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Classification of EMG signals based on Deep learning with continuous wavelet transformation.

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Abstract :

the human hand is the primary tool for grasping and moving objects, losing hand causes a significant impact on daily life. A prosthetic hand is a alternative human hand that is the most effective and acceptable solution for people who lost their hands. In recent years, EMG signals have become more prevalent in the design of prosthetic hands and as a tool for producing device control commands for rehabilitation equipment, such as robotics and prosthetics. The goal of the study is developing an EMG-based technique to recognizing hand grasps. so that persons with impairments can use their prosthetic hands more easily. This study uses a CNN methodology to propose a method of detecting Emg signals for hand movements. A continuous wavelet transform is used to convert the EMG signals into spectral pictures (SCALOGRAMs) . The proposed method generated EMG images using continuous wavelet transformation and classifying images by GOOGLENET technology. CWT first converts EMG signals into pictures (SCALOGRAM). Then, at the classification stage, the GOOGLENET classification model is used. It was utilized to classification EMG features to multi hand grips. According to studies, the accuracy of proposed method is 93.70%.

Keywords- Electromyography (EMG), continuous wavelet transformation (CWT), Googlenet.

1.Introduction

The skeletal muscle connected to the bone is responsible for the movement of the limbs, when contracting , movement occurs. The contraction leads to the generation of an electrical signal called an electrical muscle signal . Electromyography (EMG) is an diagnostic technique that usages motor neurons to control And assess the health of muscles and nerve cells. where responsible for transferring electrical signals through the muscles when shrinking them [1]. many of the applications of EMG is used in clinical and biomedical dom. where can either be used as a diagnostic means to control prosthetic hand movement or to locate neuromuscular diseases. Medically ,the studies refer that various parts of the forearm muscles and EMG signals correlated to hands and fingers can as yet be measurable even after the damage of the hand or loss [2].

The human hand, which is composed of 25 degrees of freedom and has 27 bones of movement in variant directions, is capable of doing more difficult jobs than other systems. Researchers and engineers have produced mechanical hands that allow people who have had their hands amputated to live normal lives due to the complexity of the human hand. And , Per World Health, more than a billion individuals (15 percent) are affected in any way around the globe . We all think that people with disabilities people are incapable of doing anything on their own, but that has to change in the day and age of technology[1].

a typical perc in reality, sEMG signals are a common control input in myoelectric control systems because they include a lot of information regarding muscle action. One of EMG's uses is the establishment of (MMI) man-machine interaction for disabled individuals, such as a virtual environment, a virtual mouse, electric wheelchairs, prostheses, and so on. As a result, the hands are crucial for gripping and handling various objects. The loss of even one hand has a significant influence on human activity. As a result, a prosthetic hand is an enticing option for armless patients [4]. Thus , creating a real-time standard capable of effectively classifying grasps at a minimal cost and with a high detection rate, is an excellent implementation is an excellent choice for the exoskeletal prosthetic hand project. [2013]. There are two basic techniques for evaluating EMG signals: intramuscular EMG recording and surface EMG recording. Surface EMG recording is a non-invasive technique in which electrodes linked to the skin surface just above a muscle or nerve are used to record the EMG signals. this technique is the favored mode of data assembly for research purposes. Intramuscular EMG recording includes the use of needle electrodes, which are implanted into the subject’s body to link directly to the muscle or nerve, which is to be noted. This technique is not used much among researchers and is primarily used for diagnostic purpose [5]. For faultless control of a prosthetic hand's diverse finger postures, the ability to discern between individual and combined finger movements utilizing surface EMG data is important [6]. Several EMG-based approaches were used in the experiments to create an automated model that could identify between hand grasps. As a result, optimizing new models for classifying hand movement based on the EMG signal remains a major challenge and a fascinating open problem for researchers; attempts to improve the design of the exoskeletal prosthetic hand could help persons who have lost their hands completely or partially. In most circumstances, the implementation approach consists of three consecutive steps to accomplish reliable classification of EMG signals: data pre-processing, feature extraction, and classification. Many research has been conducted using various methods, object gripping hand actions. Surface EMG signals acquired with 2-channel EMG equipment were used as data in this study. Experiential Mode Decomposition was utilized to determine intrinsic Mode Functions from raw data received from individuals. The IMFs were obtained from the raw data after eliminating eight features from the original 2-channel data. To classify the data, the authors used a linear classifier. The researchers discovered that extraction of features and classification using a combination of information from raw data and IMF data produces better results than a classifier based solely on raw data. However, the conclusions are hampered by the small size of the dataset and the small number of participants. The experimental results in this paper could be improved by using a better classifier (rather than a linear classifier).

Rabin et al.2020 [7] did another investigation that classified EMG characteristics into six hand grasps employing the Short Time Fourier Transform (STTF), concentrated on the (K Nearest method) approach. In that model, enforcement two-dimensionality lowering approaches were used to reduce the dimensionality of retrieved features using the short-time Fourier transform (STFT). The propagation map excels a Principal Component Analysis (PCA) technique in terms of the impact of dimensional reduce technique on classification accuracy rate, According to Khan et al[8] EMG signals from the superior limb between the elbow and the wrist are used to control the prosthetic hand, which has only (15) joints, five fingers, and the trigger powered by three integrated motors. The Support Vector Machine (SVM) classification of EMG signals recognizes eighteen distinct hand motions . Due to the fact that EMG signals are easily disrupted by noise and muscle fatigue, this prosthetic hand does not have many actuators . Yavuz et al.2019, [9] recommended employing the neural network for regression to recognize hand grips. To classify EMG data, they employed a spectrums based on features technique combined with the neural network for regression . Using a same dataset, Akben [16] identified hand grips. Histogram energy values and concordance association were used to extract characteristics. A cascaded organized classifier with a divisive hierarchical classification technique and the K-means algorithm was employed to classify hand grasps. The technique, according to the author, can be used to assist medical experts in the design of robotic and prosthetic exoskeleton hands. Nishad et al. [12] proposed a basic hand movement categorization technique based on filter banks based on the tunable-Q wavelet transform (TQWT-FB). Krakow entropy was employed to extract the features later (TQW-FB) was employed to deconstruct the cross covariance of sEMG signals. The proposed method was then evaluated on the same dataset using a k-NN classifier. According to the study's authors, the method could be used to treat a variety of muscular diseases.

The same dataset was used in the study presented by Iqbal et al,[14] employed a classification system to categorize hand movements (SVD and PCA). After obtaining principal components(PA) and singular values with the SVD, the PCA was employed to reduce dimension. After that, the classified k-NN was employed to recognize hand activities. Hand movements are classified with high accuracy and in a short amount of time using the proposed technique. To categorize EMG signals, Tuncer et al. 2020[4] created the ternary pattern combined with the discrete wavelet transform (DWT) method . The most influential characteristics were chosen using a two-leveled feature selection approach, and the selected features were classified using a k-nearest classifier. The suggested method was tested using the sEMG dataset, which was gathered from amputee individuals at three force levels (low, medium, and high), as well as the TP-DWT-based sEMG dataset . Jiang et al.2020 [6] used time-domain characteristics to categorize hand movements. In that work, The EMG signals were partitioned into windows., and time domain properties were extracted and fed into a linear discriminant analysis classifier. Subasi et al. [33] developed a feature extraction approach that is based on multiscale (PCA) with wavelet packet decomposition, and used a decision-tree classifier system to categorize the obtained features.

Methods based on observable technique disintegration , PA, and wavelet transform (WT) have unquestionably shown impressive results[6-22]. "While these approaches are accurate, they now have certain limitations, particularly because the amount of important features and method implementation time were not taken into account, resulting in the disregard of the significance of these two objectives in real-time applications."

In light of these prior findings, an effective CNN-based technique for hand grasp categorization from EMG data is provided in this paper. EMG signals were automatically transformed into EMG pictures using CWT without any preprocessing in the suggested method. Hand grab recognition from EMG photos using a trained Google Net model.

To summarize, the following are the main characteristics of this paper:

1. Using CWT to convert EMG signal for EMG images (scalograms).
2. GOOGLENET is used to classify hand grasp. EMG images (scalograms) is used as input to GOOGLENET.
3. The accuracy of the proposed method is best than current methods.

The remainder of the paper is structured as follows: Part 2 will present and explain the experimental data; Part 3 will go over the basis of the proposed system and related essential information; Part 4 will show the experimental outcomes and our outcomes, and Part 5 will interpret the results. Finally, in part 6 Conclusion, the paper comes to a close.

2. EMG Dataset Experiment

For this study, EMG for basic hand movements data set is downloaded from UCI Machine Learning Repository of URL:

http://archive.ics.uci.edu/ml/datasets/sEMG+for+Basic+hand+movements#.

These EMG signals were collected from 5 Healthy subjects (3 females AND 2 males), AGE between(20 -22) years. Included (Flexor Carpi Ulnaris, Extensor Carpi Radialis, Longus, and Brevis) to record information about muscle activities. The National Labview instrument was used to sample EMG signals recorded at 500 HZ. Then, the noise was removed from these recorded signals employed a Butterworth pass filter by employed low and high cutoffs of (15 Hz) and (500 Hz) , respectively. Also, a Notch filter at 50 Hz was employed to eliminate line interferences. Subjects are asked to make six different hand grasps and repeat each basic movement, 30 times, each recording six seconds long: Lateral (LA), palmar (PA), extremity (TI), spherical (SP) , cylindrical (CY) , and Hooked (HO). For each hand movement, the strength and speed of each hand movement were at the discretion of each subject, fig.1. , shows the six styles of the handgrip. which is obtained from two electrodes. More details about this data set are available [9].Fig. 2. shows the samples of EMG signals that were considered when designing the proposed methodology.

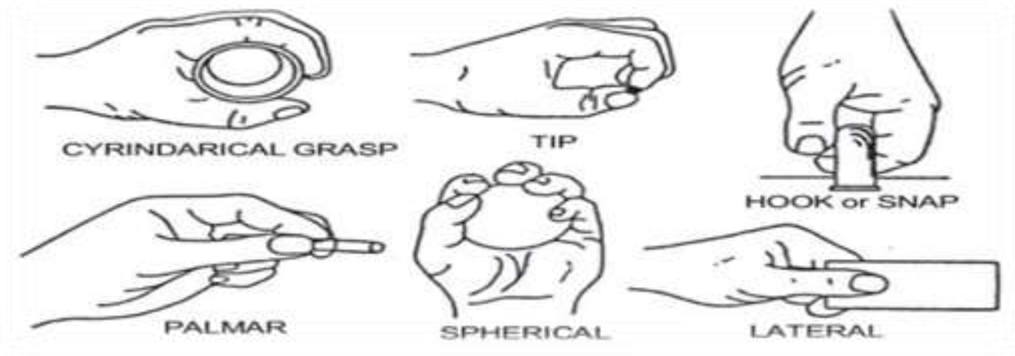


Fig 1. The basic movement, Cylindrical (CYL),TI P(T) , Hook (HO or snap), Palmar (pa),Spherical (sp) ,Lateral (LAT), [10].

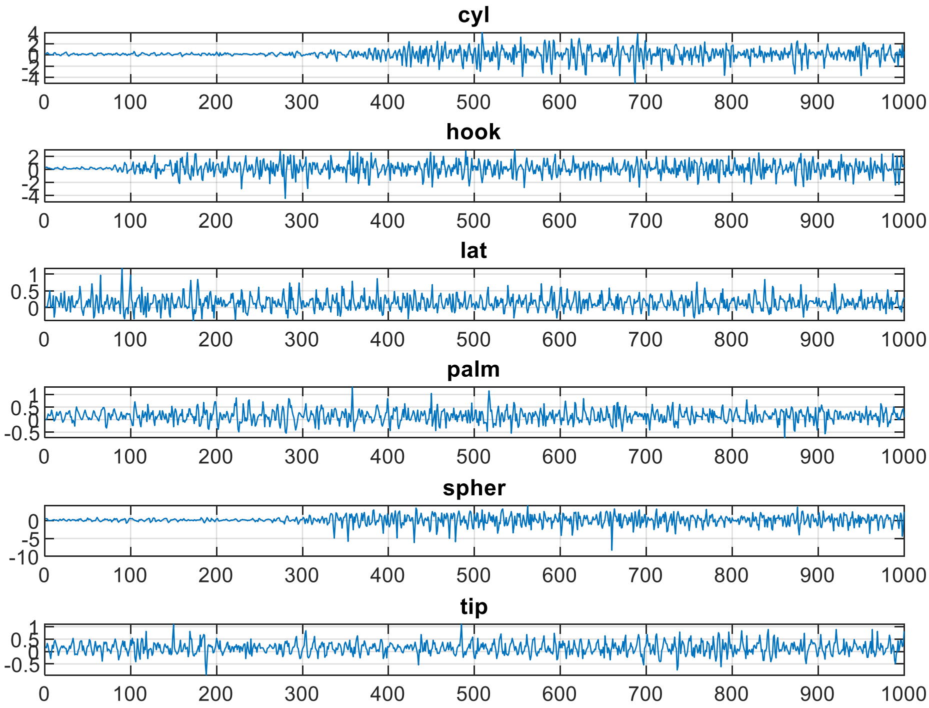


fig. 2. Typical forms of EMG signals matching to hand grips. A EMG signals is: cy1, hook , lat ,palm, sphere and tip

3.PROPOSED METHOD

The novel goal of the study create a suitable model based on neural networks for distinguishing hand grasps from EMG signals. Figure 1 depicts the fundamental hand movements. The proposed design is divided to two stages. First, Using the CWT, EMG signals are transformed into EMG images (scalograms). Second, The scalogram image is classified using the CNN approach. In different applications, an appropriate amount of training data is not existing, and manufacturing new realistic training examples is not possible. In these cases, advantage present neural networks that have been trained on big data sets for abstractly similar tasks is necessary. This advantage of training a deep CNN from scratch is computationally expensive and requires a large amount of training data. the advantage of existing neural networks is called transfer learning. In this paper googLeNet pretrained is used to image classification based on a time-frequency representation.GoogLeNet are deep CNNs firstly designed to classify images into six categories. We recycle the network architecture of the CNN to classify EMG signals based on images from the CWT of the time series data..

3.1. Convert Time series (EMG signals) to EMG image(scalogram).

The logarithmic spectrogram image is one of the most operative forms of representing the time-frequency domain[20-21]. The time-frequency analysis methods were found implements used to exhibit the significant advantages of high directional and non-stationarity signals by trying to represent them in both the time domain and frequency domain.

The EMG signals are directly transformed into (scalogram) EMG pictures by CWT at this point in the proposed approach. The wavelets are the most important part of the continuous wavelet transform (CWT). We can obtain the wavelets as follows by scaling and translating a basic wavelet function h(.).

$$h_{a,\tau} = \frac{1}{\sqrt{|a|}} h\left(\frac{t - \tau}{a}\right) \qquad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where (a)is a scale and (τ) is known as interpretation. The scale factor determines whether to extend or shrink the basic wavelet (i.e., the mother wavelet). transform, It has a close connection with the "frequency" notion in Fourier transform, i.e., for some wavelet function, a is contrariwise proportionate to frequency. As the scale increases . can view the signal in the more contracted form through a fixed length filter. This is since big scales mean worldwide views and minor scales denote to concerned views. on the other hand, the version factor controls of the position the wavelet, which could be converted along the time axis . So, by changing a and τ concurrently, we can acquire wavelets that reverse locations at distinct times and scales of the spectrum. Without else definite, we will employ scale and frequency reciprocally in the paper[28]. The CWT of an EMG signal can be defined as

$$WT_x\,(a - \tau) =< x(t), h_{a,\tau}\,(t) >= \frac{1}{|a|^2} \int x(t)\bar{h}\left(\frac{t - \tau}{a}\right) dt \quad (2)$$

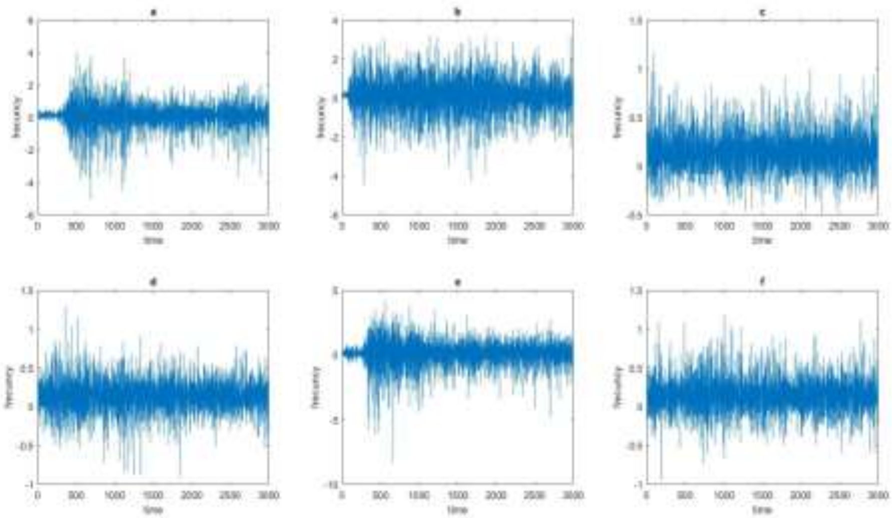
where x (t) is the input signal, h ̅(t) is represents the operation of complex conjugate , a is the scale Parameter representing indirectly the frequency, τ is the translation factor, and (1)/|a|^2 illustrate energy standardization at distinct scales. Parameters a and s are repeatedly changed. In this case, the wavelet basic function is defined as: Provided that let h (t) be a square integral function, the Fourier transform accept h (t) ∈L^2(R) when the following conditions are satisfied

$$C_{h=\int \frac{|\hat{h}(w)|^2}{|w|}}\ dw < \infty \qquad (3)$$

where(h) ̂(w) is the fourier transform of basic wavelet. Therefore, the main wavelet function can be defined as follows:

$$h_{a,\tau}\,(t) = \frac{1}{|a|^2} h\left(\frac{t-\tau}{a}\right)\ a \neq 0 \qquad (4)$$

As the main wavelet, CWT employs functions such as Mexican, Morlet, Morse, and Gaussian. Because it can automatically regulate the window lent and scale values counting on the TF canes in the EMG signals, the CWT was used to translate EMG signals to EMG images (SCALOGRAM). In Figure 3, examples of EMG signals (sort extracts are utilized for clarity) and their matching scalogram are shown



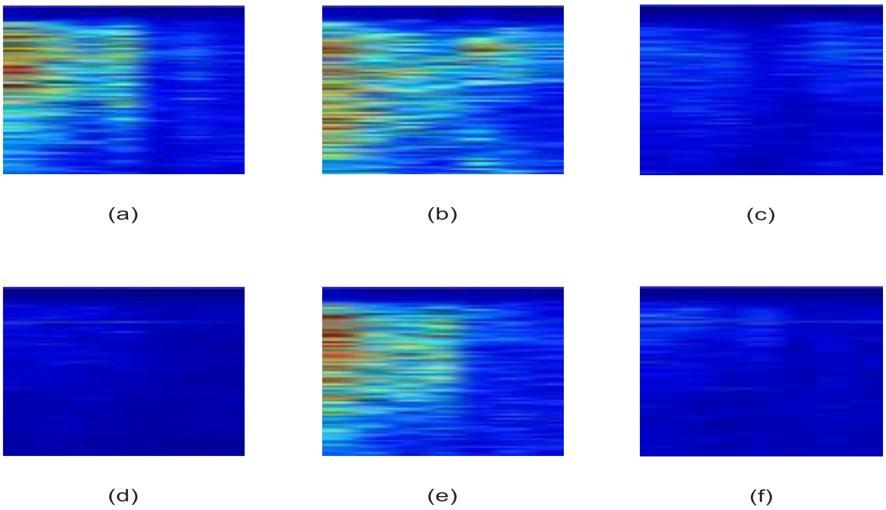


Figure 3.Example of EMGs and associated scalograms of six variants movements:(a- cylender),(b - Hook) ,(c -lat) ,(d -palm) , (e -sphere) , (f-tip).

For better observing For EMG signals transformed to EMG images, we generated six separate models, One for each movement. By checking the created Scalograms Of the 6 motion sites, we can qualitatively note The variances that decide them from each other, which You should be able to feat it done deep learning. That The example is shown in Fig.3 above.

3.2. Classification SCOLAGRAM EMG image with CNN

After the EMG signals are converted to the EMG image (SCALOGRAM), All images is used by googlenet .A classifier with proper speed, adequacy and ability to handle much of image and in low cost and in standard time . For deep classification Pre-trained CNN models are favored, as CNN-centered models have recognizable advantages [30]. These benefits include (a) the ability to extract operative features without the use of input picture processing, (b) better performance over previous techniques, and (c) a 6.67 percent error rate.

3.2.1 Googlenet

The GoogLeNet model includes more layers than traditional CNN models., which concentrates the number of factors and calculation costs. Convolution layers are also preferred since they have better learning capacities and so provide better accuracy. The GoogLeNet design comprises 22 layers, with five pooling layers outside of these levels [30]. In the current design, a GoogLeNet model that has been pre-trained was used for this purpose. GoogLeNet was fine-tuned in the current method based on the established training. In MATLAB, Table 1 shows the last six layers of the googleNet mode

Table 1.Final six layers of GoogLeNet.

Layer description	Additional details
dropout	**60% dropout**
CONVOLUTION	**1000 1x1x1024 convolutions**
RELU	
Global AVG Pooling	
SOFTMAX	
Classification	**crossentropyex with 'tench' and**
Output	**999 other classes**

For our Experiment offer in the authorized phase, we improved the layers shown above as follows . We replaced the networks final dropout layer with a dropout layer with a probability 6 percent instead of 5 percent .The 1 by 1 convolution layer, which is not a completely connected layer , was swapped with the completely connected layer 'loss3-classifier' with a new completely-connected layer with the number of filters equivalent to the number of modules. The last layer was swapped the classification layer with a new one without class labels. . This modified model is shown in Figure 4, and training parameters for the model are shown in Table 2.[31].

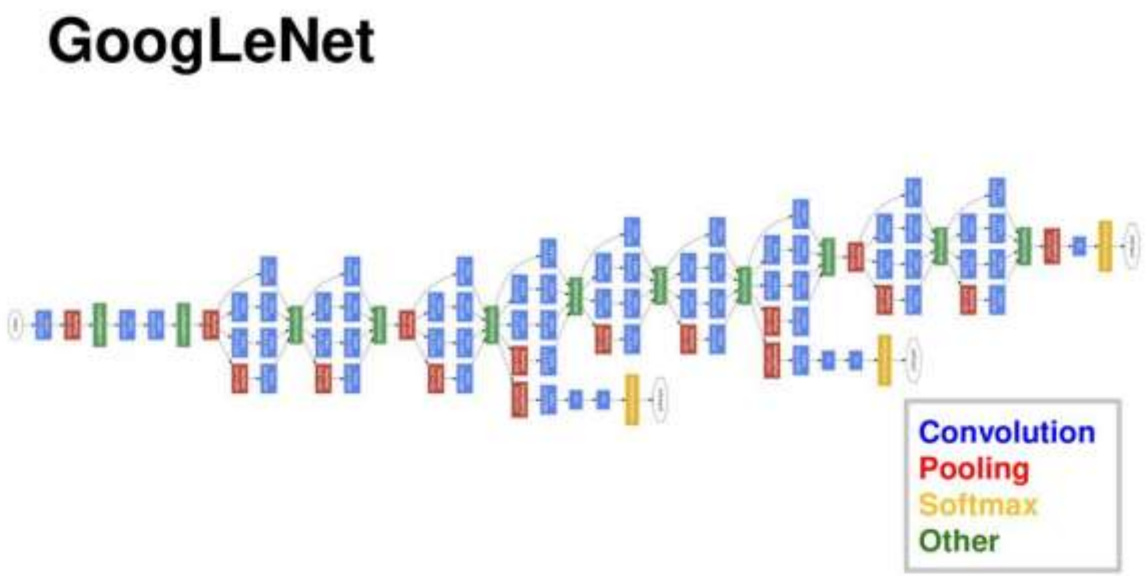


Figure 4. googleNet Layer Graph

Table2. Model training parameter

Parameter	Value
Initial Learn Rate	**3e-4**
Mini Batch Size	**10**
Max Epochs	**200**
Validation Frequency	**10**

3.3 .Implementation

All of the experiments in this technique were performed with MATLAB (R 2020 a), which was installed on a machine with a quad-core Intel i7 processor, an NVIDIA GTX 850 M GPU, and 16 GB of RAM. In addition, the MATLAB Deep Learning Toolbox was used for the GoogLeNet module. In experimental studies, the UCI dataset was used. The dataset of EMG signals extracted from 5 participants (three females and two males) with six movements where each movement has 2 channels. Figure 6 shows the process of transforming EMG signals into EMG images using CWT. The primary EMG signals for each subject were recorded for 6 movements for each movement of two channels taken in (30 attempts * 3000) for each channel of the movements. As shown in Figure 5, In the first stage, one channel was taken for each of the six movements of each subject and placed next to the other, yielding a data array of size 30 * 6000 for the EMG signal. In the second stage, this CWT converts these signals to images(scalogram) into grayscale images based on the scale factor. Changes in pixel brightness and contrast values in the grayscale image are colored using the homogeneously changing jet128 color map and transformed into EMG color images in the third stage. Finally, the color images were resized to 3 224 224 to match the GoogLeNet form entry size. When were completed for all participants, The data set was converted into such an image array (224 224 3 900). (RGB width samples for height). The 900 value is based on 30 attempts for 6 channels and 5 participants..

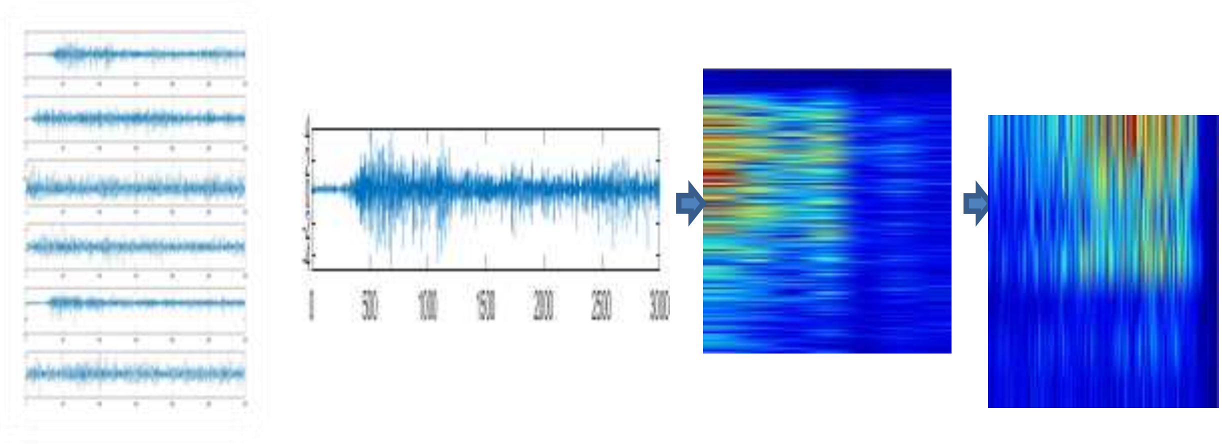
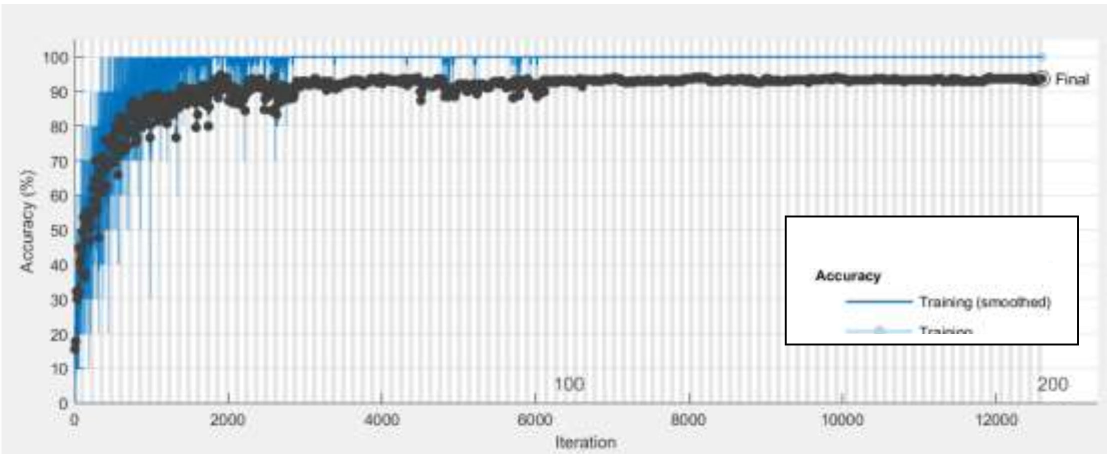
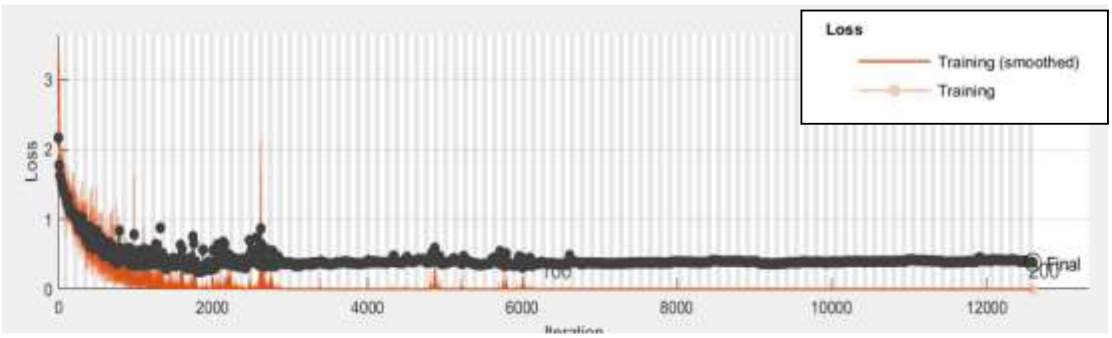


Figure5. The process of transforming EMG signals to EMG images BY CWT.

Following that, these scalograms were split into 2 groups for classification: training (70%) and validation (30%). within this paper, for the proposed method learning procedure the training dataset was employed . It was used as portion of the training dataset, and it was also employed to form the model, define factors, and regulate GoogLeNet's Factors Verification dataset. Images have been entered into googlenet. The data has been divided into 630 and 270 according to the above ratios for training and verification , Straight. To obtain the better model, GoogLeNet limits (learning rate, evaluation frequency, and the number of epochs) are increased during the training procedure. Several trials have been carried out for this purpose to discover appropriate values for various factors. As a result, the primary learning rate, verification frequency, and batch size are all small with maximum epochs of 0.003, 10, 10, 200 Straight. The training taken (64) minutes and (52) seconds. The training validation loss and the training validation accuracy are two metrics for the GoogLeNet model, It is depicted in Fig. 6(a), Fig. 6(b), and separately. Figure 6 shows the training accuracy and validation at the end of 12600 iterations. The accuracy reached 93.70 percent at training values, with a validation loss of around 0.5 percent. Table3 displays a portion of the training and verification results.



(a)-Training –Verification Accuracy



(b)-Training–Verification Accuracy

Fig. 6. Network training based on several iterations.

Table3: Displays the result of the classification using Googlenet.(training and validation).

Epoch	Iteration	Time Elapsed hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learn Rate)
199	12520	01:04:31	100.00%	93.33%	2.0171e-05	0.3951	0.0003
199	12530	01:04:34	100.00%	93.33%	2.2873e-05	0.3918	0.0003
200	12540	01:04:36	100.00%	93.33%	2.9370e-05	0.3909	0.0003
200	12550	01:04:39	100.00%	93.33%	4.9972e-05	0.3908	0.0003
200	12560	01:04:41	100.00%	93.33%	3.0945e-05	0.3905	0.0003
200	12570	01:04:44	100.00 %	93.70 %	0.0002	0.3894	0.0003
200	12580	01:04:47	100.00%	93.70 %	0.0001	0.3873	0.0003
200	12590	01:04:49	100.00%	93.70%	7.6247e-05	0.3863	0.0003
200	12600	01:04:52	100.00%	93.70%	6.0997e-05	0.3859	0.0003

4.Experimental Results

The findings of experimental research using the proposed approach on a dataset with five subjects are provided in this study (three female, two male). The investigative results were from the work that used multi-classification, with six different types of movements (cyl, hook, palm, lat, sphere, tip). The accuracy, precision, recall, sensitivity, f-score, analyses of the proposed model were all assessed. These percentages were arrived at by using the following formula:

$$\text{Accuracy (Acc)} = \frac{\text{true positive+true negative}}{true\ positive+true\ negative+false\ negative+false\ positive} \quad (5)$$

$$\text{Precision} = \frac{true\ positive}{rue\ positive + \text{ false positive}} \quad (6)$$

$$\text{Recall} = \frac{true\ positive}{rue\ positive + \text{false negative}} \quad (7)$$

$$\text{F} - \text{score} = \frac{2\ X\ precision\ X\ recall}{Precision\ +\ recall} \quad (8)$$

where the true positive (TP) is the number of results correctly classified as positive by the proposed model; The number of True Negative (TN) results in which the proposed model correctly classifies the negative class, while the number of False Positive (FP) results in which the proposed method incorrectly classifies the negative class. The proposed design categorizes the positive class incorrectly; The number of incorrect results produced by the proposed method that incorrectly classifies the negative class is referred to as the False Negative (FN). The performance of the proposed model (i.e., CWT joined with the Googlenet model in hand movement classification) was evaluated using a 70% to training and 30% to validation scheme for the EMG dataset that was transformed to a scalogram (images) . The presented model was validated ten times, and the average accuracy was recorded each time. The GOOGLENET model achieved a 93.70 percent accuracy rate for all hand grasps. Table 1 displays the classification results of the GOOGLENET model for 5 participants with 6 hand grasps. and what is worth mentioning, the Googlenet model produced highly similar results from five subjects' validation EMG images, with no significant differences in precision, recall, or f-score. To evaluate the resilience of the suggested Googlenet model, a second experiment was carried out. The proposed Google net model was put to the test six times with each person in this experiment.

Table4.

Google net's classification performance for five subjects.

Classification rates for 5 subjects as a whole

hand movements	Accuracy	Precision	Recall	f-score
CY	93.7	93.3	93.3	93.3
HO	93.7	97.6	91.1	94.2
LA	93.7	95.4	93.3	94.3
PA	93.7	93.1	91.1	92.1
SP	93.7	89.5	95.5	92.4
TI	93.7	93.6	97.7	95.6

one example of LA and classified it as T The proposed googlenet model achieved average accuracy, recall, and f-score of 93.70 % , 93.70 % , and 93.70 % , respectively.

4.1 . Performance evaluation of GoogleNet model using a confusion matrix

Tables 5–9 show the confusion matrices generated by the GOOGLENET model for classifying EMG hand grasps for individuals of 1 to 6. The prediction of the proposed method is shown in the second row, while the classification of the 6 hand grips is shown in the second left column. When comparing the classification outcomes in Tables 5 to table 10 , it is obvious that our model correctly predicted all hand grasps (the Googlenet model). The Googlenet model, for example, correctly identified all six hand grasps, according to the prediction findings in Table 5. However, Googlenet model misclassified one (cyl) example and classified it as (SP), one (SP) example and classified it as (HO), and one (LA) example and classified it as (TI).

Our results revealed that certain statistical aspects were deceptive, and a Googlenet model struggled to determine which traits were associated with which kinds of hand grasps.

The proposed Googlenet model's performance for subjects 3 and 4 is shown in Tables 7 and 8. In terms of outcomes, the design model appears to have done a good job at detecting the majority of hand grasps. The proposed Googlenet model, on the other hand, was still unable to distinguish T and LA activity, misclassifying it as PA and T. To address this issue and improve the performance of the suggested Googlenet model in LA and T hand actions categorization, we ran an additional trial in which the noisy features were removed during the training phase. Confusion matrices for subject 5 are displayed in Table 9. Googlenet performance that has been suggested Because the model mistook the PA and SP and classified it as LA and CY for only one case, it produced findings that were comparable to the previous results.

Table5

Subject 1's confusion matrix for the Googlenet model

		The proposed technique prediction					
		Cyl	Ho	TI	PA	Sp	LA
classify	Cyl	30	0	0	0	3	0
	HO	0	27	0	0	0	0
	TI	0	0	30	0	0	0
	PA	0	0	0	30	0	0
	Sp	0	3	0	0	27	0
	LA	0	0	0	0	0	30
	(Sen%)	100	88	100	100	88	100

*Cylindrical(CY),Hook(HO),Tip(T),Palmer(PA),Spherical(SP)and Lateral(LA).

Table6

Subject 2's confusion matrix for the Googlenet model

The proposed technique prediction							
		CyL	HO	TI	PA	Sp	LA
Actual classify	CY	27	0	0	0	0	0
	HO	0	30	0	0	3	0
	TI	0	0	30	0	0	3
	PA	0	0	0	30	0	0
	SP	3	0	0	0	27	0
	LA	0	0	0	0	0	27
	(Sen%)	88	100	100	100	88	88

*Cylindrical(CY),Hook(HO),Tip(T),Palmer(PA),Spherical(SP)and Lateral(LA).

Table7

Subject 3's confusion matrix for the Googlenet model

The proposed technique prediction							
		Cyi	Ho	TI	PA	Sp	LA
Actual	Cyi	30	0	0	0	0	0
	Ho	0	30	0	0	0	0
	TI	0	0	37	0	0	0
	PA	0	0	3	30	0	0
	Sp	1	0	0	0	30	0
	LA	0	0	0	0	0	30
	(Sen%)	100	100	88	100	100	100

*Cylindrical(CY),Hook(HO),Tip(T),Palmer(PA),Spherical(SP)and Lateral(LA).

Table8

Subject 4's confusion matrix for the Googlenet model

The proposed technique prediction							
		CyI	HO	TI	PA	Sp	LA
Actual Classify	Cyi	30	0	0	0	0	0
	HO	0	30	0	0	0	0
	TI	0	0	30	0	0	3
	PA	0	0	0	30	0	0
	Sp	1	0	0	0	30	0
	LA	0	0	0	0	0	27
	(Sen%)	100	100	100	100	100	88

*Cylindrical(CY),Hook(HO),Tip(T),Palmer(PA),Spherical(SP)and Lateral(LA).

Table9

Subject 5's confusion matrix for the Googlenet model.

The proposed technique prediction							
		CyI	HO	TI	PA	Sp	LA
Actual Classify	CyI	30	0	0	0	3	0
	HO	0	30	0	0	0	0
	TI	0	0	30	0	0	0
	PA	0	0	0	27	0	0
	Sp	0	0	0	0	27	0
	LA	0	0	0	3	0	30
	(Sen%)	100	100	100	88	88	100

*Cylindrical(CY),Hook(HO),Tip(T),Palmer(PA),Spherical(SP)and Lateral(LA).

5.Discussion

Our findings demonstrated that the proposed and pre-trained Googlenet model could correctly classify EMG hand grasps. The following are the key important points:

1. The proposed approach model's performance was compared with other classification techniques such as support vector machine (SVM), K-Mean, CNN, and k - nearest neighbors. Fig. 7 reports the comparisons results. The simulation results showed that the proposed Googlenet algorithm effectively categorized hand grasps and outperformed the other classification algorithms.

Table10

Comparisons of the GOOGLENET model with several existing method

		Classification rates				
Authors	Classification models	Subject1	Subject2	Subject3	Subject4	Subject5
Iqbal et al.[14]	k-nearest	82.78%	87.67 %	83.11 %	90.00 %	90.00 %
Akben et al.[16]	k-means	93.4 %	86.66 %	97 %	99.23 %	97.66 %
Song et al.[32]	CNN	87.5%	87.5%	87.5%	87.5%	87.5%
subasi et al. [33]	Rotation Forest	95.56 %	88.88 %	92.22 %	92.22 %	98.33%
The proposed method	Googlenet	96.30%	94.44%	98.15%	98.15%	96.30%

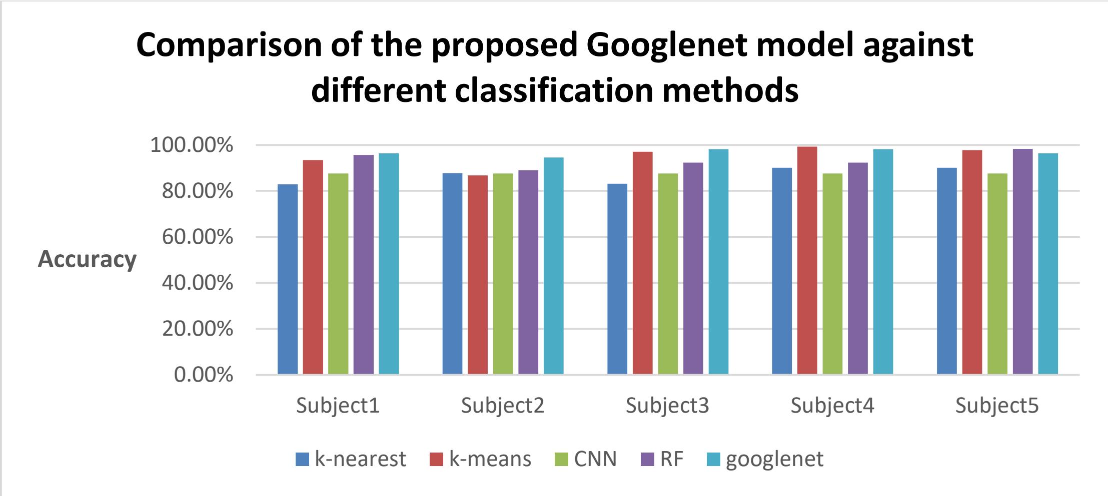


Fig.7. Googlenet vs. other classification techniques.

2. Based on our results, converting EMG signal into image forms can reflect the changes in EMG signals during hand movements. The spectrum components of a scalogram image change correspondingly with hand movements fig5.

3. Table 3 reports the performance of the proposed technique based on epochs numbers. It was proved that it had a highest accuracy for categorizing hand grips although the number of epochs changed.

4. The proposed googlenet model's performance was compared to that of numerous existing techniques in the literature. Iqbal et al.[14]) used use same dataset decomposition to classify hand grasps; Subasi et al[33], employed multiscale principal component analysis joined with wavelet packet decomposition . Nishad et al. (2019) employed the tunable-Q wavelet transform technique. Akben and colleagues (2017), It should be observed that the proposed model was evaluated employing that dataset as the other approaches in order to fairly compare it to the other methods (as described in Table 10). In this part of the procedure, the proposed google net model was tested with data from each individual. For the purposes of comparison, all findings were recorded and given in Table 10; it can be seen from these results (shown in Table 5) that Subasi et al. (2018)'s wavelet transformation-techniques-based approach produced less desirable outcomes than our proposed Googlenet model. Akben et al., (2017) employed a histogram-based technique to detect hand grips in another investigation. Individual results varied widely in that study; for example, subject 3 had a classification accuracy rate of 97 %, whereas subject 2 had an accuracy rating of 86.66 %. The Googlenet model provided here, on the other hand, has a subject 3 accuracy rate of 98.15 % and a subject 2 accuracy rate of 94.44 %. As a result of these comparisons, All of the methods throughout Table 10 were outperformed by the Googlenet model. The EMG hand grasp classification accuracy has been increased by 1.5 percent**.**

6.CONCOLUSION

In this paper, a new approach is presented to recognize hand movement based on CWT. Our results showed that converting EMGs to image forms using the CWT for improve the performance of EMG hand grasp classification system. The experiments showed that the use of CNN can use to create a real-time system for the detection and identification of hand grasps. We will improve the classification of EMG signals by finding out the powerful features. One of method limitations is that the channel selection methodology did not investigate .

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