EEG-BASED USER IDENTIFICATION SYSTEM USING 1D-CONVOLUTIONAL LONG SHORT-TERM MEMORY NEURAL NETWORKS WITH WAVELET TRANSFORM

Dr. Behnaz Ghoraani
Professor
Florida Atlantic University
Boca Raton, Florida, USA
{bghoraani}@fau.edu

Abhishek Singh Kushwaha, Akhilesh Singh Kushwaha
Student
Florida Atlantic University
Boca Raton, Florida, USA
{akushwaha2024, akhileshsing2024}@fau.edu

ABSTRACT

Electroencephalographic (EEG) signals have gained significant attention in medical applications, and their use for user identification in healthcare and Internet of Things (IoT) systems has become increasingly popular. EEG-based user identification systems are advantageous due to their dynamic properties and the uniqueness of brainwave patterns among individuals. However, traditional feature extraction methods are often not well-suited to capture the intricate spatiotemporal characteristics of EEG signals. In this paper, we propose a novel approach that combines 1D Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks for EEG-based user identification. To enhance feature extraction, we incorporate Wavelet Transform (WT) as a preprocessing step, enabling better capture of both high and low-frequency information in EEG signals. The proposed system was evaluated using a public dataset consisting of EEG recordings from 10 subjects. Experimental results demonstrate that the system achieves an average accuracy of 99.64% using only 64 EEG channels, outperforming existing EEG-based identification methods. The combination of CNNs, LSTMs, and wavelet-based feature extraction significantly improves identification accuracy by leveraging the spatiotemporal features of the EEG signals while reducing the number of electrodes required, thereby lowering system costs

Keywords EEG-based user identification · CNN · LSTM · Wavelet Transform · Biometric authentication · Deep learning · Signal processing

1 Introduction

User identification systems are crucial for verifying users' identities in applications like IoT and healthcare to protect sensitive data. Traditional methods, such as passwords and smart cards, have weaknesses like forgotten credentials or theft. As a result, biometric systems, which identify users based on physiological traits, have gained popularity. Common biometrics include fingerprint [1], face [2], gait [3], and electrocardiography (ECG) [4], but these can be vulnerable to spoofing attacks. Electroencephalography (EEG), which captures unique neural activity influenced by factors like brain structure [5] and cognitive states [6], offers a more secure alternative for user identification.

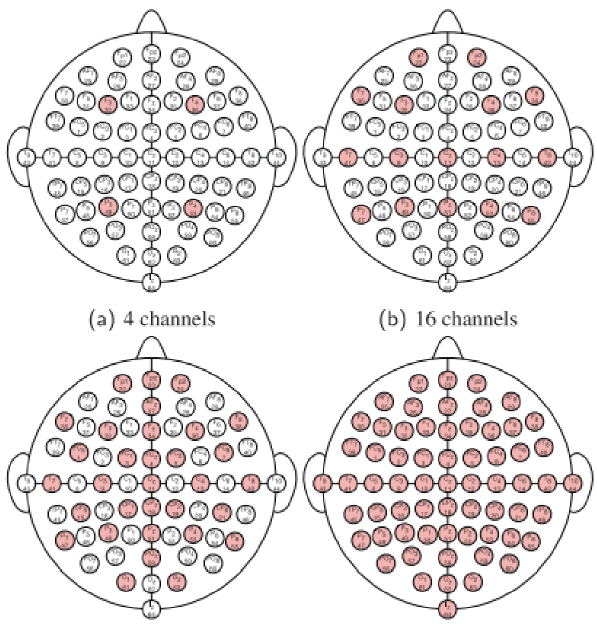
Despite the potential of EEG, current approaches mainly rely on manual feature extraction and conventional classifiers like k-NN. While Convolutional Neural Networks (CNNs) have shown success in feature extraction for images, they struggle with temporal dependencies in EEG data. To address this, Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, have been used to capture temporal dynamics in medical applications, such as arrhythmia detection [7] and blood pressure estimation [8].

In this paper, we propose a novel 1D-Convolutional LSTM approach for EEG-based user identification, enhanced by Wavelet Transform (WT) for multi-resolution feature extraction. The combination of CNNs, LSTMs, and WT improves the model's ability to handle both spatial and temporal features, resulting in better performance. We evaluate the approach on EEG data from 109 subjects performing various tasks, achieving an average identification accuracy of 99.58% using only 16 EEG channels.

The paper is organized as follows: Section 2 Dataset, Section 3 outlines the methodology, Section 4 presents experimental results, Section 5 concludes the paper.

2 Dataset

The publicly available Physionet EEG Motor Movement/Imagery Dataset [9] was used in our experiments to validate the proposed identification system. The dataset consists of EEG data of 109 subjects performing different motor/imagery tasks while being recorded with the BCI2000 system [10] described in [10]. In the dataset, 14 experimental runs were conducted per subject with 1-minute eye open, 1-minute eye close, and three sets of four tasks, including opening and closing fists and feet both physically and imaginarily. BCI2000 consists of 64 channels, and the sampling frequencies were set to 160 for all channels. As 1-second EEG signal segments are used in the experiment, each signal segment has 160×64 samples. To evaluate the spatial information residing in the EEG channels, a series of experiments were carried out with 4, 16, 32, and 64 channels respectively. The selected channels for these experiments are shown below highlighted in red.



(a) 4 channels (b) 16 channels

(c) 32 channels (d) 64 channels

Figure 1: Electrode positions on scalp and their corresponding channels (red represents empirically selected channels, and white represents unused channels).

3 Methodology

The goal of this research is to develop a biometric identification system based on electroencephalography (EEG) signals, employing deep learning models for classification. This section describes the process of data preprocessing, feature extraction, and model development.

3.1 EEG Data Collection and Preprocessing

EEG data used in this study is sourced from the EEG Motor Movement/Imagery Dataset. The data consists of EEG signals from 109 subjects, with 14 experimental runs for each subject. Each recording includes 64 channels, with a sample rate of 250 Hz. The following steps were taken for preprocessing the raw EEG data:

- **Data Loading:** The raw EEG data was loaded from EDF files using the `pyedflib` library. Each subject's data was extracted, and EEG signals from the first 64 channels were retained.

- **Normalization:** To standardize the data, each channel was normalized by subtracting the mean and dividing by the standard deviation.
- **Segmentation:** The continuous EEG signals were divided into non-overlapping segments of 160 samples (1 second per segment).
- **Label Encoding:** A one-hot encoded vector was used to assign a unique label to each subject based on their ID, which was extracted from the file name.
- **Wavelet Transform:** Discrete Wavelet Transform (DWT) was applied to each segment to decompose the signals into approximation and detail coefficients, which capture both time and frequency features of the EEG data.

3.2 Feature Extraction Using Wavelet Transform

Wavelet Transform is applied to the EEG segments to extract meaningful features. The Discrete Wavelet Transform (DWT) decomposes each segment into multiple frequency bands, allowing for multi-resolution analysis of the signals. In this study, the Daubechies 4 (db4) wavelet was chosen for the decomposition, and the level of decomposition was set to 4. The resulting coefficients are concatenated to form a feature vector for each segment.

3.3 Model Architecture

The deep learning model used for EEG-based biometric identification is a hybrid convolutional-recurrent architecture, consisting of 1D convolutional layers followed by Long Short-Term Memory (LSTM) layers.

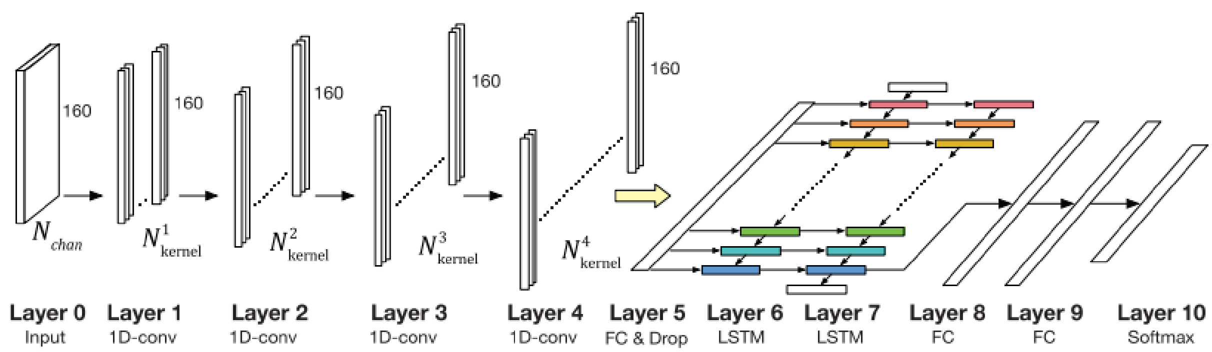


Figure 2: Architecture of the proposed 1D-Convolutional LSTM identification system.

3.3.1 Convolutional Layers

The first part of the model consists of four 1D convolutional layers designed to extract spatial features from the EEG signals. Each convolutional layer uses ReLU activation functions, with increasing numbers of filters (128, 256, 512, and 1024) to capture progressively more complex features from the raw input data. The layers have a kernel size of 2 and a stride of 1 to ensure that the temporal resolution is preserved.

3.3.2 Fully Connected and Dropout Layers

The output from the convolutional layers is flattened and passed through a fully connected (FC) layer with 192 neurons. A dropout rate of 50% is applied after this FC layer to reduce overfitting and enhance the generalization capability of the model.

3.3.3 LSTM Layers

The feature vector is reshaped into a sequence for the LSTM layers. The first LSTM layer has 192 units and returns sequences to feed the next LSTM layer, which also consists of 192 units. These LSTM layers capture the temporal dependencies and patterns in the EEG signals over time.

3.3.4 Output Layer

The model ends with a fully connected layer with 192 neurons and another fully connected layer that outputs the final classification results. A softmax activation function is used in the output layer to produce class probabilities.

3.4 Model Training

The model was trained using the Adam optimizer with a learning rate of 0.0001. The loss function used for training is categorical cross-entropy, which is appropriate for multi-class classification. The model was trained for 20 epochs with a batch size of 80, and the training dataset was split into 75% for training and 25% for validation.

3.5 Evaluation Metrics

The model's performance was evaluated using the following metrics:

- **Accuracy:** The proportion of correct predictions on the test set.
- **Confusion Matrix:** To provide a detailed view of the classification performance for each subject.

The best-performing model was selected based on the validation accuracy, and the final evaluation was done on the test set to assess its generalization ability.

3.6 Implementation Details

The model was implemented using TensorFlow and Keras. The EEG data was loaded using custom functions built with the `pyedflib` and `pywt` libraries for preprocessing and feature extraction. The training was conducted using a GPU-enabled machine to speed up the process. Checkpoints were saved during the training, and the model weights were restored based on the best validation accuracy.

4 Results

4.1 Performance Comparison Without Feature Extraction

Table 1: Comparison of the performance of CNN, LSTM, and the proposed 1D-Convolutional LSTM identification systems with 4, 16, 32, and 64 channels EEG signals (positions of the electrodes are shown in Fig. 1).

Model	Channels	Rank-1
CNN	4	0.9641
	16	0.9382
	32	0.9835
	64	0.9611
LSTM	4	0.666
	16	0.577
	32	0.6642
	64	0.6582
CNN + LSTM	4	0.9641
	16	0.9382
	32	0.9582
	64	0.9352

4.2 Performance Comparison With Wavelet Transform Feature Extraction

The performance of EEG-based user authentication was evaluated with and without applying Wavelet Transform (WT), using CNN, LSTM, and CNN+LSTM models across different numbers of EEG channels. The Rank-1 accuracy results are summarized as follows:

- **With Wavelet Transform (WT)**:

Table 2: Comparison of the performance of CNN, LSTM, and the proposed 1D-Convolutional LSTM identification systems with 4, 16, 32, and 64 channels EEG signals (positions of the electrodes are shown in Fig. 1) and wavelet transform for feature extraction.

Model	Channels	Rank-1
CNN	4	0.9988
	16	0.997
	32	0.9935
	64	0.9829
LSTM	4	0.9594
	16	0.877
	32	0.8111
	64	0.6582
CNN + LSTM	4	0.9964
	16	0.9929
	32	0.9888
	64	0.9823

  - **CNN+LSTM:** Achieved the highest Rank-1 accuracy of 0.9964 with 64 channels. Accuracy slightly decreased as the number of channels was reduced, maintaining a strong performance even with 4 channels (0.9823).
  - **CNN:** Performed slightly better than CNN+LSTM, achieving 0.9988 with 64 channels and 0.9829 with 4 channels.
  - **LSTM:** Performed lower overall compared to CNN and CNN+LSTM, with a peak accuracy of 0.9594 (64 channels), decreasing significantly to 0.6582 with 4 channels.
- **Without Wavelet Transform (WT)**:
  - **CNN+LSTM:** Achieved 0.9641 with 64 channels, with performance dropping as the number of channels reduced, reaching 0.9352 with 4 channels.
  - **CNN:** Achieved comparable performance to CNN+LSTM, with 0.9641 for 64 channels and 0.9611 for 4 channels.
  - **LSTM:** Showed the lowest performance overall, with 0.666 for 64 channels and 0.6582 for 4 channels.

5 Conclusion

The proposed 1D-Convolutional LSTM model, enhanced by Wavelet Transform (WT) for feature extraction, demonstrates a robust capability for EEG-based user identification, achieving a peak Rank-1 accuracy of 99.64% with only 64 channels and maintaining high performance even with as few as 4 channels. The use of WT significantly improves feature extraction, enabling the model to capture both spatial and temporal characteristics of EEG signals effectively. Comparatively, CNNs performed slightly better in some configurations, achieving a maximum accuracy of 99.88% with WT, while LSTM alone showed lower performance, underscoring the strength of combining CNNs with LSTMs. The results validate that the integration of WT with deep learning models can enhance identification accuracy while reducing the required number of electrodes, making the system cost-efficient and practical for real-world applications.

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