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Detecting Depression Using Single-Channel EEG and Graph Methods

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Abstract: Objective: This paper applies graph methods to distinguish major depression disorder (MDD) and healthy (H) subjects using the graph features of single-channel electroencephalogram (EEG) signals. Methods: Four network features—graph entropy, mean degree, degree two, and degree three—were extracted from the 19-channel EEG signals of 64 subjects (26 females and 38 males), and then these features were forwarded to a support vector machine to conduct depression classification based on the eyes-open and eyes-closed statuses, respectively. Results: Statistical analysis showed that graph features with degree of two and three, the graph entropy of MDD was significantly lower than that for H ($p < 0.0001$). Additionally, the accuracy of detecting MDD using single-channel T4 EEG with leave-one-out cross-validation from H was 89.2% and 92.0% for the eyes-open and eyes-closed statuses, respectively. Conclusion: This study shows that the graph features of a short-term EEG can help assess and evaluate MDD. Thus, single-channel EEG signals can be used to detect depression in subjects. Significance: Graph feature analysis discovered that MDD is more related to the temporal lobe than the frontal lobe.

Keywords: mental health; classification; isolate nodes; graph entropy; mean degree

MSC: 05C90

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1. Introduction

Depression (MDD) is one of the most common threats to mental health globally. According to the WHO, about 3.8% of the global population suffers from depression [1]. It is a heavier burden on patients' life if it happens recurrently with a more severe intensity. In the worst case, it can lead to suicidal tendencies, resulting in life loss. However, more than 75% of the population with MDD in developing countries receives no treatment due to misdiagnosis, although many psychological treatments and medications are effective for depression [1]. Thus, an accurate, cost-effective, and convenient method for the diagnosis of depression is crucial for patients to receive appropriate treatment options.

Currently, the diagnosis of depression is based on psychiatric evaluations, including self-reports and some questionnaires, such as the Beck depression inventory [2] and Hamilton Depression Rating Scale [3]. These traditional methods are conducted by psychiatrists, depending on their professional experience, which may be affected by subjective judgments, as blind reviews are seldom performed due to cost and time constraints. In recent years, some more objective methods using neurological data have been introduced. Among those neurological measurements, the electroencephalogram (EEG) is advantageous as it is nonintrusive and economical. Many machine learning methods have been used to classify depression using EEG data [4–6]. A logistic regression outperforms other classifiers and achieves 90% accuracy using nonlinear features from the 4-band EEG signals [4]. The theta wave is potentially powerful in predicting depression and provides an accuracy of 86.98% by combining the theta wave with other features [5]. The convolutional neural network is also applied to detect depression, with accuracies of 93.5% and 96.0% using EGG signals from the left and right hemispheres, respectively [6]. The above studies are based on multi-channel EEG signals, while some note that single-channel EEG signals can provide a same-level classification result [7,8]. Wan et al. [7] obtained an accuracy of 94% using the nonlinear feature set of the Fp1 channel. However, a recent study [9] showed that EEG sensors in the temporal area performed better in the classification results than those in other areas.

This paper investigates depression classification based on the eyes-closed and eyes-open statuses using graph features with a support vector machine. An oblique visibility graph method is applied to extract the four graph features: mean degree (MD), graph entropy (GE), and degree equal to two and three. The eye-open and eye-closed EEGs will be investigated independently. All extracted features are forwarded into a support vector machine classifier to distinguish the MDD participants from the healthy ones. This work's outcome is determining which channel is suitable for single-channel EEG according to the data used in this paper. The proposed method would provide versatility for use in remote hospital situations.

The rest of the paper is organized as follows. Section 2 presents the overall workflow and datasets used in this study and describes the methodology. Section 3 provides the experimental results. Section 4 discusses the findings and compares the proposed method with some existing works, and the conclusion is given in Section 5.

2. Datasets and Methodology

As shown in Figure 1, the proposed EEG-based depression detection method can be summarized as follows:

- Each EEG segment is mapped onto oblique visibility graphs (OVGs);
- Four features—the mean degree (MD), graph entropy (GE), and degree equaling two and three—are extracted from each OVG;
- All extracted graph features are forwarded into an SVM classifier to identify the MDD and healthy subjects;
- Finally, leave-one-out cross-validation is applied to evaluate the performance of the proposed method.

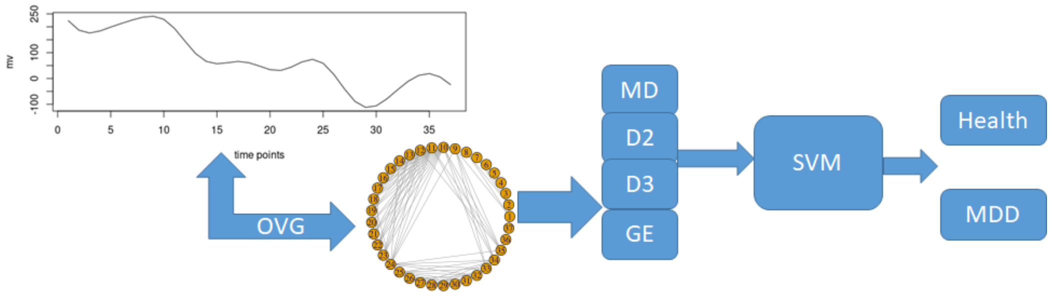

Figure 1. The workflow of the depression classification with EEG signal data, where GE = graph entropy, MD = mean degree, D2 = degree of 2, D3 = degree of 3, GE = graph entropy, and SVM = support vector machine.

2.1. Depression EEG Database

In this study, the EEG signals of 34 MDD and 30 healthy subjects under resting states were obtained from an open-source database collected by Aamir Saeed Malik of the Petronas University of Technology in Malaysia [10]. With the left ear (A1) as a reference, 19 channels (Fp1, F3, C3, P3, O1, F7, T3, T5, Fz, Fp2, F4, C4, P4, O2, F8, T4, T6, Cz, and Pz) of EEG data were recorded using the Brain Master Discovery EEG device. Each recording was between 3 and 8 minutes with the eyes open and closed. There were 34 MDD subjects (17 males and 17 females) and 30 healthy volunteers (21 males and 9 females). The sampling rate of the EEG signals was 256 Hz with a 50-Hz notch and 0.5–70-Hz bandpass filter by the Discovery EEG device. The EEG was recorded in 2013. The scope of the paper was restricted to the examination of the first 3 minutes of EEG signals from all records. Figure 2 shows a healthy subject and an MDD subject on FP1 during the eyes-closed status.

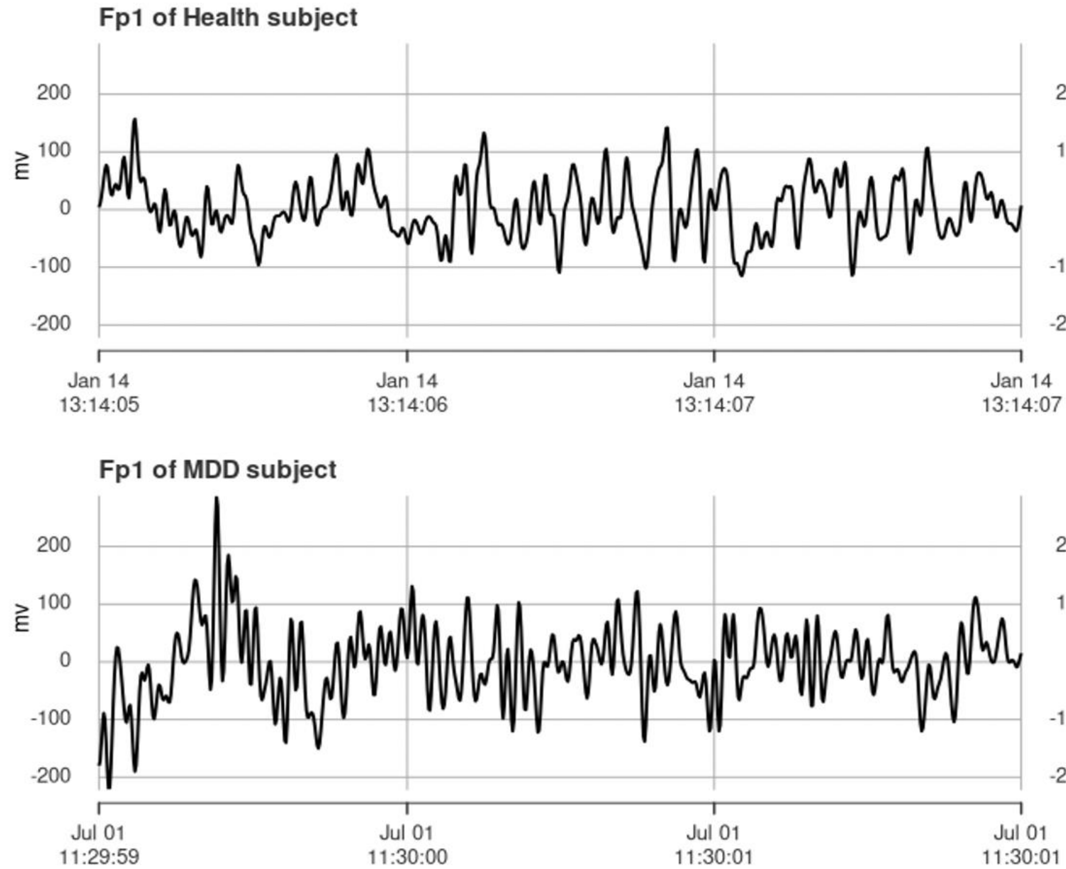

Figure 2. EEG signals of Fp1 channel from two subjects—depressed (MDD) and healthy subject—over about 3 minutes.

2.2. Oblique Visibility Graph

An oblique visibility graph (OVG) is a kind of complex network, proposed as a different visibility graph by Zhu et al. [11]. An OVG is a mapping of a time series based on its geometric visibility features. This method has also been applied to study sleep ECG signals for the aging process [12] and cognitive load identification [13]. However, OVG-based methods have not yet been used to analyze and classify depression EEGs.

Usually, a time series $\{x_i\}_{(i=1,\ldots,n)}$ is mapped onto a graph G (V, E), where a time point x_i is mapped onto a node $v \in V$. The edge relation between any two points $\left(x_i, x_j\right)$ exists if and only if

$$\forall k \in (i,j); \frac{\left(x_j - x_k\right)}{j-k} > \frac{\left(x_j - x_i\right)}{j-i} \wedge \left(x_k \geq x_i \vee x_k \geq x_j\right) \wedge (j - i \neq 1) \quad (1)$$

Figure 3 shows an OVG associated with a time series collected from a depressed subject (ID: MDD S3 EC) recorded in the EEG database. The number of time points in Figure 3a is 37. Node 3 can be obliquely seen from node 1 or 5, but it is not visible from node 2 or 4. Thus, an edge is connected between nodes 1 and 3 and not between nodes 2 and 4.

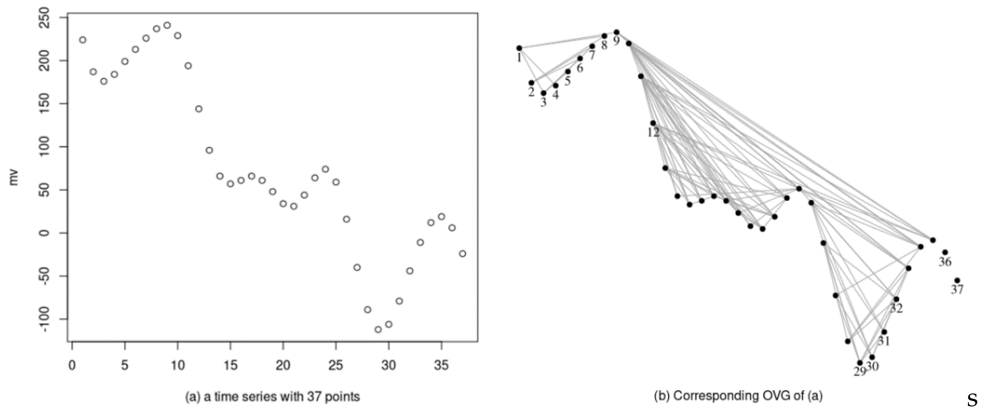

Figure 3. (**a**) An EEG times series and (**b**) its oblique visibility graph (OVG).

2.3. Degrees and Level Nodes

In a complex network, the node degree is one of the basic characteristics of graphs. The degree d_i f node v_i is the number of edges from v_i. The average degree $\bar{d}$ of a graph G with n nodes is defined as follows:

$$\bar{d} = \frac{1}{n}\sum_{j=1}^{n} d_j \tag{2}$$

Those nodes having zero degrees are named isolated nodes in this paper. For example, in Figure 3b, the last node (d_37 = 0) is isolated. These values of a degree equaling one and isolated nodes were not used in this paper, as they also happened at the end of the time series, where the degree equaling two is named degree 2 and the degree equaling three is named degree 3. Node 8 is a degree 2 node in Figure 3b. Unlike other time-complex network method applications, the features of node degrees 2 and 3 were used as the primary application methods for EEG processing in this research.

2.4. Graph Entropy

Graph entropies have been applied efficiently for alcoholism EEG identification [14,15]. The graph entropy *GE* of the degree distribution *p(i)* is defined as follows:

$$\overline{GE} = -\sum_{i=1}^{n} \big(p(i)\log\big(p(i)\big)\big) \tag{3}$$

where *p(i)* is the degree distribution of the degree *i* in the graph *G*. The degree distribution describes the probability of having a number of nodes with a degree *i*.

2.5. Support Machine Vector

To identify depressed subjects and healthy subjects, a support vector machine (SVM) algorithm was used to conduct binary classifications. SVMs have been successfully used to classify graph features associated with alcoholics [14], depression EEGs [9], and sleep EEG signals [9,11]. They perform linear space discrimination and nonlinear classification by choosing different kernel functions, which can be linear, polynomial kernel, radial basis functions (RBF), or sigmoid functions. An SVM has two hyperparameters to tune: the cost C and gamma δ. A grid search was used to estimate C and δ to obtain the optimal performance [16]. The former (C) took care of regularization in the model. The parameter comes from the RBF kernel and intuitively represents the influence of each data point on the model prediction [17]. In this paper, the SVM algorithm with an RBF kernel was implemented in the R package kernlab [18]. When SVM tuning was not considered, C and δ for the RBF kernel of the SVM were fixed to 20 and 0.78, respectively.

2.6. Performance Measures

To evaluate the performance of the proposed algorithm in this paper, the accuracy, sensitivity, and specificity were assessed for two-group classification. These parameters are defined below:

$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FN}) \tag{4}$$

$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP}) \tag{5}$$

$$\text{Accuracy} = (\text{TN} + \text{TP})/(\text{TN} + \text{TP} + \text{FN} + \text{FP}) \tag{6}$$

where TP is true positive, TN is true negative, FP is false positive, and FN is false negative. Regarding the three-group classification, we defined the accuracy as all true positive values divided by all testing data.

2.7. Preprocessing and Normalization

It can be noticed that the length of the EEG recording for each subject was not the same. Some records were more than 8 min, and others were only 3 min. Thus, all EEG signals were examined for the first 3 minutes for analysis and classification.

In addition, degree 2 and degree 3 were divided by the length of the input EEG points, which could be normalized in roughly 0–3 ranges.

3. Results

We provide the experimental results and their interpretation in the following three subsections.

3.1. Statistical Analysis Features from the Three Groups

To evaluate different graph features from the three group subjects, Figure 4 shows the statistical result plots on D2 from six channels: Fp1, Fp2, T3, T4, Fz, and Cz. It was found that the MDD patients had lower D2 values than the healthy people in all six channels for the both eyes-open and eyes-closed statuses.

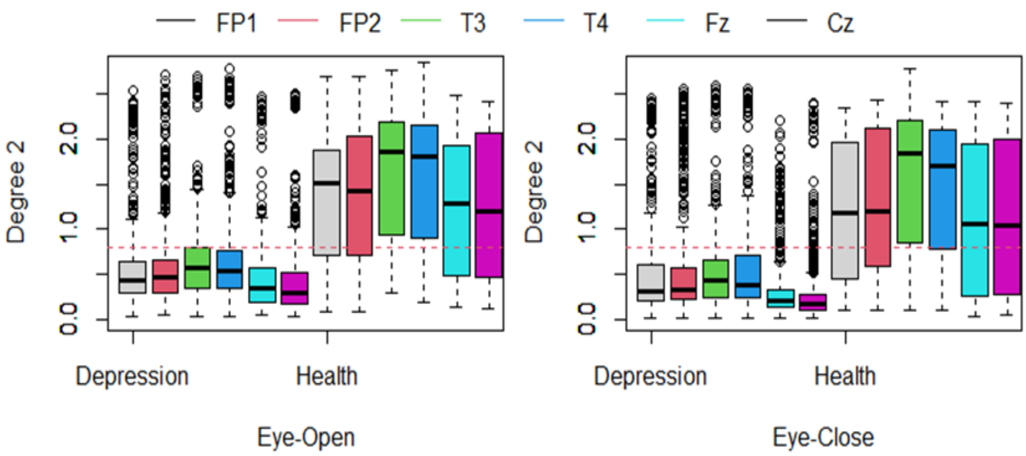

Figure 4. Feature D2 on channels Fp1 (black color), Fp2 (red color), T3 (green color), T4 (blue color), Fz (cyan-blue color), and Cz (fuchsia color), where the depression group has lower D2 values than healthy subjects for both eyes-closed and eyes-open statuses.

Two statistical tests were conducted to check the difference between the eyes-closed and eyes-open statuses for the depressed and healthy subjects. First, Shapiro–Wilk tests showed that the 19-channel OVG EEG did not meet the normal distributions. Then, nonparametric Wilcoxon tests were applied to compare the differences of the eyes-closed and eyes-open differences between the healthy and MDD group from the 19 channels with degrees equaling 2, as shown in Table 1.

Table 1. The Wilcoxon test results for eyes-closed and eyes-open statuses between depressed and healthy subjects at graph degree 2 (p values).

Channel (Left)	Eyes Closed	Eyes Open	Channel (Right)	Eyes Closed	Eye Open
FP2	1.1×10^{-22}	8.5×10^{-30}	FP1	4.1×10^{-06}	3.1×10^{-20}
F8	4.5×10^{-25}	7.3×10^{-36}	F7	1.8×10^{-27}	4.5×10^{-43}
T4	2.5×10^{-36}	1.1×10^{-38}	T3	4.6×10^{-30}	8.8×10^{-34}
T6	5.5×10^{-21}	6.7×10^{-28}	T5	6.0×10^{-30}	7.5×10^{-27}
O2	4.3×10^{-29}	3.9×10^{-44}	O1	9.0×10^{-19}	9.8×10^{-28}
F4	5.0×10^{-27}	8.9×10^{-36}	F3	2.3×10^{-28}	1.2×10^{-39}
C4	8.1×10^{-37}	3.7×10^{-39}	C3	5.4×10^{-28}	2.1×10^{-32}
P4	5.9×10^{-13}	1.5×10^{-21}	P3	5.7×10^{-26}	1.1×10^{-35}
Fz	7.1×10^{-19}	1.3×10^{-29}	Pz	9.0×10^{-29}	8.0×10^{-32}
Cz	3.0×10^{-29}	2.1×10^{-34}			

In addition, a correlation matrix was analyzed based on four features, as shown in Figure 5. The four features were the mean degree (MD), degree of 2, degree of 3, and graph entropy (GE) from 19 channels of two groups of subjects: MDD and healthy (H). To obtain good visualization, the degree of 2 (D2) was divided by 300, and the degree of 3 (D3) was divided by 300 as well.

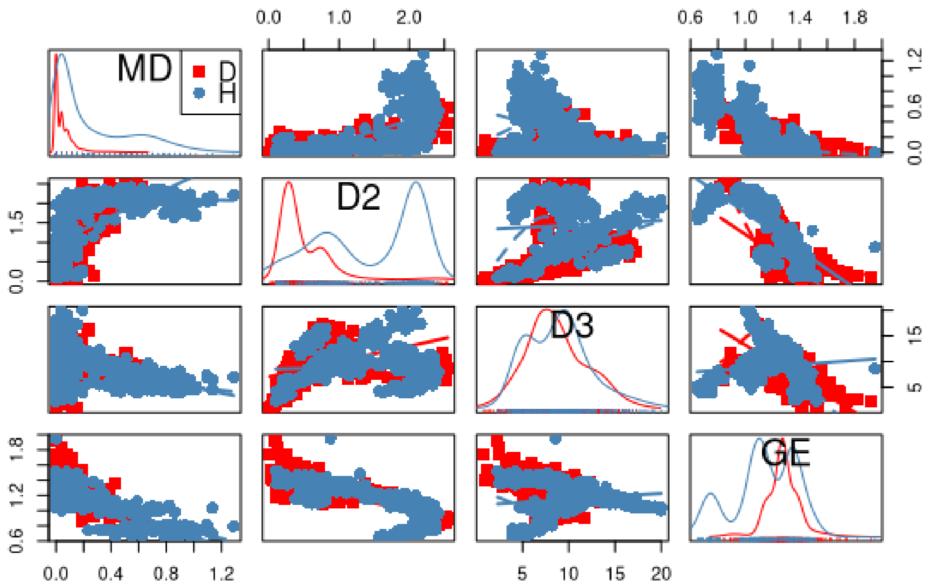

Figure 5. Features correlation on MD, D2, D3, and GE for eyes-open status. It can be seen that the depression group's results are lower than those of the health group for MD, D2, and GE.

3.2. *Classification with Individual Single-Channel EEG Signals for Eyes-Open Status*

All graph features from the eyes-open status were divided into training and testing datasets. A leave-one-out cross-validation scheme was implemented to verify the performance, in which the whole dataset was split into 1045 EEG segments, and thus 1045 row graph features were extracted. Each time, 1044 models were trained. Each dataset was tested on the remaining one-segment EEG. The output accuracy was the average of the 1045 rows. The classification performance for each classification problem is listed in Table 2. The best classification performance was 90.1% accuracy on channel T4 and 89.2% accuracy on channel T4, whereas FZ was the single channel with the lowest accuracy of 84.0%. A 95% confidence interval for the accuracy is also provided in Supplementary Table S1.

Table 2. The classification results based on leave-one-out cross-validation using a single channel per time for eyes-open status.

Channel (Left)	Sen	Sep	ACC	Channel (Right)	Sen	Sep	ACC
FP2	0.89	0.88	**88.5%**	FP1	0.88	0.85	86.8%
F8	0.89	0.82	85.9%	F7	0.89	0.81	85.1%
T4	**0.87**	**0.91**	**89.2%**	T3	**0.94**	0.82	**88.0%**
T6	0.86	0.88	86.9%	T5	0.87	0.89	88.3%
O2	0.89	0.81	84.8%	O1	0.90	0.87	88.4%
F4	0.90	0.81	85.3%	F3	0.82	0.88	85.2%
C4	0.89	0.81	84.7%	C3	0.88	0.88	88.1%
P4	0.88	0.89	88.4%	P3	0.84	0.89	86.6%
Fz	0.84	0.84	84.0%	Pz	0.86	0.88	87.2%
Cz	0.83	0.91	86.9%				

3.3. Classification with Individual Single-Channel EEG Signals for Eyes-Closed Status

To understand the eyes-closed and eyes-open status difference, all graph features from the eyes-closed status were found similarly to the method in Section 3.2. The classification performance for each classification problem is listed in Table 3. The best classification performance had 92.0% accuracy on channel T4 using the SVM, whereas the lowest single-channel accuracy was 83.2% on O2. A 95% confidence interval for the accuracy is also provided in Supplementary Table S2.

Table 3. The classification results based on leave-one-out cross-validation using a single channel per time for the eyes-closed status.

Channel (Left)	Sen	Sep	ACC	Channel (Right)	Sen	Sep	ACC
FP2	0.87	0.88	87.3%	FP1	0.89	0.85	86.7%
F8	0.90	0.82	86.5%	F7	0.89	0.87	87.9%
T4	**0.93**	**0.91**	**92.0%**	T3	**0.96**	0.85	**90.8%**
T6	0.91	0.87	89.4%	T5	0.89	0.88	88.8%
O2	0.89	0.77	83.2%	O1	0.89	0.78	83.6%
F4	0.89	0.87	88.1%	F3	0.88	0.88	88.0%
C4	0.91	0.82	86.6%	C3	0.91	0.85	88.2%
P4	087	0.83	85.0%	P3	0.89	0.82	85.8%
Fz	0.84	0.84	83.7%	Pz	0.89	0.86	87.5%
Cz	0.87	0.89	88.3%				

4. Discussion

4.1. Graph Methods can Provide Efficient Features for Detecting Depression

The existing results for the single-channel EEG analysis show that the higher accuracy in identifying depression was on channel Fp1 (86.67% accuracy) using the same EEG database [7] or on channel Pz in the depression EEG signals [19]. However, this proposed method found that channel T4 had the highest performance with 92.0% accuracy, as shown in Table 4 for the eyes-closed status. This result agrees with a recent study by Zhang et al. [9], which stated that the temporal region has the highest performance in depression classification using two channels: T3 and T4. In addition, the proposed approach also showed that the results for the single channels in the right hemisphere (T4 or Fp2) were higher than those on the left side (T3 or Fp1), which aligns with the results of Acharya et al. [6], who found that the right hemisphere EEG signals had higher performance than those of the left hemisphere in depression disorder classification.

Table 4. Comparing existing methods with the proposed method for depression detection.

Authors	Methods	Database	Channels	Accuracy	Experiment
Wan et al. 2019 [7]	CART + GA	15 MDDs and 15 H	Fp1	86.67%	Eyes closed
Cai et al. 2020 [5]	K-NN	86 MDDs and 92 H	Fp1, Fp2, fpz	86.98%	Stimuli task
Li et al. 2019 [20]	Ensemble + PSD	14 MDD and 14 H	16 channels	89.02%	Stimuli task
Shen et al. 2020 [21]	SVM + mKTA	15 MDD and 20 H	50 channels	81.50%	Eyes closed
Zhang et al. (2022) [9]	SVM + transfer entropy + phase lag index	30 MDD and 30 H	T3, T4	97.96%	Sleep
Proposal	SVM + graph features	34MDD and 30 H	T4 T4	92.0% 89.2%	Eyes closed Eyes open

The graph features also indicate that the results for the depression group were significantly lower than those for the healthy participants. For example, Table 1 shows that the Wilcoxon test analysis result for graph degree 2 for the depressed and healthy participants from all 19 channels was statistically less than 0.0001. This partially confirms our previous study [13], which demonstrated that a single-channel EEG using graph features could identify the cognitive loads. Moreover, it is established for the first time in this study that the depressed individuals significantly differed from the healthy participants based on the graph features (such as isolated nodes).

4.2. Comparison with Existing Depression Detection Methods

Table 4 compares the proposed classification results using different classification algorithms and multi-channel and single-channel cases. As shown in Table 4, our results regarding the MDD classification problem using graph features were significantly higher than those for the methods using time or frequency domain features.

Although the existing methods of Zhang et al. [9] have higher accuracy than the proposed methods, it is noted that the accuracy of the proposed method is merely when using a single channel (T4) with eyes-closed rest EEG signals over a short time period.

5. Conclusions

There are two main contributions in this paper. First, this is the first study using short-term T4 channel EEG signals to identify depressed participants and healthy participants. Although Zhang et al. [9] have shown that the inter-hemispherical T3 and T4 long-term sleep EEG could discover depression patterns, this paper shows that the graph features in the T4 channel can achieve 92.0% accuracy in identifying H and MDD individuals with leave-one-out cross-validation within 3 min using the T4 channel. Secondly, it is proven that the temporal region has high performance in depression identification during both the eyes-closed and eyes-open rest statuses. Both the T3 and T4 channel EEGs could achieve higher accuracies than those of the Fp1 and Fp2 channels regardless of the eyes being open or closed. These results imply that those novel graph features within EEG signals could be employed to detect other brain disorders without strongly restricting test subjects to having their eyes open or closed.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/math10224177/s1. Table S1: The classification results are based on leave-one-out cross-validation using single-channel per time on eye open status with a 95% confidence interval (CI); Table S2: The classification results are based on leave-one-out cross-validation using single-channel per-time on eye closed status with a 95% confidence interval (CI).

Author Contributions: Conceptualization, G.Z. and X.Z.; methodology, G. Z.; software, G.Z. and Y.D.; validation, T.Q., Y.D., S.G., and R.G.; formal analysis, X.Z and F.L..; investigation, T.Q. and N.Z.; resources, Y.D.; data curation, S.G.; writing—original draft preparation, G.Z.; writing—review and editing, R.G., X.Z., and F.L.; visualization, G.Z.; supervision, F.L.; project administration, G.Z.; funding acquisition, G.Z. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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