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Performance Enhancement of EEG Signatures for Person Authentication Using CNN BiLSTM Method

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Abstract: Despite their vulnerability to competent forgers, signatures are one of the most widely used user verification methods. Recent research has revealed that EEG signals are harder to reproduce and give superior biometric information. This study aims to improve the effectiveness of person authentication by using deep learning techniques on electroencephalogram (EEG) signals. The broad implementation of EEG-based authentication systems has been hindered by problems such as noise, variability, and inter-subject variances despite the potential distinctiveness of EEG signals. We propose a multiscale convolutional neural network (CNN) and a Bidirectional LSTM (BiLSTM) model called CNN-BiLSTM to extract features and classify raw EEG data. This methodology involves acquiring raw EEG data, preprocessing for noise reduction, standardization, normalization, and employing deep learning techniques for feature extraction and classification. Experimental results exhibit a notable improvement in accuracy and reliability compared to existing EEG authentication methods such as LOF, CNN, FCN, EfficientNet-B0, and BiLSTM. The results showcase the performance of the proposed deep learning model utilizing established metrics such as precision, sensitivity, specificity, and accuracy. The proposed methodology outperforms existing methods and achieves a training and validation accuracy of 98.9% and 92.2%, respectively. The findings of the research demonstrate that the proposed approach has been successful in achieving highly effective results by using EEG signals for the purpose of resolving issues related to person identification.

Keywords*:* Deep Learning, EEG signals, BiLSTM, CNN, Person Authentication (PA), Classification
Categories: G, I, L
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1 Introduction

In the contemporary biometric authentication landscape, exploring novel and robust methods is imperative to meet the evolving demands of security and user identification. Electroencephalogram (EEG) signals, which capture the brain's electrical activity, have emerged as a promising avenue for person authentication due to their intrinsic individuality [Chaladar et al., 21 Bidgoly et al., 22]. However, traditional EEG-based authentication methods face challenges such as susceptibility to noise, inherent variability, and significant differences among individuals. The use of EEG signals for person authentication holds significant potential owing to the unique neural patterns that distinguish one individual from another. Traditional methods often relied on manual feature extraction and simplistic classification algorithms, struggling to cope with EEG data's inherent complexity [Shams et al., 22 Wu et al., 22]. The need for more sophisticated techniques has spurred interest in the application of deep learning, which excels at learning hierarchical representations from data.

An individual's brain signals may be obtained using several methods, such as electroencephalography (EEG) and electrodermal response (EDR). EEG is a technique that is capable of recording cerebral electrical activity. Electroencephalography (EEG) is a straightforward and less invasive technique for measuring brain electrical activity. It involves the placement of electrodes on the surface of the scalp [Fidas et al., 23]. The EEG signals that have been recorded have a limited ability to determine spatial information accurately and possess a suboptimal ratio of signal strength to background noise, making them susceptible to interference from extraneous signals and artifacts [TajDini et al., 23]. Furthermore, the captured signals exhibit non-stationarity, implying that the properties of the signal vary with time. Therefore, it is essential to use advanced data analysis techniques in order to extract valuable information pertaining to specific activities from the unprocessed EEG signals. EEG-based authentication has prompted the development and use of several machine learning techniques, with deep learning emerging as the most recent and popular option [Yap et al., 23 Tatar et al., 23]. This method has garnered significant interest, particularly the growing use of CNN in the field of image classification, owing to its promising efficacy. The complicated structure of the human brain serves as a source of inspiration for a kind of machine learning known as deep learning. The purpose of the deep model is to extract meaningful and discriminative properties from the input data. This is accomplished by repeatedly altering the data over many layers and then generating predictions based on these alterations [Gorur et al., 23 Li et al., 22][Sahoo et al., 23].

This research addresses these challenges by incorporating deep learning methodologies into the person authentication process based on EEG signatures. Deep learning, with its ability to automatically extract intricate patterns from complex data, presents a compelling solution to improve the accuracy and reliability of EEG-based authentication systems. Convolutional neural networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks have been widely used as versatile methods for extracting spatiotemporal features from electroencephalogram (EEG) data in many experimental scenarios, including motor imagery, event-related potentials (P300 speller), and extraction of EEG features from task-independent data [Kingsy et al., 22] [Yadav et al., 22].

The motivation of the proposed CNN-BiLSTM method, utilizing for EEG-based person authentication, aims to address the limitations of existing diagnosis methods and enhance the accuracy and reliability of authentication system. The key problems are tackling is the need for robust and accurate identification of individual using EEG signatures, which can vary significantly between individuals and can be susceptible to noise and variability. Existing diagnosis methods, such as LOF, FCN, EfficientNet-B0, and BiLSTM, while effective in certain contexts, have limitations when applied to EEG-based person authentication. LOF, is struggled with the high-dimensional and complex nature of EEG data, while FCN and EfficientNet-B0 may not effectively capture temporal dependencies crucial for authentication. BiLSTM, although capable of capturing temporal dynamics, may not fully leverage spatial information inherent in EEG signals. The advantages of the proposed CNN-BiLSTM method lie in its ability to effectively combine spatial and temporal features of EEG data. By leveraging the convolutional layers of CNNs to extract spatial features and the recurrent nature of BiLSTM to model temporal dependencies, CNN-BiLSTM method offers a holistic approach to EEG-based person authentication. This enables a more resilient and precise identification, particularly in situations including interference and fluctuation.

The primary objectives of this research are twofold: first, to enhance the accuracy and reliability of person authentication using EEG signals, and second, to address the challenges associated with noise, variability, and inter-subject differences. By integrating the deep learning (CNN-BiLSTM) method into the authentication process, we aim to unlock the latent potential of EEG data and provide a more robust solution for user identification. The significant contribution of this paper is as follows:

- Develop and implement CNN-BiLSTM models to automatically extract relevant features from EEG data, aiming to improve the overall accuracy of person authentication compared to existing methods.
- To address the challenges associated with EEG-based authentication, such as noise, variability, and inter-subject differences, by leveraging the inherent capabilities of deep learning for robust feature extraction and pattern recognition.
- Systematically evaluate the performance of the proposed deep learning-based authentication system using appropriate metrics, comparing it with conventional EEG authentication approaches.
- Investigate and compare different deep learning models, such as LOF, CNN, FCN, EfficientNet-B0, and BiLSTM, to identify the most effective model for EEG-based person authentication.
- Contribute insights to the field of EEG-based person authentication by demonstrating the feasibility and effectiveness of deep learning methods, potentially paving the way for broader adoption and practical implementation.

The remaining sections of the paper are organized as follows: Section 2 provides a comprehensive analysis of the literature research, Section 3 covers dataset, preprocessing, and proposed deep learning model integration with the CNN and BiLSTM methods. Section 4 discusses experimental findings and these results. Section 5 describes the conclusion and future research directions.

2 Literature Review

The literature reviewed highlights the transition from traditional methods to deep learning approaches in EEG-based person authentication. The utilization of deep learning techniques has shown considerable promise in addressing the challenges posed by EEG signals, paving the way for more accurate and reliable identification systems.

[Li et al., 22] introduced the use of deep learning and suggested 7 classifiers that utilize Convolutional Neural Networks (CNN) for the P300 speller application. The models comprised three multi-classifiers and four standalone classifiers, each with its unique collection of features. The second data set from the third BCI competition was used to evaluate and compare the models. A reduction in sampling rate and filtering within the frequency range of 0.1 to 20 Hz were applied to the original EEG data of 2 subjects before classification. The results demonstrated that deep learning is capable of correctly recognizing EEG signals. With a recognition rate of 95.5%, the recommended multi-classifier model produced the most remarkable results. Using extracted frequency, time, and location data from EEG recording signals, CNNs have also been employed for motor imagery categorization [Tabar et al., 16]. Compared to previous approaches, the results showed that the proposed deep learning techniques produced better classification results.

Usman et al. [Usman et al., 20] introduced a seizure prediction algorithm for epilepsy on 24 participants. In order to classify the data, the authors used a Support Vector Machine (SVM) and a CNN to extract features. The results showed promise, with a sensitivity level of 92.7% and a specificity of 90.8% on average. In the last few years, deep learning has shown it can help with EEG data processing. Computer models with several layers may learn data representations with different levels of abstraction using deep learning. Using this approach to decipher complex data, including text, images, and audio signals, has shown promising results in the past [LeCun et al., 15]. Unlike classic linear classifiers like SVM and LDA, which assume linear separability, deep learning models can efficiently handle complex, non-linear correlations in EEG signals. It enables them to catch intricate patterns and improves their categorization ability. Furthermore, models using deep learning techniques have shown resilience to fluctuations in EEG readings. Machine learning models can acquire knowledge from a wide range of data and apply that knowledge effectively to new and unfamiliar situations. This adaptability allows them to manage various sessions and users effectively. It can extract distinctive characteristics from the raw data and streamline the data processing procedures within the EEG domain. It allows for an automated learning approach, including preprocessing, feature extraction, and classification, while maintaining its strong performance in particular tasks [Roy et al., 19].

[Li et al., 16] discovered the beta and gamma frequency bands of the EEG signal exhibit superior authentication accuracy compared to other frequency bands. Visual information processing activities mainly produce an EEG signal in the gamma frequency band, while visual-related cognitive processes primarily produce an EEG signal in the beta frequency band. After computing a cosine correlation between individual EEG data, [Zhang et al., 20] discovered that the delta frequency band had the lowest average similarity. Put simply, the signal is the most constant frequency range across different situations since it contains the most distinguishable features and information for identification. The researchers postulated that the improved EEG signal stability in the delta band may be explained by the essential function of the delta band in sustaining physiological activities in all states.

[Kumar et al., 19] introduced that the gamma band may exhibit more chaos and complexity than other bands, resulting in a higher degree of nonlinearity and unpredictability [Rodriguez-Bermudez et al., 15]. While some researchers categorize EEG signals into various frequency bands for authentication purposes, remarkably, the unique characteristics of individual differences in brain neural activity are evident over all frequency ranges. Consequently, there isn't a single frequency range that can capture all the data that matters for identification [Altahat et al., 15]. Because they used different stimulus tasks, the researchers got different results across different frequency bands.

Several frequency bands include the main components of the electroencephalogram (EEG) signals induced by various stimulation actions, allowing for a heightened level of precision in the frequency band that closely aligns with the task at hand.

In their study, [Cho et al., 20] presented an improved input form that utilizes a three-dimensional format. They also demonstrated that the CNN model effectively combines diverse and complementary elements in the field. Neural networks have gained widespread use due to the growing popularity of end-to-end learning in deep learning frameworks. As a result, automated and non-linear feature fusion approaches based on neural networks are now frequently used. These methods, which combine features using neural networks, offer improved efficiency and performance compared to traditional empirical methods. More precisely, the multi-scale convolution model was used to handle two-dimensional images. It allowed for the automated extraction and fusion of features from multiple scale fields using a parallel framework. Extensive research has been conducted on the multi-scale CNN in the domain of EEG. The application scenarios included tasks such as emotion detection, fatigue driving, epilepsy prediction [Ozcan et al., 19], and motor imagery [Zhang et al., 21].

[Hernández-Álvarez et al., 22] presented the IF and LOF models for user identification based on EEG data. This particular approach has yet to be investigated. In addition, it will build a hybrid system that combines OC and MC classifiers to enhance the performance of OC models by using MC algorithms while simultaneously demanding input from the genuine user. In order to lessen the complexity of the issue, they investigate various ways. Given that artificial intelligence authentication systems often need significant time and computing resources [Hernández-Álvarez et al., 21], reducing the dimensionality of the data the model uses is advantageous. By using EEG data, the researchers are focusing on user authentication, a separate and more appropriate concern than device authentication, it is essential to take notice of this fact. Determine the ways in which the parameters of the classifiers may be altered to provide improvements in both the usability and the security of the systems.

[Wang et al., 22] introduced a specific transformation method designed for EEG biometrics. This method combines several elicitation protocols to improve verification accuracy while ensuring the templates' security. This research has established the basis for the practicality of using EEG as a biometric verification method. However, they have also brought up issues about security and privacy due to the fact that EEG data includes confidential information. Cancellable template design demonstrates that previous research on EEG data security relied on cryptographic methods and hash functions, but these methods could not invalidate compromised templates. The primary motivation for creating a cancellable EEG template was to protect sensitive information, including health records, identifying details, and mental state, in the raw EEG signals used in EEG-based verification systems. A new conversion procedure is developed using a non-invertible transformation to generate cancellable templates from EEG properties recorded by a deep neural network.

[Demir et al., 22] used one dimensional multi-layer co-occurrence matrices (1D-MLGLCM) for individuals is identified based on their electrocardiogram (ECG) signals. For the purpose of the research, the open-source dataset that was supplied by Physionet was used. There are 90 volunteers whose electrocardiograms are included in the dataset. There are 46 females and 44 males, and their ages vary from 13 to 75. The electrocardiogram (ECG) data from each person has been segmented into 32 distinct smaller sections after being adjusted. In order to generate co-occurrence matrices, the 1D-GLCM approach is used to undergo processing on these tiny portions.

[Kuncan et al., 19] processed the extracting features from signals is one of the most important steps of GI processes. 1D-LBPs, 1DRLBPs, and W-1D-RLBPs are some of the transformation methods that have been applied to the signals that have been obtained from sensors. This is due to the fact that the success of GI is dependent on the attributes. For the purpose of classification, a variety of machine learning techniques, including RF, SVM, Knn, and ANN were developed by making use of these qualities. Within the scope of this research, three distinct feature extraction techniques are presented for the purpose of gender identification. These techniques make use of data collected from accelerometers, magnetometers, and gyroscope sensors that have been put in five distinct body areas of the humans. The success rates that were perceived with the prescribed procedures were, respectively, 96.04%, 96.72%, and 97.28%.

[Akdag et al., 22] introduced 1D-DS-LBP technique is used to provide data to the LSTM model by merging histograms that represent the connection between bigness and smallness on the sign. LSTM has been used to analyze ECG data using both unidirectional and bidirectional 1D-DS-LBP transformations. This paradigm is expected to be effectively applicable in other intelligent systems via study and may be customized for other domains [Kaya et al., 22]. The ELM approach is used during the categorization stage. ELM is an artificial neural network (ANN) model that uses input hidden weights and random output weights, which are calculated analytically. It exhibits much higher speed compared to traditional artificial neural network (ANN) models [Kuncan et al., 19].

[Kuncan et al., 22] introduced the Gray Level Co-Occurrence Matrix (GLCM) technique, which is extensively used in image processing. However, in contrast to GLCM, the proposed methodology is applied to signals that are only one dimension in size. For the purpose of testing the suggested method, two datasets were used. The signals that were acquired from the accelerometer, gyro, and magnetometer sensors were used to build the datasets. Following the application of 1D-GLCM to the signals, Heralick characteristics were derived from the co-occurrence matrix that was formed. Through the use of these characteristics, HAR operations have been carried out for a variety of circumstances [Kaya et al., 22]. Two different datasets each had success rates of 96.66 and 93.88%, respectively, when compared against one another.

Moreover, EEG signals exhibit significant intra-user variability that may impede the biometric performance. Several elicitation methods are implemented to enhance system performance and resilience. Decision-level fusion is often used in many works, and voting systems are used to accomplish this. An alternative method for protocol fusion involves combining the EEG data obtained from several elicitation procedures to generate a dataset that encompasses each user's distinctive and generalized patterns [Debie et al., 21]. This approach has been used in several EEG biometrics investigations to address the within-group differences, particularly those relying on supervised learning models [Yang et al., 18 Landau et al., 20]. These approaches include a crucial training phase that adapts the model to a training dataset. The model's efficacy is contingent not only upon its inherent capabilities but also upon the training technique and the quality of the training dataset.

3 Multiscale CNN-BiLSTM Methodology

This section outlines the proposed framework for the classification of EEG signals into the authentication claim. The claim authentication framework comprises several primary approaches, which are as follows:

3.1 EEG Data Acquisition

Our studies were conducted using two datasets: BCI Competition IV-2a and BCI Competition IV-2b. Fifty-two individuals had their electroencephalograms (EEGs) recorded as they performed an ERP task, including four movements: left and right hands, feet, and tongue. In all, 52 healthy candidates (aged 20 to 40) had their EEGs recorded twice on separate days utilizing one of two distinct elicitation methods (ERP, MI). A total of sixty-two electrodes (including four for electromyography) were used to collect data at a sample rate of one thousand hertz by the international 10-20 standard. Electrode AFz served as a reference and ground for the signals.

The ERP protocol is widely regarded as a popular application for BCI because of its straightforwardness and dependability [Won, 19]. The methodology used a standard 6X6 grid speller job. A total of 36 symbols are evenly dispersed throughout six rows and six columns, appearing on the screen in a random sequence. Each flickering symbol is regarded as an individual stimulus and lasts 80 milliseconds, while the inter-stimulus interval (ISI) is set at 135 milliseconds. A sequence is the term used to describe the presentation of stimuli in all rows and columns. In the experiment, each target symbol has been given five sequences for sixty flashes. In the first era, the player was asked to spell the statement using all 33 symbols. The second epoch's task was to have participants spell out the phrase, which included 36 symbols (spaces included). Once the fifth sequence was finished, the participant had 4.5 seconds to locate, focus on, and notice the next target symbol. The EEG data was collected during a time range of -150 to 750 ms in relation to the stimulus start. To achieve baseline correction, we took the whole signal and subtracted the average voltage from the first 200 ms of each segment. Therefore, a total of 1500 trials (750 samples each) make up the EEG data collected during epoch 1. There is a grand total of 1850 trials in Epoch 2 of the EEG data, and each trial has 750 samples.

The motor imagery (MI) elicitation technique included the implementation of an imaging task where members were trained to imagine gripping objects with either their right or left hand, resulting in two distinct classes. The participants were instructed to execute mental images of grasping an object with the corresponding hand when a visual signal in the shape of a left or right arrow appeared on the screen. Each trial began with the display of a center fixation cross on the screen, which remained visible for a period of three seconds. Next, the subject mentally imagined holding onto something tightly using the same hand for a period of four seconds. EEG signals were subsequently obtained between the time window of 750 to 3000 ms after the stimulus was shown. Hence, the EEG data gathered for each epoch consists of a total of 100 trials, with each trial including 2000 samples. Figure 1 shows the preprocessing verification system for user authentication architecture of EEG signal data.

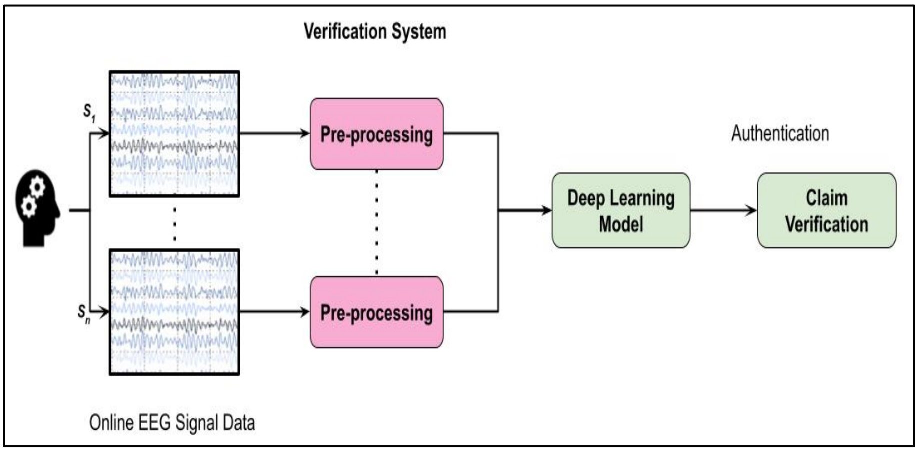

Figure 1: Verification system for user authentication paradigm

3.2 Multiscale Convolution Module

The multi-scale convolution module was primarily responsible for extracting the individual identification characteristic of the EEG, and numerous modules were combined to create the overall structure of the network. Following the application of the prior data, various branch operations were carried out, with each branch linking a convolution kernel of a different size. Figure 2 illustrates the multi-scale vision convolution module under discussion. The multi-scale convolution processing flow consisted of individual convolution layers, branch structures, feature concatenation, and pooling. The first input layer used a 1 x 1 convolution layer to reduce the dimensions. This layer effectively decreased the parameters of the network and included local correlation. Therefore, to get the target feature size consistency after multi-scale convolution, the three-dimensional tensor was required to be padded according to the convolution kernel's scale. Multi-branch convolution was a crucial structure for multiscale feature extraction, and this study focused on the diversified convolution kernel combination method. Researchers looked at many rectangular convolution kernels with different edge lengths, considering that ERP signals sometimes include unbalanced data in the frequency and time domains. This was compared to the standard imaging-related square convolution kernel. The experimental findings for the outstanding multi-scale technique [($6 \times 3 \times 3$), ($6 \times 5 \times 3$), and ($6 \times 7 \times 3$)] are shown in Figure 2. One of three domains, space, time, or frequency, corresponds to each of the three 3D convolution kernels. When collecting EEG data, combining the multi-branch structure and the multi-scale convolution kernel worked well. In addition, the multi-branch structure was able to extract complementary and diverse identifying data. Batch normalization was used to regularize the feature output layer to improve the model's generalizability and convergence speed. Using maxpool eliminated the need for the concatenate feature layer, and as network complexity increased, the pooling kernel area decreased. The output of the feature layer contains complete features that were extracted by the multi-convolution kernel. This is what transmits the three-dimensional information onto the subsequent step of the process.

The general design of the EEG authentication system consisted of the stacking and the multi-scale convolution modules. It is possible to enhance and combine the characteristics taken from the basic module by the multi-branch structure, which could extract diverse features from the basic module. The features are sent via a 768 × 32 fully connected two-layer network after flattening them by the end multiscale convolution module. A dropout with a probability of 0.4 was introduced between the fully connected layers to reduce the possibility of overfitting. A learning rate of 0.0005 and an epoch of 5 were the parameters that were selected for the network. The fact that the scale convolution architecture should find a happy medium between training cost and network performance should be carefully considered. To reduce the time and computer resources utilized, the primary methods are to create branches and remove modules. This is because there will be an exponential growth in the number of parameters as the number of modules and branch structures increases. The structure of the network that was used in the research is both flexible and diverse.

3.3 Multiscale CNN Method

The signal obtained from each electrode site will be transformed into a vector format as part of preparing EEG data for CNN. The data sampling rate will dictate the per-specified window size. Afterward, the data collected from each sensor is stacked vertically. The result is a single image where the y-axis details the different electrodes used in electroencephalography, and the image's width denotes the temporal dimension. Input snapshots, sometimes known as simply 1D pictures, are what are used to feed these images into the CNN. Three distinct layer types are included in the design of CNN: (1) a convolutional layer, (2) a pooling layer, and (3) a fully connected layer, which is referred to as the convolutional layer. This layer is responsible for extracting features from the data being entered (the data is often represented in picture format). Convolution filters are used in this layer to determine the weighted average by using EEG samples that are near to one another. Furthermore, each EEG sample is reused by its neighbors many times. EEG data and kernel are the two components required for the mathematical operation known as convolution. This procedure involves applying filters to the input of EEG data. Regulating the number of samples the filter skips throughout the input snapshot is accomplished using a stride parameter. Before applying the filter, this parameter is applied to the EEG snapshot. This layer performs convolutions on EEG data in line with Equation 1, where I represent the snapshot of the EEG signal that is being input. An EEG snapshot is used to produce a feature map, which is the output produced after applying each filter. The convolutional layer's input is denoted as I and can be expressed as follows:

$$I = \{I_1, I_2, \ldots I_b, \ldots, I_k\} \tag{1}$$

Here, k indicates the overall count of convolutional layers. Depending on the input, the convolutional layers provide output, and a unit centered at L, M also produces output, as seen in the following.

$$F_{i\ \ L,M}^{j} = U_{i\ \ L,M}^{j} + \sum_{w=1}^{K_1^{w-1}} \sum_{q=-K_1^h}^{L_1^h} \sum_{t=-K_2^h}^{K_2^h} \left(E_{i\ ,w}^{h}\right) * \left(F_{w\ \ L+q,M+t}^{h-1}\right) \tag{2}$$

where * represents the convolutional operator, $F_{i\ L,M}^{j}$ indicates the fixed feature map from F[th] convolutional layer centered at L, M. Consider that the weights of the convolutional layers are indicated as, $E_{i,w}^{h}$, and $U_{i\ L,M}^{j}$ be the bias, which is adjusted optimally by the LSTM. The parameters w, q, and t indicate the feature maps producing the output from each convolutional filter. The dimension of the convolution layer is 10×1×1. A neural network's output is determined by use of an activation function. The Rectified linear activation unit (RELU) and the Classification output activation function are two activation functions that are often used with CNN in research literature. The RELU stands for the Rectified Linear Activation Unit. As specified in Equation 2, RELU is a piecewise linear function that returns the same input if the value of the input is positive; else, it will return zero. It is usual practice to utilize RELU after the convolution layer.:

$$F_i^j = fun\left(F_w^{j-1}\right) \tag{3}$$

Pooling layers: The pooling procedure is employed as a down-sampling step in this layer, which is an optional layer. The primary purpose of this layer is to minimize the number of feature maps created by the convolutional layer. Not only does this help minimize the model's complexity, but it also helps prevent over-fitting. Down-sampling the feature maps may be accomplished by using a variety of procedures, such as the average, maximum, minimum, and so on. Layer that is really connected: To classify the input EEG snapshot into the appropriate categories, this layer uses the feature maps learned in the layers that came before it. In order to include non-linearity in the model, activation functions are often used.

Fully connected layers: Prediction mode and a fully connected layer are used to safely identify nodes using the abstractive characteristics extracted from convolutional layers. The result of a layer that is completely linked may be expressed as,

$$O_n^j = J\left(F_i^j\right) with\ \mathrm{F}_{i\ L,M}^{j} = U_{i\ L,M}^{j} + \sum_{w=1}^{K_1^{w-1}} \sum_{q=-K_1^h}^{L_1^h} \sum_{t=-K_2^h}^{K_2^h} \left(E_{i,w}^h\right) * \left(F_{w\ L+q,M+t}^{h-1}\right) \tag{4}$$

Here, $E_{i,w}^{h}$ specifies weight associating a unit at (L, M) in w^{th} feature map of layer $(i-1)$ and j^{th} unit in layer i. H_n^j is defined as the predicted output. Figure 1 describes the architecture of Deep CNN.

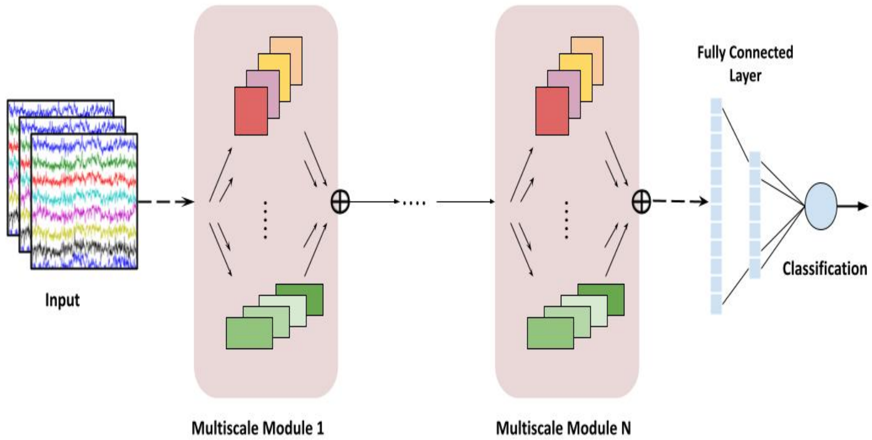

Figure 2: Structure of Multiscale CNN

3.4 BiLSTM Method

Multiscale CNN's output is used to derive key traits of electricity consumption, which are then stored in BiLSTM, the network's bottom layer [Yan et al., 23]. The Bidirectional Long short-term memory (BiLSTM) is a response because it safeguards information over time by combining memory components that can refresh the hidden state. As a result of using this function, comprehending time connections on a lengthy series is straightforward. The gate units receive the results of the prior CNN layer. The LSTM network's ability to deal with exploding and disappearing gradient issues makes it an excellent choice for estimating future energy consumption. The forget, input, and output gates are parts of the LSTM cell's four interconnected neural networks. A vector whose all the elements have values between zero and one is what comes out of the forget gate. It acts as a forgetter by being multiplied by the previous time step's cell state C_{t-1} to throw out irrelevant values while keeping relevant ones for the forecast. Figure 3 depicts the fundamental structure of an LSTM memory cell.

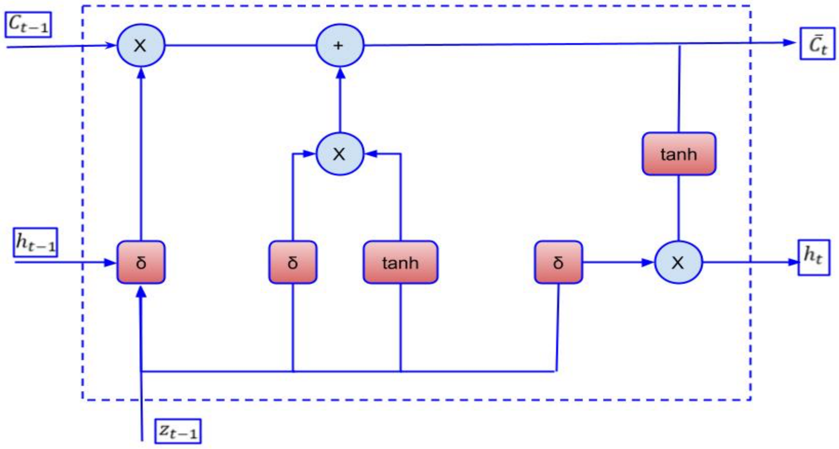

Figure 3: Structure of LSTM memory cell

$$f_t = \delta\,(W_f * [h_{t-1}, z_t] + b_f) \tag{5}$$
$$I_t = \delta\,(W_i * [h_{t-1}, z_t] + b_i) \tag{6}$$
$$C_t = tanh(W_c * [h_{t-1}, z_t] + b_c) \tag{7}$$
$$\bar{C}_t = f_t + C_{t-1} + I_t + C_t \tag{8}$$
$$O_t = \delta\,(W_o * [h_{t-1}, z_t] + b_o) \tag{9}$$
$$h_t = O_t * \tanh\,(\bar{C}_t) \tag{10}$$

Point-wise multiplication with the cell state is performed after the Sigmoid function in Eq. (5) changes the inputs, h_{t-1} and z_t, to the range [0, 1]. The fraction of prior cell state numbers that would be passed on to the next stratum is determined by a value between 0 and 1, inclusive. Eq. (6-8) defines operations at the input gate. Using h_{t-1} and z_t, the tanh function determines a set of potential new values, t, for the present cell state. Using the Sigmoid output from the previous layer, we can choose which of the new potential values to retain and which to discard (Eq. (6) and (7)). The final state of the cell is calculated by adding the previous state, C_{t-1}, to the new potential numbers, in Equ. (8), the term $\bar{C}_t$ decides how much data from the prior state to keep, and the term I_t decides which portions of the current potential cell state to keep. Equ. (9) and (10) produces the ultimate result. The portions of the cell state that are kept for output are determined by a Sigmoid function applied to the inputsh_{t-1} and z_t. Cell states are converted to the range [1, 1] using the tanh function in Equ. (9), and the Equ. (10) pertinent outputs are retained in the LSTM run by elementwise multiplying the transformed values with the sigmoid activation output.

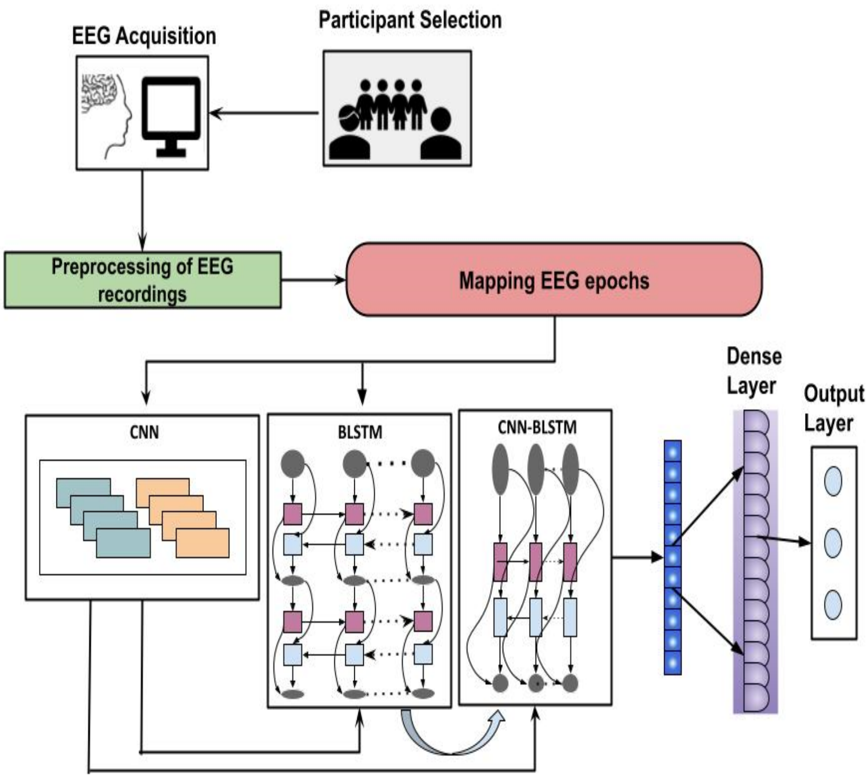

Figure 4: Proposed method (CNN-BiLSTM) architecture

The proposed technique extensively incorporates additional variations of Convolutional Neural Networks (CNN) and attention mechanisms to enhance the performance of the Bidirectional Long Short-Term Memory (BiLSTM) model in classifying EEG recordings obtained from individuals under suspicion. The ultimate pre-processed dataset is used to train the deep learning model, according to the architecture shown in Figure 4, for the classification task outlined in this method.

4 Experimental Results and Discussion

4.1 Training Setup

The evaluation of our technique was conducted using the two datasets from BCI Competition IV-2a and BCI IV-2b, enabling a direct comparison with several contemporary state-of-the-art methodologies. EEG data were obtained from a group of 25 individuals while they were engaged in a motor imagining task involving four distinct movements: left-hand, right-hand, foot, and tongue. Two recording sessions were held on separate days. Every epoch comprises six consecutive runs, with brief intervals in between. Each run has 50 trials, with 10 dedicated to each motor activity. Hence, a total of 220 trials were logged for each period. Every trial started with a central fixation cross that remained on the screen for a duration of 2 seconds. Subsequently, a cue, represented by an arrow indicating the left, right, up, or down direction, was shown for 1.25 seconds. Subsequently, the subjects engaged in a cognitive exercise of mental imagery lasting 2.75 seconds. Furthermore, a passive activity including both open and closed eye conditions was performed alongside the motor imagery task at the beginning of each epoch. During this work, EEG data were recorded for two minutes while participants kept their eyes open and focused on a fixation cross shown on the screen, followed by one minute of closed eyes. The EEG data were obtained using 22 electrodes and recorded at a sampling rate of 250 Hz. The signals underwent band pass filtering with a range of 0.5 Hz to 100 Hz, and a 50 Hz notch filter was further used to reduce line noise. Within this area, an examination is conducted to assess the effectiveness of the primary elements of our methodology. Furthermore, we perform a comparative analysis of our suggested technique with other widely used deep learning models that have gained popularity in recent years. Furthermore, we replicate these models by training them on the same dataset. Split the dataset into training, validation, and testing sets. Allocate a significant portion for training to ensure the model learns diverse features.

4.2 Performance Evaluation

The CNN-BiLSTM model is proposed for analysis using evaluation measures, including testing accuracy, precision, sensitivity, and specificity. Compare the performance of the proposed deep learning models with existing EEG authentication methods such as LOF, CNN, FCN, EfficientNet-B0, and BiLSTM. Analyze the impact of different deep learning architectures on authentication accuracy. This results in the training process being terminated and the model is evaluated on the test dataset using well-established classification metrics.

True Positives (T_{Pos}): this metric of pertains to the quantity of positive EEG signals that have been accurately identified as positive.

True Negative (T_{Neg}): this metric refers to the count of negative EEG signals that are accurately identified as negative

False Positives (F_{Pos}): refers to the quantity of negative EEG signals that are erroneously identified as positive.

False Negative (F_{Neg}): refer to the quantity of positive EEG signals that are incorrectly classified as negative.

The evaluation metric of accuracy involves the comparison of the predicted labels with the actual labels. The score has a maximum value of 1 and a minimum value of 0.

$$Accuracy = \frac{T_{Pos}+F_{Neg}}{T_{Pos}+F_{Pos}+T_{Neg}+F_{Neg}} \tag{11}$$

where F_{Pos} stands for false positive detections, F_{Neg} for false negative authentications, and T_{Pos} for true positive. Sensitivity, sometimes referred to as the true positive rate of EEG signal authentication, quantifies the percentage of positive instances that are accurately classified as such.

$$Precision = \frac{T_{Pos}}{T_{Pos}+F_{Pos}} \tag{12}$$

The assessment of the accuracy of classifiers is accomplished through the utilization of precision. The precision measure is the number of true positives divided by the total of true positives and false negatives.

$$Sensitivity = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{13}$$

$$Specificity = \frac{T_{Neg}}{T_{Neg} + F_{Pos}} \tag{14}$$

The primary aim is to examine the suitability of using specific EEG datasets obtained by CNN-BiLSTM with different pre-trained models, such as LOF, CNN, FCN, EfficientNet-B0, and BiLSTM in the training phase. Each dataset was divided into a training set of 70% of the data and a testing set of 30% of the data. This division was done for six pretrained models. Tables 1 to 3 show the classification precision, sensitivity, and specificity of the six pre-trained models for both Dataset 1 and Dataset 2, respectively. According to the tables, both pre-trained models had impressive results, each attaining a specificity score above 0.99. According to the findings from epoch 1, EfficientNet-B0 and CNN-BiLSTM achieved the highest specificity score of 0.998 in Dataset 1 and Dataset 2. On the other hand, CNN and FCN obtained a specificity score of 0.996 in both datasets. While some models demonstrate superior performance, the distinctions between the different variants are minimal. Furthermore, the low standard deviations observed in the presented performance measures illustrate the reliability and consistency of the suggested strategy in user authentication. Figures 5, 6, and 7 show the precision, sensitivity, and specificity performance of several pre-trained models.

Models	**Precision**	
	Dataset 1	**Dataset 2**
CNN-BiLSTM	0.991	0.798
BiLSTM	0.887	0.777
EfficientNet-B0	0.863	0.763
FCN	0.858	0.751
CNN	0.872	0.76
LOF	0.841	0.745

Table 1: Precision analysis on two datasets of different training model

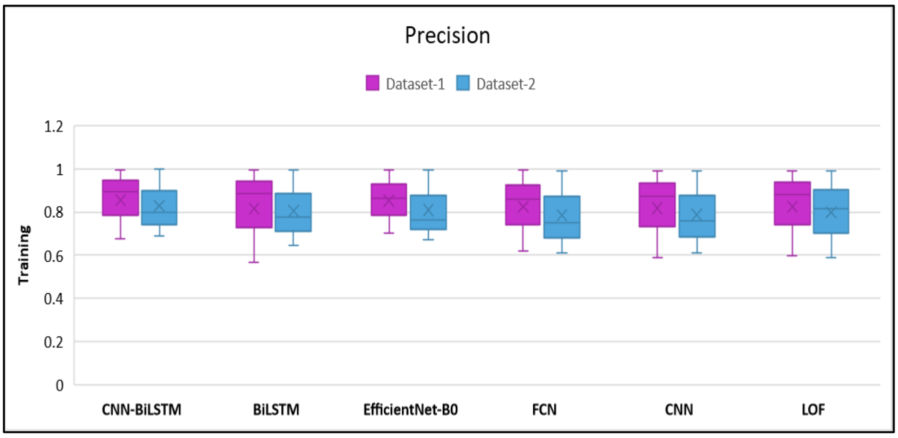

Figure 5: Comparison analysis of training model

Models	Sensitivity	
	Dataset 1	Dataset 2
CNN-BiLSTM	0.893	0.827
BiLSTM	0.888	0.751
EfficientNet-B0	0.871	0.734
FCN	0.876	0.728
CNN	0.858	0.736
LOF	0.849	0.727

Table 2: Sensitivity analysis on two datasets of different training model

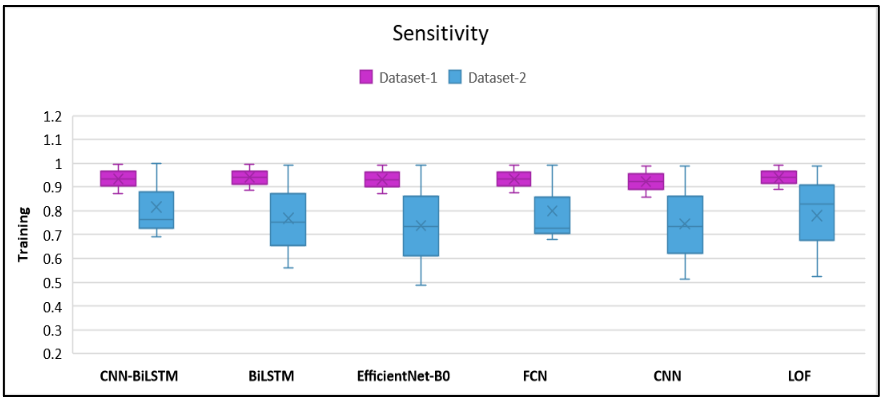

Figure 6: Comparison analysis of training models

Models	**Specificity**	
	Dataset 1	**Dataset 2**
CNN-BiLSTM	0.999	0.997
BiLSTM	0.991	0.994
EfficientNet-B0	0.992	0.991
FCN	0.991	0.99
CNN	0.993	0.991
LOF	0.991	0.993

Table 3: Specificity analysis on two datasets of different training model

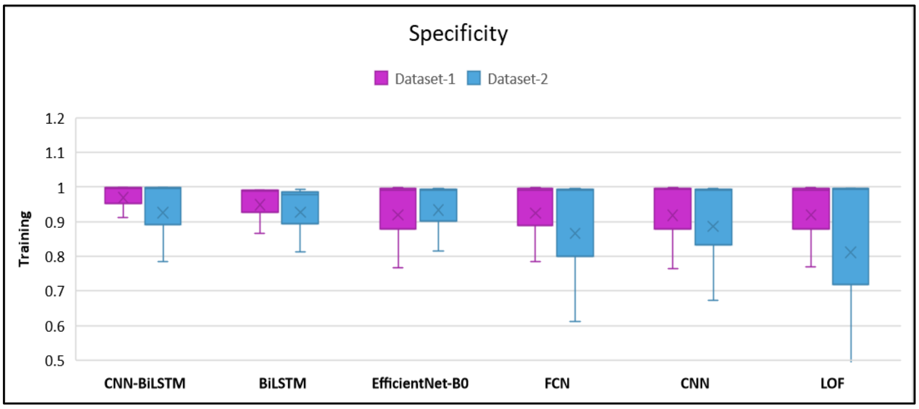

Figure 7: Comparison analysis of training model

In the validation phase, examine the suitability of using specific EEG datasets obtained by CNN-BiLSTM with different pre-trained models, such as LOF, FCN, EfficientNet-

B0, and BiLSTM, in the validation phase. Table 4 shows the classification precision, sensitivity, and specificity of the four pre-trained models for both Dataset 1 and Dataset 2, respectively. According to the tables, both pre-trained models had impressive results, each attaining a specificity score of the validation above 0.96. According to the findings from epoch 1, EfficientNet-B0 and CNN-BiLSTM achieved the highest specificity score of 0.992 in Dataset 1 and Dataset 2. The LOF and FCN models obtained a specificity score of 0.991 in both datasets. While some models demonstrate superior performance, the distinctions between the other variants are minimal. Figures 8, 9, and 10 show the precision, sensitivity, and specificity validation performance analysis for several pre-trained models.

Models	**Precision**		**Sensitivity**		**Specificity**	
	Dataset 1	**Dataset 2**	**Dataset 1**	**Dataset 2**	**Dataset 1**	**Dataset 2**
CNN-BiLSTM	0.871	0.762	0.862	0.745	0.995	0.992
EfficientNet-B0	0.728	0.612	0.732	0.676	0.99	0.982
LOF	0.781	0.714	0.771	0.665	0.98	0.967
FCN	0.794	0.722	0.685	0.675	0.991	0.969

Table 4: Validation analysis on two datasets of different training models

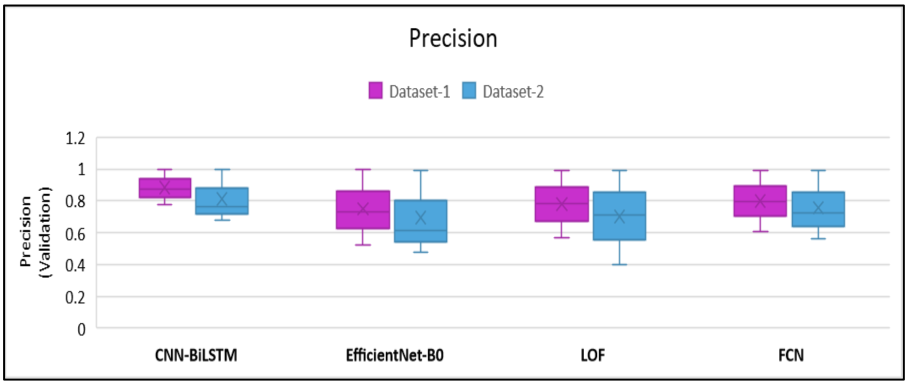

Figure 8: Comparison analysis validation performance of precision score

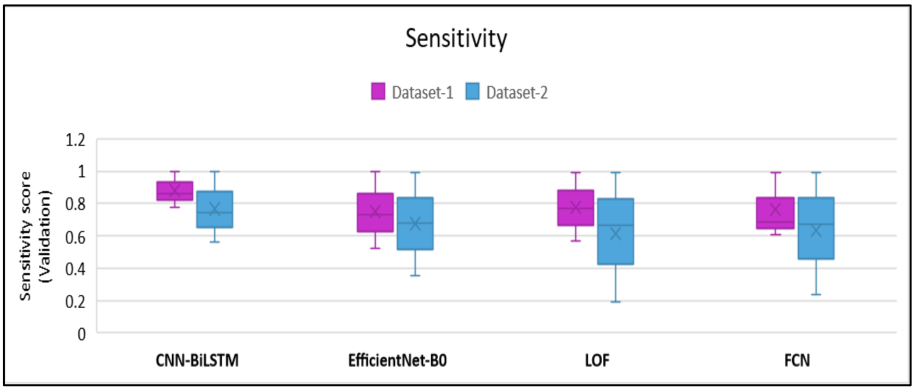

Figure 9: Comparison analysis validation performance of sensitivity score

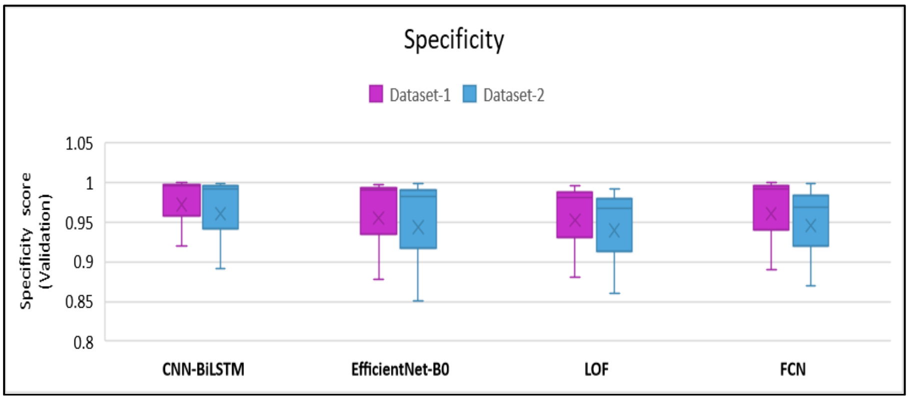

Figure 10: Comparison analysis validation performance of specificity score

Figure 11 presents a comparative analysis of the CNN-BILSTM model developed and utilized with the BCI Competition IV-2a dataset. Figure 11 illustrates the analysis of testing accuracy. The study reports the testing accuracy achieved by various techniques, including LOF, CNN, FCN, EfficientNet-B0, BiLSTM, and CNN-BiLSTM, for a training data set of 60%. The reported testing accuracy values are 0.794, 0.781, 0.842, 0.857, 0.865, and 0.885, respectively. The CNN-BiLSTM technique has demonstrated a performance improvement of 10.288 %, 11.751 %, 4.858 %, 3.163 %, and 2.259 % compared to existing methods.

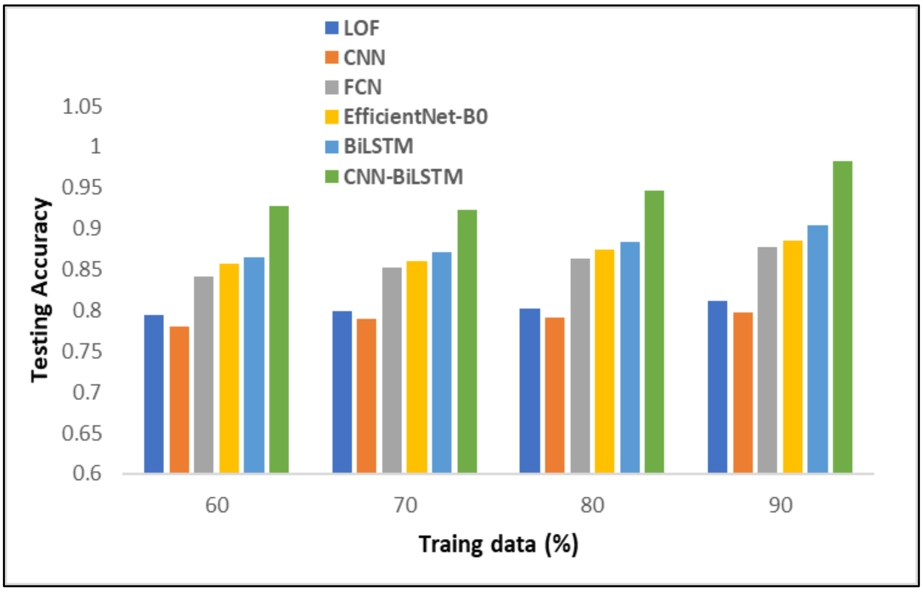

Figure 11: Comparison analysis average testing accuracy

The comparative advantage of the proposed technique in relation to other contemporary methodologies, even when using the most effective classifier, is clearly shown by the outcomes depicted in Figures 12 and 13. These findings were achieved via testing conducted on the publicly available BCI Competition IV-2b dataset. The primary justification for using this technique is the utilization of the pre-trained CNN-BiLSTM on a dataset that incorporates the Inception module.

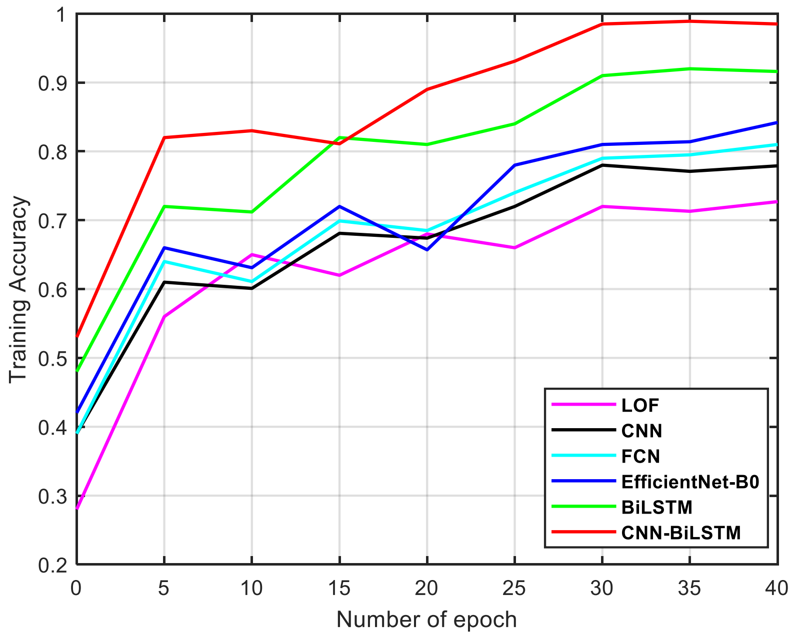

Figure 12: Comparison analysis of training accuracy

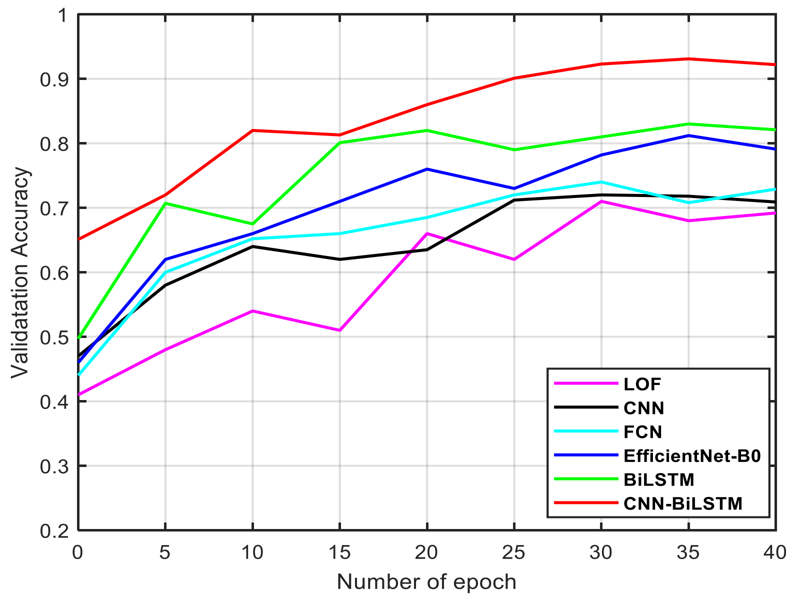

Figure 13: Comparison analysis of validation accuracy

As a result, this approach successfully combines the advantages provided by both elements. Using a pre-trained module is a fundamental mechanism for extracting rudimentary characteristics, while the remaining layers are responsible for extracting and categorizing features of a higher dimensionality. Although pre-trained weights are used instead of training the models from scratch, it is still necessary to get the optimal results for these models. The proposed methodology achieves a training and validation accuracy of 98.9% and 92.2%, respectively, after 40 training epochs, as shown in Figures 12 and 13.

5 Conclusion

In this paper, we have presented a novel approach for person authentication leveraging CNN-BiLSTM through the fusion of electroencephalogram (EEG) data. The exploration began with acknowledging the challenges posed by traditional EEG-based authentication methods, emphasizing the need for innovative approaches to address issues related to noise, variability, and inter-subject differences. Adopting deep learning techniques proved to be a transformative step in the authentication process. By leveraging convolutional neural networks (CNNs) for spatial feature extraction and BiLSTM for capturing temporal dependencies and aimed to unlock the latent potential embedded in EEG signatures. The proposed method is encompassed a rigorous preprocessing pipeline, innovative feature extraction strategies, and diverse neural network architectures to comprehensively explore the intricate patterns within EEG data. Our experiments demonstrated a marked improvement in the accuracy and reliability of person authentication compared to traditional methods. The CNN-BiLSTM models exhibited a heightened capacity to discern individual neural patterns, showcasing the efficacy of automated feature extraction in the context of EEG-based authentication. The existing methods reported testing accuracy values are 0.794, 0.781, 0.842, 0.857, 0.865, and 0.885, respectively. The CNN-BiLSTM technique has demonstrated a performance improvement of 10.288 %, 11.751 %, 4.858 %, 3.163 %, and 2.259 % compared to existing methods.

In the future research, explore the advance fusion techniques, model optimization strategies, and the incorporation of additional modalities to further improve authentication performance and address emerging challenges in security and privacy. Overall, proposed method contributes the advancement of person authentication and lays the foundation for more secure and reliable authentication systems in the digital era.

Declaration

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The authors declare that they have no known competing financial interests in this paper.
Informed Consent:
Data used in this work from https://www.kaggle.com/competitions/ucsd-neural-datachallenge/data.
Competing interests:
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and material
Data used in this work from https://www.kaggle.com/competitions/ucsd-neural-datachallenge/data.

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