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Deep Learning Approaches For EMG-Based Motion Recognition and Force Estimation

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Abstract. *In this study, we study the use of deep learning methods, in this case Convolutional Neural Networks (CNNs) to analyze EMG signals in order to improve prosthetic performance in upper limb disabled patients. This study focuses on gripping actions which are an important part of prosthetic hand function. Using a curated database, we analyze EMG signals with MATLAB R2023b and convert them into grayscale images with palm movements using an algorithm proposed in this paper. We then categorize the generated images from the algorithm into eight different categories using CNNs and find very promising results. SSAE-f and CNN performed similarly (p = 0.55) and reduced the differences in accuracy among the subjects compared to conventional methods which indicates their robustness and reliability. The study suggests that deep learning is effective for EMG-based gesture detection and will help in human-computer interface and healthcare technology, which will be applicable to prosthetic devices.*

Keywords: *Electromyography (EMG); Deep Learning; Convolutional Neural Networks (CNN); Prosthetics; Gesture Recognition.*

1. INTRODUCTION

The ability to interact seamlessly with one's environment is fundamental to human autonomy and quality of life. Limb loss, often resulting from severe injuries or armed conflict, significantly impacts individuals' ability to perform daily activities and causes considerable psychological and social consequences. With the raise cases of resection world. the Necessity for more effectual prosthetic advent has turn into crucially. Prosthetic limbs have encounter considerable evolution moreover, advance from plain mechanical appliance to progressing systems that use (motors, sensors, and electronic control, units, leading to improved performance and greater effectiveness in meeting users' needs).Prosthetics are now fully computer-driven thanks to the AI and deep learning (DL) algorithms. These new computational techniques have opened a new era in prosthetic control in which devices are able to simulate human limb movements in a very real way. The first challenge of building a very intelligent and responsive prosthetic device is the interpretation of human intention. EMG signals due to contraction of muscles are a direct and non-invasive method to interpret human intentions. The information in EMG signals relating to muscle activity makes them quite suitable to control the mechanical devices so that the user can intuitively understand what is going on and apply the appropriate force. Despite the impressive progress on the technology side, the high cost of sophisticated prosthetic limbs still makes them inaccessible for a good portion of the population. We are not able to solve the problem in this way and we are constantly looking for creative, cost-effective solutions for the sake of keeping the limb working. In this regard, the development of affordable, high-performance, and intelligent prosthetic systems is of great importance to researchers and engineers.

In this work, we have developed a novel approach to detect and analyze EMG signals using deep learning networks. We are working on a good system for classification of EMG data to predict what is happening and estimate force, which is crucial to the control of a prosthetic arm. The aim of this project is to improve the efficiency and functionality of our prosthetic limbs, in order to develop devices that can provide the human limb function while also meeting the practical accessibility situation of our arms and hands. In the following, we describe the theoretical background, the proposed methods for signal processing and deep neural network modeling, and evaluate our system's performance. In the next section, we review some of the developments in prosthetic control, especially EMG signals and deep learning techniques. The bones of the arm and hand support each other and the muscle is attached to one another to support the upper limb movement. They also enable a necessary range of motion and strength for manipulating objects and withstanding forces during daily activities, sports, and work [1]. EMG signals are often acquired from forearm and arm muscles, with the forearm housing approximately 20 complex muscles. These include intrinsic hand muscles and extrinsic muscles in separate flexor and extensor compartments, controlling wrist/finger flexion and extension, respectively [2]. Electromyography (EMG) is a technique that employs electrodes to measure the electrical activity or response of muscle tissue when stimulated by a nerve [3]. EMG signals originate in the brain and travel via spinal motor neurons (α-motor neurons) to muscle fibers. A motor unit (MU) comprises an α-motor neuron and its innervated fibers, with size varying based on force generation needs [4]. MU size varies; small MUs regulate eye/hand movements, while large ones (thousands of fibers) power legs/back Activation of a motor neuron causes all associated muscle fibers to contract simultaneously. Motor units vary in the types of muscle fibers they control, allowing for a wide range of movements. When a motor unit is stimulated, an action potential known as the motor unit action potential (MMAP) is generated. This potential is a key component of the electromyography (EMG) signal, reflecting the activity and contraction of muscle fibers. EMG signals are random in nature, with amplitudes typically ranging from 0 to 1.5 mV at effective modulation (RMS) or from 0 to 10 mV at peak-to-peak measurement. Their frequency components range from 0 to 500 Hz, with most of the signal's useful power concentrated in the 20 to 450 Hz band. The frequency spectrum of an EMG signal can be analyzed using the Fast Fourier Transform (FFT) algorithm, and the results can be graphically displayed. While gas-based electrodes can accurately measure the activity of individual muscle fibers, their invasive nature limits their widespread clinical and commercial use. In contrast, non-invasive electrodes are placed on the skin's surface, making them more comfortable and easier for both the patient and the examiner. However, these electrodes can sometimes experience signal distortion and interference. Interference from adjacent muscle tissue can also affect the accuracy of the scan and the electrodes; this phenomenon is called crosstalk, which in turn affects timing and amplitude measurements. Nevertheless, their ease of use and lack of pain make them suitable for clinical applications. Recent advancements in medical technology, particularly in dry electrodes, have improved the quality of EMG (electromyography) signals without prior skin preparation or any specific procedure. These electrodes are often manufactured using hydro-printing techniques, offering better fit and greater comfort compared to traditional wet electrodes, or they can be made from materials such as titanium. Currently, machine learning, its algorithms, and artificial intelligence techniques are gaining significant traction and attention as an excellent alternative to traditional gait analysis methods. These algorithms can apply the complex, nonlinear relationships characteristic of human gait dynamics, often achieving superior predictive accuracy compared to conventional methods. Neural networks, particularly multi-layered perceptual networks, have demonstrated accuracy exceeding 97% in distinguishing, analyzing, and detecting different phases and steps of walking, such as swaying and stabilizing, using inertia as the unit of measurement. It's worth noting that studies using pressure and motion data have achieved the highest classification rates, ranging from 83% to 99.7%. Furthermore, long-term and short-term memory networks have demonstrated excellent performance, achieving accuracy rates close to 92% when employing inertial accelerometer signals as the unit of measurement. [18].

ATU- AJIEA, Volume: 2, Issue: 01, 06, 30, 2026,

Despite challenges in managing signal variability, Electromyography (EMG) data is also being extensively utilized in AI models for gait analysis. A key advantage of EMG signals is their temporal pre-motion information (approximately 120ms ahead of kinematic data), making them highly suitable for real-time joint position estimation. This capability can effectively mitigate the inherent delay issues in online control systems, such as those used in exoskeletons [19 20]. For example, in the recent work, using Convolutional Neural Networks (CNNs) for four EMG signals, the average classification accuracy of these models is 79% for gait phases, which is only slightly worse than the current best methods that focus on only the main EMG features extraction [21]. Based on the extensive literature of EMG signal analysis, we aim to significantly enhance the field by utilizing deep learning CNNs to provide a robust and optimal approach for decoding and interpreting complex EMG signals, and to further improve prosthetic limb control. While conventional methods are widely used and based on sound scientific principles, they often fail to capture the complex, temporal patterns and detailed characteristics of muscle contractions and relaxations during continuous movement under natural conditions. Therefore, they are unable to provide the adaptive and intuitive control necessary for the advancements in prosthetics. This research addresses this problem by utilizing and developing convolutional neural network (CNN) architectures to enhance their ability to handle the complex temporal properties of muscles and their signals. The aim is to improve real-time adaptability, response speed, and computational accuracy, which are essential for the application of smart prosthetics today. These models (deep learning in convolutional neural networks) are used to bridge the gap between the real-time mechanical movement of prosthetics and the biological signals emitted by the human body. The main research objectives are:

1- To improve effective methods for identifying characteristics from continuously changing and distorted electromyography (EMG) signals.

2. Comparing traditional signal processing techniques with the performance of these methods. 2. Designing methods that contribute to improved control of muscle contraction and relaxation, as well as reducing noise.

3. Advanced work focused on deep learning to improve the performance of prosthetic limbs. In my opinion, this research increases the efficiency, adaptability, and ease of use of these prosthetic limbs.

4. Improving the understanding of patient motor intentions by ensuring more accurate analysis of muscle signals using artificial intelligence algorithms.

5. Developing smarter upper and lower limb prostheses, giving amputees in wars, accidents, etc., greater control over movement, enabling them to live easier lives by performing tasks such as efficiently lifting and grasping objects, and contributing to the development of intelligent robotic arm applications.

2. METHODOLOGY

Deep learning algorithms currently play a significant role in industrial sectors and scientific computing by accurately processing complex problems [14]. They rely on multiple neural network structures to learn primarily from data and examples, closely resembling human learning mechanisms. These modern technologies contribute to advancements in various fields, such as vehicles with features like autonomous driving and navigation systems. These systems can recognize numerous and diverse objects, distinguishing between pedestrians, stationary objects, and surrounding stop signs.

Al Furat Journal of Innovations in Engineering Applications (AJIEA)

They are also integrated into the manufacturing of consumer electronics, enabling hands-free operation through voice control in smartphones and smart speakers. This highlights one of the most important applications of artificial intelligence. The widespread use of AI technologies today stems from their ability to achieve precise results and surpass human performance in tasks such as text and audio classification, and image classification. These models are trained using large datasets containing pre-classified examples through multi-layered neural network architectures. Neural networks are based on a concept inspired by biological neurons, where signal processing is represented as a weighted sum of the activation values entering the model. This sum is then processed by a nonlinear function that includes a threshold value and a bias coefficient to produce the neuron's output signal [20], as shown in Figure(1). Similarly, artificial neural networks are formed by interlinking processing units, commonly referred to as neurons, which perform a non-linear transformation on the weighted inputs they receive.

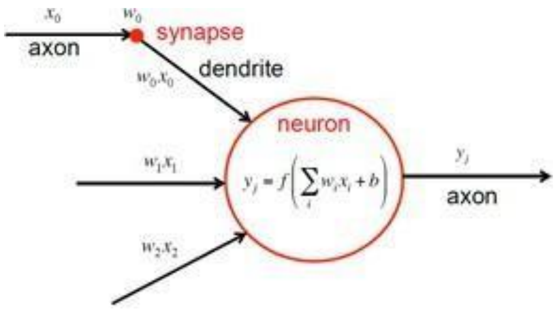

Fig. 1: Analogy between biological neuron signal processing and artificial neural network operation

Figure 2 demonstrates that a neural network, analogous to the human brain, consists of interconnected artificial neurons, typically known as nodes. The nodes are methodically arranged into separate levels: an input layer, one or more hidden layers, and an output layer.

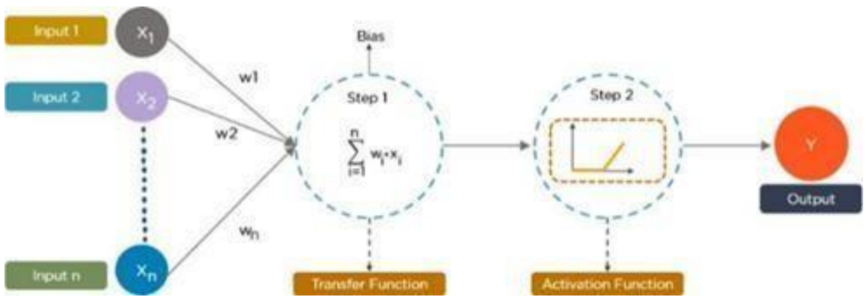

Fig. 2: Basic architecture of a neural network, showing input, hidden, and output layers

In deep learning, many strategies are used to solve a complex problem, which requires a lot of data and computing resources. Some examples are Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs), and Multilayer Perceptron's (MLPs). These are all designed for different purposes in different fields. Convolutional Neural Networks (CNNs) or ConvNets are mainly used in image processing and object detection owing to their hierarchical structure. Their roots date back to 1988 when Yann LeCun introduced LeNet for character recognition. In the present era, CNNs are also used in satellite image classification, medical image analysis, and time series forecasting. Convolutional Neural Networks are made of multiple

Al Furat Journal of Innovations in Engineering Applications (AJIEA)

layers, which are used to evaluate and extract features from information. The layers usually consist of a Convolution Layer with filters for convolution, a Rectified Linear Unit (ReLU) layer for non-linear transformations, a Pooling Layer for reducing the size of the input and consolidating the feature maps, and a Fully Connected Layer for classifying and recognizing the image. The CNN works from the picture perspective; an RGB image is a 3D array of pixel values and a grayscale image is a 2D array. The main function of a CNN is to perform convolution and multiply the input matrix (image) by a filter (pixel). The dot product process outputs a feature map of the image by moving the kernel from one point in the input to another and aggregating the values of the two parts. The feature map then enters the pooling layer for reduction of spatial dimensions and thus reduction of computational burden. Finally, the feature maps are aggregated into a single linear vector and fed into a neural network to be sorted. Justification for architectural design and hyperparameter optimization. The Convolutional Neural Network (CNN) architecture is designed to extract hierarchical spatial-temporal The Convolutional Neural Network (CNN) architecture was designed to extract hierarchical spatial and temporal features from 128×128 pixel scalogram images generated using continuous wavelet transform (CWT). To achieve a gradual and efficient extraction of features, a standard sequence of convolutional layers followed by batch normalization and max-pooling layers was adopted. This arrangement allows the network to learn features starting from simple patterns such as edges and progressing to more complex dynamic patterns. The depth of the network, represented by the number of layers, was determined through practical experiments to achieve a suitable balance between the complexity of the model and its ability to generalize to different participants, thus contributing to reducing the probability of overfitting. This research develops innovative methods for signal analysis. Superficial electromyography (sEMG) is used to interpret and identify hand movements. The complete methodology, as shown in Figure 3, illustrates a precise sequence of processing stages performed on these applications. First, high-quality signals are collected directly from the upper extremities, such as the patient's or participant's arm, at the time they perform the desired hand movements. These signals are then converted into tensors, which are image-like representations. Each tensor must have a precise name that corresponds to the corresponding hand movement recorded at the time of signal recording. At this stage, the primary procedures focused on the arm and recording the electrophysiological state of the arm surface at specific time points. As the research progressed, particularly with the application of sequential time intervals—an advanced technique—the data processed in the first stage was carefully divided into groups and categories, such as training, testing, and validation. These groups were then used scientifically and systematically to evaluate and train convolutional neural network models. It can be said that the main differences between the tasks that were previously modified and studied in detail are the processing stages we mentioned earlier, which were chosen with different levels of complexity for convolutional neural network models.

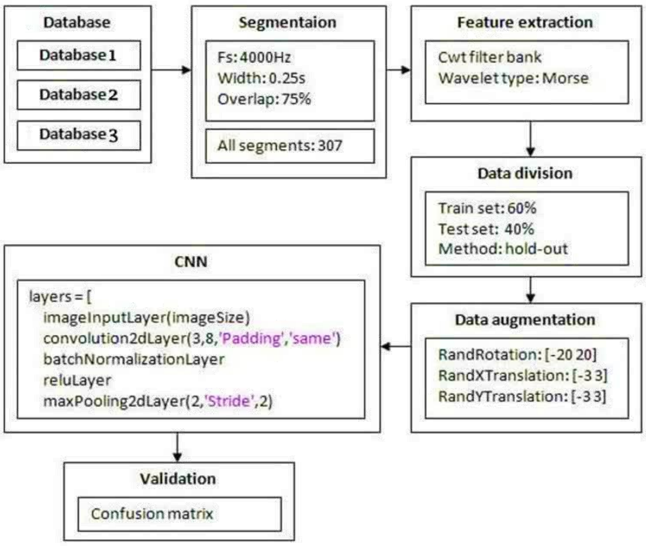

Fig. 3: This figure illustrates the systematic approaches chosen for processing superficial electromyography (sEMG) signals and detecting hand classifications and movements.

We used an array consisting of eight pairs of Ag/AgCl electrodes to collect superficial electromyography (sEMG) signals. These electrodes were placed in a specific arrangement (bipolar arrangement). The purpose of this arrangement is to cover the forearm being examined to ensure that all features are obtained, which helps in obtaining accurate classifications of hand movements. The electrodes were placed in the distal part of the forearm, aligned with the muscular prominences of the extensor carpi radialis and flexor carpi ulnaris muscles, at a position approximately one-third the distance between the elbow and the wrist. This strategy contributed to improving the quality of signal acquisition while reducing signal interference from adjacent muscles, based on previous recommendations adapted to the objectives of this study. Skintact F-TC1 gel-coated electrodes, specifically designed for sEMG signals, were used. The pre-applied electrode, manufactured by Leonhard Lang GmbH in Austria, was used for skin preparation, which also involved Nuprep abrasive gel produced by Bio-Medical Instruments in the United States. A reference electrode was placed on the bone opposite the elbow joint. For data recording, a 16-bit data collection system from National Instruments was used, with a sampling rate of 1000 samples per second. Signal amplification was achieved using amplifiers from the German company Bio vision with an amplification factor of 1000. Participants were guided during the data collection sessions through a special software program developed for the LabVIEW environment and connected to an NI6212 USB AD adapter. During each session, participants were asked to perform specific hand movements for five seconds when the LED was on, followed by a three-second rest period when the LED was off, with visual and audible feedback provided to support the participants. In EMG signal-based analysis frameworks, Continuous sEMG data are typically divided into specific time windows. It was found that using a specific window length, such as 8192 samples, produces a segmented and structured dataset.

In studies involving different groups such as amyotrophic lateral sclerosis (ALS), muscular disorders, and healthy individuals, the databases are usually balanced to ensure an equal number of samples are available for each group.

The arithmetic mean of the coefficients of each subrange:

$$\text{Mean} = \frac{\sum_{i=1}^{n} C_i}{n} \tag{1}$$

Standard deviation used for each coefficient for each subrange:

$$\text{Average} = \frac{\sum_{i=0}^{N} (C_i)^2}{N} \tag{2}$$

Standard deviation of transactions for each sub-range:

$$\text{Standard deviation} = \sqrt{\frac{\sum_{i=1}^{n} (C_i - \mu)^2}{n}} \tag{3}$$

The ratio of arithmetic means for adjacent sub-ranges:

$$\text{Ratio} = \frac{\frac{\sum_{i=1}^{n} C_i}{n}}{\frac{\sum_{j=1}^{n} C_j}{n}}. \tag{4}$$

After the segmentation phase, the surface electromyography (sEMG) signals were analyzed using a set of twenty-seven different properties. Equations (1) and (2) were used to study the overall frequency distribution of the signal, while Equations (3) and (4) were used to analyze the dynamic variations within this distribution. From the equations mentioned previously (1) to (3), we understand that we were able to determine 2 properties, and from equation (4), we found six properties. The 27 properties included in this set can be categorized into metric properties such as:

1- The arithmetic mean.

2- The average power of the wave coefficients across the sub bands (D1–D6, A6).

3- The standard deviation.

4- The ratios of the averages of adjacent sub bands.

We then used the db4 wave filter in the feature acquisition process, which demonstrated and proved the precise balance between low computational cost and high classification efficiency. The most important outcome of this process is that it generated a final dataset of approximately 3600 samples and 27 properties. Its key advantage is that it is ready for use by incorporating it into classification algorithms. After completing the previous operations, we proceed to segment the extracted signal, sEMG, and then extract and identify its properties. There are (27) properties identified using the techniques mentioned previously. This data was used to train and evaluate the model to achieve optimal performance and good generalizability. It can be observed that we meticulously and carefully segmented the dataset of (3600) samples. These methods are considered effective; approximately 70%

ATU- AJIEA, Volume: 2, Issue: 01, 06, 30, 2026,

of the data is allocated to training, while (30%) is allocated to the test and validation sets, kept separate. This is due to the precise and scientific evaluation of the model's generalizability, which is not directly observable in the new, invisible electromyography (EMG) dataset. We also note:

1- Greater data diversity.

2- Increased training data volume.

3- Reduced overshoot risk.

Increased dataset size. Techniques were used to develop a more robust model capable of addressing problems in electromyography (EMG) signals. Given the importance of this topic, we must discuss the components of these networks. They typically consist of an input layer for enclosing and storing property vectors, also known as characteristic vectors, such as a set containing 27 property elements. Data is transmitted through a series of interconnected layers, each with a varying number of nodes. These nodes are often hidden. Data transmission occurs via activation functions like ReLU and Leaky ReLU. These functions are nonlinear and are used to detect complex patterns in the data. The third and final layer, the output layer, uses the Softmax function to generate class probabilities.

2.1 SIGNAL TO IMAGE CONVERSION:

Initially, we segmented the one-dimensional electromyography (EMG) data across a 0.25-second time window, with 0.25 seconds considered the interference period. To produce a frequency- and time-dependent 2D representation, the continuous wavelet transform (CWT) function was applied. We used MATLAB and implemented the CWT function to represent this signal with a matrix of dimensions (128×128 pixels).

3. RESLUT

This research used MATLAB (MathWorks) to build the computational framework, a powerful program for numerical calculations. The Deep Learning Toolbox, and especially Convolutional Neural Network (CNN) models, were fundamental in the network design. MATLAB was also used in the processes of purifying, organizing, and preparing data to ensure a smooth and consistent workflow. The experimental methods began by collecting a set of sEMG data, cleaning, labeling, and dividing it into training and testing. The data consisted of ten healthy individuals (five females and five males) and included nine hand movements, recorded at three electrode positions (P1, P2, P3). Eight pairs of Ag/AgCl electrodes around the dominant forearm were used to collect the signals. Each participant's data consisted of 27 files, with the exception of participant ID7's data for wrist extension (EX). The data size ranged between 117 and 194 MB. Participants were asked to sit at a 90-degree angle and watch an instructional video before the experiment. The movements included: ball grip (PS), tri-finger grip (3F), cylindrical grip (PP), wrist flexion and extension (FL, EX), radial and ulnar deviation (RD, UD), and pronation and rosinus (PR, SU). The movements began from a state of relaxation, and standard gripping objects were used. The electrodes were placed three centimeters away from the elbow to cover the major forearm muscles. The recording was performed at 16-bit resolution and a rate of 1000 samples per second, with amplification of 1000. Subsequently, the signals were segmented into time windows and converted into a pictogram using CWT and MATLAB, to produce a scalogram (128×128). This representation preserves the temporal and frequency properties of the EMG signals.

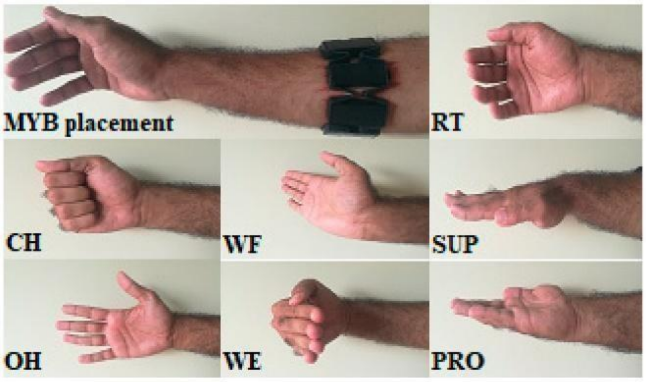

Fig. 4: A diagram showing the positions of the sMEG electrodes on the forearm and their relationship to the superficial muscles.

Electromyography (EMG) signal analysis, enhanced with MATLAB's deep learning capabilities, and especially convolutional neural networks (CNNs), showed very promising results in classifying forearm movements. CNN models have shown high accuracy in identifying different forearm positions and movements, through precise correlation between EMG signal patterns and corresponding actions. Despite signal variations resulting from electrode position changes and model interference, classification performance remained excellent. This performance demonstrates high accuracy in identifying forearm positions, even when some data was unknown. Standardized measures such as positive accuracy, precision, and F1 recall are used to assess the accuracy of the evaluation. Trained models in various studies have shown their ability to predict upper limb positions, such as the forearm, in real-time using input electromyography (EMG) signals. Current industrial applications have proven highly promising in prosthetic limb manufacturing, amputation rehabilitation techniques to ensure patients regain vital mobility, motion detection systems, and other crucial applications that improve the lives of those who need these technologies. Beyond the scientific aspect of the research, it also has a humanitarian dimension., hyperparameters, data preparation, and data augmentation techniques, with the aim of continuously enhancing accuracy, durability, and reliability. Figure (5) shows Unprocessed EMG data from a randomly selected session, showing a single repetition of each movement with a rest period between them. These signals are fed directly into CNN without any prior modification, to serve as direct input to the model. The results are measured as the mean classification error (CE) with standard deviation (SD), calculated across participants, providing an accurate assessment of the models' performance in classifying forearm positions. The most important feature of this matrix is its accuracy and ability to classify the model. It classifies each category with high precision. Sometimes, similar movements are generated that traditional matrices might take into account, but the model I used can reveal and detect these errors. The values displayed on the main diagonal of the matrix show the number of correct predictions, while the values outside the diagonal represent classification errors resulting from the mixing of similar movements, as mentioned earlier. This makes the model and its algorithms highly effective in distinguishing hand movements, which contain a large amount of similarity.

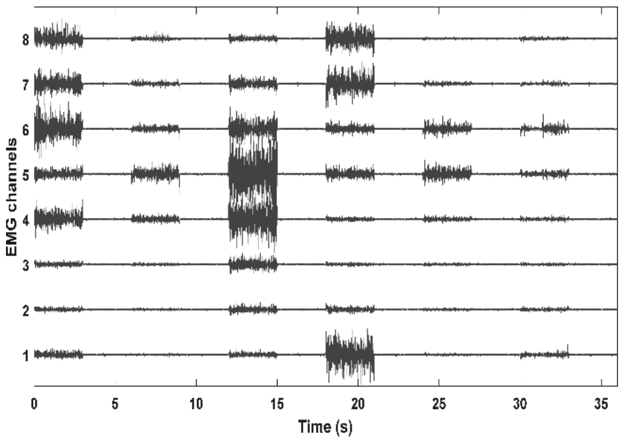

Fig. 5: Raw EMG data from a randomly selected session, showing a repetition of each movement with a rest period.

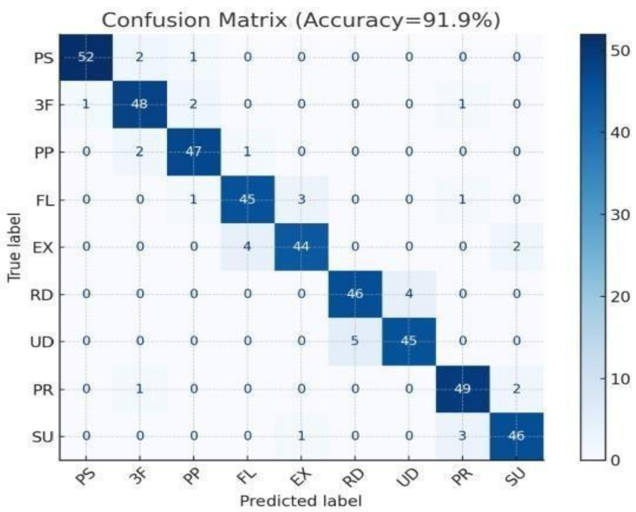

Fig. 6: Confusion matrix array for the signal class (ID1_3F_P1).

Having identified and studied the variance—a crucial aspect of this research, as studying variance between sessions is equally important—we then conducted an internal analysis of the model to determine the quality and performance of signal recognition for each movement within specific sessions. We also identified errors in this classification. A key feature of our work is that we analyzed each session individually using a method called cross-validation (10 folds).

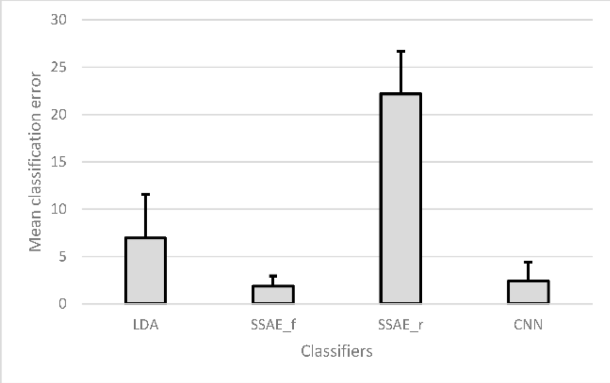

Fig. 7: Average classification errors (CEs) across 30 sessions for each individual participant, calculated using cross-validation (10 folds) within each session.

The subsequent study revealed minor differences in performance between the classifiers. No significant difference was observed between the SSAE-f and CNN models ($p = 0.55$). Both deep learning-based methods showed statistically significant better performance ($p < 0.001$) compared to the other classifiers, particularly LDA and SSAE-r. It is also noticeable that there is a large standard deviation in traditional algorithms, which indicates a large variation in the average accuracy between individuals. The variability between participants was significantly reduced when using the proposed SSAE-f and CNN methods, confirming their resilience and stability across different individuals. The high performance in this study is attributed to the custom CNN network architecture, designed to classify eight different grasping movements using a specific structure. Simplified. The network consists of the following layers:

1. Input layer: Receives scalogram images generated by CWT at 128x128 pixels. Our model consists of several layers, each responsible for the classification process.

2. Convolutional Layer: This is the first layer in the model structure and uses eight 3x3 filters. These filters maintain the input dimensions without change to extract spatial properties from the data.

3. Batch Normalization Layer: This layer accelerates the training process and is crucial for network stability, resulting in a more accurate model.

4. ReLU: Known among deep learning functions as a nonlinear activation function, ReLU can be used to learn and improve the model using various complex patterns.

5. Max Pooling Layer: In our model, a 2x2 window with a step of 2 is used. Its purpose is to reduce the computational load on the model. This function facilitates repetitive calculations within the model and also reduces the dimensions while preserving the most important resulting properties. In the final stages, the properties are passed to.

6. Fully Connected Layer: This is the final layer in the model's layers. It consists of eight nodes, each representing a class. Next, a Softmax layer is used. This layer converts the processed output into

probabilities. Finally, a Classification Layer is used to select the class with the highest probability, which is the most accurate final result.

1.1 TRANINING SETUP

The network was trained for 15 epochs using the SGDM optimizer with data scattering in each epoch to reduce retention and enhance generalization.

1.2 DATA AUGUMINTATION

It aims to increase the volume without collecting additional data, reduce excessive concordance, and enhance generalization and stability in the face of minor changes. To ensure a fair assessment, it was applied only to the training set, while the test data remained unaltered. The confusion matrix shows some classification errors between similar categories, due to the similarity of EMG signal patterns and the presence of noise in the data. However, the model demonstrates strong overall performance, indicating its effectiveness in classifying EMG signals.4.

4. CONCLUSIONS

This study improves the effectiveness of prosthetic limbs for people with upper limb disabilities by providing a comprehensive framework for deep learning to detect EMG signalsTo get rid of the traditional methods that are largely dependent on the ordinary manual extraction of those characteristics and this method is often affected by differences between working individuals, examiners or volunteers, as this method is considered old and primitive, in modern methods as in our research, the raw electromyography signals were converted into two-dimensional representations, and these diagrams are a conversion of the raw electromyography signals into two-dimensional representations in the form of frequency-time diagrams through the application of the continuous wavelet transform function (CWT). One of the most important benefits of this transformation is leveraging the capabilities of convolutional neural networks (CNNs) to extract features hierarchically. This model has become more accurate in identifying complex patterns without the need for the manual intervention we previously discussed and described as primitive methods. This is clearly evident in the results obtained in this research, where the convolutional neural network model has the potential to achieve better performance than traditional methods. There are many examples of the benefit of these results, such as linear discrimination analysis (LDA), which is statistically significant ($p < 0.001$), with a significant reduction in the effect of inter-individual variance on classification accuracy. In other words, there is no significant effect from user differences, which is a major advantage and a significant development in this field. This approach, following this major scientific shift, provides the ability to interact between computer systems and algorithms and humans.

4.1 STRENGTHS AND LIMITATIONS ON WHICH THE ROBUSTNESS OF THE MODEL DEPENDS

One of the most significant problems affecting signal processing algorithms in general, and biomedical signals in particular, is electronic interference. This interference negatively impacts the desired results and distorts the signal. Furthermore, the placement of electrodes on the patient is another issue. Incorrect or improperly positioned electrodes can lead to instability and distortion of electromyography (EMG) signals, as well as unstable patient movements. Therefore, our primary focus in this research is to eliminate and address these problems that arise in the design of convolutional neural networks (CNNs). We aim to transform signals using continuous wavelet (CWT) technology, which converts raw signals into frequency and time representations. Various studies, including this

ATU- AJIEA, Volume: 2, Issue: 01, 06, 30, 2026,

one, have focused on addressing signal problems such as electrode positioning. Therefore, I must clarify for the reader that the current model used was based on data recorded from a stationary volunteer. Since we have entered this field, I must focus in the future on studying all types of interference, including artificial interference caused by electrode movement, to serve the research in general, enhance the system's accuracy, and ensure optimal testing even under less-than-ideal conditions. The model I used can be evaluated by comparing it to several deep learning techniques. Techniques such as regressive neural networks (RNN/LSTM) and transfer learning (VGG-16, ResNet) are widely used in processing electromyography (EMG) signals.

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Authors Maideen, Ajmisha; Mohanarathinam, A. DOI

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