Schizophrenia Detection of EEG Signals using Deep Learning Neural Networks

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Abstract

Schizophrenia (SZ) is a complex mental disorder affecting cognitive, emotional, and behavioral functioning. This study presents a robust approach for SZ detection using EEG signals by leveraging advanced deep learning techniques. The dataset is created of EEG signals from 14 patients with paranoid SZ, comprising seven males and seven females, with average ages of 27.9 ± 3.3 and 28.3 ± 4.1 years, respectively. Preprocessing involves image transforms for noise reduction and feature enhancement. A sequential CNN-LSTM model is employed to classify the spectrograms, effectively capturing spatial and temporal patterns in the data. Our proposed model achieves a classification accuracy of 96%, demonstrating superior performance in terms of training time, memory efficiency, and predictive capability. This methodology provides a scalable and automated framework for SZ detection, offering clinicians a reliable decision-support tool to facilitate early diagnosis and treatment planning.

Keywords: Schizophrenia, EEG, Convolutional Neural Networks, LSTM, Image Transform, Classification, Deep Learning

Contents

1 Introduction

Schizophrenia is the major mental illness of our time. It was first described by Kraepelin (1896) as "dementia praecox" and later given the name "schizophrenia" by Bleuler in 1911. It is a condition characterized by disturbances of thought, perception and a blunting of affect. These disturbances "involve the most basic functions that give the normal person a feeling of individuality, uniqueness, and self-direction" (WHO 1992). In 1959 a German Psychiatrist identified what he considered to be first rank symptoms of schizophrenia (Schneider 1959). Schneider grouped the collection of symptoms into three main categories, namely, auditory hallucinations, passivity experience and delusional thinking. Schizophrenia sufferers experience hallucinatory "voices" which may either provide a running commentary on one's movements or instruct the person to carry out certain tasks (1). Some sufferers experience voices which are derogatory or insulting. Passivity feelings refer to those feelings, thoughts or behaviors which the individual experiences as being under the influence of a third party. Delusional thinking arises from perceptions which may be distorted. Delusional thinking is often insight less and unamenable to reason. Although these symptoms are no longer used as the sole diagnostic aid Schneider's categorization of the symptoms gives a glimpse of the level of disturbance those with schizophrenia experience Schizophrenia however is also associated with a wide range of other symptoms including social withdrawal, incongruent affect and thought disturbances, which contribute to the devastating effects this illness can have on the person. The cost of schizophrenia in both human terms and in its cost to the nation is immense. As well as the symptoms described above loss of social contacts and career prospects often go hand-in-hand with the illness schizophrenia, working towards a more objective and accurate diagnosis of schizophrenia. Ford et al. presented a study to classify schizophrenic patients using EEG through N100, in which brain waves are given auditory stimulation and then stimulation is decreased after 100 ms (2).

Neuroimaging techniques, such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG), have shown promise in aiding diagnosis, but they face challenges related to cost, accessibility, and sensitivity. EEG, in particular, offers a low-cost, non-invasive, and high-temporal resolution method for monitoring brain activity, making it an ideal candidate for early schizophrenia detection. EEG provides valuable information about brain dynamics by recording electrical activity, revealing disturbances in neural oscillations, and changes in connectivity patterns that are characteristic of schizophrenia.

This study focuses on the use of EEG signals for detecting schizophrenia, using a dataset of EEG signals from 14 patients with paranoid SZ, comprising seven males and seven females, with average ages of 27.9 ± 3.3 and 28.3 ± 4.1 years, respectively. This dataset was collected from the Institute of Psychiatry and Neurology in Warsaw, Poland. In this project, we explore a novel approach that leverages wavelet transforms for signal preprocessing, Gabor filters for feature extraction, and a sequential convolutional neural network (CNN) model combined with a Long Short-Term Memory (LSTM) layer for classification. The goal is to design an efficient model capable of achieving high accuracy while maintaining low memory requirements and fast training times.

Recent research has shown the utility of deep learning techniques, such as CNNs and recurrent neural networks (RNNs), in classifying brain states and detecting abnormalities associated with schizophrenia. Studies have demonstrated that deep learning models can automatically extract relevant features from EEG data, leading to better diagnostic accuracy compared to traditional methods. However, the application of CNN-LSTM architectures to the analysis of EEG signals in the context of schizophrenia remains an emerging area of research. In this work, we aim to contribute to this field by developing an optimized deep learning model that can accurately differentiate between schizophrenic patients and healthy controls based on their EEG characteristics.

2 Motivation

In our previous evaluation of approaches designed to classify EEG of patients into normal and schizophrenic categories, we decided on fMRI data as a suitable starting point due to its impressive role in mapping neural activity and investigating neurological disorders like schizophrenia and Alzheimer's disease. fMRI measures brain activity through blood oxygen level-dependent (BOLD) signals and finds various applications in both clinical and basic neuroscience, and its utility in studying brain functions such as sensory processing, cognition, and motor control. Our base paper also uses fMRI data to diagnose patients with schizophrenia.

However, on deeper views, we found research utilizing fMRI data to have overfitted, less accurate and disadvantagingly niche models (4). The main problem currently facing the development of deep learning methods for fMRI data analysis is that the training methods used a smaller amount of data. Therefore, the studies of small sample may lead to obvious over-fitting problems. The training methods may take more time when number of sample increase, and more training time makes it more difficult to conduct in-depth and meticulous parameter adjustment work, resulting in hindered improvement of method performance.

Due to the lack of data augmentation and exclusion of feature engineering provided by fMRI Response Amplitudes, we concluded our models will learn better using an EEG dataset.

EEG has an excellent temporal resolution: events occurring at millisecond timescales can typically be captured. (5) EEG picks up the electric potential differences, on the order of tens of μ **V** , that reach the scalp when tiny excitatory post-synaptic potentials produced by pyramidal neurons in the cortical layers of the brain sum together. The potentials measured therefore reflect neuronal activity and can be used to study a wide array of brain processes.

Early and accurate detection of SZ is critical for timely intervention and improved patient outcomes. Electroencephalography (EEG) has emerged as a cost-effective and non-invasive tool for analyzing brain activity, but the nonlinear and high-dimensional nature of EEG signals poses significant challenges for traditional diagnostic methods. This study presents a robust approach for SZ detection using EEG signals by leveraging advanced deep learning techniques. Preprocessing involves image transforms for noise reduction and feature enhancement. A sequential CNN-LSTM model is employed to classify the spectrograms, effectively capturing spatial and temporal patterns in the data.

3 Literature Survey

There has been a substantial amount of introduced studies that analyze the relationship between EEG and patients have hearing impairment due to auditory cortex dysfunction, it has been demonstrated that N100, a large, negative evoked potential that is elicited by auditory stimulus, differs in schizophrenic patients compared to the general population. In addition, Kim et al and Thilakavathi et al. Analyzed the pattern of EEG or compared EEG numerical values to validate the correlation between schizophrenia and EEG. Ruxandra et al. (10) trained on a deep learning model without transforming time series data. This study suggests the importance and limitations of learning time series data in deep learning methods.

In Zhang et al., data analyzed in Ford et al was classified through machine learning technology. The Random Forest was used to differentiate EEGs of osed a system for automatically diagnosing epilepsy by learning EEG data in the CNN model without any other conversion of EEG. The classification between epilepsy patients from the general public had the highest classification accuracy was 81.1%. In addition to schizophrenia, the utilization of EEG was also recommended as methods for diagnosing mental disorders such as epilepsy and depression. Archarya et al. propatients and healthy subjects was 88.67%. Naira et al. used a new EEG methodology to improve classification accuracy of schizophrenic patients and healthy subjects.

There are various studies that convert EEG into images to learn from artificial intelligence.

WeiKoh et al. used EEG data to limit new methods of diagnosing patients with schizophrenia. In this study, EEG is transformed into a spectrogram and then trained with KNN, one of the machine learning models. Sobahi et al. (11) converted the EEG into an image form using a local binary pattern. Then, using the transformed image, the CNN is trained. In this research, Recurrence Plot (RP) and Gramian Angular Field (GAF) were used as methods of converting time series data into images (12), (13).

The two methods calculated numerical conversion information of time series data using nonlinear analysis and represented the data as a square image. RP and GAF are techniques to which algorithms to analyze patterns of time series data are applied (14). Therefore, specific changes in EEG data can be efficiently checked, and the overall flow is expressed in one image, which is effective for CNNs where receptive fields are important. In addition, RP and GAF change the patient's EEG into an image for each channel, so it has the advantage of accurately learning a deep learning model with more data.

Between 2014 and 2018, more than 55% of neuroimaging studies of brain diseases used support vector machine (SVM) (7). Lu et al. (8) proposed schizophrenia as MRI study calculated the gray matter and white matter volumes of each brain region of interest (ROI) and took the significant difference between the two as input features and used SVM classification. Liu et al. (9) constructed a hierarchical brain network by measuring the cortical thickness of each ROI of the brain, extracting the node and edge features of the network, and inputting it into the SVM to realize the auxiliary diagnosis of schizophrenia. Huang et al. use the mathematical tool Pearson's correlation coefficient to calculate the correlation coefficient between fMRI brain regions, and the features after dimensionality reduction by principal component analysis are used for SVM learning. Yang et al. used three methods to analyze fMRI images to obtain three fMRI features, and the three features were used to train three capsule neural networks. Finally, the classification result is obtained through the method of ensemble learning. Yang et al. input the functional connection coefficients after PCA dimensionality reduction as features into the neural network to obtain a classification model.

In Oh et al (3), authors have explored subject-based and non-subject-based methods of testing using CNNs. For subject-based testing, the validation of the system is executed in three phases: training the data, validation, and testing of data, respectively. During the training phase, k-fold validation is employed, wherein the full data pool is split into fourteen equal parts (subjects). Of these subjects, twelve were used for training, one subject for validation, and one subject for testing, respectively. This process was repeated fourteen times so that all of the fourteen subjects were subjected to the training, validation, and testing phases. In non-subject based testing, the system is validated through the training and testing phases.

Shoeibi et al (6) tried out various linear classifiers. In the classification step, two different approaches were considered for SZ diagnosis via EEG signals. In this step, the classification of EEG signals was first carried out by conventional machine learning methods, e.g., support vector machine, k-nearest neighbors, decision tree, naïve Bayes, random forest, extremely randomized trees, and bagging.

However none of the approaches facilitate non-GPU or trivial memory requirements, and instead have a higher compute as well as longer training times, higher latency during inference on T4 GPUs (the traditional Colab GPU). A lot of the previous survey reflects minimal usage of image preprocessing techniques to extract relevant features. This article aims to explore a memory-efficient way of schizophrenia detection that also explores image transformation and processing methods.

4 Problem Statement

Schizophrenia is a chronic and severe mental disorder that affects cognitive and emotional functioning. Early detection through non-invasive methods like EEG can significantly aid in diagnosis and intervention. However, analyzing EEG signals for schizophrenia detection remains challenging due to the complex and subtle nature of brain activity. This project aims to develop a deep learning-based model using EEG signals from schizophrenic and healthy individuals. By implementing Gabor wavelet transformation layers for feature extraction, and a CNN-LSTM hybrid model for classification, the goal is to achieve accurate and efficient schizophrenia detection while maintaining low memory usage and fast training times. A low compute model allows for inexpensive and faster inference on consumer hardware, making it more practically usable than other models.

5 Objective

The primary objective of this project is to develop a reliable system for the detection of schizophrenia using EEG signals. The first goal is to preprocess EEG data from both schizophrenic and healthy individuals by applying Gabor wavelet transforms to improve the signal quality. The Gabor wavelets are effective in capturing frequency-specific patterns in the EEG spectrograms. The Deep Learning Neural Network is a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model that classifies these signals accurately. The final objective is to create a tool that provides early, non-invasive diagnosis of schizophrenia, contributing to improved healthcare outcomes.

6 Methodology

6.1 Dataset

The dataset used in this work was provided by Olejarckyz et al in 2017 (24) which is publicly available. Recordings include 14 paranoid schizophrenia patients (7 females) with age ranging from 27 to 32 and 14 normal subjects (7 females) with age ranging from 26 to 32. EEG data was recorded with eyes closed for fifteen minutes. Recordings were obtained from 19 electrodes that were placed on the scalp according to 10-20 international standard electrode position classification system. The sampling frequency was 250Hz. Data was obtained via the typical International 10–20 System. The electrodes used were Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2.

6.2 CNN

The convolutional neural network (CNN) (15) includes a convolutional layer, a downsampling layer, and a fully connected layer. Each layer has multiple feature maps, and each feature map has multiple neurons, and the input features are extracted through the convolution filter (16). The parameter sharing mechanism of the convolutional layer greatly reduces the number of parameters (17). In the classification problem, the convolutional layer, the nonlinear unit, and the pooling layer are used as the feature extraction layer to extract features, and the fully connected layer is used as the classification layer for classification.

Convolutional layers apply a linear transformation using a specific kernel. Filters are a way of extracting features from input patterns. **Pooling layers** are a technique to reduce the input size while extracting features with convolutional layers, the most conventional form is called MaxPooling. **Fully-connected layers**, also called Dense Layers, use linear regression like transformations to give more importance to features that can improve the decision boundary.

6.3 LSTM

RNNs are a group of DL models employed in speech recognition (18), natural language processing (NLP) (19), and biomedical signal processing. CNN models are of Feed-Forward types. However, the RNNs have a **FeedBack layer**, in which the network output returns to the network along with the next input. Because of having internal memory, RNNs memorize their previous input and use it to process a sequence of inputs. Simple **RNN, LSTM, and GRU** networks are three important groups of RNNs (20).

LSTM is a special kind of recurrent neural network (RNN) architecture used in the deep learning field, which may be possible to connect previous information to the current task (21). LTSM has been used for the diagnosis and prediction of diseases (e.g., Alzheimer's disease) (21). LSTMs are used to solve tasks that require long-range memory, such as speech recognition, music generation, and forecasting building energy consumption. LSTMs are designed to overcome the vanishing gradient problem and prevent long-term dependence issues. They use specialized structures called gates to control the flow of information into and out of the system's memory. These gates are made up of a sigmoid layer and a point-wise multiplication operation, and act as a filter to selectively allow information to pass through.

6.4 Gabor Wavelet

A Gabor filter, introduced by Dennis Gabor (22), is a linear texture analysis filter in image processing. It examines whether the image contains any specific frequency content in specific directions in a localized region around the point or region of the assessment. A twodimensional Gabor filter is a Gaussian kernel function induced by a sinusoidal plane wave in the spatial domain.

6.5 CNN-LSTM Models

The CNN LSTM architecture involves using Convolutional Neural Network (CNN) layers for feature extraction on input data combined with LSTMs to support sequence prediction. CNN LSTMs were developed for visual time series prediction problems and the application of generating textual descriptions from sequences of images (e.g. videos). Specifically, the problems of: In CNN-LTM models, the convolutional layers are used in the first layers of the model to extract the features and find the local patterns (20). Then, their outputs are applied to LSTM layers. Experimentally, the convolutional layers extract the local and spatial patterns of EEG signals better compared to RNNs. Besides, adding convolutional layers to LSTM allows a more accurate examination of data.

7 Implementation

The signals acquired were then divided into segments, in which the signals can be considered to be stationary. Each segment consisted of a 25 s (6250 sample) window length and was normalized with Z-score, before feeding to the one-dimensional deep convolution network for training and testing. A total of 1142 EEG segments were used and each segment consisted of 6250×19 sampling points.

The CNN-LSTM model is used on variant tasks like finding spatiotemporal relations in input text for text classification (23) or depressive disorder diagnosis on EGG signals (17) CNN-LSTM results from a series of convolutional layers followed by some LSTM layers. First, it extracts rich features using convolutional layers from input data. Then feeds these features to LSTM layers responsible for extracting temporal information. Finally, the classification is done by applying fully-connected layers to the temporal information obtained by LSTM layers. The CNN-LSTM used in this study consisted of three one-dimensional convolutional layers with a kernel size of 5 and filter sizes of 8, 4, and 2, respectively. Then a dropout layer with a 50% chance of dropping input neurons is applied to avoid overfitting. Following that, a one-dimensional max-pooling layer with a pool size of 2 is applied to reduce the size of the features and, consequently, the required computation power. After that, an LSTM layer with a filter size of 512, which is then followed by the second dropout layer with a 25% drop chance, was used. Following that, a fully connected layer with 128 units pursued by the third dropout layer with a 25% drop chance was used. Eventually, a fully connected layer with one neuron unit is used to perform classification. All Activation functions were ReLU, except for the classification layer which was the sigmoid function.

We implemented a Gabor wavelet layer in this study with defined number of parameters in each layer, filter sizes, and strides. First, to achieve the output of the first layer, a two-dimensional Gabor wavelet transform operation was implemented. A Gabor filter, introduced by Dennis Gabor (22), is a linear texture analysis filter in image processing. It examines whether the image contains any specific frequency content in specific directions in a localized region around the point or region of the assessment. A twodimensional Gabor filter is a Gaussian kernel function induced by a sinusoidal plane wave in the spatial domain.

8 Results and Discussions

In this section, the results of applying the proposed approaches on the dataset are provided for four proposed models. Each signal is converted into an image using GASF and GADF methods. Since there are 2 measures (GASF and GADF) and 19 different channels, 38 images are obtained for each signal. These images were used as inputs for the convolutional neural networks, enhanced by an LSTM layer. For the model training section, a batch size of 4 was selected and the network was trained for 50 epochs. Larger epochs could not be run since they took hours of training on normal T4 GPUs provided by Google Colab notebooks.

Additionally, the initial learning rate was set to 0.001 and if there were no improvements after 10 epochs, learning rate was decreased with a factor of 0.1. Binary Cross Entropy was chosen as the loss function and in the optimization phase, ADAM algorithm was chosen due to its superior results and shorter run-time. Training was performed on 80% of the data for the classification of schizophrenia patients and healthy subjects and the rest of the data was used for evaluating the performance of the classifier using various metrics (accuracy, sensitivity, and specificity). The best result is reached by the proposed CNN-LSTM model.

The base paper reported as achieving the highest classification performance using an improved VGG16 model, with an average classification of 84.3%. We compared our accuracy against the base paper model architecture of feature extraction using CNN models, and found our CNN-LSTM model with a singular LSTM layer, and only 50 epochs, to supercede the base paper results. Without custom layers, like the Gabor filter, our model suffered from overfitting or a high variance. Highest Accuracy of 95.98% is achieved by our CNN-LSTM model, enhanced with a Gabor wavelet layer, and has a specificity of 95% and a sensitivity of 97%, which also performed better than the base model.

In this experiment, we employed custom deep learning and Gramian angular field (GAF) approaches to automate the identification of schizophrenia patients and healthy controls. The use of GADF and GASF approaches to transform a 1-D EEG signal into a 2-D representation that can be directly fed to CNN architecture is one of the work's key innovations.

9 Conclusion and Future Work

We conclude that our study reports a deep learning neural network architecture of a CNN combined with an LSTM model to report the highest accuracy, mean sensitivity and specificity values of 95.98%, 95% and 97% respectively. This is a significant improvement from our base paper which only implements VGGnet16 convolutional neural networks to achieve an accuracy of 84.3%. We also realized the upper hand of EEG signal based deep learning, over neural network analyzing models based out of fMRI data, due to the problems of overfitting associated with model design on fMRI datasets. The training methods may take more time when number of sample increase, and more training time makes it more difficult to conduct in-depth and meticulous parameter adjustment work, resulting in hindered improvement of method performance. Our approach suggests a CNN model enhanced with LSTM layers, to inculcate temporal analysis of EEG signals, which have different auditory characteristics for normal and schizophrenic patients. These auditory differences are reflected in features learnt through LSTM models. Our approach also conducts the training in a memory-efficient and time-saving manner, allowing for the model to be compactly saved. Faster inference on consumer hardware thus makes our model practically more efficient than other models.

For our future goals we wish to explore different image transformation and enhancement techniques like performing Fast Fourier Transforms on images extracted from EEG signals. We would like to also challenge the performance-efficiency tradeoff by training for more epochs, longer times on the model while not compromising the memory constraints of a normal user's hardware. Our long-term goal is to extend the experimental area by gathering more data.

10 References

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