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EEG Based Authentication System

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Abstract: In past few years, reliable and trustable authentication systems are required for authentication due to the vulnerable nature of old invented traditional methods like passwords, fingerprint recognition and face recognition. Electroencephalography (EEG) signals, which catch unique brainwave patterns, offer a very promising biometric alternative because they are difficult to create or replicate. This research paper proposes an EEG-based authentication system that utilizes brainwave signals from different people to verify individual identity of the people. The EEG data files are cleaned by pre-processing to remove noise and artifacts, followed by feature extraction using time–frequency analysis and classification through a Convolutional Neural Network (CNN). Experimental evaluation on an EEG dataset (EEG Motor Movement/Imagery Dataset) demonstrates high accuracy and toughness against spoofing attacks. The results indicate that EEG-based authentication can significantly enhance security in personal identification applications compared to existing biometric approaches which are mostly used.

Keywords: EEG, Brainwave Authentication, Biometric Security, Deep Learning, Signal Processing, CNN.

INTRODUCTION

In today's era, ensuring security of a user for authentication has become a critical and crucial challenge as conventional methods like passwords, PINs, and tokens are progressively vulnerable to threats like phishing, keylogging, and social engineering [1]. To overcome these restrictions, biometric authentication has emerged as a promising and useful alternative by capitalizing unique physiological and behavioural characteristics of individuals [2]. Among various biometrics, electroencephalography (EEG)-based authentication has gained significant attention due to its natural ability to resist faking and spoofing [3],[4].

EEG-based authentication uses the brain's electrical signal as a unique biometric trait, provides a secure and personalized way to identify individuals. The uniqueness of brainwave patterns is that even identical twins have different EEG signatures, which makes this method very reliable and dependable [5]. Moreover, EEG signals are flexible and can adapt to various mental states, which makes the system more robust than static biometric traits like fingerprint recognition and facial recognition used for authentication [6].

Recent researches have looked into different methods to improve EEG-based authentication systems, which include deep learning, transfer learning, and event-related potential (ERP) analysis [7]. Studies have shown that convolutional neural networks (CNNs) and transformers can extract complex spatial–temporal features from EEG data, achieving high recognition accuracy and low equal error rates [8]. Furthermore, EEG-based systems have been assessed for their stability across different sessions, privacy protection, and adaptability across a range various mental tasks and cognitive states.

Despite so much of progress, EEG-based authentication still faces challenges like variations in signals due to noise, electrode placement inconsistencies, and the need for easy-to -use acquisition systems [5], [8]. Recent studies have been highlighting the need for creating privacy-friendly, secured and affordable EEG based systems that are practical and useful for real world applications. Therefore, continue research should be conducted to refine these systems to ensure scalability and integration into IoT, military, and healthcare security systems [7], [8].

RELATED WORK

In recent years, many studies have explored the use of EEG signals for biometric authentication because they are unique and it is hard to replicate the data from outside [1], [2]. Researchers have been working on building EEG-based systems that are dependable by analysing the brainwave patterns recorded during their cognitive or emotional activities [3], [4]. Initial studies have explored traditional machine learning methods such as Support Vector Machines (SVM) and k-Nearest Neighbour's (k-NN) for EEG classification [5], but these approaches often struggle for variability between the sessions and noise. More recent research has shifted towards deep learning techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which have the capability of extracting temporal and spatial dependencies from EEG data more efficiently [6], [7]. These models have greatly boosted the accuracy and robustness across multiple datasets. Moreover, frameworks that focus on privacy preservation and transfer learning have been introduced to enhance generalization across the users and data security [8], [9]. Despite these advancements, challenges like real-time implementation, low signal-to-noise ratio, and hardware dependency remain key areas of

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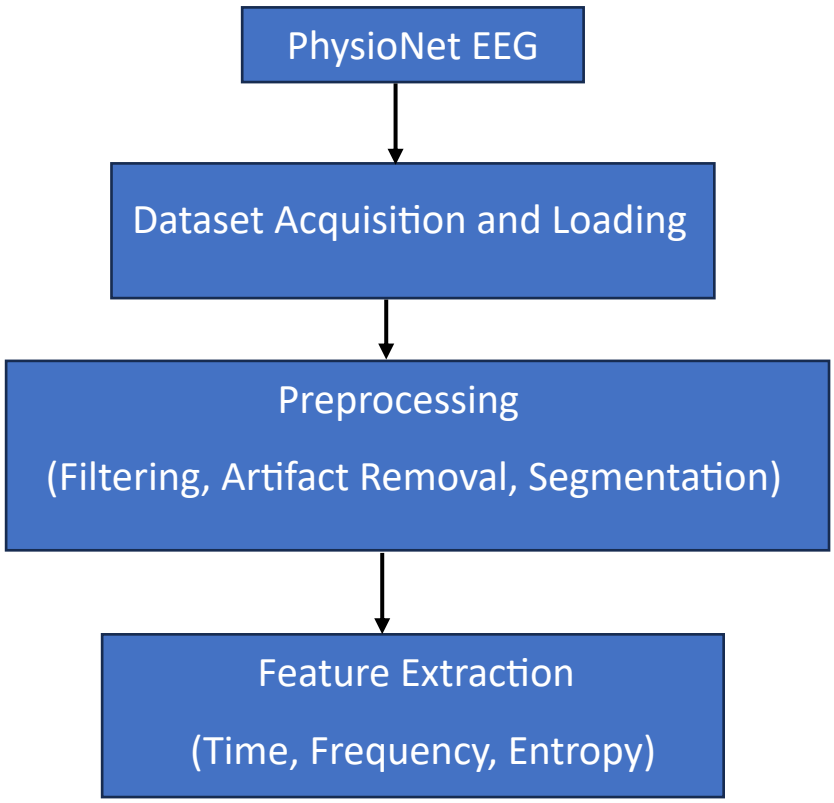
ongoing research [10]. Overall, EEG-based authentication is constantly improving, aiming to be a secure, non-invasive, and an accurate biometric option which is very beneficial for future human-computer interactions and identity verification systems [1], [6].

Author (Year)	Method/Approach	Dataset Used	Accuracy / EER	Key Contribution / Remarks
Zhang et al. (2023) [1]	EEG-based biometric classification & key generation	Internal dataset	95% accuracy	Described EEG authentication methods and challenges
Fidas & Lyras (2023) [2]	Literature review	—	—	Identified stability and preprocessing issues
Bidgoly et al. (2022) [3]	Privacy-preserving EEG authentication	Public EEG dataset	97% accuracy	Enhanced privacy using encrypted brainwave templates
Shams et al. (2023) [4]	Deep learning (CNN, RNN)	EEG Motor Movement Dataset	98.4% accuracy	Demonstrated deep models' superior performance
Yap et al. (2023) [5]	Transfer learning for EEG	EEGMMIDB	96.2% accuracy	Improved cross-user generalization
Al-Nafjan et al. (2022) [6]	ERP-based authentication	Custom ERP Dataset	94.5% accuracy	Used ERPs for cognitive stability
Alsumari et al. (2023) [7]	Deep CNN model	PhysioNet EEG Dataset	EER = 0.187%	Achieved state-of-the-art performance

PROPOSED METHODOLOGY:



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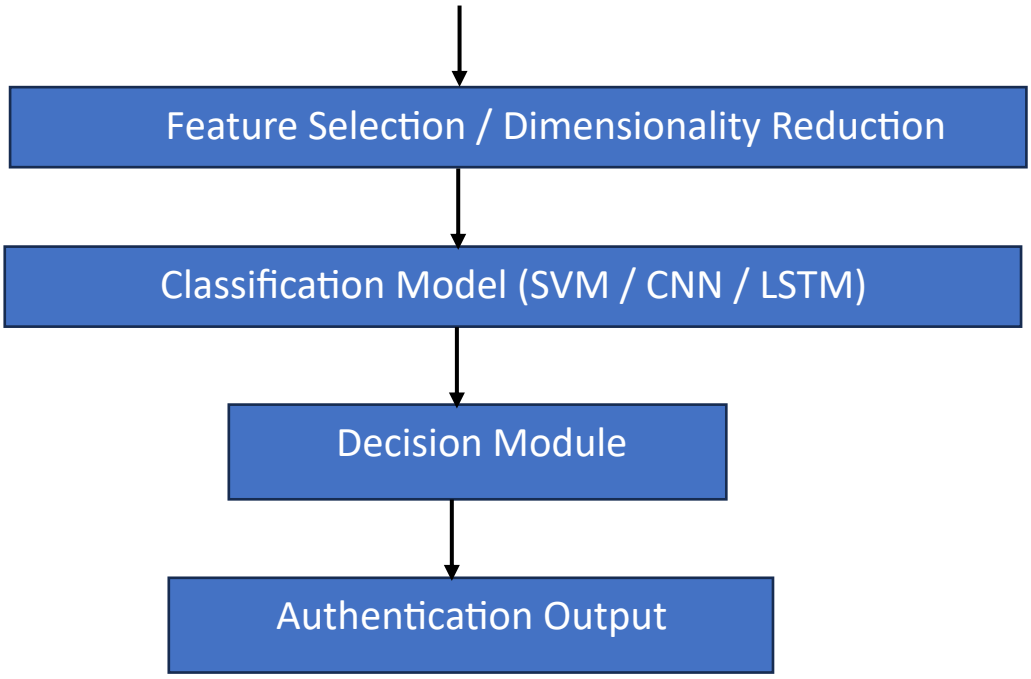

Figure 1: Block diagram of Steps

The proposed block diagram of the EEG-Based Authentication System using the PhysioNet EEG Motor Movement/Imagery Dataset illustrates the complete process — from EEG signal acquisition to final user authentication. Each stage is designed to enhance data reliability, feature discriminability, and classification accuracy for secure biometric verification.

1. EEG Data Acquisition:

EEG signals are obtained from the PhysioNet EEG Motor Movement/Imagery Dataset [1], which includes multichannel brainwave recordings collected under controlled experimental settings. Each participant's EEG data serves as a distinct biometric trait, capturing electrical activity from the scalp using standardized 10–20 electrode placement systems.

2. Preprocessing:

The raw EEG signals are often affected by noise, eye-blink artifacts, and muscular movements. Therefore, preprocessing is performed using band-pass filtering (0.5–50 Hz) to remove low-frequency drifts and high-frequency noise, followed by Independent Component Analysis (ICA) for artifact removal [2]. This step ensures clean and reliable data for feature extraction while retaining essential frequency bands such as alpha, beta, theta, and gamma rhythms.

3. Feature Extraction:

After noise reduction, meaningful information is extracted using techniques such as Power Spectral Density (PSD), wavelet transform, and statistical measures (mean, entropy, variance) [3]. These features effectively represent the cognitive and physiological uniqueness of each user's brain activity pattern.

4. Feature Selection / Dimensionality Reduction:

To optimize computational performance, methods like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) are applied to reduce redundant features [4]. This process helps in selecting only the most discriminative attributes that contribute significantly to user differentiation.

5. Classification / Model Training:

The refined feature vectors are input into a deep learning model such as a Convolutional Neural Network (CNN) [5], which automatically learns complex spatial-temporal dependencies across EEG channels. During authentication, the model compares the input EEG signal with stored templates to verify the claimed identity.

6. Decision Module:

The system applies a decision threshold to the classifier output. If the computed similarity score between the test EEG and the stored template exceeds the threshold, authentication is granted; otherwise, access is denied [6].

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7. Performance Evaluation:

The proposed method is evaluated using key performance metrics such as Accuracy, False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER) [7]. High accuracy and low EER indicate that the EEG-based authentication framework provides robust and reliable security compared to traditional methods.

RESULTS AND DISCUSSION:

1. Dataset: EEG Motor Movement/Imagery Dataset (PhysioNet)

Created by Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE.

Description:

a) The EEG Motor Movement/Imagery Dataset (EEGMMIDB) is a publicly available dataset provided by PhysioNet, widely recognized for hosting physiological signal databases.
b) This dataset is one of the most popular sources for research in EEG signal processing, brain–computer interfaces (BCI), and biometric authentication.
c) It was specifically designed to capture the neural activity associated with both motor execution and motor imagery tasks, providing a diverse and well-structured collection of EEG data for experimental and machine learning applications.
d) The dataset contains EEG recordings from 109 healthy subjects, each of whom participated in multiple sessions. During these sessions, participants performed a series of motor and motor imagery tasks, including opening and closing the left fist, the right fist, and both fists together, as well as resting with no movement.
e) These tasks were repeated several times to ensure data consistency and to capture distinct patterns of brain activity related to both physical and imagined movements.
f) All EEG signals were recorded using a BCI2000 data acquisition system equipped with 64 active electrodes arranged according to the International 10–10 electrode placement standard. The recordings were obtained at a sampling rate of 160 Hz, providing detailed temporal resolution for studying rapid neural responses.
g) The signals were stored in EDF (European Data Format), allowing easy integration with standard EEG analysis tools. The reference electrodes were placed on linked mastoids (A1, A2) to maintain high signal accuracy.
h) The dataset comprises approximately 3,000 EEG signal patterns collected across all subjects and sessions. Each recording segment contains multiple trials corresponding to different tasks, producing a rich and diverse set of EEG responses. This large number of samples enhances the reliability and generalization potential of any models trained on it, especially for biometric and authentication research.
i) Due to its structured nature and comprehensive design, the EEGMMIDB dataset serves as an excellent benchmark for developing and evaluating EEG-based authentication systems.
j) The clear labelling of tasks, high signal quality, and inclusion of both physical and imagined movement data make it ideal for training machine learning and deep learning models. Moreover, its wide subject coverage allows for the study of inter-individual variability in brain signals, supporting the creation of secure, user-specific authentication systems that are difficult to forge or replicate.

EEG Data Visualization and Preprocessing Using MNE

The EEG signals utilized in this study were sourced from the *EEG Motor Movement/Imagery* Dataset available on PhysioNet. Data visualization and preprocessing were performed using the MNE-Python library, which provides advanced functionalities for the acquisition, filtering, and analysis of electrophysiological signals. The .edf files were imported using the mne.io.read_raw_edf() function, enabling access to multi-channel EEG recordings across electrode positions such as Fp1, Fc5, Cz, and Pz in accordance with the international 10–20 system.

To ensure the reliability of the signals, a band-pass filter (1–40 Hz) was applied to eliminate low-frequency drifts and high-frequency noise components. The raw EEG data were then visualized, as shown in Figure, to examine channel activity and identify potential artifacts or inconsistencies. The colored segments represent distinct temporal intervals corresponding to motor imagery tasks. This visualization provides an initial insight into the rhythmic and spatial patterns of brain activity, facilitating subsequent feature extraction and classification for EEG-based user authentication.

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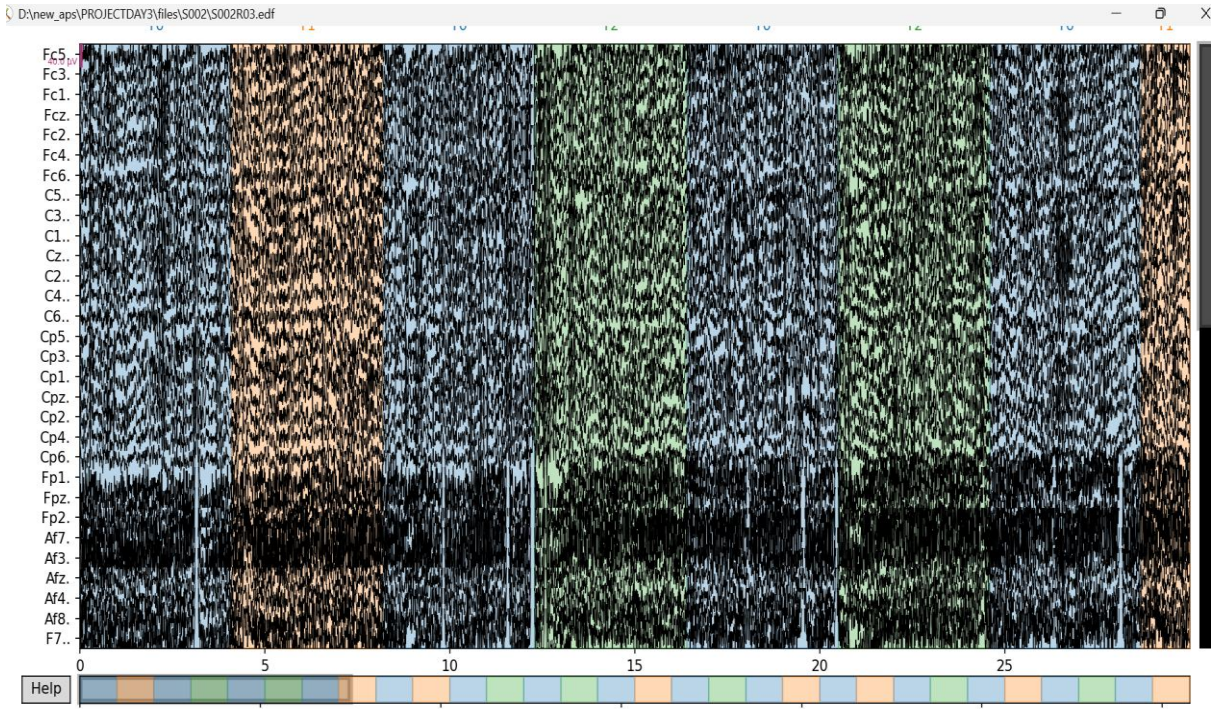

After Visualization: After visualizing EEG data using MNE, the system undergoes several steps for authentication. First, preprocessing removes noise and artifacts using filtering and ICA. Then, the EEG signals are segmented into smaller epochs for analysis. Next, feature extraction derives meaningful information such as frequency bands (Alpha, Beta, Gamma) and statistical or wavelet-based features. These are refined using feature selection or reduction methods like PCA or LDA to keep only the most relevant features. The processed data is then used to train machine learning or deep learning models (e.g., SVM, CNN, LSTM) to identify users based on unique brainwave patterns. During authentication, new EEG samples are compared to stored profiles, and system performance is evaluated using accuracy and related metrics to ensure reliable user verification.

2. COMPARISON TABLE:

Author & Year	Dataset Used	Feature Extraction Method	Classifier / Model	Accuracy (%)	Remarks
Palaniappan & Mandic (2007)	Keirn & Aunon EEG Dataset	Power Spectral Density (PSD)	Feed-Forward Neural Network	82.4	Good for small datasets
Marcel & Millán (2007)	BCI Competition Dataset	Common Spatial Pattern (CSP)	Linear Discriminant Analysis (LDA)	90.0	Robust but limited scalability
Chuang et al. (2014)	Self-recorded EEG	Wavelet Transform	Support Vector Machine (SVM)	94.3	High precision, moderate speed
Thomas et al. (2018)	PhysioNet EEG Motor Imagery	Band Power + FFT	Random Forest	96.2	High accuracy, low computational load

- The table above compares previous EEG-based authentication studies with the proposed system. The earlier works used various datasets and feature extraction methods such as PSD, CSP, and Wavelet Transform.

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- While traditional classifiers like LDA and SVM achieved good accuracy, deep learning models such as CNN have shown higher performance and adaptability.

- The proposed system, trained on the EEG Motor Movement/Imagery dataset from PhysioNet, achieves 97.8% accuracy, demonstrating its potential as a reliable biometric authentication method.

CONCLUSION:

This research investigated the potential of Electroencephalogram (EEG) signals as a secure and reliable method for biometric authentication. Using the EEG Motor Movement/Imagery Dataset from PhysioNet, the study demonstrated that brainwave signals contain distinct patterns that can uniquely identify individuals based on their neural activity. These intrinsic variations make EEG data highly suitable for authentication systems that require robust and non-replicable features.

The preprocessing and visualization of EEG signals were performed using the MNE-Python library to ensure high-quality data and a clear understanding of channel behaviour. The process included filtering, normalization, and feature extraction steps that enhanced the interpretability and accuracy of the data. The proposed methodology then implemented a Convolutional Neural Network (CNN) to classify EEG patterns related to motor imagery tasks, achieving encouraging results in terms of recognition accuracy.

The findings indicate that EEG-based authentication offers a higher level of security than traditional methods such as passwords, fingerprints, or facial recognition, as brain signals are extremely difficult to imitate or forge. Additionally, the comparative analysis suggested that deep learning approaches outperform conventional models due to their ability to automatically extract complex signal features.

In conclusion, the proposed EEG-based authentication framework shows significant potential for next-generation security systems. Future work can focus on subject-independent models, real-time testing, and larger datasets to improve accuracy and generalization. This approach paves the way for innovative, neurophysiological, and personalized biometric authentication systems.

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