Major depressive disorder diagnosis based on PSD imaging of electroencephalogram EEG and AI

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ABSTRACT

One of the most common causes of functional frailty is major depressive disorder (MDD). MDD is a chronic condition that requires long-term therapy and professional assistance. Additionally, MDD effective treatment requires early detection. Unfortunately, it has intricated clinical characteristics that make early diagnosis and treatment difficult for clinicians. Furthermore, there are currently no clinically effective diagnostic biomarkers that can confirm an MDD diagnosis. However, electroencephalogram (EEG) data from the brain have recently been used to make a quantitative diagnosis of MDD. In addition, As being among the most cutting-edge artificial intelligence (AI) technologies, deep learning (DL) has exhibited superior performance in a wide range of real-world applications, from computer vision to healthcare. However, an additional challenge could be the extraction of information from the ECG raw data. This paper presents a method for converting EEG data to power spectral density (PSD) images, and then they were classified as healthy or MDD using a deep neural network for feature extraction and a machine learning (ML) classifier. When employing the proposed approach, the images formed from the PSD show a considerably improved performance in classification results.

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1. INTRODUCTION

Depression and other mental illnesses are significant public health concerns because they contribute significantly to the global disease burden and considerably impact people's social and economic [1]. According to the World Health Organization (WHO), mental diseases are expected to be the leading cause of disability worldwide by 2020. The WHO implies that around 264 million individuals of all ages are believed to have some sort of mental illness, indicating that up to 27% of the general population will experience mental health disorders at some point in their lives. Depression symptoms include despair, loss of interest and focus, physical malfunction, insomnia, guilt, difficulty making decisions, and suicidal thoughts [2], [3]. Nevertheless, the precondition for treatment is the requirement for an accurate diagnosis [3].

Mentally problems are typically diagnosed through an individual's self-report of responses to specific questions helps to identify specific types of emotion or social interaction, in contrast to other physical illnesses diagnosed through laboratory results and assessments [4]. Unfortunately, half of the depressed patients are either ignorant of their condition or misdiagnosed (WHO 2017). Therefore, electroencephalogram (EEG) is extensively used in medical settings. Due to its high temporal resolution, economical, intrusive method, and ease of setup [5]-[9], EEG is a valuable technique for diagnosing mental illnesses such as depression [10]-[13]. The EEG system collects data from the many locational areas of the brain. However, the raw EEG signal is complex due to its temporal and spatial fluctuation [14]. Therefore, in major depressive disorder (MDD) classification, specific subject knowledge is necessary for traditional hand-crafted feature extraction. Traditional data preprocessing, on the other hand, expenses quadratically increase as the number of features increases [15]. Therefore, mature extraction research has concentrated on the time [16]-[21], frequency [22]-[24], or the EEG signal's time-frequency components [25], [26], with little attention paid to the spatial dimension.

As more data on an individual's mental health status becomes available, AI and machine learning techniques have been used to increase our understanding of mental health issues and aid mental health clinicians in making more informed therapy decisions [27]-[29]. Deep learning (DL) is a technique for automatically extracting meaningful information or patterns from data through multilayered neural networks [28]. Many notable advancements in DL approaches include Autonomous vehicles, natural language processing, face detection, synthesis of text-to-speech, transcription of handwriting, medical analysis, personal digital assistants, and recommender systems [30]. Convolutional neural networks (CNNs) have proven superior in various applications. Object recognition, medical diagnosis and prognosis, classification algorithms, and clustering are just a few examples [30], [31]. Furthermore, recent research has shown the importance and value of deep learning architectures in neurology, mainly when using neuroimaging data [32]. Numerous studies in the recent literature in brain-computer interfaces (BCI) have established the reliability, durability, and trustworthiness of the EEG-based technique in combination with DL. Particularly useful in the classification of motor imagery tasks [33]-[36], the prediction and detection of epileptic seizures, the prediction and detection of driver fatigue [37], the classification of emotion and affective states [21], the detection of sleep stages [38].

According to recent research, the CNN approach is particularly effective in tasks like feature extraction and classification. However, using CNN for feature extraction and traditional classifiers (such as support vector machine (SVM), k-nearest neighbor (KNN)) for classification would be more effective for a small dataset. The scope of this study is to extract Power spectral density (PSD) from a multichannel EEG signal and convert it into images to characterize mental states accurately. Therefore, to classify EEG data, a data mining methodology was built. First, the features are extracted into a new space using a CNN. After that, based on the features gathered, a prediction model was created to identify patterns in the data. The main contributions of this work are as shown in:

- Propose an end-to-end model to diagnose depression using row ECG data after using PSD images without any complex converting process costing time and computational power.
- The proposed method was tested using EEG data in three cases, eyes open, eyes closed, and task given.
- A comparison contacted with similar methods on the same data proved that the proposed method reached the highest value in terms of accuracy, sensitivity, f-1 score, and AUC.

The article's content is divided into the following sections: section 2 demonstrates the related work, section 3 discusses the data collection, representation, and methods presented. Sections 4, 5 summarizes the results of this study and compares them to those of other recent studies. Finally, section 6 concludes the paper and makes recommendations for future research.

2. RELATED WORKS

Historically, to diagnose depression, a variety of EEG-based ML techniques were used. For example, [39] analyzed the 5-minute EEG signals of 30 patients using relative wavelet energy, entropy, and an artificial neural network (ANN) [40]. Studied the frontal brain waves of 12 depressed individuals and 12 healthy subjects using Higuchi and Katz Fractal measures. In addition, Ahmadlou *et al*. [41] conducted experiments on 22 MDD patients and developed a novel nonlinear approach: spatial-temporal analysis of EEG signals' relative convergence [42]. Used a variety of nonlinear approaches such as detrended fluctuation analysis and greatest Lyapunov to determine the degree of signal complication.

Additionally, researchers used correlation dimension and Welch's power spectral density to assess power in specific frequency bands [43]. Extracted relevant characteristics from 15 healthy and 15 depressive individuals combining haar wavelet decomposition with various entropies [3]. Diagnosed depression in 37 university students using an event-related potential approach. Two alternative feature selection procedures have been used to discover the more effective characteristics for classifying the two groups: greedy stepwise and genetic search [44]. Evaluated characteristics using linear parameters from EEG signals, band power, and alpha interhemispheric imbalance to determine accuracy [45]. Classified 34 participants into depressive and healthy groups using the spectral asymmetry index and detrended fluctuation analysis approaches.

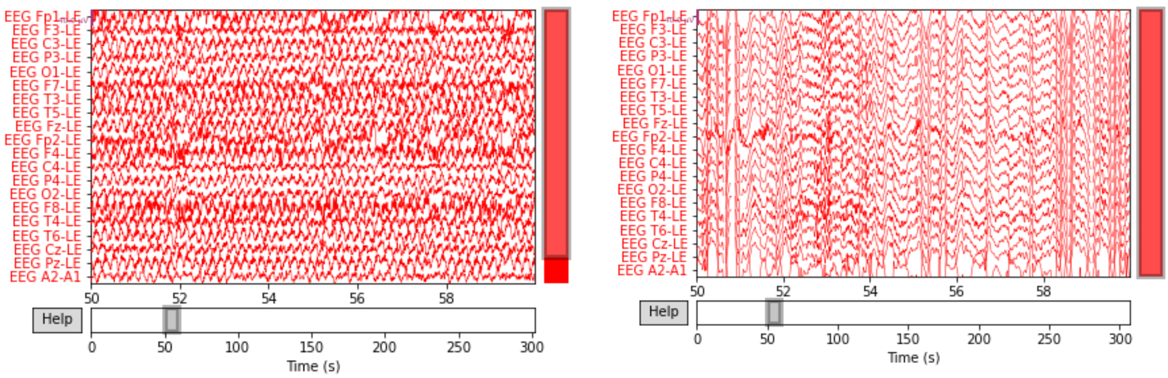
Numerous studies on brain signal categorization have used various techniques to convert EEG signals to visual representations. One study, for instance, converted EEG time series to 2D images using the short-term Fourier transformation approach then classified EEG motor imagery signals using a combination of 1D CNNs and stacking autoencoders [46]. This technique outperformed the winning algorithm by 9%. In addition, [47] developed a new format for EEG signals that maintain the pattern of EEG data over a wide range of space, time, and frequency. The spectral power within three principal frequency bands was determined for each point by projecting three-dimensional electrode sites onto a two-dimensional surface using azimuthal equidistant projection. This two-dimensional surface was then utilized to create topographical maps, which were combined to create three-channel views. Next, the samples were identified using these three-channel images fed into a deep convolutional recurrent neural network. Mohammadi *et al*. [48] the EEG data of 53 MDD and 43 healthy subjects were classified using a data mining algorithm. The features were first mapped into a new feature space using linear discriminant analysis, and then the most significant characteristics were determined using a genetic algorithm. Then, using a decision tree classifier, a prediction model was constructed to identify rules and patterns in the data based on the decreased and mapped data. The model achieved an identification rate of 80% using this strategy, which significantly decreased the overall number of features needed.

Li *et al*. [49], EEG data from 37 participants were obtained using a 128 channel HydroCel Geodesic Sensor Net in an experiment. Support vector machine (SVM), Bayesian Network, random forest (RF), logistic regression (LR), and k-nearest neighbor (KNN) techniques were used to differentiate between MDD patients and healthy controls. In addition, a feature selection approach, to achieve the best results, a stepwise greedy algorithm for the beta frequency band relying on correlation feature selection and a KNN were applied. The accuracy was 92% and 98%, respectively, while the area under the curve (AUC) was 0.957 and 0.997. However, most investigations focused on features engineering and classification improvement with limited outcomes, as indicated by the previous research, and finally, precisely diagnosing this mental disease remains a complex undertaking.

3. MATERIALS AND PROPOSED METHOD

3.1. Dataset

The dataset utilized in this study was supplied by [44] and is freely available online (www.figshare.com). Furthermore, the ethics committee of Hospital University Sains Malaysia approved the methodology. 34 MDD ranging from (27-53) years (average=40) and 30 healthy volunteers ranging from (22-53) years (average=38) were recorded. According to the diagnostic and statistical manual IV, the depressed group met the criteria for participation in the study (DSM-IV) [50]. Figure 1 shows (a) EEG samples for MDD and (b) healthy individuals.



(a) (b)

Figure 1. EEG samples from the dataset (a) MDD and (b) healthy

3.2. Acquiring and preparing data

The EEG data were acquired (with the eyes closed, eyes opened, and task given) for 5 minutes using a 19-channel EEG cap placed on the head following the international standard electrode position scheme of 10–20. The sampling rate of the EEG was set to 256 Hz. Figure 1 illustrates a sample of EEG data from healthy and depressed participants.

3.3. Power spectral density (PSD)

Since the amount of EEG data is constrained, a parametric method is the only way to approximate the actual spectrum. Therefore, The AR Burg approach is used to calculate the PSD. We employ a sliding Hamming window with 256 data points (250 milliseconds) and 128 data points overlap (125 milliseconds) to improve spectrum estimation performance. The spectrum estimation process is divided into two phases. First, with a specified data sequence, estimate the model-based technique's parameters $x(n)$ $0 \leq n \leq N$-1. Second, using such estimates, calculate the PSD.

Essentially, the AR technique works by stimulating the input data $x(n)$ as the outcome of a discrete causal filter with white noise for the input, as defined in (1):

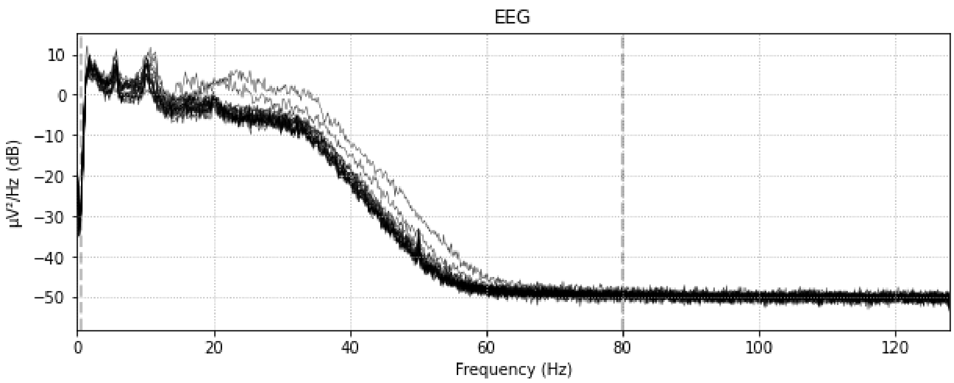
$$x(n) = -\sum_{k=1}^{p} a(k) \cdot x(n-k) + w(n), \tag{1}$$

where *a(k)* denotes the AR coefficient, n is white noise with a variance σ^2, and p denotes the AR model's order. The recursive Burg approach is used to estimate AR coefficients in this study, which reduces forward and backward error rates [51]. PSD estimate is obtained from the Burg method's calculation of AR parameters as defined in (2):

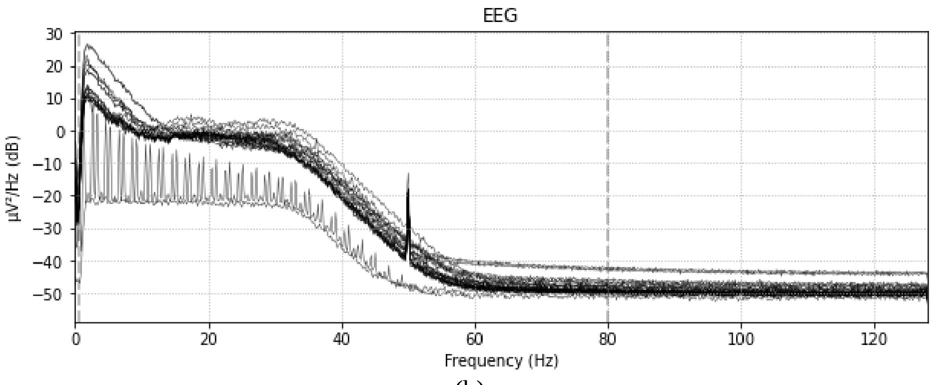
$$\hat{P}(f) = \frac{\hat{e}_p}{|1+\sum_{k=1}^{p} \widehat{a_p}(k) e^{-j2\pi fk}|}, \tag{2}$$

where $\hat{e}_p$ denotes the sum of the least-squares errors. The Akaike information criterion is used to calculate the model order p of the AR technique.

The model order is set at p=10 throughout this study. After calculating PSD for raw ECG data, images of these plots were used as input of the CNN model for feature extraction. Figure 2 shows (a) PSD plots for each healthy and (b) PSD plots for MDD.



(a)



(b)

Figure 2. PSD plot samples (a) healthy and (b) MDD

3.4. Feature extraction

The MobilenetV2 network is one of the most widely utilized and lightweight CNNs [51]. It is developed for images and may be used for both classification and feature extraction. It employs an inverted residual and a linear bottleneck. Figure 3 illustrates how the blocks are stacked together. It starts by using 1×1 point convolution to extend input channels. The input feature is then extracted using deep convolution, and the convolution aggregator is used to aggregate the output while maintaining the network size low linearly. Finally, it replaces the ReLU6 with a linear function to adjust the output channel size to the input.

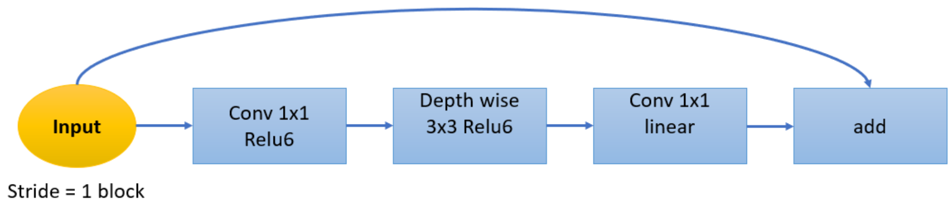


Figure 3. MobilNetV2 model

The reverse block is used by the MobilenetV2 model to obtain additional functionality by combining features over layers. Furthermore, the input channels and filters are separated into separate channels using depth convolution, using a 1×1 kernel to combine the outputs. Due to its low number of parameters compared to other regularly used CNN models (as shown in Table 1), MobileNetV2 is targeted for usage with mobile or low-cost devices.

Table 1. Number of trainable parameters for some well-known models

Model	No. trainable parameters
Xception	22,910,480
VGG16	138,357,544
ResNet50	25,636,712
InceptionV3	23,851,784
InceptionResNetV2	55,873,736
MobileNet	4,253,864
MobileNetV2	3,538,984

The MobileNetV2 is a reliable network with a quick response time. This work used the MobileNetV2 pre-trained model (ImageNet-based) and generated 250,880 features from each image.

3.5. Classification

The suggested model is presented to classify EEG data for MDD and healthy samples accurately. The features extracted by MobileNetV2 are classified using well-known classifiers (RF, SVM, and LR). Figure 4 shows a schematic representation of the proposed method.

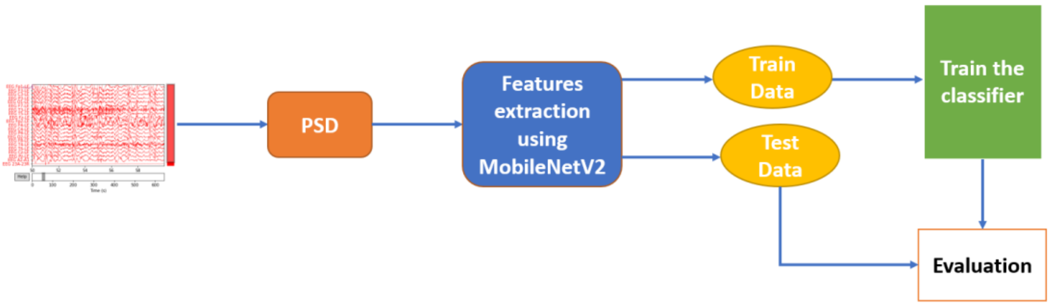


Figure 4. The proposed method structure

The proposed method has been applied and evaluated using the following explained performance metrics to show the superiority of our method. The working steps are explained:
Step 1: read the EEG file from the dataset for eyes opened EO, eyes closed EC, and given task case.
Step 2: use PSD for each EEG sample and make a plot image.
Step 3: feature extraction using MobileNetV2.
Step 4: split data obtained from step 3 into train and test (54 samples for train and 10 for test equally distributed between MDD and healthy).
Step 5: use proposed classifiers.
Step 6: evaluate the results using performance matrices.
All processing, feature engineering, and data classification steps were implemented in Keras library and Python 3.8 on a computer with Intel(R) Core (TM) i7-10750H CPU @ 2.60GHz with 2.59 GHz 32.0 Gigabyte of RAM, and a display adapter from NVIDIA GeForce GTX 1650 Ti.

3.6. Performance matrices

The model's performance on the testing set was examined using five performance parameters in this study: accuracy rate, sensitivity, F1-Score, precision, and area under the curve (AUC). AUC is the likelihood of the model correctly categorizing a random positive image sample over a random negative image sample. It is determined using different thresholds to calculate the true positive rate (TPR) and false positive rate (FPR). As shown in (3)-(6) indicate the first four performance matrices:

$$Accuracy = \frac{TP + TN}{TP+TN+FP + FN}, \tag{3}$$

$$Sensitivity = \frac{TP}{TP+ FN}, \tag{4}$$

$$Precision = \frac{TP}{TP + FP}, \tag{5}$$

$$F1 - Score = 2\ \mathrm{X} \frac{(\text{Precision X Sensitivity})}{(\text{Precision+Sensitivity})}, \tag{6}$$

where TP (true positive) denotes the number of MDD individuals successfully classified, TN the number of healthy people (true negative) individuals accurately classified, FN represents the number of MDD patients who were incorrectly classed as healthy FN (false negative), and FP (false positive) is the number of healthy people who have been misclassified with MDD.

4. RESULTS

The test data accuracy, sensitivity, precision, f1-score, and AUC for features extracted obtained from MobileNetV2 model by each classifier are given in Table 2. The evaluations were calculated using EEG taken with eyes opened, eyes closed, and while task given for the volunteers. The test data contains five MDD and five healthy samples, which the model did not have been trained on to prove the generalization ability of the method.

Table 2. Performance matrices for each classifier in different cases

Classifier	Accuracy	Sensitivity	Precision	F1-score	AUC
RF while eyes opened	0.7000	0.7000	0.7083	0.6970	0.70
RF while eyes closed	1.0000	1.0000	1.0000	1.0000	1.00
RF while task given	0.9000	0.9000	0.9167	0.8990	0.90
SVM while eyes opened	0.8000	0.8000	0.8000	0.8000	0.80
SVM while eyes closed	1.0000	1.0000	1.0000	1.0000	1.00
SVM while task given	0.8000	0.8000	0.8571	0.7917	0.80
KNN while eyes opened	0.9000	0.9000	0.9167	0.8990	0.90
KNN while eyes closed	1.0000	1.0000	1.0000	1.0000	1.00
KNN while task given	0.7000	0.7000	0.7083	0.6970	0.70
LR while eyes opened	0.8000	0.8000	0.8000	0.8000	0.80
LR while eyes closed	1.0000	1.0000	1.0000	1.0000	1.00
LR while task given	0.9000	0.9000	0.9167	0.8990	0.90

Figure 5 shows the confusion matrix for each model with each case using test data. Figure 5(a) random forest, Figure 5(b) SVM, Figure 5(c) KNN, Figure 5(d) LR it is noticeable that the best results were obtained for EEG data taken while eyes closed. However, the results were identical for all classifiers, too, with 100% for each performance matrices. Moreover, the results of EEG data while a task is given are better than the results while eyes opened in general.

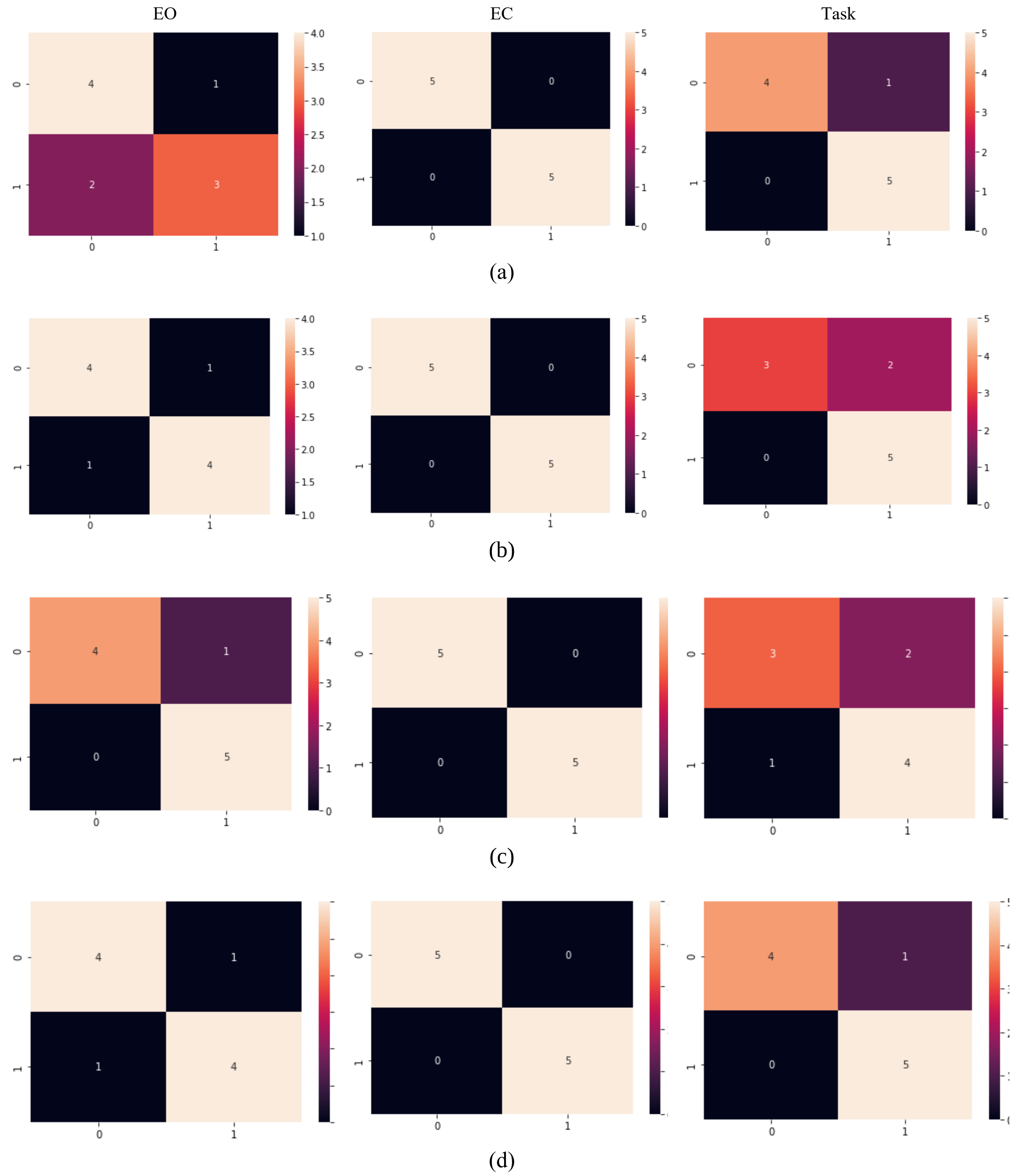


Figure 5. Confusion matrix for each classifier in different cases, (a) random forest, (b) SVM, (c) KNN, and (d) LR

5. DISCUSSION

Depression screening is critical for early diagnosis and treatment. However, artificial intelligence techniques can circumvent this barrier and enable widespread use without highly skilled professionals. Our method successfully employed deep learning and machine learning classifiers to detect MDD patients and healthy controls. When applied to 19 channels of EEG signals with closed eyes, the MobilNetV2 architecture with a classifier achieves a precision of 100%. One of this work's primary innovations is its use of PSD plot images obtained from EEG data and classification is made after feature extraction, and this method is tested using data obtained while eyes closed, eyes opened, and given a task to the participants. There is no need for complex pre-processing steps for feature extraction in this method, significantly reducing the running time. However, the classifier cannot analyse the PSD plot images. While using light-weighted MobileNetV2 for feature extraction enabled the classifiers to make perfect results.

In Table 3, the findings of this study are compared to those of recently published comparative research that used EEG from the same and a different dataset. As can be shown, the accuracy obtained in this study is higher than that obtained in previous studies using classic machine learning approaches for linear and nonlinear feature extraction, demonstrating the suggested method's superiority. Furthermore, these results are more accurate than those obtained using alternative DL techniques on EEG time series data. As a result, as shown in Table 3, this work obtained the highest results in the automated detection of depressive and healthy people to date. This study's primary limitation is the size of the dataset used to train the classifier. However, by conducting features extraction using the pre-trained MobilNetV2 network, we overcame this limitation.

Table 3. Results comparison with similar works

Study	Method	Accuracy	Sensitivity
Acharya *et al.* [51]	SVM	0.98	0.97
Mumtaz *et al.* [44]	Naive Bayes, LR, SVM	0.98	0.96
Acharya *et al.* [52]	1Dimentional -CNN	0.95	0.95
Ay *et al.* [53]	CNN- long short-term memory (LSTM)	0.99	0.98
Mumtaz and Qayyum [54]	CNN-LSTM, 1Dimentional-CNN	0.98	0.98
Suggested research	CNN- RF, SVM, LR, and KNN	1.00	1.00

6. CONCLUSION

This study conducted a detailed investigation using a CNN with a pre-trained model (MobilNetV2) and many well-known machine learning algorithms for feature extraction (RF, SVM, LR, and KNN). As a result, the highest accuracy of 100% in classifying MDD and normal was reached for eyes closed individuals. Relying upon the outcomes, the newly released deep learning model can effectively assess brain EEG data and give the best findings compared to all current studies. As a result, suggested technologies can assist health care providers in identifying MDD patients for early identification and prevention. In addition, this method can be adapted for future work to classify other EEG-based diagnoses of various neurodegenerative diseases, such as schizophrenia, Parkinson's disease, and Alzheimer's disease.

REFERENCES

[1] M. Marcus, M. T. Yasamy, M. van Ommeren, D. Chisholm, and S. Saxena, "Depression: a global public health concern," *World Mental Health Day*, 2016.

[2] A. L. *et al.*, "The epidemiology of major depressive episodes: Results from the International Consortium of Psychiatric Epidemiology (ICPE) Surveys," *International Journal of Methods in Psychiatric Research*, vol. 12, no. 1, pp. 3–21, 2003, [Online]. Available: http://ovidsp.ovid.com/ovidweb.cgi?T=JS&PAGE=reference&D=emed6&NEWS=N&AN=2003226474.

[3] X. Li, B. Hu, S. Sun, and H. Cai, "EEG-based mild depressive detection using feature selection methods and classifiers," *Computer Methods and Programs in Biomedicine*, vol. 136, pp. 151–161, 2016, doi: 10.1016/j.cmpb.2016.08.010.

[4] M. Hamilton, "Development of a rating scale for primary depressive illness," *British Journal of Social and Clinical Psychology*, vol. 6, no. 4, pp. 278–296, Dec. 1967, doi: 10.1111/j.2044-8260.1967.tb00530.x.

[5] A. Shalbaf, R. Shalbaf, M. Saffar, and J. Sleigh, "Monitoring the level of hypnosis using a hierarchical SVM system," *Journal of Clinical Monitoring and Computing*, vol. 34, no. 2, pp. 331–338, 2020, doi: 10.1007/s10877-019-00311-1.

[6] A. Shalbaf, M. Saffar, J. W. Sleigh, and R. Shalbaf, "Monitoring the Depth of anesthesia using a new adaptive neurofuzzy system," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 3, pp. 671–677, May 2018, doi: 10.1109/JBHI.2017.2709841.

[7] F. Afshani, A. Shalbaf, R. Shalbaf, and J. Sleigh, "Frontal–temporal functional connectivity of EEG signal by standardized permutation mutual information during anesthesia," *Cognitive Neurodynamics*, vol. 13, no. 6, pp. 531–540, Dec. 2019, doi: 10.1007/s11571-019-09553-w.

[8] E. Kabir, Siuly, J. Cao, and H. Wang, "A computer aided analysis scheme for detecting epileptic seizure from EEG data," *International Journal of Computational Intelligence Systems*, vol. 11, no. 1, pp. 663–671, 2018, doi: 10.2991/ijcis.11.1.51.

[9] W. V. Rosenberg, T. Chanwimalueang, V. Goverdovsky, D. Looney, D. Sharp, and D. P. Mandic, "Smart helmet:wearable multichannel ECG and EEG," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 4, pp. 1–11, 2016, doi: 10.1109/JTEHM.2016.2609927.

[10] G. Laje *et al.*, "Genetic Markers of suicidal ideation emerging during citalopram treatment of major depression," *Focus*, vol. 6, no. 1, pp. 69–79, 2008, doi: 10.1176/foc.6.1.foc69.

[11] G. Pfurtscheller and C. Andrew, "Event-Related changes of band power and coherence: methodology and interpretation," *Journal of Clinical Neurophysiology*, vol. 16, no. 6, p. 512, Nov. 1999, doi: 10.1097/00004691-199911000-00003.

[12] M. A. Rahman, A. Anjum, M. M. H. Milu, F. Khanam, M. S. Uddin, and M. N. Mollah, "Emotion recognition from EEG-based relative power spectral topography using convolutional neural network," *Array*, vol. 11, p. 100072, Sep. 2021, doi: 10.1016/j.array.2021.100072.

[13] D. Jain and V. Singh, "Feature selection and classification systems for chronic disease prediction: A review," *Egyptian Informatics Journal*, vol. 19, no. 3, pp. 179–189, 2018, doi: 10.1016/j.eij.2018.03.002.

[14] W.-L. Zheng, J.-Y. Zhu, and B.-L. Lu, "Identifying stable patterns over time for emotion recognition from EEG," *IEEE Transactions on Affective Computing*, vol. 10, no. 3, pp. 417–429, Jul. 2019, doi: 10.1109/TAFFC.2017.2712143.

[15] W. Zheng, "Multichannel EEG-based emotion recognition via group sparse canonical correlation analysis," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 9, no. 3, pp. 281–290, Sep. 2017, doi: 10.1109/TCDS.2016.2587290.

[16] M. Murugappan, M. Rizon, R. Nagarajan, and S. Yaacob, "Inferring of human emotional states using multichannel EEG," *European Journal of Scientific Research*, vol. 48, no. 2, pp. 281–299, 2010.

[17] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from brain signals using hybrid adaptive filtering and higher order crossings analysis," *IEEE Transactions on Affective Computing*, vol. 1, no. 2, pp. 81–97, 2010, doi: 10.1109/T-AFFC.2010.7.

[18] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from EEG using higher order crossings," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 2, pp. 186–197, Mar. 2010, doi: 10.1109/TITB.2009.2034649.

[19] M. Murugappan, N. Ramachandran, and Y. Sazali, "Classification of human emotion from EEG using discrete wavelet transform," *Journal of Biomedical Science and Engineering*, vol. 03, no. 04, pp. 390–396, 2010, doi: 10.4236/jbise.2010.34054.

[20] W. L. Zheng and B. L. Lu, "Investigating critical frequency bands and channels for EEG-Based emotion recognition with deep neural networks," *IEEE Transactions on Autonomous Mental Development*, vol. 7, no. 3, pp. 162–175, 2015, doi: 10.1109/TAMD.2015.2431497.

[21] S. Jirayucharoensak, S. Pan-Ngum, and P. Israsena, "EEG-based emotion recognition using deep learning network with principal component based covariate shift adaptation," *The Scientific World Journal*, vol. 2014, pp. 1–10, 2014, doi: 10.1155/2014/627892.

[22] N. Thammasan, K. Moriyama, K. Fukui, and M. Numao, "Continuous music-emotion recognition based on electroencephalogram," *IEICE Transactions on Information and Systems*, vol. E99.D, no. 4, pp. 1234–1241, 2016, doi: 10.1587/transinf.2015EDP7251.

[23] L. Xin, Q. Xiaoying, S. Xiaoqi, X. Jiali, F. Mengdi, and K. Jiannan, "An improved multi-scale entropy algorithm in emotion EEG features extraction," *Journal of Medical Imaging and Health Informatics*, vol. 7, no. 2, pp. 436–439, Apr. 2017, doi: 10.1166/jmihi.2017.2031.

[24] Z. Yin, Y. Wang, L. Liu, W. Zhang, and J. Zhang, "Cross-subject EEG Feature selection for emotion recognition using transfer recursive feature elimination," *Frontiers in Neurorobotics*, vol. 11, no. APR, Apr. 2017, doi: 10.3389/fnbot.2017.00019.

[25] A. Wongkoblap, M. A. Vadillo, and V. Curcin, "Researching mental health disorders in the era of social media: Systematic review," *Journal of Medical Internet Research*, vol. 19, no. 6, 2017, doi: 10.2196/jmir.7215.

[26] C. A. Lovejoy, "Technology and mental health: The role of artificial intelligence," *European Psychiatry*, vol. 55, pp. 1–3, Jan. 2019, doi: 10.1016/j.eurpsy.2018.08.004.

[27] D. B. Dwyer, P. Falkai, and N. Koutsouleris, "Machine learning approaches for clinical psychology and psychiatry," *Annual Review of Clinical Psychology*, vol. 14, no. 1, pp. 91–118, May 2018, doi: 10.1146/annurev-clinpsy-032816-045037.

[28] Y. LeCun, G. Hinton, and Y. Bengio, "Deep learning (2015), Y. LeCun, Y. Bengio and G. Hinton," *Nature*, vol. 521, pp. 436–444, 2015.

[29] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep learning for healthcare: Review, opportunities and challenges," *Briefings in Bioinformatics*, vol. 19, no. 6, pp. 1236–1246, 2017, doi: 10.1093/bib/bbx044.

[30] S. Vieira, W. H. L. Pinaya, and A. Mechelli, "Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications," *Neuroscience & Biobehavioral Reviews*, vol. 74, pp. 58–75, Mar. 2017, doi: 10.1016/j.neubiorev.2017.01.002.

[31] D. Durstewitz, G. Koppe, and A. Meyer-Lindenberg, "Deep neural networks in psychiatry," *Molecular Psychiatry*, vol. 24, no. 11, pp. 1583–1598, 2019, doi: 10.1038/s41380-019-0365-9.

[32] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, H. Adeli, and D. P. Subha, "Automated EEG-based screening of depression using deep convolutional neural network," *Computer Methods and Programs in Biomedicine*, vol. 161, pp. 103–113, 2018, doi: 10.1016/j.cmpb.2018.04.012.

[33] S. Kumar, A. Sharma, K. Mamun, and T. Tsunoda, "A deep learning approach for motor imagery EEG signal classification," in *2016 3rd Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE)*, Dec. 2016, pp. 34–39, doi: 10.1109/APWC-on-CSE.2016.017.

[34] J. Zhang, C. Yan, and X. Gong, "Deep convolutional neural network for decoding motor imagery based brain computer interface," in *2017 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*, Oct. 2017, vol. 2017-Janua, pp. 1–5, doi: 10.1109/ICSPCC.2017.8242581.

[35] P. N. Paranjape, M. M. Dhabu, P. S. Deshpande, and A. M. Kekre, "Cross-correlation aided ensemble of classifiers for BCI oriented EEG Study," *IEEE Access*, vol. 7, pp. 11985–11996, 2019, doi: 10.1109/ACCESS.2019.2892492.

[36] K. M. Tsiouris, V. C. Pezoulas, M. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. I. Fotiadis, "A long short-term memory deep learning network for the prediction of epileptic seizures using EEG signals," *Computers in Biology and Medicine*, vol. 99, pp. 24–37, Aug. 2018, doi: 10.1016/j.compbiomed.2018.05.019.

[37] M. Hajinoroozi, J. M. Zhang, and Y. Huang, "Driver's fatigue prediction by deep covariance learning from EEG," in *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Oct. 2017, vol. 2017-Janua, pp. 240–245, doi: 10.1109/SMC.2017.8122609.

[38] S. Chambon, V. Thorey, P. J. Arnal, E. Mignot, and A. Gramfort, "A deep learning architecture to detect events in EEG signals during sleep," in *2018 IEEE 28th International Workshop on Machine Learning for Signal Processing (MLSP)*, Sep. 2018, vol. 2018-Septe, pp. 1–6, doi: 10.1109/MLSP.2018.8517067.

[39] S. D. Puthankattil and P. K. Joseph, "Classification of EEG signals in normal and depression conditions by ANN using RWE and signal entropy," *Journal of Mechanics in Medicine and Biology*, vol. 12, no. 04, p. 1240019, Sep. 2012, doi: 10.1142/S0219519412400192.

[40] M. Ahmadlou, H. Adeli, and A. Adeli, "Fractality analysis of frontal brain in major depressive disorder," *International Journal of Psychophysiology*, vol. 85, no. 2, pp. 206–211, Aug. 2012, doi: 10.1016/j.ijpsycho.2012.05.001.

[41] M. Ahmadlou, H. Adeli, and A. Adeli, "Spatiotemporal analysis of relative convergence of EEGs reveals differences between brain dynamics of depressive women and men," *Clinical EEG and Neuroscience*, vol. 44, no. 3, pp. 175–181, Jul. 2013, doi: 10.1177/1550059413480504.

[42] 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, Mar. 2013, doi: 10.1016/j.cmpb.2012.10.008.

[43] O. Faust, P. C. A. Ang, S. D. Puthankattil, and P. K. Joseph, "Depression diagnosis support system based on eeg signal entropies," *Journal of Mechanics in Medicine and Biology*, vol. 14, no. 3, p. 1450035, Jun. 2014, doi: 10.1142/S0219519414500353.

[44] W. Mumtaz, L. Xia, S. S. A. Ali, M. A. M. Yasin, M. Hussain, and A. S. Malik, "Electroencephalogram (EEG)-based computer-aided technique to diagnose major depressive disorder (MDD)," *Biomedical Signal Processing and Control*, vol. 31, pp. 108–115, 2017, doi: 10.1016/j.bspc.2016.07.006.

[45] M. Bachmann, J. Lass, and H. Hinrikus, "Single channel EEG analysis for detection of depression," *Biomedical Signal Processing and Control*, vol. 31, pp. 391–397, Jan. 2017, doi: 10.1016/j.bspc.2016.09.010.

[46] Y. R. Tabar and U. Halici, "A novel deep learning approach for classification of EEG motor imagery signals," *Journal of Neural Engineering*, vol. 14, no. 1, p. 016003, Feb. 2017, doi: 10.1088/1741-2560/14/1/016003.

[47] P. Bashivan, I. Rish, M. Yeasin, and N. Codella, "Learning representations from EEG with deep recurrent-convolutional neural networks," 2016, *arXiv*:1511.06448.

[48] M. Mohammadi *et al.*, "Data mining EEG signals in depression for their diagnostic value," *BMC Medical Informatics and Decision Making*, vol. 15, no. 1, p. 108, Dec. 2015, doi: 10.1186/s12911-015-0227-6.

[49] X. Li, D. Song, P. Zhang, G. Yu, Y. Hou, and B. Hu, "Emotion recognition from multi-channel EEG data through Convolutional Recurrent Neural Network," in *Proceedings - 2016 IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2016*, Dec. 2017, pp. 352–359, doi: 10.1109/BIBM.2016.7822545.

[50] R. Cooper, "Diagnostic and statistical manual of mental disorders (DSM)," *Knowledge Organization*, vol. 44, no. 8, pp. 668–676, 2017, doi: 10.5771/0943-7444-2017-8-668.

[51] U. R. Acharya *et al.*, "A novel depression diagnosis index using nonlinear features in EEG signals," *European Neurology*, vol. 74, no. 1–2, pp. 79–83, 2015, doi: 10.1159/000438457.

[52] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals," *Computers in Biology and Medicine*, vol. 100, pp. 270–278, Sep. 2018, doi: 10.1016/j.compbiomed.2017.09.017.

[53] B. Ay *et al.*, "Automated depression detection using deep representation and sequence learning with EEG signals," *Journal of Medical Systems*, vol. 43, no. 7, p. 205, Jul. 2019, doi: 10.1007/s10916-019-1345-y.

[54] W. Mumtaz and A. Qayyum, "A deep learning framework for automatic diagnosis of unipolar depression," *International Journal of Medical Informatics*, vol. 132, p. 103983, Dec. 2019, doi: 10.1016/j.ijmedinf.2019.103983.

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