Biometric Authentication Based on EMG Hand Gestures Signals Using CNN

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***Abstract*—Biometric identification systems are increasingly important today compared to traditional recognition/classification systems. Electromyography (EMG) signals and person identification/classification systems are preferred for high-security systems as they include physiological and behavioural movements. This study investigates biometric EMG signals based on convolutional neural networks (CNNs) and personal identification/classification systems. Bioelectric signals were recorded at six different wrist movements from five volunteer participants with a four-channel EMG device. To determine the spectrum characteristics of EMG signals, the frequency subbands of the signals were found using the discrete wavelet transform (DWT), empirical wavelet transform (EWT), and empirical mode decomposition (EMD) methods. In addition, statistical methods are used to improve the effectiveness of the feature vector. The CNN model was used to define or classify people. The performance of the developed system was evaluated using Accuracy, Precision, Sensitivity, F-score parameters. As a result, a classification success of 95.66 % was achieved with the developed EMD-CNN method, 94.10 % with the DWT-CNN method, and 93.33 % with the EWT-CNN method. The artificial intelligence model presented in this study explains the effectiveness of EMG signals in person recognition or classification as a biometric identification system. Furthermore, the developed model shows promise for the development and design of future biometric recognition systems.**

***Index Terms*—Biomedical informatics; CNN; EMG; Person identification.**

I. INTRODUCTION

With the development of technology, it is important to protect people's information security. In general, security systems are divided into three categories. These are knowledge-based systems (password, personal identification number (PIN), etc.), belonging-based systems (wristbands, magnetic cards, etc.), and biometrics-based systems (fingerprint, iris, face, voice, electromyography (EMG), electroencephalography (EEG), etc.) [1], [2]. Biometric systems are systems, developed to identify/confirm the identity of a person using the unique physical and behavioural characteristics of the body [3]. Recently, with the development of biometric sensors and machine learning algorithms, the use of biometric technologies in the field of security has increased. Conventional knowledge and belonging recognition systems are known to be fraud, theft, forgetfulness, and insufficient to protect personal information regarding information leakage [2]. Furthermore, the risks caused by personal faults cause major problems at the security level. Due to the problems that may occur in conventional recognition systems, usage is gradually decreasing. For higher security, biometric systems are widely used in financial instruments, military areas that require high security, and mobile phone access applications.

Biometric systems are divided into two groups, physiological and behavioural. The data obtained based on the physical and immutable characteristics of people are physiological biometric systems. Iris, face, retina, fingerprint, etc. are in the physiological category. Behavioural biometric systems based on the behavioural characteristics of the person are the data such as voice, wet signature, hand movements, and body signals.

Although biometric identification systems have a much higher level of security than traditional identification systems, they can be copied. For example, the reproduction of the face model with 3D printers, the copying of fingerprints using latex gloves, the recording of voice data with the help of recorders, and the copying of the iris using contact lenses are some of these [1].

Consequently, new biometric systems are needed that provide a high level of security. Especially with the development of wearable sensor technology, researchers have turned to biometric systems based on electrical signals that include physiological and behavioural features such as EEG [4], [5], EMG [1], and electrocardiography (ECG) [6]. The latent nature of electrical biosignals makes these signals difficult to mimic or synthesise and provides an advantage in distinguishing them from biological targets [7]. The ECG signals obtained from the heart muscles do not change due to the voluntary movements of the person. Therefore, it can only create a biometric signature, like other biometric data (iris, fingerprint, etc.). Electrical signals such as EEG and EMG include both voluntary behaviour (hand movement, gesture, etc.) and physiological characteristics of the person. It has been stated that as the number of movement types in EEG signals increases, the success rate of person classification decreases below 70 % [1]. Due to the high-accuracy of EMG-based biometric systems in motion recognition, individuals can create signatures with high-security features by identifying different muscle movements. This is the focus of our study.

In this study, EMG signals obtained from arm muscles

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were used. The convolutional neural network (CNN) model was developed to create a personal identification/classification system for the signals obtained.

Behavioural and physiological biometric data were generated with EMG signals collected during six different hand movements of two female and three male volunteers. With these data, 95.62 % accuracy was obtained with the empirical mode decomposition (EMD)-CNN model. It is believed that the proposed study will contribute significantly to biometric person identification problems.

II. RELATED WORKS AND CONTRIBUTIONS

Few studies have been conducted in the literature on EMG-based person identification/classification using the properties of biosignals for identification purposes. The most widely used methods are methods for determining the spectral characteristics of EMG signals based on conventional machine learning algorithms. The feature vector can be obtained using fast Fourier transform (FFT), discrete wavelet transform (DWT), and average frequency methods. These feature vectors can be classified by conventional methods such as support vector machines (SVM) [8], [9], multilayer perception (MLP) [8], [10], k-nearest neighbours (kNN) [11], and artificial neural network (ANN) [3].

Kim and Pan [12] obtained the vector of features of various wrist and hand movement activities using EMG signals and filterbank and waveform length (WL) feature extraction methods. Dimension reduction analysis was performed with the principal component analysis (PCA) and linear discriminant analysis (LDA) methods. A person recognition model was proposed with an accuracy rate of 86.66 % using SVM and kNN classification methods. Raurale, McAllister, and Del Rincon [10] proposed EMG signals of arm movement activity from five volunteer subjects for person recognition using an armband and 92 % success was achieved. Shin, Kang, Jung, and Kim [9] performed a person identification/classification analysis using EMG signals from five wrist movements. The root mean square (RMS), WL, integral EMG (IEMG), simple square integral (SSI), and variance (VAR) feature extraction methods were used and achieved an accuracy value of 87.1 % using the SVM algorithm for person classification. Shioji, Ito, Ito, and Fukumi [13] proposed a person identification and classification model using biometric-based EMG signals and achieved an average accuracy of 94.5 % using the CNN model.

Contribution 1: This paper is the first study to develop a model using EMG signals to determine frequency components in signals with DWT, EWT, and EMD methods. Results were found with a 95.62 % validation with CNN deep learning algorithm.

Contribution 2: A model is proposed that uniquely identifies or classifies people with six wrist movements of EMG signal data. The model, developed with the data set that detects the activities in four different muscle groups with the help of sensors, raises the level of accuracy to higher levels.

Contribution 3: By combining two different strengths with EMG signals, both voluntary behaviour and physiological characteristics, a model was developed to evaluate high-security person identification/classification problems. Thus, a new person authentication system is proposed based on a neuromuscular password.

Contribution 4: The CNN model is preferred because it has high-accuracy classification/recognition capacity by determining the feature vectors of the EMG signals coming from the input signals without expert knowledge.

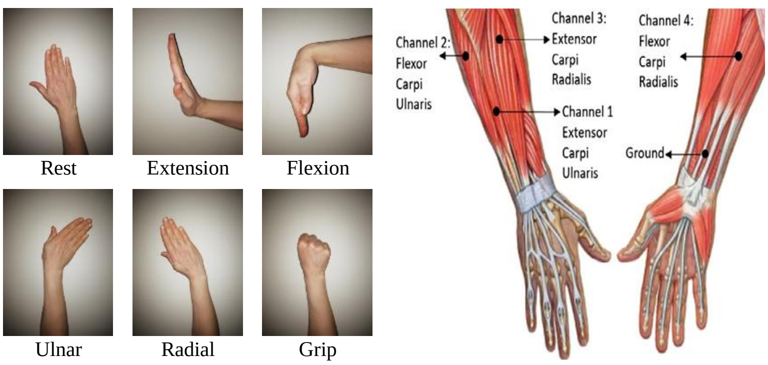
Contribution 5: Collecting EMG data with a portable armband sensor will be easy to apply to areas requiring high security, using this system in daily life.

III. MATERIALS AND METHODS

This study aims to develop a 1D-CNN model by obtaining the feature vector in EMG signals with DWT, empirical wavelet transform (EWT), and empirical mode decomposition (EMD) methods. The model was developed using EMG data (Fig. 1) recorded with six wrist movements by five subjects.

A. Data Set

The publicly available Mendeley data set [14] was used in this study. EMG signals were recorded at the Central Research Laboratory of İzmir Katip Çelebi University using the MP36 BIOPAC device with a sampling frequency 2000 Hz. Five participants/subjects, two women (ages 23, 24) and three men (ages 22–24), participated in the experiments. The EMG data were collected from the dominant hand of each participant. EMG signals were obtained from the surface muscles of the extensor carpi radialis, flexor carpi radialis, extensor carpi ulnaris, and flexor carpi ulnaris (Fig. 1(b)) near the skin surface using a four-channel electrode system. Subjects were asked to perform the REST, EXTENSION, FLEXION, ULNAR, RADIAL, and GRIP movements as shown in Fig. 1(a).



(a) (b)

Fig. 1. (a) Six different hand gestures; (b) EMG measurement locations.

During the experiment, participants were asked to perform six movements with a duration of four seconds and a total length of 52 seconds with a rest period of four seconds in between. The experiment is repeated with five cycles for a total recording time of 380 seconds with 30-second rest intervals. Data were recorded for 380 s from each channel (Fig. 2).

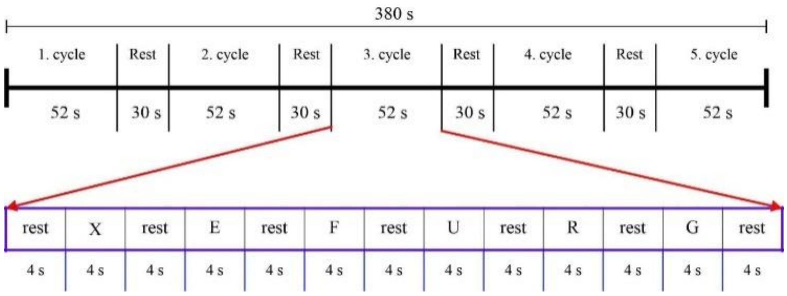


Fig. 2. Timeline of recordings (X: Rest, E: Extension, F: Flexion, U: Ulnar Deviation, R: Radial Deviation, G: Grip).

B. Discrete Wavelet Transform

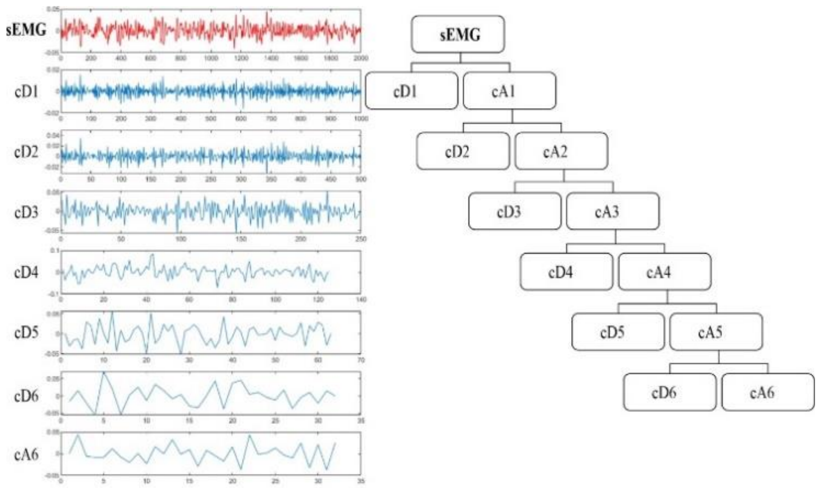
DWT is a conventional multiresolution analysis method for nonstationary signals. In general, wavelet-based techniques are a viable method in the analysis of variable signal types such as EMG [15].

DWT decomposes the signal to be analysed into frequency components using a variable window [16]. In the wavelet transform method, large time windows for low frequencies and short time windows for high frequencies are used [17]. It also offers the advantages of low computational cost and ease of implementation [18]. In DWT decomposition, signals are decomposed into multiple resolution coefficients using low- and high-pass filters. Different frequency bands make up the DWT coefficients. The detail (D) coefficients have a larger frequency and are more resolved over time. The approximation (A) coefficients at lower frequencies achieve superior frequency resolution [19], [20]. The original signal, filtered through a high-pass filter h(n) and a low-pass filter g(n), produces the output of the first decomposition level [16]. Equations (1) and (2) express these filters, respectively, as follows:

$$Z_{low} = \sum_{k=1}^{L} x[k] \times g[2n-k], \tag{1}$$

$$Z_{high} = \sum_{k=1}^{L} x[k] \times h[2n-k], \tag{2}$$

where Z_{low} represents the approximation and Z_{high} is for detail coefficients; $x[k]$ represents the EMG signal, L represents the width of the signal, $h[n]$ the high-pass filter, and $g[n]$ the low-pass filter. In this study, $N = 6$, in short, seven vectors will be obtained for each wavelet function to be used (Fig. 3). With the DWT method, important information can be obtained from EMG signals with a sampling frequency of 2000 Hz with a six-level analysis. In this study, the coefficient vector was obtained using the Db1 wavelet function.



(a) (b)

Fig. 3. EMG signals six coefficients (a) and DWT decomposition tree (b).

C. Empirical Wavelet Transform

EWT is an adaptive signal decomposition method based on the information content of the input signal [21], [22]. Unlike wavelet transform and Fourier transform methods, they do not use predetermined basic functions. Instead of predefined filterbank structures, such as conventional wavelet transform methods, EWT uses structures adaptively according to the spectral distribution of the signal [23].

When analysing the signal in the EWT method:

1. Due to the need for symmetry, the signal must be real-valued;
2. The frequency axis of the signal with 2pi period is considered.

However, due to Shannon's sampling criteria, analyses are performed in the range of [0, pi]. The N mode is predefined, which determines how many segments the input signal will divide into in the range [0, pi]. In this study, the analysis was performed by dividing the input signal into $N = 6$ segments.

Each segment is associated with the Littlewood-Paley wavelet function. Thus, six empirical wavelet coefficients (Fig. 4) are obtained corresponding to the approximation (low frequencies) and detail (high frequencies) coefficients [21].

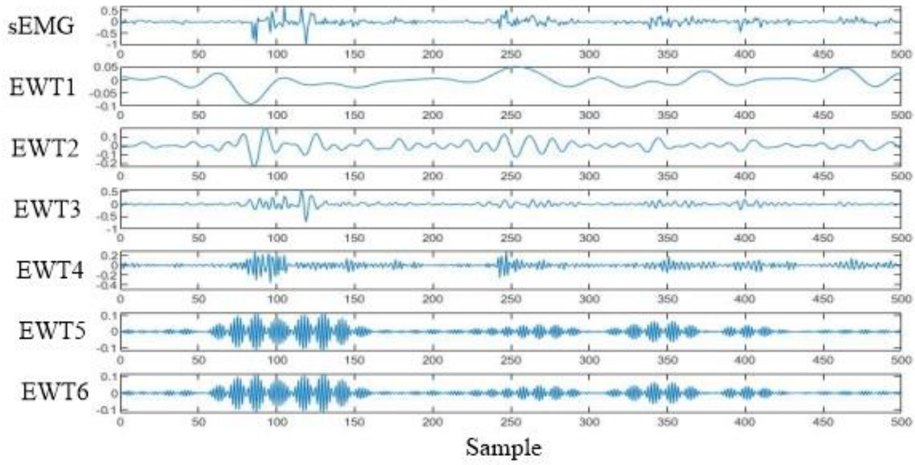


Fig. 4. EWT decomposition modes.

D. Empirical Mode Decomposition

The EMD method is a method developed by Huang *et al.* [24] to analyse stationary and nonlinear data [25]. EMD is a method in which a complex data set can be decomposed into adaptive finite and intrinsic mode functions (IMF). It is a widely used model in biomedical analysis because it preserves the properties of the input signal after decomposition [24]. Two conditions must be met for each IMF to be established:

1. The number of extremums and zero crossings in the data set must be equal or differ by at most 1;
2. The mean value of the envelope defined by the local maximum and local minimum should be 0.

The EMD algorithm follows these steps to split the signal into IMFs [25]–[29]. Input signal $x(t)$:

Step 1: Find all the maximum and minimum points in the input signal $x(t)$. By combining these points with interpolation, the upper range $u(t)$ and the lower range $v(t)$ are obtained.

Step 2: By averaging the upper envelope $u(t)$ and the lower envelope $v(t)$, the average envelope of the input signal $x(t)$, m_1, is obtained.

Step 3: Using (3), the h_1 signal is obtained by subtracting the mean envelope m_1 from the input signal $x(t)$

$$h_1 = x(t) - m_1. \tag{3}$$

Step 4: If the h_1 signal obtained does not meet the IMF characteristics, the first three steps are repeated. This is called the elimination process. h_{1k} is obtained by repeating (4) k times. The iteration is terminated when the number of zero crossing points and the number of endpoints do not change. The first IMF component $c_1 = h_{1k}$ is obtained

$$h_{1k} = h_{1k-1} - m_{1k}. \tag{4}$$

The first IMF component c_1 is subtracted from the input signal $x(t)$ and the residual signal r_1 is obtained (5)

$$r_1 = x(t) - c_1, \tag{5}$$

$$r_n = r_{n-1} - c_n. \tag{6}$$

The c_1 signal represents the highest frequency component of the EEG signal. r_1 is treated as a new signal, and the operations are repeated (6).

Step 5: Finally, the EMD process generates n IMFs $c_1(t)$ to $c_n(t)$ IMFs. The input signal $x(t)$ can be represented by (7)

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t). \tag{7}$$

In this study, 10 IMF component levels were obtained in the EMD method applied to EMG signals. The first four levels of IMF components (IMF1, IMF2, IMF3, and IMF4), which are high-frequency components, were used to obtain the feature vector (Fig. 5). The IMF0 component represents the highest frequency signal of the EMG signal.

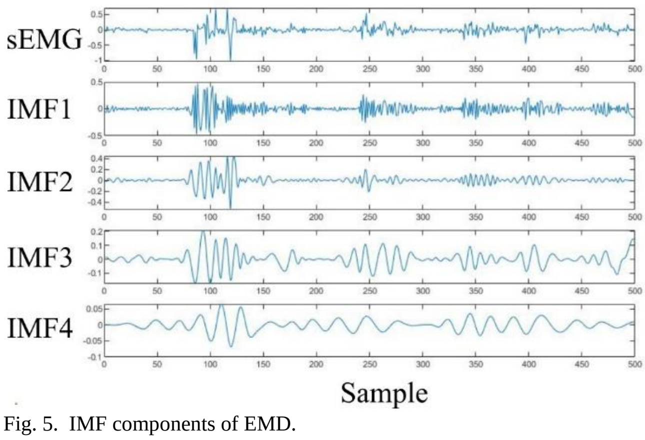


Fig. 5. IMF components of EMD.

E. Feature Extraction

Determining the time and frequency characteristics of EMG signals in biometric person recognition/classification problems directly affects the performance of the model [30]. DWT and EWT decomposition techniques represent EMG signals as six-wavelet coefficient signals. The EMD method, on the other hand, will represent the four IMF components with the highest frequency, whose size is the same as the input

EMG signal. These data (wavelet coefficients and IMF components) are transformed into a reduced feature vector, representing an important step in classification processes [31]–[33]. Since these features characterise the behaviour of EMG signals, their selection is very important. Seven statistical methods are selected below for the classification of EMG signals.

1. Average of the absolute value (8) of signals in each subband

$$\mu = \frac{1}{N}\sum_{i=1}^{N}|y_i|. \tag{8}$$

2. The standard deviation (9) of the signals in each subband

$$\delta = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left((y_i-\mu)\right)^2}. \tag{9}$$

3. The skewness (10) of the signals in each subband

$$\varnothing = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{(y_i-\mu)^3}{\delta^3}}. \tag{10}$$

4. The kurtosis (11) of signals in each subband

$$\varnothing = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{(y_i-\mu)^4}{\delta^4}}. \tag{11}$$

5. The median (12) of the signals in each subband

$$Median = \begin{cases} \dfrac{(N+1)}{2}, \text{ when } N \text{ is odd}, \\ \dfrac{N}{2}+\dfrac{(N+1)}{2}, \text{ when } N \text{ is ever}. \end{cases} \tag{12}$$

6. RMS values (13) of signals in each subband

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}y_i^2}. \tag{13}$$

7. The ratio of the mean absolute values of the coefficients of adjacent (14) subbands

$$X = \frac{\sum_{i=1}^{N}|y_i|}{\sum_{i=1}^{N}|z_i|}. \tag{14}$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this study, a computer with an IntelCore i7 2.2 GHz processor and 32 GB RAM was used. The Python programming language was used in the developed classification model. TensorFlow, Keras, and basic Python libraries were used as model tools.

Signals were collected using bioarmband sensors from five different volunteers to perform six different wrist movements. For each movement pattern, a five-class classification issue was constructed independently. The suggested approach worked to solve the five-class person identification problem for six distinct movement patterns. The recording times of the four-channel EEG data set are shown in Fig. 2. 85 % of this data set was used as training data and 15 % as test data, and the data were randomly separated.

The architecture of the proposed person identification method using the DWT, EWT, EMD feature extraction algorithms, and CNN classification algorithm is shown in Fig. 6. First, EMG signals were obtained from six different wrist movements in four-channel form with bioarmband sensors from volunteers. By selecting six wrist movement signals recorded for 4 s from each volunteer, a 96 s (=24 s × 4 channels) long, five cycles (Fig. 2) repetition of 480 s (1 × 960000 samples) long vectors were obtained. The EMG signals of five volunteers (5 × 960000 samples) were determined as input to the developed model.

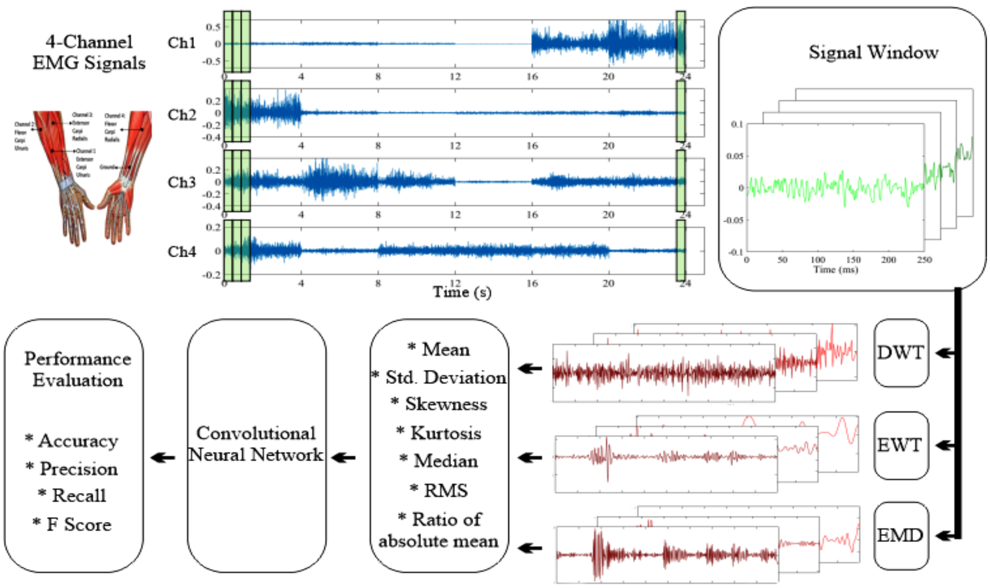


Fig. 6. The architecture of the personal identification method.

The input vector is divided into 250 ms (500 samples) windows and prepared for the feature vector (9600 × 500 samples) The 250 ms long signal was first analysed by the six-level-DWT method.

Wavelet coefficients were obtained at six different frequency levels for the analysed signals using the Db1 (Haar) wavelet function. In the EWT method, a six-level wavelet coefficient vector was obtained by using the Littlewood-Paley wavelet function. In the same way, the IMF coefficients were calculated at four levels to analyse the high-frequency components in the EMD method. To characterise the statistical properties of the coefficients by the DWT, EWT, and EMD methods, the mean, standard deviation, skewness, kurtosis, median, RMS, and ratio of the mean absolute values of the subvectors of each method were calculated and the feature vector was obtained for classification.

Finally, the obtained feature vector was classified using the CNN deep learning algorithm. There are generally three main layers in the structure of the CNN algorithm:

1. Convolutional layer;
2. Pooling layer;
3. Fully connected layer.

The convolutional layer is the main part of the CNN model. The primary purpose of the convolutional layer is to extract features from the input data. The pooling layer is used to reduce the amount of parameters and computational load used in the CNN architecture. The purpose of pooling is to reduce the size of the data set and prevent overlearning. A fully connected layer is used to connect each neuron in the previous layer to each neuron in the next layer [34], [35]. The CNN architecture proposed in this study consists of an input layer, two convolutional layers, and three fully connected layers. The layer output values are obtained by multiplying the input values in the convolutional layers with the weight values in the layers. In addition, filters in layers are used for learning.

The filters are randomly generated at startup. During training, the optimum filters are tried. The parameter values of the CNN architecture are presented in Table I.

TABLE I. CNN LAYER FEATURES OF THE PROPOSED MODEL.

Layers	**DWT-CNN**	**EWT-CNN**	**EMD-CNN**
Input Data	Input Train Data: 8160 × 48 × 1	Input Train Data: 8160 × 40 × 1	Input Train Data: 8160 × 28 × 1
Convolution_1	Num Filter: 32 Filter_Size: 4 Activation: ReLu	Num Filter: 32 Filter_Size: 4 Activation: ReLu	Num Filter: 32 Filter_Size: 4 Activation: ReLu
Convolution _2	Num Filter: 16 Filter Size: 4 Activation: ReLu	Num Filter: 16 Filter Size: 4 Activation: ReLu	Num Filter: 16 Filter Size: 4 Activation: ReLu
FullyConnected_1	Size: 120 Activation: ReLu	Size: 120 Activation: ReLu	Size: 120 Activation: ReLu
FullyConnected_2	Size: 60 Activation: ReLu	Size: 60 Activation: ReLu	Size: 60 Activation: ReLu
FullyConnected_3	Output: 5 Activation:sigmoid	Output: 5 Activation:sigmoid	Output: 5 Activation:sigmoid

The feature vector obtained from the DWT, EWT, and EMD methods consists of a total of 9600 samples. 8160 samples are for the training and 1440 samples are randomly allocated for testing. Except for the last layer of the model, which consists of two convolutional layers and three fully connected layers, rectified linear units (ReLU) were used as the activation function in other layers. The softmax function is used in the last layer. ADAM was used as the optimisation function of the model, and cross-entropy was used as the loss function.

The Accuracy, Precision, Sensitivity, and F-score parameters were used to analyse the performance of the methods proposed in this study. Accuracy is the ratio of the number of correctly classified samples to the total number of samples (15), Precision is the ratio of correct positive values to the classified positive values (16), Sensitivity is the ratio of the number of correctly classified samples to the number of positive samples (17), and F-score is the harmonic mean of Sensitivity and Precision values (18):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \quad (15)$$

$$Precision = \frac{TP}{TP+FP}, \quad (16)$$

$$Sensitivity = \frac{TP}{TP+FN}, \quad (17)$$

$$F-score = 2\times\frac{Precision\times Sensitivity}{Precision+Sensitivity}. \quad (18)$$

True Positives (TP) are the number of correctly predicted samples, False Negatives (FN) are the number of incorrectly predicted samples, True Negatives (TN) are the number of correctly predicted negative samples, and False Positives (FP) represent incorrectly predicted negative samples [36].

In the proposed method, the Accuracy, Precision, Sensitivity, and F-score parameters were calculated after running 100 iterations. The results of the performance analysis of the five-class person classification problem are presented in Table II.

TABLE II. THE MODEL PERFORMANCE FOR PERSON IDENTIFICATION.

	DWT-CNN	**EWT-CNN**	**EMD-CNN**
Accuracy	%94,10	%93,33	%95,62
Precision	%94,11	%93,40	%95,64
Sensitivity (Recall)	%94,14	%93,42	%95,65
F-Score	%94,11	%93,41	%95,64

According to Table II, the lowest classification accuracy of 93.33 % was obtained with the EWT-CNN model. The highest accuracy value of 95.62 % was calculated with the EMD-CNN model. Furthermore, in the EMD-CNN method, the precision value was 95.64 %, the Sensitivity value was

95.65 %, and the F-Score value was calculated as 95.64 %. The confusion matrix expressions for all three models are presented in Fig. 7.

In this study, a new nonlinear model-based classification method was developed for people's classification/recognition problems using EMG signals. With the proposed model, high-accuracy recognition/classification of people can be achieved. The comparison of the results obtained in this study with the person classification/recognition studies using EMG signals is shown in Table III. The EMG signal has the feature of showing a different signal for each movement when a person makes different movements

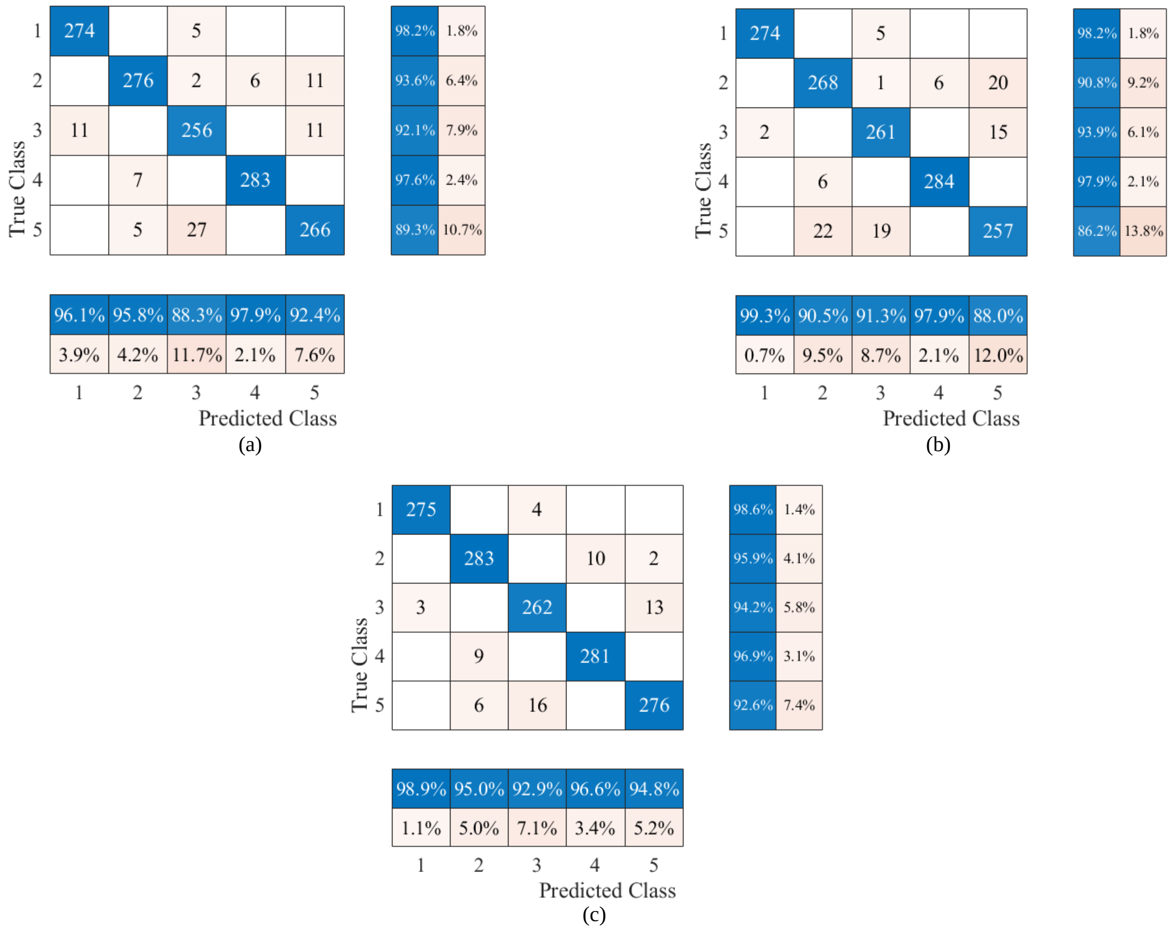


Fig. 7. Confusion matrix for each model: (a) DWT-CNN confusion matrix; (b) EWT-CNN confusion matrix; (c) EMD-CNN confusion matrix.

TABLE III. PERSON IDENTIFICATION COMPARISON EXPERIMENT.

Reference	Feature extraction method	Classification method	Account of pattern	Gesture	Accuracy
Shin, Kang, Jung, and Kim [9]	RMS, WL, IEMG, SSI, VAR	SVM (Cubic)	5	5	%87,1
Raurale, McAllister, and Del Rincon [10]	BP, RSS	DT	5	8	%90,2
		MLP			%91,6
		SVM			%91,3
		RBF-NN			%91,7
Shioji, Ito, Ito, and Fukumi [13]	-	CNN	3	1	%94.6
Khan, Choudry, Aziz, Naqvi, Aymin, and Imtiaz [30]	EMD	SVM kNN DT	10	1	%95,3
Lu, Mao, Wang, Ding, and Zhang [35]	DWT, CWT	CNN	21	1	%99,2
Li, Dong, and Zheng [37]	MAV, VAR	SVM	10	1	%98,2
Morikava, Ito, Ito, and Fukumi [38]	-	CNN	6	5	%47,6
Shioji, Ito, Ito, and Fukumi [39]	-	CNN	8	3	%94,6
Proposed	DWT, EWT, EMD	CNN	5	6	%95,62

For this reason, the performance of biometric classification studies that involve a large number of gestures is low. In this study, six different biometric movements were classified using EMG signals based on the CNN model. Most similar studies given in Table III have conducted biometric studies using less than five movements. However, in our study, a higher accuracy was obtained with six movements than in other studies. The proposed EMG-based person recognition/classification system may not be suitable for people with neurodegenerative disorders due to its ability to detect signals. Additionally, it may be necessary to generate larger data sets for further research on the robustness and stability of EMG-based person recognition systems.

V. Conclusions

In this study, a new CNN-based method was developed for person recognition/classification using EMG signals recorded during hand movements, and high-accuracy results were obtained in person classification/recognition problems with the proposed model. According to the results obtained, a classification success of 95.62 % was achieved with the EMD-CNN method. These results demonstrated the success of the person classification/recognition problem using nonlinear physiological and behavioural biometric EMG signals. Physiological EMG electrical signals that occur in the arm muscles during voluntary wrist behaviour movements of the person cannot be copied, recorded, or played by others. The model developed in this study provides higher security than the existing conventional methods. Banks, Military zones requiring high security, R&D and Test centers, etc. Biometric recognition systems, iris, and fingerprint encryption methods can be copied using contact lenses and latex gloves. However, since EMG signals, obtained with physiological and behavioural movements, cannot be copied in person recognition/classification problems, it is thought to provide very high security.

In addition, the proposed method is thought to be used in wearable bioarmband sensor devices and to be used in real-time person recognition/classification problems.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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