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Diagnosis of Major Depressive Disorder from EEG Signals Using Empirical Wavelet Transform and Machine Learning Methods

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***Abstract*— In this study, Empirical Wavelet Transform (EWT), a time-frequency analysis method, was applied to EEG signals to diagnose Major Depressive Disorder (MDD). The EEG signals in the Fp1, Fpz, and Fp2 channels of MDD patients and healthy individuals resting in the MODMA dataset were analyzed in delta and theta frequency bands. By applying EWT to EEG signals, three channels of EEG signals were decomposed into 6 sub-signals. A total of 126 features were obtained by extracting 21 features from each of these sub-signals. The obtained features were classified using machine learning (ML) algorithms (Decision Trees, Support Vector Machine, k-nearest Neighbor, Ensemble Bagged Trees, Wide Neural Network). According to the results of the analyses, it was observed that the Theta band was more effective in distinguishing the MDD patients and healthy individuals. Additionally, the Ensemble Bagged Trees classifier provided the highest accuracy rates. This algorithm provided 98.88% accuracy in the Theta band, but its performance was lower in the Delta band like the other classifiers. This study emphasizes the promising potential of EWT based features in MDD diagnosis and their potential to improve diagnostic processes. The accuracy results demonstrate the usability of EWT in MDD diagnosis and the effectiveness of ML techniques in this process.**

Keywords*— *major depressive disorder; empirical wavelet transform; machine learning.

I. INTRODUCTION

Major depressive disorder (MDD) is a mental health disorder that negatively affects individuals' self-control and motivation. People with MDD have health problems such as sleep disorders, immune system weakening, chronic fatigue, weight fluctuations, and digestive problems. According to the World Health Organization's (WHO) 2021 statistics; approximately 280 million people worldwide are struggling with depression, which covers 4.4% of the population. It is predicted that the depression will be the most common disorder worldwide and one of the biggest causes of diseases in the future. In addition, the long-term depression in societies leads to economic problems and the risk of developing other chronic diseases. According to WHO, stress, depression, and anxiety disorders are estimated to cost the global economy approximately 1 trillion dollars annually [1-3]. Depression is currently diagnosed by psychiatrists by using interviews and clinical scales such as PHQ-9 (Patient Health Questionnaire), BDI (Beck Depression Inventory), HAM-D (Hamilton Rating Scale for Depression) and GDS (Geriatric Depression Scale). However, this diagnostic method based on clinical scales is time-consuming for doctors and makes accurate diagnosis difficult due to the lack of physiological indicators. In addition, it is difficult for people to access the right treatment because of the prejudice in society about going to the doctor for diseases related to mental disorders. For these reasons, the search for effective methods in the diagnosis of MDD is growing continuously and new technological developments are getting involved in this field. With the emergence of tools such as artificial intelligence and data mining, investigating the effectiveness of physiological indicators in the diagnosis of MDD and creating new methods for diagnosis has become a new research topic recently [4-8].

EEG signals play an important role in the diagnosis of MDD. They can be analyzed in five different frequency bands; delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (>30 Hz). It has been proven in many studies that these frequency bands show significant differences between MDD patients and healthy individuals [9, 10]. In this study, EWT was applied to the resting 3-channel (Fp1, Fpz, Fp2) EEG signals of MDD patients and healthy individuals in the MODMA dataset, and the differences between brain activities were examined and classified. This study contributes to detecting complex neurological and psychiatric disorders such as MDD by extracting more detailed features using the EWT-based signal decomposition method. Although some EEG analysis methods can be seen in the literature for the diagnosis of MDD, current studies do not provide such a detailed analysis by applying the EWT method to the signals and decomposing them into sub-bands. In addition, time, frequency, and non-linear features from the sub-signals of EEG signals decomposed by EWT were used together to detect MDD more precisely. We defend that the method proposed in this study will help to detect MDD more accurately and improve treatment processes. Furthermore, another aim of this study is to determine the frequency band associated with MDD in EEG signals by using EWT, and it is shown that the theta band is the most important band at distinguishing MDD patients from healthy people.

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II. Literature Review

Significant contributions have been made in the literature on the diagnosis of MDD using EEG signals, and the studies have focused on the findings obtained using different analysis methods and classifiers. Khan S. et al. [11] divided the EEG signals into 10-second non-overlapping windows and extracted 12 temporal domain features from each window. They classified the EEG features determined by a feature selection algorithm with different ML methods. The Best-first Tree (BF-Tree) method showed the highest performance with a 96.36% accuracy rate. Rehman M. et al. [12] proposed a correlation-based technique for the selection of important features. They extracted time-domain features from each electrode and obtained a classification accuracy of 95.75% using a decision tree classifier. Shi Q. et al. [13] classified patients with depression and healthy individuals using linear and non-linear features. They obtained 72.25% accuracy with the K-NN classification method.

III. Material and Method

In this study, EEG signals of Fp1, Fpz, and Fp2 channels in the frontal lobe region of the brain from MDD and healthy individuals were decomposed by applying the EWT method and analyzed with classification methods. The methodology of the study is summarized in the flow diagram shown in Figure 1. The raw EEG signals were preprocessed to make them suitable for analysis and divided into segments with 10-second time intervals. The preprocessing steps include signal filtering, noise removal, and normalization. Next, the signals were separated into Delta and Theta bands. Then, the EEG signals in Fp1, Fpz, and Fp2 channels were separated into their subcomponents by applying the EWT method to these two frequency bands. This process makes the features in the signal more prominent and easier to analyze. A total of 21 features representing time, frequency, and nonlinear features of the signals were extracted from the sub-signals obtained by EWT. The extracted features were converted into separate feature matrices for the Delta and Theta frequency bands. These matrices were analyzed by five different machine learning (ML) algorithms (Decision Trees, Support Vector Machine, k-Nearest Neighbor, Ensemble Bagged Trees, and Wide Neural Network) for classification. A 10-fold cross-validation method was employed for the classification process. The performances of the classifiers were evaluated using the criteria such as accuracy, sensitivity, specificity, precision, and F1 score. These steps allowed for an investigation into the usability and effectiveness of the features obtained by applying EWT to EEG signals in the diagnosis of MDD.

A. Dataset

The MODMA (Multi-modal Open Dataset for Mental Disorder Analysis) dataset used for MDD diagnosis was published in 2020 and consists the EEG data of MDD patients and healthy individuals treated at Lanzhou University Hospital in China. The dataset consists of participants aged 16-56 years with primary school education or higher. The diagnosis of MDD was determined by the Mini-International Neuropsychiatric Interview (MINI) conducted by at least one clinical psychiatrist according to DSM-IV criteria. The MDD group were selected from individuals with a PHQ-9 score of 5 or above who had not used psychotropic medication in the last two weeks. The control group consisted of individuals with no history of mental disorders. The data set included 3-electrode EEG signals of 55 participants (26 MDD patients and 29 healthy) at rest; there were 15 males and 11 females in the MDD group and 19 males and 10 females in the control group. Those with a PHQ-9 score below 5 were classified as a control group and those with a score above 5 were classified as MDD [14].

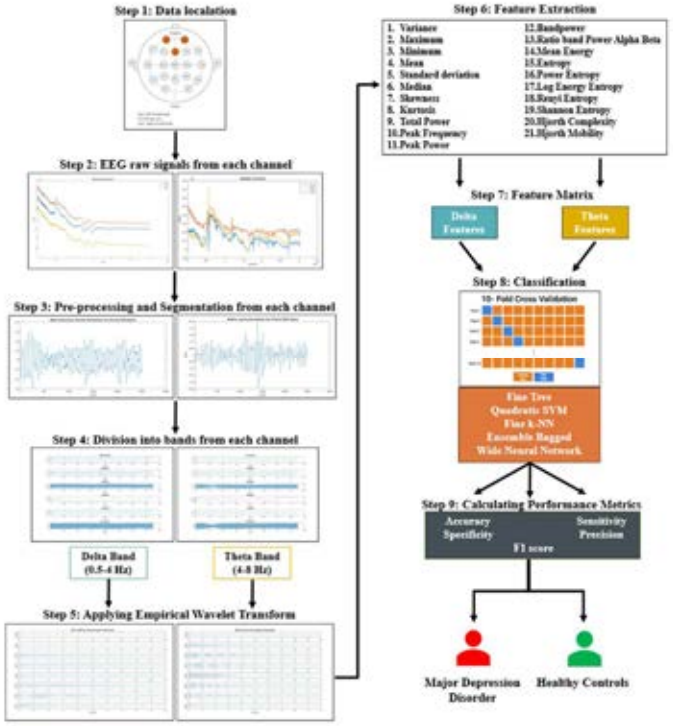


Fig. 1. Flow diagram of the proposed method

B. EEG Signal Pre-processing and Segmentation

A total of 26 patients with major depressive disorder (MDD) and 29 control subjects underwent band-pass filtering and normalization of electroencephalogram (EEG) signals recorded from the Fp1, Fpz, and Fp2 channels. The EEG signals were collected with a sampling frequency of 250 Hz, filtered between 0.5 and 60 Hz, and their amplitudes were scaled to a standard range. The process of normalization entailed the subtraction of the mean value from each signal and the subsequent division by the standard deviation. The application of band-pass filtering and normalization to the EEG signals resulted in enhanced signal accuracy and noise reduction. Furthermore, the signals were segmented into 10-second time intervals, yielding a total of 6156 signal samples from the EEG data in the MODMA dataset for analysis. The time-based segmentation approach facilitated a comprehensive data analysis with an increased data sample size.

C. Empiricial Wavelet Transform (EWT)

In 2013, Jerome Gilles developed a TF analysis method, designated EWT, which employs adaptive wavelets for the decomposition of signals into discrete frequency components. This method identifies local maxima in signals and generates a wavelet filter bank based on the information contained within the spectrum. The EWT method comprises four principal stages, which can be delineated as follows [15-17]:

1) The Fast Fourier Transform (FFT) is employed to ascertain the frequency components of the signal. Let us consider a discrete signal, f(t), where t is a set of discrete values, t = {ti}, with i = 1, 2, 3, ... n. The frequency spectrum, X(w), is then calculated by applying the FFT to f(t). Subsequently, the Fourier spectrum of the set n = {ni}, i = 1, 2, 3, ... m is calculated, and the frequencies w = {wi}, i = 1, 2, 3, ... m corresponding to this spectrum are obtained. Consequently, the frequency components of the signal are identified by transforming the signal in the time domain into the frequency domain.

2) A variety of modes are derived by dividing the Fourier spectrum into discrete frequency ranges. Each mode represents the characteristics of the signal within a specific frequency range. The boundaries of each segment are calculated using the formula in equation (1). The frequency values w_i and w_{i+1}, and the defined boundaries $\acute{\Omega}_i$, are determined.

$$\acute{\Omega}_i = \frac{w_i + w_{i+1}}{2} \tag{1}$$

3) In this step, the wavelet and scaling coefficients are calculated. The empirical wavelet kernels Ψ(w) and the scaling function ϕ(w) are calculated by equation (2) and equation (3). The parameter γ ensures that each subdivision is separated without blending and is described mathematically by equation (4). β(x) is a random function and is defined by equation (5).

$$\phi_i = \begin{cases} 1, & |w| \le (1-\gamma)\acute{\Omega}_i \\ \cos\left(\frac{\pi}{2}\alpha(\gamma,\acute{\Omega}_1)\right), & (1-\gamma)\acute{\Omega}_1 < |w| \le (1+\gamma)\acute{\Omega}_1 \\ 0, & otherwise \end{cases} \tag{2}$$

$$\Psi_i = \begin{cases} 1, & (1+\gamma)\acute{\Omega}_i < |w| < (1-\gamma)\acute{\Omega}_{i+1} \\ \cos\left(\frac{\pi}{2}\alpha(\gamma,\acute{\Omega}_{i+1})\right), & (1-\gamma)\acute{\Omega}_{i+1} \le |w| \le (1+\gamma)\acute{\Omega}_{i+1} \\ \sin\left(\frac{\pi}{2}\alpha(\gamma,\acute{\Omega}_i)\right), & (1-\gamma)\acute{\Omega}_i \le |w| \le (1+\gamma)\acute{\Omega}_i \\ 0, & otherwise \end{cases} \tag{3}$$

$$Where\ \alpha(\gamma,\acute{\Omega}_i) = \beta\left(\left(\frac{1}{2\gamma\acute{\Omega}_i}\right)(|w| - (1-\gamma)\acute{\Omega}_i)\right) \quad \gamma < min_i\left(\frac{\acute{\Omega}_{i+1}-\acute{\Omega}_i}{\acute{\Omega}_{i+1}+\acute{\Omega}_i}\right) \tag{4}$$

$$\beta(x) = \{0,\ x \le 0\ ;\ 1,\ x \ge 1\ ;\ \beta(x) + \beta(1-x) = 1,\ x \in (0,1) \tag{5}$$

4) Finally, sub-bands representing different components of the signal are reconstructed using the wavelet and scaling coefficients. In equation (6), the approximation coefficients are calculated by multiplying the signal f by the scaling function. By multiplying the signal f by the empirical wavelet kernels, the detailed coefficients of the signal are determined as given in equation (7). $W_f(i,t)$ denotes the detailed coefficients for the i-th filter bank at the t-th time point. The reconstruction of the sub-band signals is calculated by equation (8).

$$W_f(0,t) = \langle f, \phi_i \rangle = \int f(\tau)\,\overline{\phi_i(\tau - t)}d\tau \tag{6}$$

$$W_f(i,t) = \langle f, \Psi_i \rangle = \int f(\tau)\,\overline{\Psi_i(\tau - t)}d\tau \tag{7}$$

$$f(t) = W_f(0,t)^*\phi_i(t) + \sum_{i=1}^{N} W_f(i,t)^*\Psi_i(t) \tag{8}$$

D. Feature Extraction

The extracted features from EEG signals can be broadly classified into three main categories: time domain, frequency domain, and nonlinear features. Although time-domain features are effective in elucidating the general behavior of brain signals, they are inadequate in capturing the intricate and disordered of these signals. In contrast, nonlinear features are better able to detect sudden changes in signals [18]. In this study, an analysis of EEG signals is conducted with regard to their characteristics in the time domain, frequency domain, and with respect to nonlinear features. In the time domain, the following features were employed: variance, maximum, minimum, standard deviation, median, skewness, and kurtosis. In the frequency domain, an evaluation was conducted of total power, band power, peak frequency, peak power, and ratio and power alpha beta attributes. Furthermore, mean energy, entropy, power entropy, log energy entropy, Renyi entropy, Shannon entropy, Hjorth mobility, and Hjorth complexity were employed in conjunction as nonlinear attributes. Following preprocessing and band analysis of the EEG signals, they were decomposed into six sub-signals using the EWT method. The aforementioned features were then extracted for each window interval. From the six sub-bands of each EEG channel, 21 features were extracted, resulting in a total of 126 features being analyzed in the study.

IV. Experimental Results

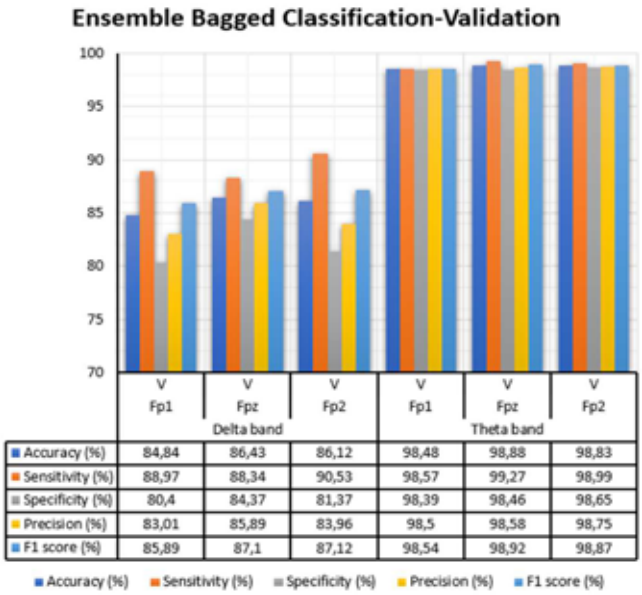
In this study, a classification system for MDD was developed by applying the EWT method to EEG signals and using ML models. Accuracy values of different ML classifiers used in Fp1, Fpz, and Fp2 EEG channels in Delta and Theta bands are presented in Table I. In the Delta band, the Ensemble Bagged Trees classifier provided the highest accuracy values. In the delta band, the Ensemble Bagged classifier achieved 84.84% and 82.76% accuracy in the Fp1 channel, 86.43% and 82.60% in the Fpz channel, and 86.12% and 84.88% in the Fp2 channel in the training and test sets, respectively. Furthermore, the DT classifier showed the second-highest performance in the Delta band with accuracies up to 81.54%. In the Theta band, the Ensemble Bagged classifier was remarkable with accuracies of 98.48% and 98.54% in the Fp1 channel, 98.88% and 98.37% in the Fpz channel, and 98.83% and 98.37% in the Fp2 channel in the training and test sets, respectively. In the theta band, K-NN and SVM classifiers presented lower accuracy rates. In general, the Theta band showed higher classification performance, while the Ensemble Bagged classifier was found to be the most effec-

Table I. Classification Accuracies of Delta and Theta Bands

EEG Band	Channel	ACCURACY VALUES (%)					
		Tr/Te[a]	*DT*[b]	*SVM*[c]	*K-NN*[d]	*ENS. Bag.*[e]	*WNN*[f]
Delta Band (0.5-3 Hz)	Fp1	Tr	79.90	69.70	62.84	**84.84**	69.50
		Te	76.75	67.64	61.79	**82.76**	67.15
	Fpz	Tr	81.54	67.33	62.82	**86.43**	66.59
		Te	77.89	68.94	61.95	**82.60**	66.50
	Fp2	Tr	79.75	63.58	59.83	**86.12**	63.53
		Te	78.86	63.25	57.07	**84.88**	64.07
Theta Band (4-8 Hz)	Fp1	Tr	97.71	85.85	83.56	**98.48**	89.37
		Te	97.40	85.69	81.14	**98.54**	88.62
	Fpz	Tr	97.40	82.51	82.21	**98.88**	88.59
		Te	97.56	83.90	81.95	**98.37**	89.59
	Fp2	Tr	98.01	87.06	84.46	**98.83**	89.00
		Te	97.56	87.15	84.07	**98.37**	89.59

[a] Tr: Training, Te: Test. [b] DT: Decision Trees (Fine). [c] SVM: Support Vector Machine (Quadratic). [d] K-NN: k-Nearest Neighbor (Fine). [e] ENS. Bag.: Ensemble Bagged Trees. [f] WNN: Wide Neural Network.

tive classifier with the highest accuracies at both frequencies. These results suggest that the Theta band is more effective in diagnosing MDD and Ensemble Bagged is a high-performing classifier.



	V Fp1	V Fpz	V Fp2	V Fp1	V Fpz	V Fp2
	Delta band			Theta band		
Accuracy (%)	84,84	86,43	86,12	98,48	98,88	98,83
Sensitivity (%)	88,97	88,34	90,53	98,57	99,27	98,99
Specificity (%)	80,4	84,37	81,37	98,39	98,46	98,65
Precision (%)	83,01	85,89	83,96	98,5	98,58	98,75
F1 score (%)	85,89	87,1	87,12	98,54	98,92	98,87

Fig. 2. Performance Metrics of Ensemble Bagged Classifier in Delta and Theta band (Validation)

As shown in Figure 2, the high sensitivity, specificity, and F1 scores obtained in the Theta band indicate that this band is more effective in distinguishing between depressed and healthy individuals. In the delta band, the performance metrics are lower and the accuracy and overall performance of the model are more limited compared to the Theta band. Theta band stands out as the preferred frequency band in this study by applying the EWT analysis method to EEG signals and extracting features.

V. Conclusions

The analyses made in this study show that the sub-signals of electrical activity in the brain's frontal region obtained using EWT contain important information about MDD. According to classification accuracies, the Theta band is more reliable and more accurate than the Delta band in discriminating between MDD patients and healthy controls. Ensemble Bagged Trees outperformed the other classifiers in all frequency bands, especially in the Theta band. k-NN classifier performed poorly in all scenarios. These findings emphasize that the selection of the appropriate frequency band and classifier in EEG signal analysis is important in improving the accuracy of MDD diagnosis. A validation accuracy of 98.88% was achieved with the Ensemble Bagged Trees classifier in the Fpz channel in the theta band. This demonstrates the effectiveness of the chosen ML approach and the suitability of the features extracted by the EWT signal analysis method for classifying MDD. The high precision and recall scores confirm that the system is capable of accurately identifying MDD. Despite the promising results, the dataset used in this study consists of records from only 55 patients and may not fully represent the variability observed in larger populations. Future studies should aim to add more comprehensive and diverse patient data to improve the generalizability of the MDD classification system. In addition, the integration of other physiological signals can further improve the accuracy of the system. Existing studies in the literature show that EWT, one of the TF analysis methods related to MDD, has not been sufficiently examined. Thanks to this technique, brain activity differences between MDD and healthy individuals can be better understood, and diagnostic processes can be improved. The results obtained in this study show that the features extracted with the EWT method and ML techniques are potentially effective in the diagnosis of MDD.

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