Biometric Identification Using Default Mode Network Features Extracted from Eyes-Open Resting-State EEG Data

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Abstract—**Electroencephalogram (EEG)-based biometric identification systems leverage participants' unique neuronal activity to identify users. The neuronal connections of each participant are unique and hence their neuronal signatures are hard to replicate. EEG recording systems are portable, non-invasive and have high temporal resolution, making them a promising method for high-security biometric applications. To capture neuronal signatures from the brain's default mode network (DMN), we used EEG signals collected following the eyes-open resting state protocol. In this work, EEG data from the publicly available PhysioNet dataset, consisting of 109 participants, were utilized for biometric identification. Various EEG features, including Hjorth parameters, band power features, frequency-weighted power, Shannon entropy, and statistical features, were extracted to represent default mode network (DNN) neuronal signatures of each participant. A Support Vector Machine (SVM) classifier with linear kernel was used for participant identification. Classifier-based electrode selection and feature selection methods were implemented to improve the person identification accuracy. The proposed eyes-open resting state EEG-based biometric identification system, achieved an averaged classification accuracy of 99.54%, with a specificity of 0.9999 and a sensitivity of 0.9954 using the selected EEG features extracted from 12 electrodes.**

I. Introduction

Biometrics leverages unique physical traits to identify or authenticate individuals with precision. Identification determines an individual's presence or identity within a database, while authentication validates an identity claim [1]. Traditional biometric systems, including fingerprint, facial recognition, and iris scans, are widely used across various applications. Despite their popularity, these systems face significant challenges, such as security vulnerabilities, privacy risks, and susceptibility to spoofing attacks [2]. Cognitive biometrics is the approach of utilizing biological signals which indicate the mental state of an individual to establish identity. The basic idea is to record these signals and use them as biometric signatures [3]. In this technique, biological signals represent internal traits that are not visible externally. Many of these features are non-volitional which means, the participant cannot disclose their identifiers. Additionally, with current sensing technologies, it is highly improbable to capture these signals remotely, making them less vulnerable to spoofing attacks [4]. The cognitive biometric systems have some major advantages when compared to traditional biometric systems since they are resilient to physical injuries, difficult to reproduce and cannot be secretly captured at a distance [5, 6]. The electroencephalogram (EEG) records the brain's neuronal activity by measuring the potential differences detected using the electrodes placed on the scalp [7]. Previous studies have shown that EEG-based brain patterns are unique for every individual [8]. The EEG used in this work is a subset of a collection of data recorded during various motor and imagery tasks using a 64-channel EEG system (BCI2000) from 109 volunteers [9].

Significant research has been conducted in the field of biometric identification, in [10] an equal error rate (EER) of 11.24% was achieved within the 1-50 Hz frequency band, 6.25% within the 10-30 Hz frequency band and 0.19 within the 30-50 Hz frequency band using 64 electrodes by using the convolutional neural network (CNN) approach. Suppaiah et. al. [11] were able to achieve an accuracy of 95.3% to 97.2% using all 64 channels with the resting state eyes-opened (EO) EEG by extracting the power spectral density (PSD) feature along different frequency bands. Yang et al. [12] achieved accuracies of 98.24% using 4 electrodes with 105 participants, 96.9% using 64 electrodes with 109 participants, 86.91% using 56 electrodes with 108 participants and 75.86% using 56 electrodes with 108 participants. They had extracted Wavelet-Log-DCT, Eigenvector Centrality, Power Spectral Density and Spectral Coherence Density features respectively for each of these accuracies. Svetlakov et. al. [13] were able to achieve an EER of 14.63% by using 8 electrodes after extracting the Hilbert-Huang transform feature from the resting state EEG recording (both eyes opened and eyes closed). Thomas et. al. [14] were able to achieve an accuracy of 98.31% using 64 electrodes by implementing the sample entropy features. Thomas et. al. [15] were also able to achieve an EER of 0.0196 with 19 electrodes by employing the simple cross-correlation values of PSD features in the EO resting state condition. While earlier studies using eyes-open resting EEG reported accuracies between 95–98% with 64 electrodes, our system surpasses them by reaching 99.54% accuracy with only 12 electrodes, demonstrating a more efficient yet highly accurate solution.

Monsy et. al. [16] were able to achieve an EER of 0.0039 using just 20 electrodes by implementing the frequency weighted feature (FWP) feature. While these approaches achieve high performance, they require larger electrode setups, whereas our method achieves superior accuracy using only 12 electrodes, thereby improving practicality and reducing acquisition complexity.

Fan et. al. [17] were able to achieve an accuracy of 99.32% and an EER of 10.8% by using 14 electrodes in a convolutional neural network (CNN)-based approach for EEG based biometric identification. Das et. al. [18] were able to achieve an accuracy of 99.95% for resting state eyes closed (EC) and 98% accuracy for resting state EO EEG with 64 electrodes by implementing the CNN based approach. Lai et al. [19] achieved a validation accuracy of 83.21% and a testing accuracy of 79.08% by employing a CNN- based approach using 64 electrodes for EEG-based biometric identification. Ibrahim et al. [20] attained an accuracy of 98.54% by utilizing a CNN-based approach with 64 electrodes for EEG-based biometric identification. Alsumari et al. [21] achieved an accuracy of 99% by employing a deep CNN-based approach using 2 channels for EEG-based person identification. Although CNN-based approaches have achieved remarkable accuracies, they often rely on heavy computational resources and large datasets, whereas our approach achieves 99.54% accuracy with lightweight feature extraction and minimal electrodes, ensuring efficiency and scalability.

In this work, we have utilized the resting-state EEG from the eyes-open condition. Eyes closed EEG introduces drowsiness [22], which can be minimized using eyes opened recordings. Additionally, some EEG acquisition protocols involving tasks cannot be completed by people with disabilities [23]. Resting state eyes-opened EEG is more representative of an awake, relaxed and fully conscious condition. The EEG features were extracted during a non-task-related mental state - a resting condition where participants perform no specific cognitive tasks, which is particularly relevant for studying default mode network (DMN) neural activity [24]. While multiple studies mentioned earlier that used eyes-open resting EEG reported accuracies between 95–98% with 64 electrodes, this study aims to improve the classification accuracy of the biometric system that uses eyes-open, resting-state EEG with fewer electrodes.

The rest of the paper is organized as follows: Section II covers the details of the dataset used in this work. Section III is dedicated to explaining the methodology followed in this work and the Section IV presents the experimental evaluation results with its discussion. Finally, Section V concludes the work and outlines future research scopes.

II. Dataset

In this work, the EEG data were taken from the publicly available online database called PhysioNet [9]. The original dataset consists of the EEG recordings from 109 participants who perform 14 different tasks, there are two one-minute-long baseline recordings (one with eyes opened (EO) and one with eyes closed (EC)), twelve other two-minute-long recordings involving certain motor/imagery tasks. We have considered the EO resting state EEG for this work. During the recording, the participants are comfortably seated following the resting state protocol on a reclining chair in a dimly lit room. The EEG signals were recorded using a set of 64 wet electrodes placed on the scalp following the 10-10 international system of electrode placement. The reference electrodes were placed on the ear lobes and the sampling frequency used was 160 Hz. The recorded EEG signals were publicly available in the EDF+ format.

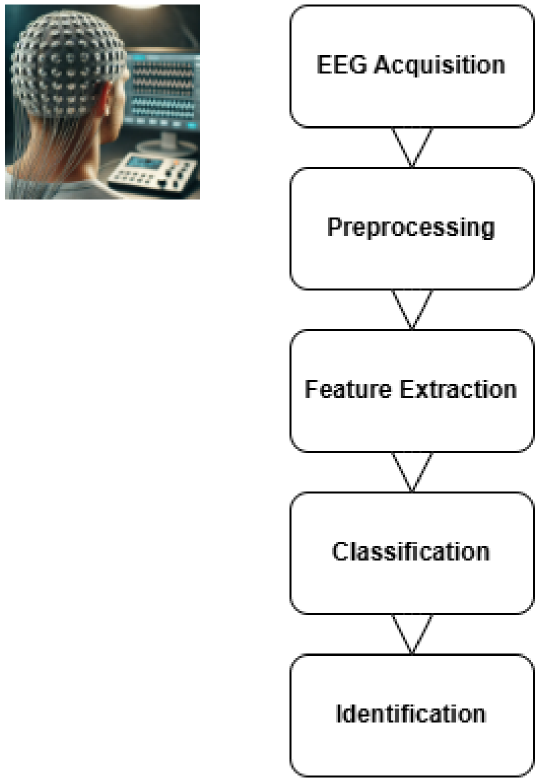

Fig. 1. Block diagram of the EEG-based biometric identification system.

III. Methodology

After EEG acquisition, the four main stages in the proposed biometric identification are preprocessing, feature extraction, multiclass feature classification, and identification (Figure 1). Preprocessing enables the removal of baseline shifts and unwanted artifacts from the EEG data. While, feature extraction helps to represent the relevant information from EEG signals into meaningful numeric values that can be used for classification [25]. Classification enables data to be matched with the corresponding individual, thereby supporting identification.

A. EEG Signal Preprocessing

The one-minute-long eyes open EEG signals were windowed into 6 non-overlapping segments of ten seconds each, with a view to facilitate the six-fold cross-validation. Further, a fifth-order Butterworth high-pass filter with cutoff frequency of 0.5 Hz was applied in order to remove the DC component and the low-frequency components to remove the baseline shift.

B. EEG Feature Extraction

The windowed EEG signals are used to extract the features. Multiple EEG features were extracted from a window and then combined into a single feature vector and used for biometric identification. There were a total of six feature vectors extracted from each participant. The extracted features include statistical features (mean, variance, skewness and kurtosis of EEG signals), which were used to summarize the distributional properties of EEG signals,

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i, \tag{1}$$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2, \tag{2}$$

$$\text{Skewness} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^3, \tag{3}$$

$$\text{Kurtosis} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^4, \tag{4}$$

Here:

- x_i is the i^{th} EEG sample in the window
- N is the total number of samples in the window
- μ is the mean of the EEG signal
- σ is the standard deviation of the EEG signal

The power spectral density (PSD) [25] is calculated to extract other power features. PSD measures how the power of a signal is distributed over its frequency and is calculated using the averaged modified periodogram method. The frequency-weighted power [16] calculated from different EEG bands, quantified the contribution of each frequency weighted by its magnitude. While FWP was originally defined and tested for biometric identification under eyes-closed conditions, we evaluated its efficacy under the eyes-open condition, which provides a more natural representation of the default mode network.

$$\mathit{FWP} = \sum w \cdot P_w, \tag{5}$$

where w is the specific frequency and P_w is the corresponding power density value [16], both of which are frequency-domain features. Hjorth parameters [26], are time-domain descriptors used to assess signal shape and complexity

$$\text{Activity} = \text{Var}(x), \tag{6}$$

$$\text{Mobility} = \sqrt{\text{Var}(dx/dt)/\text{Var}(x)}, \tag{7}$$

$$\text{Complexity} = \text{Mobility}(dx/dt)/\text{Mobility}(x), \tag{8}$$

Here:

- x is the EEG signal
- $\frac{dx}{dt}$ is the first derivative of the signal
- Var denotes variance

Entropy features are used to quantify the randomness and information content in EEG signals, out of which Shannon entropy (H), spectral entropy (H_{spec}), and permutation entropy (H_{perm}) were considered here.

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i, \tag{9}$$

$$H_{\text{spec}} = -\sum_{f} P(f)\log_2 P(f), \tag{10}$$

$$H_{\text{perm}} = -\sum_{j=1}^{n!} p_j \log_2 p_j. \tag{11}$$

Here:

- p_i, p_j: probabilities of amplitude or permutation patterns
- $P(f)$: normalized power at frequency f
- n: number of histogram bins (Shannon) or embedding dimensions (Permutation).

C. SVM-based Classification

For biometric identification, participants' EEG features were classified using a Support Vector Machine (SVM) classifier with a linear kernel. SVM is a widely used machine learning classifier and is effective when the number of samples is limited [27]. Kernel functions play a crucial role in enabling efficient implementation of nonlinear mappings [28]. We took the assumption that selected features were linearly separable in the original feature space and hence a linear kernel is used for classification. Using a linear kernel enables fast training and identification as well as the linear kernel being less prone to overfitting.

In addition to the final classification performed using the selected features, the classification process was also employed to identify the most relevant features and determine the most significant electrodes. This methodology contributed to the improvement of accuracy in person identification tasks. In this project, a six-fold cross-validation approach was employed to ensure robust evaluation. Feature vectors were grouped on the basis of their corresponding window indices, with each participant's EEG recording divided into six 10-second windows. In each fold, one window group served as the test set, while the remaining five were combined to form the training set. This process was repeated six times, allowing each group to serve as the test set once. With 109 participants and six windows per participant, each fold comprised 109 test vectors and 545 training vectors. This strategy provided a comprehensive and balanced validation framework, ensuring that the model's performance was evaluated across all temporal segments of the EEG recordings.

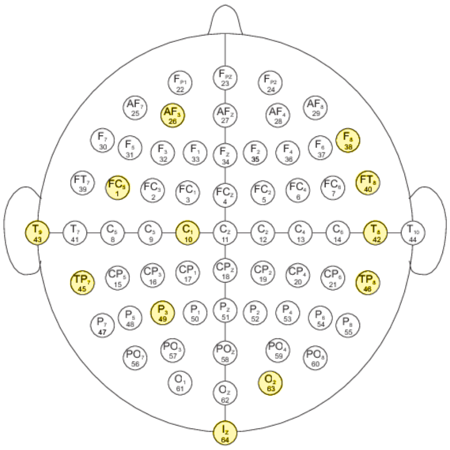

Fig. 2. Electrode Layout highlighting the selected electrodes used in the proposed biometric system.

D. EEG Electrode and Feature Selection

In the first stage of analysis, all the extracted features were assessed using a linear SVM classifier with 6-fold cross-validation over the complete 64-electrode set. As shown in Table I, features with classification accuracies greater than 70% were selected for further consideration, narrowing down to 22 candidate features.

To further narrow down the feature set, the 22 features that initially achieved accuracies above 70% were individually reassessed using the same linear SVM classifier with 6-fold cross-validation. For each feature, the associated electrodes were selected through a systematic stepwise evaluation: electrodes were added to the feature vector one at a time, and their impact on classification accuracy was tested. Only those electrode subsets that sustained or improved accuracy were retained, while those electrodes that reduced the accuracy were discarded. This process yielded a refined set of six features that maintained accuracies above 90% after electrode reduction. These included beta power, gamma power, higher band power(60-80 Hz), and their frequency-weighted power (FWP) variants, as reported in Table II.

To further balance system simplicity with identification accuracy, the retained feature–electrode pairs were subjected to the same selection procedure using the linear SVM classifier. In this stage, each candidate pair was systematically re-evaluated, retaining only those pairs that consistently improved or preserved accuracy and discarding those that introduced redundancy or reduced performance. This approach allowed us to refine both the features and their corresponding electrode subsets simultaneously. The process ultimately reduced the system to 12 electrodes and preserved only the FWP-based features (beta, gamma, and higher band power). The final configuration, presented in Table III, provided the optimal trade-off between efficiency and accuracy, achieving a peak classification performance with the linear SVM classifier.

TABLE I
AVERAGED CLASSIFICATION ACCURACIES FOR EEG FEATURES USING 64 ELECTRODES, SHOWING RESULTS ABOVE 70%

Feature	Accuracy with 64 electrodes (%)
Delta Power	76.45
Alpha Power	74.92
Beta Power	98.62
Gamma Power	97.24
Higher Band Power	98.17
Theta Power	74.46
Standard Deviation	88.99
Variance	85.78
Maximum	76.61
Minimum	76.14
Range	80.27
FWP Delta	77.52
FWP Gamma	97.40
FWP Alpha	77.21
FWP Beta	98.01
FWP Theta	75.84
FWP Higher	98.32
Hjorth Activity	85.78
Hjorth Mobility	86.09
Hjorth Complexity	89.30
Spectral Entropy	85.17
Permutation Entropy	81.50

TABLE II
SIX HIGHEST AVERAGE CLASSIFICATION ACCURACIES OBTAINED WITH REDUCED ELECTRODE SETS

Feature	Accuracy achieved (%)
Beta Power	97.71
Higher Band Power	97.09
Gamma Power	95.87
FWP Beta	95.11
FWP Gamma	92.05
FWP Higher	97.55

TABLE III
SELECTED FEATURES AND CORRESPONDING ELECTRODES FOR THE PROPOSED BIOMETRIC SYSTEM

Features Extracted	Electrodes Used
FWP Gamma	C_1, TP_8
FWP Beta	FC_5, AF_3, F_8, FT_8, T_8, P_3,O_2
FWP Higher	T_9, TP_7, O_2, I_Z

E. Identification

Each EEG file corresponded to a unique participant and the file path serves as a proxy identifier for that participant. Features are extracted from each windowed EEG recording and tagged with the corresponding participant ID. The classification model used this as the identity labels during training. During testing, all the testing vectors are provided to the model and model's predicted labels are matched with the participant's original identities. If a prediction and the original identity of a participant is same, then we consider it as correct identification and the biometric identification performance parameters such as averaged accuracy, sensitivity, and specificity were calculated.

TABLE IV
COMPARISON OF THE PROPOSED WORK WITH OTHER STUDIES USING EO EEG FOR PERSON IDENTIFICATION

Ref.	N. Part.	Acc.	EER	Elec.	Cond.
[11]	109	95.3% - 97.2%	-	64	EO
[13]	109	-	14.63%	8	EO, EC
[20]	109	98.54%	-	64	EO, EC

IV. RESULTS AND DISCUSSION

The accuracy obtained from the six-folds of cross-validation are averaged and presented as the final performance parameters of the biometric system. The proposed biometric identification system achieved high performance, with an averaged accuracy of 99.54% using the SVM classifier and with features extracted from 12 electrodes (see Table III). Sensitivity reached 0.9999, and specificity was 0.9954, demonstrating the robustness of this approach.

This approach minimized drowsiness-related artifacts and reflects naturalistic brain activity, making it ideal for biometric identification. Features such as Hjorth parameters, power spectral density, and statistical measures were considered but later removed since it failed to demonstrate a high averaged classification accuracy. Feature selection further refined the system, underscoring the potential of EEG signals as a secure and efficient solution for biometric identification. Frequency-weighted power across gamma, beta, and higher band power was considered, with the system optimized to use only 12 electrodes. The Table III lists the final selected features along with the corresponding electrodes chosen to achieve the above specified accuracy.

With the selected features and electrodes, the proposed system achieved the person identification accuracy of 99.54%. The performance of other works which used eyes open resting state EEG data are given in Table IV. The work [11] used the EO EEG for identification and were able to achieve an accuracy of about 95.3% to 97.2% by utilizing all 64 electrodes. While, both [13] and [20] utilized both EO and EC EEG were able to achieve an EER of 14.63% using 8 electrodes and an accuracy of 98.54% using 64 electrodes respectively. Our work was able to achieve an accuracy of 99.54% by utilizing only 12 electrodes which is a significant improvement when compared to the previous works.

Out of the 64 channels, the 12 channels selected were C_1, TP_8, FC_5, F_8, FT_8, AF_3, T_8, P_3, I_Z, O_2, T_9 and TP_7. The minimum number of channels helped overcome redundancy and thereby improved accuracy. By selecting the 12 electrodes that contributed most significantly to accuracy, we achieved a streamlined yet highly accurate model with 99.54% accuracy, significantly reducing computational complexity. To the best of the authors' knowledge, this is the first work to attain such high accuracy using only 12 electrodes and eyes-open resting-state EEG data.

It should be noted, however, that the reported results are based on within-session validation. While the high accuracy achieved is promising, robust validation across multiple sessions and days is necessary to account for natural physiological variability and potential confounding factors. Furthermore, the data used in this study was collected under controlled conditions with standard preprocessing steps such as filtering. This highlights the importance of future work extending the evaluation to real-world scenarios that involve environmental noise, artifacts, and larger participant samples in order to fully establish the system's efficacy, robustness, and generalizability.

V. CONCLUSION

The proposed EEG-based biometric system focuses on utilizing eyes-open resting-state EEG data collected from 109 participants. The EEG signals were preprocessed, and selected features from specific EEG frequency bands were extracted, providing high accuracy for person identification. Feature vectors created using the 12 selected electrodes were then classified using an SVM classifier with a linear kernel. The six-fold cross-validation technique resulted in an average person identification accuracy of 99.54%. The proposed system was evaluated under closed conditions within a single session, and future work will involve extending the evaluation to cross-session and more realistic real-world conditions.

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