Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

A DECADE OF ADVANCES IN EEG-BASED AUTHENTICATION: A REVIEW

ABOOTHAR MAHMOOD SHAKIR *
Department of Information Technology and Computer Engineering, University of Qom, Iran.
Computer Techniques Engineering Department, College of Technical Engineering, The Islamic University, Najaf, Iraq. *Corresponding Author Email: abathermahmood560@gmail.com

AMIR JALALY BIDGOLY
Department of Information Technology and Computer Engineering, University of Qom, Iran.

Abstract

This paper provides a comprehensive review of the state-of-the-art in brain signal processing, classification, and security research conducted from 2013 to 2023. Summarize the key advances in signal processing techniques, feature extraction methods, and machine learning algorithms used for brain signal classification. Also discuss the various security challenges and solutions for protecting brain signals from unauthorized access and attacks. The review highlights the importance of developing a robust and reliable EEG-based authentication system that can handle the variability and complexity of brain signals. Also emphasize the need to develop secure and privacy-preserving brain-computer interfaces (BCIs) that protect users' sensitive brain data from potential threats. Furthermore, it critically analyses the limitations and future directions of the current research in EEG-based authentication, identifying several promising research directions, including developing explainable and interpretable machine learning models, integrating multi-modal brain signals, and exploring new applications in affective computing and social signal processing. Also, this review discusses the challenges and opportunities of the future of authentication systems.

1. INTRODUCTION

Over the past decade, there has been a significant increase in research focused on processing, classifying, and securing brain signals for various applications, including biometric authentication [40], medical diagnosis [50], and neuroproteins [42] and understanding these aspects and research directions, this paper conducts a comprehensive comparative analysis of previous research on brain signal acquisition devices.

Two main factors need to be discussed to understand the research directions. The first is the interpretation, which investigates how the data collected from these devices is analyzed and understood. This might involve exploring different feature extraction and selection methods and various classification algorithms used to identify patterns in the data [1].

The second is the protection of brain signaling devices, particularly in ensuring users' security and privacy. May want to look into how different devices address these concerns, such as through robust and discrete technology that doesn't limit movement [2].

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

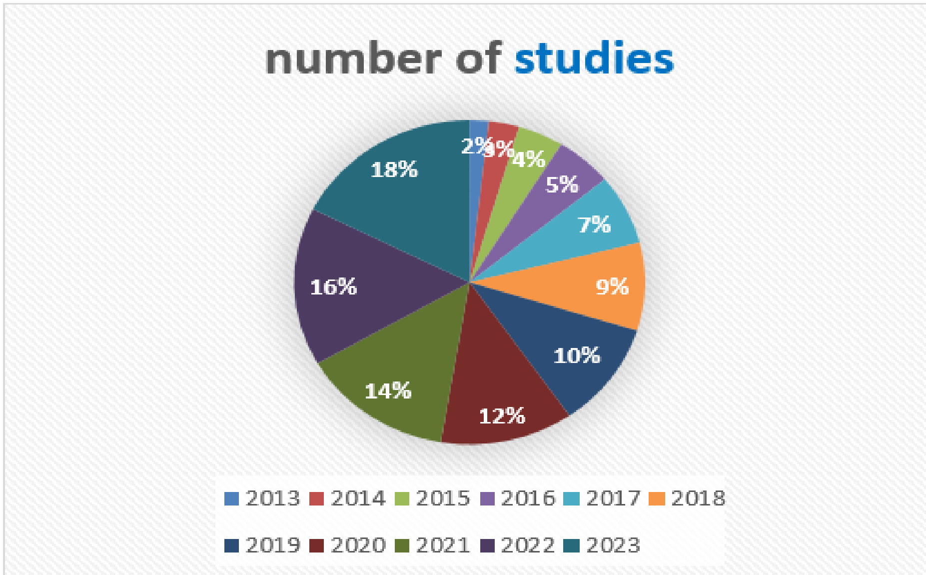

Figure 1: Number of documents published about EEG-based authentication

Fig. 1 represents several research studies on brain signal data conducted in the period (2013-2023). The data is based on a comprehensive review of academic literature and conference proceedings. Some are subject to slight variations depending on the source and methodology used. The data shows a steady increase in the number of studies over the years, indicating a growing interest in this field of research.

This article aims to investigate EEG-based authentication systems with a comprehensive understanding of:

1) EEG signal definition and its types.
2) The techniques used in the Authentication system during the preprocessing, classification, and authentication stages.
3) The main matrices of authentication approaches.
4) Stimuli types, single task, and multi-task authentication.
5) Studies findings and the limitations.
6) Conclusion and potential future work.

2. ELECTROENCEPHALOGRAPHY (EEG)

EEG is a non-invasive technique for measuring the electrical activity of the brain. It involves placing electrodes on the scalp to detect the tiny electrical signals generated by the synchronized firing of neurons in the brain. These signals are then amplified and recorded, providing a direct measure of brain activity [3].

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

The electrodes are, therefore, positioned based on the 10-20 system of electrode placement, which resulted from the International Federation of Societies for EEG.[6] This system is founded on the location of an electrode concerning the area of the cerebral cortex, as depicted below; Fig 2.

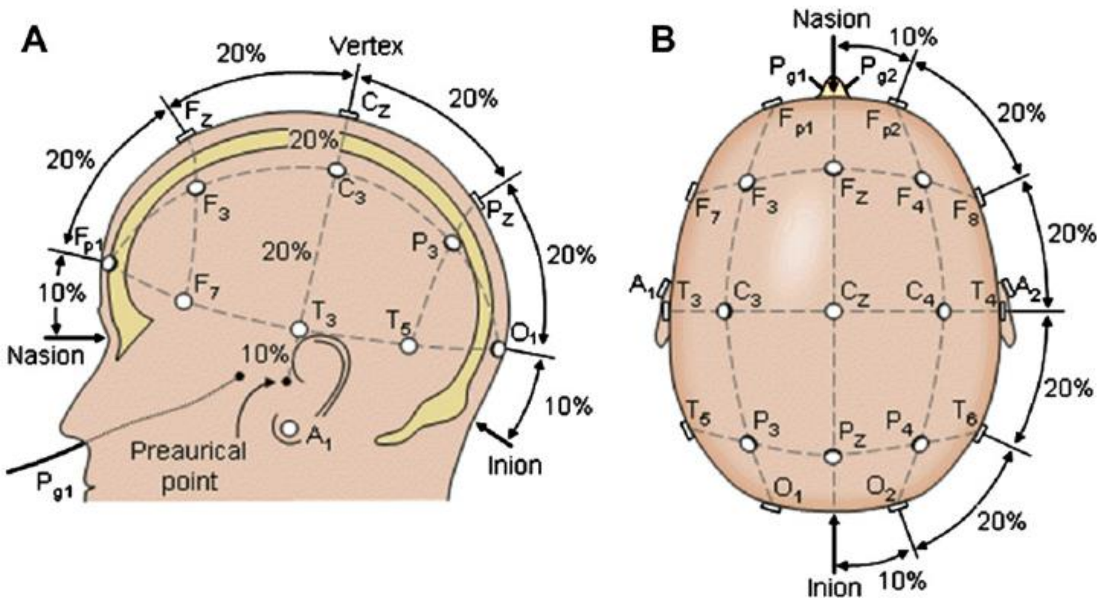

Figure 2: Electrode placement according to the international 10-20 system. Left image lateral view, right image top view [11]

EEG signals are characterized by their frequency, amplitude, and location on the scalp. The frequency of EEG signals ranges from 0.5 to 40 Hz and is classified into five frequency bands: Delta, Theta, Alpha, Beta, and Gamma. Each frequency band is associated with different states of consciousness and cognitive processes. [4]

i. **Delta** waves (1-4 Hz) are the slowest and highest amplitude waves, typically observed in infants and during deep sleep in adults.

ii. **Theta** waves (4-8 Hz) are associated with drowsiness and memory recall and are observed in children. [5]

iii. **Alpha** waves (8-12 Hz) are the dominant frequency band during relaxed wakefulness or when the eyes are closed.

iv. **Beta** waves (12-25 Hz) are associated with thinking, active concentration, and focused attention.

v. **Gamma** waves (over 25 Hz) are the fastest frequency band associated with multiple sensory processing. [6]. Frequency bands correlated with their associated mental state are present in Table 1:

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

Table 1: Brain frequency bands and their respective frequency range [15]

Frequency Band	Frequency Range	Associated State
Delta (δ)	0.5 – 4 Hz	Deep sleep, healing, regeneration
Theta (θ)	4 – 8 Hz	Light sleep, relaxation, meditation
Alpha (α)	8 – 13 Hz	Relaxation, calmness, wakefulness
Beta (β)	13 – 30 Hz	Active thinking, concentration
Gamma (γ)	30 – 100+ Hz	High-level cognitive processing

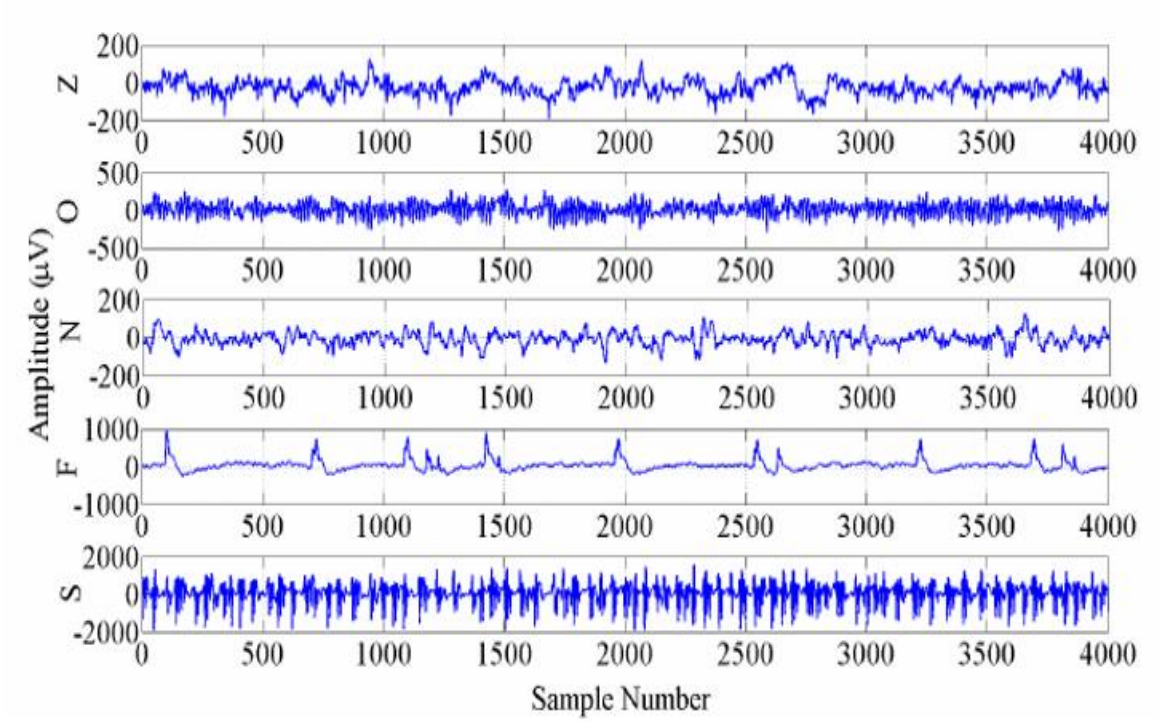

Figure 3: Brain frequency bands extracted from an EEG signal

Analyzing the dominant frequencies and amplitude of EEG waveforms in different parts of the brain can provide valuable insights into a person's physical or mental state. For example, changes in EEG patterns have been linked to various neurological and psychiatric disorders, such as epilepsy, Parkinson's disease, and depression. EEG has numerous applications, including biometric authentication, sleep studies, cognitive neuroscience, and clinical neurophysiology.

Its non-invasive nature, high temporal resolution, and low cost make it a popular choice for researchers and clinicians alike. However, EEG signals can be affected by various factors, such as muscle activity, eye movement, and electrical interference, [7] which can make interpretation challenging. Therefore, careful signal processing and analysis techniques are required to ensure accurate and reliable results.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

Table 2: Functions Associated with Different Parts of the Brain

Brain Region	Functions
Cerebrum	
Frontal Lobe	Executive functions, decision-making, planning, problem-solving, motor control, language processing [36]
Parietal Lobe	Sensory processing, spatial awareness, attention, and memory [40]
Temporal Lobe	Auditory processing, memory, language processing, and emotion regulation [37]
Occipital Lobe	Visual processing, and object recognition [41]
Cerebellum	Motor coordination, balance, learning, and memory [33]
Brainstem	
Midbrain	Auditory and visual processing, motor control, sleep, and arousal [38]
Pons	Sleep and arousal, respiration, and swallowing [35]
Medulla Oblongata	Regulation of involuntary functions (heart rate, blood pressure, breathing)
Limbic System	Emotion regulation, motivation, memory, and learning [43]
Hippocampus	Memory formation, spatial navigation [39]
Amygdala	Emotional processing, fear response
Hypothalamus	Regulation of body temperature, hunger, thirst, sleep [46]
Basal Ganglia	Movement control, habit formation, and reward processing [48]
Thalamus	Sensory processing, relaying information to the cortex [47]
Hypothalamus	Regulation of body temperature, hunger, thirst, and sleep [35]

This table is not an exhaustive list of all brain regions and their functions, but rather a selection of some of the most well-known and important ones. Some brain regions have multiple functions, and some functions are distributed across multiple regions. The functions listed are not mutually exclusive, and there is often overlap between them. This table provides a concise overview of the main functions associated with different parts of the brain. It is a useful reference for understanding the complex relationships between brain regions and their roles in various cognitive and physiological processes.

3. BIOMETRIC EEG-BASED SYSTEM

A biometric system is a pattern recognition system consisting of acquiring biometric data from an individual, extracting a feature set from the acquired data, and comparing the extracted feature set against a template set stored in the database [51], The subsequent discussion provides a comprehensive analysis of the research papers, structured according to three criteria which will be systematically elucidated throughout our examination.

3.1 Preprocessing Techniques

This paper elaborates on preprocessing as a vital step in EEG-based authentication systems because it removes noise and artifacts, including muscle movements and eye blinks to improve the quality of the data passed through the filter. It also performs re-referencing and normalization to standardize the signal and make sure these are consistent across different sessions and with other individuals, which is helpful for comparison and training machine learning models. Preprocessing helps to increase the

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

signal-to-noise ratio so that better features are extracted from the original image, and classifiers are better at minimizing false positive and negative values. It also encompasses data dimensionality reduction that helps manage the data complexity and accelerate the data processing rate to make real-time analysis possible. Preprocessing is crucial for the proper working, high security, and performance of EEG-based authentication systems.

Many different techniques are used in the preprocessing step to prepare the data for the next step, like applying filters such as the Butterworth bandpass filter during signal acquisition to eliminate the noise or subtraction to subtract the raw EEG dataset of each electrode measurement. Fares Yousef et al. in [18] used context including signal filtering, notch filtering, band-pass filtering, noise removal (specifically for eye blinks), and normalization of EEG signals. These techniques enhance the quality of the EEG data before further analysis. Independent Component Analysis (ICA) is also mentioned as a method for identifying and removing blink artifacts in the EEG data, as well as using the Adaptive Mixture ICA (AMICA) algorithm and REG ICA methodology. Ocular artifacts, particularly challenging during eyes-open conditions, were addressed using the EEGLAB toolbox called ICLABEL [28].

Yang et al in [4] manipulated the signal data by applying filtering techniques, down-sampling, epoch extraction, and segmenting [19], where they separated the data into matrices of size C×T×S, where C represents channels (C = 18), S denotes all trials of one experiment (S = 30), and T represents the length of a single trial (T = 1000). They mentioned that raw information is preserved as input without preprocessing procedures, except for scaling and centering the input vector. To enhance the quality of the data after the acquisition process and prepare it for the feature extraction step, Bidgoly et al. [53] normalized the data and applied orthogonalization and augmentation to improve the overall accuracy and efficiency of the EEG-based authentication system.[7]

Alzahab et al. [8] and Kralikova et al. [24] worked on capturing EEG signals from four channels (T7, F8, Cz, and P4) at a sampling rate of 200 Hz. The data then underwent a first-order bandpass Butterworth filter with a frequency range of 3 - 40 Hz to preprocess the EEG signals in [8] while applying a Butterworth low-pass and high-pass filter in [24]. A simple technique is used by Qiong Gui et.al. [9] to reduce noise efficiently by applying, after averaging, the standard deviation of the noise is reduced by the square root of the number of measurements. After ensemble averaging, a 60 Hz low-pass filter is also applied to remove noise from the EEG signals. Emanuele Maiorana in [19] used filtering to retain frequencies within the sub band [α, β] = 8 ÷ 30Hz, which have been shown to contain the most discriminative and permanent EEG content.

Following this, downsampling to a rate of 64Hz was performed to reduce computational complexity, allowing for shorter sequences as inputs to the convolutional neural networks (CNNs). Additionally, a spatial common average referencing (CAR) filter was employed to minimize the effects of potential incorrect reference positioning. Liew et al. in [32] used many preprocessing techniques for segmentation, filtering, and artifact rejection. Filtering aimed to enhance signal quality by minimizing background noise or interference, utilizing

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

a bandpass filter with high-pass and low-pass cutoffs set at 1 Hz and 30 Hz, respectively. Segmentation was performed based on the stimuli to prepare the raw EEG signals for further analysis, including feature extraction and classification. Additionally, artifact rejection was crucial to avoid misleading information during signal interpretation, leading to the exclusion of trials with excessive body movements or artifacts that exceeded an amplitude of 100 μV. Kaur et al [11] applied the Savitzky-Golay filter to the recorded EEG signals to enhance the SNR by smoothing the captured data. While a 9th order Butterworth bandpass filter was applied in [12]. The filter was set between 1-55Hz to eliminate irrelevant frequencies. A lot of preprocessing techniques were performed in [13] on the EEG datasets, including a standardized, automated EEG preprocessing pipeline called PREP, which encompassed band-pass filtering from 0.1 to 55 Hz, robust signal referencing, identification and interpolation of bad channels (those with low recording signal-to-noise ratio), and baseline removal using EEGLAB. The EEG data was preprocessed using a band-pass frequency filter that spawned from 4.0 to 45.0 Hz, and Electrooculography (EOG) artifacts were removed to enhance signal quality [15].

Zeng et al. in [30] re-referenced the data using REST (Reference Electrode Standardization Technique) and then filtered it by a low-pass Chebyshev digital filter with a passband of 40 Hz and a stopband of 49 Hz. After that, they applied downsampling, Epoch Extraction and Baseline Correction. To ensure the quality and relevance of the signals for person identification, Kumar et al. [21] computed raw power spectral density (PSD) features for each channel within the frequency range of 3Hz to 30Hz, using a spectrogram estimation with a window size of 360ms and no overlap 3. For recordings taken under open eye conditions, artifacts such as eye blinks were removed using artifact subspace reconstruction techniques 3. This preprocessing aimed to clean the EEG signals, making them suitable for subsequent analysis in the context of person identification. In [27], the preprocessing techniques for the EEG-based user authentication system included feature extraction using Power Spectral Density (PSD) and Autoregressive (AR) modelling. While in [22], the MA filter is used to clean and smooth the data from the BCI interface. In [23], Gopal and Shukla worked to ensure the quality of the EEG signals before analysis by taking the first 10 samples of each user’s data, which were discarded to eliminate any initial noise. Following this, a second-order Infinite Impulse Response (IIR) filtering was applied to the cleaned data to smooth the signals and obtain a more accurate representation of the brain activity. In this study [34], the preprocessing techniques included the removal of powerline noise using a second-order infinite impulse response (IIR) notch filter.

Additionally, a zero-phase-shift low-pass Chebyshev Type-I filter was applied to the channel-wise steady-state visual evoked potential (SSVEP) signals to extract the low-frequency components, with a passband edge at 7 Hz and a stopband edge at 8 Hz. The preprocessing techniques in [25] involve converting the obtained EEG data from a time series into a time-frequency series using a Morlet transform. Each sensor produces Alpha band (frequencies between 8 and 13 hertz) and Beta band (continuation from 13 to 30 hertz) time series. The preprocessing techniques applied by Zeynali and Seyedarabi in [29] to the EEG signals included the use of a bandpass filter with a frequency range of

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

0.1 to 64 Hz to reduce noise effects, as well as segmenting each recorded signal into 10 segments of 1 second each, resulting in 250 samples per segment. This segmentation allowed for the application of feature extraction methods on each segment, thereby optimizing the utilization of the data. Yap et al. [33] applied filtering to the EEG signals to remove direct current shifts using a Finite Impulse Response (FIR) linear filter set to a frequency range of 1 to 55 Hz. Following this, an Automatic Artifact Removal (AAR) process was utilized specifically for the visual stimulation data sets to correct ocular artifacts within the recorded EEG signals.

3.2 Classification Techniques

In the process of authentication and identification in EEG-based systems, classification techniques are employed to separate the genuine users and imposter users based on extracted EEG features. Some of the most used learning algorithms are Support Vector Machines (SVM) when dealing with the high dimension data and or non-linearity, K-Nearest Neighbors (KNN) for simple models and small data sets while Neural Networks such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for large data sets and complex models. There is probabilistic modeling using Bayesian Networks; moreover, the Random Forest model is used for robustness and feature importance using ensemble learning. Need a further explanation for the class separability, LDA provides linear boundaries while QDA provides quadratic boundaries. Recurrent Neural Networks are appropriate for temporal sequence data while Decision Trees are aimed at interpreting by splitting data. That is why the methods that use several classifiers simultaneously, for example, bagging, boosting, and stacking, are effective for the various demands such as in the case of real-time or high/low accuracy, and time/accurate relationship.

Three classification methods were employed in [29] Euclidean distance (ED), Support Vector Machines (SVM), and Linear Discriminant Analysis (LDA). These methods were utilized to evaluate the identification performance of spectral features extracted from EEG signals. All three methods achieve impressive results, exceeding 95%. These findings are consistent with those reported in various studies. Three other classification methods for personal identification using EEG signals were Euclidean Distance, Support Vector Machines (SVM), and Linear Discriminant Analysis (LDA) [4]. These methods evaluated and compared the classification performance of the extracted spectral features from resting-state EEG data. The classification accuracies achieved by these methods were reported to be high, with nearly 99% for single-run data and up to 97% when using two-run data as a training set, demonstrating the effectiveness of these classifiers in identifying individuals based on their EEG patterns. In this study [11], the authors employed two classification approaches for user identification based on EEG signals recorded while listening to music. They utilized a Hidden Markov Model (HMM) based temporal classifier, achieving a user identification performance of 97.50%, and a Support Vector Machine (SVM) classifier, which recorded a performance of 93.83%. The classification technique in this study [13] involved the use of a CNN designed explicitly for EEG-based biometric identification, referred to as the GSLT-CNN model. This model

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

operated directly on raw EEG data without requiring prior feature extraction, showcasing its efficiency and robustness. Trung et al. [27] used the Support Vector Machine (SVM) as the EEG-based user authentication system classification approach. They implemented a two-step classification process, including brain model building and user matching. Vahid and Arbabi [15] utilized the SVM with a Radial Basis Function (RBF) kernel to identify individuals based on their EEG signals. The researchers applied a 10-fold cross-validation method to evaluate the classification performance and employed feature selection algorithms, including t-test and sequential floating forward selection (SFFS), to identify the most relevant features for each experimental scenario.

Those techniques were compared in terms of their identification accuracy for different datasets. SVM on PSD feature with SFFS feature selection achieved the best performance of 93%, LDA achieved 63%, and GSLT-CNN outperformed them all with 96% accuracy. The study also highlighted the efficiency and robustness of the proposed GSLT-CNN model in training and identifying subjects without the need for feature extraction [13]. With VSM [27], the study also utilized 10-fold cross-validation in all experiments and scenarios. The feature selection methods employed were t-test and sequential floating forward selection (SFFS) as filter and wrapper, respectively. In [7], the CNNs automatically extracted features and classified EEG data from the Resting State with Open Eyes (REO) and the Resting State with Closed Eyes (REC) and the entire process is jointly optimized using gradient descent. The approach, utilizing CNN for resting state EEG, showed promise for developing EEG-based biometric systems with strong classification performance [7]. Another approach compared the performance of deep learning approaches with hand-crafted features, such as the fusion of auto-regressive (AR) and mel-frequency cepstral coefficients (MFCC) modelling, to achieve efficient classification [19].

It highlighted the use of low-frequency components of steady-state visual-evoked potentials (SSVEP) as the biometric feature for authentication [34]. Employed in the study on the impact of the auditory stimuli on the biometric identification system using EEG signals are the (i) Multilayer Perceptron (MLP), (ii) k Nearest Neighbours (KNN), and (iii) eXtream Gradient Boosting (XGBoost). These methods were used to evaluate the effectiveness of the developed EEG-based biometric authentication system under exposure to auditory signals[8]. Some of the techniques mentioned include k-nearest Neighbors (k-NN) and Eigenvector, which are traditionally used for classification. the article also highlights the utilization of deep learning approaches, specifically Convolutional Neural Networks (CNN) and Long Short-term Memory (LSTM)[31] networks for EEG-based identification.[17] using Universal Background Model - Gaussian Mixture Model (UBM-GMM): UBM-GMM[21] is a probabilistic framework used for EEG subject recognition. The UBM-GMM system is evaluated across sessions in a verification setting and is found to be more robust in intersession testing compared to k-NN and ANN. The UBM-GMM system is trained using feature vectors from all subjects and sessions, and subject-specific models are built through maximum-a-posteriori (MAP) adaptation.[20] showcasing the effectiveness of deep learning algorithms, specifically 1D-CNN, in-person identification based on EEG signals.[24] The research paper discusses

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

using machine learning algorithms for classification in an EEG-based authentication system. Some of the popular classification algorithms mentioned include K-nearest neighbours (KNN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM).[25] The study on EEG-based biometrics employed several classification techniques, including Multilayer Perceptron (MLP), K Nearest Neighbours (KNN), and eXtreme Gradient Boosting (XGBoost)[26]. The study also considered two decomposition strategies within SVM: one-vs-one (OVO) and one-vs-all (OVA). OVA outperformed OVO in most performance metrics for both EC and visual stimulation tasks.[33]

In this paper, Alyasseri et al. employed ANNs as the classifier for EEG pattern classification.[16]. The Correct Classification Rate (CCrate) was used to evaluate the performance of each scenario, which was calculated based on the total number of correct classifications and total number of testing trials. The accuracy rates varied depending on the scenario and the number of neurons in the hidden layer of the neural network. **Scenario I** (Identifying all 32 subjects): Accuracy ranged from 5.75% to 10.68%. **Scenario II** (Side-by-side identification of all 32 subjects): Accuracy ranged from 28.71% to 36.27% for 32 sub-models and 46.34% to 47.50% for 496 sub-models. **Scenario III** (Identifying one subject from all others): Accuracy ranged from 83.40% to 99.87%. **Scenario IV** (Identifying a small group from others): Accuracy ranged from 70.06% to 99.20% for 496 cases. The best average accuracy achieved was 94.04% in Scenario III with 45 neurons in the hidden layer. The results showed that identifying a single subject from others had the highest accuracy while recognizing all 32 subjects had the worst performance [9].

The study utilized Auto-WEKA software to select the optimal classification algorithm that best fits each user's data. The study evaluated the proposed EEG-based authentication methodology using a dataset from 15 subjects. The evaluation involved creating individual datasets for each participant, where half of the instances were from the user and the other half from other users. This allowed for a robust user authentication algorithm to be developed and tested. The accuracy of the system was reported to be 95.6%, with a False Acceptance Rate (FAR) of 0.023, a False Rejection Rate (FRR) of 0.065, and an Equal Error Rate (EER) of 0.064.

The study utilized the Auto-WEKA algorithm for feature selection and classifier optimization, resulting in an efficient and accurate user authentication system that could grant or deny access based on EEG signals [10]. Frank et al. [12] utilized EEG data obtained from consumer-grade BCI devices to analyze different sensory pass-throughs using ERP analysis. The analysis included data acquisition, signal processing, ERP derivation, and ERP comparison to assess user identification accuracy. In [18], SVM is the primary classification technique, but LDA is also employed to compare results and accuracy rates. Brain-computer interfaces (BCIs) due to their simplicity, speed, and low computational cost. Białas et al. [22] presented the implementation of machine learning techniques, particularly ML [28] Model Builder - Auto ML, for classifier training. The models were trained and optimized using the Adam optimizer and binary cross-entropy loss function. Additionally, the paper discusses a wide range of extracted features and

ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

feature selection using the correlation-based feature subset (CFS) algorithm. The optimal feature subsets selected were used in the neural network classifiers for authentication.[23]

The paper discusses the use of two classification techniques in the context of EEG-based identity authentication: Hierarchical Discriminant Component Analysis (HDCA) and Genetic Algorithm (GA).[30]

The Incremental Fuzzy-Rough Nearest Neighbor (IncFRNN) technique and the Incremental K-Nearest Neighbor (IBk) technique. These techniques are compared regarding their performance metrics such as accuracy, the area under the Receiver Operating Characteristic (ROC) curve (AUC), and Cohen's Kappa coefficient. The IncFRNN technique, which incorporates heuristic update methods and incremental learning, is shown to outperform the IBk technique in the context of the study [32]

3.3 Authentication Techniques

The authentication step in the EEG authentication process is very crucial as it confirms the identification of an individual using their brain signals and thus increases the security of the system. It is at this step that the credibility and efficiency of the authentication process are upheld to keep out intruders and simultaneously admit only genuine persons into the system. The authentication process is used to analyze and compare the obtained EEG features from the classification process with stored ones, thus guaranteeing the correct identity of the subject. Many studies used different techniques and approaches to achieve high accuracy.

Yang et al. Previous studies on EEG-based identification have faced several limitations, including challenges related to data acquisition, protocol design, performance evaluation, and the overall stability of the identification system. [4] Used SVM, and Linear Discriminant Analysis (LDA). The framework involves classifying users based on their music preferences, capturing EEG signals, and processing them using filters like the Savitzky-Golay filter to remove noise. Two classifiers, the Hidden Markov Model (HMM) and Support Vector Machine (SVM), were faced with several limitations many existing systems have primarily relied on traditional tasks or stimuli, such as mental activity, motor imagery, or visual stimuli, which do not adequately capture the unique neural responses associated with personal preferences or emotional states. [11]

Model has demonstrated high accuracy in identifying subjects, outperforming traditional shallow classifiers like SVM, Bagging Tree, and LDA on selected features like PSD and AR coefficients. The study also highlights the importance of feature selection methods, such as SFFS, for improving classification performance. The GSLT-CNN model showed robustness in cross-session identification, especially in the context of time-locked RSVP experiments. Have several limitations, primarily stemming from their reliance on relatively small datasets, which raises concerns about overfitting and the robustness of their findings. [13] The study suggests that Gamma frequency bands in the left posterior quarter of the brain are significant for human identification. The Correct Classification Rate (CCR) achieved through SVM classification ranges from 88% to 99%. Were the

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

limitations They primarily focus on conventional traits like fingerprints, voice, and facial recognition, which can be easily mimicked or affected by injuries, thereby compromising their effectiveness.[15]

The study explores the use of resting state EEG data collected from individuals to create a biometric identification system. Utilizing Convolutional Neural Networks (CNNs), has several limitations, primarily due to the reliance on single-session datasets, which can lead to performance estimates that are more influenced by session-specific recording conditions rather than individual characteristics. Many investigations have focused on task-dependent recognition, failing to adequately explore the feasibility of task-independent recognition. [19] The study achieved a high degree of accuracy (88%) for individual identification using EEG data. This method allows for the extraction of unique neural features automatically from EEG data, making it a potential authentication technique. EEG-based biometrics can offer a high level of security, especially for scenarios where traditional methods like fingerprints or retinal scans may not be applicable, have limitations primarily in their reliance on manually designed feature extraction methods, which may not effectively capture the unique characteristics of an individual's brainwave patterns due to the absence of task-related features in resting state EEG.[6] uses a 1D-Convolutional LSTM neural network to extract spatial and temporal features from EEG signals, enhancing identification accuracy.

This approach outperforms traditional methods and other deep learning techniques like CNNs [34] and LSTMs, (SSVEP) with several limitations, including the reliance on a single or few techniques for stimulating brain signals, which can restrict the effectiveness of identity discrimination. Many existing methods primarily focus on specific areas of EEG data, resulting in vulnerabilities due to their limited scope of study.[31] achieving a very high average accuracy of 99.58% with only 16 channels of EEG signals. These systems often utilized relatively small datasets and did not exploit deep learning methods effectively, potentially leading to suboptimal performance in real-world applications. Furthermore, the existing identification methods frequently necessitated longer EEG signal recordings for feature extraction [17] the study UBM-GMM framework is highlighted as being more robust across sessions for intersession testing, making it a suitable technique for authentication based on EEG signals. The paper also mentions techniques like maximum-a-posteriori (MAP) adaptation for building subject-specific models from a common model have several limitations. signals required for identification have not been adequately addressed they often did so with a limited number of subjects, and the variability across tasks was not thoroughly analyzed issues surrounding the repeatability of EEG signatures over time have received insufficient attention from the engineering community, which limits the reliability of EEG as a biometric system[20] The study proposes a novel paradigm that involves escalating cognitive brain load from relaxation to playing a serious game with increasing difficulty levels. The EEG data collected from 21 subjects is processed using a 1D Convolutional Neural Network (CNN) in MATLAB to achieve high accuracies exceeding 99% for individual tasks and over 98% for task fusion.[24]

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

The system stores the fingerprint instead of the raw EEG signals to preserve user privacy. The authentication function in this system compares the similarity between the stored and presented EEG biometric fingerprints to verify a user's claimed identity. The system is designed to work for all users, including those who were not part of the initial training data, to achieve universality. Additionally, the system reduces the number of required EEG channels to just three, making it more user-friendly and practical. The authentication model reaches around 98% accuracy in authenticating completely new users. Limitations, primarily concerning universality, privacy preservation, and the number of required electrodes. Most existing methods struggle with universality as they typically require retraining the model for new users, making them impractical for large-scale applications and a significant number of studies rely on a high number of electrodes—averaging around 33 or more—which is not feasible for most commercial EEG devices, potentially complicating user experience and limiting accessibility [7]

The study is a brief description of the methodology for the study because of Electroencephalography (EEG). The researchers employed three different classifiers for classification: Some of the algorithms that can be applied while working on a machine learning project are; Multilayer Perceptron, K Nearest Neighbor KNN, and eXtreme Gradient Boosting. These classifiers were used to establish the efficiency of the biometric authentication that utilized the EEG data. As described in the study, MLP architecture was used with some layers present and they include the number of neurons and the activation functions.

K-Nearest Neighbors (KNN) classifier is among the simplest classifiers that predict the class label based on a majority rule and a given number of neighbors. On the other hand, XGBoost belongs to Ensemble Learning as several simple models are combined to get a better result. The limitations of previous studies include a lack of diversity in sample populations, which may lead to results that are not generalizable to broader demographics.

Many studies also suffer from small sample sizes, which can affect the statistical power and reliability of findings. Additionally, there may be biases in data collection methods, such as reliance on self-reported measures that can be influenced by social desirability. [8][26] Using machine learning algorithms, such as K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Support Vector Machine (SVM), to create user-specific models for authentication. Additional considerations include stress detection to prevent coercive attacks and ensuring data security and participant selection criteria. These EEG-based authentication techniques offer promise in providing a secure and user-specific authentication system.

The limitations. Many of these studies focus on a variety of tasks for EEG data collection, such as viewing images or imagining sounds, which can introduce variability and may not yield user-specific models. [25] The Incremental Fuzzy-Rough Nearest Neighbour (IncFRNN) technique and the Incremental K-Nearest Neighbour (KNN) technique. Limitations, reliance on static data environments, which do not account for the non-stationary nature of EEG signals that can vary due to physiological and environmental factors. Many existing methods fail to incorporate uncertainty modeling, which is crucial given the inherent variability of EEG signals. Additionally, the incremental learning approaches in traditional frameworks often treat new data as noise unless retrained, which can lead to the loss of potentially useful information [32]

The techniques included ensemble averaging and low-pass filtering for noise reduction, wavelet packet decomposition for feature extraction, and a neural network for classification. Different scenarios were tested to emulate authentication cases, with high accuracy rates of around 90% for identifying one subject or a small group of individuals. However, recognizing each individual from a large pool had the worst performance, with a classification rate of less than 11%. The side-by-side method showed improvement in identifying all the subjects with classification rates of around 40%. They exhibit several limitations. Many approaches rely on a limited number of subjects, which restricts the generalizability of their findings. For instance, some studies achieved classification rates only for small groups, with the best results around 90% but significantly lower rates when attempting to identify individuals from larger pools, often below 11% 1. Additionally, the methodologies often struggle with the inherent variability of EEG signals influenced by factors such as mood and mental state, which can lead to misclassifications.[9]

The study achieved a mean accuracy of 95.6% for user authentication across 15 subjects, demonstrating the potential of EEG signals for real-time human authentication with advanced accuracy and reliability. The system's efficiency, with data collection and processing in under one minute, compared to deep learning methods with higher computational costs, is also outlined. Additionally, the study suggests future directions for improving EEG-based authentication systems, addressing issues like user disinterest affecting brainwave data and the need for larger datasets for generalizability.[10] This approach aims to extract useful features from denoised signals, achieving comparable results to state-of-the-art methods. The proposed method evaluates performance based on accuracy, true acceptance rate, and false acceptance rate. The study suggests that EEG signals can be used effectively for biometric security and authentication applications.[16]

The proposed system involves a machine learning model, classifier, and mobile application for experiments. The authentication system achieved an accuracy rate of 77.78% for user authentication. The study explored the feasibility of using EEG signals as a biometric authentication method, highlighting EEG's confidentiality and resistance to mimicry due to person-dependent signals.[22] The system uses EEG signals and deep learning models for authentication, achieving high performance with an average Equal Error Rate (EER) of 0.137%. The study also presents a comparative analysis of different neural network-based authentication models for each user, showing the viability of EEG-based continuous user authentication systems.[23] The study in the article achieved a high accuracy of around 97-98% mean accuracy for single-channel authentication using neural network classifiers. Different mental activities were used to select the optimum electrode placement, and the O2 channel was identified as the optimum channel with an accuracy of 95%.[29]

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

The experiment conducted in the research paper aimed to analyze the effectiveness of different sensory pass-thoughts among individuals to enhance the accuracy of a brainwave-based authentication system. Overall, the study suggests that incorporating customized stimulus choices based on each user's training can significantly improve the security and accuracy of a brainwave authentication system. Have identified several limitations, including limited usability, the short lifespan of sensors, and the invasiveness of certain systems. Additionally, there are challenges related to the accuracy of brainwave data obtained from consumer-grade brain-computer interface (BCIs), as inconsistencies in electroencephalogram (EEG) readings have made it difficult to achieve high correlation between reference and challenge event-related potentials (ERPs) [12]

The use of brainwaves as a unique identifier for authentication is explored by predicting image memorability and employing mental imagery as a visualization pattern for security purposes. The brainwave signals are collected using EEG technology, and various signal processing and classification methods are applied to authenticate users based on their brain patterns. This brainwave authentication approach is considered a promising strategy for enhancing security and overcoming the limitations of traditional biometric methods [18] These modified approaches incorporate multi-channel EEG data to enhance person-specific signature extraction, suppressing task-related information.[21] The watermarking technique embeds information into EEG data for integrity verification, tampering authentication, and copyright protection. This integration aims to strengthen the security of the system without significantly degrading the authentication performance. The proposed method uses a combination of Discrete Wavelet Transform-Singular Value Decomposition (DWT-SVD) and Quantization Index Module (QIM) for watermarking EEG signals. These have notable limitations, particularly regarding security vulnerabilities in remote applications using unsecured channels. Many existing systems fail to address the potential risks of spoofing, relay, and communication attacks, which can compromise the integrity of biometric data. [27]

The study proposed a data-driven EEG-based authentication method using machine learning techniques to optimize the classification algorithm for individuals. The results showed an impressive mean accuracy of 95.6% and a viable option for real-time applications, with training procedures completed in under a minute. limitations, most methods focus on optimizing feature combinations and classification algorithms without tailoring them to the unique patterns of individual users, which can negatively impact classification accuracy and the limited number of participants in studies raises concerns regarding the generalizability of results, threatening their external validity [28] The authentication method is effective, robust, and stable over time, achieving high accuracy rates within a short time frame. The EEG signals are used to evoke specific and stable traits for authentication, and significant differences are found between self-face and non-self-face responses. The limitations. Some studies have shown promising accuracy rates, but they often lack comprehensive testing against real imposters and do not fully explore the potential for practical application in real-world scenarios [30] for the authentication of individuals using EEG signals. Two acquisition protocols are examined: eyes-closed (EC) and visual stimulation. The study evaluates the performance of these protocols using a

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

consumer-grade EEG device to authenticate individuals. The results show that the visual stimulation protocol achieves better accuracy compared to the EC protocol. Has several limitations. Many of them utilized high-density EEG devices that are costly and require time-consuming setup processes, making them impractical for widespread application, these studies often involved lengthy acquisition periods for data recording, which can deter user participation and lead to distorted signals due to participant fatigue or impatience Lastly, many existing methods focused on clinical-grade devices, limiting their applicability in real-world scenarios where consumer-grade alternatives might be preferred[33]

4. AUTHENTICATION METHODS METRICS

Due to the need to assess the authentication methods on EEGs, several criteria are used to measure the usability, efficiency, and stability of the protocols. Here are the key evaluation metrics commonly used:

1) **Accuracy**: It is the rate at which true positives and true negatives out of the total are matched correctly.

$$\text{Accuracy} = TP + TN / TP + TN + FP + FN \ [25]$$

Where TP, TN, FP, and FN are true positives, true negatives, false

2) **False Acceptance Rate (FAR):** In other words, the rate of fakers that the system is admitting into the authorized users club.

$$FAR = FP / FP + TN \ [23]$$

A lower FAR indicates better security

3) **False Rejection Rate (FRR):** The rate by which the authorized users are locked out from the systems.

$$FRR = FN / FN + TP \ [23]$$

A lower FFR indicates better security

4) **Confusion Matrix:** A table used to present the performance of an authentication algorithm with the actual and anticipated classification results. TP, TN, FP [22], and FN values are contained in it and aid in coming up with other measures.

5) **Precision (Positive Predictive Value, PPV):** The degree of fairness of the sample as more people are correctly identified.

$$\text{Precision} = TP / TP + FP \ [20]$$

6) **F1 Score: Precision/recall trade-off; F-measure;** A single number providing both precision and recall.

$$\text{F1 Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} \times \text{Recall}) \ [21]$$

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

These metrics then can be used by researchers and developers to have comprehensive assessment and benchmarking to the preferred security level as well as the usability level of the authentication

Table 3: Summarizes the metric Mentioned in the Text

Study	Classifier/Method	Accuracy/Performance Metric
1	Different classifiers	Mean F1 score
2	-	High distinctive characteristics
3	-	Accuracy rate
4	-	Number of channels
5	Classifier	Classification accuracy rate
6	Proposed authentication system	Accuracy rate, False rejection rate
7	-	Suggestion
8	-	Average Equal Error Rate
9	Low-cost EEG-based system	Viability

5. ACOUSTIC STIMULI IN EEG AUTHENTICATION

Acoustic stimuli are an event-related potential (ERP) that can be used in EEG-based authentication systems. In this approach, participants listen to a piece of music or a special tone, which elicits a distinct EEG response. This response can be used as a biometric identifier, similar to other ERP-based authentication methods such as visual evoked potentials (VEP).

The studies investigated the use of different genres of music to induce different emotions and interests in participants. In this study, participants were also asked to provide their music preferences, which were used as a personal identification mechanism [17] and [18]. In the following, there are some common types of stimuli used in EEG authentication [14]:

1. Visual Stimuli: Images, Videos, and Flashing Lights.
2. Auditory Stimuli: Sounds Speech and White Noise.
3. Cognitive Tasks: Mental Arithmetic, Word Association administered word, and Memory Tasks.
4. Motor Imagery: Imagined, Movement and Motor Tasks.
5. Emotional Stimuli: Emotional Images and Emotional Sounds.
6. Tactile Stimuli: Touch and Temperature.

5.1 Single-Task Feature Extraction

In this approach, the model undergoes signal pre-processing before being exclusively trained on examples from a specific "source task." Following training, feature vectors are extracted from individuals' data for the source task and stored in the system. When individuals interact with the system, they choose one of the suggested "target tasks" to perform.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

The corresponding feature vector is then extracted and compared to the stored feature vectors for authentication. The method's process is illustrated in Fig. 4.

This method is referred to as *STFE* (Single-Task Feature Extraction). In simple terms, the *STFE* method involves training the model on a single task, but it can be used for authentication purposes with other tasks present in the dataset. The primary objective of this step is to assess the model's generalizability.

By training the model on the source task and evaluating its performance on target tasks, we aim to demonstrate that our proposed model can accurately identify individuals' identities without relying on a specific task.

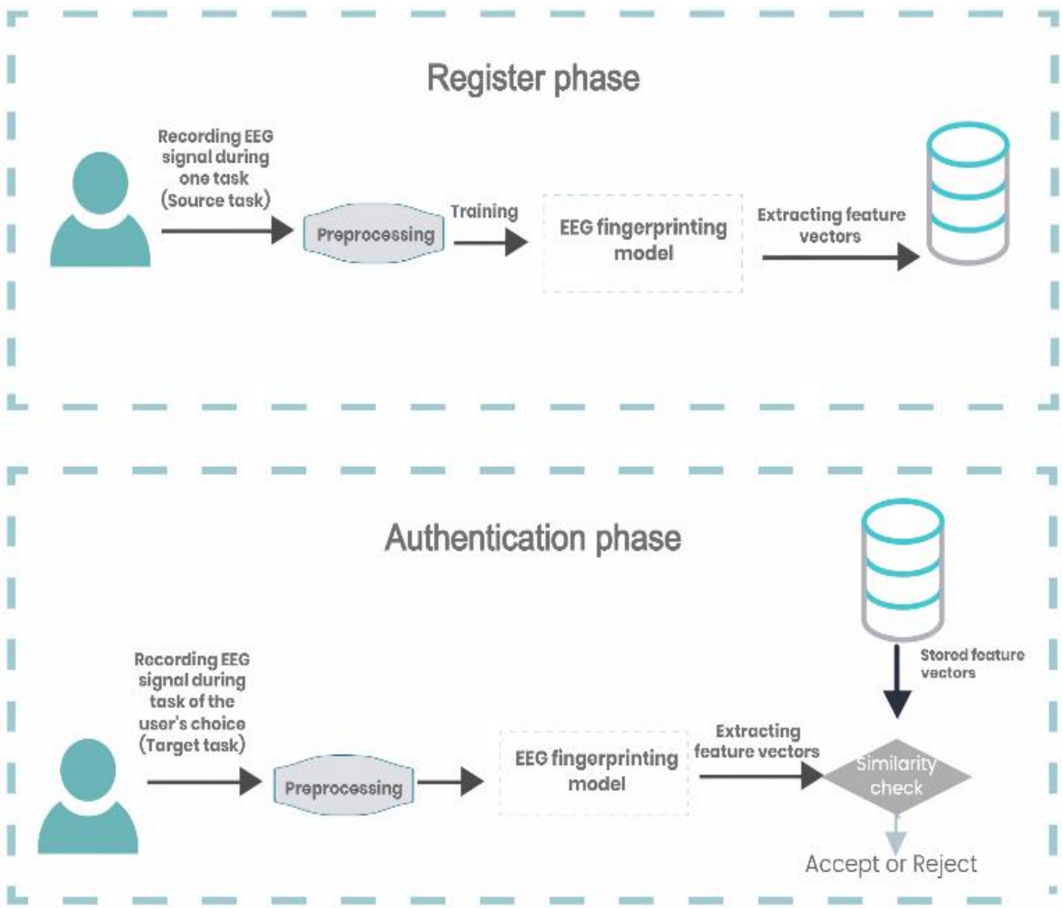

Figure 4: **STFE Feature Extraction**

5.2 Multi-Tasks Feature Extraction

In EEG-based authentication, multi-tasks refer to protocols that involve recording EEG signals in response to more than one type of stimulus. This approach combines the benefits of different stimuli to create a more robust and accurate biometric identification system.

5.2.1 Examples of Multi-Tasks

- **Multimodal Stimuli:** One example of a multi-task protocol is to ask individuals to watch short music videos that induce different emotional states. This approach combines visual and auditory stimuli to elicit a unique EEG response as explored by [19], [20], and [21] Studies.
- **Fusion of EEG and EOG Signals:** Another example of a multi-task protocol is to fuse EEG and EOG (Electrooculography) signals to improve the accuracy of classification. EOG signals measure eye movements, which can provide additional information to complement EEG signals [22] have demonstrated the effectiveness of this approach.

5.2.2 Advantages of Multi-Tasks [52], [53]:

- **Improved Accuracy:** By combining multiple stimuli or signals, multi-task protocols can improve the accuracy of EEG-based authentication systems.
- **Increased Robustness:** Multi-task protocols can reduce the impact of noise or variability in individual signals, leading to more robust biometric identification.
- **Enhanced Security:** The use of multiple stimuli or signals can make it more difficult for attackers to spoof or replicate an individual's EEG response.

Overall, multi-task protocols offer a promising approach to enhancing the performance and security of EEG-based authentication systems. These preprocessing methods are often used in combination to extract meaningful features from the EEG signal and improve the accuracy of classification or other downstream analyses.

6. RESULTS ANALYSIS

This section provides a comprehensive review of the comparative assessment of numerous investigations centered on the use of EEG for authentication. The overall methods and the techniques used by the various researchers, the attained results, and the observed limitations in the various studies are also captured in Table 4. For the analysis of stimuli and different paradigms the various classifiers, including SVM, neural networks, and CNNs were used, as well as the methods of i-vector systems, modified for specific purposes.

The accuracy rates that were recorded in the studies ranged from 70-99%, with the overall means reaching 99%, especially with the application of higher-order machine learning algorithms and feature extraction. However, issues like difficulty in capturing the signals, variation from one person to another, and the fact that it might be computationally intensive were mentioned. It is also necessary to mention that finally, this analysis is intended to reveal the advantages and disadvantages of each approach, and thus, the potential of the applied methods for EEG-based authentication, as well as the directions that require further enhancement.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

Table 4: Summary of the studies

study	Methods/Techniques	Accuracy/Results	Limitations
N. A. Alzahab rt al. [12]	new neurological framework and BCI	highest average accuracy with SMELL=0.167120	The proposed system was only a theoretical
[13]	GSLT-CNN model	Investigated use in EEG-based authentication	focuses on specific datasets, not real-world applications
[15]	Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel	The Correct Classification Rate (CCR) achieved ranged between 88% and 99%	The stability of EEG signals concerning emotional states was not thoroughly explored beyond the limited situations studied, indicating that further research is needed to generalize findings across more emotional conditions
[16]	multi-objective Flower Pollination Algorithm combined with the Wavelet Transform (MOFPA-WT)	A TAR of 85.71% and FAR of 14.28% were achieved. A TAR of 91.42% and FAR of 8.58% were reported.	The dataset used is relatively small
[17]	combines Convolutional Neural Networks (CNNs) and LSTMs	LSTM achieved a high Rank-1 accuracy of 99.58%	LSTM in the network architecture increases computational complexity, which results in longer training times.
[18]	Using a non-invasive BCI device while feature extraction was performed using Power Spectral Density (PSD).	Achieving an average accuracy rate of 88% with a 0.93 AUC for the SVM classifier.	The experiments focused primarily on short-term memory, and the results may vary for long-term memory
[19]	using Siamese convolutional neural networks (CNNs)	with EERs as low as 11.1% for single-protocol enrolment and 9.7% for multiple-protocol enrolment	the reliance on a specific number of EEG channels which could affect usability
[20]	k-NN, ANN, UBM-GMM.	High classification accuracy rate: 83.33%	Inter-session Variability, Chunk Size Dependency, Generalization Issues, Data Quantity.
[21]	Universal Background Model-Gaussian Mixture Model (UBM-GMM)	High accuracy (77.78%), low false rejection rate	used only 8 standard electrodes for real-time biometrics, which may limit the generalizability and effectiveness of the results compared to using a full 128-channel system
[22]	EEG Brain-Computer Interface (BCI) based on the NeuroSky MindWave Mobile device and machine learning (ML) model development	achieving up to 86.72% on the EEG dataset an overall accuracy of 77.78% was reported	The NeuroSky MindWave Mobile device is considered primarily a commercial entertainment device rather than a full-fledged research instrument,

[23]	two-dimensional space to represent emotions	Accuracies: >99% for individual tasks, >98% for task fusion	utilized data from only 26 participants, which may not be representative enough for broader applicability
[24]	Convolutional Neural Network (CNN) implemented in MATLAB	99% accuracy for individual tasks and more than 98% accuracy for task fusion.	The use of only one scalp region for classification was found to yield unsatisfactory results.
[25]	K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Support Vector Machine (SVM)	Classification accuracy 80.942%	Compromise of Biometric Data, Coercive Attacks, Challenge of Stress Detection, Variability in EEG Signals, Initial Setup and Cost.
[26]	Multilayer Perceptron (MLP) k-Nearest Neighbours (KNN) eXtream Gradient Boosting (XGBoost)	MLP: 84.10% (full), 87.99% (reduced) KNN: 88.88% (full), 88.00% (reduced) XGBoost: 97.91% (full), 96.65% (reduced)	the noise reduction techniques used in preprocessing might not yield the cleanest EEG signals, which could affect the overall accuracy
[27]	Support Vector Machine (SVM)	Equal Error Rate (EER)=0.019,	Performance Degradation, Potential Vulnerabilities, Limited Dataset Testing.
[28]	EGI Geodesic, Independent Component Analysis (ICA), Auto-WEKA software	mean accuracy of 95.6%, accuracy was above 94%, the highest accuracy recorded was 100%, the lowest was 87%, False Acceptance Rate (FAR) of 0.023, a mean False Rejection Rate (FRR) of 0.065, and a mean Equal Error Rate (EER) of 0.064	Sample Size, Outlier Impact, EEG Feature Scope, User Compliance.
[29]	Neural Network, Bayesian Network, Support Vector Machine (SVM)	mean accuracy of 97-98%	The dataset was limited to seven subjects, which may not generalize well across a broader population
[30]	Using a face image-based rapid serial visual presentation (RSVP) paradigm. and Hierarchical Discriminant Component Analysis (HDCA), Genetic Algorithm (GA)	average accuracy of 88.88% the FAR decreased from 10.97% to 6.27%, and the FRR decreased from 10.77% to 5.26	Time Requirement for Training, Model Stability, Generalization.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

[31]	steady-state visual evoked potential (SSVEP), event-related potential (ERP), Long Short-Term Memory (LSTM)	Average accuracy of 91.44%. The average FAR was 6.58%, and the average FRR was 10.53%	The existing methods primarily focus on one or a few techniques for signal stimulation and have vulnerabilities due to their limited scope.
[32]	Fuzzy-Rough Nearest Neighbour (IncFRNN), KNN (IBk), ROC curve (AUC).	AUC: 0.8843 for IncFRNN vs. 0.8675 for IBk, AUC: 0.8798 for IncFRNN vs. 0.8647 for IBk.	Accuracy Bias, Imbalanced Classes, Real-world Validation.
[33]	device (Emotiv EPOC+). EEGLAB, (SVM) one-vs-one (OVO) and one-vs-all (OVA) and eyes-closed (EC) protocol	The accuracy for the EC task ranged from 83.70% to 96.42%, while the visual stimulation task achieved accuracy rates of 87.64% to 99.06%. Specifically, during the morning session, the visual stimulation task achieved an accuracy of 96.91% (OVO) and 99.06% (OVA), significantly higher than the EC task's 83.70% (OVO) and 82.73% (OVA)	Sample Size, Device Limitations, Session Variability, Protocol Duration.
[34]	convolutional neural network (CNN), tate visual-evoked potentials (SSVEP)	the overall accuracy of approximately 97%, (FAR) 0.06%, and (FRR) was 3.15% when using 10 SSVEP epochs	the relatively small sample size,
[35]	signal-to-noise ratio (SNR), CNN	Individual tasks 99% for task fusion (combining tasks)98%.	Channel Reduction, Level Performance, Generalization.
[36]	IncFRNN vs KNN	Classification accuracy 82.94%	Compromise of Biometric Data
[37]	EC protocol, visual stimulation protocol	83.70-96.42% (EC), 87.64-99.06% (visual)	Accuracy performance
[38]	CNN-based brain decoding	~97% cross-day accuracy	Practical EEG-based biometric

7. CONCLUSION AND FUTURE WORK

In conclusion, this review is beneficial for further investigations of brain signal processing, classification, and security field specialists. The review indicates substantial progress in the topic and/987 the areas of improvement based on the main achievements in signal processing techniques and feature extraction methods used for brain signal classification during 2013–2023. This highlights the need to establish sound and effective methods of working with signals that characteristically possess variability alongside complex scenarios. Also, the necessity of developing safe and 'off-the-person' brain-computer interfaces (BCI) is discussed in the review, stating that users' brain data can be vulnerable and endangered by various threats. moreover, the critical analysis of the state of the art in the review also describes the limitations of current work and the possibility for future work which include the work on explainable and interpretable artificial intelligence, the work on multi-modal brain signal integration as well as the work that proposes new application areas such as affective computing and social signal processing. In conclusion, this review has provided future researchers with information on past achievements, present issues, and future directions to turn out the enhanced, safe, and personalized brain-computer interface technology.

Reference

1) Abo-Zahhad, Mohammed, Sabah Mohammed Ahmed, and Sherif Nagib Abbas. "State-of-the-art methods and future perspectives for personal recognition based on electroencephalogram signals." *IET Biometrics* 4.3 (2015): 179-190.

2) J. Klonovs, C. Petersen, H. Olesen, and A. Hammershoj, "ID proof on the go: Development of a mobile EEG-based biometric authentication system," *IEEE Veh. Technol. Mag.*, vol. 8, no. 1, pp. 81–89, 2013, doi: 10.1109/MVT.2012.2234056.

3) Niedermeyer, Ernst, and FH Lopes da Silva, eds. *Electroencephalography: basic principles, clinical applications, and related fields*. Lippincott Williams & Wilkins, 2005.

4) Sanei, Saeid. *Adaptive processing of brain signals*. John Wiley & Sons, 2013.

5) Klimesch, Wolfgang. "Memory processes, brain oscillations, and EEG synchronization." *International journal of psychophysiology* 24.1-2 (1996): 61-100.

6) Zhang, Yan, et al. "Response preparation and inhibition: the role of the cortical sensorimotor beta rhythm." *Neuroscience* 156.1 (2008): 238-246.

7) Di, Yang, et al. "Robustness analysis of identification using resting-state EEG signals." *Ieee Access* 7 (2019): 42113-42122.

8) J. Klonovs, C. Petersen, H. Olesen, and A. Hammershoj, "ID proof on the go: Development of a mobile EEG-based biometric authentication system," IEEE Veh. Technol. Mag., vol. 8, no. 1, pp. 81–89, 2013, doi: 10.1109/MVT.2012.2234056.

9) T. Schons, G. J. P. Moreira, P. H. L. Silva, V. N. Coelho, and E. J. S. Luz, "Convolutional network for EEG-based biometric," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10657 LNCS, pp. 601–608, 2018, doi: 10.1007/978-3-319-75193-1_72.

10) L. Ma, J. W. Minett, T. Blu, and W. S. Y. a, "Resting State EEG-based biometrics for individual identification using convolutional neural networks," *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, vol. 2015-Novem, pp. 2848–2851, 2015, doi: 10.1109/EMBC.2015.7318985.

11) A. J. Bidgoly, H. J. Bidgoly, and Z. Arezoumand, “Towards a universal and privacy preserving EEG-based authentication system,” *Sci. Rep.*, vol. 12, no. 1, pp. 1–9, 2022, doi: 10.1038/s41598-022-06527-7.

12) N. A. Alzahab, A. Di Iorio, M. Baldi, and L. Scalise, “Effect of Auditory Stimuli on Electroencephalography-based Authentication,” *2022 IEEE Int. Work. Metrol. Ext. Reality, Artif. Intell. Neural Eng. MetroXRAINE 2022 - Proc.*, pp. 388–392, 2022, doi: 10.1109/MetroXRAINE54828.2022.9967652.

13) Q. Gui, Z. Jin, and W. Xu, “Exploring EEG-based biometrics for user identification and authentication,” *2014 IEEE Signal Process. Med. Biol. Symp. IEEE SPMB 2014 - Proc.*, 2014, doi: 10.1109/SPMB.2014.7002950.

14) Stergiadis, Christos, et al. "A personalized user authentication system based on EEG signals." *Sensors* 22.18 (2022): 6929.

15) H. L. Chan, P. C. Kuo, C. Y. Cheng, and Y. S. Chen, “Challenges and Future Perspectives on Electroencephalogram-Based Biometrics in Person Recognition,” Front. Neuroinform., vol. 12, no. October, pp. 1–15, 2018, doi: 10.3389/fninf.2018.00066.

16) Zhou, Si, et al. "Dynamical behaviours of an impulsive food-chain system with Hassell-Varley functional response and mutual interference." *International Journal of Dynamical Systems and Differential Equations* 8.4 (2018): 243-269.

17) Kaur, Barjinder, Dinesh Singh, and Partha Pratim Roy. "A novel framework of EEG-based user identification by analyzing music-listening behavior." *Multimedia tools and applications* 76.24 (2017): 25581-25602.

18) Frank, Dennis, Jasmine Mabrey, and Kenji Yoshigoe. "Personalizable neurological user authentication framework." *2017 International Conference on Computing, Networking and Communications (ICNC)*. IEEE, 2017.

19) Chen, J. X., et al. "EEG-based biometric identification with convolutional neural network." *Multimedia Tools and Applications* 79 (2020): 10655-10675.

20) Pham, Tien, et al. "A study on the stability of EEG signals for user authentication." *2015 7th International IEEE/EMBS Conference on Neural Engineering (NER)*. IEEE, 2015.

21) Vahid, Amirali, and Ehsan Arbabi. "Human identification with EEG signals in different emotional states." *2016 23rd Iranian Conference on Biomedical Engineering and 2016 1st International Iranian Conference on Biomedical Engineering (ICBME)*. IEEE, 2016.

22) Bhateja, Vikrant, et al. "Artificial neural networks based fusion and classification of EEG/EOG signals." *Information Systems Design and Intelligent Applications: Proceedings of Fifth International Conference INDIA 2018 Volume 2*. Springer Singapore, 2019.

23) Alyasseri, Zaid Abdi Alkareem, et al. "EEG-based person authentication using multi-objective flower pollination algorithm." *2018 IEEE congress on evolutionary computation (CEC)*. Ieee, 2018.

24) Tatar, Ahmet Burak. "Biometric identification system using EEG signals." Neural Computing and Applications 35.1 (2023): 1009-1023.

25) Y. Sun, F. P. W. Lo, and B. Lo, “EEG-based user identification system using 1D-convolutional long short-term memory neural networks,” *Expert Syst. Appl.*, vol. 125, pp. 259–267, 2019, doi: 10.1016/j.eswa.2019.01.080.

26) F. Yousefi, H. Kolivand, and T. Baker, “SaS-BCI: a new strategy to predict image memorability and use mental imagery as a brain-based biometric authentication,” *Neural Comput. Appl.*, vol. 33, no. 9, pp. 4283–4297, 2021, doi: 10.1007/s00521-020-05247-1.

27) E. Maiorana, "Learning deep features for task-independent EEG-based biometric verification," *Pattern Recognit. Lett.*, vol. 143, pp. 122–129, 2021, doi: 10.1016/j.patrec.2021.01.004.

28) V. D *et al.*, "Task-Independent EEG based Subject Identification using Auditory Stimulus," *Proc. Work. Speech, Music Mind*, vol. 2018, no. 2018, pp. 26–30, 2018, doi: 10.21437/smm.2018-6.

29) M. G. Kumar, M. S. Saranya, S. Narayanan, M. Sur, and H. A. Murthy, "Subspace techniques for task-independent EEG person identification," *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, pp. 4545–4548, 2019, doi.

30) Xu, Xin, Lan Jiang, and Tingting Xu. "Identity authentication based on music-induced autobiographical memory EEG." *Journal of Circuits, Systems and Computers* 31.11 (2022): 2250201.

31) Gondesen, Florian, Matthias Marx, and Dieter Gollmann. "Eeg-based biometrics." *Biometric-based physical and cybersecurity systems* (2019): 287-318.

32) Białas, Katarzyna, et al. "Multifactor authentication system using simplified EEG brain-computer interface." *IEEE Transactions on Human-Machine Systems* 52.5 (2022): 867-876.

33) Fidas, Christos A., and Dimitrios Lyras. "A review of EEG-based user authentication: trends and future research directions." IEEE Access (2023).

34) Gopal, Sindhu Reddy Kalathur, and Diksha Shukla. "Concealable biometric-based continuous user authentication system an eeg induced deep learning model." 2021 IEEE International Joint Conference on Biometrics (IJCB). IEEE, 2021.

35) Kralikova, Ivana, Branko Babusiak, and Maros Smondrk. "EEG-Based Person Identification during escalating cognitive load." Sensors 22.19 (2022): 7154.

36) Patel, Meetkumar J., and Mohammad I. Husain. "An approach to developing EEG-based person authentication system." 2020 IEEE International Conference on Big Data (Big Data). IEEE, 2020.

37) Alzahab, Nibras Abo, Marco Baldi, and Lorenzo Scalise. "Efficient feature selection for electroencephalogram-based authentication." 2021 IEEE International Symposium on Medical Measurements and Applications (MeMeA). IEEE, 2021.

38) Trung, Pham Duy, Nguyen Nhat Hai, and Nguyen Thi Hong Ha. "Secure eeg-based user authentication system integrated with robust watermarking." Proceedings of the 10th International Symposium on Information and Communication Technology. 2019.

39) Stergiadis, Christos, et.al. "A personalized user authentication system based on EEG signals." Sensors 22.18 (2022): 6929.

40) Ortega, Jordan, et al. "Biometric person authentication using a wireless EEG device." Innovation in Information Systems and Technologies to Support Learning Research: Proceedings of EMENA-ISTL 2019 3. Springer International Publishing, 2020.

41) Shinde, Sonal Suhas, and Swati S. Kamthekar. "Person Authentication Using EEG Signal that Uses Chirplet and SVM." Computational Vision and Bio-Inspired Computing: ICCVBIC 2019. Springer International Publishing, 2020.

42) Zeynali, M., and H. Seyedarabi. "EEG-based single-channel authentication systems with optimum electrode placement for different mental activities. Biomed J 42 (4): 261–267." (2019).

43) Zeng, Ying, et al. "EEG-based identity authentication framework using face rapid serial visual presentation with optimized channels." Sensors 19.1 (2018): 6.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 09:2024
DOI: 10.5281/zenodo.13734747

44) Sayel, Nadhim Azeez, Salah Albermany, and Bayan Mahdi Sabbar. "Use Multichannel EEG-Based Biometrics Authentication Signal in Real Time Using Neural Network." International Conference on New Trends in Information and Communications Technology Applications. Cham: Springer Nature Switzerland, 2022.

45) Yang, Gi-Chul. "Personal authentication based on EEG signal and deep learning." Advances in Computer Science and Ubiquitous Computing: CSA-CUTE 2019. Springer Singapore, 2021.

46) Puengdang, Supawich, et al. "EEG-based person authentication method using deep learning with visual stimulation." 2019 11th International Conference on Knowledge and Smart Technology (KST). IEEE, 2019.

47) Liew, Siaw-Hong, et al. "EEG-based biometric authentication modelling using incremental fuzzy-rough nearest neighbour technique." IET Biometrics 7.2 (2018): 145-152.

48) Yap, Hui Yen, et al. "Person authentication based on eye-closed and visual stimulation using EEG signals." Brain informatics 8 (2021): 1-13.

49) Ting, Yu, Wei Chunshu, and K. J. Chiang. "EEG-based user authentication using a convolutional neural network." (2019): 1011-1014.

50) Ortega, Jordan, et al. "Biometric person authentication using a wireless EEG device." Innovation in Information Systems and Technologies to Support Learning Research: Proceedings of EMENA-ISTL 2019 3. Springer International Publishing, 2020.

51) Jain, Anil K., Arun Ross, and Salil Prabhakar. "An introduction to biometric recognition." *IEEE Transactions on circuits and systems for video technology* 14.1 (2004): 4-20.

52) Zhang, Shuai, et al. "Review on EEG-Based Authentication Technology." Computational intelligence and neuroscience 2021.1 (2021): 5229576.

53) Bidgoly, Amir Jalaly, Hamed Jalaly Bidgoly, and Zeynab Arezoumand. "A survey on methods and challenges in EEG based authentication." Computers & Security 93 (2020): 101788.