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Deep Learning Technique for Detection of Depression Using EEG Data By ANN

[1] *Sristi Sagar*, [2]*Prof. Jayshree Boaddh*

[1]*M.Tech Scholar*, [2]*Assistant Professor,*

[1,2] *Mittal Institute of Technology, Bhopal*

Abstract— Electroencephalogram (EEG) signal-based emotion recognition has attracted wide interests in recent years and has been broadly adopted in medical, affective computing, and other relevant fields. Depression has become a leading mental disorder worldwide. Evidence has shown that subjects with depression exhibit different spatial responses in neurophysiologic signals from the healthy controls when they are exposed to positive and negative. Depression is a common reason for an increase in suicide cases worldwide. EEG plays an important role in E-healthcare systems, especially in the mental healthcare area, where constant and unobtrusive monitoring is desirable. EEG signals can reflect activities of the human brain and represent different emotional states. Mental stress has become a social issue and could become a cause of functional disability during routine work. This dissertation presents machine and deep learning technique for detecting depression using EEG. The algorithm first extracts features from EEG signals and classifies emotions using machine and deep learning techniques, in which different parts of a trial are used to train the proposed model and assess its impact on emotion recognition results. The simulation is performed using the Python spyder software.

Keywords— EEG, Emotion, Stress, E-healthcare, Accuracy, Depression, Deep Learning, Machine Learning.

I. INTRODUCTION

Depression, as a common illness worldwide, is classified as a mood disorder and described as feelings of sadness or anger that interfere with a person's everyday activities. According to the World Health Organization, it is likely to be the leading global disease by 2030. Depression disorder is a pathological process that causes many symptoms, resulting in limited mental and physical functionality. It is often accompanied by cognitive impairments, which may increase the risk of Alzheimer's disease and suicide and accelerate cognitive decline.

The earlier depression is detected, the easier it is to treat. As a low-cost, noninvasive acquisition, and high temporal resolution technique, electroencephalography is widely used in neural systems and rehabilitation engineering. This work is focused on the experimental paradigm, emotion feature extraction, feature selection, machine learning, and the dataset for training and testing, particularly on spatial information feature extraction and selection. This focus was chosen because many studies have shown that subjects with depression exhibit different spatial responses in neurophysiological signals compared to healthy controls, when they are exposed to stimuli.

Figure 1 Mental health data (Indian health report)

EEG signals are nonstationary and nonlinear signals, similar to many other physiological signals. To analyze these signals, linear and nonlinear features are typically used, such as the power spectrum density, Lempel-Ziv complexity, variance, mobility, fluctuations, Higuchi fractal, approximate entropy, Kolmogorov entropy, correlation dimension, Lyapunov exponent, and permutation entropy. To analyze our hypothesis effectively, it was necessary to select optimal features, as some dimension features may mislead the classifiers.

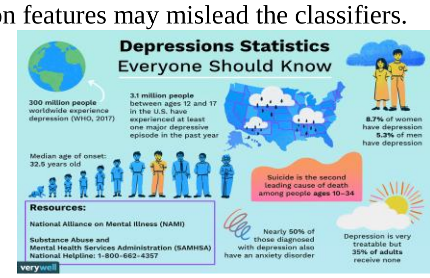

Figure 2: Depression statics (WHO report)

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1.2 EEG SIGNAL

The Electroencephalography (EEG) is a method to record an electro gram of the electrical activity on the scalp that has been shown to represent the macroscopic activity of the surface layer of the brain underneath. It is typically non-invasive, with the electrodes placed along the scalp. Electrocorticography, involving invasive electrodes, is sometimes called "intracranial EEG".

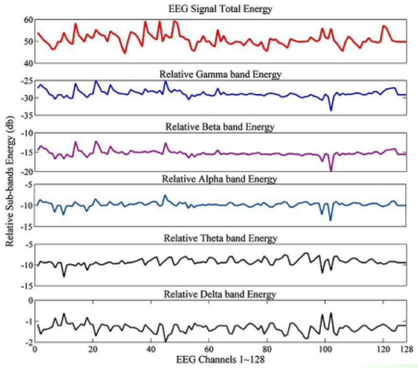

Figure 3: EEG Signal

II. LITERATURE REVIEW

A. Seal et al. present DeprNet in two investigations, specifically, the recordwise split and the subjectwise split, is introduced in this review. The outcomes accomplished by DeprNet have an exactness of 0.9937, and the region under the recipient working trademark bend (AUC) of 0.999 is accomplished when recordwise split information are thought of. Then again, a precision of 0.914 and the AUC of 0.956 are acquired, while subjectwise split information are utilized. These outcomes propose that CNN prepared on recordwise split information gets overtrained on EEG information with few subjects. The exhibition of DeprNet is astounding contrasted and the other eight gauge models. Besides, on picturing the last CNN layer, it is observed that the upsides of right terminals are unmistakable for discouraged subjects, while, for ordinary subjects, the upsides of left cathodes are conspicuous [1].

S. Sun et al., This Electroencephalography (EEG)- based research is to investigate the viable biomarkers for wretchedness acknowledgment. Resting-state EEG information were gathered from 24 significant burdensome patients (MDD) and 29 typical controls utilizing 128-anode geodesic sensor net. To more readily recognize despondency, we separated multi- kind of EEG highlights including straight elements (L), nonlinear elements (NL), useful availability highlights stage slacking list (PLI) and organization measures (NM) to thoroughly portray the EEG signals in patients with MDD. Also, AI calculations and factual examination were utilized to assess the EEG highlights. Consolidated multi-types includes (All: L+ NL + PLI + NM) beat single-type highlights for characterizing discouragement [2].

W. Zheng et al., presents explore stable examples of electroencephalogram (EEG) over the long haul for feeling acknowledgment utilizing an AI approach. Up to now, different discoveries of initiated designs related with various feelings have been accounted for. In any case, their strength over the long run has not been completely examined at this point. In this work, we center around distinguishing EEG strength in feeling acknowledgment. We efficiently assess the presentation of different well known include extraction, highlight choice, highlight smoothing and design characterization techniques with the DEAP dataset and a recently evolved dataset called SEED for this review. Discriminative Diagram regularized Outrageous Learning Machine with differential entropy highlights accomplishes the best normal exactnesses of 69.67 and 91.07 percent on the DEAP and SEED datasets, separately[3].

W. Tooth et al. This review proposed an electroencephalogram (EEG)- based ongoing feeling acknowledgment equipment framework engineering in view of multiphase convolutional brain organization (CNN) calculation carried out on a 28-nm innovation chip and on field programmable entryway cluster (FPGA) for double and quaternary characterization. Test entropy, differential unevenness, brief time frame Fourier change, and a channel reproduction technique were utilized for feeling highlight extraction. In this work, six EEG channels were chosen (FP1, FP2, F3, F4, F7, and F8), and EEG pictures were produced from spectrogram combinations [4].

P. J. Bota et al. The original work on Full of feeling Processing in 1995 by Picard set the base for registering that connects with, emerges from, or impacts feelings. Emotional processing is a multidisciplinary field of examination traversing the areas of software engineering, brain research, and mental science. Potential applications incorporate computerized driver help, medical care, human-PC connection, amusement, promoting, instructing and numerous others [5].

III. PROBLEM IDENTIFICATIONS & OBJECTIVE

There has been continues research done from EEG with different result. This different result has been due to diversity in different aspects of methods used in the research. The diversities are mainly in aspects of emotion selection, experiment environment, techniques of data preprocessing and feature selection. Due to all this factors, it is not easy to compare and chose the method which can be said as the best classifier. Hence, there is always room for the development of better classifier suitable for specific application.

3.1 Problem Identification

There are many of the challenges for android malware detection in this research area-

Low accuracy rate of true data prediction from given dataset.

Using traditional System Analysis alone not sufficient for proper feature extraction.

More classification error and system analysis does not provide exact results.

3.2 Objective

Depressive disorder is one of the leading causes of burden of disease today and it is presumed to take the first place in the world in 2030. Early detection of depression requires a patient-friendly inexpensive method based on easily measurable objective indicators. This study aims to compare various single-channel electroencephalographic (EEG) measures in application for detection of depression. The main objective is to develop the AIML based model to prediction of the depression using EEG signal prediction with the improvement in the performance parameters. Therefore an efficiently detect the depression from the dataset is the prime objective of this research work.

IV. RESULT ANALYSIS

The main contributions of this work will be summarized as follows. To collect stress emotion EEG based dataset from kaggle website. To implement proposed approach based on machine/deep learning technique. To simulate proposed method on spyder python 3.7 software.To prediction of various parameters like precision, recall, f-measure and accuracy. To generate results graph and compare from previous work.

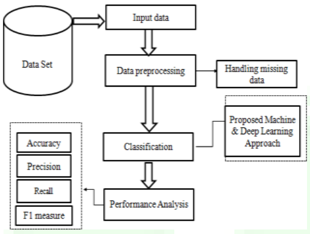

Figure 4 : Flow Chart

Steps-

1.Firstly, download the EEG dataset from kaggle website, which is a large dataset provider and machine learning repository Provider Company for research.

2.Now apply the preprocessing of the data, here handing the missing data, removal null values.

3.Now extract the data features and evaluate in dependent and independent variable.

4.Now apply the classification method based on the machine learning (KNN) and deep learning (LSTM) approach.

5.Now generate confusion matrix and show all predicted class like true positive, false positive, true negative and false negative.

6.Now calculate the performance parameters by using the standard formulas in terms of the precision, recall, F_measure, accuracy and error rate.

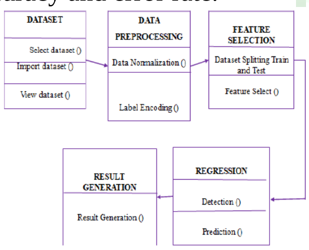

Figure 5: Class Diagram

4.2 Methodology

The proposed model shows the main steps for preprocessing stage, feature extraction, and classification. Develop an effective EEG-based detection method for depression classification by employing spatial information technique. In this process take EEG signal dataset to predict depression patients emotion as positive and negative. For that the first process is to pre- process the dataset to remove missing values and null values from the taken EEG dataset. In order to classify different emotions, we need to record EEG signals from different subjects and then process them to extract different features. The data sets are made from the features and then we classify the dataset. In this process we propose machine learning (KNN) and deep learning (LSTM) algorithms to classify the depression patient's emotion as positive and negative. Finally it improves the accuracy of classifying depression patients emotion as positive and negative.

Module Description

Data selection and loading

Data Preprocessing

Feature Selection

Classification

Prediction

Result Generation

4.2.1 Data Selection and Loading

The data selection is the process of selecting the data for predicting the depression patient emotion from the EEG emotion dataset. This is a dataset of EEG brainwave data that has been processed with our original strategy of statistical extraction. The data was collected from two people (1 male, 1 female) for 3 minutes per state - positive, neutral, negative. We used a Muse EEG headband which recorded the TP9, AF7, AF8 and TP10 EEG placements via dry electrodes. Six minutes of resting neutral data is also recorded, the stimuli used to evoke the emotions.

V. IMPLEMENTATION AND RESULT ANALYSIS

5.1 Simulation Software

Python- It is an interpreter, raised level, comprehensively helpful programming language. Made by Guido van Rossum and first delivered in 1991, Python's plan reasoning stresses code clarity with its famous utilization of critical whitespace. Its language builds and article organized philosophy hope to help developers with forming clear, genuine code for little and colossal scale projects. Python is continuously made and garbage accumulated. It upholds various programming ideal models, including procedural, object-organized, and utilitarian programming. Python is frequently depicted as a "batteries included" language on account of its exhaustive standard library.

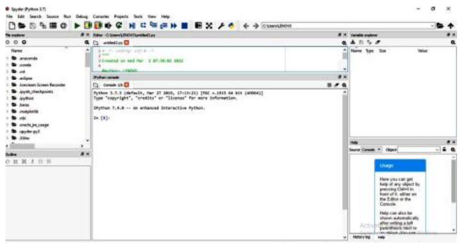

Figure 6: Snap shot of Spyder environment

Spyder is extensible with first-and untouchable modules, incorporates support for natural devices for data assessment and inserts Python-explicit code quality confirmation and thoughtfulness instruments, **like Pyflakes,** Pylint and Rope. It is available get stage through Boa constrictor, on Windows, on macOS through MacPorts, and on critical Linux dispersions like Bend Linux, Debian, Fedora, Gentoo Linux, open SUSE and Ubuntu.

5.2 Result And Analysis

The simulation starts from taking the dataset. In this dataset the various features value mention like mean_d_10_a, mean_d_11_a , mean_d_12_a, mean_d_13_a, mean_d_14_a, mean_d_15_a, mean_d_16_a, mean_d_17_a, mean_d_18_a, mean_d_19_a, mean_d_20_a mean_d_21_a, mean_d_22_a etc.

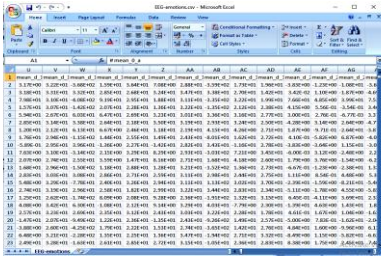

Figure7: Original dataset in .csv file

The figure 7 is showing the dataset, which is taken from the kaggle machine learning website.

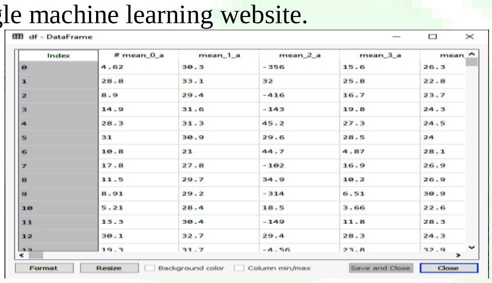

Figure 8: Dataset frame

Figure 8 is showing the dataset in the python environment. The dataset have various numbers of rows and column. The signal features name is mention in index.

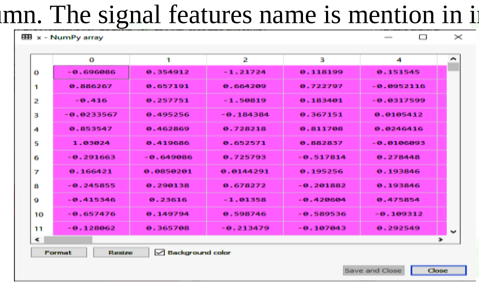

Figure 9: X label of data

Figure 9is showing x label of dataset view, here all the EEG signal values shows in the form of numeric.

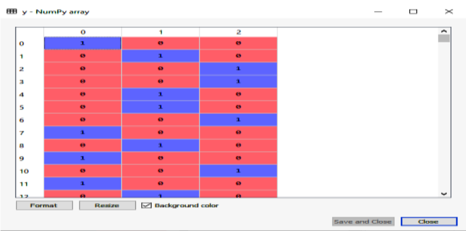

Figure : 10 Y label of data

Figure 10 is showing y label dataset view, here all the values shows in the form of the 1 with blue colour and o with red colour.

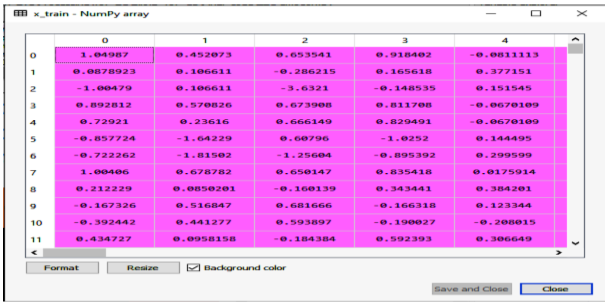

Figure 11: X train

Figure 11 is showing the x train of the given dataset. The given dataset is divided into the 70- 80%% part into the train dataset.

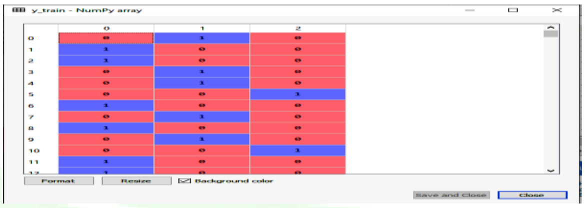

Figure 12: Y train

Figure 12 is showing the y train of the given dataset. The given dataset is divided into the 70- 80%% part into the train dataset.

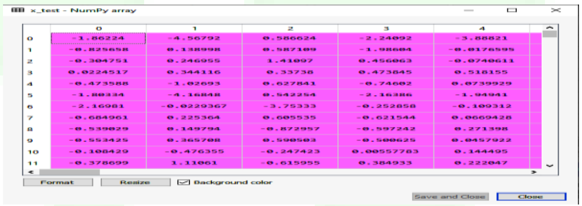

Figure 13: X test

Figure 13 is showing the x test of the given dataset. The given dataset is divided into the 20- 30% part into the train dataset.

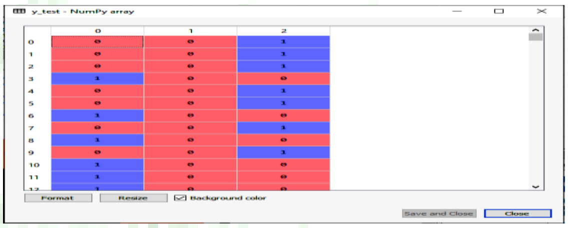

Figure 14: Y test

Figure 14 is showing the y test of the given dataset. The given dataset is divided into the 20- 30% part into the train dataset.

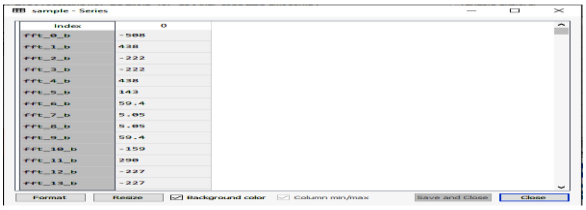

Figure 15: Sample of data

Figure 15 is presenting dataset sample in this view. It also calculates distance of the data. All the dataset view generate in the variable explorer of python software.

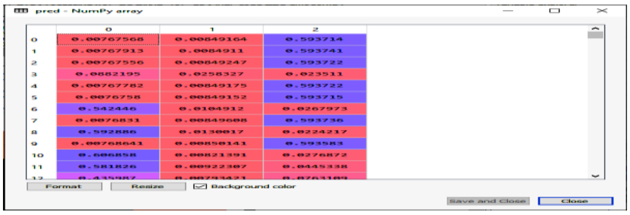

Figure 16: Prediction

Figure 16 is presenting the prediction from given dataset values. The upper and lower values are classified with different colour.

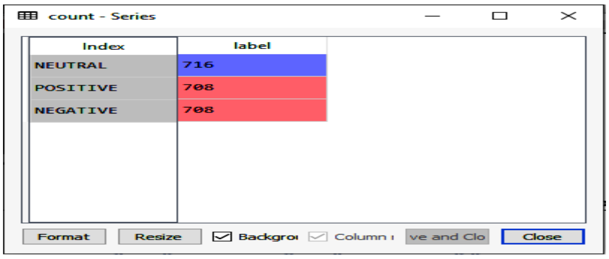

Figure 17: Count

Figure 17 is presenting signal label count, either it is neutral, positive or the negative signal on the other hand how many data is positive class, negative or neutral class.

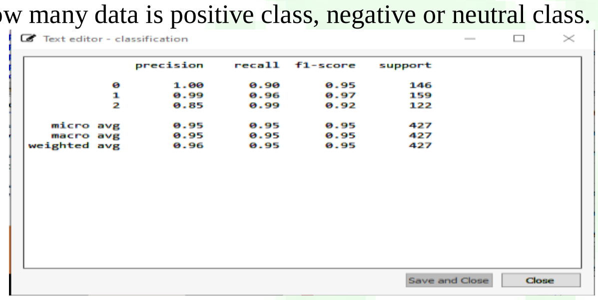

Figure 18: Classification

Figure 18 is presenting classification model. The values of precision, recall, f1 shown with respect of micro, macro and weighted average is shown.

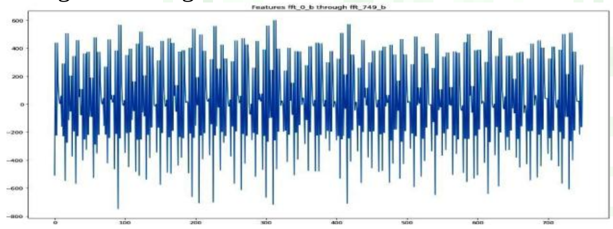
Figure19: EEG signal

Figure 19 is presenting EEG signal in graphical representation form. The EEG signal shown from 0 to 700 label.

```
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 1, 64)             668928
dropout (Dropout)            (None, 1, 64)             0
lstm_1 (LSTM)                (None, 32)                12416
dropout_1 (Dropout)          (None, 32)                0
dense (Dense)                (None, 3)                 99
=================================================================
Total params: 681,443
Trainable params: 681,443
Non-trainable params: 0
Train on 1705 samples, validate on 427 samples
```

Figure 20: Layer details

Figure 20 is presenting layer details of long short term memory techniques. The trainable prams is 681443 and non trainable param is o, therefore all params is trained.

```
Epoch 1/10
1705/1705 [==============================] - 7s 4ms/sample - loss: 0.8137 - acc: 0.8211 -
val_loss: 0.6246 - val_acc: 0.9110
Epoch 2/10
1705/1705 [==============================] - 2s 1ms/sample - loss: 0.5560 - acc: 0.9320 -
val_loss: 0.4895 - val_acc: 0.9204
Epoch 3/10
1705/1705 [==============================] - 2s 880us/sample - loss: 0.4398 - acc: 0.9437
- val_loss: 0.4145 - val_acc: 0.9157
Epoch 4/10
1705/1705 [==============================] - 2s 897us/sample - loss: 0.3519 - acc: 0.9455
- val_loss: 0.3334 - val_acc: 0.9227
Epoch 5/10
1705/1705 [==============================] - 1s 786us/sample - loss: 0.2928 - acc: 0.9455
- val_loss: 0.2954 - val_acc: 0.9204
Epoch 6/10
1705/1705 [==============================] - 2s 1ms/sample - loss: 0.2492 - acc: 0.9513 -
val_loss: 0.2574 - val_acc: 0.9227
Epoch 7/10
1705/1705 [==============================] - 2s 1ms/sample - loss: 0.2009 - acc: 0.9613 -
val_loss: 0.2309 - val_acc: 0.9438
Epoch 8/10
1705/1705 [==============================] - 2s 974us/sample - loss: 0.1749 - acc: 0.9648
- val_loss: 0.2263 - val_acc: 0.9415
Epoch 9/10
1705/1705 [==============================] - 2s 960us/sample - loss: 0.1412 - acc: 0.9806
- val_loss: 0.1872 - val_acc: 0.9461
Epoch 10/10
1705/1705 [==============================] - 2s 922us/sample - loss: 0.1126 - acc: 0.9859
- val_loss: 0.1878 - val_acc: 0.9532
427/427 [==============================] - 0s 129us/sample - loss: 0.1878 - acc: 0.9532
(427,)
```

Figure 21: Iteration

Table 1: Simulation Results of KNN

Sr. No.	Parameter Name	Value
1	Accuracy	94.14%
2	Classification error	5.86 %
3	Precision	97%
4	Recall	94%
5	F-measure	95%

Table 1 is showing the simulation results of the K-Nearest Neighbor machine learning technique. The overall accuracy is 94.14% with 5.86% error rate.

Table 2: Simulation Results of LSTM

Sr. No.	Parameter Name	Value
1	Accuracy	96.48 %
2	Classification error	3.52 %
3	Precision	99%
4	Recall	94%
5	F-measure	97%

Table 2 is showing the simulation results of the long short term memory technique. The overall accuracy is 96.48% with 3.52% error rate.

Table 3: Result Comparison

Sr. No.	Parameters	Previous Work [1]	Proposed Work
1	Accuracy	91%	96.48 %
2	Classification Error	9 %	3.52 %
3	Precision	91%	99%
4	Recall	88%	94%
5	F-measure	89%	97%

Figure 21 is showing the result comparison of the previous and proposed work. The precision of the proposed work is 99 % while in the previous work it is 91.00 %. Similarly the other parameters like Recall and F_Measure is 94 % and 97 % by the proposed work and 88.00 % and 89.00 % by the previous work. The overall accuracy achieved by the proposed work is 96.48 % while previous it is achieved 91.00 %. The error rate of proposed technique is 3.52 % while 9.008 % in existing work. Therefore it is clear from the simulation results; the proposed work is achieved significant better results than existing work.

VI. CONCLUSION AND FUTURE WORK

6.1 Conclusion

As a mood disease, depression is affecting an increasing number of people. As a face-in-the- crowd task stimulus experiment based on frequency information filtering, time information feature extraction, and spatial information feature selection, we developed an improved EEG- based feature classification method employing spatial information, which is useful for the detection of patients with depression. By employing the classification performance was significantly improved, which indicates

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that can enhance the spatial differences before feature extraction; however, we should be aware of the limitation of the datasets. Depression as a mental disorder with clinical manifestations such as significant depression and slow thinking is always accompanied by abnormal brain activity and obvious emotional alternation. Therefore, as a method tracking the brain functions, EEG can detect these abnormal activities.

This dissertation presents machine and deep learning techniques for detecting depression using EEG. Simulation is performed using python sypder 3.7software.The precision of the proposed work is 99 % while in the previous work it is 91.00 %. Similarly the other parameters like Recall and F_Measure is 94 % and 97 % by the proposed work and 88.00 % and 89.00 % by the previous work. The overall accuracy achieved by the proposed work is 96.48 % while previous it is achieved 91.00 %. The error rate of proposed technique is 3.52 % while 9.008 % in existing work. Therefore it is clear from the simulation results; the proposed work is achieved significant better results than existing work.

6.2 Future Scope

In the future, we will continue to focus on correlation studies to obtain more detailed results.

A variety of methods can widely used to extract the features from EEG signals, among these methods are time frequency distributions (TFD), fast fourier transform (FFT), eigenvector methods (EM), wavelet transform (WT), and auto regressive method (ARM), and so on.

A small SNR and different noise sources are amongst the greatest challenges in EEG- based BCI application studies. Unwanted signals contained in the main signal can be termed noise, artifacts, or interference. There are two sources of EEG artifacts: external or environmental source and physiological source.

EEG Data Pre-processing Strategies can be further enhanced.

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