Noname manuscript No.
(will be inserted by the editor)

Person Identification using Autoencoder-CNN Approach with Multitask-based EEG Biometric

Banee Bandana Das* · Saswat Kumar Ram · Korra Sathya Babu · Ramesh Kumar Mohapatra · Saraju P. Mohanty

Received: date / Accepted: date

Abstract In this research paper, we propose an unsupervised framework for feature learning based on an autoencoder to learn sparse feature representations for EEG-based person identification. Autoencoder and CNN do the person identification task for signal reconstruction and recognition. Electroencephalography (EEG) based biometric system is vesting humans to recognize, identify and communicate with the outer world using brain signals for interactions. EEG-based biometrics are putting forward solutions because of their high-safety capabilities and handy transportable instruments. Motor imagery EEG (MI-EEG) is a maximum broadly centered EEG signal that exhibits a subject's motion intentions without real actions. The Proposed framework proved to be a practical approach to managing the massive volume of EEG data and identifying the person based on their different task with resting states. The experiments have been conducted on the standard publicly available motor imagery EEG dataset with 109 subjects. The highest recognition rate of

* Corresponding author.

Banee Bandana Das
Computer Science and Engineering, SRM University, Andhra Pradesh, India
E-mail: banee.bandana@gmail.com

Saswat Kumar Ram
Electronics and communication Engineering, SRM University, Andhra Pradesh, India
E-mail: saswatram01@gmail.com

Korra Sathya Babu
Computer Science Engineering, IIITDM Kurnool,India
E-mail: ksb@iiitk.ac.in

Ramesh Kumar Mohapatra
Computer Science and Engineering, National Institute of Technology, Rourkela,India
E-mail: mohapatrark@nitrkl.ac.in

Saraju P. Mohanty
Computer Science and Engineering, University of North Texas, Denton, USA
E-mail: saraju.mohanty@unt.edu

87.60% for task-based identification and 99.89% recognition rate for resting-state has been recorded using the Autoencoder-CNN model. The outcomes imply that the overall performance of our proposed framework is similar or advanced to that of the state-of-the-art method. The shape is a realistic technique to control the full-size extent of EEG data and to pick out the individual based totally on their specific task.

Keywords Electroencephalography (EEG) · Biometric Authentication · Person Identification · Autoencoder · Convolutional Neural Network

1 Introduction

Despite the general studies of MI-EEG in latest years, it is miles nevertheless hard to elucidate EEG signals efficiently because of the considerable noises in the EEG signals (e.g., low signal-noise ratio and incomplete EEG signals) and problems in capturing the discreet relationships among EEG signals and certain specific brain activities. Most current works [26, 20, 25] only consider EEG as chain-like sequences neglecting complicated dependencies among adjoining signals or appearing easy temporal averaging over EEG sequences. It is vital to accurately investigate and identify the individual based on EEG signals and for an extended time. Researchers have tried to extract new features from the signals for Person recognition [28, 29, 30, 31]. However, it is not easy to choose beneficial features from a massive variety of them on this EEG-based biometric security application [32]. As per the progress and improvement of artificial intelligence, unsupervised feature learning based on the deep learning model [33] can gain features that can better describe identified objects from unlabeled data. Biometrics characteristics are distinct. They are used to identify and authenticate [34, 35, 36, 37, 38] persons. Brain neurons carry information required for a particular activity and communicate using electrical spikes forming a vast neural network. Electroencephalogram (EEG) is the standard means we record neural signals with specific features [39, 40, 41]. These signals are captured by placing several electrodes on the scalp's surface. Electrical interference is one of the primary challenges in recording the EEG signal that will result in noisy EEG. Sometimes the signal recorded with electrical activity needs to be reacquired as it is entirely corrupted. Noncerebral actions can also cause noisy EEG signals from external physiological activities like muscle and limb movements. External environmental disturbances are also an essential factor for noncerebral activities. The quality of the EEG signals degrades because of the noise generated by cerebral and noncerebral activities. The quality of the captured EEG signal is vital in different domains of EEG applications. This paper proposes an unsupervised framework for feature learning based on an autoencoder to learn sparse feature representations for EEG-based person identification. We proposed an autoencoder-CNN-based biometric system with EEG motor imagery inputs for dimensionality reduction and denoising (extracting original information from noisy data). The autoencoder extracts essential features from input EEG and ignores the noises during the training

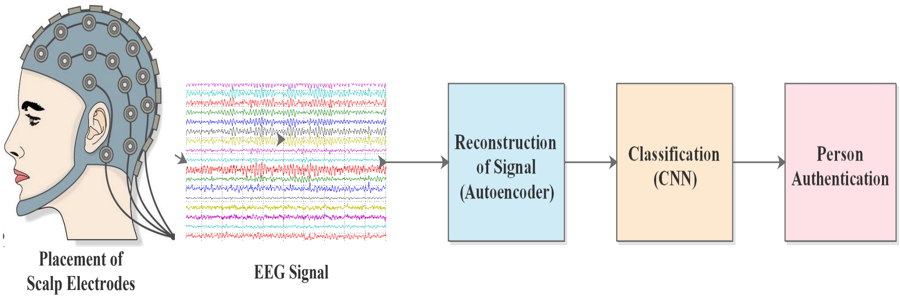


Fig. 1 Flow diagram of the proposed EEG-based person identification model.

because the labels have no noises. A denoising autoencoder is trained to reconstruct the original input from the noisy version. Autoencoders are data-specific and best capable of compressing data like they had been trained. Autoencoder and CNN do the person identity venture for signal reconstruction and recognition [42]. The outcomes imply that the overall performance of our proposed framework is similar or advanced to that of the latest method. The simple flow diagram of the proposed version is depicted in Fig. 1.

Novelty in the proposed scheme:

1.To develop a personal identification system using MI-EEG data.
2.This work is about an Autoencoder-CNN-based biometric system with EEG motor imagery inputs for dimensionality reduction and denoising (extracting original input from noisy data).
3. The designed Autoencoder-CNN-based biometric architecture to model MI-EEG signals is efficient for cybersecurity applications.

The rest of the paper is structured as follows: Section 2 describes the related work, and section 3 presents the novel contributions of this paper. section 4 presents the adopted methodology for EEG-based person identification, Section 5 describes the experimental setup and simulation results. We concluded along with future possibilities of this research in Section 6.

2 Related Work

Handcrafted features are derived features mainly used for some machine learning algorithms for the available data, but learned features by CNN significantly outperform the handcrafted ones. It also beats most computer vision approaches. It acts as a feature extractor and classifier and has been used widely for its excellent performance. CNN is already used for many person identifications and recognition work using EEG brain signals of a different person. We here propose an EEG signal-based new person identification biometric system. This work deals with EEG-based person identification using different motor imagery movements using a vast dataset having 109 subjects. Some studies have presented EEG-based biometrics using a different method-

Table 1 Summary of Related Work

Author Name & Year	Approach (Feature & Classifier)	Subjects	State & Accuracy
Poulos *et al.* [23], 1999	ANN	4	EC with 80%
Poulos *et al.* [24], 1999	Computational geometry algorithms	4	EC with 95%
Paranjape *et al.* [27], 2001	Autoregressive	40	EO and EC with 80%
Palaniappan *et al.* [11], 2007	KNN,ENN	102	(EO) Snodgrass and Vanderwart data set with 95-98%
Marcel and Millan *et al.* [9], 2007	GMM	9	Thee imagery task with 93.4%
Napflin *et al.* [9], 2007	PSD, Linear regression	55	EC with 88%
Riera *et al.* [14], 2008	AR(100th order)+PSD+MI+COH +Correlation, Linear Classifier	51	EC with EER 3.4 -5.5%
Cecotti *et al.* [2], 2008	CNN	2	Motor imagery classification with Accuracy 53.47%
HU Jian-feng [43], 2009	Multilayer backpropagation neural networks	3	Satisfactory TAR and FAR
Abdullah *et al.* [1], 2010	AR(21st order), k-NN	10	EC with 97% EO with 96%
Kostilek *et al.* [6], 2012	FZ-AR(7th order), Mahalanobis dist.	9	EC with 87.1%
Su *et al.* [18], 2012	PSD, MMSE	40	EC with 95%
La Rocca *et al.* [7], 2014	AR(10th order), Linear Classifier	108	EC with 100% EO with 97.5%
Thomas *et al.* [19], 2016	PSD, Cross Correlation	109	EO/EC with 90.21%
Nurse *et al.* [10], 2016	CNN	1	BCI with Accuracy 81%
Schirrmeister *et al.* [16], 2017	CNN	109	EEG Decoding and Visualization with 89.8%
Spampinato *et al.* [17], 2017	CNN	6	Discriminate brain activity with Accuracy 86.9%
Barjinder *et al.* [4], 2017	DWT, SVM,RF	109	SVM-EO with 96.88% EC with 96.02% RF-EO with 95.78% EC with 93.21%
Yingnan Sun *et al.* [46], 2019	CNN-LSTM	109	Person Identification with accuracy 99.58%
Wilaiprasitporn T *et al.* [47], 2019	CNN-GRU	32	Person Identification with accuracy 99.10%
Mari Ganesh Kumar *et al.* [45], 2021	IX-VECTOR	30	Person Identification with accuracy 86.40%
Proposed approach	CNN, Autoencoder-CNN	109	CNN-EC Vs EC 83.44% , EOEC Vs Task1 80.95% Autoencoder-CNN-EC Vs EC 99.89% EOEC Vs Task1 87.60%

ology. This approach is more secure and challenging as the EEG signal features are highly person dependent and unique with variable parameters. Poulos et al. (1999) [12, 24] observed around 80% and 95% performance accuracy, respectively, with a data set of four subjects and 255 EEG trials using two classification algorithms (artificial neural network and computational geometry algorithms (convex polygon intersections)). Paranjape et al. (2001) [27]

obtained a classification accuracy of around 80% by using a data set of 40 subjects and 349 EEG trials. Palaniappan and Mandic (2007) [11] analyzed 102 subjects' EEG data based on visually evoked potentials and experimented with personal identification. The author got the performance accuracies around 95-98%. Marcel and Millán (2007) [8] observed a person identification accuracy of 93.4% by using a data set of nine subjects appearing mental imagery tasks of left-hand movements, right-hand movements, and phrase technology starting with the identical letter. Napflin et al. (2007) [9] proposed a model with 55 subjects' eye-closed resting-state data and obtained a recognition accuracy of 88% using PSD and linear regression approach. HU Jian-feng (2009) [44] used a dataset of BCI competition 2003 with three subjects and proposed multi-feature fusion architecture for an authentication system based on EEG signals. He used Multilayer back-propagation neural networks to classify different persons. He observed the model's performance by noting other True Acceptance Rate (TAR) and False Acceptance Rate (FAR) thresholds. Abdullah et al. (2010) [1] modeled an authentication system using four-channel EEG recording data of ten subjects and got 70-97% accuracy using a multilayer neural network and AR model. Su et al. (2012) [18] experimented with eye-closed state data of 40 subjects using PSD and MMSE approach and reported recognition accuracy of 95% Kostilek et al. (2012) [6] have designed a person identification method using the autoregressive model and Mahalanobis distance-based classifier and noted the performance accuracy of 87.1% by utilizing the eye-closed state data of nine subjects. La Rocca et al. (2014) [7] have modeled a person authentication system based on power spectral density and spectral coherence-based features by using a dataset of 108 subjects and obtained 97.5% and 96.26% accuracy in eye closed and eye open resting state respectively. Some researchers have experimented with the most emerging deep-learning methods for the processing and application of EEG data. For example, Cecotti et al. (2008) [2] have modeled motor imagery classification with CNN and observed classification accuracy of 53.47% by using two subjects' EEG data in different trials. Nurse et al. (2016) [10] used one subject's data to develop a BCI application using CNN and noted an accuracy of 81%. Spampinato et al. (2017) [17] designed a model using six subjects' EEG. The author has modeled CNN with different subjects' discriminated brain activity. Schrimster et al. (2017) [16] used CNN for EEG decoding and visualization on a dataset of 109 subjects and obtained an accuracy of 89.8%.EEG signals for motor imagery actions are used in many studies of Brain-computer interfaces. This paper offers further perspective on the possibility of using EEG signals of motor imagery movements in biometric applications. Yingnan Sun et al. (2019) [46] designed a EEG-based user identification model and noted the accuracy of 99.58% with convolutional long short-term memory neural networks. Wilaiprasitporn T et al. [47] (2019) modeled an affective EEG-based person identification system and observed accuracy of 99.10%. They explored a deep learning approach with CNN and GRU (Gated Recurrent Unit). The summary of the related work is presented in Table 1. The related work concluded that research is carried out on EEG-based person identification and

EEG signal analysis. As per the author's knowledge, this is the first work to use the weights of the autoencoder and classification done by CNN using those weights for EEG-based person identification.

3 Novel contributions of the current paper to the state of art

The current paper addresses a unified design of the person identification models using multi-task and emotion-based EEG signals. Motor imagery EEG (MI-EEG) is a maximum broadly centered EEG signal that exhibits a subject's motion intentions without real actions. This work proposes an unsupervised framework for feature learning based on an autoencoder to learn sparse feature representations for EEG-based person identification. Autoencoder and CNN do the person identification task for signal reconstruction and recognition for different models. The outcomes imply that the overall performance of our proposed frameworks is similar or advanced to that of the state-of-the-art method. The shape is a realistic technique to control the full-size extent of EEG data and pick out the individual based totally on their emotions, resting states, or specific tasks.

3.1 Research Question and Challenges Addressed in the Current Paper

EEG-based biometric system has been proven to be a growing research interest over the past few years. However, a decay in performance has been noticed when more subjects are enrolled in the system. The performance of a person identification system can also be explored by using emotion and task-based approaches for Person Identification with efficient deep learning algorithms that help in dimensionality reduction. These discussions raised many research questions, and the authors tried their best to address these challenges in this paper.

3.2 Proposed Solution of the Current Paper

This research proposes unsupervised frameworks for feature learning based on autoencoder to learn sparse feature representations for EEG-based person identification. Emotion-related EEG signals will be used here to create the Biometric Identification System. One cannot manipulate the EEG signal according to their will. It depends on various parameters like the external conditions and the internal mindset of the person. Hence, they will not be able to escape the identification system. We explored different person identification models using task-based EEG signals with autoencoder and CNN.

3.3 Novelty of the Proposed Solution

In this research for dimensionality reduction and denoising (extracting original input from noisy data), we have also proposed an autoencoder-CNN-based biometric system with EEG motor imagery inputs. The autoencoder extracts essential features from input EEG and ignores the noises during the training because the labels have no noises. Denoising autoencoders create a corrupted copy of the input by introducing some noise. This helps to avoid the autoencoders to copy the input to the output without learning features about the data. These autoencoders take a partially corrupted input while training to recover the original undistorted input. The model learns a vector field for mapping the input data towards a lower dimensional manifold which describes the natural data to cancel out the added noise. Convolutional Autoencoders learn to encode the input in a set of simple signals and then try to reconstruct the input from them. We have used the concept of Convolutional autoencoder with CNN to explore the effectiveness both in transformation and classification. In reconstructing the original information from the noisy version, denoising autoencoders are proved to be more efficient. Autoencoders are data-specific and best capable of compressing data like they had been trained. Autoencoder and CNN do the person identity venture for signal reconstruction and recognition. The outcomes imply that the overall performance of our proposed framework is similar or advanced to that of the latest method. To address the security issues in different applications, a robust and secure person identification system is designed.

The novel contributions of this paper are summarized as follows:

- Identifying individuals based on different states using deep learning techniques.
- Two deep learning model in a single architecture to design a biometric authentication system for EEG-based person identification.
- Implementation of autoencoder-CNN architecture for person identification was intensely successful with improved recognition performance with most notable autoencoder architecture.

4 Proposed Model

This section elaborates on the detailed methodology adopted for identifying people based on different states using deep learning. For this, we have trained the autoencoder and CNN in two phases. In the first phase, the first autoencoder reconstructs the input EEG signal. The reconstruction of signals has been done using the weights of the first autoencoder. In the second phase, we used the weights of the starting layers of the first autoencoder to initialize the weights of starting layers of CNN. Afterward, CNN was used to recognize or identify a different person. The detailed architecture is depicted in Fig 2. The following subsection describes the details of the autoencoder and CNN architecture used to reconstruct and recognize EEG signals.

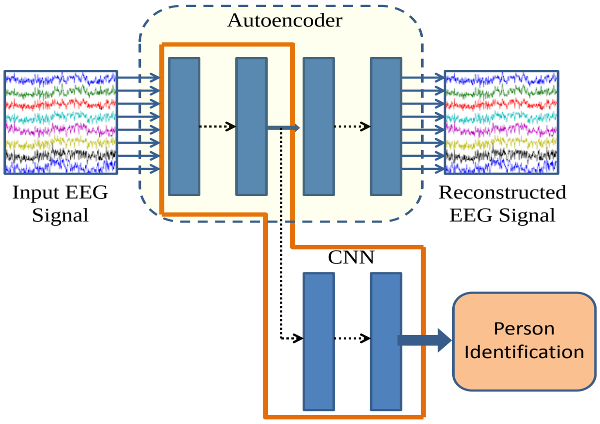


Fig. 2 Architecture of EEG-based Autoencoder-CNN model.

4.1 Architechture of Autoencoder

The primary aim of the convolutional autoencoder network is to minimize the reconstruction error by learning the compressed features from high dimensional feature space. The number of nodes in the input layer is the same as that of the output layer. Autoencoder is also used to reduce data dimension by reconstructing the feature descriptor set of the hidden layers having fewer nodes. To reconstruct the EEG signal inputs, the intuition behind the design of the autoencoder is that the autoencoder is best suited to rebuild the input data, and its weight is best suited for recognition task learning in place of random initialization of the weight. In this work, we use an autoencoder network consisting of two stages, encoding, and decoding. The autoencoder architecture is depicted in Fig.3, consisting of fifteen convolution layers, two max-pooling, and two upsampling layers. We have used 3x3 receptive fields for all the convolutional layers and 2x2 receptive fields for the max-pooling and upsampling layers. Input and output layers are of size 32x64. We have used zero padding for each convolutional layer to maintain the output size with the input size. After two max-pooling, the feature map size reduces to 8x64, and after two upsampling, it grows to the original size of 32x64. Each convolutional autoencoder layer, except the last convolutional layer, is embedded with a Relu activation function. The sigmoid activation function follows the final convolutional layer to output the probabilities of belongingness for classes.

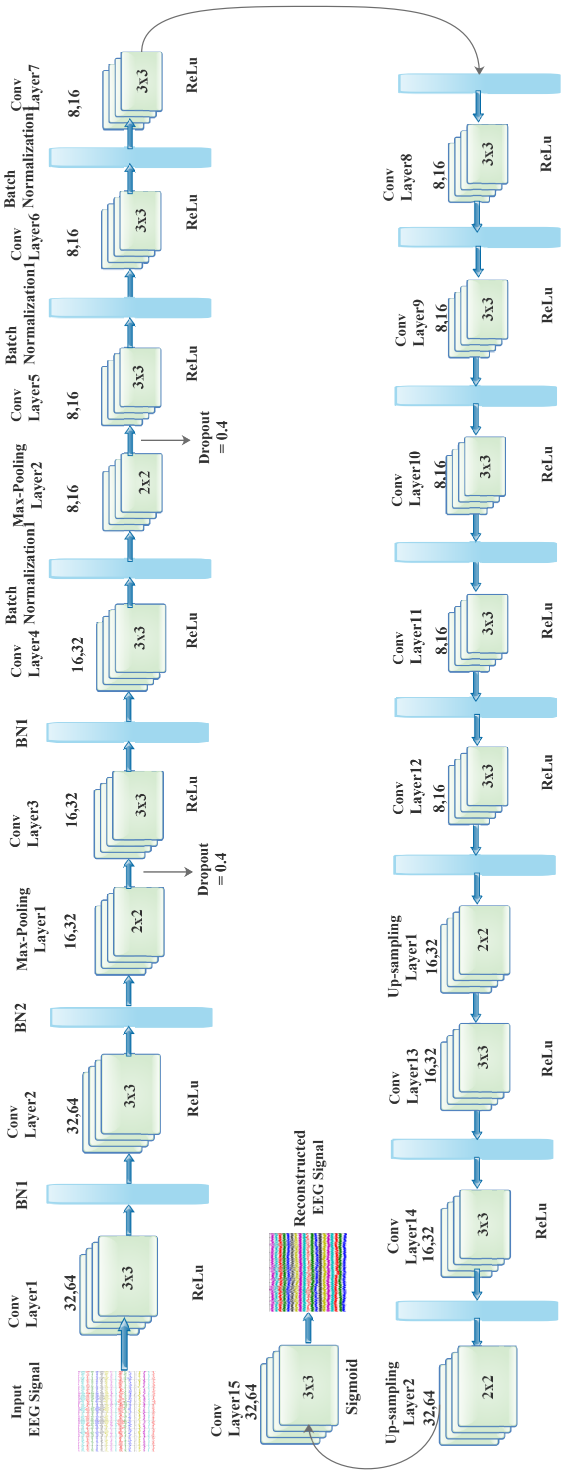


Fig. 3 Architecture of Autoencoder with EEG as input.

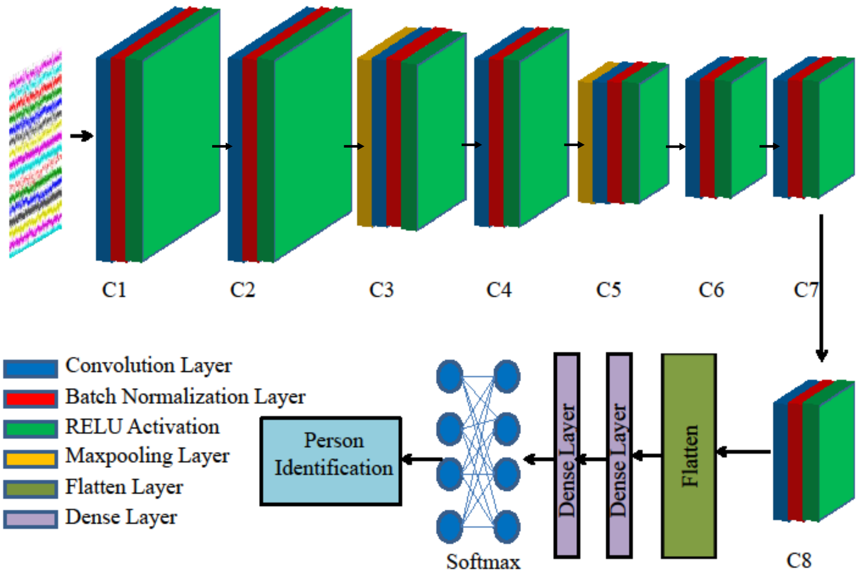


Fig. 4 Architecture of convolutional neural network (CNN) with reconstructed EEG as input.

4.2 Architechture of CNN

The convolutional neural network is used for classification and recognition purposes, and the derived weights of the first autoencoder are used in the layers of CNN. Eight convolution layers increase the depth of the CNN. Zero padding has been added to make the input and output sizes identical. The kernel size of each layer is 3x3, which helps to reduce the number of parameters and adds nonlinearity to the network. ReLu is connected with each convolutional layer and fully connected layers except the last layer embedded with softmax that transforms all the net activations in the final output layer to a series of values that can be interpreted as probabilities. To achieve this, the softmax function is applied to the net outputs (without an activation function or bias). The overall architecture of CNN with reconstructed input is depicted in Fig.4.

An n-D convolution is when two functions or tensors are convolved along n axes. Standard CNNs (i.e., 2D CNNs) are typically used for classifying two-dimensional inputs. Using a 2D CNN rather than other neural network structures, we aimed to capture many hidden spatial features. This approach guarantees the correctness of the generated features: the more hidden layers generated, the more hidden attributes developed in CNN to identify quickly. A 2-d convolution 'convolves' along two spatial dimensions. It has a minimal kernel, essentially a window of pixel values, that slides along those two dimensions. Based on the weight dimension, whenever we use Conv2D, one filter of weights has an equal number of channels as the previous layer, so one filter outputs one 2D channel. While in Conv3D, one filter has dimensions that are lesser than the input channels of the last layer; therefore, it forms more channels in the output layer.

5 Experimental Results and Discussion

The modeled network architecture experiments discussed in the previous section have been done on the system with 64 GB RAM. We have used Keras (Chollet (2015)) for various experiments. To evaluate the performance of the EEG-based person identification model, we have used motor imagery EEG data of 109 subjects. Resting-state data (eye open, eye closed) and four different tasks (motor imagery)are taken for training and testing, proving the biometric system's robustness. We have conducted various experiments by taking resting-state versus resting-state and resting-state versus different tasks (motor imagery) for training and testing our proposed model alternately.

The identification results are computed using the CNN without weights, which is the only CNN architecture, and CNN with weights, which is the autoencoder-CNN architecture, where the autoencoder network was trained with the mean squared function for the reconstruction of inputs. The autoencoder's mean squared error loss function is used to measure the closeness of reconstructed input and original input. Mean Squared Error (MSE) $J(x, z) = \|x - z\|^2$, where x and z are the original and reconstructed input, respectively. The subsection presents the dataset's details, results with experiment steps, and details of training the autoencoder and CNN.

5.1 Dataset Description

The dataset used for this study was collected from the publicly available physionet database [3]. The original recordings of Brainwave EEG motor imagery signals were gathered by using 64 channels of the BCI2000 system [15] with a sampling rate of 160 Hz. The brain signals were collected from 64 electrodes arranged with the international 10-10 standard as depicted in Fig.5. The dataset consists of two minutes of EEG recordings by 109 healthy and alcohol-free subjects. They performed different tasks in 14 runs, including two 1-minute baseline runs with resting state and three 2-minute runs (each of four various motor/imagery tasks). In this paper, we have considered baseline resting states separately for training and testing in one part and four different motor imagery tasks as described in Table 2 for testing along with resting-state training. Every recording lasts one minute for the resting state and two minutes for each of the four tasks. We have segmented the EEG data into multiple files (approximately 300) for the same subject for training. For this, a non-overlapped window is utilized, and the corresponding EEG recorded is segmented into equal parts for both EO and EC states for training.

Table 2 Description of the dataset used for the Proposed Model.

State	Description
Resting States	Eye Open (EO) and Eye Closed (EC)
Task1	open and close left or right fist
Task2	imagine opening and closing left or right fist
Task3	open and close both fists or both feet
Task4	imagine opening and closing both fists or both feet

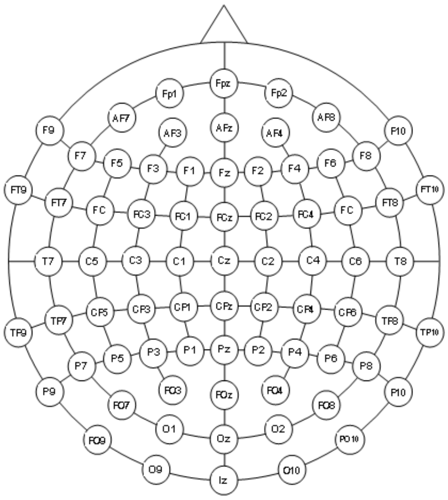


Fig. 5 Representation of 64 electrodes following the international 10-10 system.

5.2 Training of Autoencoder

Unsupervised learning was adopted to train the autoencoder. The input data was also considered as a target. The trained autoencoder was able to reconstruct the input EEG signals. The RMSprop gradient descent optimization algorithm [48] (proposed by Geoffrey Hinton) was used to train the autoencoder. The advantage of using RMSprop is that it dynamically adapts the learning rate and quickly adopts various architectures for selecting hyper-parameters.

5.3 Training of CNN

The CNN was trained with a definite loss function for classification and person identification. Here, we used this loss to train a CNN to output a probability over the classes for each signal. It is mainly used for multi-class classification. The softmax activation function is applied before the cross-entropy loss computation. The loss function is also known as the objective function. We want our neural networks to optimize their weights according to it. Therefore, it is task-specific and empirical. Out of the total data,90% and 10% of data were used for training and testing, respectively. The training of the model was terminated when we observed constant validation loss.

5.4 Training and Testing on Same State

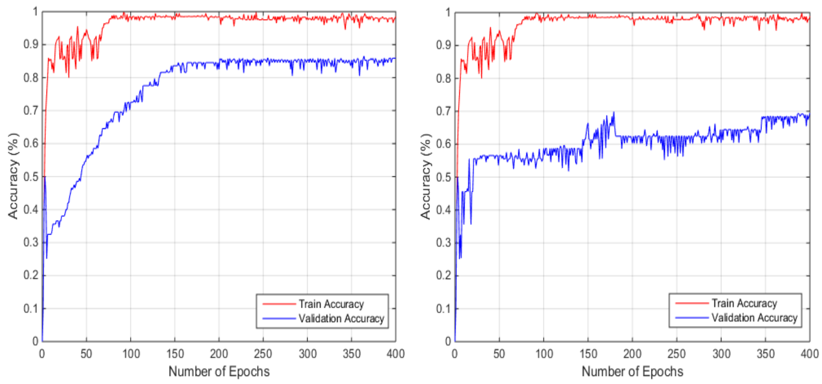
We have variously explored our models to find their efficiency. We have noted the results with the same train data and test data, for example, EO used for training and testing and the same for EC. We achieved train and validation accuracy of 99.63% and 99.45%, respectively, for eye open (EO) data using the autoencoder-CNN-based person identification model. We have noted train and validation accuracy of 99.53% and 98.27% eye closed (EC) data. We have also modeled the data using CNN to test the robustness of our model and noted train and validation accuracy of 100% and 77% for EO data, respectively. Likewise, we observed train and validation accuracy of 98.66% and 86% for EC data, respectively, as noted in Table 3. The highest person identification accuracy has been achieved up to 86% with EC Vs. EC in CNN. In the autoencoder-CNN model, the highest person identification accuracy has been achieved up to 99.63% with EO Vs. EO. The perfermance metrics in terms of train and validation loss plot for both the models have been observed as depicted in Fig. 12.

Table 3 Observation of Performance [Accuracy] with EO Vs EO and EC Vs EC.

Model	Accuracy(%) EO VS EO Train/ Validation/ Test	Accuracy(%) EC Vs EC Train/ Validation/ Test
CNN	100/ 77.00/ 81.00	98.66/ 86.00/ 83.44
Autoencoder+CNN	99.76/ 99.63/ 99.45	99.53/ 98.27/ 99.89

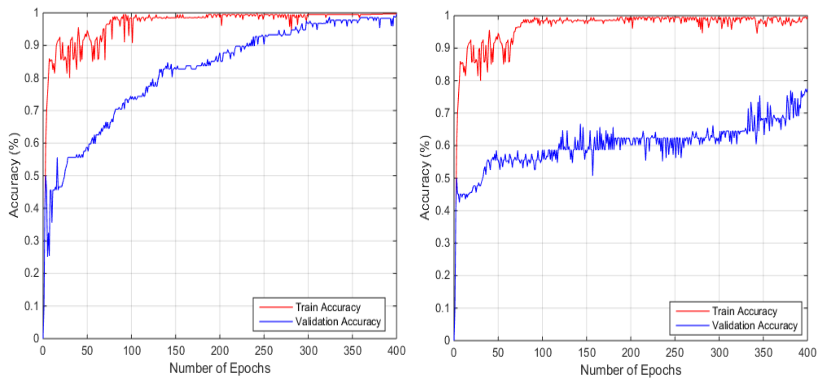
5.5 Training and Testing on Different States

To prove the robustness of our model, we have used the different training and testing data of the dataset. Firstly, we alternately used eye open and closed state for training and testing and observed person identification accuracy of 77.58% and 73.76% respectively, as noted in Table 8. The plot of train and validation accuracy of both the models CNN and Autoencoder-CNN is depicted in 6 and 7 respectively. We have also experimented by using EO and EC separately as train data with four different tasks as test data to observe the identification accuracy of the proposed model as recorded in Table 5 for EO Vs. Tasks and Table 6 for EO Vs. Tasks. We have noted the train, validation, and test accuracy for both the CNN and Autoencoder-CNN model.



(a) (b)

Fig. 6 Performance [Accuracy] with number of epochs using CNN.: (a) EC Vs EC (b) and EO Vs EC.



(a) (b)

Fig. 7 Performance [Accuracy] with number of epochs using Autoencoder-CNN Model.: (a) EO Vs EO (b) and EO Vs EC.

The highest performance noted for EO Vs. Task2 as depicted in Fig. 8 and 9 for Autoencoder-CNN and CNN model respectively.We have also observed the performance of both the models interms of train and validation loss as depicted in Fig.13. Likewise, we have noted the highest performance for EC Vs. Task1 for Autoencoder-CNN and EC Vs. Task2 for CNN model as shown in Fig. 8 and Fig.9 respectively.Secondly, we have used the whole resting-state data EO, and EC combined for training our proposed model and four different motor imagery tasks for testing one by one and noted the accuracy as shown in Table 7. The highest person identification accuracy has been achieved up to 87.93% with task1 (open and close left or right fist) for Autoencoder-CNN model as depicted in Fig.10. We have used the CNN model to observe the performance of the model with the same states and got the highest accuracy

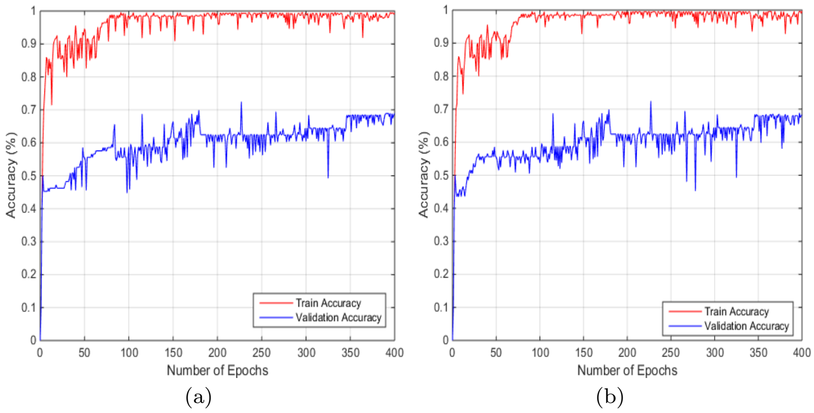


Fig. 8 Performance [Accuracy] with number of epochs with different states using Autoencoder-CNN Model.: (a) EO Vs Task2 (b) and EC Vs Task1.

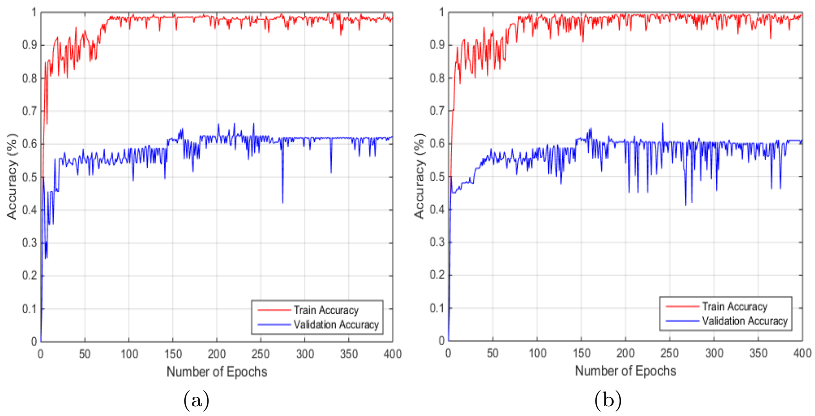


Fig. 9 Performance [Accuracy] with number of epochs with different states using CNN Model.: (a) EO Vs Task2 (b) and EC Vs Task2.

of 81.84% with Task1 (open and close left or right fist) as mentioned in Table 7 and shown in Fig. 10. We have also observed and noted the performance of both the models interms of train and validation loss as depicted in Fig.14.We have also compared and analyzed the performance with the EO, EC, and EOEC with increased number of training data in EOEC with different tasks as testing data and noted the highest accuracy with different motor imagery tasks for the two different model as depicted in Fig 11.

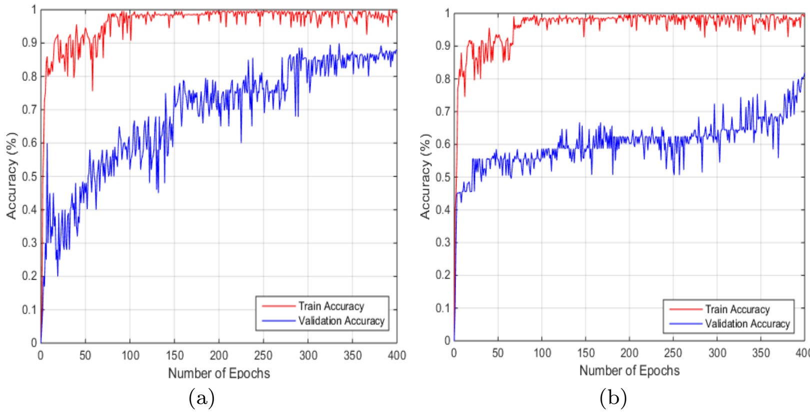


Fig. 10 Performance [Accuracy] with number of epochs with different states using : (a) EOEC Vs Task1 in Autoencoder-CNN (b) and EOEC Vs Task1 in CNN.

Table 4 Observation of Performance Accuracy with EO VS EC and EC Vs EO Tasks .

Model	Accuracy(%) EO VS EC Train/ Validation/ Test	Accuracy(%) EC Vs EO Train/ Validation/ Test
CNN	98.87/ 69.45/ 67.23	98.56/ 66.00/ 65.38
Autoencoder+CNN	99.63/ 77.58/ 75.33	97.34/ 73.76/ 72.91

Table 5 Observation of Performance [Accuracy] with EO (Train Data) Vs Tasks (Test Data).

Tasks	Accuracy(%) with weight(Autoencoder-CNN) Train/ Validation/ Test	Accuracy(%) without weight(CNN) Train/ Validation/ Test
Task1	99.55/ 65.65/ 65.13	99.13/61.77/61.25
Task2	99.44/ 68.91/ 66.79	98.67/62.31/61.98
Task3	99.60/63.27/ 63.11	99.27/60.63/60.28
Task4	99.49/ 67.39/ 66.54	97.21/59.56/60.19

5.6 Comparative Analysis

We have compared the proposed framework of EEG-based person identification with existing techniques. The authors in [21], used CNN for user identification, and obtained 94.01% and 97.00% accuracy using two different data sets the Dreamer and BCIT EEG datasets, respectively.Thomas *et al*. [19] have proposed a biometric recognition system to improve the recognition performance using EEG signals. They have applied the band-pass filter method on EEG data to remove the artifacts and considered Individual Alpha Fre-

Table 6 Observation of Performance [Accuracy] with EC (Train Data) Vs Tasks (Test Data).

Tasks	Accuracy(%) with weight(Autoencoder-CNN) Train/ Validation/ Test	Accuracy(%) without weight(CNN) Train/ Validation/ Test
Task1	99.71/68.29/67.33	98.11/58.89/ 59.12
Task2	99.32/62.97/62.88	99.37/ 61.17/ 61.00
Task3	99.57/64.78/63.41	97.72/59.76/ 59.27
Task4	99.23/65.21/64.98	98.69/ 60.98/ 60.11

Table 7 Observation of Performance [Accuracy] with EOEC (Train Data) Vs Tasks (Test Data).

Tasks	Accuracy(%) with weight(Autoencoder-CNN) Train/ Validation/ Test	Accuracy(%) without weight(CNN) Train/ Validation/ Test
Task1	99.96/ 87.93/ 87.60	99.63/ 81.84/80.95
Task2	99.90/ 82.56/ 82.74	99.82/78.28/79.09
Task3	99.89/ 85.79/ 84.99	99.92/ 77.63/78.40
Task4	99.91/ 83.88/ 83.71	99.87/75.12/76.90

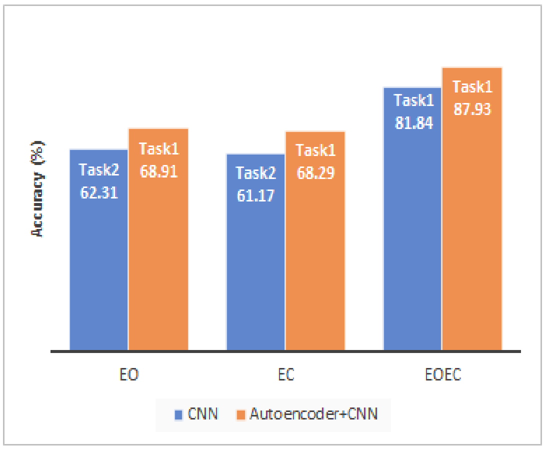
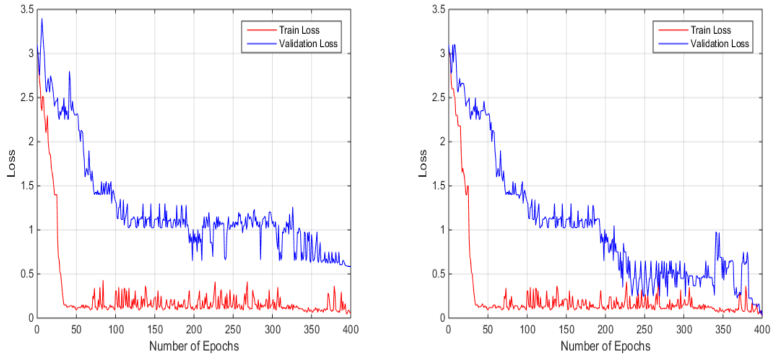


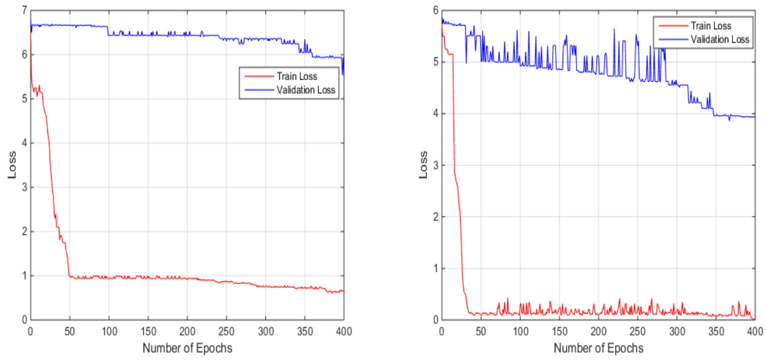
Fig. 11 Pictorial representation of the Highest performance [Accuracy] with Tasks for EO, EC and EOEC.

quency Peak (IAF), IAF power (IAFP), and Delta Band (0.5- 4 Hz) Power (DBP), respectively, for making six subject-specific templates in both EO/EC conditions. Similarly, the authors in [4] have modeled the EEG signal using both Random Forest (RF) and Support Vector Machine (SVM). They have extracted some features using DWT analysis of feature extraction. ChiQin Lai *et al.* [22] proposed a CNN model combined with a majority voting set of



(a) (b)

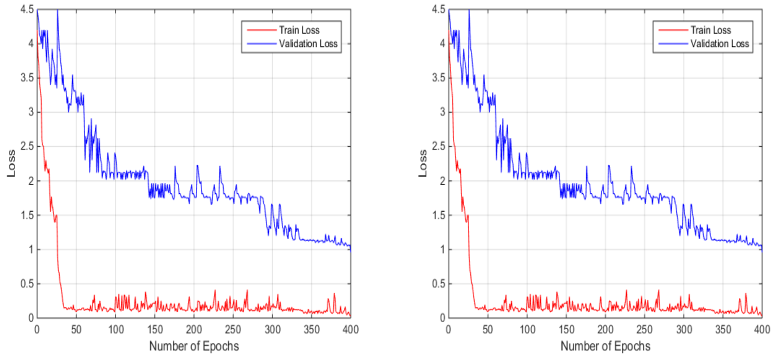
Fig. 12 Performance [Loss] with number of epochs for resting states using : (a) CNN (b) and Autoencoder-CNN.



(a) (b)

Fig. 13 Performance [Loss] with number of epochs for EO vs. Task2 using : (a) CNN (b) and Autoencoder-CNN.

error-correcting output codes of support vector machines (CNN-ECOC-SVM) for EEG-based biometrics architechture, and noted recognition accuracy of 98.49%. Keshishzadeh et al. [5] have used Autoregressive (AR) coefficients as the feature set, selecting the features using a statistical-based method and using an SVM classifier to propose an EEG-based person authentication system. The authors in [7] have designed the authentication connectivity using a Mahalanobis distance-based classifier. They have applied a proper anti-aliasing low-pass filter to restrict the available frequency range up to 50 Hz. The PSD of the EEG signals was extracted from each segmented epoch (10s) by computing Welch's averaged modified periodogram. The authors in [20] have designed a spatio-temporal model for person identification using CNN and LSTM lay-



(a) (b)

Fig. 14 Performance [Loss] with number of epochs for EOEC vs. Task1 using : (a) CNN (b) and Autoencoder-CNN.

ers with different time segments and observed notable performance with EEG data for identification.

For biometric identification, the proposed identification model includes autoencoder and CNN layers using EEG signals to enhance the performance of recognition accuracy with a large number of subjects. Comparison between the state-of-the-art biometric authentication systems using captured scalp EEG is presented in Table 8. These works used one publicly available popular large motor imagery EEG dataset. Some author used their own created EEG dataset for measuring performance. In Table 8, all use baseline state (eye closed and open state) for performance evaluation. The proposed biometric system provides better comparable performance with many subjects, a step toward realistic application in the biometric identification and verification.

6 Conclusion

This paper explored the capability of two deep learning models in a single architecture to design a biometric authentication system for EEG-based person identification. Here we have used the encoder and decoder of the autoencoder model to extract the features of the reconstructed EEG signals. The CNN model uses the saved weights of the autoencoder model to classify the reconstructed EEG signal for person identification. We have used more profound CNN architecture here, which proved reliable and got better performance. It was observed that implementing the autoencoder-CNN architecture for person identification was intensely successful, with improved recognition performance with the most notable autoencoder architecture. We have used eye open and closed resting state data as training data, while four different motor imagery tasks have been considered test data in this biometric model. Training and testing of variable state data of the same person have been proven to be the

Table 8 Comparison between the state-of-the-art biometric authentication systems using non-invasive EEG signals.

Reference	Subjects	Classifier	Number of channels	Time Segment	Performance[Accuracy(%)]
[19]	109	Mahalanobis distance	19	10	90 (EC/EO)
[4]	109	RF	64	2	95.78(EO) 93.21(EC)
[4]	109	SVM	64	2	96.88(EO) 96.02(EC)
[5]	104	SVM	64	0.5	97.43 (EO,EC)
[7]	108	Mahalanobis distance	56	10	96.26(EO) 97.5(EC)
[21]	23	CNN	64	1	94.01
[22]	109	CNN-ECOC-SVM	64	1	98.49 (EO,EC)
[20]	109	CNN+LSTMs	64	4	95.00 (EO) 95.33 (EC)
[20]	109	CNN+LSTMs	64	8	96.2 (EO) 97.00 (EC)
[20]	109	CNN+LSTMs	64	16	92.5 (EO) 93.2 (EC)
Proposed	**109**	**Autoencoder-CNN**	**64**	**8**	**99.45 (EO) 99.89 (EC)**

most robust and versatile EEG-based biometric system. In the future, different deep learning and machine learning methods can be merged to explore better performance in this EEG-based security field and other signal processing areas.

7 Declarations

Funding and/or Conflicts of interests/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.

Data availability Statement
The datasets analysed during the current study are available in the [Physionet] repository, [https://physionet.org/content/eegmmidb/].

References

1. Abdullah, M. K., Subari, K. S., Loong, J. L. C., and Ahmad, N. N. (2010). Analysis of the eeg signal for a practical biometric system. *World Academy of Science, Engineering and Technology*, 68:1123–1127. 4, 5
2. Cecotti, H. and Graeser, A. (2008). Convolutional neural network with embedded fourier transform for eeg classification. In *19th International Conference on Pattern Recognition*, pages 1–4. 4, 5
3. Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C.-K., and Stanley, H. E. (2000). Physiobank, physiotoolkit, and physionet. *Circulation*, 101(23):e215–e220. 11

4. Kaur, B. and Singh, D. (2017). Neuro signals: A future biomertic approach towards user identification. In *7th International Conference on Cloud Computing, Data Science & Engineering-Confluence*, pages 112–117. 4, 17, 20
5. Keshishzadeh, S., Fallah, A., and Rashidi, S. (2016). Improved eeg based human authentication system on large dataset. In *24th Iranian Conference on Electrical Engineering*, pages 1165–1169. 18, 20
6. Kostílek, M. and Št'astnỳ, J. (2012). Eeg biometric identification: Repeatability and influence of movement-related eeg. In *International Conference on Applied Electronics*, pages 147–150. 4, 5
7. La Rocca, D., Campisi, P., Vegso, B., Cserti, P., Kozmann, G., Babiloni, F., and Fallani, F. D. V. (2014). Human brain distinctiveness based on eeg spectral coherence connectivity. *IEEE transactions on Biomedical Engineering*, 61(9):2406–2412. 4, 5, 18, 20
8. Marcel, S. and Millán, J. d. R. (2007). Person authentication using brainwaves (eeg) and maximum a posteriori model adaptation. *IEEE transactions on pattern analysis and machine intelligence*, 29(4). 5
9. Näpflin, M., Wildi, M., and Sarnthein, J. (2007). Test–retest reliability of resting eeg spectra validates a statistical signature of persons. *Clinical Neurophysiology*, 118(11):2519–2524. 4, 5
10. Nurse, E., Mashford, B. S., Yepes, A. J., Kiral-Kornek, I., Harrer, S., and Freestone, D. R. (2016). Decoding eeg and lfp signals using deep learning: heading truenorth. In *Proceedings of the ACM International Conference on Computing Frontiers*, pages 259–266. 4, 5
11. Palaniappan, R. and Mandic, D. P. (2007). Biometrics from brain electrical activity: A machine learning approach. *IEEE transactions on pattern analysis and machine intelligence*, 29(4):738–742. 4, 5
12. Poulos, M., Rangoussi, M., and Alexandris, N. (1999a). Neural network based person identification using eeg features. In *IEEE International Conference on Acoustics, Speech, and Signal Processing*, volume 2, pages 1117–1120. 4
23. Poulos, M., Rangoussi, M., Chrissikopoulos, V., and Evangelou, A. (1999b). Person identification based on parametric processing of the eeg. In *The 6th IEEE International Conference on Electronics, Circuits and Systems.*, volume 1, pages 283–286. 4
14. Riera, A., Soria-Frisch, A., Caparrini, M., Grau, C., and Ruffini, G. (2008). Unobtrusive biometric system based on electroencephalogram analysis. *EURASIP Journal on Advances in Signal Processing*, 2008:18. 4
15. Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., and Wolpaw, J. R. (2004). Bci2000: a general-purpose brain-computer interface (bci) system. *IEEE Transactions on biomedical engineering*, 51(6):1034–1043. 11
16. Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., and Ball, T. (2017). Deep learning with convolutional neural networks for eeg decoding and visualization. *Human brain mapping*, 38(11):5391–5420. 4, 5
17. Spampinato, C., Palazzo, S., Kavasidis, I., Giordano, D., Souly, N., and Shah, M. (2017). Deep learning human mind for automated visual classi-

fication. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6809–6817. 4, 5

18. Su, F., Zhou, H., Feng, Z., and Ma, J. (2012). A biometric-based covert warning system using eeg. In *5th IAPR International Conference on Biometrics*, pages 342–347. 4, 5
19. Thomas, K. P. and Vinod, A. P. (2016). Utilizing individual alpha frequency and delta band power in eeg based biometric recognition. In *IEEE International Conference on Systems, Man, and Cybernetics*, pages 004787–004791. 4, 16, 20
20. B. B. Das, P. Kumar, D. Kar, S. K. Ram, K. S. Babu, and R. K. Mohapatra (2019) A spatio-temporal model for EEG-based person identification. *Multimedia Tools and Applications*, 78(19), pp. 28,157–28,177. 2, 18, 20
21. P. Arnau-González, S. Katsigiannis, N. Ramzan, D. Tolson, and M. Arevalillo-Herrez (2017) Es1d: A deep network for eeg-based subject identification. *IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE)*, pp. 81–85. 16, 20
22. C. Q. Lai, H. Ibrahim, M. Z. Abdullah, and S. A. Suandi (2022) Eeg-based biometric close-set identification using cnn-ecoc-svm. *Artificial Intelligence in Data and Big Data Processing Proceedings of ICABDE*, pp. 723–732. 17, 20
23. M. Poulos, M. Rangoussi, V. Chrissikopoulos, and A. Evangelou, "Person identification based on parametric processing of the eeg," in *The 6th IEEE International Conference on Electronics, Circuits and Systems, 1999. Proceedings of ICECS'99.*, vol. 1. IEEE, 1999, pp. 283–286. 4
24. ——, "Parametric person identification from the eeg using computational geometry," in *The 6th IEEE International Conference on Electronics, Circuits and Systems, 1999. Proceedings of ICECS'99.*, vol. 2. IEEE, 1999, pp. 1005–1008. 4
25. B. B. Das, S. K. Ram, B. Pati, C. R. Panigrahi, K. S. Babu, and R. K. Mohapatra, "Svm and ensemble-svm in eeg-based person identification," in *Progress in Advanced Computing and Intelligent Engineering*, 2021, pp. 137–146.
26. M. Hammad, P. Pławiak, K. Wang, and U. R. Acharya, "Resnet-attention model for human authentication using ecg signals," *Expert Systems*, vol. 38, no. 6, p. e12547, 2021. 2
27. R. Paranjape, J. Mahovsky, L. Benedicenti, and Z. Koles, "The electroencephalogram as a biometric," in *Electrical and Computer Engineering, 2001. Canadian Conference on*, vol. 2. IEEE, 2001, pp. 1363–1366. 2
28. R. Giot, M. El-Abed, and C. Rosenberger, "Fast computation of the performance evaluation of biometric systems: Application to multibiometrics," *Future Generation Computer Systems*, vol. 29, no. 3, pp. 788–799, 2013, special Section: Recent Developments in High Performance Computing and Security. [Online]. Available: `https://www.sciencedirect.com/science/article/pii/S0167739X12000362` 4
29. A. Balaji, V. HS, and S. OK, "Multimodal fingerprint spoof detection using white light," *Procedia Computer Science*, vol. 78, pp. 330–335, 2016. 2

30. N. Lalithamani, R. Balaji, M. Ramya, S. Sruthi, and A. Aiswarya, "Finger knuckle biometric authentication using convolution neural network," *Int. J. Pure Appl. Math.*, vol. 117, no. 10, pp. 31–35, 2017. 2
31. J. J. Winston and D. J. Hemanth, "Performance-enhanced modified self-organising map for iris data classification," *Expert Systems*, vol. 38, no. 1, p. e12467, 2021. 2
32. G. Jaswal and R. C. Poonia, "Selection of optimized features for fusion of palm print and finger knuckle-based person authentication," *Expert Systems*, vol. 38, no. 1, p. e12523, 2021. 2
33. S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Mekhtiche, and M. Shamim Hossain, "Deep learning for eeg motor imagery classification based on multi-layer cnns feature fusion," *Future Generation Computer Systems*, vol. 101, pp. 542–554, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167739X19306077 2
34. I. Dua, A. U. Nambi, C. Jawahar, and V. N. Padmanabhan, "Evaluation and visualization of driver inattention rating from facial features," *IEEE Transactions on Biometrics, Behavior, and Identity Science*, vol. 2, no. 2, pp. 98–108, 2019. 2
35. N. Sae-Bae, J. Wu, N. Memon, J. Konrad, and P. Ishwar, "Emerging nui-based methods for user authentication: A new taxonomy and survey," *IEEE Transactions on Biometrics, Behavior, and Identity Science*, vol. 1, no. 1, pp. 5–31, 2019. 2
36. P. Drozdowski, C. Rathgeb, B.-A. Mokroß, and C. Busch, "Multi-biometric identification with cascading database filtering," *IEEE Transactions on Biometrics, Behavior, and Identity Science*, vol. 2, no. 3, pp. 210–222, 2020. 2
37. R. Sujitha and N. Lalithamani, "Counter measures for indirect attack for iris based biometric authentication," *Indian Journal of Science and Technology*, vol. 9, no. 19, pp. 1–7, 2016. 2
38. H. Arshad, M. A. Khan, M. I. Sharif, M. Yasmin, J. M. R. Tavares, Y.-D. Zhang, and S. C. Satapathy, "A multilevel paradigm for deep convolutional neural network features selection with an application to human gait recognition," *Expert Systems*, p. e12541, 2020. 2
39. D. Carrión-Ojeda, R. Fonseca-Delgado, and I. Pineda, "Analysis of factors that influence the performance of biometric systems based on eeg signals," *Expert Systems with Applications*, vol. 165, p. 113967, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S095741742030748X 2
40. H. Zhao, Y. Chen, W. Pei, H. Chen, and Y. Wang, "Towards online applications of eeg biometrics using visual evoked potentials," *Expert Systems with Applications*, vol. 177, p. 114961, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417421004024 2
41. V. Menon, B. Jayaraman, and V. Govindaraju, "Spatio-temporal reasoning in biometrics based smart environments," *Procedia Computer Science*, vol. 5, pp. 378–385, 2011. 2
42. G. H. de Rosa, M. Roder, and J. P. Papa, "Neighbour-based bag-of-samplings for person identification through handwritten dynamics and con-

volutional neural networks," *Expert Systems*, p. e12891, 2021. 2
43. H. Jian-feng, "Multifeature biometric system based on eeg signals," in *Proceedings of the 2nd International Conference on Interaction Sciences: Information Technology, Culture and Human.* ACM, 2009, pp. 1341–1345. 3
44. B. Hu, C. Mao, W. Campbell, P. Moore, L. Liu, and G. Zhao, "A pervasive eeg-based biometric system," in *Proceedings of 2011 international workshop on Ubiquitous affective awareness and intelligent interaction.* ACM, 2011, pp. 17–24. 4
45. Kumar, M., Narayanan, S., Sur, M. & Murthy, H. Evidence of task-independent person-specific signatures in EEG using subspace techniques. *IEEE Transactions On Information Forensics And Security.* **16** pp. 2856-2871 (2021) 5
46. Sun, Y., Lo, F. & Lo, B. EEG-based user identification system using 1D-convolutional long short-term memory neural networks. *Expert Systems With Applications.* **125** pp. 259-267 (2019) 4
47. Wilaiprasitporn, T., Ditthapron, A., Matchaparn, K., Tongbuasirilai, T., Banluesombatkul, N. & Chuangsuwanich, E. Affective EEG-based person identification using the deep learning approach. *IEEE Transactions On Cognitive And Developmental Systems.* **12**, 486-496 (2019) 4, 5
48. Tieleman, T., Hinton, G. & Others Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude. *COURSERA: Neural Networks For Machine Learning.* **4**, 26-31 (2012) 4, 5