

# Common Spatial Filter for Improving the Classification of EEG using Artificial Neural Network

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## ABSTRACT

*Machine learning in motor imagery, the classifier performance of electro-encephalo-graphy (EEG) data varies for different subjects. The performance of classifier is degraded when applied on different subject. To overcome this issue, common spatial pattern (CSP) method is proposed. The dataset contains 9 subjects EEG data. Common spatial pattern is used in feature extraction for the improvement of the classifier of different subjects and tested with artificial neural network (ANN). Based on the classification, random forest is implemented to train the data accuracy. The obtained results show 0.96% of performance improvement compared with existing methodology.*

**Keywords:-**Common Spatial Pattern (CSP), Electroencephalography (EEG), Motor imagery (MI), Machine learning techniques

## INTRODUCTION

Machine learning techniques has made significant progress in machine learning and computer vision. DNN has indeed been proved to be suitable for complete learning deprived of background knowledge of the objective issue and to scale effectively to enormous data sets. DNN is rarely used in EEG data processing because of the properties of EEG data.

EEG signals, on the one side, are often sample-limited and high-dimensional. When applied to data from such a related but separate field, the efficiency of a classifier trained on information from that field often diminishes. While identifying a large number of examples from the new forum might solve this problem, it is frequently too costly or unfeasible. Domain Adaptation has thus developed as an answer to this challenge; it uses statistical features from a source domain,

where it is plentiful, to build a model to work in a target domain, where it is minimal or non-existent. In this regard, a new trend is to learn structural features with shared weights for both domains, which would be fundamentally the same as learning domain texture features [1].

The presented method's goal is to extract discriminant features from electroencephalography (EEG) signals for conceptual intent identification, and thereby play an important role in EEG-based brain computer interfaces (BCI). Without previous understanding of the objective problem and a large data set, DNN could be used for end-to-end learning.

This research is being conducted to determine the method's technical viability, that is, to build classifier solely on EEG data from several subject with low ability

on a new subject. Any strategy established should not be unduly dependent on computing expertise. This will put a lot of pressure on the available technology tools [2,3]. As a result, the customer would be under a lot of stress. Because relatively minor or no adjustments are needed to execute the established method, it should have a low constraint. Two datasets of BCI are used here with three Machine learning algorithms such as Support Vector Machine, Random Forest Algorithm, Naive Bayes, Multilayer Perceptron, Decision Tree, are used. These algorithms are compared in terms of performance accuracy [4]. The remaining section of the article is organized as follows. Section 2 gives the literature review of related papers in the research domain. Section 3 illustrates the proposed work with mathematical equations. Section 4 provides the information of implementation of the paper. Section 5 analyses result of the work and conclusions along with future work are described in section 6.

## RELATED WORK

Artem Rozantsev et. al., [5] demonstrate that formally modelling the transition from one domain to the other is more efficient. To accomplish this, a two-stream structure is established, one in the source domain and another in the destination domain. The weights in comparable layers are connected but not shared, as in other techniques. On numerous object identification and detection tasks, authors show that this improves state-of-the-art approaches and persistently outperforms systems with shared weights in both unsupervised and supervised environments. On conventional Domain Adaptation image processing evaluations, authors demonstrate that the technique performs state-of-the-art weight-sharing methods. They also show that it is well adapted to using artificial data to improve a classifier's accuracy on actual pictures.

Chunchu Rambabuet. al., [6] presents a summary of artifacts in EEG recordings and how to remove them, where artifacts of signals are a combined of EMG and EOC that effect EEG signals. EEG signals are gathered and pre-processed with different metrics before being analyzed for characteristics. Measurement of EEG signals is critical for medical diagnostics.

Because capacitive sensors are commonly employed in biomedical science, they are being used for evaluation to solve the EEG signal issues which does not involve in skin reactions that could not grow while long-term measurement. It uses capacitive sensors to perform non-contact biopotential measurements in a variety of ways. It created a capacitive device for ECG and EEG surveillance, as well as a small capacitive sensor for biopotential measurements.

Patricia Becerra-Sánchez et. al., [7] describes a new features extraction model for pattern identification utilizing data from EEG recordings. A new fitness function is created using a machine learning technique that identifies and chooses essential EEG factors that can contribute to distinguishing lower and higher intellectual loads and builds a novel data set potential of enhancing the model's forecasting process. In latest years, various pattern recognition models based on FS techniques based on physiological inputs have been suggested. Traditional strategies for reducing the minimal proportion of original dataset features, creating strong prediction models, or evaluating data from a given signal to evaluate many characteristics employing tiny datasets were used to create the models.

Deepa R et. al., [8] discussed feature extraction strategies for identifying various diseases. The most widely used technique for disease categorization is the support vector machine. It is commonly used to

categorize disorders such as Alzheimer's, epilepsy, and Parkinson's. It is a supervised learning algorithm that analyze signal for regression and classification problems. By using some functional mapping and maintaining as much information in the data as feasible, the feature extraction technique is used. The goal of feature extraction for classification is to find a transformation that extracts a subset of new features from the dataset while optimizing class separation. This task can make use of a variety of time domain and frequency domain properties.

The electrodes on the participant's scalp are used in the electroencephalogram (EEG) procedure. The electrical signals from the brain are amplified by those electrodes. It is important to eliminate artifacts from the EEG prior analyzing it, which is known as pre-processing. In research activities and diagnosis, EEG has been shown to be a trustworthy technique.

Geeta Sharma et. al., [9] studied diverse uses of EEG-based signals in various diseases such as spinal injury, post-stroke, and so on. The brain computing interface (BCI) is a computer-based technology which enables the mortal mind to interact with electronic equipment such as motorized wheelchairs, robotic arms, and artificial limbs without the use of peripheral devices such as muscles and nerves. The goal of BCI is to analyze electrical signals transmitted by the brain, then amplify and filter them to exclude undesired signals.

The analogue signal is then converted to a digital signal, which is subsequently displayed on the screen in the output form. This occurs when various brain processes are generated by the mortal mind, which are recognized by the system and translated into commands depending on classification algorithms.

Dipti Pawar et. al., [10] provides a thorough examination of feature extraction strategies for EEG- based BCI, as well as their characteristics. Additionally, open challenges for more progression in BCI investigations are mentioned. BCI is a structure that converts brain activity sequences into commands or messages for an application interface, allowing direct connection between the human mind and computer systems.

Electroencephalography (EEG) is a straightforward, simple to use, and low-cost technology for measuring brain activity patterns.

This study examines various feature extraction strategies for EEG-based BCI. The methodologies for feature extraction and classification for various major works in the BCI field are summarized. EEG signals from all networks are taken into account by time domain characteristics. Time domain attributes are simple to calculate and need a less set of variables to be selected. In general, time domain characteristics are used with additional feature extraction techniques such as spatial features or artificial intelligence to provide a comprehensive performance evaluation.

Swati Vaidet. al., [11] gives a brief summary of EEG signals and the BCI system. An overview of the traditional approaches for signal feature extraction is also included in the publication. BCI is a interaction channel between the human mind and a computer system. It permits consumers to operate peripherals that are not controlled by peripheral nerves or muscles via brain activity. A brain-computer interface system helps a user to deliver orders to an external device utilizing brain signals. Due to inherent constraints such as temporal dependency, high feature vector set dimensions, and uncertainty, engineers must make quick

and precise conclusions for EEG signals. To achieve this, the system latency and reaction time must be minimized so that the BCI system can work in physical - world environments. The fact that EEG is a straightforward technology, in which signals are obtained by an electrode inserted on the scalp, is one of the factors that contribute to noise.

K. Saranyaet. al., [12] conducted a survey of all the enhanced strategies to filter the EEG signal, as well as a comparative analysis of the numerous classification techniques that used categorize the emotions. A multimodal classification method that uses EEG signals while also measuring performance with Natural Language Processing is proposed for enhancing the precision.

Multi-emotions may be classified using the developed model, which is based on brain EEG signals. To collect a significant range of signals, an EEG signal recording headset with a small number of providers is required. The system consists of three steps, the first of which is receiving the signals inactive and performing preprocessing, which includes distortion and outlier reduction.

The data is then used to train a classifier on many emotions, and the second stage is testing data, in which the data can be collected in actual environments and the classifier is used to determine the subject's emotion. In the third stage, the subjects were instructed to look at an image or listen to music and then write a textual response to it. The text is analyzed for emotion using NLP, which is obtained respectively with the analysis of the EEG data acquired at the time. To improve the findings, both of the results were pooled.

Chetan Umaleet. al., [13] focuses on the EEG signal's utility in identifying human anxiety levels. It also compares different preprocessing strategies and different

categorization algorithms. The research presents a system that will evaluate the EEG output and assess human anxiety levels using a variety of classifiers. This study examines a variety of feature extraction approaches and classification algorithms for detecting stress levels. Based on findings, a method is designed that would utilize a distinct EEG electrode headset to collect signals, that will be pre-processed with Discrete Wavelet Transform and categorized utilizing a variety of classifiers to determine points.

Early stress identification can prevent the occurrence of chronic mental disease. EEG signal recording and analysis can be a useful tool in this case. This study recommends using a EEG channel headset as a compact and cost-effective substitute to typical different technology.

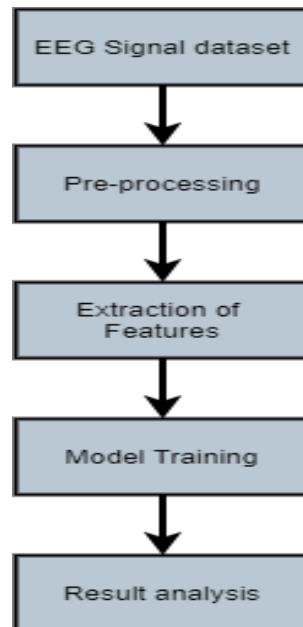
Ugur Halici et al [14] have proposed deep learning methods for the improvement of performance of EEG classification motor tasks brain signals. To categorize the motor tasks of EEG signals, author proposed convolutional neural network (CNN) and stack auto encoders (SAE). One dimensional convolutional and max-pooling layers has been introduced to combine the time and frequency of EEG signals. They have also proposed deep network by synthesizing SAE and CNN. The deep network of SAE is classified by extracting the features in CNN. Their method results in improvement of 9% over the existing system. These methods can be applied to large amount of BCI data.

## **PROPOSED SYSTEM**

The model proposed here considers the peripheral and restricted distribution mismatch among the source and target areas for learning the deep classification model. This is accomplished by combining the efforts of three components. This work proposes the new approach of domain adaptation method which is further

classified as extraction, discriminator and classifier of Convolution Neural Network (CNN) model along with relu unit. The

system framework is shown below in Figure 1. It depicts how the system is created and how it works.



**Fig.1:-System Architecture.**

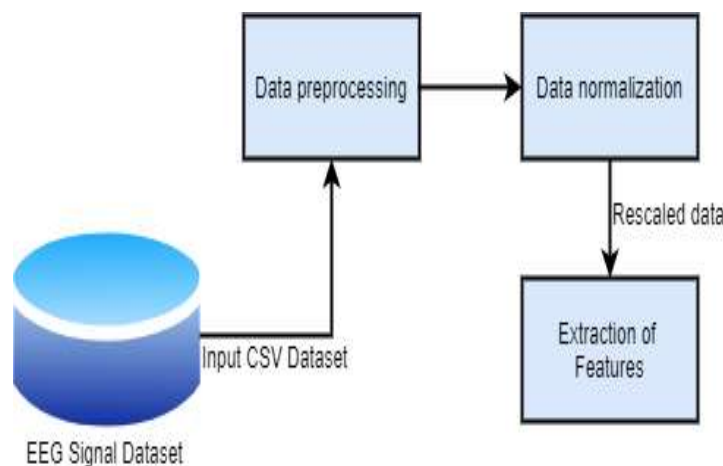
The steps of the proposed system are as follows:

1. Feature Extractor: It maps the original EEG data into feature representation to learn discriminative information.
2. Classifier: It uses the collected feature representations from the feature extractor to forecast the output labels.

3. Domain Discriminator: Its purpose is used to determine from which domain the features originate in order to limit the feature distribution across domains to be identical.

Visual representation is a useful communication tool among the user and the system designer.

Figure 2 shows a broad overview hierarchy diagram.



**Fig. 2:-Flow Diagram.**



## EXTRACTION OF DATA

CSV (comma-separated value) files are a typical data transformation and storage form. Python has the capacity to read, modify, and write data to and from CSV files. Pandas is the most widely used Python data manipulation library, and data frames are a Pandas data type for sorting 2D data.

## PREPROCESSING OF DATA

Noise from various forms and sources contaminates raw EEG. Filtering away undesirable noise is a vital step in extracting meaningful information from EEG due to its tiny amplitude. We were able to reduce visual artifacts caused by physical movement. The notch is a highly selective filter that rejects all except a small frequency band across the selected frequency. It will not interfere with other frequencies in the EEG signal.

## RESULT

The equipment should be linked to the web in order to select the individual element with ocular artifact as an output requirement. All electrode data attached to the scalp of people should be included in the data. As per the data set provided, the program will also provide the prediction performance of the emotion level evaluated.

## IMPLEMENTATION

This section includes network model and energy model.

### a. Naïve Bayes Algorithm

Naive Bayes is a machine learning model which is used for big volume of information. It is suggested to utilize Naive Bayes if one is working with data that has millions of records. When it pertains to NLP tasks like sentimental analysis, it performs admirably. It is a simple and quick categorization algorithm.

### b. Support Vector Machine

Support Vector Machine (SVM) is machine learning approach that could be used for classification and regression analysis. SVMs are more typically employed in classification difficulties. The objective of SVMs is to find a hyper-plane. Text classification activities like category assignment, spam detection, and sentiment analysis are all done with SVM. It is especially popular for image recognition tasks, where it excels at aspect-based recognition and color-based classification. SVM is also used in a variety of pattern classification applications, including postal automation.

### c. Random Forest Algorithm

Random forest is a learning-based supervised method. The basic steps of random forest algorithm are as follows:

From the train set, random data is selected.

The data points that are selected should be built on the decision tree.

Select the number of decision trees that has been constructed.

Repeat Step 1 & 2.

Find predictions of each tree of the new data sets, and assign the data points which wins majority votes in the prediction category.

### d. Multilayer Perceptron

A feedforward ANN called a multilayer perceptron (MLP) is a type of feedforward ANN. The name MLP is indistinct; it could be used to refer to any feedforward ANN, or it could denote networks made up of many layers of perceptrons [15]. There are at smallest three stages of nodes in an MLP: an input, hidden, and an output layer. Each layer consists with an exception of the first layer, a node with activation function. Back

propagation is a supervised learning method used by MLP [16].

**e. Decision Tree**

For partitioning datasets, decision trees give a nonparametric technique. Regression models that depict correlations between variables as cross-products between them are examples of alternative data mining strategies. Because of their capacity to integrate vast complex datasets into incredibly simple yet information-rich graphs and charts, decision trees were selected for this study. The resulting graphical tree representation was thought to be a helpful tool for quickly elucidating the crucial parameter combinations that result to undesirable potential losses, which can then be turned into a system of regulations. Additional benefits of employing decision tree algorithms comprise minimum data preparation requirements and reliability on large datasets [14].

**f. CNN Model**

A convolutional neural network (or

CNN) is a multilayer neural network or deep learning framework influenced by a human being's visual system. The CNN is well-suited to a variety of machine learning and natural language processing tasks. In Convolutional Neural Networks, the Rectifier Linear Unit (ReLU) is the most widely employed activation function. It converts all of the input values into positive numbers. When compared to other algorithms, ReLU has the benefit of requiring extremely little computation.

**g. Common Spatial Pattern (CSP)**

The CSP algorithm has been shown to be useful in BCI for features extraction in motor imaging tasks, however it is susceptible to over-fitting. Many techniques for normalizing CSP for two-class problems have been devised, but when it comes to multiclass CSP, they haven't worked. The CSP algorithm is frequently utilized in the BCI area, and it is used to find spatial filters that optimize variation among classes [15].

The following are the steps for CSP algorithm:

Let  $X^k = (X_c^k, t)$ ,  $c = 1, \dots, C$ ,  $t = t_0, \dots, T$

Denotes the EEG recording of the  $k^{\text{th}}$  trial.

Where  $C$  is the number of electrodes,  $Y^k \in \{1, 2\}$  is the class label of the  $k^{\text{th}}$  trail.

Two class-covariance matrices are as follows:

$$\Sigma_1 = (X^k X^{kT})(k: yk = 1) \text{ and } \Sigma_2 = (X^k X^{kT})(k: yk = 2) \quad (1)$$

$$W \Sigma_1 W^T = D \text{ and } W \Sigma_2 W^T = I - D \quad (2)$$

$W$  is a matrix and  $D$  is a Diagonal matrix.

Determine a matrix  $P$

$$P(\Sigma_1 + \Sigma_2) P^T = I \quad (3)$$

Define  $S_1 = P \Sigma_1 P^T$  and  $S_2 = P \Sigma_2 P^T$

Compute a matrix R and a diagonal matrix D by spectral concept

$$S_1^T = RDR^T \quad (4)$$

From  $S_1 + S_2 = I$  it observed that  $S^T = R(I-D)R^T$ . For class 1 trail row matrix of  $p^{th}$  R has variance of D element and class 2 train has  $1-d_p$  variance. For class 1 trail if  $d_p$  is nearer to 1 then R row is maximized and for class 2, if  $d_p$  is nearer to 0 then R row is minimized.

The final result that satisfies (2) can be achieved from

$$W = R^T P \quad (5)$$

The EEG recording  $X^k$  are projected onto

$$Z^k = W X^k \quad (6)$$

The analysis of W is twofold, the W rows are the spatial filters, while the  $W^{-1}$  columns can be seen as the CSPs

## RESULTS

The performance and web application of the proposed system is shown in this results section. Figure 3 depicts the dataset preprocessing outputs.

```
In [20]: X = data.drop('Label', axis=1)
         y = data['Label']

In [21]: X
```

Out[21]:

	lagf_mean_0	lagf_mean_1	lagf_mean_2	lagf_mean_3	lagf_mean_d_h2h1_0	lagf_mean_d_h2h1_1	lagf_mean_d_h2h1_2	lagf_mean_d_h2h1_3	lagf_mes
0	25.781648	33.836367	-92.769629	19.187957	-1.542262	0.197462	-119.561133	2.032854	21
1	29.357091	26.792588	417.203810	19.472121	-36.797263	-16.897194	-29.368531	-9.055370	44
2	26.451926	31.076434	72.231301	14.245838	-13.225057	-0.614138	-28.331680	-8.856742	31
3	21.282184	19.985184	16.220094	39.787312	1.847866	0.670216	-1.020355	20.220724	21
4	20.431516	28.982168	27.540246	19.960398	2.491458	-6.020503	-1.071168	2.855259	16
...	...	...	...	...	...	...	...	...	...
2474	15.762328	10.113555	23.696867	7.568395	-8.503336	6.867187	-11.955386	-16.519912	19
2475	34.675582	34.200645	-57.624820	-4.825809	7.382353	2.324416	-1.341288	-4.178625	26
2476	29.813608	29.623031	-86.563988	7.532121	-19.501287	-0.628400	133.947180	-2.048096	45
2477	58.453873	17.944332	-10.164238	42.568211	-1.300655	-19.983890	-54.331690	12.947622	55
2478	22.893855	-30.412723	26.029090	14.248789	-7.101478	-0.551013	3.735563	-9.372750	36

2479 rows x 988 columns

**Fig.3:-Data Preprocessing**

Figure 4 shows Graph of EDA missing values

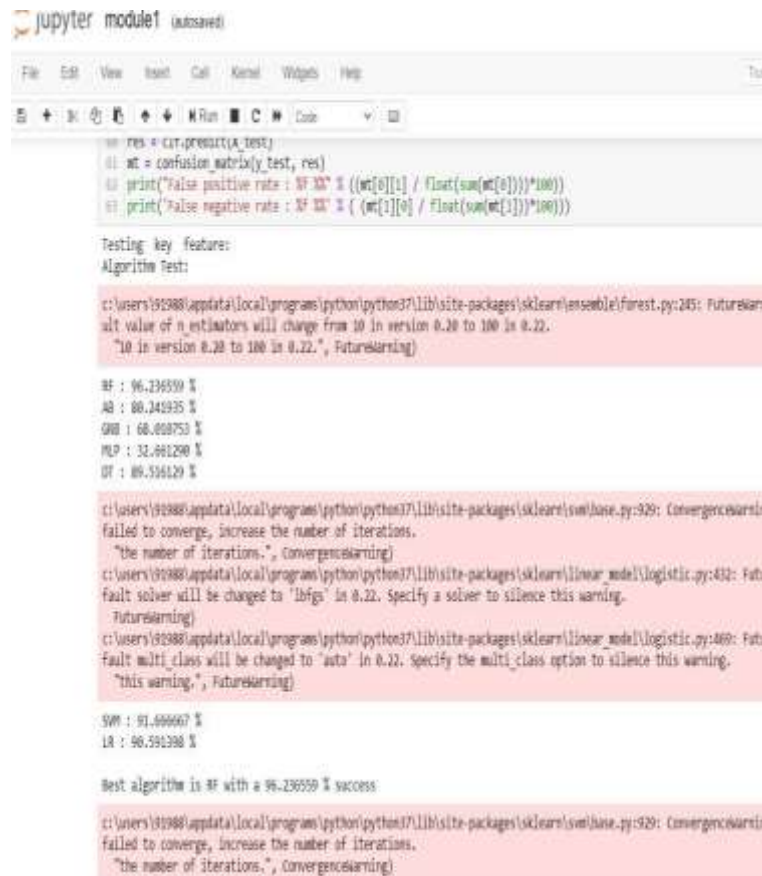


**Fig.4:-EDA-Graph-Missing value**



Figure 5 shows the screenshot of Jupyter Notebook execution in which each individual machine learning algorithm's accuracy is depicted. The Random forest is described as the best algorithm with respect to efficiency exhibiting accuracy of

96.23%. The efficiency of Naive Bayes, Support Vector Machine, Multilayer Perceptron, Decision Tree, Linear Regression and Alpha Beta pruning is 68.01%, 91.66%, 32.66%, 89.51%, 90.59% and 80.24% respectively.



```

res = car.predict(X_test)
cm = confusion_matrix(y_test, res)
print("False positive rate: %f" % ((cm[0][1] / float(sum(cm[0])))*100))
print("False negative rate: %f" % ((cm[1][0] / float(sum(cm[1])))*100))

Testing key features:
Algorithm Test:

c:\users\92388\appdata\local\programs\python\python37\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning:
alt value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)

RF : 96.236559 %
AB : 80.343935 %
GNB : 68.008753 %
MLP : 32.661290 %
DT : 89.516129 %

c:\users\92388\appdata\local\programs\python\python37\lib\site-packages\sklearn\svm\base.py:929: ConvergenceWarning:
Failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
c:\users\92388\appdata\local\programs\python\python37\lib\site-packages\sklearn\linear_model\logistic.py:432: FutureWarning:
Fault solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
c:\users\92388\appdata\local\programs\python\python37\lib\site-packages\sklearn\linear_model\logistic.py:469: FutureWarning:
Fault multi_class will be changed to 'auto' in 0.22. Specify the multi_class option to silence this warning.
  "this warning.", FutureWarning)

SVM : 91.666667 %
LR : 90.591398 %

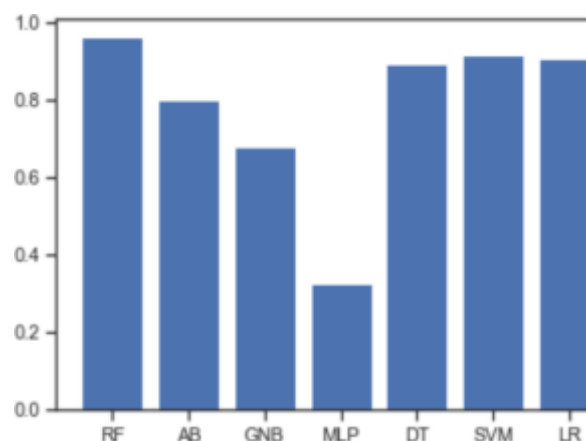
Best algorithm is RF with a 96.236559 % success

c:\users\92388\appdata\local\programs\python\python37\lib\site-packages\sklearn\svm\base.py:929: ConvergenceWarning:
Failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)

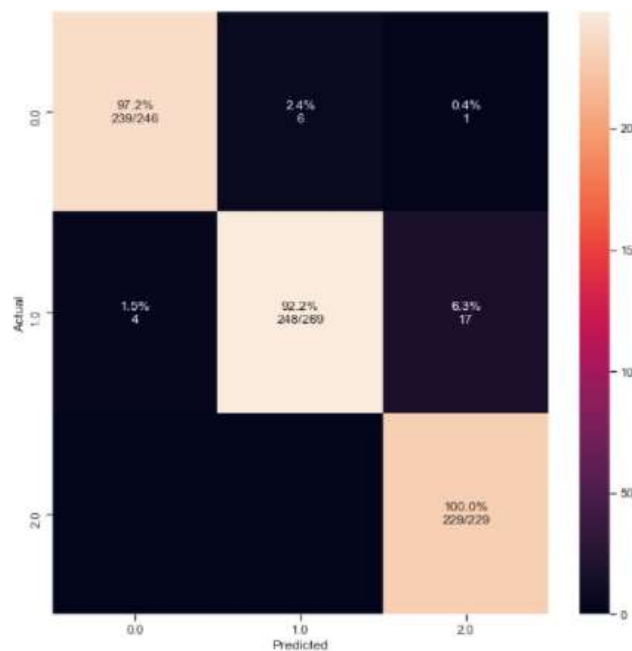
```

**Fig.5:-Training performance of Machine learning algorithms**

The training performance is also depicted in Fig. 6 in a graphical representation.



**Fig.6:-Training performance graph**



*Fig.7:-Confusion matrix representation*

F1 Score is : 96.268825 %

Confusion Matrix

```
[[239  6  1]
 [ 4 248 17]
 [ 0  0 229]]
```

False positive rate : 2.439024 %

False negative rate : 1.486989 %

Winner algorithm is RF with a 96.236559 % success

False positive rate : 2.439024 %

False negative rate : 1.486989 %

*Fig.8:-Confusion matrix screenshot inJupyter Notebook*

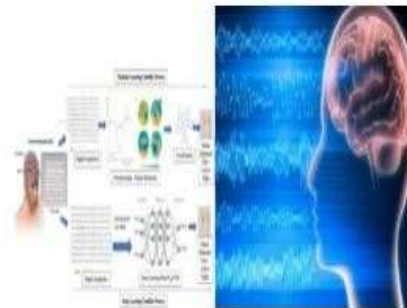
The performance of best algorithm is also represented using confusion matrix. It is a method to summarize the performance a classification method efficiency. If there is a disturbed quantity of samples in every class or if it has multiple class datasets, then the classification performance only could be inaccurate. Figure 7 and 8 shows the matrix representations.

The web application is implemented for the proposed system whose result screenshots are presented in Figure 9 and

10. Figure 9 shows the home page which has button to select the EEG signals that has to be tested.

When clicked on button it will redirect to the local files to select the EEG Signal. Once the signal is selected, the signal is tested and result is displayed. In Figure 10, "eeg\_signal1.csv" file is selected and result is displayed as "Motion Intention level is: Right hand".

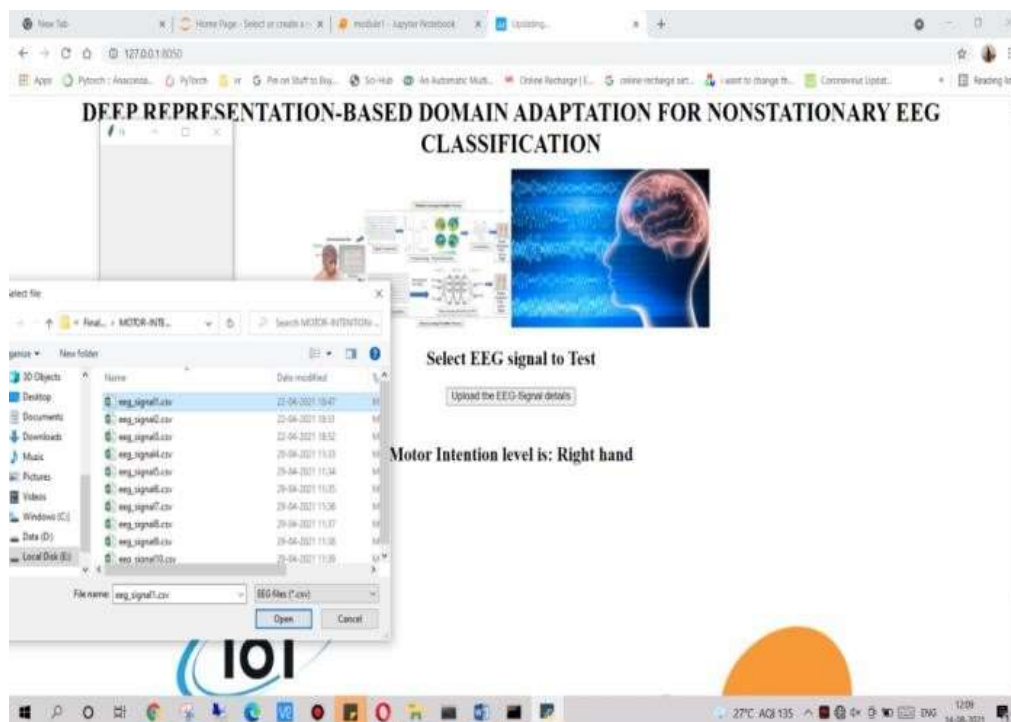
## DEEP REPRESENTATION-BASED DOMAIN ADAPTATION FOR NONSTATIONARY EEG CLASSIFICATION



Select EEG signal to Test

Upload the EEG-Signal details

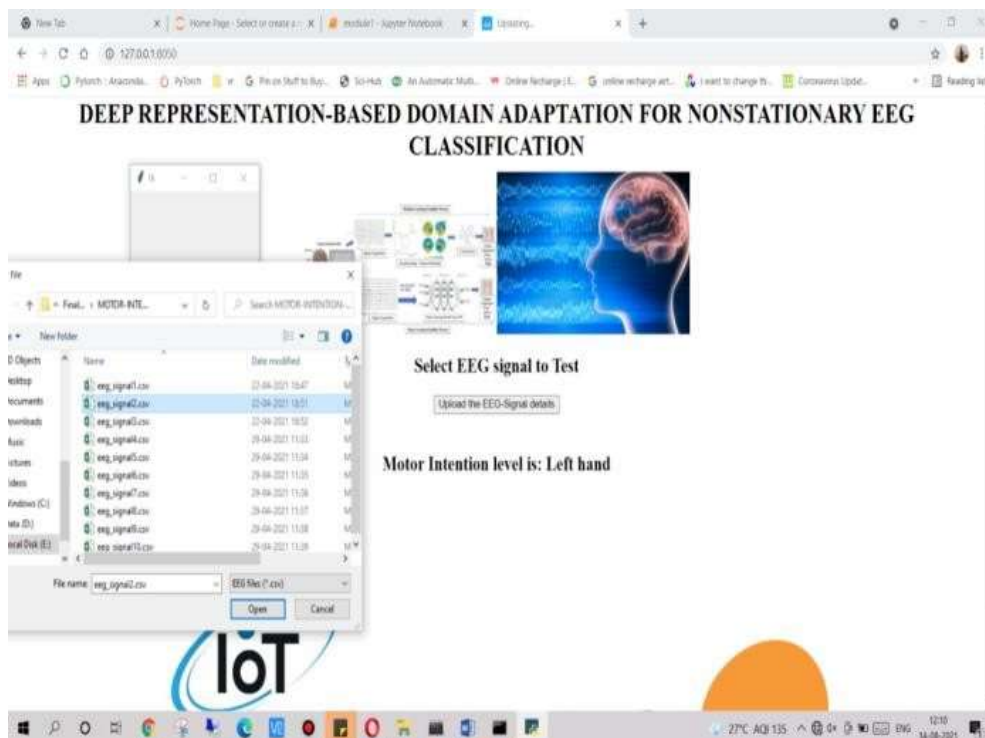
**Fig.9:-Home page of Web application**



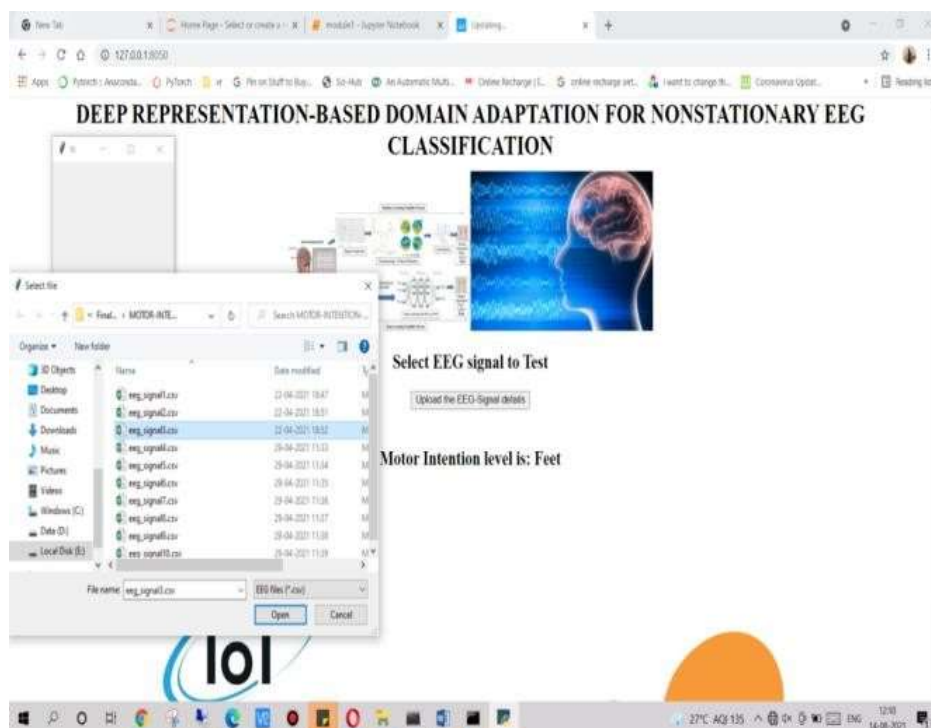
**Fig.10:-Signal selection and first result display**

Similarly, in Figure 11 “eeg\_signal2.csv” file is selected and result is displayed as “Motion Intention level is: Left hand”. In Figure 12 “eeg\_signal3.csv” file is selected and result is displayed as “Motion Intention level is: Feet”.

The Epoch graphs for the above results are shown in below figures. Figure 13 shows Right hand epoch. Figure 14 shows Left hand epoch. Figure 15 shows Feet epoch.

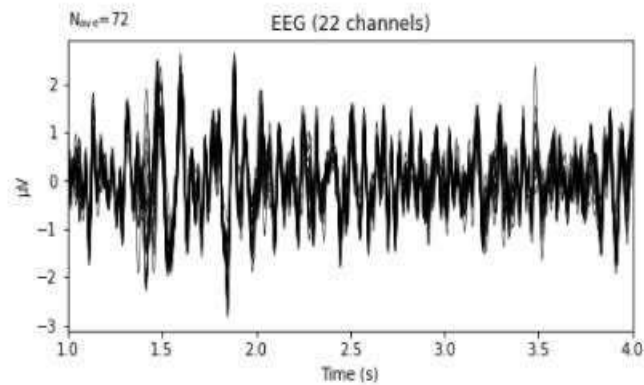


*Fig.11:-Second result display*



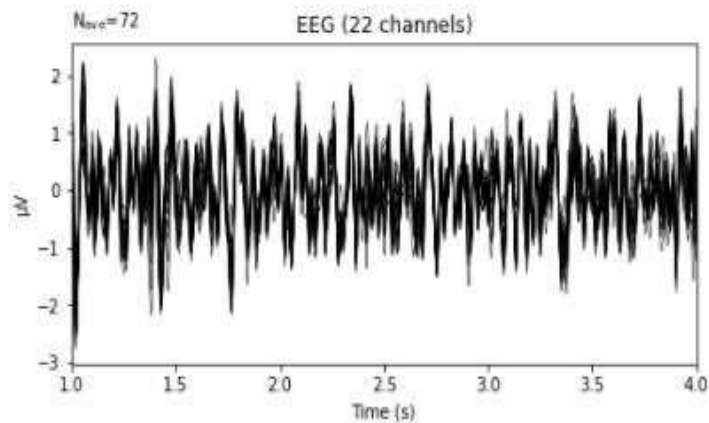
*Fig.12:-Third result display*

<Evoked | '770' (average, N=72), 1 - 4 sec, baseline off, 22 ch, ~155 kB>

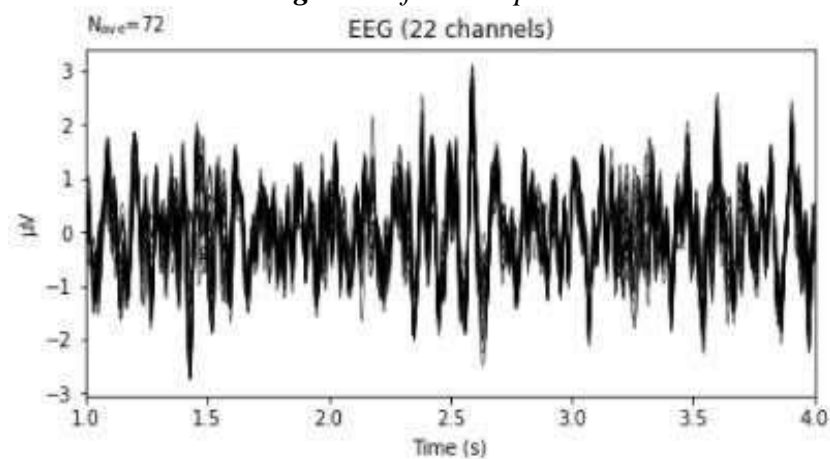


*Fig.13:-Right hand epoch*

<Evoked | '769' (average, N=72), 1 - 4 sec, baseline off, 22 ch, ~155 kB>

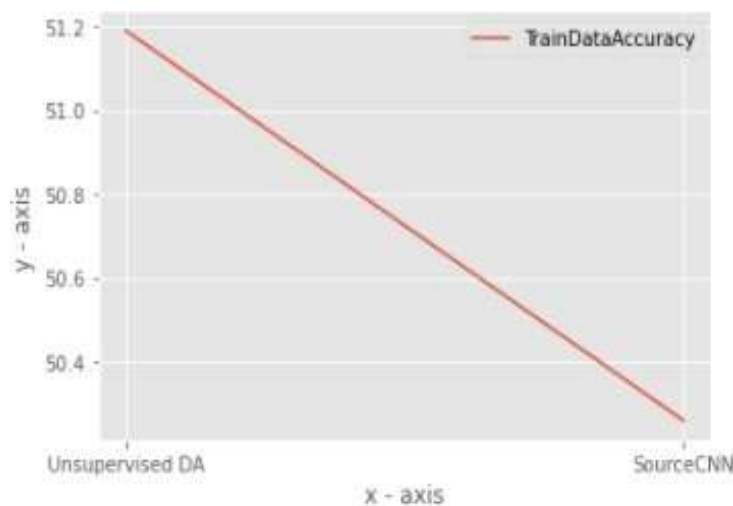


*Fig.14:-Left hand epoch*

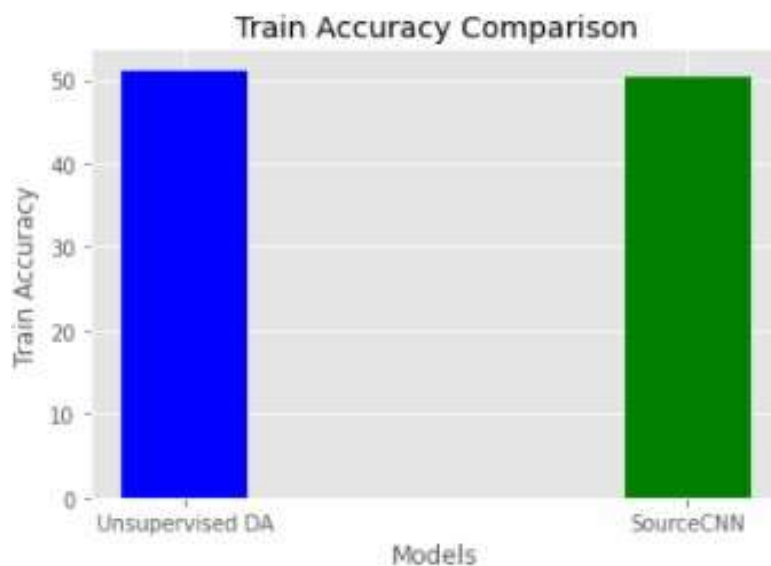


*Fig.15:-Feet epoch*

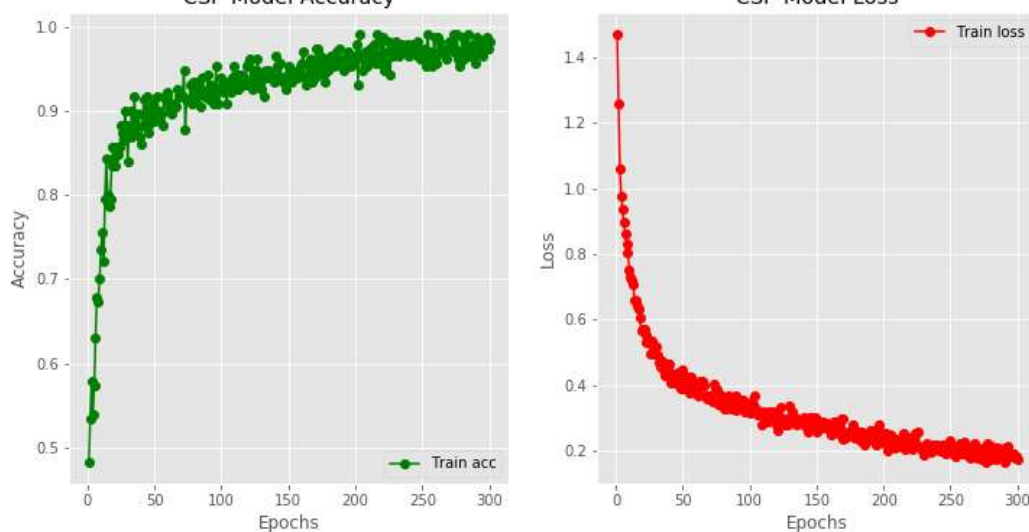




**Fig.16:-**Comparison of Unsupervised DA and CNN models



**Fig.17:-**Training accuracy of UnsupervisedDA and CNN models



**Fig.18:-**CSP model accuracy and CSP model loss

The comparison of Unsupervised Domain Adaptation and the proposed CNN model is shown in Figure 17. The Training accuracy is also compared for these two models which is depicted in Figure 17. Figure 18 displays the CSP model accuracy and CSP model loss which is used for feature extraction.

## CONCLUSION AND FUTURE WORK

To tackle the EEG-based MI classification job, a CSP method is used in feature extraction to maximize the covariance between the subjects. As a result, the characteristics created from the source domain are distributed similarly to those created from the target domain. The findings show that the suggested system results state-of-the-art techniques in detecting motor intention from EEG data.

It also indicates that the suggested adversarial reduction and the centre deficit could greatly decreases inter subject and intra subject non stationary, and that they can be used to various BCI applications.

The seven algorithms are compared with respect to efficiency. The performance accuracy of all algorithms is as follows. The efficiency of Random Forest algorithm, Naive Bayes, Support Vector Machine, Multilayer Perceptron, Decision Tree is 96.23%, 68.01%, 91.66%, 32.66%, 89.51%, respectively.

From this analysis, it is cleared that Random Forest has resulted in best accuracy in this proposed work. The output is now a web site, but future work would be included creating an Android app for people to use and translating the existing network into their EEG Motor intention signal for deep learning models.

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