Turkish Journal of Science & Technology
18(1), 207-214, 2023

Research Paper
https://doi.org/10.55525/tjst.1242881

Electroencephalogram-Based Major Depressive Disorder Classification Using Convolutional Neural Network and Transfer Learning

Şüheda KAYA[1], Burak TAŞCI[2*]
[1] Elazıg Mental Health Hospital, Elazig 23200, Turkey
[2] Vocational School of Technical Sciences, Firat University, Elazig 23119, Turkey
[1] suheda_sener@hotmail.com, [2*] btasci@firat.edu.tr

(Geliş/Received: 26/01/2023; Kabul/Accepted: 02/03/2023)

Abstract: Major Depressive Disorder (MDD) is a worldwide common disease with a high risk of becoming chronic, suicidal, and recurrence, with serious consequences such as loss of workforce. Objective tests such as EEG, EKG, brain MRI, and Doppler USG are used to aid diagnosis in MDD detection. With advances in artificial intelligence and sample data from objective testing for depression, an early depression detection system can be developed as a way to reduce the number of individuals affected by MDD. In this study, MDD was tried to be diagnosed automatically with a deep learning-based approach using EEG signals. In the study, 3-channel modma dataset was used as a dataset. Modma dataset consists of EEG signals of 29 controls and 26 MDD patients. ResNet18 convolutional neural network was used for feature extraction. The ReliefF algorithm is used for feature selection. In the classification phase, kNN was preferred. The accuracy was yielded 95.65% for Channel 1, 87.00% for Channel 2, and 86.94% for Channel 3.

Key words: Major Depressive Disorder; EEG; ReliefF; Knn

Konvolüsyonel Sinir Ağı ve Transfer Öğrenme Kullanılarak Elektroensefalogram Tabanlı Majör Depresif Bozukluk Sınıflandırması

Öz: Major Depresif Bozukluk (MDB), yüksek oranda kronikleşme, intihar ve yineleme riski taşıyan, iş gücü kaybı gibi ciddi sonuçları olan ve dünya çapında yaygın olan bir hastalıktır. MDB tespitinde EEG, EKG, beyin MR, doppler USG gibi objektif testler tanıya yardımcı olarak kullanılmaktadır. Yapay zeka alanındaki gelişmeler ve depresyonla ilgili objektif testlerden elde edilen örnek verilerin ile, MDB'den etkilenen bireylerin sayısını azaltmanın bir yolu olarak erken depresyon teşhis sistemi geliştirilebilir. Bu çalışmada EEG sinyallerini kullanarak derin öğrenme tabanlı bir yaklaşımla MDB otomatik teşhis edilmeye çalışılmıştır. Çalışmada veri seti olarak 3 kanallı modma veri seti kullanılmıştır. Modma veri setinde 29 kontrol ve 26 MDB hastasının EEG sinyalinden oluşmaktadır. ResNet18 evrişimli sinir ağı öznitelik çıkarmak için kullanılmıştır. Öznitelik seçimi için ReliefF algoritması kullanılmıştır. Sınıflandırma aşamasında ise k-EYK tercih edilmiştir. kanal 1 için %95.65, kanal 2 için %87.00 ve kanal 3 için 86.94 doğruluk elde edilmişti.

Anahtar kelimeler: Major Depresif Bozukluk; EEG; ReliefF; k-EYK

1. Introduction

Major Depressive Disorder (MDD) is a mental illness that presents with symptoms such as not enjoying life, loss of interest and desire, distress, irritability, cognitive disorders, deterioration in thought processes, negative thoughts such as worthlessness, thoughts of guilt, hopelessness, hypochondriac preoccupation, and suicidal thoughts. In the fifth edition of the diagnostic and statistical manual of mental disorders (DSM-5), the criteria for the diagnosis of MDD are either a depressed mood or a lack of pleasure for at least two weeks [1]. MDD was found in 2.0-4.0% of the significant population sample and is a prevalent public health problem. Less than half of people with MDD seek treatment; if not treated, the depression period of people can last up to 6-12 months and become chronic. Diagnosis of the disease is based on subjective methods such as a one-on-one interview with a psychiatrist or psychologist and psychometric scales. The absence of a known biomarker makes the diagnosis difficult due to the patient's subjectivity in responding to psychological assessment scales and heterogeneous symptoms such as sleep, appetite, and attention level. Factors such as the patient's statements at the time of the interview, the variety of symptoms, and the experience of the specialist significantly affect the diagnosis, the chosen treatment, and the healing process. For these reasons, developing an objective diagnostic method for early and accurate diagnosis and appropriate and effective treatment is important. Recently, automatic recognition of mental states and mental disorders has attracted significant interest from the computer vision and artificial intelligence community. Neural activity and mental disorders in the brain affect the bioelectrical activity of the brain. Previous work has mostly been on functional magnetic resonance imaging (fMRI) [2]. Non-invasive sensor-

* Corresponding author: btasci@firat.edu.tr, ORCID Number of authors: [1] 0000-0002-0853-5777, [2] 0000-0002-4490-0946

based devices such as electroencephalogram (EEG) have been widely used in the literature in recent years. With the help of electrodes placed on the scalp with the EEG device, the electrical activity between nerve cells is recorded as oscillations [3]. The processing of EEG signals to be recorded from this device plays an important role in detecting different diseases such as MDD, bipolar disorder, anxiety, schizophrenia, and sleep disorders [4].

In particular, in MDD, the release of cortisol in the body increases, which affects the production and communication of neurons, and as a result, slows down the functionality of some parts of the brain and changes electrical activity patterns. Measuring voltage changes caused by ionic current flows within the brain's neurons with the non-invasive method, EEG, may help diagnose MDD objectively [5]. Detection of these irregularities in brain physiology plays an important role in the early diagnosis of the depression process. Electrophysiological differences were found in literature studies examining depression patients and healthy controls in terms of EEG signals [6]. In this context, many computer-assisted different studies have been developed. In our country, Mumtaz et al., EEG signal energy and interhemispheric asymmetry in the frontal, temporal, parietal, and occipital lobes were found to be significant in the diagnosis of depression [7].

Some studies in the literature for MDD detection with EEG signals are given below.

Sharma et al.[8] used EEG signals from 21 drug-free depressed and 24 normal patients. It achieved 99.10% accuracy with LSTM-CNN. Seal et al.[9] classified depression with the 18-layer CNN network. It had achieved 99.37% accuracy. Saaedi et al.[10] detected MDD using the EEG signals of 30 healthy and 34 MDDs. They achieved 95.283% ± 2.109 accuracy with CNN 1D, 96.226% ± 1.208 with CNN 2D, 89.057% ± 1.849 with LSTM, 99.245% ± 1.152 with CNN 1D-LSTM and 96.415% ± 3.422 with CNN 2D-LSTM. Čukić et al.[11] detected depression using 23 depression and 20 normal EEG signals. HFD achieved 97.56% accuracy with the SampEn method and Naive Bayes classifier. Mumtaz et al. [12] detected depression using 33 depression and 30 normal EEG signals. He achieved 98.20% accuracy, 99.78% specificity, and 98.34% sensitivity with CNN-LSTM. Uyulan et al.[13] detected 46 healthy and 46 MDD EEG signals as MDD using deep learning architectures. With MobileNet, it achieved 92.66% accuracy. Khan et al.[14] obtained 100% accuracy of EEG signals of 30 MDD and 30 healthy controls with 3D-CNN.Tasci et al.[15] had classified MDD using the modma dataset. In the method they proposed, Twin Pascal's Triangles Lattice Pattern was used. The feature was selected with NCA. It achieved 100% accuracy of 128-channel EEG signals with 10 fold CV. Wang et al.[16], had classified MDD using the odma dataset. ALexNet was used in their proposed method. 13, 17, 28, 40, 46, 66 and 69 channels were found to be associated with depression.

In this study, MDD was tried to be diagnosed automatically using EEG signals. For this, EEG signals were first converted into spectrogram images. These images were trained on the ResNet-18 deep learning model, and their features were extracted. The extracted features were selected by the Relieff algorithm. These features were classified using the kNN algorithm.

2. Material and Method

2.1. Dataset

In this study, the multi-modal open dataset for mental-disorder analysis: 3-channel EEG datasets of MODMA were used [17]. Lanzhou University's UAIS laboratory published this EEG dataset in 2020. The sampling frequency of the EEG signals in the MODMA 3 channel dataset is 250Hz. It contains the EEG signal of 3 channels in total. Psychiatric disorders have a strong relationship with the prefrontal lobe. Therefore, EEG signals were collected from Fp1, Fpz, and Fp2 electrodes. The connection of the electrodes is shown in Figure 1.

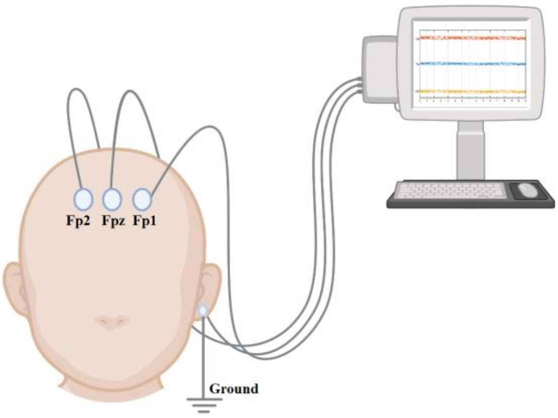


Figure 1. Electrode placement for the 3-Channel EEG dataset

Table 1. Properties of MODMA 3 channel dataset

Class	MDD		Control	
Gender	Female(n=11)	Male(n=15)	Female(n=10)	Male(n=19)
Age+sd	27.09±8.34	33.33±11.94	28.5±7.32	31.94±8.84
Max Age	45	56	41	43
Min Age	18	16	22	19
Education(years)	15.54±1.96	11.73±3.65	17.4±2.36	16.26±1.52
PHQ-9	18.27±5.79	17.4±4.25	2.1±2.37	2.47±1.64
CTQ-SF	46.90±12.06	52.66±11.70	43.7±10.19	39.78±4.79
LES	-61.63±76.67	-35.26±50.82	0±19.04	8.78±34.79
SSRS	34.36±8.24	31.86±9.21	42.3±5.53	42.31±6.87
GAD-7	13.27±6.58	12.86±4.58	1.2±1.68	1.84±2.00
PSQI	12±4.17	12±6	2.6±2.17	3.84±2.14

* CTQ-SF, Childhood Trauma Questionnaire; GAD-7, Generalized Anxiety Disorder; LES, Life Event Scale; PHQ-9, Patient Health Questionnaire; PSQI, Pittsburgh Sleep Quality Index; SSRS, Social Support Research Scale.

EEG signals obtained from each individual were divided into 15-second dimensions. As a result, 2348 15-second MDD EEG signals and 2108 15-second healthy control EEG signals were obtained from the dataset.

2.2. Method

In this study, MDD detection was made from EEG signals of health and MDD cases. The 3-channel EEG signals of the MODMA dataset were used in the study. EEG signals are divided into 15-second segments. One spectrogram image was obtained from each 15-second signal segment. Then the obtained images were resized (224x224) according to the input of the ResNet-18 network. The Resnet-18 network is trained using the images obtained from the first channel. One thousand features were obtained from the fc1000 layer of the trained network. Five hundred of the obtained features were selected with the help of relieff feature selection algorithm. Then, 500 selected features were classified with the help of kNN classifier. A graphical summary of the proposed method is given in figure 2.

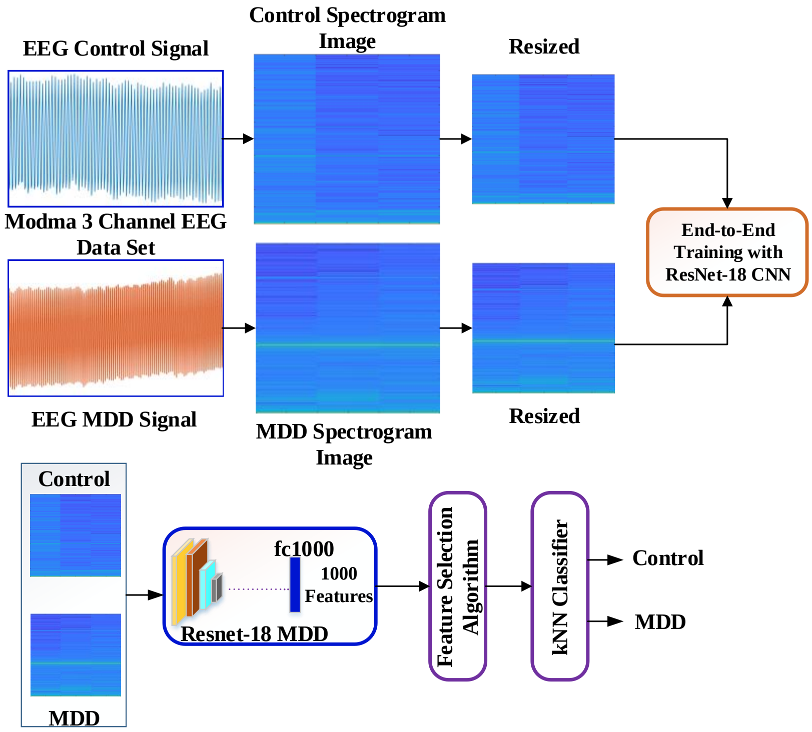


Figure 2. Graphical representation of the proposed method

2.2.1. Creation of spectrogram images

The Fourier Transform can describe all the frequency components included in the stationary signal. However, not all signals are stationary. Short-Time Fourier Transform (STFT) provides simultaneous frequency and time analysis of the signal. [18]. STFT is obtained by multiplying the Fourier transform function of a signal by the window function. Displaying a 2-D function of a signal, time, and frequency is called a spectrogram. [19].

2.2.2.Resnet 18

Resnet-18 is a convolutional neural network with 72 layers, 18 in-depth, 44MB in size, and 11.7 million parameters. The image input size is 224x224. Resnet network model has 2-D convulation, batch normalization, ReLU, 2-D Global average pooling, fully connected, addition , and softmax layers [20]. The general structure of the Resnet 18 architecture is given in figure 3.

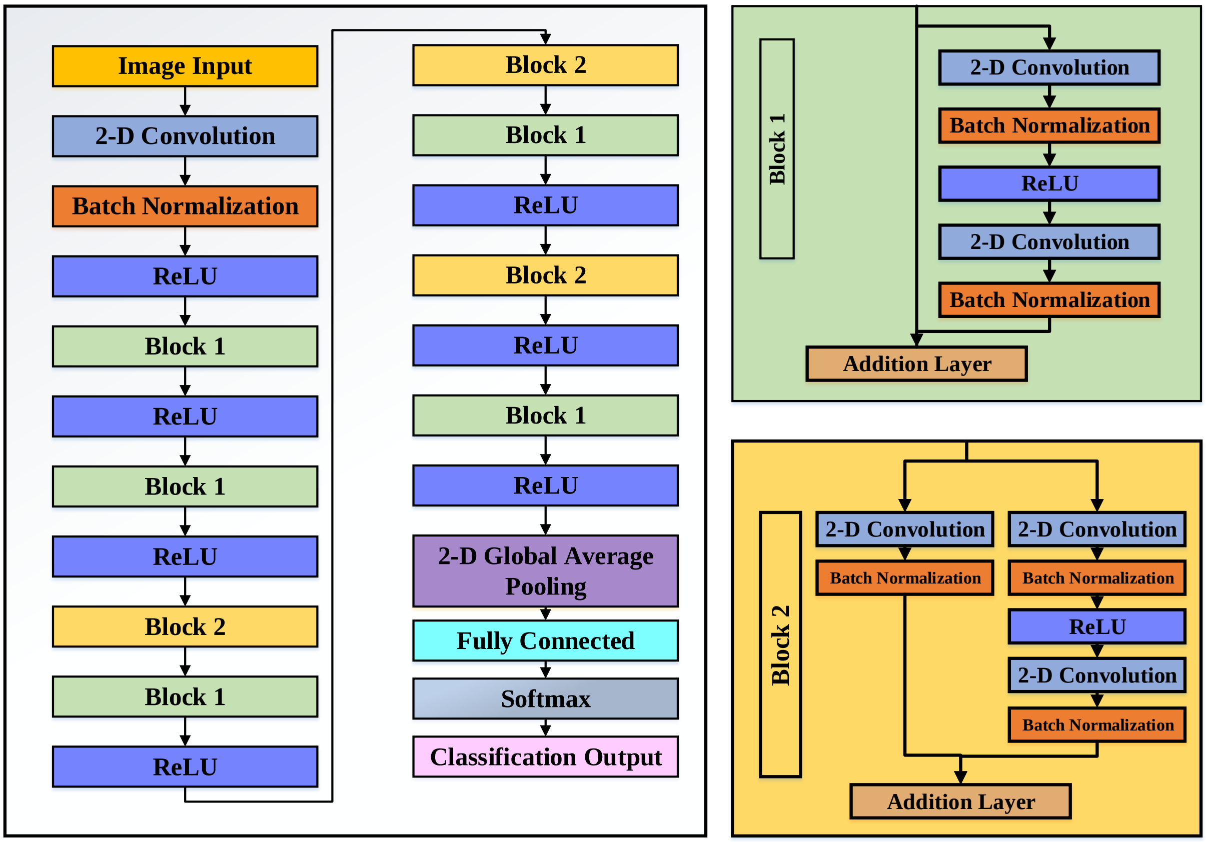


Figure 3. General structure of the ResNet18 architecture

2.2.3. ReliefF Algorithm

Relief algorithm is a feature selection method developed by Kira et al. in 1992. The main purpose of this method is to weigh the features according to their correlation [21]. Relief algorithm gives successful results on the data of two classes. However, it did not give successful results for datasets containing more than two classes. To eliminate this problem, Kononenko developed the ReliefF algorithm in 1994, which works on datasets with more than two classes [22].

2.2.4 kNN Classifier

kNN is a classification method used in data mining. The k-Nearest Neighbor classifier is one of the easiest and most frequently used classification algorithms that classifies data based on the closest training data in the feature space. This method performs the classification process according to the class of the nearest neighbor as much as the k value given. The k-NN algorithm classifies a vector using vectors of known class. In the k-NN method, the distance of the test data to the training data is calculated by the Euclidean method as specified. The k-training data, which is closest to the test data, belongs to the same class with the highest ratio [23].

3. Experimental Results

All coding in the study was carried out in the MATLAB 2010a simulation program installed on a desktop computer with an 11th Generation Intel brand i9-11900 processor, 2.500Ghz, 64GB DDR4 memory, and 1024GB SD storage capacity. As the first step in coding, EEG signals were converted to spectrogram images. The ResNet18 network was trained using the spectrogram images obtained from the first channel. Loss and accuracy graphs are given in Figure 4. The weights of the fully connected layer named fc1000 of the ResNet 18 model trained for feature extraction were used. There are 1000 nodes in this layer. Therefore, 1000 features were extracted. Five hundred features were selected using the ReliefF algorithm. The classification accuracies obtained with these classifiers are tabulated in Table 2. A 10-fold cross-validation technique was used for all classifiers. As can be seen in Table 2, the best classification accuracy was obtained with the 95.60% kNN classifier, while the worst classification accuracy was obtained with the fine-tree classifier.

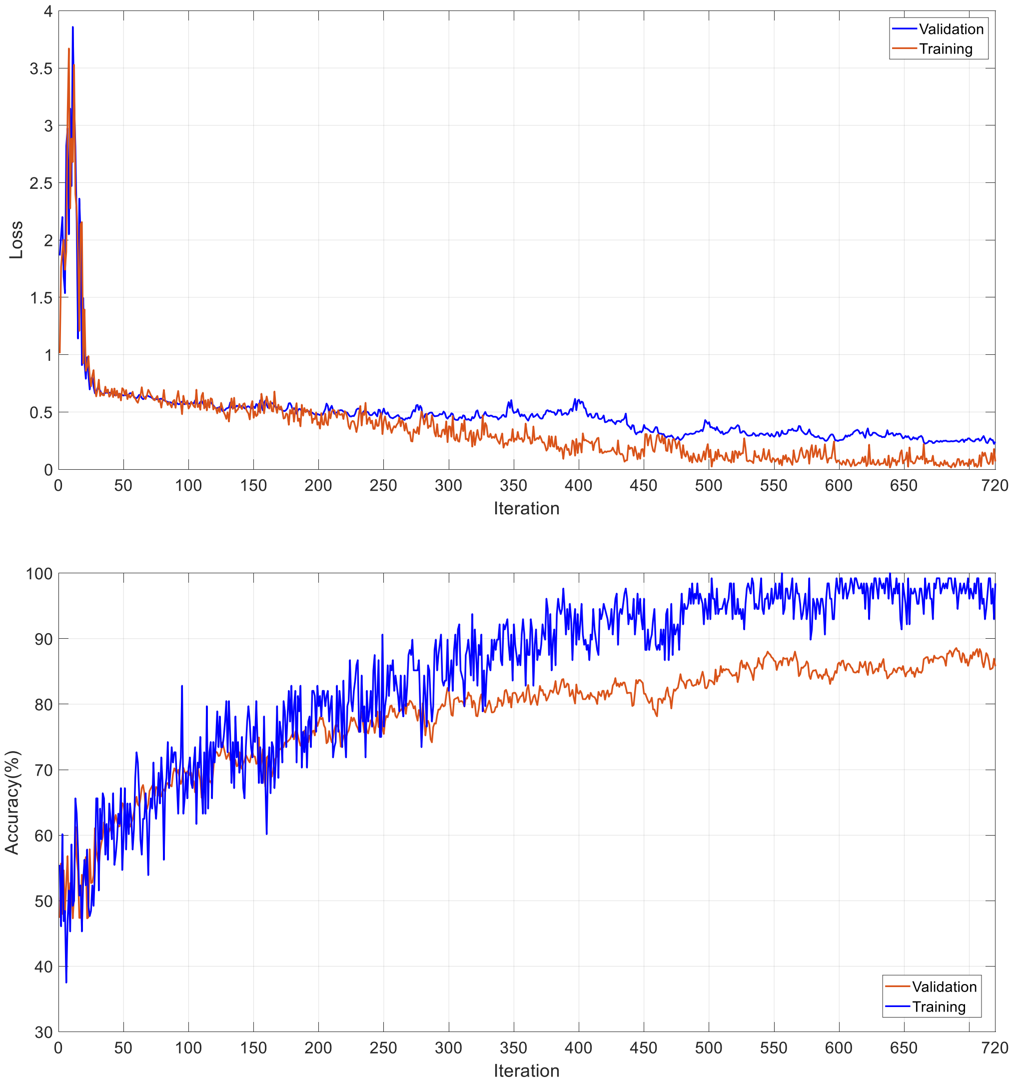
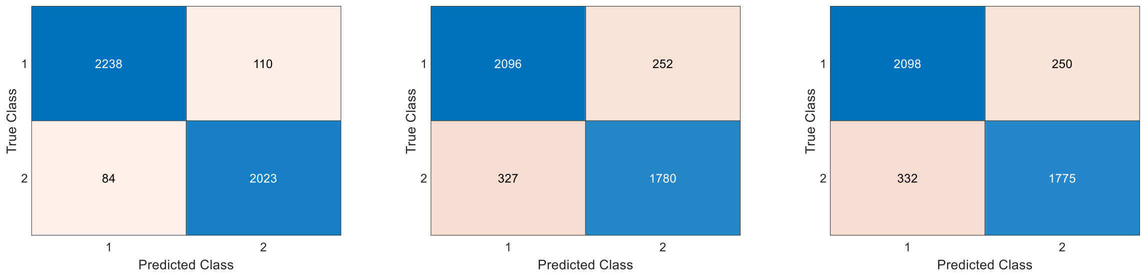


Figure 4. Training and validation curves of the ResNet 18

The complexity matrix for the kNN classifier with the best performance is given in Figure 5. Sensitivity, specificity, precision, and F-score performance metrics were calculated using true positive, true negative, false positive, and false negative values in the complexity matrix. These values are given in Table 3.

Table 2. Accuracy results of channel-1 according to classifiers

Classifier	Accuracy(%)
kNN[23]	**95.6**
SVM[24]	94.5
Naive Bayes[25]	93.3
ANN[26]	93.2
Logistic Regression[27]	91.6
Fine Tree[28]	90.8



a) 1. Channel b) 2.Channel c) 3.Channel

Figure 5. Confusion matrix results: 1: MDD, 2: Healthy

Table 3. Results of other performance metrics

	Class	Accuracy(%)	Precision(%)	Recall(%)	Sensitivity(%)	Specificity(%)
Channel 1	MDD	95.65	96.38	95.32	95.32	96.01
	Healthy		94.84	96.01	96.01	95.32
Channel 2	MDD	87.00	86.50	89.27	95.32	96.01
	Healthy		87.60	84.48	96.01	95.32
Channel 3	MDD	86.94	86.34	89.35	95.32	96.01
	Healthy		87.65	84.24	96.01	95.32

Using the same dataset in Table 4, Soni et al. [29], used Euclidean distance and Node2vec methods. With this method, 82.30% classification accuracy was obtained.

Table 4. Comparison with the method using the same dataset

Reference	Method	Split Ratio	Results
Soni et al.[29]	Euclidean distance, Node2vec	10-fold CV	Accuracy:82.30; Precision: 78.90; Recall: 71.80;
Proposed Model	Spectrogram, ResNet18, ReliefF, kNN	10-fold CV	Channel 1 Accuracy:95.65; Precision: 96.38; Recall: 95.32; Channel 2 Accuracy:87.00; Precision: 86.50; Recall: 89.27; Channel 3 Accuracy:86.94; Precision: 86.34; Recall: 89.35;

5.Conclusion

In this study, a deep learning-based approach was used to detect MDD from EEG signals. In this approach, spectrogram images were created to obtain strong 2D representations. These representations are used in the ResNet 18 model. One thousand features were extracted from this model. Five hundred of the extracted features were selected by Relieff algorithm. The best classification performance for the selected features was obtained in the kNN classifier with 95.65%. The proposed approach was developed based on the performance of another method using the same dataset. The classification accuracy has been increased by approximately 13.35%. However, the result obtained is not at a sufficient level of performance to be used in decision support application. For this, the size of the dataset needs to be increased. In addition, performance can be increased with CNN models created from scratch with a larger dataset.

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