*Biomedical & Pharmacology Journal*, March 2024. Vol. **17**(1), p. 71-82

# Human Hand Movement Classification based on EMG Signal using different Feature Extractor

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https://dx.doi.org/10.13005/bpj/2835

(Received: 27 September 2023; accepted: 28 November 2023)

**Electromyography (EMG) based hand movement classification plays a significant role in various fields, namely in prosthetics, rehabilitation, biomechanics, etc. This paper presents the study of EMG-based hand movement classification of 3 human hand gestures (hand at rest, wrist flexion, and wrist extension). The dataset was officially collected from the University of California, Irvine (UCI) machine learning repository. The dataset contains 8 channels and 3 classes representing 3 human hand gestures, with 15000 rows of EMG data for each class. The dataset obtained was raw and unprocessed, to filter this dataset Notch and Butterworth filters were used. After filtering, the sliding window was performed. Various feature extraction techniques, namely frequency domain features (FD) and discrete wavelet transform (DWT) were applied separately on the window dataset and then accuracy was tested on different classifiers, namely random forest (RF), k- nearest neighbor (KNN), and decision tree (DT). As a novel approach, time domain (TD) and DWT extracted features were fused together and then given to the classifiers to test accuracy. Among all these feature extractors, the features extracted by FD provided the highest accuracy of 81.69 for the RF classifier.**

**Keywords:** Bandpass filter; DWT; Electromyography; Hand movement; Machine learning; Notch filter.

One of the most crucial fields of research in the field of biomedical engineering is the classifying of human movement based on EMG processing of data. Electrical impulses produced by muscles during movement, or EMG signals, convey significant details about muscle activity and movement patterns. Researchers have developed models that can effectively categorize various forms of human movement based on EMG analysis of information due to advancements in machine learning techniques. There is still a lack of studies in ensuring the development of highly accurate and efficient techniques for categorizing human motions based on EMG data, despite the advancements that have been made in the last decade. This gap has been highlighted as a need for further investigation in two recent studies that have been done in the field.

One such work suggested a deep learning method for categorizing hand motions based on EMG information, which was published in the IEEE Journal of Biomedical and Health Informatics. The study emphasized the need for additional investigation in order to enhance the accuracy of the categorizing approach and broaden its relevance to various types of actions, considering the fact that the results demonstrated promising accuracy. Similar to this research's suggestion, another study offered a feature extraction technique for grouping dynamic hand motions based on EMG data in the IEEE Transactions on Biomedical Engineering. Although the study revealed great classification accuracy, researchers also emphasized the need for more investigation to develop a more dependable grouping technique. The current study offers a methodology for identifying human motions in light of these research gaps based on DWT and machine learning methods for EMG signal interpretation. The EMG signals are analyzed through the DWT to extract features, which are subsequently sent into a classification machine learning model. On a dataset of EMG signals collected by individuals in good health running a variety of movements, the suggested technique is reviewed.

**Literature Review**

The paper presents a hand gesture recognition system using EMG signals and machine learning. The EMG signals are pre-processed to extract relevant features, and an SVM classifier is used for recognition. The system achieves a recognition accuracy of up to 96.25% for six hand gestures. It is implemented on a Raspberry Pi and a Myo armband for real-time recognition in less than 10 ms. The system can have applications in human-computer interaction, virtual reality, and prosthetic control. The study highlights the potential of EMG signals as a promising input modality for hand gesture recognition[1]. The paper presents a hand gesture classification system that uses EMG signals and machine learning techniques. The authors evaluate the performance of three machine learning algorithms, including artificial neural networks (ANN), support vector machine (SVM), and KNN, on a dataset of eight hand gestures. The proposed system achieves a recognition accuracy of up to 98%. The authors also investigate the impact of different preprocessing and feature extraction techniques on classification accuracy. The study highlights the effectiveness of EMG signals and machine learning techniques[2]. The paper proposes a system for recognizing hand gestures using EMG signals and machine learning algorithms. The system captures EMG signals from the user's forearm muscles using a Myo armband and applies four machine-learning algorithms to classify the signals into specific hand gestures. The study found that the random forest algorithm performed the best, with an average accuracy of 93.63%. The proposed system has potential applications in prosthetics and human-machine interfaces. The study demonstrates the feasibility of using EMG signals and machine learning for hand gesture recognition and provides valuable insights for future research in this field[3].

The paper introduces a novel approach for classifying EMG signals, utilizing a Radial Basis Function (RBF) neural network. The method involves pre-processing EMG signals through a bandpass filter and feature extraction using both time-domain and frequency-domain features. The RBF neural network is then employed for the classification of the EMG signals into various hand gestures. The results demonstrate high accuracy, surpassing previous state-of-the-art methods. This technique has potential applications in prosthetic devices and rehabilitation systems, and its robustness enables the processing of noisy data[4]. The paper proposes a novel technique for hand gesture classification using multi-channel EMG signals, scale average wavelet transform (SAWT), and convolutional neural networks (CNN). SAWT is utilized for feature extraction, which involves analyzing the frequency characteristics of the EMG signals at various scales. CNN is then employed for classification, utilizing the extracted features. The proposed method is evaluated on a forearm EMG signal dataset, and the results demonstrate higher classification accuracy than previous state-of-the-art methods. This method could be used in various applications, such as human-computer interaction and prosthesis control systems[5]. The paper presents a technique for recognizing hand gestures using EMG signals and an ANN. The method involves preprocessing the signals, extracting features using time-domain features and power spectral density (PSD) features, and training an ANN model for recognizing hand gestures. The proposed method achieves high classification accuracy, surpassing previous state-of-the-art methods, and is evaluated on a dataset of EMG signals collected from ten individuals. This technique has potential applications in human-computer interaction and prosthesis control systems[6].

The paper presents a technique for identifying human hand movements using electromyographic (EMG) signals. Nonlinear dimensionality reduction and data fusion techniques are applied to the data to extract relevant features for classification. The proposed method is found to be effective in accurately classifying different hand movements. The approach is expected to have applications in prosthetics, robotics, and rehabilitation. The results indicate that the method has the potential to provide more accurate and reliable control of prosthetic devices[7]. This paper proposes a method for classifying surface electromyography (sEMG) signals generated during basic hand movements using bagging and DWT techniques. The sEMG signals are preprocessed using DWT to extract features, and the bagging algorithm is used to ensemble multiple classifiers for improved accuracy. The proposed method is evaluated using a dataset of sEMG signals generated by ten healthy subjects performing five hand movements. The results indicate that the proposed method outperforms alternative approaches., achieving an average accuracy of 97.66%[8]. This literature review presents a method for classifying sEMG signals generated during human hand movements for myoelectric control. The proposed method involves the extraction of time-domain features from sEMG signals, the selection of features is done using various genetic algorithms, and they are classified using SVM. The method is evaluated using a dataset of sEMG signals generated by ten subjects performing six hand movements. The performance of the proposed model shows a high accuracy of 97.57%, demonstrating its potential for myoelectric control applications[9].

This research provides a method, for classifying EMG signals with the help of DWT and forest rotation. EMG signals are often used in prosthetic devices and rehabilitation systems to control the movements of artificial limbs or assistive devices. The classification of EMG signals is a challenging task due to the variability and complexity of the signals[10]. The paper presents a novel method for recognizing hand gestures from video input using a combination of DWT and SVM algorithms. The DWT is used to extract features from the video frames, which are then used as inputs to the SVM classifier[11]. The author provides an approach for recognizing human actions based on EMG with the help of deep belief networks (DBN). The EMG signals are preprocessed using a sliding window and feature extraction techniques, and then the presented approach is evaluated using a dataset of EMG signals generated by ten subjects performing six movements of the hand. 97.65% of the highest accuracy was obtained for the proposed methodology, demonstrating the effectiveness of using DBN for EMG-based action recognition[12]. This research paper provides a method for detecting the voice activity and classification of noise using DWT and sub-band selection. The proposed method involves preprocessing the audio signal using DWT to extract features in different frequency bands, followed by selecting the most discriminative sub- bands and classification SVM. For the presented method highest accuracy was obtained for voice activity detection and noise classification, demonstrating its potential for speech enhancement applications[13]. This case report investigates the potential of a virtual reality gaming system that combines EEG and EMG for the rehabilitation of facial palsy. The patient showed improvements in muscle strength, coordination, and facial symmetry after four weeks of using the system, suggesting its potential as a rehabilitation tool[14]. This study examines. The study considers the bond between the moment of ARM on electromyographic activity and the length of the muscle. Results suggest that the length of the muscle and moment arm have a significant impact on muscle activity, indicating the importance of considering both factors in muscle function studies[15].

The study presents a method for recognizing finger movements using EMG signals and image processing. Electromyographic signals were obtained from the hand muscles and processed to generate an EMG map, which was then used to identify the specific finger movement. The proposed method showed promising results in accurately recognizing finger movements[16]. The paper investigates the heterogeneity or redundancy in the activity of the brachial muscle biceps during isometric contractions using multi-channel EMG signals and PCA. The study measures the EMG signals from the biceps brachii muscle of healthy individuals and processes the signals using PCA to estimate the muscle activation patterns. The muscle's electrical activity during isometric contractions is heterogeneous, and the use of PCA multiple channels EMG. The study highlights the potential applications of PCA multiple channel EMG signals in assessing the functions of muscles in clinical and research settings[17].

The paper proposes a method to enhance hand gesture classification by applying Gaussian filtering to EMG signals. The study involves collecting EMG signals from eight hand muscles during the execution of six different hand gestures. The signals are preprocessed and then filtered using a Gaussian filter. The filtered signals are then used as inputs in SVM classifiers so that the hand gestures can be classified. The study demonstrates that the proposed method significantly improves the classification accuracy of hand gestures compared to using unfiltered signals. The results highlight the potential applications of Gaussian filtering of EMG signals in improving hand gesture recognition for various human-machine interface systems[18]. This paper investigates the use of wearable sensors for classifying the EMG patterns which are based on the changes in the joint elbow angle. The authors collected EMG signals and elbow joint angle data from healthy participants during three different elbow movements. They applied machine learning algorithms to the data and achieved an average classification accuracy of 97.67%. The study demonstrates the potential of using wearable sensors for accurate and non-invasive classification of EMG signals based on joint angle changes[19]. This paper proposes an infinite hidden Markov model (IHMM) based classification approach for recognizing human hand movements using surface EMG signals.

The method was tested on a dataset of 8 hand movements and obtained an average rate of recognition of 94.4%. The IHMM approach showed improved performance compared to other classification methods and has potential for applications in prosthetic control and human-computer interaction[20].

This paper introduces a novel ensemble approach for the precise diagnosis of cardiac arrhythmia (ARR), normal sinus rhythm (NSR), and congestive heart failure (CHF) is presented. It is based on shifted one-dimensional local binary patterns (S-1D-LBP) and long short-term memory (LSTM). With a remarkable 99.6% success rate, the suggested method successfully captures the temporal dependencies and discriminative features of ECG signals. Its dependability and robustness make it a useful tool for categorizing different signals[21]. Difficulties arise in the identification of posture and recognition of human actions for computer vision systems. Such tasks find significance in healthcare and robotics. Artificial intelligence (AI) techniques can be employed in the analysis of repetitive postures and physical movements. This study evaluated the performance of convolutional neural networks (CNNs) in classifying videos by utilizing the Kinect Activity Recognition Dataset (KARD) and the Microsoft Research (MSR) Pairs dataset. These CNN models, however, are problematic to train with video data since their efficiency is poorer in comparison with image data. By determining human poses and extracting video frames at set intervals, a unique solution to eliminating extraneous visuals was proposed in the study. Essentially, this involves the extraction of frames from datasets based on videos, with a laser focus on human poses. The frames are extracted using a specific frequency, and the human pose of each extracted frame is then established[22]. A suggested technique for short-term hand gesture recognition uses Myo armband signals analysis. The method divides long-term signals, which stand for several gestures, into short-term signals, which stand for a single gesture. From the short-term signals, five statistical time domain features are extracted. For 17 gestures, the average precision, sensitivity, and F1-score obtained in the results were 86.5%, 83%, and 82.2%, respectively. The suggested short-term identification approach performs better than the current long-term identification approach[23].

This paper presents a novel method using Support Vector Machines (SVM) to categorize upper limb movements based on myoelectric signals. It examines post-processing techniques, feature selection, data segmentation, and SVM model tuning as means of optimizing SVM-based myoelectric control. The study also highlights the good accuracy, robustness, and computational efficiency of SVM by comparing it to neural networks such as Multilayer Perceptrons (MLP) and Linear Discriminant Analysis (LDA)[24]. This paper presents a novel approach for low-power, real- time analysis of Electromyography (EMG) signals, which are essential for gesture control and prosthetic devices. It achieves over 99% accuracy in identifying nine wrist-hand movements by using minimal time-domain features, Kernel Fisher discriminant feature projection, and Radial Basis Function neural network classifiers. Implemented on the ARM Cortex-A53, it provides 50 times faster processing times than the state-of-the-art time-frequency techniques[25].

## MATERIAL AND METHODS

### Data Collection

The dataset was obtained via the UCI Machine Learning Repository. The signals are collected using a PC equipped with a Bluetooth receiver and a MYO Thalamic bracelet worn on the forearm. Eight sensors equally spread around the forearm on the bracelet hold the ability to collect myographic signals. The signals are sent to a PC through a Bluetooth link. The 36 patients' raw EMG data are shown while they made a series of static hand motions. Two series are executed by the subject, each with six (or seven) main motions.

The duration of each motion was 3 seconds, with a 3-second break in between each gesture. The original dataset consists of seven classes: 0 denotes unmarked data, 1 denotes a hand at rest, 2 denotes a hand clenched in a fist, 3 denotes wrist flexion, 4 denotes wrist extension, 5 denotes radial deviations, and 6 denotes ulnar deviations.

For this specific problem statement, three classes - hand at rest, wrist flexion, and wrist extension were considered. A total of 8 channels and 15000 samples are considered for each class.

### Pre-processing

Bandpass filtering is a technique used in signal processing to isolate a specific frequency range of a signal while suppressing or blocking frequencies outside that range. This can be useful for removing unwanted noise or interference or for identifying specific frequency components of the signal that are of interest. As there are 8 channels, the signals from each channel are sampled at 1000Hz with a low cutoff of 10Hz, a high cutoff is set at 400Hz, and the order is 4.

On the other hand, notch filtering is a method for removing a certain band of frequencies from a signal while leaving the remainder of the frequency spectrum unaffected. This can be useful for removing unwanted harmonics from the signal as well as for removing noise or interference that is concentrated in a specific frequency band.

The parameters for the notch filter are the Q factor set at 10 and the notch frequency at 60Hz. Fig. 2, 3 & 4 represent original & filtered 8-channeled signals, where (A) represents original signals and (B) filtered signals. By observation, filtered signals look more uniform as compared to the original signals. That's the advantage of filtering the signal.

After applying bandpass filter and notch filter to each channel of EMG signal, the most important step is to divide or segment each channel into a fixed number of window sizes and overlaps. Overlap refers to the number of samples that overlap between adjacent windows, window size refers to the number of samples or data points in each window.

For this proposed methodology the highest results were observed after setting the window size to 100 and overlapping of 50% of the window size. When related work was reviewed, it was observed that when the window size and overlap is small, there will be fewer chances of data loss during this process.

For calculating the total window for each channel Eq. 1 is used.

$$\text{Total Window} = \left(\frac{Total\ rows - Window\ Size}{overlap}\right) + 1 \quad ...(1)$$

Considering 15000 samples for each class. By applying the formula of step 5 in the above algorithm.

Total rows = 15000, Window size = 100 & Overlap = 50 For above case,

$$\text{Total Window} = \left(\frac{15000-100}{50}\right) + 1 \quad ...(2)$$

By doing the above calculations, for each channel, 299 rows were generated. As there are 8 channels 299*8, it will generate 2392 rows for each class.

Algorithm 01: Algorithm of Sliding Window
Start
*For* each *channel* in the *column*
Get the data from the current channel
Get the number of rows present in current_channel
Calculate total number of windows using (*Total_*

*rows – Window_size*) / *Overlap* + 1
Store the result in variable '*new_window*'
*For each window i -> new_window*
Calculate the start_index of current_window using (i*overlap)
Calculate the end_index of current_window as (start_index + window_size)
If (end_index > Total_rows)
End_index = Total_rows
Extract the data from *current_window*
Store the data in list
*End* of Algorithm

**Feature Extraction**

After the pre-processing step, reducing the number of parameters, or features, is a crucial technique for characterizing EMG signals. The wavelet transform is a useful tool for decomposing the signal with high time resolution, breaking it down into basic wavelets obtained by dilating and translating a single function.

For feature extraction, the signals can be handled in the FD, DWT, and fusion of TD and DWT.

Frequency Domain features: These features are based on the frequency content of the EMG signal. Some examples of frequency domain features include the power spectrum and the frequency of the dominant peak.

**Mean Frequency**

MNF, or mean normalized frequency, is computed as the weighted average frequency in an EMG (electromyography) power spectrum. It is determined by taking the sum of the products of the power spectrum and their respective frequencies, which is then divided by the total sum of the power spectrum[24]. Furthermore, MNF is also referred to as mean power frequency and mean spectral frequency in various works. The equation for MNF is as follows:

$$MNF = \frac{\sum_{j}^{M} f_j P_j}{\sum_{j=1}^{M} P_j} \quad \text{...(3)}$$

Where, $f_j$ represents the frequency value of the EMG power spectrum at the frequency bin *j*, *Pj* represents the EMG power spectrum at the same frequency bin *j*, and *M* denotes the length of the frequency bin. When analyzing EMG signals, *M* is is commonly defined as the next power of 2 based on the length of the EMG data in the time domain.

**Variance**

The measure of how spread out the EMG signal is.

$$VAV = \frac{\sum_{z=1}^{Z} (x_n - \mu)^2}{N-1} \quad \text{...(4)}$$

**Skewness**

The measure of the asymmetry of the EMG signal distribution. A data set is said to be symmetric if it looks the same to both the right and left of the center point.

$$skew = \frac{\sum_{i=1}^{N} (Y_i - \bar{Y})^3 / N}{\sigma^3} \quad \text{...(5)}$$

The mean is denoted as *Yi*, the standard deviation as σ, and N represents the number of data points. It's important to note that when computing skewness, the standard deviat $\sigma^3$ is calculated with *N* in the denominator, as opposed to N-1.

The formula for skewness mentioned in Eq(5) is commonly known as the Fisher- Pearson coefficient of skewness.

A skewness of zero characterizes a normal distribution, and data that exhibits symmetry should have skewness values close to zero. Negative skewness values suggest a leftward skew, while positive skewness values indicate a rightward skew in the data.

**Kurtosis**

Kurtosis is a statistical technique in the time domain that characterizes data distribution and identifies the presence of data peaks. It quantifies the degree to which data deviates from a normal distribution curve by comparing the inclination of the data distribution curve's peaks to that of a normal curve.

$$kurtosis = \frac{\sum_{i=1}^{N} (Y_i - \bar{Y})^4 / N}{\sigma^4} \quad \text{...(6)}$$

The mean is denoted as *Yi*, the standard deviation as σ, and *N* represents the number of data points.

A positive kurtosis value indicates heavy-tailed data, while a negative value suggests light tails. This comparison with a standard normal distribution helps determine whether the data distribution is flatter or more peaked than the normal distribution. It's important to note that the kurtosis value for a standard normal distribution is 3.0. If the standard normal distribution is 3, then the equation becomes a bit different. It's often referred to as "excess kurtosis".

$$kurtosis = \frac{\sum_{i=1}^{N} (Y_i - \bar{Y})^4 / N}{\sigma^4} - 3 \qquad ...(7)$$

Time Domain Features: These features are based on the time variation of the EMG signal. Some examples of time domain features include the mean, standard deviation, and kurtosis of the signal.

**Mean Absolute Value**

This feature provides the absolute values of all amplitude.

$$MAV(\mu) = \frac{1}{N} \sum_{n=1}^{N} |x_n| \qquad ...(8)$$

Here *xn* is a signal time series for n=1,2,3 … N, and N is the number of data points.

**Standard Deviation**

The measure of the dispersion or variability of the EMG signal. The standard deviation is a metric that quantifies the extent of fluctuations in a signal relative to its mean.

$$std(\sigma) = \sqrt{\frac{1}{N-1} \sum_{n=1}^{N} (x_n - \mu)^2} \qquad ...(9)$$

**Table 1.** Comparison of Dataset and Performance of Different Paper

| Paper | Dataset | Technique | Performance |
|---|---|---|---|
| Subasi et al., 2018[8] | Multiple Dataset | ANN, K-NN, SVM, DT | ANN provided the highest Accuracy of 98% |
| Agarwal et al., 2019[11] | Independently collected | DWT & SVM | Cross-validation shows 94% accuracy |
| Abdullah et al., 2021[13] | TIMIT | Evaluation Method by Voice Activated Device (VAD) | VDA provides Accuracy of 91.5% |
| Wen et al., 2021[20] | Independently collected | SVM, KNN & bagged trees ensemble | Bagged trees ensemble modelgives 96.2% |

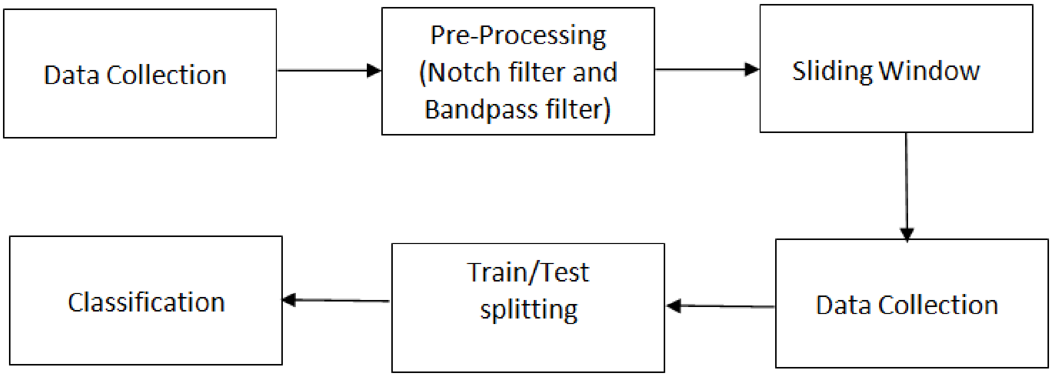



**Fig. 1.** Block Diagram

Here, $xn$ is the $n^{th}$ data point, μ is the mean of the dataset, and $N$ is is the total number of data points in the dataset.

DWT: A mathematical method known as the DWT is used to divide a signal into many sets, each of which has a time series of coefficients that describe the signal's behavior in a particular frequency range. The signal can now be represented in terms of its frequency constituents and the corresponding temporal development thanks to this transformation.

A three-level wavelet decomposition is employed by using the Daubechies 4 algorithm. The details and approximation coefficients are separated according to the level of decomposition. $n$ stands for the center of shift, and $S$ for the scale factor.

$$DWT_{X}^{\psi} = \frac{1}{\sqrt{s_{\upsilon}^{i}}}\int x(t)\psi\left(\frac{1}{s_{\upsilon}^{i}}t - n\pi\right)_{\upsilon} \quad ...(10)$$

**Table 2.** Features description

| Feature Extractor and Feature Count (In columns) | Description |
|---|---|
| DWT8 columns | The 8 columns of features extracted by DWT: standard deviation of Level 1 approximation coefficients, mean absolute Values of level 1 approximation coefficients, standard deviation of level 2 approximation coefficients, mean of absolute values of level 2 approximation coefficients, standard deviation of level 3 approximation coefficients, mean of absolute values of level 3 approximation coefficients, standard deviation of the level 3 Detail coefficients, and mean of absolute values of the level 3 detail coefficients |
| FD4 columns | The 4 columns of features extracted by FD: Mean of the frequency domain values, Variance of the frequency domain values, Skewness of frequency domain values, and Kurtosis of frequencydomain values |
| Fusion of TD and DWT 10 columns | Mean of the time domain values, Standard Deviation of the time domain values, standard deviation of level 1 approximation coefficients, mean of absolute values of level 1 approximation coefficients, standard deviation of level 2 approximation coefficients, mean of absolute values of level 2 approximation coefficients, standard deviation of level 3 approximation coefficients, mean of absolute values of level 3 approximation coefficients, standard deviation of the level 3 detail Coefficients, and mean ofabsolute values of the level 3 detail coefficient |

(1) (2) (3)

**Fig. 2.** Hand Gestures - (1) hand at rest, (2) wrist flexion, and (3) wrist extension

Following the extraction of features from different feature extractors, it obtained distinct numbers of columns for each method. Specifically, the DWT yielded 8 columns, the FD method provided 4 columns, and the combination of TD and DWT resulted in 10 columns. A comprehensive description of each column for every feature extractor is presented in the respective tables.

Table 2 briefly describes 3 feature extractors. After extracting the feature from these 3 above feature extractors it is necessary to use principal component analysis (PCA) this is because PCA is used to reduce the number of features from the above feature extractor without losing too much information, and it identifies the most important features. It makes features more recognizable for classification. This can be helpful for machine learning algorithms and classification. Also, it is useful for getting accurate results.

**Training and Testing**

After extracting the features from DWT FD for 3 classes, the next step is to assign a class label to each extracted feature class. For DWT each class contains 2092 features extracted. After assigning the class label to the feature it is necessary to append all the data frames of 3 classes before passing them to a classifier. Before passing to the classifier, it is essential to split the dataset into 70-30 portions. Same procedure is done for FD. Usually, the training portion of the data should be greater or higher than the testing data, as it allows the model to identify and learn the

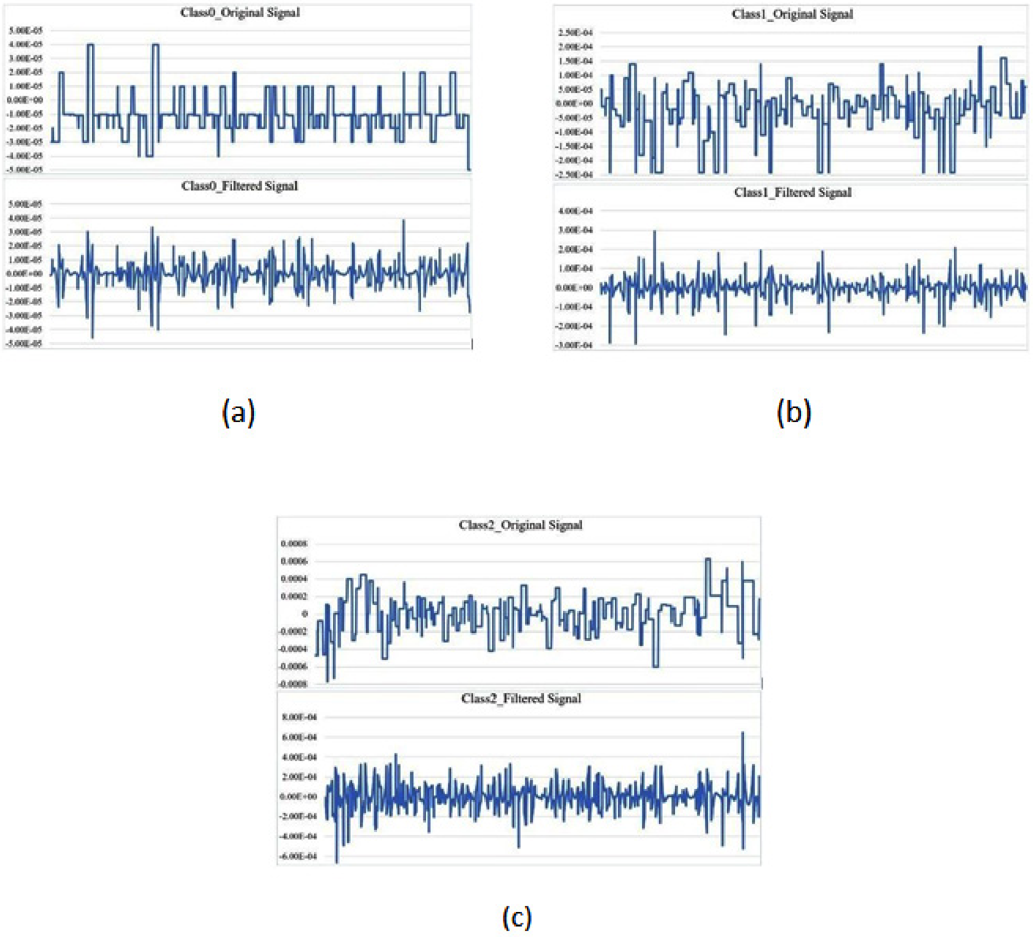



**Fig. 3.** (1) Class0 Original vs Filtered Signal; (2) Class1 Original vs Filtered Signal; (3) Class2 Original vs Filtered Signal

significant pattern. This is necessary for the model to accurately predict outcomes when presented with new, unseen testing data.

Once the model is trained, it internalizes the patterns it has learned from the training data and uses this knowledge to make predictions based on the testing data. To determine the performance of the model 3 classifiers are used: random forest, decision tree(DT), and K–nearest neighbor. Random Forest is an effective machine learning (ML) algorithm utilized for predictive tasks, such as classification and regression, where input variables or features are used to make predictions. DT is an ML classifier, and it is a representation of the decision-making process, it is a model that takes the shape of a tree. The internal nodes of DT represent tests on input variables, and branches indicate outcomes. KNN is a non-parametric algorithm used in machine learning for classification and regression tasks. Unlike other algorithms, KNN does not make any assumptions about the underlying distribution of the data.

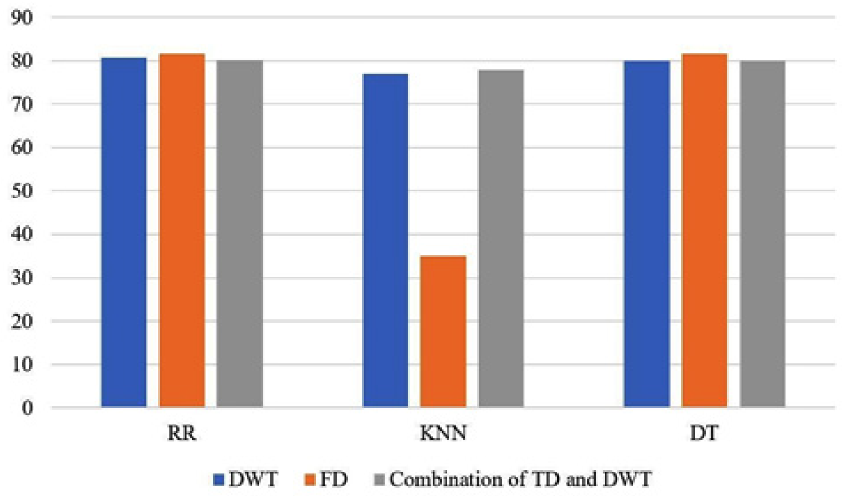
## RESULTS AND DISCUSSION

Table.3 shows the results for all the feature extractors and their performance on different classifiers. 3 classifiers were used, among all these classifiers, the RF classifier provided the highest accuracy of 81.69% when applied to FD-extracted features, along with the RF, the DT classifier also provided promising results with an accuracy of 80.77% for TD-extracted features. The idea of fusing TD and DWT features also resulted in promising results and achieved an accuracy of 81.21% for the DT classifier.

One noteworthy observation was that the RF classifier exhibited exceptional performance when applied to features extracted from the frequency domain. This suggests that the frequency- related characteristics of EMG signals played a pivotal role in distinguishing between different hand movements. This indicates that features related to the temporal characteristics of EMG signals provided valuable information for classification. In addition, the researchers explored a novel approach by fusing time domain and DWT features, yielding noteworthy results. The combined features achieved an accuracy of 81.21% with the DT classifier, implying that the fusion of both temporal and frequency-related information enhanced classification accuracy, underscoring the potential of utilizing multiple feature extractors in tandem. These findings not only highlight the effectiveness of specific feature extractors and classifiers in EMG-based hand movement

**Table 3.** Classifier model result

| | DWT Feature Extractor | | | |
|---|---|---|---|---|
| Classifier | Accuracy | Precision | Recall | F1-Score |
| Random Forest | 80.77 | 80.95 | 80.77 | 80.77 |
| K-nearest Neighbor | 77.10 | 76.85 | 77.10 | 76.67 |
| Decision Tree | 80.77 | 80.93 | 80.77 | 80.76 |
| | FD Feature Extractor | | | |
| Classifier | Accuracy | Precision | Recall | F1-Score |
| Random Forest | 81.69 | 81.53 | 81.69 | 81.61 |
| K-nearest Neighbor | 35.57 | 35.70 | 35.57 | 34.99 |
| Decision Tree | 81.69 | 81.89 | 81.69 | 81.78 |
| | Fusion of TD and DWT | | | |
| Classifier | Accuracy | Precision | Recall | F1-Score |
| Random Forest | 80.21 | 80.30 | 80.21 | 80.19 |
| K-nearest Neighbor | 78.07 | 77.47 | 78.77 | 77.71 |
| Decision Tree | 81.21 | 80.36 | 81.21 | 80.22 |




**Graph 1.** Bar graph of the accuracy comparison

classification but also suggest the advantage of exploring hybrid feature extraction methods to further improve classification performance.

**Future Scope and Conclusion**

The developed EMG-based hand moment classification model shows promising results and holds potential for deployment in various sectors and applications. Particularly in the medical sector, it can aid in diagnosing and monitoring conditions by analyzing muscle activity patterns. Clinicians can leverage the model to identify abnormalities such as muscle weakness, dystonia, or peripheral nerve injuries affecting hand movements. Additionally, the model has implications for prosthetics and orthotics, providing intuitive control for prosthetic hand movements. By utilizing diverse feature extraction techniques and preprocessing methods, the project achieved an accuracy rate of 80% in classifying hand gestures, including hand at rest, wrist flexion, and wrist extension.

The authors of this research have currently focused on three specific hand movements. In the future, they plan to expand their investigation to encompass a broader range of hand movements commonly utilized in daily life, such as wrist pronation, wrist rotation, wrist radial deviation, and more. Upon the inclusion of these additional hand movements, the authors intend to extract relevant features for each movement. Subsequently, they will work towards integrating these features into a model designed for prosthetic hands. This research is expected to have a greater impact on the biomedical field in the future.

## ACKNOWLEDGEMENT

This work is carried out under the support received from AICTE, New Delhi, India.

**Conflict of Interest**

Authors have no conflict of interest to declare.

**Funding Sources**

All India Council for Technical Education (AICTE) File no. 8-53/FDC/RPS (POLICY-I) /2019-20.

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