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Using a convolutional neural network features to EMG signals classification with continuous wavelet transformation and LS-SVM .

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Abstract:

The various hand EMG signal grasps are classified in this study. Because EMG signals offer critical information about muscle activity, they are commonly used as input to electro muscular control systems. Each muscle performs a specific function in each movement. Electromyography is a medical, healthcare, and human-machine interaction diagnostic technique for acquiring an EMG signal (MMI). e most important component of the locomotion system is the muscular system. Accordingly, sensors were developed to detect the movement system and diagnose the electromyogram. Nowadays, While maintaining a modest size, it has improved and become more accurate. In this paper, The EMG signals are converted into images using CWT, then the EMG images features are extracted based on convolutional neural network (CNN) , and finally, the EMG features are categorized by an LS-SVM classifier in Matlab. The main objective of this study is to classify grasps into six basic hand movements: (1) cylindrical, (2) palm, (3) lat (4) sphere(5) Tip, and (6) Hook. Finally, electrophysiological patterns of each movement were extracted by extracting features from the images using CNN where EMG images are divided into (70 percent) training and (30 percent) validation, and then these features are fed into classification using the least square support vector machine. It produced an accuracy of 94.81%.

Keywords: : (EMG), (CWT), GoogleNet,LS-SVM.

Introduction:

Humanity has constantly attempted to comprehend its own movement system from the dawn of time. The muscular system is the most significant component of the movement system[3].

In terms of structure and mechanism, the human hand is one of the most complex muscular-skeletal systems. It is composed of 27 bones with 25 degrees of freedom of movement in various directions, and it is used to perform more complex tasks than other systems. [1]. Electrical signals generated by muscles are commonly used to deduce the muscle's functioning principle[2]. In reality, EMG signals include a lot of information on muscle activity is frequently used as a signal input for myoelectric control systems. The electromyography (EMG) is an electrodiagnostic tool used in medicine, healthcare, and man-machine interface (MMI)[4] . One of the sEMG applications is the development of man machine interface for disabled people like a virtual world,a virtual mouse, electric wheelchairs, prosthesis control etc[5]. 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. It is to be noted that this technique is not used much by researchers and is primarily used for diagnostic purposes [6]. This EMG signal can be used to recognize hand gestures, with the goal of developing a more affective and lifelike hand prosthesis [10]. EMG signals are an intriguing means of linking our neural activity to our body processes. Surface EMG signal collecting provides a lot of potential for wearable data collection tools, especially when compared to EEG-based devices[6].

1. RELATED WORKS

There have been several different approaches for classification of EMG signals. In this part some related studies will be examined.

Sapsanis et al.[17] present a pattern recognition model to classify object gripping hand actions. Surface EMG signals acquired with 2-channel EMG equipment were used as data in this study. In order to classify the data, authors used a linear classifier. Results were hampered by the small size of the dataset and the small number of participants.

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 were 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 . Employing the neural network for regression to recognize hand grips has been recommended by Yavuz et.,al.[9] . For EMG data classification , they employed a spectrums based on features technique combined with the neural network for regression . Using a same dataset, Akben [10] 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. [11]

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. [12] in which they have 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. In order 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 [14] used time-domain characteristics to categorize hand movements. In that work, the EMG signals were partitioned into windows. Time domain properties were extracted and fed into a linear discriminant analysis classifier. Subasi et al. [13] 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.

In light of the foregoing, it was noted that these studies extract features from databases and then these extracted features were used in different classifications techniques. In addition, the choice of powerful features is an important issue. Another factor to consider is the classifier you use, especially if you have a lot of data. Therefore, deep learning tools suggest solutions to these problems. Thus, in this study, data is converted into images using CWT, and then features are extracted from images using one of the CNN models, and then these features are fed into the LSVM classifier to obtain high classification accuracy for basic fists.

2. PROPOSED METHOD

2.EMG Data Collection

The data used in this study are obtained from UCI Machine Learning repository Of URL[9].
http://archive.ics.uci.edu/ml/datasets/sEMG+for+Basic+hand+movements#.
The data set used consists of five people aged (20-22) holding different objects. This database aims to reveal the basic movements of the hand and how to grasp and the different fists. Three surfaces of electrodes connected to the forearm are used to record the EMG signal, two of them are in (Flexor ulna Capri and extensor Capri radials and reference electrode in the middle), the signal is recorded for each person There are six basic movements and each movement is repeated 30 times. These movements cross the basic movements of the human hand. As shown in Figure 1.

1. Lateral (LA)
2. palmar (PA)

3. TIP (TI)
4. spherical (SP)
5. cylindrical (CY)
6. and Hooked (HO).

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 interferenceso obtain better information from signal without noises[3].Figure2 shows samples of EMG signals those were considered when designing the proposed methodology.

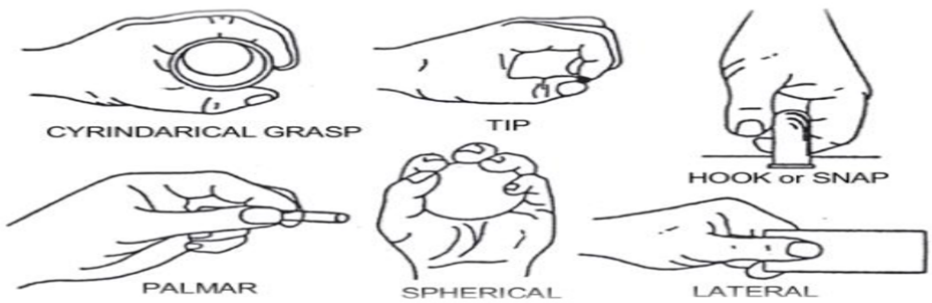


Figure 1. The basic movement, Cylindrical (CYL),TI P(T) , Hook (HO or snap), Palmar (pa),Spherical (sp) ,Lateral (LAT), [10].

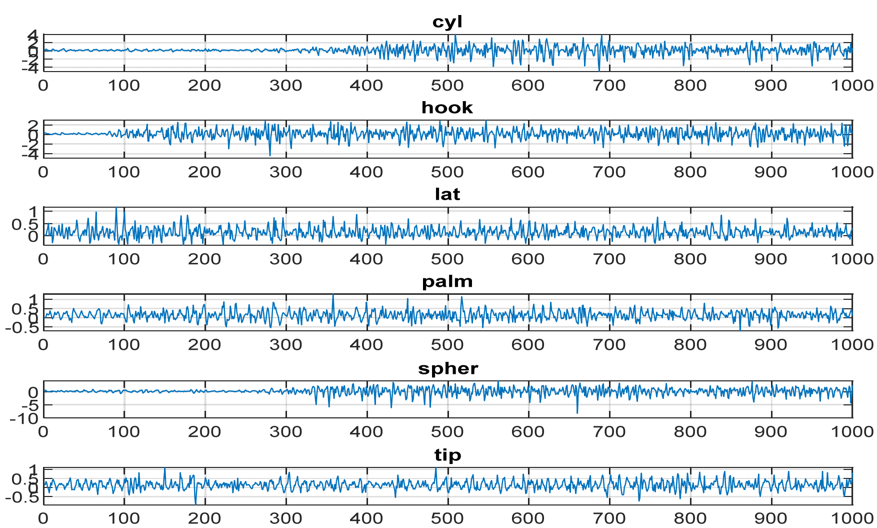


Figure. 2. Typical forms of EMG signals matching to hand grips. A EMG signals is: cy1, hook , lat ,palm, sphere and tip.

3-METHODOLOGY

Figure. 3 is a brief illustration of the whole method implemented from the acquisition of EMG data through UCI available that were converted into scalogram images until the classification of the image group using least Square support vector machine (LSSVM). This study first begins with obtaining EMG signals from a publicly available database of five subjects for six basic hand movements, the next step she converts these signals into images, and to do that the continuous wavelet transform method was used. After the process of converting the reference to images image features were extracted from spectral images and these features it was entered into the workbook to classify and distinguish the 6 basic movements of the human hand.

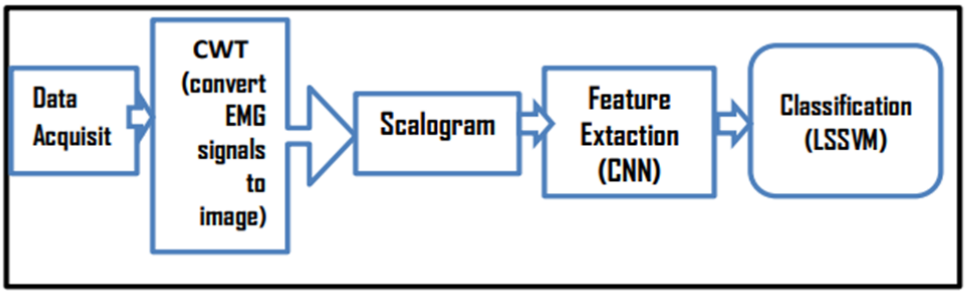


Figure 3. Block diagram of the Proposed Methodology

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[16-15]. 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). Wavelets can be obtained as follows by scaling and translating a basic wavelet function h(.).

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

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).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 those reverse locations at distinct times and scales of the spectrum. Without else definite, scale and frequency will be employed reciprocally in the paper[18]. The CWT of an EMG signal can be defined as

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

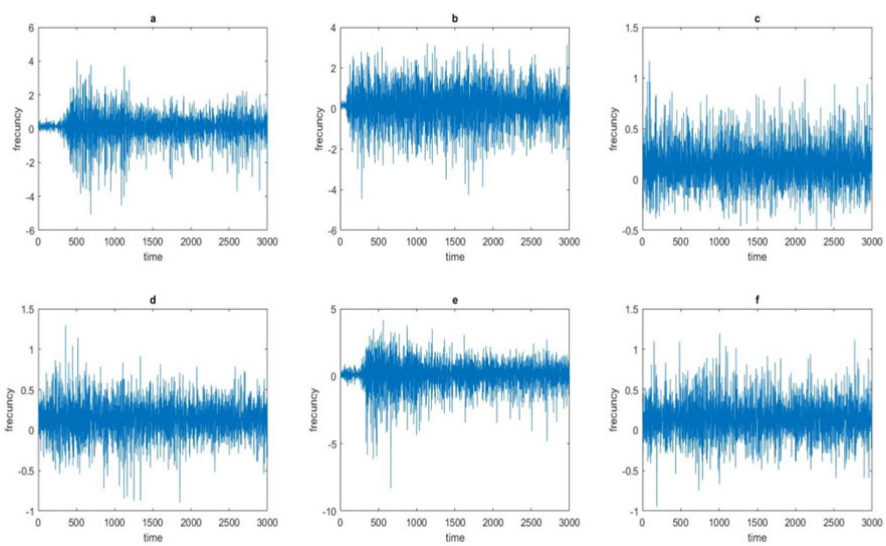
where x (t) is the input signal, $\bar{h}(t)$ is represents the operation of complex conjugate , (a) is the scale Parameter representing indirectly thefrequency, (τ) is the translation factor, and((1)/| a |^2) illustrate energy standardization at distinct scales. Parameters (a) and (s) are repeatedly 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

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

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

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

As the main wavelet, CWT employs functions such as Mexican, Morlet, Morse, and Gaussian. This is 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 4, examples of EMG signals sort extracts are utilized for clarity and their matching scalogram are shown



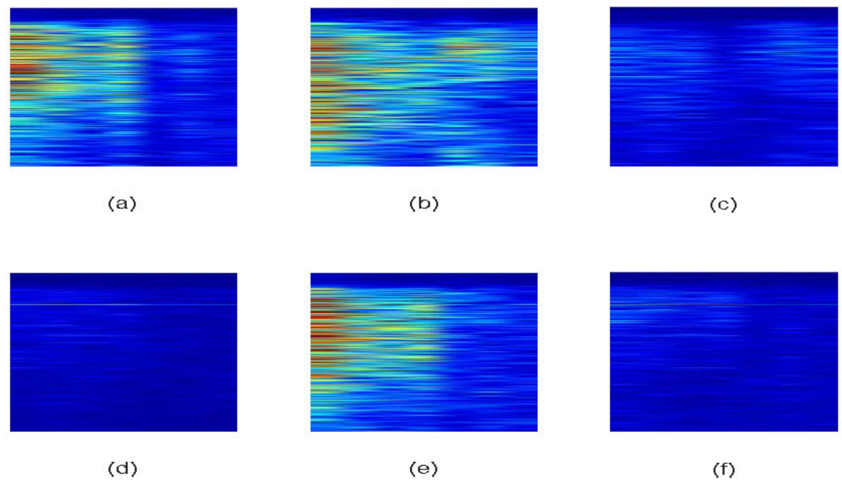


Figure 4 .Example of EMGs and associated scalograms of six variants movements:(a- cylender),(b - Hook) ,(c -lat) ,(d -palm) , (e -sphere) , (f-tip).

For better observing For EMG signals transformed to EMG images, we generated six separate models have been generated, one for each movement. By checking the created scalograms of the 6 motion sites, we can qualitatively note the variances those decide them from each other, which You should be able to feat it done deep learning. The example is shown in figure.3 above.

3.2- Feature Extraction

After the process of converting signals into images (scalogram) by means of continuous wavelet transformation, the EMG image is inserted into the depth Feature extractor model, which extracts important features that will be used to classify EMG images. The feature extraction stage is a critical stage in image classification, and features must be extracted strong against variations in movement position according to different basic movements, So, these features must contain the required information to distinguish between the different grasps. The aim of the features extraction process is to get the most important information from The original data (photo). In this study, this goal was achieved using one of the models CNN is GoogleNet model.

The network creates a hierarchical representation of the images it receives. Higher-level features are produced using the lower level features of prior layers in deeper layers. Use activations on the concatenation layer "incepthion_5b " to get feature representations of the training and test pictures. Use an earlier layer in the network to get a lower level representation of the images. In this paper, the features are taken the concatenation layer "incepthion_5b" in GoogleNet architecture, since best estimate Accuracy is achieved by 'incepthion_5b' class properties.It is where high-level layer features are best and most differentiated in classification tasks.

3.3- Classification Stage

The features collected from the GoogleNet model are employed in a classifier suitable for the job in the EMG picture classification stage. This categorization procedure can employ a variety of classifiers. Deep learning and machine learning are coupled to provide excellent classification and feature extraction results from pre-trained CNN models linked to the LS-SVM classifier.

3.3-1. Least Square Support Vector Machine (LS-SVM) for Classification

To classify 6 classes, the technology being adopted to do this is the LS-SVM classifier. The primary goal of this strategy is to identify basic hand movements between distinct types of data sets while also reducing the system's complexity and computing expense

. The LS-SVM classifier is a powerful image-discrimination algorithm. It was used for the purpose of classifying EMG images. The LS-SVM classifier was developed by Suykens and Vandewalle [20]. A modified version of the SVM.

5. EXPERIMENTS and PERFORMANCE ANALYSIS

4.Experimental Results

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 .

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 findings came from a study that employed multi-classification to classify 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 by using the following formula:

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

$$\textbf{Precision} = \frac{\boldsymbol{true\ positive}}{\boldsymbol{true\ positive} + \textbf{ false positive}} \quad (6)$$

$$\textbf{Sensitive} = \frac{\boldsymbol{true\ positive}}{\boldsymbol{true\ positive} + \textbf{ false positive}} \quad (7)$$

$$\textbf{Recall} = \frac{\boldsymbol{true\ positive}}{\boldsymbol{rue\ positive} + \textbf{false negative}} \quad (8)$$

$$\textbf{F} - \textbf{score} = \frac{\boldsymbol{2\ X\ precision\ X\ recall}}{\boldsymbol{Precision\ +\ recall}} \quad (9)$$

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 positive class. 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 method was evaluated (for example, image extraction using gGoogleNet model and classification of figurines extracted by LS-SVM) Where the images EMG that are constructed using CWT are divided into 70% for training and 30% for validation scheme. The presented model was validated ten times, and the average accuracy was recorded each time. Proposed method achieved 94.81 % accuracy rate for all hand grasps Table 1 presents the classification results for features extracted from GoogleNet and categorized by LS-SVM for 5 participants with 6 hand grips. Notably, results from validated EMG images of five subjects were very similar, with no significant differences in accuracy, recall, or f-score.Table2 ,present the confusion matrix for each subject. For the class subject, the highest and the lowest sensitivities occur for the gestures palm,sphere (100%) and Tip (84.61%).

Table1:classification performance of GoogleNet-LSSVM for five subjects

hand movements	Accuracy	Precision	Recall=sen	specifity	f-score
CY	94.81	100	95.74	100	97.82
HO	94.81	95.45	91.3	99.07	93.33
LA	94.81	93.33	95.45	98.61	94.38
PA	94.81	91.07	100	97.61	95.32
SP	94.81	91.48	100	98.15	95.55
TI	94.81	100	84.61	100	91.66
Mean	**94.81**	**95.22**	**94.51**	**98.91**	**94.68**

confusion matrix for the five sebject

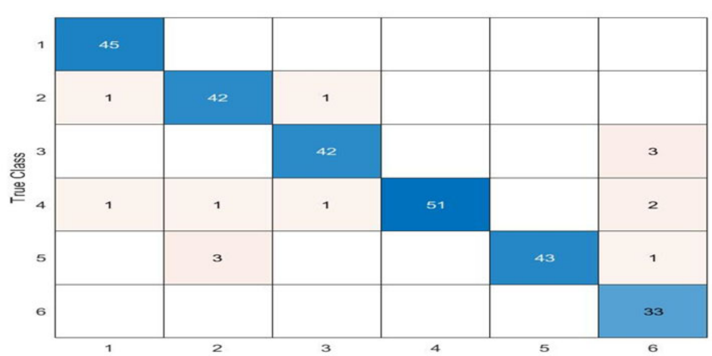


Table2: confusion matrix for the five subject

The proposed technique prediction

		Cyl	Ho	TI	PA	Sp	LA
	Cyl	45	0	0	0	0	0
	HO	1	42	1	0	0	0
classify	TI	0	0	42	0	0	3
	PA	1	1	1	51	0	2
	Sp	1	3	0	0	43	1
	LA	0	0	0	0	0	33
	(Sen%)	95.74	91.3	84.61	100	100	95.45

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

5. Discussion

Our results showed that features extraction using Deep learning and classification using machine learning can provide high accuracy rate . Here are the main 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 in table3. Figure. 5 reports the comparisons results. The simulation results showed that the proposed algorithm LS-SVM effectively categorized hand grasps and outperformed the other classification algorithms

4.23 Table3

4.24 Comparisons of the SL-SVM classifier with several existing method

Classification accuracy rate

1) Authors	Classification models	Subjec1	Subject2	Subject3	Subject4	Subject5
Iqbal et al.[12]	k-nearest	82.78%	87.67 %	83.11 %	90.00%	90.00 %
Akben et al.[11]	k-means	93.4 %	86.66 %	97 %	99.23%	97.66 %
Song et al.[19]	CNN	87.5%	87.5%	87.5%	87.5%	87.5%
subasi et al.[13]	RF	95.56 %	88.88 %	92.22 %	92.22%	98.33%
The proposed method	SL-SVM	96.29%	100%	100%	96.29%	98.14%

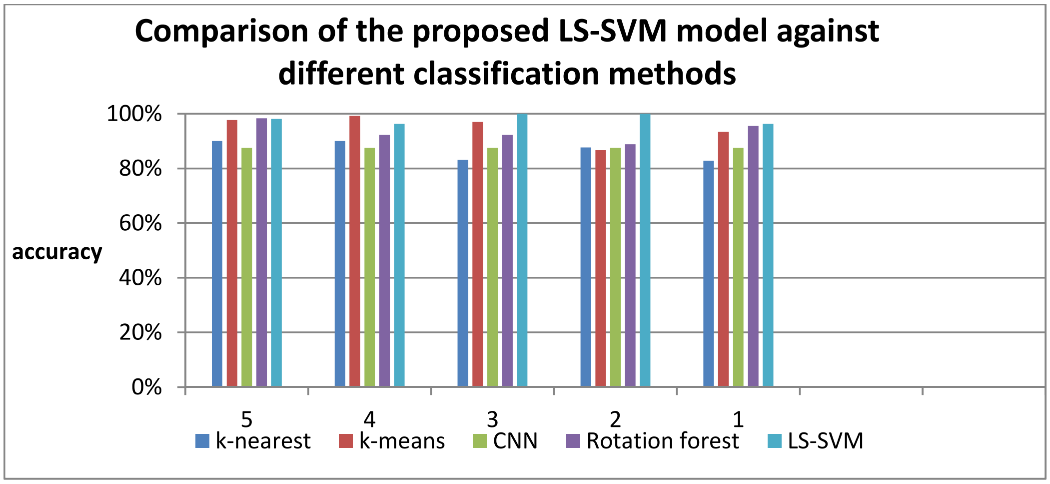


Figure.5.LSSVM vs. other classification techniques.

2- Based on our results, converting EMG signals 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 Figure6.

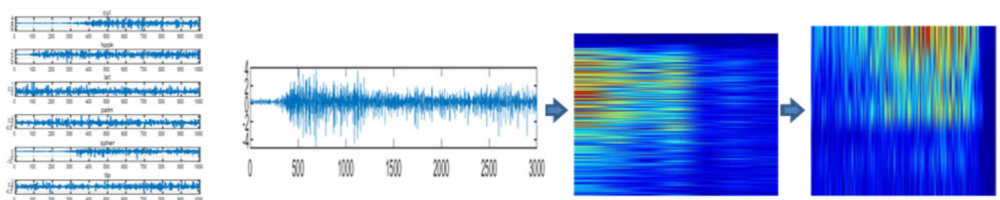


Figure.6. The process of transforming EMG signals to EMG images using CWT.

3- The performance of the proposed LSSVM classifier has been compared with several techniques found in the literature. Iqbal et al. [12]) used the same data set decomposition to classify hand holders. Subasi et al. [13] used multiband principal component analysis associated with wavelet beam decay. Akben et al (10) identified hand grips used Histogram energy values and concordance association were used to extract characteristics, and Song et al.[19] who used CNN to classify fists using the same dataset, it should be noted that the proposed model was evaluated using this data set as other approaches in order to compare it with other methods (as shown in Table 3). In this part of the procedure, the proposed LS-SVM classifier is tested with data from each individual. For comparison purposes, all results were recorded and presented in Table 3; It can be seen from these results that song et al. [19] The approach based on CNN techniques yielded less desirable results than the proposed LSSVM classifier. Iqbal et al., (12) used classification system to classify hand movements based on (SVD and PCA), individual outcomes differed widely in that study; For example, Subject 1 had a classification accuracy rate of 82.78%, while Subject 2 had an 87.67% accuracy rate. The LS-SVM classifier presented here, on the other hand, has a subject 1 accuracy rate of 96.29% and a subject 2 accuracy rate of 100%. As a result of these comparisons, the presented classifier outperformed all methods in Table 3.

6. CONCLUSION

1- This study presents a classification of the EMG signal of multiple hand grasps by extracting features on a CNN basis grasps and rated by LS-SVM for 6 hand grasps movement namely (1) cylindrical (2) Lateral (3)palmar (4)Tip (5)spherical (6) Hooked.
2- The goal is to extract features using a convolutional neural network and classify them using supervised machine learning.
3- A GoogleNet model has been used to Feature extraction from EMG images and classifies these features extracted using LS-SVM classifier.
4- Classification in the command window of the MATLAB platform.
5- The input and target values are used to train and test the neural network to extract the important features and then classify them.
6- Thus, it can be concluded that extraction of significant features from EMG images of multiple hand grasps using convolutional neural network (CNN) and insertion of these features into LS-SVM was achieved without major defects.
7- least square support machine (LSSVM) produced 94.81% accuracy it can be concluded that the extraction of features in MATLAB using CNN Capable of extracting powerful important features through which EMG images of hand grasp can be successfully discerned with high accuracy rate.

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