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Biometric Personal Classification with Deep Learning Using EMG Signals

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Abstract: Biometric person recognition systems are becoming increasingly important due to their use in places requiring high security. Since it includes the physical and behavioral characteristics of people, the iris structure, which is a traditional person recognition system, is more secure than methods such as fingerprints or speech. In this study, a deep learning-based person classification/recognition model is proposed. The Gesture Recognition and Biometrics ElectroMyogram (GrabMyo) dataset from the open access PhysioNet database was used. With the 28-channel EMG device, 10 people were asked to make a fist movement with their hand. During the fist movement, data were recorded with the EMG device from the arm and wrist for 5 seconds with a sampling frequency of 2048. The Empirical Mode Decomposition (EMD)) method was chosen to determine the spectral properties of EMG signals. With the EMD method, 4 IMF signal vectors were obtained from the high frequency components of the EMG signals. The classification performance effect of the feature vector is increased by using statistical methods for each IMF signal vector. Feature vectors are classified with CNN and LSTM methods from deep learning algorithms. Accuracy, Precision, Sensitivity and F-Score parameters were used to determine the performance of the developed model. An accuracy value of 95.57% was obtained in the model developed with the CNN method. In the LSTM method, the accuracy value was 93.88%. It is explained that the deep learning model proposed in this study can be effectively used as a biometric person recognition system for person recognition or classification problems with the EMG signals obtained during the fist movement. In addition, it is predicted that the proposed model can be used effectively in the design of future person recognition systems.

Keywords: EMG, Personal Classification, Empirical Mode Decomposition, CNN, LSTM.

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1. INTRODUCTION

Electromyography (EMG) is a test used to measure the electrical activity of muscles. When muscles contract, muscle fibres produce electrical signals. By measuring these signals, EMG can give information about how well the muscles are working and whether the nerves are sending signals to the muscles.(Phinyomark et al., 2011; Shin et al., 2017) "Electro" means muscles and "myography" means measuring the activity of muscles. EMG works by recording the electrical signals that muscles in the body produce during their contraction. Muscles are controlled by nerves, and nerves transmit electrical signals to the muscles from the brain, making them move. EMG records the electrical signals obtained from these muscles using small metal electrodes called electrodes. Electrodes are placed on the skin surface and detect the electrical activity from the muscles. They are used for many diseases, especially Peripheral neuropathy, Muscular dystrophy, Myoclonus, Shivering, Amyotrophic lateral sclerosis (ALS), Polymyositis, Rheumatoid arthritis, Muscle injuries. EMG is performed by a neurologist or physical therapist(Shioji et al., 2018; Taşar, 2022; Venugopalan et al., 2015).

Person recognition systems are technologies used to authenticate, recognize or classify a person. These systems perform the recognition process using a person's unique physical or behavioural characteristics. There are different types of person recognition systems used to recognize people. Biometric Identification Systems is the process of authenticating or recognizing people using their unique physical or behavioural characteristics(Fan et al., 2022; Kim & Pan, 2017). Individuals are recognized using different biometric features such as fingerprint recognition, face recognition, iris recognition, retinal scan, finger vein, hand geometry, voice recognition and gait biometrics(Morikawa et al., 2019).

Face Recognition Systems, Face recognition systems are a type of biometric recognition that performs authentication or recognition using people's faces. Face recognition classifies or matches people using the unique features and structures of the face. Fingerprint Recognition Systems, Fingerprint recognition is authentication or recognition using the fingerprints of people. Fingerprints are different for each person, thanks to the unique patterns on the outer surface of the fingers. Voice Recognition Systems: Voice recognition systems perform authentication or recognition processes using people's voices. Persons are recognized using their speaking styles, tones, and other vocal features. Retinal Scanning Systems: Retinal scanning is a type of biometric recognition used in person recognition using unique vascular patterns in the retinal layer of the eye. Finger Vein Recognition Systems, Finger vein recognition is authentication or recognition using vein patterns on the inner surface of the fingers. Hand Geometry Recognition Systems classify people using features such as hand geometry, the general shape of the hand, and the lengths of the fingers(Gui et al., 2019; Kim et al., 2021; Lu et al., 2020).

Person identification systems are used in security, access control, fraud prevention, person identification and other applications. However, it is important that these systems are implemented with ethical and confidentiality issues in mind(Jamaluddin et al., 2023; Kang et al., 2023). Appropriate measures should be taken to ensure the security of personal data and prevent misuse. There are very few studies of person identification/classification using EMG signals in the literature. For person classification problems, machine learning algorithms are generally used together with the method of determining the spectral properties of EMG signals. A feature vector can be obtained by methods such as the Fast Fourier Transform (FFT), DWT, EWT. It can be classified by methods such as Artificial Neural Network (ANN)(Shin et al., 2017), Support Vector Machines (SVM)(Raurale et al., 2021; Shin et al., 2017), Multi-Layer Perception (MLP)(A. Raurale et al., 2020; Raurale et al., 2021), Decision Tree (DT)(Ramírez-Arias et al., 2022).

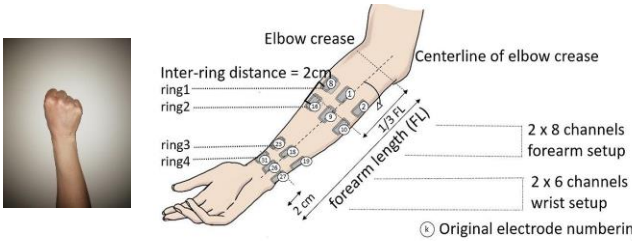
Kim et al.(Kim & Pan, 2017) proposed a person classification study using EMG signals of different wrist and hand movements and SVM and kNN algorithms. In his study, he achieved 86.66% accuracy. Raurale et al. (Raurale et al., 2021)proposed EMG signals of eight different arm movement activities from five volunteers for person classification. Accuracy values were 90.2% with the DT method, 91.6% with the MLP method, 91.3% with the SVM method and 91.7% with the ANN method. Shin et al.(Shin et al., 2017) obtained 87.1% accuracy in person classification problems with EMG signals using the SVM algorithm. Shioji et al. (Shioji et al., 2017) obtained an average accuracy of 94.5% with the proposed method using the CNN model. The aim of this article is to look into the capabilities of sEMG signals, electrical signals produced by various muscle actions. This study also explores how well the EMD approach can identify people. The suggested methodology is anticipated to significantly improve issues with biometric person recognition.

2. MATERIAL AND METHOD

In this study, the feature vector of EMG signals was found by using the EMD method and statistical parameters. A person recognition/classification model has been developed with CNN and LSTM methods, which are deep learning algorithms.

2.1. Dataset

In this study, the Gesture Recognition and Biometrics ElectroMyogram (GrabMyo) dataset from the open-access PhysioNet database was used (Pradhan et al., 2022). A personal recognition model was developed (Fig.1). Data were recorded with the EMG device for 5 seconds at a sampling frequency of 2048 Hz (Figure 3). Each person repeated the fist movement of the hand seven times.



a b

Figure 1. (a) Fist gesture of the hand, (b) EMG measurement regions

The data obtained from each channel was divided into 500 ms (1024 samples) windows and 4 level IMF components were analysed by EMD method.

2.2. Feature Extraction

Huang et al. The Empirical Mode Decomposition (EMD) method proposed by(Huang et al., 1998) is a method developed to analyse nonlinear signals (Mishra et al., 2016). It is a method that can be decomposed into frequency subcomponents (IMF) when applied to complex signals with the EMD method. It is used in the analysis of biomedical signals because it preserves the characteristics of the input signal after decomposition into sub-bands (Huang et al., 1998).
In this study, 4 levels of IMF components were obtained in the EMD method applied to the EMG input signal. The highest frequency components IMF0, IMF1, IMF2 and IMF3 levels were used to create the feature vector (Fig.2).

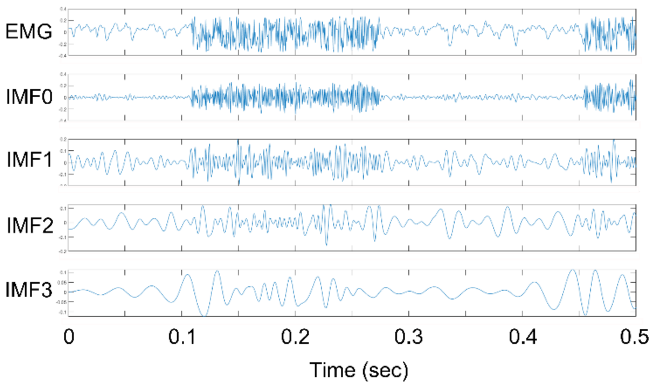


Figure 2. Four IMFs levels of EMD

In biometric person classification problems, the properties of time and frequency components in EMG signals affect the success of the model(Khan et al., 2020). The feature vector to be obtained will be determined by the EMD method with 4 IMF components whose dimensions are the same as the input signal. Seven statistical methods were chosen to characterize the frequency behaviour of signals in the IMF components(Albaqami et al., 2021; Gaso et al., 2021).

1. The mean of the absolute value of each IMF signal

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

2. Standard deviation of each IMF signal,

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

3. The skewness of each IMF signal,

$$\emptyset = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{(y_i - \mu)^3}{\delta^3}}$$

4. Kurtosis of each IMF signal

$$\emptyset = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{(y_i - \mu)^4}{\delta^4}}$$

5. The median of each IMF signal

$$Median = \begin{cases} \dfrac{(N+1)}{2}, When\ N\ is\ odd \\ \dfrac{N}{2} + \dfrac{(N+1)}{2}, When\ N\ is\ ever \end{cases}$$

6. RMS values of each IMF signal

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

7. The ratio of the average absolute values of the coefficients of the adjacent IMF signal

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

3. RESULTS

The model developed in this study was implemented in the Python programming language and in the Spyder editor. Deep learning algorithms were implemented using Tensorflow and Keras libraries.
Data were collected with the bio-armband sensor placed on the wrists and arms of 10 different volunteers by making a fist movement of the hand. The obtained data were separated into 4 different frequency sub-bands with the EMG algorithm and a feature vector was obtained with statistical methods. Classification was done with CNN and LSTM methods, which are deep learning algorithms. 85% of the dataset was used as training data and 15% as test data.

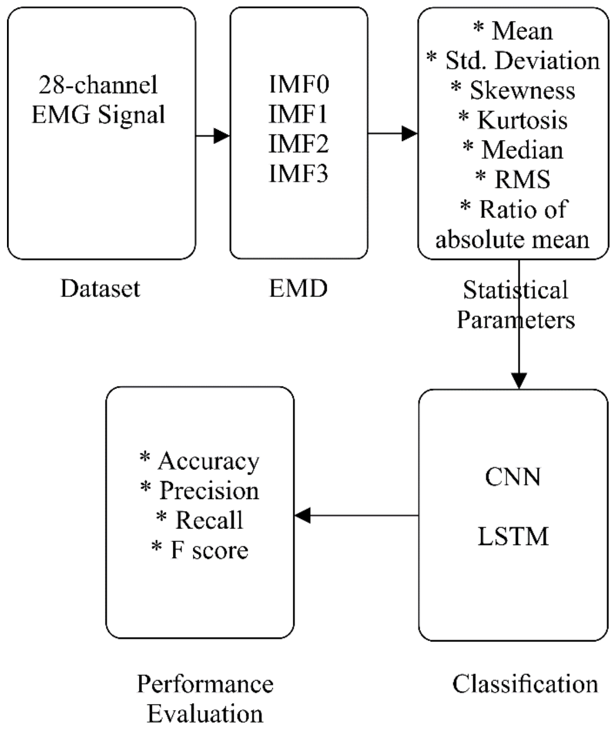


Figure 3. Architecture of the personal classification method

The classification model of the feature vector obtained by EMD and statistical parameters with CNN and LSTM deep learning algorithms is shown in Figure 3.
With the 28-channel EMG device, 10 different volunteers made fist movements for 5 s, and EMG signals were obtained with the bio-armband sensor. The data set was created by repeating the fist movement of each volunteer hand 7 times. Signals were collected with a sampling frequency of 2048 Hz.

The signals obtained from each volunteer were divided into 500 ms (1024 samples) long windows and analysed. The highest 4 level IMF coefficients of the input signal were calculated with the EMD method. In order to characterize the properties of these coefficients, the Mean, Standard deviation, Skewness, Kurtosis, Median, RMS and Ratio of absolute mean values of each IMF vector were calculated and a feature vector was obtained to classify with CNN and LSTM methods from deep learning algorithms.

The resulting feature vector was first classified by the CNN method. The CNN algorithm generally consists of three main layers. The first layer, the Convolutional layer, forms the main layer of the model. The main task of the first layer is to calculate the features from the input data. The second layer pooling layer performs less computation by reducing the number of parameters used in the model. The third layer, Fully-connected layer, is used to connect each neuron in the previous layer to the next layer.

In the model developed with the CNN method, 2 convolutation layers and 3 fully-connected layers are used. In the output layer, the softmax function is chosen as the activation function and ADAM is chosen as the optimization function of the model.

In order to compare the results obtained with the CNN model, the second classification method was classified with the LSTM algorithm. The LSTM algorithm is a special type of RNN model developed by Hochreiter & Schmidhubert at the end of 1990, which is applied for the analysis of sequential data.

In the LSTM model, each block consists of three layers: forget input and output. The forget layer uses the sigmoid function to decide which of the input signals to delete. In the second layer, the input signals are updated using the sigmoid and tanh functions. By using the tanh function in the output layer, it provides learning by the model in a way that minimizes the difference between the training values and the output values.

In the LSTM model implemented in this study, the LSTM layer consisting of 100 blocks was first created. 2 Dense layers (1st Dense layer 60 neurons, 2nd Dense layer 30 neurons) were used to transfer information between layers. In the last layer, the output values of each class were obtained with the softmax function used in multiple classification problems.

In this study, accuracy, precision, sensitivity and F-score parameters were used to evaluate the classification performance of the feature vector obtained by the EMD method.

Table 1. Model performance for personal classification

	CNN	**LSTM**
Accuracy	%95,57	%93,88
Precision	%95,65	%94,15
Sensitivity (Recall)	%95,57	%93,82
F-Score	%95,58	%93,86

After running 100 iterations with the CNN algorithm and 200 iterations with the LSTM algorithm, the accuracy, precision, sensitivity and F-score values are shown in Table 1. In the proposed method, it is seen that CNN and LSTM methods make classification with high accuracy. However, with the CNN method, higher classification performance was obtained with an accuracy rate of 95.57%.

4. DISCUSSION AND CONCLUSIONS

In this study, a nonlinear model was developed for person classification problems by using the EMG signals obtained with the fist movement of the hand. In both proposed models, person classification can be made with high accuracy. In Table.2, it is seen that higher accuracy was obtained than the related studies.
In the biometric person classification model, the physiological EMG signals that occur in the wrist and arm muscles during the voluntary behavioural fist movement of the individuals are non-reproducible. Since both behavioural and physiological features are used in person recognition with EMG signals, it provides much higher security than existing traditional methods.

Table 2. Personal classification comparison experiment

Reference	Classification method	Account of pattern	Accuracy
Shin et al. (Shin et al., 2021)	SVM (Cubic)	5	%87,1
Khan et al. (Khan et al., 2020)	SVM kNN DT	10	%95,3
Shioji et al. (Shioji et al., 2017)	CNN	3	%94.6
Li et al. (Li et al., 2020)	SVM	10	%98,2
Raurale et al (Raurale et al., 2021)	DT	5	%90,2
	MLP		%91,6
	SVM		%91,3
	RBF-NN		%91,7
Morikava et al (Morikawa et al., 2019)	CNN	6	%47,6
Ryohei Shioji et al. (Shioji et al., 2018)	CNN	8	%94,6
Proposed	**CNN**	**10**	**%95,57**
	LSTM		**%93,88**

The model developed in this study will provide safer access with the use of banks, military zones, R&D centres and places requiring high security. It can be said that EMG, which is a safer person recognition method than traditional methods such as face recognition and iris recognition, will be safer by using electrical signals and behavioural and physiological features.

Ethics Committee Approval
N/A

Author Contributions
All authors have read and agreed to the published version of manuscript.

Conflict of Interest
The authors have no conflicts of interest to declare.

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