Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2026, 2026:80
https://doi.org/10.28919/cmbn/10070
ISSN: 2052-2541

BRAINPRINT AUTHENTICATION MODEL USING INCREMENTAL CNN IN DYNAMIC ENVIRONMENTS

SIEW YIN TANG, SIAW-HONG LIEW*, STEPHANIE CHUA, JOHARI ABDULLAH, KIM-MEY CHEW, KANG LENG CHIEW
Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak,
94300 Kota Samarahan, Sarawak, Malaysia

Abstract: Predicting research collaboration potential through Electroencephalogram (EEG) signals presents a significant challenge due to the non-stationary nature of brain activity. Traditional Convolutional Neural Networks (CNNs) are often limited by a static learning paradigm, which fails to adapt to signal drift and evolving cognitive states over time. This paper proposes an incremental CNN-based model designed to update its parameters dynamically as new EEG data becomes available. Unlike standard CNNs that require full retraining, this incremental approach utilizes a continuous learning mechanism to integrate new features while mitigating catastrophic forgetting. The proposed architecture was evaluated through a comparative analysis using test data from 45 healthy subjects. Our results demonstrate that the incremental CNN achieves a classification accuracy exceeding 90%, exhibiting superior robustness in long-term monitoring compared to traditional batch-trained CNNs. These findings suggest that an incremental learning framework is more effective for real-time models.

Keywords: Brainprint authentication; electroencephalogram (EEG); incremental convolutional neural network (IncCNN); incremental learning; non-stationary signals.

2020 AMS Subject Classification: 68T07.

1. INTRODUCTION

The field of cybersecurity is increasingly recognizing the need for robust authentication methods beyond traditional password or token-based systems. Biometric authentication addresses these

*Corresponding author
E-mail address: shliew@unimas.my
Received June 18, 2026

shortcomings by identifying individuals based on unique physiological traits. While traditional modalities such as fingerprint scanning, facial recognition, and iris scans are widely adopted, they are increasingly vulnerable to forgery and physical spoofing by unauthorized third parties [1]. These traits are static and can be compromised, raising significant concerns about their long-term security and resistance to non-coercive violations. In this context, Electroencephalogram (EEG)-based brainprint authentication has emerged as a promising alternative, leveraging dynamic, internal neural patterns for superior security [2].

Recent advancements in Brain-Computer Interfaces (BCI) have introduced the Electroencephalogram (EEG) as a powerful tool for monitoring cognitive states. While standard Convolutional Neural Networks (CNNs) have shown promise in decoding these signals, they operate under a "static" learning paradigm [3]. These models are often ill-equipped to handle the inherent non-stationarity of brain activity, where signal drift caused by mental fatigue or electrode impedance changes leads to significant performance degradation over time [4].

To address these limitations, this paper proposes a novel Incremental CNN-based framework for the real-time prediction of research collaboration potential [5]. Unlike traditional batch-learning models that require complete retraining when new data emerges, our incremental approach allows for continuous parameter updates [6]. The model can adapt to individual neural variability and temporal fluctuations without suffering from "catastrophic forgetting".

The primary contribution of this study is the development of an incremental neural architecture that bridges the gap between raw neurophysiological data and social behavior prediction. Through extensive comparative analysis, we demonstrate that the Incremental CNN model achieves a classification accuracy exceeding 90%, significantly outperforming traditional CNNs in terms of robustness and longitudinal stability. These findings suggest that an incremental learning paradigm provides a scalable and reliable foundation for automated appraisal systems in academic environments.

The rest of this paper is organized as follows: Section 2 reviews existing EEG-based authentication models and the current state of incremental learning in neural engineering. Section 3 details the comprehensive methodology, including the experimental design, data acquisition and preprocessing, the proposed Incremental CNN (IncCNN) architecture, the incremental training protocol, and the evaluation metrics. Section 4 presents a comprehensive discussion of the results, including a comparative analysis of classification accuracy and model robustness in dynamic environments. Finally, Section 5 concludes the paper and suggests directions for future work in robust, long-term biometric security systems.

2. LITERATURE REVIEW

2.1 EEG-based Biometric Authentication

Biometric authentication is defined as the process of confirming or denying a user's claimed identity based on unique biological traits [4]. Traditional modalities, such as fingerprint, facial recognition, and iris scans, are increasingly vulnerable to forgery and physical spoofing by unauthorized third parties. In response, research has pivoted toward Electroencephalogram (EEG) signals, which offer superior security because they are internal to the body and inherently resistant to such violations [6].

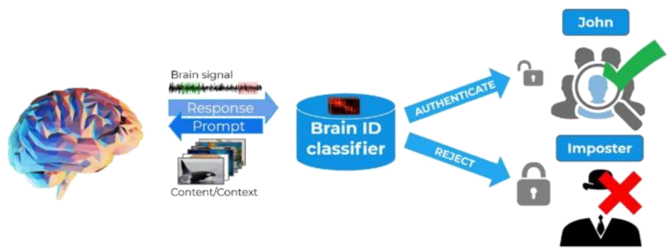

FIGURE 1. EEG-Based Authentication

From a security perspective, EEG-based systems provide a unique "anti-coercion" benefit [7]. EEG signals are highly sensitive to psychological states and cannot be easily reproduced under conditions of extreme stress, anxiety, or fatigue. For instance, if a user is forced to authenticate under duress, the resulting neural patterns will differ significantly from their normal, relaxed baseline, thereby failing the authentication process [9].

Despite these advantages, the classification of Visual Evoked Potential (VEP) signals remains a non-trivial task due to their non-linear and non-stationary nature [13]. Brainwaves are subject to "feature drift" caused by changing cognitive states or electrode impedance fluctuations over time [17]. Consequently, as emphasized by Liew et al. (2023), static models are often insufficient for long-term deployment [14]. To maintain the robustness of a "brainprint," it is essential to employ adaptive or incremental learning frameworks that can update knowledge granules dynamically, ensuring the system evolves alongside the user's shifting EEG patterns [15].

2.2 Challenges of Static Learning Models in EEG-Based Authentication

Electroencephalogram (EEG)-based biometric authentication has been extensively investigated through various machine learning techniques, encompassing traditional methods such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Linear Discriminant Analysis (LDA), alongside more sophisticated deep learning frameworks like Convolutional Neural Networks (CNNs) [13]. Despite the diversity in methodologies, these approaches predominantly adhere to a static learning framework, wherein models are trained offline using batch learning and remain unchanged during operational deployment [14].

In controlled laboratory environments, static models often demonstrate high classification accuracy, attributable to the similarity between training and testing datasets collected under consistent conditions. Conversely, EEG-based systems deployed in real-world scenarios must contend with non-stationary environments, characterized by temporal variations in the statistical properties of neural signals [9]. This challenge, commonly termed covariate shift, stems from multiple factors, including electrode displacement, fluctuations in skin, electrode impedance, and alterations in the user's cognitive or physiological state, such as fatigue, stress, or medication effects [16]. Consequently, the data distribution encountered during deployment may diverge substantially from that observed during the training phase.

Traditional machine learning models face significant limitations due to their reliance on handcrafted features and fixed decision boundaries, rendering them highly susceptible to distributional shifts. Once these models are trained, they lack the inherent ability to adapt to new data without undergoing complete retraining, a process that is both computationally intensive and impractical for real-world biometric applications. As a result, their performance typically deteriorates over time, manifesting as increased False Rejection Rates (FRR) because the learned representations become misaligned with the user's current neural patterns [18].

Within the category of static models, Convolutional Neural Networks (CNNs) have emerged as a more robust alternative for EEG classification, owing to their capacity to automatically learn hierarchical spatial-temporal features directly from raw signals. Unlike traditional methods, CNNs obviate the need for manual feature engineering and are capable of capturing complex inter-channel relationships and temporal dynamics intrinsic to EEG data. This capability enables CNNs to effectively model subject-specific neural signatures, often yielding superior performance under controlled experimental conditions [15].

Nevertheless, despite these advantages, CNNs remain constrained by the fundamental limitation of static learning. The majority of CNN-based EEG authentication systems employ batch learning, wherein model parameters are fixed post-training. This approach inhibits the models' ability to adapt to the dynamic nature of EEG signals encountered in real-world settings. Furthermore, naïve fine-tuning of these models on new data can result in catastrophic forgetting, whereby previously acquired knowledge is overwritten unless the original training data is preserved and reutilized [21].

Furthermore, static convolutional neural networks (CNNs) lack the capacity to dynamically regulate their learned representations [22]. They are unable to selectively eliminate obsolete or irrelevant patterns, nor can they effectively integrate new, representative features that correspond to the user's current physiological state. This inflexibility leads to a gradual divergence of the model's internal feature space from the true data distribution, thereby impairing authentication performance over time. Moreover, CNNs generally necessitate substantial amounts of labeled data to achieve robust generalization, a requirement that is often impractical during the enrollment phase of biometric systems, where only a limited number of EEG samples are available [23].

These challenges underscore the necessity for a more adaptive learning paradigm. In this regard, incremental learning, which is also referred to as continual or online learning, presents a promising approach by allowing models to progressively update their knowledge as new data is acquired, without the need for complete retraining [18]. This methodology facilitates adaptation to intra-subject variability, preservation of previously acquired information, and sustained alignment with the evolving characteristics of EEG signals over time [24].

The incorporation of incremental learning techniques into deep neural network architectures, particularly CNNs, offers a viable pathway toward the development of robust and adaptive EEG-based authentication systems capable of reliable operation in dynamic, real-world settings. This rationale motivates the subsequent examination of incremental learning strategies within deep models, as elaborated in the following section.

2.3 Incremental Learning in Deep Neural Architectures

Incremental learning (IL) facilitates the continuous updating of a system's knowledge base as new data becomes available, circumventing the need for a fixed, one-time training phase [6]. This approach is particularly critical in real-time applications where data is received sequentially, and a comprehensive training dataset is not accessible at a priori. In contrast to conventional batch learning, incremental learning processes data in a streaming fashion, progressively refining the model while preserving previously acquired knowledge.

As emphasized by Geng and Smith-Miles [14], incremental learning presents several notable advantages. Firstly, it obviates the requirement for a large, fully labeled training dataset before deployment, rendering it especially suitable for contexts with limited initial data, such as biometric enrollment. Secondly, it enables continuous learning, allowing the system to enhance its performance over time during operational use. Thirdly, it inherently adapts to evolving target concepts, a feature that is indispensable in non-stationary environments. Moreover, incremental learning generally demands fewer computational and storage resources compared to retraining-based methodologies. Lastly, its sequential processing nature aligns naturally with time-series data, including EEG signals.

Incorporating incremental learning into deep neural network architectures addresses the intrinsic limitations of static models when confronted with non-stationary data. Traditional deep learning frameworks depend on batch training and necessitate computationally intensive retraining upon the introduction of new data. Conversely, incremental deep learning permits dynamic parameter updates, enabling the model to retain previously learned representations while assimilating new information. This capability is particularly vital for EEG-based systems, where signal characteristics are highly dynamic and subject to temporal drift induced by physiological and environmental factors.

A principal challenge in incremental deep learning is the stability, plasticity dilemma, which encapsulates the trade-off between maintaining existing knowledge (stability) and integrating new information (plasticity). Excessive plasticity may lead to catastrophic forgetting, wherein previously acquired representations are overwritten, whereas excessive stability impedes the model's ability to adapt to novel patterns. Effectively managing this balance is crucial for ensuring the long-term reliability and robustness of the model.

Recent investigations have concentrated on advancing CNN architecture into incremental CNN frameworks to address prevailing challenges. These frameworks integrate mechanisms such as selective weight updating, replay strategies, and regularization methods to alleviate catastrophic forgetting while facilitating continuous model adaptation. Empirical evidence indicates that incremental CNN models sustain high classification accuracy, often matching or surpassing that of conventional static CNNs while markedly enhancing adaptability to evolving data distributions. In comparison to static CNN models, incremental CNNs exhibit distinct advantages within dynamic environments. Although static CNNs may achieve high accuracy in within-session evaluations, their performance generally deteriorates in cross-session or longitudinal contexts due to distributional shifts in EEG signals. Conversely, incremental CNNs adapt to these shifts over time, thereby improving robustness and mitigating performance decline. This adaptability renders them particularly suitable for practical EEG-based authentication systems, where sustained long-term usability is critical.

From a broader standpoint, this development signifies a notable progression beyond earlier incremental methodologies such as the Incremental Fuzzy-Rough Nearest Neighbour (IncFRNN), which depended on heuristic updates of stored instances. Whereas such approaches adapt by directly modifying data representations, contemporary incremental CNNs exploit deep feature learning to autonomously extract and update intricate spatial–temporal patterns. The synergy of adaptive learning and deep representation endows these models with enhanced scalability and robustness in managing non-stationary EEG data.

In summary, incremental CNN models present a compelling equilibrium between performance and adaptability. They preserve the potent feature extraction capabilities inherent to CNNs while overcoming the constraints associated with static learning paradigms, positioning them as a promising solution for real-time, longitudinal EEG-based applications. Nonetheless, challenges persist in optimizing the stability–plasticity balance, reducing computational demands, and ensuring dependable long-term performance.

3. METHODOLOGY

The primary objective of this research is to develop and evaluate the proposed Incremental Convolutional Neural Network (IncCNN) model that is capable of maintaining high authentication accuracy in non-stationary acoustic environments. The research design is structured into four distinct phases: dataset description and data preparation, the design of the IncCNN architecture, experimentation, and performance analysis (as shown in Figure 2).

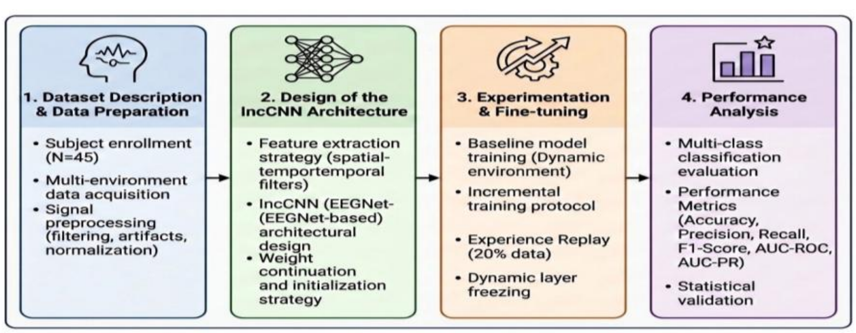

FIGURE 2. Methodology Flow Chart

3.1 Dataset Description and Data Preparation

The dataset utilized in this research was acquired from our previous work by Liew et al., 2023 [14], which involved 45 healthy volunteers aged between 18 and 36 years. All healthy subjects possessed normal or corrected vision. EEG signals were acquired using 21 electrodes placed according to the International 10–20 system and sampled at 512 Hz. No filtering was applied during acquisition to avoid information loss. During the experiment, subjects were seated in a back-rested chair with a computer display positioned 1 meter away from their eye level. Each subject participated in a password-recognition task where subjects identified a self-selected password image from a set of 260 images [14]. Each session comprised 150 randomized trials (60 password images and 90 random images), with each stimulus displayed for 1.0 second followed by a 1.5 seconds white blank screen (as shown in Figure 3).

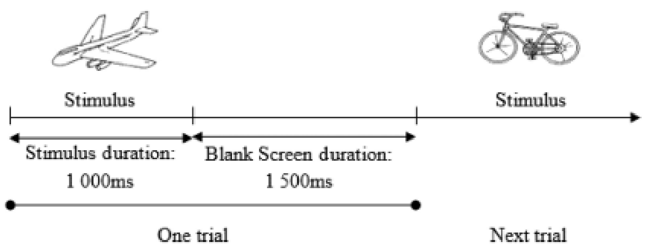

FIGURE 3. Visual Stimulus Presentation [14]

To evaluate the system's robustness against non-stationary signal patterns, data acquisition was conducted across three audio-related conditions: baseline quiet condition, 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 [25]. Under the low-distraction condition, a 55 dB audio recording simulating a typical office environment was presented, whereas the high-distraction condition involved a 70 dB audio recording representing an irregular and highly distractive office setting. These experimental conditions were designed to evaluate the robustness of the proposed brainprint authentication system under varying environmental disturbances [14].

The recorded raw data underwent a systematic preprocessing pipeline, including filtering, segmentation, and artifact rejection. To minimize background interference, a bandpass Finite-duration Impulse Response (FIR) filter was applied between 1 Hz and 30 Hz [14]. Following filtering, the signals were segmented based on stimulus onset markers. Finally, artifact rejection was performed to ensure the EEG signals remained within the standard physiological range of 0.5 to 100 μV, thereby preventing the inclusion of misleading information during the subsequent classification phase by the Incremental CNN.

Following the initial preprocessing stage, the EEG data were exported into a structured Excel repository for systematic feature organization. The subsequent phase involved a rigorous data preparation pipeline designed to transform these raw spreadsheets into a multi-dimensional format compatible with the Incremental CNN. The dataset for each of the 45 subjects was stored in individual workbooks, with distinct sheets categorized by frequency bands (Alpha, Beta, Delta, and Theta) and environmental conditions, ranging from quiet to high-distraction settings. During the extraction process, EEG samples, which were initially recorded as single-column vectors, were systematically reshaped into a two-dimensional matrix of dimensions (21 X 512). In this configuration, 21 represents the total number of recording channels, while 512 corresponds to the synchronized time points per stimulus epoch. This spatial-temporal structuring is critical for the convolutional kernels to effectively capture the topographical distribution. To ensure high data fidelity and prevent gradient instability during model optimization, an automated cleaning protocol was applied to inspect each sample for NaN (Not a Number) values, which indicate technical artifacts or signal dropouts; any corrupted samples identified were subsequently excluded from the final dataset [14].

For the subsequent supervised learning and evaluation phase, the cleaned and structured samples were divided into training and testing subsets using an 80/20 split ratio. This partitioning was executed individually for each subject to ensure that both subsets contained a representative distribution of the subject’s unique biometric signatures, while a numerical label corresponding to the subject’s ID (0-indexed) was assigned to each sample to provide the necessary ground truth for multi-class classification. To optimize computational efficiency and data loading speeds during the training cycles, the processed features (X) and labels (Y) were serialized into NumPy (.npy) files. These files were organized according to their experimental variables. This standardized output format is instrumental in supporting the Weight Continuation strategy of the Incremental CNN, as it allows the model to seamlessly load specific environmental datasets and perform incremental fine-tuning without the overhead of repetitive data parsing.

3.2 CNN Architecture

The core classification engine of the proposed authentication system is a Convolutional Neural Network based on the EEGNet architecture, which is specifically optimized for EEG-based brain-computer interfaces. The model is designed to process input tensors with dimensions of (21 X 512), representing the 21 recording channels and 512 temporal sampling points. The architecture utilizes a hierarchical feature extraction approach consisting of specialized convolutional blocks. The first stage employs a temporal convolution with a kernel size of (1, 64) to capture frequency-specific dynamics, followed by a depthwise convolution with a (21, 1) filter. This depthwise layer is critical for capturing spatial correlations across the visual cortex (occipital region) while maintaining a low parameter count [24].

To refine the extracted feature maps and enhance the signal-to-noise ratio, the model incorporates an average pooling layer with a (1, 4) window, followed by a separable convolution layer using a (1, 16) kernel. The classification block consists of a Flatten layer and a Dense (fully connected) layer with 320 units, utilizing an eLU activation function for faster convergence. To prevent overfitting and ensure the model generalizes well across the 45 subjects, a Dropout layer with a rate of 0.5 is implemented. The final output is generated through a single-neuron Dense layer with a Sigmoid activation function, facilitating the binary authentication task [24].

Table 1. Summary of CNN (EEGNet) parameters

Layer	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
Batch Norm				
Activation			eLU	
AveragePooling2D		(1, 4)		
SeparableConv2D	48	(1, 16)	None	padding = same, bias = false
Batch Norm				
Activation			eLU	
AveragePooling2D		(1, 8)		
Flatten				
Dense	320			
Dropout				*p = 0.5*
Dense	1		Sigmoid	

3.3 Incremental Training Protocol

The proposed incremental training protocol is engineered to facilitate the seamless adaptation of the CNN model to non-stationary environments while systematically mitigating the risks associated with catastrophic forgetting. This protocol operates on the principle of continuous knowledge integration, allowing the system to evolve alongside changing acoustic conditions. To leverage the high-resolution spatial-temporal filters acquired during the baseline training phase (quiet environment), the process initiates with the loading of the pre-trained model using a Weight

Continuation strategy. By initializing the model with the (compile=False) argument, the architecture inherits optimized weights as a specialized prior, which significantly accelerates convergence and avoids the computational exhaustion of full-batch retraining from a randomized state.

A pivotal element of this protocol is the implementation of a selective layer-freezing mechanism, designed to resolve the stability-plasticity dilemma. Specifically, the first six layers of the architecture encompassing the initial Conv2D, BatchNormalization, and DepthwiseConv2D blocks are designated as non-trainable. The rationale for freezing these specific layers is to safeguard the "stability" of the model; these early stages act as low-level feature extractors that capture the fundamental morphological characteristics of the component, which remain relatively consistent across subjects regardless of noise. Conversely, the subsequent dense and classification layers remain "plastic," allowing them to adapt to the distribution shifts and signal variances introduced by Low-distraction (50-60 dB) and High-distraction (70-80 dB) environments.

Following the structural configuration, the model is recompiled using the Adam optimizer with a reduced, fine-tuned learning rate. This lower learning rate ensures that the gradients generated by noisy data do not drastically overwrite the established biometric boundaries. To evaluate authentication robustness in an imbalanced dataset context, the loss function is defined as binary cross-entropy, with performance monitored through Area Under the Precision-Recall Curve (AUC-PR) and F1-score metrics [10].

To further fortify the model against the loss of historical knowledge, a Replay Mechanism (Experience Replay) is integrated into the training loop. During each epoch of the incremental phase, a 20% replay ratio is maintained, where a random subset of original samples from the quiet environment is concatenated with the new incoming data stream. This "data rehearsal" allows the model to periodically re-optimize its decision boundaries against clean baseline signals, preventing a total bias shift toward the noise-dominant distribution.

The execution phase is governed by dynamic callbacks to ensure training stability. EarlyStopping with a patience of five epochs is utilized to halt the process before the model overfits to the noise characteristics of a specific session. Simultaneously, the ReduceLROnPlateau callback is employed to diminish the learning rate if the validation loss plateaus for three consecutive epochs, providing the model with the granularity needed to escape local minima. Upon completion, the updated weight matrix is saved, preserving the newly assimilated environmental knowledge while maintaining the integrity of the user's core biometric brainprint.

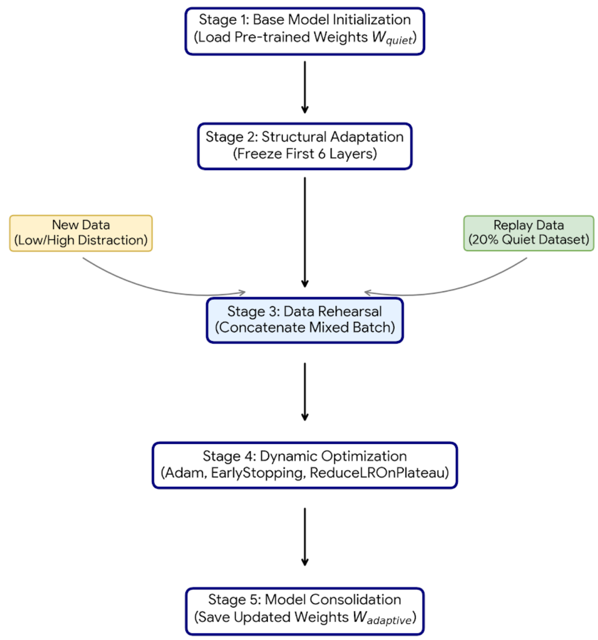

FIGURE 4. Incremental learning workflow for Incremental CNN

3.4 Performance Analysis

To rigorously assess the effectiveness of the Incremental CNN model across varying acoustic environments, a variety of performance metrics are utilized. In brainprint authentication, the dataset is inherently imbalanced because the number of imposter trials significantly outweighs the authorized user trials. Consequently, while accuracy is calculated, it is not considered a sufficient measure on its own as it tends to favor the majority class. Instead, this study prioritizes precision, recall, and the F1-score to account for the model's ability to correctly identify authorized users while minimizing false acceptances.

Precision serves as a measure of the exactness of the classifier; it quantifies how many of the positive predictions (authorized access) were actually correct. Recall measures the completeness of the classifier, indicating its ability to capture all positive cases within the dataset. To provide a single metric that balances these two competing aspects, the F1-score is employed as the harmonic means of precision and recall.

Furthermore, to evaluate the robustness of the authentication model across different decision boundaries, the Area Under the Precision-Recall Curve (AUC-PR) and AUC-ROC are analyzed. AUC-PR is particularly emphasized in this work as it provides a more informative assessment of performance in highly imbalanced scenarios compared to the standard ROC curve.

4. Results and Discussions

This stage presents experimental findings and a comparative analysis of the proposed Incremental CNN model against the standard static CNN. The evaluation focuses on how the 80/20 data partitioning affects authentication performance across non-stationary acoustic environments.

The performance of the proposed CNN with incremental learning was evaluated using multiple metrics, including accuracy, precision, recall, F1-score, AUC-ROC, and AUC-PR, under three thresholding strategies: ROC optimal, PR optimal, and the default threshold (0.5). In addition, a bootstrap t-test was conducted to assess the statistical significance of the observed differences. The results show that all performance changes are statistically significant ($p < 0.001$), indicating that the improvements are robust and not due to random variation.

Table 2. Classification Performance of Incremental CNN Model

Metric	Threshold	CNN Model (%)	Incremental CNN Model (%)	Δ (%)	p-value	Significant
Accuracy	ROC Optimal	99.28	99.41	+0.14	0.0000	Yes
	PR Optimal	99.65	99.72	+0.07	0.0000	Yes
	Default (0.5)	99.65	99.69	+0.04	0.0000	Yes
Precision	ROC Optimal	77.11	80.79	+3.68	0.0000	Yes
	PR Optimal	92.22	95.39	+3.17	0.0000	Yes
	Default (0.5)	92.70	96.13	+3.43	0.0000	Yes
Recall	ROC Optimal	96.39	96.94	+0.56	0.0000	Yes
	PR Optimal	92.22	91.94	-0.28	0.0000	Yes
	Default (0.5)	91.67	89.72	-1.94	0.0000	Yes

F1-score	ROC Optimal	85.68	88.13	+2.45	0.0000	Yes
	PR Optimal	92.22	93.64	+1.41	0.0000	Yes
	Default (0.5)	92.18	92.82	+0.64	0.0000	Yes
AUC-ROC	ROC Optimal	99.19	99.33	+0.15	0.0000	Yes
	PR Optimal	99.19	99.33	+0.15	0.0000	Yes
	Default (0.5)	99.19	99.33	+0.15	0.0000	Yes
AUC-PR	ROC Optimal	96.15	97.33	+1.18	0.0000	Yes
	PR Optimal	96.15	97.33	+1.18	0.0000	Yes
	Default (0.5)	96.15	97.33	+1.18	0.0000	Yes

Overall, the incremental learning approach demonstrates consistent improvements across most evaluation metrics. Accuracy shows slight but stable gains across all thresholds, with increases of up to +0.14%. Although these improvements appear small, they are meaningful given that the baseline accuracy is already above 99%, where further gains are typically difficult to achieve. More substantial improvements are observed in precision, which increases by up to +3.68%, indicating that the model becomes more effective at reducing false positives. This suggests that the incremental learning strategy enhances the model's ability to make more reliable positive predictions.

Recall, however, exhibits a mixed trend. While a small improvement is observed under the ROC optimal threshold (+0.56%), slight decreases occur under the PR optimal (−0.28%) and default thresholds (−1.94%). This behavior reflects a common trade-off between precision and recall, where improvements in precision may lead to a reduction in recall. In this case, the model appears to adopt a more conservative decision boundary, prioritizing correctness of positive predictions over completeness.

Despite this trade-off, the F1-score shows consistent improvement across all thresholds, with the largest increase of +2.45% under the ROC optimal threshold. This indicates that the overall balance between precision and recall has improved, confirming the effectiveness of the incremental learning approach. Furthermore, AUC-ROC shows a modest but consistent increase of +0.15%, suggesting enhanced discriminative capability of the model. A more notable improvement is observed in AUC-PR (+1.18%), which indicates better performance in handling class imbalance and improving the precision–recall relationship.

The choice of threshold also plays a significant role in performance variation. The ROC optimal threshold provides the most balanced improvements across metrics, while the PR optimal threshold emphasizes precision and F1-score at the expense of slight recall reduction. The default threshold (0.5), although commonly used, demonstrates less consistent performance, particularly for recall. These findings highlight the importance of threshold selection in optimizing classification performance for different application requirements.

In summary, the results demonstrate that the proposed incremental learning strategy effectively enhances model performance, particularly in terms of precision, F1-score, and AUC-PR, while maintaining high accuracy and statistical reliability. Although minor reductions in recall are observed under certain thresholds, the overall improvements confirm that incremental learning provides a practical and efficient approach to improving model performance without the need for full retraining.

5. Conclusion

This study proposed an incremental learning strategy for a convolutional neural network (CNN) aimed at improving classification performance while reducing the need for full model retraining. The experimental results demonstrate that the proposed approach effectively enhances model performance across multiple evaluation metrics, including accuracy, precision, F1-score, AUC-ROC, and AUC-PR. In particular, notable improvements were observed in precision and F1-score, indicating a better balance between false positives and false negatives. Although minor decreases in recall were observed under certain thresholding strategies, the overall performance gains remained consistent and statistically significant ($p < 0.001$). This confirms the robustness and reliability of the proposed method. Furthermore, the results highlight the importance of threshold selection, as different strategies influence the trade-off between precision and recall.

Overall, the incremental learning approach provides a practical and efficient solution for updating CNN models, enabling performance improvement without the computational cost of training from scratch. This makes it particularly suitable for real-world applications where data evolves over time and continuous model adaptation is required.

For future work, further optimization of the precision–recall trade-off could be explored, along with the application of the proposed method to larger and more diverse datasets. Additionally, integrating adaptive thresholding or advanced learning strategies may further enhance model performance and generalization capability.

ACKNOWLEDGEMENT

The authors acknowledge Universiti Malaysia Sarawak under the PILOT Research Grant Scheme (UNI/F08/PILOT/85807/2023) for supporting this project.

CONFLICT OF INTERESTS

The authors declared that there is no conflict of interest.

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