

Fast and Lightweight CNN Model for EEG Person Identification on Constrained Hardware

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Abstract. Electroencephalography (EEG)-based person identification has emerged as a secure and spoof-resistant biometric solution, leveraging the uniqueness of individual brain activity. While convolutional neural networks (CNNs) have demonstrated strong performance in this domain, existing models often require large numbers of parameters and high-dimensional inputs due to reliance on many EEG channels, leading to excessive computational demands. Recent works have attempted to introduce lightweight models by reducing the number of EEG channels and network parameters. Yet, these approaches still generate excessive amounts of input data, which significantly slows down training and increases computational cost. This undermines the core objective of lightweight modeling by shifting the computational burden to the data pipeline, making the overall system far from efficient. We introduce a CNN-based EEG identification model that is lightweight in every aspect from architecture to data pipeline. The model uses only three EEG channels and 3-second input segments, keeping data compact and efficient. With approximately 64,000 learnable parameters—making it, to the best of our knowledge, the most lightweight CNN-based EEG identification model reported—it trains rapidly, requiring only 2 seconds per epoch on a modest CPU. Despite its simplicity, the model achieves a 98.2% rank-1 test accuracy. This balance of accuracy, speed, and ultra-low complexity makes the model especially suitable for small-scale applications, portable EEG devices, and scenarios where developers lack access to high-end GPUs or CPUs.

Keywords: Electroencephalography (EEG) · Person Identification · Biometric Authentication · Convolutional Neural Networks (CNN) · Lightweight Models · Low-Resource Environments

1 Introduction

Biometric authentication refers to a cybersecurity process that verifies a user’s identity using their unique biological traits, such as fingerprints, voice, retina, or facial features [3]. In recent years, various biometric authentication technologies have emerged to replace traditional methods like PINs and passwords. By

leveraging these physiological or behavioral characteristics, biometric systems offer a more intuitive, secure, and often faster way to verify identity [13]. As we dive deeper into these techniques, it becomes essential to understand their advantages, limitations, and potential for future applications.

Despite the widespread adoption of traditional biometric modalities, these systems face notable limitations [7]. Fingerprint recognition, for instance, has been shown to be vulnerable to spoofing attacks using fake fingerprints, overriding feature extractors, or Hill Climbing Attack [12]. Similarly, facial recognition systems are susceptible to aging, thermal images, IRIS, occlusion, facial expression, etc. [16]. Moreover, these biometric traits are typically static and, once compromised, cannot be changed like a password. Subsequently, several biometric attacks have emerged [14]. Such vulnerabilities have raised critical concerns regarding privacy, identity theft, and system robustness under adversarial conditions. These limitations highlight the need for more secure, dynamic, hard-to-replicate biometric modalities, and EEG appears to address all of these challenges.

Electroencephalography (EEG) offers a compelling alternative for biometric authentication due to its intrinsic link to individual brain activity, which is highly unique and difficult to replicate [4]. Unlike external physical traits, EEG signals are generated internally and are influenced by complex neural processes that vary significantly between individuals [20]. This makes EEG inherently resistant to common spoofing techniques. Additionally, EEG can support continuous authentication [23], where the system verifies the user over time rather than at a single entry point. Recent advancements in wearable EEG devices and signal processing have made this modality more practical for real-world applications [17], including high-security environments such as defense systems, where traditional biometrics may fall short. For such merits, the main challenge is just to design and implement an appropriate approach for people’s identification and authentication using their EEG signals. Most of the existing approaches that rely on hand-engineering features fail to obtain sufficiently high accuracy, as reported in [10,8]. Meanwhile, methods implementing Convolutional Neural Network (CNN) have achieved remarkable results [11,18], but these methods still involve a large number of learning parameters compared to the amount of available training data. Moreover, existing approaches usually require excessive EEG channels or a prolonged signal length of 10s or more for identification [15,19]. Some authors have proposed methods to address these issues by using only three EEG channels [5] or even two channels with lightweight model architectures [1]. However, their approaches rely on very small overlap intervals (less than 0.05s) within a sliding window framework for data augmentation, which introduces significant redundancy in the input data and increases computational overhead. Furthermore, such dense overlapping contradicts the core intention behind reducing the number of channels—namely, to minimize data volume for faster processing, reduced storage requirements, and lower transmission costs. As a result, although these models technically meet the criteria for low channel count or reduced parameter size, their overall system pipelines remain resource-intensive due to excessive

segment generation and preprocessing demands. This challenges the notion that they are truly lightweight in practical deployment.

In response to these challenges, this work proposes a lightweight convolutional neural network (CNN) architecture for EEG-based person identification, optimized for deployment on resource-constrained devices. The model is trained on the PhysioNet EEG dataset [6], which includes recordings from 109 subjects. Our approach restricts the number of trainable parameters to under 70,000 while relying on only three EEG channels, ensuring both compactness and efficiency. Unlike prior models that demand heavy computation or long training times, our design achieves high accuracy while converging within minutes, with per-epoch training taking less than two seconds. This combination of ultra-low parameter count, fast training, and strong performance demonstrates the practicality of our system for real-world, low-resource biometric applications.

2 Related Work

During the past decade, several models have been published using different architectures involving hand engineering or deep learning. Rocca et al. [15] proposed a method of using spectral coherence-based functional connectivity between different brain regions as a biometric feature for EEG-based person recognition. Unlike other models focusing on analyzing the features of individual brain regions, their method captures the temporal dependency and coupling across regions. The approach achieved up to 100% accuracy when tested on a dataset of 108 subjects (PhysioNet) under eyes-closed (EC) and eyes-open (EO) resting state conditions, using connectivity from the frontal lobe. However, the paper did not provide proper justification for one missing subject from the PhysioNet database, which offers EEG data from 109 subjects [6]. Maiorana et al. [9] examined the permanence of EEG signals for biometric recognition by conducting a longitudinal analysis on EEG recordings from 50 healthy subjects using AR coefficients, power spectral density (PSD), and spectral coherence (COH) under eyes-closed (EC) and eyes-open (EO) resting state conditions, achieving up to 90% using 7 channels. The following year (2016), they [10] investigated the impact of preprocessing techniques on EEG-based biometric recognition. They explored the use of Blind Source Separation (BSS) and Sample Entropy (SE) to eliminate unwanted components and improve signal quality. Evaluated under both eyes-closed and eyes-open conditions using EEG data from 50 subjects examined on 19 channels, their approach achieved up to 94.9% accuracy with AR features and BSS+SE preprocessing. These results demonstrate that recognition performance is highly dependent on effective preprocessing, especially due to the presence of artifacts and noise in raw EEG signals. In the same year, they [8] discovered a new approach with PCA and MPCA, resulting in an accuracy of 70%. A biometric identification approach based on single-channel EEG recordings collected during relaxed resting states, using data from 109 subjects under both eyes-open and eyes-closed conditions, was proposed by Suppiah et al. [19]. Their technique introduced a novel mind relaxation metric to select optimal sig-

nal epochs for classification and verification. Eventually, the approach achieved impressive performance, with reported accuracy ranging from 97% to 99%, but the time needed to complete the identification process is 12s, which is a long time. Wang et al. [23] introduced a graph-based method for EEG biometric identification. They applied Relative Phase Synchronization (RHO) to analyze brain connectivity networks and obtained the accuracy of 98.83% on eyes-open (EO) resting state condition. Their approach utilized RHO, among other connectivity metrics, to capture functional relationships between brain regions, leading to enhanced identification accuracy and stability across different cognitive states. However, their system relied on a high-density setup with 64 EEG channels, which may limit its practicality. Mao et al. [11] developed an approach based on convolutional neural networks (CNNs) to optimize model training for EEG-based biometric identification, achieving an accuracy of 97% on a dataset comprising 100 subjects, but they faced the same problem as Wang et al. [23]: their method also relied on a 64-channel EEG system. Sun et al. [18] explored an EEG-based user identification system by combining one-dimensional convolutional neural networks (1D-CNN) with long short-term memory (LSTM) networks to automatically extract temporal and spatial features from raw EEG signals. Their method utilized the spatiotemporal features of EEG signals and was evaluated on the PhysioNet dataset consisting of 109 subjects. It achieved 99.58% accuracy using 16 electrodes and 94.28% accuracy using 4 electrodes, respectively. However, despite the promising accuracy, their model is computationally intensive, comprising approximately 500 million parameters. A graph convolutional neural network (GCNN), combined with phase-locking value (PLV) features extracted from EEG signals to perform biometric identification, was adopted by Wang et al. [22]. Using the PhysioNet dataset, their model achieved an accuracy of 99.98% over 5.5-second segments. A second evaluation on a private dataset with 59 subjects yielded 98.96% accuracy, confirming the robustness of the method across datasets. However, both of their models relied on 64 channels, the same problem as the previous authors. Bidgoly et al. [5] introduced a deep learning-based EEG biometric authentication system designed to address key challenges in universality, privacy preservation, and usability. This approach’s accuracy rose to approximately 98% using only three EEG channels (Oz, T7, and Cz), but their model’s complexity is still too heavy. In 2023, a deep convolutional neural network (CNN) for EEG-based person identification and authentication, released by Alsumari et al. [1], aimed to address issues such as overfitting and the limited availability of EEG data. Their system achieved a remarkable 99% rank-1 identification accuracy and an equal error rate (EER) of 0.187%. The method required only two EEG channels and a 5-second signal window, demonstrating its potential for practical deployment in high-security biometric systems. However, it did not fully resolve the challenge of lightweight design, as the input data fed into the model remains significantly large. A summary of these representative studies is provided in Table 1, which highlights the key datasets, number of subjects and channels, signal duration, accuracy, and model complexity of each approach.

Table 1. Summary of representative EEG-based person identification methods.

Paper	DB	S,C	PL	Acc (%)	Params
Rocca et al. [15]	PhysioNet	108, 56	10s	100.00	N/A
Maiorana et al. [9]	Private	50, 7	5s	90.00	N/A
Maiorana et al. [10]	Private	50, 19	5s	94.9	N/A
Maiorana et al. [8]	PhysioNet	30, 19	5s	71.00	N/A
Suppiah et al. [19]	PhysioNet	109, 1	12s	97.00	N/A
Wang et al. [23]	PhysioNet	109, 64	1s	98.83	N/A
Mao et al. [11]	BCIT	100, 64	1s	97.00	N/A
Sun et al. [18]	PhysioNet	109, 16	1s	99.58	505,281,566
Sun et al. [18]	PhysioNet	109, 4	1s	94.28	505,281,566
Wang et al. [22]	PhysioNet	109, 64	5.5s	99.98	81,901
Wang et al. [22]	Private	59, 46	5.5s	98.96	N/A
Behrouzi et al. [2]	PhysioNet	109, 64	1s	99.78	258
Bidgoly et al. [5]	PhysioNet	109, 3	N/A	98.04	22,563,077
Alsumari et al. [1]	PhysioNet	109, 2	5s	99.00	74,071

Notes. DB—Database; S—Number of subjects; C—Number of channels; PL—Pattern length; Params—learnable parameters (estimated).

3 Methodology

3.1 Problem Definition

Let $\mathbb{R}^{C \times T}$ denote the space of EEG signal segments collected from P subjects, where each segment $x \in \mathbb{R}^{C \times T}$ represents a temporal EEG window of n seconds sampled at f_s Hz, with C channels and $T = n \cdot f_s$ time points. Each signal can thus be expressed as:

$$x = [x(t_1), x(t_2), \dots, x(t_T)]^T$$

where $x(t_i) \in \mathbb{R}^C$ denotes the EEG values at time t_i across all selected channels. In our case, $C = 3$, corresponding to the electrodes Iz, O2, and Oz, and $T = 480$ for a 3-second window at 160 Hz sampling rate.

Let $L = \{1, 2, \dots, P\}$ be the set of subject labels, where each label $l \in L$ uniquely identifies a subject.

We address the EEG-based identification problem, defined as follows:

Definition 1 (EEG-based Identification Problem). *Given an EEG segment $\mathbf{x} \in \mathbb{R}^{C \times T}$ from an unknown subject, the goal is to predict its identity label $l \in L$. This is formulated as a multi-class classification problem over 109 subjects, using a CNN trained on features extracted from EEG spectrograms.*

In this work, raw EEG segments are transformed into spectrograms via STFT before being used as CNN input. Details of this transformation are presented in the following section.

Table 2. Top-10 per-channel classification accuracy of the proposed model (our results).

Channel	Accuracy
Iz	0.89235 ± 0.00198
O2	0.80725 ± 0.00363
Oz	0.80645 ± 0.00744
O1	0.80606 ± 0.00275
Po7	0.78889 ± 0.00250
P1	0.78532 ± 0.00340
C4	0.77131 ± 0.00173
P5	0.76799 ± 0.00123
Po3	0.76514 ± 0.00480
Cz	0.76443 ± 0.00122

3.2 Data Preprocessing and Spectrogram Computation

EEG signals are obtained from the PhysioNet Motor Movement/Imagery Dataset (109 subjects). To balance accuracy and hardware efficiency, we evaluate individual channels and report the Top-10 results in Table 2, where Oz, Iz, and O2 emerge as the most effective.

Each raw signal is segmented into 3-second windows with a 0.3-second stride, producing overlapping samples. For each segment, a spectrogram is computed via the Short-Time Fourier Transform (STFT), as defined in Eq. (1), implemented using the Fast Fourier Transform (FFT).

$$\text{STFT}(x)[m, k] = \sum_{n=0}^{N-1} x[n] w[n-m] e^{-j \frac{2\pi kn}{N}} \quad (1)$$

In the preprocessing stage, the raw EEG signals were converted into spectrogram representations by applying a combination of the *Fast Fourier Transform (FFT)* and the *Short-Time Fourier Transform (STFT)*.

Step 1. Fast Fourier Transform (FFT) The FFT decomposes a discrete signal $x[n]$ of length N into its frequency components, as expressed in Eq. (2):

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\pi \frac{k}{N} n}, \quad k = 0, 1, \dots, N-1 \quad (2)$$

where $X[k]$ represents the spectral coefficient at the k -th frequency bin.

Step 2. Short-Time Fourier Transform (STFT) Since EEG signals are non-stationary, FFT is extended to the short-time case by applying it on sliding windows, as shown in Eq. (3). Before each FFT, the segment is tapered with a **Hann window** $w[n]$ to reduce spectral leakage:

$$X(k, m) = \sum_{n=0}^{N-1} x[n + m] w[n] e^{-j2\pi \frac{k}{N} n} \quad (3)$$

where:

- $x[n]$: EEG time-series,
- $w[n]$: Hann window,
- $N = \text{nperseg} = 64$: segment length,
- $\text{noverlap} = 32$: overlap between adjacent windows (stride = 32 samples $\approx 0.2s$),
- m : time index of the window,
- k : frequency bin index.

Thus, the STFT is essentially a sequence of FFTs, each computed on a Hann-windowed segment of the signal. We implement this using SciPy’s `ShortTimeFFT` (STFFT), which efficiently reuses FFT plans.

Step 3. Log-scaling and Normalization The magnitude spectrogram is log-transformed to stabilize variance, as shown in Eq. (4):

$$S(f, t) = \log(1 + |X(f, t)|^2) \quad (4)$$

producing a tensor of shape (channels, freq_bins, time_bins). This is transposed into (freq_bins, time_bins, channels) for compatibility with CNN input. Finally, all spectrograms are flattened and normalized via *z-score normalization* (StandardScaler), fitted on the training set and applied consistently to validation and test sets.

3.3 CNN Model Architecture

The CNN model is designed with three convolutional blocks followed by fully connected layers for embedding and classification. A detailed layer-wise summary is provided in Table 3.

- A `Conv2D` layer with `ReLU` activation and L2 regularization,
- A `BatchNormalization` layer,
- A `MaxPooling2D` layer.

After the last convolutional block, the feature map is flattened and passed through:

- A fully connected layer `Dense(64)` that acts as the embedding layer,
- A `Dropout(0.3)` layer to reduce overfitting,
- A `Dense(109)` layer with `softmax` activation for classification.

Table 3. CNN architecture summary.

Layer	Output Shape	Parameters
Input	$33 \times 14 \times 3$	0
Conv2D (16) + Normalization + MaxPool	$16 \times 7 \times 16$	512
Conv2D (32) + Normalization + MaxPool	$8 \times 3 \times 32$	4 768
Conv2D (64) + Normalization + MaxPool	$4 \times 1 \times 64$	18 752
Dense (64)	64	32 832
Output Dense (109)	109	7 085
Total		63 949

3.4 Training Strategy

The proposed CNN model was trained with a batch size of 64, resulting in 193 iterations per epoch. Each iteration required 9–11 ms, which corresponds to an average of 1.9 seconds per epoch. The model typically converged within 130 ± 20 epochs, which means the entire training process finished in about 3.5–4.8 minutes. This remarkable efficiency highlights the advantage of using a lightweight architecture with low input density, making the model highly practical for environments without access to powerful computing resources, as illustrated in Fig. 1.

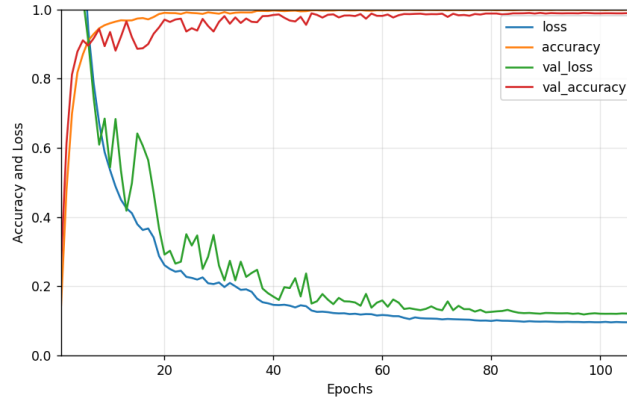


Fig. 1. Training and validation accuracy/loss curves. The model converges quickly, stabilizing around 130 epochs with minimal gap between training and validation performance.

3.5 Implementation

The model was developed in Python 3 with TensorFlow 2.18.0 and its built-in Keras API. All experiments were conducted on an **Acer Nitro 5 AN515-45**

laptop equipped with an AMD Ryzen 5 5600H CPU (6 cores, 12 threads), 8 GB of RAM, and an NVIDIA GeForce GTX 1650 GPU with 4 GB VRAM. Despite being a mid-range consumer laptop rather than a high-end workstation or server, the model achieved an average training time of only 1.9 seconds per epoch and required less than 5 minutes to converge. This demonstrates the practicality of the proposed lightweight model, making it suitable for researchers or developers who may not have access to powerful computing resources.

4 Experimental Results and Discussion

4.1 Data Preparation

To make the most of the dataset and improve generalization, we adopted a simple yet effective augmentation strategy based on sliding-window segmentation. Instead of cutting EEG recordings into non-overlapping chunks, we used 3-second windows with a 0.3-second stride. This overlap provided the model with different “views” of the same signal while preserving the underlying brain patterns. As a result, the training set was expanded to more than twelve thousand spectrogram samples without introducing artificial distortions. By avoiding extremely small strides such as 0.025 seconds [5] and 0.03125 seconds [1], we controlled the input density and computational cost while still ensuring sufficient diversity. Additionally, converting each segment into spectrograms using STFT naturally introduced time–frequency variations, further strengthening the augmentation process as illustrated in Figure 2.

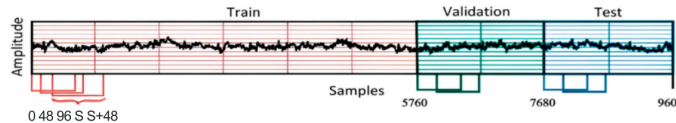


Fig. 2. Partition and segmentation strategy.

Each EEG recording lasted 60 seconds (9,600 samples at 160 Hz) and was divided into three subsets: 36 seconds for training, 12 seconds for validation, and 12 seconds for testing. The training data were drawn from the first portion of each recording, the validation set from the middle, and the test set from the last segment. This ensured that no overlapping segments appeared across sets, preventing data leakage and guaranteeing that the reported accuracy reflects the model’s ability to generalize to unseen EEG signals, as also shown schematically in Figure 2.

4.2 Evaluation Metrics

To measure how well the model works, we mainly rely on **accuracy**, which tells us the percentage of correct predictions out of all predictions. This metric is especially important because the main goal of our system is to reliably identify individuals from their EEG signals. Alongside accuracy, we also track the **loss** during both training and validation. Monitoring the loss helps us see how well the model is learning and whether it is generalizing properly, rather than simply memorizing the training data.

4.3 Performance Evaluation

The experiments show that the model performs extremely well even when using only three EEG channels. With the combination of Iz, O2, and Oz, the system achieves a training accuracy of about 98.8% and maintains strong generalization with a test accuracy of 98.2%. These results confirm that, with such a lightweight design—both in terms of the compact CNN architecture (only 64k parameters) and the reduced input density (12,315 training instances per epoch)—the proposed approach can deliver reliable and practical identification performance.

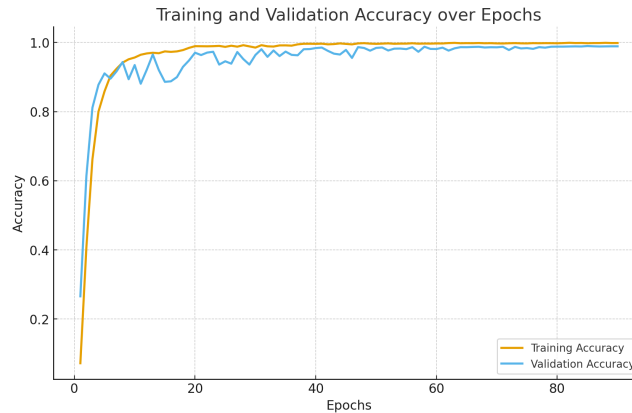


Fig. 3. Training and validation accuracy for three EEG channels (Iz, O2, Oz).

As shown in Figure 3, the model steadily improves during training and converges after roughly 130 epochs. Importantly, each epoch takes only about 1.9 seconds (193 iterations at 8–11 ms per step), highlighting the exceptional efficiency of the model. This indicates both stable learning and strong generalization, demonstrating that even with just three channels the model can achieve accuracy above 98%. By combining a low-parameter design and sparse input density with very fast training, the system becomes highly practical and cost-effective for deployment in real-world biometric identification applications, even on consumer-grade hardware.

4.4 Equal Error Rate (EER) Evaluation

Although the proposed model is primarily designed for the identification task (multi-class classification), we additionally evaluate its verification capability by computing the Equal Error Rate (EER). To this end, embeddings were extracted from the penultimate dense layer of the CNN, and pairwise cosine similarities were computed between all test samples. Genuine scores were obtained from pairs belonging to the same subject, while impostor scores were generated from pairs of different subjects. The EER was then determined as the operating point where the False Acceptance Rate (FAR) equals the False Rejection Rate (FRR).

The system achieved an EER of 1.015% at an optimal similarity threshold of 0.8116, as illustrated in Figure 4. This extremely low error rate highlights that the embeddings learned for identification are also highly effective for verification, demonstrating the versatility of the proposed lightweight model.

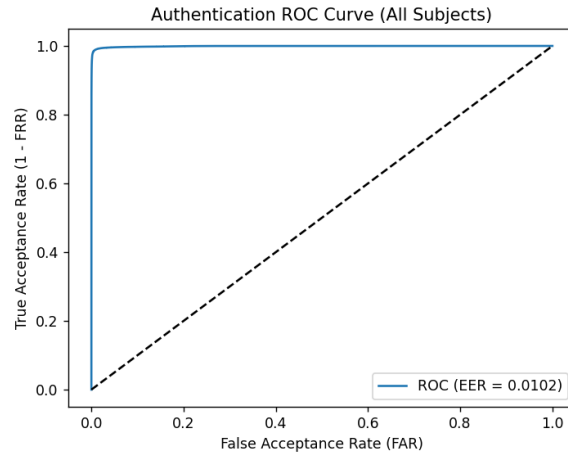


Fig. 4. ROC curve for authentication evaluation. The Equal Error Rate (EER) was found to be 1.015% at threshold 0.8116.

4.5 Discussion

This section discusses the findings, including the strengths and limitations of the proposed method, and highlights the contributions as well as potential real-world applications.

Comparison with Previous Studies Compared to prior works, our method offers a more favorable trade-off between accuracy, training efficiency, and computational cost. While earlier studies often relied on large networks with millions

of parameters or very dense input segmentation, our approach achieves comparable accuracy with a much smaller footprint in both model size and input requirements. See Table 4 for a side-by-side comparison of recent methods and our model in terms of channels, parameters, accuracy, data volume per epoch, and total training time.

Table 4. Comparison of EEG-based identification methods.

Paper	CH	Params	Acc (%)	Seg/Ep	Total s
Sun et al. [18]	16	~500M	99.58	—	—
Sun et al. [18]	4	~500M	94.28	—	—
Bidgoly et al. [5]	3	22.5M	98.04	213,749	—
Alsumari et al. [1]	2	74k	99.00	230,426	1,750–3,000
Vadher et al. [21]	65	—	99.86	~9,781	~13,750
Ours (This work)	3	64k	98.20	12,315	247

Notes. CH—number of EEG channels (electrodes); Params—learnable parameters; Acc (Seg/Ep—number of training segments per epoch; Total s— Time to converge (seconds)).

In terms of overall efficiency, our model required only 247 seconds in total to complete training (130 epochs at 1.9 seconds/epoch) on a consumer laptop. By contrast, Alsumari et al. (2023) reported 70–120 seconds per epoch, resulting in 1750–3000 seconds for 25 epochs, while Vadher et al. (2023) reported approximately 550 seconds per epoch, i.e., about 13,750 seconds for 25 epochs. This demonstrates that our approach achieves comparable accuracy with two orders of magnitude faster training time.

Strengths (Merits) The proposed approach demonstrates several key advantages:

- **Fast training:** converges within minutes, with per-epoch time ~1.9s on a laptop.
- **Low cost:** efficient training/inference on mid-range hardware (Ryzen 5, GTX 1650), no high-end GPUs needed.
- **Compact:** only 64k parameters and 3 EEG channels, suitable for portable or embedded devices.
- **Practical:** cost-effective for small user groups (clinics, labs, personal BCI).

Limitations (Drawbacks) Despite the promising results, several limitations remain:

- **Scalability:** validated on 109 subjects; larger-scale deployment and cross-subject generalization remain open challenges that will be explored in future work.

- **Dataset bias:** limited to PhysioNet, not yet tested on more diverse real-world EEG data.
- **Noise sensitivity:** robustness under motion, noise, or sensor artifacts remains unverified.

Future work will include testing on more diverse and noisy EEG datasets, performing ablation studies on channel number and input window length, and evaluating scalability to larger populations.

5 Conclusion

This work introduced a lightweight CNN for EEG-based person identification, combining compact design (64k parameters, 3 channels) with high accuracy. Despite using only 12,315 training instances per epoch, the model achieved over 98% accuracy on the PhysioNet dataset with 109 subjects. Training is highly efficient, converging in approximately 4 minutes (1.9 s per epoch) on a consumer laptop. These results demonstrate that a carefully optimized lightweight architecture and reduced input density can deliver strong accuracy at low computational cost, offering a practical and deployable solution for real-world, resource-constrained environments.

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