WEARABLE TECHNOLOGIES (867H1)

HAND GESTURE RECOGNITION WEARABLE TECHNOLOGY

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1. INTRODUCTION

Recently, the market for wearable technology has grown significantly in popularity and is expanding quickly. Wearable technology, such as smartwatches, fitness trackers, and virtual reality headsets, are becoming more and more prevalent in today's culture due to the wide range of functions they can do. These devices are used to monitor health indicators, improve exercise performance, and enhance gaming experience; as a result, they have become an indispensable part of daily life. It would be an intriguing application of wearable technology to enhance hand gesture detection using electromyography (EMG) signals.

When muscles contract, electromyography (EMG) signals are produced. These signals can be used to identify and categorize different kinds of manual motions. Electromyography (EMG) signals have found use in a wide range of fields, such as prosthetics, robotics, and rehabilitation. Wearable technology may make use of electromyography (EMG) signals to help with the construction of a unique interface that allows users to interact with the device through physical movements. Electromyography (EMG) signals are used to achieve this. The aim of this discussion is to go into further detail on how to create a proof of concept for wearable technology that uses EMG signals for gesture recognition.

The aim of this study is to analyze the EMG signal dataset for hand gesture identification that was gathered from the UCI using machine learning techniques. Specifically, this research includes building, training and testing of several models followed by an analysis of the model's performance.

2. OBJECTIVES

The aim of this project is to develop a wearable device that accurately detects and classifies hand gestures using electromyography (EMG) data. Electromyography (EMG) data from the user's forearm will be collected by wearable technology sensors, which is then analyzed using machine learning algorithms and provide instantaneous detection and categorization of various hand gesture movements. The goal is to create a wearable technology proof of concept that demonstrates its viability and potential for use in a variety of fields, such as prosthetics, rehabilitation, human-machine interaction, gaming, and virtual reality.

3. FEASIBILITY ANALYSIS

3.1 EXISTING LITERATURE REVIEWS

In recent decades, a great deal of study has been done on the use of EMG signals for gesture detection. Electromyography (EMG) signals, which can be used to recognize and categorize each gesture, are produced by the myoelectric activity of muscle fibers. This section aims to provide a complete analysis of the relevant research about the use of EMG signals in the field of hand gesture recognition within the context of wearable technology.

Hargrove et al. (2013) conducted research in which they built a prosthetic arm control system using pattern recognition and EMG signals. The user's natural movements could be mimicked by the arm due to this control mechanism. The degree of muscle activity from the amputated person's remaining leg was measured and analyzed by the researchers using an electromyography (EMG) wristband. An algorithm for pattern recognition was used to distinguish different hand motions after EMG signals were acquired. The authors' research demonstrated the system's high degree of hand motion recognition precision, which raised the possibility of using EMG signals in prosthetic devices.

A research study was conducted by Castellini et al. (2016) to see if surface electromyography (EMG) signals might be used in a wearable device to recognize different hand motions. The researchers used a device called a Myo armband to capture electromyography (EMG) signals that were coming from the forearm muscle of healthy individuals. Following the gathering of data, machine learning techniques were used to process the electromyographic (EMG) data with the aim of differentiating between various manual actions. One of the findings of the researchers was the great degree of accuracy of the system in recognizing hand movements. They concluded that EMG signals have the potential to be used in wearable technology for the purpose of recognizing hand gestures.

In a study by Lee et al. (2019), a wearable gadget that uses EMG signals to recognize hand motions was created. The researchers used a specially made electromyography (EMG) sensor module to capture muscle activity in the forearm area of people in excellent health. A deep learning system was used to categorize various hand movements after the acquisition of EMG signals. The researchers' examination revealed that the wearable gadget has a remarkable ability to detect manual movements with accuracy. From their research, the scientists concluded that the gadget might serve a variety of purposes, such as facilitating human-machine interactions and the implementation of virtual reality.

In a study by Wang et al. (2020), they created a wearable gadget for hand gesture identification using a combination of EMG signals and accelerometer data. The researchers used a Myo wristband to record electromyography (EMG) signals, and an accelerometer to record manual forearm motions from volunteers who were fit. The data was subsequently processed using machine learning methods in order to categorize various manual motions. According to the study the authors did, using accelerometer data and EMG signals together improved the accuracy of hand gesture detection when compared to using EMG signals alone.

According to existing research, electromyography (EMG) signals may possibly be a practical way to recognize gestures in wearable electronics. The research shows that EMG signals have potential applications in a variety of industries, such as virtual reality, prostheses, and human-machine interfaces. The classification of distinctive hand motions based on EMG data serves as an example of the usefulness of machine learning algorithms, particularly deep learning. Additionally, combining electromyography (EMG) signals with several kinds of sensor data, such accelerometer data, has the potential to improve the precision of gesture detection in wearable technologies.

A wearable device that uses EMG signals and a capacitive touch sensor to recognize hand movements was developed in a study by Li et al. (2019). The researchers used an armband called Myo to record electromyography (EMG) data and a capacitive touch sensor to track finger movements in non-disabled people's hands. Following the data gathering procedure, machine learning algorithms were used to categorize different manual movements into separate groups. According to the authors' study, combining capacitive touch sensor technology with electromyographic (EMG) signals enhanced hand gesture recognition accuracy compared to using just EMG signals.

Samiappan et al.'s (2018) study focused on the use of EMG signals in a wearable device to recognize hand motions in order to facilitate human-robot interaction. For the goal of recording electromyography (EMG) data coming from non-disabled people's forearm muscles, the researchers used a Myo armband gear. The EMG signals were acquired, and then machine learning methods were used to separate and categorize discrete manual movements. The study's conclusions show that the wearable gadget is remarkably accurate at recognizing hand motions, pointing to its applicability in settings involving human-robot interaction.

Ho et al. (2018) designed a wearable gadget for their investigation that uses a flex sensor and electromyography (EMG) data to detect hand motions. The researchers used a Myo armband to record electromyography (EMG) signals and a flex sensor to measure the manual dexterity of non-disabled people's fingers. Following the data gathering procedure, machine learning algorithms were applied to the acquired data to categorize particular manual movements. According to the authors' research, flex sensor and EMG signals combined with EMG signals alone enhanced hand gesture detection accuracy compared to using only EMG signals.

The development of a wearable device that uses EMG signals to recognize hand motions in gaming was the focus of a study by Mousavi et al. (2019). The researchers used a Myo armband device to monitor electromyography (EMG) signals coming from the forearm muscles of non-disabled people. The electromyography (EMG) signals were then exposed to machine learning algorithms with the goal of categorizing distinct manual motions. Wearable technology shown a considerable degree of precision in identifying hand motions, according to the authors' study. The device may be effectively used in gaming scenarios, the authors inferred from their findings.

In the Cognolato et al. (2017) study, a wearable device that uses EMG signals to recognize hand motions in the context of rehabilitation was developed. Electromyography (EMG) signals coming from the forearm musculature of participants with neurological disorders were recorded in the study using a Myo armband device. After being acquired, the EMG signals were put through machine learning algorithms to categorize various manual gestures. According to the authors' investigation, the wearable technology was remarkably accurate at recognizing hand motions. The devices potential for use in rehabilitative applications was inferred by the authors from the findings.

In order to create a wearable device that could recognize hand movements for patients with spinal cord injuries, Zardoshti-Kermani and colleagues conducted a study in 2013. The individuals in the study who had sustained spinal cord damage had their forearm electromyographic signals generated by it recorded using a wireless electromyography (EMG) system. After being acquired, the electromyographic (EMG) data were put via machine learning algorithms in order to categorize distinct manual gestures. According to the study's findings, the wearable device was remarkably accurate in identifying manual gestures, pointing to its potential use in assistive technology.

The feasibility study of deploying a wearable system for hand gesture detection utilizing EMG signals comprises examining its practicality and viability in the different sectors discussed below.

1. **Technical Feasibility**: The gesture detection EMG signal dataset supports machine learning model training and evaluation. The Python libraries used can handle missing data, outliers, and signal processing algorithms. Scikit-learn and Keras make the use of Random Forest Classifiers, Support Vector Machines, KNN Classifiers and Decision Trees easy to construct. Data augmentation and Feature Extraction/Selection can improve model performance. Making the development of an EMG-based hand gesture recognition system is practical and accessible.

2. **Data Feasibility:** The EMG signal dataset for gesture detection which was used for model training helps train and evaluate machine learning models. MYO Thalmic bracelet recorded labelled EMG signal samples for various hand motions from 36 Subjects. The dataset was acquired using a specific wearable device, therefore generalizing the models to different devices or scenarios may require more data or changes. Thus, while the dataset is sufficient for proof of concept, future implementations should collect more varied and representative data.

3. **Financial Feasibility:** The cost of hardware like Myo Thalmic Bracelets and computational resources for training and deploying machine learning models could affect the financial feasibility. However, with the increased demand and purchase of other wearable technology

devices it shows that it is affordable and economically viable. Furthermore, as technology advances, maintenance, upgrades, scalability and other expenses should be taken into consideration.

4. **Practical Feasibility:** Considering that Wearable equipment like EMG sensors can now precisely measure muscle activation. Machine learning methods, open-source frameworks, and the EMG signal dataset aid system development and evaluation. These technologies used from rehabilitation to human-machine interactions, demonstrate their practicality and potential significance showing that the EMG signal-based wearable hand gesture recognition is viable.

5. **Ethical and lawful Feasibility:** Wearable technology must be ethical and lawful. Privacy and permission are ethical concerns while recording EMG signals. Data protection laws must be followed when handling personal data. Data Usage and Informed Permission are essential. Compliance with legislation, intellectual property rights, and liabilities are important factors to be considered.

4. CONCEPTUAL DESIGN

The proposed wearable technology for hand gesture recognition comprises a compact device that is worn on the forearm and is equipped with electromyography (EMG) sensors to capture muscle activity. The device will be designed to maximize user comfort and mobility, enabling simple use across a range of activities. Machine learning methods that are implemented on either a microcontroller or a linked computing device will be used to process collected EMG data in real time. The device is made to provide the user with feedback, either visual or haptic, indicating the detected manual gesture. The main goal of the conceptual design is to create wearable technology that is durable, accurate, and user-friendly. This technology should seamlessly integrate into daily activities while also enabling natural interaction through hand gestures.

5. PROOF OF CONCEPT

The following steps were taken to prove the concept of building a viable wearable hand gesture recognition technology.

1. Data Acquisition: EMG sensors were used to record forearm muscle activation during hand motions. The Noise and interference will be removed by amplifying and filtering EMG signals.

2. Data Preprocessing: EMG signals will be cleaned, go through Signal Filtering, Sliding Windowing, Feature Extraction and Normalization (to be used for scaling). The signals' frequency and temporal properties will resemble hand motions.

3. Model Development: The Preprocessed EMG signal data will be trained on several machine learning models to see their performance.

4. Model Evaluation: The Testing dataset will assess trained models. To evaluate models' hand gesture classification accuracy and F1 score.

5. Performance evaluation: The results gotten from the models would be evaluated to check their performance in recognizing these hand gestures using the F1- Score and Accuracy results.

The proof of concept would show that EMG-based wearable technology can properly recognize and classify hand gesture motions. The system's successful deployment and performance evaluation will prove the concept and lay the groundwork for actual wearable technology development.

5.1 DATASET DESCRIPTION

The dataset consists of raw EMG data gotten from 36 Subjects while they performed various static hand gestures. A MYO Thalmic bracelet was worn on their forearms and a PC with a Bluetooth receiver. The bracelet has eight sensors equally spaced around the forearm to get the myographic signals simultaneously which are sent through a Bluetooth interface to a PC. Each subject performs two series which consists of six or seven basic gestures each.

The total dataset consists of 4,237,908 rows and 10 columns which includes the Class, Time and Channels 1 to 8. The gestures were grouped into different classes with each class representing a type of hand gesture as described below.

Class 0: Unmarked data

Class 1: Hand at rest

Class 2: Hand clenched in a fist

Class 3: Wrist flexion,

Class 4: Wrist extension

Class 5: Radial deviations

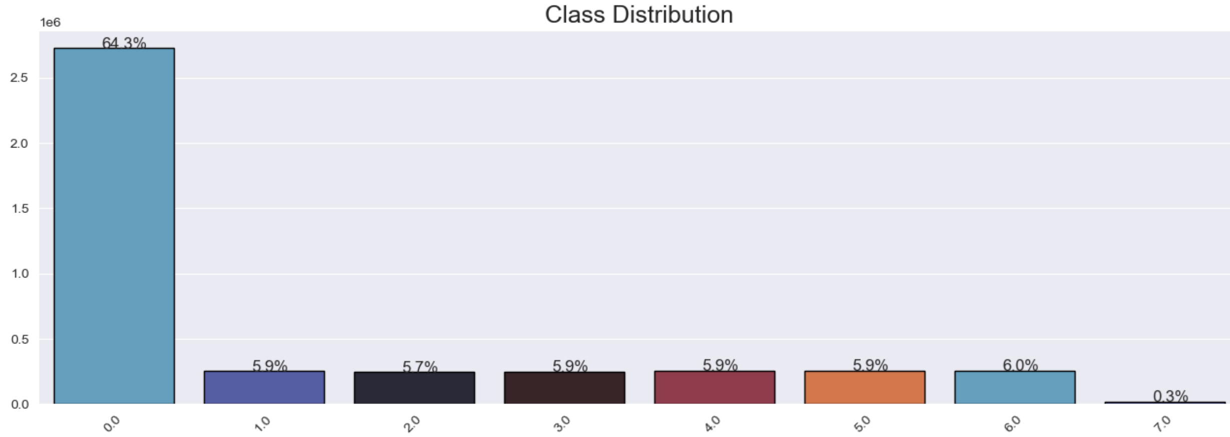
Class 6: Ulnar deviations

Class 7: Extended palm (this gesture was not performed by all subjects).

5.2 METHODOLOGY

For this project, a lot of crucial steps were taken to achieve an accurate result for the EMG data set for recognizing hand gestures. The following steps described below were implemented in achieving an accurate result.

1. **DATA LOADING:**
   The data was loaded into the Jupyter Notebook which had 4,237,908 rows and 10 columns. However, an extra column was created which was named as "Subject" to identify the features that were associated with each subject wearing the wristband.
2. **DATA PREPROCESSING AND EXPLORATORY DATA ANALYSIS (EDA):**
   The first step was to clean the data. Although the EMG dataset is not too dirty as it had no duplicated cells. There was 1 null value which was dropped.
   For the EDA, a function was defined to make plots that showed the distribution of the Classes and Subjects. From the plot gotten, it shows that Class 0 contained 64.3% of the class distribution making it the highest class with Class 7 being the lowest.



However, Class 0 contains unmarked data which means that the sensor could not detect any hand gestures from the wristband so in order to improve the accuracy of our machine learning models, the Class 0 was dropped to enable the model focus on other classes that contained visible hand motions. Additionally, Class 7 was also dropped as it had very little data signals containing just 2 gestures.

3. **POSITIVE RECTIFICATION:**

Positive rectification is a preprocessing step in EMG signal analysis that helps to emphasize the magnitude of muscle activation, simplify signal analysis, and improve signal consistency, thereby aiding in the extraction of meaningful information from the EMG dataset. In the EMG dataset, the channels contain a lot of negative values, hence the positive rectification was implemented on all channels from Channel 1 to 8 converting them to positive values.

4. **SIGNAL FILTERING:**

Signal filtering is used to modify or remove specific frequency components from a signal. It plays a crucial role in preprocessing the EMG data. It enhances its quality, removes noise, extracts relevant information, and facilitates further analysis and interpretation. It also helps to obtain reliable and meaningful insights from the EMG signals, leading to better understanding of gesture recognition, muscle activity and other related factors to be considered in modeling the data.

The dataset has a sampling frequency of 1000Hz so in carrying this out, a cut-off frequency of 5 was used with an Order of 4. Also, the Nyquist frequency and Normalized cut-off was gotten. The filtering was implemented on the 8 channels from Channel 1 to 8 then a Low-Pass Butterworth filter was applied.

5. **WINDOWING:**

   Windowing is a technique used in signal processing to divide a continuous signal into smaller segments called windows or frames. For this project, I used the Sliding window technique. Sliding windowing, also known as window sliding or window shifting, is an extension of windowing where the windows are shifted along the signal with a certain stride or step size. This is important for the dataset as it allows us to capture temporal dynamics, extract relevant features, and perform accurate classification or pattern recognition tasks. It enables the analysis of localized segments of the signal, providing insights into muscle activity and facilitating further analysis and interpretation of the EMG dataset.

   A window size of 100 and Slide Length of 50 were used to obtain the windowed data.

6. **FEATURE EXTRACTION:**

   Feature extraction is the process of transforming raw data into a reduced and meaningful set of features that capture the essential characteristics of the data. For the EMG dataset, feature extraction involves extracting relevant information from the raw EMG signals to represent muscle activity and gestures in a more concise and informative manner. It allows for more efficient analysis, improved classification or recognition performance, noise robustness, and provides interpretable and meaningful representations of muscle activity and gestures. It aids in extracting the most relevant information from the EMG signals and provides valuable insights to make informed decisions based on the extracted features.

   In carrying this out, the windowed dataset was grouped into Subject and Class. A class was created to extract 3 major features which are the Root Mean Square, Simple Square Integral and the Absolute Differential Signal. Also, the dataset was aggregated with the features extracted including the Min and Max values.

7. **MACHINE LEARNING MODELING:**

   In this section, four different machine learning methods were used to find the best and most accurate prediction. These includes the Random Forest Classifier (RFC), Support Vector Machine (SVM), K-Nearest Neighbors Classifier and Decision Tree.

   The first step was to get the features and labels to be used in splitting the data. Then the data was divided into train and test sets.

Note: Normalization was used to carry out scaling on the dataset. The data was normalized using the Mean and Standard Deviation. By normalizing the data, it ensured that all features have zero mean and unit variance, making them comparable and suitable for various machine learning algorithms. This helps in improving the stability, performance, and interpretability of the models trained on the data.

The four different modeling were carried out and the F1-Score and Accuracy was used to determine the model with the best prediction accuracy using specific parameters to optimize the results.

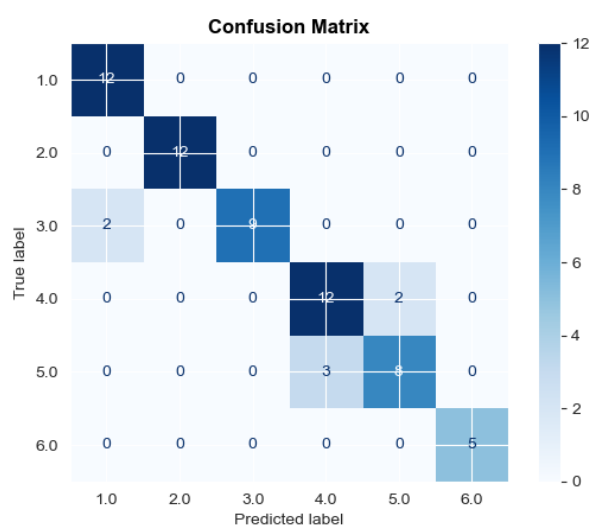
6. RESULTS

The following results were gotten from the different machine learning models.

1. Random Forest Classifier (RFC):

   Random Forest is a versatile modeling method that can handle the complexities and challenges present in the EMG dataset. It offers robustness, nonlinear modeling capability, feature importance analysis, generalization performance, and some interpretability, making it a suitable choice for analyzing and predicting hand gestures. For this model, it gave an F1- macro score of 0.90 and Accuracy of 0.89.

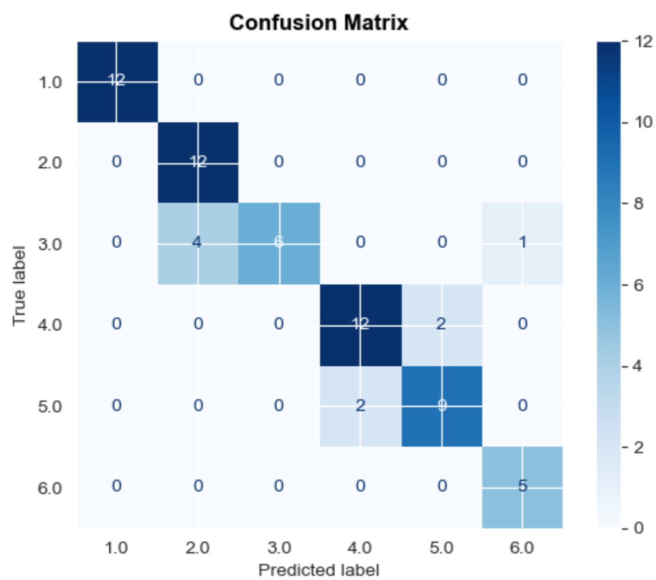
```
F1 Macro Score: 0.9020946486463727
Confusion Matrix:
[[12  0  0  0  0  0]
 [ 0 12  0  0  0  0]
 [ 2  0  9  0  0  0]
 [ 0  0  0 12  2  0]
 [ 0  0  0  3  8  0]
 [ 0  0  0  0  0  5]]
Accuracy Score: 0.8923076923076924
OOB Validation Score: 0.9337748344370861
```



2. Support Vector Machines (SVM):

SVM offers the advantages of handling nonlinear classification, robustness to noise, ability to handle high-dimensional data, performance with small training datasets, control overfitting, interpretable support vectors, and a well-established methodology. These characteristics make SVM a good modeling method for the EMG dataset, enabling accurate gesture classification and pattern recognition. Using this method, it gave an F1-Score of approximately 0.86 and Accuracy of 0.86 as shown below.

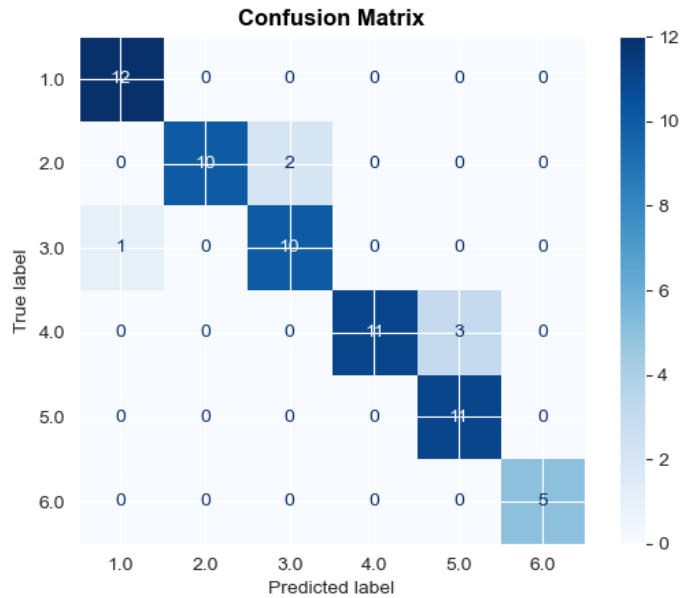
```
F1 Macro Score: 0.8579067990832696
Confusion Matrix:
[[12  0  0  0  0  0]
 [ 0 12  0  0  0  0]
 [ 0  4  6  0  0  1]
 [ 0  0  0 12  2  0]
 [ 0  0  0  2  9  0]
 [ 0  0  0  0  0  5]]
Accuracy Score: 0.8615384615384616
```



3. K-Nearest Neighbors (KNN) Classifiers:

KNN's reliance on similarity-based classification, ability to handle nonlinear relationships, robustness to noise, no training phase, interpretable results, simple implementation, and suitability for small to medium-sized datasets make it a good modeling method for the EMG dataset. It can effectively classify gestures based on their similarity to neighboring samples, capturing the underlying patterns in the EMG signals. It produced a result with an F1-Score of 0.92 and Accuracy of 0.91 as shown below.

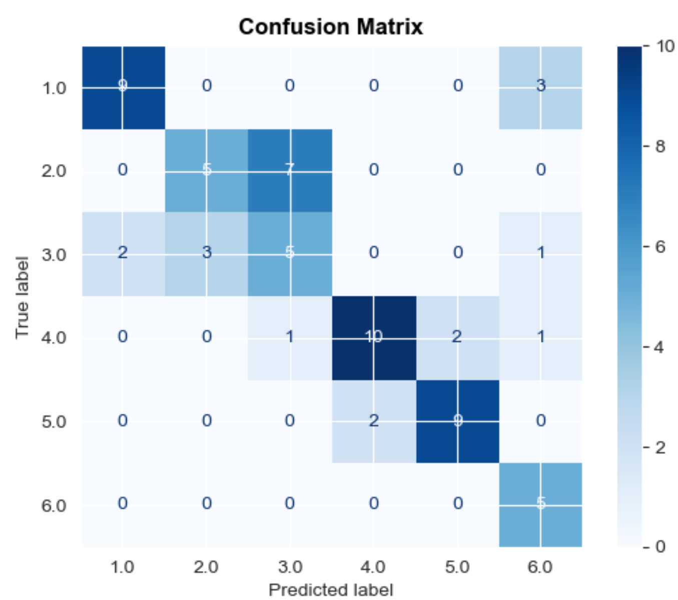
```
F1 Macro Score: 0.9164426877470356
Confusion Matrix:
[[12  0  0  0  0  0]
 [ 0 10  2  0  0  0]
 [ 1  0 10  0  0  0]
 [ 0  0  0 11  3  0]
 [ 0  0  0  0 11  0]
 [ 0  0  0  0  0  5]]
Accuracy Score: 0.9076923076923077
```



4. Decision Trees:

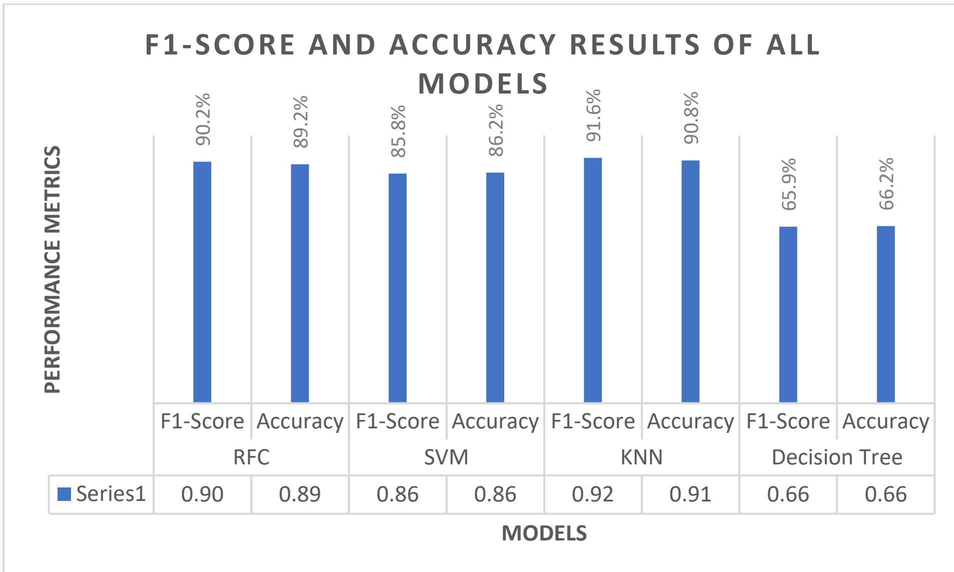
   Decision Trees' interpretability, ability to handle nonlinear relationships, feature importance analysis, robustness to outliers, capability to handle mixed data types, ease of interpretation and visualization, and scalability make them a good modeling method for the EMG dataset. They can provide insights into the classification process, capture complex patterns in the EMG signals, and yield accurate and interpretable results for gesture recognition tasks. This model produced a result with an F1-Score of 0.66 and Accuracy of 0.66 making it the least performance as shown below.

```
F1 Macro Score: 0.6588924360663491
Confusion Matrix:
[[ 9  0  0  0  0  3]
 [ 0  5  7  0  0  0]
 [ 2  3  5  0  0  1]
 [ 0  0  1 10  2  1]
 [ 0  0  0  2  9  0]
 [ 0  0  0  0  0  5]]
Accuracy Score: 0.6615384615384615
```



7. DISCUSSION

The plot below shows a comparison of the results gotten from the different machine models used for the prediction.



Comparing the results shown above, it indicates that the K-Nearest Neighbor Classifier (KNN) had the best performance with an accuracy of 91% and F1-Score of 92%. This was followed closely by the Random Forest Classifier (RFC) with an accuracy of 89% and F1- Score of 90%. The Support Vector Machine (SVM) model gives an accuracy of 86% with an F1- Score of 86% while the model with the least performance was the Decision Tree with an accuracy of 66% and F1- Score of 66% respectively.

8. CONCLUSION

Various steps have been taken in developing a wearable technology device that accurately detects and classifies manual movements using electromyography (EMG) data. The preparation of the data which involved several preprocessing steps such as cleaning the data, analyzing it, Signal filtering, Feature Extraction and Normalizing the data have all been used as a measure to ensure that the data is processed efficiently before being modeled. The use of

Feature Selection and Data Augmentation techniques would enhance the accuracy of the machine learning models.

For this project, several machine learning algorithms such as Random Forest Classification, Support Vector Machines, K-Nearest Neighbors and Decision Trees were used. The selection of an algorithm is dependent on the data type and assessment of its performance metrics which is the F1- Score and Accuracy.

The results obtained from the models show that Machine Learning has significant potential to be used in accurately and precisely categorizing hand gestures through the EMG signals. The K-Nearest Neighbor had the highest performance followed by the Random Forest Classifier (RFC) then Support Vector Machine (SVM) and the Decision Tree having the least performance.

In conclusion, the use of wearable technology devices to recognize hand gestures using the EMG signals shows significant potential for various applications such as Virtual Reality, Human- Computer Interaction, Rehabilitation etc. The use of machine learning algorithms for creating precise and accurate hand gestures recognition systems can lead to the development of other future applications that would be useful to humans.

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