few conventions and advancements are required in the heterogeneous design of an IoT application. Likewise, a wide scope of IoT administrations or applications like speed exchanges, similarity, or setting mindful applications are requested. IoT is acquiring notoriety overall in various circumstances of the high-level remote correspondences network while supporting the presence of brilliant things around us. IoT is fit for impacting the world. There has been a wealth of data and this cutting-edge innovation has opened numerous ways to get to this data. All aspects of our lives are getting changed by the improvement of IoT. IoT structures are seriously utilized in numerous applications as a portion of the crucial regions and uses of IoT which incorporates savvy traffic framework, brilliant climate, shrewd medical care, brilliant home, shrewd farming, brilliant office, and supply chains operations IoT (Uppal et al., 2021).

2.4.3 Application in Healthcare

The continuous checking of human movement is a valuable and effective device in medical care as it is connected with keeping up with everyday exercises, wellbeing observing, and improving the security and security of old individuals. However, fall discovery of the client is the great concentration, the acknowledgment of various exercises can likewise be utilized to break down the client conduct. According to the information given by the World Health Organization, over 28% of the matured populace gets impacted by falls every year. It is likewise expected that an absence of preventive measures might twofold this worth by 2030. A fall occasion may cause actual wounds as well as have mental results including uneasiness, wretchedness, and feeling of dread toward falling. The IoT gadgets that are equipped for following human action can add to diminishing this sort of antagonistic occasion. This can be accomplished by utilizing progressed calculations and different body-worn sensors in an IoT climate. Various examinations in the past have explored the capability of IoT in conveying various answers for action acknowledgment and fall discovery. There was different best in class wearable advances in medical care for action acknowledgment, position checking, and important bodily function observing. It explored the utilization of different sensors and their reconciliation in observing positions and exercises. A structure for IoT-empowered Personalized Intelligent Assistant has been proposed for aiding geriatric patients in playing out their day-to-day exercises. The framework additionally dissects the day to day exercises and reports assuming any irregularity in conduct was noticed (Sahu et al., 2021).

2.4.4 Activity Recognition

Arifoglu and Bouchachia have fostered a wearable gadget that utilized a 3D-pivot accelerometer implanted with a 6LoWPAN for falls identification in older individuals. The sensor information was handled utilizing a tree-based huge information model that worked in an IoT entryway. In the event that falls were identified, a crisis alert was actuated to advise the guardians. Further, it produces a crisis caution to the relatives or guardians when a fall was identified. The IoT-based frameworks have utilized different machine learning calculations for identifying and characterizing various exercises. Arifoglu and Bouchachia have proposed a comparative technique for geriatric patients with dementia. Three variations of Recurrent Neural Network have been utilized for the discovery of strange way of behaving and action. In patients with Parkinson's sickness, whirligigs and triaxial accelerometers have been utilized for detecting these exercises. Also, machine learning calculations were utilized for perceiving these exercises. And furthermore, a fall location cum crisis reaction framework has been introduced. The framework utilized profound sensors to get twofold pictures of the old people who were followed by Microsoft Kinect SDK. The elements of the twofold picture were removed utilizing the histogram of oriented gradient (HOG) strategy. The situation with the fall was assessed utilizing the support vector machine (SVM) calculation. Along these lines, combination of IoT for movement or fall discovery in medical care achieves many benefits and has been broadly utilized with regards to remote access (Sahu et al., 2021).

2.5 Machine Learning

2.5.1 Background

The term machine learning (ML) was first introduced in 1959 by Arthur Samuel, a prominent computer researcher at the time. AI and ML terms are often used interchangeably, however in the wrong way; AI refers to the general concept of a 'thinking machine' or a self-propelled robotic guide even though it has shown the ML as giving 'computers the ability to read without being changed without hesitation'. The main reason for ML is to present data that enters the input information, to use a computer survey to predict prices within the right field of accuracy, to distinguish patterns and patterns within the information ultimately benefit from what has happened in the past. ML is not new from the beginning of the current enrollment, this conceptual machine is designed with the full intention of using computer-based calculator to explain examples and conclusions that can be challenging to come up with common strategies that rely on human managers to design and provide a common basis or suspicion (Handelman et al., 2018).

2.5.2 Supervised Learning

In supervised learning, the computer is provided with features related to the purpose of the study, (for example, the patient's social status and risk factors) and the required steps to be performed (such as analysis or clinical times) determined to detect the interaction between the two databases. The commonly used model prepares a model that will distinguish between apples, oranges and lemons. The ‘mark’ of each type of natural product is given first in the calculation close to the characteristics, for example, variety, size, weight and shape and the calculation reads the combination of substances that distinguish organic products. Then, at that point, when a new product, ‘not labeled’, is introduced, the model should have the option to foresee what kind of natural product it is (Handelman et al., 2018).

2.5.3 Unsupervised Learning

In unsupervised reading, the computer is provided with separate information records to detect and determine whether there are current silent models available, sometimes bringing two answers and questions that may not have been submitted by experts. From a special point of view, while controlled progression basically controls character segregation and recurring problems, learning without assistance controls the consolidation and decrease in size. Examples that are recognized in individual development should usually be evaluated for use in human testing or for use within a managed learning task (Handelman et al., 2018).

2.5.4 Development of Machine Learning

Names, AI and ML are not new. It has been researched, used and re-created by computer researchers, engineers, analysts, students and industry experts for over 60 years. ML number support is based on statistics based on variables, estimates, and probability. The great development of ML and AI began in the 1950s and 1960s with the dedication of scientists such as Alan Turing, John McCarthy, Arthur Samuels, Alan Newell and Frank Rosenblatt. Samuel suggested a major ML model in the Checkers Development program. Rosenblatt makes Perceptron; the calculation of ML is well-known in the light of living neurons that established support for the brain's artificial brain (Alzubi et al., 2018).

In 1950, Alan Turning conducted a "Turning Test" to actually test machine information. In order to breathe a sigh of relief at Turning Assessment, the machine should have the option of persuading people that they are actually talking to someone and not the machine.

In 1952, Samuel did a much more sophisticated math test than playing the Checkers round and preparing himself.

In 1956, Martin Minsky and John McCarty and Claude Shannon and Nathan Rochester convened an assembly at Dartmouth in 1956 where real AI was invented.

In 1958, Frank Rosenblatt developed Perceptron, which laid the foundation stone for the development of the artificial neural network (ANN).

In 1967, a Nearest Neighbor Algorithm was proposed that could be used for "Pattern Recognition".

In 1979, students at Stanford University built the "Stanford Cart", a modern robot that can scan a room and away from obstacles along its path.

In 1981, Explanation Based Learning (EBL) was proposed by Gerald Dejong, through which the computer separated the preparation information and enacted waste disposal rules.

In 1985, NetTalk was designed by Terry Sejnowski, who discovered how English words can be interpreted in the way young people learn.

In the 1990s, the ML focus area shifted from Knowledge-headed to Data Driven. The ML was executed to separate large volumes of information and draw conclusions from it.

In 1997, IBM envisioned a Deep Blue computer that had the option to beat world chess champion Gary Kasparov.

In 2006, the term "Deep Learning" was developed by Geoffery Hinton which focused on other sensory network engineering involving various layers of neurons for learning.

In 2011, Watson of IBM, who worked to answer questions presented in a special language, won the Human Competition at the Jeopardy Game.

In 2012, Jeff Dean of Google, created Google Brain, the Deep Neural Network to separate designs from videos and images.

In 2014, Facebook created a number of "DeepFace" in proportion to Deep Neural Networks that are qualified to detect human visibility in photos.

In 2015, Amazon proposed its own Machine Learning Platform. Microsoft has developed a "Circulated Machine Learning Toolkit" to successfully stream ML content on different computers so that it can run sequentially accordingly. Elon Musk and Sam Altman, formed the nonprofit organization OoeaAI, with the goal of using computerized thinking to help individuals.

In 2016, Google made a proposal to DeepMind which is considered the most mind-blowing board game. The Google AlphaGo program is changing into a mainstream Computer Go program to defeat the professional human player. It depends on the mixing of ML with the tree in terms of strategy.

In 2017, Google proposed Google Lens, Google Clicks, Google Home Mini and Google Nexus-based phones using Machine Learning and Deep Learning Algorithms. Nvidia has made a proposal for NVIDIA GPUs - In-depth Learning Engine. Apple has proposed the Home Pod which is a Machine Learning gadget (Alzubi et al., 2018).

2.5.5 Machine Learning and Healthcare

ML has been around for a long time due to advances in software engineering, promoted by the innovative business, which relies heavily on the use of ML diversity. Medicine has not resisted this development and is actually a mature ML site. The idea of using AI in medicine is not new, as applications go back to the 1970s but many medical professionals want to know about ML as an idea, how it can be used effectively or widely distributed in ML as it is now within their prestigious applications. The previously completed work commends the ability to continue to develop expectations and the quality of representation in the study should the ML be taken and used. With the continued development of ML processes in medical practice, scientists and therapists may face rejection as standards in medical services change. Most clearly these strengths, reflecting the discontinuation of studies and the use of ML across the entire field of clinical capacity. Custom ML of customized medicine is a developing area of interest. The ability to use large data sets and intelligent models that looks to physicians to analyze without hesitation, anticipate and treat their patients. Customized medicine is an individualized one, recognizing small features within a patient that may make him or her stand out from the crowd. The power of ML permits going forward is individualized at many levels: analysis, expectation and treatment. Within this program, it is perhaps a challenge for a physician to have the option to determine in advance which patient groups are available and where the ability to borrow tuition fees has not been assisted in handling information; it does not require 'liberated' cases or pre-determined classes to be given to make merged organizations and expectations from the information, and the review has shown how small patient groups are not yet in the air by exploring information on a single strategy. Salgadoet al. demonstrated the use of ML to anticipate a vasopressor organization requirement by considering 24 clinical features usually kept in a state of deep meditation using non-assisted processing to exclude features that would be used in demonstrations and used in isolated effective cases. W adjust al. used general clinical information in 378,256 patients from the UK Clinical Practice Research Datalink (CPRD) used by a wide range of specialists to correct various ML statistics to measure the risk of cardiovascular events and compared this with the fluctuations and flow of the American College of Cardiology / American Heart Association (ACC / AHA). The data-based study found that the figure was not only comparable, it also identified major clinical features excluded from other common factors, such as chronic obstructive pneumonic syndrome and severe mental retardation. Data sets, for example, these are valuable and will in the future allow for the creation of specific human and patient support services (Handelman et al., 2018).

2.6 Logistic Regression

Logistic regression is used to discuss the issue of classification. It provides a binomial effect as it provides the probability that an event will occur or not (about 0 and 1) due to an increase in cognitive factors. For example, predicting whether growth is dangerous or harmless or email is spam or not are examples that can be considered as a result of a logistic binomial regression. There may be a result of many Logistic regressions and e.g., anticipation of popular foods: Chinese, Italian, Mexican and more. There may also be an ordinal effect as well: something that checks 1 to 5 and so on. Logistic regression therefore manages the prediction of targeted variables that are completely accurate. Although the decline in the line control predicts the continuous rise in volatility e.g., anticipation of land costs over a 3-year period. Postponement of order enjoys the benefits that come with it: integrity, computer production, expertise in terms of point of view correction, simplicity of doing so. No rating rated for input features. This figure is widely used to address industry scale problems. As the result of Logistic regression is a result of opportunities so to use it to take care of a business matter it is expected to determine the modified performance measures to obtain a conclusion that can be used to create objective planning. Similarly, retrospect is not affected by the slightest disturbance in information and multicollinearity. The performance deficit has a related disadvantage: the inability to deal with the indirect problem as the selected area is straightforward, prone to excessive equilibrium, cannot be clearly seen unless all independent factors are excluded. A few examples of logical use of Logistic regression are: predicting gambling to promote a specific illness, end-of-life growth, predicting the death of injured patients and planning to anticipate the risk of embarrassment for a particular cycle, framework or object (Ray, 2019).

2.7 Support Vector Machine

Support vector machine (SVM) can deal with both classification and regression problems. In this strategy, hyperplane should be marked which is the limit of choice. Where there are plenty of space with multiple classrooms then the preferred plane is expected to differentiate itself. Articles may be directly separated when complex numerical forces called fragments are expected to separate human objects from different categories. SVM focuses on accurately interpreting articles in the light of models in the preparation information index. The following are the SVM upsides: can deal with both infinitely systematic information; can deal with complex volume in the event that the appropriate episode volume can be determined. As speculation is taken from SVM so it is less likely to be very appropriate. It can grow with high horizontal knowledge. It does not sit well with the neighbors. The following are the obstacles to SVM: its introduction comes down to a large amount of information due to increased preparation time. It will be difficult to track the activity of the appropriate component. SVM does not work optimally when a data set is audio. SVM does not provide possible gauges. Understanding the final SVM model is difficult. SVM finds its work grounded in the world in analyzing negative growth, Visa distortion, transcription approvals, face recognition and message collection and more. Therefore, between the three Logistic regression methods, the Decision Tree and the SVM the main approach to the effort will be the Logistic Regression method, next Decision Trees (Random Forests) can be attempted to assess whether there is significant improvement. When the number of ideas and objects is high then SVM can be tested (Ray, 2019).

2.8 Naive Bayes

This algorithm is straightforward and depends on the limited possibilities. In this process there is a table of modeling opportunities and by preparing the information it is updated. The "Probability Table" is based on the values of the component where one requirement is to look at the class opportunities to foresee a rational idea. The basic concept of interdependent freedom and for that reason is described as "naive". In the real system it is assumed that all aspects of the information are independent of each other and may not appear as expected. Naive Bayes (NB) enjoys the benefits associated with this theme: easy execution, offers good execution, works with minimal preparation information, directly measured with a number of indicators and interesting data, handles static and clear data, can handle paired order and multi-level variability, and news, make hopes possible. It contains consistent and diverse information. It is not soft to the touch. NB has some drawbacks: adjusted and properly tuned models often outperform NB models as they are the most important. In the event that there is a need for one of the features such as "continuous variable" (as time) then, at the same time, it is challenging to use NB directly, despite the fact that one can make "containers" of "non-stop features" is 100 percent wrong. There are no visible differences based on the NB web, so all information must be retained in order to retrain the model. It will not measure if the number of classes is too high, over 100K. In any case, expectation takes more working time memory compared to SVM or easy login retrieval. It is mathematically difficult for models that include many things. NB can be used in performance programs, for example, recommendation program and to measure the harmful decline in growth or movement after radiotherapy (Ray, 2019).

2.9 k-nearest Neighbors

The K-Nearest Neighbor (KNN) Algorithm is a classification issue. It uses a knowledge base with focus information collected from several classes and counting attempts to order a sample information guide provided as a collection story. KNN does not anticipate the transfer of basic information and is therefore referred to as non-parametric. The benefits of the KNN calculation go hand in hand with this: the precise method is done manually. It is modest to build a model. It is a very flexible planning system and is suitable for multi-layered classes. Records with multiple class marks. The Blunder rate is all things considered twice as much as the Bayes error rate. Now often it would be the best strategy. KNN defeats SVM with the expectation of activity using speech profiles. KNN disruption goes hand in hand with this: it is often expensive to collect obscure records. Requires distance calculations for KNN. With the advent of setting the size of the calculation set is growing electronically. Noisy or insignificant features will bring about accuracy. It is a tired student; considers distance over neighbors. It does not guess at the preparation information and keeps all of them. It handles large chunks of information and an expensive scale. Higher horizontal information will result in a decrease in the accuracy of the locations. KNN can be used in the recommendation framework, for various clinical diagnoses showing comparative adverse outcomes, FICO scores using the analogy, place of writing, pre-approval fundraising tests, video approvals, waiting for votes in favor of diverse groups and approving the image (Ray, 2019).

2.10 Decision Tree

Decision Tree (DT) is a ML-supervised method of dealing with the care of planning and retrospective problems by separating information by looking at a specific boundary. Options are in the leaves and information is divided into hubs. In the split tree, the alternate choice is not reduced (the result is Yes or No) and in the split tree, the alternative selection does not end. DT enjoys the benefits associated with this topic: it makes sense to duplicate and order delivery, easy to understand, the ease of caring for explicit and numerical attributes, equipped to fill non-credit attributes at a very reasonable price, high quality display due to production. calculator for crossing a tree. DT may have a problem with over-equilibrium of which random forest is a system that depends on the group display method. The weakness of DT is that it is prone to fluctuations, may be difficult to control the size of the tree, may be prone to error checking and provides a good local setting that is not a good global setting. DT can be used in programs such as detecting future use of library books and cancer waiting problems (Ray, 2019).

2.11 Multi-layer Perceptron

The imagination of physicists can comprehend the complexity of different and simultaneous events in nature. The explanation for why such an understanding can be raised among humans is that growth has gradually improved the structure of our cerebrums as a highly balanced organization of neurons. This was an ongoing fact that began with the incentive for McCulloch and Pitts in 1943 to develop a numerical concept to mimic the nervous system, which in turn urged various scientists to study artificial neural network (ANN). ANNs are remarkable methods used in picking, measuring, and evaluating different stages of complex problems. It is agreed that ANNs can be more effective in controlling machine perception conditions, where it is difficult to determine key aspects of a problem separately. Later, ANNs were recognized as robust learning strategies that produced acceptable results in a wide range of acceptance, accumulation, order, and back problems. Single layer perceptron (SLP) networks are computer models that contain only two information and results layers, which is a very complex form of ANNs. It has been shown that SLPs are not ready to create and manage non-linear examples. To oversee the affairs of SLPs, scientists have promoted a specialty from ANNs, called the multi-layer perceptron (MLP). MLP networks often use a few secret layers to stay away from SLP downsides. Thus, MLPs are known as the most widely used ANN class in writing. The main advantages of MLP are high learning ability, aggressiveness, ambiguity, similarity, adaptability and insignificant failure, and high ability to summarize tasks. In view of Kolmogorov's hypothesis, MLP with a single-layer encryption can measure any unchanging power. However, the introduction of ANNs is far below the learning strategy used to adjust the measurement vectors. Guided MLP Advisors are usually implemented from two accredited classes: slope-based statistics and stochastic-based statistics. Although slope-based counselors have a good presentation on neighborhood searches, meta-heuristic-based trainers (meta trainers) can reveal high-end intelligence away from optima (LO). Lack of search can be considered an important advantage of meta trainers over slope-based trainers. By following these lines, they can end the pursuit of a better world than angular-based counselors. They are clear and flexible. Besides, when previous information about a job can be disclosed, meta-coaches are often the right decision makers. Angle-based processes can deal with continuous and varied work programs, while simple meta-heuristic agents can also manage indirect and indistinct skills. However, they actually need more time to calculate (Heidari et al., 2020).

2.12 Application of Machine Learning

This is a popular real use of ML. The computer program demonstrates how a test game is played, while the ad is still in the air with its ability to succeed in a different category of game-related activities, with information gained through the conflict. Highly refined speech recognition systems these days transfer ML statistics to specific structures. Model: The SPHINX Framework acquires sounds and a speaker that encapsulates the text in speech signals. The various Neural Network learning processes for describing the Markov Models have been very successful in refining speakers, word reference, chaos and more. ML models these days are used to drive private cars like Cars, Drones and more model: Google Driver Less Cars, Tesla Cars. ML techniques are deeply rooted in sensory-based applications. ML can be used in channel spam messages. The ML-based model will store all messages sent by a client spam. In the event that a new email comes out of the inbox, an ML-based model will look at, analyze and view past spam messages. In the event that the new email is similar to any of them, it will be classified as spam; otherwise, it will be moved to the client inbox. ML is considered an advanced means of dealing with critical thinking. By using basic knowledge and preparing information on ML models, learning can be improved and that will take mechanical and ML technology to the next level. NB categories have been used successfully in the field of text mining, be it spam editing or editing a web page, email and any report. Facebook uses NB to check out an announcement about positive and sad feelings. In a record sequence, Google includes NB counts to split the report. K-means clustering is used by web search tools like Google, Yahoo to collect site pages by comparison. Apriori is used by sites, for example, Amazon or Flipkart to suggest which items are purchased together most of the time. Another common use of Apriori is Google's automatic completion. In the event of a name-calling, Google web search tool searches for related keywords that match the predefined name. Hearing inquiries about interactions between people is a common problem of measuring text characters solved using a variety of ML statistics. TRISS: Trauma and Injury Severity Score, widely used to predict the deaths of injured patients, was originally developed by Boyd et al. using calculated multiplication. Many other clinical scales that are used to assess a patient's sensitivity are created using regression. Bayes' Theorem is perhaps the most popular way to create limited computer opportunities guesswork. It can best be used to deal with complex information science and research issues by linking different models of machine learning and arithmetic. A few examples of verified news that can be handled using Bayesian techniques are: ideas on Netflix, automatic reviews, charging card location, google page layout, face recognition, location display specs and trading platforms (Alzubi et al., 2018).

2.13 Related Research

Evaluation of neuromuscular fatigue is fundamental for early discovery and counteraction of dangers related with business related outer muscle problems. As of late, discrete wavelet transform (DWT) of surface electromyography (sEMG) has been utilized to assess muscle fatigue, particularly during dynamic compressions when the sEMG signal is non-fixed. Nonetheless, its application to the evaluation of business-related neck and shoulder muscle exhaustion isn't deeply grounded. In this manner, the motivation behind the investigation of Chowdhury et al. was to lay out DWT examination as a reasonable strategy to direct quantitative evaluation of neck and shoulder muscle exhaustion under unique monotonous circumstances. Ten human members performed 40 min of exhausting dreary arm and neck efforts while sEMG information from the upper trapezius and sternocleidomastoid muscles were recorded. The ten of the most normally utilized wavelet capacities were utilized to direct the DWT investigation. Unearthly changes assessed involving force of wavelet coefficients in the 12-23 Hz recurrence band showed the most elevated aversion to fatigue prompted by the unique redundant efforts.

Albeit a large portion of the wavelet capacities tried in this concentrate sensibly showed the normal power pattern with fatigue improvement and recuperation, the general exhibition of the "Rbio3.1" wavelet as far as power assessment and measurable importance was superior to the leftover nine wavelets (Chowdhury et al., 2013).

Preparation for clear muscle strength has recently been shown to be effective in restoring the continuous tension of the neck muscles in women. The research by Andersen et al. was to determine the level of cervical and shoulder muscle authorization using surface electromyography (EMG) during selected strengthening procedures for women recovering from frequent neck muscle trauma (considered a clinical diagnosis of trapezius myalgia). The subjects were 12 female specialists (age = 30-60 years) with a clinical outcome of trapezius myalgia and a mean pain concentration of 5.6 (range = 3-8) with a magnitude of 0 to 9. Electromyographic movements in the trapezius and deltoid muscles were measured between activities (longitudinal, vertical columns, shoulders, single arm lines, and converse fly) and corresponded to the EMG action recorded during the major voluntary contraction (MVC). In most cases, the level of muscle movement was moderately high (> 60% of MVC), indicating the effectiveness and specialization of the various functions. With trapezius muscle, the highest level of muscle actuation was achieved during shrug (102 ± 11% MVC), sidelong height (97 ± 6% MVC), and high line (85 ± 5 % of MVC) is active. , however the last 2 operations required additional moderate preparation loads (3-10 kg) compared to shoulder extensions (20-30 kg). The horizontal line of lift and height may be appropriate options unlike shrugs during the recovery of continuous neck muscle relaxation. A few strength exercises had a high regulation of neck and shoulder muscles in women with persistent neck pain. These activities can be used in a similar way in an effort to achieve a therapeutic effect on chronic neck pain (Andersen et al., 2008).

Information on muscle use and the development of muscle fatigue may provide additional internal effects of long-distance driving in the event of medical problems in the neck, shoulder, and back area. Significant suspicions behind the field of electromyography (EMG) fatigue are an increase in EMG sensitivity and a decrease in mean frequency (MF) frequency. Hostens and Ramon point out in testing this consideration for performing low-level hard work while driving. Surface electromyography was detected from the left and right trapezius and deltoid muscles, during shock, unstoppable, driving (equipping and controlling) and the flexible segments were divided into fixed segments. Muscle stiffness was calculated for most of the studies after driving for 1 hour. In the variable components a significant decrease in MF was observed. In addition, however, EMG adequacy is completely reduced. Two possible components have been submitted in writing to this discovery: no additional registration of motor units (MU) and muscle strength. The same writing assumes that the function associated with low-energy words connects only a small part of the MU accessible to the enrollment and that these units are type I (Cinderella) muscle fibers. The initiators of this unusual phenomenon are undoubtedly the delays between the rules and the pressures from driving and vibration openings (Hostens & Ramon, 2005).

Human fatigue reduces the ability to work part-time because of unusual or delayed activities. In this case, electromyography (EMG) is used to measure the actual strength of a muscle. Each muscle in the human body sends signals that are delivered when the muscle makes various improvements. In Ayaz et al. work, lower arm muscles were tested using the MyoWare EMG sensor (AT-04-001), Arduino Uno, keypad and LCD. The EMG sensor detected a signal containing 235 samples from a human lower arm muscle within 30 seconds. Recorded examples of RMS (Root Mean Square) were cut. Studies have shown that RMS looks for an increase in BMI (Body Mass Index), the level of fatigue later expanded as BMI indicates muscle strength, as more energy, less will be fatigue. Frame adjusted by level (0.25, 0.35], (0.35, 0.45], 0.45+ and (0.37, 0.48], (0.48, 0.65], 0.65+ for low, medium and high fatigue including comparing fingerprint locations in class1 (low or normal weight person) and class2 (obese person) separately. After preparation, a BMI class was installed that included a keypad with 1 for class 1 or 2 for class2 and the LCD showed individual fatigue level (Ayaz et al., 2020).

Hachisuka et al. introduced the crucial review for understanding and evaluating the muscle fatigue decrease impact of strolling help. They concentrated on a leg muscle movement to comprehend how the strolling help framework upholds sound individuals' strolling. As indicated by their past exploration, they found that a mobile help framework (ACSIVE) upholds the muscle action of Gastrocnemius which is one of the rear arm muscles surae muscle which produces a main thrust for strolling forward. Then, at that point, they attempted to make a fundamental Electromyography (EMG) map with two records of EMG, for example, normal RMS and mean recurrence to explain the few muscle conditions. As per the consequences of EMG files of wearing and not wearing a mobile help framework, they affirmed the likelihood to comprehend the inclination of upheld muscle properties and muscle fatigue decrease during strolling on a treadmill (Hachisuka et al., 2020).

In the study of Lim et al., the point was to contemptuously contemplate the augmented reality glasses (ARG) and the standard video screens that aid the medical process and classify its ergonomic benefits in a way. Three specialists (thoracic, laparoscopic, and thyroid specialists) participated in the review. Six thoracoscopic metastasectomies, six laparoscopy subtotal gastrectomies, and six thyroidectomies performed with or without ARG. Emotional experiences were assessed using the NASA-Task Load Index (NASA-TLX)-based index. Standing during medical procedures were recorded. Gambling of external muscle problems related to video-assisted medical procedures was evaluated using a rapid entire body assessment (REBA). Surface electromyography (EMG) was recorded. Tissue fatigue is measured indiscriminately. NASA-TLX scores of three specialists were lower when ARG was used compared to those with standard screens (66.4 versus 82.7). The minimum liability during the medical procedure was calculated by ARG. The laparoscopic specialist showed a significant decrease in psychological and physical interest [-21.1 and 12.5%)] and the thyroid specialist performed (- 40.0 and - 66.7%). The total effect of REBA was reduced by ARG (8 to 3.6). Gambling of external muscle problems was performed on the neck and shoulder areas. Root mean square (RMS) of EMG signal decreased from 0.347 ± 0.150 to 0.286 ± 0.130 ($p = 0.010$) with ARG use; a decrease was seen in all professionals. The best decrease in RMS was observed in the trapezius and sternocleidomastoid muscles. The muscle contraction of the brachioradialis was minimal. ARG helped to correct the condition of specialists while assisting with video treatment and reducing the risk of severe chest fatigue. This study incorporates the common ergonomic production of ARG into a video-assisted medical procedure (Lim et al., 2021).

In 2020, Arteaga et al. concentrated on the recuperation of hand movement, which was one of the most difficult viewpoints in stroke recovery. This paper introduced an underlying way to deal with robot-helped hand-movement treatments. Their objective was twofold: they, first and foremost, had applied ML strategies to distinguish and portray finger movement designs from solid people. To this reason, Electromyographic (EMG) signals had been obtained from flexor and extensor muscles in the lower arm utilizing surface electrodes. Time and recurrence features were utilized as contributions to ML calculations for acknowledgment of six hand motions. Specifically, they looked at the exhibition of Artificial Neural Networks (ANN), Support Vector Machines (SVM) and k-Nearest Neighbor(k-NN) calculations for arrangement. Besides, each distinguished motion was transformed into a joint reference direction by applying interjection techniques. This permitted them to recreate the hand or finger movement kinematics and to mimic the elements of each movement design. Tests were done to make an EMG information base from 20 control subjects, and a VICON camera global positioning framework was utilized to approve the accuracy of the proposed framework. The typical relationship between the EMG-based produced joint directions and the followed hand-movement was 0.91. Moreover, measurable examination applied to 14 unique SVM, ANN and k-NN setups showed that Fine k-NN and Weighted k-NN have a superior presentation for the order of motions (98% of accuracy). In a future, the directions constrained by EMG signs could be applied to an exoskeleton or hand-mechanical prosthesis for restoration (Arteaga et al., 2020).

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Overview of the System

This study proposes a framework for recognizing muscle fatigue in the office environment using surface electromyography (sEMG) and ML. The objectives were to promote consistent fatigue recognition in office disruption using surface electromyography (sEMG) and ML and to obtain the best fit of features and comparisons of various character models by promoting the best accurate and most efficient model. The framework first collected the sEMG information from the shoulder blade header with the sEMG sensor. The sEMG signal was then transferred to a microcontroller, which was a NodeMCU V2 ESP8266. Thus, the sEMG data displayed in the Arduina IDE, which was later tested and developed by the appropriate model.

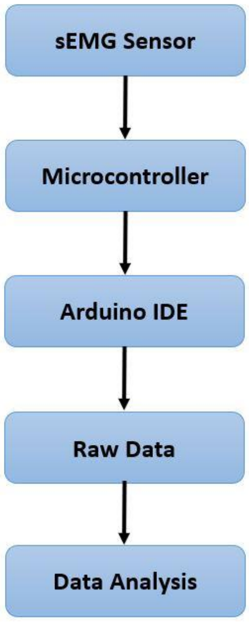

Figure 3.1 Overview of the System.

3.2 Research Tools and Equipment

3.2.1 Hardware

1) NodeMCU V2 ESP8266

2) EMG sensor board

3) Disposable surface electrodes

4) EMG cable

5) 9V batteries

6) Breadboard

7) Cable

3.2.2 Software

1) Arduino IDE

2) Excel

3) Anaconda Navigator

4) Jupyter Notebook

5) Google Colaboratory Notebook

3.3 Internet of Things (IoT) System

The EMG connector is connected to three additional usable terminals (red optical electrode, green area electrode, and yellow reference terminal) and EMG sensor board using a single-channel EMG sensor. The board was supplied with two 9V batteries in the series and was connected to the NodeMCU V2 ESP8266, which later communicated to the computer via a USB connector as shown in Figure 3.2 and Figure 3.3. We have connected the positive terminal of the first 9V battery to the +Vs pin of EMG sensor board. Next, the negative terminal of the second 9V battery was connected to the -Vs pin of EMG sensor board. At the same time, we connected the leftover terminal of both 9V battery with the GND pin of EMG sensor board. Finally, we linked the SIG pin of the EMG sensor board with the analog (A0) pin on the NodeMCU V2 ESP8266 and also connected the GND pin of the EMG sensor board to the GND nail in the NodeMCU V2 ESP8266. Therefore, this IoT framework was controlled by Arduino IDE. The sensitivity of the sensor was analog Read A0 with consecutive baud rate of 500000 as shown in Figure 3.4.

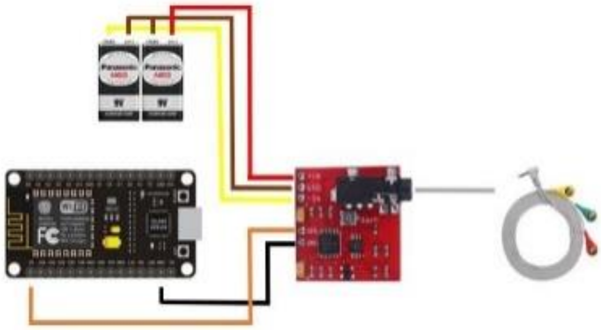

Figure 3.2 IoT System 1.

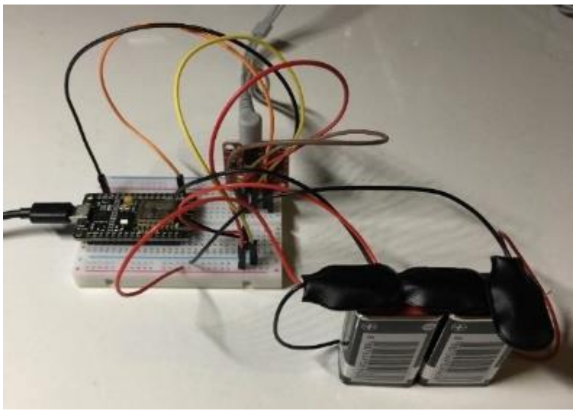

Figure 3.3 IoT System 2.

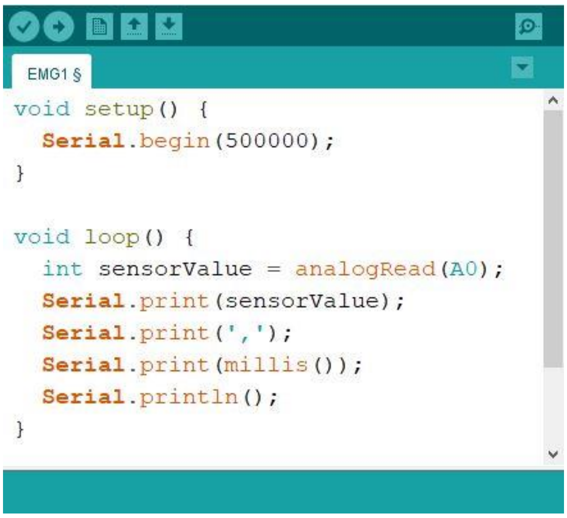

Figure 3.4 Arduino IDE.

3.4 Data Acquisition

The investigation had a single subject that had never encountered any real effort or real discomfort. Three available terminals were placed on the shoulder of the story and found as shown in Figure 3.5. The red connector is inserted on the muscular body. The green connector is positioned on one side of the muscle body. The yellow connector places a strong or fragile body piece as a reference point near the selected muscle. The study worked in a sitting position such as an office.

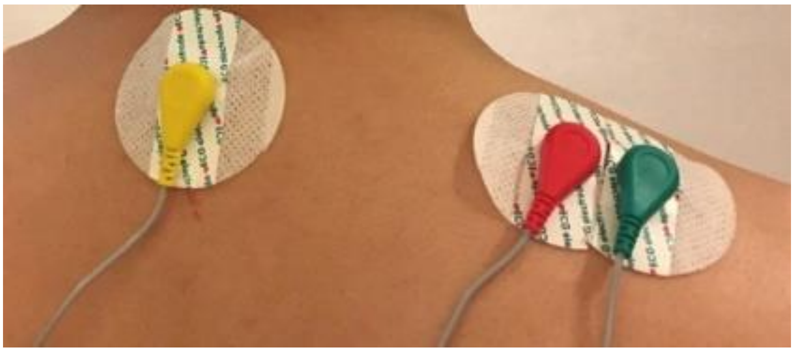

Figure 3.5 Disposable surface electrode placement.

In the event that the sensor was repaired and the signal was stable, an EMG signal and a state of muscle fatigue (fatigue or fatigue) were recorded at the beginning of the test. During the trial, the matter was initially kept in a state of non-fatigue. Assuming the article has caused significant stress, the subject would tell the scientist and the specialist and they later recognize the time when the subject began to be in a state of fatigue bringing a sign of fatigue status from this point on. Thus, we collected fatigue data for another 90 seconds and then adjourned the trial to strengthen the subject. In this trial, one study was tested for 15 minutes and directed at one time.

3.5 Data Analysis Framework

The information testing framework began with the release of information. This was re-reviewed, featured, and modified for Jupyter Notebook and Google Colaboratory Notebook. Therefore, a model of persistent fatigue identification was created as shown in Figure 3.6.

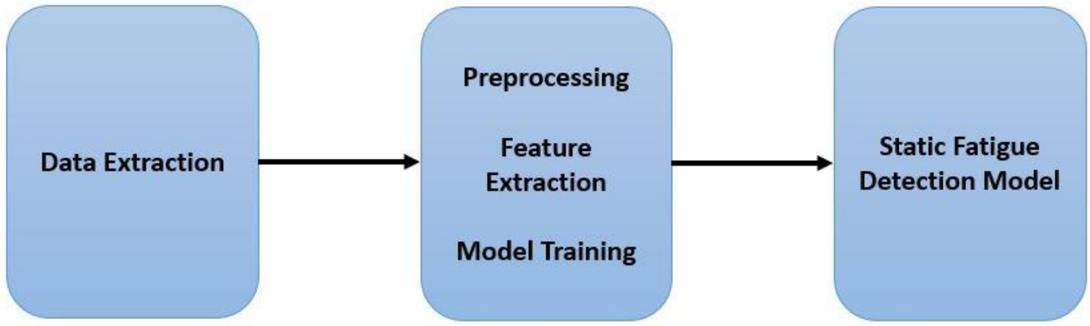

Figure 3.6 Data analysis framework.

3.5.1 Data Extraction

The recorded information from Arduino IDE was then transferred to Excel for investigation. The test system made it easy to detect that the database was out of balance. SEMG fatigue information was sEMG information during the study and detailed fatigue, and was actually less than general sEMG information. We had to use a certain method such as small samples to manage unequal data sets. The undersampling strategy was decided to build awareness of circles of fatigue and non-fatigue. In order to achieve consistency between data sets that are good and bad models, a small set of all the non-fatigue information was collected to obtain the same amount as the fatigue information.

3.5.2 Data Preprocessing

Since test planning was never good, dirty EMG flags often had moderate outbursts. This removal should have been terminated with an EMG pull. The development of the link has resulted in a lower recurrence of the signal and an electrical disturbance caused the recurring residues in the signal. These low and high frequency waves had to be removed from the signal, bringing it somewhere in the range of 20 and 450 Hz as most of our muscles work here. In order to have the option to create methods and analyze the sizes, we also expect to discard the swing between good and bad opportunities in the brand. To that end, we can take positive steps. In addition, in conclusion, in order to have the option of looking more closely at the size of the muscle suspension we will use a low pass frequency with an end frequency of 2 Hz to make an envelope as shown in Figure 3.7.

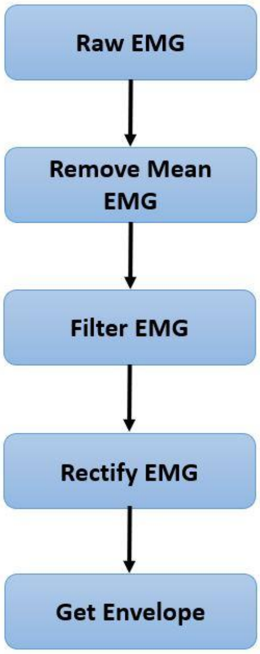

Figure 3.7 Data preprocessing.

3.5.3 Feature Extraction

For the most part the current tests of muscle fatigue, combined electromyogram (EMG), root mean square (RMS), and general repetition are often used as indicators of violation of muscle fatigue properties. Considering the characterization, computer output and variability, we determined the time-varying localities of the window size corresponding to 10 samples in this analysis, which are expressed as mean, integrated EMG (IEMG), mean absolute value (MAV), mean absolute value1 (MAV1), mean absolute value2 (MAV2), simple square integral (SSI), and root mean square (RMS) in the formula (1) - (7).

We recorded $x[n] = [x_1, x_2, \dots, x_i, \dots, x_n]$ as signal sequence of length n:

$$mean = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

$$IEMG = \sum_{i=1}^{n} |x_i| \tag{2}$$

$$MAV = \frac{1}{n}\sum_{i=1}^{n} |x_i| \tag{3}$$

$$MAV1 = \frac{1}{n}\sum_{i=1}^{n} w_i|x_i| \ ;$$

$$w_i = \begin{cases} 1, if \ \ 0.25n \ \leq i \leq 075n \\ \quad 0.5, otherwise \end{cases} \tag{4}$$

$$MAV2 = \frac{1}{n}\sum_{i=1}^{n} w_i|x_i| \ ;$$

$$w_i = \begin{cases} 1, if \ \ 0.25n \ \leq i \leq 075n \\ \quad \frac{4i}{n}, if \ i \leq 0.25n \\ \quad \frac{4(i-n)}{n}, otherwise \end{cases} \tag{5}$$

$$SSI = \ \sum_{i=1}^{n} {x_i}^2 \tag{6}$$

$$RMS = \ \sqrt{\frac{1}{n} \ \sum_{i=1}^{n} {x_i}^2} \tag{7}$$

We determined the commitment of each item to the plan and selected the best ones using recursive feature elimination (RFE) techniques with the assessors of logistic regression and decision tree in cross-approval of ten to choose the quantity of features. In this way, rfecv = RFECV(estimator = estimator, cv = StratifiedKFold(10, random_state = random_state, shuffle = True), scoring = "accuracy"), which other parameters were in default. The objective of recursive feature elimination was to choose features by recursively thinking about increasingly small arrangements of elements. In the first place, the assessor was prepared on the underlying arrangement of elements and the significance of each component was gotten either through a particular property or callable. Then, the fewer specific elements were pruned in the current arrangement of elements. That approach was repeated over and over again until the right number of features to be selected was finally reached.

3.5.4 Model Training

Following feature extraction, include bunches were extricated from the first sensor information and exploratory datasets. The gathered information is separated into preparing information and tried information. We involved 20% of the information as tried cases to test the order. For grouping, we picked Logistic Regression, Support Vector Machine (linear kernel), Naive Bayes, k-nearest Neighbors, Decision Tree, and Multi-layer Perceptron as classifiers to make the ML model, and looked at their presentation for the first and component chose datasets.

3.5.4.1 Logistic Regression

In Logistic Regression, we utilized LogisticRegression(penalty = 'l2', *, double = False, tol = 0.0001, C = 1.0, fit_intercept = True, intercept_scaling = 1, class_weight = None, random_state = random_state, solver = 'lbfgs', max_iter = 100, multi_class = 'auto', verbose = 0, warm_start = False, n_jobs = None, l1_ratio = None). Punishment {'l1', 'l2', 'elasticnet', 'none'}, default='l2'. Indicate the standard of the punishment: 'none': no punishment is added; 'l2': add a L2 punishment term and it is the default decision; 'l1': add a L1 punishment term; 'elasticnet': both L1 and L2 punishment terms are added. Cautioning Some punishments may not work for certain solvers. Dualbool, default=False. Double or base detailing. Double detailing is just executed for l2 punishment with liblinear solver. Incline toward dual=False when n_samples > n_features. Tolfloat, default=1e-4. Capacity to bear halting rules. Cfloat, default=1.0. Converse of regularization strength; should be a positive float. Like in help vector machines, more modest qualities determine more grounded regularization. Fit_interceptbool, default=True Indicates if a steady (a.k.a. inclination or block) ought to be added to the choice capacity. Intercept_scalingfloat, default=1. Helpful just when the solver 'liblinear' is utilized and self.fit_intercept is set to True. For this situation, x becomes [x, self.intercept_scaling], for example a 'engineered' feature with consistent worth equivalent to intercept_scaling is added to the case vector. The block becomes intercept_scaling * synthetic_feature_weight. Note! the engineered feature weight is likely to l1/l2 regularization as any remaining elements. To decrease the impact of regularization on manufactured feature weight (and in this manner on the capture) intercept_scaling must be expanded. Class_weightdict or 'adjusted', default=None. Loads related with classes in the structure {class_label: weight}. On the off chance that not given, all classes should have weight one. The 'adjusted' mode utilizes the upsides of y to naturally change loads conversely relative to class frequencies in the info information as n_samples/(n_classes * np.bincount(y)). Note that these loads will be duplicated with sample_weight (went through the fit technique) assuming sample_weight is indicated. Random_stateint, RandomState occurrence, default=None. Utilized when solver == 'hang', 'adventure' or 'liblinear' to rearrange the information. Solver {'newton-cg', 'lbfgs', 'liblinear', 'droop', 'saga'}, default='lbfgs'. Calculation to use in the streamlining issue. Default is 'lbfgs'. For little datasets, 'liblinear' is a decent decision, though 'droop' and 'adventure' are quicker for huge ones; For multiclass issues, just 'newton-cg', 'hang', 'adventure' and 'lbfgs' handle multinomial misfortune; 'liblinear' is restricted to one-versus-rest plans. Cautioning The decision of the calculation relies upon the punishment picked: Supported punishments by solver: 'newton-cg' - ['l2', 'none'], 'lbfgs' - ['l2', 'none'], 'liblinear' - ['l1', 'l2'], 'hang' - ['l2', 'none'], 'adventure' - ['elasticnet', 'l1', 'l2', 'none']. Note 'hang' and 'adventure' quick intermingling is just ensured on features with roughly a similar scale. Max_iterint, default=100. Greatest number of cycles taken for the solvers to combine. Multi_class{'auto', 'ovr', 'multinomial'}, default='auto'. In the event that the choice picked is 'ovr', a double issue is good for each name. For 'multinomial' the misfortune limited is the multinomial misfortune fit across the whole likelihood appropriation, in any event, when the information is twofold. 'multinomial' is inaccessible when solver='liblinear'. 'auto' chooses 'ovr' assuming the information is parallel, or then again if solver='liblinear', and in any case chooses 'multinomial'. Verboseint, default=0. For the liblinear and lbfgs solvers set verbose to any certain number for verbosity. Warm_startbool, default=False. At the point when set to True, reuse the arrangement of the past call to fit as instatement, in any case, simply delete the past arrangement. Futile for liblinear solver. N_jobsint, default=None. Number of CPU centers utilized while parallelizing over classes if multi_class='ovr'. This boundary is disregarded when the solver is set to 'liblinear' whether or not 'multi_class' is indicated or not. None means 1 except if in a joblib.parallel_backend setting. - 1 method utilizing all processors. L1_ratiofloat, default=None. The Elastic-Net blending boundary, with 0 <= l1_ratio <= 1. Possibly utilized if penalty='elasticnet'. Setting l1_ratio=0 is comparable to utilizing penalty='l2', while setting l1_ratio=1 is identical to utilizing penalty='l1'. For 0 < l1_ratio <1, the punishment is a mix of L1 and L2.

3.5.4.2 Support Vector Machine

In Support Vector Machine, we utilized SVC(*, C = 1.0, bit = 'direct', degree = 3, gamma = 'scale', coef0 = 0.0, contracting = True, likelihood = False, tol = 0.001, cache_size = 200, class_weight = None, verbose = False, max_iter = - 1, decision_function_shape = 'ovr', break_ties = False, random_state = random_state). C float, default=1.0. Regularization boundary. The strength of the regularization is contrarily relative to C. Should be totally certain. The punishment is a squared l2 punishment. Piece {'linear', 'poly', 'rbf', 'sigmoid', 'precomputed'} or callable, default='rbf'. Determines the piece type to be utilized in the calculation. In the event that none is given, 'rbf' will be utilized. If a callable is given it is utilized to pre-figure the part network from information frameworks; that lattice ought to be a variety of shape (n_samples, n_samples). Degree int, default=3. Level of the polynomial part work ('poly'). Disregarded by any remaining pieces. Gamma {'scale', 'auto'} or float, default='scale'. Piece coefficient for 'rbf', 'poly' and 'sigmoid'. In the event that gamma='scale' (default) is passed it utilizes 1/(n_features * X.var()) as worth of gamma, If 'auto', utilizes 1/n_features. Coef0float, default=0.0. Free term in piece work. It is just huge in 'poly' and 'sigmoid'. Shrinkingbool, default=True. Whether to utilize the contracting heuristic. Probabilitybool, default=False. Whether to empower likelihood gauges. This should be empowered preceding calling fit, will dial back that strategy as it inside utilizes 5-overlay cross-approval, and predict_proba might be conflicting with anticipate. Tolfloat, default=1e-3. Capacity to bear halting basis. Cache_sizefloat, default=200. Determine the size of the piece reserve (in MB). Class_weightdict or 'adjusted', default=None. Set the boundary C of class I to class_weight[i]*C for SVC. In the event that not given, all classes should have weight one. The "adjusted" mode utilizes the upsides of y to naturally change loads contrarily relative to class frequencies in the information as n_samples/(n_classes * np.bincount(y)). Verbosebool, default=False. Empower verbose result. Note that this setting exploits a for each cycle runtime setting in libsvm that, whenever empowered, may not work as expected in a multithreaded setting. Max_iterint, default=-1. Hard breaking point on cycles inside solver, or - 1 for no restriction. Decision_function_shape{'ovo', 'ovr'}, default='ovr'. Whether to return a one-versus rest ('ovr') choice capacity of shape (n_samples, n_classes) as any remaining classifiers, or the first one-up against one ('ovo') choice capacity of libsvm which has shape (n_samples, n_classes * (n_classes - 1)/2). In any case, one-against one ('ovo') is constantly utilized as multi-class methodology. The boundary is disregarded for twofold order. Break_tiesbool, default=False. If valid, decision_function_shape='ovr', and number of classes > 2, anticipate will break ties as per the certainty upsides of decision_function; in any case, the top of the line among the tied classes is returned. Kindly note that breaking ties comes at a moderately high computational expense contrasted with a basic foresee. Random_stateint, RandomState occasion or None, default=None. Controls the pseudo arbitrary number age for rearranging the information for likelihood gauges. Disregarded when likelihood is False. Pass an int for reproducible result across numerous capacity calls.

3.5.4.3 Naïve Bayes

In Naïve Bayes, we utilized GaussianNB(*, priors = None, var_smoothing = 1e-09). Gaussian Naïve Bayes classifier expects that the information from each mark is drawn from a basic Gaussian dispersion. Multinomial Naïve Bayes expects that the elements are drawn from a straightforward Multinomial circulation. In Bernoulli Naïve Bayes, the suspicion in this model is that the features parallel (0s and 1s) in nature. A use of Bernoulli Naïve Bayes order is Text grouping with 'pack of words' model Complement Naïve Bayes was intended to address the extreme suppositions made by Multinomial Bayes classifier. This sort of NB classifier is appropriate for imbalanced informational collections. Priorsarray-like of shape (n_classes,). Earlier probabilities of the classes. In the event that predetermined the priors are not changed by the information. Var_smoothingfloat, default=1e-9. Part of the biggest change of all features that is added to fluctuations for estimation soundness.

3.5.4.4 K-nearest Neighbors

In k-neaarest Neighbors, we utilized KNeighborsClassifier(n_neighbors = 5, *, loads = 'uniform', calculation = 'auto', leaf_size = 30, p = 2, metric = 'minkowski', metric_params = None, n_jobs = None). The K for the sake of this classifier addresses the k-nearest neighbors, where k is a number worth indicated by the client. Subsequently as the name proposes, this classifier carries out learning in view of the k-nearest neighbors. The decision of the worth of k is subject to information. In RadiusNeighborsClassifier, the Radius for the sake of this classifier addresses the nearest neighbors inside a predetermined sweep r, where r is a drifting point esteem determined by the client. Thus, as the name proposes, this classifier carries out learning in view of the number neighbors inside a decent span r of each preparing point. N_neighborsint, default=5.

Number of neighbors to use as a matter of course for kneighbors questions. Loads {'uniform', 'distance'} or callable, default='uniform'. Weight work utilized in forecast. Potential qualities: 'uniform': uniform loads. All focuses in every area are weighted similarly. 'distance': weight focuses by the opposite of their distance. for this situation, closer neighbors of a question point will have a more noteworthy impact than neighbors which are further away. [callable]: a client characterized work which acknowledges a variety of distances, and returns a variety of a similar shape containing the loads. Calculation {'auto', 'ball_tree', 'kd_tree', 'brute'}, default='auto'. Calculation used to figure the nearest neighbors: 'ball_tree' will utilize BallTree. 'kd_tree' will utilize KDTree. 'savage' will utilize a beast force search. 'auto' will endeavor to conclude the most suitable calculation in view of the qualities passed to fit technique. Note: fitting on inadequate information will abrogate the setting of this boundary, utilizing animal power. Leaf_sizeint, default=30. Leaf size passed to BallTree or KDTree. This can influence the speed of the development and question, as well as the memory expected to store the tree. The ideal worth relies upon the idea of the issue. Half quart, default=2. Power boundary for the Minkowski metric. At the point when p = 1, this is comparable to utilizing manhattan_distance (l1), and euclidean_distance (l2) for p = 2. For erratic p, minkowski_distance (l_p) is utilized. Metricstr or callable, default='minkowski' The distance metric to use for the tree. The default metric is minkowski, and with p=2 is identical to the standard Euclidean measurement. In the event that measurement is "precomputed", X is thought to be a distance network and should be square during fit. X might be a scanty diagram, in which case as it were "nonzero" components might be viewed as neighbors. Metric_paramsdict, default=None. Extra watchword contentions for the measurement work. N_jobsint, default=None. The quantity of equal tasks to run for neighbors' hunt. None means 1 except if in a joblib.parallel_backend setting. - 1 method utilizing all processors. Doesn't influence fit strategy.

3.5.4.5 Decision Tree

In Decision Tree, we utilized DecisionTreeClassifier(*, basis = 'gini', splitter ='best', max_depth = None, min_samples_split = 2, min_samples_leaf = 1, min_weight_fraction_leaf = 0.0, max_features = None, random_state = random_state, max_leaf_nodes = None, min_impurity_decrease = 0.0, class_weight = None, ccp_alpha = 0.0). Basis — string, discretionary default= "gini". It addresses the capacity to gauge the nature of a split. Upheld models are "gini" and "entropy". The default is gini which is for Gini contamination while entropy is for the data gain. Splitter — string, discretionary default= "best". It tells the model, which procedure from "best" or "arbitrary" to pick the split at every hub. Max_depth — int or None, discretionary default=None. This boundary chooses the greatest profundity of the tree. The default esteem is None which implies the hubs will extend until all leaves are unadulterated or until all leaves contain not exactly min_smaples_split tests. Min_samples_split — int, float, discretionary default=2. This boundary gives the base number of tests expected to part an inside hub. Min_samples_leaf — int, float, discretionary default=1. This boundary gives the base number of tests expected to be at a leaf hub. Min_weight_fraction_leaf — float, discretionary default=0. With this boundary, the model will get the base weighted part of the number of loads expected to be at a leaf hub. Max_features — int, float, string or None, discretionary default=None. It gives the model the quantity of elements to be thought about while searching for the best parted. Random_state — int, RandomState occurrence or None, discretionary, default = none. This boundary addresses the seed of the pseudo arbitrary number produced which is utilized while rearranging the information. Followings are the choices. Int — For this situation, random_state is the seed utilized by arbitrary number generator. RandomState occasion — For this situation, random_state is the arbitrary number generator. None — For this situation, the arbitrary number generator is the RandonState occasion utilized by np.random. Max_leaf_nodes — int or None, discretionary default=None. This boundary will let grow a tree with max_leaf_nodes in best-first design. The default is none which implies there would be limitless number of leaf hubs. Min_impurity_decrease — float, discretionary default=0. This worth functions as a standard for a hub to part on the grounds that the model will part a hub on the off chance that this split incites a decline of the pollutant more noteworthy than or equivalent to min_impurity_decrease esteem. Min_impurity_split — float, default=1e-7. It addresses the limit for early halting in tree development. Class_weight — dict, rundown of dicts, "adjusted" or None, default=None. It addresses the loads related with classes. The structure is {class_label: weight}. Assuming that we utilize the default choice, it implies every one of the classes should have weight one. Then again, whenever picked class_weight: adjusted, it will utilize the upsides of y to change loads consequently. Presort — bool, discretionary default=False. It tells the model whether to presort the information to accelerate the finding of best parts in fitting. The default is misleading yet of set to valid, it might dial back the preparation cycle.

3.5.4.6 Multi-Layer Perceptron

In Multi-Layer Perceptron, we utilized MLPClassifier(hidden_layer_sizes = (100,), actuation = 'relu', *, solver = 'adam', alpha = 0.0001, batch_size = 'auto', learning_rate = 'consistent', learning_rate_init = 0.001, power_t = 0.5, max_iter = 1000, mix = True, random_state = random_state, tol = 0.0001, verbose = False, warm_start = False, force = 0.9, nesterovs_momentum = True, early_stopping = False, validation_fraction = 0.1, beta_1 = 0.9, beta_2 = 0.999, epsilon = 1e-08, n_iter_no_change = 10, max_fun = 15000). Hidden_layer_sizestuple, length = n_layers - 2, default = (100,). The ith component addresses the quantity of neurons in the ith stowed away layer. Enactment {'identity', 'strategic', 'tanh', 'relu'}, default='relu'. Enactment work for the secret layer. 'character', no-operation initiation, valuable to carry out straight bottleneck, returns f(x) = x. 'calculated', the strategic sigmoid capacity, returns f(x) = 1/(1 + exp(- x)). 'tanh', the exaggerated tan capacity, returns f(x) = tanh(x). 'relu', the corrected direct unit work, returns f(x) = max(0, x). Solver {'lbfgs', 'sgd', 'adam'}, default='adam'. The solver for weight improvement. 'lbfgs' is a streamlining agent in the group of semi-Newton techniques. 'sgd' alludes to stochastic inclination plummet. 'adam' alludes to a stochastic inclination-based enhancer proposed by Kingma, Diederik, and Jimmy Ba. Note: The default solver 'adam' functions admirably on generally enormous datasets (with large number of preparing tests or more) as far as both preparation time and approval score. For little datasets, in any case, 'lbfgs' can join quicker and perform better. Alphafloat, default=0.0001. L2 punishment (regularization term) boundary. Batch_sizeint, default='auto'. Size of minibatches for stochastic streamlining agents. Assuming that the solver is 'lbfgs', the classifier won't utilize minibatch. At the point when set to "auto", batch_size=min(200, n_samples). Learning_rate{'constant', 'invscaling', 'adaptive'}, default='constant'. Learning rate plan for weight refreshes. 'steady' is a consistent learning rate given by 'learning_rate_init'. 'invscaling' bit by bit diminishes the learning rate at each time step 't' utilizing a reverse scaling example of 'power_t'. effective_learning_rate = learning_rate_init/pow(t, power_t). 'versatile' keeps the learning rate consistent to 'learning_rate_init' insofar as preparing misfortune continues to diminish. Each time two successive ages neglect to diminish preparing misfortune by essentially tol, or neglect to increment approval score by basically tol if 'early_stopping' is on, the ongoing learning rate is separated by 5. Possibly utilized when solver='sgd'. Learning_rate_initfloat, default=0.001. The underlying learning rate utilized. It controls the progression size in refreshing the loads. Possibly utilized when solver='sgd' or 'adam'. Power_tfloat, default=0.5. The type for opposite scaling learning rate. It is utilized in refreshing successful learning rate when the learning_rate is set to 'invscaling'. Possibly utilized when solver='sgd'. Max_iterint, default=200. Most extreme number of cycles. The solver emphasizes (not entirely settled by 'tol') or this number of cycles. For stochastic solvers ('sgd', 'adam'), note that this decides the quantity of ages (how frequently every information point will be utilized), not the quantity of angle steps. Shufflebool, default=True. Whether to rearrange tests in every emphasis. Possibly utilized when solver='sgd' or 'adam'. Random_stateint, RandomState occasion, default=None. Decides arbitrary number age for loads and inclination instatement, train-test split assuming that early halting is utilized, and clump inspecting when solver='sgd' or 'adam'. Pass an int for reproducible outcomes across various capacity calls. Tolfloat, default=1e-4. Capacity to bear the improvement. At the point when the misfortune or score isn't improving by basically tol for n_iter_no_change continuous cycles, except if learning_rate is set to 'versatile', combination is viewed as reached and preparing stops. Verbosebool, default=False. Whether to print progress messages to stdout. Warm_startbool, default=False. At the point when set to True, reuse the arrangement of the past call to fit as instatement, in any case, simply delete the past arrangement. Momentumfloat, default=0.9. Energy for inclination drop update. Ought to be somewhere in the range of 0 and 1. Possibly utilized when solver='sgd'. Nesterovs_momentumbool, default=True. Whether to utilize Nesterov's energy. Possibly utilized when solver='sgd' and energy > 0. Early_stoppingbool, default=False. Whether to utilize early halting to end preparing when approval score isn't moving along. Whenever set to valid, it will naturally save 10% of preparing information as approval and end preparing when approval score isn't improving by basically tol for n_iter_no_change sequential ages. The split is defined, besides in a multilabel setting. On the off chance that early halting is False, the preparation stops while the preparation misfortune doesn't work on by more than tol for n_iter_no_change successive disregards the preparation set. Just successful when solver='sgd' or 'adam'. Validation_fractionfloat, default=0.1. The extent of preparing information to save as approval set for early halting. Should be somewhere in the range of 0 and 1. Possibly utilized assuming that early_stopping is True. Beta_1float, default=0.9. Dramatic rot rate for appraisals of first second vector in adam, ought to be in [0, 1). Possibly utilized when solver='adam'. Beta_2float, default=0.999. Outstanding rot rate for assessments of second vector in adam, ought to be in [0, 1). Possibly utilized when solver='adam'. Epsilonfloat, default=1e-8. An incentive for mathematical strength in adam. Possibly utilized when solver='adam'. N_iter_no_changeint, default=10. Greatest number of ages to not meet tol improvement. Just compelling when solver='sgd' or 'adam'. Max_funint, default=15000. Possibly utilized when solver='lbfgs'. Greatest number of misfortune work calls. The solver repeats (not entirely settled by 'tol'), number of emphasess comes to max_iter, or this number of misfortune work calls. Note that number of misfortune work calls will be more prominent than or equivalent to the quantity of emphasess for the MLPClassifier.

3.5.4.7 Conclusion of the Model Training

In conclusions, the parameters of classifiers were set as [LogisticRegression(), SVC(kernel = "linear"), GaussianNB(), KNeighborsClassifier(), DecisionTreeClassifier(), MLPClassifier(max_iter = 1000)] , which other parameters were in default.

CHAPTER 4

RESULTS

4.1 Overview of the Research Methodology

This study proposed the detection of persistent fatigue in office disturbances using surface electromyography (sEMG) and ML. Examined the increase in the detection of static fatigue syndrome in the office environment using surface electromyography (sEMG) and ML. The objectives of the experiment were to promote a consistent fatigue environment in office disruption using surface electromyography (sEMG) and ML as well as to find the best fit for features and compare different group models by promoting the best accurate and most efficient model. The trial had one subject that had never met any real effort or real stress. SEMG was recorded by the EMG sensor board associated with NodeMCU V2 ESP8266 during seating with the upper shoulder terminals. In the event that the sensor was repaired and the signal was stable, an EMG signal and a state of muscle fatigue (non-fatigue or fatigue) were recorded during the test. Analysis has been suspended when the article announces a clear disruption for a few minutes. In this study, one study was tested for 15 minutes. This IoT framework was manipulated by Arduino IDE. Symbols were extracted and analyzed in advance to detect various features of the data sets. Six ML models (Logistic Regression, Support Vector Machine, Naive Bayes, k-nearest Neighbors, Decision Tree, and Multi-layer Perceptron) have seven features (mean, integrated EMG, mean absolute value, mean absolute value1, mean absolute value2, simple square integral, and root mean square) of the actual data sets and the selected input information were corrected and tested, predicting the effect phase of non-fatigue or fatigue. The information investigation program began with the release of information. This information was previously reviewed, including removal, and model modification by Jupyter notebooks and Google colaboratory notebooks with python. Thus, a model for the detection of static fatigue was proposed.

4.2 Data Acquisition from IoT System

The high-resolution EMG sensors from the Arduino IDE have been transmitted for maximum time recognition in millisecs as shown in Figure 4.1 - 4.3. They were also marked by a state of fatigue or non-fatigue such as F or N respectively. Thereafter, complete information contained 361,749 samples at 398.63 seconds (907.48 samples / sec), sent by a non-fatigue class of 272,626 samples and a fatigue class of 89,123 samples.

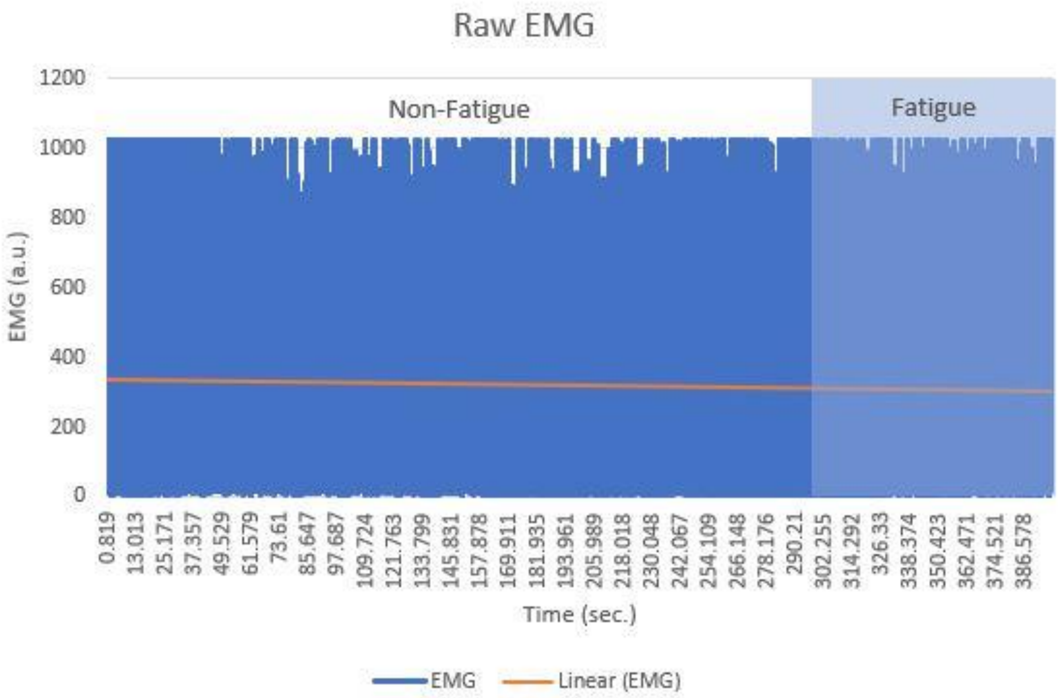

Figure 4.1 Raw EMG.

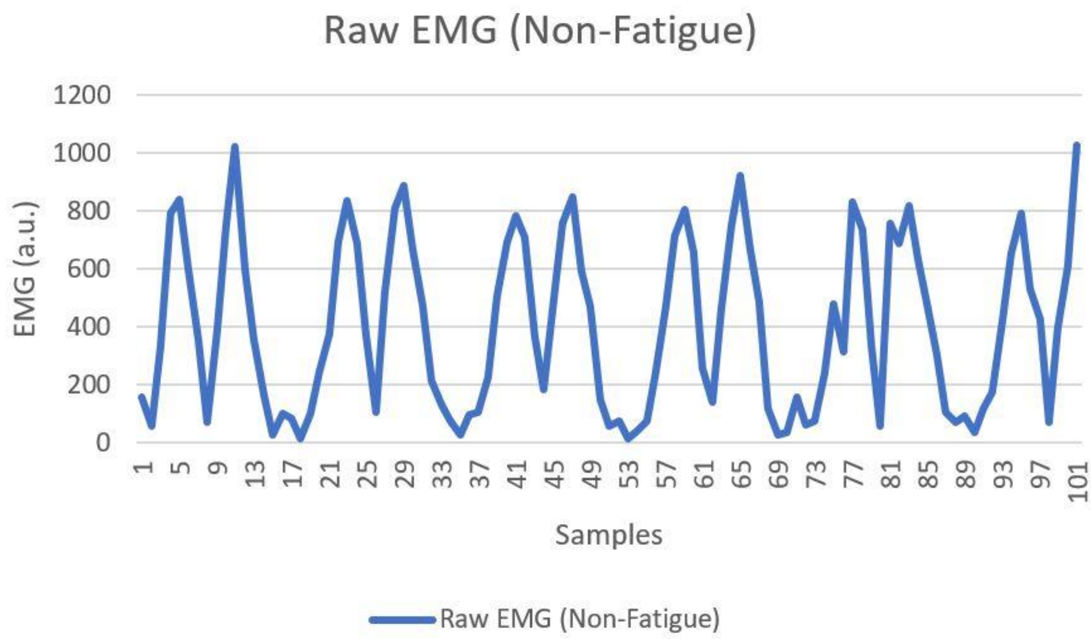

Figure 4.2 Raw EMG in non-fatigue state (Zoom in).

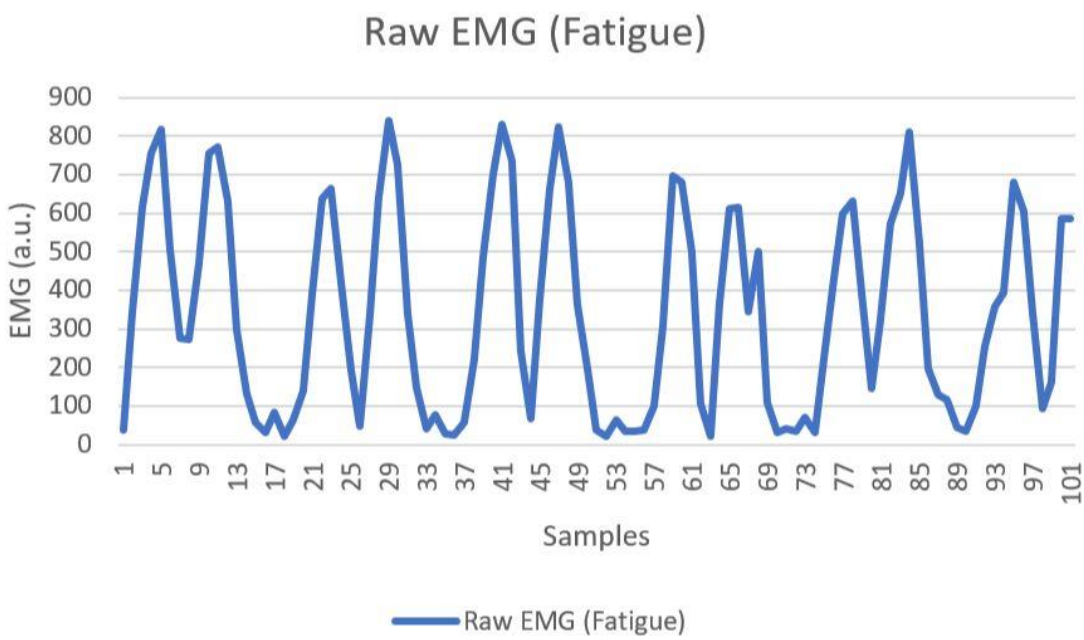

Figure 4.3 Raw EMG in fatigue state (Zoom in).

4.3 Data Analysis Framework

4.3.1 Data Extraction

As mentioned earlier, sEMG fatigue information was sEMG knowledge when the subject experienced detailed fatigue, and was actually less than general sEMG information. Non-fatigue information was 272,626 samples, and fatigue information was 89,123 samples. We had to use a certain method such as small samples to manage unequal data sets. A small sample design was determined to improve the knowledge of the fatigue and non-fatigue circles. In order to achieve consistency between the data sets for the good and the bad, a small set of all the non-fatigue information was collected to obtain the same amount as the fatigue information as shown in Figure 4.4. After testing, each data collection contains 89,123 samples. In this way, all data sets were 178,246 samples.

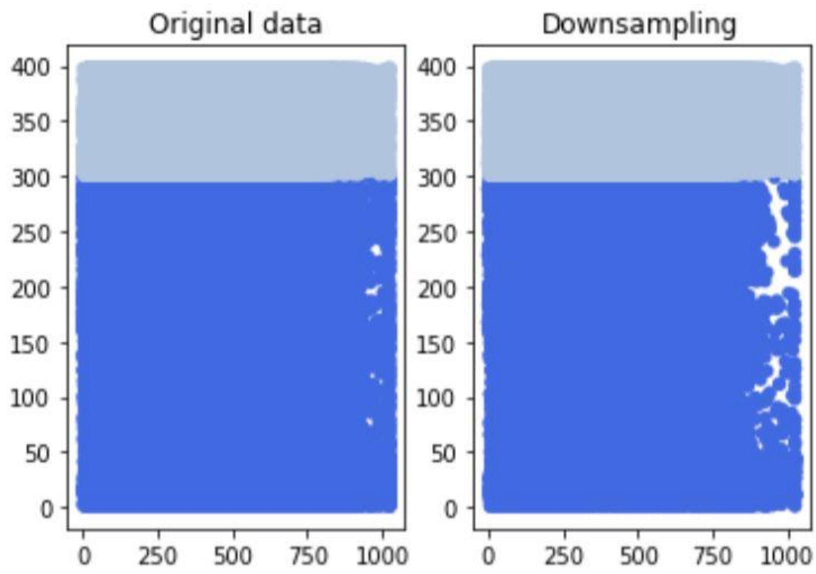

Figure 4.4 Original and downsampling data.

4.3.2 Data Preprocessing

The crude EMG flags typically had a counterbalanced from nothing. This offset should have been taken out as displayed in Figure 4.5 - 4.7.

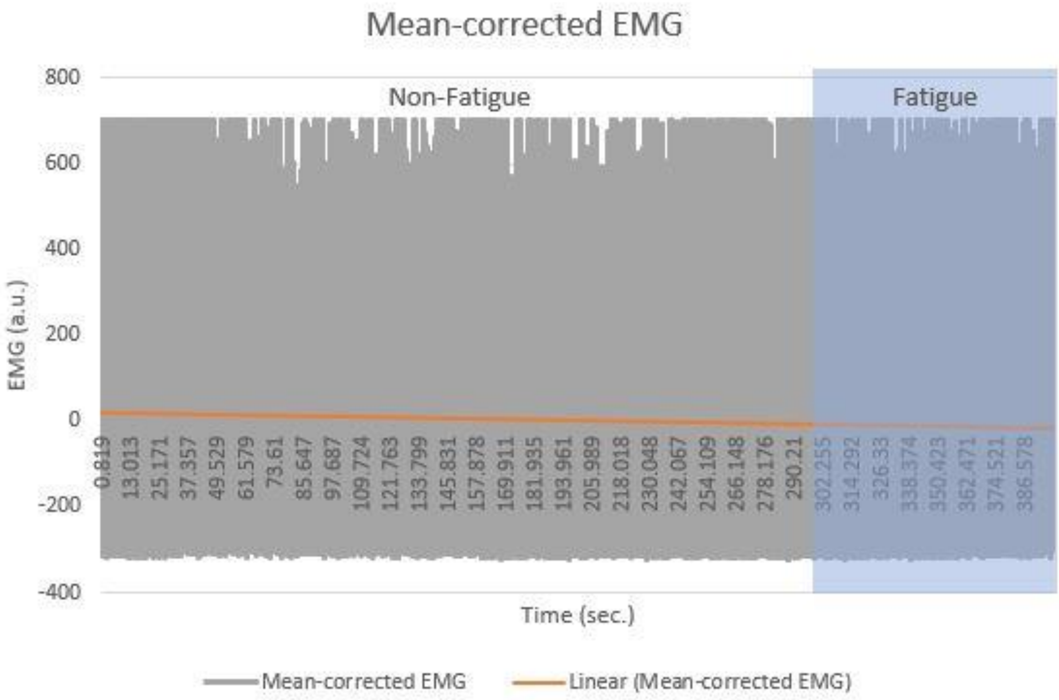

Figure 4.5 Mean-corrected EMG.

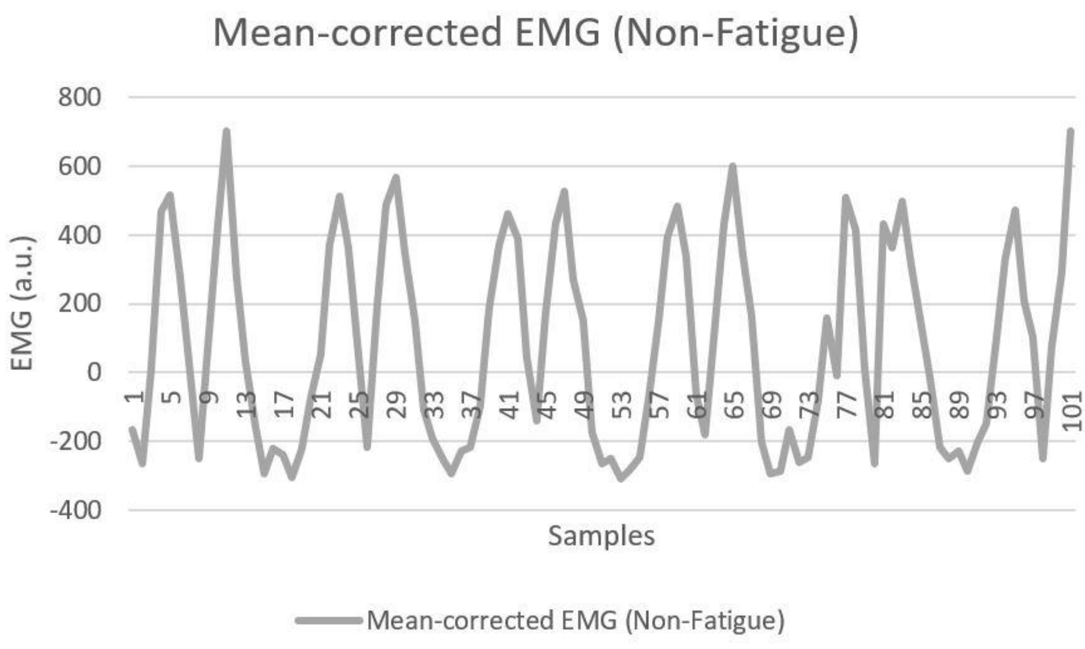

Figure 4.6 Mean-corrected EMG in non-fatigue state (Zoom in).

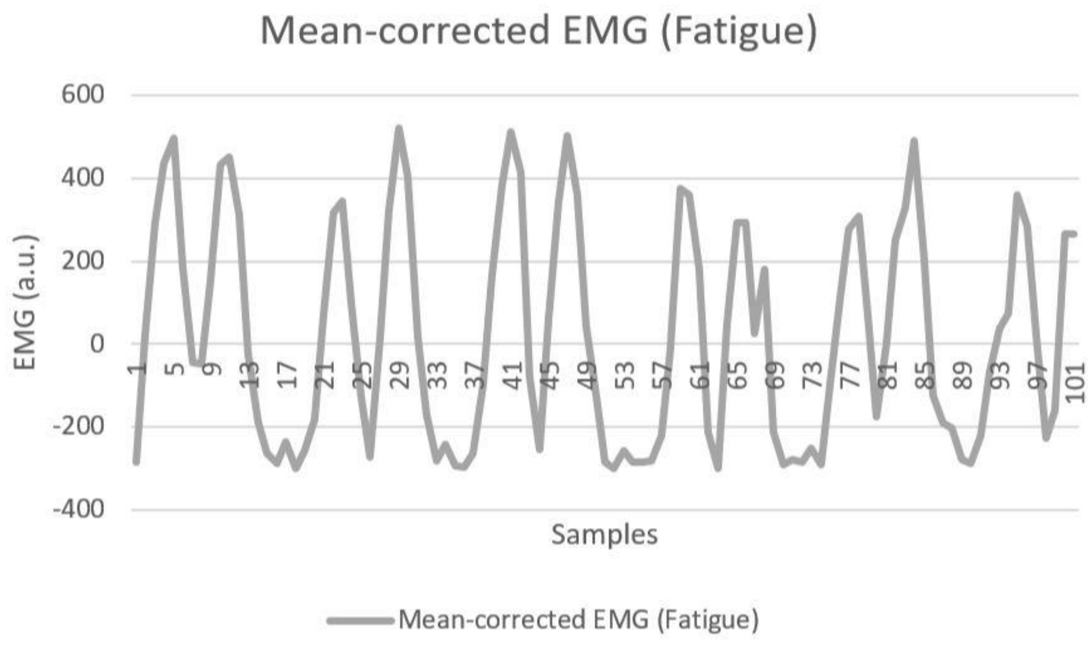

Figure 4.7 Mean-corrected EMG in fatigue state (Zoom in).

Link developments prompted low recurrence ancient rarities in the sign and electrical commotion prompted high recurrence curios in the sign. These undesirable low and high frequencies should have been eliminated from the sign as displayed in Figure 4.8 - 4.10

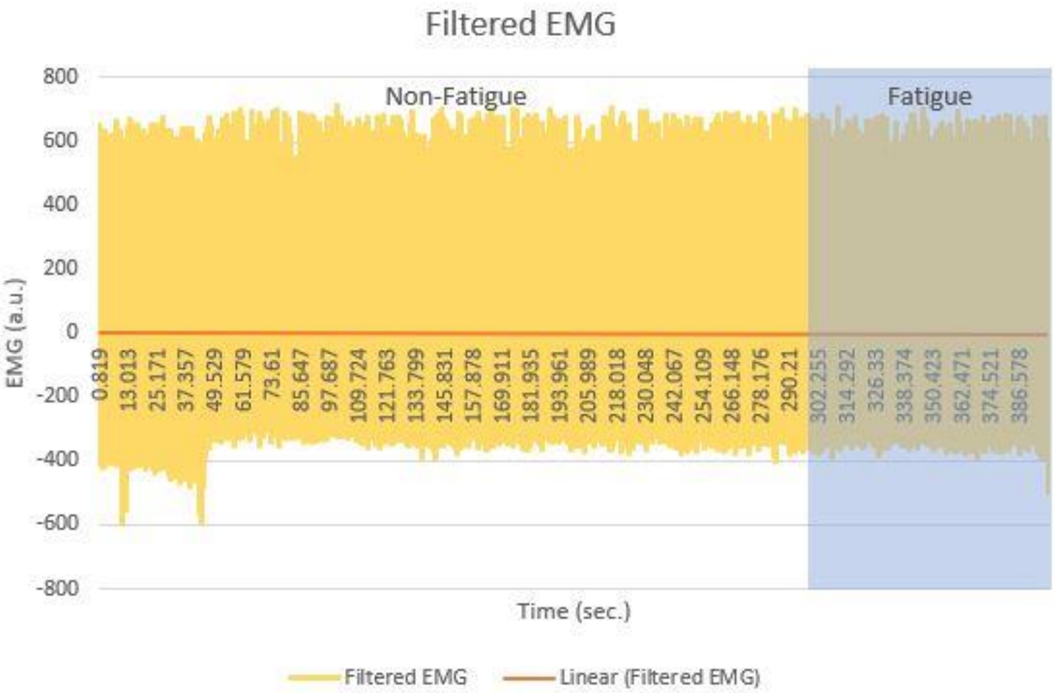

Figure 4.8 Filtered EMG.

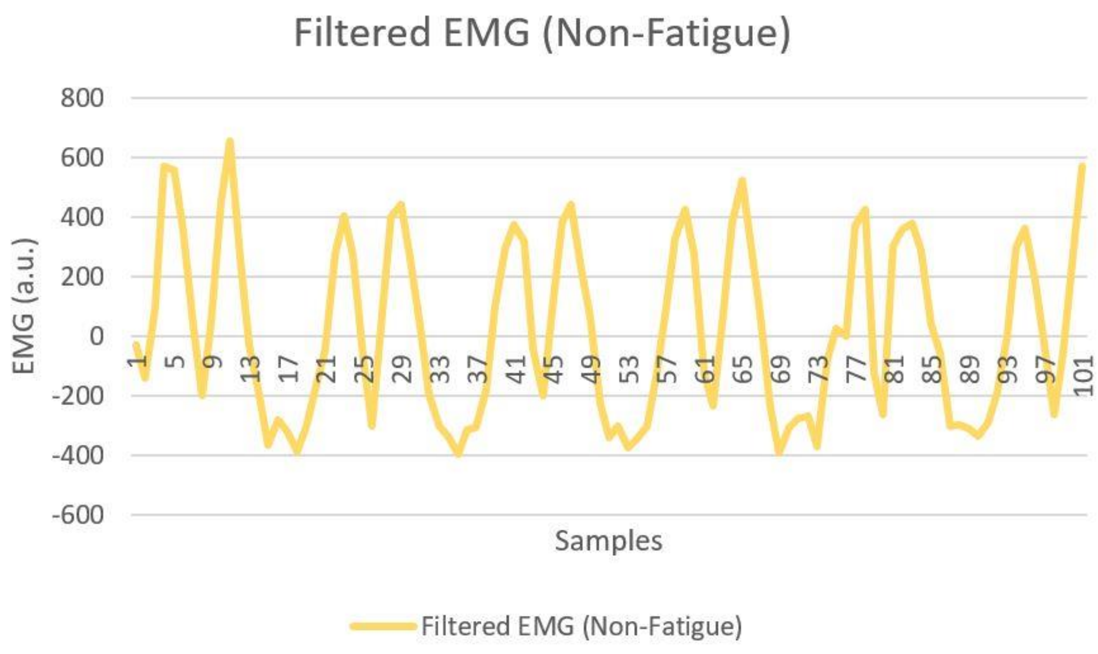

Figure 4.9 Filtered EMG in non-fatigue state (Zoom in).

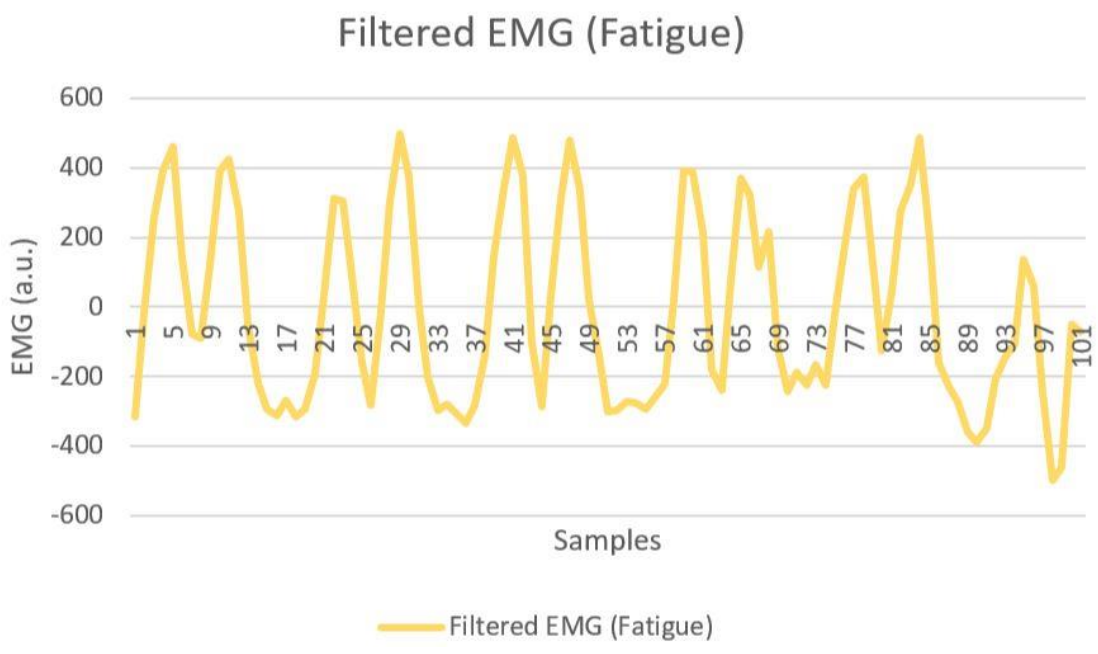

Figure 4.10 Filtered EMG in fatigue state (Zoom in).

In order to be selective in our approach and to think about size, we also expected to discard the swing between good or bad opportunities in a brand. To do so, we could accept the specific qualifications as set out in Figure 4.11 - 4.13.

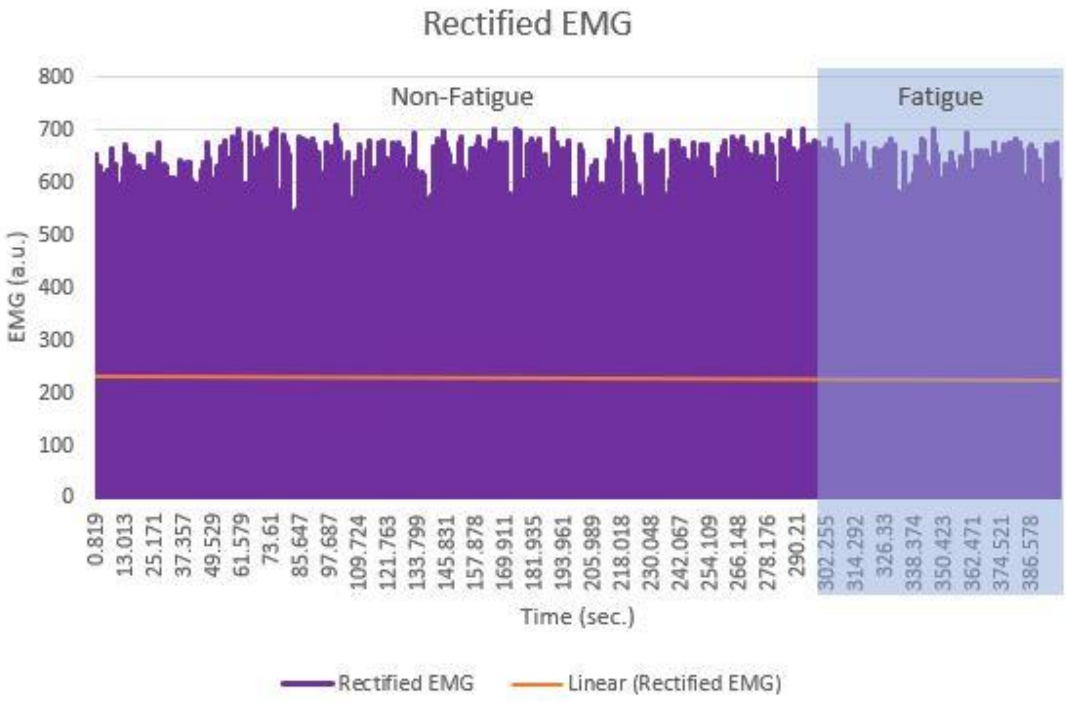

Figure 4.11 Rectified EMG.

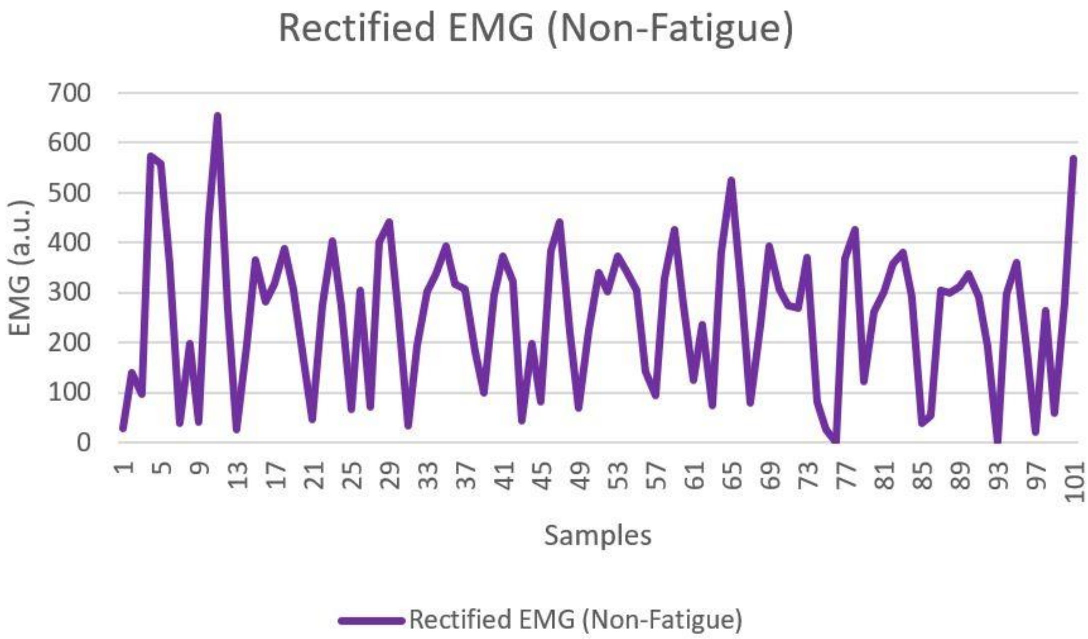

Figure 4.12 Rectified EMG in non-fatigue state (Zoom in).

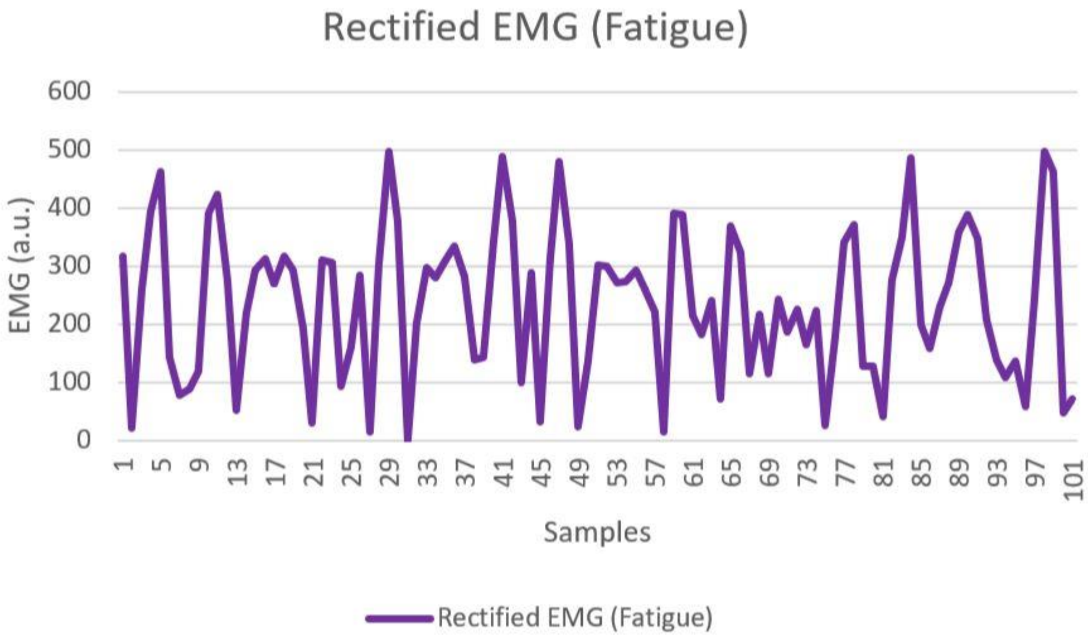

Figure 4.13 Rectified EMG in fatigue state (Zoom in).

And, in conclusion, in order to have the option to think easily about the size of the muscle suspension we would go through the lower channel mark again, making an envelope as shown in Figure 4.14 - 4.16.

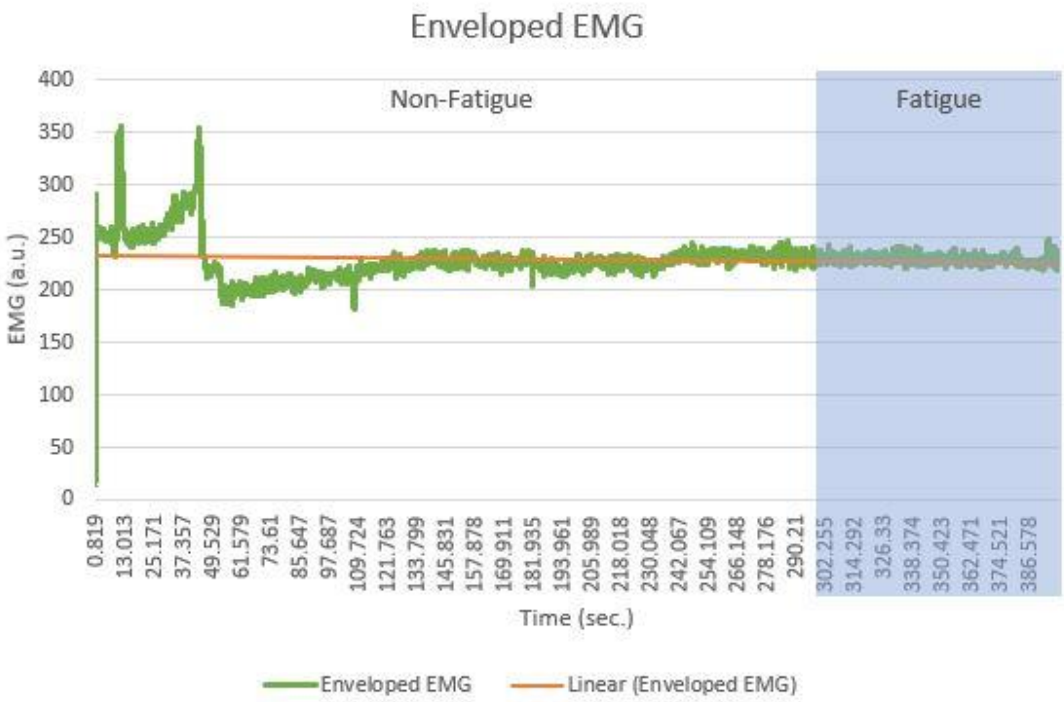

Figure 4.14 Enveloped EMG.

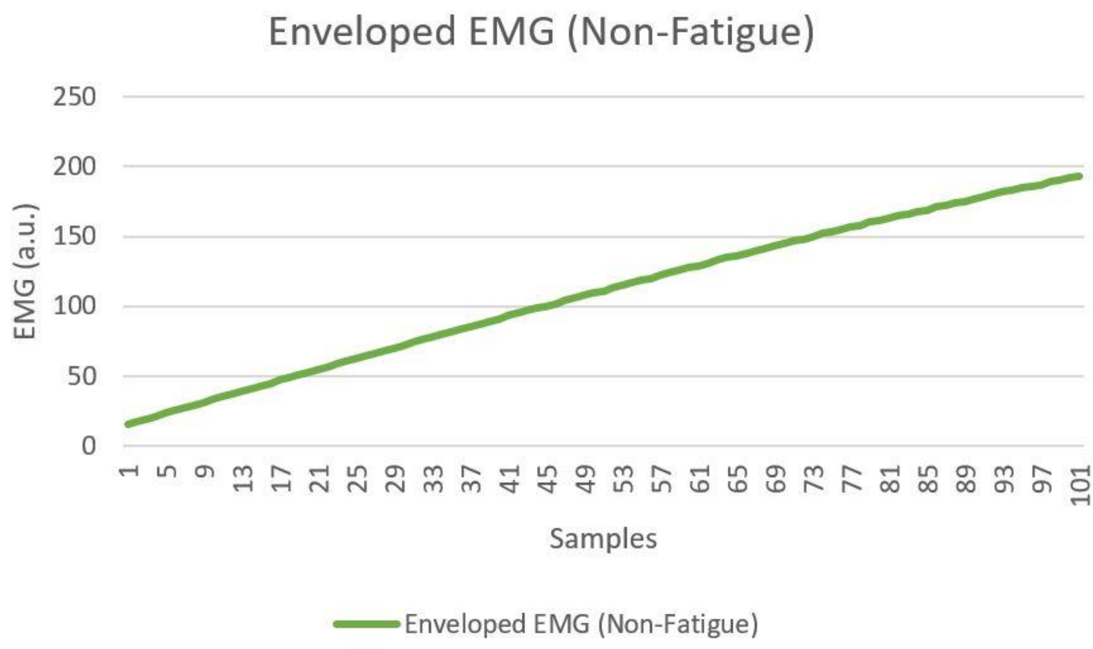

Figure 4.15 Enveloped EMG in non-fatigue state (Zoom in).

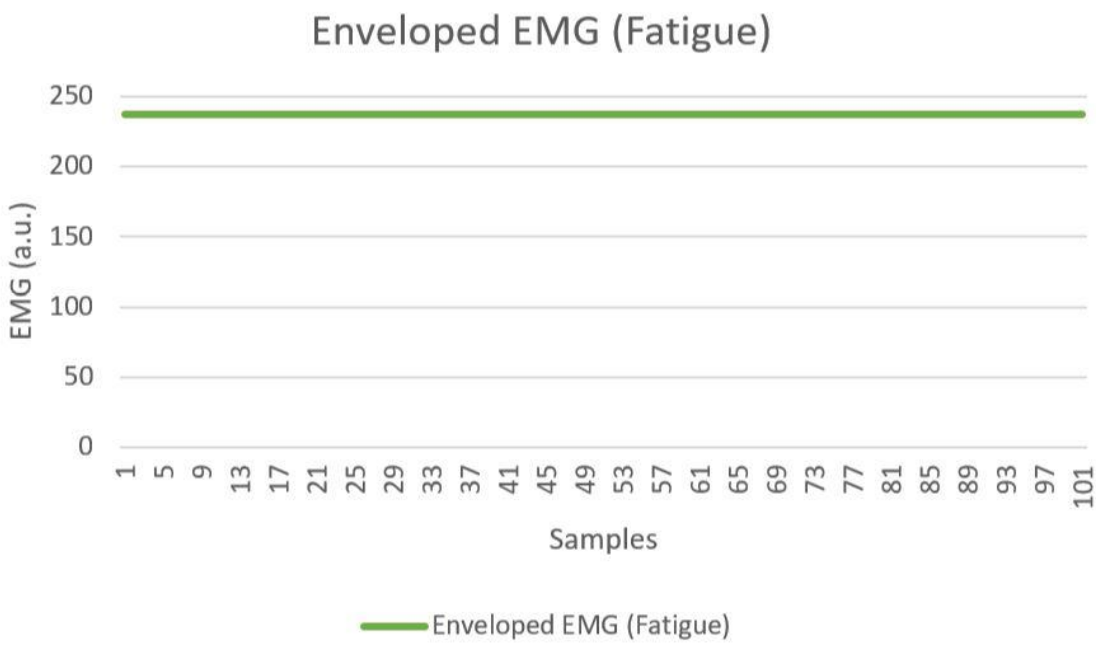

Figure 4.16 Enveloped EMG in fatigue state (Zoom in).

4.3.3 Feature Extraction

We determined the commitment of seven features from enveloped EMG that had as of now preprocessed with order of fatigue and non-fatigue as displayed in Figure 4.17 and Figure 4.18. The charts of each component were displayed in Figure 4.19 - 4.39. Thus, the component extricated datasets were 17,824 samples.

	mean_envelope	IEMG	MAV	MAV1	MAV2	SSI	RMS
0	232.8	2328.0	232.8	174.30	120.04	543786.0	233.192195
1	231.7	2317.0	231.7	171.95	121.92	540677.0	232.524622
2	236.3	2363.0	236.3	178.00	124.74	561509.0	236.961811
3	224.9	2249.0	224.9	166.60	112.88	508941.0	225.597207
4	228.4	2284.0	228.4	171.90	120.06	524808.0	229.086883
...	...	...	...	...	...	...	...
17819	237.0	2370.0	237.0	177.75	123.24	561690.0	237.000000
17820	237.0	2370.0	237.0	177.75	123.24	561690.0	237.000000
17821	237.0	2370.0	237.0	177.75	123.24	561690.0	237.000000
17822	237.0	2370.0	237.0	177.75	123.24	561690.0	237.000000
17823	237.0	2370.0	237.0	177.75	123.24	561690.0	237.000000

17824 rows × 7 columns

Figure 4.17 Seven features of original datasets.

	ClassFatigue
0	0
1	0
2	0
3	0
4	0
...	...
17819	1
17820	1
17821	1
17822	1
17823	1

17824 rows × 1 columns

Figure 4.18 Class of original datasets.

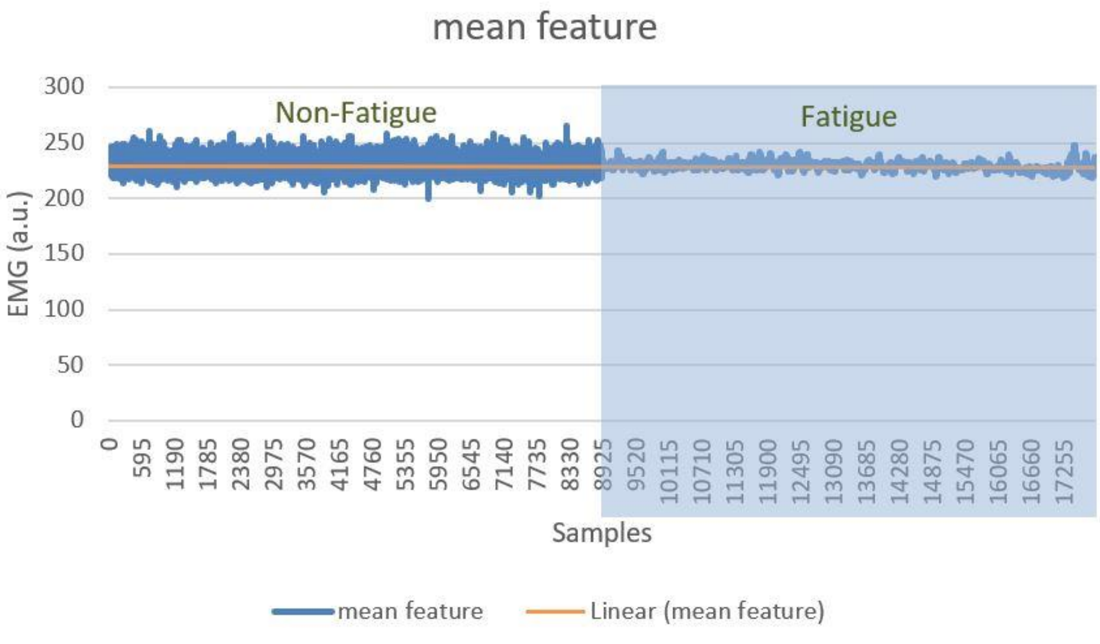

Figure 4.19 Mean feature.

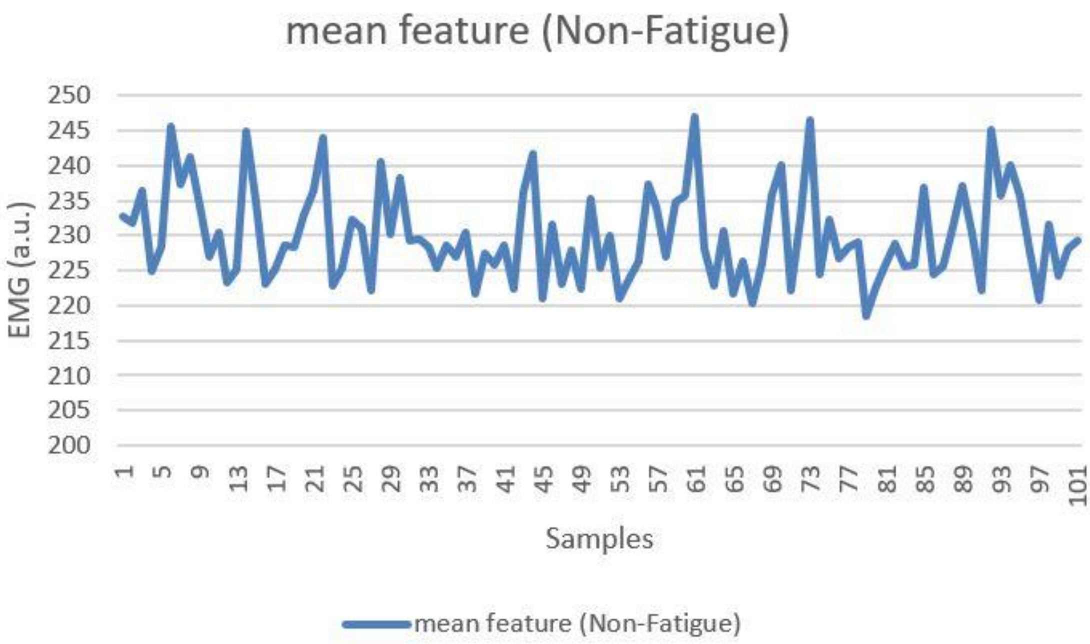

Figure 4.20 Mean feature in non-fatigue state (Zoom in).

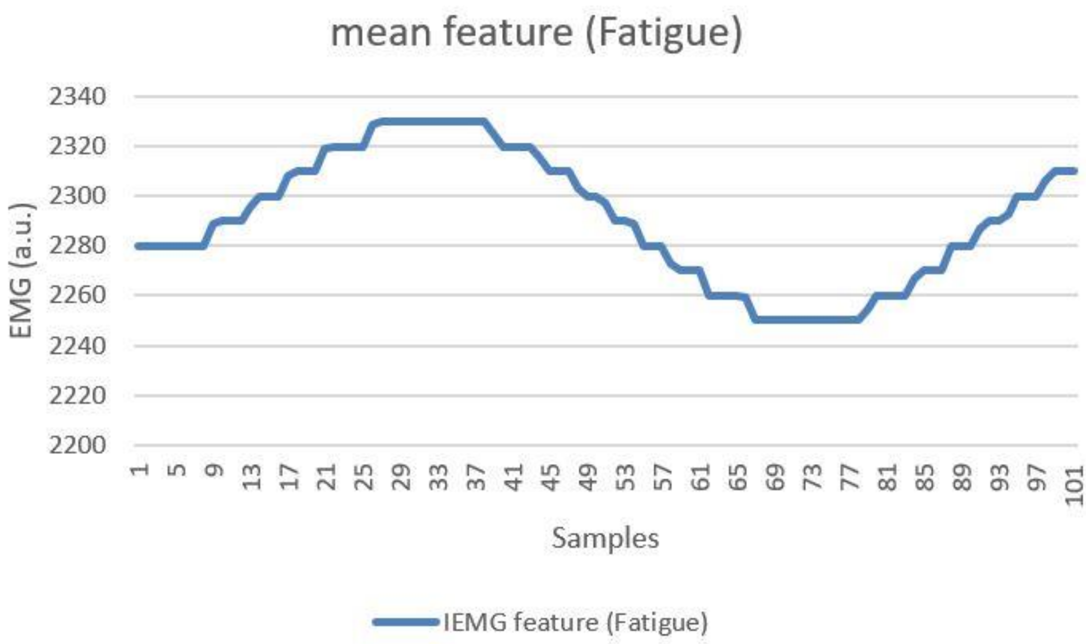

Figure 4.21 Mean feature in fatigue state (Zoom in).

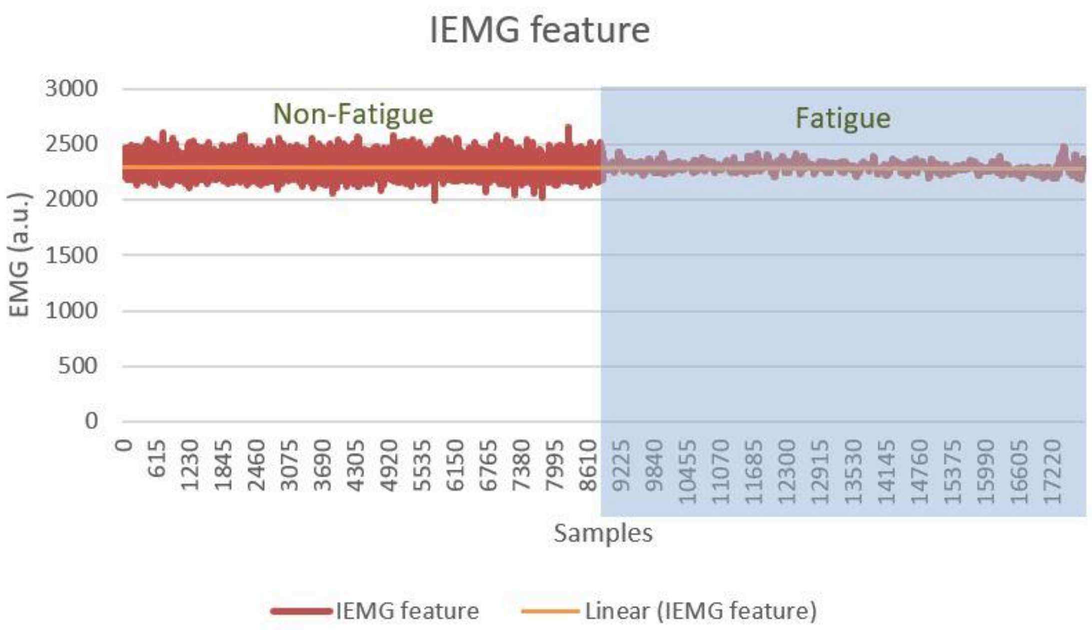

Figure 4.22 IEMG feature.

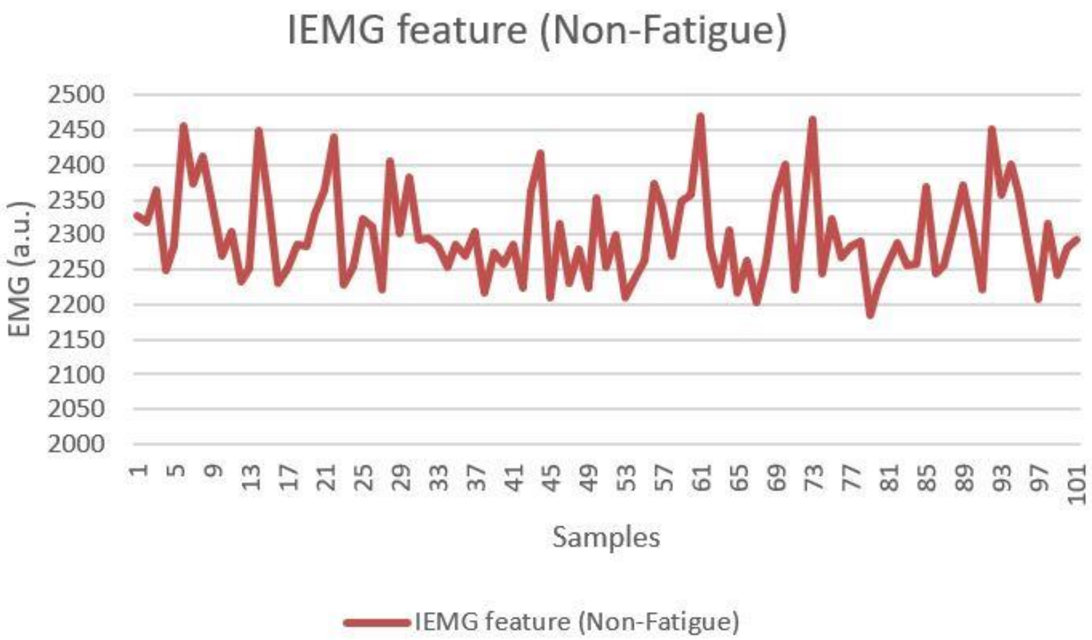

Figure 4.23 IEMG feature in non-fatigue state (Zoom in).

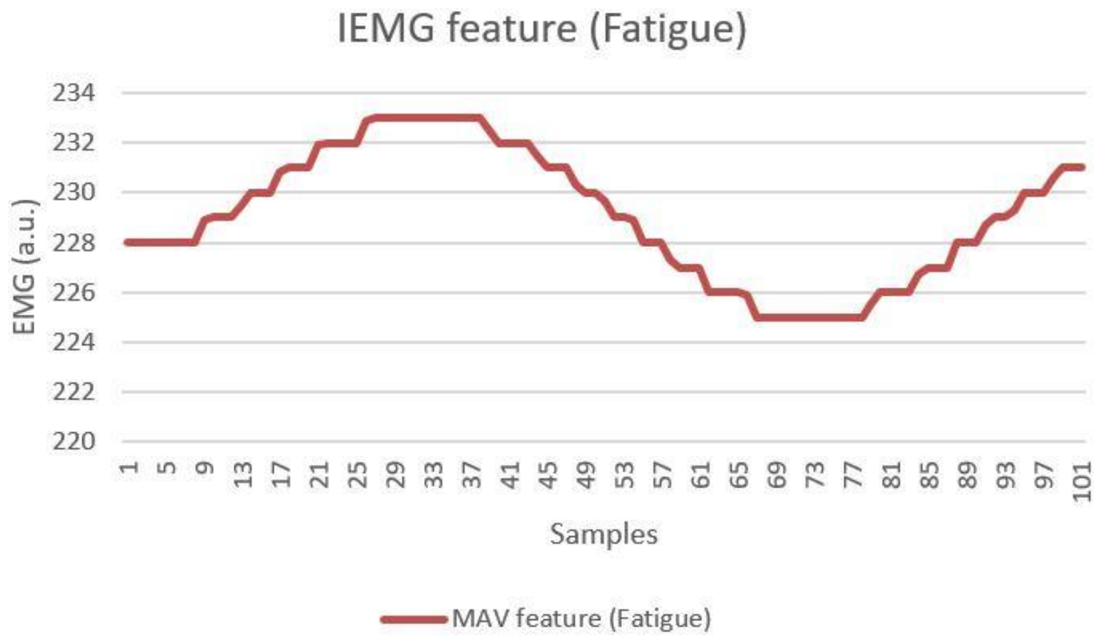

Figure 4.24 IEMG feature in fatigue state (Zoom in).

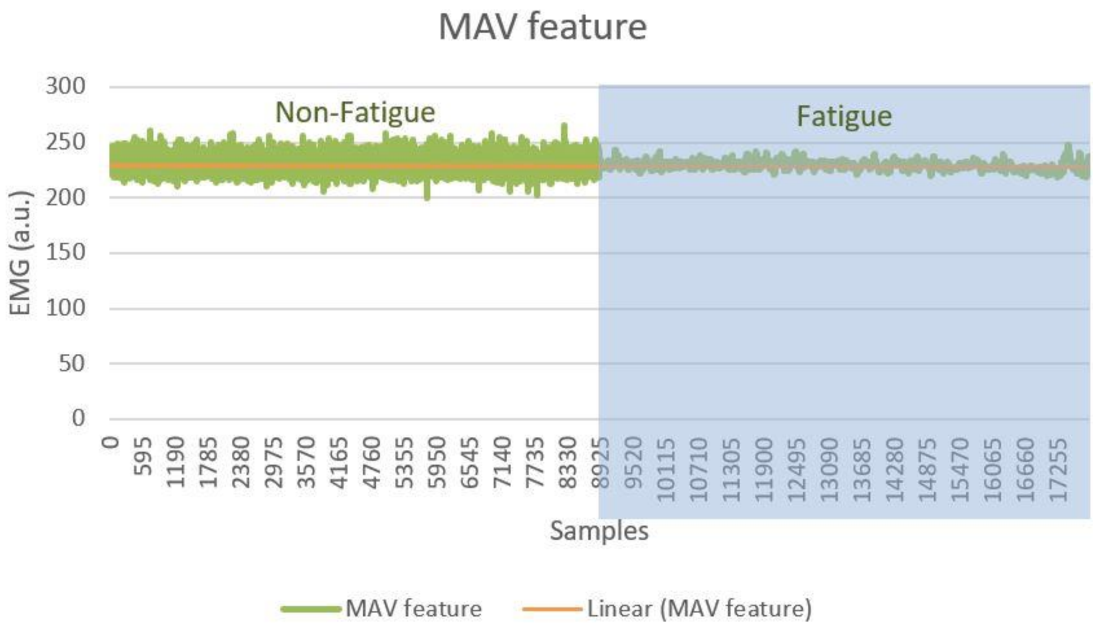

Figure 4.25 MAV feature.

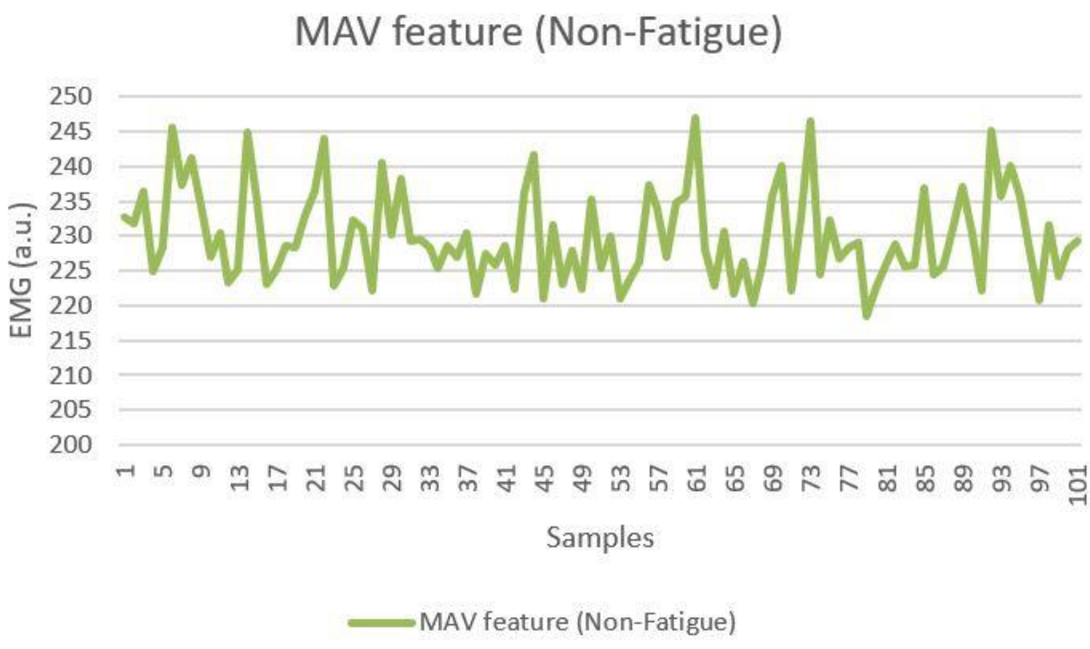

Figure 4.26 MAV in non-fatigue state (Zoom in).

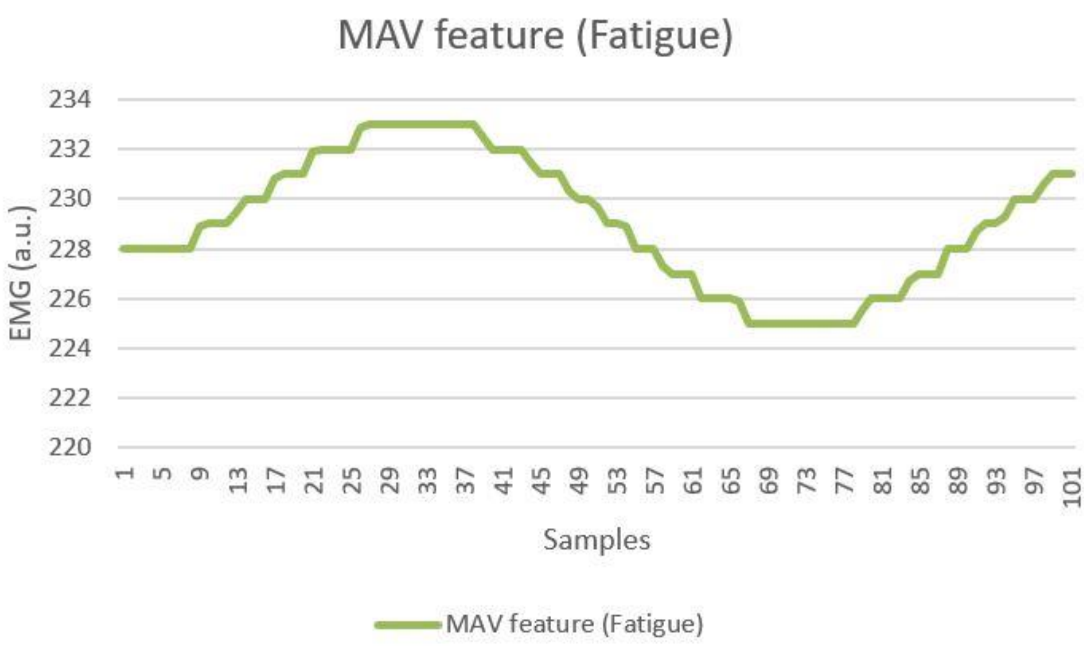

Figure 4.27 MAV feature in fatigue state (Zoom in).

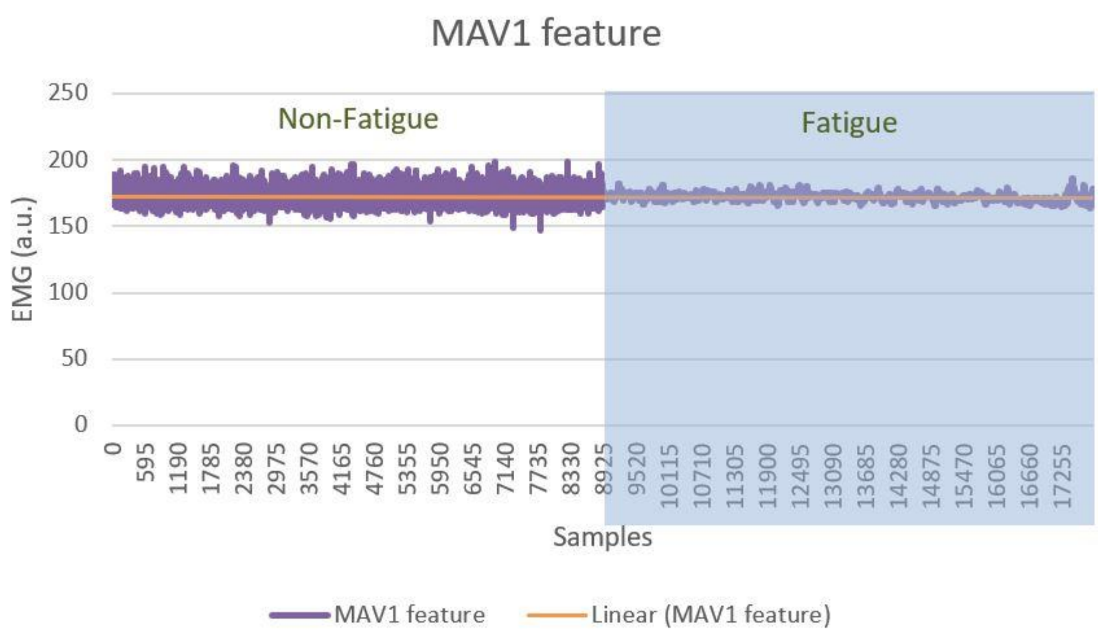

Figure 4.28 MAV1 feature.

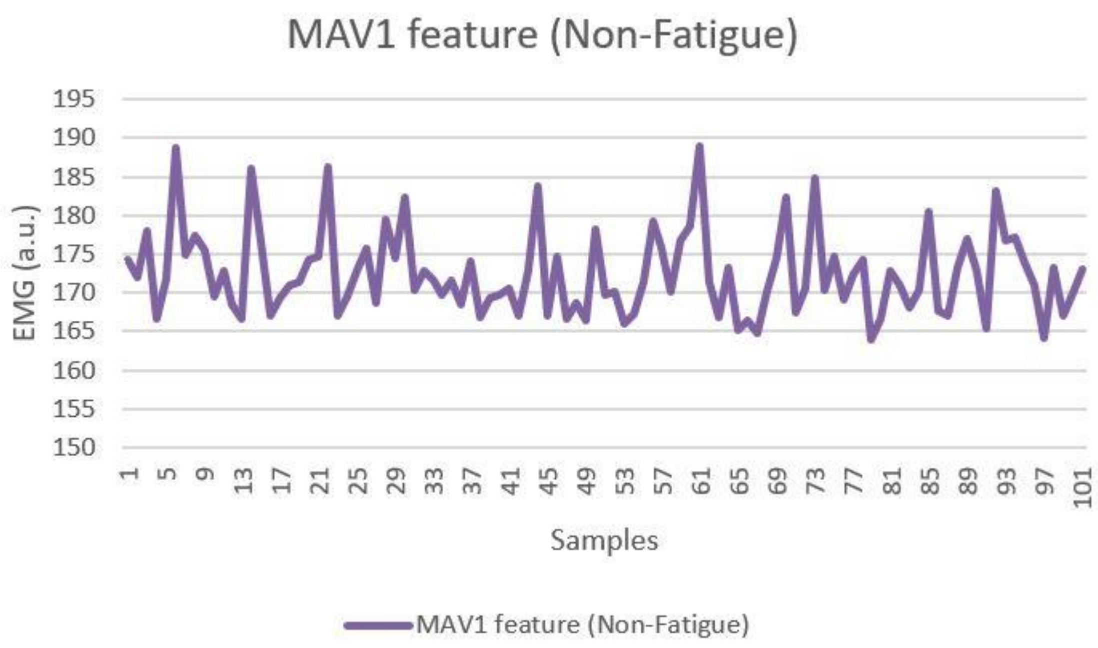

Figure 4.29 MAV1 feature in non-fatigue state (Zoom in).

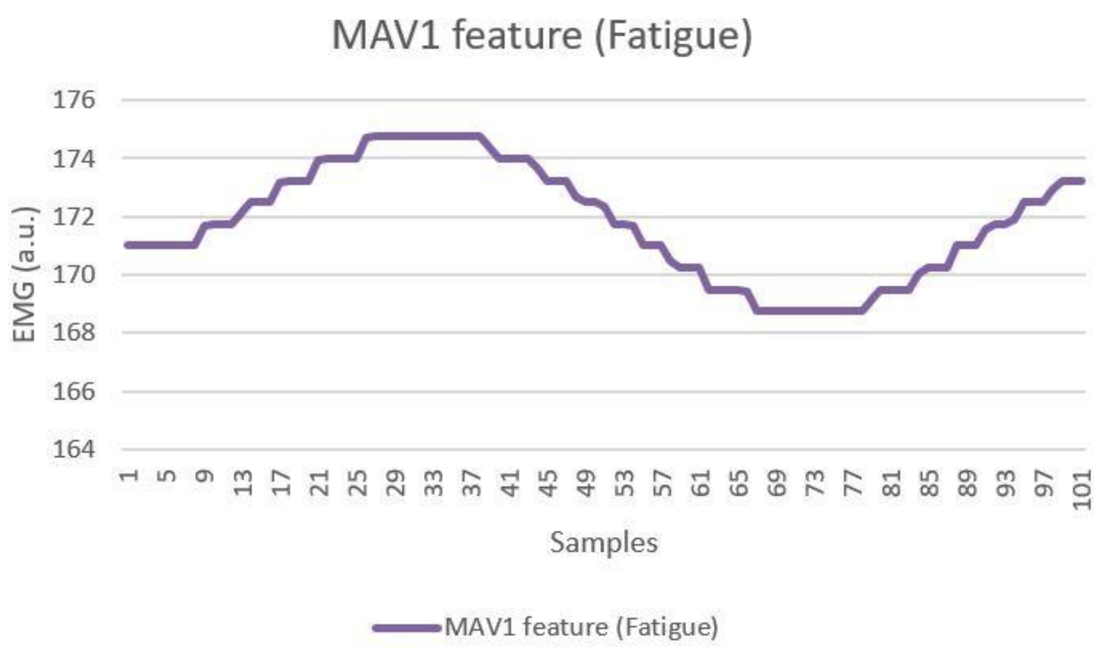

Figure 4.30 MAV1 feature in fatigue state (Zoom in).

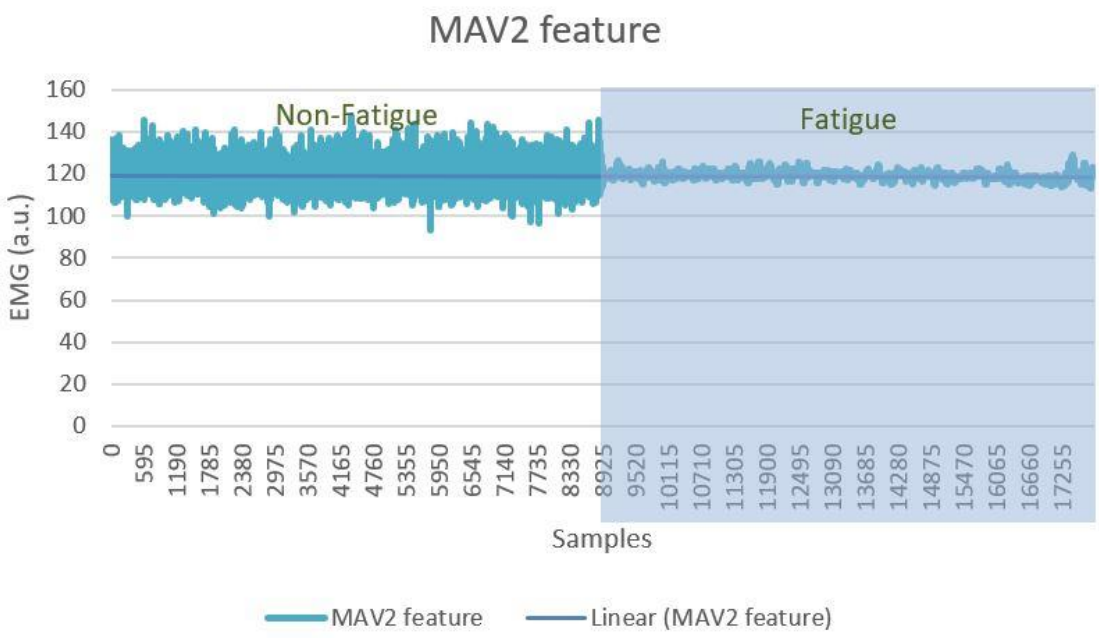

Figure 4.31 MAV2 feature.

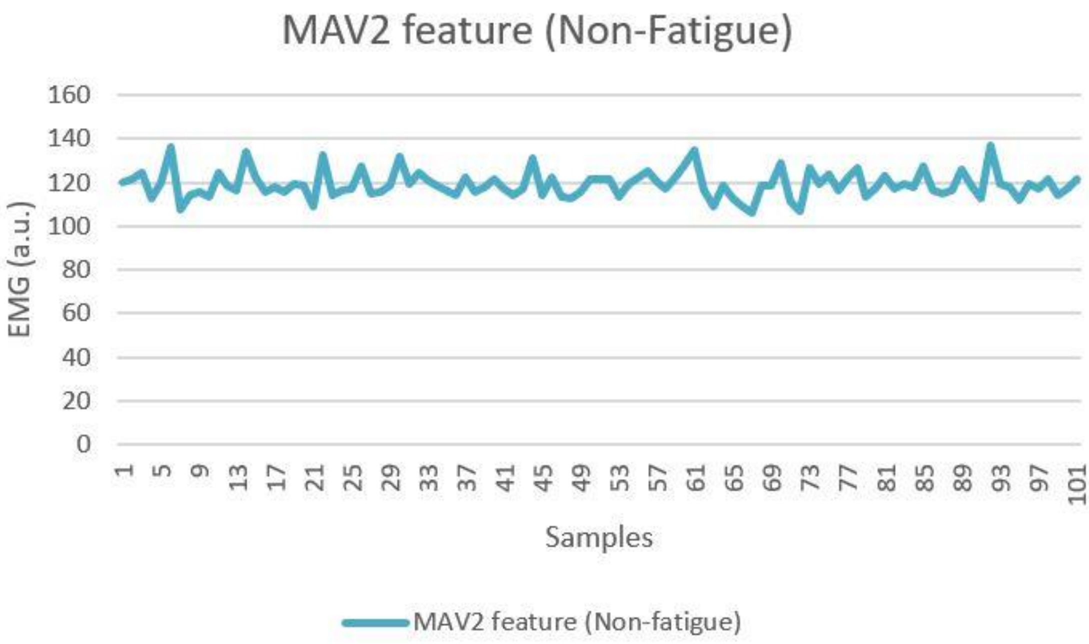

Figure 4.32 MAV2 feature in non-fatigue state (Zoom in).

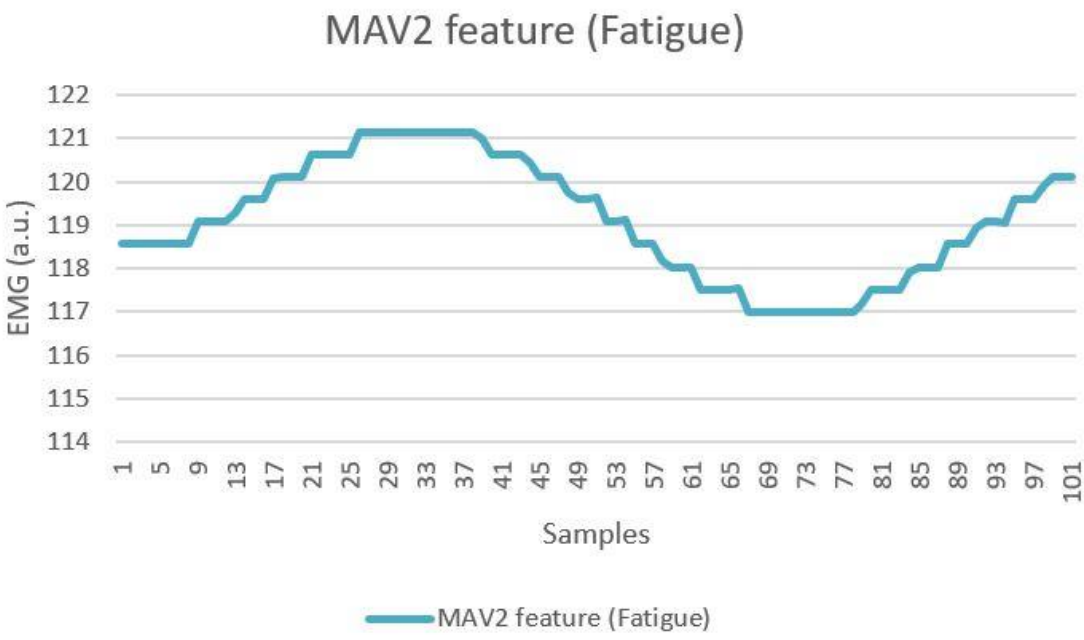

Figure 4.33 MAV2 feature in fatigue state (Zoom in).

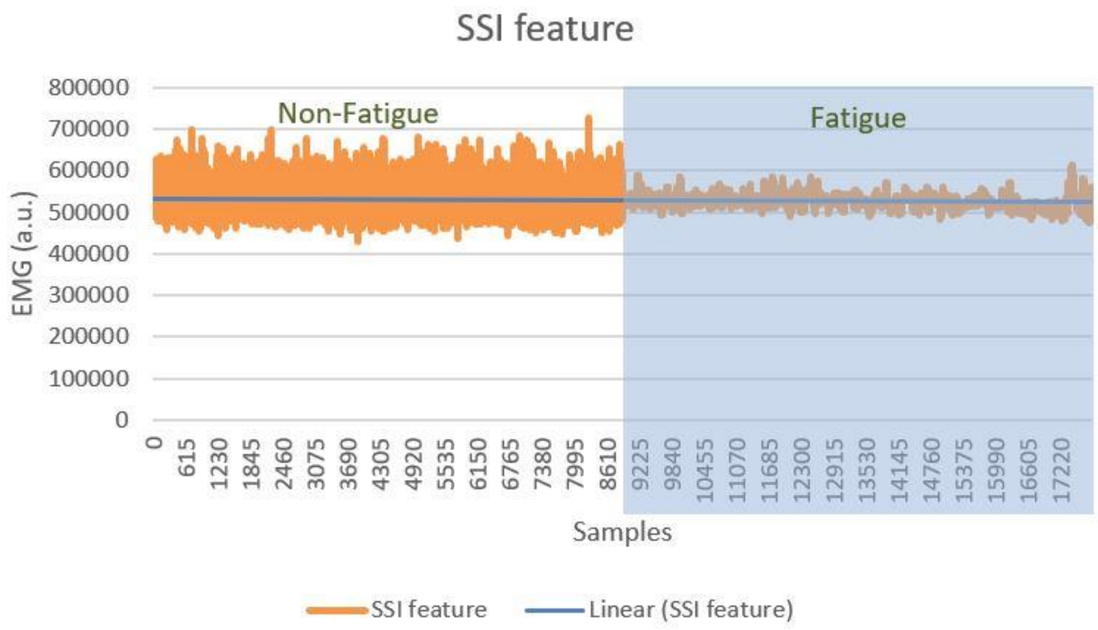

Figure 4.34 SSI feature.

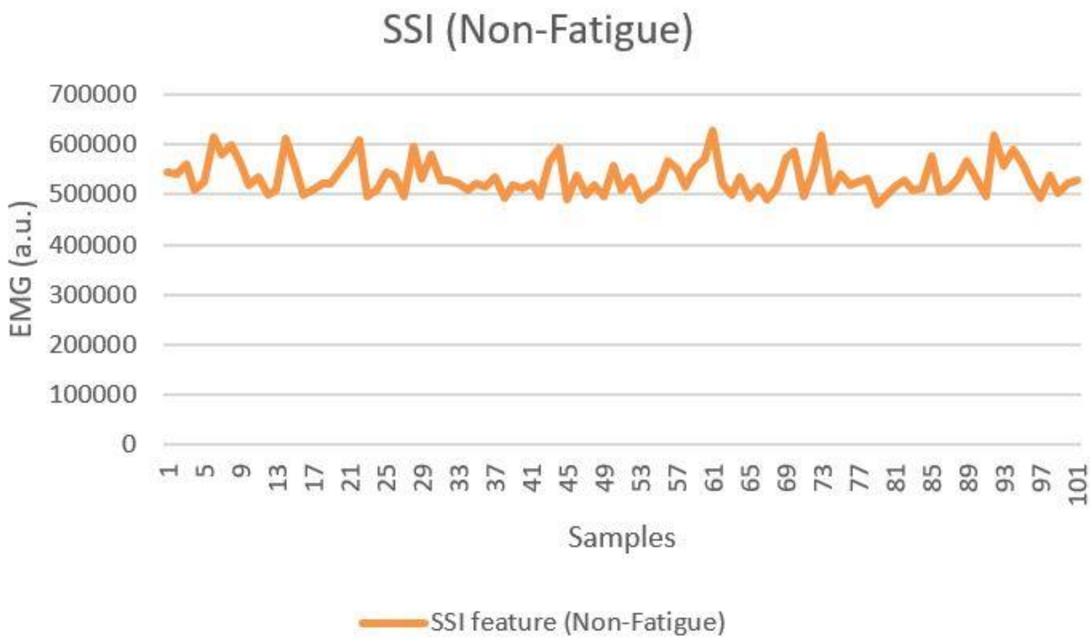

Figure 4.35 SSI feature in non-fatigue state (Zoom in).

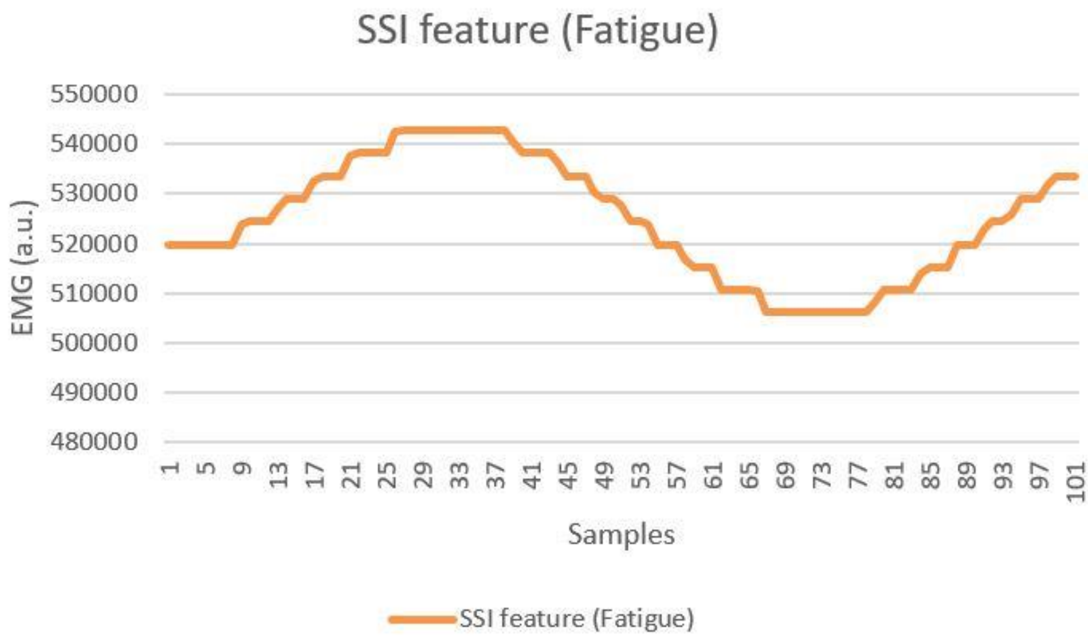

Figure 4.36 SSI feature in fatigue state (Zoom in).

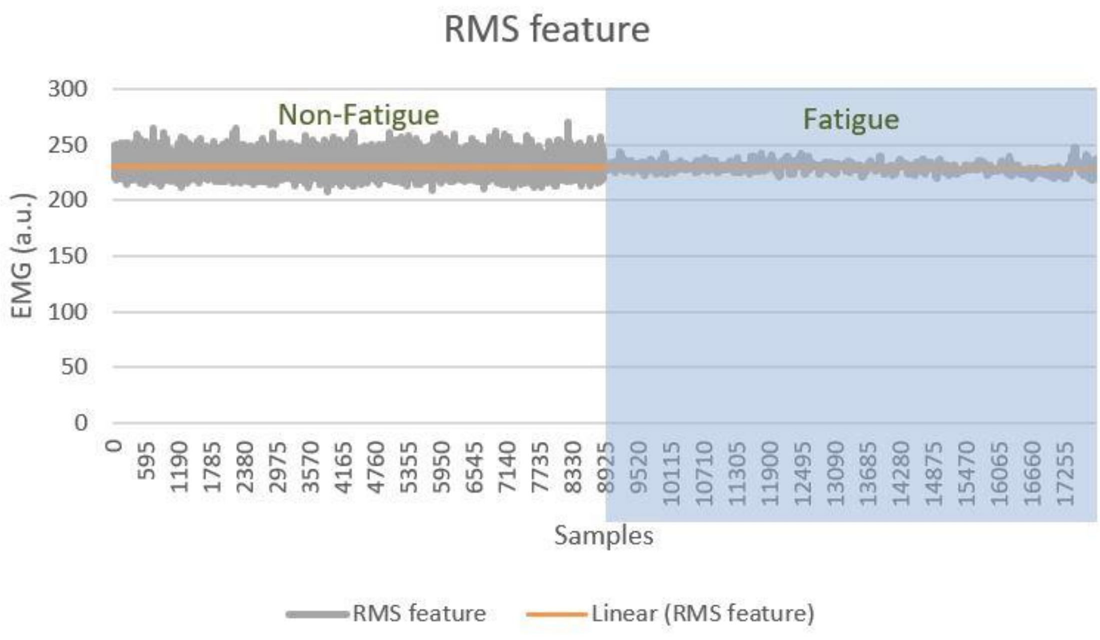

Figure 4.37 RMS feature.

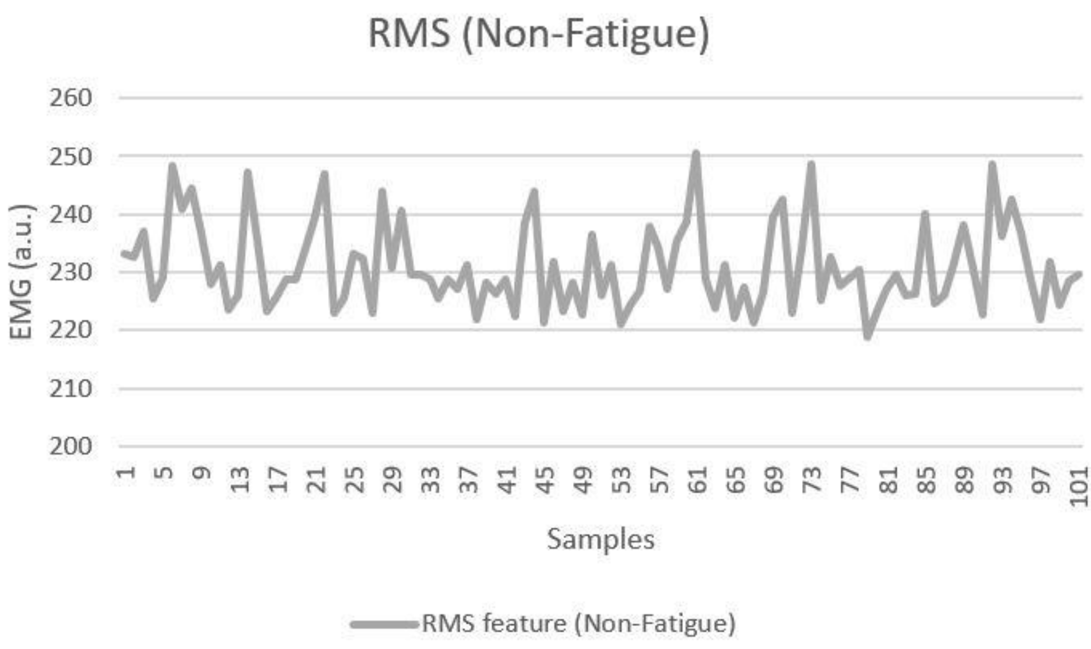

Figure 4.38 RMS feature in non-fatigue state (Zoom in).

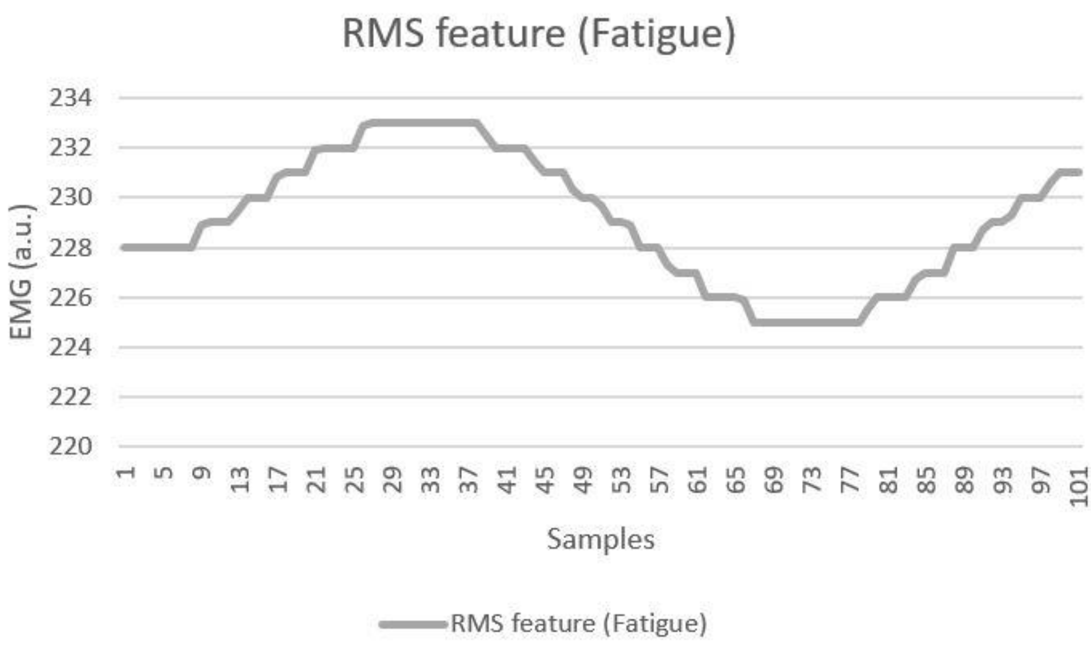

Figure 4.39 RMS feature in fatigue state (Zoom in).

We picked the ideal number of elements by utilizing recursive feature elimination (RFE) strategies with the assessors of calculated logistic regression and decision tree in cross-approval of ten to choose the quantity of features as displayed in Figure 4.40 and Figure 4.41. The ideal number of features by utilizing recursive feature elimination (RFE) strategies with the assessors of calculated logistic regression were five including features of mean, IEMG, MAV, SSI, and RMS. In augmentations, the ideal number of features by utilizing recursive component end (RFE) strategies with the assessors of decision tree were three including elements of IEMG, MAV2, SSI.

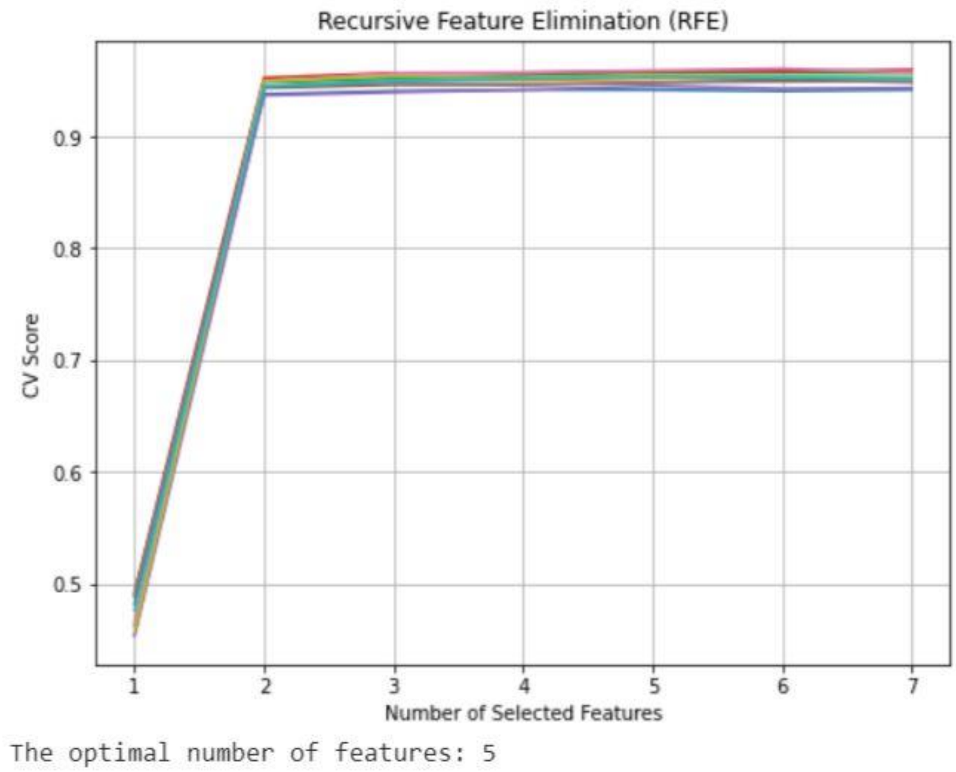

Figure 4.40 Recursive feature elimination (RFE) methods with the estimators of logistic regression.

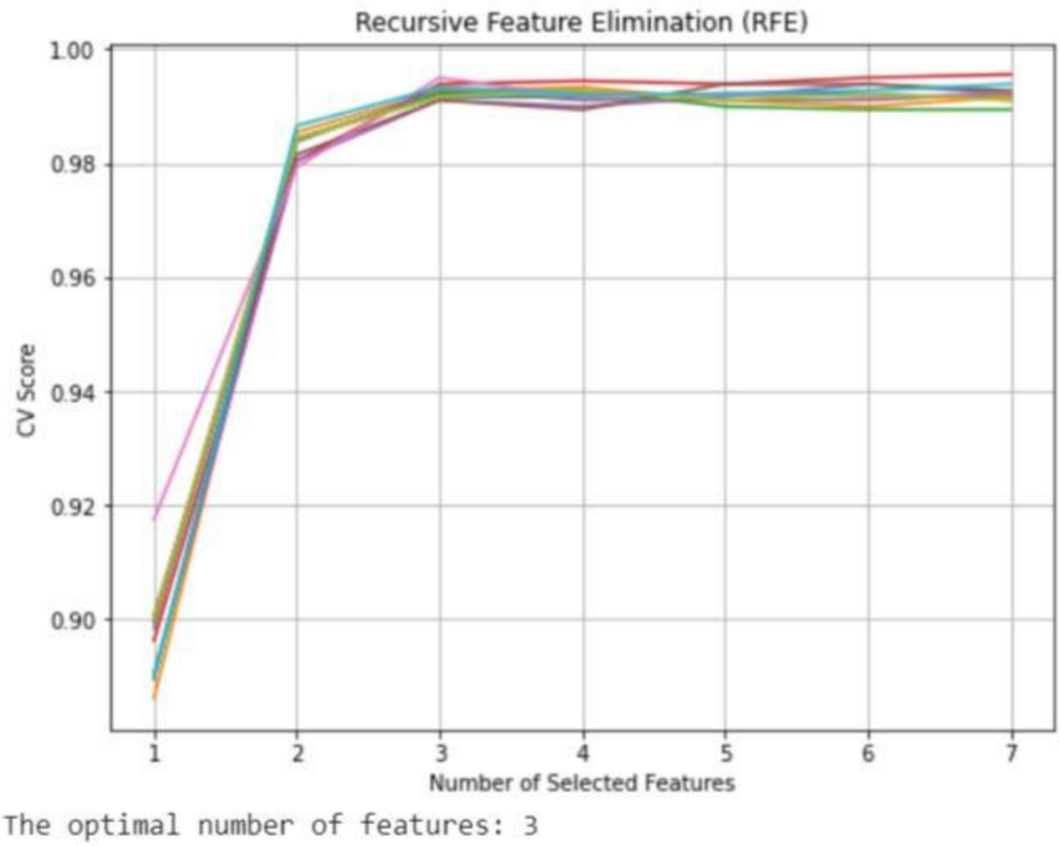

Figure 4.41 Recursive feature elimination (RFE) methods with the estimators of decision tree.

Subsequently, the features after aspect decrease were mean, IEMG, MAV, MAV2, SSI, and RMS. In view of the component extraction, we got feature sets out of seven elements in original datasets as follows:

Feature set I: mean, IEMG, MAV, SSI, and RMS.

Feature set II: IEMG, MAV2, SSI.

4.3.4 Model Training

The results of the aggregate results for each separator model with the initial and partial selected data are shown in Table 4.1.

Table 4.1 Classification accuracy results

Model	Accuracy (%)		
	Original Datasets	***Feature set I***	***Feature set II***
Logistic Regression	95.4558	95.3156	92.9313
Support Vector Machine	97.2511	97.3072	95.2875
Naive Bayes	66.8724	63.0856	70.0701
k-Nearest Neighbors	98.5414	99.1865	98.9902
Decision Tree	99.1024	99.5512	99.1585
Multi-layer Perceptron	99.8036	99.6914	99.6353
$mean$	92.8378	92.3562	92.6788

The accuracy of the actual data sets was slightly higher (0.4816% higher) than the accuracy of the element I set set and was slightly higher (0.159% higher) than the accuracy of the feature element list set II. The model with the best accuracy was a multi-layer perceptron optimized for real databases with 99.8036% accuracy. The perceptron accuracy of multiple layers was not improved by preparation for both element I and II sets. However, there were a few dividers (support vector machine, Naive Bayes, k-nearest neighbours, and decision tree) who benefited from preparing to include selected information.

Table 4.2 Cross-validation accuracy results

Model	Accuracy (%)		
	Original Datasets	***Feature set I***	***Feature set II***
Logistic Regression	95.1301	95.1750	92.9757
Support Vector Machine	97.2397	97.2958	94.7543
Naive Bayes	66.1244	62.5224	69.0474
k-Nearest Neighbors	98.8162	99.2594	98.9060

Model	Accuracy (%)		
	Original Datasets	***Feature set I***	***Feature set II***
Decision Tree	99.2145	99.5231	99.2482
Multi-layer Perceptron	99.8036	99.7419	99.6690
$mean$	92.7214	92.2529	92.4334

To confirm this effect, we tested the model using the cross-validation. This cycle validated the result of accuracy and evaluated the presentation of these models in addition as the opposite allowance for k-overlay and k = 10 total database. The measurements to be approved were the accuracy, receiver operating characteristic (ROC) curve and area under the curve (AUC) score as shown in Tables 4.2 and 4.3. The accuracy of the actual data sets was slightly higher (0.4685% higher) than the accuracy of the element I set and was slightly higher (0.288% higher) than the accuracy of the element II factor. The model with the best accuracy was a multi-layer perceptron optimized for real databases with 99.8036% accuracy. The perceptron accuracy of multiple layers was not improved by preparation for both element I and II sets. However, there were a few class dividers (logistic regression, support vector machine, Naive Bayes, k-nearest neighbours, and decision tree) who benefited from the preparation of selected feature information.

Table 4.3 Cross-validation ROC AUC Score

Model	ROC AUC Score		
	Original Datasets	***Feature set I***	***Feature set II***
Logistic Regression	0.994963	0.995043	0.988057
Support Vector Machine	0.999323	0.999335	0.992526
Naive Bayes	0.752217	0.662796	0.777382
k-Nearest Neighbors	0.996622	0.998336	0.996537
Decision Tree	0.992146	0.995232	0.992482
Multi-layer Perceptron	0.999922	0.999937	0.999915

Model	ROC AUC Score		
	Original Datasets	***Feature set I***	***Feature set II***
$mean$	0.955865	0.941780	0.957816

The average ROC AUC rating for feature II was slightly higher (0.001951 higher) than the ROC AUC average for real data sets and was slightly higher (0.016036 higher) than the ROC AUC standard for element factor I. The model with the leading ROC School of the AUC was a multi-layered perceptron set on element I set at 0.999937. The Multi-layer perceptron ROC AUC score has been improved by preparation for feature set I. In addition, there were different class dividers (logistic regression, support vector machine, Naive Bayes, k-nearest neighbours, and decision tree) who benefited from the preparation including selected information.

Table 4.4 Cross-validation fit time

Model	Fit Time (seconds)		
	Original Datasets	***Feature set I***	***Feature set II***
Logistic Regression	0.110257	0.085269	0.053444
Support Vector Machine	4.991964	4.274448	4.604983
Naive Bayes	0.005438	0.004873	0.004216
k-Nearest Neighbors	0.023773	0.019868	0.015509
Decision Tree	0.065681	0.046956	0.027955
Multi-layer Perceptron	17.016905	21.746648	18.322849
$mean$	3.702336	4.363010	3.838159

The fit time for this test was a good opportunity to put the inspector on the train set in all the cv classification as shown in Table 4.4. The average timeframe of the original data sets was somewhat faster (0.660674 seconds faster) than the average time factor of the set element I and somewhat faster (0.135823 seconds faster) than the average time factor of the element II. The model that had the fastest fit time was the naive bayes set in feature II set at 0.004216 seconds. The horizontal timing of the multi-layer perceptron was not improved by selecting the selected feature information. However, there were different class dividers (logistic regression, support vector machine, Naive Bayes, k-nearest neighbours, and decision tree) who benefited from the preparation including selected information.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of the Findings

Office syndrome is one of the most important medical problems worldwide. Staying in the same position for a set period of time causes muscle fatigue. This study proposed the detection of muscle fatigue syndrome in the office environment using surface electromyography (sEMG) and ML. The sEMG is recorded by the EMG sensor board associated with the NodeMCU V2 ESP8266 during seating with the upper electrode on the shoulder. Records are categorized and analyzed in advance to determine the various features of the data sets. Six ML models (Logistic Regression, Support Vector Machine, Naive Bayes, k-nearest Neighbors, Decision Tree, and Multi-layer Perceptron) with seven features (mean, integrated EMG, mean absolute value, mean absolute value1, mean absolute value2, simple square integral, and root mean square) of the original data sets and selected feature information was adjusted and tested, predicting the effect phase of fatigue or non-fatigue. Selected feature information in this test is filtered to include set I (mean, integrated EMG, mean absolute value, simple square integral, and root mean square) and list of capabilities set II (integrated EMG, mean absolute value2, and simple square integral). Thus, the multi-layer perceptron in setting the element II set has an excellent accuracy of 99.6690 percent in a fit time of 18.322849 seconds.

5.2 Discussion

We performed experiments to compile data and created sEMG data sets for the area of muscle fatigue in the office disruption during the session stay. For this reason, we prepared and tested six ML models with seven features of real data and included selected data that predicts the stage of fatigue or non-fatigue effect and obtained the accuracy and performance of the layout.

5.2.1 Logistic Regression

In logistic regression, it is easy to complete and convince. Rating is not required. Hyperparameters are not expected. Either way, it is left to indirect data, unimportant or related features. It is not a very attractive model, yet it is often overpowered by various machine readings. High reliability of satisfactory data. Each part must be visible in order to function with dignity. It will be commonly used to make multiclass exposures, but pairs are popular.

5.2.2 Support Vector Machine

In SVM, do well with higher ideas. In the real world, there are countless features, not just 2D and 3D. Basically, when the number of items or segments is high, SVM develops well. It is the best calculation when classes are visible, where the two categories can be easily separated by a straight or indirect line. The difference makes little difference. SVM is ready for an incredible duplicate model. In any case, it is slow. For a large database, it needs a ton of investment to process. It is discarded in merged classes. It influences the selection of appropriate hyperparameters. That will think of the execution of a satisfying hypothesis. Choosing the official component limit can be curious.

5.2.3 Naïve Bayes

In the Naïve Bayes, it can make the gauges unchanged. It is incredibly fast and can be used with persistence. It works in many ways with large data sets. It is harsh on the intangible. Multiclass speculation has successfully ended in Naive Bayes. Enough performance with high horizontal data, which is a number of very large items. However, the independence of the elements is not limited. The best guessing of the Naive Bayes that can be avoided is that each item contributes to the result. However, this situation does not meet many events. It is a terrible inspector. Data preparation should speak to people well. So, in a situation where configuration data is not the expert of most people, Naive Bayes is not working well. For KNN, it is not difficult to understand and practice. Can't guess about data. It is a model that browses endlessly. Once introduced to new data, it changes to bind new data centers. Multiclass problems can be solved. It has one hyper limit.

5.2.4 K-nearest neighbor

K-nearest neighbor may take some time while selecting the most important limit however after those limitations have become accustomed to it. In any case, it is backed up to big databases. It is a large, unprecedented pandemic for data sets with a large number of features. Data measurement should be considered. It does not work well on unbalanced data. It is weak in special cases. Unable to manage missing features. It can be used for any problem where the database is small, and has a small number of items so that the measurement time taken by KNN is minimal. In a situation where we do not have a very bad idea about the state of the data and how important the results and sources are, the KNNs are one decision.

5.2.5 Decision Tree

In the decision tree, performance is normal or unpredictable in data size. Managing non-gifted features, there is no significant impact of missing features. It is easy to disclose to indirect partners. It is a direct understanding. It is usually designed to include determination, which are insignificant factors that will not influence the treatment of choice. Over time, it tends to become overcrowded. Soft on data. In a situation where data changes, the results can change to a very large extent. It has long been expected that you will prepare the selected trees.

5.2.6 Multi-layer Perceptron

In a multi-layer perceptron, it can be used for complex indirect issues. It works well with big data. It provides a quick guess that leads to editing. Comparative accuracy can be achieved even with the smallest data. However, it is not known how much of the independent variables are affected by the dependent variables. The models are attractive and appealing. Proper ML performance depends on the preparation concept.

5.2.7 Interpretations and Implications

Zhou et al focused on the sEMG signal that deals with awareness of shoulder development. This study operated with ML precision, which included SVM, logistic regression, and a neural network of operations in response to sEMG signals for shoulder development. Eighteen subjects were enrolled in this review, their EMG signals collected from twelve muscles during activities of daily living (ADL) exercises that included drinking, moving or pulling, and holding or ingesting. The results showed that there was a baseline fit between the three ML strategies. The specific accuracy was 97.41 ± 1.8% using the SVM process with a sliding time of 270 millisecs (Zhou et al., 2021).

Long et al conducted a procedure to assess the extent of the impact of back rub. The sEMG mark may indicate a state of muscle fatigue. The Wavelet audio channel was designed to kill the white Gaussian turmoil of the sEMG signal. Seven elements selected for sound signal, cover time space, repetition space, and time multiplication space. The Tired Fatigue Phase was built using seven features for SVM models, which achieved 98% accuracy (Long et al., 2019).

In our review, the multi-layer perceptron showed the best accuracy in all data sets for static fatigue in the office setting including real data sets, feature I, and II as it can work very well with big data. Organizational design has a knowledge base, a curved, flexible background and a result layer. A private layer can be seen as a filter layer that breaks down a portion of important models from data sources and transfers them to the corresponding layer. It makes the organization faster and more useful by seeing only sensitive information from sources leaving out obscure information. The actuation function performs two amazing targets. It detects indirect links between sources. It helps to turn a commitment into a very important harvest. This is assigned to the feed network, as we can see that the data signals broadcast in a unique way from commitment to production. In additions, we can create input networks when signals are broadcasting in two ways.

It is a perfect model with high precision gauges that are very close to the real situation. How to find the right model with accurate statistics to track good weight loss is limit. This is achieved by a retrospective calculation and this causes the multi-layer perceptron to be taken in by accidental reading, the model reaching the next level. The most notable process is the reversal of the descending inclination order, in which different weight upsides are used and an error is detected. In line with these lines, in order to get the right weight, it has changed with the limit values and the impact on the error forecast. Finally, those weight upsides are considered appropriate, whereas with additional weight movement, the errors do not decrease progressively.

Memon et al proposed an ML-based graphic design that categorized the potential dangerous and harmless people in the IoT article. In the proposed structure, the SVM of the ML section is used to classify intimidating and harmless people. To encourage application of game application system application, use repetitive feature calculation to select logical features from the database. Test results show that the calculation of the repetitive factor determines the best small set of features, and the SVM separator has benefited from the use of the ideal character in this best small piece. A straightforward SVM piece has developed high accuracy (about 100%), clarity (close to 100%), and sensitivity (98%), and Matthews' correlation coefficient is almost 100%. Based on these results, they have declared that the use of the proposed framework is good due to the determination of additional qualifications that are selected to calculate the recurring component determination (Memon et al., 2019).

In our review, all seven features we created from the database did not increase the accuracy of the displayed statistics, but could make the model work faster. Other than that, our selective information did not work on the accuracy of the multi-layer perceptron. The original data accuracy was 99.8036 percent in the multi-layer perceptron higher than 99.7419 percent and 99.6690 percent in the element I and II sets respectively. Additionally, ROC AUC scores have been slightly different in both the actual data sets and selected information included. Therefore, it may be necessary to reduce the information with a lot of features and this selected part of the data will give a more comparable result to a multi-layer perceptron compared to the original information. In this way, we have decided to use the multi-layer perceptron in element II in the position of fatigue standing in the office position with an accuracy of 99.6690 percent at present. In any case, in the case where we consider the fit time of the ML model. It was shown that the multi-layer perceptron used much longer than the other ML model as 18,322849 seconds, which was slower (14.48469 seconds slower) than the equivalent time range of the element II series. We should consider the decision tree as one special ML model decision in diagnosing muscle fatigue in an office environment with an accuracy of 99.2482 percent and a fit time of 0.027955 seconds.

5.3 Limitations and Recommendations

Regardless of how these findings provide general information, it will not be the same for each effect of diagnosing muscle fatigue in all workplace conditions using SEMG and ML. In this review, sEMG communication sensors are used to combine information and use a standard fatigue test framework. Wearing these sensors can make the client experience worse and requires a new sensor development. Another temptation to replace EMG information with unaffected information may be created in future work to improve client knowledge. As it grows, it can transform over the cut-off function of the above function into a constant check function and create a continuous framework of the fatigue environment that is easily understood.

5.4 Conclusion

As with the growing pattern of office disruption, this study focuses on the issue of fatigue associated with the office environment. We linked the test to collect information on the EMG sensor with NodeMCU V2 ESP8266, and sEMG process data sets to diagnose muscle fatigue in the office environment during the study session. On this basis, we prepared and tested six ML models (Logistic Regression, Support Vector Machine, Naive Bayes, k-nearest Neighbors, Decision Tree, and Multi-layer Perceptron) with seven components (mean, IEMG, MAV, MAV1, MAV2, SSI, and RMS) for real data sets and selected information feature that predicts the stage of fatigue or non-fatigue and determines the accuracy of group formation. Therefore, we found that the multi-layer perceptron in the set of elements II (IEMG, MAV2, and SSI) had an excellent accuracy of 99.6690 percent with a fit time of 18.322849 seconds. By the way, due to the 99.2482 percent accuracy and optimal time of 0.027955 seconds, we would recommend the decision tree as another ML model in this review.

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CURRICULUM VITAE

Name	Parama Pratummas
Educational Background	2021 Doctor of Philosophy (Anti-Aging and Regenerative Medicine)
	School of Anti-Aging and Regenerative Medicine
	Mae Fah Luang University
	2019 Master of Business Administration
	Faculty of Business Administration
	University of the Thai Chamber of Commerce
	2019 Bachelor of Laws
	Faculty of Law
	Ramkhamhaeng University
	2019 Bachelor of Economics
	Faculty of Economics
	Sukhothai Thammathirat Open University
	2012 Doctor of Medicine
	Faculty of Medicine Siriraj Hospital
	Mahidol University
Work Experience	2021-Present Lecturer
	School of Anti-Aging and Regenerative Medicine
	Mae Fah Luang University
	2019-Present General Practitioner Doctor
	The Icon clinic
	2013-2019 General Practitioner Doctor
	Nitipon clinic
	2012-2013 Medical internship and training
	Maharajnakhonsithammarat hospital