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Research Article

DETECTION OF SPECIFIC PSYCHIATRIC MENTAL DISORDERS FROM MULTI-CLASS EEG SIGNALS WITH MODIFIED ARTIFICIAL INTELLIGENCE MODELS

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Abstract-Psychiatric disorders have been very common among people and have gained popularity from pyschiatric and artificial intelligence communities. There are many different types of diseases related to the psychiatric based problems. Intelligent recognition methods that based on CAD systems for classifying mental disorders are essential tools in neurogical research area. Various studies have been given to detect mental disorders from neuroimages, EEGs and other radiological based images in literature. In this study, a hybrid method that includes Machine Learning and Deep Learning methods and also their comparison for multi-class mental disorder case detection is given with using a publicly available EEG database. In this study, we used 100 different subjects for each type of disorders which have been diagnosed as Major Depressive Disorder (MDD), Autism Spectrum Disorder (ASD), Schzophrenia (SZ) and healthy. Indeed, additional feature extraction methods with some parameters are used for Machine Learning method of k Nearest Neighbor (kNN) and with no need of feature extraction, modified versions of CNN (Convolutional Neural Network) with LSTM (Long Short Term Memory Network) and YOLOv5 (You Only Look Once) Deep Learning methods are used and all results are compared in detail. The hybrid modified versions of DL models can also acquire detailed knowledge without preprocessing step. For three class classification of psychiatric diseases, the accuracy, specificity, sensitivity and ROC results are obtained as the highest accuracy for modified YOLOv5 model as %99.5 with the average prediction time of 20.38 min, the average prediction speed is 0.083 sec per EEG. Moreover, this study can give a chance for decrease the rate of manual interventions, making the models sufficient for doctors to pre-diagnose during the clinical progress for neurologists, brain surgery area and other related doctors/clinicians.

Keywords- EEG, CNN, LSTM, Yolov5, Feature Extraction, Classification.

I. INTRODUCTION

In healthcare area, the change and the development of Computer Aided Systems(CAD) have become an important part in human life nowadays. Identifying and analyzing diseases have also gained importance and become dependent on medical and biomedical technologies such as MRI, CT, EEG etc.

Autism Spectrum Disorder (ASD) is generally explained as a combination of neurological problems in social area [1, 2]. This mainly consists from eye situation problems, facial and specific gesture problems [3, 4]. There are some tests which are used to determine the child's mental condition. Behavioral evaluation and therapy screening are these tests. However, every methods has some advantages and some aspects [5]. They are a lot of time-needed and require perfect clinicians [6]. Some studies in the literature for ASD detection with EEG signals are given in detail. Plitt et al. [7] applied logistic regression to obtain teh ASD biomarkers on fMRI data. Duda et al. [8] chose Support Vector Classification, Categorical Lasso and Logistic Regression to distinguish between ASD and ADHD EEG signals. Chen et al. [9] used Support Vector Machine (SVM) with particle swarm optimization (PSO) for feature extraction, SVM and Random Forest for classifying ASD EEG-signals. Choe et al. [10] used the power spectral density from EEG signals, using the multi-taper method for estimation with LDA. Bascil et al. [11] used the power spectral density (PSD) from EEG signals with SVM and ANNs with 2-D cursor movements. Zabihi et al. [12] investigated the performance of five different CNN architectures and achieved comparisons to determine the best model for classification.

Major Depressive Disorder (MDD) is a problem that have some aspects such as mental problems in especially cognitive area [13, 14]. If MDD is not treated, the depression period may finish between 6-12 months and also may become chronic [15, 16]. For the reasons, preparing an ultimate diagnostic method for early and accurate diagnosis is important [17]. Some studies in the literature for MDD detection with EEG signals are given in detail. Sharma et al. [18] used EEG signals from 24 depressed and 24 normal patients. The accuracy was obtained as 99.10% with LSTM-CNN. Seal et al.[19] used a classifcaiton model for depression with the 18-layer CNN network. 99.37% accuracy was obtained from that model. Saaedi et al.[20] used the MDD group using the EEG signals.. They achieved 95.283% ± 2.109 accuracy with CNN 1D, 89.057% ± 1.849 with LSTM. Cukic et al.[21] used depression groups using 23 depression and 20 normal EEG signals. They achieved 97.56% accuracy with Naive Bayes classifier. Mumtaz et al. [22] used a detection system for 33 depression and 30 normal EEG signals. He achieved 98.20% accuracy, 99.78% specificity, and 98.34% sensitivity with CNN-LSTM. Uyulan et al.[23] developed a detection system for 46 healthy and 46 MDD EEG signal with deep learning architectures. Wang et al.[24], used modma dataset and classified MDD. AlexNet was chosen in their method. Finally, the channel of 13, 17, 28, 40, 46, 66 and 69 were obtained to be belonged with depression.

Schizophrenia is an important mental ilness that patients often have psychotic problems, and these do not belong to the reality [25, 26, 27, 28]. Some studies in the literature for SZ detection with EEG signals are given in detail. Liu et. al [28], used a technique for avoiding EEG signal ocular artifacts. After the EEG signals were decomposed with using Discrete Wavelet Transform (DWT), ocular artifacts were obtained and analyzed. Some parameters such as kurtosis, variance, Shannon's entropy, and a few more were calculated. Then, a machine learning technique known as Neural Network is used to identify ocular artifacts from the data. Prasad et al. [29] analyzed performance metrics of the methods to identify states using EEG signals from the Bonn dataset. Shi et al. [30] used the semantic segmentation method to detect the artifacts in EEG recordings. Tosun et al. [31] suggested and analyzed a deep learning model to detect their situation and classify the type of artifact. Classification accuracy is 67.59 percent, with a true positive rate of 80 percent. Baygin et al. [32] analyzed the machine learning model for EEG Schizophrenia classification model with machine learning model. Barros et al. [33] proposed a RLNDiP model based on the classification.

In this study, 3 specifically chosen groups of mental diseases of Major Depressive Disorder (MDD), Autism Spectrum Disorder (ASD) and Schizophrenia (SZ) were tried to be analyzed and diagnosed automatically by common Machine Learning methods of kNN method with Feature Extraction part and with no need of Feature Extraction, two popular Deep Learning models were modified and these were called modified Convolutional Neural Network (CNN) with Long Short Term Memory Network) LSTM and modified You Look Only Once (YOLOv5) integrated models. For this, 100 EEG signals of every three data groups and healthy group were chosen randomly and used in the anonymized versions. Signals first were pre-processed with some additional parts and noise removal and then, signals were analyzed with the windowing methods into epochs and Feature Extraction part was performed and feature selection was achieved and fed into the common Machine Learning method and these were classified with k Nearest Neighbor (kNN) method. Then, with no needof Feature Extraction part, the Spectrogram version of the processed signals were obtained and they were resized and fed into the Deep Learning models of modified CNN with LSTM and modified YOLOv5 in detail. Indeed, modification process was achieved with the modification of some layers of the DL models and some setting parameters. Finally, all models and obtained results were analyzed and compared in detail according to the accuracy, specificity, sensitivity and ROC results.

II. MATERIALS AND METHODS

2.1. Dataset Collection

In this study, the dataset for automatic diagnosis of mental problems contains EEG open datasets of Kaggle [34], MODMA [35] and NIH [36] were used between 2020 and 2022. Generally, 19 channels are used in the EEG part with 10/20 scheme [37, 38]. The channels selected were Fp1, Fp2, F3, F4, F7, F8, T3,T4, C3, C4, T5, T6, P3, P4, O1, O2, Fz, Cz, Pz.

Moreover, these raw 60 minutes EEG signals for three groups were divided/windowed into 15-second dimensions according to World Health Organization (WHO) Polisomnography-EEG analzying criteria.

2.2. Methodology

Mainly, our customized detection system of specific mental diseases from EEG signals consisted of the important modules and these were given in Fig. 1. in detail.

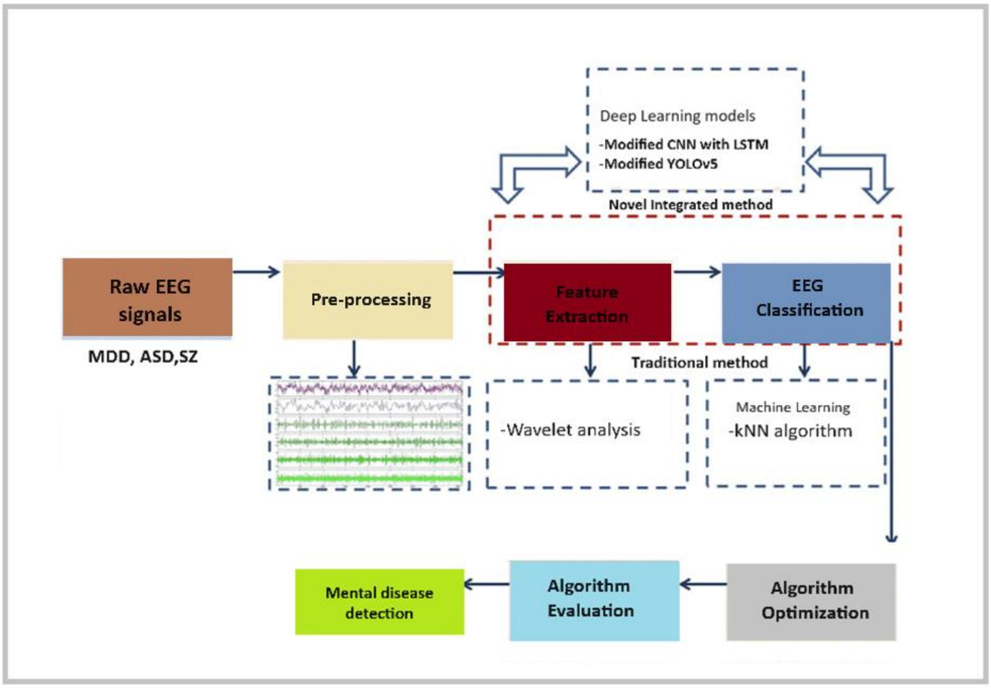

Figure 1. System flowchart of mental disease detection from EEGs

In this study, detection of specific mental diseases was achieved from EEG signals of healthy and MDD, ASD, SZ cases. The 19 channels EEG signals of open source EEG dataset were used in this study. These EEG signals were segmented/windowed into 15-second segments. After obtaining the original/raw EEG signals for three mental diseases, it could be seen that these could not be used directly for MDD, ASD and SZ recognition and interpretation.

The first process was mainly Pre-processing. This module performed filtering, removing bad-unknown channels, base collection operations on the dataset. For this part, Independent Component Analysis (ICA) was chosen and used to decrease some types of artifacts from the EEG signals [39].

Then, for the second part, processed data were performed with Feature Extraction and the obtained graycomatrix was fed into the traditional Machine Learning (kNN) algorithm. For this stage, the whole procedure was given graphically in Fig. 2.

Figure 2. Classification with the traditional Machine Learning method

Some features for Feature Extraction process was chosen as discrete wavelet transform and dependent some time variables for extract EEG features. Then, these features were used as inputs for kNN-Machine Learning part. For the next module, due to the obtained hyper parameters during algorithm training, algorithm optimization was used for this stage. For the next module, for evaluating the effectiveness of the three-class-classification results, Accuracy (ACC), Confusion matrix (CM) and Receiver Operating Characteristic (ROC) curve parameters were obtained and analyzed.

For the third step, DL models of CNN with LSTM and YOLOv5 were chosen and the modified versions of them were developed and used. For this stage, raw EEG signals were processed with modules. For the next step, the processed signals were divided into 15-second signal segments and then, Spectrogram images were obtained from these specific segments. Indeed, the images were sent to the automatic extraction and classification module, which combined modificated version of CNN with LSTM network [40]. Finally, the dropout and fully connected layers are added to the network. A graphical version of the proposed method is given in Fig. 3.

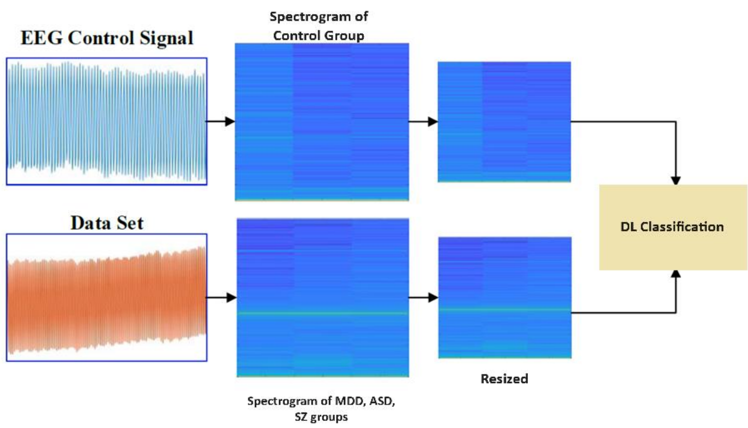

Figure 3. Classification with DL models

2.2.1. Pre-processing

The raw EEG signal dataset were used from the open source dataset with the recording of 10-20 system with a sampling frequency of 174 Hertz with 23.6 sec duration. For this study, generally, MATLAB 2019

b and 2020a versions were used with ASUS Zenbook Pro Duo and Macbook Pro advanced laptops in detail.
For the data augmentation of AI deep models, the parameters were chosen and used after some specific trials as;

Number of epochs=[40, 45, 50, 55];
Batch size=[5, 10, 15, 20];
Learning rate=[0.001];

With using the Grid search method, the most optimal parameters were identified and used as;
Number of epochs=55;
Batch size=25;
Learning rate= 0.001;

Moreover, after more trials, the most optimal parameters were identified and used as;

Number of epochs=100;
Batch size=20;
Learning rate= 0.001;

2.2.2. Feature Extraction

For this step, processed EEG signals were used for extracting some special features before fedding into the common ML model. These EEG signals were divided/segmented/windowed into 15-second segments. The whole signals were in 60 minutes format, so totally 240 epochs were obtained and used for each disease case. The spatial features were calculated and obtained via Wavelet analysis.

Wavelet analysis was generally a common feature extraction method for biomedical signal processing area [41]. For this step, db4 type wavelet transform was chosen and used according to the algortihm flow given in Fig. 4 below. The graycomatrix was obtained from the feature extraction process and the spatial features were used and saved in the matrix form. Then, these matrixes were collected and saved in an excel form for being an input for the ML model.

```
% Extract features using DWT
x = double(seg_img);
m = size(seg_img,1);
n = size(seg_img,2);
signal1 = seg_img(:,:);

[cA1,cH1,cV1,cD1] = dwt2(signal1,'db4');
[cA2,cH2,cV2,cD2] = dwt2(cA1,'db4');
[cA3,cH3,cV3,cD3] = dwt2(cA2,'db4');

DWT_feat = [cA3,cH3,cV3,cD3];
G = pca(DWT_feat);

[g] = graycomatrix(G);
%stats = graycoprops(g,{'contrast','homogeneity','correlation','Energy'});
stats = graycoprops(g,'Contrast Correlation Energy Homogeneity');
 Contrast = stats.Contrast;
%sprintf('Contrast is: %g%%',Contrast)
Correlation = stats.Correlation;
Energy = stats.Energy;
Homogeneity = stats.Homogeneity;
Mean = mean2(G);
Standard_Deviation = std2(G);
Entropy = entropy(G);
RMS = mean2(rms(G));
Variance = mean2(var(double(G)));
a = sum(double(G(:)));
Smoothness = 1-(1/(1+a));
Kurtosis = kurtosis(double(G(:)));
Skewness = skewness(double(G(:)));

% Inverse Difference Movement
m = size(G,1);
n = size(G,2);
in_diff = 0;
for i = 1:m
   for j = 1:n
      temp = G(i,j)./(1+(i-j).^2);
      in_diff = in_diff+temp;
   end
end
IDM = double(in_diff);
```

Figure 4. Wavelet db4 MATLAB feature extraction code flowchart

2.2.3. Classification with the Machine Learning Algorithm

There are some data mining classification methods especially one of these is k Nearest Neighbor (kNN) method. This method was performed according to the k value for the classification process with the class of the nearest neighbor [42]. The kNN algorithm used classification of the known class. In the kNN method, the distance was also obtained by the Euclidean method [43].

2.2.4. Creating Spectrogram Images

However all signals were not stationary, all the frequency components of the signal could be obtained and explained by the Fourier Transform. Displaying a 2-D function of a signal, time, and frequency is called a spectrogram [44]. In data augmentation phase, Spectrogram images were mainly created and used for DL models [45]. In Table 1, the sample size of each collected dataset was given in detail.

Table 1. The sample size of each dataset in this study

Used Data	**Total Sample Value**
ASD (Autism Spectrum Disorder)	**100**
MDD (Major Depressive Disorder)	**100**
SZ (Schizophrenia)	**100**
Normal/Healthy subjects	**100**
ASD augmented	**1000**
MDD augmented	**1000**
SZ augmented	**1000**

2.2.5. AI Model Approaches

In this phase, a modified CNN with LSTM model and modified YOLOv5 DL models were used and results were compared in detail. Mainly, a pre-trained phase, an up-todate layer and an estimation class are the fundamental parts of the models [45, 46].

2.2.5.1. Modified CNN model with LSTM

For the DL part, feature extraction was not needed and the characteristics of EEG data were extracted using the CNN network. The developed CNN and the modified version with LSTM could be described using algorithm implementation shown below.

Algorithm 1: Convolutional Neural Network (CNN)

1. Input: Number of samples, channels
2. $a_b^l=\sum_{c\in r} a_c^{l-1} \otimes K_{bc}^l+ d_b^l$
3. The features belonged to the signals were down smapled in an average small neighborhood for obtaining new features after convloution process. Indeed, pooling process was achieved via this formula given below.
   F= f($a_b^l=\sum_{c\in r} a_c^{l-1} \otimes K_{bc}^l+ d_b^l$) = f($x_c^l$down($a_c^{l-1}$)+ d_b^l)
4. The output was the first fully connected layer and this could be obtained by weighting the input via given formula.

$$u^I = w^I a^{I-1} + d^I$$

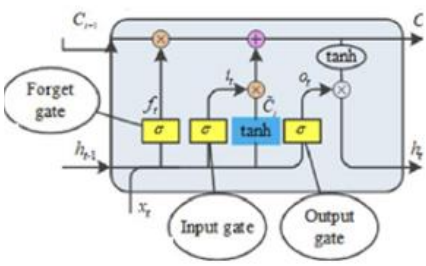

Figure 5. Network structure of LSTM of CNN

- Long-short term memory network [47]

The LSTM network was used to extract the features from mental disorders of EEGs. Conventional neural networks could learn time information within an input data. Their fundamental architecture was given in Fig. 5. The developed architecture of the CNN amd the modified version with LSTM could be described using algorithm implementation shown below.

Algorithm 2: LSTM network

1. For the t time, the candidate value cell was calculated with the formula given below.
   $C_t = \tanh\,(W_{xC}x_t + W_{hC}h_{t-1} + b_C)$
2. The input gate a_t was used for calculating the new information to add to the cell state.
   $$a_t = \alpha(\,W_{xt}\,x_t +\, W_{ha}\,h_{t-1} +\, b_a)$$
3. THe forget gate (f_t) was used to analyze/decide the information of the removed cell.
   $$a_t = \alpha(\,W_{xf}\,x_t +\, W_{hf}\,h_{t-1} +\, b_f)$$
4. The hidden layer value of C_t was calculated via the formula given below.
   $$C_t = f_t * C_{t-1} + a_t * C_t$$
5. a_t was defined as the value of output gate. This determined the right output cell.
   $$o_t = \alpha(\,W_{xo}\,x_t +\, W_{ho}\,h_{t-1} +\, b_o)$$
6. LSTM outputs were calculated via the formula given below.
   h=$o_t$tanh(C_i)
7. A dropout function was added to fully connected layer.
8. Interpretation and prediction of multi class mental diseases from EEGs were completed. The output was the label of datasets.

2.2.5.2. Modified YOLOv5 model

The YOLO model used input as photos to create characteristics for object detection. After that, a prediction system performed these attributes to draw boxes around objects and determined which classes they belong to. The first object detector to link the process of class label prediction with bounding box prediction in an end-to-end differentiable network was the YOLO model. There are three primary components to the YOLO network [48]:

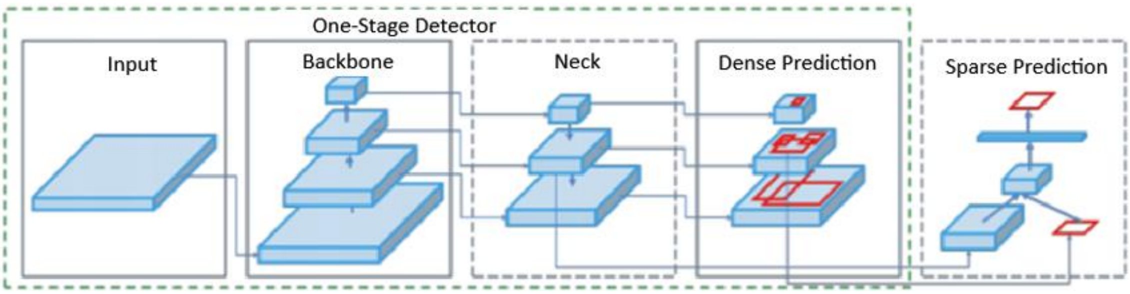

Figure 7. YOLOv5 architecture

As given above, there were many ways to combine various architectures at each significant component. YOLOv5's primary contribution is to incorporate advances from other fields of computer vision and demonstrate how, taken together, they enhance YOLO object detection.
Though they are frequently less mentioned, the steps used to train a model are just as crucial to the overall effectiveness of an object recognition system as any other component. Indeed, there were two primary YOLOv5 training processes as given below.

- Data augmentation; contains modifying the initial training data to expose the model to a larger variety of semantic variation than what would be found in the training set alone [48].

- Loss Calculations; YOLO uses the GIoU, obj, and class losses functions to compute a total loss function. The goal of mean average precision can be maximized by carefully crafting these functions [48].

III. RESULTS AND DİSCUSSİON

The experimetal part of the study was achieved via MATLAB 2019 and 2020 versions. 100 images for each mental diseases, 100 images for healthy group, 1000 augmented images for each mental disease and healthy groups were used from an open source dataset. These images were then anonymized and preprocessed through signal labeling using MATLAB tool.

As the first step in the experimental part, EEG signals were processed and Feature Extraction was performed. With using wavelet method, features were obtained and these feature matrix (graycomatrix) was classified with the common Machine Learning kNN algorithm. According to the traditional classifcation, the obtained accuracy graph was given in Figure 8. According to the figure, the best classification accuracy was obtained with the %95.65 for MDD disease for kNN classifier. Indeed, all classification results for multimodal classification were given in Table 2 in detail.

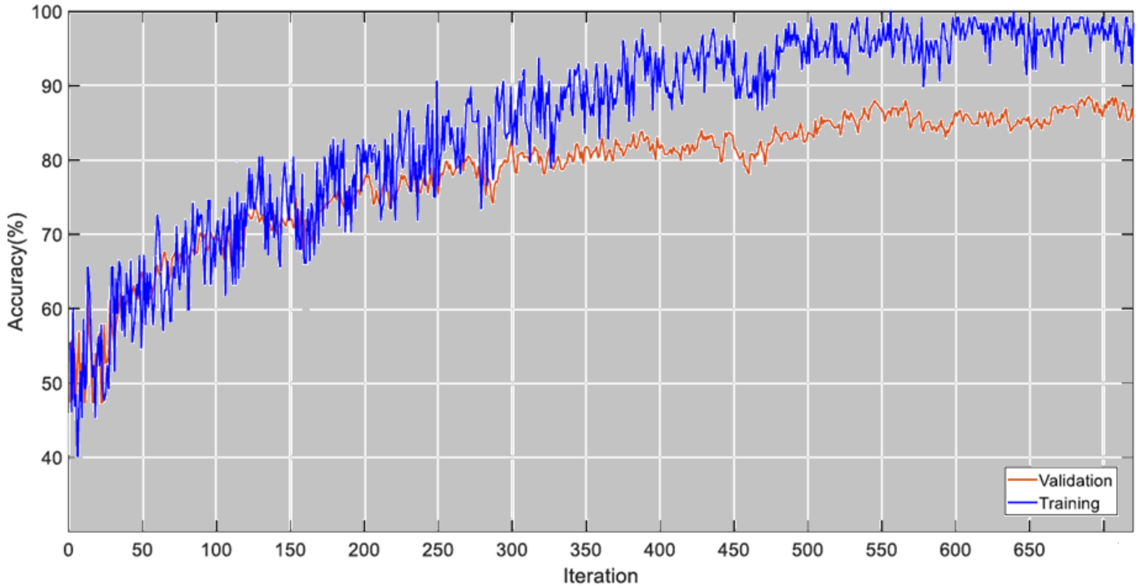

Figure 8. Accuracy result for kNN classification

Table 3. Results for other performence analysis for kNN classifier

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

As the second step in the experimental part, EEG signals were processed with the Spectrogram images and these were fed into the DL model of modified CNN with LSTM model. Indeed, CNN and LSTM were both different models in classification but we combined and modified the two method and finally modified CNN with LSTM model was obtained and used.

According to the DL classifcation, the flowchart of training process was given in Figure 9. According to 10-fold cross-validation technique, the best classification accuracy was obtained with the %97.6 for SZ disease for CNN with LSTM classifier. Indeed, all classification results for multimodal classification were given in Table 3 in detail.

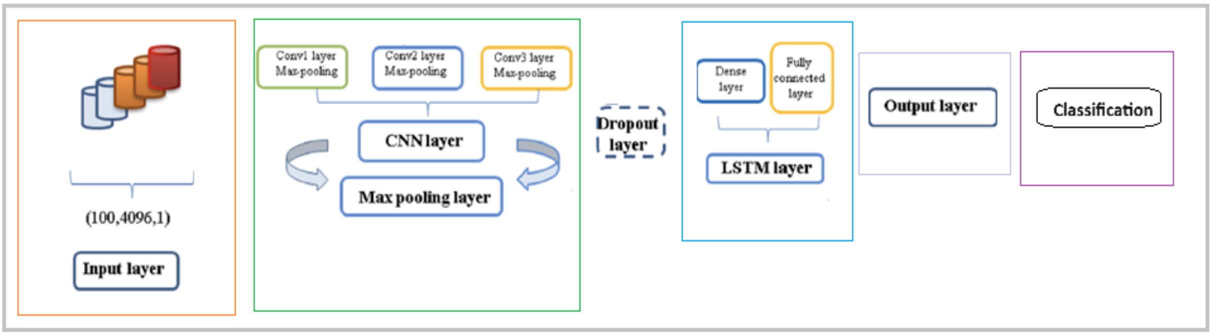

Figure 9. Flowchart of training for CNN-LSTM model

Table 3. Results for other performence analysis for CNN with LSTM classifier

	Class	Accuracy(%)	Precision(%)	Recall(%)	Sensitivity(%)	Specificity(%)
Channel 1	SZ	97.6	97.8	96.32	96.32	97.01
	Healthy		97.4	96.01	97.01	96.2
Channel 2	MDD	92	90.50	89.7	95.2	96.1
	Healthy		88.60	86.8	96.1	95.32
Channel 3	ASD	89.4	87.34	89.35	92.32	94.01
	Healthy		88.65	87.24	94.01	94.32

In this paper, a hybrid extraction and classification were performed via CNN with LSTM model. The LSTM network was improved by adding a LSTM unit in detail. Therefore, hybrid CNN with LSTM method could maximize the spatial information of EEG, gave a chance to improve recognition ACC. According to Fig. 10 and 11, ROC AUC curve and confusion matrix results for CNN-LSTM model were given in detail.

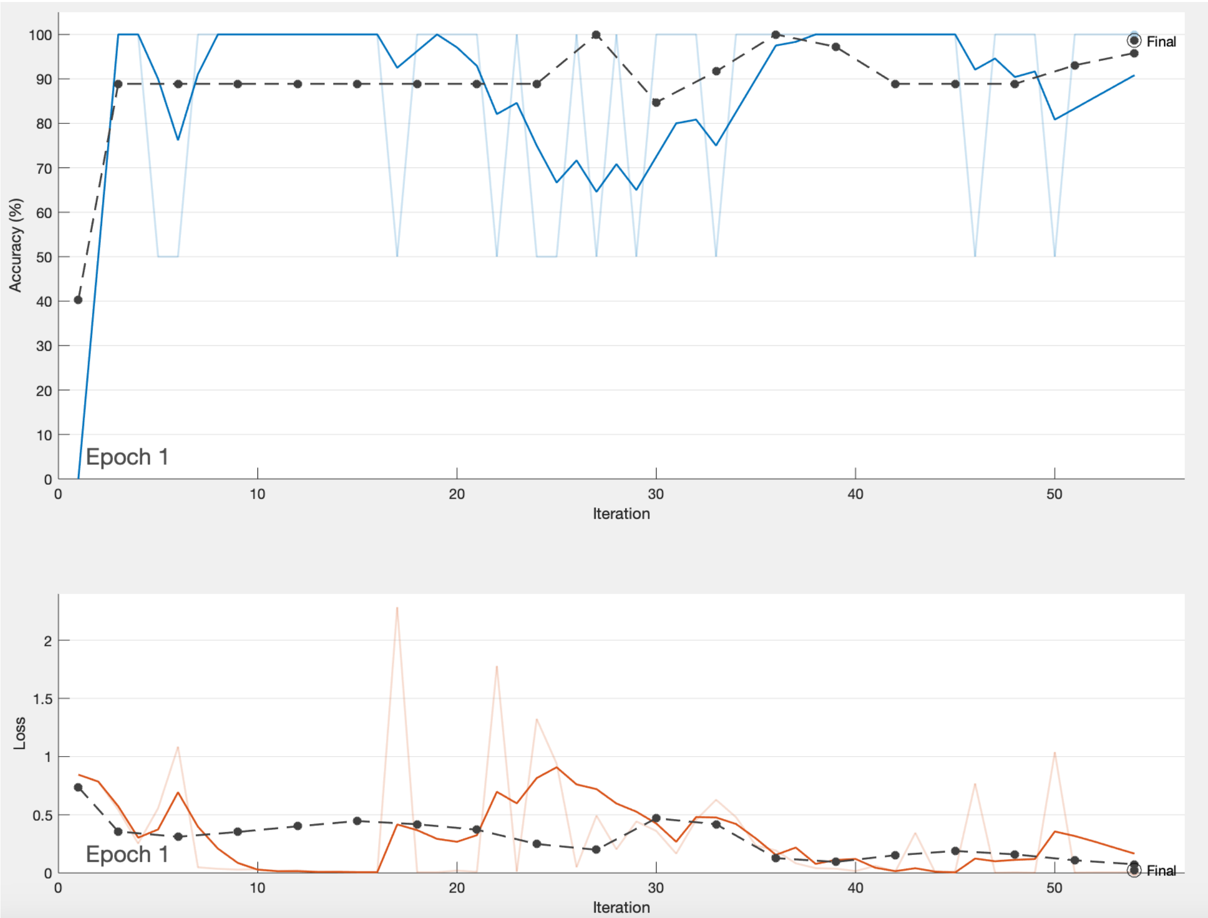

Figure 10. ROC results for CNN with LSTM model classification

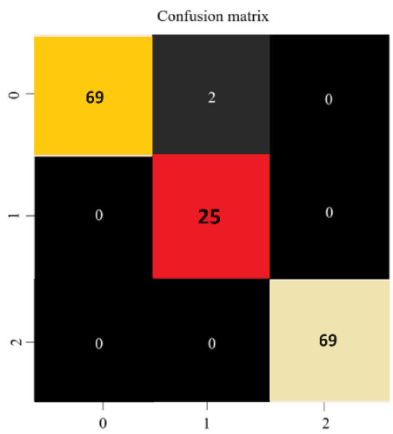

Figure 11. Confusion matrix for CNN-LSTM model

Every image in the sample has a label corresponding to the name of the disease, and the disease name corresponds to the class name that is used to represent the disease during training and detection. YOLOv5 runs training data through a data loader, which enhances data online, with each training batch. The experiment performed on the dataset. The experiment conducted on 100 epochs on the labeled Spectrogram image dataset.

Following training completion, the trained batches' results are kept in the final model and annotated with the class numbers. There will be many duplicate detections with overlapping bounding boxes even though we disregarded weak detections. High overlapping box removal is achieved using non-max suppression.

The output shows precision and recall with a high accuracy reaches to 99.5% for the three class mental diseases. Results for other performence analysis YOLOv5 classifier were given in Table 4 and the presicison recall curve and confusion matrix were given in Fig. 12 and 13 in detail.

Table 4. Results for other performence analysis for YOLOv5 classifier

	Class	Accuracy(%)	Precision(%)	Recall(%)	Sensitivity(%)	Specificity(%)
Channel 1	SZ	99.5	99.4	97.32	96.32	97.01
	Healthy		98.4	97.01	97.01	96.2
Channel 2	MDD	92	90.50	89.7	95.2	96.1
	Healthy		88.60	86.8	96.1	95.32
Channel 3	ASD	89.4	87.34	89.35	92.32	94.01
	Healthy		88.65	87.24	94.01	94.32

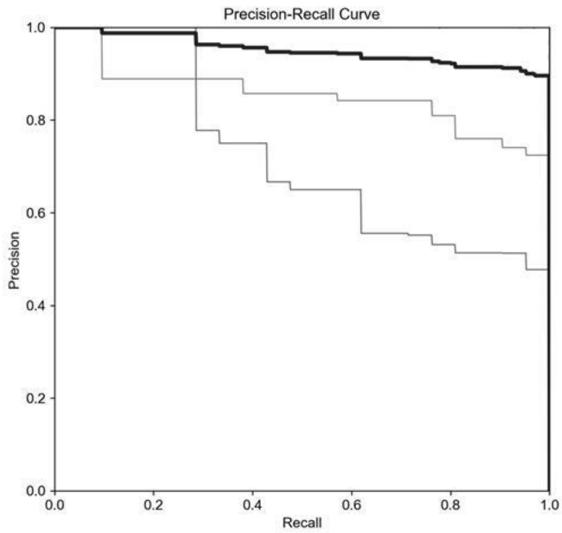

Figure 12. Precision Recall curve for YOLOv5 model

Even while our suggested model performed well in classification on datasets with significant imbalances or few samples, it was still far from perfect and contained flaws. For instance, the training and labeling of the photos for the sample preparation in our suggested model required a significant amount of processing power, and the training speed was comparatively slow. As a result, we will be providing more image labeling and more samples in our future work to improve the detection quality, as it has been demonstrated that some diseases are still not correctly diagnosed because of inadequate data sources.

When we analyzed the all results, the highest and best results were obtained from YOLOv5 classifier, then CNN with LSTM and then kNN classifiers. Indeed, every training and classification results were different in each other for detecting the mental disease case. For YOLOv5, the best results were obtained for SZ classification with %99.5 accuracy. Then, for CNN-LSTM model, the best results were obtained for SZ classification with %97.6 accuracy. Finally, for kNN traditional machine learning classifier, less higher but important accuracy result was obtained as %95.65. All models used in the study could be succesfully used for different cases or EEG types for helping clinicians via CAD pre-diagnosis systems.

IV. CONCLUSION

In this study, we used EEGs of specific mental diseases of ASD, MDD and SZ cases and we created a CAD pre-diagnosis system for these EEGs. First, signals were processed and then traditional Machine Learning process was performed via kNN classifier. With the common method, less higher but important accuracy result was obtained as %95.65. Then, more advanced and modified DL models of CNN with LSTM and YOLOv5 were created and used. With these models, for YOLOv5, the best results were obtained for SZ classification with %99.5 accuracy. Then, for CNN-LSTM model, the best results were obtained for SZ classification with %97.6 accuracy. In addition, the system's performance could be increased with YOLO and CNN based models with a larger dataset. Moreover, in the literature, there have not been a database such as ASD, MDD, SZ were used together and also different specific and important ML and DL classifiers have not been used in a specific study, so we achieved a novel study and obtained higher and best results for multi modal EEG classification. This system and models could help clinicians for pre-diagnosis of mental diseases or other types of diseases based on EEGs for better diagnosis and understanding of the signals and cases.

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