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Non-Invasive Bio-Signal Data Classification Of Psychiatric Mood Disorders Using Modified CNN and VGG16

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Abstract

In this study, the aim is to develop an ensemble machine learning (ML) based deep learning (DL) model classifiers to detect and compare one type of major psychiatric disorders of mood disorders (Depressive and Bipolar disorders) using Electroencephalography (EEG). The diverse and multiple non-invasive biosignals were collected retrospectively according to the granted ethical permission. The experimental part is consisted from three main parts. First part is the data collection&development, the second part is data transformation and augmentation via Spectrogram image conversion process and online Keras data augmentation part, respectively. The third and final part is to fed these image dataset into modified Convolutional Neural Network (CNN) and VGG16 models for training and testing parts to detect, compare and discriminate mood disorders types in detail with a specific healthy group. As the performance evaluation background of the mood disorder classification models, confusion matrices and receiver operating characteristics (ROC) curves were used and finally, the accuracy achieved by CNN model was 88% and VGG16 model was %90, which is an improvement of 10% compared to the previous studies in literature. Therefore, our system can help clinicians and researchers to manage, diagnose and prognosis of the mental health of people.

Key Words

"Psychiatric disorders, Mood disorder, Depressive disorder, Bipolar Disorder, Deep Learning, Pretrained model classification"

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1. Introduction

Mood disorders (MDs) are the most common and prevalent type of mental illness after Anxiety disorder in the world, affecting millions of people worldwide. The main types of MDs are Depressive and Bipolar disorders and the clinical features of MD include persistent uneasiness, unstable sudden mood change as well as bad feelings in the brain etc. all of which are related to the nervous system.

Traditional psychological studies which were not used AI and ML based models frequently show no important correlation and coherence between psychological parameters and sudden mood change levelsn. Indeed, other studies (Acharya et. al., 2018; Aristizabal et. al., 2021; B˘alan et. al., 2019; B˘alan et. al., 2020) which used AI and ML based techniques show that mood disorder such as Depressive and Bipolar disorders recognition and estimation through EEG bio-signals and psychological analysis are possible. Indeed, different biomarkers such as Electromyogram (EMG), Electrocardiogram (ECG) and Electroencephalography (EEG) can be chosen and used to optimally detect and discriminate physiological responses related to depression and bipolar situation (Dubreuil-Vall et. al., 2020).

In mental healthcare area, the development in data and computational science has been suddenly and rapidly changing. Also, the usage of Artificial Intelligence (AI) in medicine sciences has been increasingly chosen and become more popular (Biship, 2007). The main advantage of AI based systems is to prospectively assess the performance of estimation in unseen data for testing and training phases (Murphy, 2012). Although these systems have become popular, these are contrary to fundamental inference based on some hypothesis tests related to the variance variable. AI and Machine Learning (ML) based systems are expected to help and possibly replace doctors' or clinicians' decisions in especially diagnosis, prediction and prognosis outcomes (Miotto et. al., 2017).

The electrical activity of the brain neurons in the cortex can be recorded via EEG. This approach becomes ideal and appropriate for researching the electrophysiological and cognitive situation of the brain because of the neural activity with a high temporal resolution. Many imaging studies have compared healthy control groups (HCs) with one or several disorders, but only few have comprehensively compared many common and important mental diseases. This occasion might be caused because acquiring image data may be related to the high costs and time for applying any ML models. Another alternative way is to obtain the metric parameters of the brain is EEG, that delivers information from scalp of the brain and EEG is a non-invasive and cost-effective method for obtaining brain waves and brain activity (Saeed et. al., 2015). Moreover, in modern technological area, EEG is more preferable in brain human interaction computer systems area (Saeed et. al., 2020). One recent EEG study showed that with using ML methods, EEG could be used to optimally detect schizophrenia between a specific group and HCs in detail. In mental healthcare area, the main popular trend has been to disseminate and evaluate among patients with single mental disorders such as depression, schizophrenia, stress disorders etc.

To better investigate the mental health conditions and provide better outcomes, early detection of mental health problems is an important process. Apart from the diagnosis of other possible diseases, mental illnesses are commonly diagnosed with the individual based self-report according to the specific questionnaires that is designed for the specific patterns of the feelings etc (Zhang et. al., 2020). In this area, AI and ML based integrated models have gained more popularity and usage for detecting and discriminating diseases (Najafabadi et. al., 2015). In recent years, more superior results have been obtained from DL models and algorithms in medical area (Mumtaz and Qayyum., 2019).

There have been a lot of studies published approximately past 10 years and they have been reviewed (Widge et. al., 2019; Xie et. al., 2020, Zhang et.al., 2020; Oh et. al., 2019; Kuang and He, 2014). These studies were generally related to the detection of mental disorders except whole Mood disorder types such as depressive and bipolar disorders and novel modified Deep Learning models such as ResNet-50 and VGG16. Neuroimaging on the human brain has gained more popularity for decade and some methods such as Magnetic Resonance Imaging (MRI) and Electroencephalography (EEG) were highly chosen and became more popular than in the past. Neuroimaging gives a chance to analyze a lot of mental disorders such as autism spectrum disorders (ASD), schizophrenia, bipolar disorder, major/minor depressive disorder etc.

Depressive and bipolar disorders have common all over the world and a lot of people suffered from these types of mental diseases. Fear and anxiety have been reported as the main emotions among people for many years. Mood disorders especially depressive disorder can be characterized by childhood and early adolescence. According to worldwide, mood disorders constitute an important range after anxiety disorder (12.6% of people worldwide) (Kuang et. al., 2014). In bipolar disorder, there are seen more hybrid symptoms than depressive disorder and in some aspects, the same symptoms are clearly seen in both of these disorder types. Indeed, mood disorders are often seen together with anxiety disorder.

Psychosocial, neurobiological and neuropsychological factors have been thought to be effective in the evaluation of mood disorders (Schnack et. al., 2014). Fast processing for obtaining outcomes is very important for evaluating mental diseases and mood disorders. The more usage of AI and ML integrated DL models have given access to identify many disorders at an earlier stage and because of this occasion, more efficient interventions will be provided in near future.

Biomarker can be defined as one of the screening and pattern methods and has been generally used in the diagnosis of the brain image. Wolfers et al. was examined the utilization of patient screenings for psychiatric diseases and they obtained that pattern screening was highly improvable in the diagnosis of the brain based and mental diseases since the day from the past. Indeed, Garcia,Ceja et al. were achieved a mental based health monitoring system with ML methods. They have achieved the detection, classification and interpretation parts in detail in this study. It has been obtained that the usage of the multiple sensing based technologies with ML methods could provide some pros in the treatment of mental diseases. Continuous effective monitoring of some different mental situations such as depression, stress, anxiety etc. with some implementations could give more efficiency and these could be integrated with multiple medical technologies. Moreover, Shafiei et al. were analyzed and examined the shape based features of the brain images during dynamic emotional facial image based processing. Totally 228 subjects were chosen and used in this study and all of the subjects applied to the treatment of DSM-5 diagnoses of depressive disorder, anxiety disorder etc. In addition, the most average age of the study was comprised from women. MRI imaging has been achieved for fearful, angry and happy faces situations. Then, these data were analyzed via Gaussian Process Regression and it was obtained that neuroimaging could be an effective tool for analyzing mental diseases in detail. Depression and Bipolar disorder could be appeared with panic disorder among many people. For this progress, the brain waves could be an effective tool for analyzing subject-brain attitudes/situations, so EEG was chosen and used in this study. MRI images of the subjects were examined with ML methods and it was obtained that according to Random Undersampling Boost algorithm, 73% accuracy was obtained from the evaluation part.

ML methods have also been used to determine the measurements of patient outcome which are important for anxiety and major/minor depressive disorders. Indeed, they were trained via neural network (NN) models. Kumar et al. collected and applied the data on eight different ML methods by using depression, anxiety and stress scale questionnaire (DASS42 and 21). Moreover, these algorithms were gathered in four different classes; these were probabilistic, nearest neighbour, NN and decision tree. According to the results, Radial basis function network had the highest accuracy for detecting anxiety, depression and stress, respectively for DASS42 database. When DASS21 data were used, the best accuracy was obtained from Random Forest Algorithm.

In this study, we aimed to achieve successful classification with modified classifiers for discriminating/analyzing patients with several mental disorders from a specific healthy subject group. We retrospectively collected and classified raw EEG data of patients with two main categories: depressive and bipolar disorders. To improve and increase the usage of the classifiers performance metrics, models were utilized using spectral power and functional connectivity that are common in EEG signal parameter settings. Indeed, to improve the accuracy, batch normalization, flatten layers and fully connected layers were added in the Deep Learning models. Also, confusion matrices, receiver operating characteristic (ROC) curves were used for analyzing the performance of the whole systems and models. Via this study, the main advantage of the mood disorders classifier proposed in this study can be explained as a helpful system in mental health diagnosing and mental health management via a fast and an accurate classifier to discriminate the disorder types by doctors and clinicians.

2. Material and Methods

2.1. Data collection

Data were collected retrospectively from 10 years' medical records from Yıldırım Beyazıt University Hospital and one doctor who is expert in this area was reviewed and analyzed the dataset. The original diagnostic decision was made this doctor/psychiatrist based on DSM-IV criteria and psychological assessments with subjects' EEG recordings. In addition, a specific healthy control subject group was included to this study for achieving an optimal classification. The inclusion criteria was consisted from the subjects' age from 18 to 65 according to the primary diagnosis and these subjects were disseminated from 2 main categories; depressive (n=100) and bipolar disorders (n=100). Generally, the exclusion criteria were as follows; current medical history of a neurological disorder of the subject and lifetime parameter. Indeed, this retrospective study was approved by institutional review board from Yıldırım Beyazıt University (2019-16).

2.2. EEG parameter settings

EEG data was obtained from resting state with 19 to 64 channels acquired with 500 Hz sampling rate via Siemens Somatom. In the experimental phase, the analysis frequency was determined as 128 Hz and 19 channels were selected via 10-20 sculp distribution system (FP1, FP2, F3, F4, F7, F8, Fz, T7, T8, C3, Cz, P3, P4, P7, P8, Pz, T8, 01 and O2 channels).

Indeed, to obtain and use Spectrogram phase images, these EEG data were converted from time domain to frequency domain via Fast Fourier Transform according to these parameters given as follows; epoch = 2.5 seconds, sample rate = 128 samples/s, frequency = (0,5 to 50 Hz). According to the transformation, pre- processing and and artifact elimination processes were clearly achieved.

2.3. Statistical analysis

In the statistical analysis phase, to test the difference of variables between subjects and HC group, t-tests were performed, respectively. Indeed, the demographic characteristics of subjects are clearly given below in Table 1.

Table 1. Detailed demographical characteristics of Mood disorders subjects

Specific group	**Age**	**Sex**
	Mean (Std. Dev.)	Proportions
Healthy (n=100)	27,72 (4.59)	Male: 50 / Female: 50
Mood disorders (n=200)	31.97 (13.60)	Male: 50 / Female: 50
Depressive disorder (n=100)	33.26 (14.23)	Male: 50 / Female: 50
Bipolar disorder (n=100)	30.02 (11.58)	Male: 50 / Female: 50

2.4. Classification of mood disorders

For used EEGs, the Spectrogram version of the signals were chosen and used via using Fast Fourier Transform (FFT) (Khan et. al., 2022). Then, these images which were consisted from different frequency distribution were fed into customized CNN and VGG16 Deep learning models. All specific details were given below. Subsequently, the EEG Spectrogram data were processed with Data Augmentation part.

2.4.1. Data augmentation

For data augmentation, Keras Image processing library was used with ImageDataGenerator (Boudouh et. al., 2022). This tool is generally gives access to users for rotation, width and height customization and flipping options. In this study, the parameters of the augmentation process of images were given in Table 2.

Table 2. Information about collected dataset in the study

Dataset	Total Sample
Depressive disorder Spectrograms	100
Bipolar disorder Spectrograms	100
Healthy subjects Spectrograms	100
Depressive disorder augmented	550
Bipolar disorder augmented	550
Normal augmented	500
Total samples	1900

Indeed, data augmentation methods used in this study were clearly given below, respectively.

Width shift value: Up to 2%;
Rotation range value: Randomly 0 to -40 degrees;
Zoom range value: 2%;
Height shift value: Up to 2%;
Fill mode: Reflective;
Horizontal flip: True;
Vertical flip: True;

2.4.2. CNN model design

Generally, Fig. 1 illustrates the whole architecture of the whole modified model given in this study. Mainly, the classification architecture was consisted from totally 14 levels.

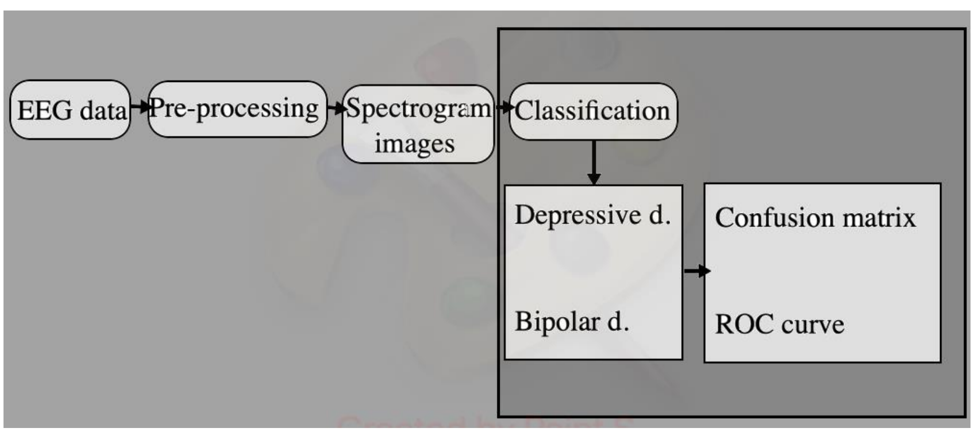

Figure 1. Classification procedure of Mood disorders and Healthy EEG signals (Spectrogram images) and validating the models

In Table 3, the detailed information about the structure of CNN layers was given. First, 124x124x3 image dataset were fed into this deep learning model as inputs. Then, the augmented EEG data were converted into the array version using a custom folder layer and then this was fed into to the convolution layer. The main purpose for choosing this layer was so that the image set could be arranged and then fed into the 2-dimensional convolutional layer (Li et. al., 2020). Moreover, the first 2-dimensional convolutional layer contains ten filters of size 3x3.

Table 3. Classification layers of modified CNN model

Number	Layer information	Activation values	Weight values
1	Input layer	124x124x3	-
2	Folding layer	124x124x1	-
3	2D convolution layer	124x124x6	3x3x3x10
4	Batch normalization layer	124x124x6	-
5	Max. pooling layer	62x62x6	-
6	2D convolution layer	62x62x12	3x3x6x20
7	Batch norm. layer	62x62x12	-
8	Max. pooling layer	31x31x12	-
9	Unfolding layer	31x31x12	-
10	Flatten layer	-	-
11	Fully connected layer	2	2x300
12	Softmax layer	2	-
13	Classification	-	-

The convolution layer with using Eq. (1) was calculated and the size of the output value was obtained as 124x124x6. Equation (1) gives information about the process for the convolution layer. Then, when padding and stride progresses were applied to the data, the output value was calculated and in Eq. (1) K and L are the input data size, FH is the filter height value and FW is the filter weight value, respectively. S and P are the stride and padding parts, respectively. Also, OK is output height and OL is the output weight values.

$$(OK, OL) = \left(\frac{H+2P-FH}{S} + 1, \frac{W+2S-FW}{P} + 1\right) \tag{1}$$

After this progress, the output data were connected to the batch normalization layer. After normalization step, the layer was fed into the max pooling layer. According to Eq. (2), the size of the output data (ORs, OCs) was obtained by equation given below.

$$\text{(ORs, OCs)} = \left({}^{Height\ value}/_{Padding\ value}, {}^{Weight\ value}/_{Padding\ value}\right) \tag{2}$$

Then, the obtained output was fed into a normalization layer and a max pooling layer. The max pooling layer is consisted from 2x2 filter with a stride of 2 value, so the original data was reduced to the half of the first value. The second 2-dimensional convolution layer was consisted from 20 filters of size 3x3, so the data was re-reduced to a size of 31x31x12. Then, the normalization step was performed and the data were processed with flatten, fully connected layer and softmax layers. Then, the classification step was successfully achieved and completed.

2.4.3. VGG16 model design

For this model design, to investigate and analyze the performance metrics of DL models on the developed dataset, transfer learning model of VGG16 was applied for testing phase. In the experimental part, a modified VGG16 was developed and used. The core of the model was consisted from three main parts: a pre-trained part, an updated layer and an estimation part (Md Manjurul et. al., 2021). The first part was used so that to identify the high level features and transferred to the modified layer. Figure 2 gives information about the modified VGG16 architecture. Mainly, this model was consisted from sixteen CNN based layers with varying filter sizes and stride parameter values (Gisele et. al., 2015). According to the Fig. 2, the first part was the initial input layer and in this part, 224x224 images were used only. Then, two convolutional layers were performed and this part contained a 3x3 size filter. Then, this was followed by a max pooling layer and another two convolutional layers and one max pooling layer until the modification has been achieved successfully. Finally, the modified layer flattened the whole model architecture, followed by the three dense and one dropout layer.
Indeed, the used batch size, total number of epochs and learning rate parameters were given below in detail.

Batch size = [5, 10, 15, 20];
Learning rate = [0.1, 0.01, 0.001];
Number of epochs = [35, 40, 45, 50];

With using the grid search method the parameters given above were optimized and identified optimally as given below.

Batch size = 15;
Learning rate = 0.01;
Number of epochs = 40;

Moreover, in this part, an adaptive momentum estimation was performed to obtain better results and optimize the model loss (Kim et. al., 2015). One of the pros of this technique is mainly obtaining higher successful results in binary classifications.

2.5. Details of experiment setup

In the experimental part, the study was conducted using a common Windows based laptop. (Windows 10, 16 GB RAM and Intel). The whole experiment was performed one time and final result was given optimally in the final part. The study included that the dataset contained 100 Depressive, 100 Bipolar mood disorders and 550 augmented depressive and 550 augmented bipolar disorders in detail. Moreover, we designed 80% of the sample data to train and 20% of the data to test the whole models.

2.6. Performance metrics

After the experimental part, the overall performance metrics have been calculated. For the first deep learning model (CNN), due to the limited samples, the overall statistical results were obtained with %95 confidential value. Again, for the second model (VGG16), the overall statistical results were obtained with 95% confidential interval value. Indeed, the designated statistical metric calculations were given below.

$$\text{Accuracy} = \frac{True\ positive + True\ negative}{True\ positive + True\ negative + False\ positive + False\ negative} \quad (1)$$

$$\text{Sensitivity} = \frac{True\ positive}{True\ positive + False\ negative} \quad (2)$$

$$\text{Specificity} = \frac{True\ negative}{True\ negative + False\ positive} \quad (3)$$

$$\text{Precision} = \frac{True\ positive}{True\ positive + False\ positive} \quad (4)$$

$$\text{Recall} = \frac{True\ positive}{True\ negative + False\ negative} \quad (5)$$

$$\text{F1 score} = 2\ x\ [(Precision\ x\ Recall)\ /\ (Precision + Recall)] \quad (6)$$

3. Results and Discussion

After the experimental part, in this study, Table 4 and Figure 2 gave information about the results of the classification models' performance metrics using a confusion matrix.

Table 4. Proposed models' performance metrics on the dataset used in this study with 95% confidence level

CNN					
Metrics	Accuracy	Sensitivity	Specificity	Precision	F1 score
Train set	0.88 ± 0.018	0.873 ± 0.017	0.88 ± 0.018	0.88 ± 0.018	0.88 ± 0.018
Test set	0.74 ± 0.080	0.99 ± 0.0080	0.66 ± 0.012	0.65 ± 0.072	0.74 ± 0.080

VGG16					
Metrics	Accuracy	Sensitivity	Specificity	Precision	F1 score
Train set	0.90 ± 0.080	0.85 ± 0.010	0.88 ± 0.010	0.88 ± 0.060	0.88 ± 0.060
Test set	0.80 ± 0.022	0.65 ± 0.025	0.76 ± 0.023	0.76 ± 0.022	0.76 ± 0.022

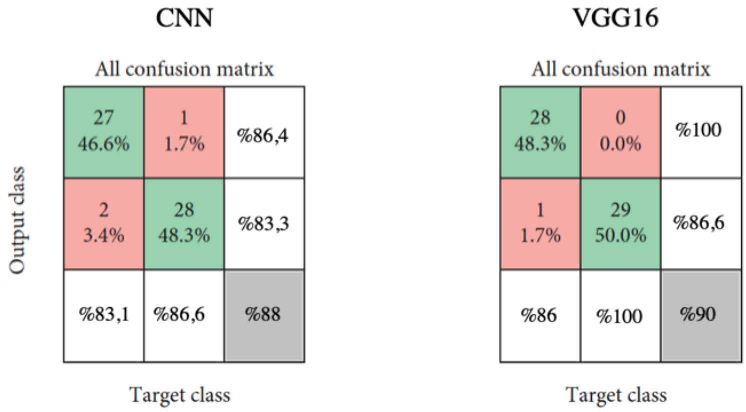

Figure 2. Classification performance evaluation of DL models using a confusion matrix

Figure 2 given above indicates the classification performance according to the EEG signals' Spectrograms. According to these signals, in the time domain, the lowest signal has 220 epochs due to the validation curve. Indeed, Fig. 3 shows the ROC curve metrics according to the epochs and images for the time domain. Generally, the ROC curve is an evaluation method for performance metric applicable to an binary system that shows how the performance of classification model changes. Moreover, with using ROC curves, according to the Area Under of Curve (AUC), when this value range falls approximately between 0.92 and 1, the excellent classification has achieved. Also, the AUC of ROC curve was 87,88% for CNN and 90,42% for VGG16. According to the obtained performance metrics, it was obtained that the detailed proposed models in this study gives 10% improvement.

When the ROC curves were considered, if the data used in this study was unbalanced, the shape of the curve could be skewed to one another side and the whole classification performance could not be obtained successfully. Precision and recall values could be identified the detailed performance evaluation metrics. The detailed ROC curves were given in Fig. 3 according to the True Positive-False Positive rates and Precision-Recall axes.

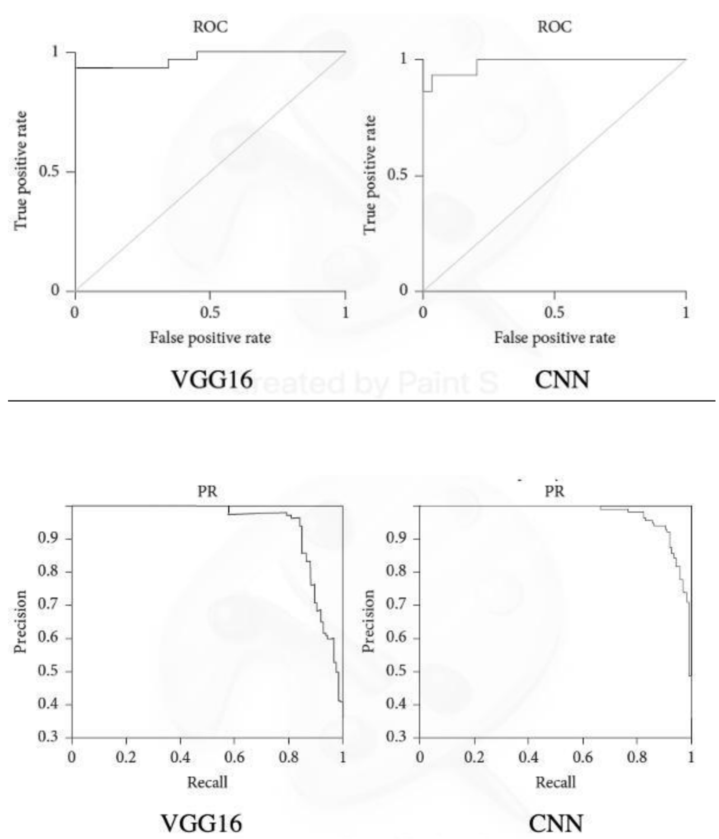

Figure 3. Evaluation of the classification performance of DL models via ROC curves

According to Fig. 3, two different graphs were given as ROC curves. The first one was the performance evaluation according to the True Positive-False Positive rates and the second one was the performance evaluation according to the Precision-Recall axes. Therefore, compared to the other studies in the literature, the average precision obtained and improved by 9-10% using the models in this study. In addition, the precision value of the second model was 3.4% was higher than that of the first model in our models.

In previous studies using related models with EEG signals, the epochs were adapted to the value of 10, the batch size was also 65. As a result, the first and the second models' performance values were obtained as 88% and 90%, respectively. However, the models structures were susceptible to overfitting, the whole accuracies were achieved after approximately 15 epochs could eliminate this problem.

In this study, to improve the performance values of mood disorder classification and prevent overfitting, optimized models were developed by data using spectrograms and adding specific layers to the DL models. The performance of the classifiers were evaluated using two different confusion matrixes and ROC curves. According to the results, totally, 88% accuracy was obtained for CNN and 90% accuracy was obtained for VGG16 models. Indeed, the proposed classification models achieved the successful estimation performance when the number of epochs was 220 for the first model and 215 for the second DL model. Also, these models' performance values were obtained using ROC and PR curves. It was confirmed that, ultimately, 10% improvements were obtained compared to the other studies in the literature.

4. Conclusion

In this study, we proposed two different improved DL models based on CNN architecture in accurately classify Mood disorders such as Depressive and Bipolar disorders. To prevent the overfitting and improve the classifiers' accuracy values, EEG signals were compared by Spectrogram version and the signals were classified separately in the time domain by two DL models. Indeed, %88 accuracy value was obtained from the first proposed ensemble model and 90% accuracy value was obtained from the second proposed ensemble model. These results were given detailed information about the 10% improvement compared to the other some related studies in the literature (Soroush et al., 2018; Zeng et al., 2019; Rafiei et al., 2022). In the future, we will improve the pre-process method such as adding different noise and artifact removal methods, and to improve the whole accuracy values of the models detailed Fourier transform may be chosen and developed. The mood disorders classifier proposed in this study can be explained as a helpful system in mental health diagnosing and mental health management via a fast and an accurate classifier to discriminate the disorder types by doctors and clinicians. Indeed, it is also expected to manage the decrement of various diseases such as depression and other specific diseases etc.

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