Proceedings of the 5th International Conference on Computing and Data Science
DOI: 10.54254/2755-2721/17/20230942

EEG signals of depression diagnosis in recognition using deep learning methods

Xianyang Chen

Department of Measurement and Control Technology and Instrument, Beijing University of Technology, Beijing, China

Chen_xianyang@emails.bjut.edu.cn

Abstract. Depression is a mental disease which symptom is people feel negative about life during long period. With the fast-paced social lifestyle, increasingly stress make people tired toward their life and work. The prevalence rate of depression become higher worldwide. However, the frequent way to detect the depression is depended on the Self-Rating Depression Scale (SDS) and the diagnosis given by the Professional psychologist. Those methods' performance is always unstable and inefficiency. Electroencephalogram (EEG) as a functional neuron signal have been widely used in neurology diagnosis. It has been testified as a great tool to diagnose the depression. Deep learning (DL) can extract some latent features from complex data which tradition way can't analyze efficiently. For this reason DL intensely utilized in Medical field.This paper aims to analyze the general and feasible solution of applying deep learning to diagnose depression through EEG signals. It reviews the relevant literature in this field in recent years, summarizes the corresponding methods and breakthroughs used in this paper, and systematically constructs this solution. Finally, based on the shortcomings and deficiencies found in these papers, the main problems that need to be addressed in the future are proposed, and the future potential of this field is discussed.

Keywords: deep learning, EEG, depression diagnosis.

1. Introduction

Depression, a common mental disease which phenomenon is being involved in a long-term negative thought, keeping a low spirit. Even more, patients will become so inferiority, misanthropy and painful that generating suicidal idea if they don't be treated on time. A booming trend of depression diagnosis rate demands an effective way to detect depression. However traditional diagnosis methods such as Self-Rating Depression Scale (SDS) and the clinical interview are subjective, ineffective and can be floated by factors like different principle of doctor or patient. Therefore, there is a requirement of more scientific and accurate means of diagnosis [1].

A non-invasive, inexpensive way to measure brain activity is via electroencephalography (EEG). Using EEG signals to track and identify depression has drawn more attention in recent years. EEG data, which are recordings of the brain's electrical activity, are frequently utilized in clinical and academic contexts to identify and investigate neurological problems. Traditional approaches to analyzing EEG signals involve handcrafted feature extraction and signal processing techniques, which can be time-consuming and require domain-specific knowledge [2]

Machine learning's area of deep learning has shown rapid growth and advancement in recent years. Deep learning has proven to perform better in various applications, including computer versions, speech recognition, and natural language processing, among others. The analysis of EEG signals is one application of deep learning that has shown a lot of promise. Without the requirement for feature engineering or specialized knowledge, deep learning enables end-to-end learning from unprocessed EEG signals [3].

Deep learning has been applied to a range of EEG analysis tasks, including seizure detection, emotion recognition, and cognitive state classification, among others. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown superior performance compared to traditional approaches in these tasks [4].

The advantages of deep learning in EEG analysis stem from its ability to automatically learn relevant features from raw signals, its ability to model complex temporal relationships, and its ability to generalize to new data. Deep learning models can learn to recognize patterns and features that may not be immediately apparent to human experts and can leverage large amounts of data to improve their performance [5].

In conclusion, deep learning has become a potent tool for EEG signal interpretation. It has outperformed conventional methods in a variety of tasks because to its capacity to learn from unprocessed data and simulate complicated temporal relationships. We may anticipate even more fascinating uses in EEG analysis and other disciplines as deep learning technology develops. This article's primary goal is to discuss pertinent research on using deep learning to analyze EEG signals from patients to diagnose depression. This research compares and evaluate the methods and achievements of these papers. Moreover, a systematic way will be found out to apply the clinic detection of depression.

2. Depression detection methods and classification process

This section systematically analyzed and summarized how to implement deep learning models to analyze EEG signals for monitoring depression. This paper has summarized a general framework for addressing this type of problem, as shown in Figure 1.

2.1. EEG data acquisition

EEG signals have attracted widespread attention in the medical field as a non-invasive and low-cost means of obtaining brain electrical activity. By attaching electrodes to the patient's scalp, EEG signals are easier to obtain compared to traditional monitoring methods such as fMRI. In addition, EEG signals can provide a large amount of reliable temporal information. However, due to its non-linear and complex features, extracting informative features manually from EEG signals is quite difficult. Therefore, relying on computer-based big data analysis and training deep learning models with extracted EEG signals can efficiently extract features from the EEG signals and distinguish between patients with depression and healthy individuals.

EEG signals are commonly divided into five frequency bands: delta (< 4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13-30 Hz) and gamma(30-80Hz) Previous studies have used EEG data obtained from different regions. This paper will compare how different properties of datasets affect the performance of models.

2.2. Pre-processing and feature extraction

Pre-processing is a necessary process to make EEG data more effective for deep learning models. Typically, we need to first clean the data, set the filter frequency range, exclude brainwave activities caused by other environmental factors, remove significant noise in the EEG signal, and improve the signal quality. The signal is normalized to ensure that it is scaled in the same range, preventing the influence of different signal amplitudes. The signal is segmented to adapt to the model's ability to process data for a certain period of time. In traditional methods, it is generally necessary to extract features manually and reduce the data to a 2D data table for use in machine learning. The commonly used methods include extracting time domain (TD), frequency domain (FD), time-frequency domain

(TFD), discrete wavelet transform based (DWT), and other features for data processing, and then using these features for model processing. After this part of the processing, the dataset can be used very efficiently and conveniently for deep learning model training, in order to achieve higher precision and sensitivity.

2.3. Traditional approaches

Traditional approaches for analyzing EEG signals involve the use of machine learning, which is a type of artificial intelligence decision model that enables machines to learn automatically from data through data analysis, statistical learning, and other methods. It mainly includes supervised learning and unsupervised learning, such as Support Vector Machines (SVM), Probabilistic Neural Network (PNN), Enhanced PNN, or Artificial Neural Network (ANN). In traditional methods, it is crucial to extract features from nonlinear and complex EEG signals and then select features for analysis. By reducing the dimensionality of the data, the features of the EEG signal can be learned by a computer, which can then predict and classify signals with similar features. The drawback of this approach is that the feature extraction process is very cumbersome, requiring repeated attempts to determine which features train the model more effectively, and may overlook some important features in the process. Despite the many feasible models that use machine learning to monitor depression, traditional methods cannot directly learn features from EEG images, leading to low accuracy, low sensitivity, and other issues.

2.4. DL methods

Deep learning algorithms have been used more frequently recently in the medical industry. Deep learning is a subfield of machine learning that uses more and more complex hidden layers to enable computers to learn features from complex information and make predictions. The model works like a "black box" and lacks interpretability. However, compared to traditional methods, deep learning can learn deeper and higher-dimensional features, does not require manual data processing to obtain features from the signal, and can achieve higher accuracy, sensitivity, and lower error rates.

For the classification models of EEG signals, most papers use CNN or Long Short-Term Memory (LSTM) models. CNN is a type of neural network architecture in deep learning. In recent years, CNN has achieved significant results in image recognition, computer vision, natural language processing, and other fields. Its main structure includes convolutional layers, pooling layers, and fully connected layers. By performing convolution operations on input data through convolutional kernels and using pooling layers to achieve dimensionality reduction, high-dimensional data can be mapped to classification results through multiple layers of operation, and the model can be trained for prediction. The success of the CNN model in image processing also applies to the processing of two-dimensional signal images such as EEG, which makes it promising for biological signal analysis.

LSTM is a special type of RNN model designed to solve the shortcomings of RNN models in dealing with long-term dependence problems. It is now widely used to analyze time-series data. LSTM uses gate structures to selectively remember important information or forget information with poor relevance, allowing it to store features over longer time sequences.

In the related works recently this paper reviews.Rajendra Acharya et al. proposed a deep neural network model using a CNN for depression screening. ZHIJIANG WAN et al. proposed a hybrid CNN model for classifying normal individuals and patients with depression using EEG data. Avik Sarkar et al. conducted a comparative study on tracking psychological depression using different machine learning and deep learning techniques. The RNN and LSTM-based RNN models performed the best, while SVM and logistic regression models performed well in the training phase and had high accuracy in the testing phase.Min Kang et al. proposed a deep-asymmetry method using an EEG-based image asymmetry matrix along with a CNN. Pristy Paul Thoduparambil et al. used a 12-layer CNN LSTM hybrid model for classification, Xiaowei Li et al. conducted a detailed comparison and analysis of feature extraction and selection in data [6-11].

DOI: 10.54254/2755-2721/17/20230942

2.5. Evaluation matrix of DL model

Metrics must be established for this study in order to evaluate the model's effectiveness. Typically, sensitivity (SEN), accuracy (ACC), and specificity (SPEC) measurements are employed. (SPE). The results can be determined using the following formulas based on our classification of the findings as true positives, true negatives, false positives, and false negatives:

$$Sensitivity = \frac{\text{True Positives}}{\text{True Positives } + \text{False Negatives}} \times 100\% \tag{1}$$

$$Specidicity = \frac{TrueNegatives}{TrueNegatives + FalsePositive} \times 100\% \tag{2}$$

These indicators are commonly used numerical values to evaluate model performance, with Sensitivity representing the true positive rate and Specificity representing the true negativec rate.

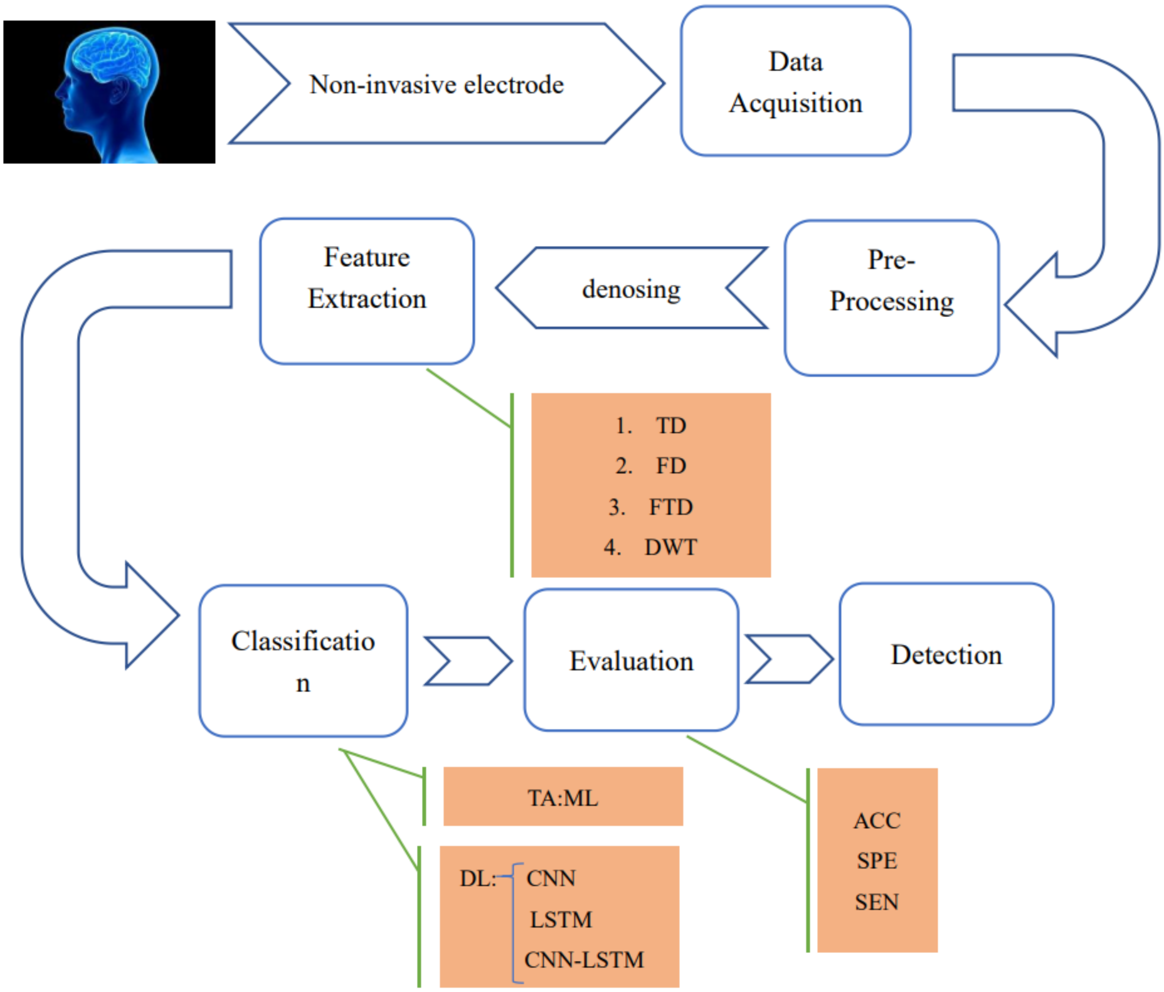

Figure 1. Framework of using Deep learning methods to diagnose Depression with EEG signal.

3. Discussion

3.1. Perspective of previous works

Researchers [6] offer a computer model that tests for depression using deep neural networks. It employs a convolutional neural network (CNN) for adaptive feature extraction and autonomous learning.It demonstrated the first CNN and deep neural network application for diagnosing depression. The semi-manual feature extraction and selection for classification in the proposed CNN model is not necessary. The EEG signals from the right hemisphere were shown to be more discriminative than those from the left, according to the researchers. When the model used EEG inputs from the left and right hemispheres, it achieves an accuracy of 93.5% and 96.0%, respectively.

A convolutional neural network model dubbed HybridEEGNet has been proposed in prior works [7] for the classification of healthy individuals and depressed patients using electroencephalogram (EEG) data. Two parallel sub-models make up the model; one is used to learn synchronous EEG data, while the other is used to learn regional EEG features. The HybridEEGNet model has an average sensitivity of 68.78%, a typical specificity of 84.45%, and an average accuracy of 79.08%. In addition, the paper examines the traits that the model learnt and discovers that variations in the spatial distribution and amplitude range of alpha rhythms may be crucial for differentiating depression. The new aspect of the model is its capacity to immediately learn features from the raw data without the need for manual feature engineering, hence enhancing the effectiveness of automated categorization.

Previous works [8] discusses a comparative study on tracking psychological depression using different machine learning and deep learning techniques. The study investigates the applicability of MLP, CNN, RNN, LSTM-based RNN, SVM, and logistic regression models. The results show that the RNN and LSTM-based RNN models have the highest accuracy in both training and testing sets, while SVM and logistic regression models perform well in the training phase and have high accuracy in the testing phase. The relative recognition rates of SVM and LR models on the test set were 97.65% and 97.18%..

Researchers [9] looked at a deep-asymmetry technique that combines a CNN with an EEG-based picture asymmetry matrix. The dataset utilized in this study contains data from 30 healthy controls and 34 individuals with depression. A 50 Hz notch filter was employed to minimize power line noise after the data was filtered between 0.7 and 70.0 Hz. EEG noise was further eliminated using independent component analysis (ICA). The 5-minute dataset used in this study was split up into 4 second epochs. (1024 samples). The transformation of the brain asymmetry matrix into a 2D picture and input into a 2D CNN model, which finally attained an accuracy of 98.85%, is one of the study's key achievements.

In order to achieve classification, researchers [10] employed a 12-layer CNN LSTM hybrid model, which first uses a CNN to learn local features before feeding the information into an LSTM to understand the long-term relationships in the data. The dataset had a 0.5-100 Hz bandpass filter and a sampling rate of 500 Hz. The EEG signal noise was removed using the FASTER algorithm and independent component analysis, and standardization was accomplished using Z-score normalization. The model's accuracy was 99.07%, and it was discovered that right-brain EEG signals' accuracy was higher than left-brain EEG signals', making it a useful tool for clinical diagnosis.

Previous works [11] conducted a detailed comparison and analysis of feature extraction and selection in data. The paper selected 16 electric-grade HydroCel Geodesic Sensor Net (HCGSN) data, used filters and FastICA to denoise the data, and used the AR (Auto Regressive) model to calculate the PSD (power spectrum density) to obtain 816 features. Five feature selection methods, namely BestFirst (BF), GreedyStepwise (GSW), GeneticSearch (GS), LinearForwordSelection (LFS), and RankSearch (RS) based on Correlation Features Selection (CFS), were used to select these features, and five classifiers (BN, SVM, LR, KNN, and RF) were used to learn and classify the features. The accuracy of the β frequency band was significantly better than other frequency bands, reaching 92%. The performance of differentiating features between mild depression patients and normal individuals was good.

DOI: 10.54254/2755-2721/17/20230942

3.2. Analysis in the DL approaches

By reviewing multiple papers in this field, we summarized the methods they chose under the conventional process framework and their main innovations in studying this type of problem. By analyzing the progress of existing work, we can answer some questions in this field and summarize the shortcomings of existing work. For example, CNN has advantages in feature extraction and recognition and can achieve high accuracy for monitoring depression. The model trained by LSTM has good performance in predicting depression due to its long dependency on time series. At the same time, models that combine CNN and LSTM have both the feature learning ability of CNN and the memory properties of LSTM, achieving more significant accuracy. At the same time, these papers also reveal some shortcomings in this research field, such as the lack of data sets, the problem of overfitting caused by excessive data, and many research methods that solve overfitting and low accuracy problems through dropout and sample expansion. The quality of the data set affects the performance of the model, and it is a big challenge to obtain high-quality data sets systematically. On the other hand, the methods in the preprocessing and feature extraction stages have not reached a relatively systematic uniformity. Researchers generally choose their own methods to process data, and these processing methods may directly lead to different accuracy and learned features of the model. A systematic approach is still needed for the data processing stage. In fact, although the accuracy and sensitivity achieved by these models are already applicable to medical diagnosis, there is still a distance from clinical application, including the instability of EEG acquisition affected by the environment, the mismatch between the model's training data and individual differences, and the fact that most researchers only verify the model at the signal data level and have not practiced on patients.

4. Conclusion

This paper mainly studies and reviews the main methods of using deep learning algorithms based on electroencephalogram (EEG) signals to monitor and predict depression. The main methods and breakthroughs of relevant papers are reviewed, and the deficiencies and future development directions of existing research are discussed. By analyzing the research methods and results of six papers, it is found that most of the papers use the expected research framework, that is, obtaining EEG signals, removing artifacts and noise, extracting features, and finally using CNN, LSTM, or hybrid models for classification, and achieving good performance. Therefore, this monitoring method has strong prospects and potential in medical depression prediction, but there are still many immature aspects in clinical applications, such as the lack of EEG data and individual differences leading to the model unable to be used directly. This paper summarizes the general research methods of medical applications in this area through a review of several relevant papers, and lays the foundation for future breakthroughs in this field.

References

[1] James SL, Abate D, Abate KH, Abay SM, Abbafati C, Abbasi N, et al. Global, regional, and national incidence, prevalence, and years lived with disability for 354 Diseases and Injuries for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. Lancet 2018;392(10159):1789–858.

[2] Shen J, Zhang X, Li J, Li Y, Feng L, Hu C, Ding Z, Wang G, Hu B. Depression detection from electroencephalogram signals induced by affective auditory stimuli. In: In2019 8th international conference on affective computing and intelligent interaction (ACII). IEEE; 2019 Sep 3. p. 76–82.

[3] Goodfellow I, Bengio Y, Courville A, Bengio Y. Deep learning. Cambridge: MIT press; 2016.

[4] Craik A, He Y, Contreras-Vidal JL. Deep learning for electroencephalogram (EEG) classification tasks: a review. J Neural Eng 2019 Apr 9;16(3):031001.

[5] Pinto MF, Leal A, Lopes F, Dourado A, Martins P, Teixeira CA. A personalized and evolutionary algorithm for interpretable EEG epilepsy seizure prediction. Sci Rep 2021;11:1–12.

DOI: 10.54254/2755-2721/17/20230942

[6] Acharya U R , Oh S L , Hagiwara Y , et al. Automated EEG-based Screening of Depression Using Deep Convolutional Neural Network[J]. Computer Methods & Programs in Biomedicine, 2018:S0169260718301494.
[7] Wan Z, Huang J, Zhang H, Zhou H, Yang J, Zhong N. Hybrideegnet: a convolutional neural network for eeg feature learning and depression discrimination. IEEE Access 2020;8:30332–42.
[8] Avik Sarkar ,, Ankita Singh , Rakhi Chakraborty A deep learning-based comparative study to track mental depression from EEG data,Neuroscience Informatics 2022;2(4);100039.
[9] Kang M, Kwon H, Park JH, Kang S, Lee Y. Deep-asymmetry: asymmetry matrix image for deep learning method in pre-screening depression. Sensors 2020;20(22): 6526.
[10] Thoduparambil PP, Dominic A, Varghese SM. EEG-based deep learning model for the automatic detection of clinical depression. Phys Eng Sci Med 2020 Dec;43(4): 1349–60.
[11] Li X, Zhang X, Zhu J, Mao W, Sun S, Wang Z, Xia C, Hu B. Depression recognition using machine learning methods with different feature generation strategies. Artif Intell Med 2019;99:101696.