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ROLE MODEL OF ELECTROMYOGRAPHY SIGNAL WITH PRE-TRAINED DNN FEATURES USING HAND GESTURE RECOGNITION

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ABSTRACT
Due to technological advancements, electromyography (EMG) is now used for more than only diagnosis, with potential applications including movement analysis and the precise and flexible control of manipulators in the field of aided medicine. Intuitive and precise recognition of multiple motions is possible with a powerful classifier using surface electromyography-based gesture recognition systems. The Mayo armband is a Bluetooth-enabled, low-power wireless sensor that generates a reliable EMG reading. The Myo armband detects and records upper-limb electrical muscle activity. Artificial intelligence and deep learning-based models generally adopted with excellent outcomes in many fields. In this paper, an artificial neural network-based method for EMG gesture prediction using pre-trained DNN characteristics is proposed. The proposed method analyses the CapgMyo standard benchmark dataset, which maps eight classes of hand movement recognition to data collected from participants via the Myo wristband EMG signals. The results demonstrate that the suggested classification method, which employs an artificial neural network classification model with deep features of EMG signals, beats the other current methods by a significant margin with accuracy of 94.8%.
Keywords: DNN, DWT, Electromyography, Hands Gesture Recognition, Machine Learning

INTRODUCTION
With the advancement of computer technology, PCs and other technical gadgets are now an incontestable part of our everyday lives. It's not simply the ubiquitous nature of personal computers in today's society, but how pervasive their use has become in every sector of commerce, government, and culture. However, the most significant difficulty brought on by the prevalence of computers is in the area of communication. Human-computer interaction (HCI) has branched out in many directions over the past few decades, and not simply in terms of improved interaction quality. Various academics have been consistently focusing on improving human computer interfaces by making use of fundamental human communication and manipulation abilities [1]. Hand gestures are widely recognised as an effective mode of communication in daily life. Hand-gesture recognition, a way of categorising important hand movements, is gaining a lot of popularity recently. Gesture-based interaction is a common technique used in many contexts, such as sign language interpretation, sports, human-robot interaction, and human-machine interaction [2]. Medical applications of hand gesture recognition systems often rely on bioelectrical signals rather than visual cues to ensure accuracy. Many facets of daily life, including gaming, healthcare, education, and commerce, call for the usage of hand gestures. Hand gesture recognition is the process by which a computer

is able to identify the actions of a user's hands through the automated detection and analysis of bioelectrical signals [3-4]. There has been a lot of focus on developing human-computer interfaces that make use of natural human behaviours including gestures, vision, and speech. Gesture recognition on the human hand is an ingenious, relaxed, and natural way for humans to interact with computers. Its primary applications are gesture-based control and sign language recognition. Deaf people may find it easier to communicate with the world around them if signs could be automatically translated by computers, which is exactly what sign language recognition hopes to achieve. Despite its rigid organisation and foundation in an alphabet and symbols, this system may be used to build generic gesture-based HCI [5].

Multiple sensors can be utilised to gather information for gesture recognition. Some examples of sensors you could encounter are cameras, data gloves, IMUS, Electromyographic (EMG), and image sensors. Although installing sensors in strategic places might be the answer, gesture recognition technology has a number of limitations that make it less than ideal. EMG has advantages over the other two identifying methods in terms of power consumption and mobility. EMG signals are the most dependable and established source of control signals and may be utilised to reflect a number of different movements [6]. Electromyography (EMG) provides data on muscle flexion and extension, as well as the shape and position of the limbs at movement's end by superimposing the action potentials of the muscle tissue that occur during a voluntary contraction. Hand gesture identification using EMG has several benefits over ocular detection. The EMG sensor is not affected by its environment due to its simple design. Biomechanics, neuromuscular physiology, gesture-based control, sign language interpretation, military applications, gaming, and virtual reality are just few of the many scientific areas where EMG is used. Recognizance systems that utilise EMG signals have challenges in signal collection, among other areas. The procedure is affected by ambient noise. This needs robust recognition algorithms in addition to efficient signal processing techniques for minimising noise [7-8]. The main contributions of this paper are as follows:

- Generate Electromyography signal-based hand movement using different network approach.
- Proposed Pre-trained DNN features, which utilizes rich set feature layer from pretrained convolutional neural network using transfer learning approach.

ACTUAL WORK

The bulk of these studies relied on vision-based methods, while the rest relied on glove, sensor, or wearable band implementations of hand gesture detection. This section elaborates on each of these methods. The approach employs a neural network architecture to categorise the EMG signals, and it was created [9] on the basis of the extraction of time-domain information. The findings show that the artificial neural network classifier stabilises with minimal mean square error at 6 epochs for finger movement datasets and at 4 epochs for hand grasps datasets, where the major emphasis [10] was on categorising separate finger movements of a single hand. In [11], we presented a technique for developing and fine-tuning feature models using a multichannel sEMG amplifier. In [12], a novel architecture for Hand Gesture Recognition (HGR) using Few-Shot Learning was developed. As a subset of domain adaptation, "few-shot learning" seeks to infer the required output from a single or limited set of training observations. This is why [13] presented an unique autonomous learning framework that automatically identifies the class of acquired EMG data using depth information, bringing together the benefits of depth vision and EMG signals. With regards to processing surface electromyographic (sEMG) signals across several channels, [14] compared and contrasted the efficacy of several machine learning strategies based on artificial neural networks. [15] proposed using a multi-stream residual network to identify dynamic hand motions. In [16], we saw a sensor fusion architecture that takes data from several sources, such as electromyography (EMG) of muscle activity and visual data, and merges them. [17] demonstrated the usage of HDC in a smart prosthesis application dubbed hand gesture identification using a stream of EMG data. With this method, the four analogue channels of EMG signal production may be combined into a single hyper vector. To perform accurate identification despite illumination changes, backdrop clutter, rapid movement, and partial occlusion, a method based on multi-level feature fusion of a two-stream convolutional neural network was released [18]. In order to improve online categorization of hand movements using EMG data collected from the forearm muscles, [19] proposes the use of recurrent neural networks. [20] developed a deep learning model that combines convolutional auto-encoder and convolutional neural network to classify an EMG dataset consisting of 10 different types of hand gestures. To guide the action potential signal, a surface potential electrode was devised [21]. After being corrected and filtered, it is gathered by the NRF52832 single-chip CPU. When compared to other, more complex state-of-the-art models, our work classifying sEMG signals [22] regularly achieves better results. Our novel attention-based model achieves state-of-the-art performance on a wide variety of state-of-the-art datasets, including 53 datasets including finger, wrist, and gripping motions.

There was a proposal for a model that could detect hand gestures in real time using sEMG. The armband is used to gather sEMG signals, and the data is segmented using a sliding window approach so that features may be extracted. A data-forwarding ANN is developed and trained using the training dataset. For this purpose, classifiers for hand/finger movements based on electromyographic data were developed using machine learning methods. Ensemble techniques and time-domain variables were used to categorise eight distinct types of hand movements. Raw EMG signals were processed to extract eight different time-domain features used to train and test machine learning models: integrated EMG (IEMG), variance, mean absolute value, modified mean absolute value type1, waveform length, root mean square, average amplitude change, and difference absolute standard deviation value. The Quantization-based position Weight Matrix (QuPWM) feature extraction technique has shown promise in the capacity to extract important features from a range of biological data, including EEG and MEG signals, in an effort to improve their interpretation. An app on a single smartphone was able to accurately categorise 8 different hand gestures using just inaudible high-frequency sound, with a classification accuracy of 94.25%.

METHODOLOGY

In order to process, analyse, and recognise the hand gesture signal, an EMG signal-based HGR system has been developed. Training and testing are the two main phases of any hand gesture recognition system's process. Figure 1 is a simplified example of a hand gesture recognition system.

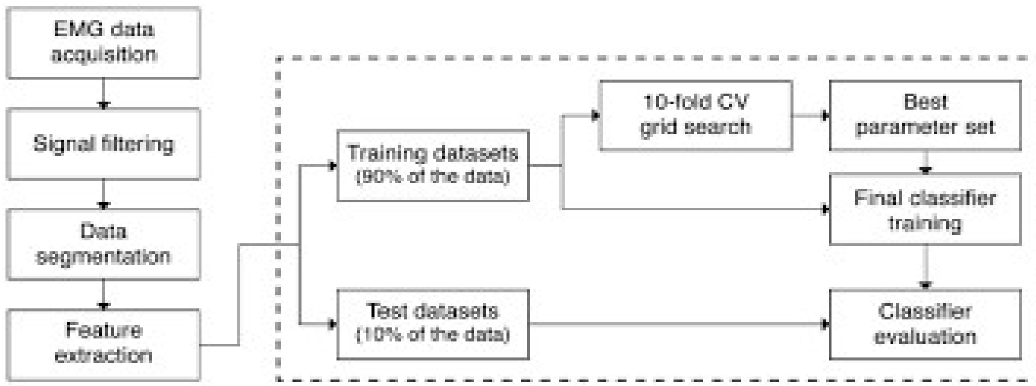


Fig 1: Framework of a HGR system.

1. Hand Gesture Dataset (CapgMyo EMG) and Dataset Splitting

The CapgMyo is a standard-setting database comprising HD-sEMG recordings of various hand gestures from a wide range of subjects. the acquisition setup that was used to get the data from 9 healthy participants utilising an 8x16 electrode array with 128 channels. The dataset signals are further splitter for train and test procedure into 90-10% of dataset samples respectively.

2. Pre-process

The extreme vulnerability of EMG signals makes them susceptible to contamination by artefacts and environmental noise. Bad classification outcomes can be achieved by avoiding the usage of such tainted signals. Noise, interference and artefacts from several sources can corrupt EMG data. Some of the most prevalent sources are electrode noise, power line noise, motion artefacts, inherent noise and ambient noise in electronic and electrical equipment. Using high-quality gear with the appropriate electrode position, or employing traditional filtering methods like a band stop filter or band pass filter, will get rid of the first three forms of noise. It is difficult to filter out the background noise, artefacts, and interferences that occur in the principal EMG frequency range. Wavelet-based techniques are useful for investigating non-stationary data, such as EMG. This coefficient measures the degree to which the signal and wavelet functions share characteristics. Do this again and again until all of the coefficients for the low pass approximation of the filtered signal have been obtained. The focus of this research is on the many quantifications of frequency. Variable frequency ranges of the EMG signals are reflected in the finely granular coefficients generated by the DWT decomposition. The best performance in this experiment was attained by combining DWT with DB wavelet. Wavelet-based feature extraction approaches provide a vector that is too huge to be used as a classifier input, unfortunately. The method limits the number of distinguishing features that may be extracted using wavelet coefficients. Once the DWT coefficients are obtained, the statistical properties of the EMG signal in each of the five DWT sub-bands may be extracted and used to extract the relevant information. Waveform of the test signal after discrete wavelet transformation pre-processing, as seen in Fig. 2.

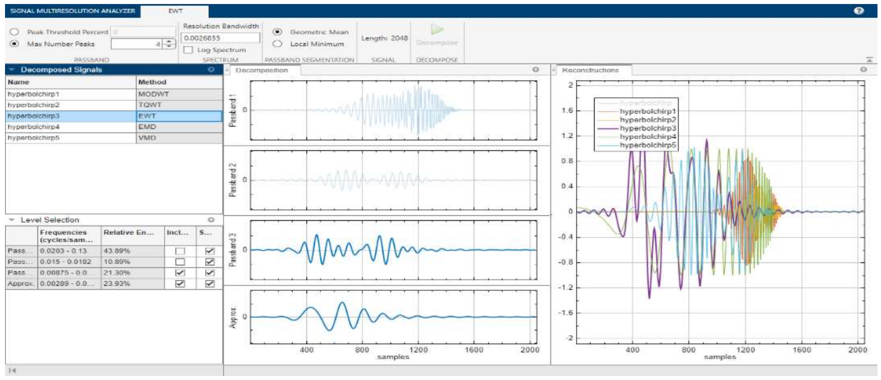


Fig 2: Decomposition of test signal using DWT

3. *Pre-trained CNN Features*

Accurate categorization of EMG signals requires thoughtful feature selection due to the signals' complexity. The accuracy with which patterns are classified is strongly influenced by the qualities used to describe the raw EMG signals. The categorization of EMG signals requires several feature parameters since it is challenging to extract a feature parameter that successfully ties each unique property of the recorded EMG signals to a motion command. After a signal has been processed with a wavelet transform or a three-level DB decomposition, deep network transfer learning is used. The primary argument for using transfer learning to train the CNN is that it allows for the acquisition of more generalizable and robust characteristics. The CNN might then utilise these shared features to better understand a new person's sEMG behaviour.

4. *Classification (train, validate and test)*

After gathering feature datasets for train and test with appropriate output labels, an artificial neural network was utilised to categorise hand gestures through a series of train, validate, and test phases. The ANN utilised in this research, of the back-propagation (BP) variety, is adaptive and durable. If the training is effective, the system's state will eventually evolve to a new equilibrium point. In order to create BP, a multilayer network with a nonlinear differentiable transfer function is trained using Widrow-Hoff methods. The difference in weights between the layers of a neural network is set by the learning procedure used for its propagation. To optimise the training process validation, an ANN is utilised to tune or train the classifier with hyperparameters such as the learning rate, error rate, epoch, activation function and hidden layer. Classifiers from a supervised learning model can be used in circumstances where the training data has already been labelled. The feature set, network design, and training strategy selected are considered to impact the classification accuracy of artificial neural networks. The obtained sEMG signal characteristics are sent into the ANN, and the network produces a classification or estimated motion due to its input.

The neurons in the neural network in this research were selected by trial and error. To avoid overfitting, the input data used for training was randomly divided into three sets: a training set including 70% of the samples, a validation set comprising 15% of the samples, and a test set comprising 15% of the samples. The experiments are conducted with different densities of hidden neurons, from 1 to 15, to see how the size of the hidden layer affected the precision with which we could estimate classes. The optimal number of hidden neurons for neural networks is 5, since anything more than that causes over-fitting and anything less than that causes under-fitting. The input feature in the input layer consists of four neurons, whereas the two classes in the output layer each consist of two neurons. The back-propagation technique is used to adjust the network's weights and biases during training in order to reduce the margin of error between the network's output and the target. More data isn't necessarily better when it comes to machine learning applications, as demonstrated by feature selection techniques. The results of feature extraction revealed that some compiled sets of features might be detrimental to the classifier's efficiency. One statistic for feature selection is the number of times a feature causes a tree to divide. The following computations are utilised when developing the proposed architecture.

Algorithm

Input - *EMG Signals of Various Hand Gestures*

Output - *Hand Gestures Type*

Procedure

Step1: The separation of EMG data sets into training and testing data

Step2: Train EMG signals are pre-processed using wavelet decomposition for noise reduction.

Step3: Use a transfer learning method for feature extraction on the wavelet-decomposed train signals.

Step3: The dataset's features and labels must be extracted in order to train the model.

Step4: Initialize and create a model ANN by setting its initial hyperparameters.

Step5: Perform ANN model training and verification.

Step6: Assuming successful validation, save the ANN model training data.

Step7: Load test feature data and apply on step2 and step 3.

Step8: Infer the sort of hand gesture from the test signals used for prediction.

EXPERIMENTAL RESULTS AND DISCUSSION

For this experiment, proposed experimentation used MATLAB R2018b to create a model of the proposed architecture and test it. An Intel® CoreTM i5 processor and 8 GB of RAM were used in the analysis of the suggested concept. Using an 8x16 electrode array and state-of-the-art collection technology, an extensive collection of high-density surface electromyography (sEMG) recordings of hand gestures from a variety of individuals is available in the CapgMyo dataset (able-bodied persons aged 23 to 26). Figure 3 shows the eight distinct hand gestures employed in this analysis. Ten repetitions of each exercise, held for three to ten seconds at a time with 10 trials. Our evaluation procedure consists of three phases: training, validation, and testing. For the training and validation phases, 90% of the samples are used, whereas only 10% are used during testing.

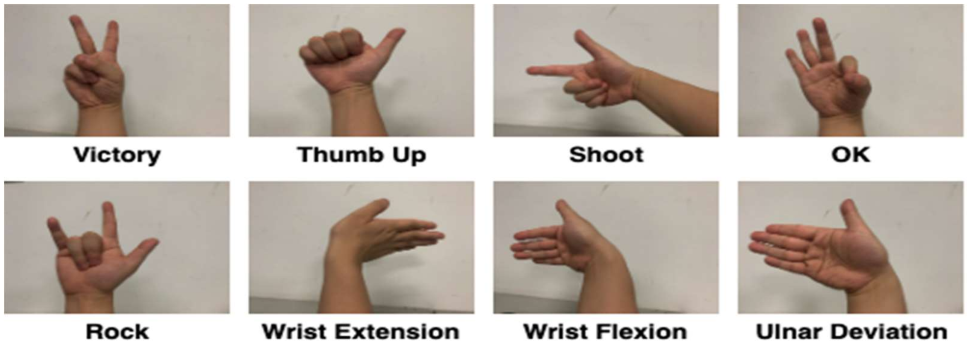
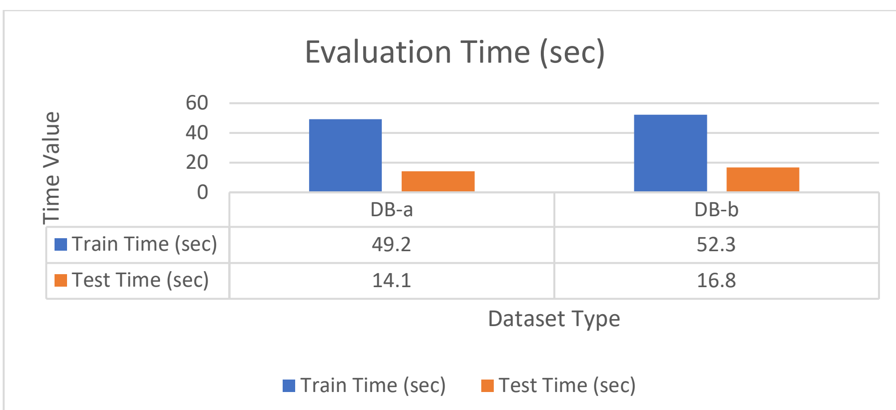


Fig 3: CapgMyo Dataset's eight hand motions.

Our evaluation procedure consists of three phases: training, validation, and testing. For the training and validation phases, 90% of the samples are used, whereas only 10% are used during testing. Once the accuracy of the train data has been established, test data may be used to identify which hand gesture will yield the most accurate predictions. Both the training and testing assessment times are shown in Table 1, and the results are visually shown in Figure 4. Both procedures were found to take the longest with DB-b datasets.

Table 1: Performance of Evaluation Time

Datasets/Time	Train Time (sec)	Test Time (sec)
DB-a	49.2	14.1
DB-b	52.3	16.8



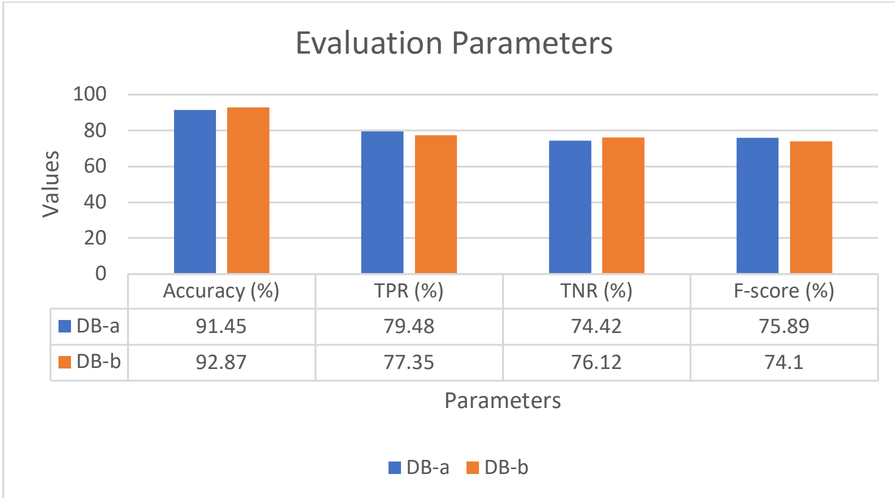


Fig 4: Evaluation parameters performance

The parameters that were evaluated for testing are listed in Table 2 along with comparisons to currently employed research methods, which are also represented visually in Fig. 5.

Table 2: Comparative Results

Performance Parameters	**Values (%)**			
	Ref [15]	**Ref [38]**	**Ref [39]**	**Proposed Work**
Accuracy	81.25	83.1	86.0	92.87
TNR	59.72	-	-	76.12
TPR	70.48	-	-	77.35

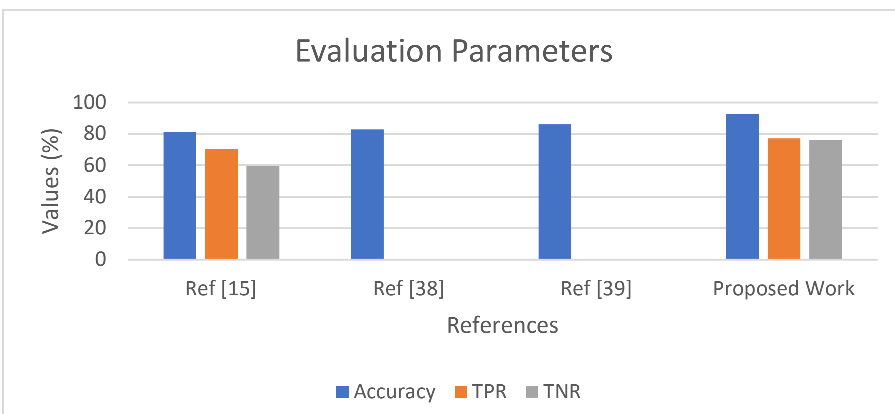


Fig 5: Comparative performance results.

CONCLUSION

In order to enhance EMG-based hand gesture identification with CapgMyo datasets from the Myo armband device, this research proposes a novel artificial neural network-based technique with pre-trained DNN features. The suggested hybrid method can improve accuracy over the alternative by being used to construct the classifier. This technique applies a transfer learning strategy to the data after it has been pre-processed. To create a classifier, an artificial neural network is trained using feed forward backpropagation using the remaining 90% of the dataset's feature vectors. This experiment looks at the remaining 10% of feature vectors. A classifier is required to classify each test feature vector for accurate identification, rather than merely having the results recognised by any motion. If no gesture is recognised for a feature vector, it is categorised as no gesture. On the DB-b dataset, our proposed model achieves a greater accuracy of 92.87% than the state-of-the-art methods. A future possibility is a real-time implementation. Also, surgical robots and other applications that rely on hand gestures will be able to be remotely controlled thanks to advancements in future technology.

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