Classification of Activities of Daily Living (ADLs) Based Upper Limb Movements Using Machine Learning & Neural Network Classifiers

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Declaration

I certify that this research work titled "*Classification of Activities of Daily Living (ADL) Based Upper Limb Movements Using Machine Learning and Neural Network Classifiers"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged / referred.

Signature of Student

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Copyright Statement

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I am thankful to my Creator Allah Subhana-Watala 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

Real time natural control of assistive, rehabilitation and prosthetic devices has gained significant importance over the last few decades for the people suffering from motor disabilities due to stroke, any spinal cord injury or amputation. Although surface electromyography (s-EMG) has been used as a viable controlling interface for several robotic devices specifically designed for post stroke therapeutic services. But these conventional controlling strategies are not feasible to design the rehabilitation or HMI systems based on simultaneous movements of multiple degrees of freedom (DOF). This paper presents a novel control strategy for HMIs which is based on the coupled use of EMG and inertial sensors. EMG and kinematic data of healthy and stroke subjects for commonly used daily life activities has been recorded. Multiple machine learning models including LDA, QDA, LSVM, QSVM, Fine KNN, Ensembled discriminant, and ensembled KNN have been applied. Besides this a tri-layered neural network classifier has also been implemented. A comparative analysis has been performed for the classification outcomes of all the applied models for EMG, IMU & EMG+IMU data. Overall, the KNN model performed well for all types of datasets with an average accuracy of 98.5% but results clearly demonstrated that average classification accuracies for all the applied models have significantly improved for EMG+IMU data which indicates that sensor fusion based control strategy for prosthesis can achieve higher performance than conventional control systems for each task. This study is an effort to provide a new EMG+IMU based technique for fast, efficient, and reliable control of robotic, rehabilitation and assistive devices for multiple movements with varying DOF.

Key Words: *EMG, Inertial measurement unit (IMU), HMI, Stroke, Rehabilitation, Prosthesis*

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CHAPTER 1: INTRODUCTION

1.0 Problem Statement

Stroke is ranked as the third-leading global cause of physical disability. Ageing is one of the powerful stroke drivers. According to the recent statistics, there are approximately 650 million population over the age of 60, but by 2050, that figure is expected to be increased up to 2.00 billion [1]. If the statistics persist, the need for post-stroke care (PSC) services will rise as well, imposing an unsustainable financial burden, particularly on emerging economies like Pakistan. Thats is why it is necessary to replace the conventional therapeutic strategies with technologically advanced systems. It is very difficult for people with upper limb disabilities to perform daily life activities such as holding objects, eating meals and opening\closing of doors etc. The use of assistive devices particularly targeting the hand can be significantly beneficial for such population. Depending upon the type of disability this device can be orthosis (supporting the functionality of existing limb), prosthesis (for amputated limb) or rehabilitative (for physical therapy). EMG signals have not only been used as the natural interface for controlling the artificial limbs but to design the rehabilitation devices as well [2]. The aim of this study is to decode the activities of daily living (ADL) based Electromyogram data using multiple machine learning and neural network classifiers to design an efficient rehabilitation system to achieve the ultimate goal of self-training for post stroke rehabilitation. Beside EMG the kinematic information of the subjects has also been recorded using IMU sensors to investigate the overall impact of sensor fusion strategy on the classification accuracy of algorithms. But before going into the technical depth of this study a brief introduction to understand the theoretical background of stroke disease, its' causes, types, recovery stages during the post stroke rehabilitation, EMG, and assistive devices has been discussed.

1.2 Stroke

Stroke is termed as cerebrovascular accidents (CVA's). "Cerebrum" is the Latin word refers to the brain and "vascular" is used for blood vessels. Stroke is one of the major reasons of brain damage especially in elderly people. In this condition the flow of blood to the brain is stopped. Arterial vessels which feed the brain can be blocked temporarily or permanently [3]. The term stroke is associated with the long-time blockages damaging the brain and leaving several mental and physical deficits because the brain cannot get enough oxygen and nerve cells die. Thus, abilities controlled by that part of the brain are partially or completely lost.

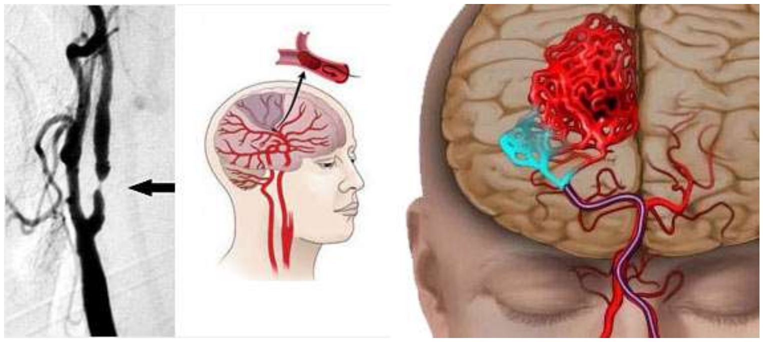


Figure 1.1 Brain attack (Stroke)

1.2.1 Types of Stroke

Five types of stroke conditions are considered as medical emergencies which interrupt the blood supply to brain. These 5 types are:

- Ischemic stroke.
- Hemorrhagic stroke.
- Transient Ischemic stroke (TIA).
- Cryptogenic stroke.
- Brain stem stroke.

1.2.1.1 Ischemic stroke

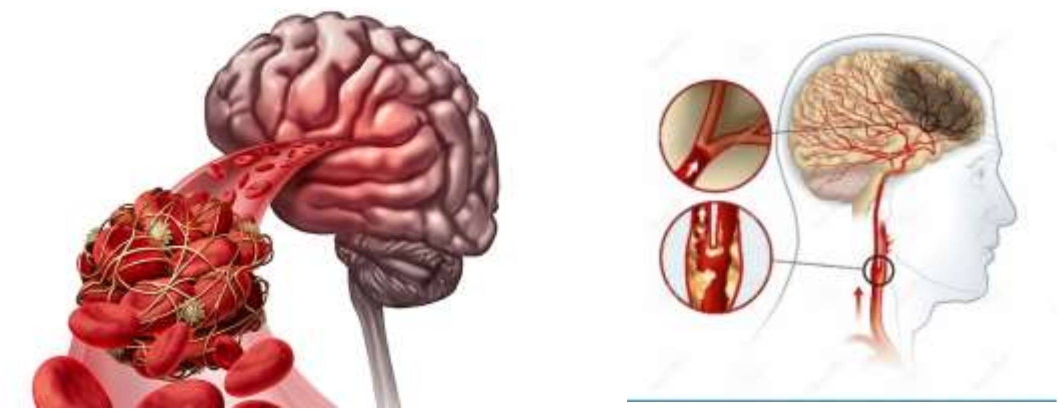
Ischemic stroke is occurred when blood vessels get blocked due to any clot called “thrombi” and blood supply to any specific part of brain is interrupted causing the associated brain cells (neurons) to die. The occurrence rate of ischemic stroke is approximately 87.00% of all stroke types [4].

Figure 1.2 Ischemic Stroke

1.2.1.2 Causes of Ischemic Stroke

Fatty substances deposit on the inner side of blood vessels causing the hardening or thickening of the arterial vessels[5]. This state is called atherosclerosis which is the main reason for ischemic stroke. Deposition of fatty substances can mainly cause the following two kinds of obstructions:

- **Cerebral thrombosis:** A kind of blood clot called thrombus which develops in the blood vessel at fatty plaque. This blood clot is formed at venous sinuses of the brain preventing the draining of blood out of the brain.
- **Cerebral embolism:** This is a blood clot which can develop at any location of blood circulatory system, generally in the heart & the arteries of neck and upper chest. But sometimes it breaks and travelling through the main blood stream may reach the blood vessels of brain till it gets stuck in too narrow spaces to let it pass. Arterial fibrillation is considered as the main reason for embolism. In embolism, a clot is formed in the heart, and travels to the brain [5]–[8].



(a) (b)

Figure 1.3 Two types of clots because of fatty deposits (a) Cerebral thrombosis (b) Cerebral embolism

- Silent stroke [8]**:**

Silent cerebral infarction (SCI) is a kind of brain injury which is caused due to the interruption in the blood flow because of the formation of blood clot in the brain and this is the major risk factor of getting stroke in future and a symptom of progressive damage to brain.

SCI is related to some other serious conditions as well:

- **Atrial fibrillation:** In the people >65 the problem of irregular heartbeat is very common which increases the risk of silent cerebral infarction.
- **High blood pressure:** Increased levels of blood homocysteine and high blood pressure

are also the main risk factors of SCI. That’s why early diagnosis of hypertension is very important to minimize the risk of getting SCI.

1.2.1.3 Symptoms of the Ischemic Stroke

Symptoms of the ischemic stroke depends upon the affected brain part. But some of the symptoms are common such as:

- **Vision problems:** Double vision or blindness in one eye.
- **Paralysis:** Patient may suffer from physical immobility, paralysis, or weakness in single or both sides.
- **Dizziness:** is taken as the common symptom of transient ischemic attack (TIA).
- **Loss of coordination:** If the stroke attacks a person’s cerebellum, then he/she may suffer from problems with muscle control and coordination. Briefly the nervous system will struggle in coordinating with the movement and this state is called ataxia.
- **Confusion:** Stroke patients generally struggle with the problem called delirium which is an extreme state of disorientation/confusion which means he will not be able to take quick decisions. If this situation persists for a long time, it may also be the system of another neurological disorder called dementia. This state badly affects the memory, behavior, judgement, and everyday activities of a person.

1.2.1.4 Hemorrhagic stroke [7]

A hemorrhagic stroke occurs when any of the brain arteries is ruptured, and blood is spilled inside the brain. It exerts pressure and damages the delicate brain tissues. As a result, the affected area of brain doesn’t work properly and loses the capability of controlling the associated body part and its functionality.

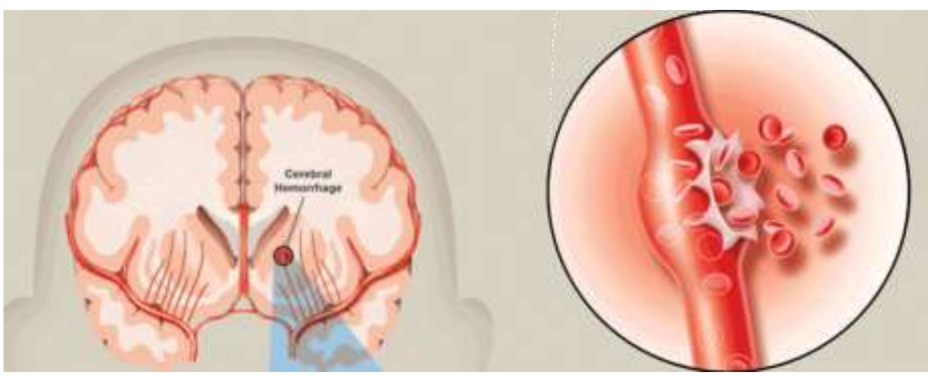


Figure 1.4 Hemorrhagic Stroke

Generally hemorrhagic stroke falls in two categories:

- **Intracranial hemorrhages:** It occurs when nerve bleeds inside the brain.
- **Subarachnoid hemorrhages:** It happens when the bleeding is occurred between the brain and its covering membranes.

1.2.1.5 Symptoms of hemorrhagic stroke

- Body stiffness.
- Paralysis of single or both sides of body.
- Hand tremors.
- Nausea or vomiting.
- Sudden fluctuations in breathing and heart rate.

1.2.1.6 Causes & risk factors of hemorrhagic stroke [6]

The main risk factors for hemorrhagic stroke have briefly been discussed below:

- **Head injuries:** A direct relation has been observed between the traumatic head injury and both hemorrhagic & ischemic stroke.
- **High blood pressure** is one of the major risk factors of stroke. Hearts' workload is increased with the high blood pressure which damages the arteries, and it has been proven that the people with the problem of high blood pressure are at greater risk of getting stroke.
- **Cerebral aneurysm:** is the creation of a bulge in the brain artery. It seems like a small balloon filled with the blood. It is also defined as the brain aneurysm or intracranial aneurysm. It makes the artery to rupture from that area.
- **Rheumatoid vasculitis:** People suffering from a long-time condition of rheumatoid arthritis (RA) has the problem of rheumatoid vasculitis in which blood vessels are inflamed and thus, risk of the hemorrhagic stroke is high in such patients.

1.2.1.7 Transient ischemic attack (TIA)

Mini stroke/Transient ischemic attack (TIA) of stroke is caused due to the temporary blockage of blood supply to any part of the brain. It persist for a very short time and the resulting effects of TIA [9] last for a few minutes to hours. Patients can recover from TIA within the time period of 24 hours. It has the same risk factors as the other stroke types like high cholesterol, high blood pressure, smoking ,Obesity, and depression etc.

1.2.1.8 Cryptogenic stroke

Cryptogenic stroke (CS) is categorized as the stroke of unknown origin as the cause of cryptogenic stroke remains undetermined. This is because the CS is reversible or transitory. Almost 1/3rd cases of ischemic stroke are cryptogenic. It is more common in younger population than older patients due to coagulopathy, vasculopathy and cardiac embolism [10].

1.2.1.9 Brain stem stroke

Brain stem stroke is occurred when the base section of brain is deprived of the blood supply because of some reason i.e., clot or ruptured blood vessel. It affects numerous body functions such as breathing, blood pressure, and heart rate. It can be cured by removing the clot through embolectomy or by using the medicines like blood thinners to remove the clot in case of ischemic stroke. Brain stem stroke has very complex symptoms. Person suffering from this may feel dizziness, vertigo, and severe imbalance. It can cause slurred speech, decreased consciousness and double vision. Recovery from brain stem stroke is possible with the rehabilitation therapy of several weeks [11].

1.3 Stages of Stroke Recovery

Stroke affects the coordination, movement, speaking, cognition, and other normal body functions making the person dependent on the post stroke care (PSC) services. Recovery from stroke is a difficult, emotional, and challenging process and different for every patient [12]. Outlook for stroke recovery is directly linked with the extent of lesion, time before the treatment and many other factors. However, a general pattern of motor recovery after stroke has been identified with the collaborative consultation of researchers, clinical & rehabilitation experts. Brunnstrom approach describes the seven well recognized stages of stroke recovery. This framework includes the monitoring of different involuntary and spastic movements as a part of recovery process and to help in physical rehabilitation [13]. Normally the physical movements occur due to the joint functioning of different group of muscles. This collaboration between the muscles is termed as “synergies”. Normally the brain performs the task of coordination among these movements which is severely affected after stroke. Stroke greatly affects this coordination resulting the muscle synergies to function abnormally. Brunnstrom approach mainly focus on teaching the patients to use these abnormal synergies for their advantage. This approach has gained a wide range of acceptance among the community of physical and occupational therapists. These seven stages have briefly been discussed below:

1.3.1 Flaccidity

The initial stage includes an immediate shock after stroke according to Brunnstrom's approach in which flaccid paralysis occur. Flaccidity or flaccid paralysis is a complete loss of voluntary movement. This kind of paralysis occurs due to nerve damage preventing the muscles from acquiring the appropriate brain signals. Stroke survivors are not able to initialize any volunteer muscle movement in the early stage of flaccid paralysis. If the patients remain deprive of certain physical therapy for long time in such state it may cause the muscles to become weak. This is the stage when muscle atrophy begins. That's why it is compulsory to provide the effected muscle with certain kind of therapy in order to regain the normal muscle tone. But flaccid paralysis restricts the muscles from this.

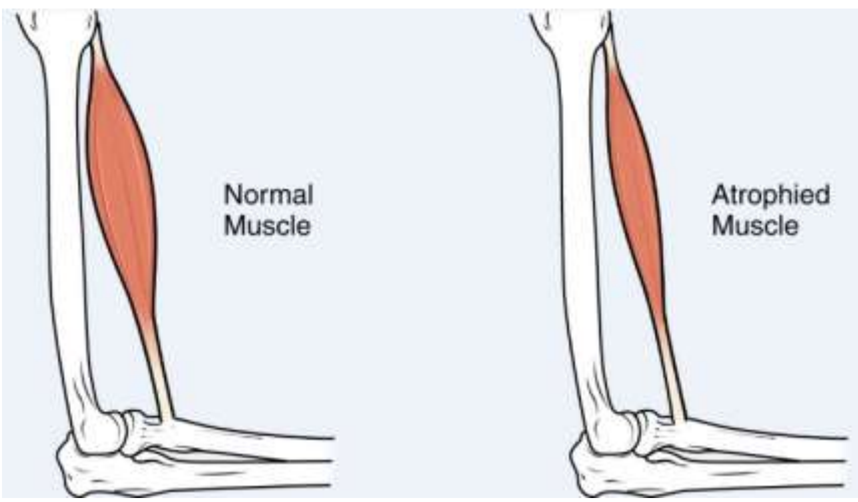


Figure 1.5 Muscle Atrophy

In medical terms such a kind of muscle loss is called Hypotonia. Hypotonia weakens the muscles affecting the daily life activities of the patient. Hypotonia can be reduced with medical treatments and therapeutic exercises. This stage 1 of the Brainstorm's approach also needs some modifications in routine life activities to keep the affected muscles protected from injury.

1.3.2 Dealing with Spasticity

In the 2nd stage of stroke recovery some of the fundamental limb synergies are marked because some muscles start to respond when they are stimulated. This is the stage when muscles start making certain small, abnormal, and spastic movements involuntary, but this is an encouraging sign during the recovery process of any stroke patient. However, this stage may lack even the minimal volunteer movements.

1.3.3 Increased Spasticity

During the 3rd stage of stroke recovery muscles' spasticity increases up to its peak. Patients sense a feeling of unusual tightness, muscle pull or stiffness. During this stage synergy patterns start emerging and certain volunteer actions can be expected. In-volunteer actions are because muscles are now capable of initiating movement but cannot control it. Appearance of the muscle coordination and synergy patterns assist the volunteer actions which can be improved with physical and occupational therapy. To increase the range of motion (ROM) passive exercises must be performed during this stage. Actions involve bending the knee and raising the hand over head etc.

Figure 1.6 Passive movements

1.3.4 Decline in Spasticity

The spasticity of muscles starts to decline during the 4th stage of stroke recovery. A limited ability of performing the normal movements is developed. Although these movements may be out of synchronization, but patient recovers quickly during this stage. The actual focus throughout this stage is to strengthen the muscle control. During this stage the patient is asked to perform active exercises and he can perform these actions without any assistance. These movements involve lifting the limb to its' full range of motion etc.

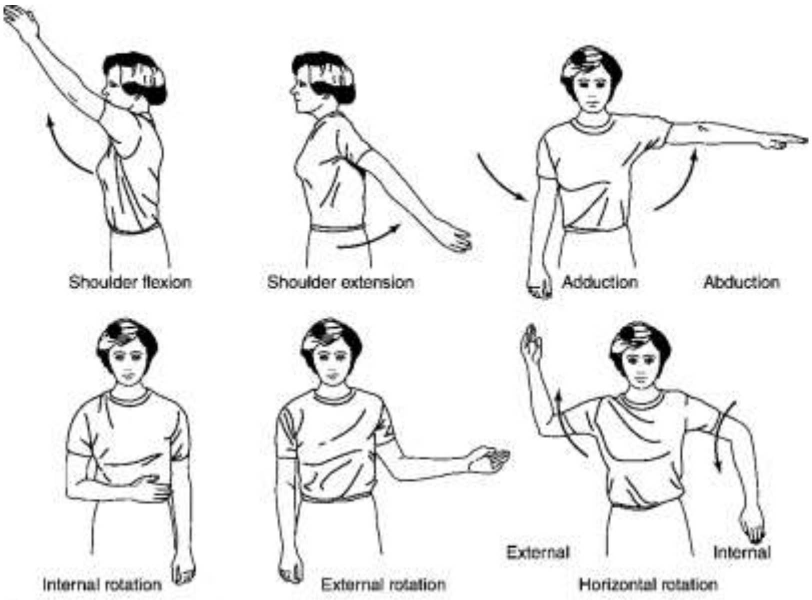


Figure 1.7 Active ROM movements

1.3.5 Combination of Complex Movements

Synergy patterns of the muscles become coordinated allowing the patient to perform more complex activities. During this stage abnormal movements dramatically decrease, and the patient becomes able to make more deliberate and controlled movements in the stroke affected limbs. Some of the complex movements involve combing the hairs and swinging the bat etc.

1.3.6 Spasticity Disappears

Spasticity completely disappears during the 6th stage of stroke recovery. This is the stage where patients regain the full functional capability in the stroke affected parts of the body.

1.3.7 Regaining of normal Actions

This is the last stage of Brunnstrom's Approach in which patient is able to move the hands, feet, arms, and legs in a volunteer and controlled manner. Synergy patterns becomes completely normal which is the ultimate goal of physical therapists and stroke patients.

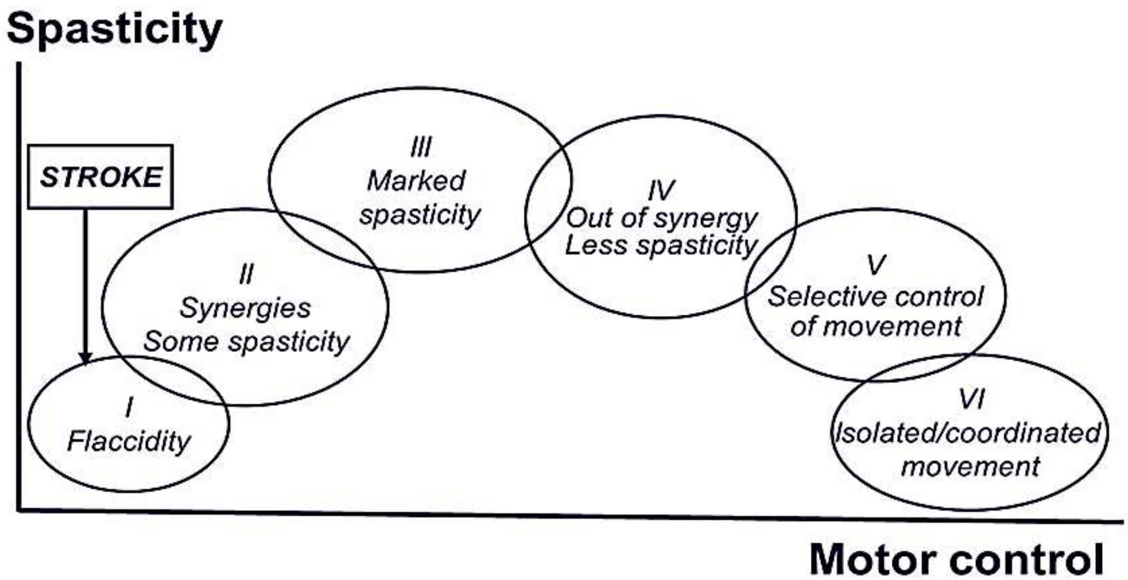


Figure 1.7 Brunnstrom Stages of stroke recovery

1.4 Hand grasping actions[14]

Grasping actions performed by hand can be classified into two categories:

- **Precision grasping:** Combination of functions and processes required to keep an object in a specific position.
- **Dynamic grasping:** Handling of objects on the inner side of the hand with the coordinated movements of fingers.

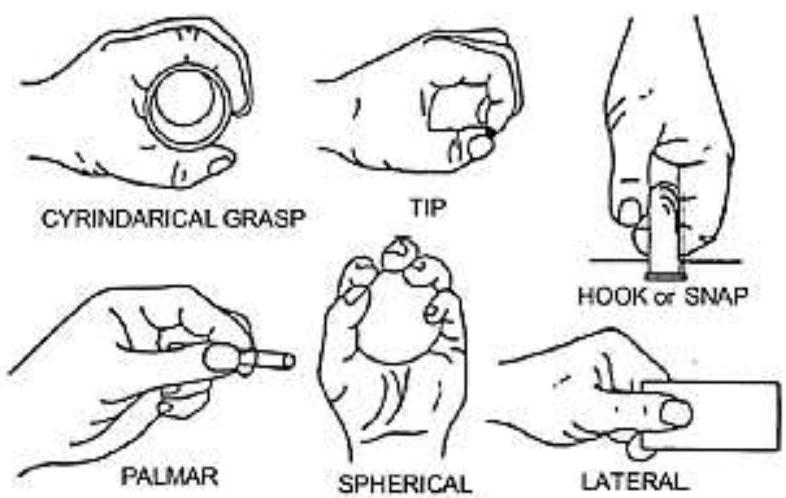


Figure 1.8 Basic hand grasping actions

In dynamic grasping thumbs' abductor stabilizes the object against the palm keeping the hand still for example hold the cylinder or glass and lift the dumbbell etc. whereas precision grasping includes some palmar actions such as grasping a pencil or touch the thumb to the index finger. There is also a 3rd kind of **lateral grasping** which can belong to both classes for example it is called dynamic when thumb is in adduction position and precision when thumb is in the opposite position.

1.5 Electromyography (EMG)

Recording the electrical activity of muscle contraction is called 'Electromyography'. Muscles are made up of the group of muscle fibers in the form of extended tubular cell. EMG signal is formed by the superposition of each muscle signal which depends upon the physiology of a person. The recorded EMG bio signal is called 'Electromyogram'[15]. The variation in muscle membrane potential provides the electrical source of EMG readings. This occurs due to the transfer of potassium ions as a result of muscular contraction with the ions of calcium across the membrane. The best interpretation of the electric activity of certain activity can be achieved through the manifestation of neuromuscular activation related to certain contracting muscle and resulting signal is called 'myo-electric signal (ME)'.

There are 2 methods of EMG signal acquirement [16].

- Invasive or intramuscular.
- Non-invasive via surface electrodes **(s-EMG)**. In this study we have used surface EMG electrodes considering the feasibility and comfort of the participated subjects **(Figure 1.10)**.

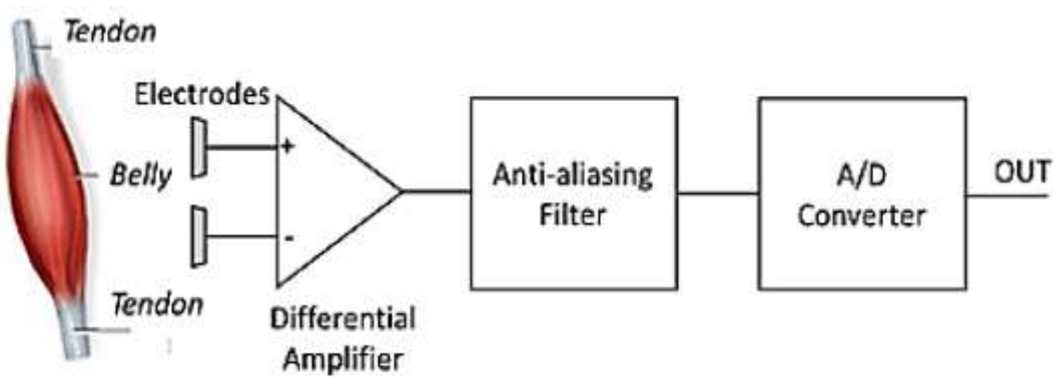


Figure 1.9 Sequence of s-EMG recording

s-EMG signal is acquired by positioning the electrodes on the muscle belly over the skin surface whereas in invasive EMG recording needle electrodes are mostly used which are placed under the skin [17]. Although invasive electrodes provide the opportunity of deeply analyzing the activity of targeted muscle but practically, they are not generally feasible as it depends upon the willingness of the participated subjects. Moreover, s-EMGs have demonstrated an excellent reliability for multiple applications in numerous studies [18].

(a) **(b)**

Figure 1.10 EMG recording with Delsys Trigono Avanti wireless sensors **(a)** at rest **(b)** performing an activity

1.6 Applications of s-EMG

Some of the important applications of s-EMG have been discussed below [17], [19]:

1.6.1 Rehabilitation & Physiotherapy

Doctors can analyze the Patients' electromyogram to evaluate the electrical activity of the muscles to determine whether the muscles are working properly or not. Now the rehabilitation experts and medical research community are working collaboratively to automate such detections along with the development of a real time bio feedback system to assist the doctor for the rehabilitation assessment of the patient. In areas where needle electrodes are not appropriate, such as rehabilitation medicine, sports, neurology and the control of assistive equipment, surface EMG has vital applications. Biomedical and clinical research community is exploring the new horizons to achieve the ultimate aim of self-training in the field of physical and neurorehabilitation.

1.6.2 Human machine interface (HMI)

In the field of AI human computer interactions have the capability to provide a natural way of controlling different devices. For patients with any physical or motor disability surface EMG has the potential to enhance the useful interacting experiences of human and machines with the purpose of controlling any device.

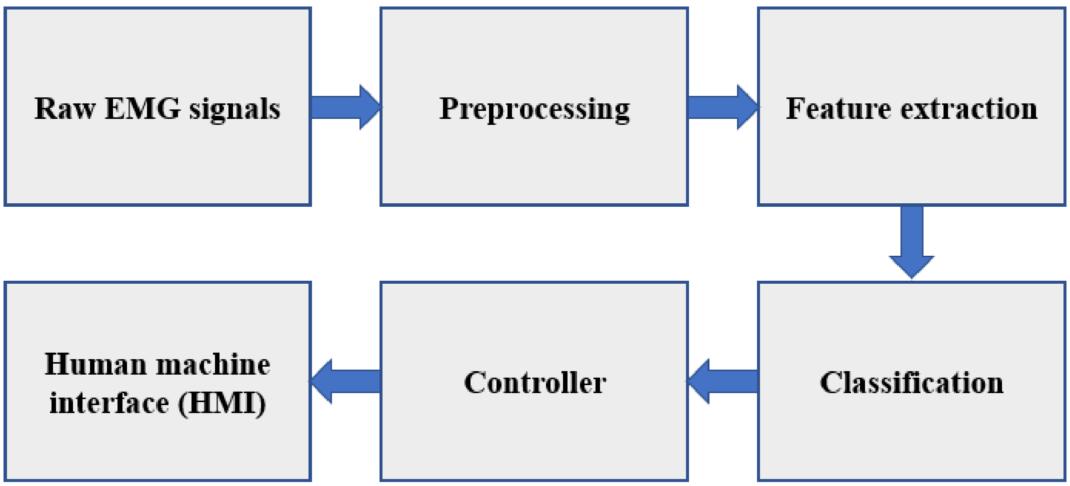


Figure 1.11: A simple overview of HMI

- **Prosthetic control**

It is one of the emerging areas of surface EMG. It secures a superior position over neural interfaces as it does not create neural scarring. Now the possibility of growing the new muscles and nerve clusters has increased particularly to control any prosthetic device through targeted muscle re innervation.

- **Robotic control**

Besides prosthetic control surface EMGs are widely being used to control the robotic interfaces as well such as robotic arms and humanoid robots etc. Robotic control of the robotic limbs is very necessary to reduce the overall training time of operations. Other applications of EMG include speech recognition, recognition of fascial expressions, to create a diagnostic database for diseases, and design a full proof robotic mechanisms to deal with limb amputees.

Figure 1.12 Use of EMG for prosthesis

1.7 Aims & Objective

- To design a protocol for the data recording of ADLs.
- To decode the data of daily living based upper limb activities.
- To use the advanced concept of sensor fusion.
- Statistical analysis of the results to reach any concluded statement about the overall impact of EMG and kinematic data fusion on classification accuracy

1.8 Relevance to National Needs

In a developing country like Pakistan where public health care system is not well maintained and literacy rate is only 62.1 % people have very less knowledge about the stroke and its health consequences, Mostly, population cannot afford expensive rehabilitation treatments and post stroke care (PSC) services. If the stroke disease keeps on prevailing with the persistent rate then it will cause disastrous impact over the country's economy. That is why providing an economical, physically comfortable, and technologically suitable self-rehabilitation training concept is the need of the hour.

1.9 Advantage of the study

The proposed concept of ADL based rehabilitation training system:

- Will be economically feasible to implement.
- Will be comfortable & enjoyable for the patients of physical mobility disorder.
- Will make stroke patients physically independent.
- Will minimize the dependency over clinical therapist.

1.10 Areas of Application

The proposed concept of ADL based rehabilitation training system will be:

- Implementable for the physical rehabilitation and motor training of post stroke chronic patients.

CHAPTER 2: LITERATURE REVIEW

2.1 Fundamentals of EMG

Research on EMG based control systems for human machine interfaces (HMI) applications, particularly in rehabilitation, is progressing. EMG is a technique that relies on experimentation to assess and record a stream of electrical impulses coming from the muscles of the body. The physiological variations in the state of the membrane of the muscle fibers produce the EMG signals. The excitability of muscle fibers is regulated by brain control, which is a significant aspect in muscle physiology [20]. EMG signals are generated through action potentials generated by depolarization & repolarization of the fiber membrane. When a muscle is not contracting, the interior and the exterior spaces of the cell combine to create a resting potential at the muscle membrane. This potential varies between **-80 & -90 mV**. Based on the condition and muscle types throughout the observation process, amplitude of the surface EMG signals varies from microvolts (*u*V) to millivolts (mV). Terminals of a motor neuron stimulate the multiple muscle fibers thus creating a motor unit (MU) [19], [20].

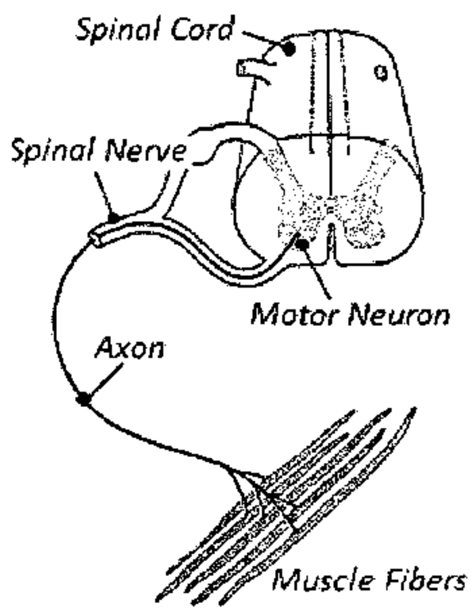


Figure 2.1: A motor unit is formed by multiple muscle fibers that are innervated by nerve fibers that originate in the spinal cord.

Motor unit (MU) is the tiniest part of the muscle which the central nervous system (CNS) can control. Each motor neuron-innerved muscle fiber experiences an action potential when a motor unit is activated, which causes the muscle to briefly contract or twitch (delay for few m-sec from AP origin). This spatial & temporal superposition of Individual fiber result in electrical signal known as motor unit action potential (MUAP). Both invasive and non-invasive methods may be used to detect these motor unit action potentials (MUAP).

An invasive method involves inserting the wire or needle electrode in the muscle tissue to record EMG signals, while a non-invasive technique involves placing the electrodes directly to the skin. Generally, the non-invasive method is favored to detect the EMG signals as it spares amputees from pain and poses the lowest risk of infection. Surface electromyography (s-EMG) signals have a frequency range of **10-500.0 Hz** & range of the amplitude is **0.0-10.0 mV** [21].

There are 2 main concerns that affect the fidelity of EMG signals while they are being detected and recorded:

- Signal-noise ratio.
- Noise signal

Ratio of energy in EMG to noise signals is termed as **signal to noise ratio** and electrical signals which should not be the part of desired EMG are defined as 'noise'.

2.1.1 Noises in EMG Signal [21]– [24]

- **Inherent noises:** This is electrical noise which is produced by the electronic devices with the freq. components ranging from 0.00 Hz to thousand Hz is known as inherent noise.
- **Ambient noise:** Such noise is produced by electromagnetic radiation. Sometimes, amplitude is 1-3 times larger than relevant EMG signals. Power-Line Interference is an example of the ambient noise caused by the radiation of power source at 60 Hz or 50 Hz. If frequency of the interference is high, a high pass filter may eliminate it. However, it is crucial to understand the nature of EMG signal if frequency content of PLI is present in the EMG signal.
- **Motion artifacts:** When a muscle is contracted, its length reduces. Additionally, electrodes, skin, and muscle all move relative to one another. Electrodes will display some movement artefacts during this time. Data abnormalities are caused due to the motion artefacts. The electrode interface and cable are the two major causes of such artifacts. The setup and proper design of the electrical circuitry may eliminate these

motion artifacts. Motion noise often has the frequency range of **1.00-10.00 Hz** and a voltage that is similar to EMG's amplitude.

- **Electrocardiographic (ECG) Artifacts:** The main source of an ECG artefact, also known as interference, for EMG in the shoulder girdle is the electrical activity of heart. EMG data are often contaminated by this artefact, particularly in trunk muscle EMG. The amount of ECG contamination in EMG is often determined by the positioning of EMG electrodes, which is carried out by the selection of diseased muscle groups. It is highly challenging to eliminate ECG distortions from EMG data because the frequency spectra of the two signals overlap and because of their relative features, such as non-stationarity & variable temporal shape.
- **Crosstalk:** Crosstalk is the term for an unwanted electromyographic signal from a muscle area that is not often checked. Crosstalk damages the EMG signal and may result in a misinterpretation of the information it contains. Crosstalk is affected by the variety of physiological factors, although it may be decreased by carefully choosing the electrode size and inter-electrode spacing (generally 1.00-2.00 cm or the radius of electrode).

2.2 EMG signal processing

To increase the precision and computational speed, a variety of methods for managing EMG data are utilized such as feature extraction & pre-processing phases (such as data filtration, segmentation, and then rectification). Initially data is segmented from the raw EMG signal. A feature set is created for each separated segment that has been corrected and filtered. The results will then be sent to the classifier. The windowing method and data length are two key considerations for data segmentation.

The classification error of EMG data is affected by its length [25]. This claim was demonstrated by Farina and Merletti, who found that classifier performance suffers when segments are shorter than 128 ms, resulting in considerable feature bias and variation [26]. The accuracy of categorization increases as the length of segment rises from 125.00-500.00 ms, in line with a 2013 study [27]. This is so that a longer segment can supply more information and produce an estimation of the feature with less bias and volatility. For upper limb applications, this segment condition offers great precision and is operable in real-time. In [28], the EMG data sample length is set to 256.00 ms at the start of the movement. Data windowing can be done using either the adjacent or the overlapping methods. Adjacent windowing is the method of using feature extraction and classification after a specific processing delay on adjacent disconnected segments of a predetermined length. This is the time needed to compute a feature & classify the data. The main disadvantage of this method is that it will keep the processor in an idle state throughout the remaining duration of the segment length [29]. This issue can be resolved using the concept of overlapping windowing in which the new segment slides over the previous segment and increment duration is less than the overall segment length. Although overlapping windowing doesn't increase the classification accuracy, it is important for large segments to decrease the delay time [30] EMG signals require to be filtered to decrease the artifacts in order to combat the numerous noises listed in the previous section (2.1.1). A band pass filter was used to reduce the effects of motion artifacts with the cut off frequencies 20 Hz & 500 Hz for high and low pass filtration respectively [30].

2.3 EMG Feature Extraction

Feature selection and extraction has a pivotal role in improving the classification accuracy for motion pattern identification in EMG signal data. In this procedure, raw EMG signals are converted into feature vectors. Generally, there are three categories of features used in the analysis of EMG data [31]:

- Time-domain features (TD)
- Frequency-domain features (FD)
- Time-frequency domain features (TFD)

2.3.1 Time Domain Features

For TD features, the features are calculated using a time-varying signal amplitude. During the process of, the signal's amplitude is influenced by the types and conditions of the muscles. Mostly studies have concentrated on time domain features in order to keep the computing complexity minimum . These features don’t require any additional transformation of signal. Some of the TD features used in previous studies have been listed below:

Table 2.1:TD features

Features	Abbreviations	Reference
Mean Absolute Value	MAV	[32]
Variance	V	[33]
Root mean square	RMS	[34]
Zero crossing	ZC	[32], [33]
Standard deviation	SD	[35]
Maximum amplitude	MAX	[32]

2.3.2 Frequency Domain Features

Unlike time domain features, FD features are computed using parametric methods or a periodogram and include the power spectrum density (PSD) of the signals. Only a few studies had used FD features for the identification of motion patterns. Generally, the analysis of motor unit (MU) recruitment and the measurement of muscle strain consider spectral or frequency domain (FD) features.

Table 2.2: FD features

Features	Abbreviations	Reference
Median frequency	MDF	[33]
Mean frequency	MNF	[33]
Total power	TTP	[33]
Peak frequency	PKF	[32], [33]
Energy	EN	[36]
Signal to noise ratio	SNR	[37]
Modified mean frequency	MMNF	[38]

2.3.3 Time-Frequency Domain Features

TFD features are described as time & frequency combination of information. TFD characteristics may distinguish between distinct frequency information at various time intervals, offering very useful non-stationary information about the preprocessed signals. The important parameters in every domain of signal analysis were illustrated by Oskei and Hu [39]. The computing time of TFD features is more than TD features.

Table 2.3: TFD features

Features	Abbreviations	Reference
Discrete-Wavelet Transform	DWT	[40]
Wavelet-Packet Transform	WPT	[40]
Continuous-Wavelet Transform	CWT	[41]
Empirical-Mode Decomposition	EMD	[41]

Dimensionality reduction is used to decrease the dimensionality of the data while preserving its ability to discriminate in order to deal with the complexity of TFD features. There are two basic methods of dimensionality reduction:

- Feature selection
- Feature projection

Feature projection technique is implemented to evaluate the best pattern of original features and creates a new feature set usually smaller than the previous one whereas feature selection technique selects the subset of original features as per specified criteria to assess whether it is better than other subset.

2.4 EMG Classification

The classifier will then use the data from the EMG signals to map distinct patterns and match them properly. To discriminate between distinct categories of the retrieved features, classifiers should be used. The resulting categories will then be employed in the next step as controller control commands. Artificial neural network (ANN), Bayesian classifiers (BC), fuzzy logic (FL), multilayer perceptron (MLP), support vector machines (SVM), linear discriminant analysis (LDA), hidden Markov models (HMM), and K-nearest neighbor are some of the techniques used to categorize EMG data (KNN). Many scientists have recently expressed interest in finding efficient ways to classify the EMG signal pattern.

Although the LDA's design and training algorithm does not need to comply the heuristic criteria, it regularly outperforms other methods. This is most likely because the PCA's dimensionality reduction has the effect of linearizing the data. In 2013, Phinyomark et al. [30] compared the performance accuracies of Support vector machines (SVM), k-nearest neighbor (KNN), random forests (RFS), and decision trees (DT), Additionally, quadratic discriminant analysis (QDA) &

multi-layer perceptron neural networks (MLP-NN) by classifying the 10 upper-limb movements using the TD features. LDA performed well with classification accuracy of 98.87%. However, the work of Khushaba & Al-Jumaily generated a nearly 99% accuracy by classifying human forearm motions based on TFD characteristics with MLP [42].

On the other hand, an ANN technique is appropriate for modelling nonlinear data since it can distinguish between various conditions, such as hand gestures (left, right, up and down). Based on TD characteristics and research by Ahsan et al., the overall performance for a single trial was found to be 89.20%, with an average success rate of 88.40% .

EMG classification accuracies with different classifier algorithms have been listed in Table 2.4:

Table 2.4: Comparison of EMG classification accuracies

Classifiers	**Feature type**	**Average Accuracy**	**Reference**
LDA	TD	98.87%	[38]
ANN	TD	89.2%	[43]
SVM	TD	73%	[44]
SVM	TD	90%	[45]
LDA	TFD	93.75%	[40]
ANN	TFD	88.40%	[43]

CHAPTER 3: METHODOLOGY

3.1 Data recording

A total of 30 including 15 stroke patients & 15 healthy subjects participated in this study. Data recording sessions were conducted in the 'Fauji Foundation Hospital, Rawalpindi with the ethical consent of medical board of 'Department of Physical medicine and Rehabilitation, FFH' (approved ref # **FFHO Itr no 6015/HD/50/Misc/18AK15DQ dated 26 Aug 2022**). The group of healthy subjects include total 6 females and 9 males, and they had no previous record of any musculoskeletal disorder. The ages of the participants of the healthy group vary between **(22 ± 5yr to 50 ± 5yr)**. In the 2nd group of stroke subjects mostly participants were in chronic phase **>1year** from stroke onset and they were receiving rehabilitation and occupational therapies from physiotherapist. The ages of 2nd group vary between **(30±5yr to 70±5yr)**. Electrodes used are '**Delsys Trigno Wireless Sensors**' to record the surface electromyographic (s-EMG) data and **MPU6050** sensors for patients' kinematic data. A total of six EMG electrodes have been used in the study to record the EMG data from upper limb (UL) Targeted muscles for EMG recording are listed in **Table 3.1**:

Table 3.1: List of targeted muscles for EMG

Sr#	Targeted muscle
1	Extensor carpi ulnaris
2	Extensor carpi radialis
3	Flexor carpi radialis
4	Extensor digitorum
5	Bicep
6	Tricep

To record the kinematic data of the subjects an arm band was used to place the electrode on the upper limb. As mentioned above, Inertial measurement unit (IMU) data has been recording with MPU6050 sensor. A total of two IMU sensors have been used in this study. Sensors were attached with an arm band to make sure their fixed safe placement without trembling during the recording. Data recording was accomplished in a separate room to ensure the comfortability of all the subjects. Participants were asked to sit on a chair in a straight position.

Figure 3.1: Trigno Avanti wireless sensors for EMG recording

First of all, EMG electrodes were placed at the targeted places of the forearm and upper arm. Then IMU-1 sensor was placed on the wrist and IMU-2 sensor was placed on the upper arm. The direction of the IMU sensors was kept symmetrical. The purpose of placing the IMU sensors was to record the kinematic information of upper limb including wrist, hand, finger, and complete arm movement.

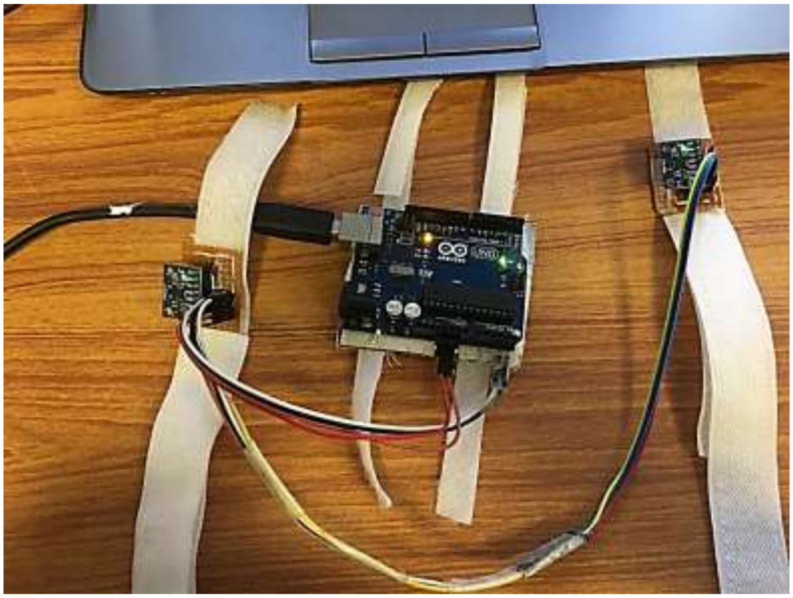


Figure 3.2: MPU 6050 sensors for IMU data

3.1.1 Delsys Trigno wireless sensors

Delsys Trigno EMG sensors have been designed specifically to study a range of human movements. It offers a complete system of biomechanical and physiological tools to accomplish the complex research studies by recording a high-quality data. It captures the muscles movement and activity data in reliable and accurate way. Some specifications of the Delsys Trigno sensors have been listed in Table 3.2.

Table 3.2: Specification of Trigno Avanti sensors

Sr#	**Specification**	**Value/description**
1	Size	27.0 x 37.0 x 13.0 mm
2	Mass	14g
3	Battery Life	4 to 8 hours
4	Operating range	40 m in RF mode host
5	Wireless protocol	2.4-2.48 GHz ISM Band
6	EMG bandwidth	20-450 Hz
7	EMG sampling rate	2000-4370 sa/sec
8	Contact material	99.90% silver
10	Electrode spacing	10.00mm

Figure 3.3: Trigno sensors **Left-** Base station **Right-**sensor

3.1.2 MPU6050 sensor

MPU6050 sensor module is a comprehensive 6-axis motion tracking device in a compact size. it includes a 3.00-axis gyroscope, 3.00-axis accelerometer, and a digital motion processor. Additionally, it incorporates an on-chip temperature sensor as an extra function. In order to connect with the microcontrollers, it has an I2C bus interface. Pin configuration of the MPU6050 sensor is listed in (Table 3.3).

- **Gyroscope**

Micro-Electromechanical system (MEMS) technology is used in the 3-axis gyroscope of MPU6050. As seen in the figure below, it can be used to measure the rotational velocity component along the X, Y, and Z axes.

1- MEM inside the MPU6050 sensor detects a vibration produced by the Coriolis Effect when the gyroscopes are rotated around any of three axes.
2- A voltage that is directly proportional to an angular rate is produced by amplification, demodulation, and filtering the resulting signal.
3- A 16-bit ADC is used to digitise this voltage and sample each axis.
4- The output's full-scale ranges are +/-250.00, +/-500.00, +/-1000.00, and +/-2000.0
5- It calculates the angular velocity in degrees per second (deg./sec) along each axis.

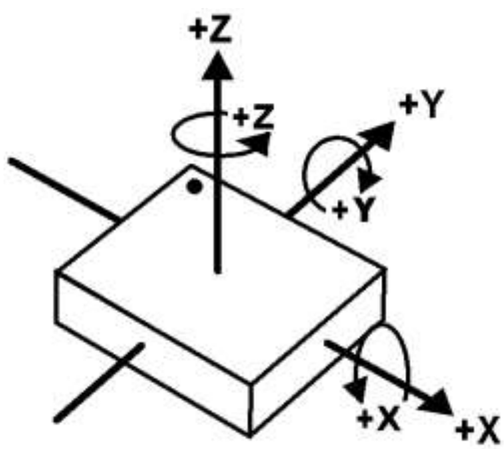


Figure 3.4: Polarity & orientation of rotation

- **Accelerometer**

MPU6050 sensor has a 3-axis accelerometer as well with micro-electromechanical (MEM) technology. It is used to evaluate the inclination or tilt angle along three x, y & z as shown in (Figure 3.5).

1- The movable mass is deflected by the 3-axis accelerometer.
2- The movable mass is bent when there is acceleration along the axes.
3- The differential capacitor becomes out of balance due to the movement of the moving plate, which generates the sensor output. o/p amplitude is directly proportional to the acceleration.
4- The output is converted to digital using a 16.00-bit ADC.
5- The full-scale acceleration ranges are +/- 2.00 g, +/- 4.00 g, +/- 8.00 g, and +/- 16.00 g.
6- It is measured in units of g, or gravity force.
7- The device will measure 0.00g on the X and Y axes and +1.00g on the Z axis when placed on a level surface.

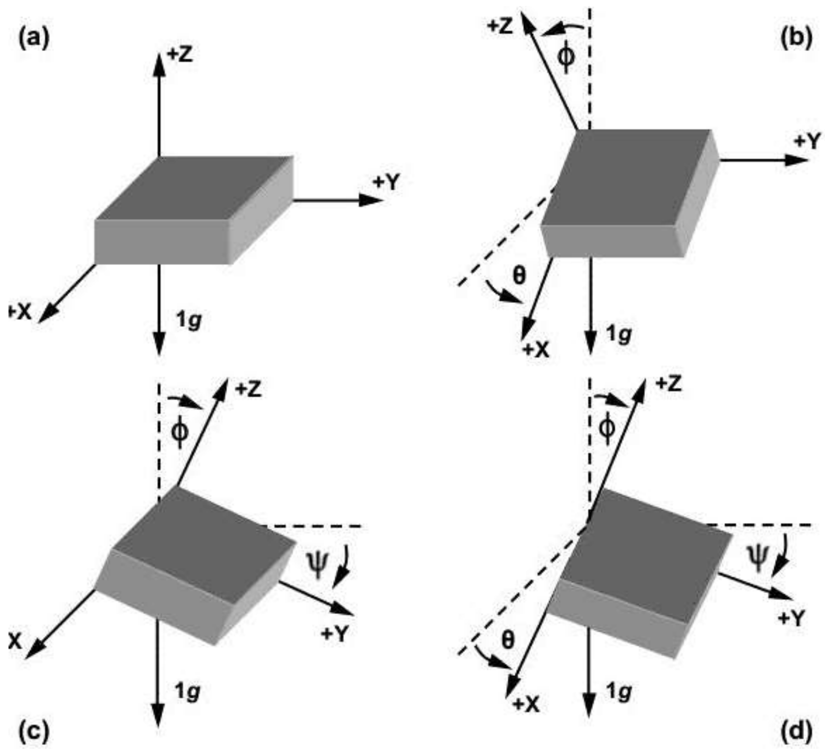


Figure 3.5: Accelerometer rotation and deflection angle

- **Digital motion processor (DMP)**

Motion processing algorithms are calculated by the integrated DMP. It processes data from the accelerometer, gyroscope, & extra third-party sensors such the magnetometer. It offers motion information such as roll, yaw angles, & pitch, as well as landscape & portrait sensing. It reduces the host's processing requirements for computing the motion data. From DMP registries, the obtained information can be read.

- Temperature sensor

ADC is used to digitize the output of the on-chip temperature sensor. The sensor's data register can be used to read the temperature sensor reading.

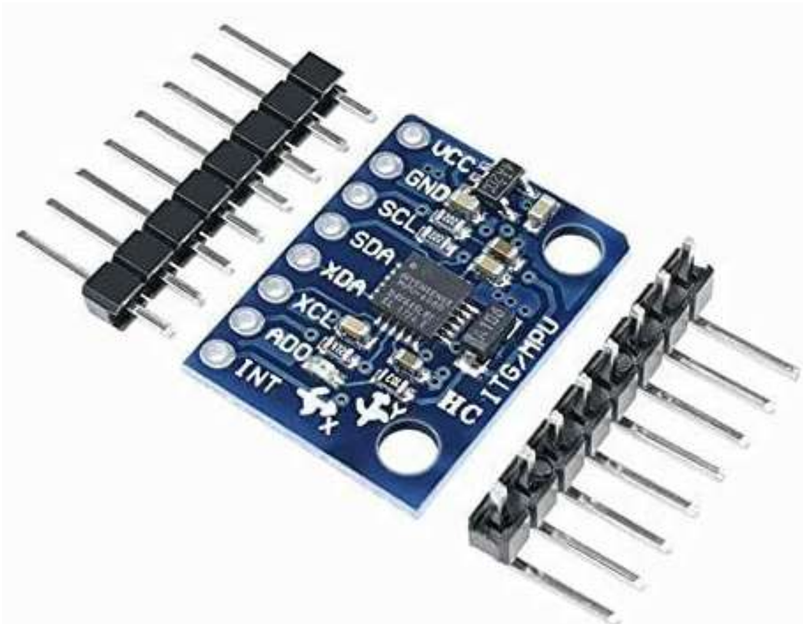


Figure 3.6: MPU6050 sensor

Table 3.3: Pin configuration of MPU6050

Sr#	Pins	Description
1	INT	Interrupt digital o/p pin.
2	AD0	Slave address I2C. It is wired with VCC.
3	XCL	Serial clock pin
4	XDA	Serial data pin.
5	SCL	Serial clock pin.
6	SDA	Serial data pin.
7	GND	Ground
8	VCC	Pin for power supply +5.00 DC.

3.2 Recording Protocol

Participants of both (Healthy & stroke) groups were asked to sit in a straight position on a chair. A protocol based on the composite of some activities which are frequently used in daily life has been designed. The designed protocol contains the usual movements of main upper limb (UL) joints including fingers, wrist, elbow, and shoulder. Briefly, this protocol reflects the gross motor actions of the entire UL. This protocol consists of 9 different movements of the upper limb generally replicating some complex activities of daily living (ADL). These tasks have been described in (**Table 3.4)**.

To provide the subjects, especially the patients, with an ease and comfort of performing the activities in sitting position a visual interface has been developed illustrating all the movements through the pictorial representation. It may be categorized as a GUI showing the details about the duration of activity, how to perform it and the sequence of activities. This visual graphic based interface has been designed in 'App Designer, MATLAB version 2019' **(Figure 3.7).** This pictorial presentation of required activities made it very easy for all subjects specially the stroke patients to understand and accomplish the complete protocol.

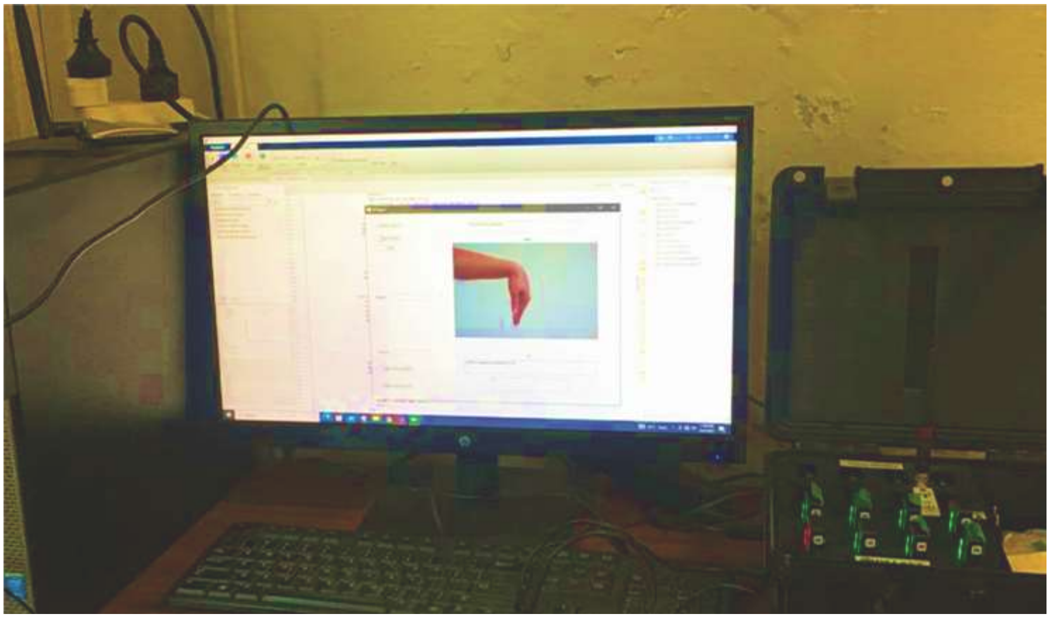


Figure 3.7: Visual interface for data recording

Table 3.4: List of activities for data recording protocol

Sr#	Task	Description
Activity 1	Wrist extension	Include wrist joint, hand move upward
Activity 2	Wrist flexion	Wrist joint hand move downward
Activity 3	Shoulder-flexion to 90.0º & elbow at 0º	Move the shoulder joint & entire upper limb
Activity 4	Shoulder-abduction to 90.0º & elbow at 0º	Keeps forearm pronated & move the elbow joint
Activity 5	Flip the paper placed on the table	Involve the movement of fingers, wrist & elbow joint.
Activity 6	Hold a cylindrical object placed on the table, include shoulder flexion to 90º	Move the forearm from elbow joint & helps in enhancing the ability of holding an object
Activity 7	Keep hand palm down and hold a ball with support grip	Include fingers movement and works on grip strength ability
Activity 8	Keep the shoulder 0.00º with hand pronated and then do supination	Include shoulder joint, & elbow joint
Activity 9	Rest position	Forearm in a specified relaxed position

Each participant was seated in upright position with the shoulder abducted at an angle of ‘0’ degrees. It was declared as the neutral or rest position of the participant. For every participant the experimental recording protocol consisted of ‘9’ activities in a specific order. In the start of protocol there is an initial rest time of ‘5’ seconds. There were three repetitions **(Figure 3.8)** for each movement.

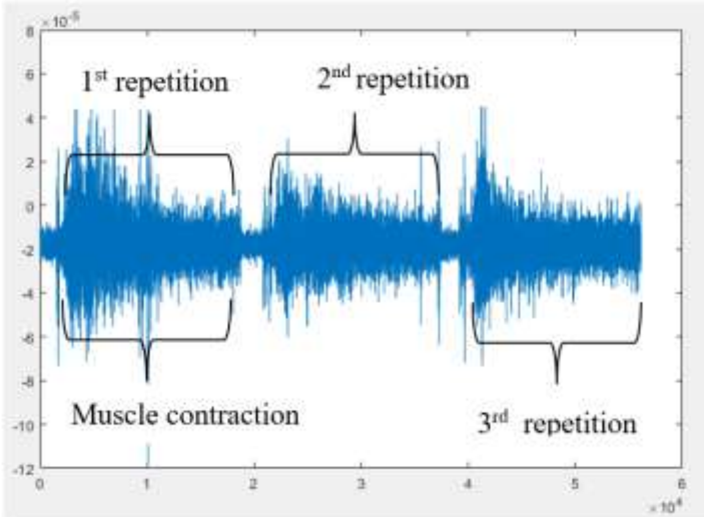


Figure 3.8: Recorded Electromyogram of one subject

Each activity was to be performed for '10' seconds and then there was a rest time of '10' seconds before the next activity started. Participant goes through the entire sequence of activities first and then the second trial/repetition starts. After competition of one task the tested upper limb was to return to the defined neutral position for the time interval of '10' seconds before starting the next task. This rest time was allowed to avoid muscle fatigue and mental stress especially for the stroke subjects.

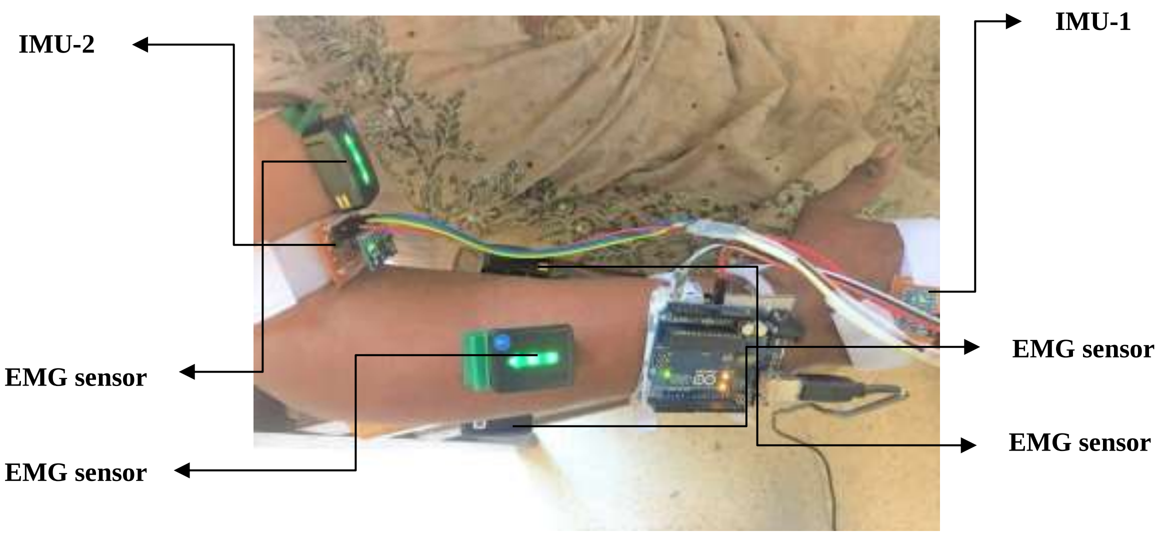
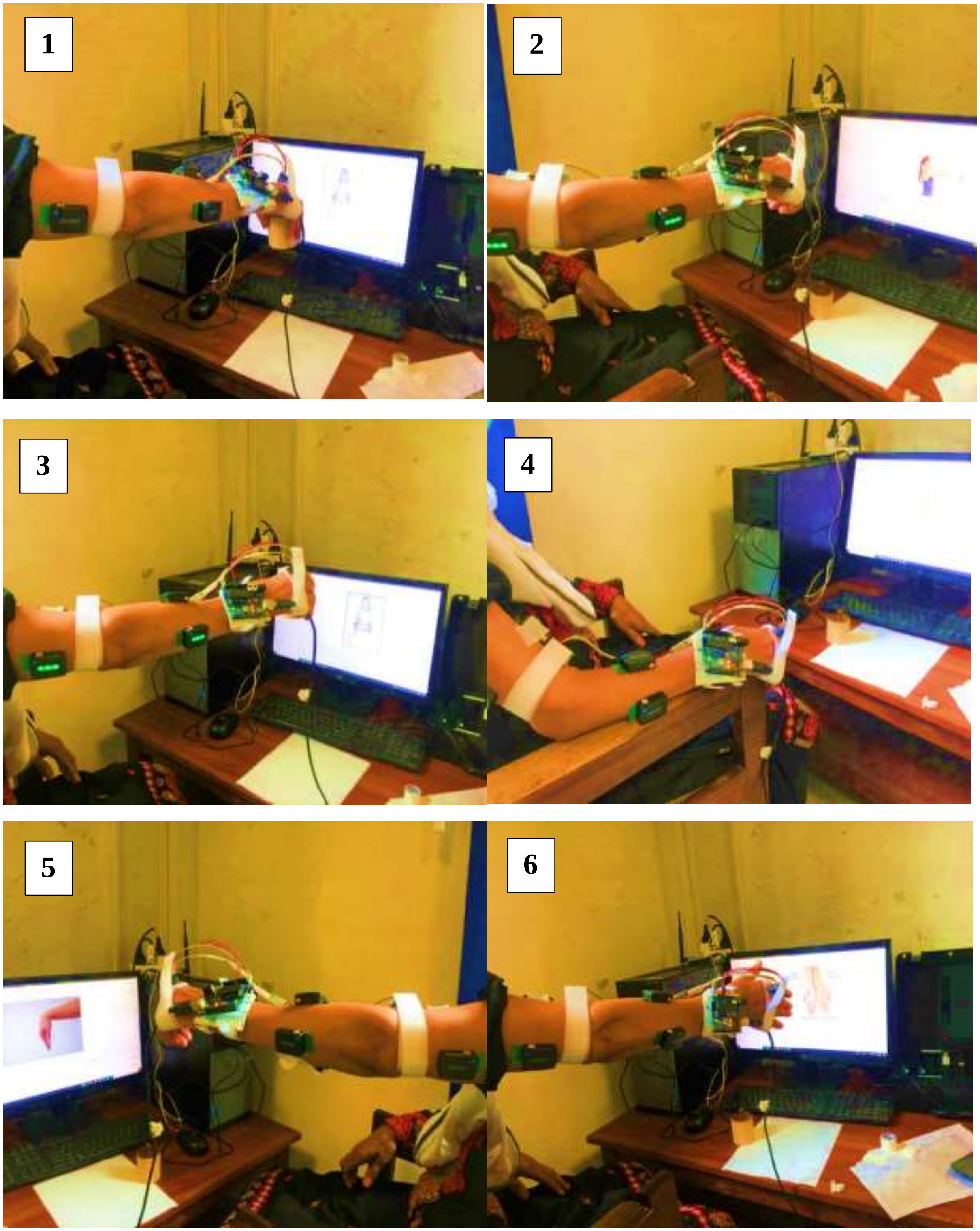


Figure 3.9: Sensor's placement on upper limb

Group of healthy subjects always performed every task comfortably at their regular daily speed. Stroke subjects were encouraged and advised to try their best to complete the protocol which truly reflected their motor function ability.


1
2
3
4
5
6

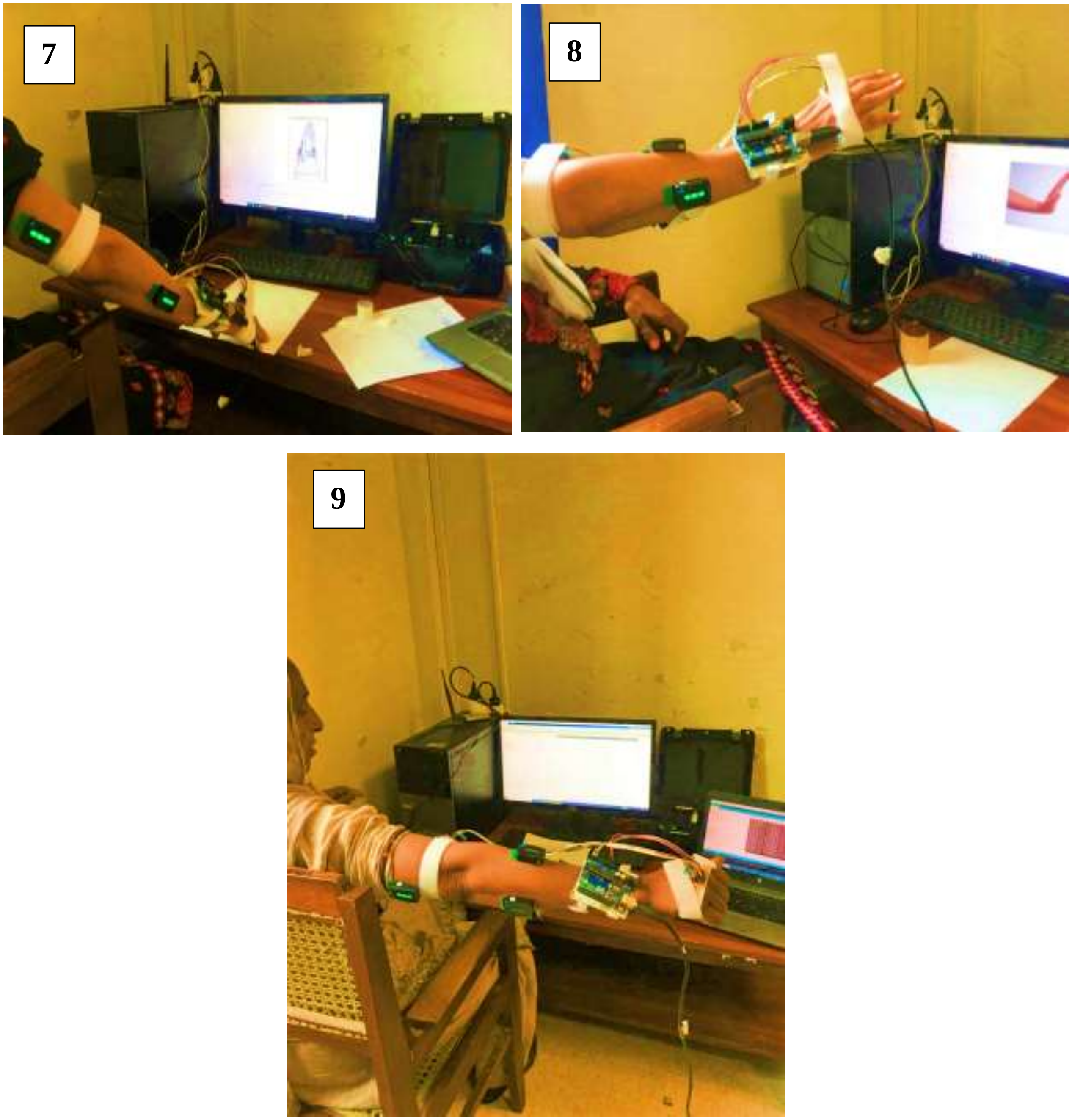


Figure 3.10: Participant performing the upper limb activities **(1)** Holding an object with support grip, shoulder flexion at ‘90º’, palm downwards & elbow at ‘0º’ **(2)** Shoulder flexion at ‘90º’ **(3)** Hold a cylindrical roll placed on the table with palm directing towards the body **(4)** Rest (Neutral position) **(5)** Wrist flexion **(6)** Palm supination **(7)** Flip the paper **(8)** Wrist extension **(9)** Shoulder abducted to ‘90º’.

3.3 Data Processing

- EMG data processing

To remove the motion artifacts and low frequency components a 2nd order butter-worth filter with the cut off frequencies of 20Hz & 500Hz respectively was applied to the raw EMG signals. Then filtered EMG signals were rectified. Rectified EMG signals were applied with a moving average filter to generate an EMG envelope for each movement. It has been done by applying the moving average with the sliding window of 150 data points to each channel. Then EMG data is normalized in the amplitude to the maximal value. Normalization is applied to all the EMG channels simultaneously.

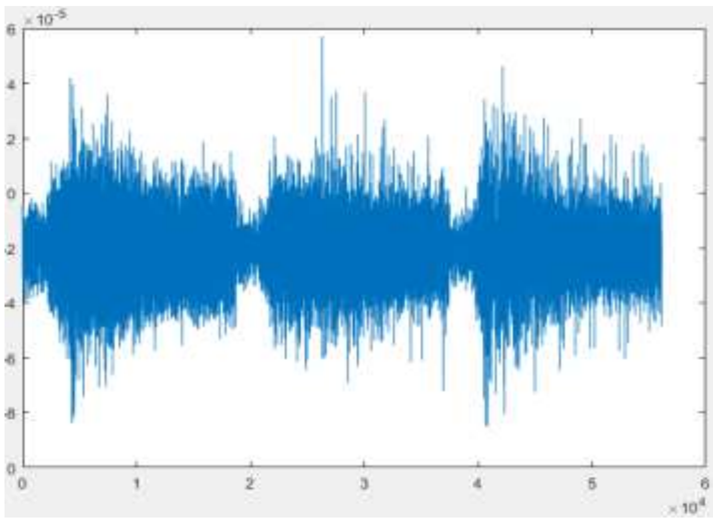


Figure 3.11: Raw EMG data of shoulder abduction for 1 channel

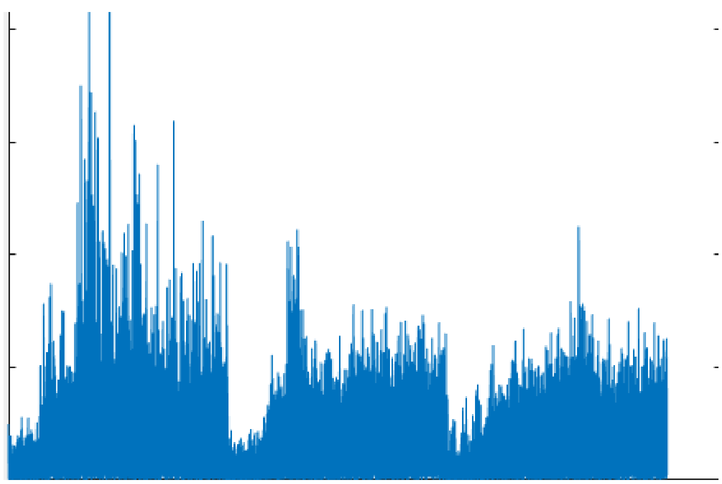


Figure 3.12: Rectified EMG data

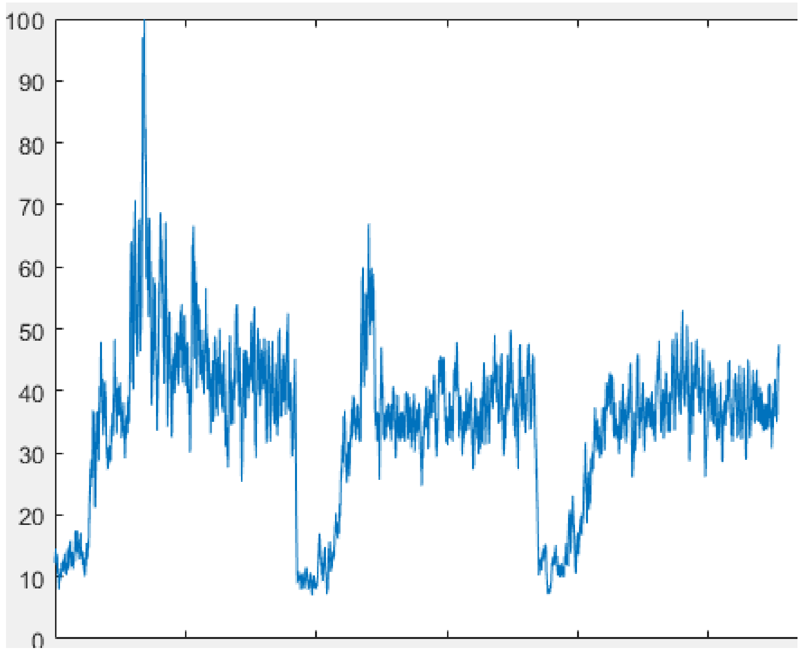
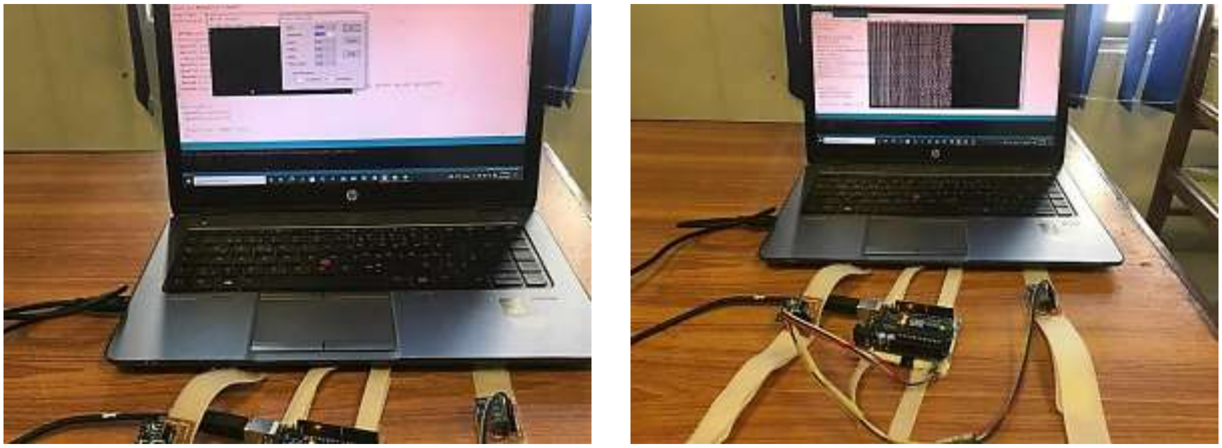


Figure 3.13: EMG signal after applying mov-avg and normalization

- **IMU data processing**

As mentioned earlier, two IMU sensors MPU6050 have been used in this study. One is placed on the wrist joint to record the kinematic information of hand wrist & hand movement and second is placed on the upper forearm to record the data of shoulder joint. These IMU sensors have been integrated with the laptop via 'Arduino' interface. To record the raw kinematic data from accelerometer and gyroscope of IMU sensor **MPU6050_tockn** library has been used. IMU sensors are auto calibrated through this library at the stand still position and start taking the raw IMU data after the duration of '3' seconds. **'Tera-Term 4.10'** has been used for data logging in this study. It provides the choice of **'time stamp'** as well. A baud rate of **'115200'** was set for logging. Data sampling rate for accelerometer and gyroscope has been set to **'103Hz'**. A terminal emulator program called Tera Term is open-source and free software. It can simulate a variety of computer terminals, including the DEC VT100 and DEC VT382. Telnet, SSH versions 1 and 2, and serial port connections are supported as well. Additionally, it includes some helpful plugins and a built-in macro scripting language as well **(Figure 3.13)**.



(a) (b)

Figure 3.14: Tera term **(a)** Configurational settings **(b)** Data logging

To remove the gravity components and low freq. drift movement artifacts the raw IMU data was applied with a 2nd order high pass Butterworth filter with cut off frequency set as 25 Hz (0.48π rad/sample). Then filtered IMU data was applied with mov-avg filter with sliding window of 150 to each channel of accelerometer and gyroscope. Then triaxial data of accelerometer of IMU-1 was combined with the triaxial accelerometer data of IMU-2. Data was then normalized in the amplitude to the maximal value. Similarly, the gyroscope data was applied with mov-avg, concatenated, and normalized.

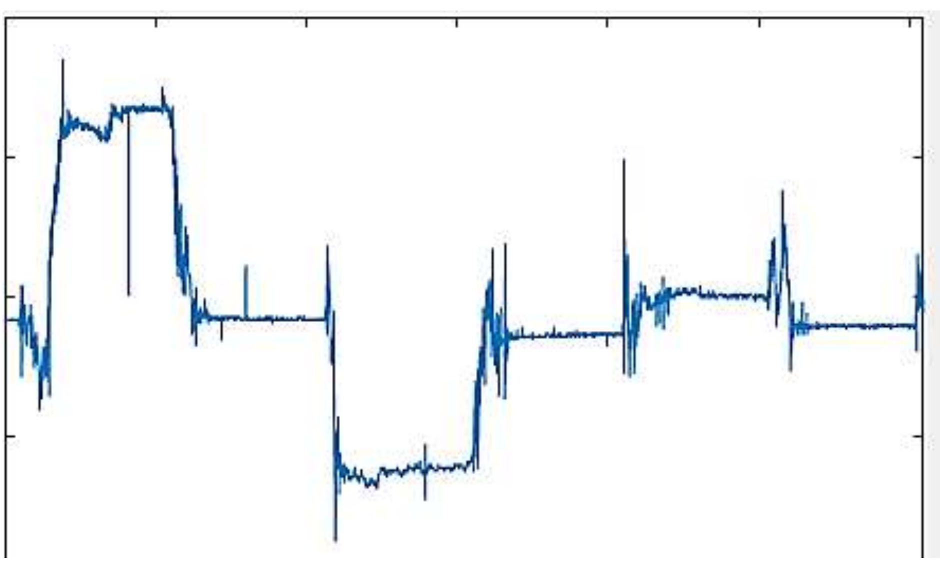


Figure 3.15: Raw accelerometer-1 data of x-axis

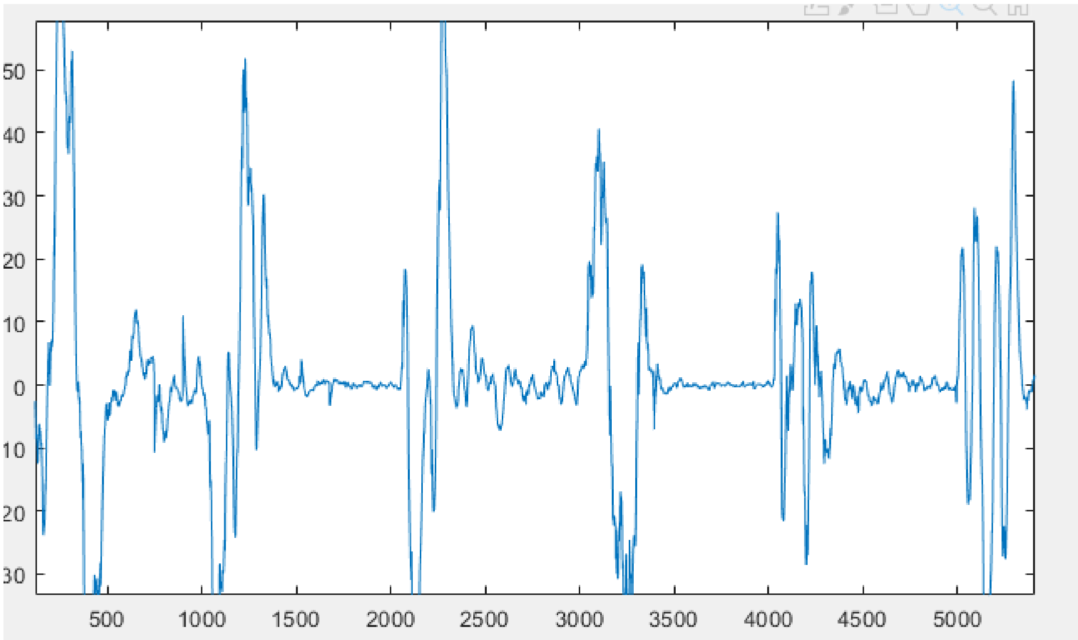


Figure 3.16: Processed accelerometer-1 data of x-axis

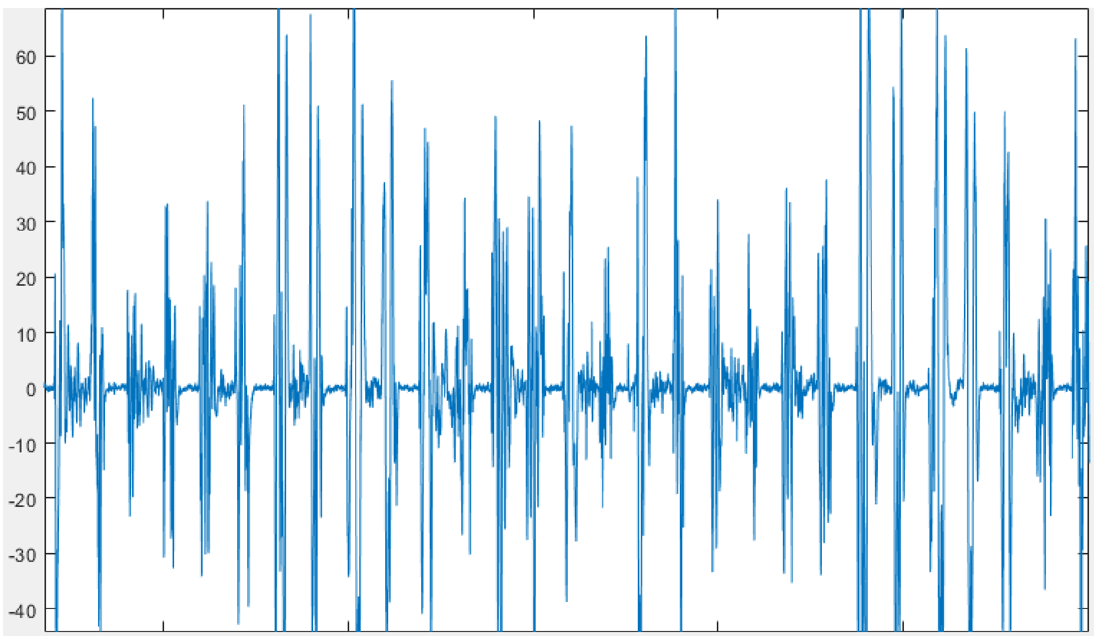


Figure 3.17: Processed gyroscope-1 data of x-axis

After concatenating and normalizing the accelerometer & gyroscope data of both the IMUs separately, they were concatenated again to generate a complete data matrix of IMU with 12 columns (1-6 columns contain the accelerometer data & 7-12 columns contain data from both the gyroscopes).

3.4 Feature Extraction

Processed EMG data has been applied with an overlap window of 50ms **(Fs=1926Hz, Window =50ms or 0.05, 96samples)** with an overlap of 20samples (10ms) for feature extraction and segmentation. In this study time domain (TD) features have been considered due to their least computing complexity. One more benefit of using time domain features is that signal does not require any additional transformation. Extra number of samples from EMG feature set have been discarded to coincide the dimensions of IMU data's feature set as this study also discuss the combine effect of EMG and IMU data fusion to analyze the overall impact on the classification accuracy. TD features **(Table 3.5)** have been extracted from both the data sets separately.

Table 3.5: Extracted TD features for recorded data

Sr#	**Features**	**Abbreviations**
1	Mean_Absolute_Value	MAV
2	Root_Mean_Square	RMS
3	Variance	Var
4	Mean absolute value slope	MAVS
5	Integrated EMG	IEMG
6	Simple square integral	SSI
7	Waveform length	WL

Similarly processed IMU data has been applied with a sliding window of 50ms and overlap size of 10ms. A set of 6 statistical features (Mean, RMS, Standard deviation, variance, Kurtosis, & skewness) has been extracted for the IMU data.

3.5 Classification Models

- **Data label:** After processing, feature extraction and segmentation, the data was assigned with unique labels before applying any supervised classification model. In this study there are a total of nine different classes assigned with distinctive labels listed in **(Table 3.6).**

Sr#	**Class**	**Label**
1	Extension	Ext
2	Flexion	Flx
3	Shoulder abduction	Sh-abd
4	Shoulder flexion	Sh-flx
5	Flip the paper	Flip-paper
6	Hold cylindrical roll	Hold-cyl
7	Fetch an object/ball	Fetch-ball
8	Rest	Rest
9	Hand supination	Supp

- **Test train split:** For implementation of classification models labeled data has been divided with 80:20 ratio:

Train data	80%
Test data	20%

- **Machine learning Classifiers:** In this study multiple machine learning classification models have been implemented including linear discriminant analysis **(LDA)**, Quadratic discriminant analysis **(QDA)**, Linear support vector machine **(Linear-SVM)**, Quadratic support vector machine **(Quadratic-SVM)** and Fine **KNN**. Beside this recorded data has been tested for ensembled models also. These ensemble models include **subspace discriminant** and **subspace KNN**. These machine learning models have briefly been discussed in the next section:

1- Linear discriminant analysis (LDA)

LDA as the name suggests is a linear dimensionality reduction and classification model. It is widely being used in classification problems for features extraction. In this study LDA has been implemented for multiclass classification. Nonlinear separable classes may not be efficiently separated by linear decision boundaries. We want boundaries that are more adaptable. When there are more observations than features, LDA might not work as it should. It is called Small Sample Size (SSS). Regularization of data is necessary. LDA is utilized to identify a linear transformation that categorizes several classes. However, if the groups really aren't linearly separable, it is unable to project into a lower-dimensional space. This issue emerges when classes have similar meanings, i.e., that the discriminatory information is present in the data scatter rather than the mean. Kernel functions are a tool we can apply to solve this problem. such as in SVM, SVR, etc. The goal is to use a non-linear mapping to convert the input data into the new, high dimensional feature space where kernel functions can compute the inner products.

2- Quadratic discriminant analysis (QDA)

The only significant difference between linear and quadratic discriminant analyses is the relaxation of the assumption that the covariance and mean of all classes were equal. That is why it needs to be calculated independently. A brief summary of QDA is given below:

- QDA is categorized as a generative model.
- Each class is thought to have a Gaussian distribution according to QDA.
- The proportion of data points that belong to the class is the class-specific prior.
- The average of the input variables that are part of the class makes up the mean vector particular to that class.
- Covariance matrix is generated by the vector covariance which belongs to that class.

3- Linear support vector machine (LSVM)

Finding a hyperplane in the space with dimension N (N is No. of features) that categorizes the data points clearly is the goal of the support vector machine algorithm. There are a variety of different hyperplanes that might be used to split the two distinctive classes/categories of data points. Finding a plane with the greatest margin, that is, the largest separation between data points from both classes is the goal. Maximizing the distance of margin adds some support, increasing the confidence with which future data points can be categorized successfully.

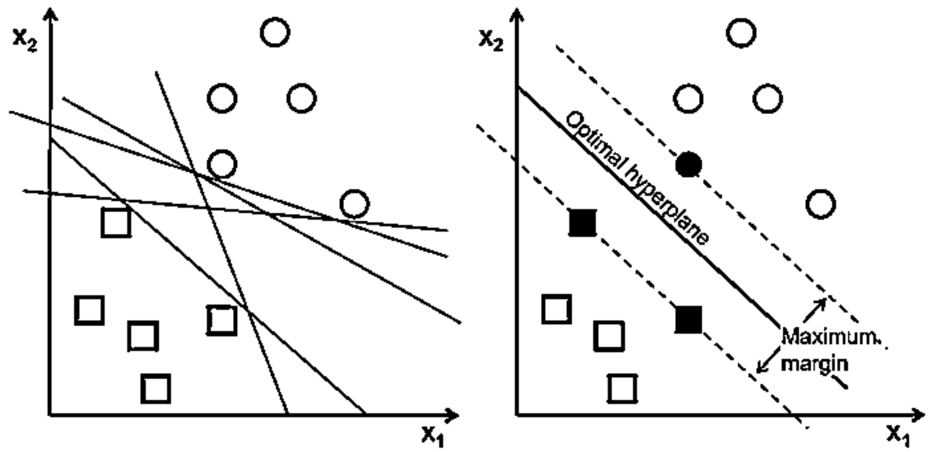


Figure 3.18: Possible hyperplane in LSVM

4- **Quadratic SVM**

The QSVM is a new non-linear SVM model without a quadratic kernel. It is possible to state the optimization problem of SVM as follows: With a functional margin bigger than a constant, maximize the geometrical margin subject to all training data. The equation of the hyper-plane used for linear separation, W T X + b, yields the functional margin. 1 ||W || is the geometrical margin. And in this instance, the constant is one. while implementing the QSVM It is considered that the geometrical margin is equivalent to the inverse of the norm.

5- **Fine KNN**

KNN is a supervised machine learning (ML) method that can be used to solve classification and regression problems. It is mostly used in industry, nevertheless, to solve classification issues. The following two traits apply to KNN and are accurate:

- KNN is actually a lazy learning algorithm because it uses all of the classification data as training rather than having a separate training phase.
- Due to its lack of assumptions on the underlying data, KNN is also a non-parametric learning model.

6- **Ensemble ML models**

Ensembled classifiers are machine learning (ML) classifiers to combine the multiple other ML models for prediction process. These models are called base estimators. Ensemble models have proven to offer the solution to counter all the technical challenges in building a single estimator. These technical challenges include:

- High variance: when model is sensitive to the given inputs for learned features.
- Low accuracy: Implementation of single model may not fit in the complete training data and thus will not provide the desired results/accuracy.
- Feature noise: Single model heavily relies on few features while computing any prediction.

For a specific data set, a single ML model might not produce the ideal prediction. ML algorithms have their own limitations, and it might be difficult to create a model with high accuracy. Overall accuracy can be increased if we create & merge numerous models. After that, we combine the output from each model with the following two goals:

- Reducing the models' prediction error.
- Maintaining the generalization of model.

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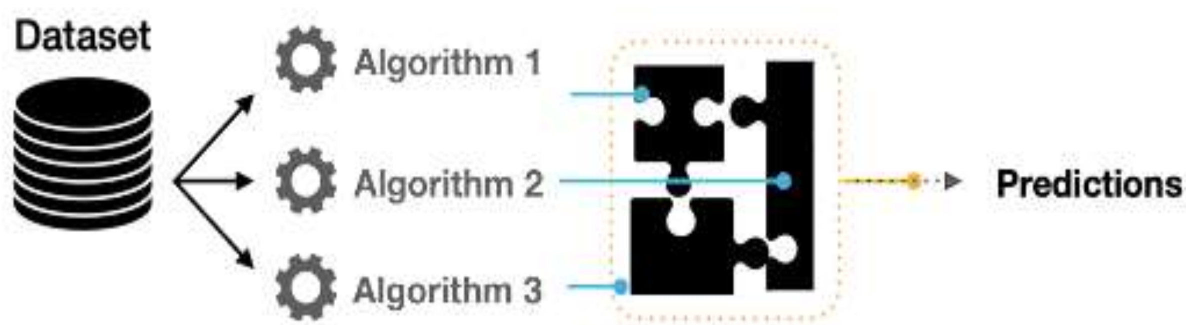


Figure 3.19: Ensemble modeling concept

In this study two ensembled models have been implemented for the created feature set of EMG & IMU data:

1- Ensemble subspace discriminant.
2- Ensemble subspace KNN.

- **Neural network classifiers**

An i/p vector is transformed into an o/p by units (neurons), which are grouped in layers in a neural network. Each unit receives an input, performs a nonlinear operation on it, and then transfers the result to the next layer. The networks are typically categorized as feed-forward, meaning that each unit transmits its output to every unit on the layer next to it, but no feedback to the previous one. Signals travelling from one unit to another are given weightings, and these are the weightings that are tweaked throughout the training phase for adapting a neural network to the specific issue. This is called learning phase.

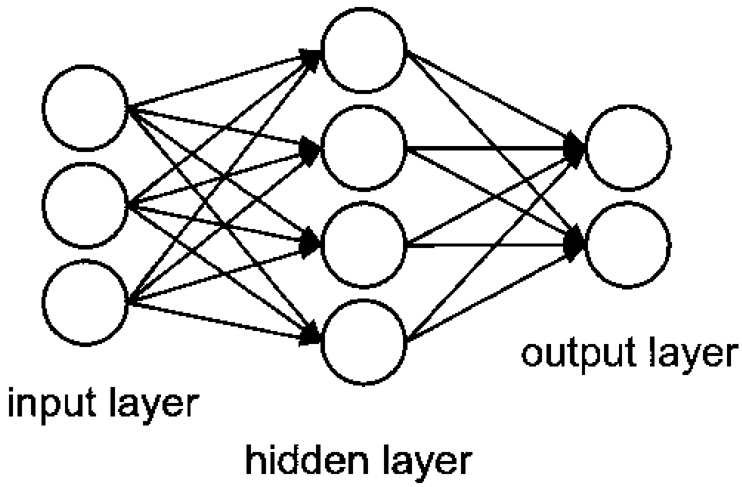


Figure 3.20: Basic structure of neural network classifier

Neural networks find its applications in numerous problems ranging from pattern recognition to function representation etc. Neural networks are famous classification techniques, but they are implementable for regression problems as well. Advantages of using neural networks include their high tolerance towards noisy data.

In this study a tri-layered neural network classifier has been implemented. Applied neural network model contains 3 fully connected layers each of size 10 and one activation layer with regularization strength ‘λ’ equals to ‘0’.

CHAPTER 4: RESULTS & DISCUSSION

In this study multiple machine learning models have been implemented for the long-term classification of Activities of daily living (ADLs) based upper limb movements to design a rehabilitation system for chronic stroke patients. These ML and neural network models have been implemented on three types of data sets (EMG, IMU & EMG+IMU) to perform a comparative analysis. This study also addresses the impact of sensor fusion (EMG+IMU) to present a novel strategy for prosthetic control based on the coupled utilization of EMG & inertial sensors. This comparison will allow us to evaluate the performance of proposed control for robotic, myoelectric, and prosthetic control as compared to the traditional only EMG based control systems.

As mentioned earlier in 'section 3.1' there are two groups healthy and chronic stroke subjects with varying age dynamics. Each group consists of 15 subjects. In total we have a data set of 30 subjects. Classification models include linear, quadratic, ensemble, and tri-layered neural networks with two different activation functions. A five-fold cross validation has been applied to each model before training.

4.1 Classification results of EMG data

- **ML models**

The classification results for the recorded EMG data have been demonstrated in **(Table 4.1)**. which summarizes the statistical characteristics mean, standard deviation and standard error for LDA, QDA, LSVM, QSVM and fine KNN.

Table 4.1: Statistical analysis of ML model for EMG data

Model	Mean	STD	Standard Error
LDA	70.22	8.17	1.54
QDA	81.62	6.63	1.25
LSVM	79.5	7.19	1.35
QSVM	82.76	6.04	1.14
KNN	83.95	5.17	0.97

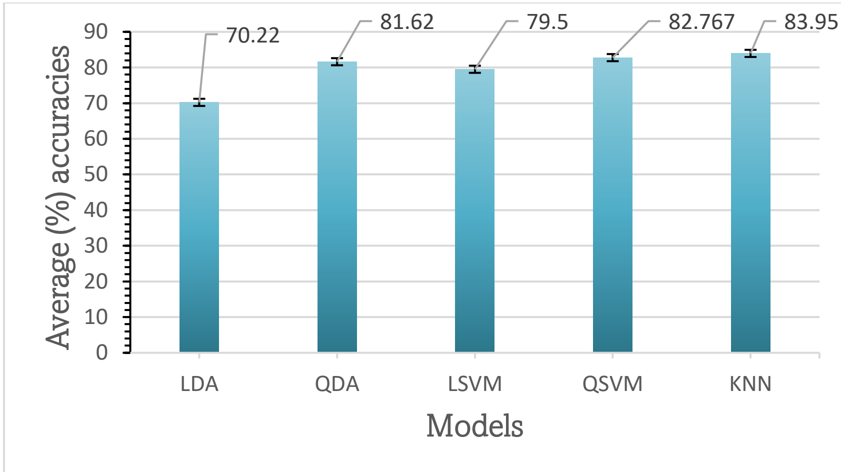


Figure 4.1: Comparison of avg. accuracies of ML models for EMG data

- **Ensemble ML Models**

Two ensembled models have been implemented in this study:

1- Ensembled subspace discriminant

2- Ensembled subspace KNN

Statistical outcomes of the applied ensembled models have been listed in **Table 4.2**:

Table 4.2: Statistical analysis of ensembled ML model for EMG data

Model	**Mean**	**STD**	**Standard Error**
Ensembled subspace discriminant	69.53	5.18	0.947
Ensembled subspace KNN	81.26	6.21	1.13

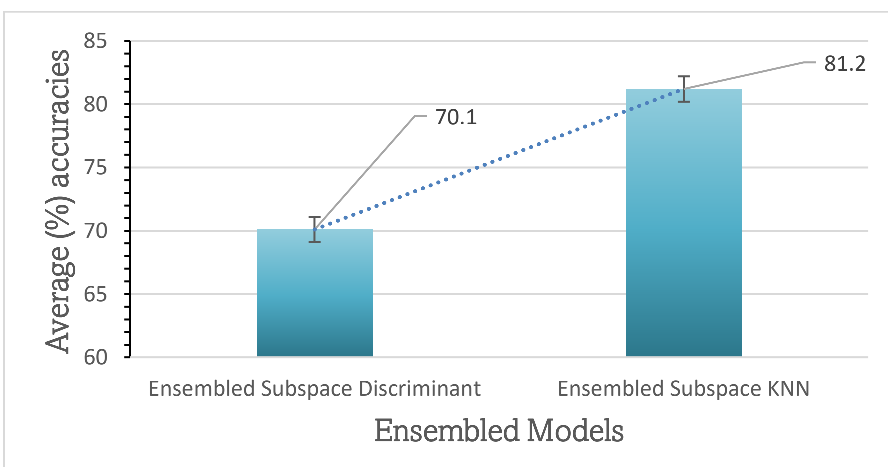


Figure 4.2: Average accuracies of ensembled ML models for EMG data

- **Neural Network model**

A tri-layered neural network classifier has been implemented for all types of data sets. specifications of the applied classifier have been mentioned in **Table 4.3**:

Table 4.3: Specification of neural network classifiers

Sr#	**Specifications**	**Description**
1	No. of fully connected layers	3
2	Size of each layer	10
4	Iteration limit	1000
5	Regularization strength (λ)	0
6	Standardize data	Yes
7	Avg. training speed	18000 obs./sec

Table 4.4: Statistical analysis of neural network classifier for EMG data

Activation function	**Mean**	**STD**	**Standard Error**
Relu	81.26	5.18	0.947

Multiclass machine learning classification models have been implemented for the classification of upper limb movements. Results demonstrate that among linear and quadratic QD & SVM models quadratic models performed well with the average accuracies of **81.62%** & **82.76%** for **QDA** & **QSVM** respectively. Average accuracies for **LDA** and **LSVM** are **70.22%** & **79.5%** respectively. But the performance of **KNN** for the given EMG data was best among all the models with the highest average accuracy of **83.95%,** STD **5.17** and standard error of **0.97**. Ensembled subspace KNN models showed better performance than ensembled subspace discriminant with average accuracies of **69.53%** & **81.25%** respectively. With ANN the average accuracy was **81.153%.**

Overall, the KNN model has been found to be best among all the applied ML models in terms of performance accuracy and training time. Classification results for neural networks can be significantly enhanced after optimization which has not been included in the presented study. Confusion matrix for the best performed models have been shown below.

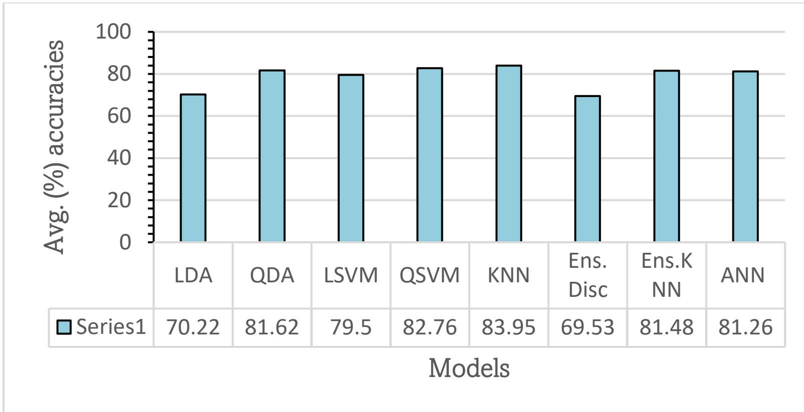
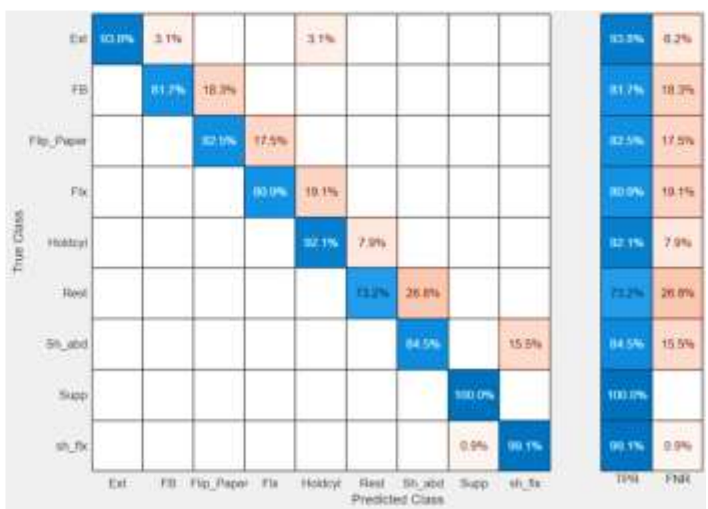


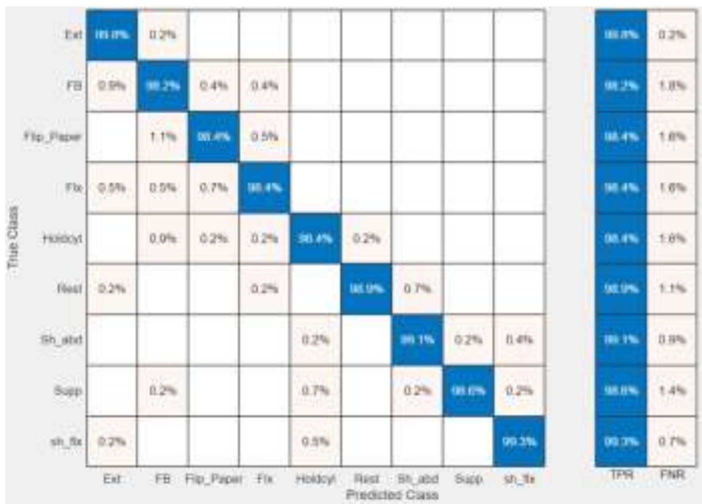
Figure 4.3: Comparison of applied classification models for EMG data

Confusion matrix of fine KNN



Confusion matrix for quadratic SVM

Confusion matrix of ANN



Confusion matrix of ensembled KNN

4.2 Classification results of IMU data

Above mentioned classification models have also been applied for the kinematic data across 30 subjects. Classification results, statistical outcomes and confusion matrices of the best performing classifiers have been presented below.

Table 4.5: Statistical outcomes of IMU data classification

Model	**Average accuracies**	**STD**	**Standard Error**
LDA	50.5	3.66	0.81
QDA	64.9	7.93	1.77
LSVM	52.35	4.90	1.09

QSVM	**74.035**	3.33	0.74
KNN	**95.64**	2.95	0.66
Ensemble Discriminant	49.5	3.04	0.68
Ensemble KNN	**89.49**	4.59	1.02
Neural network	60.525	2.92	0.65

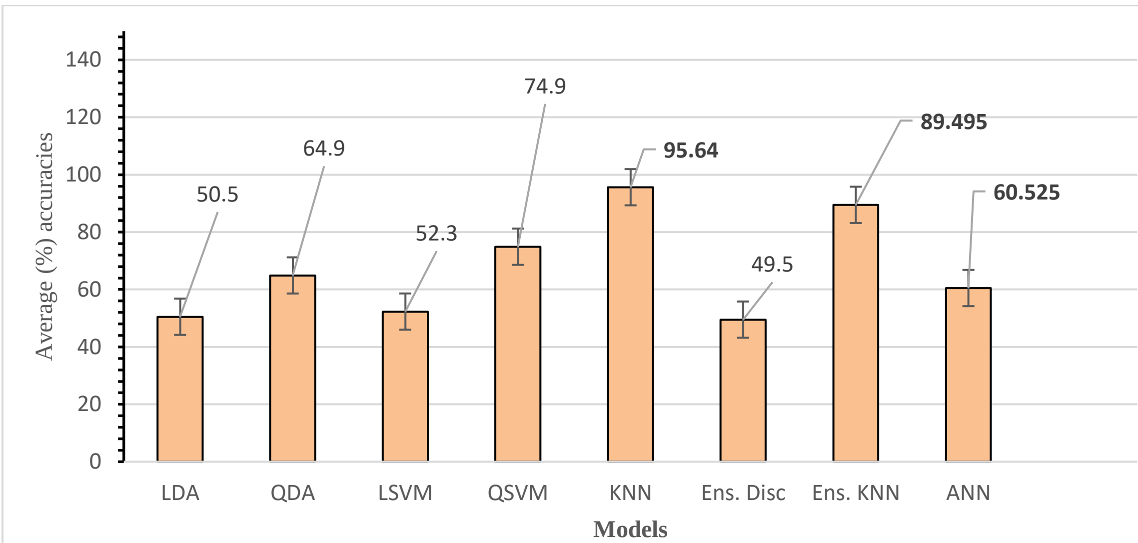
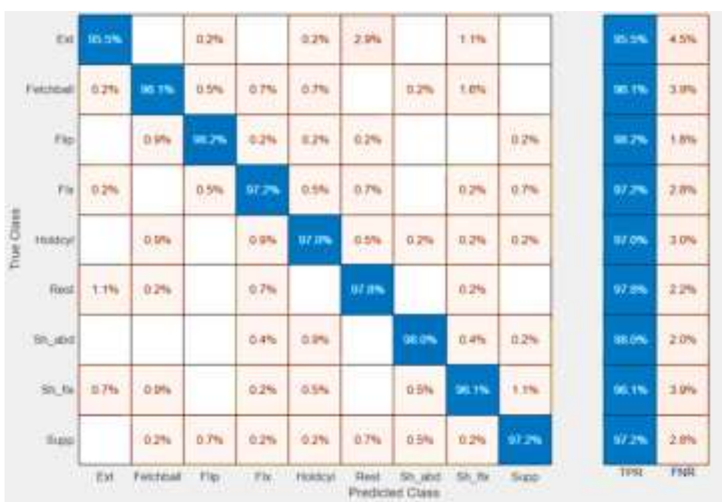
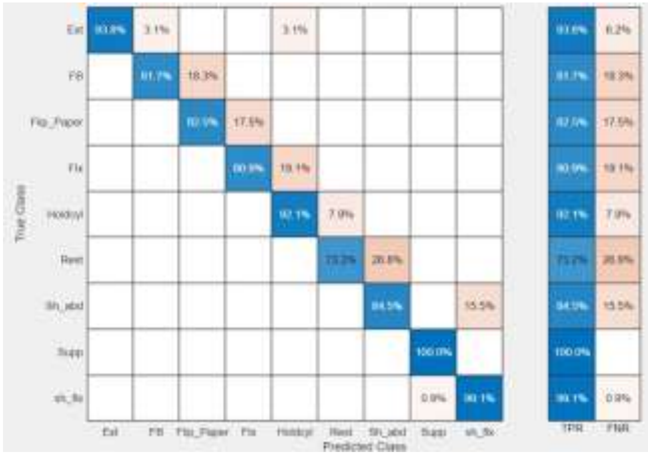


Figure 4.4: Comparison of applied classification models for IMU data



Classification result of KNN



Classification result for QSVM

Classification result of ensemble KNN

4.3 Classification result of EMG+IMU

Impact of sensor fusion technique on the overall classification accuracies of the applied models is the one of the main objective of the presented study. All the above-mentioned classifiers have been implemented for (EMG+IMU) data and the resulting outcomes have been demonstrated below:

Table 4.6: Statistical outcomes of EMG+IMU data classification

Model	**Average accuracies**	**STD**	**Standard Error**
LDA	85.64	4.53	0.67
QDA	96.585	5.4	0.60
LSVM	93.10	3.98	0.89

QSVM	97.235	2.94	0.399
KNN	96.87	4.25	0.45
Ensemble Discriminant	82.83	3.72	0.95
Ensemble KNN	96.68	2.67	0.43
ANN	96.51	3.94	0.41

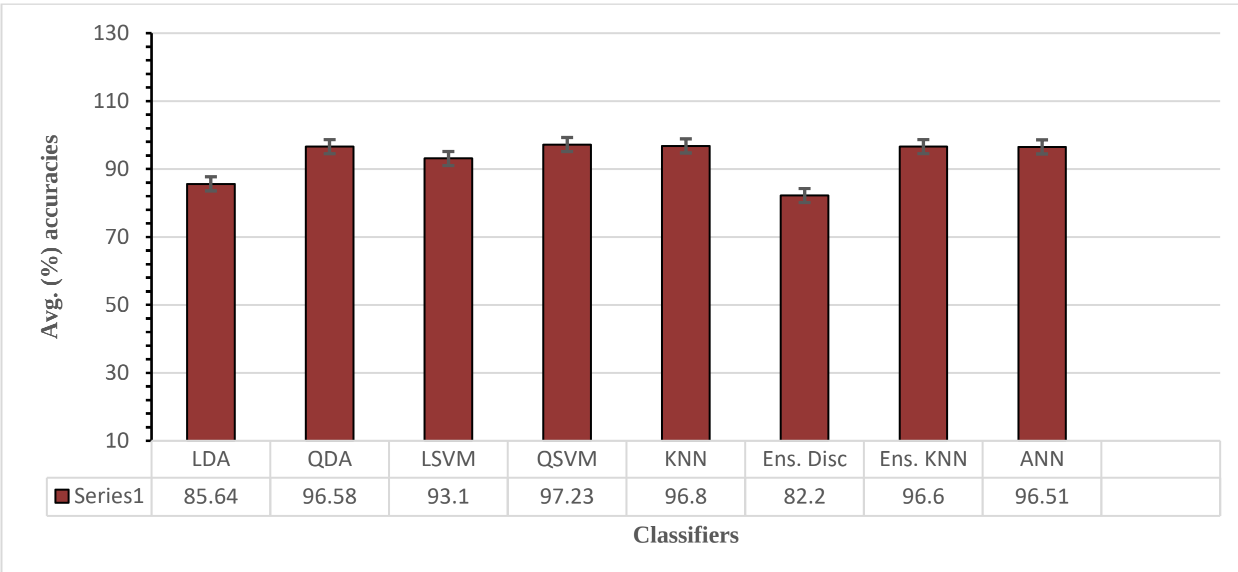
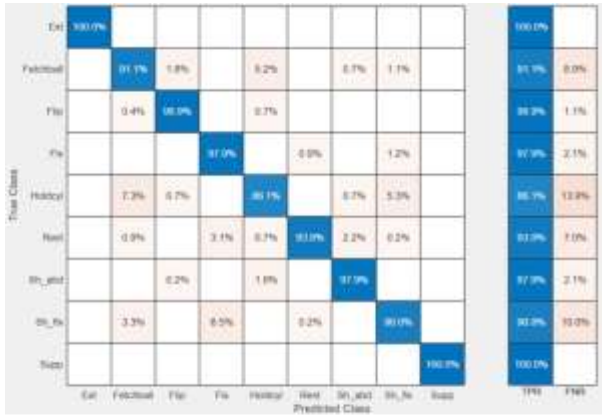
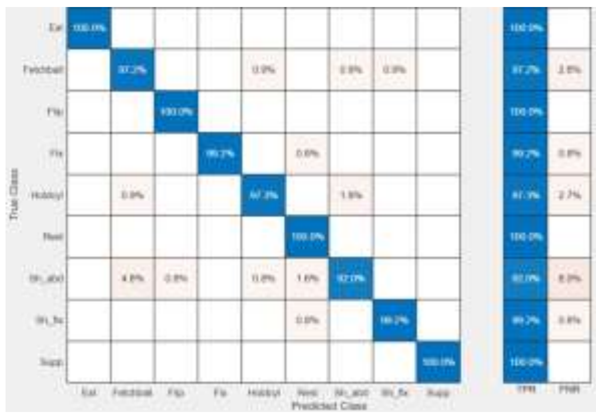


Figure 4.5: Comparison of classification models for EMG+IMU data

Classification result of LDA

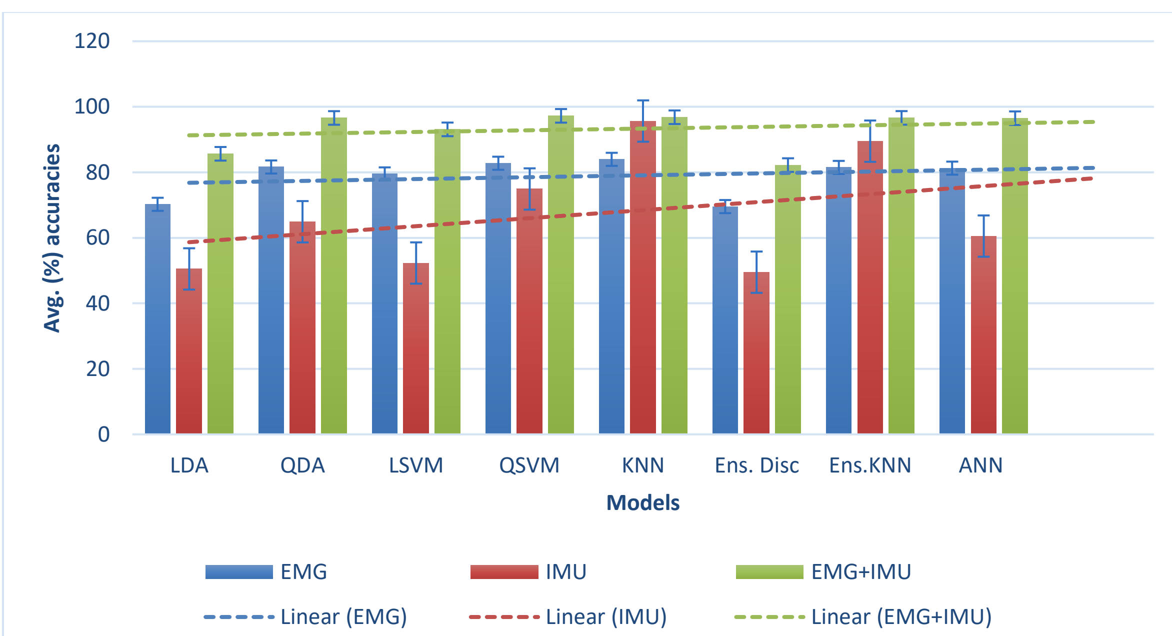


Classification result of LSVM



Result of ANN classifier

4.4 Comparison of results



CHAPTER 5: CONCLUSION

Classification of hand gestures from Electromyographic signals finds a wide range of applications in designing different human machine interfaces (HMI), prosthetic and rehabilitation control systems for the chronic stroke patients with mobility disorders or the people with limb amputee. But when there is a matter of simultaneous complex movements of varying degrees of freedom, conventional control techniques have proved not to be so efficient. Considering the above-mentioned problem, this study presents an idea of activities of daily living (ADLs) based rehabilitation systems for chronic stroke patients based on the idea of coupled use of EMG and inertial sensors. Nine different upper limb movements replicating the daily life activities have been classified using multiple machine learning and neural network classifiers. Besides this a comparative analysis have been performed to analyze the overall impact of sensor fusion over the classification accuracy. It has been observed that KNN models performed well for all types of data sets with average accuracy of 98.9% for EMG and IMU datasets. Other models include LDA, QDA, LSVM, QSVM, ensembled KNN and ensembled discriminant. Neural network classifier with three convolutional layers and two different activations functions have been implemented also. For EMG and IMU data SVM models performed better than LDA models with average accuracies of 82.76% & 74.5% respectively. Fine KNN model has been found to be best for both EMG & IMU data types with average accuracies of 83.95% and 95.64% respectively. Similarly, ensembles KNN was more efficient than ensembled discriminant for both EMG and IMU data with mean accuracies of 81.56% & 89.49% respectively. ANN performed well with accuracies of 81.26% for EMG and 60.58% for IMU data. However, the average accuracies of all these models significantly improved for EMG+IMU data. All the applied models surprisingly produced >90.5% accuracies for EMG+IMU data (LDAs= 91.1%, SVMs= 95.16%, ensembled= 90.1% and ANN=95.13%). Experimental outcomes indicate that rehabilitation control systems designed on the concept of coupled utilization of EMG & inertial sensors will not only be significantly efficient than conventional control systems but will allow the complex movements with varying degrees of freedom.

REFERENCES

[1] A. Sala *et al.*, "healthcare Rehabilitation of Upper Limb Motor Impairment in Stroke: A Narrative Review on the Prevalence, Risk Factors, and Economic Statistics of Stroke and State of the Art Therapies," 2022, doi: 10.3390/healthcare.

[2] C. M. Stinear, C. E. Lang, S. Zeiler, and W. D. Byblow, "Advances and challenges in stroke rehabilitation," *The Lancet Neurology*, vol. 19, no. 4. Lancet Publishing Group, pp. 348–360, Apr. 01, 2020. doi: 10.1016/S1474-4422(19)30415-6.

[3] D. Toni, E. di Angelantonio, M. T. di Mascio, R. Vinisko, and P. M. W. Bath, "Types of stroke recurrence in patients with ischemic stroke: A substudy from the PRoFESS trial," *International Journal of Stroke*, vol. 9, no. 7, pp. 873–878, Oct. 2014, doi: 10.1111/ijs.12150.

[4] Y. Li and G.-Y. Yang, "Pathophysiology of Ischemic Stroke," 2017, pp. 51–75. doi: 10.1007/978-981-10-5804-2_4.

[5] S. E. Khoshnam, W. Winlow, M. Farzaneh, Y. Farbood, and H. F. Moghaddam, "Pathogenic mechanisms following ischemic stroke," *Neurological Sciences*, vol. 38, no. 7. Springer-Verlag Italia s.r.l., pp. 1167–1186, Jul. 01, 2017. doi: 10.1007/s10072-017-2938-1.

[6] "ymj-39-229".

[7] S. D. Smith and C. J. Eskey, "Hemorrhagic stroke," *Radiologic Clinics of North America*, vol. 49, no. 1. pp. 27–45, Jan. 2011. doi: 10.1016/j.rcl.2010.07.011.

[8] M. Saini, K. Ikram, S. Hilal, A. Qiu, N. Venketasubramanian, and C. Chen, "Silent stroke: Not listened to rather than silent," *Stroke*, vol. 43, no. 11, pp. 3102–3104, Nov. 2012, doi: 10.1161/STROKEAHA.112.666461.

[9] D. Ivanov Hadjiev and P. Pencheva Mineva, "A reappraisal of the definition and pathophysiology of the transient ischemic attack."

[10] C. Zhang and S. Kasner, "Diagnosis, prognosis, and management of cryptogenic stroke," *F1000Research*, vol. 5. Faculty of 1000 Ltd, 2016. doi: 10.12688/f1000research.7384.1.

[11] A. O. de Mendivil, A. Alcalá-Galiano, M. Ochoa, E. Salvador, and J. M. Millán, "Brainstem Stroke: Anatomy, Clinical and Radiological Findings," *Seminars in Ultrasound, CT and MRI*, vol. 34, no. 2, pp. 131–141, Apr. 2013, doi: 10.1053/j.sult.2013.01.004.

[12] S. Naghdi, N. N. Ansari, K. Mansouri, and S. Hasson, "A neurophysiological and clinical study of Brunnstrom recovery stages in the upper limb following stroke," *Brain Inj*, vol. 24, no. 11, pp. 1372–1378, 2010, doi: 10.3109/02699052.2010.506860.

[13] Y. Tu, Z. Zhang, X. Gu, and Q. Fang, "Surface electromyography based muscle fatigue analysis for stroke patients at different Brunnstrom stages," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, Oct. 2016, vol. 2016-October, pp. 3781–3784. doi: 10.1109/EMBC.2016.7591551.

[14] M. Vergara, J. L. Sancho-Bru, V. Gracia-Ibáñez, and A. Pérez-González, "An introductory study of common grasps used by adults during performance of activities of daily living," *Journal of Hand Therapy*, vol. 27, no. 3, pp. 225–234, 2014, doi: 10.1016/j.jht.2014.04.002.

[15] B. Mokhlesabadifarahani and V. K. Gunjan, "Introduction to EMG technique and feature extraction," *SpringerBriefs in Applied Sciences and Technology*, no. 9789812873194. Springer Verlag, pp. 1–9, 2015. doi: 10.1007/978-981-287-320-0_1.

[16] A. Khan, R. C. Pearlman, D. A. Bianchi, and K. W. Hauck, "Experience With Two Types of Electromyography Monitoring Electrodes During Thyroid Surgery," 1997.

[17] "323327665004".

[18] "X1888754611201253".

[19] J. Y. Hogrel, "Clinical applications of surface electromyography in neuromuscular disorders," *Neurophysiologie Clinique*, vol. 35, no. 2–3, pp. 59–71, 2005, doi: 10.1016/j.neucli.2005.03.001.

[20] R. G. Whittaker, "The fundamentals of electromyography," *Pract Neurol*, vol. 12, no. 3, pp. 187–194, Jun. 2012, doi: 10.1136/practneurol-2011-000198.

[21] N. Nazmi, M. A. A. Rahman, S. I. Yamamoto, S. A. Ahmad, H. Zamzuri, and S. A. Mazlan, "A review of classification techniques of EMG signals during isotonic and isometric contractions," *Sensors (Switzerland)*, vol. 16, no. 8. MDPI AG, Aug. 17, 2016. doi: 10.3390/s16081304.

[22] A.-E. Hassanien, A. Taher Azar, T. Gaber, D. Oliva, · Fahmy, and M. Tolba Editors, "Advances in Intelligent Systems and Computing 1153 Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020)." [Online]. Available: http://www.springer.com/series/11156

[23] D. Dissertations and J. M. Fontana, "Louisiana Tech Digital Commons Classification of EMG signals to control a prosthetic hand using time-frequesncy representations and Support Vector Machines," 2010. [Online]. Available: https://digitalcommons.latech.edu/dissertations

[24] N. Supervisor, A. Pedrocchi Co-supervisor, and M. Gandolla, "Classification of EMG signals for hand movement intention detection," 2018.

[25] K. Englehart and B. Hudgins, "A Robust, Real-Time Control Scheme for Multifunction Myoelectric Control," *IEEE Trans Biomed Eng*, vol. 50, no. 7, pp. 848–854, 2003, doi: 10.1109/TBME.2003.813539.

[26] D. Farina and R. Merletti, "Comparison of algorithms for estimation of EMG variables during voluntary isometric contractions," 2000. [Online]. Available: www.elsevier.com/locate/jelekin

[27] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard, and Y. Laurillau, "EMG feature evaluation for improving myoelectric pattern recognition robustness," *Expert Syst Appl*, vol. 40, no. 12, pp. 4832–4840, 2013, doi: 10.1016/j.eswa.2013.02.023.

[28] K. Englehart, B. Hudgins Member, and P. A. Parker Senior Member, "A wavelet-based continuous classification scheme for multifunction myoelectric control A Wavelet Based Continuous Classification Scheme for Multifunction Myoelectric Control."

[29] S. A. Ahmad, "Moving Approximate Entropy and its Application to the Electromyographic Control of an Artificial Hand," 2009.

[30] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard, and Y. Laurillau, "EMG feature evaluation for improving myoelectric pattern recognition robustness," *Expert Syst Appl*, vol. 40, no. 12, pp. 4832–4840, 2013, doi: 10.1016/j.eswa.2013.02.023.

[31] M. Asghari Oskoei and H. Hu, "Myoelectric control systems-A survey," *Biomedical Signal Processing and Control*, vol. 2, no. 4. Elsevier BV, pp. 275–294, 2007. doi: 10.1016/j.bspc.2007.07.009.

[32] W. M. B. W. Daud, A. B. Yahya, C. S. Horng, M. F. Sulaima, and R. Sudirman, "Features Extraction of Electromyography Signals in Time Domain on Biceps Brachii Muscle," *International Journal of Modeling and Optimization*, pp. 515–519, 2013, doi: 10.7763/ijmo.2013.v3.332.

[33] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Syst Appl*, vol. 39, no. 8, pp. 7420–7431, Jun. 2012, doi: 10.1016/j.eswa.2012.01.102.

[34] "The heat of shortening and the dynamic constants of muscle," 2022. [Online]. Available: https://royalsocietypublishing.org/

[35] H. M. Al-Angari, G. Kanitz, S. Tarantino, and C. Cipriani, "Distance and mutual information methods for EMG feature and channel subset selection for classification of hand movements," *Biomed Signal Process Control*, vol. 27, pp. 24–31, May 2016, doi: 10.1016/j.bspc.2016.01.011.

[36] H. M. Al-Angari, G. Kanitz, S. Tarantino, and C. Cipriani, "Distance and mutual information methods for EMG feature and channel subset selection for classification of hand movements," *Biomed Signal Process Control*, vol. 27, pp. 24–31, May 2016, doi: 10.1016/j.bspc.2016.01.011.

[37] C. Kendell, E. D. Lemaire, Y. Losier, A. Wilson, A. Chan, and B. Hudgins, "A novel approach to surface electromyography: an exploratory study of electrode-pair selection based on signal characteristics," 2012. [Online]. Available: http://www.jneuroengrehab.com/content/9/1/24

[38] A. Phinyomark, C. Limsakul, and P. Phukpattaranont, "A Novel Feature Extraction for Robust EMG Pattern Recognition," 2009.

[39] M. A. Oskoei and H. Hu, "GA-based feature subset selection for myoelectric classification," in *2006 IEEE International Conference on Robotics and Biomimetics, ROBIO 2006*, 2006, pp. 1465–1470. doi: 10.1109/ROBIO.2006.340145.

[40] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," 1999. [Online]. Available: www.elsevier.com/locate/medengphy

[41] A. Turgunov, K. Zohirov, S. Rustamov, and B. Muhtorov, "Using different features of signal in EMG signal classification," in *2020 International Conference on Information Science and Communications Technologies, ICISCT 2020*, Nov. 2020. doi: 10.1109/ICISCT50599.2020.9351392.

[42] " ."

[43] M. I. Ibrahimy, M. R. Ahsan, and O. O. Khalifa, "Design and optimization of levenberg-marquardt based neural network classifier for EMG signals to identify hand motions," *Measurement Science Review*, vol. 13, no. 3, pp. 142–151, Jun. 2013, doi: 10.2478/msr-2013-0023.

[44] T. Matsubara and J. Morimoto, "Bilinear modeling of EMG signals to extract user-independent features for multiuser myoelectric interface," *IEEE Trans Biomed Eng*, vol. 60, no. 8, pp. 2205–2213, 2013, doi: 10.1109/TBME.2013.2250502.

[45] A. C. Tsai, T. H. Hsieh, J. J. Luh, and T. te Lin, "A comparison of upper-limb motion pattern recognition using EMG signals during dynamic and isometric muscle contractions," *Biomed Signal Process Control*, vol. 11, no. 1, pp. 17–26, 2014, doi: 10.1016/j.bspc.2014.02.005.