EEGAuthNet: End-to-End Deep Learning for Person Authentication Using Raw EEG Signals

Sachin Kukkar, Rajesh Rajaan, Loveleen Kumar
Department of Computer Science & Engineering, Swami Keshvanand Institute of Technology, Management & Gramothan Jaipur, 302017 (India)
Email:sachinkukkar1998@gmail.com, raaj0028@skit.ac.in, loveleen.kumar@skit.ac.in

Received 10.04.2026 **received in revised form** 21.04.2026, **accepted** 24.05.2026
DOI: 10.47904/IJSKIT.16.1.2026.20-24

Abstract—Biometric authentication using Electroencephalogram (EEG) signals is getting more popular because it is hard to fake or steal as compared to things like fingerprints, iris or face scans. Electroencephalogram(EEG) is unique to each person and we cannot just sneak up and generate or grab those brain waves easily. But most of the systems nowadays use these handpicked features from the spectrum and they only test on a few people. So it does not really work well for everyday use. In this paper, we came up with EEGAuthNet, a deep learning based setup that takes raw EEG signals from 64 channels and authenticates without the need to extract features manually. The model combines one-dimensional Convolutional Neural Networks (CNN) to pull out spatial features and then it adds Bidirectional Long Short-Term Memory (Bi-LSTM) layers that go both ways to handle the longer patterns in time across the EEG bits. We tested it on PhysioNet dataset for motor movements and imagery which contains 106 subjects. The accuracy for identifying came out to be 97.89%. Equal Error Rate (EER) was 2.0%. To check what each part does, we did an ablation study which confirmed that each component contributes meaningfully with combination of CNN and Bi-LSTM which beats only CNN by 3.8Overall this shows EEG could be a good secure way for biometrics if you pair it with this hybrid setup.

Keywoeds—EEG biometrics, person authentication, convolutional neural network, LSTM, end-to-end learning, brain-computer interface, PhysioNet, deep learning.

1. INTRODUCTION

With all the digital stuff growing so fast there is a big need for access control that is strongly scalable and difficult to trick. Traditional biometrics like fingerprints, face recognition or iris scans are very common but they can still get hit by replay attacks or data breaches [1].Signals from the central nervous system offer a different approach for security. EEG measures the electrical potentials from neuron activity on the scalp and it captures pattern based on someone's unique brain structure and thinking style [2].Also, it allows for ongoing authentication during a session without user doing much after signing up [3].

Even with these perks, EEG authentication has run into issues. Raw EEG is non-stationary high dimensional and full of artifacts from eyes, muscles or heart which makes it hard to read reliably .Older systems used handcrafted features like power spectra in frequency bands wavelet stuff or autoregressive parameters and those need a lot of expertise and they might miss key information in the raw signals [4], [5].

Deep learning changes things for EEG processing by finding features automatically from raw data. Convolutional Neural Networks learn spatial and spectral filters from multichannel EEG and LSTMs handle the sequential temporal side well [6], [7]. Hybrids of these have worked in other EEG tasks [10] but using them end to end for large scale identity auth on raw signals hasnt been explored much.

To fill this gap we have came up with EEGAuthNet a hybrid CNN and Bi LSTM framework for EEG person authentication. It takes raw epochs and outputs identity without extra steps.The main contributions of this work are:

1) An end-to-end deep learning pipeline for EEG biometric authentication that jointly learns spatial, spectral, and temporal representations from raw 64-channel EEG recordings, removing the dependency on handcrafted features.
2) A hybrid CNN and Bidirectional LSTM architecture, EEGAuthNet, evaluated on 106 subjects from the PhysioNet EEG Motor Movement/Imagery dataset, achieving an EER of 2.11% and AUC of 0.9978.
3) A comprehensive ablation study that quantifies the individual and combined contribution of each architectural component, providing design insights for future EEG deep learning systems.

The remainder of this paper is organised as follows. Section II surveys related work. Section III describes the dataset and preprocessing pipeline. Section IV presents the EEGAuth-Net architecture. Section V defines the experimental setup and metrics. Section VI reports and analyses results. Section

VII concludes the paper and outlines future work.

2. RELATED WORK

2.1 Traditional EEG Biometric Systems

Early EEG systems pulled features from set frequency bands. Pouloset al. [4] and others used autoregressive coefficients from alpha band EEG with neural nets to tell subjects apart getting okay accuracy on ten people. Palaniappan and Mandic [5] showed approximate entropy and gamma power spectra with SVM worked well on small groups. These proved EEG could be biometric but the features and small tests limit them for bigger use.

2.2 Convolutional Neural Networks for EEG

EEGNet by Lawhern*et al.* [6] was a big step with compact CNNs using depthwise separable convolutions to learn frequency and spatial filters with few params and it generalized across BCI types. Schirrmeister *et al.* [7] showed deeper CNNs could match hand engineered filter banks for motor imagery and the filters looked like real brain frequencies.

A. Recurrent Architectures for EEG

LSTMs tackle the sequential non stationary EEG better than CNNs alone. Zhang*et al.* [8] used spatial temporal recurrent nets for emotion recognition from EEG and beat SVMs by catching long range correlations. Schuster and Paliwal [9] laid out bidirectional LSTM which processes time both ways for richer context at each step and thats useful for EEG where later parts can clarify earlier ones.

B. Hybrid CNN and LSTM Models

Bashivan*et al.* [10] proposed a recurrent convolutional setup for cognitive load from EEG and it captured spatial and temporal info that single models miss. Supratak*et al.* [11] used CNN and Bi LSTM for sleep staging and the LSTM added gains over just CNN features. But end to end CNN Bi LSTM for large scale auth on raw EEG hasnt been studied much which is why this paper does it. It seems like combining them could work well here.

3. DATASET AND PREPROCESSING

3.1 Motor Movement/Imagery Dataset

We have used the PhysioNet EEG Motor Movement and Imagery dataset [12]. It has 106 healthy subjects doing fourteen runs like resting eyes open closed motor tasks for left right both hands and feet. Recorded with 64 channels CI2000 system at 160 Hz using 10-20 placement. Table I. I sums it up.

3.2 Preprocessing Pipeline

Raw EEG goes through five stages before the model.

Stage 1 - Bandpass Filtering : A zero phase 4th-order Butterworth filter with [0.5, 40] Hz which cuts DC and high noise while keeping delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and low-gamma (30–40 Hz) bands.

Stage 2 — Artefact rejection. Independent Component Analysis (ICA) with 64 components separates and removes ocular (EOG) and muscular (EMG) artefact components identified via a spectral threshold criterion applied to component activation maps.

Stage 3 — Epoch segmentation. Continuous recordings are partitioned into non-overlapping epochs of $T = 2$ s, corresponding to 320 samples per channel at 160 Hz. Each subject contributes approximately 400 epochs across all experimental runs.

Stage 4 — Normalization. Each epoch is standardized to zero mean and unit variance per channel, mitigating amplitude differences arising from variable electrode impedance and inter-subject physiological variability.

Stage 5 — Dataset partitioning. An 80/20 stratified split is applied at the subject level, ensuring that no epoch from the same recording session appears in both training and test sets.

Table 1: Physionet EEG Dataset Summary

Parameter	Value
Nominal subjects in dataset	109
Subjects excluded (data quality)	3
Subjects used in this study	106
EEG channels	64 (extended 10–20 system)
Sampling rate	160 Hz
Experimental runs	14 per subject
Tasks	Rest (eyes open/closed), motor execution/imagery
Approximate duration	14 minutes per subject
File format	EDF+
Genuine verification attempts	7,758
Impostor verification attempts	7,864

4. PROPOSED METHOD

4.1 Problem Formulation

Let $\mathbf{X} \in \mathrm{R}^{C \times T}$ denote a preprocessed EEG epoch, where $C = 64$ is the number of channels and $T = 320$ is the number of time samples. Authentication is formulated as a closed-set identification problem: given $\mathbf{X}$, produce a prediction $\hat{y} \in \{1, 2, \ldots, 106\}$ identifying the subject among the 106 enrolled individuals. The model is trained to minimise categorical cross-entropy:

$$\mathrm{L} = -\frac{1}{M} \sum_{i=1}^{M} \sum_{n=1}^{106} y_{i,n} \log \hat{p}_{i,n} \qquad (1)$$

where $M = 64$ is the batch size, $y_{i,n} \in \{0, 1\}$ is the one-hot ground truth, and $\hat{p}_{i,n}$ is the predicted probability for subject n on epoch i.

4.2 Architecture Overview

EEGAuthNet processes $\mathbf{X}$ through three sequential stages: (1) a three-block CNN for spatial and spectral feature ex- traction, (2) a two-layer Bidirectional LSTM for temporal sequence modelling, and (3) a fully connected classification head. The complete layer-wise configuration is given in Table II.

Stage 1: Convolutional Feature Extraction

Three successive Conv1D blocks operate along the time dimension. Each block applies a learnable convolution followed
by Batch Normalisation and a ReLU activation:

$$\mathbf{h}^{(l)} = \mathrm{BNReLU}\ \mathbf{W}^{(l)} * \mathbf{h}^{(l-1)} + \mathbf{b}^{(l)} \quad (2)$$

where $*$ denotes 1-D convolution and $\mathbf{W}^{(l)}$ are learnable filter weights for block l. Filter counts follow the progression 32 → 64 → 128 with a fixed kernel size of $k = 3$. Max Pooling with pool size and stride of 2 is applied after the second block.

Spatial Dropout with rate $p = 0.3$ follows the third block.

Stage 2: Bidirectional LSTM Temporal Modelling

The CNN feature maps are reshaped into a temporal sequence and passed to a two-layer Bidirectional LSTM. The standard LSTM cell computes:

$$\mathbf{f}_t = \sigma(\mathbf{W}_f[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f) \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

$$\mathbf{i}_t = \sigma(\mathbf{W}_i[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i)\ldots\ldots\ldots\ldots\ldots\ldots\ (4)$$

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c)\ldots\ldots\ldots\ldots\ (5)$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

$$\mathbf{h}_t = \sigma(\mathbf{W}_o[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o) \odot \tanh(\mathbf{c}_t)\ldots.(7)$$

The Bidirectional LSTM processes each sequence in both temporal directions and concatenates the resulting hidden states:

$$\mathbf{h}_t = \overrightarrow{\mathbf{h}}_t ; \overleftarrow{\mathbf{h}}_t \quad (8)$$

The first Bi-LSTM layer uses 128 hidden units per direction and returns the full output sequence. Dropout ($p = 0.3$) is applied
between the two LSTM layers. The second LSTM layer uses 64 hidden units and returns only the final hidden state, producing a compact 64-dimensional identity embedding.

Stage 3: Classification Head

The 64-dimensional embedding is projected to 106 logits and normalised with Softmax:

$$\hat{\mathbf{p}} = \mathrm{Softmax}(\mathbf{W}_{\mathrm{fc}}\, \mathbf{h}_{\mathrm{final}} + \mathbf{b}_{\mathrm{fc}}) \quad (9)$$

At inference time, the predicted identity is arg max($\hat{\mathbf{p}}$) and the associated confidence score supports threshold-based accept/reject decisions for verification use cases.

4.3. Training Configuration

The model is trained using the Adam optimiser [13] with initial learning rate $\alpha = 10^{-3}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 10^{-7}$. A ReduceLROnPlateau schedule halves α when validation loss does not improve for five consecutive epochs, with a minimum of 10^{-5}. Training runs for a maximum of 100 epochs with early stopping triggered after 10 epochs of no improvement in validation accuracy. Batch size is 64. Model weights are checkpointed at peak validation accuracy. The full architecture is summarised in Table II.

Table 2: EEGauthnet Layer-Wise Architecture Summary

Layer	Configuration	Outout Shape	Parameters
Input	-	64×320	0
ConvID-1	32 filters, k=3, BN, ReLU	64×318×32	3,104
ConvID-2	64 filters, k=3, BN, Pool	64×158×64	12,352
ConvID-3	128 filters, k=3, BN, Drop	64×156×128	49,280
Reshape	—	156 × 128	0
Bi-LSTM-1	128 units × 2, Drop	156 × 256	263,168
LSTM-2	64 units, final state	64	82,176
Dense	106 units, Softmax	106	6,890
Total trainable parameters		**391,050**	

5. EXPERIMENTS

5.1 Implementation Details

All experiments are implemented in Python 3.10 using TensorFlow 2.12 and Keras. EEG preprocessing is performed with MNE-Python 1.4. Training and evaluation are conducted on Google Colaboratory with an NVIDIA Tesla T4 GPU (16 GB VRAM). The ModelCheckpoint callback retains the configuration with the highest validation accuracy across all epochs.

5.2 Evaluation Metrics

Authentication performance is assessed using four metrics standard in the biometric literature:

- **Identification Accuracy (ACC):** Proportion of test epochs for which the top-1 predicted subject matches the ground truth, reported at the EER operating threshold.
- **Equal Error Rate (EER):** The decision threshold at which the False Acceptance Rate (FAR) equals the

False Rejection Rate (FRR); lower EER indicates stronger genuine-impostor separation.

- **AUC:** Area under the ROC curve, integrated across all decision thresholds; a value of 1.0 represents perfect discrimination.
- **Score Separation (d'):** Standardised distance between genuine and impostor score distributions, providing a signal-theoretic measure of biometric discriminability.

6. RESULTS AND DISCUSSION

6.1Authentication Performance

Table III reports the full suite of authentication metrics for EEGAuthNet evaluated on the held-out test partition of the PhysioNet dataset, comprising 7,758 genuine verification attempts and 7,864 impostor verification attempts across 106 enrolled subjects.

Table 3: EEGauthnet Authentication Performance (106 SUBJECTS, PHYSIONET DATASET)

Metric Value	Value
Genuine verification attempts	7,758
Impostor verification attempts	7,864
Equal Error Rate (EER)	2.11%
EER Decision Threshold	0.5605
FAR at EER	2.11%
Accuracy at EER Threshold	97.89%
ROC AUC	0.9978
Mean Genuine Score	0.8818 ± 0.1144
Mean Impostor Score	0.1318 ± 0.1825
Score Separation (d′)	4.9255

EEGAuthNet achieves an EER of 2.11%, meaning that at the optimal operating threshold of 0.5605 the system simultaneously attains a False Acceptance Rate and False Rejection Rate of approximately 2.1%, yielding an overall accuracy of 97.89%. The ROC AUC of 0.9978 reflects near-perfect rank ordering of genuine scores above impostor scores across all decision thresholds.

The score separation metric $d' = 4.93$ provides further evidence of strong biometric discriminability. Mean genuine scores (0.882 ± 0.114) are well separated from mean impostor scores (0.132 ± 0.183), indicating that the 64-dimensional identity embeddings produced by the Bi-LSTM stage form compact, well-separated clusters in feature space. Table IV presents system performance across three fixed operating points, enabling practitioners to select an appropriate

FAR/FRR trade-off for their deployment context.

6.2 Ablation Study

Table V presents an ablation study varying CNN depth and LSTM configuration while holding all other hyperparameters fixed, illustrating the contribution of each architectural component to the final system performance.

Table 5: EEGauthnet Performance At Fixed Operating Points

Threshold	FAR (%)	FRR (%)	Accuracy (%)
0.3789	10.01	0.46	94.73
0.4606	5.01	0.88	97.04
0.5605	2.11	2.1	97.89
0.6106	1	3.65	97.68

Table 5: Albation Study Effect of Architectural Depth o EEGauthnet

Configuration	ACC (%)	EER (%)
1 Conv block + 1 LSTM (64 units)	89.1	6.7
2 Conv blocks + 1 LSTM (64 units)	91.8	5
3 Conv blocks + 1 LSTM (64 units)	93.7	3.8
3 Conv blocks + 2 LSTM (unidirectional)	94.9	3.1
3 Conv blocks + Bi-LSTM (full EEGAuthNet)	97.89	2.11

Results show a consistent monotonic improvement with increasing CNN depth, confirming that hierarchical feature abstraction across three convolutional blocks is necessary to capture the multi-scale spectral structure of EEG. The transition from unidirectional to bidirectional LSTM yields an additional improvement in both accuracy and EER, consistent with the theoretical advantage of full-context temporal modelling in offline settings where the complete epoch is available at inference time.

6.3 Discussion

EEGAuthNet beats baselines by mixing Convolutional Neural Network(CNN) spatial spectral with LSTM temporal for biometrics. CNNs learns like band decomps but tuned for subjects. Bi-LSTM gets rhythms phases transients lost in static features. Ablation shows both parts needed hybrid best. Errors mostly from artifacts so preprocessing limits it. Maybe adding learnable artifact removal inside could help more. That part stands out as easy to miss.

The score separation of $d' = 4.93$ and the wide margin between mean genuine and impostor scores confirm that the learned identity embeddings are highly discriminative across the 106-subject cohort. Residual authentication errors arise predominantly for subjects with elevated artefact contamination in their recordings, suggesting that the quality of the preprocessing stage directly constrains the upper bound of authentication accuracy. Future work investigating learnable artefact suppression layers integrated within the model architecture could further improve robustness.

7. CONCLUSION

This presents EEGAuthNet hybrid CNN and Bi-LSTM for authentication from raw EEG signals. We have evaluated a total of 106 subjects from Physionet EEG Motor Movement/Imagery dataset. It achieved an accuracy of 97.89% , an Equal Error Rate of 2.11% and AUC of 0.9978. Three main conclusions from this work: First , deep learning cuts feature bottleneck without losing accuracy.Second, CNN and Bi-LSTM complement for authentication at scale. Third, EEG constitutes a viable and spoof-resistant biometric modality when paired with an appropriately expressive deep learning architecture.

Limitations include problem with single-session as we cannot assess cross-session stability and Bi-LSTM compute heavy for embeddings. Future work will include : (1) cross-session studies for authentication stability ; (2) integration & use of Transformers instead of LSTM for parallel processing ; (3) model compression and distillation for wearables ; (4) attempt for applying Quantum Machine Learning approaches for EEG representation learning with upcoming quantum level neural network architectures.

8. ACKNOWLEDGMENT

The author thanks the PhysioNet team and the BCI2000 project for providing open access to the EEG Motor Movement/Imagery dataset, and acknowledges the computational resources provided by Google Collaborator.

9. REFERENCES

[1]. A. K. Jain, A. Ross, and S. Prabhakar, “An introduction to biometric recognition,” *IEEE Trans. Circuits Syst. Video Technol.*, vol. 14, no. 1,pp. 4–20, Jan. 2004.

[2]. R. Palaniappan, “Electroencephalogram signals from imagined activities:A novel biometric identifier for a small population,” in *Proc. Int. Conf. Intell. Data Eng. Automated Learn. (IDEAL)*, Springer, Berlin, 2006, pp. 604–611.

[3]. M. Fraschini, S. M. Pani, L. Didaci, and G. L. Marcialis, “Robustness of functional connectivity metrics for EEG-based personal identification over task-induced intra-class and inter-class variations,” *Pattern Recognit.Lett.*, vol. 125, pp. 49–54, Jul. 2019.

[4]. M. Poulos, M. Rangoussi, V. Chrissikopoulos, and A. Evangelou, “Person identification based on parametric processing of the EEG,” in *Proc. 6th IEEE Int. Conf. Electron., Circuits Syst. (ICECS)*, Paphos,Cyprus, 1999, vol. 1, pp. 283–286.

[5]. R. Palaniappan and D. P. Mandic, “Biometrics from brain electrical activity: A machine learning approach,” *IEEE Trans. Pattern Anal.Mach. Intell.*, vol. 29, no. 4, pp. 738–742, Apr. 2007.

[6]. V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung,and B. J. Lance, “EEGNet: A compact convolutional neural network for EEG-based brain-computer interfaces,” *J. Neural Eng.*, vol. 15, no. 5, p. 056013, 2018.

[7]. R. T. Schirrmeister *et al.*, “Deep learning with convolutional neural networks for EEG decoding and visualization,” *Hum. Brain Mapp.*, vol. 38, no. 11, pp. 5391–5420, Nov. 2017.

[8]. T. Zhang, W. Zheng, Z. Cui, Y. Zong, and Y. Li, “Spatial-temporal recurrent neural network for emotion recognition,” *IEEE Trans. Cybern.*,vol. 49, no. 3, pp. 839–847, Mar. 2019.

[9]. M. Schuster and K. K. Paliwal, “Bidirectional recurrent neural networks,”*IEEE Trans. Signal Process.*, vol. 45, no. 11, pp. 2673–2681,Nov. 1997.

[10]. P. Bashivan, I. Rish, M. Yeasin, and N. Codella, “Learning representations from EEG with deep recurrent-convolutional neural networks,” in *Proc. Int. Conf. Learn. Represent. (ICLR)*, San Juan, 2016.

[11]. A. Supratak, H. Dong, C. Wu, and Y. Guo, “DeepSleepNet: A model for automatic sleep stage scoring based on raw single-channel EEG,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 11, pp. 1998–2008, Nov. 2017.

[12]. G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, “BCI2000: A general-purpose brain-computer interface (BCI) system,” *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1034–1043, Jun. 2004.

[13]. D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in *Proc. Int. Conf. Learn. Represent. (ICLR)*, San Diego, 2015.