ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

Improving classifier performance in neuroimaging data with the help of optimal machine learning technique

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Abstract: In the past decades, the study of human brain evolved rapidly through radiographic imaging techniques in both healthy and diseased state. Neuroimaging considered as a segment of brain image mapping that exhibit a peerless form of technique. Medical-imaging tools like magnetic resonance (MR) scanners, is most frequently used sources of quantitively data on brain structure. Study of these data results in complex data involving multidimensional images to noisy data, this leads to misinterpretation. Even with its analyses, the diagnose predictions of clinical assets has not been preferred to neuroimaging, hence we use machine learning algorithms. A Machine Learning is a smart computer programming which boost algorithms that masters to arrange the regression and classified data. Machine learning collects functional magnetic resonance image (fMRI) of human brain activity and infuses these data with the training process of decision tree algorithm making it more congruous with human brain. Once the training is done a Gaussian Naïve-Bayes classifier begin to arrange the images leaving any necessitate of supplementary neural datasets. This approach allows classification in all searchlights equally and is faster than previously Naïve-Bayes implementations. Machine learning enhances the potential of neuroimaging by focusing to overcome biases by optimizing complex brain patterns to predict targets. The aim of this paper will be to summarize the optimal algorithms which can lead to a performance gain when compared to traditional machine visions. Finally, this approach will give a way better strategy in the field of neuroinformatic.

Keywords: *Neuroimaging, fMRI, Machine learning, Decision tree, Training process, Gaussian Naïve-Bayes.*

1.Introduction

Neuroimaging organized through an extension of methods like magnetic resonance imaging (MRI). Numerous studies of non-intervention learning are obtained by methods such as weight imaging and functional magnetic resonance imaging (fMRI) [30]. These data are huge in number covering up to terabytes. An optimal machine algorithm tool guarantees a mapping of input data with recognized output data. In [22], representation of human or non-human brain is accomplished by the predicted set of brain mapping. The working of brain includes producing of continuous electrical impulses inside nervous system. A distinctive pattern is marked in other conditions like Alzheimer, Anxiety etc. A visual pattern is conjectured from images obtained from brain for encoding and decoding. In [27], the data of fMRI can be linked with the images obtained by the subject also the random images are collected in training set while testing set is made of well-organized dataset.

Machine learning is an evolution of regular algorithm. It makes our programming techniques spruce by automatically learning from the previous data. Considering a subcategory of artificial intelligence, machine learning involves statically techniques such as neural network [5], which inform about how human brain works. Machine learning algorithm is divided into two i.e. first a training phase, in this randomly selected data from the storage is withdraw and a table

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

is formulated including of all the attributes [39]. This is then fed to machine learning algorithm and it learns a model of correlations. Second, a testing phase, the training data is tested and then fetched to classifier to evaluate. The algorithm may internally use the rules, like the one manually. The algorithm later can be improved over time to edify the different models. It can create one each for anticipate the quality as it gets trained on more and more training dataset. If it makes a wrong prediction it will update its rule by itself [43]. Decision tree sets a great example of machine learning algorithms.

A Decision tree is a flow diagram in visual representation of decision tree. In this conjecturing of class label for a record begins from the root. Comparison of values of the root attribute with recorded attribute is performed. The original data set is first fetched to a training set where data is recognised with patterns and finally to testing process.An involvement of two major procedure includes building of a tree and a decision tree. (a) Building of a tree begins with complete training set starting from the root.By allowing to diminish subset created between the mixture of classes the goal here is to find impute of each node of the tree. For each sub division the continuity is maintained. (b) Classification, here new objects were classified on the tree. The object starts from the root and cycled until a leaf is encountered [43]. Labelling leaf is classified as a new object.The work of decision tree is to distribute data items into a predefined class.Various parts are labelled like the arc with all possible ways of travelling, a node as impute and leaf as a different class.Increased entropy subset is achieved by dividing the possible tests by looking up the criterions which was missing in [17]. The information gain is an expected reduction whereas the impurity of arbitrary set is separated by entropy. Occurrence of entropy by partition of the sets are based on the attributes. An algorithm is more effective with a classifier, it is a machine learning model which separates abnormal objects based on certain features [11]. The classification of data is done by a probabilistic machine learning algorithm that is, Gaussian Naïve Bayes classifier. Bayes theorem is as follows,

$$\mathrm{P}(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

By Bayes theorem, for given B which has been occurred already one can discover the probability of A happening. Where B is the evidence and hypothesis are A. The hypothesis which is evolved are the independent predictor, assuring that the attribute of one doesn’t affect the other [39]. Therefore, it is known as Naïve.

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

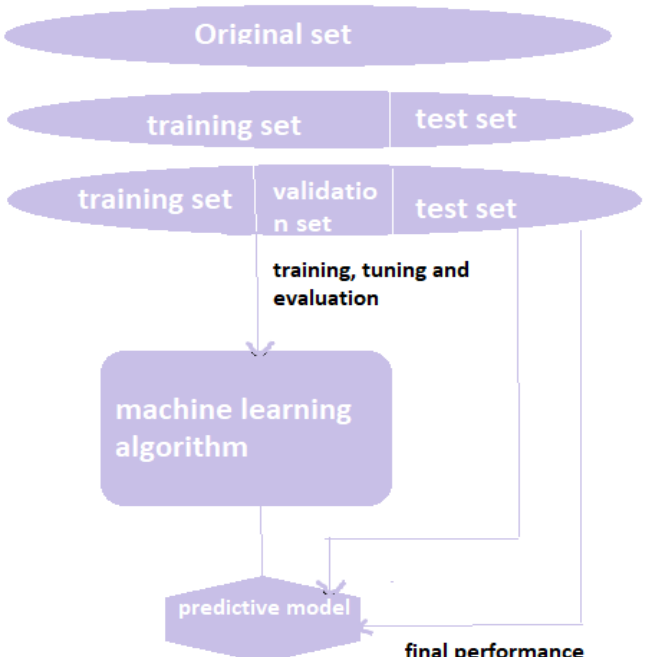

Fig 1: Flow diagram of a decision tree in machine learning

2.Review of the existing Literature

This section provides the existing techniques presented for neuroscience imaging tools in field of medical by empowering the deep learning and the machine learning together. In [2], it shows how fast diagnosis is evaluated having increased in number of dementia disease. While diagnosis of dementia, a deep learning of image analysis has shown a great outcome. For diagnosis of various dementia future extraction of machine learning and deep learning technologies such as neuroimaging MRI, SPECT and PET are used. Conclusion is represented by the performance measures among algorithms. In [3], it represents a clinical classifier acquired with structural magnetic resonance imaging (MRI). Disease such as Alzheimer's, Parkinson's, Autism shows a pattern recognition to be recognized by classifiers [10]. A unified framework of neuroimaging which work as a clinical predictor is assimilated by extraction of machine learning. It represents both classifiers learning and a trait classifier. Feature dimensionality is reduced as per the averaged voxel. Also, network analyses predict the parameters for the upcoming values. Disease patterns are studied once they are fed into machine learning algorithms by enumerating all images. In [4], the brain-computer interface technology fails vigorously on functional network outside of the motor network. During different points, scans of the state-testing functional resonance imaging (rs-fMRI) are collected at, pre-, mid-, post and one-month post-therapy. For this a support vector machine (SVM) classifier is used as mentioned in [24]. This transforms the component-based data to classify each participant into therapy stage. But SVM is not suitable when it comes with large data set and doesn't perform well when data set is noisy.

In [8], assisting the optimal strategies a clinical psychiatry is being translated from neuroimaging.To predict the targets overcoming biases is specially focused by optimizing the

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

complex brain patterns, leading to hikes in translation potential of neuroimaging.For the classification of applications community of machine learning is considered which includes a decision tree. The popularity is measured by producing classification in logical rules where the complex problems are handled. These are easy to compute and can be detected by providing an easier representation.Possibility of future translation is maximized whereas balancing of initial result is done.In the field of clinical translation an inspiring future is viewed where further research and analysis can be done.Packages which are used in machine learning field requires coding that are sci-kit learn learning. In [15], the first goal is to predict the stroke subject measures in the domain of brain-computer interface (BCI) that are applied data-driven assets if functional connectivity (rs-FC) is predicted.The support vector regression models (SVR) of machine learning outcomes are entitled in future stages. Sequential forward goes with the selected procedure narrowed the important search.In the contribution for the evaluation of individual it correlates to an important aided models rs-FC changes with bilateral primary motor. Prediction of outcomes showing high accuracy in non-linear SVR and seeded regions.

In [28], For calculating the probabilities Bayes classification is used. Because of the mass K-nearest neighbor (Knn) the outcome of new dataset is classified as Knn supervised algorithm with Bayes learning method. By varying the k, there's a great scope for k-nearest neighbor classifier. Whereas in [35], just like other technologies like MRI and computed tomography (CT) on neuroimaging strokes can be evaluated. But these two mainly applicable for information on vascular and cerebral health. Small changes in CT and MRI shows the effected region of stroke. This turns to segment and classify the data to overcome the abnormality. The method focused here is a computer aided design (CAD). It's a tool in mammography showing the radiography of chest. The rapid increase in the number of strokes rises a serious concern in the medical field. CAD imaging process reduces the error probability in image datasets. The performance of a system is being measured by checking the factors like precision, specificity. However, evolvement of CAD is still a common concern. Because the state-of-art technology is not being able to cope-up with the newly developed products. For achieving the improvement in CAD, the evolution time for examining the various false positives have been increased. This leads to high accuracy outcomes. In [40], comparing of machine learning algorithm culminates in analyzing the fast performance of different algorithm with classifiers. Based on the factors as loss function, decision boundary, regression function shapes a table of comparison to enumerate. These image pixels are then used for recognition models. To reduce the number of false positive pre-surgical and post-surgical procedures are developed for the accurate timing. It includes specialist intra-variability for correction. Many promising techniques advances these concerns. The rate of False positive is higher during dense diagonal networks. From diffusion weighted imaging the input data gray matter, which is obtained from cortical thickness change in white matter.

3.Machine learning approaches of neuroimaging

There are various approaches for neuroimaging but to choose a classifier wisely for the relevant application is a scheme. In [5], various traditional approaches are predicted with machine learning algorithm such as Random Forest (RF). As an example, by using Ensemble Learning technique random forest has been created based on the bagging algorithm. It combines the output of all the trees by creating as many trees on the subset data hence reducing the problem of overfitting in decision tree. It also improves the accuracy by reducing the variance. Continuous

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

and categorical variables work well with random forest. Also, regressions and classification problems are solved by using Random Forest. Missing values can be handles automatically by Random Forest. It uses rule-based approach and not distance calculation, hence it doesn't require feature scaling. Random Forest is not affected by non-linear parameters, hence outperforming if there is any non-linearity between independent values. It is very stable and robust. The algorithm will not be affected even if there is a new data point introduced. In [22], Neuroimaging datasets for future reduction is a high-resolution neuroimaging image. Using the neuroimaging dataset clinical labels are obtained from the feature reduction. The role of Random Forest algorithm is to precisely envisage the Alzheimer's disease (AD) [36]. With Random forest, one can edify a model with a small number of samples and get better results. In variance, a deep neural network needs more samples for the same level of accuracy. Also, a random forest may not work if the dependent variables considered in the model are linearly related. Hence one must eradicate correlated variable by some other technique. Decision trees are flexible and easy to understand and can be easily debug. They are well suited for classification and regression problems making them suitable for large datasets [36]. It also does well with categorical values as well as predicted values. In the given Fig 2, a decision tree with nodes x1, x2 and x3 travelled iteratively with T(true) and F(false) insert a sort algorithm.

Decision tree only requires a data table, without implementing of a front design it will directly build a classifier. A classifier such as Naïve-Bayes will escalate the performance of decision tree.Gaussian Naïve Bayes used in computers performs quite well with those tasks. It is based on the Bayes theorem.

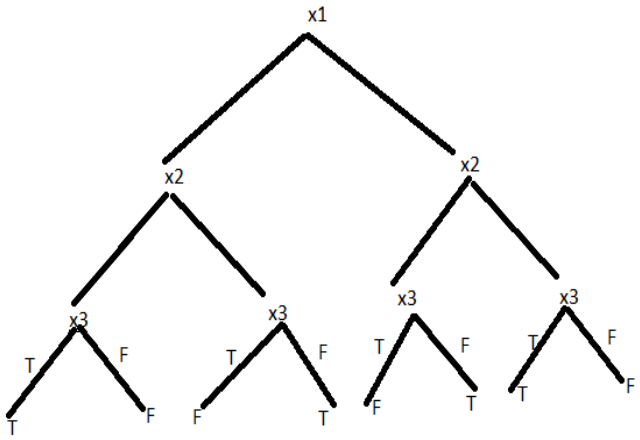

Fig 2: Decision tree with different nodes

A collection of algorithms where all group of algorithms share a standard principle is known as Bayes theorem. In this independent pair of featuresis being classified.With low amount of data as Naive Bayes does very well when all the possibilities are not mentioned in the training data [31]. When it compares to the large amount of data decision tress applies well. The assumption distribution of conditional independence instances is satisfied because a very few instances on leaf ismentioned.The advantage of decision trees is obtained concurrently if the leafs are

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

replaced by Gaussian Naïve Bayes. This classifier is used for constructing a leaf node whereas decision tree learning algorithm method is used for discretizing continues attributes.By applying an entropy-based method, the decision tree algorithm pre-discretizes the dataset.The leaf node at Gaussian Naïve Bayes is handled by ingress to discrete attributes.As the leaf nod is replaced with a Gaussian Naïve Bayes classifier, the algorithm applies post-discretization to build a self-adapting algorithm.

This handles the continuous attributes directly, lessening the negative effect. The decision tree theorem is given below,

Input: Pre-classified instances from training set Y.

Output:Gaussian Naïve-Bayes (GNB) with a Decision tree at a leaf node.

1. X1……..Xn selected test from Xi are of a predictive feature set.
2. According to the subset partition of values into discrete set of intervals, Xi found to be continuous if the values are discovered.
3. If a continuous multi-way split is done in Xi for all possible values, divide the values of Y.
4. Create a leaf node as a labeled class if the descent node belongs to the same level and return.
5. Create a GNB as leaf node if node fulfills the specific halt criterions and return.
6. To match the leading test to a node the process is recursively repeated on parts of Y for each given descent node.

As it has been shown that a random forest is slow in training dataset whereas decision tree is easy to interpret. To conjecture the predictions of the neural network a decision tree is trained, thus numerical and categorical predictor variables is accepted by opening the neural network [7].

In Gaussian Naive Bayes (GNB), let discrete or real valued property X1….Xn and Y be in any discrete variable. The intension to get the probability distribution over possible values of Y is to train a classifier. On the kth predicted value, the expression for the probability that Y will take is by assuming the Xi to be independent. According to Bayes rule, given Y is,

$$P(Y = yk|X1 \ldots..Xn) = \frac{P(Y = yk)\pi iP(Xi|Y = yk)}{\sum jP(y = yj)\pi iP(Xi|Y = yj)}$$

All possible values yj of Y is assumed. If Y is the most probable value, then the Naïve Bayes classification rule is:

$$Y \leftarrow arg\ max \frac{P(Y=yk)\pi iP(Xi|Y=yk)}{\sum jP(Y=yj)\pi iP(Xi|Y=yj)}$$

which simplifies to the following result,

$$Y \leftarrow arg\ max\ yk\ P(Y=yk)\pi i\ P(Xi|Y=yk)$$

One way to construct a simple model is to assume that the data described by Gaussian distribution is with no co-variance. This model can be adjusted by evaluating the mean and standard deviation of the points within each label, which is all required to expound such distribution which is not seen in [5]. The Gaussian generative model shows that each label with larger probability towards the center is the outcome. With this generative model in place for each class, we have a simple method to compute the p(features|L1) for any data point in result and thus we can immediately compute the posterior ratio and can determine which label is the most probable for the given point.

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

4.Clinical/statistical analysis of neuroimaging

Here we represent a review of data analysis of neuroimaging in comparison with different algorithms of machine learning. Publications that uses a structural MRI data mining [30], aimed at two things to construct a classifier that are, (a) regions related to brain disease is being extracted and (b) a clinical state is predicted [10]. Formulation of data matrix is done before proceeding with the main pipeline, as it is beneficial to perform preprocessing of an initial attribute. To represent data in equal level, a certain algorithm is formulated which is usually a scaling operation. Comparison with other models are done below to provide an overview of different ML algorithms.

1) Logistic regression (LR) vssupport vector machine (SVM):
    - SVM can lift non-linear solutions whereas logistic can only linear solutions.
    - SVM linear handles outliers as it derives the maximum margin solution.
2) Decision tree vs k-nearest neighbor (knn):
    - Decision tree cannot derive the significance of feature.
    - Knn is a non-parametric model whereas decision tree is best at categorical values.
3) Gaussian Naïve-Bayes (NB) vs logistic regression (LR):
    - LR is discriminative and Gaussian Naïve Bayes is a generative model.
    - Collinearity is high in LR including variability, validity and reliability as in [27], whereas Gaussian Naïve Bayes works well with all dataset.

LR doesn't work at the circular dataset while GNB could succeed in performing that. Both methods qualify at the rectangular dataset. GNB boundary is quadratic while the LR decision boundary is linear [39]. GNB the circular dataset is applied to give two means in roughly the same position, but with different variances, resulting in circular decision boundary. As the radius increases, the probability of the higher variance classifier increases compared to that of the lower variance. In this case, many of the inner points on the circle are incorrectly classified. The two plots below show a GNB solution with fixed variance. In the plots, the Gaussian Naive Bayes contours represents probability of Naïve-Bayes solution. Gaussian NB solution leads to an axis-aligned covariance in the solution by investigating the variance of a single parameter.

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

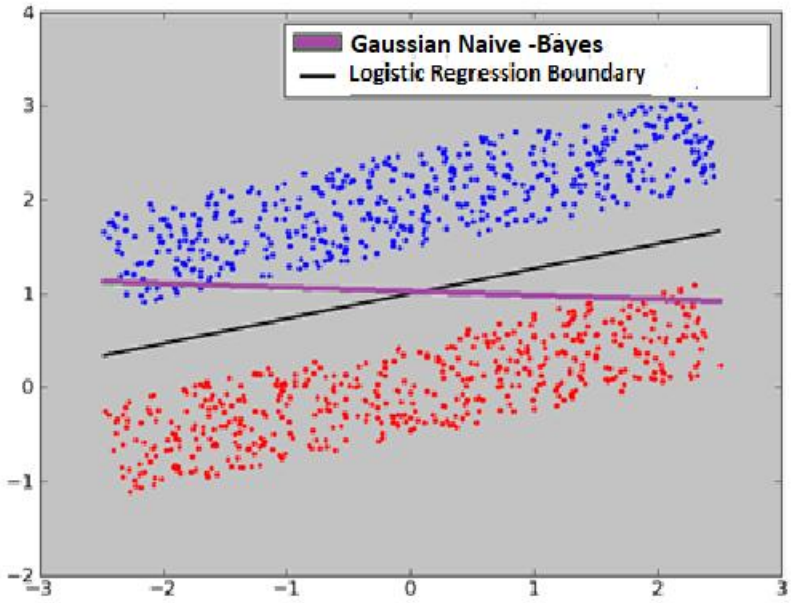

Fig 3: Gaussian Naïve Bayes vs logistic regression contours.

5.Performance measurement

When we obtain any data, a pre-processing and wrangling of data is obtained. To acquire the output probabilities firstly, we provide an effective model.For achieving the better performance, machine learningperformance classification measurement is used i.e. a confusion matrix. Performance measurement are used to evaluate algorithms in machine learning [9]. Likewise, we use confusion matrix for evaluation.

A confusion matrix is a table with four different predicted values and actual values combination. Its output includes two or more classes. This breakdown helps to overcome the limitations by using classification accuracy [30]. Every row represents instances of actual class and column represents instances of predicted class.

Actual values

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

Predicted values	Positive (1)	negative(0)
Positive (1)	TP	FP
Negative (0)	FN	TN

Where the accuracy is predicted by,

$$\text{Accuracy} = TP + TN/TP + TN + FP + FN$$

Here class 1: Positive &
Class 2: Negative.
Terms which are used:
(P)Positive: observation resulted as positive.
(N)Negative: observation resulted as not positive.
(TP) True Positive: observation as positive and it resulted to be positive.
(FN) False Negative: observation as positive and itresulted to be negative.
(TN) True Negative: observation as negative and itresultedto be negative
(FP) False Positive: Observation as negative, but it resulted to be predicted positive.
The confusion matrix shows how any classification model is confused when it makes predictions. It also gives us insight into errors being made by classifiers. Another analysis is done using the concept of independent component analysis (ICA) technique.ICA is a technique to filter a multivariate signal into multi-independent non-gaussian signals. It implies on independence of two random variables which shows uncorrelation between variables. The patterns observed during examining the various neuroimaging is checked with the previous recognized patterns. The matched patterns are then get saved in smart classifiers. Each regular variable is replaced by new one, obtained from subtracting the original mean and dividing by the original standard deviation, creating variables with mean=0 and standard deviation=1. During this phase, for independent component analysis (ICA) or principal component analysis (PCA) reduction of dimensionality steps are conducted [15].

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

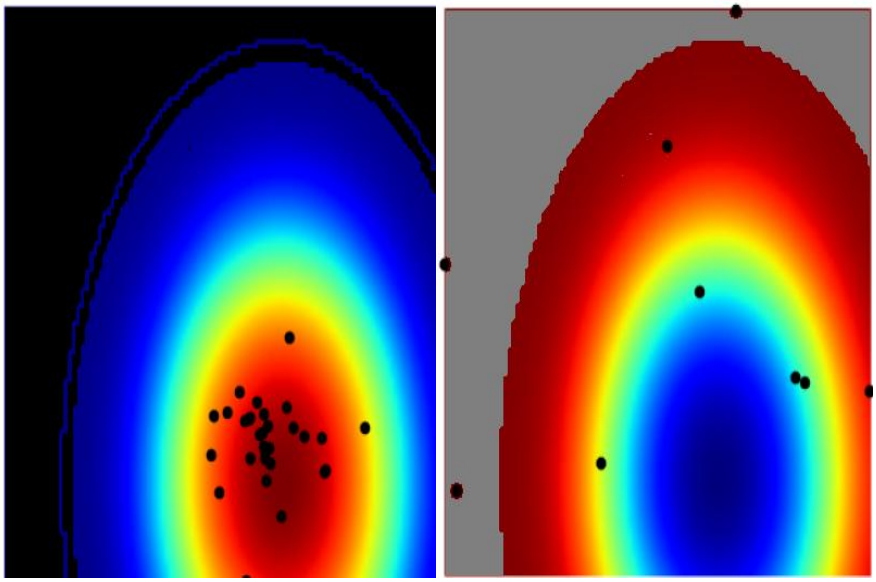

Fig 4: Using Gaussian Naïve-Bayes for ICA a various plot for regression/classification is shown.

6.Major existing challenges and future aspects

Decision trees are poorly generalized into new vector products. In this operation the new sample is assigned to replace the subtrees by leaf nodes to the most frequent class [4]. Even if a single class is related to each leaf node there's a possibility that each class relates to new vector. If some samples are taken from the abnormal class and few sets are takes from the normal class, the result indicates a new vector obtained on the leaf node to be abnormal [34]. The optimized Naïve-Bayes and the independent component analysis has given the accurate result. Using the improved classifier, the resting-state fMRI brain scan structures a current proposed model which counts the extracted features [30]. It is predicted that any difference between the group is the outcome. There are no differences in the performance but there is a difference between the group at baseline using improved classifiers. Some of the main perspective that outlooked from this work includes sample size, test data and testing pipelines.For future work, in order to maximise the information for training process, deep learning with much improved classifiers can be employed. A relevant image sets can be obtained before and after the process. To maximize the training process, the neural network can be trained employing different kernels within network topology. To predict on fMRI scans the training model can be used. Also, it includes the disadvantage of decision tree that they spread out in data applications. They become complex to evaluate because of decision tree.

7.Conclusion

The objective of this research isa process ofanalyzing all the data of neuroimaging obtained from various diagnosed datasetsisto expound the fMRI datasets deployed on the decision tree with improved classifier. The machine learns the recognized data by following the steps of patterns occurred with further self-adapting nature using a classifier. To promote hike in the productivity of machine learning algorithms a confusion matrix was extricated from the brain images data. Upcoming matrix is then fed to machine learning classifiers which includes Decision tree and Gaussian Naïve Bayes. This shows an accuracy which says that predicted data based on testing

ISSN:0975-3583,0976-2833 VOL11,ISSUE03,2020

state fMRI images are correctly detected. Lastly, the performance can be calculated by confusion matrix predicting up to 99% accurately. The purpose of this approaches may prognosis in better clinical applications in the future.

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