2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

EEG-based Major Depressive Disorder Detection Using Data Mining Techniques*

Danqi Hong[1], Xingxian Huang[2], Yingshan Shen[1], Haibo Yu[2], Xiaomao Fan[1,†], Gansen Zhao[1], Wenbin Lei[3] and Haoyu Luo[1]

Abstract— Major depressive disorder (MDD) is a common mental illness characterized by a persistent feeling of low mood, sadness, fatigue, despair, etc.. In a serious case, patients with MDD may have suicidal thoughts or even suicidal behaviors. In clinical practice, a widely used method of MDD detection is based on a professional rating scale. However, the scale-based diagnostic method is highly subjective, and requires a professional assessment from a trained staff. In this work, 92 participants were recruited to collect EEG signals in the Shenzhen Traditional Chinese Medicine Hospital, assessing MDD severity with the HAMD-17 rating scale by a trained physician. Two data mining methods of logistic regression (LR) and support vector machine (SVM) with derived EEG-based beta-alpha-ratio features, namely LR-DF and SVM-DF, are employed to screen out patients with MDD. Experimental results show that the presented the LR-DF and SVM-DF achieved $F1$ scores of 0.76 ± 0.30 and 0.92 ± 0.18, respectively, which have obvious superiority to the LR and SVM without derived EEG-based beta-alpha-ratio features.

Clinical relevance— The performance of data mining methods of LR and SVM to detect MDD are greatly improved with the derived EEG-based beta-alpha-ratio features. Especially, the SVM-DF with the best performance for MDD detection can be potentially deployed in a medical decision support system to aid physicians to screen out patients with MDD and intervene in advance to prevent malignant events.

I. INTRODUCTION

The major depressive disorder (MDD) has become one of the three major diseases worldwide, and its prevalence is still on the rise [1]. It severely affects the patient's work, study, and everyday social life. Currently, the most used diagnostic methods for MDD are mainly depended on professional depression rating scales such as the 17-item Hamilton rating scale (HAMD-17) [2]. However, the scale-based diagnostic methods are subjective and highly relied on a trained physician. It is difficult for medical providers like community and township hospitals to conduct MDD assessments without a trained physicians. Herewith, it has great significance for developing an automatic MDD detection method with data mining techniques to aid physicians to screen out patients with MDD and intervene in advance.

EEG signals are also a widely used tool to diagnose mental disorders [5], [7], which are formed by the summation of postsynaptic potentials occurring simultaneously in many neurons in the brain, divided into delta, theta, alpha, beta, and gamma bands. EEG signals also can reflect the electrophysiological activity of brain nerve cells to a certain extent [3], thus widely being used in clinical practice applications. Bruder et al.[4] found that depressed and non-depressed individuals exhibited different EEG activity, which demonstrated that using EEG signals to identify MDD is feasible. Thibodeau et al. [5] described the specific patterns of association between EEG signals and depression comprehensively. Hughes et al. [6] discovered some abnormal brain electrical activity displayed by patients with mood disorders. Hosseinifard et al. [8] mixed multiple machine learning algorithms to achieve a classification accuracy of 83.3%. Bachmann et al. [9] used SASI(Spectral Asymmetry Index Method) and HFD (Higuchi's Fractal Dimension Method) , achieving 85% classification accuracy in both groups. Sang-Choong et al.[7] found a significant negative correlation between MDD and frequency band of beta and gamma. Cai H et al. [10] used a pervasive prefrontal-lobe three-electrode EEG system at Fp1, Fp2, and Fpz electrode sites to collect EEG signals and achieved MDD detection accuracy of 79.27% . Mahato et al. [11] extracted features from EEG signals and achieved the highest MDD detection accuracy of 88.33% . Even though aforementioned MDD detection methods obtained promising results, it is still on far for real clinical practice.

In this work, first of all, two kinds of EEG-based features are derived from alpha and beta frequency band, namely beta-alpha-ratio features. Subsequently, two kinds of data mining methods of logistic regression (LR) and support vector machine (SVM) are employed to detect MDD with EEG-based beta-alpha-ratio features.

*This work is supported in part by National Key R&D Program of China(No.2018YFB1404402), Guangdong Science and Technology Fund(No.2019B010137003, No.2018A07071702, No.201804010314), Guangzhou Science & Technology Fund (No.201804010314), and VeChain Foundation(No.SCNU-2018-01).

[1]Danqi Hong, Yingshan Shen, Xiaomao Fan, Gansen Zhao, and Haoyu Luo are with the School of Computer Science, South China Normal University, Guangzhou 510631, China. (1129969314@qq.com; shenys@m.scnu.edu.cn; xmfan@scnu.edu.cn; gzhao@m.scnu.edu.cn; hluo@m.scnu.edu.cn)

[2]Xingxian Huang and Haibo Yu are with the Department of Acupuncture and Moxibustion, Shenzhen Traditional Chinese Medicine Hospital, Shenzhen 518033, China. (732545909@qq.com; 13603066098@163.com)

[3]Wenbin Lei is with the Otorhinolaryngology Hospital, the First Affiliated Hospital, Sun Yat-sen University, Guangzhou 510080, China. (leiwb@mail.sysu.edu.cn)

[†]Xiaomao Fan is the corresponding author

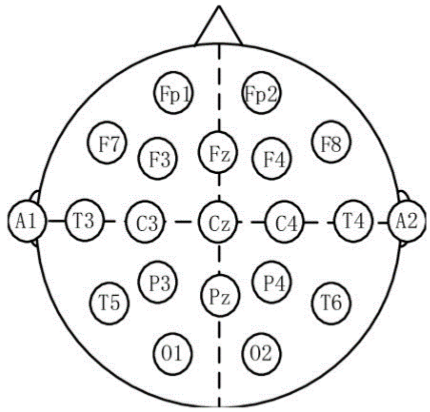

Fig. 1. 10-20 System of EEG electrode placement

Experimental results show that LR and SVM with derived EEG-based beta-alpha-ratio features can achieve promising performance, which have obvious superiority to that without derived EEG-based beta-alpha-ratio features.

II. Methods

A. Data acquisition

92 participants, who had been in more than two weeks of mental disorder illness duration, conscious, and did not get aphasia or mental retardation, were recruited from the Shenzhen Traditional Chinese Hospital with signed informed consent form (IRB Number of 2017-8) to collect EEG signals and HAMD-17 rating scores. According to the HAMD-17 criteria described in subsequent section, 34 patients are with MDD versus 58 patients are without MDD. Each participant has one entry, totally 92 entries are collected. We used a 10-20 System of electrode placement to place scalp electrodes, as shown in Fig. 1, and acquired smooth EEG signals with the Nerron-spectrum-5 EEG device for 30 seconds under closed-eye conditions. The Nerron-spectrum-5 EEG device has totally 19 channel leads, which are FP1-A1, FP2-A2, F3-A1, F4-A2, FZ-A2, C3-A1, C4-A2, CZ-A1, P3-A1, P4-A2, PZ-A2, O1-A1, O2-A2, F7-A1, F8-A2, T3-A1, T4-A2, T5-A1, and T6-A2. Each channel-lead calculates EEG-related features automatically based on rhythm waveform amplitude indexes and rhythm index information in terms of frequency bands of delta, theta, alpha, and beta. Therefore, 154 EEG-related features are obtained for each participant. With additional demographic features of gender and age, there are totally 156 features as base features for subsequent processing and analysis.

B. Data preprocessing

According to previous studies [12], there exist a close relationship between a beta-alpha ratio and depressive performance, which is associated with EEG frequency bands of alpha and beta. In this work, the EEG-related features are derived by calculating the ratio between beta band and alpha band on each channel-lead in terms of EEG waveform amplitude indexes and rhythm index information, which are defined to be:

$$A_r = \frac{A_\beta}{A_\alpha} \tag{1}$$

$$I_r = \frac{I_\beta}{I_\alpha} \tag{2}$$

where features of A_r and I_r are derived from extracted features of EEG waveform amplitude indexes and rhythm index information, respectively. A_β and A_α are features from EEG waveform amplitude indexes on beta and alpha frequency bands. I_β and I_α are features from EEG rhythm index information on beta and alpha frequency bands. A total of 40 EEG-based beta-alpha-ratio features are derived. For reference labels used in this work, patients are divided into two groups in response to MDD severity based on HAMD-17 scores. One group with HAMD-17 scores greater than 17 are defined to be MDD, labeled as 1. Another group with HAMD-17 scores no more than 17 are defined to be mild depression or not with depression, labeled as 0 for LR-related models but -1 for SVM-related models. In order to minimize the scale difference among features, we standardized the data on each feature using z-score standardization for numerical data to shift different features distributions to the uniform distribution. In addition, for the non-numerical feature of gender, male is marked to be 1 and female is to be 0.

High dimension of features would introduce too much noise into data mining models, leading to poor performance for MDD detection. To solve this problem, the recursive feature elimination (RFE) method were used [15]. Its main idea is that after the model training, weight importance of all features is calculated and the feature with the best importance is selected. The above process is repeated until the selected features can achieve the optimal performance for MDD detection. After RFE feature selection process, there are 45 and 26 selected features as inputs for LR and SVM models, respectively.

C. Data mining methods

1) LR method: LR [13] is a widely used classification model, which utilizes Sigmoid function as a posteriori probability distribution function to classify the input data set. It can be used for both binary classification problems and multi-classification problems. The LR is with merits of less computation, interpretability, and easy implementation. For the MDD detection problem, it is a binary classification to discriminate patients with MDD or not.

2) SVM method: SVM [14] is a kind of generalized linear classifier that classifies data in a supervised way, and its decision boundary is the maximum-margin hyperplane. Owing to the merit of human-interpretability, the SVM used in this work is with a linear kernel function.

TABLE I

Classification performance for MDD detection

Model	Precision	Recall	Accuracy	$F1$ score
LR	0.71±0.29	0.65±0.31	0.78±0.14	0.65±0.28
SVM	0.83±0.15	0.83±0.21	0.86±0.08	0.80±0.13
LR-DF	0.80±0.31	0.73±0.30	0.86±0.15	0.76±0.30
SVM-DF	0.95±0.15	0.90±0.21	0.96±0.10	0.92±0.18

III. Results and discussion

A. Environment

The presented models were implemented with python 3.7.0 and sklearn 0.22.2. All experiments were trained and tested on a server equipped with a Intel i5-8265U CPU and 8.0 GB memory.

B. Classification performance

In this work, tenfold cross-validation was implemented to evaluate the performance of LR and SVM models with metrics of precision, recall, accuracy, and $F1$ score. As shown in Table I, it is observed that the presented SVM and LR with derived EEG-based beta-alpha-ration features, namely SVM-DF and LR-DF, have superiority to SVM and LR, respectively. The LR-DF obtained 0.80±0.31, 0.73±0.30, 0.86±0.15, and 0.76±0.30 in terms of precision, recall, accuracy, and $F1$ score, respectively. The MDD detection performance of the LR-DF is greater than that of the LR, over at least 8.0 %. The SVM-DF achieved 0.95 ± 0.15, 0.90 ± 0.21, 0.96 ± 0.10, and 0.92 ± 0.18 in terms of precision, recall, accuracy, and $F1$ score, respectively. The MDD detection performance of the SVM-DF is greater than that of the SVM, over at least 7.0 %. It means that the derived EEG-based beta-alpha-ratio features can greatly improve LR and SVM models' performance for MDD detection. Among the LR-DF and SVM-DF, the SVM-DF with much more capability of processing small dataset has the superiority to the LR-DF for MDD detection. The presented SVM-DF with promising performance can be potentially deployed into a medical decision support system to aid physicians to screen out patients with MDD precisely.

C. Discussion

In this work, we proposed a method to screen out MDD patients using features derived from EEG signals. A linear kernel SVM model was used for classification, which is less sensitive to distributions of classes in feature space. Thus the model is more adaptable to real clinical practice, where the patients' information can be very dispersed. As the dataset used in this work is rather small and with high dimensionality, it is more appropriate to use a linear kernel function than a Gaussian kernel function.

It is well known to us that feature selection is a critical step for data mining methods, particularly on dataset with high dimensions. As shown in Fig. 2, the SVM-DF performance for MDD detection varies greatly in

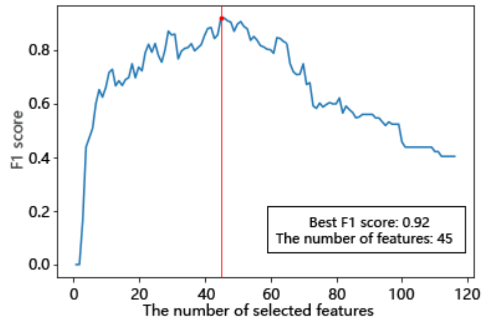

Fig. 2. SVM-DF: $F1$ score versus the number of selected features

response to the number for selected features as input. It is noted that the SVM-DF obtains its best performance for MDD detection when the number of selected features with the RFE is 45, the description of which is shown in the Table II. What's more, a large proportion of the derived EEG-based beta-alpha-ratio features are selected after the RFE step, which indicates that the derived EEG-based beta-alpha-ratio features are critical for data mining methods for the task of MDD detection.

Meanwhile, the model weight importance of selected features obtained in the SVM-DF is shown in Fig. 3. The coefficients of the SVM-DF with a linear kernel can be interpreted as indicators of feature importance. The selected features of I_α^ϑ, A_r^ϑ, A_θ^ϑ, I_r^ϕ, A_δ^ϕ, A_α^ι, I_α^κ, I_r^κ, A_r^κ, I_α^ρ, I_r^χ, A_θ^χ, I_r^λ, A_δ^σ, I_θ^σ, I_θ^ζ, I_α^ν, I_β^ν, A_θ^ν, and A_α^ς are with positive weight importance, while remained selected features are with negative weight importance.

IV. Conclusion

In this work, two popular data mining methods of LR and SVM for MDD detection are presented. Experimental results show that the derived EEG-based beta-alpha-ratio features can greatly improve MDD detection performance for the LR and SVM, which achieved the best performance of 0.95 ± 0.15, 0.90 ± 0.21, 0.96 ± 0.10, and 0.92±0.18 in terms of precision, recall, accuracy, and $F1$ score, respectively. Compared with the LR and SVM without the additional derived EEG-based beta-alpha-ratio features, both of the LR-DF and SVM-DF have much more power in MDD detection than the LR and SVM with a big margin. The presented MDD detection model with promising performance can be potentially deployed into a medical decision support system to help physicians to screen out patients with MDD and intervene in advance to avoid malignant events.

References

[1] S. L. James, D. Abate, K. H. Abate, S. M. Abay, C. Abbafati, N. Abbasi, H. Abbastabar, F. Abd-Allah, J. Abdela, A. Abdelalim 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," The Lancet, vol. 392, no. 10159, pp. 1789–1858, 2018.

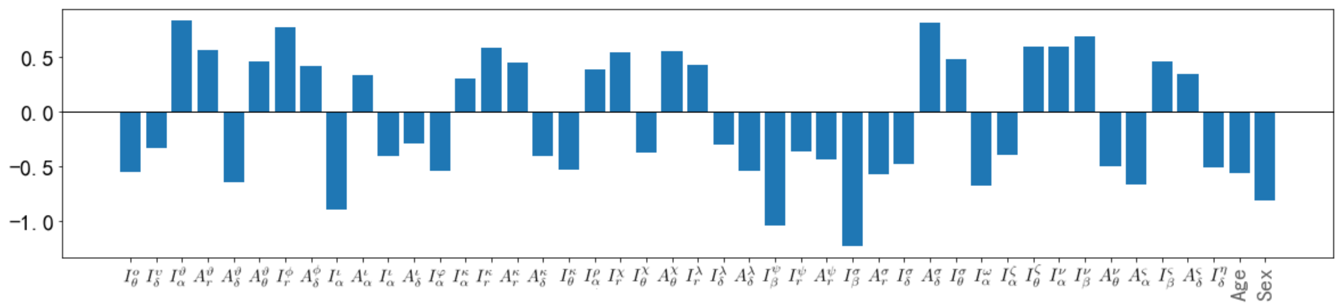

Fig. 3. Weight importance of the SVM-DF on selected features.

TABLE II

Features and descriptions

Feature	Description
I_{θ}^{o}	C3-A1 rhythm index on theta band
I_{δ}^{υ}	C4-A2 rhythm index on delta band
I_{α}^{ϑ}	CZ-A1 rhythm index on alpha band
A_{r}^{ϑ}	CZ-A1 amplitude index ratio on beta/alpha band
A_{δ}^{ϑ}	CZ-A1 amplitude index on delta band
A_{θ}^{ϑ}	CZ-A1 rhythm index on theta band
I_{r}^{ϕ}	F4-A2 rhythm index ratio on beta/alpha band
A_{δ}^{ϕ}	F4-A2 amplitude index on delta band
I_{α}^{ι}	F7-A1 rhythm index on alpha band
A_{α}^{ι}	F7-A1 amplitude index on alpha band
I_{α}^{ι}	F7-A1 rhythm index on beta band
A_{δ}^{ι}	F7-A1 rhythm index on delta band
I_{α}^{φ}	FP1-A1 rhythm index on alpha band
I_{α}^{κ}	FP2-A2 rhythm index on alpha band
I_{r}^{κ}	FP2-A2 rhythm index ratio on beta/alpha band
A_{r}^{κ}	FP2-A2 amplitude index ratio on beta/alpha band
A_{δ}^{κ}	FP2-A2 amplitude index on delta band
I_{θ}^{κ}	FP2-A2 rhythm index on theta band
I_{α}^{ρ}	FZ-A2 rhythm index on alpha band
I_{r}^{χ}	O1-A1 rhythm index ratio on beta/alpha band
I_{θ}^{χ}	O1-A1 rhythm index on theta band
A_{θ}^{χ}	O1-A1 amplitude index on theta band
I_{r}^{λ}	O2-A2 rhythm index ratio on beta/alpha band
I_{δ}^{λ}	O2-A2 rhythm index on delta band
A_{δ}^{λ}	O2-A2 amplitude index on delta band
I_{β}^{ψ}	P3-A1 rhythm index on beta band
I_{r}^{ψ}	P3-A1 rhythm index ratio on beta/alpha band
A_{r}^{ψ}	P3-A1 amplitude index ratio on beta/alpha band
I_{β}^{σ}	P4-A2 rhythm index on beta band
A_{r}^{σ}	P4-A2 amplitude index ratio on beta/alpha band
I_{δ}^{σ}	P4-A2 rhythm index on delta band
A_{δ}^{σ}	P4-A2 amplitude index on delta band
I_{θ}^{σ}	P4-A2 rhythm index on theta band
I_{α}^{ω}	PZ-A2 rhythm index on alpha band
I_{α}^{ζ}	T3-A1 rhythm index on alpha band
I_{θ}^{ζ}	T3-A1 rhythm index on theta band
I_{α}^{ν}	T4-A2 rhythm index on alpha band
I_{β}^{ν}	T4-A2 rhythm index on beta band
A_{θ}^{ν}	T4-A2 amplitude index on theta band
A_{α}^{ς}	T5-A1 amplitude index on alpha band
I_{β}^{ς}	T5-A1 rhythm index on beta band
A_{δ}^{ς}	T5-A1 amplitude index on delta band
I_{δ}^{η}	T6-A2 rhythm index on delta band

[2] M. Hamilton and W. Guy, "Hamilton depression scale," Group, vol. 1, p. 4, 1976.

[3] A. Subasi and E. Ercelebi, "Classification of eeg signals using neural network and logistic regression," Computer methods and programs in biomedicine, vol. 78, no. 2, pp. 87–99, 2005.

[4] G. E. Bruder, R. Fong, C. E. Tenke, P. Leite, J. P. Towey, J. E. Stewart, P. J. McGrath, and F. M. Quitkin, "Regional brain asymmetries in major depression with or without an anxiety disorder: a quantitative electroencephalographic study," Biological psychiatry, vol. 41, no. 9, pp. 939–948, 1997.

[5] R. Thibodeau, R. S. Jorgensen, and S. Kim, "Depression, anxiety, and resting frontal eeg asymmetry: a meta-analytic review." Journal of abnormal psychology, vol. 115, no. 4, p. 715, 2006.

[6] J. R. Hughes and E. R. John, "Conventional and quantitative electroencephalography in psychiatry," The Journal of Neuropsychiatry and Clinical Neurosciences, vol. 11, no. 2, pp. 190–208, 1999.

[7] S.-C. Roh, E.-J. Park, M. Shim, and S.-H. Lee, "Eeg beta and low gamma power correlates with inattention in patients with major depressive disorder," Journal of affective disorders, vol. 204, pp. 124–130, 2016.

[8] B. Hosseinifard, M. H. Moradi, and R. Rostami, "Classifying depression patients and normal subjects using machine learning techniques and nonlinear features from eeg signal," Computer methods and programs in biomedicine, vol. 109, no. 3, pp. 339–345, 2013.

[9] M. Bachmann, J. Lass, A. Suhhova, and H. Hinrikus, "Spectral asymmetry and higuchi's fractal dimension measures of depression electroencephalogram," Computational and mathematical methods in medicine, vol. 2013, 2013.

[10] H. Cai, J. Han, Y. Chen, X. Sha, Z. Wang, B. Hu, J. Yang, L. Feng, Z. Ding, Y. Chen et al., "A pervasive approach to eeg-based depression detection," Complexity, vol. 2018, 2018.

[11] S. Mahato and S. Paul, "Classification of depression patients and normal subjects based on electroencephalogram (eeg) signal using alpha power and theta asymmetry," Journal of medical systems, vol. 44, no. 1, pp. 1–8, 2020.

[12] P. Rajpurkar, J. Yang, N. Dass, V. Vale, A. S. Keller, J. Irvin, Z. Taylor, S. Basu, A. Ng, and L. M. Williams, "Evaluation of a machine learning model based on pretreatment symptoms and electroencephalographic features to predict outcomes of antidepressant treatment in adults with depression: a prespecified secondary analysis of a randomized clinical trial," JAMA network open, vol. 3, no. 6, pp. e206 653–e206 653, 2020.

[13] D. R. Cox, "The regression analysis of binary sequences," Journal of the Royal Statistical Society: Series B (Methodological), vol. 20, no. 2, pp. 215–232, 1958.

[14] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," in Proceedings of the fifth annual workshop on Computational learning theory, 1992, pp. 144–152.

[15] I. Guyon, J. Weston, S. Barnhill, and V. Vapnik, "Gene selection for cancer classification using support vector machines," Machine learning, vol. 46, no. 1, pp. 389–422, 2002.