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Proposing a novel attention-based deep neural network (ABCL-EHI) for EEG-based human biometric identification

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ABSTRACT

The paper introduces a new method called ABCL-EHI for human identification using electroencephalographic (EEG) signals. EEG signals have unique information among individuals, but current systems lack accuracy and usability. ABCL-EHI addresses this by combining a convolutional neural network and a long short-term memory network with an attention mechanism which enhances the utilization of spatial and temporal characteristics of EEG signals. The proposed system is evaluated using a public dataset of EEG signals. The results demonstrate that ABCL-EHI achieves high accuracy while using high or low number of channels. This outperforms previous studies and highlights the system's reliability and ease of deployment in real-life.

Keywords: Healthcare Data Analytics, Machine Learning, Physiological Signal Processing, CNN, LSTM

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1 Introduction

The user identification system is a key component in different systems and is deployed in many real-life applications such as the internet of things (IoT), healthcare systems and is also used to manage access to physical and digital resources such as borders, buildings, cellphones and computing devices by identifying or confirming user's identity to protect the restricted content from unauthorized access [2,3].

The biometric recognition process is often performed between a human and a machine and is usually based on some unique information about the specified user called authentication factors [1,3]. Generally, there are three types of authentication factors. First, the knowledge factor, which is information only the user knows. The second, ownership factor, which is an object only the user owns, and the third one, known as a biometric factor, is the user's physical or behavioral characteristics [1].

Despite the popularity, passwords or smart cards are considered classic factors for subject identification. They suffer from some critical drawbacks, such as getting stolen or being forgotten by the user. By the passage of time, password-based security has gradually been replaced by the use of biological characteristics of the user [1-3]. Although different biometric factors such as iris, palm, voice, and fingerprint can be monitored and processed automatically, these biometric factors also have serious weaknesses, making biometric identification susceptible to possible attacks [1, 2, 4]. For instance, Biometric factors such as iris, voice, and fingerprints may be forged or imitated by attackers [5]. Some researchers have proven that fingerprints can be faked by just having a picture of one's finger or by using a fingerprint left on surfaces and obtained by malicious attackers. Moreover, irises and voices can be extracted from high-quality audio recordings, videos, and photos [3, 5].

Recently, researchers have shown great interest in taking advantage of biometric signals such as electroencephalogram (EEG), electrocardiogram (ECG), and Electromyography (EMG) as appropriate biometric factors for biometric identification [3, 6, 7]. These signals have numerous advantages over other mentioned biometric factors. For example, they are more robust and safer against attacks [1]. Among biometric signals, EEG biometrics has paramount advantages, which makes it desirable. As a result, researchers have gained a great interest in developing EEG-based biometric identification [1, 8].

EEG represents the neural activities of the human brain. It has various characteristics which depend on the person's brain structure and is highly affected by a person's memory, mood, stress, and mental state [1, 3]. Therefore, EEG signals are unique and nearly impossible to be faked or mimic [1, 9, 10].

Moreover, an EEG recording headset must be attached to the user's head to record EEG signals. As they must be conscious, it significantly reduces the chance of attacks [3]. Furthermore, EEG based biometric identification can be integrated by other fields of computer science. Brain-Computer Interface (BCI) is an outstanding example of this issue [1, 4, 11]. In the BCI, the humans control an electronic device by using explicit and direct commands and brainwaves. Since BCI is based on the brain signals, Integrating BCI and EEG-based biometric identification leads BCI systems to execute the user's commands and recognize their identity before execution of commands [1, 11, 12].

Despite numerous advantages and the growing popularity of EEG-based biometric identification, some aspects must be addressed to pave the way to utilizing these systems in real-world user identification.

For instance, while recording EEG signals, users usually must perform a specific task under predefined protocols, which may not be convenient for some of them. Furthermore, the number of channels required for sampling EEG signals in previous works is more than the number of electrodes in most commercially available EEG recorder devices, making the current EEGbased biometric identifications challenging to use in practice [1]. As a result, the number of required channels in EEG-based human identification should be reduced as much as possible without significant degradation of the system’s overall accuracy.

Another point to mention is that as far as we know, most of the previous studies have considered a small population of subjects in training and evaluation of their proposed approach, which decreases the generalization of their proposed approach [1, 3, 8]. Moreover, most of them have applied handcrafted feature extraction methods and classified them using conventional machine learning methods such as support vector machine (SVM) [13, 14], k-Nearest Neighbors and, Eigenvectors [15].

In recent years, deep neural networks have also been used for EEG-biometric identification [1, 3, 4, 8]. To the best of our knowledge, most of the previously proposed deep EEG Biometric identification systems have been based on Convolutional neural networks (CNNs) [15-21]. Although CNNs have shown an appropriate performance in extracting reliable features from static data, such as images and part of signals, they cannot take temporal and prior information in the time-series signal into account [3, 4].

In EEGbased biometric identification, the input signals are the time-series of potential electrical fluctuations recorded from different areas of the brain, and features can be extracted from any spatial domain, time domain, and frequency domain [1]. Hence, some works have applied deep neural networks, including Recurrent Neural Networks (RNNs) such as “Repeatable Gateway Units” (GRUs) and “Long-Short Term Memories” (LSTMs) in their proposed EEG Based biometric identification to consider both spatial and temporal information of EEG signals [3, 22].

Although LSTM is supposed to capture the long-range dependencies better than the RNN, it tends to become forgetful in specific cases. Another problem is that LSTM cannot give more importance to some of the inputs compared to others. [23] came up with a reasonable solution by introducing the Attention mechanism. The attention mechanism has been one of the most important breakthroughs in Deep Learning models in the last decade. As a neural network is considered to be an effort to emulate human brain actions in a simplified manner, Attention Mechanism, in deep neural networks, is also an attempt to implement the same action by selectively concentrating on a few relevant areas while ignoring others [23].

In this paper, a novel attention-based CNN-LSTM model for EEG-based human identification (ABCL-EHI) is proposed in order to extract both temporal and spatial distinguishing characteristics of EEG signals in EEG-based user identification. The proposed approach can efficiently extract spatial and temporal features of EEG signals by taking advantage of the attention mechanism. The experimental results show that the proposed approach (ABCL-EHI) outperforms CNN-LSTM models which do not use the attention mechanism. It is worth mentioning that our proposed ABCL-EHI uses only one-second segments of EEG signals to identify users.

In this paper, we have used the motor imagery dataset from the PhysioNet database, which contains EEG signals collected from 109 subjects and a wide variety of imaginary and physical tasks for each Subject [24]. By including all 109 subjects and a variety of the performed tasks in training and evaluation of our proposed approach, we demonstrate that our EEG Based biometric identification can keep its great performance in large number of subjects and its robustness to the various performed task only by using 1-second segments of raw EEG signal as input.

The main novelties of this study lie in several folds, including:

- Proposing a novel attention-based CNN-LSTM model for EEG Based human identification.
- Proposing a model that can achieve high accuracy even by using the information of fewer EEG channels make our system easier to be deployed by users in real life.
- Using EEG signals associated with the various performed task by subjects in training and evaluation of a proposed system to make it more user-friendly by giving subjects the autonomy to choose their task of interest while being identified by the system.
- Proposing a high accuracy approach EEG-Based human identification under the condition of using EEG signals more than 100 subjects, six various tasks for each subject, and using only 1 second raw EEG signal as input.
- Taking advantage of different kinds of layers in our novel deep learning approach to efficiently exploit discriminative temporal and spatial characteristics of EEG signals.

2 Related works

The proposed EEG-based biometric identification systems in the literature are usually divided into machine learning models and deep neural networks. The first category can be considered as a two-step method consisting of extraction of distinguishing features and then applying a classification method on the extracted features [1, 3]. Different features such as power spectrum density, wavelet transforms, peak amplitude eigenvector centrality, statistical descriptors including mean and variance, and other features have also been used in previous studies for EEG biometric identification [1, 3, 8]. The second category includes previous works which have used deep learning approaches in their proposed biometric identification systems [16, 25]. To the best of our knowledge, most of the proposed deep EEG-based biometric identification approaches have been based on CNNs [1]. Although CNNs have performed very well with static data such as images or part of a signal, they have not been good enough to extract information and temporal characteristics in time series such as EEG signals. Hence, other deep learning methods, including RNNs have been utilized for EEG-based biometric identification. RNNs and their families, LSTMs and GRUs, have been known as promising tools for the extraction of temporal features in sequences [1, 3] An overview of the previous works on EEG-based biometric identification are summarized in Table 1.

Table 1 A brief review of the previous studies on EEG-based biometric identification

	Paper	# of subjects	# of Channels	Task	Feature extraction method	Classifier	Acc
Conventional machine learning models	[22]	6	3	REO, REC	Wavelet	DNN	**78**
	[26]	5	1	Imaginary and Physical movement	Gama band Wavelet	ANN[1]	**88**
	[9]	37	4	VEP	Template	Euclidean distance	**90**
	[14]	60	14	Acoustic ERP	Wavelet	HMM/SVM	**97**
	[28]	45	19	REO, REC and Mental computation	AR, MFCC, and bump representation	HMM[2]	**98**
	[13]	17	20	REO, REC	PSD[3]	Euclidean distance, SVM and LDA	**98**
	[10]	10	8	Imaginary Tasks	PSD	Gaussian mixture method	**93**
	[29]	32	6	VEP	Wavelet	ANN	**99**
	[6]	10	1	Eye blinking	AR[5]	LDA[4]	**99**
	[30]	50	26	VEP	Template	Cross correlation	**100**
	[31]	20	26	VEP	Template	Cross Correlation	**100**
Deep neural networks	[21]	15	64	RSVP	1	CNN	**89**
	[15]	10	64	REC/REO	1	CNN	**88**
	[25]	157	28	RSVP	1	CNN	**96**
	[17]	100	64	Virtual Driving	1	CNN	**97**
	[18]	10	16	RSVP	5	CNN	**99**
	[20]	15	16	RSVP	3	CNN	**97**
	[19]	109	64	REC, REO	12	CNN	**99**
	[16]	23	14	VEP	6	CNN	**94**
	[32]	40	17	Imaginary and Physical Movement	6	CNN	**99**
	[3]	109	16 and 64	Imaginary and Physical Movement	1	CNN+LSTM	**99**
	[4]	109	64	Physical movement	12	CNN+LSTM	**98 (EO)**
	[22]	32	64	REC, REO	10	CNN+LSTM+GRU	**99 (EC)**

1 Artificial neural network

2 Hidden markov model

3 Power spectral density

4 Linear detrimental analysis

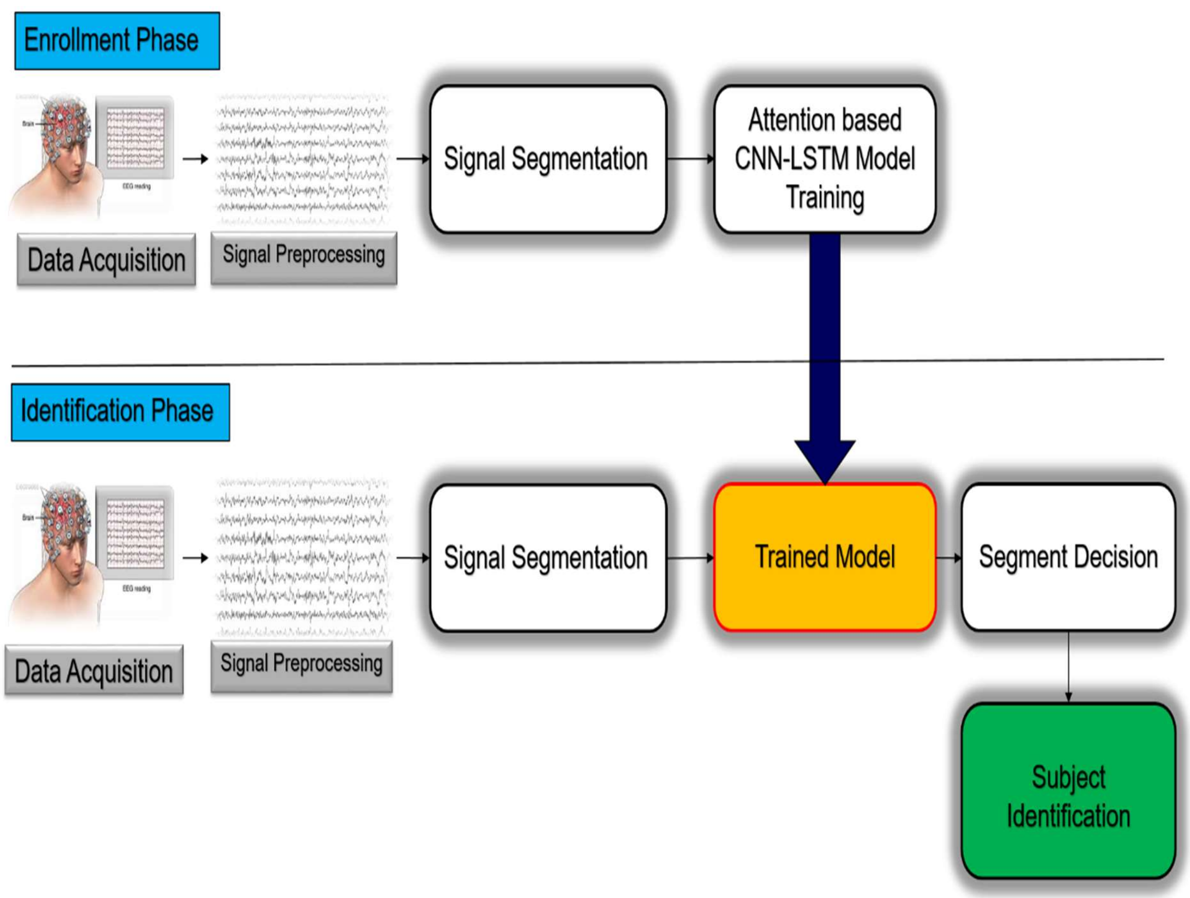
5 Auto regressive

3 Our Proposed Method

Our primary focus in this study is to propose a novel EEG-based Human identification. Our proposed ABCL-EHI approach contains two phases, including the enrollment and identification phase. In both enrollment and identification phases, the recorded EEG signals of subjects will be preprocessed and segmented into 1-second signals before feeding to the ABCL-EHI. In the enrollment phase, an initial recording of all users is used to train the model. After that, users will be able to be identified by the system in the identification phase. The output of the trained network in the identification phase would be the identifying of subjects whose 1-second EEG signals have been fed into the network.

More details of the main steps of the proposed method will be described in the following subsections.

Figure 1- The main steps of the proposed approach for EEG biometric identification



Data Acquisition

The proposed approach is being evaluated using a publicly available PhysioNet EEG Motor Movement/ Imagery Dataset that incorporates EEG signals of 109 subjects performing various motor/imagery tasks and recorded by the BCI2000 system. BCI consists of 64 channels and the sampling frequencies of 160 Hz for all channels. In this dataset, 14 experimental runs have been conducted for each subject, including Rest Eyes Open (REO) for one minute, Rest Eyes Close (REC) for one minute, and three sets of four tasks, including opening and closing fists and feet both physically and imaginarily [33].

Preprocessing

In the proposed ABCL-EHI system, the stacked layers of the neural network are used to extract features of EEG signals that are able to take raw signals as input without the requirement of any significant preprocessing procedure. As a result, in the preprocessing step, only a little action is required to be taken including normalizing data of each channel based on Eq. (1):

$$\text{Normalized\_Channel\_Data}=\frac{\sum_{i=1}^{N=64} \quad -[min]}{Ch[max]} - Ch[min] \quad (1)$$

Where N is the number of the channels, Ch refers to values of the channel, Ch[min] is the minimum value of the channel and Ch[max] is the maximum value of the channel.

Signal Segmentation

After normalizing the channel's data, the next step is to segment EEG signals into fixed-length segments. In the next step, the segmented signals will be directly fed to the neural network. In order to segment EEG signals, we use the sliding window (SW), a method that was first proposed by [34]. SW method is especially suitable for CNN models that require all samples to be of the same length. The most significant advantage of SW is retaining basic information, increasing the number and variety of data. Choosing the appropriate window size plays an essential role in the efficiency of this method in different applications. Although choosing a small window size may eliminate discriminatory information, large size leads to the high dissimilarity between different obtained segments. Moreover, in EEG-based biometric identification, window length is particularly an important factor. A long window length is inconvenient to be recorded by users. Moreover, it can also make recorded EEG signals exposed to noise that degrades the system's performance to identify subjects.

In order to make our proposed ABCL approach more convenient to be used in real-life application, as shown in Figure 2, we set window length equal to 1 second and step length equal to 80 which leads to 1-second windows, 160 samples for each window, and 80 samples overlap in each window as input of our proposed system. Overlapped windows provide the model with a larger number of training samples and helps to improve the efficiency of the learning process of the proposed deep neural network.

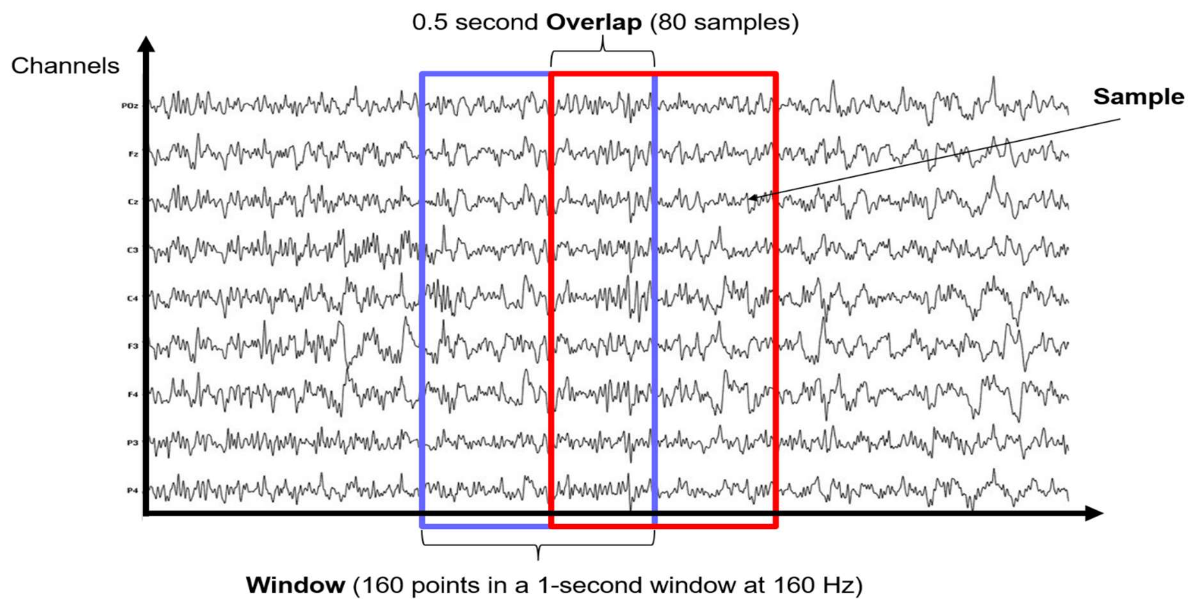


Figure 2- Overlapping windows extracted from multichannel EEG recordings

One important point in designing CNN models is how to choose the shape of input data. The input shape usually is considered as a two-dimensional matrix, one dimension is the sampling channels and the other is the samples collected in each channel[1]. In this work, after preprocessing and segmentation of EEG recordings of subjects, all the segmented signals have the format ($1*160*N_{channels}$) where 1 is windows length, 160 is a number of samples in each window, as the data have been recorded by 160 Hz frequencies each second contains 160 samples, $N_{channels}$ is the number of channels whose data is being used.

Training

At first, data is partitioned into the original training dataset and test datasets with the ratio of 9:1. Data splits are inter-subject and our considered dataset is partitioned in terms of subjects (persons) not signals. For example, if there are multiple signals captured from the same person, they all lie in the same dataset (original training dataset or test dataset) and they are not divided into both datasets. In other words, all signals for the same person belong to one of the original training and test datasets, not both of them.

The second step is dividing the original training dataset into train and validation datasets. In order to divide all created segments into train and validation datasets, we first shuffled all the created 1-second segments and considered 90% of segments as train, and validation datasets. The training and validation datasets are selected randomly by a 1:4 ratio. The training dataset is fed to the deep neural networks using a batch size of 32. In other words, each batch contains 32 records of $1*160*N_{channels}$ EEG samples. The maximum number of epochs is set to 200. In order to avoid overfitting while training the network, an early stopping technique is used, which stops the training of the network when training and validation loss are no longer reduced for 12 successive epochs. Moreover, Adam optimizer with the learning rate of.0001 is used as an optimizer of the network, and weights and biases are initialized randomly.

Attention-based CNN-LSTM Network Architecture

The prime proposed network (ABCL-EHI) consists of different layers to efficiently extract distinguishing temporal and spatial features of EEG signals and then identify users. At first, 1-second EEG signals with the shape of $1 \times 160 \times N_{channels}$ are fed to the first convolutional layer. More details of this network have shown in figure 3.

As shown in the figure 3, After convolution layers, the data will be reshaped and then pass through a LSTM layer. LSTMs include several gates which determine whether the cell stores, forgets or outputs its state. By using this procedure, LSTMs can extract and preserve temporal dependencies of the input sequence. In our proposed ABCL-EHI**,** layer 5 is a LSTM with 200 neurons. The input shape of the LSTM layer would be a 160×512 vector.

By iterating the following equations from t=1 to T, the output vector y_t is computed as Eq. (8)-(9):

$$h_t = \delta(x_t . c_{t-1} . h_{t-1}) \quad (8)$$

$$y_t = \sigma W_y h_t + b_y \quad (9)$$

Where x_t and y_t refer to the input and output in the state t, respectively, c_t represents the cell vector, and h_t refers to the hidden vector. σ is the logistic sigmoid function, W terms denote weight matrices, the b terms denote bias vector, and δ is the operator of the hidden layer. The equation of the LSTM memory cell δ can be showed as Eq. (10)-(14):

$$i_t = (W_i . [x_t, h_{t-1}, +b_i) \quad (10)$$

$$f_t = \sigma(W_f . [x_t, h_{t-1}] + b_f) \quad (11)$$

$$o_t = \sigma(W_o . [x_t, h_{t-1}] + b_o) \quad (12)$$

$$\hat{C}_t = tanh(W_c . [x_t, h_{t-1}] + b_c) \quad (13)$$

$$h_t = tanh\, tanh\, (c_t) * o_t \quad (14)$$

Where i_t denotes the input gate equation that determines how much input information should be kept, f_t refers to the forget gate equation that determines how much previous information should be removed, and o_t represents the output gate equation which indicates how much information should be output to the next state.

Although LSTMs are supposed to capture the long-term dependency better than the RNNs, it tends to become forgetful when it tries to understand long inputs in sequential data. In order to increase the efficiency of LSTMs to preserve the long-term dependencies and more efficient extraction of temporal characteristics of EEG signals, we use an attention mechanism after the LSTM layer. The attention mechanism was first introduced by [23] as an improvement over the encoder-decoder-based neural machine translation system in natural language processing (NLP). Later, this mechanism or its variants has used in other applications, including speech processing [35], computer vision [36], and so on. Using an attention mechanism after the LSTMs, it considers all the hidden states of LSTMs to generate the output vector instead of only the last hidden state of LSTMs. For this purpose, we set the return sequence of the LSTM layer equal to True, and it outputs all the hidden states to be considered by the following layer, which is the attention mechanism. Some Previous studies have studied on selecting the most appropriate sensors [37] for EEG capturing and using conventional machine learning methods for biometric identification from EEG [38].

Attention takes a weighted sum of hidden states instead of LSTM unit outputs to create the output vector. The weights are learned by a feed-forward neural network based on Eq. (15):

$$C_i = \sum_{j=1}^{H} \alpha_{ij} h_j \qquad (15)$$

Where h_j are the representation of the hidden state vectors. The output vector c_i for the output y_i is generated using the weighted sum of h_j. The weights α_{ij} are computed by a softmax function given as Eq. (16)-(17):

$$e_{ij} = \frac{exp\ (e_{ij})}{\sum_{k=1}^{H} exp\ (e_{ij})} \qquad (16)$$

$$e_{ij} = a(s_{i-1}.h_j) \qquad (17)$$

Where e_{ij} is the output score of a feedforward neural network described by the function **a** that attempts to capture the alignment between j'th and i'th inputs.

If the LSTM produces H number of the hidden state vectors, each having dimension d, then the input dimension of the feedforward network is (H, 2d) (assuming the previous state of the LSTM also has d dimensions and these two vectors are concatenated). This input is multiplied with a matrix Wa of (2d, 1) dimensions (followed by addition of the bias term) to get scores e_{ij} (having a dimension (H, 1)).

On the top of these e_{ij} scores, a tangent hyperbolic function is applied followed by a softmax to get the normalized alignment scores for output j as Eq. (18)-(20):

$$E=I[H\times 2d] \times Wa[2d\times a] \times B[H\times 1] \qquad (18)$$

$$\alpha = \text{softmax (tanh (E))} \qquad (19)$$

$$C = IT * \alpha \qquad (20)$$

To implement the so-called attention mechanism, we use the default Layer class in Keras. We define weights (Wa) and biases (B) as discussed previously. As the previous LSTM layer's output shape is (None, 160, 512), the output weight would be (512, 1), and bias should be (512, 1) dimensional. Then, to write the main logic of the attention mechanism, we create a Multi-Layer Perceptron (MLP). Therefore, it takes the dot product of weights and inputs followed by the addition of bias terms. After that, a 'tangent hyperbolic' would be applied, followed by a softmax layer. The softmax gives the alignment scores. Its dimension will be the number of hidden states in the LSTM, which is 160 in this case. Taking its dot product along with the hidden states will provide the output vector.

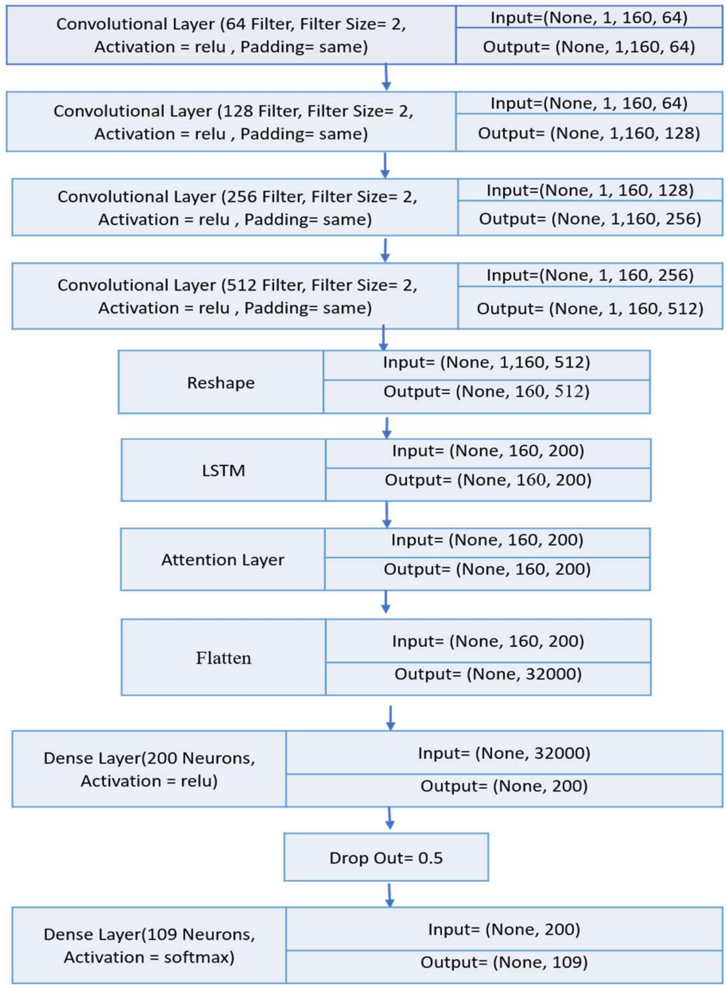


Figure 3- the detailed flow diagram of our proposed ABCL-EHI architecture

After passing the data through LSTM and attention layer, then the data is fed into two dense layers for classification. In the first dense layer, a dropout with rate of 0.5 is provided to avoid overfitting. Finally, a softmax layer with 109 neurons is used in the last layer to perform subject identification. Figure 4 shows the architecture of our proposed ABCL-EHI approach.

Evaluation

The performance of trained deep neural networks is evaluated by using different performance measures that have been used for human identification systems in previous studies, including Accuracy (Acc), False Acceptance Rate (FAR), and False Rejection Rate (FRR). The formulas of the performance measures are shown in EQ. (21)-(23):

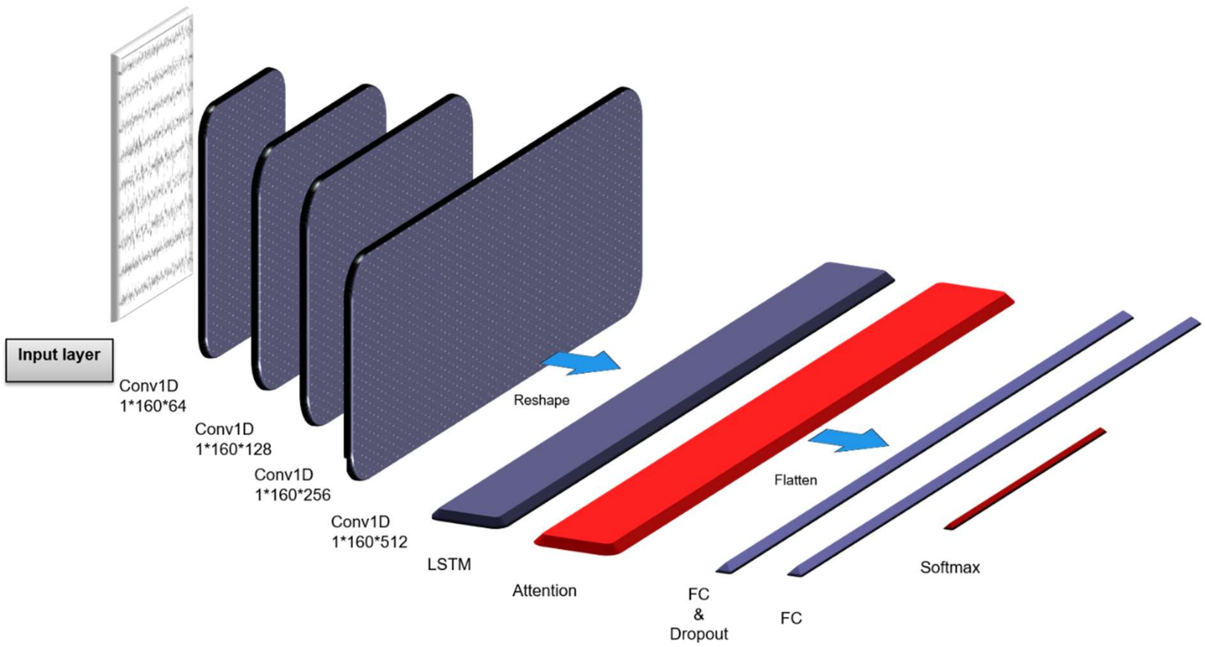


Figure 4 Architecture of our proposed ABCL-EBHI

$$ACC = \frac{Number\ of\ correct\ acceptance + number\ of\ correct\ rejection}{total\ namber\ of\ data\ records} \quad (21)$$

$$FAR = \frac{Number\ of\ incorrect\ acceptance}{total\ namber\ of\ interclass\ tests} \quad (22)$$

$$FRR = \frac{Number\ of\ incorrect\ acceptance}{total\ namber\ of\ interclass\ tests} \quad (23)$$

since human identification is kind of a classification problem, the classification performance measures such as specificity, sensitivity and F-1 score are also reported according to Eq. (24)-(26):

$$Sensitivity = \frac{TP}{TP + FN} \quad (24)$$

$$Specificity = \frac{TN}{TN+TP} \quad (25)$$

$$F - Score = 2 \times \frac{Sensitivity \times Specificity}{Sensitivity+Specifici} \quad (26)$$

In which TP and TN are the numbers of the records truly accepted and rejected by the model, respectively. FP and FN denote the number of data records incorrectly accepted and rejected by the model, respectively.

4 Numerical Results

The proposed model is trained and evaluated on the Physio Net Motor Imagery dataset using the information of all 64 EEG channels. Moreover, a similar CNN-LSTM model (CL) is designed and trained without using the attention mechanism to investigate the effectiveness of using the attention mechanism in our proposed ABCL-EHI network architecture.

Table 2- Comparing the performance of ABCL-EHI with CNN-LSTM using 64 channels EEG signals (position of the electrodes are shown in Fig. 4) with step length to 80

T-model	T-Batch	FRR	FAR	Specificity	Sensitivity	F1-Score	Accuracy	loss	Metrics / Models
19.9904	1.5621	0.00362	0.00002	99.68	99.64	99.65	99.68	0.0113	ABCL-EHI
17.7593	0.4805	0.00394	0.00005	99.36	99.40	99.38	99.38	0.0248	CNN-LSTM

Table 2 shows the results of running ABCL-EHI and CL systems on the test dataset, which are not used for training the models. The F1-score of the proposed ABCL-EHI approach is 99.65, which outperforms the state of art of the EEG-based human identification under the condition of using one-second segments of EEG signals for 6 various tasks and 109 subjects. CL model achieves F1-score of 99.35, which shows a worse performance of CL compared to ABCL-EHI. The superiority of the ABCL-EHI system lies in using the attention mechanism after LSTM layer leads to more effective exploitation of the temporal differentiating characteristics of EEG signals. As a result, it brings about an improvement in the accuracy of the network in the identification of subjects. Moreover, Tensor-flow loading times for ABCL-EHI and CL are 19.9904 and 17.0567 seconds and T-batch sampling for ABCL-EHI and CL are 1.5621 and 0.4805, respectively. since the attention mechanism takes all the hidden states of LSTM layer into account, Tensor-flow loading time and T-batch sampling for ABCL-EHI is slightly longer than CL. The loss function values and the accuracies for training and test datasets per epochs during the training process of deep neural networks in this study are shown in the figure 5-6, respectively.

Figures 5 and 6 show that both ABCL-EHI and CL have appropriate divergence speed while using the information of 64 EEG channels. Although the maximum training epochs is set to be 200, training is early stopped because of lack of improvement in the loss function after a specified number of epochs which indicates the ideal divergence rate for both models. Moreover, there is no much distance between the value of the loss function for training data and test data, which indicates the efficient training of models during training epochs.

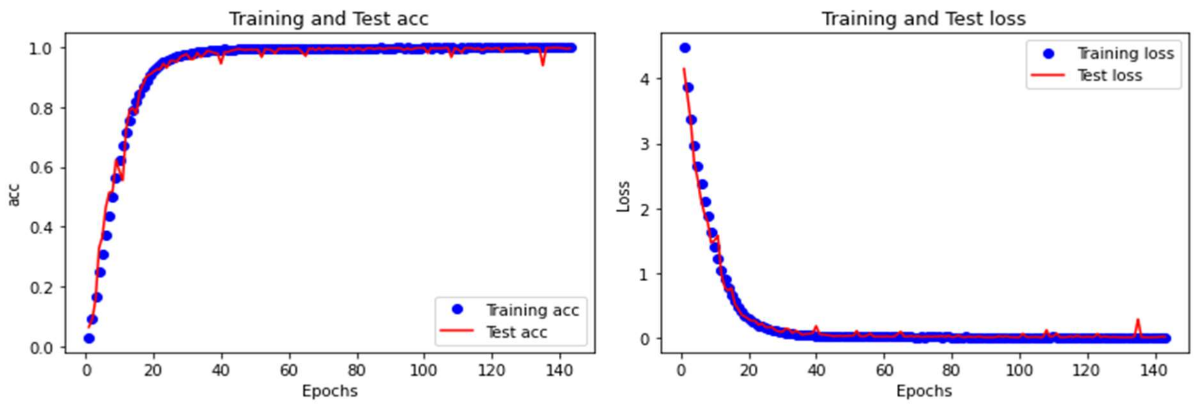


Figure 5 the training and test accuracy and loss function values per epoch for ABC-EHI trained using EEG signals with 64 channels.

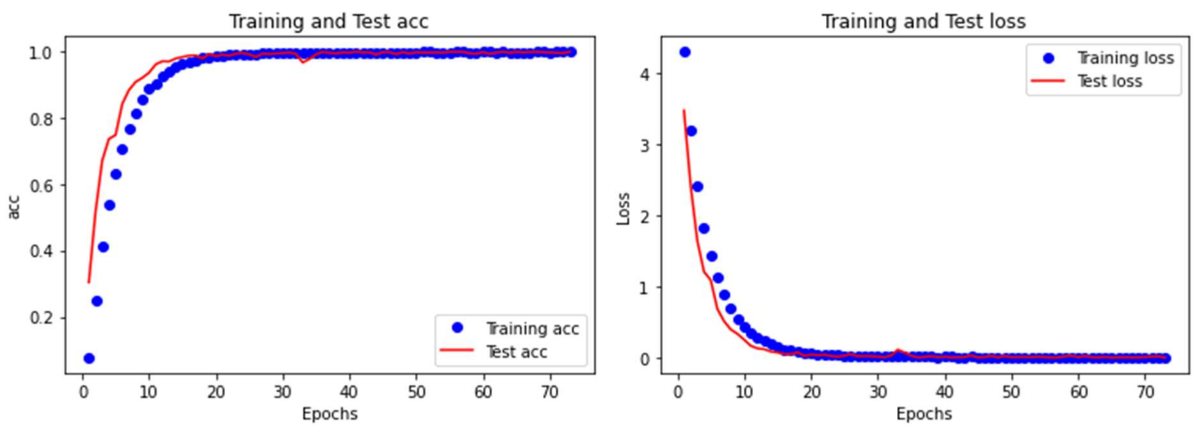


Figure 6 the training and test accuracy and loss function values per epochs for CNN-LSTM trained on EEG signals with 64 channels

Using a Smaller number of EEG Channels

As mentioned in previous paragraphs that one of the challenges of an EEG-based biometric identification system is using a large number of channels to record EEG signals. Number of the required channels in many approaches in previous studies are usually more than the number of channels in commercial EEG recorder devices. It makes them difficult to be used in the real-world applications [1].

In order to cope with this issue, we train and evaluate the proposed ABCL-EHI system considering EEG recording with 14 and 9 number of symmetrically and empirically selected electrodes on the scalp, which are depicted in Figure 7.

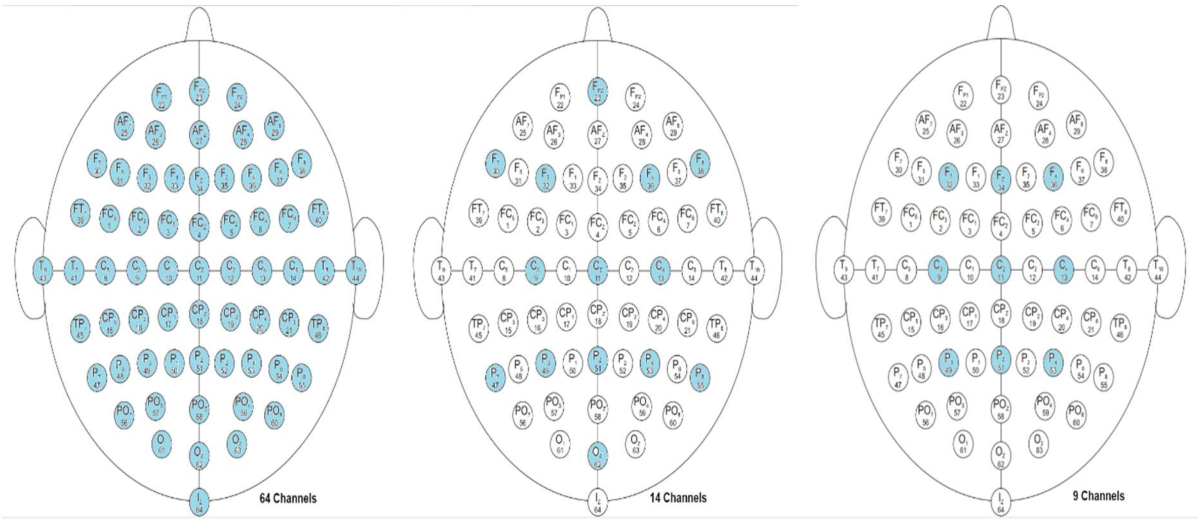


Figure 7 Electrode positions on scalp and their corresponding channels (blue represents empirically selected channels and white represents the unused channels)

By reducing the number of EEG channels that are used in EEG-based biometric identification, the distinguishing information of EEG signals decreases. Consequently, it can lead to a negative effect on the learning process which in turn degrades the performance of the system for identification of the subjects. To handle this problem and train the models more effectively under this condition, we reduced the step length in the SW phase from 80 to 40 to improve the efficiency of the learning process by providing the model with more training samples. The proposed ABCL-EHI approach and the CL model achieve F1-Score of 99.65 and 99.33 for 14 EEG channels and 99.52 and 96.34 for 9 EEG channels, respectively. More details about the performance of ABCL-EHI and CL using 9 and 14 electrodes are shown in Table 3.

Table 3 Comparison of the performance of ABCL-EHI and CNN-LSTM systems using 14 and 9 channels EEG signals (position of the electrodes are shown in Fig. 4) with step length equal to 40.

T-model	T-Batch	FRR	FAR	Specificity	Sensitivity	F1-score	Accuracy	Loss	# of Channels	Metrics / Models
19.6649	1.6635	0.00391	0.00002	99.66	99.65	99.65	99.65	0.0117	14 Channels	ABCL-EHI
19.5101	1.6736	0.00570	0.00005	99.55	99.51	99.52	99.42	0.0210	9 Channels	
18.3643	0.4128	0.00661	0.00006	99.33	99.33	99.33	99.38	0.0309	14 Channels	CNN-LSTM
17.1524	0.4102	0.0374	0.00032	96.45	96.25	96.34	96.30	0.1770	9 Channels	

Moreover, figures 8-11 show the loss function values and the accuracies for the training and the test datasets per epochs during the training process considering EEG signals with reduced number of channels. Figures 8-11 show accuracy and loss function values of ABCL-EHI and CL systems for train and test sets during training epochs while using the information of 14 and 9 EEG channels.

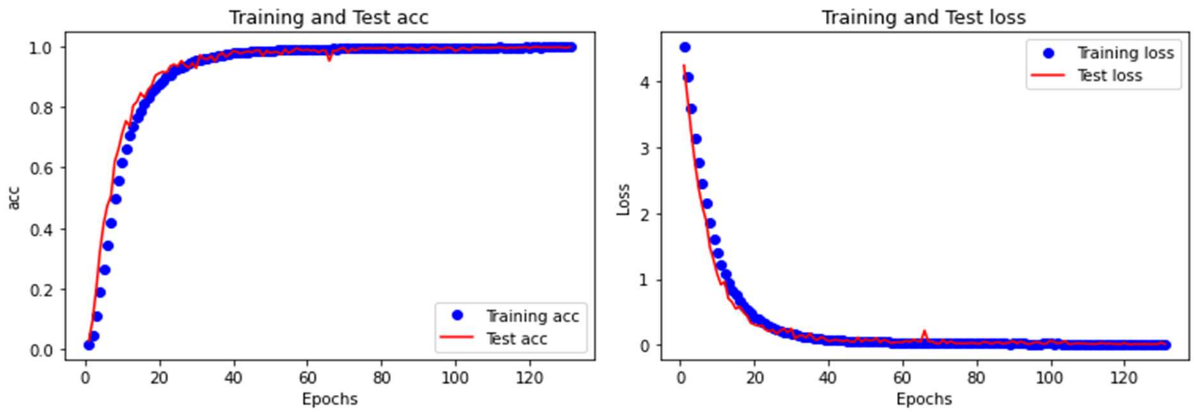


Figure 8 training and test accuracy and loss function values per epochs for ABCL-EHI system considering 14 EEG Channels

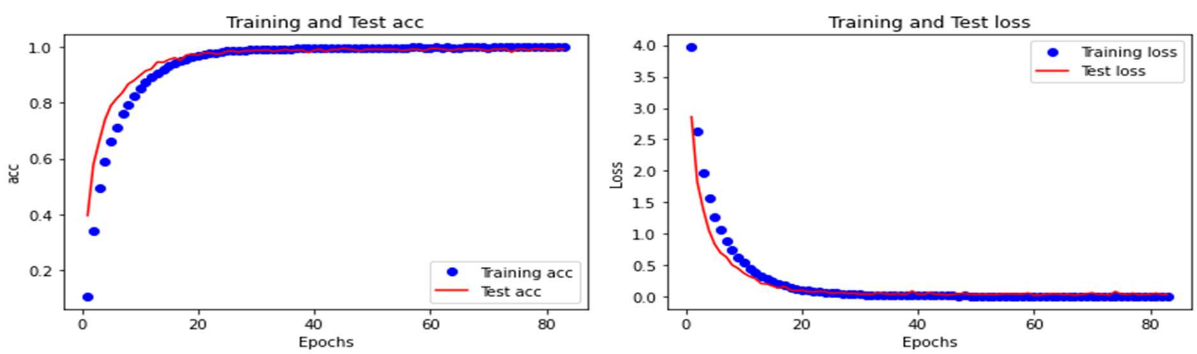


Figure 9 training and test accuracy and loss function values per epochs for CL system considering 14 EEG Channels

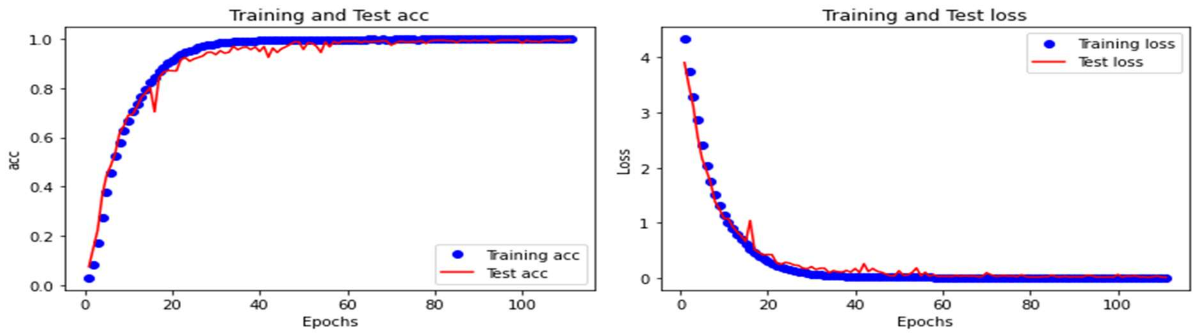


Figure 10 training and test accuracy and loss function values per epochs for ABCL-EHI considering 9 EEG Channels

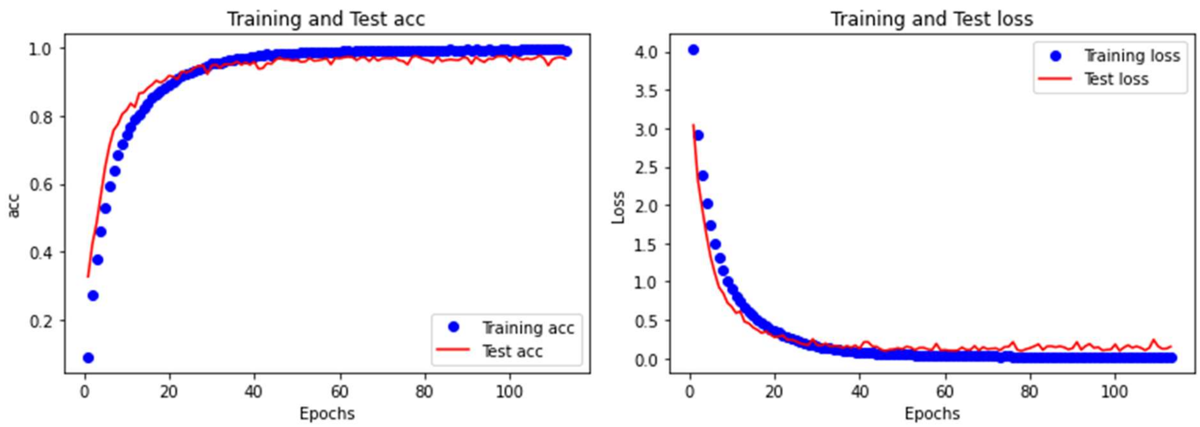


Figure 11 training and test accuracy and loss function values per epochs for CL system considering 9 EEG Channels

Considering these figures, both ABCL-EHI and CL networks have appropriate divergence speed under the condition of using the information of 14 and 9 EEG channels. Although the maximum training epochs for all scenarios are set to be 200, training is early stopped due to the lack of improvement in the loss function after a specified number of epochs, which indicates the ideal divergence rate of the models. Moreover, there is not much distance between the value of the loss function for the training and test data, which indicates the efficient training of models during training epochs.

Figure 12 shows some sample EEG segments of one channel and their corresponding model output and real output (for simplicity, other channels are not displayed).

Discussion

As shown in Figures 2 and 3, The proposed ABCL-EHI system shows 99.65, 9965, and 99.52 F-1 scores accuracy, and The CL also shows 99.38, 99.33, and 96.34 F-1 scores accuracy in identification of subjects by using the information of 64, 14, and 9 EEG channels, respectively. Although there is a slight improvement in the performance of the ABCL-EHI system compare with the CL system for 64 and 14 EEG channels, 0.27 and 0.32 higher accuracy for the ABCL-

EHI network, the ABCL-EHI has shown 3.12 accuracy higher than CL network by using the information of 9 EEG channels which is a significant improvement.

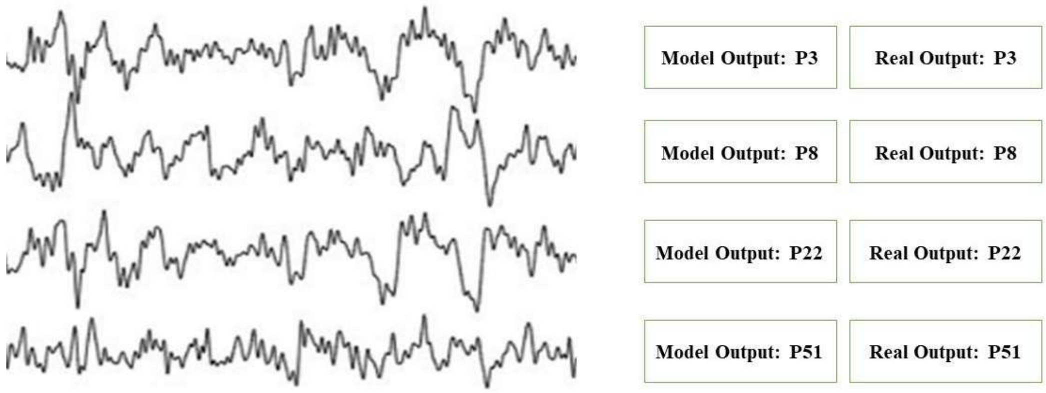


Figure 12- Some EEG segment samples (one-channel) and their corresponding model output and real output

However, even a slight improvement in the performance of a biometric identification system can lead to a significant difference in the use of these systems in identifying a large number of people in real-life applications. Another point is that our proposed ABCL-EHI system demonstrates a slighter reduction in accuracy while using a smaller number of EEG channels than the simple CL model. This superiority of the ABCL-EHI approach can lies in using the attention mechanism after the LSTM layer leads to the more effective exploitation of the temporal discriminative characteristics of the EEG signals. In other words, the attention mechanism considers all hidden states of LSTM layer and passes it to dense layers for classification. As a result, it yields better performance in the identification of subjects by using a smaller number of channels.

As shown in table 2 and 3, Tensor-flow models loading time and averaged execution time of batch testing (T-Batch) for ABCL-EHI system with attention mechanism (for all scenarios) are a little longer compare with CL system, which is due to considering all the states of the LSTM hidden layers by the attention mechanism. Although it can be interpreted as a drawback for our proposed approach, as ABCL-EHI Shows higher accuracy compare to CL system (about 7-10 seconds), its longer loading time and T-batch can be ignored by considering the prime importance of accuracy in the deployment of an EEG-based biometric identification system in real-life application.

Unfortunately, EEG signals are very complex data modalities and capturing them for better analysis requires very standard situations. Noise and artifacts that are added to EEG signals has a significant negative effect on the models' performance. Many recent studies [39] are focused on how to reduce the noise and artifact from EEGs and it is a hot topic. Therefore, it is an inevitable that the most of the previous studies as well as our study have focused on high-quality EEGs. Because analyzing EEGs having noise and artifacts can be considered as other problems and require a multi-step model. Moreover, an unavoidable limitation in the study similar to the previous studies in this field is that our analyzed EEGs have been collected in the laboratory situations not uncontrolled ones However, the noise and artifacts are the main issues for EEGs that are captured in the free situations and makes the analysis very hard if not impossible.

On the other hand, interpreting and explaining neural networks is a hard task because of their black-box nature. However, some novel methods [40] have been proposed to explain the output of the intermediate layers and can be used.

Comparison with related works:
The results of the proposed approach are compared with similar previous works in the literature as shown in Table 4.

Table 4 Comparison with some state-of-the-art EEG-based human identification systems

Paper	# of Subjects	# of Channels	Task	Segment Length (second)	Classifier	Acc/F1Score
[21]	15	64	RSVP	1	CNN	**89**
[15]	10	64	REC/REO	1	CNN	**88**
[25]	157	28	RSVP	1	CNN	**96**
[17]	100	64	Virtual Driving	1	CNN	**97**
[18]	10	16	RSVP	5	CCN	**99.30**
[20]	15	16	RSVP	3	CNN	**97.60**
[19]	109	64	REC, REO	12	CNN	**99.62**
[16]	23	14	VEP	6	CNN	**94**
[32]	40	17	Imaginary and body movement	6	CNN	**99.30**
[3]	109	16 and 64	Imaginary and body movement	1	CNN+LSTM	**99.58**
[4]	109	64	Physical movement	12	CNN+LSTM	**98 (REO)**
[22]	32	64	REC, REO	10	CNN+LSTM+GRU	**99.95 (REC)**
Proposed Approach	109	64	REC, ROC. Imaginary and body movement	1	ABCL-EHI	**99.65**
Proposed Approach	109	14	REC, ROC. Imaginary and body movement	1	ABCL-EHI	**99.65**
Proposed Approach	109	9	REC, ROC. Imaginary and body movement	1	ABCL-EHI	**99.52**

The number of electrodes, subjects, channels, performed tasks by the subjects during the recording of EEG signals, and duration of the EEG signal segments which are used as the input of the biometric identification systems are the most common and essential factors which usually have been considered in the evaluation of the proposed deep learning models for EEG-based biometric identification in the previous studies.

[19] proposed a CNN model which takes a 12-seconds length of raw EEG signals as input. They have trained and evaluated their proposed approach using REO and REC EEG signals of 109 subjects. [32] have used a CNN model with four layers of convolution and two layers of the maximum pooling. Their proposed model achieved an accuracy of 99.30 in identifying 40 subjects using 17 channels and 6-second length EEG segments.[21] have proposed a hostile convolution network for EEG biometrics which takes 1-second EEG signals as input. Their proposed approach has achieved the accuracy of 89 in identifying 15 subjects using 64 EEG channels. [25] have proposed a novel convolutional neural network with global spatial filters called GSLT-CNN. Their proposed approach has achieved an accuracy of 96.

[22] have proposed a combination of CNN and RNN networks. They have evaluated two types of RNNs, including LSTM and GRU. They have shown that although GRU and LSTM have comparable performance and accuracy, GRU training is faster and requires less data to generalize compared to the LSTM. The proposed CNN-GRU and CNN-LSTM have achieved the accuracy of 99.17 and 98.23, respectively. They have validated their proposed approach by using DEAP dataset with 32 subjects and 5 channels. [3] have proposed a CNN-LSTM neural network for EEG-based identification. The authors have proved that their proposed approach is more accurate than CNN or LSTM and has achieved high accuracy performance even with a reduced number of channels.

In this paper, we propose ABCL-EHI system Which takes 1-second EEG recordings as input to identify subjects. To the best of our knowledge, for the first time in the literature, we use an attention mechanism next to CNN, LSTM, and dense layers to improve the efficiency of biometric identification. We also use publicly available physio Net EEG motor Movement/ Imagery Dataset, which incorporates EEG signals of 109 subjects performing 6 various Motor/imagery tasks, to evaluate the proposed models. our proposed approach achieves F1-Score accuracy of 99.65, 99.65 and 99.52 for 64, 14, and 9 EEG channels, respectively, which outperforms the state-of-the-art EEG-based human identification in the previous studies.

5. Conclusion and future works

In this paper, we proposed a novel deep neural network named ABCL-EHI, which takes advantage of the attention mechanism to efficiently exploit EEG signals' spatial and temporal information to identify subjects. We also used overlapping slice windows in the segmentation of signals to 1-second signals to increase the training samples, which improved the efficiency of the learning process of the proposed system. We evaluated the system using the physio Net EEG Motor Movement/ Imagery Dataset. Results show that the proposed ABCL-EHI outperforms the simple CL approach, which does not have an attention mechanism in its architecture and outperforms the state of art of the previous studies of the EEG-based human identification.

Although most of the challenges in the field of EEG-based human identification have already been addressed, some aspects must be addressed in future studies. One recommended issue to be addressed is using EEG recordings of unhealthy subjects to develop an EEG-based human identification system that is likely to affect its performance.

Another future direction can be testing our proposed model on a larger dataset to assess its scalability. Moreover, with the development of deep learning approaches, some methods like “Generative Adversarial Networks” (GANs) are able to generate artificial EEG signals highly similar to original signals. These tools have made it easier to threat the security of the EEG-based human identification systems. It is suggested to be addressed in future works by developing a system that is able to perform EEG-based biometric identification with emphasis on distinguishing fake and real EEG signals.

In addition, we used empirically selected channels in the scenarios with the smaller number of electrodes in this study. Hence, some studies are needed to determine which EEG signal channels contain the most distinguishing information for different users to be used in Human Identification Systems. There is also room to develop automatic channel selection algorithms instead of the manual channel selection used in the current studies.

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