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Decision support system for major depression detection using spectrogram and convolution neural network with EEG signals

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Abstract

The number of Major Depressive Disorder (MDD) patients is rising rapidly these days following the incidence of COVID-19 pandemic. It is challenging to detect MDD through personal interviews and by observing electroencephalogram (EEG) signals. Hence, an automated MDD detection system developed using deep learning techniques can help reduce the workload of clinicians by diagnosing MDD accurately. In this study, we have proposed a novel deep learning model based on Convolutional Neural Network (CNN) and spectrogram images. In this work, Short-Time Fourier Transform (STFT) is first applied to the EEG signals to obtain spectrogram images of MDD patients and healthy subjects. These spectrogram images are then fed to the CNN model for automated detection of MDD patients and healthy subjects. The EEG signals used in this study were obtained from public database with 34 MDD patients and 30 healthy subjects. The highest classification accuracy, precision, sensitivity, specificity, and F1-score of 99.58%, 99.40%, 99.70%, 99.48%, and 99.55% respectively were obtained with hold-out validation. Our MDD detection model is highly accurate and needs to be validated with more diverse MDD database before it can be used in clinical settings. Also, we plan to use our developed prototype to detect depression using other physiological signals like electrocardiogram (ECG) and speech signals for accurate and faster diagnosis.

KEYWORDS

classification, CNN, deep learning, electroencephalogram (EEG), major depressive disorder (MDD), spectrograms, STFT

1 | INTRODUCTION

Depression is characterized by the sense of hopelessness and sadness which disrupts the daily activities of an individual, and the persistence of depression for 2 weeks or more is known as Major Depressive Disorder (MDD) (American Psychiatric Association, 2013; Kazama et al., 2011; Rosińczuk & Kołtuniuk, 2017). According to the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), the clinical diagnosis of MDD is defined by having at least five out of the following nine symptoms (American Psychiatric Association, 2013): Sleeping problem, loss of interest, fatigue, inability to concentrate, feeling of worthlessness, extreme weight gain or loss, depressed mood, psychomotor disturbances, and having suicidal thoughts. Currently, the number of MDD patients is rising rapidly on a global scale (Yasin et al., 2021). In 2013, the estimate of MDD patients was 32 million worldwide and the global drug sales for MDD treatment was $9.3 billion, which is expected to reach $9.7 million by 2023 (Gohil & Shah, 2015). To exacerbate the problem, studies had also shown that the number of MDD patients had multiplied several folds during the COVID-19 pandemic (Bueno-Notivol et al., 2021; Ettman et al., 2020; Iob et al., 2020). This highlights the importance of disease detection and management for MDD which increases the demands for an efficient diagnostic tool.

Electroencephalogram (EEG) is the recording of brain electrical activity, and have been employed for MDD diagnosis (de Aguiar Neto & Rosa, 2019; Hinrikus et al., 2010; Lee et al., 2018; Olbrich & Arns, 2013). A study reported that MDD is related to an increase in delta rhythm and previous depression episodes are positively correlated to the amplitude of the beta rhythm (Nystrom et al., 1986). Several Computer-Aided Diagnostic (CAD) systems have been proposed for automated and accurate detection of MDD patients using EEG signals (Acharya, Sudarshan, Adeli, Santhosh, Koh, & Adeli, 2015a; Kwong et al., 2019; M. Mohammadi et al., 2015). Figure 1 shows the sample EEG recordings of a healthy control and a MDD patient.

The studies conducted using conventional machine learning, and deep learning (DL) methodology for automated MDD detection using EEG signals are listed in Tables 1 and 6 respectively. Conventional machine learning model are also hand-modelled models, where feature extraction procedure is crucial because the model cannot handle high dimensional data like EEG signals, and will result in overfit (Loh et al., 2020; Mirza et al., 2019). Hence, there are a wide variety of feature extraction approaches used in these machine learning studies as shown in Table 1. Also, hand-modelled models require the use of classifiers such as Probabilistic Neural Network (PNN), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Support Vector Machine (SVM). Among the proposed hand-modelled models in Table 1, M. Sharma et al. (2018) achieved the highest classification accuracy score of 99.58%, by decomposing EEG signals into wavelet sub-bands and classified these features using least square SVM. Another study by Faust et al. (2014) also achieved a high classification accuracy of 99.50% using PNN classifier with EEG signals of the right hemisphere of the brain.

Since then, no other proposed hand-crafted conventional machine learning methods have reached the classification accuracy of 99%, most of them ranged from 74% to 98% as shown in Table 1. Also, 12 out of 22 automated depression studies in Table 1 managed to obtain above 90% classification accuracy, whereas 12 out of 13 DL models in Table 6 achieved more than 92% classification accuracy. Among the 12 deep learning studies, six of them have obtained classification accuracy of 99%. Hence, this shows that DL models is more suitable than hand-crafted machine learning models for automated MDD detection using EEG signals.

DL models comprised of deep neural network that can handle high-dimensional data with minimal information loss, even without the feature extraction procedure (Faust et al., 2019; Loh et al., 2020). DL models also do not require the mentioned classifiers of hand-modelled models to solve classification problem. Instead, classifiers such as Sigmoid and Softmax are commonly used for binary and multiclass classification, respectively (Hafemann et al., 2017). Currently, there are only *three* types of deep learning models proposed for automated MDD detection: Convolutional Neural Network (CNN), Multi-Layered Perceptron Neural Network (MLPNN), and hybrid model comprising of CNN and Long Short-Term Memory (LSTM) (Table 6). Figure 2 shows the percentage of hand-modelled models and DL models that have been developed for automated MDD detection. Currently, majority (63%) of the automated MDD detection studies proposed hand-crafted machine learning models. This indicates that more work is required to demonstrate that DL models can recognize EEG characteristics for automated MDD detection using EEG signals.

Therefore, this study is proposing a DL model based on CNN for automated MDD detection using EEG signals. Spectrogram images are obtained from EEG signals using Short-Time Fourier Transform (STFT) are used to train and evaluate the proposed model. The workflow of our approach is simple and reported highest classification performance.

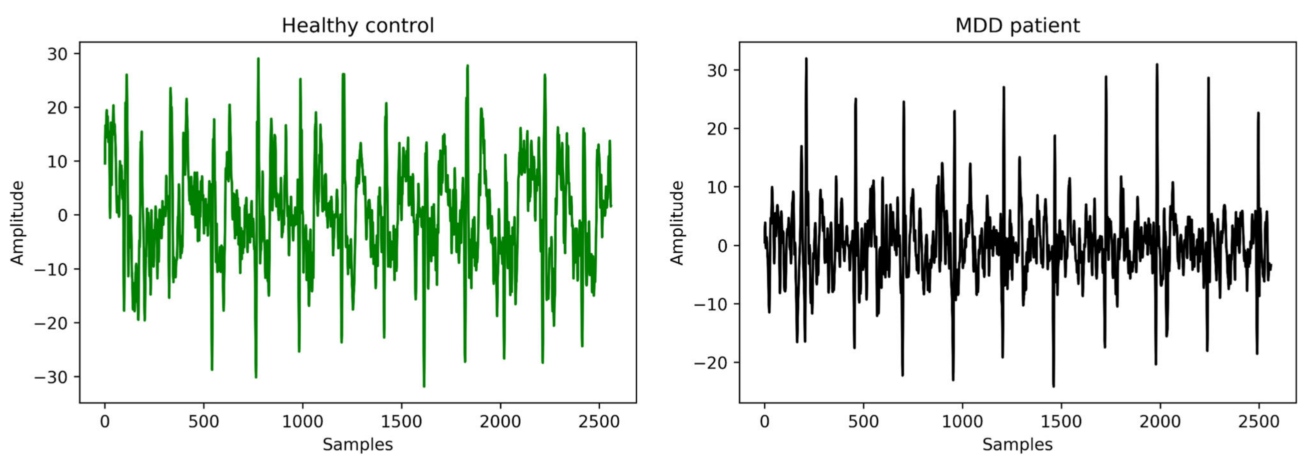


FIGURE 1 Sample EEG recordings of 1 healthy control and 1 MDD patient

TABLE 1 Summary of automated MDD detection studies proposed using hand-modelled techniques

Author	Feature	Classifier	Dataset	Accuracy (%)
Puthankattil and Joseph (2012)	Discrete wavelet transform	ANN	15 MDD 15 healthy	98.11
Ahmadlou et al. (2012)	Wavelet filter bank	PNN	12 MDD 12 healthy	91.30
Ahmadlou et al. (2013)	Spatiotemporal analysis of relative convergence	PNN	11 MDD 11 healthy	91.10
Hosseinifard et al. (2013)	Nonlinear features of EEG signals	Logistic regression	45 MDD 45 healthy	90.05
Faust et al. (2014)	wavelet packet decomposition and non-linear algorithm	PNN	15 MDD 15 healthy	99.50 (Right) 98.20 (Left)
Mantri et al. (2015)	Fast Fourier Transform	SVM	13 MDD 12 healthy	84.00
Acharya et al. (2015b)	Recurrence quantification Analysis and higher order spectra	SVM	15 MDD 15 healthy	98.00
Erguzel et al. (2016)	Particle swarm optimization	ANN	31 bipolar depression 58 unipolar depression	89.89
Mumtaz et al. (2017b)	Wavelet transform	Logistic regression	34 MDD 30 healthy	87.50
Mumtaz et al. (2017a)	alpha interhemispheric asymmetry and spectral power	SVM	34 MDD 30 healthy	98.40
Liao et al. (2017)	kernel eigen-filter-bank common spatial pattern	SVM	12 MDD 12 healthy	81.23
Bairy et al. (2017)	Linear prediction coding	Bagged tree	15 MDD 15 healthy	94.30
Kim et al. (2018)	Electrodermal activity	Decision tree	30 MDD 37 healthy	74.00
Cai et al. (2018)	Discrete wavelet transform and adaptive predictor filter	KNN	92 MDD 121 healthy	79.27
Wu et al. (2018)	Power features of EEG signals	Conformal kernel SVM	24 MDD 31 healthy	83.64
M. Sharma et al. (2018)	three-channel orthogonal wavelet filter bank	Least square SVM	15 MDD 15 healthy	99.58
Y. Mohammadi et al. (2019)	Katz fractal dimension	Fuzzy function based on neural network	60 MDD patients: 23 severe 10 moderate 10 mild 17 minimal	87.50
Lin et al. (2020	Average power ratio, waveform correlation and power spectral correlation	SVM	41 MDD 22 healthy	93.70
Eraldemir et al. (2020)	Continuous wavelet transform	KNN	30 MDD	91.30
Mahato and Paul (2020)	Power features of EEG signals and theta asymmetry	SVM	34 MDD 30 healthy	88.33
Jiang et al. (2021)	Spatial information of EEG	SVM	16 MDD 14 healthy	84.00 (Positive) 85.70 (Negative)
Akbari et al. (2021)	Centered correntropy and empirical wavelet transform	SVM	22 MDD 22 healthy	98.76

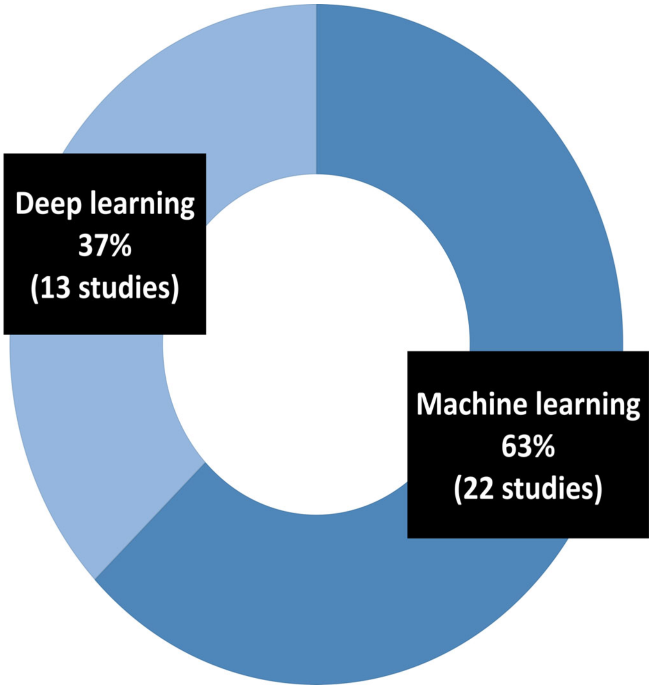


FIGURE 2 Pie chart representation of percentage of deep learning models versus hand-modelled models developed for automated MDD detection

2 | METHODS AND APPROACH

An illustration of the experimental setup is shown in Figure 3. The proposed deep learning model is trained using spectrogram images obtained from EEG signals. Section 2.1 provides the details of EEG dataset used in this study. Conversion of EEG signals to spectrograms images using STFT is described in Section 2.2. The architecture and working mechanism of the proposed model is delineated in Section 2.3.

2.1 | Data acquisition

The MDD patients and healthy controls EEG dataset collected by Mumtaz was used in this study (Mumtaz, 2016). EEG signals of 34 MDD patients and 30 healthy controls of age group between 12 to 77 years were gathered from the Hospital Universiti Sains Malaysia (HUSM). The sampling frequency of the EEG signals was 256 Hz and 20 EEG channels were considered. The EEG dataset consisted of three types of data: eyes closed (EC), eyes opened (EO), and TASK. To collect EC and EO EEG recordings, study participants were told to keep their eyes closed or opened respectively for 5 min, with minimal head movement and blinking (Mumtaz et al., 2017b). As for the TASK data, study participants were subjected to 10 min of visual stimulus, where they were instructed to enter “SPACE” on the keyboard when the target flashes on the screen (Mumtaz, Xia, Mohd Yasin, et al., 2017b). All three data types were included in this study.

2.2 | Spectrogram images

Fourier transform (FT) can be visualized with a glass prism, that separates sunlight into rainbow colours of different frequencies, and the intensity of each colour corresponds to the amplitude of each frequency (Bracewell, 1989). The role of FT is analogous to that of the glass prism; it presents time-varying signals such as EEG, into their frequency components (Bracewell, 1989). However, FT is not suitable for signals that change over time because it computes the frequency information that is averaged over the entire time interval, hence failing to capture the changes in frequency and amplitude over time (Kehtarnavaz, 2008; Yildirim, Talo, et al., 2019).

STFT is a modification of FT, that results in better temporal and frequency localization (Rajoub, 2020). Instead of applying FT to the entire signal and obtain the average frequency, STFT fixed the window size which performs FT over a fixed signal length. The operation of STFT is given in Equation (1), where $w(n)$ is the fixed-length window function, and m is the amount of shift by the window along with the signal (Rajoub, 2020).

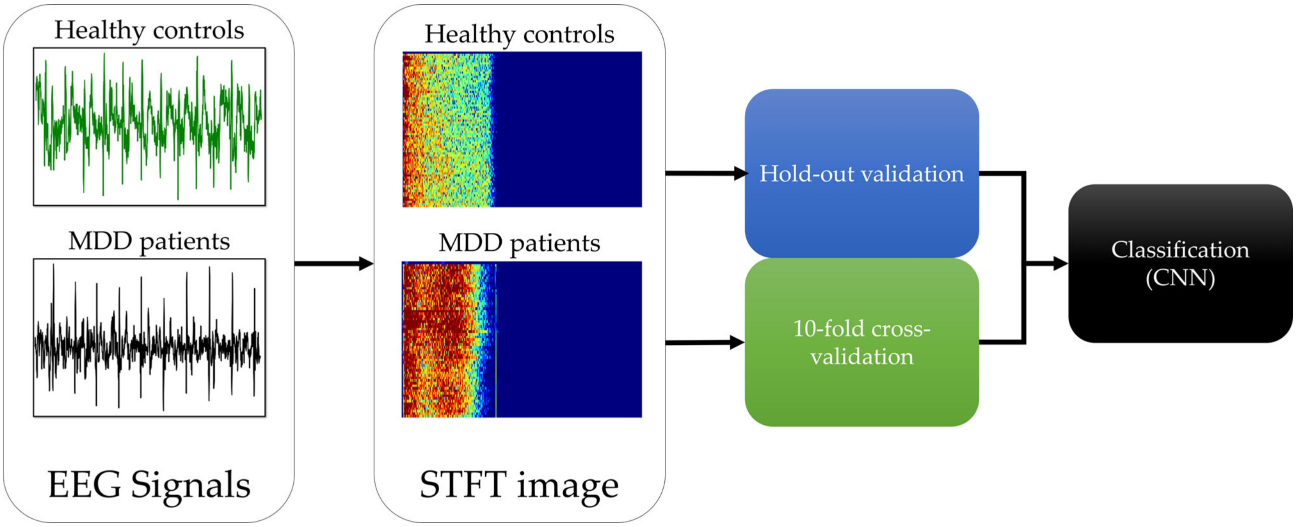


FIGURE 3 Block representation of experimental setup

$$X(k,m) = \sum_{n=0}^{N-1} x(n+m)w(n)w_N^{nk};\ k,m = 0,1,...,N-1 \tag{1}$$

In this work, EEG signals of healthy controls and MDD patients are converted into spectrograms after applying STFT. The image size of the resulting STFT images is 217×334 pixels, and representative sample images of healthy control and MDD patient are shown in Figure 4. Before feeding the STFT images into the proposed CNN models, the pixels of the image are normalized to between 0 and 1. After the conversion of EEG signals to spectrogram images, a total of 3600 images (1700 healthy controls and 1900 MDD patients) are obtained.

2.3 | Model architecture

The classifier proposed in this study is a deep learning model based on CNN. CNN is first introduced by Hubel and Wiesel (1962), to mimic the image recognition ability of the biological visual system. It aims to breakdown images into simpler representations to facilitate in image classification (Balderas Silva et al., 2018). The proposed CNN model is shown in Figure 5, and the details of layer parameters are listed in Table 2. The first portion of the proposed model is made up of 2-Dimensional (2D) convolutional layers and its operation is described in Equation (2), where S is the 2D feature input, $*$ is the discrete convolution operation, and W is the convolutional kernel weight that update itself each time the kernel slides over the input feature (Albawi et al., 2017). The resulting feature map (O) is described in Equation (3), where (i,j) describes the dimension of the feature map (Yildirim, Baloglu, et al., 2019).

$$(S*W)(i,j) = \sum_m \sum_n S(m,n)W(i-m,\ j-n) \tag{2}$$

$$O_n^l = \left(S_{W(i,j)} * W(i,j)\right)_n \tag{3}$$

$$h_{xy}^l = max_{i=0,\dots,s,j=0,\dots,s} h_{(x+i)(y+j)}^{l-1} \tag{4}$$

The proposed model consists of two convolutional layers, and a max pooling layer which operation is described in Equation (4) (Hafemann et al., 2017). The max pooling layer reduces the complexity of feature map after convolution operation, thereby reducing the risk of overfitting (Loh et al., 2020). Zero-padding is also included in the convolution operation which produces a feature map that has the same dimension as the input feature. The purpose of zero-padding is to prevent information loss at the borders of the image during the convolution operation (Albawi et al., 2017). Subsequently, the feature maps are flattened into single-list vectors using flatten layer.

As shown in Table 2, the input feature of size of 217×334 is chosen during the convolution operation due to zero-padding. The output feature maps after the convolution operation in the proposed model is illustrated in Figure 6. The dimension is further reduced to 108×167 after

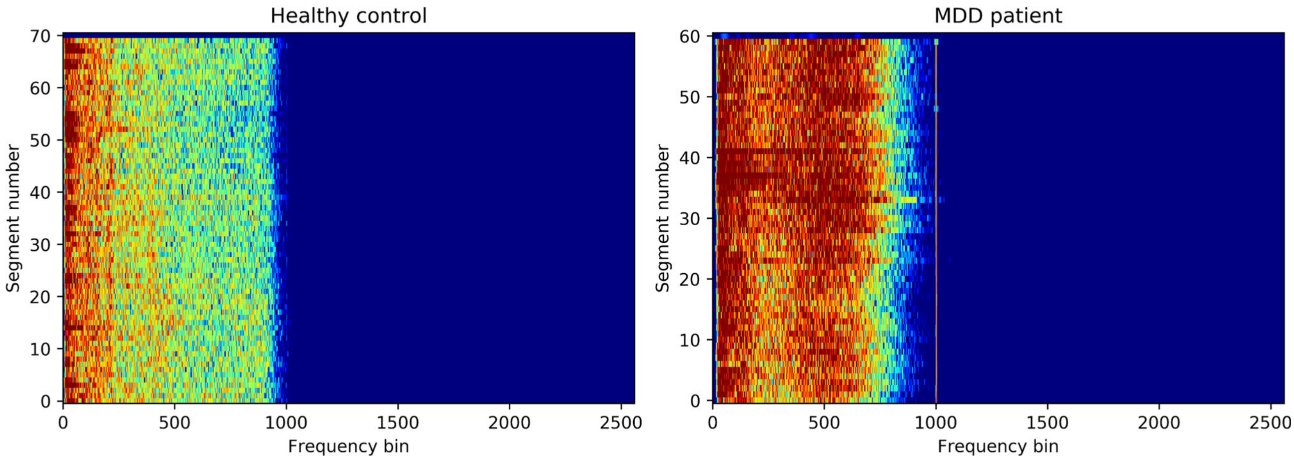


FIGURE 4 Spectrograms images of healthy control and MDD patient after application of STFT to respective EEG signals

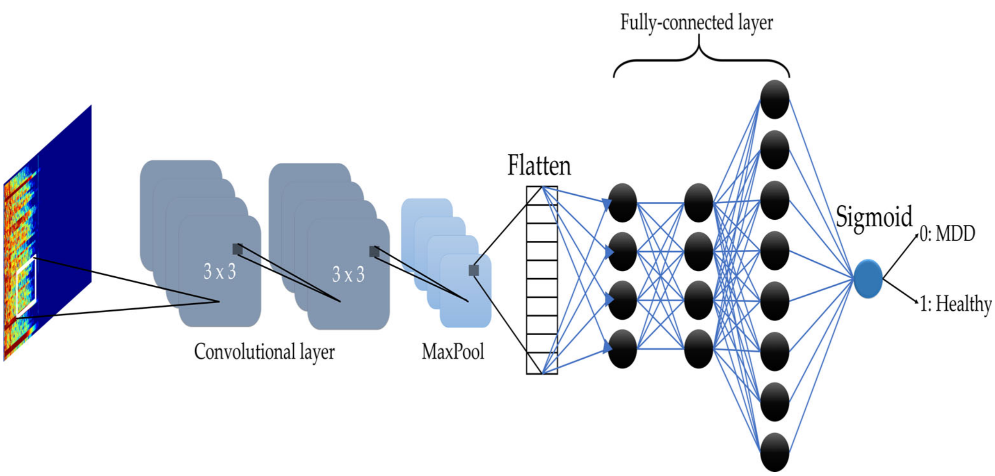


FIGURE 5 Proposed CNN architecture developed for automated MDD detection

max pooling operation and flattened into single-list vector of length 577,152. The generated single-list vectors are used to train the neurons in the fully connected layer. The last layer of the proposed model is a sigmoid classifier which produced an output value between 0 (MDD patient) and 1 (normal), and its operation is described in Equation (5) (Hafemann et al., 2017).

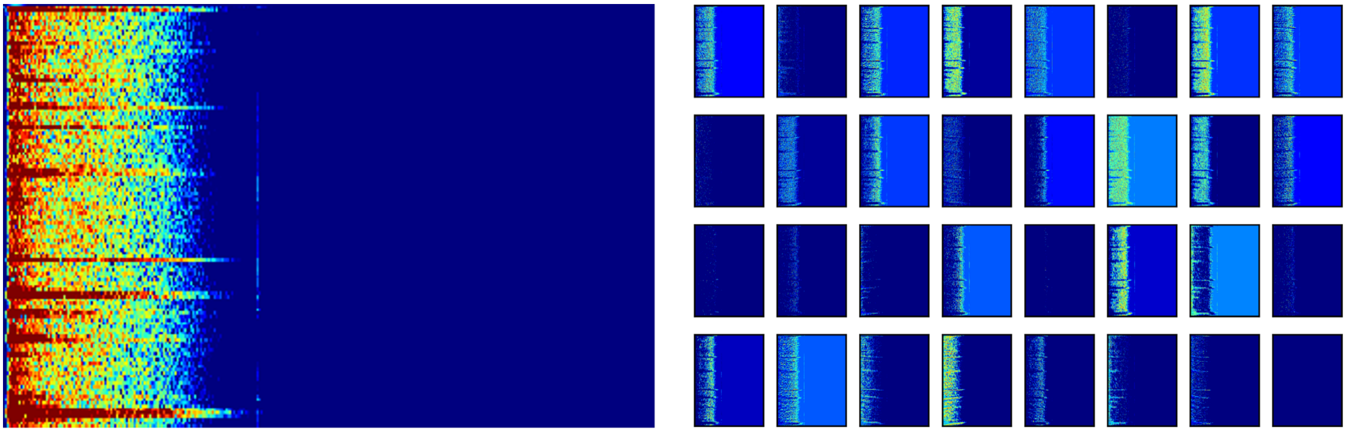
$$\sigma(z_i) = \frac{1}{1+e^{-z_i}} \tag{5}$$

The hyperparameters of the proposed model are as follows:

1. Epoch: 15
2. Batch size: 32
3. Padding: same (zero-padding)
4. Loss function: binary crossentropy
5. Optimizer: Adam
6. Learning rate: 0.001
7. Decay: 0.01

TABLE 2 Layer parameter details of proposed CNN model

No.	Layer	Filter no.	Kernel size	Unit size	Parameter	Output shape
1	2Dconv1	32	3 × 3	-	ReLu, constraint = 3	217 × 334
2	Dropout	-		-	Rate = 0.2	217 × 334
3	2Dconv2	32	3 × 3	-	ReLu, constraint = 3	217 × 334
4	MaxPool	-	-	-	-	108 × 167
5	Flatten	-	-	-	-	1 × 577,152
6	Dense	-	-	512	ReLu, constraint = 3	1 × 512
7	Dropout	-	-	-	Rate = 0.7	1 × 512
8	Dense	-	-	1	Sigmoid	1 × 1



(a) Input STFT image (b) 2DConv1

FIGURE 6 Feature maps obtained from the convolutional layers of our proposed model: (a) spectrogram image, and feature map obtained at (b) 1st convolutional layer

The STFT is used to convert the EEG signals to spectrogram images using python programming and the model is created using Keras (Tensorflow backend). The computer used to develop and train the model has the following specifications: Intel Core i7-10875H CPU, RTX 2070 Super 8GB, 32GB RAM, and 500GB NVMe SSD.

3 | RESULTS

In this study, two model validation approaches were employed: 10-fold cross-validation and hold-out validation. Sections 3.1 and 3.2 show the results obtained with 10-fold cross-validation and hold-out validation strategies. Section 3.3 summarizes the results obtained using both validation strategies.

3.1 | 10-fold cross-validation

In 10-fold cross-validation, the dataset is split into 10 folds containing an equal number of samples. Nine folds will be used for model training where it is further split into 90% training dataset and 10% validation dataset to train and tune the model, respectively. The remaining one fold will be used to evaluate the model performance. The process is repeated 10 times to ensure that every fold is used to evaluate the model performance.

The performance parameters obtained for each fold of the 10-fold cross-validation is shown in Table 3. According to Sokolova and Lapalme (2009), precision is the ability of the model to not classify the negative samples (MDD patients) as positive samples (healthy controls), sensitivity is the ability of the model to correctly distinguish the positive healthy samples, and specificity is the ability of the model to correctly

TABLE 3 Summary of various performance parameters (%) obtained with 10-fold cross-validation strategy

Fold	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
1	99.17	99.41	98.82	99.47	99.12
2	99.17	100.00	98.24	100.00	99.11
3	98.89	98.26	99.41	98.42	98.83
4	99.17	98.83	99.41	98.95	99.12
5	99.72	100.00	99.41	100.00	99.71
6	99.44	98.84	100.00	98.95	99.42
7	99.44	100.00	98.82	100.00	99.41
8	98.89	98.26	99.41	98.42	98.83
9	98.89	98.82	98.82	98.95	98.82
10	99.72	99.42	100.00	99.47	99.71
Average	*99.25*	*99.18*	*99.24*	*99.26*	*99.21*
Standard deviation	*0.32*	*0.68*	*0.56*	*0.62*	*0.34*

distinguish the negative MDD samples. In this work, we have obtained high performance parameters of above 99% with a low standard deviation of less than 1.

Figure 7 shows the confusion matrix obtained with 10-fold cross-validation strategy. Only a small percentage of the dataset are misclassified; 0.39% and 0.36% for MDD patients and healthy controls, respectively.

3.2 | Hold-out validation

In hold-out validation, the dataset is split into training (60%), validation (20%), and test (20%) sets. The training set will be used to train the model, validation set tunes the model, and test set evaluates the model performance. The classification accuracies obtained for these three datasets is shown in Table 4. A small difference is observed between the training, validation, and test accuracies, which indicates high generalization ability of our developed model. We have obtained more than 99% performance parameters with hold-out validation as shown in Table 5. We have achieved marginally higher performance measures with hold-out validation than with 10-fold cross-validation.

There is usually a trade-off between precision and sensitivity, hence F1-score can be used to depict the ability of the model to achieve the balance between precision and sensitivity (Lipton et al., 2014). Hold-out validation achieved higher F1-score of 99.55%, as compared to 10-fold cross-validation (99.21%), thus indicating that hold-out validation may be a better validation strategy for automated MDD detection using spectrogram images.

Figure 8 depicts the confusion matrix of the model obtained using the test dataset. A small percentage of the test dataset are misclassified; 0.28% and 0.14% of the test dataset are misclassified to MDD patients and healthy controls, respectively.

3.3 | Summary of results

In summary, both validation strategies yielded high model performance and did not show any signs of overfitting during model training; a small gap between training and validation accuracy is observed in Figure 9. However, the hold-out validation strategy gave the model slightly higher identification ability. This shows that high model performance can be obtained even with a smaller training dataset. Furthermore, the training time for hold-out validation is 10 times faster than 10-fold cross-validation. Hence, hold-out validation is more cost-efficient than 10-fold cross-validation.

4 | DISCUSSION

There is only 13 studies conducted on automated detection of MDD using deep learning with EEG signals (Please see Table 6). Almost all of the studies used CNN, and only three studies incorporated LSTM layers in their CNN models (Table 6). This shows that CNN-based models are

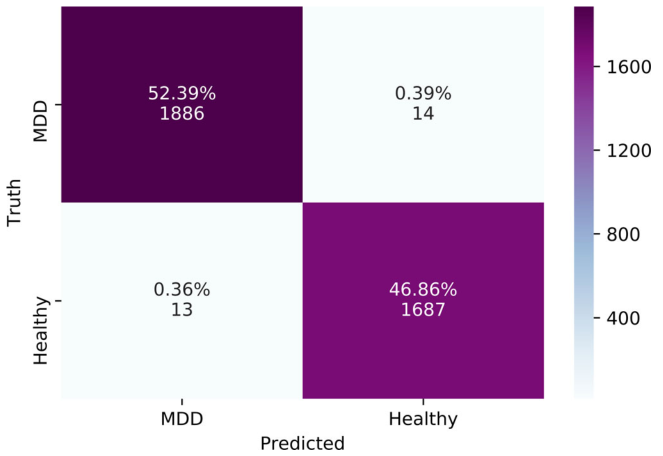


FIGURE 7 Confusion matrix obtained with 10-fold cross-validation

TABLE 4 Summary of various classification accuracies (%) obtained with hold-out validation

Approach	Training	Validation	Test
Hold-out validation	100.00	99.03	99.58

TABLE 5 Summary of various performance values (%) obtained with hold-out validation

Approach	Precision	Sensitivity	Specificity	F1-score
Hold-out validation	99.40	99.70	99.48	99.55

capable of recognizing EEG characteristic rhythms (hidden signatures) to accurately detect MDD patients from controls. Only Mahato and Paul (2019) proposed a MLPNN to automatically identify MDD patients.

Seven studies used end-to-end EEG signals to train their model and obtained good model performance (Acharya et al., 2018; Ay et al., 2019; Mumtaz & Qayyum, 2019; Sandheep et al., 2019; Seal et al., 2021; G. Sharma et al., 2021; Thoduparambil et al., 2020). Two studies extracted spectral, spatial, and temporal features from EEG signals (Li et al., 2019; Uyulan et al., 2021). Two other studies created asymmetric images of the EEG channels (Duan et al., 2020; Kang et al., 2020). Mahato et al. (2019) used wavelet transform to extract linear and non-linear EEG features. Saeedi et al. (2020) employed novel Generalized Partial Directed Coherence (GPDC) and Direct directed transfer function (dDTF) methods to obtain the images from EEG signals to effectively understand the brain connectivity. However, the constructed images of EEG were of smaller dataset which resulted in poor generalization ability and overfitting problem (Kang et al., 2020).

All the mentioned feature extraction methods had converted the EEG signals into various frequency bands such as alpha (8–13 Hz), beta (13–30 Hz), theta (4–8 Hz), and delta (0.5–4 Hz) (Kang et al., 2020). Most of the studies in Table 6 were developed using 10-fold cross-validation. Li et al. (2019) had used 24-fold cross-validation, Uyulan et al. (2021) had used 5-fold cross-validation, and Thoduparambil et al. (2020) employed random splitting of data.

Only a few studies had used right and left hemisphere brain EEG signals to train the model. Their studies showed that, right hemisphere EEG signals yielded higher classification performance as compared to left hemisphere EEG signals in the automated detection of MDD (Acharya et al., 2018; Ay et al., 2019; Sandheep et al., 2019; Thoduparambil et al., 2020).

It can be noted from Table 6 that, our study is the first to use spectrogram images for automated MDD detection. Also, the entire EEG recordings were converted into spectrogram images using STFT, instead of decomposing EEG signals into different frequency bands. Hence, the subtle changes in the EEG signals were captured in the time-frequency plot of the spectrogram. As a result, our proposed model achieved the highest classification accuracy of 99.58% with hold-out validation strategy (Table 6).

The salient features of this study are as follows:

1. Combined spectrogram images with CNN model for automated detection of MDD patients.
2. Used entire EEG dataset to develop the model instead of converting it into different frequency bands like in the previous studies (Duan et al., 2020; Kang et al., 2020; Li et al., 2019; Mahato & Paul, 2019; Saeedi et al., 2020; Uyulan et al., 2021).

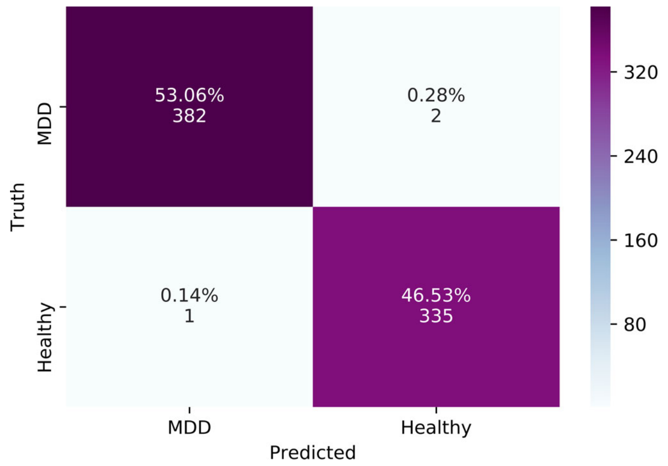


FIGURE 8 Confusion matrix obtained with hold-out validation

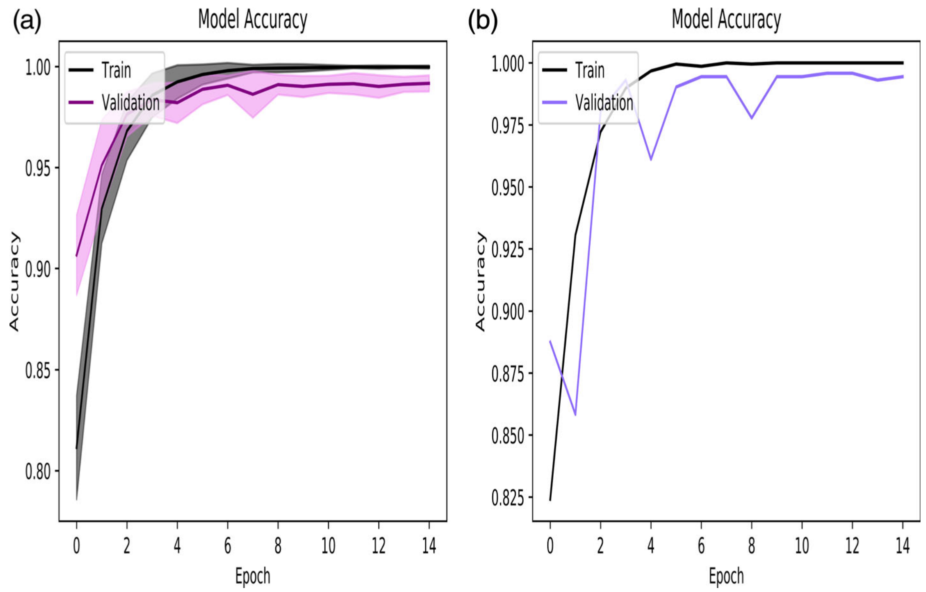


FIGURE 9 Graph of model accuracy versus number of epochs obtained for: (a) 10-fold cross-validation and (b) hold-out validation

3. Proposed CNN model is less complex with only 8-layers. The majority of the previous studies, except for Sandheep et al. (2019), had used more than 10 layers.
4. Validated the model with both 10-fold cross-validation and hold out validation strategies.
5. Developed model is robust as we obtained highest performance using both validation strategies.
6. Hold-out validation achieved higher model performance than 10-fold cross-validation.
7. Obtained highest classification performance as compared to the other state-of-the-art techniques (Refer to Table 6).

The main limitation of this study is the limited Computer Processing Unit (CPU) memory. In general, 2D-CNN-based models are computationally demanding, requiring long training time. It also limits the number of images the model can learn as there is possibility that the model may crash during training due to lack of CPU memory.

In future work, we plan to develop a practical CAD system that can be used in mental hospitals and polyclinics to detect the MDD using wearable cap to capture the EEG signals. Also, the proposed model need to be validated using electrocardiogram (ECG) signals and speech signals. It is easy to acquire the ECG signals and speech signals as compared to the EEG signals. So, an automated system developed using such signals can be used with existing wearable devices like Apple Watch. Also, such a CAD systems can be extended to detect various heart diseases in addition to depression, hence assisting the clinicians by providing more information about the patient (Dhar & Barton, 2016; Kose et al., 2021; Reddy et al., 2020).

TABLE 6 Summary of automated MDD detection studies developed using deep learning techniques

Author	Feature	Approach	Dataset	Accuracy (%)
Mahato and Paul (2019)	Wavelet transform	MLPNN	34 MDD 30 healthy	93.33
Acharya et al. (2018)	End to end	CNN	15 MDD 15 healthy	95.49 (Right) 93.96 (Left)
Mumtaz and Qayyum (2019)	End to end	CNN	33 MDD 30 healthy	98.32
Sandheep et al. (2019)	End to end	CNN	30 MDD 30 healthy	99.31 (Right) 96.30 (Left)
Li et al. (2019)	Spectral, spatial, and temporal feature	CNN	15 MDD 15 healthy	85.62
Ay et al. (2019)	End to end	CNN-LSTM	15 MDD 15 healthy	99.12 (Right) 97.66 (Left)
Uyulan et al. (2021)	Spatial and temporal feature	CNN	46 MDD 46 healthy	92.66
Duan et al. (2020)	interhemispheric asymmetry and cross-correlation	CNN	16 MDD 16 healthy	94.13
Kang et al. (2020)	Asymmetry matrix image	CNN	34 MDD 30 healthy	98.85
Thoduparambil et al., 2020	End to end	CNN-LSTM	-	99.07 (Right) 98.84 (Left)
Saeedi et al. (2020)	GPDC and dDTF images	CNN-LSTM	34 MDD 30 healthy	99.24
G. Sharma et al. (2021)	End to end	CNN-LSTM	21 MDD 24 healthy	99.10
Seal et al. (2021)	End to end	CNN	-	99.37
This work	Spectrogram images	CNN	34 MDD 30 healthy	Hold-out:99.5810-fold:99.25

5 | CONCLUSION

In this study, we proposed a 8-layer CNN-based deep learning model for automated MDD detection. Spectrogram images obtained using STFT of EEG signals coupled with CNN model have yielded the highest performance with both 10-fold cross-validation and hold-out validation. Our MDD detection model obtained the accuracy, precision, sensitivity, specificity, and F1-score of 99.58%, 99.40%, 99.70%, 99.48%, and 99.55%, respectively with hold-out validation. The limitation of our proposed system is that, we have used only 64 subjects (34 MDD + 30 healthy) to develop the CAD system. In future, we plan to validate our model with more data. Also, we intend to validate our generated depression detection system with other physiological signals like ECG and speech signals.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Wajid Mumtaz at https://doi.org/10.6084/m9.figshare.4244171.v2.

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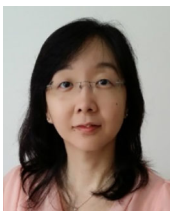

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