Decoding of Hand Motion Using State of Art Time Domain, Frequency Domain And Feature Extraction

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Dedicated to my exceptional parents and adored siblings whose tremendous support and cooperation led me to this wonderful accomplishment.

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I am thankful to my Creator Allah Subhana-Watalah to have guided me throughout this work at every step and for every new thought which You setup in my mind to improve it. Indeed, I could have done nothing without Your priceless help and guidance. Whosoever helped me throughout the course of my thesis, whether my parents or any other individual was Your will, so indeed none be worthy of praise but You.

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Abstract

Exoskeletons that are activated by the muscles and brain have been suggested to train the motor skills of stroke victims. Training can incorporate task variety since an exoskeleton allows for the execution of various movement types.Differentiating between movement types at the same time from brain activity is challenging, but it might be accessible from residual muscular activity that many patients retain regain.This study examines whether forearm EMG from five stroke patients can be used to decode seven distinct motion classes of the hand and forearm. This study evaluates classifiers like Support vector machine (SVM), Lineardiscriminant analysis (LDA) and K nearest neighbor (KNN). It investigated the relation of motor impairment with classification accuracy by the classifiers. During the following motion classes: Supination, Pronation, Hand Close, Hand Open, Wrist Extension, Wrist Flexion, and Pich, five surface EMG channels were recorded.Every motion was performed by patients three times repetition over the course of eight weeks.Support vector machines, k nearest neighbor, and linear discriminant analysis were used to classify decoding of hand moments for stroke patients. On average,73.69 ± 6.39%SVM,71.6 ± 5.09% KNNand 50±4.56 LDA of the movements were correctly classified.Seven motion classes were demonstrated to be decoded from residual EMG, and SVM proved to be the most effective classification method when compared to the other three classifiers for decoding of hand motion for stroke patients.The results of this study may have implications for the development of exoskeletons, suits, or gadgets, that are powered by EMG signals. These devices might be utilized in the comfort of the patient's home to assist stroke sufferers with their training activities. Therefore, the findings of this study may assist in improving the effectiveness and accessibility of these useful tools for stroke survivors.

Key Words: *Electromyography, Stroke, Decoding of hand motion, featureextraction, classification,MachineLearningtechniquesforclassification*

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List of Abbreviations

EMG	Electromyography
MCSs	Myoelectric Control Systems
PCA	Principle Component Analysis
LDA	Linear Discriminant Analysis
LD	Linear Discriminant
CNS	Central Nervous System
ECG or EKG	Electrocardiography
MUAP	Motor Unit Action Potential
EEG	Electroencephalography
sEMG	Surface electromyography
iEMG	Intramuscular electromyography
AP	Action Potentials
MU	Motor Unit
MVC	Maximum Voluntary Contraction
MF	Muscle Fatigue
FD	Frequency Domain
TD	Time Domain
SSC	Slope Sign Change
RMS	Root Mean Square
ZC	Zero Crossing
WL	Waveform Length
AR	Autoregression
MAV	Maximum Amplitude Value
MNF	Mean Frequency
PF	Peak Frequency
TFD	Time Frequency Domain
MDF	Median Frequency
STFT	Short Time Fourier Transform
CWT	Continuous Wavelet Transforms
ANN	Artificial Neural Network
K-NN	k Nearest Neighbor

SVM	Support Vector Machine
FIS	Fuzzy Inference System
MCA	Mutual Component Analysis
SD	Standard Deviation
IAV	Integrated Absolute Value
MAV	Mean Absolute Value
AVR	Average Rectified Value
AAV	Average Absolute Value
NP	Number of Peaks
SM	Spectral Moments
WAVE	Wavelength
WLR	Waveform Length Ratio
MPF	Mean Power Frequency
TP	Total Power
PSD	Power Spectral Density
SM	Spectral Moment
WT	Wavelet Transform
FT	Fourier Transform
PCA	Principle Component Analysis

Chapter 1

Introduction

1.1 Background:

The central nervous system (CNS) is responsible for generating the pulse, making it the source of the EMG action potential.The voluntary movement of body parts of a person is facilitated by the transmission of impulses from the brain. The motor neuron transmits signals that regulate the contraction and relaxation of muscle fibers. The brain signals that convey information through the motor neurons and nerves propagate in a repetitive manner, referred to as frequency. The action potentials now being generated are identified as Motor Unit Action Potentials [1]. The activation of motor units and the firing rate of an individual motor unit increase in direct proportion to the contraction of voluntary muscle. EMG provides information on the force generated by muscles, movement, and physiological functions, making it easier to understand physiological operations. Electromyography (EMG) plays a crucial role in stroke rehabilitation, offering valuable insights into muscle activity and aiding in the development of targeted treatment plans. EMG helps identify weakened muscles, abnormal firing patterns, and muscle spasticity, guiding therapists in designing exercises to retrain and strengthen affected muscles.Tracking changes in EMG signals over time allows therapists to monitor a patient's progress and adjust rehabilitation strategies accordingly[2].Strokes are a major global source of long-term disability, and they frequently leave victims with motor deficits that have a major negative effect on their quality of life. Interventions for rehabilitation are essential for supporting the restoration of motor function, especially in the upper limbs. Decoding hand movements using sophisticated signal processing techniques is one possible approach to improving rehabilitation strategies.

EMG signals can be used as real-time feedback during therapy exercises, motivating patients to improve muscle activation and coordination.EMG can control robotic devices that assist patients with movement, providing support and guidance while promoting active participation.EMG helps restore arm and hand function, crucial for activities of daily living[3]. EMG can assess muscle activity during walking, leading to improved gait patterns and balance. EMG can evaluate swallowing function and guide exercises to strengthen the muscles involved. EMG-guided therapy can lead to significant gains in muscle strength, coordination, and range of motion[4].EMG biofeedback can help manage muscle spasticity, improving comfort and movement control.Real-time feedback from EMG can motivate patients and make therapy more engaging.EMG data allows for tailoring rehabilitation programs to individual needs and progress.

This work investigates the decoding of hand motion in stroke patients, a population that experiences significant challenges in motor function following a stroke. With a considerable number of individuals suffering from strokes each year, the need for effective rehabilitation methods is more pressing than ever.Virtual reality as an intervention fit in perfectly with our multi-faceted analysis. Virtual reality environments can be customized to mimic real-world activities, giving stroke sufferers meaningful and inspiring tasks to complete. We can harness the neuroplasticity of the brain by submerging people in these virtual environments, for recovery.

In addition to increasing stroke patients' involvement, virtual reality's immersive quality provides them with instantaneous feedback on their hand motions. This provides an enriched dataset for decoding and is consistent with our time domain study. Furthermore, in accordance with our frequency domain insights, VR interventions can be created to specifically target particular frequency components. Virtual reality's interactive aspects make it easier to retrieve subtle features, which improves the accuracy of decoding algorithmsWhen hand movements are converted into frequency spectra, a rich brain activity tapestry is revealed. We learn more about the underlying neurophysiological mechanisms by examining the spectrum features of these motions. By identifying the frequency bands linked to various motor tasks, frequency domain analysis helps us understand the neuronal signals hidden within the frequency spectrum. This not only improves our understanding of motor control but also creates opportunities to design therapies that focus on particular frequency components, allowing rehabilitation techniques to be customized to the distinct brain patterns seen in stroke victims. After a stroke, motor function often deteriorates, necessitating specialized treatment to restore functionality and improve patients' quality of life.The research aims to advance rehabilitation by applying machine learning techniques to extract essential features from recorded data.When hand movements are converted into frequency spectra, a rich brain activity tapestry is revealed. We learn more about the underlying neurophysiological mechanisms by examining the spectrum features of these motions. By identifying the frequency bands linked to various motor tasks, frequency domain analysis helps us understand the neuronal signals hidden within the frequency spectrum. This not only improves our understanding of motor control but also creates opportunities to design therapies that focus on particular frequency components, allowing rehabilitation techniques to be customized to the distinct brain patterns seen in stroke victims. Advanced signal processing techniques have revolutionized the perception and interpretation of hand gestures. Our study in the time domain goes beyond merely following the movements. It entails segmenting hand movements into discrete parts, comprehending temporal patterns, and identifying significant occurrences within these sequences. Through the use of advanced signal segmentation techniques, we are able to identify particular movements and actions. Our capacity to perceive the nuances of hand motion is further improved by temporal pattern recognition, which offers a sophisticated understanding of the temporal dynamics of motor control and important details for rehabilitation tactics. This data typically includes inputs like muscle signals, Electromyography data, which can provide valuable insights into the intricate nature of hand motion and its recovery following a stroke. machine learning algorithms, the research team can analyze this data to decode hand motion in stroke patients. This innovative approach promises to enhance the understanding of post-stroke hand motion, offering the potential for tailored rehabilitation strategies. By personalizing therapeutic interventions based on data-driven insights, the research holds the promise of significantly improving the recovery process for stroke survivors. This work has the potential to make a profound and positive impact on the lives of stroke patients, offering them a path to a more comprehensive and efficient recovery journey.

Stroke survivors often face significant challenges in performing everyday tasks due to the debilitating effects of the condition on their motor functions. Following a stroke, individuals may experience weakness, paralysis, or impaired coordination, making even the simplest activities arduous. This reliance on assistance from family members or caregivers to carry out daily tasks can lead to feelings of frustration, dependency, and loss of autonomy. Moreover, the burden of providing continuous care and support for stroke survivors can take a toll on the emotional and physical well-being of both the patient and their loved ones. Therefore, the quest to improve the quality of life for stroke victims becomes paramount, driving the need for innovative research and interventions aimed at restoring independence and enhancing their overall well-being.

1.2 Motivation:

The population of stroke patients is increasing day by day, due to different causes people are getting affected by stroke each year.According to world health organization report around 10 million of population suffer from stroke annually out of which 5 million died and the rest

5 million are left permanently disable. These patients feel a lot of difficulties while doing work and consider it a burden on family and community[5]

Main causes of stroke are hypertension and smoking, diabetes, and many factors according to data obtained from the National Health Survey of Pakistan (NHSP), it has been revealed that hypertension, a chronic medical condition characterized by elevated blood pressure, is a prevalent health concern among the population. The survey indicates that this condition significantly impacts the health of adults in Pakistan, particularly those who are aged 15 years and above[6]. In the NHSP report, it is reported that approximately 18% of adults who are 15 years or older are affected by hypertension. This statistic underlines the widespread nature of this condition among the adult population, highlighting its significance as a public health issue in Pakistan. Small studies in Pakistan suggest that there is a high prevalenceof hyperlipidemia (11–32%) among hospitalized stroke patients. This much population of the country has been suffered from past years of strokes[7].

The potential substantial effects of this research on the lives of stroke survivors and their families serve as the driving force for it. Through exploring the complexities of hand motion decoding and comprehending the subtleties of motor impairments, our goal is to create technologies and therapies that enable people to take back control of their daily lives. By applying advanced signal processing methods and investigating novel technologies such as gadgets and virtual reality (VR), we want to equip stroke victims with resources that support their functional recovery and enable rehabilitation. Our goal is to use technology to help stroke survivors overcome their obstacles and improve their independence, dignity, and quality of life.

Now as the survivor of stroke patient that cause disability in their mobility and function and it may be long term in adults, they need rehabilitation exercises to the gain their strength back.The objective of stroke rehabilitation is to facilitate the fullest possible recovery for each patient who has been affected by a stroke. This means helping the individual regain the highest level of physical, functional, and psychosocial capabilities attainable, considering the specific limitations resulting from their stroke-related impairment.this initiative aims to significantly enhance the lives of stroke survivors everywhere. Through establishing a connection between research findings and real-world implementation, our goal is to revolutionize stroke rehabilitation and usher in a new era of individualized, patient-centered care. We work to develop novel solutions that not only address the physical limits caused by stroke but also foster resilience, hope, and a sense of purpose via interdisciplinary collaboration and a thorough knowledge of the needs and experiences of stroke survivors.

1.3 Aim and Objectives of the Study:

The primary aim of my research is to acquire a thorough comprehension of efficient techniques to aid people in their rehabilitation of hand motor skills after experiencing a stroke. Stroke survivors frequently encounter difficulties associated with compromised motor abilities, particularly in their hands. My study contributes to the advancement of specific strategies that can aid in the restoration of these crucial movements. The objective of our study is as follows.

- To Decode Hand Motion
- Comparison between sessions
- Comparison between models.

1.4 Structure of Thesis:

The structure of thesis is as follows.

This study is organized round the chief objective of Decoding of hand motion with state of art time domain frequency domain and feature extraction. The study starts with an introductory Chapter 1; Chapter 2 presents associated work in this study area. Chapter 3 describes different methods. Chapter 4 summarizes, examines, and discusses results. Chapter 5 is related to Conclusion and limitationand in future one can work in that space.

Chapter 2

Literature review

2.1 Anatomy of Upper limb:

Within the upper torso, the arm serves as a functional unit. There are three parts to it: the hand, forearm, and upper arm. It has 30 bones and stretches from the shoulder joint to the fingertips. It is also made up of several muscles, arteries, veins, and nerves. The musculature of the upperlimb is considerably larger than that of the lower limb. The anterior compartment of the upper arm houses three muscles. The coracobrachialis and brachialis are deep to the biceps, whereas the long and short heads of the biceps brachii are situated superiorly.

There are twenty muscles in the forearm, organized into five groups. Four muscles in the superficial group make up the anterior forearm: the pronator teres, flexor carpi radialis, flexor carpi ulnaris, and palmaris longus[8]. The flexor digitorum superficialis is the only muscle present in the middle compartment. Three muscles are in the deep layer of the anterior compartment: pronator quadratus, flexor pollicus longus, and flexor digitorum profundus. Many of the superficial muscles in these muscles originate from a single flexor tendon on the medial epicondyle of the humerus. These muscles are mostly composed of flexor and pronator muscles. The deep compartment of the posterior forearm has five muscles, whereas the superficial compartment contains seven. These muscles make up the superficial compartment: anconeus, brachioradialis, extensor carpi radialis longus and brevis, extensor carpi ulnaris, extensor digitorum, and extensor digiti minimi.

Abductor pollicis longus, supinator, extensor indicis, and extensor pollicis longus and brevis are in the deep compartment[8]Three categories may be used to categorize the hand muscles: palm muscles, thenar muscles, and hypothenar muscles. The three thenar muscles—opponents pollicis, flexor pollicis brevis, and abductor pollicis brevis—are situated at the thumb. All three of these muscles are innervated by the median nerve. The ulnar side of the hand, close to the fifth finger, or pinky finger, is where the hypothenar muscles are situated.

The four muscles that make up the dorsal interossei group join to the metacarpals and oversee abduction of the fingers. On the anterior surface of the metacarpals, there are three muscles that make up the second group, the palmar interossei. The abduction of the fingers is their fault. The dorsal and palmar interossei are innervated by the ulnar nerve. The hand also has four lumbrical muscles. The flexor digitorum profundus tendon is the source of origin for each of these muscles, which oversee flexion of the finger at the metacarpal-phalangeal joint and extension of the interphalangeal joints. The ulnar nerve innervates the two on the ulnar side, whereas the median nerve innervates the radial two lumbricals.[9].

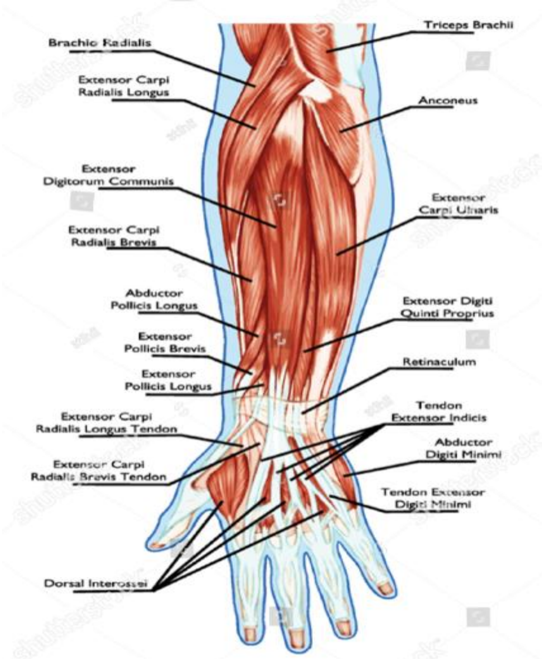

Figure 2.0-1: Anatomy of Forearm and Wrist

The Muscles that are used in my research data are Flexor digitorium superficialize(FDS) for flexion motion, extensor digitorium communis (EDC) forextension, dorsal interossei (DI) for pinch, pronatorteres (PI) for pronation, and supinator for studying supination of motion in stroke patients.

2.2 Electromyography:

Electromyography (EMG) can be defined as an electrical signal which is generated in responseto the relaxation and contraction of human muscles in the body. These signals can be recordedusing EMG electrodes which are mounted either on the surface of the body or directly intomuscles of the limbs. [10]The signals which are recorded from the skin of the body are called surface. EMG while the signals which are recorded directly from muscles are called intramuscular EMGsignals. Both signals are useful in multiple applications such as movement and gait analysis, therapy, neurology, ergonomics, and prosthetic robot devices as well as Rehabilitation.[11].

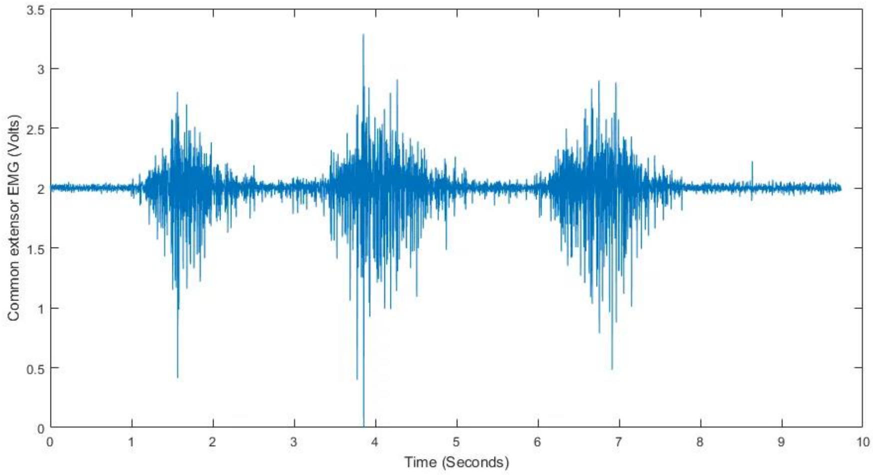

Figure 2.0-2: Emg plot from Extensor muscle for healthy person.

2.2.1 Electromyography types:

There are two types of recording one can do with Emg, we use electrode to record it from muscle one is intramuscular while other is surface Emgelectrode[4]Both have their advantages and disadvantages in intramuscular surface electrode the muscles are punctured to record data while in surface Emg the electrical signal is acquire by the motion without damaging the body[11]. The noninvasive nature of surface EMG signals makes them favorable in that they don't require surgery, there are several drawbacks to be aware of, which are outlined below.

- The signals recorded are global and do not pertain directly to muscles which cause a
- specific movement.
- The noise is also included due to recording of signal.
- Due to sweat, electrode movement and hair may produce EMG signals which are different.

2.2.1.1 Intramuscular Emg:

Intramuscular Emg signals are useful, they are intrusive and are not frequently employed. They arefurther challenging to capture since accuracy is needed to position items in the best possible way. When they are configured for the test, the EMG signals that are captured are of highquality without any noise[12] . while Due to advancement in technology, newer surface Electrodesprovide better signals. Surface EMG is often used for clinical assessments, sports science, and ergonomic studies. It is non-invasive and provides a broad overview of muscle activity. Also, intramuscular EMG recording technology has improved as well, andimplantable EMG electrodes are available, which makes recording easier to acquire signal for the required purpose[13].Intramuscular EMG provides more precise recordings of muscle activity, making it suitable for clinical diagnostics, research, and specific studies requiring detailed information a Needle electrode is inserted through the skin into the muscle for direct measurement of electrical activity[14]Needle EMG is commonly used in clinical settings to diagnose neuromuscular disorders, assess muscle, and nerve functionout individual muscle fibers.

Figure 2.0-3: Electromyography recording and stimulation from different muscles.

2.2.1.2 Surface Electromyography:

Surface Electromyography (sEMG) is a non-invasive technique that measures the electrical activity produced by skeletal muscles. It involves placing surface electrodes on the skin above the muscles of interest to record the electrical signals generated during muscle contractions.sEMG is incorporated into gait analysis systems to study muscle activity during walking and running. This helps in understanding movement disorders, gait abnormalities, and designing interventions for individuals with mobility issues[15]. sEMG is used to monitor muscle fatigue during prolonged or repetitive activities. By analyzing changes in muscle activity patterns, researchers and practitioners can assess the impact of fatigue on performance and prevent overuse injuries.

2.2.1.3 Uses of Electromyography:

The uses of electromyography is given below

- **Neuromuscular Disorders:**EMG is commonly used to diagnose and assess neuromuscular disorders such as muscular dystrophy, myasthenia gravis, and peripheral nerve injuries. It helps identify abnormalities in muscle function and detect underlying neurological issues.

- **Muscle Rehabilitation:** EMG is utilized in physical therapy to evaluate muscle function and monitor progress during rehabilitation. It assists therapists in designing targeted exercises to strengthen specific muscles and improve overall motor control.
- **Prosthetic Control:** EMG signals can be used to control prosthetic devices. Electrodes placed on the residual muscles of an amputated limb can detect muscle contractions, allowing users to control the movement of their prosthetic limbs.
- **Muscle Activity Analysis:** EMG is employed in sports science to analyze muscle activity during different activities and sports movements. This information helps in understanding muscle function, optimizing training programs, and preventing injuries.
- **Gesture Recognition:** EMG signals can be used for gesture recognition in human-computer interaction. By detecting muscle contractions in the forearm, hand, or fingers, EMG can enable users to control devices, interfaces, or virtual environments with subtle muscle movements[2]
- **Muscle Function Studies:** EMG is widely used in physiological and biomechanical research to study muscle function, activation patterns, and coordination during various activities. This research contributes to a deeper understanding of human movement and performance.
- **Workplace Assessment:** EMG is applied in assessing muscle activity and fatigue during different occupational tasks. This information helps in designing ergonomic workspaces and preventing musculoskeletal disorders related to repetitive tasks[16]
- **Biofeedback:** EMG biofeedback therapy utilizes real-time EMG data to help individuals gain awareness and control over specific muscle activities. It is used in various conditions, such as tension headaches, and stress-related muscle tension.
- **Parkinson's Disease:** EMG is sometimes used to study muscle activity and movement patterns in individuals with Parkinson's disease, contributing to the understanding of motor symptoms associated with the condition.
- **Muscle Fatigue Studies:** EMG is employed to assess muscle fatigue, studying changes in muscle activity patterns during prolonged or repetitive tasks. This information is valuable in optimizing performance and preventing injuries in various domains[17].

2.3 Stroke:

Strokes is a cardiovascular disease caused which cause effecting millions of people in which a lot of them get disabilities permanently such as paralysis[18][19]The survivor face disability in motor function when get suffered from stroke[20]. Between 50 and 70 percent of stroke patients have upper limb disability during the acute phase of the diseaseand 6 months after the stroke begins, only 5 to 20 percent of patients regain complete upper limb dexterity[21].To improve stroke recovery, a few technologies are available in addition to conventional therapeutic therapies, including neuromuscular stimulation, invasive and non-invasive brain stimulation, robotic devices, virtual reality games, and electromyography (EMG)[21].For more than 50 years, surface electromyography (sEMG), in which electrodes are positioned over the skin to record the electrical activity of a muscle or group of muscles, has been utilized in neurorehabilitation. sEMG can be used as a tool to support and improve various neuromuscular rehabilitation programs or as an evaluation to analyze muscle activation patterns[22] .

2.3.1 Types of strokes:

There are wo types of strokes:

- Ischemic strokes.
- Hemorrhagic stroke.

2.3.1.1 Ischemic Stroke:

An ischemic stroke happens when there is a partial or complete blockage of blood vessels, disrupting blood flow. Most strokes globally are ischemic strokes, which are brought on by blockages either inside or outside the brain (or other parts of the body). Atherosclerosis is a condition where fat and other materials build up and cause the blood vessel walls to narrow.

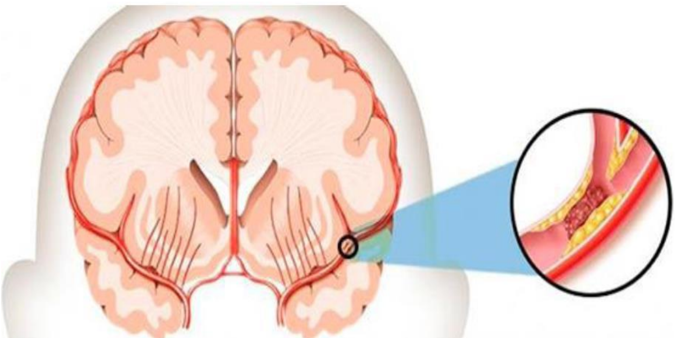

Figure 2.0-4: Formation of a clot inside the Vessel

2.3.1.2 Hemorrhagic Stroke:

Whenever a blood artery, whether it is located inside or outside of the brain, ruptures, the blood supply to the tissues of the brain is severed. A deficiency in oxygen and food can lead to the death of brain tissue, which is known as necrosis. Hemorrhagic strokes account for thirty percent of all strokes that occur around the world. These strokes also have the highest mortality rate.

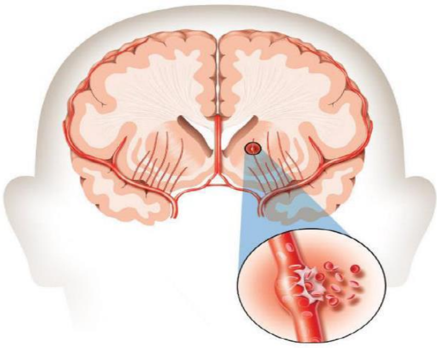

Figure 2.0-5: Broken Blood Vessels in the Brain

Our population is mostly suffered from ischemic type of stroke according to agha khan hospital report.

2.3.1.3 Stroke Rehabilitation:

A crucial component of getting back to normal living after an injury or illness is rehabilitation. Therapy for the incident's effects could focus on the affected areas of motor control, communication, vision, neurological function, mental health, or anything else. The brain heals more quickly and responds more quickly in the weeks immediately after a stroke[23]. Over the past few decades, there has been an increase in orthotic devices that rely on mechanical and electrical components to carry out their functions. This is since rehabilitation programs can be made more efficient and less expensive with the use of new technologies[24]. With the rising expense of specialized labor, robotic orthotics offer a great opportunity to treat more patients without adding therapists to the workforce and to keep patients engaged without giving them explicit instructions.

2.3.2 Stroke rehabilitation techniques:

The following are some rehabilitation techniques that are used for stroke rehabilitation. They are.

2.3.2.1.1 Physical Therapy:

Physical therapy methods are often used in stroke rehabilitation to help people regain their mobility, strength, and ability to do things. To keep joints from getting stiff and improve flexibility, range of motion movements gently move limbs through their full range of motion. During passive range of motion movements, therapists move the patient's limbs without them having to do anything. This keeps the patient flexible and stops contractures from forming.

Active range of motion workouts help people strengthen and control their muscles by letting them move their hurt limbs on their own. Resistance exercises with bands or weights are used in strength training to build muscle power. For balance, work on both sides of the body that are affected and not affected. Standing, shifting your weight, and controlled movements are all balance and coordination tasks that can help you avoid falling. To help people become more independent and improve their motor skills, functional tasks like dressing and eating are included. Gait training works on improving balance, walking skills, and the length of each step. It may involve using aids like walkers or canes. Task-specific training includes doing the same daily activities repeatedly to improve muscle memory and function[25].

Sensory stimulation includes things like touching different textures that help people with impaired awareness. Cognitive activities help you get better at coordinating your movements and doing more than one thing at once. Using the buoyancy of water in therapy lowers stress on joints and lets you work with light pressure to improve your mobility. When used regularly with the help of a trained therapist and adapted to each person's needs, these techniques make a big difference in stroke rehabilitation, speeding up recovery and raising quality of life.

Figure 2.0-6: Physical therapy session of a stroke patient

2.3.2.1.2 Occupational Therapy:

Occupational therapy for people who have a stroke works on helping them get back to doing everyday things on their own. Occupational therapists help people get better at cognitive processes, fine motor skills, and find new ways to do everyday things. This includes teaching people how to use adaptive tools, checking and making changes to people's homes to make them safer, and helping them get back into the community.

Figure 2.0-7: Occupational therapy for a stroke patient

2.3.2.1.3 Constraint-Induced Movement Therapy (CIMT):

Constraint-induced movement therapy makes it easier to do a lot of work on the affected leg by putting limits on the unaffected limb.

Figure 2.0-8: Constraint-Induced Movement Therapy for stroke patients

2.3.2.1.4 Virtual Reality Rehabilitation:

Virtual reality (VR) therapy is a new way to help people who have had a stroke get better. It provides a dynamic and immersive environment for therapeutic interventions. VR therapy for stroke recovery involves patients doing virtual tasks that are meant to improve their motor skills, coordination, and brain functions. Real-life situations are simulated in these virtual worlds, which make them safe and controlled places to practice moves and tasks.

Figure 2.0-9:VR based rehabilitation therapy for stroke patients.

2.3.2.1.5 Mirror Therapy:

Mirror treatment involves using a mirror to make the affected limb seem like it can move by reflecting the movement of the healthy limb. The goal is to encourage neuroplasticity, speed up muscle recovery, and ease symptoms.

Figure 2.0-10:Mirror therapy for stroke rehabilitation

2.3.2.1.6 Electrical Stimulation:

A new technique used to help stroke patients recover is to use electrical stimulation. Electrical stimulation uses low-level electrical currents to work on specific muscles, which helps with motor recovery and improving performance. This method works especially well for improving muscle weakness, spasticity, and motor control problems that are typical after a stroke.

Figure 2.0-11 : Electric stimulation for stroke patients

2.4 Myo Electric Control System:

A myo electric control system is system which signal from the muscle is used as in put while from the classification we can get the whole results and can say our pattern is applicable or not[26].The precision of myoelectric control has been greatly increased by the successful application of myoelectric pattern recognition as a human-machine interface to operate robotic devices like prostheses and exoskeletons[27]. Advanced systems based on machine learning and pattern recognition were developed, enabling the development of multifunctional devices with a greater number of degrees of freedom. As the system developed and its capabilities expanded, it became necessary for signals to be successfully distinguished for various muscle states to be able to carry out distinct tasks. Therefore, to make this feasible, the following things must happen[28].

- Several channels are utilised for recording, enabling the transmission of localised data.
- It is necessary to create a feature set that can efficiently transmit muscle state information.

Training is required for a classifier that can extract the data and provide control commands[29]

2.4.1 Myo Electric Signal Measurment Strategies:

EMG signals are extensively studied and applied in the field of engineering including robotics and rehabilitation devices. Ensure certain electrode placement is proper is the main goal while recording EMG signals from the surface in order to obtain as much information as possible about muscle activation[30]. For our study we have to select muscle groups which is been selected from the study of anatomy of hands, we placed electrodes that are required to get a good signal to study its nature. using a single bipolar channel and spacing the electrodes widely apart to achieve this[31]. One electrode must be applied to each of the triceps and the biceps. As a result, a large amount of muscle-related data is recorded and then overlaid into a single channel. The disadvantage is that global information is acquired but localized muscle information is not, as spatial resolution is restricted[31]. Using several bipolar channels with electrodes positioned close to one another is the alternative technique. This method offers both spatial resolution and localized muscle signal capture. Using several bipolar channels with electrodes positioned close to one another is the alternative technique. This method offers both spatial resolution and localized muscle signal capture[3].

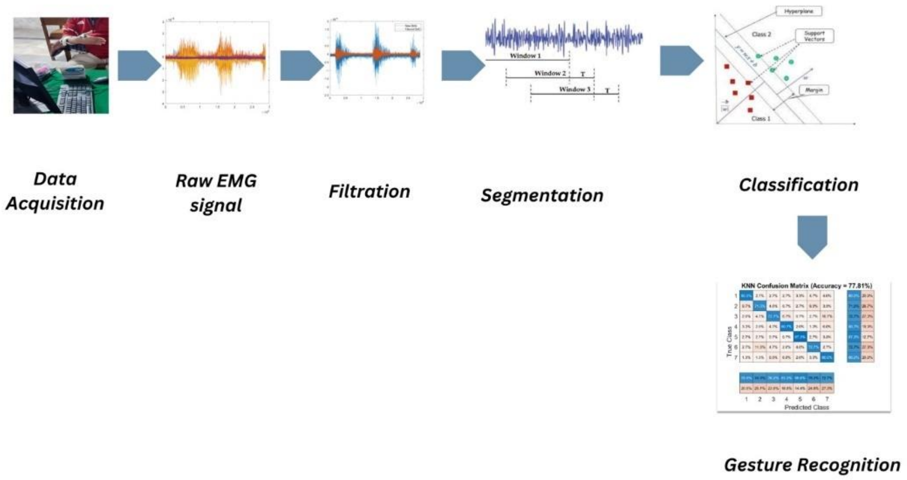

Figure 2.0-12: Myoelectric signal collection and processing

2.4.2 Pre processing:

Noise can interfere with the data that electrodes capture and the EMG signal; this noise might come from outside sources or from anatomical factors[32] The noise can be reduced with the right electrode locations and experimental setup.The following figure shows the pre processing of raw data

2.4.2.1 Interfering power hump:

There are several kinds of noises, and one of them may arise from an EMG amplifier that, when powered up, picks up ground-level noise and adds a baseline of 50/60 Hz[33]This noise is caused by improper grounding of the equipment or interference from other electrical devices. All of the instruments must be properly grounded in order to resolve this problem, and other devices shouldn't be permitted to interfere with EMG recording.

2.4.2.2 Base line Offset:

Another kind of noise resulting from baseline offset in the event that the experimental setup was altered or the calibration of the rest position was improperly carried out. The data may be corrected by applying the Offset correction function in order to address the baseline shift.This can be seen in the exiting data.

2.4.2.3 Base line shift:

Following a contraction, the normal EMG signal resets to zero, maintaining the rest line's zero position. The reason for this is because there is disturbance in placement of wires around device , which causes the baseline to shift from the zero fixed point and modifies the distance between the electrode and the muscle belly. The shift may also be observed after effort because of the way the muscles wobble or move in the belly. This problem may be resolved with proper cable and electrode repair[34]

2.5 Segmentation:

To splitting a continuous signal into meaningful and discrete intervals or segments according to specific standards or features is known as signal segmentation[35]. This method is widely applied in many domains, such as biological signal analysis, communication systems, and signal processing. Segmentation is to locate and separate distinct signal components that could correspond to certain occurrences, trends, noteworthy characteristics[36]One disadvantage of the longer segments is their processing complexity, particularly when it comes to real-time MEC[35]. There are two different kinds of segmentation: disjunct and overlap. Segment length is a property of the disjoint, and step size and segment length are properties of the overlap[36]

Types of segmenation are

2.5.1 Disjoint :

Disjoint segmentation is a technique in signal processing that involves breaking a continuous signal into non-overlapping segments. This approach facilitates the analysis of individual segments, enabling the extraction of relevant information and features from the signal.

2.5.2 Overlapping :

overlapping segmentation is a fundamental technique in signal processing that allows for a continuous and detailed analysis of signals by dividing them into overlapping segments. By preserving temporal context and capturing transient features, overlapping segmentation enhances the effectiveness of various signal processing tasks across different domains.

2.6 Feature Extraction:

In order to categorise motions resulting from motion pattern recognition, feature extraction plays a crucial role in improving performance.[37]The EMG gadget converts the raw signal it received into feature vectors. The three basic kinds of EMG signals are frequency domain (FD), time domain (TD), and frequency-time domain (FTD).[38]

These signals' amplitudes are dependent on amplitude with changing time. Additionally, the strength of the signal and the way it is perceived are altered by muscle conditions. TFD may be used to provide dynamic frequency information by characterising various frequencies at various time domains[15].Hu and Oskei have illustrated the factors influencing the signal analysis domain[39].Throughout research, additional TD and FD characteristics have been discovered at various points[37], [38].In 1993, Hudgins et al. proposed four TD features: mean absolute value (MAV), zero crossing (ZC), waveform length (WL), and slope sign changes (SSC)[40].Tsai et al. (2015) state that the time required for feature extraction is 10 ms for a 200 ms segment and can be related to both static and dynamic arm contractions. Although FD information can be roughly translated using TD's SSC and ZC features, EMG data is not converted to FD[41].characteristics were extracted and MAV, ZC, SSC, RMC, variance, and standard deviation (SD) were collected by Ashan et al. (2016)[42].

In 2013, work was completed in the area of feature extraction, and a further WL feature was sent into the classifier as an input[2].In addition to RMS and SD, another TD component called Maximum Amplitude (MAX) was discovered and utilised to interpret the signal at various loads.[43]Among those, SD was determined to be the most effective feature for classification; moreover, MAX and RMS were determined to be features that functioned best when combined with SD as a helpful feature vector.[2]RMS in TD can be utilised for every channel, according to a study conducted by Balbinot and Favieiro (2013), and they may be used as input for a classifier for windowing signals in the event of movement.[44]When compared to ZC, WL, SSC, MAV, and MAX, it was discovered that RMS was the best parameter since it could give a quantitative measure for electrode selection and, as a result, the best performance based on the facial motions of the EMG data. In addition, there exist other integrated electromyography aspects that may be employed to ascertain the signal duration, amplitude, and power associated with increased muscle fibre response to external stimuli. According to certain research, characteristics may be retrieved from the raw data from time-related EMG series, [2], [38], [41], [43], [44]. Few research have employed FD characteristics to identify patterns in movement.[2], [37], [41], [43].As revealed by Fattah et al., some frequency domain or spectral characteristics are also employed for motor unit recruitment and are used in the evaluation of muscle fatigue[45]

The FD was linked to changes in EMG signals that were connected to the median power frequency (MPF). These changes were associated to a shift towards lower frequencies, which allowed for the mapping of either an increase in high-frequency or a decrease in low-spectrum. In clinical settings, MPF power spectrum analysis is used to collect data on the alterations in brain and muscle signals that are caused in stroke survivors.According to the study, isometric contraction force causes stroke patients' paretic muscles to have a lower

MPF than their contralateral muscles.[46]As an alternative, PSD in the power spectrum paired with mean frequency (MNF) and median power frequency (MNP) can be used to characterise EMG signals, namely in the case of muscular contractions. In a research conducted by Phinyomark the features were adjusted to allow for the extraction of robust features and the monitoring of fatigue progression. In addition to MNF, bandwidth (BW), median frequency (MDF), normalised spectral moments (NSM), and MNF can also be used to assess muscular weariness in the upper limbs.[41]Studies that compare TD and FD properties have also been conducted. Phinyomark compared 27 TD and eleven FD variables related to hand movement[2]

Table 2.1: Time and frequency domain qulaities in literature review

Time Domain	**Frequency Domain**
Variance	Modefied mean frequency
Maximum amplitude	Modefied median frequency
Integral absolute value	Wavelet decomposition differences
Maximum Ampitude	Wavelength decomposition
Sample Entropy	Short Time Fourier transform
Standard deviation	Spectral moment
Mean absolute value	Signal-to-noise ratio
Mean value	Signal-to-motion artifact ratio
Histogram of Emg	Power spectrum ratio
Mean Absolute value slope	Frequency ratio
Average amplitude change	Mean power frequency
Log detector	Total power
v-Order	
Kurtosis	
Willison amplitude or Wilson amplitude	
Slope sign change	
Zero crossing	
Waveform length	
Variance	
Modified mean absolute value 2	
Modified mean absolute value 1	

Integrated Emg	
Multiple hamming windows	

Based on statistical research, it was determined about the TD features.Although the TD features' dimensions and time consumption were quicker, the performance recognition was deemed to be inadequate.

2.7 Classification:

The information obtained from EMG characteristics is given into the classifier to link patterns to movements. Classifiers receive the extracted features and apply them to categorise the characteristics into distinct control directions.After these traits are classified by the classifiers, control commands are produced. Artificial Neural Networks (ANN), fuzzy logic (FL), Bayesian Classifiers (BC), support vector machines (SVM), multilayer perceptrons (MLP), linear discriminant analysis (LDA), K-nearest neighbours (KNN), and hidden Markov Models (HMM) are some of the models that are available for classifying EMG features into a control command[47]. These classifiers have been utilised successfully in several research, and more classifiers are being employed as well[48][49]. It was demonstrated by Englehart et al. (2003) that feature extraction and dimensionality reduction affect classifier performance[50]The study employed a few statistical classifiers, including MLP and LDA, to categorise the hand gestures. The study's highest accuracy was obtained using LDA, which produced 93.75% accuracy when combined with PCA[48]. It has been shown that MLP performed better in establishing class borders[51]

2.7.1 SVM Support Vector Mchine :

An SVM classifier is a binary classifier that uses support vectors from each class to create a hyperplane that maximally separates the classes. A parameter C is supplied since it is not always feasible to segregate classes. The value was assigned as 1 in this work.The SVM algorithm was extended using a one-versus-all approach in order to facilitate the classification of multi-class data, given that SVM is originally designed as a binary classifier. Consequently, a binary classifier was generated for each class. All samples that conform to that class are classified as positive samples, while the rest are classified as negative samples. Binary classifiers collaborate to determine the output class for a multi-class classifier when categorising a new test sample[52]

2.7.2 K nearest Neighbour (KNN):

Another classifier is a K-Nearest Neighbour algorithm. The algorithm identifies the K data points that have the closest Euclidean distance to the test model, and uses them to classify a fresh test sample. The test sample is thereafter classified based on its proximity to the class that has the highest number of neighbouring points. If there is a tie, the nearest neighbour class is selected.

2.7.3 Linear discriminent Analysis(LDA):

Linear Discriminant Analysis (LDA) is commonly used to classify human hand movement using electromyography (EMG) data .The goal of Linear Discriminant Analysis (LDA) is to identify a hyperplane that can effectively classify data points belonging to different hand movements. The hyperplane is derived by seeking an estimator that exhibits a significant separation between average classes and reduces within-class variability, assuming that the data follows a normal distribution[29]The classifier's performance is improved by PCA dimensionality reduction, which made it simpler for the classifier to distinguish between other classifiers. Phinyomark et al. (2013) compared the effectiveness of RFS, LDA, KNN, MLP, and SVM in classifying 10 motions of the upper limb[41]While research by Al-Jumaily and Khushaba (2018) indicated that accuracy with MLP was 99%, the feature set employed in this situation was TFD. LDA had an accuracy of 98% on TD features[53].When dealing with nonlinear data between various movements,was shown to be more appropriate. Least-square errors were discovered to be the limit foroutput.[29].

2.7.4 Classification Accuracy:

Accuracy is a statistic commonly used to evaluate the performance of a classification system. The effectiveness of the classification system is validated by the utilization of computational data and the accuracy rate of system classification. [54]The concept of prediction accuracy has been extensively utilized in numerous studies, and it can be described as follows.

$$classification\ Accuracy = \frac{No\ of\ correct\ predictions}{total\ no\ of\ predictions} * 100\%$$

Chapter 3

Methodology

3.1 Subjects:

The study come from a group of 5 people who had suffered the severe consequences of a stroke. These patients had upper limb abnormalities that were linked to their stroke, which made it difficult for them to carry out routine duties effectively. The research participants' average age was found to be 50 years old. The study specifically recruited participants who had experienced a stroke for a period longer than six months to provide a thorough analysis of the long-term effects of this illness. some tests were taken from them to either they are suitable for this study are not we did Fugel Mayer test to see their muscle spasticity. If their score is between 25 to 55, they were included in the study also modifiedAshworth scale MOCA is been tasted for patients if their ranges come equal or greater than 21 then we included these patients for study. And another test has been taken called MAC,Montreal Cognitive Assessment if its score is less than 4 then these subjects are including in the studywith age group also if they are more than 18 years. There are some test for inclusion criteria for stroke patients they are modified Ashworth scale, Montreal cognitive Assessment and Fugl-Meyer Assessment also the age should be equal or greater than 18 years. While the exclusion criteria is wrist impairments, vestibular issues and external fixation then We carefully followed ethical guidelines, asking each participant to sign a written document indicating their informed permission. The study demonstrated the dedication to upholding the highest standards of ethical conduct throughout the whole research method by adhering to the ethical guidelines specified in the Helsinki Declaration for medical research.

Table 3.1: Patients Demographic Data

Subject	Sex and Month since injury	Affected side	Type of injury
1	Male ,10 months	Right	ischemic
2	Female,18 months	Left	ischemic
3	Male ,16 months	Left	Hemorrhagic
4	Male ,12 months	Right	ischemic
5	Male ,15 months	Right	ischemic

3.2 Data Collection:

Data protocol was design for patients, baseline was collected before VR session to examine how much the person is getting benefits from the therapy or not, the rest of Emg has been collected onward after VR session, in that VR session there are some games designs for specific hand motion been targeted in rehabilitation.

Surface Emg electrodes were positioned on the patient's hand in desired places in this system according to a carefully thought-out strategy. A non-invasive method was used to put the patients' comfort and well-being first. The procedure's non-invasiveness enhanced the patients' general sense of wellbeing and willingness to actively engage in the activities they were given.

Five electrodes were positioned at different points on the upper limb to provide a thorough examination of muscle activation. We targeted 5 electrode position with no reference they are dorsal interossei for pinch, Flexor carpusal radialus for flection motion, Extensor digtorium communis for extension,pronator teres for pronation and supinator for supination, this deliberate placement made it possible to gather subtitle information that enabled a thorough analysis of the effects of stroke-related upper limb abnormalities. For the study to make inferences about the difficulties and capacities connected with the observed muscle activity in the affected upper limbs, the patients' cooperation during task performance further improved the validity and relevance of the recorded data. The data recoding flow chart design for this study is given below.

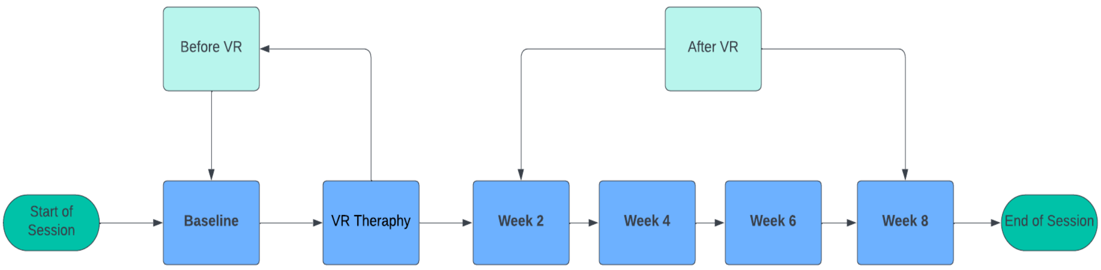

Figure 3.0-1 : Data recording Flow chart for Stroke Patient

A Graphical User Interface (GUI) in MATLAB was used to carefully design a customized procedure that streamlined the recording of electromyographic (EMG) signals. The user-friendly figure of this interface was crucial in making the patients' mobility tasks easier. In addition to being easy to use, the GUI's intuitive design made sure that patients could carry out their prescribed motions with ease, and the system captured the appropriate EMG signals in real-time with ease. The MATLAB GUI was built to gather and interpret

EMG signals concurrently with patients' functional activities. This allowed for a dynamic and interactive platform for data acquisition. In addition to improving the patients' experience, the usage of this graphical interface increased the precision and effectiveness of signal recording. The data was carefully saved in a MATLAB file format (mat file) to enable further analysis and guarantee the availability of the recorded information. With this file format option, researchers may import the recorded EMG signals into MATLAB or other compatible systems with ease and use them for more thorough analysis and interpretation. This methodical approach to data management guarantees that the captured signals will be seamlessly incorporated into the next steps of the research process.

A well-thought-out methodology was followed for gathering patient data, with a planned timeframe. Each session took place every two weeks, with the collection intervals fixed at a biweekly frequency. Over the course of this lengthy and methodical data gathering process, which lasted eight weeks, patients regularly engaged in line with the defined protocol.

We first used alcohol strips to rub the skin and make its impedance low for data recording then the electrode was placed by specially designed double tap before applying for impedance use to shave the place for noise reduction in signal acquisition and it was wireless connected to the system, so it makes it easy to acquire signal and later save it in mat file.

.For data collection the sampling frequency of 1925.8Hz was taken and a band width of 10-450Hz to record our signal.

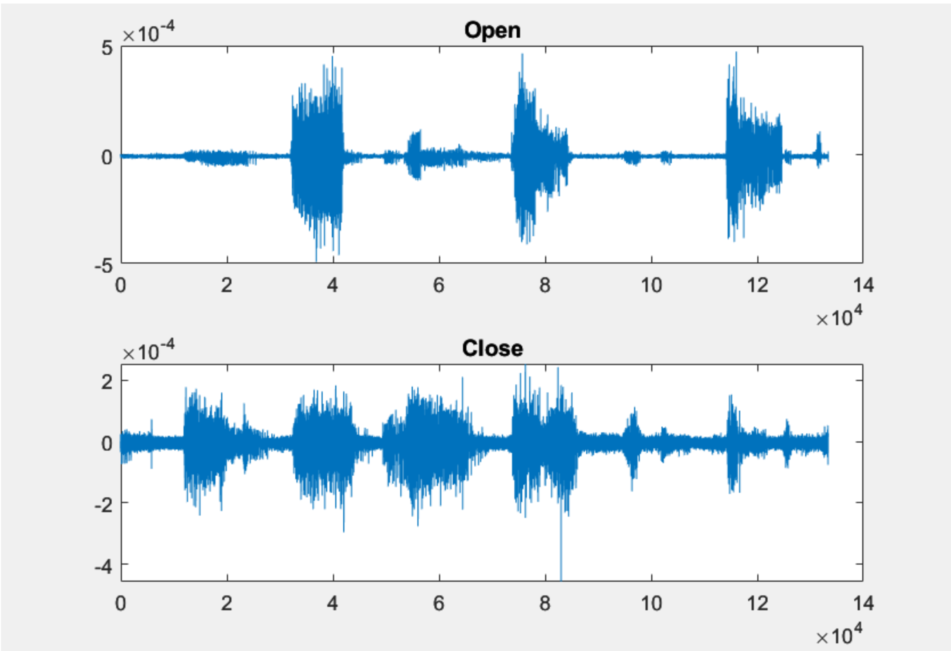

Figure 3.0-2: Emg plot of stroke patient.

3.3 Experimental Procedure:

The experimental setup is performed in Holy familyHospital. Before performing the experiment, the patients were guided according to protocol.There were also some figures for open hand, closed hand,pronation,supination, flection and extension, and pinch in the protocol which helped them to understand and perform the desiredmotion.The protocol was designed for 7 motions that are Pinch (Pi), Wrist Flection (WF),wrist Extension (WE), OpenHand (OH), Close Hand (CH), Supination (SUP), Pronation (PRO).At first, we guided the patients about the movement and about the protocol design for the task.Patients perform the motion 3 times repeatedly with a 5 sec rest then perform motion according to the protocol. With the figures attached in the design GUI make them guide about the activity they used to perform on the specific time and the data be recorded by delsys.The session of a subject costs them about 20 minutes of time for the experimental work.It is made sure that rest period and motion period are be discriminated easily and will help us in further study. Delsys trigno was used for data recording from stroke patients.

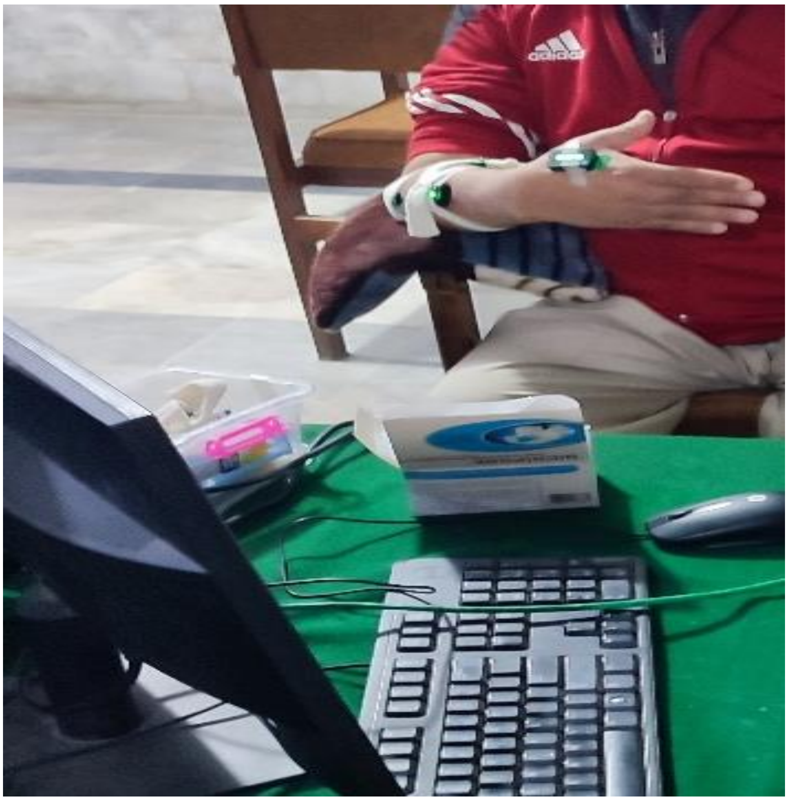

Figure 3.0-3: Delsys device used for data recording.

3.4 Pre-Processing:

The signal obtained from the stroke patients are raw signal and it is needed to be cleaned for further procedure, so in pre-processing the noise removal is done and the artifacts is removed by applying filters. This is the needforraw data to make it clean and ready for further study.A butter worth filter was designed for the signal for cut off frequency 10-450Hz. It helps to remove the motion artifacts and to remove nonstationary data a 5 second data onset and off set phase was removed from the signal.

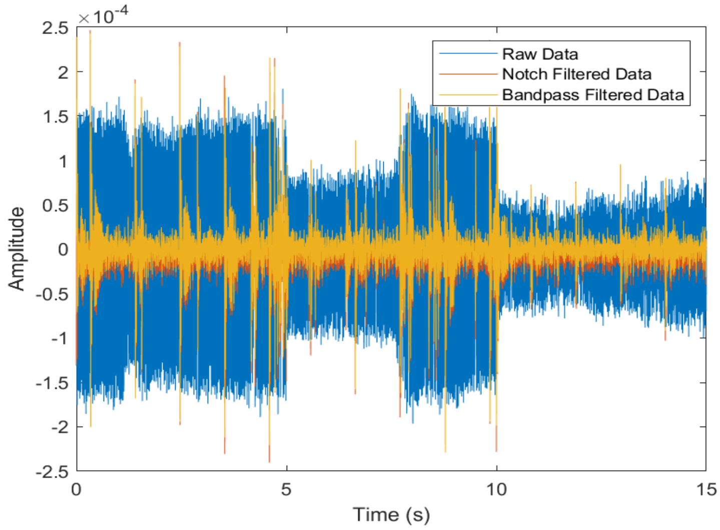

Figure 3.0-4: Preprocessed Emg data of a patient

A Butter worth filter was designed and implemented to enhance the quality of the signals obtained. The primary objective of this filter was to effectively remove motion artifacts and eliminate non-stationary data components. The Butter worth filter was specifically configured with a cutoff frequency range of 10-450Hz, ensuring that unwanted noise and interference outside this range were attenuated. By selectively allowing frequencies within the desired range to pass through, the filter successfully improved the overall signal integrity. Additionally, to further refine the datasets, a 5-second data onset and offset phase were removed from each recorded signal. This step aimed to eliminate any non-steady state portions at the beginning and end of the data, thereby focusing on the core period of interest. By implementing the Butter-worth filter and removing the initial and final transient phases, the resulting datasets achieved a higher level of reliability, enabling more accurate analysis and interpretation of the recorded signals for comprehensive research and clinical applications.The remaining data was deployed for segmentation.

3.5 Segmentation:

Segmentation technique has been employed for this with a window size of 250ms and 50ms overlap which is acquired for the desired signal for furtherprocedure. When compared to the other approach of disjoint segmentation, the study's use of overlap segmentation produced better categorization results. When using the overlap segmentation approach, 250 milliseconds for the window size and 25 milliseconds for the overlap were selected.[35]The segmentation was done for each subject with motion of all channels.

3.6 Feature Extraction:

For feature extraction we use time domain and frequency domain features to extract our features from the obtained segmented signal and then these features are used by classifier for further classification to be obtained classification accuracy.[55]. The features that are used in this study are as below.

3.6.1 Mean absolute value (MAV):

Mean absolute value is the average of the absolute deviations from a central point is known as the average absolute deviation of a data collection. It is a statistical dispersion or variability summary statistic.

$$MAV = \frac{1}{N}\sum_{0}^{N}|X_n|$$

3.6.2 Waveform length (WL):

The wavelength is the separation along all sEMG of two adjacent samples:

$$WL = \sum_{N=1}^{N}|x_{n+1} - x_n|$$

3.6.3 Zero crossing (ZC):

The number of times the sEMG amplitude changes from positive to negative is described by the zero-crossing characteristic. Its definition considers a threshold, the purpose of which is to count only the events caused by muscle contraction.

$$ZC = \sum_{n=1}^{N-1}\left[sgn\,(x_n \times x_{n+1})\bigcap|x_n - x_{n+1}| \geq 0\right], sgn(x) = \begin{cases}1, & x \geq thresould\\ 0, & otherwise\end{cases}$$

3.6.4 Root mean square (RMS):

The square root of the mean squared values is the root mean squared value (RMS), which provides information about the strength that a muscle produces. This characteristic is valued in several research studies for various tasks.

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N}x_n^2}$$

3.6.5 Cardinality (CD):

It can be defined as "A quantity correlation among the components of data se[56]t.

3.6.6 Slope Sign Change (SSC):

The slope sign things count the number of times a slope sign between these sEMG values changes by considering three adjacent samples.

$$SCC = \sum_{n=2}^{N} f\big((x_n - x_{n-1}) \times (x_n - x_{n+1})\big), \qquad f(x) = \begin{cases} 1, & f = th \\ 0, & otherwise \end{cases}$$

Where th is threshold.

3.6.7 Variance (VR):

Since sEMG is a process that is close to zero mean according to the mathematical definition of variance, its definition becomes.

$$VAR = \frac{1}{N-1}\sum_{n-1}^{N} x_n^2$$

3.6.8 Means absolute deviation (MAD):

The average distance between each data point and the mean in a dataset is called the mean absolute deviation.

$$MAD = \frac{1}{n}\sum_{i=1}^{n} |x_i - m(X)|$$

Where,

- m(X)= Average value of data set
- n=No of data values
- and Xi= data values in set

3.6.9 Simple square integral (SSI):

The Simple Square Integral (SSI) expresses the energy of the EMG signal as a usable feature.

$$SSI = \sum_{i=1}^{N} (|x_i|)^2$$

3.6.10 Average energy (AE):

A signal either has finite energy, finite power, or even infinite power. If it has finite energy, it will have zero average power.

$$P(x) = \lim_{T_o \to \infty} \frac{1}{T}\int_{-\frac{T_o}{2}}^{\frac{T_o}{2}} |x(t)|^2 . dt$$

3.6.11 Mean frequency (Mf):

A spectrum's mean frequency may be found by multiplying the intensity of the spectrogram (measured in dB) by the frequency and then dividing the result by the overall intensity of the spectrogram.

$$Mf = \frac{\sum_{i=0}^{n} I_i . f_i}{\sum_{i=0}^{n} I_i}$$

3.6.12 Median frequency(mf):

The median frequency represents the midpoint of the power distribution in the CSA and is the frequency below and above which lies 50% of the total power

$$f_{med} = \int_{0}^{f_{med}} P(f)df$$

Where,

- P is power spectral density function.

3.6.13 Total power (Tp):

When all signals have identical power, the following formula can be used to calculate total power:

$$P_{total} = P_{one} + 10\log_{10}(N)$$

Where,

- P_{total} is total power,
- P_{one} is the power of one signal, and
- N is the number of signals.

3.6.14 Mean power:

The mean power of a time-varying signal *x*(*t*) over a time intervalis calculated using the following integral.

$$P_{avg} = \lim_{T\to\infty} \frac{1}{T} \int_{T_1}^{T_2} |x(t)|^2 . dt$$

3.6.15 Frequencyratio:

Frequency ratios are crucial when working with modulation or filters. The features of the modulated signal intensity in frequency modulation are influenced by the frequency ratio between the modulating and carrier signals.

$$\Upsilon = \frac{f_1}{f_2}$$

After Extraction of these features, they are used as input for classifiers.

3.7 Classification:

The careful classification of the detected characteristics was the last step in the process. The ensuing motion prediction depended heavily on this categorization. We used three different classifier types—K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), and Support Vector Machine (SVM)—to achieve this. The reasoning for choosing these classifiers was based on the extensive literature study, which highlighted their effectiveness in the context of classification problems.

The formulas for calculation of accuracy is given below

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

Where,

- TP=True positive
- TN=True Negative
- FP= False positive
- FN = False Negative

And sensitivity /Recall is calculated by.

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

Uncovering the predictive complexities of the designated classes in comparison to their real counterparts was made possible due in large part to each of these classifiers. By using SVM, LDA, and KNN carefully, we were able to extract meaningful findings. The precision displayed by every classifier was quantified by the performance matrices, which disclosed the classification accuracy. This accuracy was crucial in helping to comprehend and decode hand motion patterns, especially when it came to stroke patients, and it also measured how well the classifiers performed in predicting outcomes.

Our utilization of SVM, LDA, and KNN as classification tools not only adhered to established literature recommendations but also provided a robust foundation for comprehending and enhancing the predictive capabilities of our model. The derived classification accuracy values, encapsulated within the matrices, served as valuable metrics in evaluating the suitability of these classifiers for the intricate task of decoding hand motion for individuals affected by stroke.The results with classification accuracy be discussed in the results section to which we can predict which classifier is better to be used further based on their accuracy.

3.7.1 Classification plots:

The classification results can be seen using a classification plot that uses a time series-based trained classifier. The classification plot is a suitable method for analyzing the output of a classifier. This graphical figure depicts the precise class represented on the y-axis, with a scale of time on the x-axis. An advantage of this graphic is that it clearly displays the distribution of errors and their corresponding temporal locations.

3.8 Statistical Analysis:

A one-way ANOVA test is performed to see whether there is a significant difference in the groups and to see which classifier is best among them to used further for classification of decoding of hand motion. As the groups were three in classification of 5 subject so this test is used, if it were two then we use t test for further analysis. Its results are being explained in the result section. The probability value <0.05 is taken as standard. Also, the standard deviation shows us how much there is variation in data points.

Chapter 4

Results and Discussion

4.1 Confusion matrix and Accuracy:

The received data input into a model after carrying out the cleaning, preprocessing, and disputing to acquire the output as a probability. The classifier correctness measurement after some training is called accuracy. Different aspects like training dataset size, dataset type, classifier type, seeding value, etc. affect accuracy.Efficacy evaluation of the categorization is necessary, and uncertainty. The matrix technique is a measure of machine learning performance for classification. From the outside looking in, it resembles an NXN matrix, where "N" represents the number of categories for secured information. The actual and expected numbers of data classes are shown in the rows and columns of this matrix, respectively. A diagonal matrix with all members set to 1 is optimal for classifiers since it allows for the most precise prediction. Of course, the matrix also displays the number of misclassifications along with their respective places, because not all predictions pan out.

The confusion Metrix is being obtained with all three classifiers for different patients individually which tells us about its true and predicted class. Their classification accuracy tells us how much this classifier classified these movements of decoding of hand motion correctly.Also, it gives us knowledge about its sensitivity in decoding of specific motion for different classes. Three different confusion matrices have been created using three classifiers—Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and k-Nearest Neighbors (KNN). The data was processed through these classifiers to determine their accuracy in classifying information. The confusion matrices, presented below, show the results of this classification process. They help in understanding how well each classifier performed, making it easier to see which one works best for the given data. These matrices provide a straightforward overview of the classification outcomes, offering insights into the strengths and potential limitations of each classifier.

The confusion matrix represents data of a stroke patient that has been classified by SVM, where 1 represent open hand,2 represent Close hand 3 represent Flexion, and 4 represent Extension, 5 represent Pinch ,6 represent supination, 7 represent pronation. The diagonal shows true positive value that it has been classified while the rest up and down shows us false positive values that it predicted wrongly. There are 7 motion that we want to decode for a stroke patient they are flexion and extension, pinch, open and close, pronation and supination. The no shows us the sequence of these motions that has been classified by this classifier. The classification accuracy is based on the average of these moments. Now comes the second classifier that is LDA, the result of this classifier is given below.

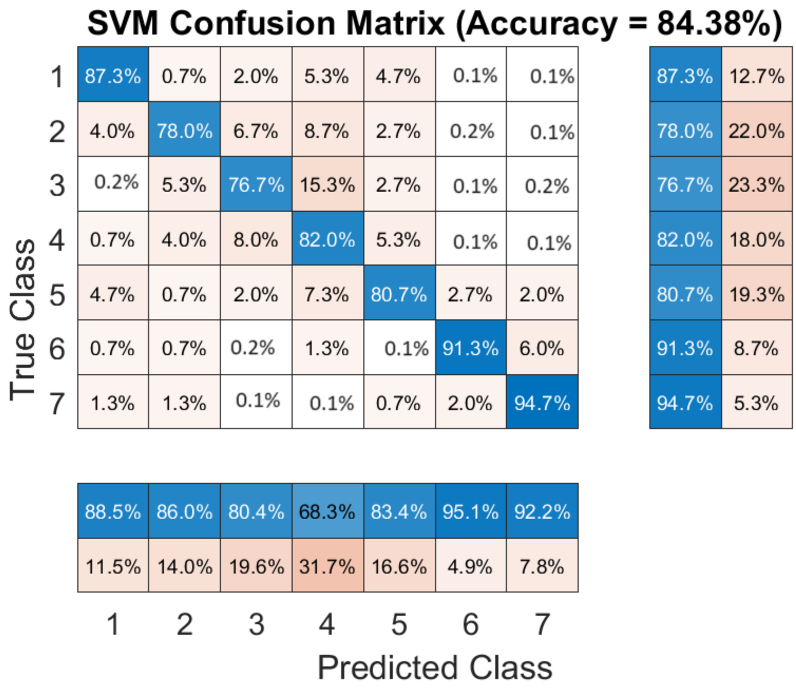

Figure 4.0-1:SVM classifier used for classification of Emg data of stroke patient

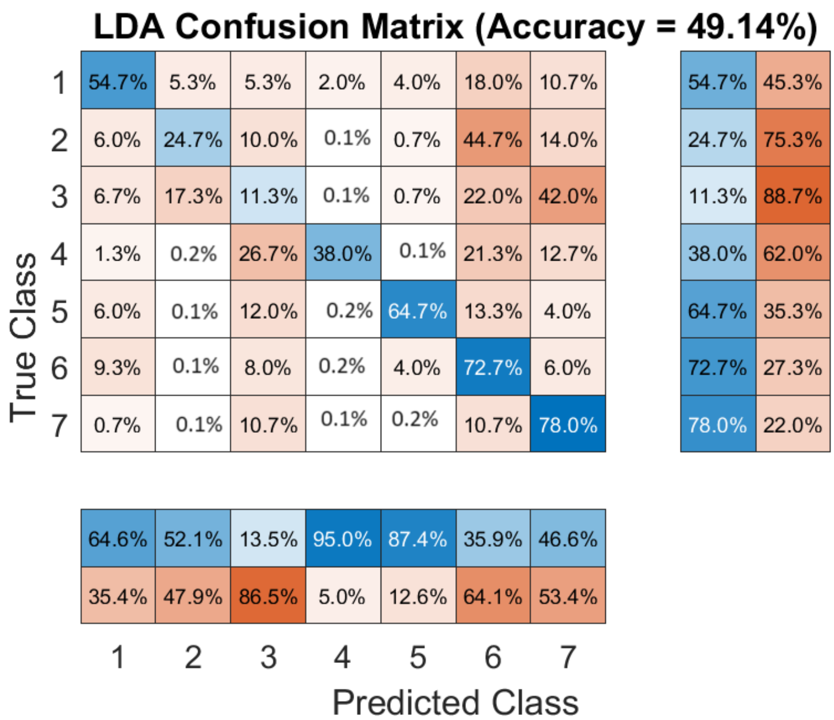

Figure 4.0-2:LDA classifier used for classification of Emg data of stroke patient.

The diagonal element shows us true hand movement classification the matrix is classified truly.The right side of the Confusion Metrix shows overall precision while the bottom side of the figure shows us Sensitivity of the classifier we used for classification.Now here it comes down to the third classifier that we used for our classification

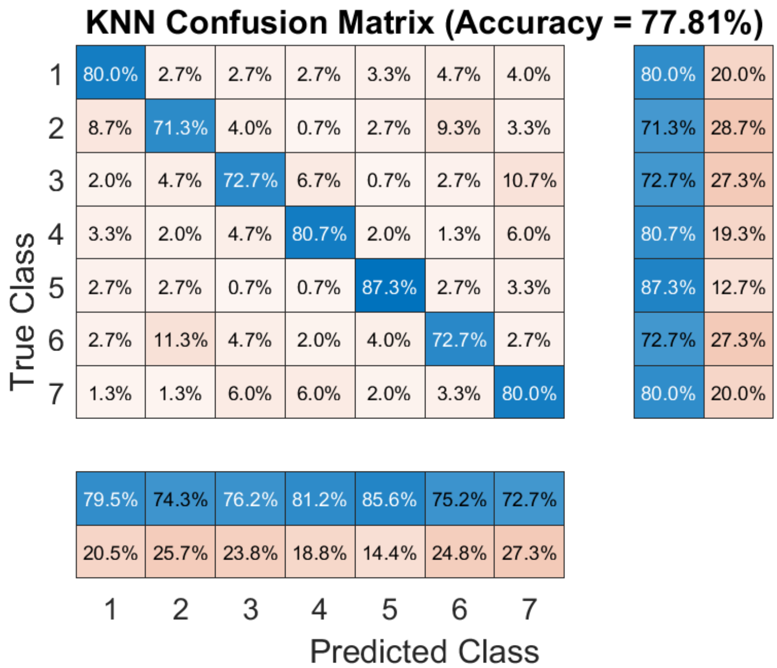

Figure 4.0-3:KNN classifier for classification of Emg data for stroke patients

From this classification accuracy we get we acquire all the results for all patients by getting its classification accuracy for all session that helps us to understand its decoding of hand moments for stroke patients.For one patient it is given below in table.

Table 4.1: Based on SessionClassification accuracy of stroke patient.

Session	SVM	LDA	KNN
Baseline	66.86	47.43	65.52
Week 2	78.76	50.76	75.24
Week 4	81.81	58.38	75.90
Week 6	84	61.71	77.14
Week 8	86.38	66.52	83.43
Mean	79.562	56.894	75.446

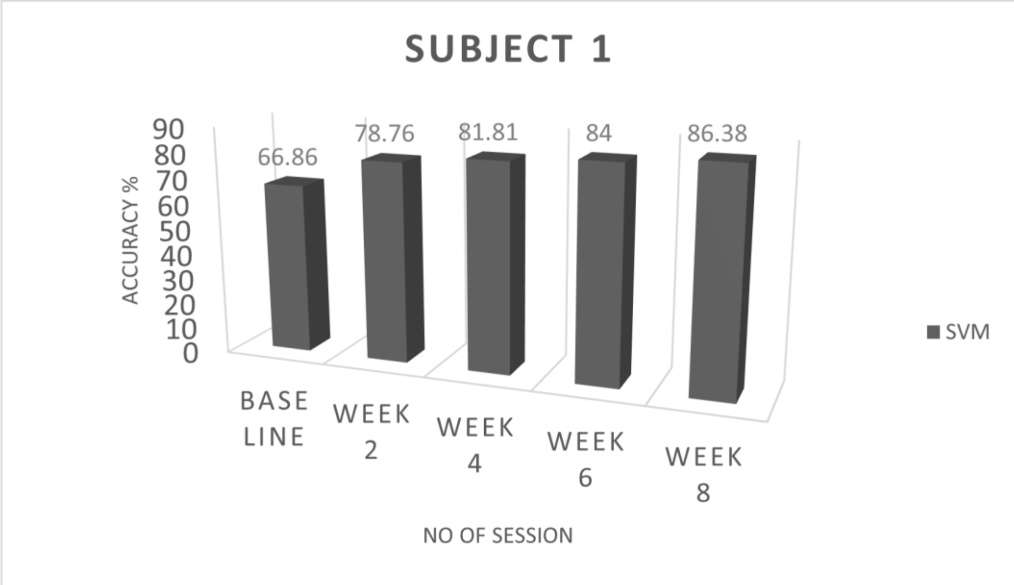

Figure 4.0-4:SVM classifier for Classification of a patient moments.

Figure 4.4 shows x-axis shows us session that are used for data collection while y axis represents percentage of classification accuracy that ranges from 0 to 100.The bars represent the classification accuracy that has been obtained by classifier our 7 motionsperformed from patients in blackbar it was around 69 till week 8 it becomes 86 percent.The trait change occurs because of improvement of patients when he perform exercise, the baseline was before our therapy while it gradually increase when the experiment goes on.. While the mean value of this patient is quite good for this classifier.

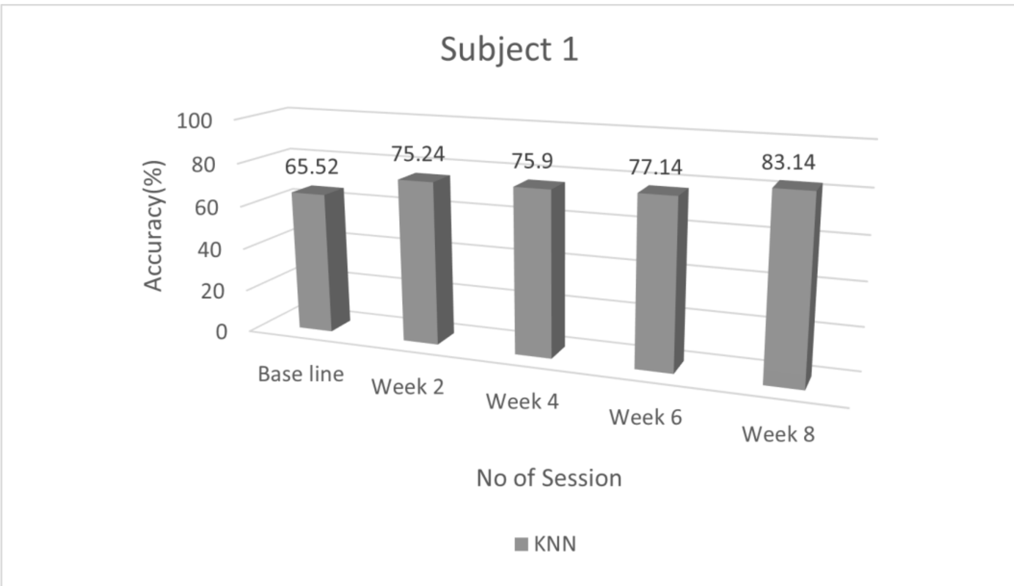

Figure 4.0-5:KNN classifier used for classification of patient.

Figure 4.5 also the x axis shows us the data recorded per session of different weeks and the y axis shows us the percentage which ranges from 0 to 90.The gray bar shows us the classification accuracy that on baseline it is around 65.52% and gradually increases to83.14%

at week 8.It means that this classifier also classifies these moments of hand motions well. where the mean value of this classier is well but less than SVM that perform better classification.

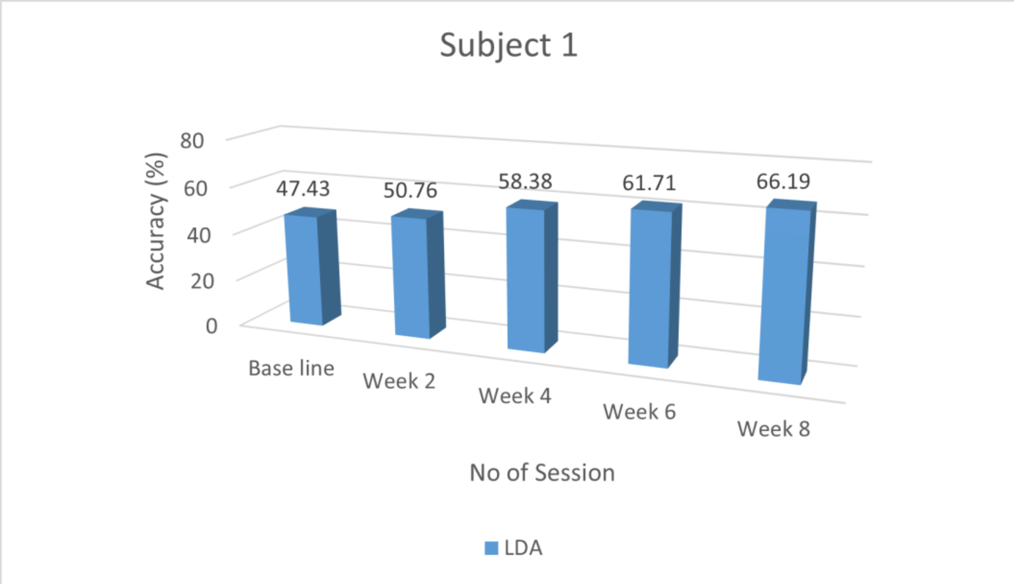

Figure 4.0-6:LDA classifier use for classification for stroke patient.

From figure 4.6 it shows the results of classification accuracy based on number of sessions in base line the accuracy is 47.43% that is been increase by applying VR therapy with till week 8 it become decrease that shows us some this classifier is the least accuracy for classification of decoding of hand motion of patients. While its mean also become the least among these three classifiers that is 56.8 from table 4.1Now the overall combine graph of these three classifiers is given below.

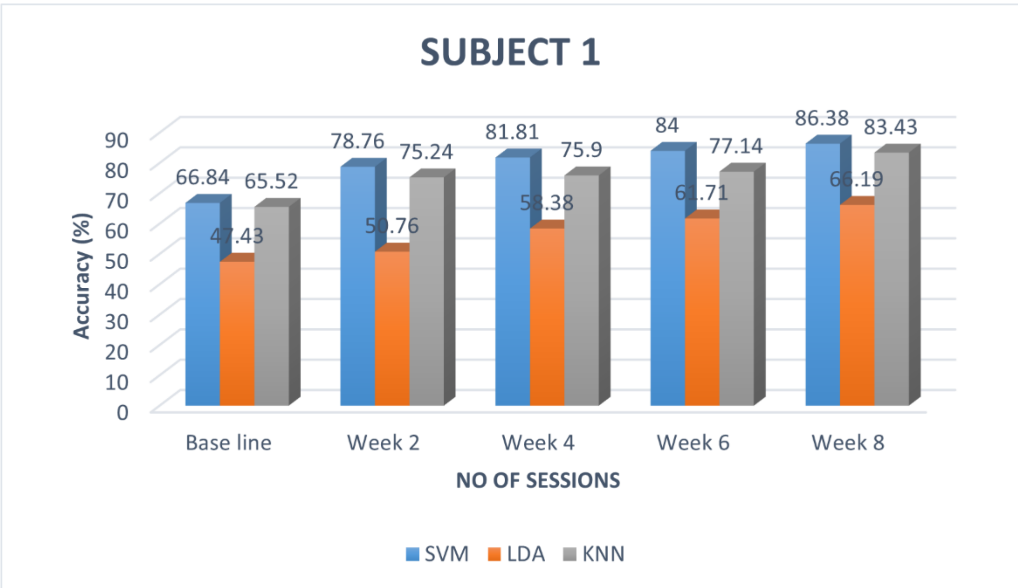

Figure 4.0-7: All three classifiers combination for a patients

While figure 4.7 shows us the comparison of these three-classifier used for a subject data to decode it moments based on features .as we see from the figure the performance of SVM is better from baseline and then second one is KNN while the LDA is least one based on their accuracy and their cumulative mean we can give this results to get one based on performance we are going to discuss it for all patients.Now for the second patient some variation comes in accuracy of patients.

Table 4.2: Classificationaccuracy-based2nd subject.

Session	SVM	LDA	KNN
Base line	68.67	37.24	67.14
Week 2	69.05	40.67	69.52
Week 4	71.71	42.1	69.14
Week 6	73.71	49.14	76.76
Week 8	75.24	52.29	77.81
Mean	71.67	44.28	72.07

The table represents the classification accuracies of three different classifiers—Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and k-Nearest Neighbors (KNN)—across various assessment sessions (baseline, Week 2, Week 4, Week 6, and Week 8).At the baseline, the classifiers achieved the following accuracies: SVM 68.67%, LDA 37.24%, and KNN 67.14%. all of these were collected before the starting of VR therapy from for stroke patients. These percentages indicate how well each classifier performed in accurately classifying data related to stroke patients at the initial assessment.

In the second week of assessment, there were changes in accuracy This reflects potential shifts in the classifiers' performance as stroke patients progressed through the second week of the study.By the fourth week, further changes in accuracies were observed. These values provide insights into the classifiers' adaptability or challenges in capturing patterns related to stroke progression.

At the eighth week, accuracies increased compared to previous weeks: SVM 75.24%, LDA 52.29%, and KNN 77.81%. These values indicate potential improvements in classifier performance as the study reached its conclusion.

The mean row provides the average classification accuracies across all sessions. On average, SVM achieved 71.676%, LDA 44.288%, and KNN 72.074%. This average helps summarize the overall performance of each classifier throughout the study.The trends in accuracy offer valuable insights into the classifiers' abilities to capture and adapt to patterns associated with stroke progression at various stages of the study. Based on the classifiers

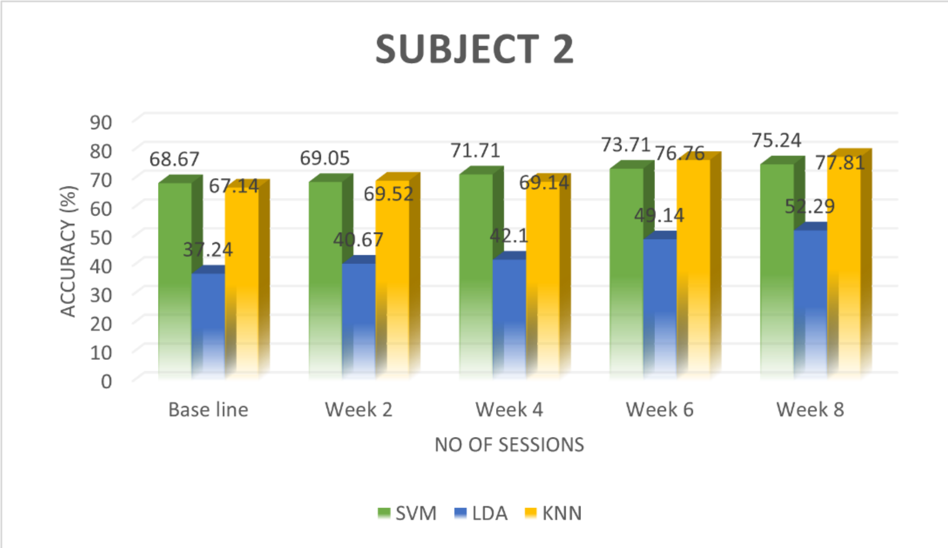

Figure 4.0-8:classification accuracy based on Classifiers for 2ndpatients.

While the rest of the study is also shown in the figure given below, all of them are based on classification accuracy.

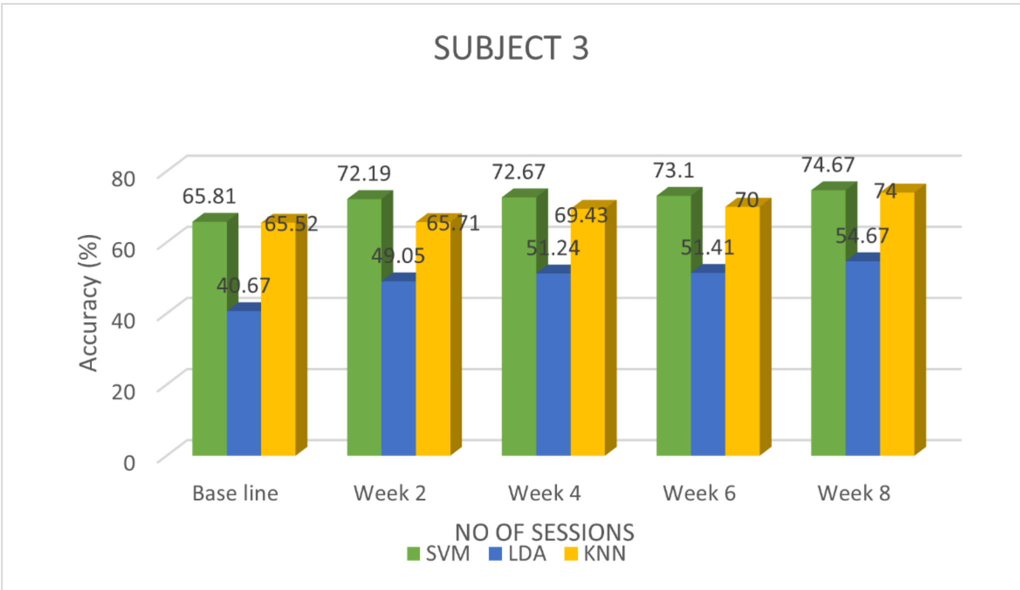

Figure 4.0-9:classification accuracy based on Classifiers for 3rd patients.

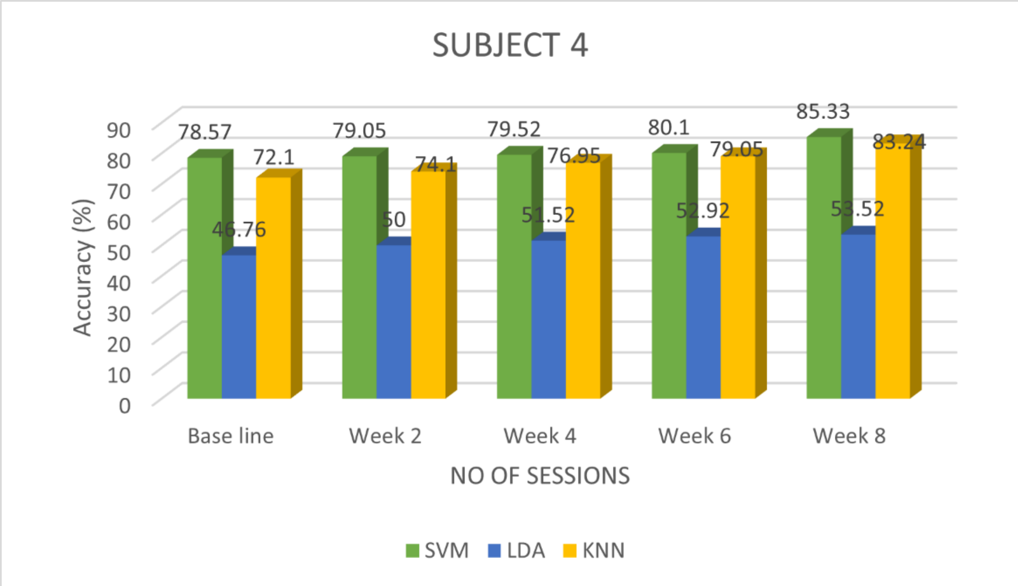

Figure 4.0-10:classification accuracy based on Classifiers for 4thpatients.

The graph shows the accuracy of stroke patients that perform VR treatment for 8 week, based on the predictions of each algorithm. The SVM algorithm had the highest mean, with 80.51% of patients completing the program. The LDA algorithm had a mean completion rate of 50.8%, and the KNN algorithm had a completion rate of 77.09%.

The graph also shows the number of sessions that patients attended each week. Patients who were predicted by the SVM algorithm to be more likely to complete the program attended more sessions on average than patients who were predicted by the other algorithms to be less likely to complete the program.

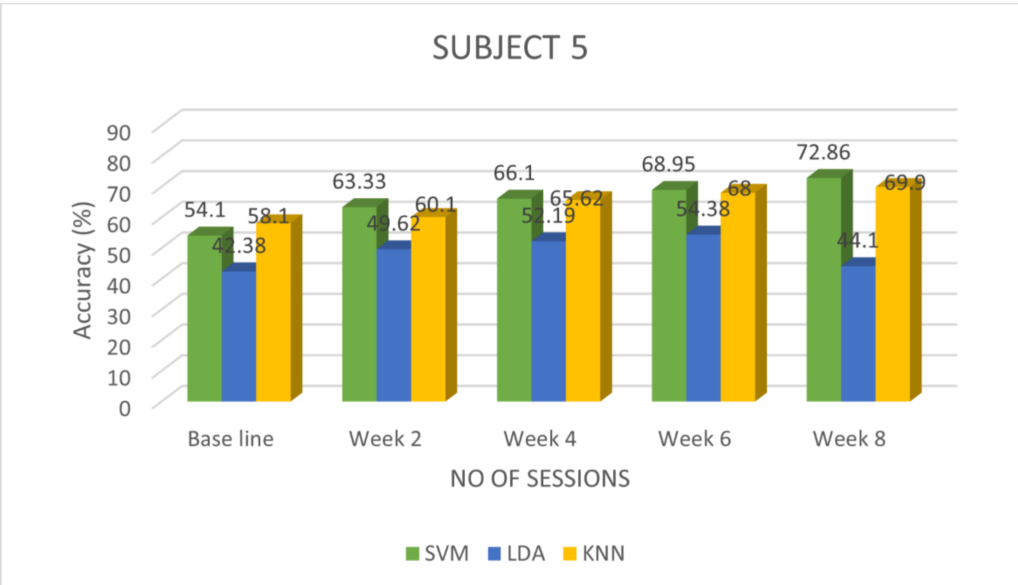

Figure 4.0-11:classification accuracy based on Classifiers for 5th patients.

Similarly, from figure 4.11 above it is shown that after baseline there is an increase in accuracy till week 8 when the therapy is done for all session for stroke patients. And here also SVM perform better results in classification among LDA And KNN, where KNN comes second better results and LDA least for decoding of hand motion .

Then results werecombining the means of all classifiers for better understanding of the data as it helps us easily in understanding.

Table 4.3: Overall mean with Classifier Means per subjects.

Subjects	**SVM**	**LDA**	**KNN**
1	79.562	56.894	75.446
2	71.676	44.288	72.07
3	71.658	49.408	69.122
4	80.516	50.818	77.098
5	65.068	48.534	64.344
Overall Mean	73.696	49.9884	71.616
Standard deviation(SD)	6.395283	4.564051	5.099739

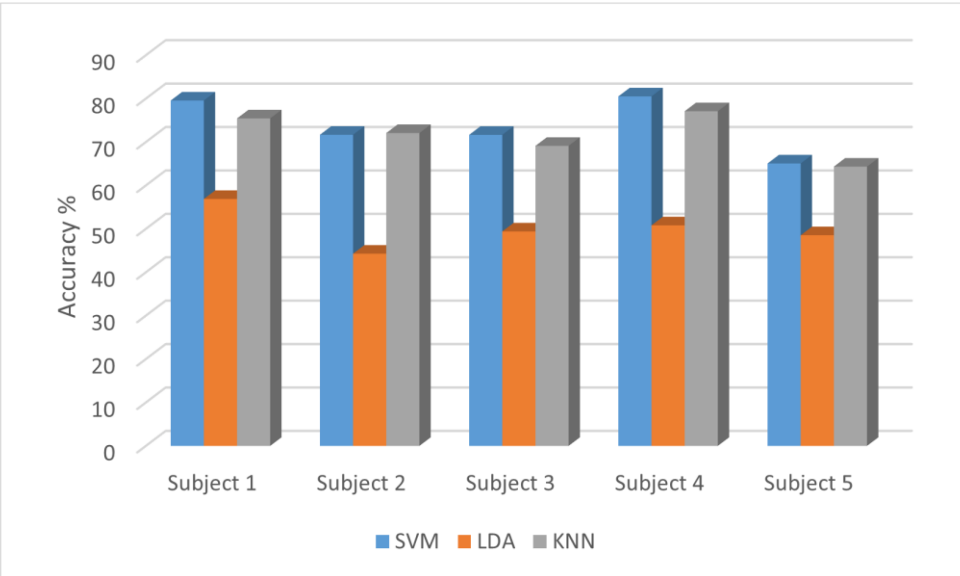

Figure 4.0-12: Comparison of classifier based on overall Accuracy for all subjects.

Figure 4.8 shows the results from classification of different subjects, their means are calculated and is shown in the graph. Based on subject variability there are some variations in classification accuracy that has been seen by the classifiers. The X axis represents no of subjects while the Y axis represent mean accuracy per subject for three classifiers.

Now as seen from the graphSVM consistently outperforms both LDA and KNN, with an overall mean accuracy of 73.696%. LDA comes in second with 49.9884%, followed by KNN with 71.616%. from table 4.3.SVM achieves the highest accuracy in all subjects except for Subject 2, where LDA slightly outperforms it.LDA consistently performs better than KNN in all subjects.

From the graph it is suggested that SVM is generally successful for this classification of the task because it is the most consistently accurate classifier across participants. Because LDA and KNN are less reliable, they might need more better work with this kind of data.Subject 2,3,5 have comparatively lower bars, which suggests that the classifier performance varies less. Subject 3 and others exhibit bigger error bars, indicating more notable variations in accuracy within each classifier.

4.2 Statistical Performance:

Table 4.4: Comparison of all classifiers

Groups	Count	Sum	Average	Variance
SVM	5	368.48	73.696	40.89965
LDA	5	249.942	49.9884	20.83056
KNN	5	358.08	71.616	26.00734

Table 4.5:ANOVA one way test results for all classifier

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1723.55	2	861.7748	29.46657	2.34E-05	3.885294
Within Groups	350.9502	12	29.24585			
Total	2074.5	14				

While investigating the performance based on statistical analysis a One-way anova test is been performed to see which classifier is most significant for classification of hand motion decoding.The results of the ANOVA showed that there was a statistically significant difference between the means of the groups ($F (2, 12) = 29.46657$, $p < 0.05$).

Table 4.6: Comparison between SVM and LDA

Groups	Count	Sum	Average	Variance
SVM	5	368.48	73.696	40.89965
LDA	5	249.942	49.9884	20.83056

The mean for group 1 i-e SVM was 73.696, the mean for group 2 i-e LDA was 49.9884, and the mean for group 3 was KNNi-e 71.616. as shown from the figure 4.8 Based on the results there is a significant difference between SVM and LDA classifier p value.

Table 4.7:ANOVA test results for SVM and LDA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1405.126	1	1405.126	45.52474	0.000145	5.317655
Within Groups	246.9208	8	30.8651			
Total	1652.047	9				

Table 4.8: Comparison Between SVM and KNN

Groups	Count	Sum	Average	Variance
SVM	5	368.48	73.696	40.89965
KNN	5	358.08	71.616	26.00734

Table 4.9: Anova test results between SVM and KNN

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	10.816	1	10.816	0.323315	0.585226	5.317655
Within Groups	267.6279	8	33.45349			
Total	278.4439	9				

While based on results by ANOVA, results suggest that there's no statistically significant difference between the means of Column SVM and KNN as their p value is greater than 0.5.

4.3 Limitation:

For every study, this theory has its limits. To start, the study didn't look at muscles in general, only specific hand motions. The selected motions, however, were primarily those that were part of regular life. There may be some variance in classification accuracies as the number of datasets increases, due to the limited datasets available for training and testing analyses. Therefore, it is suggested that all limitations or issues related to the study's use of this technique be considered.

Thirdly, this study employed offline methods for data pre-processing and categorization. The decision to process and categorize data offline means that the analysis occurred after the data collection phase rather than in real-time. One conceivable explanation for the observed suboptimal functional performance during real-time analysis is attributed to the lag time between rest and movement sessions.

The interval between rest and movement sessions introduces a temporal gap during which the electromyography (EMG) signal properties may undergo changes. EMG signals, which provide crucial information about muscle activity, can be influenced by factors such as fatigue, muscle recovery, and physiological variations. The lag time, in this context, may result in an incomplete or delayed representation of the dynamic nature of muscle activity.

The impact on the EMG signal's properties could extend to the subsequent classification performance. Real-time analysis demands immediate and accurate recognition of patterns in muscle activity, and any delay or mismatch in signal representation may compromise the effectiveness of the classification algorithms. This temporal discrepancy between the recorded data and the actual muscle activity could lead to misinterpretations and inaccuracies in the classification process, affecting the overall reliability of the study's outcomes.

Therefore, it is crucial to consider the implications of utilizing offline methods in the context of real-time analysis. Future research endeavors may benefit from exploring and implementing online or real-time data processing approaches to mitigate the potential impact of lag time on EMG signal properties and enhance the accuracy of classification algorithms in capturing dynamic changes in muscle activity.

4.4 Summary of Research Work:

Stroke can greatly impair motor function, and rehabilitation methods often lack versatility in training different movement types. Exoskeletons controlled by both brain and muscle activity have been proposed to address this, but differentiating complex movements solely from brain signals can be challenging. This study investigates whether residual muscle activity (EMG) in stroke patients can be used to decode hand and forearm movements for exoskeleton control.

Five stroke patients participated in the study. They performed seven distinct hand and forearm motions (supination, pronation, hand close/open, wrist flexion/extension, and pinch) while surface EMG signals were recorded from five forearm muscles. Each motion was repeated three times across eight weeks. The baseline was considered as reference the after-VRtherapy rest of EMGs are collected according to the designed protocol. and Three machine learning classifiers (Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Linear Discriminant Analysis (LDA)) were used to analyze the EMG data and classify the different movements.

Results were satisfactory as the therapy is working great for patients' rehabilitation also the classifiers

On average, the classifiers achieved the following accuracy in classifying the movements:

- SVM: 73.69 ± 6.39%
- KNN: 71.6 ± 5.09%
- LDA: 50 ± 4.56%

This suggests that all three classifiers could effectively decode the motions, with SVM achieving the highest accuracy. The study also found significant correlation between motor impairment severity and classification accuracy.

The study demonstrates that residual EMG activity in stroke patients can be successfully used to decode complex hand and forearm movements. This has significant implications for developing exoskeletons and other EMG-powered assistive devices for stroke rehabilitation. Such devices could offer patients more versatile and accessible training options in the comfort of their homes.

The study was limited by a small sample size 5 patients and focused on specific muscles and movements. Further research with larger and more diverse patient populations is needed to validate the findings and explore the applicability to different rehabilitation scenarios.

This study successfully decoded hand and forearm movements from EMG signals in stroke patients. This paves the way for developing EMG-controlled exoskeletons and other assistive devices for more effective and accessible stroke rehabilitation.

Future research should investigate the efficacy of EMG-controlled exoskeletons in improving motor function and functional outcomes in stroke patients. Additionally, studies with larger and more diverse patient populations are needed to further validate the findings and explore the generalizability of the approach.

Chapter 5
Conclusion and Future Recommendation

The major objective of this research project is to investigate the complex process of interpreting hand movements in stroke patients. We utilize advanced methods such as time domain analysis, frequency domain analysis, and machine learning algorithms. The experiment entails the scrupulous documentation of surface electromyography (EMG) signals from five stroke patients during various sessions. During the sessions, participants performed seven specific hand movements alternated with times of rest.

To provide a thorough examination of hand movement, we obtained a diverse range of characteristics approximately 15 in both the temporal and spectral domains. The features were used for classification, utilizing established machine learning methods such as Linear Discriminant Analysis (LDA), k-Nearest Neighbors (KNN), and Support Vector Machine (SVM). Significantly, Support Vector Machine (SVM) emerged as the most effective classifier, showcasing exceptional performance and overall precision in deciphering hand movements for individuals affected by stroke. KNN emerged as the second most proficient performer, although LDA had comparatively less accuracy.

One important discovery from our data is the variation in performance after VR therapy that is specific to each person.as a good change of this therapy is been seen in the results and the patients are getting benefits by performing the task assigned for the desired patients Specific disciplines demonstrated inferior results, which impacted the classification results. This concept is vital for comprehending motor recovery in stroke patients and emphasizes the significance of individualized approaches in rehabilitation.

The findings of our study have ramifications that go in favor of academic research, indicating potential practical uses in the creation of diagnostic or rehabilitation equipment. Due to its exceptional performance, SVM is the preferred classifier for future projects aimed at building such devices. The SVM's strong resilience and precision make it an excellent choice for incorporating into diagnostic equipment or rehabilitation devices designed to assist stroke victims in recovering hand motor skills. Our research not only provides useful insights to the profession, but also establishes the foundation for potentially translating these discoveries into concrete breakthroughs in stroke rehabilitation technologies.

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