IIVP Project Summary Report

Mental State Recognition using EEG Signal

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Abstract : Our efforts in this work tries to use the efficient EEG image classification approach to classify mental state. The proposed method is based on the representation of the wave signal at different times and then getting the temporal and statistical features out of them, which is then classified using **Support vector machines**. A three-class mental state problem is investigated, in which subjects experience either relaxation, or concentration, or neutral states. Using publicly available EEG data from a Muse Electroencephalography headband, a large number of features describing the wave at the different intervals of time are extracted of 4 subjects, and subsequently reduced based using the 5 different methods. A **Support vector machine** is then trained on this data in order to classify the mental state of subjects.

Keywords: Machine Learning,Support vector machines, Image Recognition, Mental State Classification, Mental awareness, KNN (k-nearest neighbors)

I. INTRODUCTION

Human machine interaction is often considered superior than that of the human Human interaction, as sound and visuals constitute voice recognition, human activity classification, facial recognition, can be used to get more information about an individual when the former one is used than the latter one . Though, with the availability of sensors to gather data that the human body cannot, interaction with machines can often exceed the abilities of the natural human experience. An example of this is the consideration of electroencephalographic brainwaves. The brain, based on what a person is thinking, feeling, or doing, has a unique pattern of electrical activity that emerges as a consequence of the aggregate firing patterns of billions of individual neurons [1, 2]. These electrical signals can, in principle, be detected and processed to infer the state of the brain and, by extension, the mental state of a given subject. Besides clinical applications, this possibility is also useful, e.g., for brain-machine interfacing. This work focuses on the process of feature extraction, selection and formatting in order to achieve improved classification accuracy of EEG signals. More specifically, the main contribution is a framework to perform classification of these signals, based on (i) the extraction of a large number of static statistical features of the data, followed by (ii) automated feature selection and (iii) representation of the selected attributes as a 2D matrix. The resulting matrices are (iv) then used to predict for the new data of the same kind.

II. DATASET

EEG-Feature -Generation

https://github.com/jordan-bird/eeg-feature-generation/tree/master/dataset/original_data

Timestamps :- is that instance of time where the data is collected.

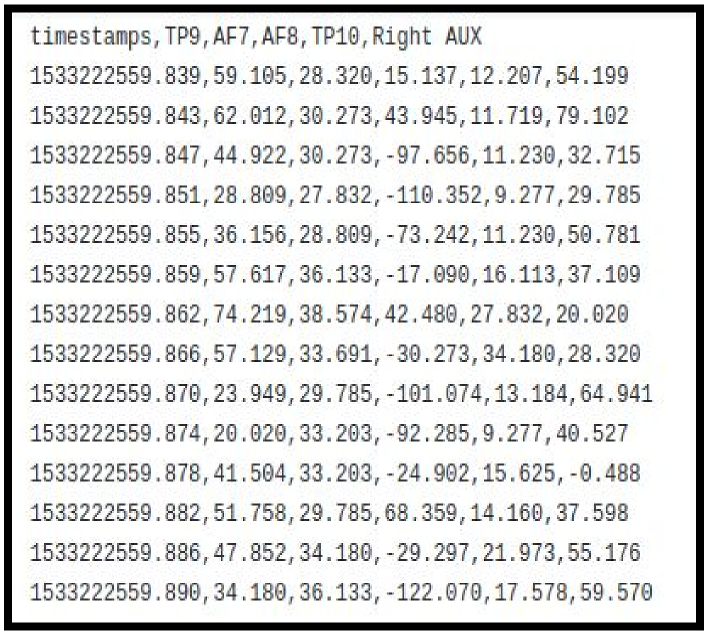
TP9,AF7,AF8,TP10, :- These are the four sensors used up for collecting dataset

Right Aux :- RAW brainwaves for the auxiliary USB sensor (MU-02 and MU-03 only)

III. SYSTEM REQUIREMENTS

A. Hardware

Multicore fast CPUs with high cache i5 or Xeon processors are required. RAM preferred is 8GB minimum but 16GB preferable as it will reduce the time



```
timestamps,TP9,AF7,AF8,TP10,Right AUX
1533222559.839,59.105,28.320,15.137,12.207,54.199
1533222559.843,62.012,30.273,43.945,11.719,79.102
1533222559.847,44.922,30.273,-97.656,11.230,32.715
1533222559.851,28.809,27.832,-110.352,9.277,29.785
1533222559.855,36.156,28.809,-73.242,11.230,50.781
1533222559.859,57.617,36.133,-17.090,16.113,37.109
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1533222559.866,57.129,33.691,-30.273,34.180,28.320
1533222559.870,23.949,29.785,-101.074,13.184,64.941
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1533222559.878,41.504,33.203,-24.902,15.625,-0.488
1533222559.882,51.758,29.785,68.359,14.160,37.598
1533222559.886,47.852,34.180,-29.297,21.973,55.176
1533222559.890,34.180,36.133,-122.070,17.578,59.570
```

taken for the heavy calculations. OS should be Unix, Windows although we have performed out work in system with Ubuntu , but windows can also be used which have the proper libraries in it, being required.

A. Software

a.) Language

We used Python-v3.7 as Python is the most common language and the most powerful language out there , which comes with a tonne of library support.

b.) Major Tools

NumPy is used to compute matrix operations

Matplotlib, a plotting library for Python is also used.

Sklearn for its great inbuilt functions

Other libraries used include the **scipy**,**os**,**sys** ,**re**,**PIL**.

IV. MODEL

A. Problem Statement:-

Our main motive is to predict among the three-class mental states of any individual , which they are experiencing either relaxation, concentration, or neutral state.

B. Methodology:-

This project has been done in 3 steps. These steps are as following:

I. Feature Generating

Firstly, an available training set of EEG signals is used and the data is containing the time series related to 4 electrodes, within a given experimental time frame, labelled in terms of **three distinct mental states (relaxed, concentrating, and neutral)**that the subjects were keeping during the data collection . From these signals a number of statistical features are extracted , resulting in a high dimensional attribute space. As Far as our efforts are taken into consideration , we have saved the output for this in the file known as out.csv.

II. Feature Extraction

Due to the temporal, auto correlated nature of the EEG waves, single-point features cannot generally provide enough information for good rules to be generated by machine learning models. In this work we follow the approach of extracting statistical features based on sliding time windows [3, 4]. More specifically, the EEG signal is divided into a sequence of windows of length one second, with
consecutive windows overlapping by 0.5 seconds, e.g., [(0s − 1s), [0.5s − 1.5s), [1s − 2s), . . .])

III. Feature Selection

Based on all the features we get, we select only the relevant ones. Scikit-learn has made it pretty much easy for us to make the feature selection. There are a lot of ways in which we can think of feature selection, but most feature selection methods can be divided into three major buckets

1. Filter based: We specify some metric and based on that filter features. An example of such a metric is correlation/chi-square.

2. Wrapper-based: Wrapper methods consider the selection of a set of features as a search problem. Example: Recursive Feature Elimination

3. Embedded: Embedded methods use algorithms that have built-in feature selection methods. For instance, Lasso and RF have their own feature selection methods.

So we used 5 methods for feature selection and we then have chosen the one with provides us with the highest accuracy on our training data :

1. Pearson Correlation : This is a filter-based method.We check the ***absolute value of the Pearson's correlation*** between the target and numerical features in our dataset. We keep the top n features based on this criterion.

$$r = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}}$$

2. Chi-Squared : This is another filter-based method.In this method, we calculate the chi-square metric between the target and the numerical variable and only select the variable with the maximum chi-squared values. We therefore calculate the chi-squared value. To do this, we first find out the values we would expect to be falling in each bucket if there was indeed independence between the two categorical variables. We then multiply the row sum and the column sum for each cell and divide it by total observations. We use the following formula :

$$\chi_c^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

3. Recursive Feature Elimination :

This is a wrapper based method. As I said before, wrapper methods consider the selection of a set of features as a search problem. The goal of recursive feature elimination (RFE) is to select features by recursively considering smaller and smaller sets of features. First, the estimator is trained on the initial set of features and the importance of each feature is obtained either through a coef_ attribute or through a feature_importances_ attribute. Then, the least important features are pruned from the current set of features. That procedure is recursively repeated on the pruned set until the desired number of features to select is eventually reached.

4. Random Forest :

This is an Embedded method.We can also use RandomForest to select features based on feature importance.We calculate feature importance using node impurities in each decision tree. In Random forest, the final feature importance is the average of all decision tree feature importance.

5. LightGBM :

We have also used a LightGBM , using its internal implementation support only and it is one of the essential as it has a feature importances attribute.

V. IMPLEMENTATION

We have used two methods :

a) SVM(support vector machine)
b) KNN(kth nearest neighbours)

A) SVM

Fundamental reason for using the support vector machine or say any other model is to classify/predict , .i.e. Firstly using the training data (combination of sample input and output) , in order to train the svm and then , for some set of input , get the output predicted, which technically is also known as the supervised learning.

The SVM is used to get classification among the different classes among the output and thus is the discrete classification and not the continuous one.

Saying that there are **n features** in the input and then the main objective of the **svm algorithm is to find a plane in n dimensional that classifies the data points , which are themself n in dimensions. The classification is taken as either the data point belongs inside or outside of the plane.**

In order to separate the classes of data , there can be many possible different planes that can be used in doing so. Task comes to get that plane that has the maximum margin , so the large margin classifier comes into the picture , that is distance between data points of both classes should be maximum w.r.t the plane .As we are maximizing marginal distance so as to get some extra reinforcement so that on the future data points we will be getting less error that means more amount of accuracy and thus better results and thus better outcome and thus will be classified with more amount of confidence.

The Scikit learn library provides the implementation for the same and just calling the related functions to implement the SVM model as it is even more reliable and accurate as well, then if we implement ourselves.

After the generation of the out.csv (the features file) and getting on the features from it , using the already mentioned feature extraction algorithms , the task comes on to train and then predict the state of an individual using the same features , which is quite basic when using the internal implementation.

X_train -> it is the set of all features for the whole of the training data which gets the corresponding output as the state of an individual.

Y_train -> it has the label , the answer for the same training data.

X_test -> it is the set of all features for whole of the testing data, being used to get the output predicted

Y_test -> it has the label , the answer for the same testing data.

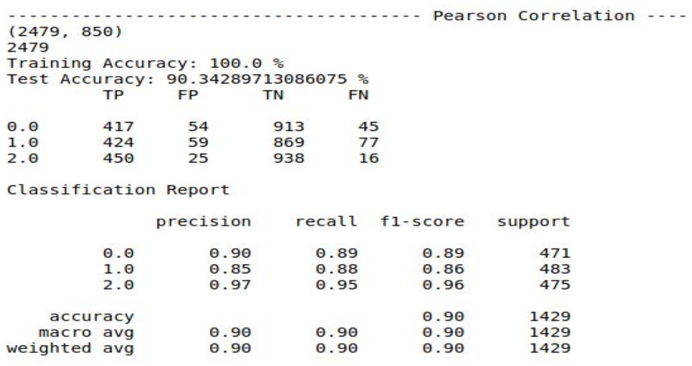
B) KNN

K- Nearest Neighbors is a Supervised machine learning algorithm as the target variable is known Non parametric as it does not make an assumption about the underlying data distribution pattern Lazy algorithm as KNN does not have a training step. All data points will be used only at the time of prediction. With no training step, prediction step is costly. An eager learner algorithm eagerly learns during the training step. It is used for both Classification and Regression. It uses feature similarity to predict the cluster that the new point will fall into.

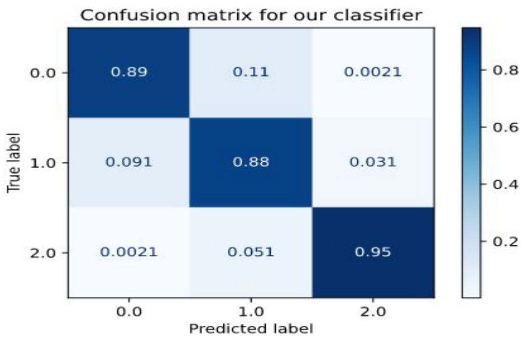
VI. RESULT

Results for SVM

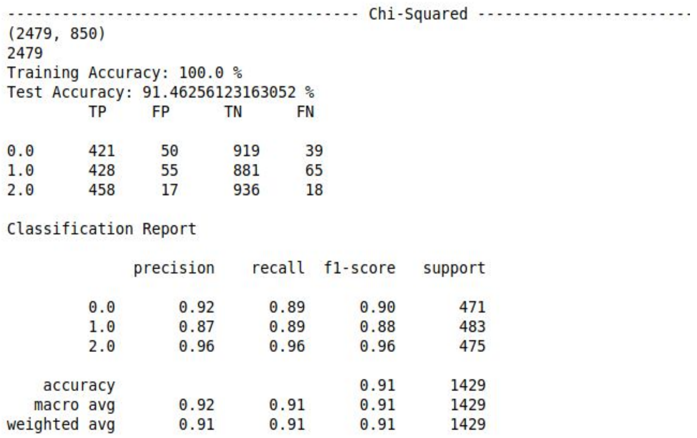
1. Pearson Correlation :



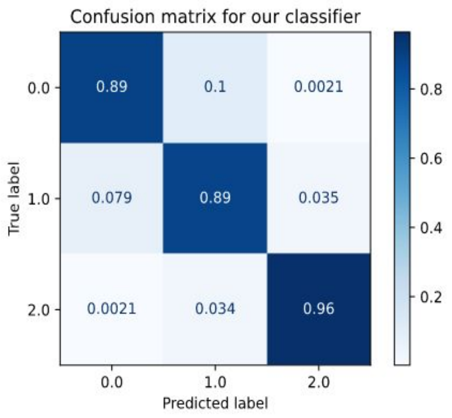
```
---------------------------------------- Pearson Correlation ----
(2479, 850)
2479
Training Accuracy: 100.0 %
Test Accuracy: 90.34289713086075 %
         TP      FP       TN       FN

0.0      417     54       913      45
1.0      424     59       869      77
2.0      450     25       938      16

Classification Report

              precision    recall  f1-score   support

         0.0       0.90      0.89      0.89       471
         1.0       0.85      0.88      0.86       483
         2.0       0.97      0.95      0.96       475

    accuracy                           0.90      1429
   macro avg       0.90      0.90      0.90      1429
weighted avg       0.90      0.90      0.90      1429
```



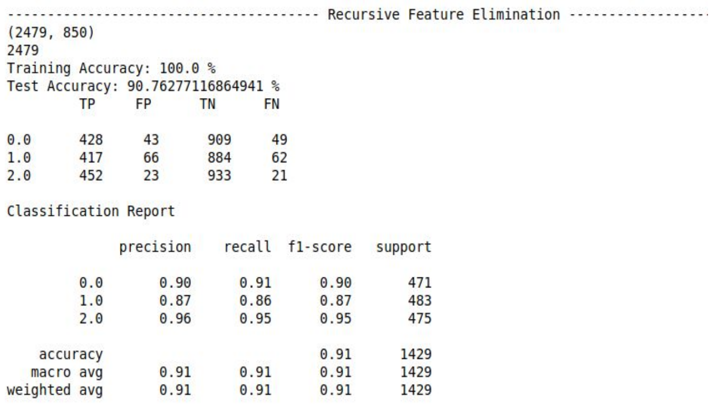
2. Chi - Squared :



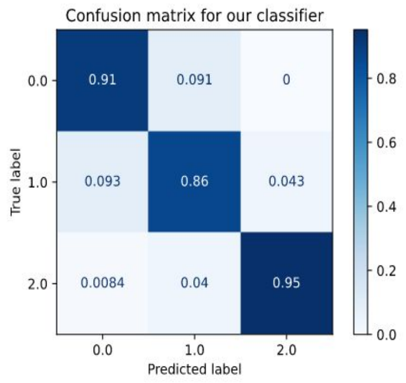
```
------------------------------------- Chi-Squared ----------------------
(2479, 850)
2479
Training Accuracy: 100.0 %
Test Accuracy: 91.46256123163052 %
         TP      FP       TN       FN

0.0      421     50       919      39
1.0      428     55       881      65
2.0      458     17       936      18

Classification Report

              precision    recall  f1-score   support

         0.0       0.92      0.89      0.90       471
         1.0       0.87      0.89      0.88       483
         2.0       0.96      0.96      0.96       475

    accuracy                           0.91      1429
   macro avg       0.92      0.91      0.91      1429
weighted avg       0.91      0.91      0.91      1429
```



3. Recursive Feature Elimination :

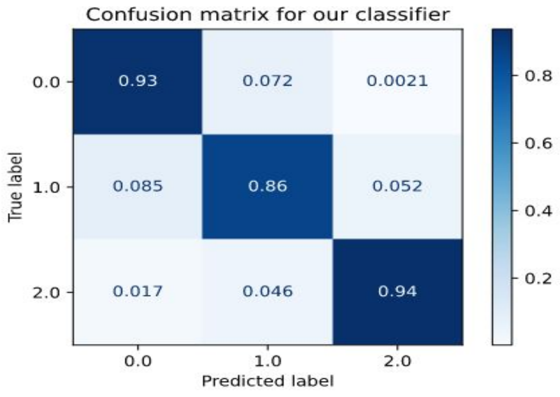


```
------------------------------------- Recursive Feature Elimination ----------------
(2479, 850)
2479
Training Accuracy: 100.0 %
Test Accuracy: 90.76277116864941 %
         TP      FP       TN       FN

0.0      428     43       909      49
1.0      417     66       884      62
2.0      452     23       933      21

Classification Report

              precision    recall  f1-score   support

         0.0       0.90      0.91      0.90       471
         1.0       0.87      0.86      0.87       483
         2.0       0.96      0.95      0.95       475

    accuracy                           0.91      1429
   macro avg       0.91      0.91      0.91      1429
weighted avg       0.91      0.91      0.91      1429
```



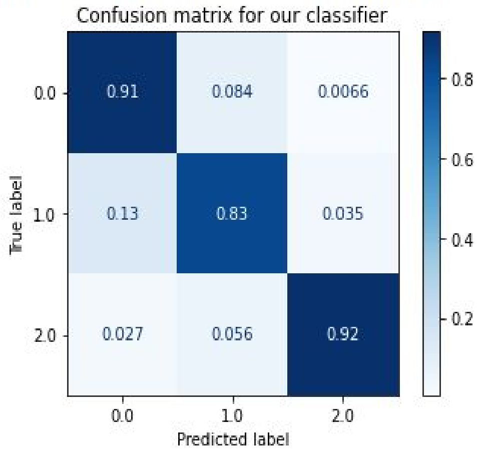
4. **Random Forest :**

```
--------------------------------------- Random Forest -----------
(2479, 206)
2479
Training Accuracy: 98.4747378455672 %
Test Accuracy: 90.83275017494752 %
         TP      FP       TN       FN

0.0      436     35       909      49
1.0      417     66       890      56
2.0      445     30       928      26

Classification Report

                 precision    recall  f1-score   support

         0.0       0.90      0.93      0.91       471
         1.0       0.88      0.86      0.87       483
         2.0       0.94      0.94      0.94       475

    accuracy                           0.91      1429
   macro avg       0.91      0.91      0.91      1429
weighted avg       0.91      0.91      0.91      1429
```



5. **Light GBM :**

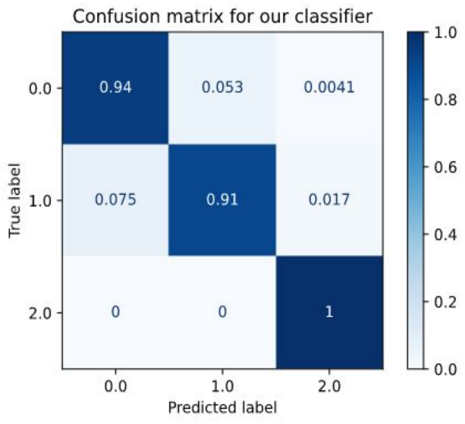
```
(2479, 199)
2479
Training Accuracy: 97.04480457578646 %
Test Accuracy: 88.52344296710987 %
```



Results for KNN:

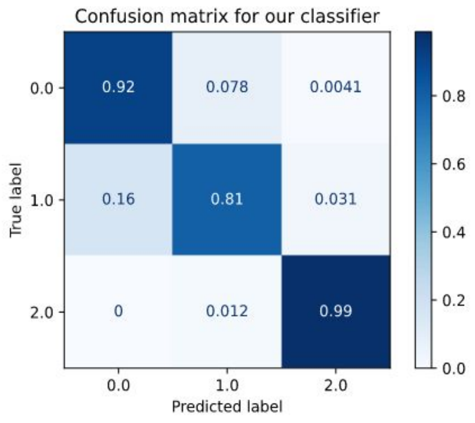
1. **Pearson Correlation :**

```
-------------------------------------- Pearson Correlation -------------
Test Accuracy: 95.16129032258065 %
         TP      FP       TN       FN

0.0      232     14       480      18
1.0      218     22       491      13
2.0      258     0        481      5

Classification Report

              precision    recall  f1-score   support

         0.0       0.93      0.94      0.94       246
         1.0       0.94      0.91      0.93       240
         2.0       0.98      1.00      0.99       258

    accuracy                           0.95       744
   macro avg       0.95      0.95      0.95       744
weighted avg       0.95      0.95      0.95       744
```

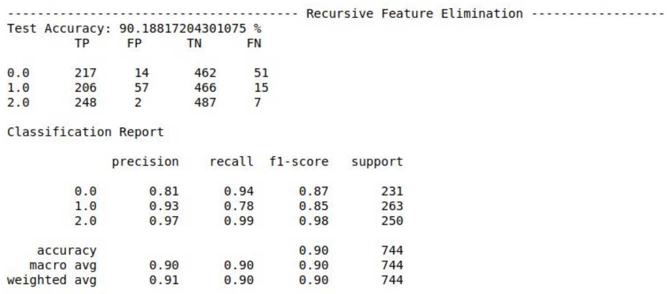


2. **Chi - Squared :**

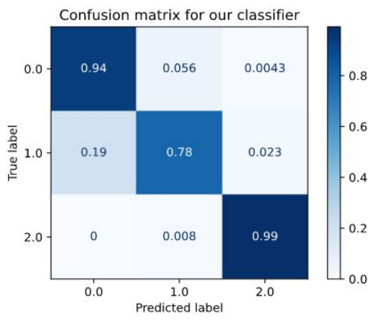
```
-------------------------------------- Chi-Squared ----------------------
Test Accuracy: 90.18817204301075 %
         TP      FP       TN       FN

0.0      224     20       458      42
1.0      208     50       464      22
2.0      239     3        493      9

Classification Report

              precision    recall  f1-score   support

         0.0       0.84      0.92      0.88       244
         1.0       0.90      0.81      0.85       258
         2.0       0.96      0.99      0.98       242

    accuracy                           0.90       744
   macro avg       0.90      0.90      0.90       744
weighted avg       0.90      0.90      0.90       744
```



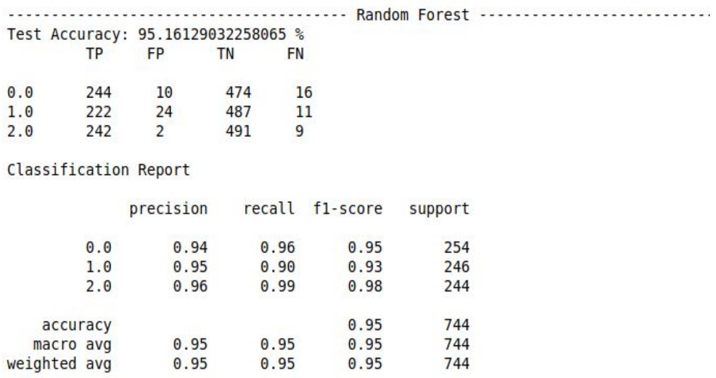
3. Recursive Feature Elimination :



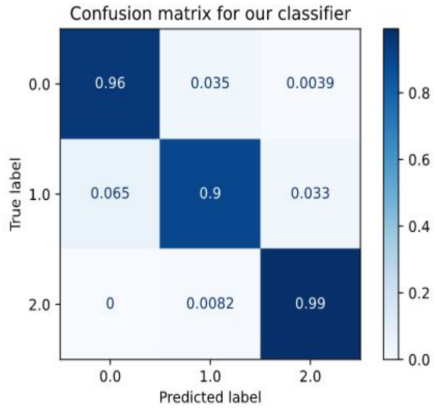
```
-------------------------------------- Recursive Feature Elimination -----------------
Test Accuracy: 90.18817204301075 %
         TP      FP       TN       FN

0.0      217     14       462      51
1.0      206     57       466      15
2.0      248     2        487      7

Classification Report

              precision    recall  f1-score   support

         0.0       0.81      0.94      0.87       231
         1.0       0.93      0.78      0.85       263
         2.0       0.97      0.99      0.98       250

    accuracy                           0.90       744
   macro avg       0.90      0.90      0.90       744
weighted avg       0.91      0.90      0.90       744
```



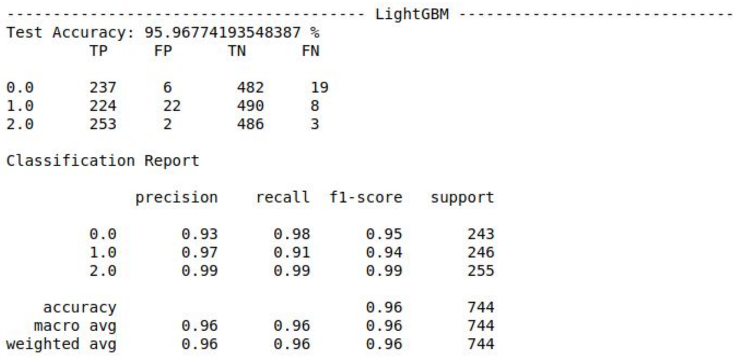
3. Random Forest :



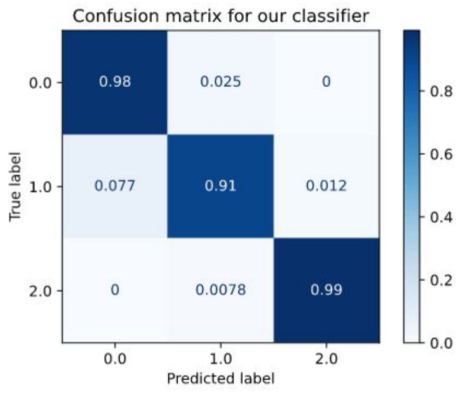
```
-------------------------------------- Random Forest --------------------------
Test Accuracy: 95.16129032258065 %
         TP      FP       TN       FN

0.0      244     10       474      16
1.0      222     24       487      11
2.0      242     2        491      9

Classification Report

              precision    recall  f1-score   support

         0.0       0.94      0.96      0.95       254
         1.0       0.95      0.90      0.93       246
         2.0       0.96      0.99      0.98       244

    accuracy                           0.95       744
   macro avg       0.95      0.95      0.95       744
weighted avg       0.95      0.95      0.95       744
```



4. Light GBM :



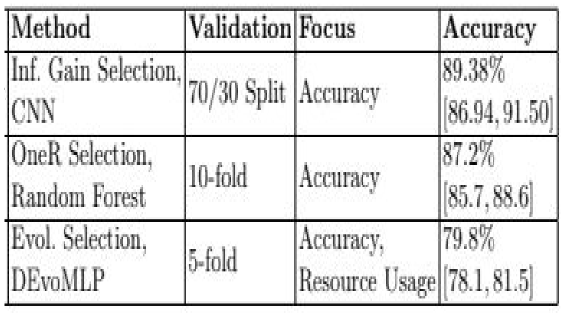
```
---------------------------------------- LightGBM -----------------------------
Test Accuracy: 95.96774193548387 %
         TP      FP       TN       FN

0.0      237     6        482      19
1.0      224     22       490      8
2.0      253     2        486      3

Classification Report

              precision    recall  f1-score   support

         0.0       0.93      0.98      0.95       243
         1.0       0.97      0.91      0.94       246
         2.0       0.99      0.99      0.99       255

    accuracy                           0.96       744
   macro avg       0.96      0.96      0.96       744
weighted avg       0.96      0.96      0.96       744
```



VII. COMPARISON

The above efforts and the attached proof shows the accuracy for both training and testing data from the validation split ,.i.e. the same split of the 70 for the training and the rest 30 for the testing , of the same dataset, we have got these results.

As we get the highest accuracy in Recursive Feature Elimination, we have then opted this method for feature selection.



Method	Validation	Focus	Accuracy
Inf. Gain Selection, CNN	70/30 Split	Accuracy	89.38% [86.94, 91.50]
OneR Selection, Random Forest	10-fold	Accuracy	87.2% [85.7, 88.6]
Evol. Selection, DEvoMLP	5-fold	Accuracy, Resource Usage	79.8% [78.1, 81.5]

Fig from the base paper

FeatureSelection\Classifier	SVM (%)	KNN (%)
Pearson Correlation	91.39258223	93.01075269
Chi-Squared	91.81245626	92.06989247
Recursive Feature Elimination	92.51224633	90.99462366
Random Forest	91.1126662	93.9516129
LightGBM	88.52344297	95.56451613

Best accuracy of the base paper :- 89.38%

and what we have achieved is 92.51% for SVM and 95.56% for KNN which is quite an amazing thing.

Why is SVM used :-

The main reasons of using SVM includes first it is one of the best candidate for prediction when the supervised learning along with the discrete classification is taken into account , secondly the C parameter of the SVM is used for the good fitting of the data and gets the most out of the predictor, thirdly the internal selection of the high polynomial powers is not our concern , as the best of it taken care by the internal implementation only and the most important one is the dependency on the inbuilt implementation of the same be it in terms of the reliability or in terms of easier to code or be it the basic logic behind the concept of SVM.

Why is KNN used :-

It is a very simple algorithm that is easy to implement and hence prediction and classification is easier and more efficient. One of the main advantages of KNN is the non parametric nature of the algorithm which makes it independent from the underlying data pattern. It can be used for both classification and Regression which makes it very easy to use. The most important point for any algorithm is Training part but it is much faster for the nearest neighbor compared to other machine learning algorithms.

VIII. CONCLUSION

In this project , a new approach for classification of EEG signals has been presented, based on the sequential application of statistical feature generation followed by the extraction and selection for the same,and then subsequent projection of the selected features and classification based on a SVM and also implemented by the kNN algorithm also.

The results obtained for this method have been shown to be very competitive with the best known results to date for the available dataset and also the accuracy by using SVM is better than the one done in the research paper. Therefore SVM is the best method for the given dataset.

IX. REFERENCES

[1] Mental Emotional Sentiment Classification with an EEG-based Brain-machine Interface by Jordan J.Bird , Anikó Ekárt , Christopher D. Buckingham and Diego R. Faria

[2] DEAP: A Database for Emotion Analysis Using Physiological Signals Sander Koelstra, Student Member, IEEE, Christian Mühl, Mohammad Soleymani, Student Member, IEEE, Jong-Seok Lee, Member, IEEE, Ashkan Yazdani, Touradj Ebrahimi, Member, IEEE, Thierry Pun, Member, IEEE, Anton Nijholt, Member, IEEE, and Ioannis (Yiannis) Patras, Senior Member, IEEE

[3] A Deep Evolutionary Approach to Bioinspired Classifier Optimisation for Brain-Machine Interaction Jordan J. Bird , Diego R. Faria, Luis J. Manso,
Anikó Ekárt, and Christopher D. Buckingham

[4] Classification of EEG Signals Based on Image Representation of Statistical Features Jodie Ashford * , Jordan J. Bird * , Felipe Campelo, and Diego R. Faria

[5] Amin HU, Mumtaz W, Subhani AR, Saad MNM and Malik AS (2017) Classification of EEG Signals Based

on Pattern Recognition Approach. *Front. Comput. Neurosci*. 11:103. doi: 10.3389/fncom.2017.00103

[6]Amorim, P., Moraes, T., Fazanaro, D., Silva, J. and Pedrini, H., 2017. Electroencephalogram signal classification based on shearlet and contourlet transforms. Expert Systems with Applications, 67, pp.140-147.

[7] Luo Tian-jian, Fan Yachao, Chen Lifei, Guo Gongde, Zhou Changle. (2020). EEG Signal Reconstruction Using a Generative Adversarial Network With Wasserstein Distance and Temporal-Spatial-Frequency Loss. Frontiers in Neuroinformatics, doi: 10.3389/fninf.2020.00015

[8] S. Hwang, K. Hong, G. Son and H. Byun, "EZSL-GAN: EEG-based Zero-Shot Learning approach using a Generative Adversarial Network," 2019 7th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea (South), 2019, pp. 1-4, doi: 10.1109/IWW-BCI.2019.8737322.

[9] Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions
Author links open overlay panel RajeevSharmaRam BilasPachori

[10] W. Zheng, J. Zhu, Y. Peng and B. Lu, "EEG-based emotion classification using deep belief networks," 2014 IEEE International Conference on Multimedia and Expo (ICME), Chengdu, 2014, pp. 1-6, doi: 10.1109/ICME.2014.6890166.

[11]Classification Of Mental Tasks From Eeg Signals Using Extreme Learning Machine Nan-ying Liang, Paramasivan Saratchandran, Guang-bin Huang And Narasimhan Sundararajan

[12] K. Li, X. Li, Y. Zhang and A. Zhang, "Affective state recognition from EEG with deep belief networks," 2013 IEEE International Conference on Bioinformatics and Biomedicine, Shanghai, 2013, pp. 305-310, doi: 10.1109/BIBM.2013.6732507.

[13] Y. Ren and Y. Wu, "Convolutional deep belief networks for feature extraction of EEG signal," 2014 International Joint Conference on Neural Networks (IJCNN), Beijing, 2014, pp. 2850-2853, doi: 10.1109/IJCNN.2014.6889383.

[14] Hartmann, Kay Gregor et al. "EEG-GAN: Generative adversarial networks for electroencephalographic (EEG) brain signals." *ArXiv* abs/1806.01875 (2018): n. pag.

[15] N. D. Truong, L. Kuhlmann, M. R. Bonyadi, D. Querlioz, L. Zhou and O. Kavehei, "Epileptic Seizure Forecasting With Generative Adversarial Networks," in IEEE Access, vol. 7, pp. 143999-144009, 2019, doi: 10.1109/ACCESS.2019.2944691.

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