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Detection of Depression of EEG Signal Using Machine and Deep Learning Technique

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Abstract*— 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. 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.

Keywords—Electroencephalography (EEG),Frontal Intermittent Rhythmic Delta(FIRDA),Regression, Occipital Intermittent Rhythmic Delta(OIRDA),Convolutional Brain Organizations (CNNs) etc…

I. Introduction

1.1 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.

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".

1.3 EEG WAVE PATTERN :- Delta Waves are the frequency range up to 4 Hz. It tends to be the highest in amplitude and the slowest waves. It is seen normally in adults in slow-wave sleep. It is also seen normally in babies. It may occur focally with subcortical lesions and in general distribution with diffuse lesions, metabolic encephalopathy hydrocephalus or deep midline lesions. It is usually most prominent frontally in adults (e.g. FIRDA – frontal intermittent rhythmic delta) and posteriorly in children (e.g. OIRDA – occipital intermittent rhythmic delta)

II. LITERATURE REVIEW

Y. Yang et al.,[11] Feelings assume a vital part in navigation, mind action, human insight, and social intercourse. This work proposes a various leveled network structure with subnetwork hubs to segregate three human feelings: 1) good; 2) nonpartisan; and 3) pessimistic. Each subnetwork hub inserted in the organization that are framed by many secret hubs, could be practical as a free secret layer for highlight portrayal. The top layer of the various leveled network, similar to the well evolved creature cortex in the cerebrum, consolidate such elements produced from subnetwork hubs, yet all the while, recast these elements into a planning space with the goal that the organization can be performed to deliver more solid insight. The proposed technique is contrasted and other cutting edge strategies. The test results from two distinct EEG datasets show that a promising outcome is gotten while utilizing the proposed strategy with both single and numerous methodology.

S. Zhang et al.,[12] Feeling acknowledgment is trying because of the passionate hole among feelings and general media highlights. Roused by the strong component learning capacity of profound brain organizations, this work proposes to connect the passionate hole by utilizing a half breed profound model, which first creates general media section highlights with Convolutional Brain Organizations (CNNs) and 3D-CNN, then, at that point, wires general media portion highlights in a Profound Conviction Organizations (DBNs). The proposed strategy is prepared in two phases. To begin with, CNN and 3D-CNN models pre-prepared for comparing enormous scope picture and video grouping errands are adjusted on feeling acknowledgment undertakings to learn sound and visual section highlights, separately. Second, the results of CNN and 3D-CNN models are consolidated into a combination network worked with a DBN model. The combination network is prepared to together get familiar with a discriminative general media fragment include portrayal. After normal pooling portion highlights advanced by DBN to frame a fixed-length worldwide video include, a direct Help Vector Machine is utilized for video feeling arrangement.

G. Zhao et al.,[13] The steady connection among character and EEG guarantees the possibility of character surmising from mind exercises. In this work, we perceive a singular's character characteristics by investigating mind waves when the person watches passionate materials. 37 members partook in this review and watched 7 normalized film cuts that describe genuine enthusiastic encounters and target seven discrete feelings. Highlights extricated from EEG signals and emotional evaluations enter the SVM classifier as contributions to foresee five elements of character characteristics. Our model accomplishes better order execution for Extraversion (81.08 percent), Suitability (86.11 percent), and Reliability (80.56 percent) when positive feelings are inspired than pessimistic ones, higher grouping correctnesses for Neuroticism (78.38-81.08 percent) when gloomy feelings, with the exception of loathing, are evoked than good feelings, and the most noteworthy arrangement precision for Receptiveness (83.78 percent) while a sickening film cut is introduced. Furthermore, the presentation of highlights from abstract appraisals increments not just grouping exactness in every one of the five character qualities (going from 0.43 percent for Uprightness to 6.3 percent for Neuroticism) yet in addition the discriminative force of the characterization correctnesses between five character characteristics in every classification of feeling. These outcomes show the upside of character deduction from EEG signals over cutting edge unequivocal conduct pointers concerning characterization exactness.

H. Kim et al.,[14] A picture is an exceptionally successful device for conveying feelings. Numerous scientists have explored feelings in pictures by utilizing different highlights separated from pictures. In this work, we center around two undeniable level elements, the article and the foundation, and accept that the semantic data in pictures is a decent signal for foreseeing feelings. An article is one of the main components that characterize a picture, and we find through tests that there is a high relationship between's the items and feelings in pictures much of the time. Indeed, even with a similar article, there might be slight contrasts in feeling because of various foundations, and we utilize the semantic data of the foundation to further develop the expectation execution

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 pre-processing 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. PROPOSED METHODOLOGY

4.1 Introduction :- The 4.1 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. To simulate proposed method on spyder python 3.7 software.

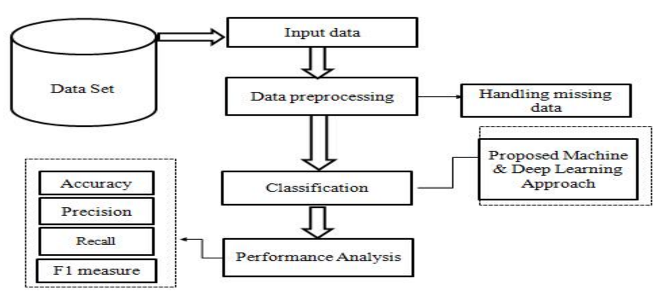


Figure 4.1: Flow Chart

To prediction of various parameters like precision, recall, f-measure and accuracy.To generate results graph and compare from previous work.

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.

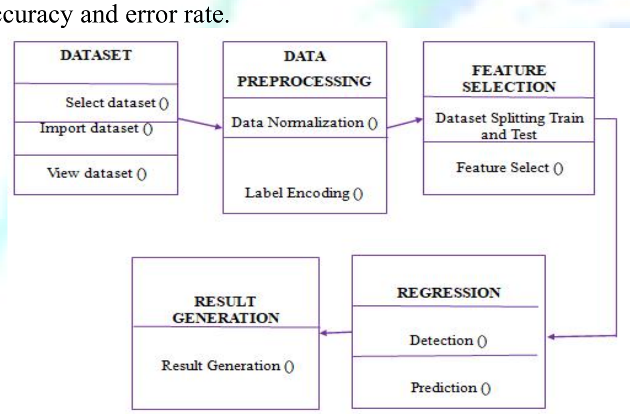


Figure 4.2: Class Diagram

V. PIMPLEMENTATION AND RESULT ANALYSIS

PYTHON

Numerical 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.

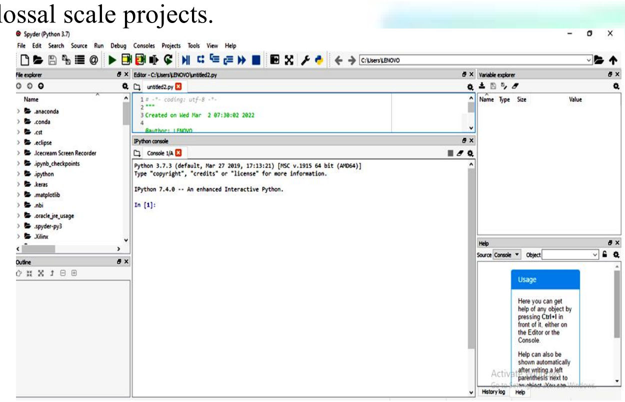


Figure 5.1: Snap shot of Spyder environment

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.

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.

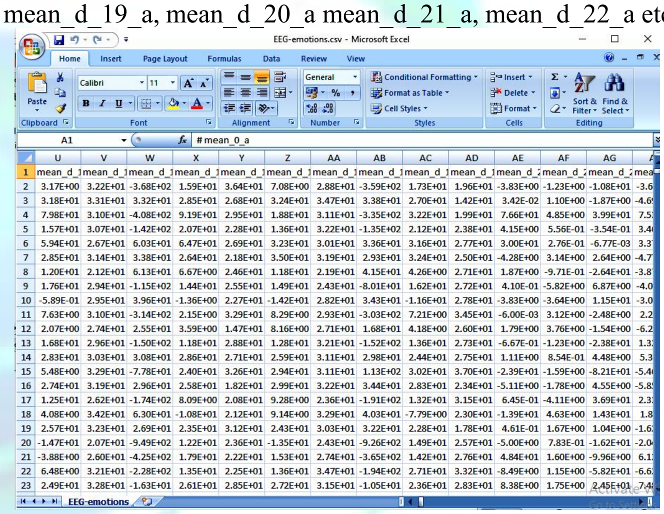


Figure 5.2: Original dataset in .csv file

The figure 5.2 is showing the dataset, which is taken from the kaggle machine learning website.

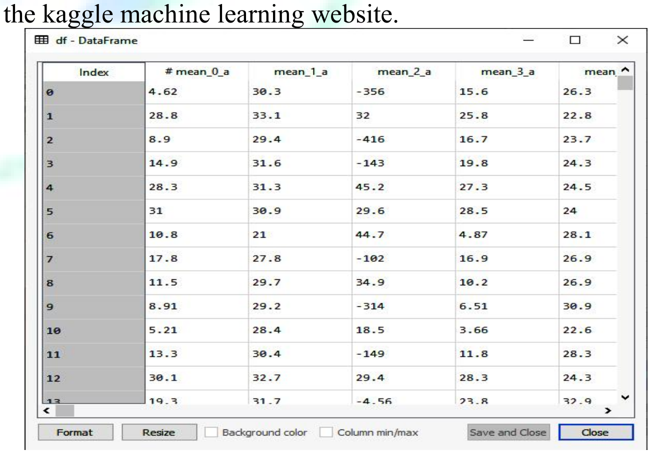


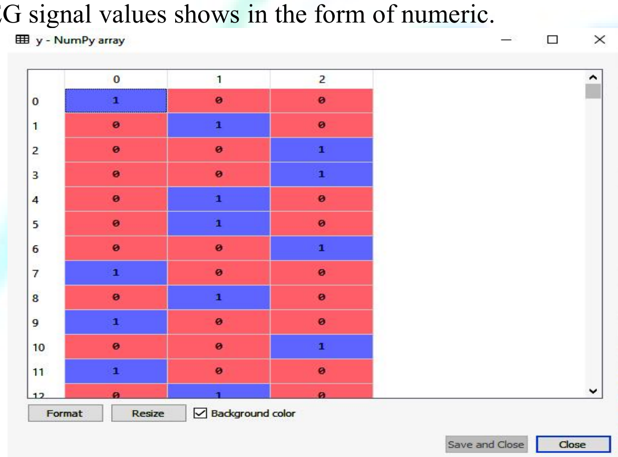
Figure 5.3: Dataset frame

Figure 5.3 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.

	0	1	2	3	4
0	-0.696086	0.354912	-1.21724	0.118199	0.151545
1	0.886267	0.657191	0.664209	0.722797	-0.0952116
2	-0.416	0.257751	-1.50819	0.183401	-0.0317599
3	-0.0233567	0.495256	-0.184384	0.367151	0.0105412
4	0.853547	0.462869	0.728218	0.811708	0.0246416
5	1.03024	0.419686	0.652571	0.882837	-0.0106093
6	-0.291663	-0.649086	0.725793	-0.517814	0.278448
7	0.166421	0.0850201	0.0144291	0.195256	0.193846
8	-0.245855	0.290138	0.678272	-0.201882	0.193846
9	-0.415346	0.23616	-1.01358	-0.420604	0.475854
10	-0.657476	0.149794	0.598746	-0.589536	-0.109312
11	-0.128062	0.365708	-0.213479	-0.107043	0.292549

Figure 5.4: X label of data

Figure 5.4 is showing x label of dataset view, here all the EEG signal values shows in the form of numeric.



	0	1	2
0	1	0	0
1	0	1	0
2	0	0	1
3	0	0	1
4	0	1	0
5	0	1	0
6	0	0	1
7	1	0	0
8	0	1	0
9	1	0	0
10	0	0	1
11	1	0	0

Figure 5.5: Y label of data

Figure 5.5 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.

	0	1	2	3	4
0	1.04987	0.452073	0.653541	0.918402	-0.0811113
1	0.0878923	0.106611	-0.286215	0.165618	0.377151
2	-1.00479	0.106611	-3.6321	-0.148535	0.151545
3	0.892812	0.570826	0.673908	0.811708	-0.0670109
4	0.72921	0.23616	0.666149	0.829491	-0.0670109
5	-0.857724	-1.64229	0.60796	-1.0252	0.144495
6	-0.722262	-1.81502	-1.25604	-0.895392	0.299599
7	1.00406	0.678782	0.650147	0.835418	0.0175914
8	0.212229	0.0850201	-0.160139	0.343441	0.384201
9	-0.167326	0.516847	0.681666	-0.166318	0.123344
10	-0.392442	0.441277	0.593897	-0.190027	-0.208015
11	0.434727	0.0958158	-0.184384	0.592393	0.306649

Figure 5.6: X train

Figure 5.6 is showing the x train of the given dataset. The given dataset is divided into the 70-80%% part into the train dataset.

	0	1	2
0	0	1	0
1	1	0	0
2	1	0	0
3	0	1	0
4	0	1	0
5	0	0	1
6	1	0	0
7	0	1	0
8	1	0	0
9	0	1	0
10	0	0	1
11	1	0	0

Figure 5.7: Y train

Figure 5.7 is showing the y train of the given dataset. The given dataset is divided into the 70-80%% part into the train dataset.

	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	-1.80334	-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	0.271398
9	-0.553425	0.365708	0.590503	-0.500625	0.0457922
10	-0.108429	-0.476355	-0.247423	0.00557783	0.144495
11	-0.378699	1.11061	-0.615955	0.384933	0.222047

Figure 5.8: X test

Figure 5.8 is showing the x test of the given dataset. The given dataset is divided into the 20-30% part into the train dataset.

	0	1	2
0	0	0	1
1	0	0	1
2	0	0	1
3	1	0	0
4	0	0	1
5	0	0	1
6	1	0	0
7	0	0	1
8	1	0	0
9	0	0	1
10	1	0	0
11	1	0	0

Figure 5.9: Y test

Figure 5.9 is showing the y test of the given dataset. The given dataset is divided into the 20-30% part into the train dataset.

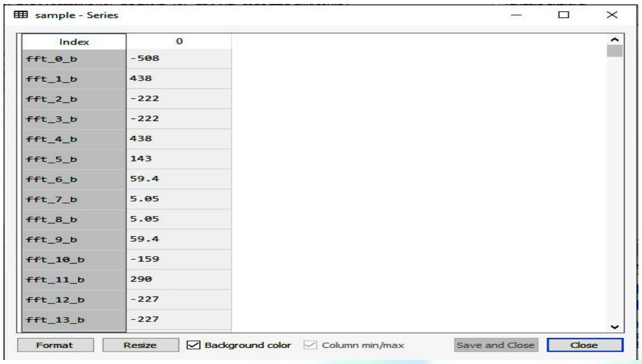


Figure 5.10: Sample of data

Figure 5.10 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.

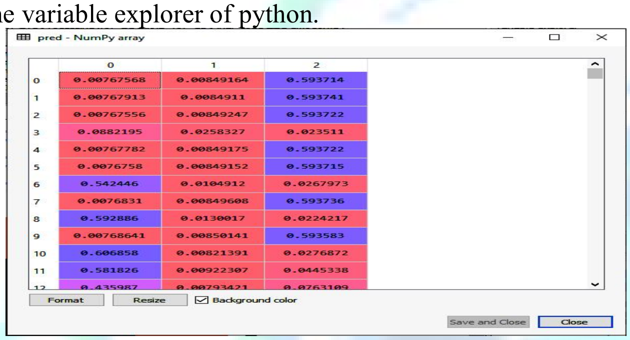


Figure 5.11: Prediction

Figure 5.11 is presenting the prediction from given dataset values. The upper and lower values are classified with different colour.

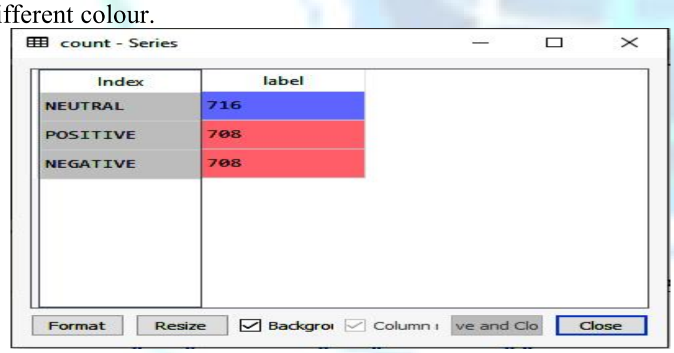


Figure 5.12: Count

Figure 5.12 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.

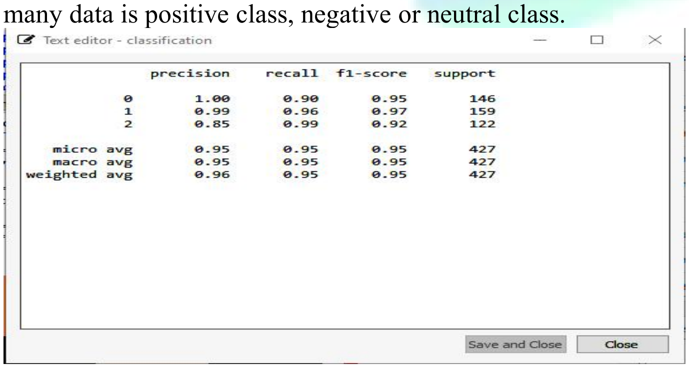


Figure 5.13: Classification

Figure 5.13 is presenting classification model. The values of precision, recall, f1 shown with respect of micro, macro and weighted average is shown.

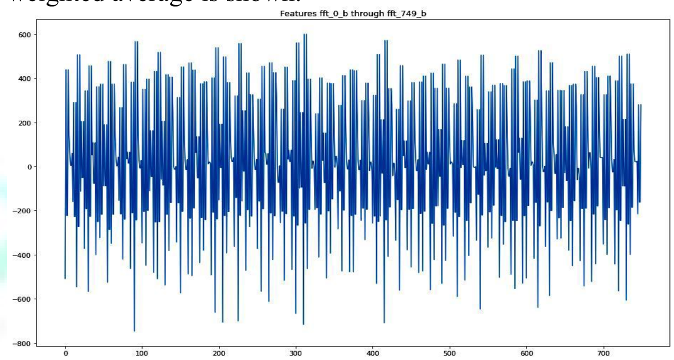


Figure 5.14: EEG signal

Figure 5.14 is presenting EEG signal in graphical representation form. The EEG signal shown from 0 to 700 label.

Table 5.1: 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 5.1 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 5.2: 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 5.2 is showing the simulation results of the long short term memory technique. The overall accuracy is 96.48% with 3.52% error rate.

Table 5.3: 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 5.3 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.

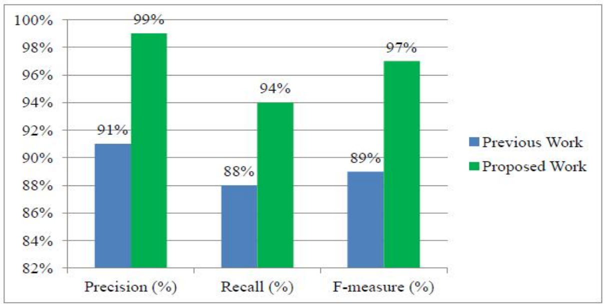


Figure 5.21: Result graph-parameters

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 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.

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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