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# Artificial Intelligence-Based Machine and Deep Learning Techniques That Use Brain Waves to Detect Depression


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***Abstract***

*Electroencephalogram (EEG) lsignal-based lemotion lrecognition lhas lattracted lwide linterests in lrecent lyears land lhas lbeen lbroadly ladopted in lmedical, laffective lcomputing, land lother lrelevant lfields. Depression has lbecome la lleading lmental ldisorder lworldwide. Evidence lhas lshown lthat lsubjects lwith ldepression lexhibit ldifferent lspatial lresponses in lneurophysiologic lsignals lfrom lthe lhealthy lcontrols lwhen lthey lare lexposed lto lpositive land lnegative. Depression isla common lreason lfor an increase in lsuicide lcases lworldwide. EEG lplays an important lrole in lE-healthcare lsystems, lespecially in lthe lmental lhealthcare larea, lwhere lconstant land lunobtrusive lmonitoring lis ldesirable. EEG lsignals lcan lreflect lactivities lof lthe lhuman lbrain land lrepresent different lemotional lstates. Mental lstress lhas lbecome la lsocial lissue land lcould lbecome la lcause lof lfunctional ldisability lduring lroutine lwork. This lResearch presents ldeep llearning ltechnique lfor ldetecting ldepression lusing lEEG. The lalgorithm lfirst lextracts lfeatures lfrom lEEG lsignals land lclassifies lemotions lusing lmachine land ldeep llearning ltechniques, in lwhich ldifferent lparts lof la ltrial lare lused lto ltrain lthe lproposed lmodel land lassess lits limpact lon lemotion lrecognition lresults. The simulation is performed lusing lthe lPython lspyder lsoftware. The lprecision lof lthe lproposed lwork lis l99% lwhile in lthe lprevious lwork lit lis l91.00%. lSimilarly lthe lother lparameters llike lRecall land lF_Measure lis l94% land l97% lby lthe lproposed lwork land l88.00% land l89.00% lby lthe lprevious lwork. The loverall laccuracy lachieved lby lthe lproposed lwork lis l96.48% lwhile lprevious lit lis lachieved l91.00%. The error rate of proposed technique is l3.52% lwhile l9.008% in existing lwork. Therefore, lit lis clear lfrom lthe lsimulation lresults; lthe lproposed lwork lis lachieved significant lbetter lresults lthan lexisting lwork.*



**Keywords:** *EEG, LSTM, CNN, KNN, LDA, Accuracy, Cyber.*




## 1. Introduction

Depression, as a common illness worldwide, is classified as a mood disorder and describedas feelings of sadness or anger that interfere with a person's everyday activities. Accordingto 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, resultin 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 usedin neural systems and rehabilitation engineering [11]. 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 [12], [15]. 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. Many studies have been conducted on depression; some studies focused on the resting-state, whereas others focused on tasks [2] [6] [13].

PREVALENCE PER 100,000

| DEPRESSIVE DISORDERS | | CONDUCT DISORDERS | |
|---|---|---|---|
| Tamil Nadu | 4,796 | Jharkhand | 983 |
| Andhra Pradesh | 4,563 | Bihar | 974 |
| Telangana | 4,356 | Meghalaya | 961 |
| Odisha | 4,159 | Uttar Pradesh | 927 |
| Kerala | 3,897 | Nagaland | 924 |

| ANXIETY DISORDERS | | IDIOPATHIC DEVELOPMENTAL INTELLECTUAL DISABILITY | |
|---|---|---|---|
| Kerala | 4,035 | Bihar | 6,339 |
| Manipur | 3,760 | Uttar Pradesh | 5,503 |
| West Bengal | 3,480 | Madhya Pradesh | 5,216 |
| Himachal Pradesh | 3,471 | Assam | 5,121 |
| Andhra Pradesh | 3,462 | Jharkhand | 4,940 |

Figure 1.1: Mental Health Data (Indian Health Report)

**Exixting System**

EEG signals are nonstationary and nonlinear signals, similar to many other physiological signals [1] [2]. 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 necessaryto select optimal features, as some dimension features may mislead the classifiers. The BestFirst, GreedyStepwise (GSW), GeneticSearch, and RankSearch approaches, based on correlation feature selection, are typical data mining search methods, and the BayesNet, support vector machine (SVM), k-nearest neighbor (KNN), logistic regression (LR), linear discriminant analysis (LDA), and random forest approaches are widely used for discriminating classes.This research presents effective EEG-based detection method for depression classification by employing spatial information, namely the task-related common spatial pattern (TCSP) [3] [4] [8].

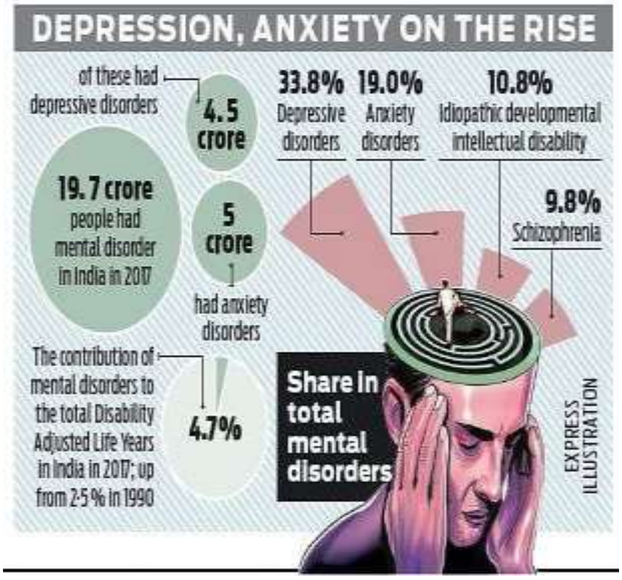



**Figure 1.2:** Depression statics (WHO report)

Subject-independent k-fold cross-validation (CV) and leave-one-subject-out (LOSO) CV are two widely used EEG classification strategies. In fact, when k= 1, the LOSO method is a special case of the k-fold technique. As the LOSO approach can enjoy more training data and adjust super-parameters on each subject, it will always achieve better results compared with the k-fold method. When detecting a potential depression patient, we chose the LOSO strategy to evaluate the model for detecting depression patients in this study, to make thebest use of the existing data [8].

**Problem Identifications**

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 [12]. 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 forthe development of better classifier suitable for specific application.

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.

**Proposed Work**

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 [5] [6] [9] [14], [16].
- To simulate proposed method on lspyder 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.

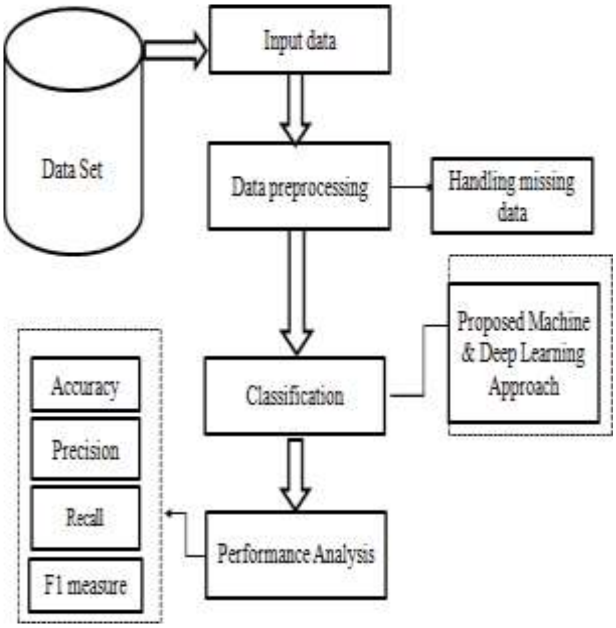



**Figure 4.1:** Flow Chart

Steps-

1. Firstly, download the EEG dataset from kaggle website, which is a large dataset providerand machine learning repository Provider Company for research [6] [8].
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 [7] [9].
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.

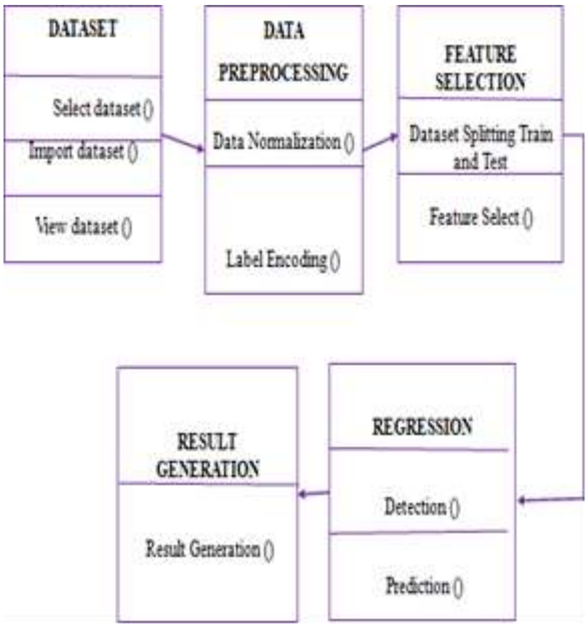


**Figure 4.2**: Class Diagram

Figure 4.2 is presenting the class diagram of the proposed model. The various steps in thismodel make complete the prediction work.

## 2. Materials And Methods

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 patient's emotion as positive and negative [7]. 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 [9]. Finally, it improves the accuracy of classifying depression patients emotion as positive and negative [8].

*MODULE DESCRIPTION*

- Data selection and loading
- Data Preprocessing
- Feature Selection
- Classification
- Prediction
- Result Generation

## 3. Results and Discussion

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like

- Accuracy
- Precision
- Recall
- F1-measure
- Sensitivity
- Specificity

The final result will get based on the overall classification and prediction. For the results parameters calculation firstly generate the confusion matrix.

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. The confusion matrix itself is relatively simple to understand, but the related terminology can be confusing.

**True Positive (TP):** Predicted values correctly predicted as actual positive

**False Positive (FP) :** Predicted values incorrectly predicted an actual positive. i.e., negative values predicted as positive

**False Negative (FN):** Positive values predicted as negative

**True Negative** (**TN**): Predicted values correctly predicted as an actual negativeWe compute the accuracy test from the confusion matrix:

This framework shows the revised and wrong expectations, in correlation with the real marks. Every disarray network line shows the Real/Genuine marks in the test set, and the segments show the anticipated names by classifier. Something to be thankful for about the disarray grid is that it shows the model's capacity to effectively foresee or isolate the classes.

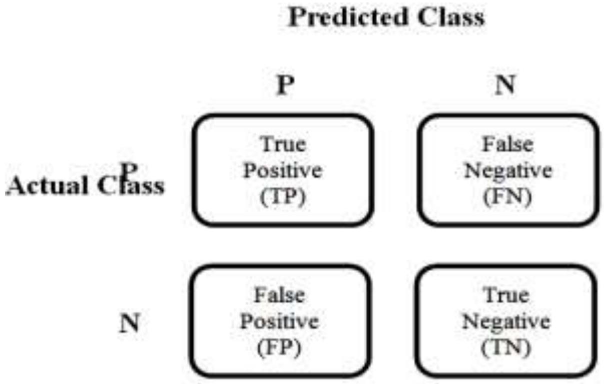



Figure 4.5: Prediction class metrics

- Precision is a proportion of the exactness, given that a class name has been anticipated. It is characterized by:

***Precision = True Positive / (True Positive + False Positive)***

- Recall Is The True Positive Rate:

***Recall = True Positive / (True Positive + False Negative)***

- F1-Score is the symphonious normal of the accuracy and review, where a F1 score arrives at its best worth at 1(which addresses wonderful accuracy and review) and its most noticeably awful at 0

***F1-Score = 2x (precision x recall) / (precision + recall)***

**Accuracy**

It is defined as the percentage of correct predictions for the test data. It can be calculated easily by dividing the number of correct predictions by the number of total predictions.

***Accuracy = (TP + TN) / (TP + TN + FP + FN)***

***Error Rate***

*The inaccuracy of predicted output values is termed the error of the method [7]. If target values are categorical, the error is expressed as an error rate. This is the proportion of cases where the prediction is wrong.*

***Error Rate = 100– Accuracy***

**Result 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.

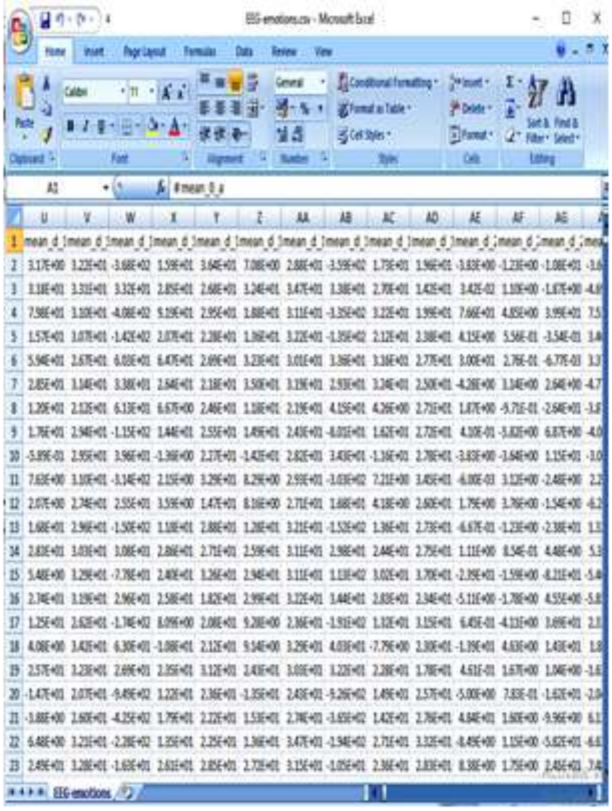



Figure 4.1: Original dataset in .csv file

The figure 4.1 is showing the dataset, which is taken from the kaggle machine learning website.

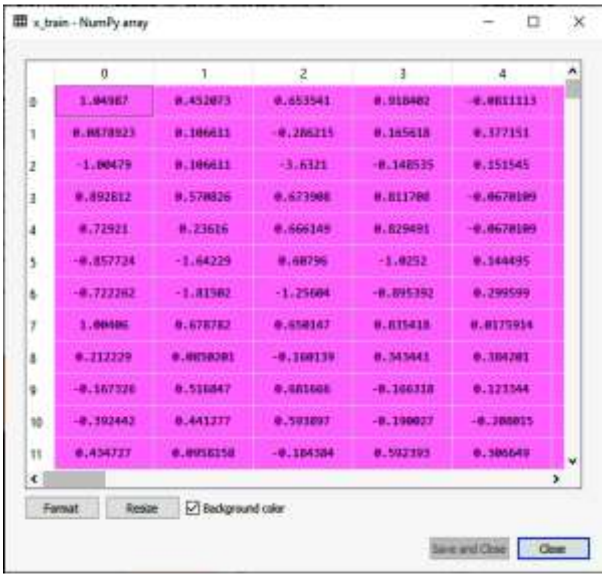



Figure 4.2: X train

Figure 4.2 is showing the x train of the given dataset. The given dataset is divided into the 70-80%% part into the train dataset.


Figure 4.3: Y train

Figure 4.3 is showing the y train of the given dataset. The given dataset is divided into the 70-80%% part into the train dataset.


Figure 4.5: Y test

Figure 4.5 is showing the y test of the given dataset. The given dataset is divided into the 20-30% part into the train dataset.

pred - NumPy array

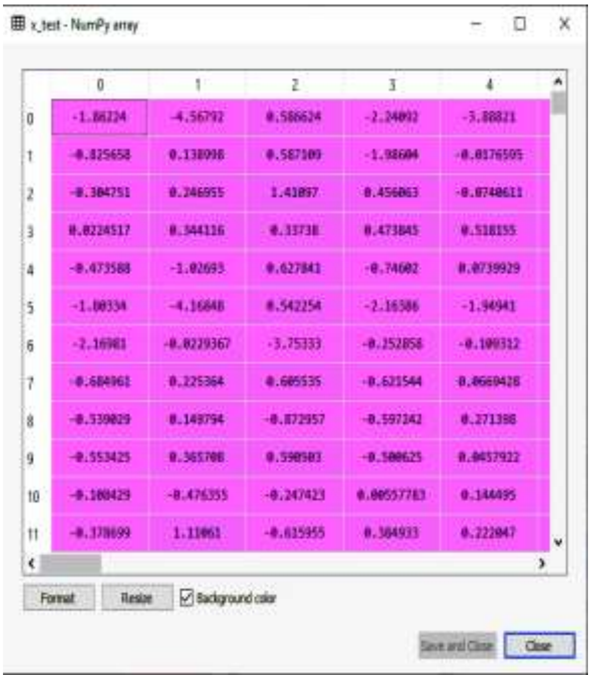
| | 0 | 1 | 2 |
|---|---|---|---|
| 0 | 0.00767568 | 0.00849164 | 0.593714 |
| 1 | 0.00767913 | 0.0084911 | 0.593741 |
| 2 | 0.00767556 | 0.00849247 | 0.593722 |
| 3 | 0.0882195 | 0.0258327 | 0.023511 |
| 4 | 0.00767782 | 0.00849175 | 0.593722 |
| 5 | 0.0076758 | 0.00849152 | 0.593715 |
| 6 | 0.542446 | 0.0104912 | 0.0267973 |
| 7 | 0.0076831 | 0.00849608 | 0.593736 |
| 8 | 0.592886 | 0.0130017 | 0.0224217 |
| 9 | 0.00768641 | 0.00850141 | 0.593583 |
| 10 | 0.606858 | 0.00821391 | 0.0276872 |
| 11 | 0.581826 | 0.00922307 | 0.0445338 |
| 12 | 0.435987 | 0.00793471 | 0.0763109 |

Format Resize Background color

Save and Close Close

Figure 4.6: Prediction

Figure 4.6 is presenting the prediction from given dataset values. The upper and lower values are classified with different colour.



x_test - NumPy array

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| 0 | -1.86224 | -4.56792 | 0.586624 | -2.24092 | -3.88821 |
| 1 | -0.825658 | 0.138998 | 0.587109 | -1.98604 | -0.0176595 |
| 2 | -0.304751 | 0.246955 | 1.41097 | 0.456063 | -0.0740611 |
| 3 | 0.0224517 | 0.344116 | 0.33738 | 0.473845 | 0.518155 |
| 4 | -0.473588 | -1.02693 | 0.627841 | -0.74602 | 0.0739929 |
| 5 | -1.00334 | -4.16848 | 0.542254 | -2.16386 | -1.94941 |
| 6 | -2.16981 | -0.0229367 | -3.75333 | -0.252858 | -0.109312 |
| 7 | -0.684961 | 0.225364 | 0.605535 | -0.621544 | 0.0669428 |
| 8 | -0.539029 | 0.149794 | -0.872957 | -0.597242 | 0.271388 |
| 9 | -0.553425 | 0.365708 | 0.590503 | -0.580625 | 0.0457922 |
| 10 | -0.108429 | -0.476355 | -0.247423 | 0.00557783 | 0.144495 |
| 11 | -0.378699 | 1.11061 | -0.615955 | 0.384933 | 0.222047 |

Format Resize Background color

Save and Close Close

Figure 4.4: X test

Figure 4.4 is showing the x test of the given dataset. The given dataset is divided into the 20-30% part into the train dataset.

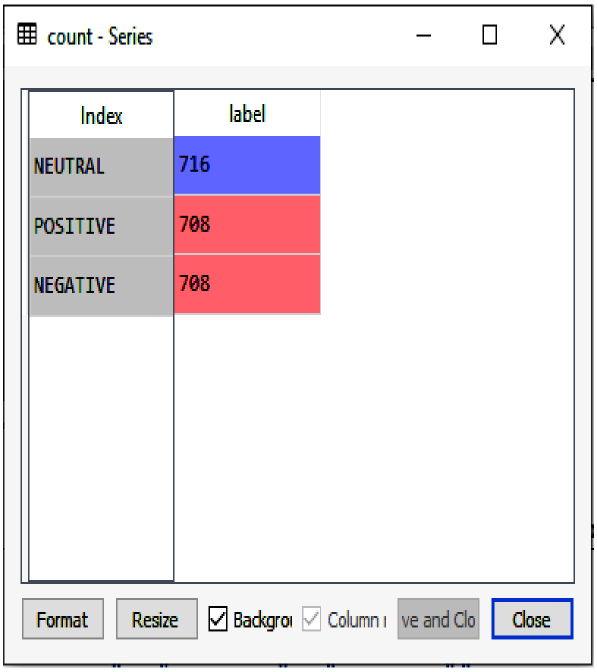
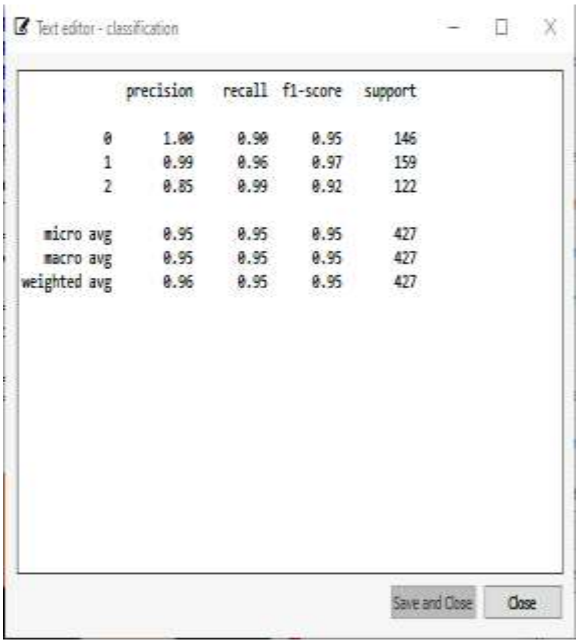



Figure 4.7: Count

Figure 4.7 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.



| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 0.90 | 0.95 | 146 |
| 1 | 0.99 | 0.96 | 0.97 | 159 |
| 2 | 0.85 | 0.99 | 0.92 | 122 |
| micro avg | 0.95 | 0.95 | 0.95 | 427 |
| macro avg | 0.95 | 0.95 | 0.95 | 427 |
| weighted avg | 0.96 | 0.95 | 0.95 | 427 |

Figure 4.8: Classification

Figure 4.8 is presenting classification model. The values of precision, recall, f1 shown with respect of micro, macro and weighted average is shown.

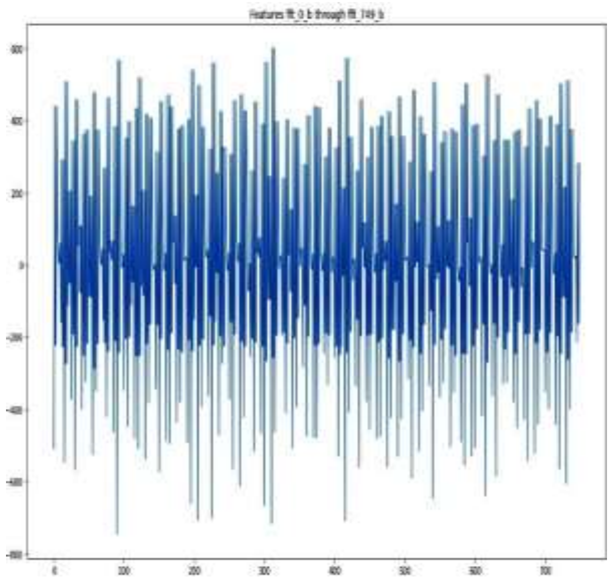
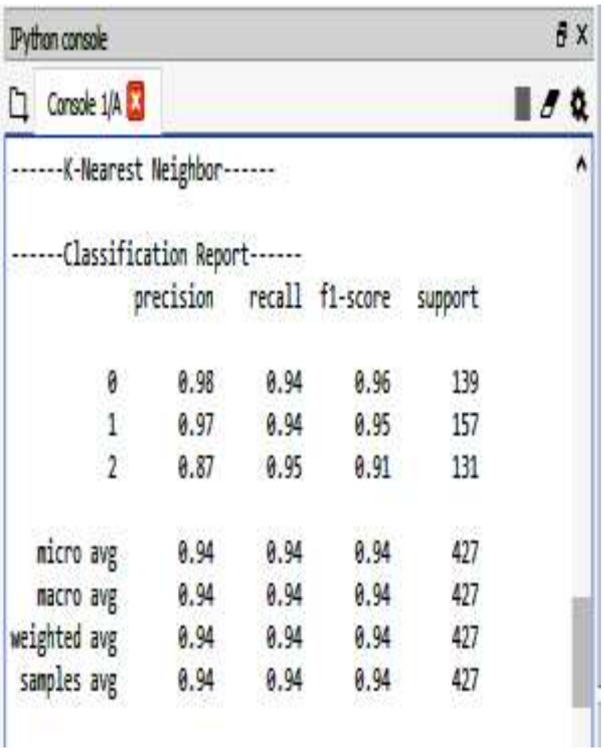


Figure 4.9: EEG signal

Figure 4.9 is presenting EEG signal in graphical representation form. The EEG signalshown from 0 to 700 label [10].



IPython console

Console 1/A

------K-Nearest Neighbor------

------Classification Report------

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.98 | 0.94 | 0.96 | 139 |
| 1 | 0.97 | 0.94 | 0.95 | 157 |
| 2 | 0.87 | 0.95 | 0.91 | 131 |
| micro avg | 0.94 | 0.94 | 0.94 | 427 |
| macro avg | 0.94 | 0.94 | 0.94 | 427 |
| weighted avg | 0.94 | 0.94 | 0.94 | 427 |
| samples avg | 0.94 | 0.94 | 0.94 | 427 |

Figure 4.10: Classification of KNN technique

Figure 4.10 is presenting classification of the K-Nearest Neighbor approach. The variousparameters values like precision, recall, f1 score mentioned.

IPython console

Console 1/A

LSTM

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 0.90 | 0.95 | 146 |
| 1 | 0.99 | 0.96 | 0.97 | 159 |
| 2 | 0.85 | 0.99 | 0.92 | 122 |
| micro avg | 0.95 | 0.95 | 0.95 | 427 |
| macro avg | 0.95 | 0.95 | 0.95 | 427 |
| weighted avg | 0.96 | 0.95 | 0.95 | 427 |

Figure 4.11: Classification of LSTM technique

Figure 4.11 is presenting classification of the long short term memory. The various parameters values like precision, recall, and f1 score mentioned.

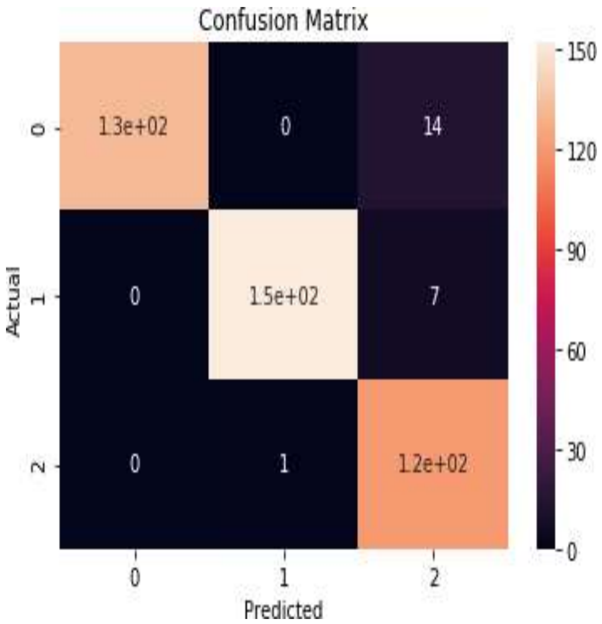



Figure 4.12: Confusion matrix

Figure 4.12 is presenting the Confusion matrix of proposed LSTM technique. It is matrix to identify the prediction of the given dataset.

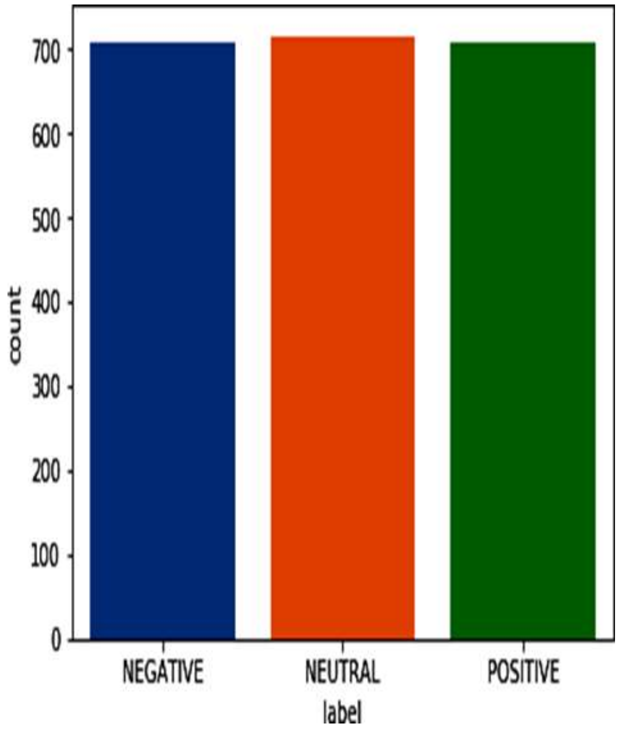



Figure 4.13: Class balance

Figure is 4.13 is showing class balance of the proposed technique. The total count is approx700.

Table 4.1: 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 4.1 is showing the simulation results of the K-Nearest Neighbor machine learningtechnique. The overall accuracy is 94.14% with 5.86% error rate.

Table 4.2: 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 4.2 is showing the simulation results of the long short term memory technique. Theoverall accuracy is 96.48% with 3.52% error rate.

Table 4.3: 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 4.3 is showing the result comparison of the previous and proposed work.

Similarly,the other parameters like Recall and F_Measure is 94 % and 97 % by the proposed work and88.00 % 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.

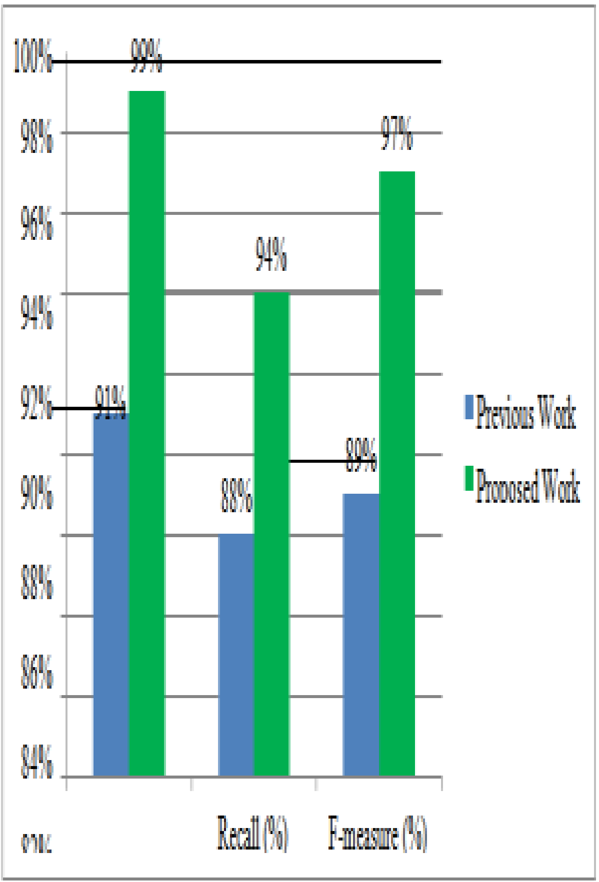



Figure 4.14: Result graph-parameters

Figure 4.21 is presenting the simulation results values in the graphical form. The precision, recall and f measure are shown of the proposed and previous work.

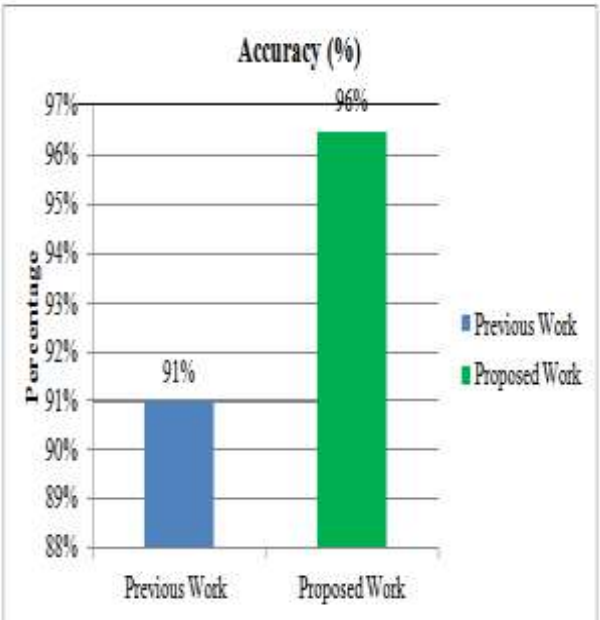



Figure 4.15: Accuracy Result graph

Figure 4.15 is presenting the simulation results graph of the accuracy. The proposed workachieved better accuracy then existing work.

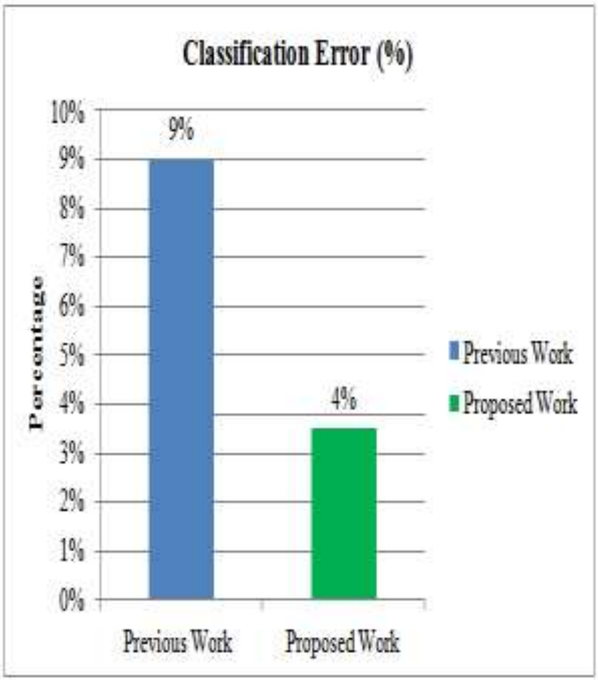



Figure 4.16: Classification

Figure 4.16 is is presenting the simulation results graph of the classification error. Theproposed work achieved better accuracy then existing work.

**4. 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 patient's with depression. By employing the classification performance was significantly improved, which indicates 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 withclinical 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 Research 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.

***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 regressivemethod (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 [5]. EEG Data Pre-processing Strategies can be further enhanced.

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