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# Effect of Data Preprocessing in the Detection of Epilepsy using Machine Learning Techniques

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Epilepsy is the one of the most neurological disorder in our day to day life. It affects more than seventy million people throughout the world and becomes second neurological diseases after migraine. Manual inspection of seizures is time consuming and laborious task. Nowadays automated techniques are evolved for detection of seizures by means of signal processing or through machine learning techniques. In this article, supervised learning algorithms are applied to the EEG dataset and performance are measured in terms of Accuracy, precision and few more. Machine learning algorithm plays a vital role in classification and regression problem in the past few decades. The most important reason for this is a large set of signal or data are trained and the test signals are evaluated using training network. To get the better accuracy, the input data are first normalized carefully. The various normalization techniques applied in this article are Z-Score, Min-Max, Logarithmic and Square Root Normalization. For simulation purpose, Electroencephalography (EEG) signal from UCI Machine Learning Respiratory are used. Dataset consists of 11500 patient details with 5 different cases and each signal are recorded for the duration of 23 seconds. Spider chart is used to show the metric value in detail. It is observed from the result that supervised learning algorithm yields a better result compared to logistic and KNN (K-Nearest Neighbor) algorithm at high iteration.

**Keywords**: Classifier, Convolutional neural network, Normalization, Precision, Regression

## Introduction

Epilepsy is the one of the most neurological disorder in our day to day life. It affects more than seventy million people throughout the world and becomes second neurological diseases after migraine. The important characteristics of Epilepsy[1] are abrupt and repetitive seizures, loss of consciousness, staring spell, uncontrollable jerking movements, and psychic symptoms like fear, anxiety and déjà vu. In human brain, seizure happens when a burst of electrical impulses exits their normal limit. These impulses create uncontrollable storms in the neighboring area and causes convulsions. Researchers can monitor these abnormalities through Electroencephalogram (EEG) signal of a patient.

Recording of EEG signal[2] will be carried out by two methods namely intra-cranial and scalp recording. In the first method, electrodes are placed under the scalp and electro movements of neurons will be read out. The advantage of this method is it contains higher frequencies information for further analyze purpose and it is free from artifact. The second method for recording EEG is scalp recording. It is non-invasively and prone to signal attenuation and external noise due to the lots of electrode connection. In terms of easy to use and cost effectiveness, it is advised to prefer scalp recording rather than intra-cranial method, since there is no need for surgery requirement.

Artifact plays a vital role in the EEG recoding[3] and also in the process of prediction of seizure detection of the patients. The most important types of artifacts are Electromyography (EMG), Eye movement and white noise. The electrical movement of skeletal muscles is recording by means of EMG signal. Basically it interfaces with the brain data and cause the contamination of EEG signals. Therefore it is necessary that whenever the recording of EEG data was done, a proper filtering mechanism is required to overcome this type of issues. The second and foremost Artifact is eye movement. The movement of eye during the EEG recording also will interfere with the EEG data, making the technician to predict the detection of seizure signal. White noise is the third artifact, this is due to the improper interfacing of instrument with the electrodes.

To overcome the artifact issue and to avoid the manual inspection of seizures, nowadays automated

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techniques are evolved for detection of seizures by means of signal processing or through machine learning techniques. In the signal processing method, EEG signals are processed and features like signal frequencies, statistical parameters are evaluated through which we can predict the presence of seizures.

On the other hand, a set of known seizure datasets are training by the different classifiers networks. Prediction of seizure in unknown EEG signals is evaluated through the trained networks and Convolution Neural Network (CNN)[4] based seizure detection was developed. The EEG signal from each probe is converted into 2D images and then all 2D images are combined as 3D images. 3D kernels are applied along with CNN for better seizure detection task. Authors have compared their results with the traditional and 2D CNN machine learning Techniques. The accuracy achieved by the 3D CNN architecture is 92.37% which is 3% higher than the 2D CNN method. Classification of Alzheimer's patients using Supervised learning algorithm[5], unsupervised learning algorithm[6], TSK fuzzy system[7] was studied in detail. Study on medical image analysis using deep learning[8] was carried out.

To detect the seizure accurately and in time, authors proposed a novel Deep Bidirectional Neural Architecture (DRNN).[9] It is modified version of Recurrent Neural Networks (RNN) wherein the information flows in bidirectional and enables the researcher to make use of past and future content for detection of seizure. They also proposed a unique mapping between the EEG electrode signal and DRNN. Seizure detection using wavelet[10], adaptive wavelet packets[11] based approach and object detection using RNN[12] was studied in detail. To analyze the health parameters of underwater animals, authors used dolphin clicks[13] signals as carrier and retrieval of the signal was done successfully even with high intersymbol interference in water medium.

Recurrent Neural Networks with Long Short Term Memory (LSTM) architecture[14] was proposed by the authors. This architecture exploits completely the temporal dependency of EEG signal and uses of fully connected layer on top of the LSTM layer. A softmax layer is connected at the end of architecture for the training of EEG signals and detection of seizures. The various other techniques applied for seizure detection are Hilbert marginal spectrum analysis[15], complex-valued classifiers[16] and weighted-permutation entropy.[17]

Stacked Sparse Auto-Encoder (SSAE)[18] architecture was developed for the seizure detection. Features are extracted by 3 hidden layers with sigmoid activation functions. The classification is carried out by the softmax layer. The number of units in the three hidden layers is 300, 250 and 150 respectively and iterated for 150 times. Dataset from university of Bonn was used by the authors for the experimental purpose. It consists 100 single channel EEG segments of five different subsets labeled from A to E. Subset A and B is EEG signals of healthy volunteers. C and D subsets are hippocampal formation of brain and epileptogenic zone. Finally subset E was recorded from epilepsy seizure signal.

Automatic detection of seizure using non-linear dimension reduction method[19], flexible wavelet with fractional dimension approach[20] and pca-csp approach[21] was carried out. Authors demonstrated automated seizure detection[22] using deep learning on power spectral density of EEG signals. Weka software was used to test the multilayer perceptron neural network with one, two and three hidden layers. The result concludes that there arise an over-fitting problem when the number of hidden layers increases. Artificial Neural Network (ANN)[23] is applied to analyze the health parameters of marine mammals underwater medium. Modelled EEG was transmitted and received back successfully without any error using ANN with 20 hidden layers. Applied tunable q wavelet transform[24] was applied for the classification of Epileptic signals. 1D CNN[25], KNN classifier[26] and LSTM[27] networks are applied to improve the detection of seizures.

Pyramidal 1D CNN model[28] was proposed by the authors with fewer learnable parameters. In this method, the EEG signals are segmented by sliding window and then pass through the Pyramidal 1D CNN subsets with different base. The final decision is taken from the majority votes from the subsets. The model was evaluated for binary detection (presence of seizure or not) and ternary detection (ictal/normal/ interictal).

Modified LSTM[29] deep learning was proposed to report the vanishing gradient problem. Three gates namely input, forget and output are included in the LSTM Network to keep the necessary information and remove the unwanted data. It has advantage over CNN in various applications like decision making prediction, emotion recognition and estimation of confusion matrix. To reduce regression error rate convolutional code[30] was successfully applied and its performance was evaluated. To calculate the loss function gradient, Back-Propagation (BP) is applied in the CNN Network.[31] BP is used to determine the error loss and feedback to the CNN to obtained updated weights of the network. The authors used 10 percent of data for validation and 90 percent for training and obtained the accuracy of 88%.

Authors performed a comprehensive analysis for Interictal epileptic discharge (IED) detection CNN based trained filters.[32] Deep convolutional neural network[33] was trained for the seizure detection on neonatal EEG signal. Neonate EEG cannot be done before the baby was born, so the authors applied leave one patient our cross validation method for the mother EEG signals. Seizure was predicted using Area under the receiver characteristic curve.

In this article, an EEG dataset is download from UCI Machine Learning Respiratory. It is free link wherein vast medical dataset such as EEG, X-ray, MRI images and all sort of biomedical application signal are available. For our study purpose, Seizure EEG signals are downloaded. It consists of Dataset consists of 100 files with 5 different classes each recorded for 23 seconds. All EEG signals are pre-processed and different supervised machine learning algorithms are applied. Parameters such as Accuracy, Sensitivity, Recall are determined for all algorithms and its comparison are discussed in detail in the conclusion section.

## Methodology

Machine learning, algorithm plays a vital role in classification and regression problem in the past few decades. The most important reason for this is a large set of signal or data are trained and the test signals are evaluated using training network. To get the better accuracy, the input data are first pre-processed carefully and this technique is referred as Feature Scaling or Normalization.

In most of the classifier problems, the data classes are differentiated in terms of the Euclidean distance. To meet this objective the input data are normalized. The secondary objective to do normalization is that the gradient descent converged faster than the un-normalized data. The various feature scaling discussed in this article are Min-Max, Z-Score, Logarithmic, Square Root and RGB Normalization. One of the simplest scaling in data pre-processing step is the min-max Normalization. In this method, the data re rescaled to the range from 0 to 1. It is described mathematically as below.

$$X' = \frac{X - Min(X)}{Max(X) - Min(X)} \quad \dots (1)$$

where x is an original value, X' is the normalized value. The EEG from the electrode will range in terms of millivolts. Using this method, the features of the EEG is rescaled between the range [0 1]. Second normalization technique which is widely used in the fields like Artificial Neural Networks and Support Vector Machine application is the Z-Score Normalization. To process image or pixel value signals, this method is best suited to attain better classification. The original signal is subtracted by its average value and that difference is divided by the standard deviation of the signal and it is illustrated by the Eq. 2.

$$X' = \frac{X - Avg(X)}{\sigma} \quad \dots (2)$$

where X is the original feature vector, Avg(x) is the mean of that feature vector, and $\boldsymbol{\sigma}$ is its standard deviation. The data from the application like psychosocial and biomedical will be in skewed form. An easy way of representing this type data is logarithmic normalization. It is also available in major statistical software packages. The primary advantages of the logarithmic scaling are reduce skewness and variability of data. Root mean square value of the signal is taken as scaling factor in the case of Square Root normalization. In the final scaling method RGB normalization, the signal is scaled in the range between 0 and 255.

The ultimate benefit of this method is that the signals can be converted into image format and advanced classifier like CNN, RNN and pre-trained neural networks can be trained and classification can be done in very effectively. In this paper, the EEG signals are taken from UCI Machine Learning Respiratory, center for intelligent and machine learning systems.

The methodology adopted in this article is demonstrated in terms of various steps as below:

**Step 1:** Read the EEG data (11500 patients with 5 different classes)

**Step 2:** Normalization of data (Min-Max, Z-Score, Logarithmic and Square Root)

**Step 3:** Divide the normalized data (80% for training and 20% validation)

**Step 4:** Set the parameter values for classifier

**Step 5:** Train the classifier using training dataset

**Step 6:** Apply the trained classier over the validation dataset

**Step 7:** Determine the performance metrics values (Accuracy, precision, F1 score, AUC, Specificity, recall)

**Step 8:** Comparison of the performance of classifier in terms of performance metrics.

As a first and foremost step, the patient data from excel sheet is read and it consists of various artifacts. To overcome the artifact free data, the normalization of dataset is done as the second step. In this stage, the data are normalized in six different ways and it is ultimately useful for the classifier to distinguish five different classes of the EEG datasets. Normalized dataset is divided for two purpose, one will be used for the training the classifier and second one for validation the performance of classifier. Trained classifier is applied to the validation dataset and evaluation metrics such as Accuracy, precision and other parameters are evaluated. In the final stage, the comparison of performance metrics of all classifier will be done.

Dataset consists of 100 files with 5 different classes each recorded for 23 seconds. The different cases described in the dataset are
Case 1: EEG signal from Epileptic patient.
Case 2: EEG signal from brain tumor patient.
Case 3: EEG signal from healthy person.
Case 4: EEG signal of a person when eyes are closed.
Case 5: EEG signal of a person when eyes are opened.

The representation of a sample signal from UCI dataset is illustrated in Fig. 1. Out of these four cases, only epileptic signal is taken out and four different rescaling methods namely positive, Z score, Logarithmic and square root are applied and it is illustrated in the Fig. 2. It is observed from Fig. 2 that normalization is also helpful in reducing the memory size as the signal is rescaled to smaller values

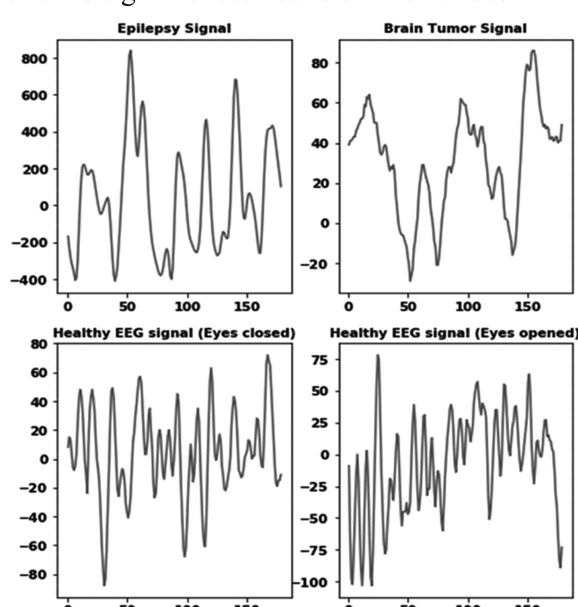


Fig. 1 — Representation of sample signal from UCI dataset

## Machine Learning Models and its Parameters

Machine learning is a technique, allows computer to perform a certain task by providing an example. For example, in the case of traditional programming model, a program is written for given input to get a desired output. In machine learning technique, computer itself gives the program for the set of input-output data. Machine learning consists of two major phases. In the first phase, a model is trained from the collection of dataset. Then the trained model is tested in the second phase with the unknown dataset and its evaluation parameters are analyzed. It is very much useful in various applications like Language translation, face detection, stock prediction, drug design, self-driving cars and so on.

The three major classification of machine learning are supervised learning, unsupervised learning and reinforcement learning. Classification or regression model comes under the category of supervised learning. In this, model is trained with the labelled data and test data is taken to predict which category it belongs to. In unsupervised learning, the model is trained and tested with the unlabelled data. Finally in the last classification reinforcement learning, a series of action is carried out to attain the learning process. Typical examples include self-driven cars, drones, playing games and warehouse robots. Machine learning algorithms comes under any one of following categories

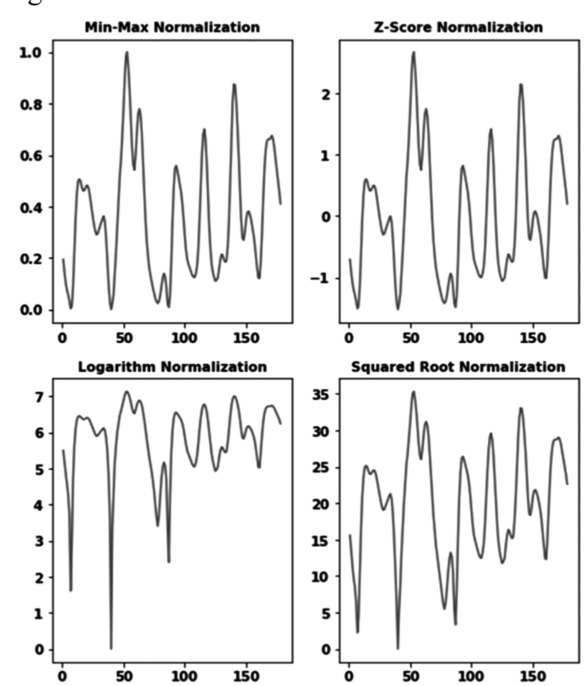


Fig. 2 — Representation of Feature Rescaled Epileptic signal

- ✓ Artificial neural networks (multi-layer perceptrons)
- ✓ Graphical models (Bayesian networks)
- ✓ Generalized linear models (logistic regression)
- ✓ Instance-based learners (K-nearest neighbors)
- ✓ Tree or rule based models (decision trees)
- ✓ Support vector machines (linear SVM, RBF-kernel SVM)
- ✓ Ensembles (Random Forest)

Stochastic Gradient Descent (SGD) algorithm is a most popular optimization technique in machine learning. It is an iterative method used to minimize the cost function. To train the data in this algorithm few samples will be taken rather than the entire dataset. By doing so, this algorithm gives less computational process compared to batch gradient descent method.

K Nearest Neighbour (KNN) classifier has no model to design, rather it will calculate the distance between input data with the reference data. the classification is done by comparing the calculated distance with the trained dataset. The various distance measure are Euclidean distance, Hamming distance, Manhatten and Minkowski distance. Euclidean distance square root of sum of the squared difference beteen the input with the refeene. Hamming distance calculate the distance between two binary codes. KNN is also referred as lazy and non-p-arametic since no learning and no assumption about the function. The working flow is KNN is as follows.

1. Load both training and test dataset
2. Choose a K value (K must be a interger)\
3. Evaluate the following step for all test dataset

a. Distance is measured between the test data with each row of training datset.
b. Sort the distacne in ascendign order'
c. Pick the first entry and obtain the label from the trained dataset.
d. For classification problems, mode of the K label is used.

Naïve bayes classifier is based on the probabilistic hypothesis value. It classify the problem from the given prior knowledge. This algorithm will be well suited for multi class and binary class problem.

Bayes classifier is represented by two types of probabilities such as class probabilities and conditional probabilities. Former one is the each class probabilities in the training dataset and latter one is the probabilty of test data for given trained dataset.

Decision tree classifier is one of the members in the supervised learning algorithm. It can be used for both classification and regression problem to attain the optimal result. The prediction of correct classes is done by the simple decision rules concluded from the prior training data. For a given dataset, prediction of correct classes start from tree root attributes. Depending on the comparison, the decision will be carried out either continue with the current branch or jump to next branch.

There are two types of decision tree namely categorical and continuous variable decision tree. Former one has categorical target variable and latter one has target variable as continuous type. Points to be considered while creating decision tree classifiers are

- Entire training dataset is considered as the root in the beginning stage**.**
- If the dataset is continuous type, then it needs to discretize in prior to model build.
- On the basis of classes, dataset are distributed recursively.
- Using statistical approach, placement of internal node of the tree and root will be done.

The mechanism of decision tree is termed as sum of product representation or Disjunctive Normal Form. For a given class, same branch ending with same class is known as product values, whereas ending with different class is known sum values.

Random forest classifier is a branch of decision tree classifier. It is collective learning algorithm to attain better predictive performance, which combine the multiple algorithms. While building the model, dataset are sampled randomly for training and validation purpose. During splitting of nodes, features are considered as random subsets. Bagging technique is applied for the prediction of classes. Entire validation dataset is divided in to N samples by sampling randomly. The model is applied to all samples and finally prediction is carried out by combining the voting.

In order to perform any machine learning algorithms for a particular tasks, the researchers have to concentrate on three important components namely representation, Optimization and Evaluation. For a given set of data, proper set of rules need to framed first. For rule based model, greedy search or combinational search can be used. Non convex optimization will be useful for neural networks based model. For SVM and Logistic regression, constrained and unconstrained convex optimization was applied. Then we need to choose appropriate measuring parameter to evaluate the model. Foremost measuring parameter is the accuracy, which tells the number of correctly classified instances.

The other available parameters to evaluate a model are Area under Curve (AUC), F1 Score, Precision, Recall and Specificity. In the article, eight different classifier namely Logistic regression, Single Graadient Descent, KNN Classifier, Gaussian, random Forest, Decision Tree and Gradient Boosting Classifier are evaluated on the EEG dataset for detection of epilepsy signal and its corresponding parameters are evaluated and analyzed.

## Results and Discussion

For simulation purpose, EEG signal from UCI Machine Learning Respiratory are used. Dataset consists of 11500 patient details with 5 different cases and each signal are recorded for the duration of 23 seconds. These input signals are first preprocessed by four different methods viz., Min-Max, Z-Score, Logarithmic, and Square Root Normalization. The objective of this article is to apply machine learning algorithm to differentiate the epilepsy signal from other signals. In the dataset, epilepsy signals are numbered as 1 and other classes namely as 0. The preprocessed data is trained using different classifiers.

The various classifier applied are Logistic regression, Single Graadient Descent, KNN Classifier, Gaussian, random Forest, Decision Tree and Gradient Boosting Classifier. During the training phase, 90 percent of data are used for training purpose and the remaining 10% of data are used for validation purpose. The first and foremost binary classification is the logistic regression. The output of this regression transformed to a probability value using sigmoid function. Predictions of the binary class are done by the maximum likelihood estimator. Classification of EEG epilepsy signal is carried out by the logictic regression and its metrics values are evaluated and displayed in the Fig. 3 for different data processing techniques. It is observed that evaluation parameters gives a better result for logarithmic and square root data preprocessing compared to other types.

In Stochastic Gradient Descent (SGD) algorithm, the sample training data are selected randomly for every iteration to produce better result. The main disadvantages of this algorithm, it is noisier and requires larger iteration to attain minimal cost function. The performance of SGD classifier on the EEG dataset is shown in Fig. 4. Log loss is taken with the alpha value of 0.7 and it is observed it yields lower accuracy for all data preprocessing. For square root preprocessing method, it gives high Specificity, Accuracy and Precision still other parameters like F1 score, recall and AUC are not up to the desired level.

Performance of KNN classfier in the classificationof EEG signal was carried out by considering the K value of 5 is taken and all the perfomrnace metric value such as accuracy, percision, F1 score and all other parameters are evaluated and displayed in the Fig 5. It is observed from the Fig. 5 that KNN classifer outperforms compared to other classifiers. It yields vlaue of more than 0.7 irrespective of the type of data preprocessing. Logarithmic, square root and positive shifted normalization gives

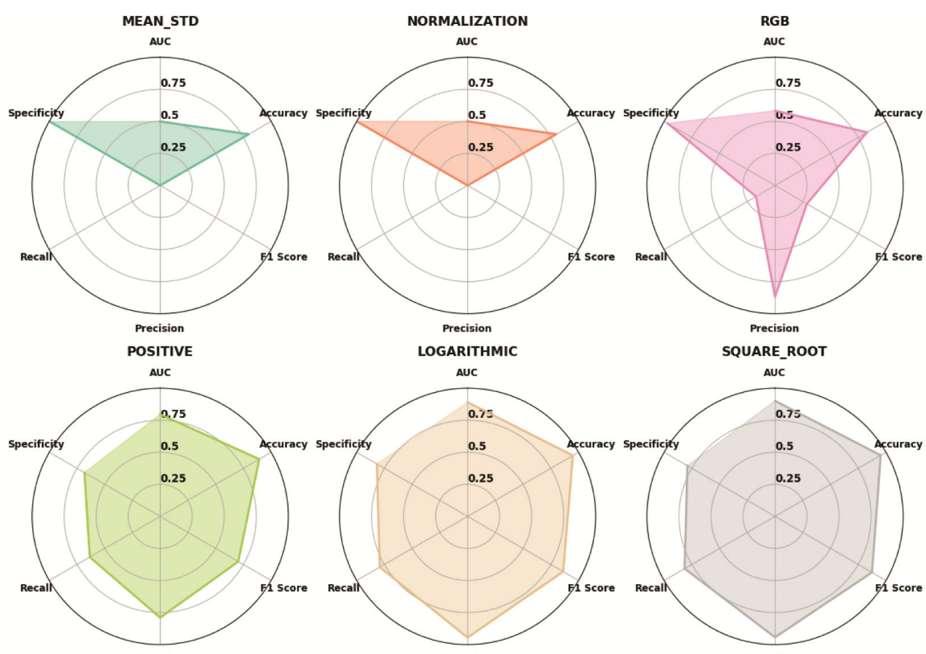


Fig. 3 — Logistic regression

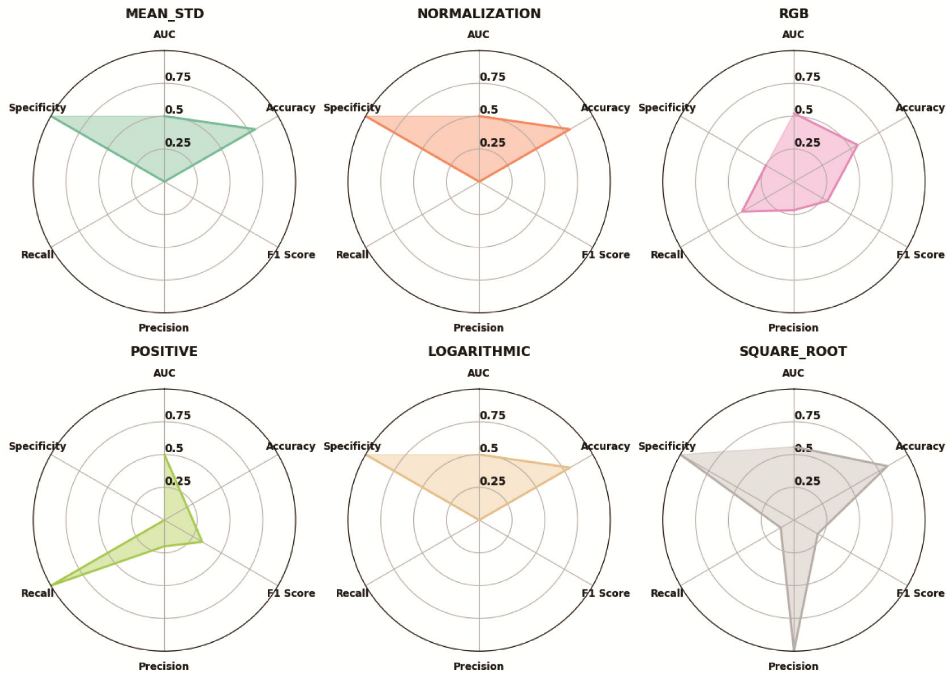


Fig. 4 — SGDC Classifier

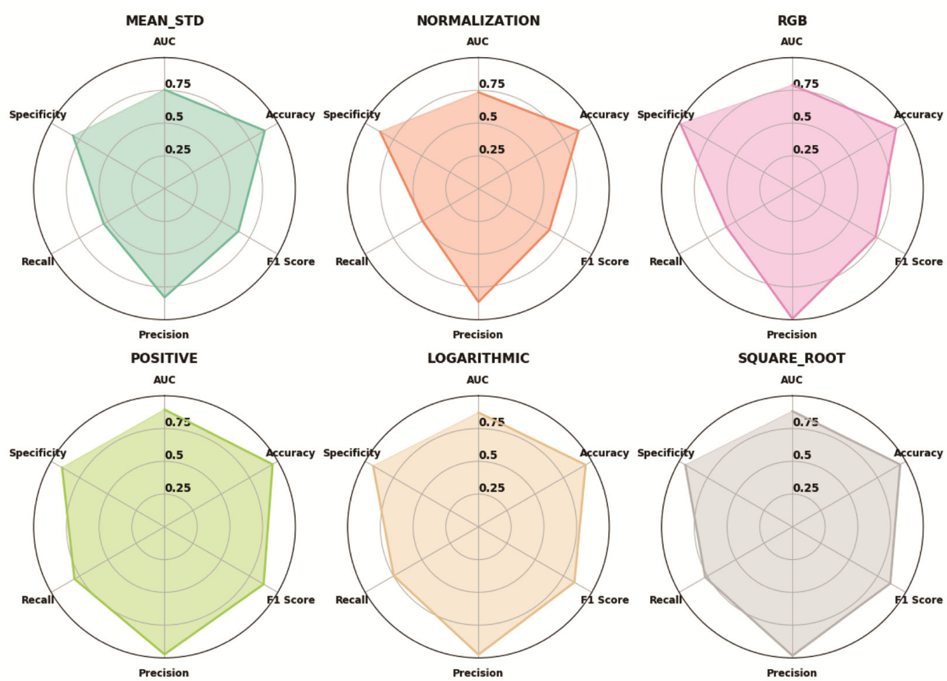


Fig. 5 — KNN Classifier

better result compared to the other three normalization methods namely RGB, Z-Score and Mean_STD.

In Bayes classifer, in addition to probabilitic value statistics value such as mean and standard deviation also included as the real valued attributes and it is referred as gaussian naïve bayes classifier. This classifier works well except the two normalizaion methods Mean_STD and Z-score and it is shown in Fig. 6. For other nomralization mehods, all the metric parameter yields a value more than 0.7

Decision tree classifier is one of the members in the supervised learning algorithm. It can be used for both

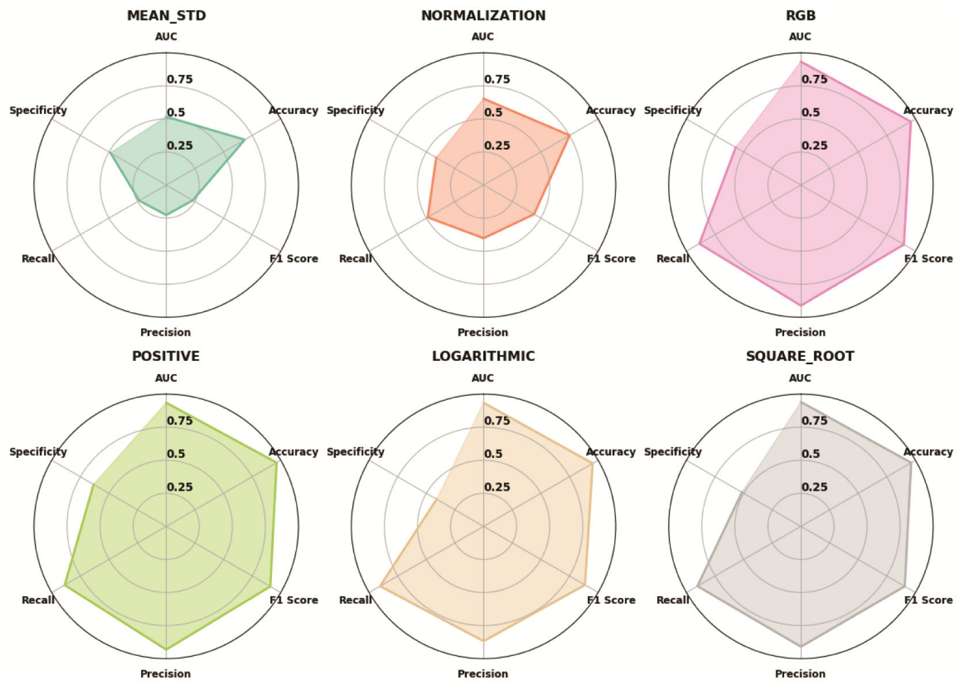


Fig. 6 — Gaussian Classifier

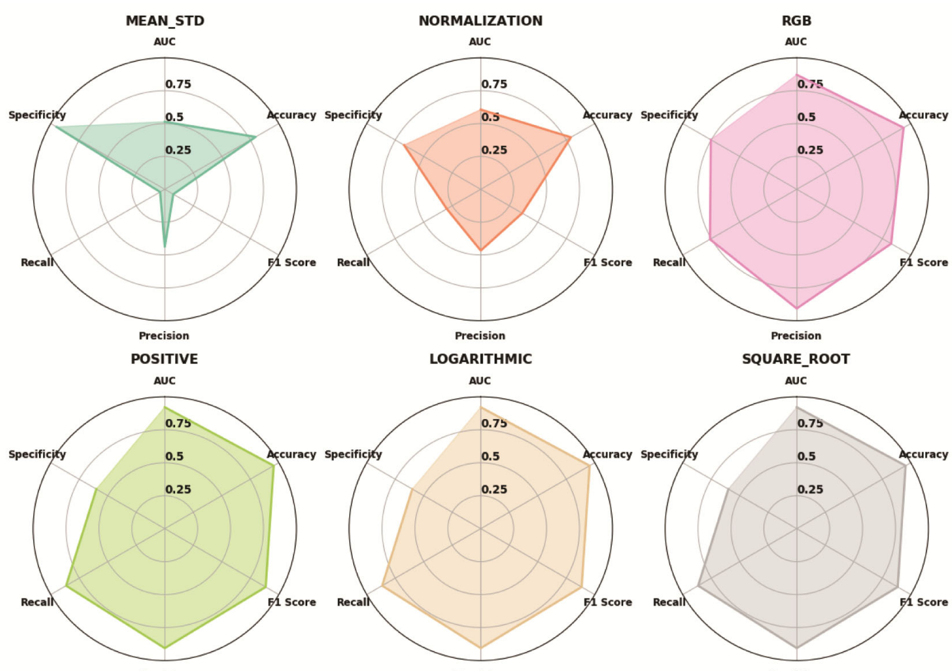


Fig. 7 — Decision Tree Classifier

classification and regression problem to attain the optimal result. Random forest classifier is a branch of decision tree classifier. It is collective learning algorithm to attain better predictive performance, which combine the multiple algorithms. Bagging technique is applied for the prediction of classes. Entire validation dataset is divided in to N samples by sampling randomly. The model is applied to all samples and finally prediction is carried out by combining the voting.

The maximum depth tree of 10 is considered for the simulation. In Fig. 7 and 8 the performance measures of decision tree and random forest classifier

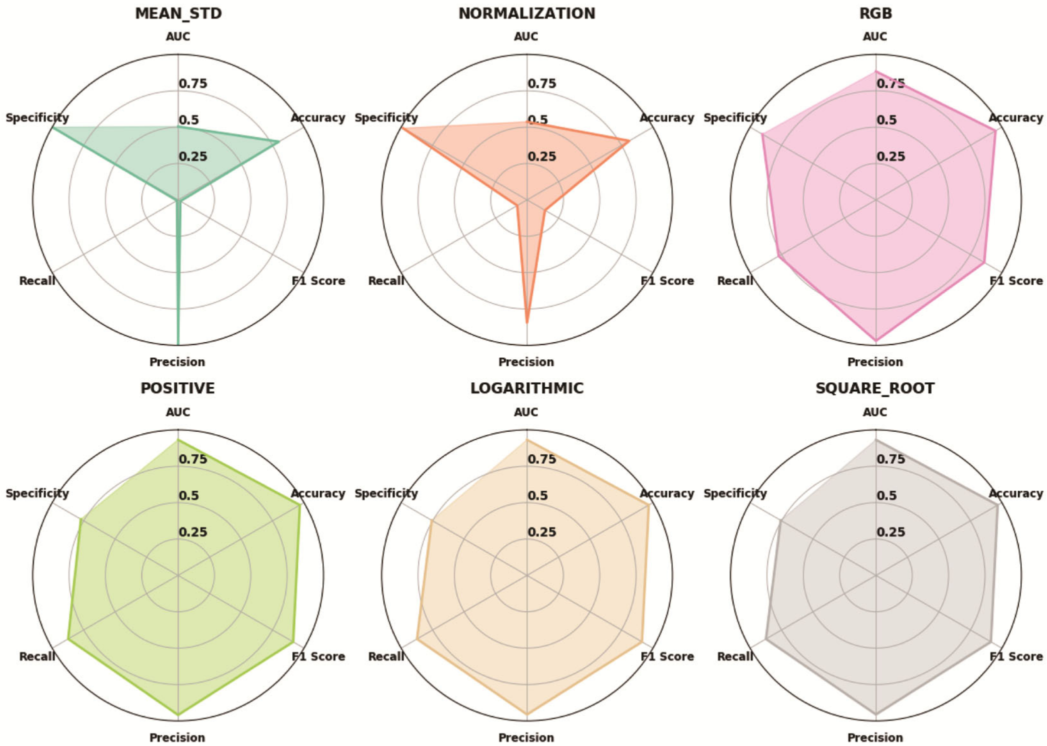


Fig. 8 — Random Forest Classifier

are shown. Like previous classifier these two classifiers also yields better accuracy and other metric value for square root and logarithmic normalization techniques.

Basically accuracy of a machine learning algorithm is improved in two different ways either by applying boosting algorithm or by investigating the features of dataset. The various boosting algorithms available in machine learning are Gradient boosting, Gentle Boost and XGBoost. Boosting technique is slightly different from bagging technique, in which selection of sample data are done intelligently. This will reduce the hardness of prediction of class during validation process. The advantage of this algorithm is to find the weak classifier and enhance its capability to predict the correct class.

The various steps involved in gradient boosting algorithm

1. Assume learning rate
2. Acquire a weak classifier.
3. Update population distribution
4. Find the next learner using step 3
5. Iterate step 1 to 4 till hypothesis is found.
6. Determine weighted average from all the learners to classification the class.

In any machine learning techniques, noise, variance and bias are the three major parameters in differentiating the actual and predicted values. Ensembling technique is the one which make use of the mean of all predictions for classification problems. It is further classified into Bagging and Boosting. In bagging, training dataset are chosen randomly so that the model will have different observation depending on the bootstrap process. This will reduce error by minimizing the variance. Example of this process is Random Forest classifier.

Boosting is slightly different from bagging in which the predicted classes are done sequentially rather than independently. Here the observations are chosen based on the error rather than bootstrap process and best example for this classifier is gradient boosting. The various advantages are reduces bias and variance. Gradient boosting classifier is applied to the EEG database and its performance is evaluated and illustrated in Fig. 9. Maximum depth of 10 and 100 estimators are applied during simulation. It produces similar result as the random forest classifier.

Extra tree classifier is a class of ensemble learning method based on decision tree. It uses random subsets features and builds multiple trees. Nodes are split randomly but not best one and don't make use of bootstrap process. It is also named as Extremely Randomized tree and has low variance. In the simulation, minimum sample leaf of 3 and minimum

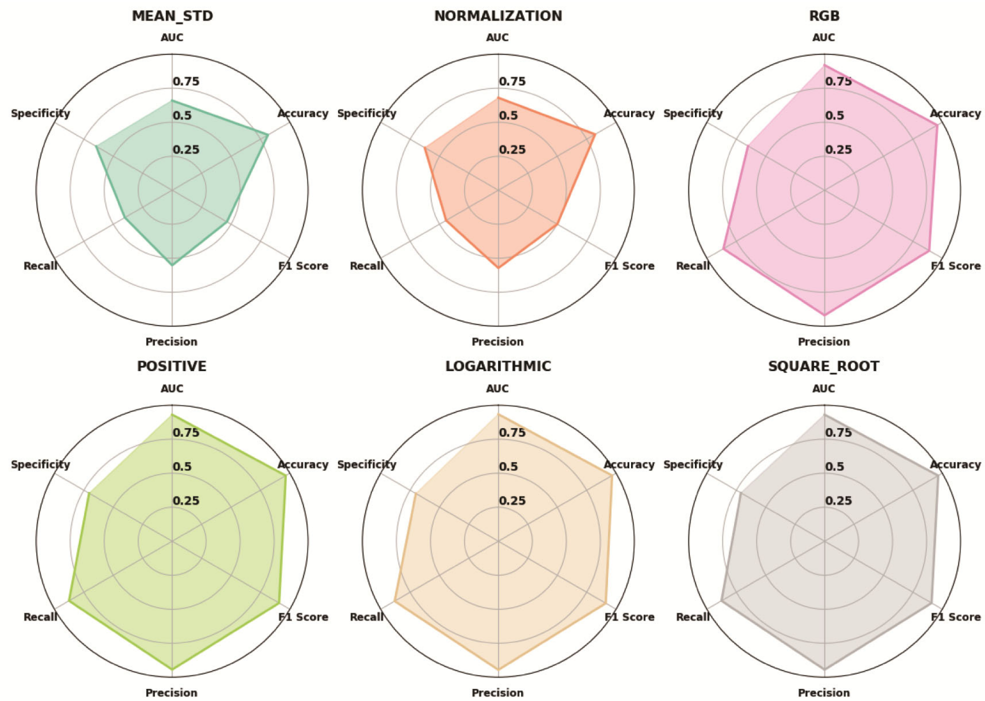


Fig. 9 — Gradient Boosting Classifier

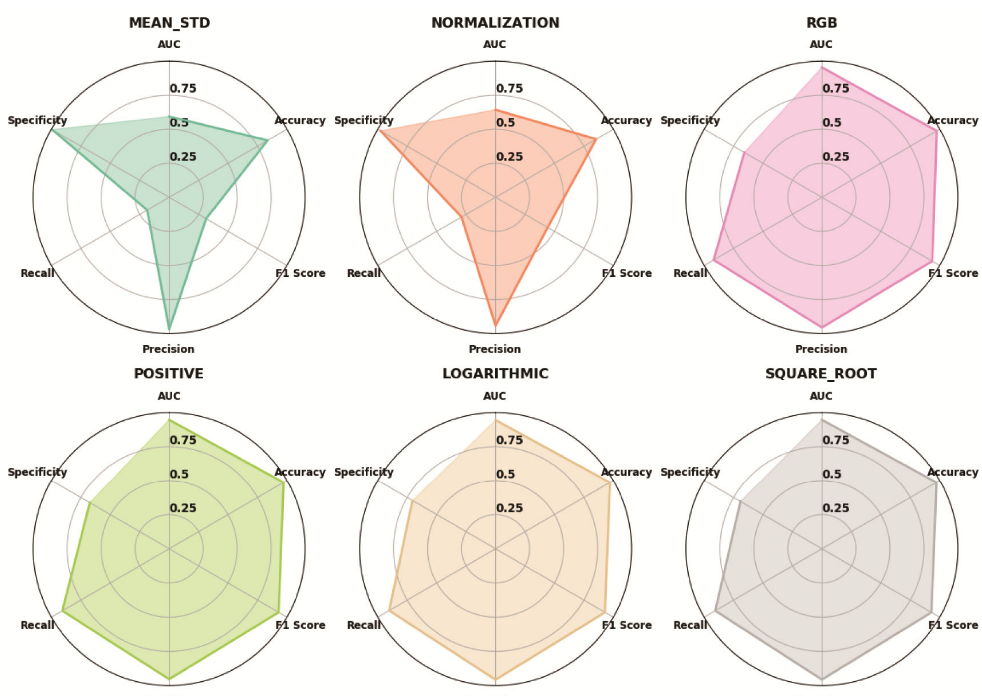


Fig. 10 — Extra Tree Classifier

sample split of 20 are considered and its metric values are evaluated and shown in the Fig. 10.

The accuracy is compared for the chosen classifiers and it is illustrated in Fig. 11. Iteration value of 1 to 200 is considered for logistic regression and Gradient Descent Algorithm. For other supervised algorithms, maximum depth values from 1 to 200 are taken.

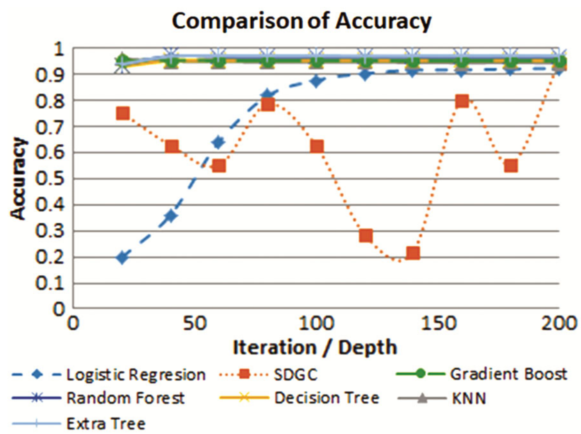


Fig. 11 — Comparison of Accuracy

## Conclusions

It is evident that supervised learning algorithm gives better result compared to Gradient descent and logistic regression at lower iteration. It also shows that for iteration more than 150. Logistic regression performs well on par with the supervised learning algorithm. As there are more iteration values and maximum depth size is required to yield better result, we can apply some pre-trained networks like Alexnet, Googlenet for the EEG classification problems.

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