# Task Based Person Identification System using Brain Signals


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***Abstract*—Biometric authentication is pivotal in identifying individuals with unique physiological or behavioral characteristics. General recognition methods, such as fingerprint, voice, iris, and face recognition, are widely used but have significant flaws. These can be sensitive to spoofing, raise privacy concerns, and often struggle in certain environments. To fix these shortcomings, we suggest a novel biometric method: Electroencephalogram (EEG) authentication. Electroencephalogram (EEG) technology measures brainwave activity through electrodes and is known for its reliability, resistance to forgery, and inherent uniqueness, similar to fingerprints. EEG is particularly significant for liveness detection, making it a strong candidate for robust biometric authentication in high-security applications. This study utilizes a publicly available dataset consisting of EEG data from 109 subjects. The raw data is first scaled and then analyzed using various classifiers, such as k-nearest neighbors (k-NN), Auto-Encoder with k-NN, and Convolutional Neural Networks (CNN). The model's performance is evaluated under four different conditions based on the subjects' activities, with the CNN achieving an authentication accuracy of 92%.**



***Index Terms*—EEG, KNN, Machine learning, CNN**


## I. Introduction

It is no longer necessary for users to carry physical tokens or memorize complicated passwords; instead, their identity can be verified swiftly and effortlessly with their biometric data. This ease of use, combined with the heightened security biometrics provide, is why they are increasingly being adopted in various sectors, from banking and healthcare to law enforcement and border control. Biometrics refers to unique individual characteristics used to distinguish each person's characteristics. In contrast to customary means of authentication, like passwords, PINs, or security questions, biometrics are inherently linked to a person's characteristics.These can be divided into two main types: behavioral and physiological identifiers. Physiological identifiers typically include iris recognition, facial recognition, hand geometry, and fingerprint recognition, while behavioral identifiers encompass traits like signatures, voice recognition, gait, and handwriting [13].

Biometrics involves analyzing and evaluating these features to identify individuals, while biometric authentication specifically uses these unique traits for secure identification. One of the key advantages is that biometric systems can operate in the background, allowing for continuous authentication, which is particularly valuable in high-security environments where constant identity verification is necessary. This ensures that access is maintained only for the legitimate user without requiring repeated manual input of credentials. For example, biometric systems can handle thousands of users in real-time, making them suitable for environments like large corporations, public transportation systems, or even nationwide identification programs.

When selecting a particular characteristic as a biometric identifier, several factors must be considered, including distinctiveness, permanence, universality, measurability, and efficiency [6]. Among physiological identifiers, there are various attributes such as fingerprint recognition, facial recognition, iris recognition, and EEG. However, a few methods can be impacted by external variables like lighting, environmental conditions, and physical alterations. Fingerprints can be worn down or damaged, facial features can change due to aging or facial expressions, and iris patterns may be obscured by glare or contact lenses. Additionally, these recognition techniques can sometimes be vulnerable to spoofing or deception, where artificial representations of the biometric trait are used to gain unauthorized access.

In contrast, EEG captures brainwave patterns, which are not easily altered or replicated by external conditions or deliberate attempts at fraud. EEG data remains consistent regardless of surface-level changes in physical appearance, making it a potentially more reliable and tamper-resistant option for biometric authentication [9]. EEG recordings are divided into two types: invasive and non-invasive. Non-invasive EEG involves placing electrodes on the scalp, while invasive EEG requires electrodes to be implanted within the skull. Although invasive EEG can provide long-term recordings, it carries risks of infection and other neurological complications. An overview of EEG-based authentication system is shown in Fig 1.

## II. Related Work

The findings from various studies demonstrates the growing use of EEG-based biometric identification. Chowdhury et al. [1] studied brain wave-based person authentication and achieved 83.2% accuracy with a random forest classifier on a dataset of 21 subjects. Alsumari et al. [2] addressed deep learning's constraints in EEG detection by developing a CNN model with few parameters that achieved a 99% identification rate using minimal data. Similarly, Bidgoly et al. [3] observed that, while shallow classifiers are still widely used, they are progressively being superseded by deep learning approaches like as CNNs for EEG authentication.

Kamaraju et al. [4] proposed a novel EEG biometric approach based on EEG data acquired while signing, which achieved up to 93.4% accuracy using fine KNN classifiers. Wibawa et al. [10] compared Gaussian NB and SVM classifiers for EEG-MI user identification, achieving nearly 99% accuracy with SVM using the CSP method. Taken as a whole, these research highlight how sophisticated machine learning methods can improve the precision and dependability of EEG-based biometric systems.

Yousefi et al. [11] developed an EEG-based biometric authentication system using machine learning algorithms like Neural Networks and SVM to address the vulnerabilities of traditional methods. Using EEG data from 43 participants and four specific channels, the study achieved a maximum accuracy of 97.7% with the Neural Network on the F7 channel. The system utilized Matlab EEGLab for preprocessing and analyzed Power Spectral Density (PSD) to identify the most effective EEG channel for authentication. Xu et al. [5], [12] explored the limitations of current biometric authentication systems in terms of usability, efficiency, and durability. They found that alpha brainwaves, particularly during deep breathing, were the most effective for authentication. Their experiments showed that SVM and Neural Network classifiers achieved 91% and 90% accuracy, respectively, highlighting deep breathing as a reliable method for enhancing alpha brainwave activity and improving authentication system reliability.

## III. Background Theory

Machines can learn from data, spot patterns, and make defensible conclusions without explicit instructions thanks to the revolutionary science of machine learning. Its applications are vast, ranging from enhancing medical diagnostics and optimizing financial trading algorithms to enabling autonomous driving and improving natural language processing. In the following section, we will delve into various classifiers, including Convolutional Neural Networks (CNN), Autoencoders, and k-Nearest Neighbors (k-NN), to understand how these models contribute to the power and versatility of machine learning systems.

### *A. Classifier Description*

*1) k-NN:* It is a method that belongs to the class of lazy, instance-based learning algorithms. A data point's classification in k-NN is based on the majority class within its k-nearest neighbours, where "k" is a user-specified parameter [4].Key aspects of k-NN include,

- Similarity Measurement: The algorithm assesses the similarity between data points using a chosen distance metric, such as Manhattan or Euclidean distance.
- Choosing "k": The selection of the parameter 'k' is critical. A large 'k' can smooth out local variations, potentially overlooking finer patterns, while a small 'k' might leave the model prone to noise.
- Decision Rule: To classify a new data point, the class label that is the most frequent among the k-nearest neighbors is assigned using the algorithm, as illustrated in Fig 2.

*2) Auto Encoder:* Typically used in unsupervised learning tasks, autoencoders are a kind of neural network. Its primary objectives include creating efficient representations of data, which can be utilized for tasks such as feature learning, dimensionality reduction, and data denoising. The autoencoder is composed of two key components: the encoder and the decoder.

**Encoder:** The encoder compresses the input data into a lower dimensional space, effectively extracting only the most essential features needed for subsequent processing. This compressed form, known as the latent representation, is a shortened copy of original data that retains critical details essential for appropriate reconstruction.

**Decoder:** The decoder's function is to reconstruct the compressed data back into its intial form. The main objective is to produce an output that closely matches the input data. The autoencoder's training goal is to reduce the variation between the input and the output that has been reconstructed. by optimizing a loss function that measures this discrepancy. The process involves backpropagation, which adjusts the network's weights to reduce the loss, thereby improving the accuracy of the reconstruction. This is illustrated in Fig 3.

*3) CNN:* Convolutional Neural Networks is a form of deep neural network distinguished by its capacity to learn complicated patterns through the hierarchical organization of layers. This approach, often referred to as hierarchical or deep representation learning, allows CNNs to progressively capture intricate features from data [2], [7], [3]. CNNs are particularly effective in tasks such as image recognition because they can identify spatial hierarchies and patterns within images.CNNs

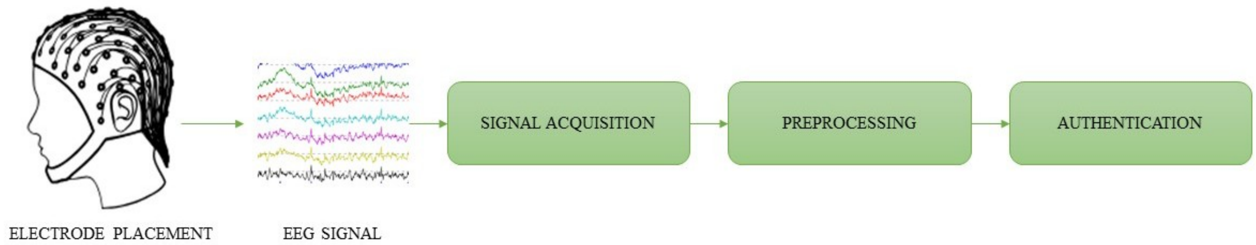


Fig. 1. Overview of the EEG-Based Identification Process.

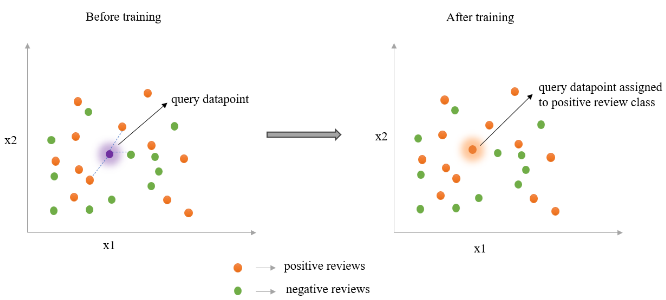


Fig. 2. Illustration for k-NN

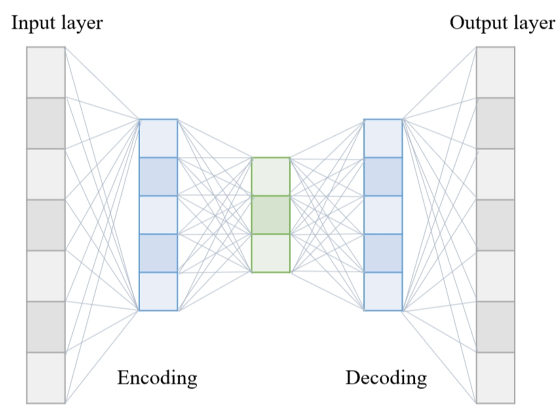


Fig. 3. Illustration for Auto Encoder

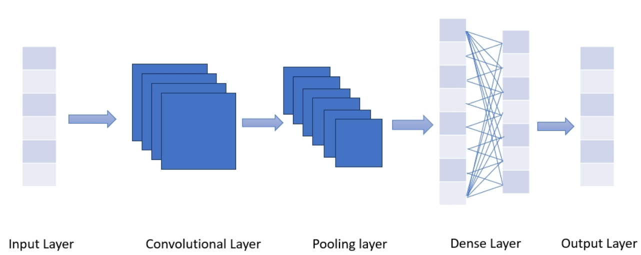


Fig. 4. Illustration for CNN

comprise several key layers, each serving a specific function in the network's architecture as shown in Fig 4.

*Convolutional layer:* This fundamental layer performs convolution operations to the input employing various filters that move across the data, extracting spatial patterns and essential features.

*Relu:* The Rectified Linear Unit layer introduces non-linearity into the model by converting all negative values in the feature map to zero, which can improve generalization and reduce overfitting.

*Pooling layer:* The Pooling layer diminishes the spatial dimensions of the feature maps, which helps manage computational complexity while preserving the most important features and mitigating the risk of overfitting.

*Flatten layer*: It turns the 2D feature maps into a 1D vector, which is necessary to feed the data into fully connected layers that require one-dimensional input.

*Dropout layer:* This regularization technique randomly drops units from the network during training, ensuring the network does not rely too heavily on specific features thereby reducing overfitting.

*Fully connected layer:* In this layer, the features extracted by previous layers are combined and subjected to nonlinear transformations. The dense layer at the end of the network produces the class probabilities, enabling the final classification of the input data.

## IV. Dataset Description

The dataset includes EEG recordings from 109 subjects, each lasting one to two minutes. The BCI2000 equipment was utilized to record these images via a 64-channel EEG system. Each subject participated in specific motor and imagery tasks [8].

Initially, participants engaged in two baseline tasks, each lasting one minute—one with eyes open and the other with eyes closed. Following this, they performed four experimental tasks, each repeated three times. The first task required participants to move their fists based on a visual target's position on the screen: the right fist for a target on the right and the left fist for a target on the left. The second task involved imagining the fist movements of the first task. In the third task, participants opened and closed both fists when a target appeared at the top of the screen and both feet when it appeared at the bottom. The fourth task involved imagining these movements. With

160 Hz as the rate of sampling, the data is recorded in the EDF+ format, adhering to international 10-10 system which is illustrated in Fig **??** [8].

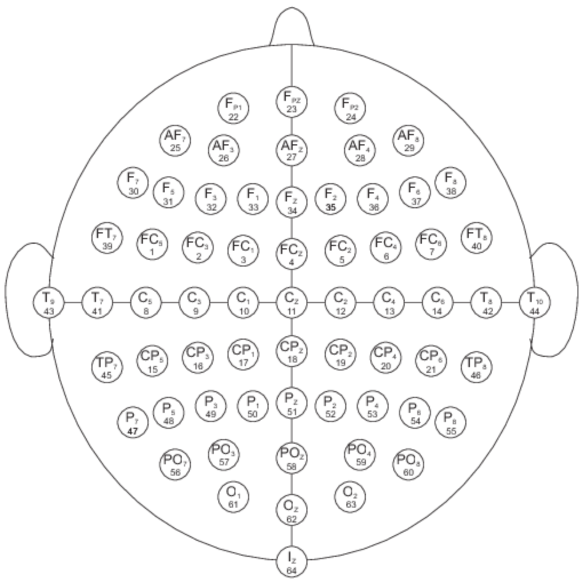


Fig. 5. Electrode placement using 10-10 system

## V. Preprocessing

Key details are extracted from the raw EEG data, including information on EEG channels and data frames. These details are crucial for understanding signal characteristics and serve as the foundation for further preprocessing steps. A train-test split method is employed to make sure that the performance of the model is thoroughly assessed on uncovered data, which is essential for assessing its ability to generalize. The datasets for training and testing are normalized using Sklearn's StandardScaler, which helps minimize the impact of differences in feature scales and enhances model convergence and performance. The training and testing datasets are then concatenated separately, maintaining consistent feature dimensions for effective model training and evaluation.

Each data point is uniquely labeled, linking it to specific subject identifiers. For the model to learn and identify patterns in EEG data that correspond to individual characteristics, this link is essential. The entire EEG data preparation process includes key stages such as data loading, preprocessing, splitting, scaling, concatenation, and label generation, providing a comprehensive framework for machine learning tasks.

The study utilized a dataset with recordings from 109 subjects, each recorded using 64 electrode channels. To explore how dataset size impacts model performance, we tested four different scenarios: training with data from 25, 50, 75, and all 109 subjects. This analysis allowed us to evaluate how variations in the number of subjects influence the overall effectiveness of our machine learning models.

## VI. Proposed Model

The input data for the CNN model is first reshaped into a three-dimensional tensor with dimensions (64, 1). This reshaping ensures consistency across all input samples, making them suitable for processing through the convolutional layers. The initial Conv1D layer uses 32 filters, each of size 11, to process the reshaped input, resulting in a feature map with dimensions (54, 32), where the spatial dimension has been reduced to 54, and the number of filters applied are 32. Next, the model employs a second Conv1D layer, which increases the number of filters to 64. This layer further processes the input data, yielding feature maps of size (44, 64).

The increased filter count enables the model to capture more complicated patterns within the data. Each of these convolutional layers is paired with a ReLU activation function, which is applied to the feature maps to introduce non-linearity. MaxPooling layers are used to downsample the feature maps in between convolutional layers. A window size of 2 is employed for pooling, thereby halving the spatial dimensions of the feature maps. This pooling operation is applied to maintain the most significant features while reducing the overall size of the data. This strategy helps manage the model's computational load and focuses on essential features detected by the convolutional layers.

The model continues with additional convolutional layers, using 64 and then 128 filters, to process the data further. Each of these layers uses the ReLU activation function. The feature maps are flattened into a one-dimensional vector after the pooling and convolutional procedures. This vector is then fed into the dense layers, which consist of two layers with 25 neurons each. These dense layers, using ReLU activation, process the flattened features to extract higher-level information.

The model includes a dropout layer with a rate of 0.2 to reduce overfitting, meaning that 20% of the neurons are set to zero, randomly during each training step. This dropout layer is positioned before the final output layer, which is a softmax layer. The softmax layer provides the final output by assigning probabilities to each class label using the characteristics retrieved and processed by the previous layers. This output facilitates the classification of input data according to the learned patterns. as shown in Fig 6.

In the kNN classifier, the distance metric used is Euclidean distance, with the value of k set to 5. For the kNN-AutoEncoder, after scaling the training and testing data, three convolutional layers with ReLU activation are added for encoding, featuring 16, 32, and 64 filters, respectively, each followed by a MaxPooling layer with a down-sampling factor of 2. The decoder mirrors this structure with three convolutional layers and Up-sampling layers to reconstruct the data. This autoencoder effectively removes noise and highlights essential features before classification with kNN.

## VII. Results

The CNN model showed an accuracy of 92% for Task 3 and 91% for Task 5 for 25 subjects. The model consistently delivered strong results across the remaining tasks,

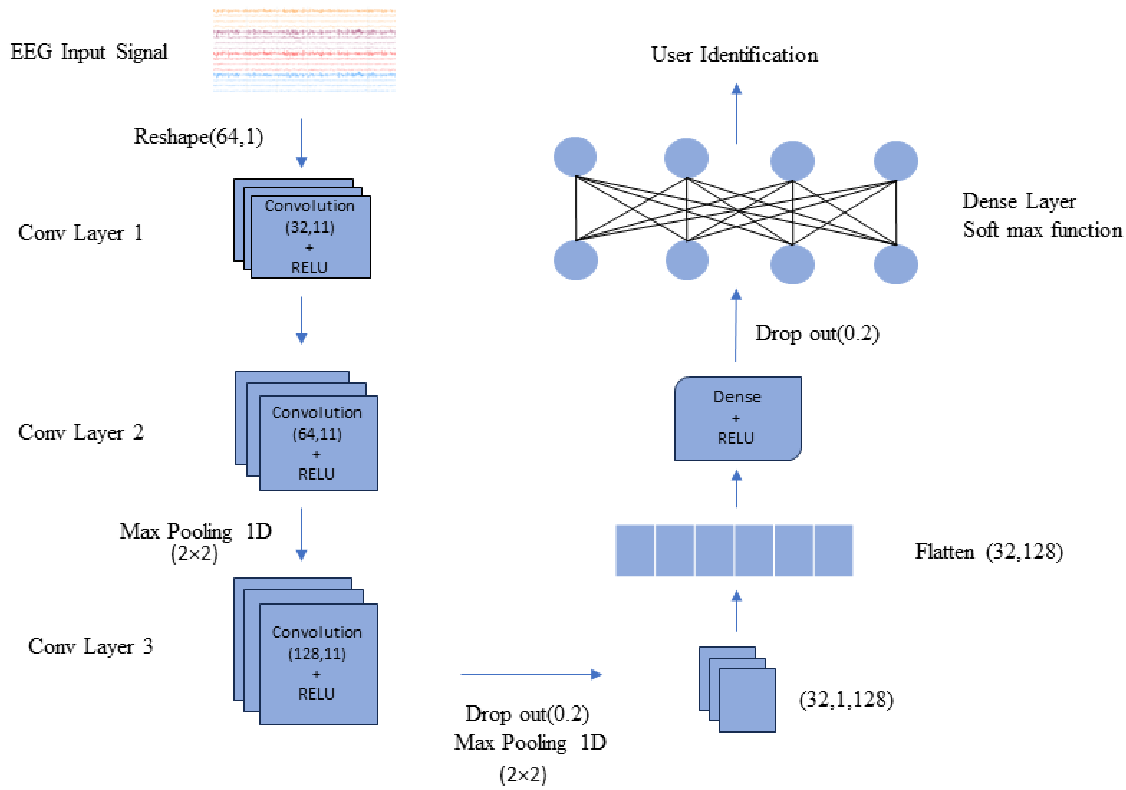


Fig. 6. Person Authentication model using CNN.

with accuracies of 88% for Task 4 and 88% for Task 6. This performance underscores the CNN model's robustness and effectiveness in handling diverse classification challenges, even with a relatively small subject pool as shown in Table I.

The kNN model, on the other hand, reached an accuracy of 54% for Task 5, with other tasks yielding results of 52% for Task 3, 45% for Task 4, and 47% for Task 6. The Autoencoder-kNN model achieved an accuracy of 45% for Task 5, with corresponding results of 44% for Task 3, 43% for Task 4, and 41% for Task 6. These results suggest that while kNN and Autoencoder-kNN are capable of performing the tasks, their outcomes are significantly less impactful compared to the CNN model as shown in Fig 8.

The CNN model's performance over the training process, both the accuracy and error rates across epochs are illustrated in Fig 7. The accuracy vs. epoch graph demonstrates how the model's accuracy improves with training, while the error vs. epoch graph highlights the reduction in error as the model learns over time.

When the subject pool expanded to 109, the CNN model continued to demonstrate its superiority, achieving an accuracy of 78% for Task 6. The model's performance remained consistent across the board, with accuracies of 74% for Task 3, 76% for Task 4, and 77% for Task 5, further solidifying its reliability in handling more complex and larger datasets.

TABLE I
SUBJECT-BASED ACCURACY ANALYSIS FOR DIFFERENT TASKS WITH 64 ELECTRODES

| Classifier | Task | 25 | 50 | 75 | 109 |
|---|---|---|---|---|---|
| **CNN** | **Task-3** | 92 | 81 | 74 | 74 |
| | **Task-4** | 88 | 80 | 78 | 76 |
| | **Task-5** | 91 | 85 | 79 | 77 |
| | **Task-6** | 88 | 82 | 79 | 78 |
| **kNN** | **Task-3** | 52 | 39 | 29 | 28 |
| | **Task-4** | 45 | 34 | 30 | 27 |
| | **Task-5** | 54 | 41 | 30 | 28 |
| | **Task-6** | 47 | 32 | 32 | 26 |
| **Auto Encoder - kNN** | **Task-3** | 44 | 30 | 14 | 20 |
| | **Task-4** | 43 | 31 | 24 | 22 |
| | **Task-5** | 45 | 32 | 25 | 21 |
| | **Task-6** | 41 | 27 | 24 | 12 |

The kNN model, with the larger subject pool, recorded an accuracy of 28% for Tasks 3 and 5, with other tasks yielding 27% for Task 4 and 26% for Task 6. The Autoencoder-kNN model recorded an accuracy of 22% for Task 4, with other tasks showing accuracies of 20% for Task 3, 21% for Task 5, and 12% for Task 6. These figures highlight the challenges faced by the kNN and Autoencoder-kNN models in scaling to larger datasets, especially when compared to the consistently high performance of the CNN model.

Overall, the CNN model consistently outperformed the kNN and Autoencoder-kNN models across all tasks and subject pools, reaffirming its effectiveness and reliability as the preferred approach for this classification problem.

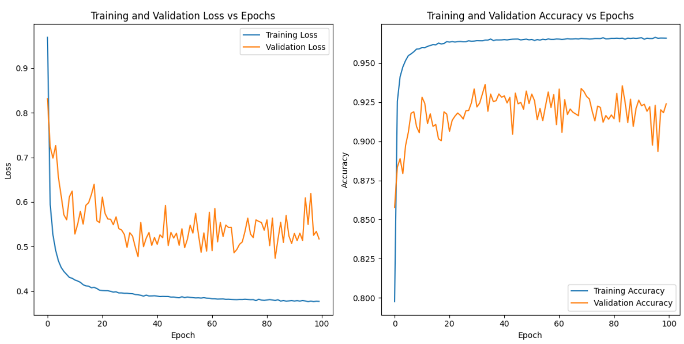


Fig. 7. CNN (accuracy vs epoch) and (error vs epoch) graph

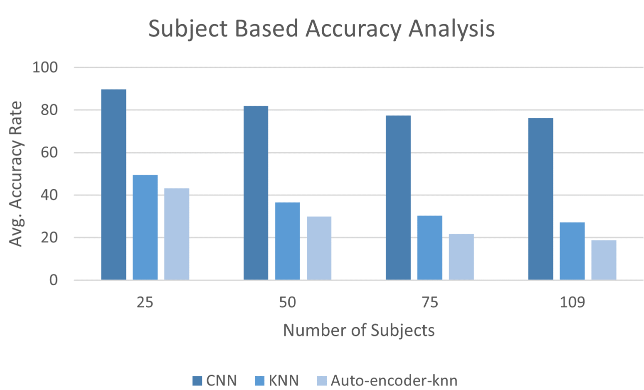


Fig. 8. Subject-Based Accuracy Analysis Chart

## VIII. Conclusion

This study has confirmed the reliability of EEG signals as a reliable method for biometric authentication, achieving a high accuracy of 92%. This result underscores the potential of EEG-based systems to provide secure and unique authentication mechanisms, particularly in applications where traditional biometric methods may be less effective. The strong performance achieved in this study highlights the viability of EEG as a promising approach to enhancing user security and privacy.

Looking ahead, we plan to explore a range of classifiers and deep learning techniques to further enhance the reliability and performance of authentication using EEG. By experimenting with various models and methodologies, we aim to enhance the system's effectiveness, making it more adaptable to diverse use cases and more resilient against potential challenges. Additionally, future research will focus on refining the current model, optimizing its accuracy, and reducing computational complexity, thereby contributing to the development of even more robust biometric authentication systems.

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