A Convolutional Neural Network Approach to Schizophrenia Detection Based on Wavelet-Transformed EEG Signals

Mohammad Reza Sheikh* Maliheh Sabeti†

Abstract

The paper introduces a novel method for detecting schizophrenia by analyzing electroencephalography (EEG) signals using convolutional neural networks (CNNs). Schizophrenia, a serious mental health condition, is often diagnosed through subjective clinical assessments, which can lead to inconsistent or delayed outcomes. To address these challenges, the proposed approach leverages EEG, a non-invasive technique with high temporal resolution for recording brain activity. The method begins by preprocessing the raw EEG data with Independent Component Analysis (ICA) to remove noise and artifacts such as eye blinks, muscle movements, and electrical interference. Then, Continuous Wavelet Transform (CWT) is applied to extract key features, capturing both temporal and spectral information crucial for distinguishing between healthy individuals and those with schizophrenia. These features are fed into a CNN, which excels at handling the 2D time-frequency representations of EEG data, automatically extracting features and identifying patterns in complex, high-dimensional data. The CNN model was trained on a public dataset containing EEG recordings from schizophrenia patients and healthy controls, achieving a classification accuracy of 94.77%, outperforming traditional machine learning methods like Support Vector Machines (SVM) and Random Forests, which rely more heavily on manually crafted features.

Keywords: EEG, Convolutional Neural Network, Deep learning, Schizophrenic disorder

1 Introduction

Schizophrenia is a complex, chronic mental health disorder that affects about 1% of people worldwide[1]. It is one of the top 15 leading causes of disability globally, often leaving a significant impact on individuals and their families. The condition presents a range of symptoms, including hallucinations, delusions, disorganized thinking, and cognitive impairments. Early diagnosis and timely intervention are crucial for better outcomes, yet achieving this remains a major challenge. Schizophrenia is highly diverse in its presentation, and its diagnosis still relies largely on subjective clinical evaluations. Traditional diagnostic methods, involving in-depth interviews and observations, demand specialized expertise and can often lead to inconsistencies and delays, ultimately worsening the prognosis for those affected.

In this context, there is a growing interest in developing automated diagnostic tools that leverage physiological data, like EEG, to assist in detecting schizophrenia more efficiently[2]. EEG is a non-invasive technique that measures the brain's electrical activity through electrodes placed on the scalp. Compared to other neuroimaging methods, such as functional magnetic resonance imaging (fMRI) or magnetoencephalography (MEG), EEG has a distinct advantage: it provides high temporal resolution, which is essential for capturing the fast neural oscillations linked to cognitive and emotional processes. Research has shown that EEG patterns in people with schizophrenia differ notably from those in healthy individuals, especially in specific frequency bands like Delta, Theta, Alpha, and Gamma. These changes in brain activity are connected to core symptoms of schizophrenia, such as impaired cognitive control, abnormal sensory processing, and disrupted communication between brain regions[3].

However, analyzing EEG data for schizophrenia detection comes with its own challenges. EEG signals are complex, constantly changing, and vulnerable to noise from various sources, such as muscle movements and eye blinks. Traditional machine learning approaches, like SVM and random forests, have been applied to these signals with moderate success, often relying on handcrafted features like power spectral densities, coherence, and phase synchrony measures[4]. While these methods have been useful, they require extensive feature engineering and domain expertise, and they might fall short in capturing the intricate temporal dynamics indicative of mental disorders.

Recent advancements in deep learning, particularly CNNs, provide a promising alternative. CNNs can automate feature extraction and learn complex patterns directly from raw or minimally processed data. Although CNNs are commonly used in image-based tasks, they also show great potential in analyzing EEG signals by identifying spatial and temporal relationships in the

*Department of Computer Engineering, North Tehran Branch, Islamic Azad University, Tehran, Iran m.sheikh@iau-tnb.ac.ir
†Department of Computer Engineering, North Tehran Branch, Islamic Azad University, Tehran, Iran sabeti@shirazu.ac.ir

data. In the context of schizophrenia detection, CNNs can be adapted to process 2D representations of EEG signals, like time-frequency maps, which capture both the evolution over time and the frequency content of brain activity [5].

In this study, we propose a CNN-based approach to automatically detect schizophrenia using EEG data. To achieve this, we transform raw EEG signals into 2D time-frequency representations using CWT, a technique well-suited for analyzing non-stationary signals [6]. This transformation helps the model effectively utilize both time and frequency information, which is key to distinguishing between healthy and schizophrenia-related brain activity. Our contributions include:

Developing a robust preprocessing pipeline, utilizing ICA and band-pass filtering, to improve signal quality and remove common artifacts such as eye blinks and muscle noise [7].

Proposing a novel CNN architecture designed to analyze 2D time-frequency features derived from CWT, enabling automatic feature extraction and classification of EEG signals.

Conducting a comparative analysis of our proposed CNN model against traditional machine learning methods on the same dataset, to assess the impact of time-frequency features on classification performance.

Providing an in-depth analysis of the learned representations, highlighting key patterns associated with schizophrenia.

Our goal is to pave the way for more reliable and accessible diagnostic tools, ultimately improving the quality of care and outcomes for those living with schizophrenia.

2 Methodology

2.1 Data Collection and Preprocessing

The dataset comprises 28 EEG recordings from two groups: 14 healthy control subjects and 14 subjects diagnosed with schizophrenia. Each recording contains 19 EEG channels (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2) sampled at 250 Hz. The EEG signals were acquired during resting-state conditions, which are known to reveal abnormalities in neural oscillations in schizophrenia patients.

2.2 Signal Denoising and Artifact Removal

The raw EEG data is preprocessed using a series of steps to remove noise and unwanted artifacts:

- **Notch Filtering**: A notch filter at 50 Hz and 60 Hz is applied to remove powerline interference. The effectiveness of this filtering is evaluated by inspecting the power spectral density (PSD) of the EEG signals before and after applying the filter. Specifically, a reduction in the power at the targeted frequencies (50 Hz and 60 Hz) without affecting nearby frequency bands confirms successful filtering[8].
- **Independent Component Analysis**: ICA is used to identify and remove artifacts related to eye blinks, muscle movements, and cardiac activity. While ICA is effective at isolating artifacts, it has limitations. One of the key challenges is its sensitivity to the number of components selected. An inappropriate choice of components can lead to either incomplete artifact removal or the loss of meaningful neural signals[9]. Additionally, ICA assumes statistical independence of components, which may not always hold true for EEG data, potentially affecting its artifact isolation performance.
- **Band-pass Filtering**: A band-pass filter (1-30 Hz) is applied to capture the relevant EEG rhythms, including Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), and Beta (13-30 Hz). This frequency range was chosen based on its relevance to cognitive processes and its established associations with schizophrenia-related neural oscillations[10]. Frequencies below 1 Hz are excluded to remove slow drifts caused by non-neural artifacts (e.g., sweat and electrode impedance), while frequencies above 30 Hz are excluded to reduce noise from muscle artifacts and electrical interference. The choice of band-pass filter parameters can significantly affect the results. For example, selecting a narrower frequency range could result in the loss of diagnostically relevant information, while a wider range might include noise and artifacts, complicating feature extraction. The 1-30 Hz range strikes a balance, capturing the key EEG rhythms associated with schizophrenia while minimizing noise.

2.3 Feature Extraction Using Continuous Wavelet Transform

The CWT is used to extract time-frequency features from EEG signals. The Morlet wavelet is chosen because it effectively captures both time and frequency details. Unlike other wavelets, such as Haar or Daubechies, the Morlet wavelet provides an optimal balance between time and frequency resolution, which is critical for analyzing the non-stationary and oscillatory nature of EEG signals. EEG data contains transient events and rhythmic activity occurring over various timescales, and the Morlet wavelet, with its Gaussian envelope, excels at detecting such localized changes without significant smearing in the time or frequency domains[11].

Additionally, the Morlet wavelet's ability to produce smooth and continuous representations of power across frequency bands makes it particularly suited for identifying patterns in EEG rhythms (e.g., Delta, Theta, Alpha, Beta), which are often linked to cognitive and neural processes affected in schizophrenia. This property enables the extraction of subtle features crucial for distinguishing between healthy and schizophrenia-related brain activity.

To determine the scales for the CWT, an empirical analysis is conducted, resulting in a range from 1 to 10. The CWT coefficients are then used to calculate wavelet energy, which is normalized and converted into a 2D matrix representing the time-frequency features for each EEG channel.

2.4 Convolutional Neural Network Architecture

The CNN model used in this study is designed to capture the spatial features from the time-frequency representation of the EEG signals, which were extracted using the CWT. The CNN consists of multiple convolutional and dense layers, structured as follows:

Convolutional Layers:

- The model begins with two convolutional layers, each with 32 filters and a 3x3 kernel size, employing the ReLU activation function. These layers introduce non-linearity and help capture complex patterns in the input.
- After applying a MaxPooling layer to reduce the spatial dimensions, another pair of convolutional layers, each with 32 filters, is added. These layers continue to extract relevant features from the input data.
- As the network deepens, two additional convolutional layers, each with 64 filters and a 3x3 kernel, are included, followed by another MaxPooling operation. This helps the model capture more complex patterns by increasing the number of filters.
- Finally, the convolutional process is concluded with three consecutive layers, each containing 128 filters with a 3x3 kernel, followed by a MaxPooling layer. This increases the depth of the feature maps and enhances feature extraction for the subsequent classification layers.

Pooling Layers:

- After every two convolutional layers, a MaxPooling layer is applied to downsample the feature maps, making the model more computationally efficient while preserving critical information.

Flatten Layer:

- After the final pooling layer, the 3D feature maps are flattened into a 1D vector to be fed into the fully connected layers.

Dense Layers:

- The model employs two fully connected (dense) layers, each with 512 neurons and ReLU activation, after flattening the feature maps. These layers help in refining the learned representations before classification.

Output Layer:

- The output layer contains 2 neurons with a softmax activation function, which generates probabilities for the two classes (healthy vs. schizophrenia).

The CNN model is optimized using the Adam optimizer, with a learning rate of 0.0001. The model's loss is calculated using Sparse Categorical Crossentropy, which works well for this kind of classification problem. The architecture is designed to extract features step by step—starting with simpler spatial features in the early layers and moving to more complex, abstract ones in the deeper layers. This approach helps the model effectively differentiate between schizophrenia patients and healthy individuals based on EEG data. Figure 1 visually illustrates the CNN model's architecture, showing the progression through convolutional, pooling, flatten, and dense layers, along with their specific configurations. This provides an easy-to-understand overview of how features are extracted and classified step by step.

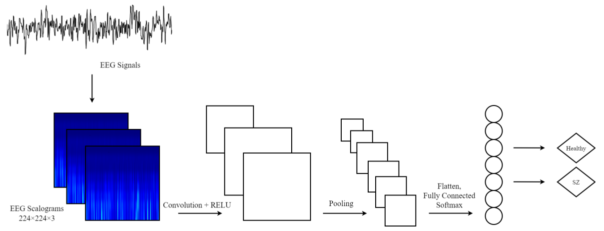


Figure 1: CNN Model Architecture

3 Experimental Results

In our experiments, the CNN model was trained for 60 epochs to evaluate its performance, focusing on accuracy and loss during both training and validation phases. We used 70% of the dataset for training and validation, while reserving the remaining 30% as a test set to assess the model's generalization to new data. Figure 2 shows the trends in accuracy and loss over the training period for both datasets, providing insights into the model's learning progress. The accuracy plots reveal a steady improvement throughout training, while the loss curves consistently decrease, demonstrating the model's effectiveness in minimizing errors and learning efficiently over time.

To further assess the model's performance, we calculated several key metrics, including precision, recall, and accuracy. Precision is the ratio of true positives to the sum of true positives and false positives, which indicates how many of the predicted schizophrenia cases were correctly identified:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall, also known as sensitivity, represents the ratio of true positives to the sum of true positives and false negatives, reflecting how many actual schizophrenia cases were accurately detected by the model:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

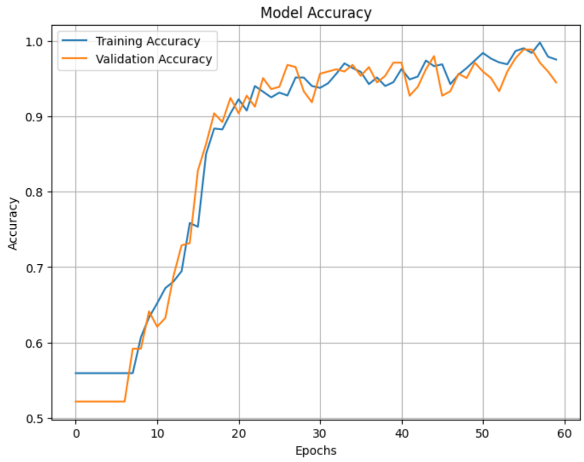
Accuracy measures the overall correctness of the model's predictions, calculated as the ratio of correctly predicted cases (both positive and negative) to the total number of instances:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Number of Instances}}$$

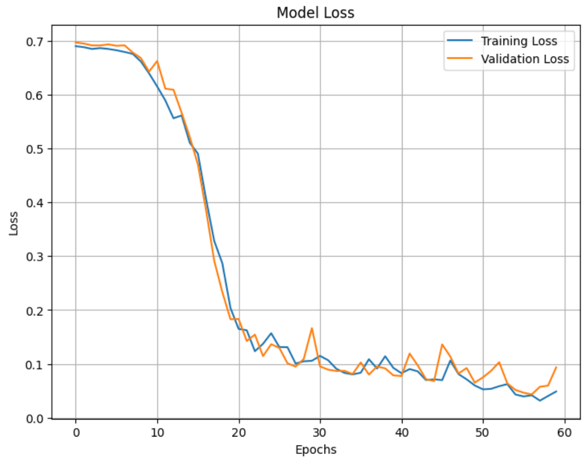
Table 1 summarizes these metrics, with an accuracy of 94.77%, a precision of 94.95%, and a recall of 94.58%, indicating strong model performance in identifying schizophrenia cases.

Metric	Value
Accuracy	94.77%
Precision	94.95%
Recall	94.58%

Table 1: Model Performance Metrics



(a) Model Accuracy over Epochs



(b) Model Loss over Epochs

Figure 2: Training and Validation Performance: (a) Model accuracy and (b) Model loss during training.

After training, we evaluated the performance of the CNN model in the test set using a confusion matrix, which is illustrated in Figure 3. The matrix compares the model's predictions with the actual outcomes, highlighting how effectively it distinguished between individuals with schizophrenia and healthy controls. The model correctly identified most schizophrenia cases (179 true positives) and accurately classified the majority of healthy individuals (145 true negatives). However, there were a few misclassifications, with 19 healthy subjects incorrectly labeled as having schizophrenia (false positives). Importantly, the model did not miss any cases of schizophrenia, as there were no false negatives, meaning every individual with schizophrenia was correctly identified. Although a small number of false positives occurred, the overall performance suggests that the model is a promising tool for accurately distinguishing between schizophrenia patients and healthy individuals.

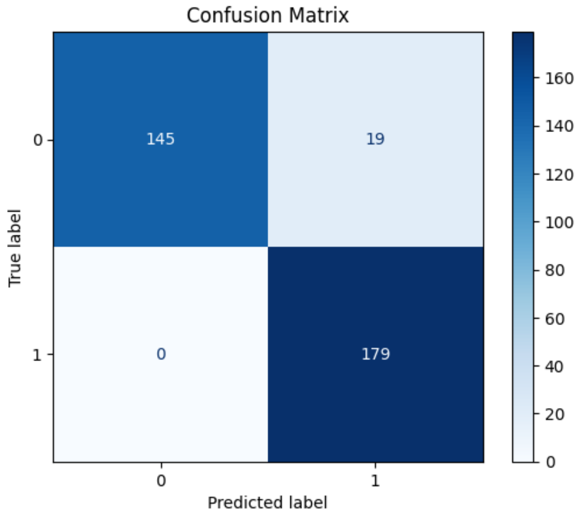


Figure 3: Confusion matrix for the CNN model's classification of schizophrenia patients and healthy controls.

4 Discussion

This study highlights the effectiveness of using CNNs for classifying schizophrenia from EEG signals, especially when combined with time-frequency features obtained through CWT. The model achieved a classification accuracy of 94.77%, notably outperforming traditional methods like SVM and Random Forests that rely on handcrafted features. The proposed CNN was able to capture both spatial and temporal patterns in the EEG data, effectively distinguishing between healthy individuals and those with schizophrenia.

The ability of CNN to capture spatial and temporal patterns is particularly significant in the context of schizophrenia, as the disorder is characterized by disruptions in neural connectivity and rhythmic oscillatory activity. Spatial patterns in the EEG signals, reflected in the differences across various electrode locations, can indicate altered functional connectivity and abnormal regional brain activity, commonly observed in schizophrenia. For example, interrupted activity in the frontal and temporal regions has been associated with impaired executive function and auditory hallucinations, respectively.

Similarly, temporal patterns, such as changes in the power and phase of neural oscillations over time, provide insight into the dynamic processes of the brain. Abnormalities in the Delta (1–4 Hz) and Theta (4–8 Hz) bands are often linked to disrupted cognitive control and attention, while alterations in the Alpha (8–13 Hz) and Beta (13–30 Hz) bands are associated with sensory processing deficits and impaired synchronization between brain regions. The CNN's capacity to process the 2D time-frequency representations of these oscillations enables it to identify these clinically relevant abnormalities and correlate them with schizophrenia-specific brain activity.

Using these spatial and temporal features, CNN can effectively model complex interactions within and between brain regions, translating these patterns into accurate classifications. This connection between the characteristics learned by CNN and the clinical manifestations of schizophrenia underscores the potential of this approach to advance objective automated diagnostic tools.

Despite these strengths, some limitations remain, including the relatively small dataset and a noticeable number of false positives. Future studies could address these issues by expanding the dataset and incorporating multimodal data, such as fMRI or behavioral metrics, to provide a more comprehensive understanding of the disorder.

5 Conclusion

In this paper, we introduced a new approach using CNNs to detect schizophrenia from EEG signals. We transformed the EEG data into time-frequency representations using CWT, which allowed us to capture valuable features for analysis. By combining effective preprocessing, wavelet-based feature extraction, and deep learning classification, our model achieved impressive accuracy, correctly identifying all schizophrenia cases without false negatives. This suggests that CNNs hold great promise for diagnosing mental disorders, providing a more automated and consistent alternative to traditional clinical assessments, which are often subjective and time-consuming.

Despite these encouraging results, there are still some challenges, such as the relatively small dataset and a noticeable number of false positives. In the future, we aim to apply this approach to larger datasets, experiment with hybrid models, and integrate other brain imaging methods to improve diagnostic precision. With continued development, our method could become a valuable tool in clinical settings, helping facilitate earlier and more objective diagnoses of schizophrenia and potentially other neurological conditions.

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