Swin Transformer Based Depression Detection Model Learning Only Single Channel EEG Signal

KEI SUZUKI[†1] MIDORI SUGAYA[†1]

Abstract: We propose a method for constructing a highly accurate depression detection model that learns only a single channel EEG signal. In recent years, in order to support diagnosis of depression, objective evaluation methods for depression have been studied. One method is based on EEG signals, which are obtained by placing channels on the scalp. In this method, multiple channels are placed on the scalp, and information from different parts of the head is trained by machine learning model to achieve highly accurate depression detection. Therefore, the depression detection methods often assume multiple channels EEG signals. However, this method has a practical problem: using multiple channels may cause a lot of fatigue for the EEG device wearer and multiple channels EEG device could be more expensive. Therefore, in order to solve these issues, purpose of this study is to realize highly accurate depression detection by analyzing only a single channel EEG signals. Then, we propose construction model method to achieve this purpose. In order to evaluate proposed construction model method, we used a public dataset containing about 60 depressed patients and healthy controls EEG signals. The EEG signals were transformed into a time series of power variation in a constant frequency band by continuous wavelet transform. The power variations were transformed into images. The images were used to fine-tune the Swin Transformer, which has been shown to be highly accurate in image classification tasks. The accuracy of this model was evaluated using Stratified Group K Fold (K=5). As a result, more than 90% was achieved in ROC-AUC metric for the binary classification of depressed patients and healthy controls. This result suggests the validity of the method used in this study. We consider the results shows that the research could make the depression detection method more practical than multiple channels methods.

Keywords: EEG, Depression, AI

1. Introduction

In recent years, the number of depression patients has been increasing[1]. This diagnostic procedures for depressed patients would be subjective: interview to patients by clinics that rely on clinicians' skills and subjectivity and patient's answers to the questionnaire that relay on patients' subjectivity. Therefore, because of these subjectivity, it has been pointed out that diagnosis may cause instability in the consistency and reliability [2]. In order to solve this problem, objective evaluating depression method have been studied[3].

Objective evaluation methods exist, such as MRI and genetic analysis[4]. However, these methods have their disadvantages. For example, high cost of equipment[4], low heritability (37%) [5], and unsuitable for routine testing[4].

In contrast to these methods, there are advantages to EEG signals obtained by contacting channels to the scalp: relatively easy obtaining, low fatigue for patients, and cost-effective, etc. [4] Therefore, objective methods of detecting depression using EEG signals are being sought. In particular, there are research that construct machine learning models learning EEG signals to detect depression[4].

Multiple channels EEG signals are often assumed to achieve high accuracy. Multiple channels are placed on the scalp, and information from different parts of the head could lead high accuracy. However, there are some issues with the multiple channels EEG device: tuning channels could increase EEG device wearer's fatigue and the multiple channels EEG devices are relatively expensive[6]. In contrast to the multiple channels, single channel EEG devices is desirable. This is because, single channel EEG could be a more practical method[7], with less EEG device wearer's fatigue and lower price.

There are studies to attempt constructing depression detection model using single channels EEG signals. Hanshu et al. constructed the model training only three channels EEG signals[6]. However, the accuracy was 78.24%, which was lower than accuracy of multiple channels EEG signals (e.g.,91.4% [7]). Thus, currently, there is no constructing model method that can achieve a high accurate learning single channels EEG signals. In particular, the method learning a single channel EEG signal is not clear.

Therefore, the purpose of this study is to construct a high accurate depression detection model using only a single channel EEG signal. To achieve this, we propose a method for constructing the depression detection model.

In this study, in order to evaluate the proposed construction model method, the model was constructed from an open dataset using the following procedure. First, the single channel EEG signal was transformed into an image by continuous wavelet transform. Second, the images were used for fine-tuning of the Swin Transformer, which has proven to be high accurate in image classification tasks. These procedures constructed a binary classification model whether the depressed patients or healthy controls. As a result, 96% was achieved in the metric of ROC-AUC with only a single channel EEG signal. This accuracy was comparable to that of previous studies[7] using 19 channels EEG signals. This suggested the superiority of this study over studies using multiple channel EEG signals. To the best of our knowledge, no one has achieved such a result.

†1 Shibaura Institute of Technology

2. Method

2.1 EEG signals

In this study, open dataset published by Mumtaz et al [8] was used. This dataset includes 64 participants EEG signals which is obtained when participants were at rest and closing eyes. The participants in this dataset were 34 depressed patients (17 women and 17 men) (age 40.3 ± 12.9) and 30 healthy controls (9 women and 21 men) (age 38.3 ± 15.6). In order to avoid any influence of any medication on the EEG signals, the EEG signal was obtained after stopping the medication for 2 weeks. The labeling of depressed patients and healthy controls were evaluated by clinicians based DSM-5 [9], the international standard for diagnosis mental disorders. A medical grade Brain Master Discovery EEG device was used to obtain the EEG signals. The sampling rate was 256Hz. Channel positions were Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2 in the international 10-20 method (Fig 1).

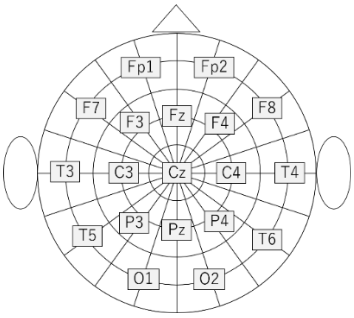

Fig 1 international 10-20 method

2.2 Constructing Dataset

In this study, explanatory variables were images and objective variables were binary variables representing depressed patients or healthy controls. The images were generated according to the following procedure.

1. EEG signals were segmented (epoching) at regular intervals.
2. Separated EEG signals(epochs) were subjected to continuous wavelet transform.
3. The transformed EEG signals were converted into images(scalograms).

In procedure 1, the window width was 4 seconds and the slide width was 0.5 seconds to separate the EEG signals. Only Fp2 channel EEG signal was separated and used in this study. In procedure 2, the continuous wavelet transforms extracted time-series power variations every 0.5 Hz between 0.5-50 Hz. The PyWavelets library [10] was used for the continuous wavelet transform. In procedure 3, the images (scalograms) were generated which the vertical axis represents frequency, the horizontal axis represents time, and the colors represent power. The power values were log-transformed and scaled 0 to 4.Fig 2 shows sample of the image.

Objective variables were generated based on the EEG device wearer the EEG signals were obtained; 1 for depressed patients and 0 for healthy controls. These procedures generated about 36,000 pieces of data.

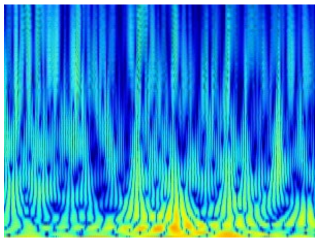

Fig 2 sample image

2.3 Constructing Model

In this study, a pre-trained Swin Transformer model [11] published by TorchVision [12] was fine-tuned to construct a depression detection model. In order to construct a binary classification model to estimate depressed patients or healthy controls, the output layer of the model was converted to a fully connected layer, making the outputs binary. Adam was used as the optimization algorithm to fine-tune the model. The learning rate was 3^{-n}. The value of n was set to optimize accuracy on validation data (n was selected in 4, 5, 6, 7, 8, or 9). As the number of epochs was counted, if there was no improvement in accuracy on the validation data, the fine-tuning was stopped (early stopping).

2.4 Model evaluation

In this study, nested cross-validation was performed to validate accuracy. First, outside of the nesting, all data were split into a mixture of training and validation data and test data. Second, inside the nesting, the mixed training and validation data were split into training and validation data. A stratified group k-fold cross-validation (SGKF) [13] (k=5) was used to split the data outside and inside the nest. This cross-validation establishes groups (in the case of this study, the groups were each participant) in the data and splits the data into some fold to avoid that the same groups' data belongs to some fold. If the participant's data were included in the training, validation, and test data, this would lead to excessively high accuracy. This cross-validation prevented this phenomenon. The Scikit-learn [13] library was used to perform this cross-validation.

3. Result and Discussion

In nested cross-validation, 96% was achieved in ROC-AUC metric. The results suggest that a highly accurate depression detection model is possible even using only a single channel EEG signals. Table 1 shows a comparison of the accuracy of the model with that of the previous studies by Seal et al. [7], [14]. In order to avoid excessively high accuracy, these previous studies used the cross validation to prevent the same participant's data were included in the training and test data. Note that [7][14] represent the results using 19 channel EEG signals and these preprocessing of EEG signals is different.

As shown in Table 1, the ROC-AUC metric was 96%, which is the same accuracy as that of a related study [7]. However, this study used only a single channel EEG signal, while previous study used 19 channels EEG signals. In other words, this study achieved high accuracy using only a single channel EEG signal, suggesting the superiority of our method. If high accuracy can be achieved using only a single channel EEG signal, this could lead to more practice: reducing patient fatigue and the price of the device.

Table 1 accuracy of this study and previous study

Ref	Channel	Pre-cision	recall	F1	Acc-uracy	ROC-AUC
This study	Only Fp2	89%	88%	87%	88%	96%
[7]	19 channels	92%	89%	90%	91%	96%
[14]	19 channels	77%	79%	75%	77%	N/A

4. Summary

In this study, we aimed to realize high accurate depression detection model using only a single channel EEG signal and proposed a method for constructing the model to achieve this.

The results suggest that a high accurate depression detection model could be constructed for the binary classification of depressed patients and healthy controls in a public dataset. However, it has not been evaluated some dataset. Therefore, we plan to evaluate this construction model method on other datasets in the future to verify its generality.

Reference

[1] A. Safayari and H. Bolhasani, "Depression diagnosis by deep learning using EEG signals: A systematic review," *Medicine in Novel Technology and Devices*, vol. 12, p. 100102, Dec. 2021.

[2] I. Shin, "Seishinigaku ni okeru AI Katuyou no Genjo, Kadai, soshite Kanousei(Current Status, Challenges, and Potential of AI Application in Psychiatry)," *Proceedings of the National Conference of the Japanese Society for Artificial Intelligence*, vol. JSAI2019, p. 2N5J1303-2N5J1303, 2019.

[3] M. de Bardeci, C. T. Ip, and S. Olbrich, "Deep learning applied to electroencephalogram data in mental disorders: A systematic review," *Biol. Psychol.*, vol. 162, p. 108117, May 2021.

[4] A. Dev *et al.*, "Exploration of EEG-Based Depression Biomarkers Identification Techniques and Their Applications: A Systematic Review," *IEEE Access*, vol. 10, pp. 16756–16781, undefined 2022.

[5] R. S. Duman, G. Sanacora, and J. H. Krystal, "Altered Connectivity in Depression: GABA and Glutamate Neurotransmitter Deficits and Reversal by Novel Treatments," *Neuron*, vol. 102, no. 1, pp. 75–90, Apr. 2019.

[6] H. Cai, X. Sha, X. Han, S. Wei, and B. Hu, "Pervasive EEG diagnosis of depression using Deep Belief Network with three-electrodes EEG collector," in *2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2016, pp. 1239–1246.

[7] A. Seal, R. Bajpai, J. Agnihotri, A. Yazidi, E. Herrera-Viedma, and O. Krejcar, "DeprNet: A Deep Convolution Neural Network Framework for Detecting Depression Using EEG," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–13, 2021.

[8] W. Mumtaz, "MDD Patients and Healthy Controls EEG Data (New)," 11 2016.

[9] D. A. Regier *et al.*, "DSM-5 field trials in the United States and Canada, Part II: test-retest reliability of selected categorical diagnoses," *Am. J. Psychiatry*, vol. 170, no. 1, pp. 59–70, Jan. 2013.

[10] G. Lee, R. Gommers, F. Waselewski, K. Wohlfahrt, and A. O'Leary, "PyWavelets: A Python package for wavelet analysis," *J. Open Source Softw.*, vol. 4, no. 36, p. 1237, Apr. 2019.

[11] "swin_v2_t — Torchvision 0.15 documentation." [Online]. Available: https://pytorch.org/vision/stable/models/generated/torchvision.models.swin_v2_t.html. [Accessed: 17-Sep-2023].

[12] T. Maintainers and Contributors, *TorchVision: PyTorch's Computer Vision library*. GitHub, 2016.

[13] F. Pedregosa *et al.*, "Scikit-learn: Machine Learning in Python," *J. Mach. Learn. Res.*, vol. 12, pp. 2825–2830, 2011.

[14] A. Seal *et al.*, "Benchmarks for machine learning in depression discrimination using electroencephalography signals," *Applied Intelligence*, Sep. 2022.