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BRAINPRINT AUTHENTICATION UNDER VARYING ENVIRONMENTAL CONDITIONS: MACHINE LEARNING VERSUS DEEP LEARNING

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Abstract: This study explores the potential of using EEG signals for biometric authentication through the development of Convolutional Neural Network (CNN) model. In particular, the electroencephalogram (EEG) signals were recorded in different ambient noise settings: quiet environment, low-distraction environment, and high-distraction environment. Traditionally, EEG-based authentication requires a separate feature extraction step prior to the use of machine learning algorithm. Feature extraction process is usually cumbersome, which relies heavily on human experts, and prone to information loss. Thus, a CNN model based on EEGNet architecture is proposed to train EEG datasets collected from 45 volunteers who were instructed to look at images presented to them in all the three acoustic conditions. Using a variety of performance metrics, notably precision and recall, the model's performance was compared across various classification thresholds to account for the imbalanced nature of the dataset. The performance was also compared across different environmental conditions, with the highest F1-score in quiet conditions. Additionally, the CNN's performance was compared against a probability-based Incremental Fuzzy-Rough Nearest Neighbour (prob-IncFRNN) model, with former outperforming the latter in all metrics.

Keywords: brainprint authentication, convolutional neural network (CNN), probability-based incremental fuzzy-rough nearest neighbour (prob-IncFRNN).

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1. INTRODUCTION

The cybersecurity field is increasingly recognizing the need for robust authentication methods beyond traditional password or token-based systems, which cannot effectively distinguish between authorized users and imposters [1]. Biometric authentication addresses these shortcomings by identifying individuals based on unique physical or behavioural traits. Traditional methods fall into the "what you know" category, while biometric methods fall into the "who you are" category. Biometrics can be divided into behavioural approaches like signature recognition and physiological approaches like fingerprints and iris scans. EEG signals represent a cognitive approach, focusing on "the way an individual thinks", making them highly secure and unique [2]-[4]. However, EEG signals are nonlinear and nonstationary, making them vulnerable to environmental noise and motion artifacts that degrade signal quality and reduce authentication accuracy in real-world settings [5]. EEG signals, particularly visual-evoked potentials (VEP), can be analyzed using machine learning algorithms like convolutional neural networks (CNN) for biometric authentication.

Many studies have demonstrated high accuracy in EEG signals classification using conventional methods such as LDA, SVM, and k-NN, which require manual feature extraction and feature selection and are time-consuming [6]. Besides, the conventional machine learning approach such as Incremental Fuzzy-Rough Nearest Neighbour (IncFRNN) technique was introduced in the past research for brainprint authentication [7]. The IncFRNN model is good at gradually reconstructing the knowledge granules from an initial trained model incrementally. It is able to capture the dynamic changes with human understandable logics. However, the input feature must be extracted first prior to the use of machine learning algorithm. Feature extraction process is usually cumbersome, which relies heavily on human experts. Besides that, the two separation modules (feature extraction and classification) may result in information loss during the feature extraction process [8]. To address this issue, deep learning simplifies the learning process by allowing end-to-end learning that performs feature extraction and classification in one scheme. This approach not only reduces reliance on human experts but also minimizes information loss while improving efficiency. With this, it is capable to capture the important characteristics of subjects' brain responses, even in the presence of environmental noise. However, this area remains underexplored.

Convolutional Neural Network (CNN) can automatically learn to extract features, reducing manual effort and improving efficiency [9], [10]. Pre-trained models further enhance performance by reducing training time and computing resources [10], [11]. Thus, this paper aims to authenticate brainprints using a CNN model under varying environmental conditions, utilizing datasets from our past research [4]. Google Colab will be employed in model development and testing. The CNN model's performance will be compared with the probability-based Incremental Fuzzy-Rough Nearest Neighbour (prob-IncFRNN) model to evaluate its effectiveness.

The rest of this paper is structured as follows: Section 2 reviews the related works about machine learning and deep learning models for brainprint authentication. Section 3 illustrates the experimentation, which includes dataset description and data preparation, models construction on both machine learning and deep learning models, and performance evaluation. Section 4 portrays the experimental results and discussions, and Section 5 draws the conclusion and suggests the direction of future work.

2. RELATED WORKS

Biometric authentication is a security process of verifying an individual identity with the unique biological characteristics to grant accessibility permission. Common biometric modalities in real world practice are fingerprints, iris, and facial recognition. However, these modalities pose different drawbacks in practical implementation, crucially because they appear on the body surface with no obligatory of liveness evidence. Impostor is able to forge access using a fake fingers, printed iris images or printed facial images since these biometrics are easily observable using digital sensors [12]. Thus, biometric modalities with liveness requirement such as Electroencephalogram (EEG) based biometric research has progressed rapidly, in conjunction with the growth of portable low cost but high time resolution acquisition devices over the past few years [13]–[15]. Electroencephalography (EEG) is a method to record an electrogram (EGM) or EEG signals of the electrical activity of the brain. Conventional scalp EEG recordings are obtained by positioning electrodes on the scalp according to the 10-20 international system. The “10” and “20” refers to the distance between two adjacent electrodes which can either be 10% or 20% of the front-back distance of the skull [2]. These recordings capture the brain’s electrical activity, which can be acquired during spontaneous neural processes, such as resting-state conditions, or in the presence of specific stimuli or events. These EEG signals also exhibit oscillatory patterns across a wide range of frequencies, predominantly within the 1 to 40 Hz spectrum, and can be characterized by their frequency, amplitude, and waveform. The main frequency bands observed in EEG signals include delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-100 Hz) waves. Each of these frequency bands is associated with different states of brain activity. For instance, alpha waves are typically seen when a person is relaxed but awake, while beta waves are associated with active thinking and concentration [2].

A critical trait of EEG signals is that it is unique, the recorded brain activity cannot be spoofed thereby being characteristically unlikely to be stolen. In other words, EEG signals are not as accessible to the attacker as traditional biometrics such as face and fingerprints which can be replicated at any time. Moreover, EEG signals are inherently confidential since they are not exposed unlike other biometric traits hence permitting a higher level of privacy compliance [2].

A study by Ong et al. [16] examined the most suitable frequency bands for human EEG-based biometric identification, applying the k-NN algorithm on EEG signals from ten subjects visualizing three items. Using a 32-channel EEG device at 512 Hz, they found that the combination of theta, alpha, beta, and gamma bands yielded an average accuracy of 89.21%. The beta band alone had an accuracy of 88.10%, followed by alpha and beta at 86.76%, and alpha alone at 83.04%.

Das et al. [17] used LDA and linear SVM for person identification with rapid visually evoked EEG signals, showing that the period 120-200 ms and visual cortex electrodes were most informative. They achieved 87.78% accuracy with LDA and 94.08% with SVM via 10-fold cross-validation. Liew et al. [7] studied the IncFRNN technique for biometric authentication with EEG signals, finding it outperformed IBk with an AUC of 0.8843. Jayarathne et al. [18] introduced the Inter-Hemispheric Amplitude Ratio for person identification, with KNN classifier and specific electrode combinations yielding 99.0±0.8% accuracy.

The potential of transfer learning in CNNs to improve EEG-based authentication systems has been brought to light by recent investigations. It has been shown by Wu et al. [19] and Yap et al. [20] that using pre-trained models can greatly enhance EEG-based authentication performance, especially for multi-class classification tasks. Even with encouraging outcomes, transfer learning is rarely used in EEG signal processing, with most results obtained for binary classification tasks. Alahaideb et al. [5] used various machine learning models on EEG dataset collected from nine female students aged 18-22 in a controlled laboratory environment. Among the tested models, the CNN achieved the highest accuracy of 99%, followed by Random Forest (RF) and Gradient Boosting (GB) classifiers with 94% and 93%, respectively. In contrast, KNN and SVM showed poor performance at 55% and 48%. This finding highlights the effectiveness of CNN for EEG-based classification, the limited sample size and highly controlled conditions restrict the generalizability of the real-world settings.

Table 1. Overview of past research works on EEG signals classifications

Paper	Task	Subjects	Classifier	Channels	Sample Rate	Accuracy
[7]	VEP	37	IncFRNN	8	256 Hz	88.43%
			KNN ($k = 5$)			86.75%
[21]	VEP	102	Elman NN	61	256 Hz	98.12%
[9]	Motor imagery	5	CNN	118	1000 Hz	99.35%
[18]	VEP	12	LDA	14	128 Hz	87.4%
			QDA			94.7%
			Linear SVM			86.3%
			Qudratic SVM			83.1%
			Gausian SVM			87.2%
			KNN			85.6%
[16]	VEP	10	KNN	32	512 Hz	89.21%
[17]	VEP	20	LDA	64	512 Hz	87.78%
			Linear SVM			94.08%
[20]	VEP	30	CNN	14	256 Hz	97.75%
[5]	ERP (N400)	9	CNN	14	128 Hz	99%
			Gradient Boosting			93%
			KNN ($k = 5$)			55%
			Decision Tree			81%
			Naïve Bayes			63%
			SVM			48%
			Random Forest			94%
			Logistic Regression			60%

In summary, Table 1 shows an overview of past research works on person authentication via EEG signals which includes the protocol used to acquire the signals, classifiers applied, and the achieved performance. The table also reveals the viability of EEG signals as a future biometric trait, almost always yielding at least 80% accuracy regardless of the classifiers used. It is also worth noting the relevancy of the studies on EEG signals as a biometric mode, which has been in the researchers' interest since 2007 until as recently as 2025.

3. EXPERIMENTATION

This section presents the brainprint authentication models, as shown in Figure 1 and Figure 2. Figure 1 illustrates the model based on conventional machine learning approach, utilizing the probability-based Incremental Fuzzy-Rough Nearest Neighbour (prob-IncFRNN) method. In contrast, Figure 2 depicts the authentication model using end-to-end learning approach via a Convolutional Neural Network (CNN). A comparison of results between both models will be discussed in Section 4.

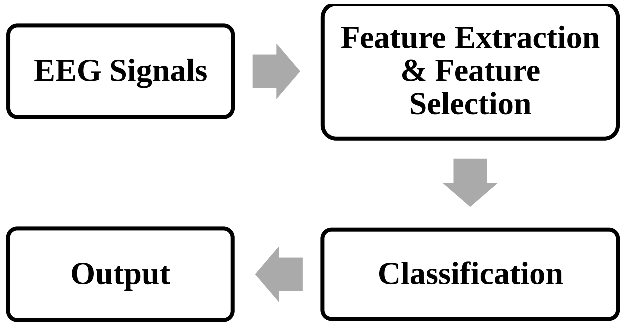

FIGURE 1. Conventional machine learning approach

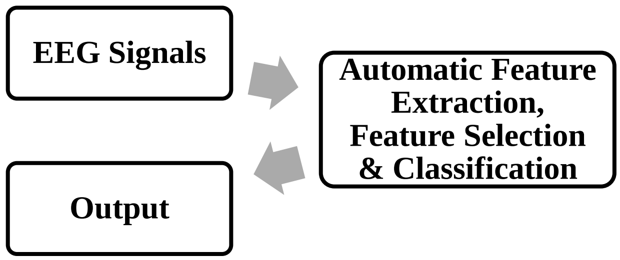

FIGURE 2. Deep learning approach *(End-to-end learning)*

3.1 Data Description and Data Preparation

The EEG dataset used in this study is collected by Liew et al. [4]. It comprises EEG signals from 45 volunteers aged 18-36, all healthy with normal or corrected vision. EEG data were collected using 21 electrodes positioned according to the International 10-20 system, sampled at 512 Hz without filtering to avoid information loss. Participants sat comfortably to reduce movement-related artifacts. Visual stimuli were placed 1 meter away at eye level to prevent attention loss from eye fatigue. Each participant selected a password image and responded by clicking a mouse when it appeared during 150 shuffled trials, with 60 trials featuring the pre-selected image and 90 trials featuring random images from a set of 260. Images were displayed for 1 second, followed by a 1.5-second white-blank screen, known as the interstimulus interval (as shown in Figure 3).

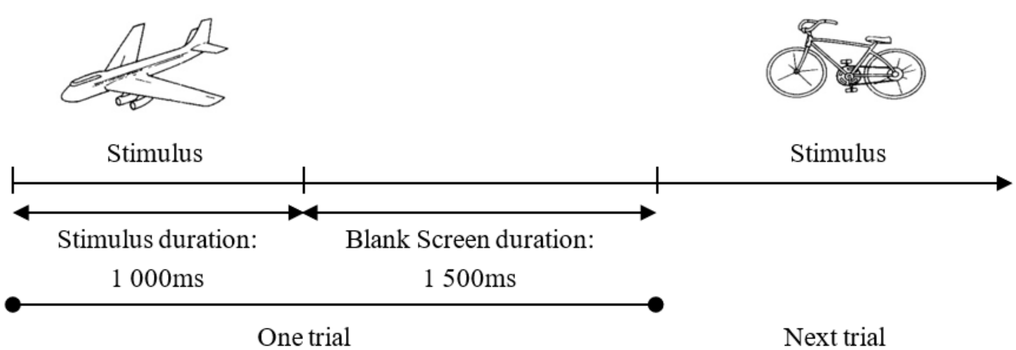

FIGURE 3: Visual stimulus presentation

To simulate real-world conditions, experiments were conducted under three audio-related scenarios: quiet, low distraction, and high distraction, with corresponding noise levels of soft (30-40 dB), moderate (50-60 dB), and loud (70-80 dB) as per the American Academy of Audiology guidelines [22]. During the “low distraction” condition, a 55 dB audio clip of a regular office environment was played, while the “high distraction” condition employed a 70 dB audio clip of an irregular office environment to represent a highly distractible setting. These scenarios were designed to assess the robustness of the proposed brainprint authentication system under varying environments.

Filtering, segmentation, and artefact rejection were implemented to eliminate unwanted signals. A bandpass filter of Finite-duration Impulse Response (FIR) type, with the cut-off frequencies of 8 to 13 to 30 Hz, was used to obtain the alpha and beta band signals. Next, the signals were segmented according to the trial.

3.2 Models Construction

3.2.1 Conventional Machine Learning Model Construction

In this study, the feature extraction and feature selection methods were selected based on literature review. Power spectral density (PSD), Wavelet phase stability (WPS) and coherence were used to extract the representative characteristics from the EEG signals in achieving robust classification results. PSD is an efficient method for converting EEG signals from time domain to frequency domain. It captures the correlation information between the measured signals from several electrode channels [14]. On the other hand, WPS used wavelet-based measure to quantify the phase information [23]. Phase information in signal processing is more useful and stable than the amplitude information [24]. It is because the phase information takes into consideration the nonstationary characteristics of the EEG signals. Furthermore, coherence provides an important approximation of functional interactions between the neural systems operating in each frequency band [25]. The coherence measures the degree of linear correlation between two signals. Coherence can reveal the correlation between two signals at different frequencies.

Next, the extracted features will be selected by using Correlation-based Feature Selection (CFS). A representative feature subset should contain a high correlation between the features and the target class. CFS chooses the best inter-correlated feature subset according to the correlation-based heuristic merit. Only 12 out of 210 features were selected for the brainprint authentication modelling.

Since brainprint authentication is a binary class problem, the output class will be either client or impostor instead of the number of subjects. Unfortunately, the dataset was imbalanced. Figure 4 shows the class distribution in the dataset which clearly illustrates the disproportionality of the two classes. In order to deal with the imbalance dataset, the minority class is oversampled to match the majority class. This is done via `scikit-learn's RandomOverSampler` class and only to the training set.

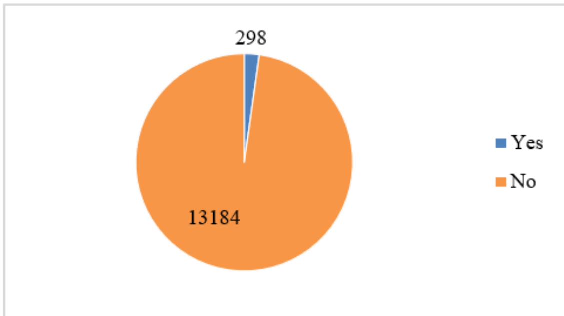

FIGURE 4. Class distribution

The probability-based Incremental Fuzzy-Rough Nearest Neighbour (prob-IncFRNN) builds on the K-Nearest Neighbours (KNN) algorithm, a widely used machine learning technique for classification and regression. KNN operates on the principle of "information gain," identifying the k closest neighbours to predict an unknown value. It uses methods like Euclidean distance for quantifying distances, and the choice of k is crucial to avoid inaccurate predictions or overfitting. However, KNN's simplicity means it does not handle data uncertainty well.

The Fuzzy-Rough Nearest Neighbour (FRNN) [26] combines fuzzy sets and rough sets with the traditional nearest neighbour approach of KNN to tackle real-world data complexities and uncertainties. FRNN uses a fuzzy similarity measure to find the nearest neighbours, calculating fuzzy lower and upper approximations of each decision class. The lower approximation includes objects certain to belong to a class, while the upper approximation includes objects that possibly belong. This method determines the membership of a test object to each class. The Incremental FRNN (IncFRNN) [7] updates knowledge based on actual class labels through object insertion and deletion, allowing it to adapt to new data characteristics.

The prob-IncFRNN algorithm [4] enhances the update strategy of IncFRNN by considering the probability of an object belonging to a class, useful when actual class labels are unavailable. The incremental update strategy involves inserting objects into the training pool based on the difference between the top two nearest neighbours and their predicted classes. The strategy ensures the training pool includes objects that represent unique features of decision classes and capture new characteristics. For object deletion, a window size threshold and frequency counter manage the training pool, removing the least used objects once the threshold is reached.

3.2.2 Deep Learning Model Construction

The convolutional neural network (CNN) is a specialized type of feed-forward neural network that is designed specifically for computer vision. It is also the most commonly applied ML algorithm in deep learning. In contrast to conventional neural networks, CNN has the capability to identify relevant features without any human supervision. The main difference between ANNs and CNN lies in their architecture and data input. In terms of architecture, a CNN comprises several distinct layers such as the convolutional layer, pooling layer and fully connected layer, each of which has a specific purpose. As for the data input, CNN utilizes data tensors typically with the shape: ("input height") × ("input width") × ("input channels").

The original EEG data were stored as Excel files which were inefficient in terms of data retrieval speed. Therefore, the EEG data were transferred into binary files in NumPy. This step was crucial to avoid any delay during training. Then, the data was rearranged such that the input shape is 21×512 for 21 electrodes, each with 512 samples, for a total of $45 \times 150 = 6750$ sets.

$$\begin{Bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,512} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,512} \\ \vdots & \vdots & \ddots & \vdots \\ x_{21,1} & x_{21,2} & \cdots & x_{21,512} \end{Bmatrix} \tag{1}$$

Any invalid set with null values or was zero-filled were removed from the dataset. The alpha and beta datasets were combined into a single dataset.

The CNN model used throughout this work was based on the EEGNet architecture, introduced by [27]. The input first undergoes two convolutional steps in succession with kernel shapes of (1, 64) and (21, 1) respectively. The output would yield a feature map containing the EEG signal at different band-pass. Then, the feature map is passed onto a pooling layer of size (1, 4). Then, the feature maps are passed to a separable convolution layer. The features are then passed to the same configuration of layer until it is passed into the classification block. A single dense layer with sigmoid activation is responsible for classifying the features. The model is compiled with the Adam optimizer while the loss function is set to `binary_crossentropy`. The CNN model summary is shown in Table 2.

Table 2. CNN model summary

Layers	***Filters***	***Shape***	***Activation***	***Options***
Input		(21, 512)		
Conv2D	16	(1, 64)	None	padding = same, bias = false
BatchNorm				
DepthwiseConv2D	48	(21, 1)	None	padding = valid, depth = 2, max norm = 1, bias = false
BatchNorm				
Activation			eLU	
AveragePooling2D		(1, 4)		
SeparableConv2D	48	(1, 16)	None	padding = same, bias = false
BatchNorm				
Activation			eLU	
AveragePooling2D		(1, 8)		
Flatten				
Dense	320			
Dropout				$p = 0.5$
Dense	1		Sigmoid	

3.2.3 Performance Measurement

The metrics used to measure the performance of the model are accuracy, precision, recall and F1-scores. The calculation formulas are shown as below:

$$\text{accuracy} = \frac{TP + TN}{\text{total samples}} \tag{2}$$

$$\text{precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{recall} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{F1-score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{5}$$

where TP, TN, FP and FN refers to true positives, true negatives, false positives and false negatives respectively. Precision is a measure of how many positive predictions made are correct (true positives) while recall is a measure of how many of the positive cases the classifier correctly classified. F1-score, on the other hand, is a measure combining both precision and recall usually described as a harmonic mean of the two.

4. Experimental Results and Discussion

In order to determine the prediction class, the precision-recall (PR) threshold is used instead of the default 0.5 or the receiver operating characteristic (ROC) threshold. A PR threshold can be obtained from a PR curve which is a plot that illustrates the performance of a binary classifier at varying classification threshold. Likewise, the ROC threshold can be obtained from a ROC curve which is a plot of the true positive rate (TPR) against the false positive rate (TPR). It is worth noting that CNNs are not deterministic, such that any measurement might differ for each run.

4.1 Comparison between Different Classification Thresholds

Table 3 presents a comparison between the performance metrics evaluated at different classification thresholds: Precision-Recall (PR), ROC and a default threshold of 0.5. This comparison is essential for understanding how varying thresholds impact the model's performance, particularly in an imbalanced dataset where 98% of the instances belong the "no" class and only 2% to the "yes" class, as shown in Figure 4. Table 3 provides several key performance metrics, including accuracy, AUC-ROC, AUC-PR, precision, recall and F1-socre for each threshold. It should be noted that the values presented in the table are the average measurement taken from all 45 subjects.

Table 3. Comparison between different classification thresholds

	Thresholds		
	PR	***ROC***	***Default***
Accuracy	0.9722	0.9448	0.9285
AUC-ROC	0.9793	0.9791	0.9729
AUC-PR	0.7787	0.7143	0.7020
Precision	0.8010	0.4148	0.5030
Recall	0.7483	0.9389	0.8651
F1-Score	0.7641	0.5492	0.5645

The accuracy of the model remains high across all thresholds, ranging from 92.85% to 97.22%. The high accuracy is largely due to the imbalanced nature of the dataset, where the model correctly predicts the majority class (i.e., "no") most of the time. However, accuracy alone is not a sufficient measure of performance in this context because it does not account for the minority class (i.e., "yes"). On the contrary, precision and recall metrics highlight the trade-off between these two aspects. The PR threshold achieves the highest precision at 80.10%, meaning it is more conservative and prioritizes correct positive predictions, but comes at the cost of lower recall of 74.83%. In contrast, the ROC threshold yields the highest recall at 93.89%, indicating a more liberal approach that captures more true positives but also includes more false positives, resulting in the lowest precision of 41.48%.

The idea that PR threshold captures more true positives without sacrificing too much recall and precision can be illustrated in Figure 4. In other words, there is a tendency to select higher PR threshold (i.e., around the mean of 0.7834) than it is for ROC threshold, which has a lower average of 0.3494.

4.2 Comparison between Different Environmental Conditions

Table 4 illustrates the classification performance of the proposed CNN model under different environmental conditions: quiet, low and high distraction environments.

Table 4. Comparison between different environmental conditions

	Environmental Conditions		
	Quiet	***Low***	***High***
Accuracy	0.9722	0.9339	0.9432
AUC-ROC	0.9793	0.9562	0.9672
AUC-PR	0.7787	0.7001	0.6626
Precision	0.8010	0.7625	0.7211
Recall	0.7483	0.7247	0.6668
F1-Score	0.7641	0.7167	0.6772

Despite the imbalanced nature of the dataset, the accuracy and AUC-ROC are relatively high across all environmental conditions, with the model performing relatively better in quiet environment, followed by high distraction environment and finally low distraction environment. However, this can be misleading because it did not adequately represent the model’s ability to distinguish between majority and minority classes. Conversely, the AUC-PR, precision, recall and F1-score all show the same inclination—with performance degrading as noise levels increase. AUC-PR drops from 0.7787 in quiet environment to 0.6626 under high distraction environment. Meanwhile, the precision, recall and F1-score display similar declines as environmental distraction increases.

Furthermore, the quiet environment generally yields the highest performance across all the metrics. It is noteworthy that some metrics in high distraction environment are higher than those in low distraction environment. This irregular trend could result from the oversampling technique used to address the class imbalance in the dataset and the impact of environmental noise on the EEG signals.

Figure 5(a) and Figure 5(b) show a few examples of EEG waveform taken from random subjects. It can be observed that different noise environments impact the amount of noise detected in the EEG signals. In quiet environment, EEG signals tend to be clearer and more stable, providing the model with clearer data to learn from. However, in low or high distraction environments, the EEG signals can be contaminated with extraneous noise, making it harder for CNN to accurately identify and extract relevant features. These noises can manifest as random fluctuations or consistent patterns that can confuse the model, leading to decreased accuracy in authentication. For instance, loud noises might induce stress or other physiological responses that alter brainwave patterns, further complicating the signal.

(a)

(b)

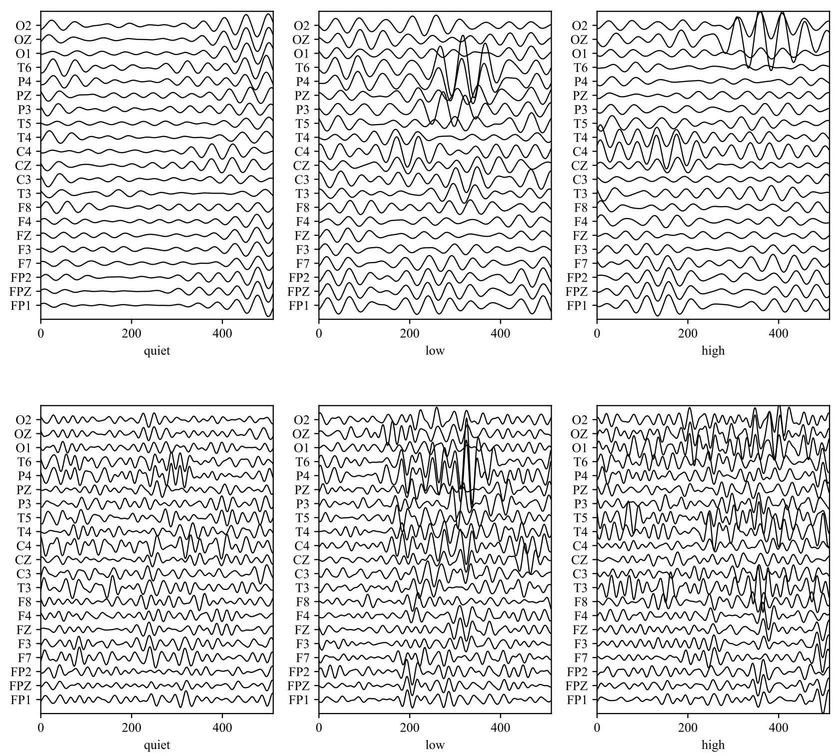

FIGURE 5. EEG signals taken from random subjects. *(a) alpha frequency; (b) beta frequency*

4.3 Comparison against prob-IncFRNN

Figure 6 shows the comparison of the performance of the proposed model (i.e., CNN) and a probability-based Incremental Fuzzy-Rough Nearest Neighbour (Prob-IncFRNN) model, for authenticating individuals based on their EEG data.

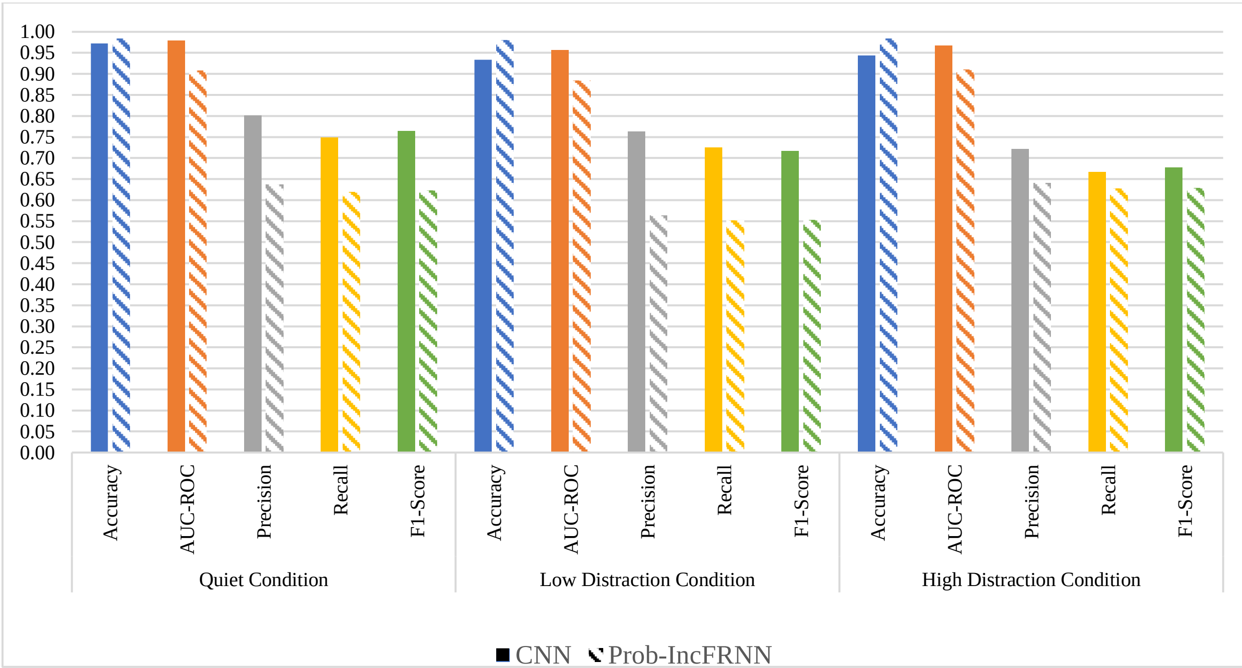

FIGURE 6. Comparison of CNN and Prob-IncFRNN models in 3 different environmental conditions

Based on Figure 6, the CNN model outperforms the prob-IncFRNN model across all performance metrics under different environmental conditions. Both models achieved relatively high classification accuracy and AUC-ROC values (exceeding 0.90), confirming the reliability of EEG-based brainprint authentication even under varying environmental conditions. However, the CNN consistently outperformed prob-IncFRNN, likely due to its end-to-end learning approach that better preserves important features throughout the process, as compared to the separate feature extraction and classification in prob-IncFRNN. Another key reason is that the input for prob-IncFRNN has less features than the input used for CNN. Instead of using the whole 21 electrodes, only 5 of the total electrodes were used in prob-IncFRNN to reduce modelling complexity: T5, T6, O1, O2 and OZ. This is because, being a nearest neighbour-based method has limited its capability to model complex relationships in the data compared to deep learning models like CNNs. This limitation affects its ability to generalize well on nuanced tasks. Another reason is that EEG signals are complex and require advanced feature extraction techniques, otherwise the features may not adequately represent the minority class very well. Prob-IncFRNN might struggle to capture these complex patterns without sophisticated pre-processing or feature engineering. In this case, three different algorithms (i.e., power spectral density (PSD), wavelet phase stability (WPS) and coherence) were applied to extract relevant features, which yields a total of 210 features. However, only 12 were chosen as the input. On the other hand, CNN have the ability to automatically extract features through its convolutional layers. This not only reduces the dependency on handcrafted features but also minimizes the risk of discarding the useful information during feature selection.

5. CONCLUSION

This study explored brainprint authentication using a CNN model on visual-evoked potentials (VEP). The CNN consistently outperformed the prob-IncFRNN model across all evaluation metrics, achieving an F1-score above 65% under varying environmental conditions. This has demonstrated the robustness of CNN model beyond the conventional machine learning approach. Challenges included dataset imbalance (98% majority, 2% minority), leading to oversampling and overfitting issues, addressed with dropout layers, simplified architecture, and batch normalization. Limited time hindered a thorough analysis of different acoustic environments' impact on EEG signals. Future work will focus on optimizing CNN architecture, and examining the effects varying environmental factors and frequency bands to enhance the scalability and real-world applicability of brainprint authentication systems.

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CONFLICT OF INTERESTS

The authors declared that there is no conflict of interests.

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