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Using Wavelet Analysis and Deep Learning for EMG-Based Hand Movement Signal Classification

Harun GÜNEŞ [*1], Abdullah Erhan AKKAYA [2]

Abstract

In this study; time series electromyography (EMG) data have been classified according to hand movements using wavelet analysis and deep learning. A pre-trained deep CNN (Convolitonal Neural Network-GoogLeNet) has been used in the classification process performed with signal processing, by this way the results can be obtained by continuous wavelet transform and classification methods. The dataset used has been taken from the Machine Learning Repository at the University of California. In the data set; EMG data of 5 healthy individuals, 2 males and 3 females, of the same age (~20-22 years) are available. Data; It consists of grasping spherical objects (Spher), grasping small objects with fingertips (Tip), grasping objects with palms (Palm), grasping thin/flat objects (Lat), grasping cylindrical objects (Cyl) and holding heavy objects (Hook). It is desired to perform 6 hand movements at the same time. While these movements are necessary, speed and power depend on one's will. People perform each movement for 6 seconds and repeat each movement (action) 30 times. The CWT (Continuous Wavelet Transform) method was used to transform the signal into an image. The scalogram image of the signal was created using the CWT method and the generated images were collected in a data set folder. The collected scalogram images have been classified using GoogLeNet, a deep learning network model. With GoogLeNet, results with 97.22% and 88.89% accuracy rates were obtained by classifying the scalogram images of the signals received separately from channel 1 and channel 2 in the data set. The applied model can be used to classify EMG signals in EMG data with high success rate. In this study, 80% of data was used for educational purposes and 20% for validation purposes. In the study, the results of the classification processes have been evaluated separately for first and second channel data.

Keywords: Deep learning, continuous wavelet transform (CWT), skalogram, electromyography (EMG), GoogLeNet

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1. INTRODUCTION

With the development of technology, people who have lost their limbs such as arms and legs, can perform the movements they want by using prosthetic structures made with the help of brain waves and Brain Computer Interface (BBI) applications. Considering that each movement with said limbs generates unique electromyography (EMG) signals, EMG signals can be useful in using these prosthetic limb structures. EMG signals can be classified according to this procedure; With advances in biosensors, pattern recognition and biosignal processing [1], this could be a very definitive step towards controlling the movement of a prosthetic arm (or hand) [2].

EMG has a particularly important place in making the lives of individuals easier. Importance of EMG signals; increased with the development of computer hardware and the increase in the amount of data. By using EMG signals [3], the classification of movements occured in different human limbs can be done for different purposes. Although the classification of hand movements is mainly done in the literature, studies such as finger movements or body positioning are also frequently performed today. On the other hand, EMG signals are widely used in the diagnosis of various diseases, in the design of prosthetic arms/hands and in the entertainment industry [4-12]. Since EMG signals are random in nature, identification can be performed with a Gaussian distribution. The amplitude of the EMG signal ranges from an average of 0 to 1.5 mV in true value or 0 to 10 mV in amplitude. Usable signal energy is between 50 and 500 Hz, and the most effective frequency range is known to be 50 Hz to 150 Hz. These EMG signals have more energy than the electrical noise level [13].

Various approaches have been proposed to solve the problem of identifying movement commands, typically daily hand movements, and multiple electrodes (typically four or less) from EMG signals with low classification errors [14]. The database used in this study has been taken from the University of California Machine Learning Archive [15]. Records are obtained by repeatedly holding the objects necessary to perform the hand movement. In these hand movements, the speed and strength of the grip movement are left to the initiative of the subject. Two anterior EMG electrodes (ExtensorCarpiRadialis/FlexorCarpiUlnaris and Longus/Brevis) held by elastic bands and a central reference electrode were placed on the arm to gather information about muscle activation [16]. In the data set used in the study, there are EMG data obtained from 5 healthy subjects (2 men, 3 women) of the same age (20-22 years). Data: Holding a spherical object (Spher), holding a small object with the fingertip (Tip), holding the palm of the hand (Palm), holding a thin/flat object (Lat), holding a cylindrical object (Cyl), a heavy object It consists of six hand movements, including holding (Hook) movements [17]. This study aimes to classify basal hand movements using surface EMG obtained with two frontal electrodes attached to two specific hand muscles. The novelty of our work is to use only 2 electrodes and use the GoogLeNet network model when classifying the scale histograms of images with deep learning and continuous wavelet transform (CWT). Our results show that it can improve classification accuracy and control prostheses more effectively.

2. MATERIAL AND METHOD

In this study, deep learning models, which is a sub-branch of machine learning, was used. The point of this decision is that deep learning works very well with large datasets. In this study, a GoogLeNet model was developed and trained. The results obtained as a result of the study were interpreted by presenting tables and figures in the application and results section of the study. In this part of the research, the dataset used, the Continuous Wavelet Transform (CWT), the structure of the deep convolutional neural network architecture used in the research (GoogLeNet) and the layers of the model used were examined.

2.1. Dataset

The dataset used in this study was taken from the University of California Machine Learning Repository [17]. The dataset is obtained by constantly holding the objects necessary to perform hand movements. With these hand movements, grip speed and strength are made according to the wishes of the subject. The dataset used in the study. EMG data are available for 5 healthy subjects of the same age (20 to 22 years), 2 males and 3 females. Data: grasping a spherical object (Spher), holding a small object with the fingertip (Tip), holding against the palm (Palm), holding a thin/flat object (Lat), holding a cylindrical object (Cyl), holding a heavy object (Hook) consists of six hand movements. Hand gestures are shown in figure 1 [17] and the data set for each participant is shown in table 1 [18].

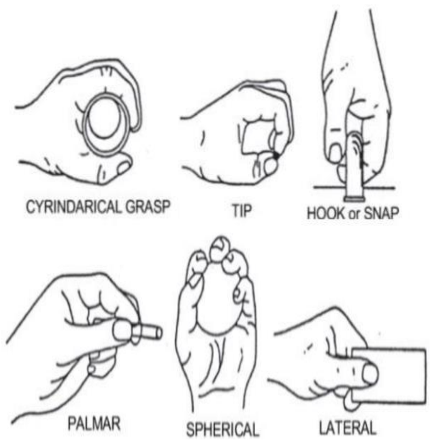


Figure 1 Six hand gestures from which data is taken

- **a) Spherical:** spherical instruments grip
- **b) Tip :** Grasping small objects with fingertips
- **c) Palmar :** Holding with palm facing object
- **d) Lateral :** Handling thin/flat objects
- **e) Clyindrical:** Handling cylindrical objects
- **f) Hook :** Holding heavy objects

Table 1 Data string of each participant

Series Name	Array Size	Array Content
Data	6x2x30x3000	Number of Hand Gestures x Number of Channels x Number of Attempts x Data
Labels	6x1	(Cyl, Hook, Lat, Palm, Spher, Tip)

The subjects were asked to perform each movement for 6 seconds and the whole process was repeated 30 times for each movement. As a result, a total of 180 6-second two-channel EMG signals were recorded from each subject. Data were collected at the National Documentation Laboratory using a 500 Hz sampling rate as the programming core. Signals were bandpass filtered using a Butterworth bandpass filter with low and high cutoff frequencies of 15 Hz and 500 Hz, respectively, and a notch filter at 50 Hz to eliminate line interference patterns.

2.2. Signal processing

The systems in the human body produce various signals while performing their functions. These signals, called bioelectric signals, contain complex information that is often difficult to understand. You need to process and interpret these signs appropriately to find out what's going on inside your body. For this, various signal processing techniques are used. Methods such as principal component analysis (PCA), fourier analysis (FA) and wavelet analysis (WA) are mainly used in the analysis of EMG signals [19]. Analysis of the EMG signals recorded as part of this study was performed using the CWT method.

2.2.1. Continuous wavelet transform (CWT)

One of the methods of performing signal analysis in the time-frequency domain is SDD. Since the window length is fixed in short –time fourier transform (STFT), signal analysis in the time and frequency domain cannot be done efficiently [20]. Based on this, the SDD method, which includes a transform window technique, is introduced. With this method, wide time resolution and narrow frequency resolution at high frequencies, narrow time resolution and wide frequency resolution at low frequencies are obtained [21]. SDD is expressed mathematically as:

$$\mathrm{CWT(a,b)} \int_{-\infty}^{\infty} \mathrm{x(t)} \frac{1}{\sqrt{\mathrm{a}}} \psi\left(\frac{t-b}{a}\right) dt \qquad (1)$$

Here, x(t) is the signal, ψ(t) is the wavelet, b is the shift parameter (time), and a is the scaling parameter (frequency). On the other hand, wavelets defined as wavelets generally do not have the same properties [21]. In this case, wavelets are divided into different groups according to their properties. These wavelets; They are different wavelet types such as Haar, Daubechies, Mexican hat, Morlet, Coiflet, and which one to use depends on the application [22]. The Morlet wavelet transform has both virtual and real parts, so it provides the possibility to analyze both phase and magnitude. Morlet wavelet analysis offers many advantages for time-frequency analysis. The most important of these advantages is that Morlet wavelets are Gaussian in the frequency domain. Due to this feature, the absence of sharp edges minimizes ripple effects that can be misinterpreted as oscillation [23]. Therefore, preferred in this study, Morlet vd. (1984) wavelet function can be written as:

$$\lambda_{\varphi}(t) = \pi^{-\frac{1}{4}}\left(exp^{i\varphi t} - exp^{-\frac{\varphi^2}{2}}\right)exp^{-t^2/2} \qquad (2)$$

Here, the parameter φ represents the center frequency parameter $\lambda\varphi(t)$ of the Morlet wavelet. In addition, φ controls the number of oscillations in the Gaussian envelope. Therefore, better frequency localization can be achieved by increasing φ [24]. The term $exp^{-\frac{\varphi^2}{2}}$ in the equation is the smoothing parameter that smooths out the nonzero mean of the complex sine wave. However, it can be ignored when $\varphi > 5$.

The filter bank is used to get the CWT of each EMG signal sample and the scale plot of each signal is derived from the coefficients. An example of an EMG signal for each type of hand movement is shown in figure 2.

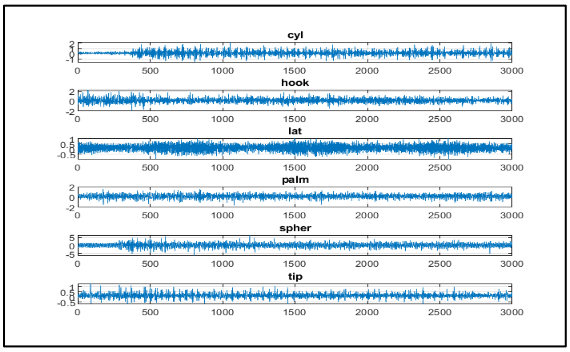


Figure 2 Example of EMG signal for each hand movement category

In figure 3 the scalogram images obtained from the given EMG signals are given.

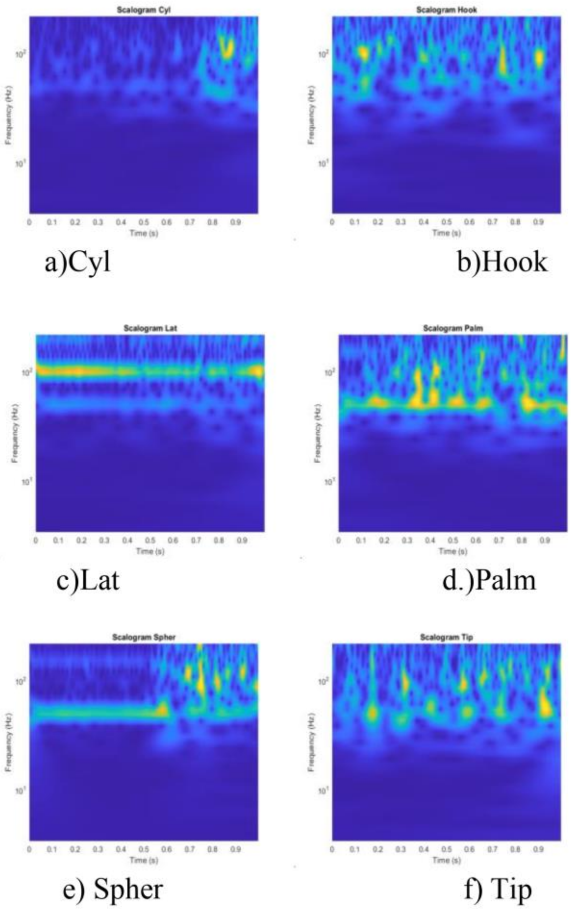


Figure 3 Scalogram images obtained from the given EMG signals

2.3. Googlenet

In 2013, the paper "Network in Network" by Min Lin et al proposed an important new solution for modeling computational complexity [25]. Thanks to this suggestion, Google immediately used the model shown on the gold plate and it was successful. In this way, flexibility in calculation is provided and it has become possible to design variable models to increase performance. The network within the network is a 1x1 convolution operation. Although many people don't understand why, this is an extremely simple math operation. However, 1x1 element processing is considered to have no effect on matrices. A simple 1x1 convolution operation is shown in figure 4 [25].

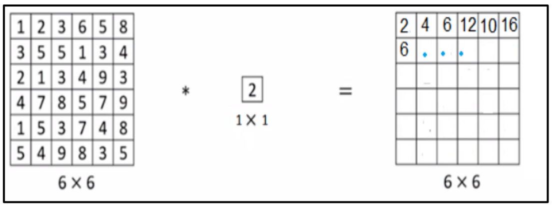


Figure 4 Simple 1x1 convolution operation

But the situation changes when the input matrix is multi-channel. For example, if the input matrix has 100 channels and a 1x1 convolution filter with 30 channels is applied to it, the output matrix has the number of channels equal to the number of filters, which is 30. Then the 1x1 convolution layer means reducing the size in depth. In the example below (figure 5), the number of output channels is calculated like a filter [25].

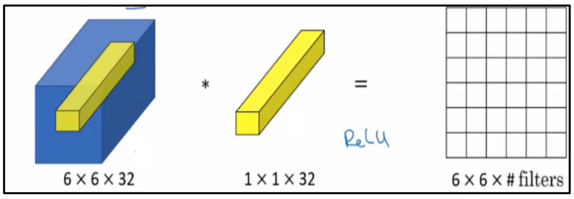


Figure 5 Calculation of output channels equal to the number of filters

It should be noted that in commonly used classical network models (LeNet-5, AlexNet, VGG-16, ResNet, etc.), the pool layer reduces the height and width of the matrix as it moves from the beginning to the end of the model. However, the number of channels is increasing. For this reason, the problem arises that 1x1 convolution layer is not added to the model and the number of channels is not limited according to the needs. The Google team raised this issue and implemented it. Impressive results were achieved with “Inception” in 2014.

2.3.1. Inception networks

It is different from the classical network models (LeNet-5, AlexNet, VGG-16, ResNet etc.) that are generally used and difficult to understand. However, computational complexity and size solutions bring speed and performance.

The structure of the Inception network model consists of modules. Each module consists of different sizes of convolution and max pooling operations. In figure 6, the 28x28x256 tensor was obtained with 3 different convolutions and maximum pooling operations [23].

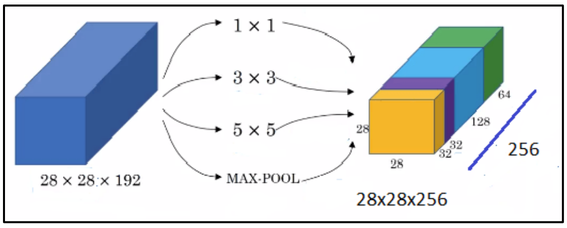


Figure 6 Naïve inception module

Based on this output, let's calculate the number of parameters in the 5x5 convolution operation and evaluate the complexity of the operation (figure 7) [23].

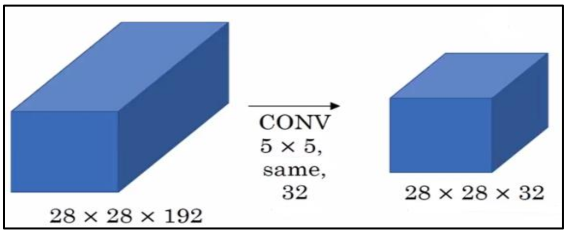


Figure 7 5x5 Convolution process

In the process, it is necessary to examine (28x28x32) x (5x5x192) = 120 million parameters only for this step. Similarly, the convolutional and maximum pooling layers must be the same. C. Szegedy, author of the "Network in Network" article, and his team focused on optimizing them using 1x1 layers before a convolution of it (figure 8) [23].

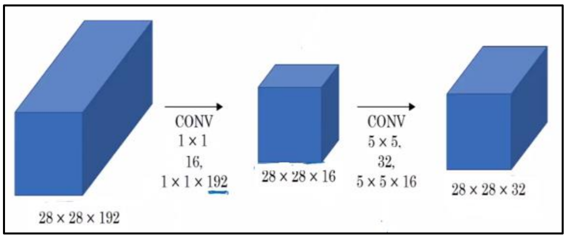


Figure 8 Network in network

In this way, there can be less programming and faster design with a more complex network model. In this case, in 1x1 convolution: (28x28x16) x(1x1x192) =2.4 million parameters, in 5x5 convolution: (28x28x32) x(55x5x16) =10 million, a total of 12.4 million parameters are calculated. To be met with the first case, the parameter calculation is surprisingly reduced by about 10 times. They called this 1x1 convolution process a 'bottleneck' (bottleneck). Each module is called "inception". The model, which consists of a total of 9 foundation blocks, was named GoogLeNet, referring to the LeNet model, which gives initial values (deep learning) for these individuals. It is designed by the model itself in the GoogLeNet model. Also this is version 1 only. The model name comes from the Hollywood movie Inception. googlenet structure is shown in figure 9 [23].

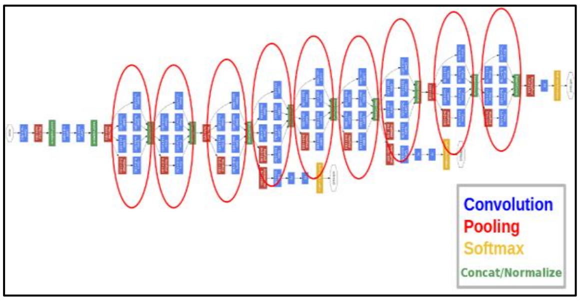


Figure 9 GoogLeNet

2.4. Method used

In this study, the EMG database obtained from the University of California Machine Learning Repository was used to test the algorithm. A deep learning neural network was applied to classify EMG data obtained from 5 healthy individuals, 2 men and 3 women, of the same age (20-22 years). Signal scale images were created using the CWT method and the generated images were collected in a data set folder. Collected scalogram images were classified using GoogLeNet, a deep learning network model.

In the presented study, the hand movement type of the EMG signal in the data set was determined by using deep learning according to the given features. The coding processes necessary to carry out the research were written in the matlab environment. The method used and the applied deep learning neural network model are given in figure 10. GoogLeNet was used as a deep learning neural network model.

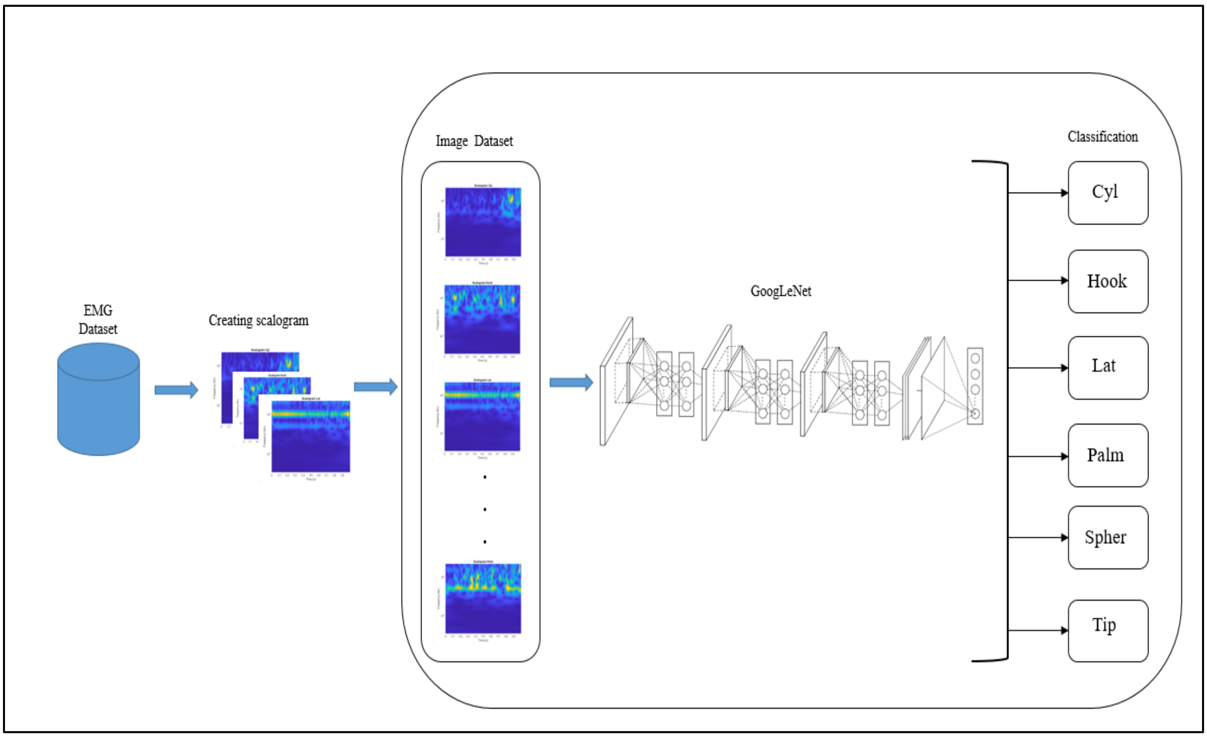


Figure 10 The method used and the deep learning model

3. IMPLEMENTATION AND CONCLUSIONS

In this study, after applying continuous wavelet analysis of EMG signals, classification process is tried to be done by using deep learning neural network. First of all, the network is trained with the randomly
taken 80% of the EMG dataset, which is applied to extract the scalograms of the signals by applying wavelet analysis. The system is then validated with 20% of randomly received data. This process was done separately for the 1st channel and the 2nd channel in the dataset. The application was prepared in Matlab environment [26]. The work done; Encoded on Intel Core-i7 6800K 3.4GHz processor, GPU Nvidia GeForce RTX 3060 Ti graphics card, 16 gb RAM and 64 bit windows 10 hardware.

In the application for channel 1, results were obtained in 2 minutes and 12 seconds. In Table 2, the number of samples, training and validation results in the classification process for channel 1 are presented. Figure 11 and figure 12 contain the performance graphics of this process.

Table 2 1. Channel sample numbers, training and validation results

Dataset	**% Rate**	**Number of samples**	**Classification results**
Total	%100	180	----------
Train	%80	144	%100
Validation	%20	36	%97,22

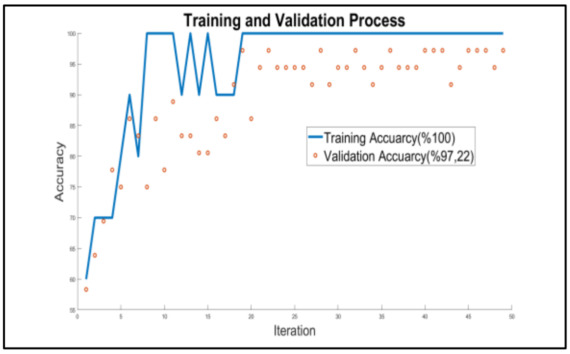


Figure 11 1. Channel performance graph (Accuarcy)

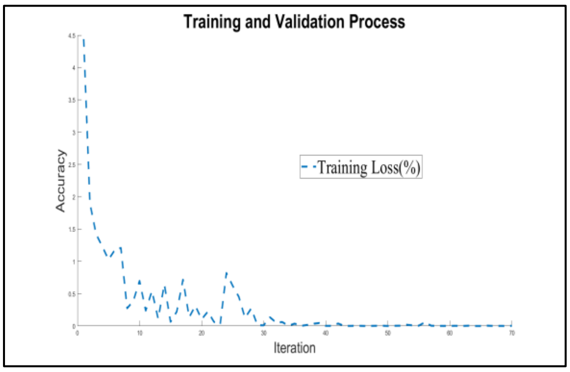
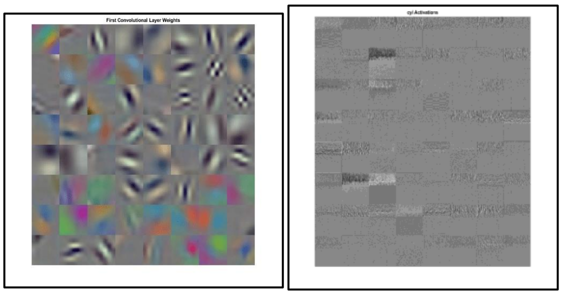


Figure 12 1. Channel performance graph (Loss)

Each layer of CNN generates a response or trigger for an input image. However, only some layers are suitable for extracting image attributes in CNN. It captures key visual features such as layers, edges, and blotches on top of the mesh. To see this, the network filter weights of the first convolution layer are shown in figure 13 a and figure 13 b. The first layer has 64 different weight groups.



(a) (b)

Figure 13 a) First convolutional layer weights of channel 1 b) First convolutional layer output of channel 1

After the training of the model was completed, the accuracy values of the sample number, training and validation data presented in table 2 for the 1st channel were obtained. The confusion matrices obtained as a result of the classification process are given in the figure 14 and figure 15.

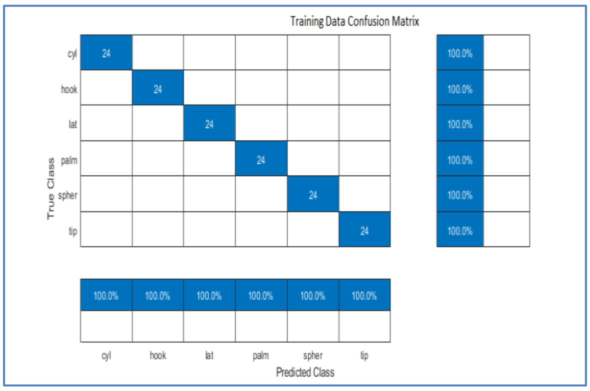


Figure 14 1. Channel training data confusion matrix

In Table 3, the number of samples, training and validation results in the classification process for the 2nd channel are presented. In the application for channel 2, results were obtained in 1 minute and 33 seconds. Figure 16 and figure 17 contain the performance graphics of the process.

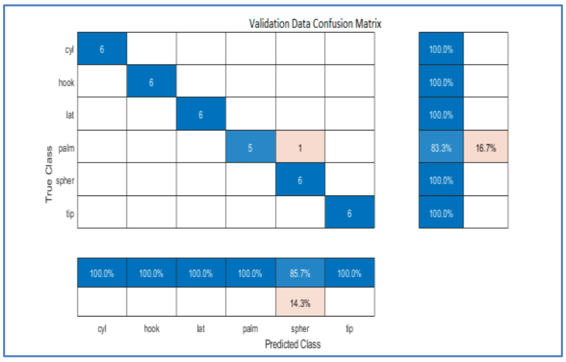


Figure 15 1. Channel validation data confusion matrix

Table 3 2. Channel sample numbers, training and validation results

Dataset	% Rate	Number of samples	Classification results
Total	%100	180	----------
Train	%80	144	%100
Validation	%20	36	%88,89

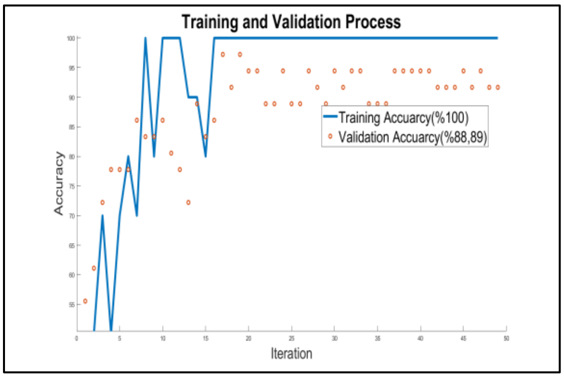


Figure 16 2. Channel performance graph (Accuarcy)

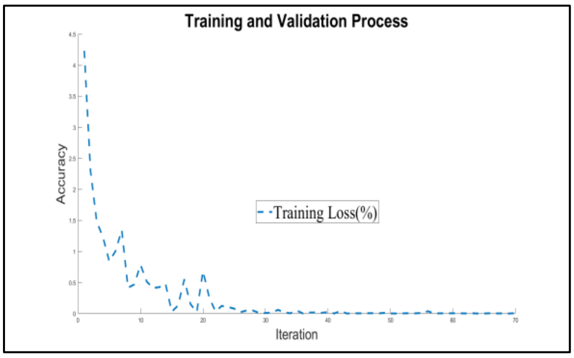
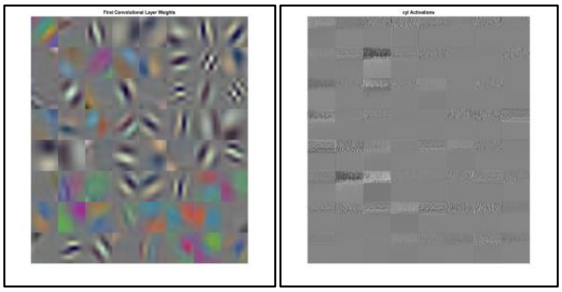


Figure 17 2. Channel performance graph (Loss)

Each layer of CNN generates a response or trigger for an input image. However, only some layers are suitable for extracting image attributes in CNN. It captures key visual features such as layers, edges, and blotches on top of the mesh. To see this, the network filter weights of the first convolution layer are shown in figure 18 a and figure 18 b. The first layer has 64 different weight groups.



(a) (b)

Figure 18 a) First convolutional layer weights of channel 1 b) First convolutional layer output of channel 1

After the training of the model was completed, the accuracy values of the sample number, training and validation data presented in table 3 for the 2nd channel were obtained. The complexity matrices obtained as a result of the classification process are given in the figure 19 and figure 20.

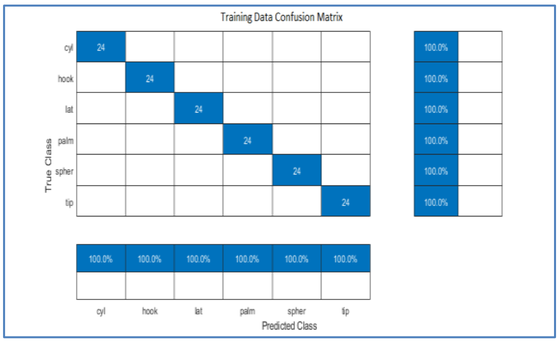


Figure 19 2. Channel training data confusion matrix

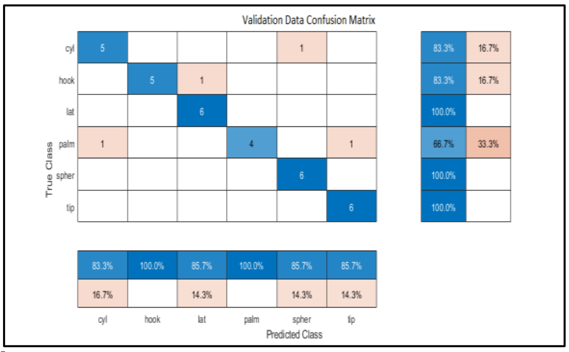


Figure 20 2. Channel validation data confusion matrix

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Authors' Contribution

All authors contributed equally to the writing of this paper. All authors read and approved the final manuscript.

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The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the authors.

The Declaration of Ethics Committee Approval

This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics

The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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