Revealing Brain Tumor Using Cross-Validated NGBoost Classifier

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Research Article

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Abstract

Brain is the most complicated and delicate anatomical structure in human body. Statistics proves that, among various brain ailments, brain tumor is most fatal and in many cases they become carcinogenic. Brain tumor is characterized by abnormal and uncontrolled growth of brain cells, and takes up space within the cranial cavity and varies in shape, size, position and characteristics viz., can be benign or malignant, which makes the detection of brain tumor very critical and challenging. The vital information a neurologist or neurosurgeon needs to have is the precise size and location of tumor in the brain and whether it is causing any swelling or compression of the brain that may need urgent attention. This paper exploits ensemble strategy based Machine Learning (ML) algorithms for reveling brain tumors. NGBoost algorithm along with 5-fold stratified cross-validation scheme is proposed as classifier model that automatically detects patients with brain tumors. The proposed method is implemented with necessary fine-tuning of parameters which is compared against ensemble based baseline classifiers such as AdaBoost, Gradient Boost, Random Forest and Extra Trees Classifier. Experimental study implies that proposed method outperforms baseline models with significantly improved efficiency. The interfering features those have impact on brain tumor classification are ranked and this ranking is retrieved from the best classifier model.

Introduction

In today's world, computer aided technology is touching every sphere of human life ranging from communication, smart systems and even medical diagnosis. One of the most challenging tasks in today's medical disease analysis is brain tumour detection from dataset containing features related to brain disease. Brain is the most complicated and delicate anatomical structure in human body. Statistics proves that, among various brain ailments, brain tumor is the most fatal and in many cases those tumor become carcinogenic i.e. brain cancer. Brain tumor is characterized by an abnormal and uncontrolled growth of brain cells, and takes up space within the cranial cavity. It varies in shape, size, position and characteristics viz, can be benign or malignant, or even spread to different parts of brain and body, which makes the detection of brain tumor very critical and challenging [1]. Using Machine Learning (ML) approaches, early prediction of any diseases can be performed accurately. This paper aims to predict whether a patient can have tumors in brain or not. ML is subfield of Artificial Intelligence (AI) that enables automatic learning of systems without being explicitly programmed. The aim of ML is to facilitate self-learning of a system by gathering knowledge from past experience. This paper exemplifies the use of ensemble based [2] ML techniques for brain tumor detection. The reason of using ensemble based techniques is to produce improved accurate results over single classifier model. Ensemble techniques are known to be as meta-algorithms that assemble decisions from multiple base models into single predictive model [2]. Boosting is a technique that produces ensemble model which is implemented in this paper. Natural Gradient Boosting (NGBoost) [3] algorithm followed by 5-fold stratified cross-validation methodology is implemented as proposed classifier that detects brain tumor abnormalities. This method

is compared against other ensemble algorithms such as AdaBoost [4], Gradient Boost [5], Random Forest [6] and Extra Trees [7] classification techniques. These classifiers accept numerous variables extracted from MRI images. The features those have impact on obtaining the best possible predictive results are also described in this paper.

Related Works

Computer aided detection of brain tumors, stroke lesions, haemorrhage lesions, and multiple sclerosis lesions are the most difficult issues in field of abnormal tissues segmentations because of many challenges [8]. The brain injuries are of varied shapes and also distort other normal and healthy tissues structures. Intensity distribution of normal tissues is very complicated and there exist some overlaps between different types of tissues [9].

Recently, e-health care system based on information technology can help better health care support to the patient. Brain tumour is due to abnormal growth of cells within the brain and it is life-threatening disease for human [10]. It hampers proper brain function so proper treatment is necessary at an early stage otherwise it is difficult to save the life of human. Brain tumour can be as benign and malignant. Malignant tumour is fast developing and harmful than benign since it grows slowly and less harmful [11][12][13][14].

Early stage cancer detection may not be feasible always and early detection can prevent death. Tumour could be benign, pre-carcinoma, or malignant. Benign generally do not spread to other organs and tissues and can be surgically removed [15]. It is not true for malign. The primary brain tumours are classified as gliomas, meningiomas, and pituitary tumors. Gliomas arise from brain tissues other than nerve cells and blood vessels. Meningiomas arise from the membranes that cover the brain and surround the central nervous system. The pituitary tumours are lumps that sit inside the skull [16]. Generaly meningiomas are typically benign and gliomas are most commonly malignant. The Pituitary tumours can cause other medical damage, even if benign. The meningiomas, are slow-growing tumours [16][17]. For differential diagnostics of tumour type, the common method is magnetic resonance imaging (MRI). Actually the early diagnosis of brain tumour depends on the experience of the radiologist [18]. The diagnosis of the brain tumour depends on classifying whether it is benign or malignant. A biopsy is usually performed In order to examine whether the tissue is benign or malignant. The biopsy of the brain tumor is not usually obtained before confirmation of brain surgery [19]. It is important to develop an effective diagnostics tool for tumor segmentation and classification from MRI images.

Artificial intelligence and machine learning has had a significant impact on medical field and are providing an important support tool for many medical branches. Different machine-learning methods are used for detecting brain tumour subject to the final decision will be taken by radiologists. Different machine learning algorithms were designed using these image databases can be found in many papers [12][20][21][22]. In the paper, authors used the small databases of 285 images and they often contain images with glioma tumor, acquired in the axial plane [22]. Classification has been carried out on small

database [23][24][25]. Some researchers used 66 images only to classify four types of images showing brain tumors: tumor-free, glioblastoma, sarcoma, and metastasis. They obtained an accuracy of 96.97% using deep neural network (DNN) [24]. There are other algorithms and different modifications of the pre-trained networks for image analysis, classification, and segmentation. Approaches have been tested on other medical databases, both on MRI images of brain tumours and on tumours from different parts of the human body [26][27].

Researchers classified the tumour types using augmented tumour region of interest, image dilatation, and ring-form partition. The method achieved an accuracy of 91.28% [28]. Different types of networks, pre-trained ones, capsule net networks, other architectures of convolutional networks, and combinations with neural networks are used for feature extraction and classifiers for the desired output. One of the known advantages of convolutional neural networks (CNN) is that the pre-processing and the feature engineering do not have to be performed. Some researchers proposed method that examine the classification first of three tumour types from an imbalanced database with a CNN.

Proposed Methodology

The objective of this paper is to recognize patients with brain tumor. A classifier model is used for this purpose that can associate input variable into output class while learning from training data. The learning procedure gained by classifier is evaluated in terms of acquiring prediction. Prediction is retrieved for unknown set of messages those are given as input to the classifier model. This paper proposes to implement NGBoost Classifier followed by 5-fold stratified cross-validation method as classifier model.

The improvement version of Gradient Boost algorithm is Naturals Gradient Boost (NGBoost) [3]. It is probabilistic prediction scheme and it trains the base learner to output for each training example such as probability distribution for minimizing the proper score. In Natural gradient (NG) descent, an optimization algorithm, the base learner is a collection of weak learners using the boosting approach. The NGBoost algorithm combines a multi-parameter boosting algorithm with the natural gradient to estimate the variation of parameters of the presumed outcome distribution with the observed features. This algorithm corrects the training dynamics of this multi-parameter boosting approach. NGBoost can be used with any base learner, any family of distributions with continuous parameters, and any scoring rule. NGBoost is flexible, scalable, and easy-to-use. It handles classification, regression, survival problems, etc. using the same software package and interface. It is thus trivially extends to a variety of use cases, such as negative binomial boosting (for counts), Gamma or Weibull boosting (for survival prediction, with or without right-censored data), etc. It scales to large numbers of features or observations with the same favorable complexity of traditional boosting algorithms [3].

The NGBoost classifier is implemented using categorical distribution which is a discrete probability distribution. The k-dimensional categorical distribution applies on k-way distribution event. It provides the probabilities of potential outcomes of a single withdraw rather than multiple drawings. The classifier is

built upon Decision Tree Regressor having maximum depth of 3. The classifier learns using 500 base estimators with a learning rate of 0.01. Friedman MSE [29] is used as default criterion which is improved version of MSE used for boosting classifier. The description of implementation of NGBoost classifier is shown in table 1.

Probability Distribution	Categorical Distribution
Base estimator	Decision Tree of max depth of 3
Number of Base estimator	500
Learning rate	0.01
Criterion	Friedman MSE

Table 1: Description of NGBoost Classifier

This implemented classifier is extended by applying 5-fold stratified cross-validation methodology which is utilised as proposed method for brain tumor detection. The cross-validation technique is known to be as resampling methodology that is used to estimate skill of a model. In this method, dataset is shuffled randomly and then it is partitioned into k groups. In this case, we consider the value of k as 5. For each group, one partition is considered as test or hold out set and rest partitions of the datasets are considered as training dataset. The NGBoost classifier is then fitted to the training dataset and evaluation is processed on testing dataset. For each of these folds, evaluation scores are accumulated and mean score is calculated as final evaluating scores. The implementation of cross-validation ensures stratified mechanism which enforces that the distributions of all folds are necessarily similar to proportion of all labels in the original data [30].

Baseline Classifiers-

This section describes ensemble technique based classifiers such as Gradient Boosting classifier, Random Trees, and Extra Trees classifier. The proposed classifier is justified against these mentioned classifiers. Hence, they are providing a baseline platform for comparing the prediction performance of proposed classifier.

AdaBoost is considered to be the first boosting technique proposed by Freund and Schapire [4]. This algorithm also belongs to the category of interpolating classifiers which defines algorithmic property of fitting the training data completely without error. This classifier is often known as a meta-estimator that proceeds by fitting a classifier on the original dataset and additional replicas of the classifiers are fitted after re-weighting the incorrectly classified instances in such a manner that the classifier is capable in handling more difficult cases [4].

Gradient Boost (GB) algorithms [5] another boosting algorithm which are suitable in fitting new models to obtain maximised efficiency while estimating response variable. The objective of this algorithm is to construct new base learners to be maximally correlated with the negative gradient of the loss function,

associated with the whole ensemble. This algorithm is highly customizable to any domain which provides freedom in model designing. One of the important issues of this algorithm is identifying and incorporating loss function to this algorithm which is subject to change as a matter of trial and error [5].

Random forest (RF) [6] exemplifies the concept of ensemble learning approach and applies regression technique for classification based problems. This classifier is a combination several tree-like classifiers which are applied on various sub-samples of the dataset and each tree cast its vote to the most appropriate class for the input [6].

Extra Trees Classifier [7] belongs to the category of ensemble learning technique. It aggregates the outcomes of various de-correlated decision trees collected in a “forest” and delivers output as classification result. An ensemble of un-pruned decision or regression tree is built by the Extra-Trees algorithm. It is based on the classical top-down procedure. It splits nodes by choosing cut-points fully at random and uses the whole learning sample (rather than a bootstrap replica) to grow the trees [7].

Implementation of baseline classifiers-

The baseline classifiers are applied on the dataset after partitioning it into training and testing dataset with a ratio of 7:3. The training set is fitted to these classifier models for extracting and learning of hidden patterns. Later the learning is evaluated for the testing dataset and prediction result is retrieved. The GB classifier is implemented with 500 base estimators, learning rate of 0.9. The RF classifier is also implemented with 500 base estimators whereas; Extra Trees classifier is designed with 100 numbers of trees in the forest. These designed ensemble models with necessary tuning will assist in attaining best results.

Dataset Used-

This paper collects *Brain Tumor Dataset* available at kaggle [31]. This dataset consists of 1644 number of patient’s records and each record is formulated as collection of 18 attributes. The dataset includes five first-order feature and eight texture feature and four quality assessment parameters with the target level. The first-order feature set contains attributes such as Mean, Variance, Standard Deviation, Skewness, and Kurtosis. Contrast, Energy, ASM (Angular second moment), Entropy, Homogeneity, Dissimilarity, Correlation, Coarseness are the attributes included in second-order texture feature set. There are four quality assessment parameters such as PSNR (Peak signal-to-noise ratio), SSIM (Structured Similarity Index), MSE (Mean Square Error), and DC (Dice Coefficient). All these features are extracted from MRI images.

Presence of Infinite values and Not a Number (NaN) values in the dataset will provide impact on the prediction efficiency. However, the presence of missing values can be ignored or deleted when the number of missing values is less in percentage. In some cases, it is required to consider unknown or missing values present in the dataset since these may contribute to the disease. In our implementation, missing values are handled by replacing mean values. Table 2 summarises the occurrence of missing values in

the dataset. All these values are replaced by mean values of their corresponding attributes. Fig1 shows the presence of brain tumor patients' distribution in the dataset.

Attribute Name	Number of missing values
Skewness	369
Kurtosis	369
PSNR	98
SSIM	369
DC	98

Algorithm Evaluation Metrics-

All the implemented methods are evaluated with respect to some pre-defined metrics such as Accuracy, f1-score, cohen-kappa score and MSE. Accuracy [32] is a metric that detects the ratio of true predictions over the total number of instances considered. The ratio of correct positive results over the number of positive results predicted by the classifier is identified by precision and recall denotes the number of correct positive results divided by the number of all relevant samples. F1-Score or F-measure [32] is a parameter that is calculated as the harmonic mean of precision and recall. The best value of F1-score, precision, and recall is known to be 1. Cohen-Kappa Score [33] is also taken into consideration as an evaluating metric in this paper. This metric is a statistical measure that finds out inter-rate agreement for qualitative items for classification problem. Mean Squared Error (MSE) [32] is another evaluating metric that measures absolute differences between the prediction and actual observation of the test samples. MSE produces non-negative floating point value and a value close to 0.0 turns out to be the best one.

Experimental Results

During training of the proposed cross-validated NGBoost algorithm, training and testing process is evaluated against accuracy, f1-score, kappa-score and MSE. In the proposed method, 5-fold cross-validation is approached and for each fold accumulated scores are depicted in Fig2. In fig 2 (a), (b) and (d) higher values of training scores and lower values of testing scores are observed. Again in fig 2 (c), testing MSE values are greater than training dataset MSE values. The scores shown in Fig 2 for training and testing scores clearly indicate that the proposed model prevents itself from over-fitting. The obtained testing scores are collected for each fold and their mean is calculated as the final testing score. These scores are shown in Table 2. A comparative study among all specified baseline classifiers is drawn with respect to specified metrics. As shown in Table 2, the proposed model achieves better result over other baseline classifiers such as Random Forest, Extra Trees, and Gradient Boost Classifier. In terms of all specified metrics, stratified cross-validated AdaBoost classifier provides the best predictive result. An accuracy of 98.54%, f1-score of 0.9917, kappa statistics score of 0.9302 and MSE of 0.0146 is reached

by the proposed model. Hence, it is clear that the proposed model outperforms the other baseline classifiers. Feature importance for the input dataset is also retrieved from this proposed classifier. Ranking of the features indicate MSE, Homogeneity, DC, SSIM, Mean, ASM, Entropy, Energy turn out to be the best important feature those have impact on classification. Fig 3 shows the ranking of the features obtained from proposed predictive analysis.

Performance Evaluating Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
Proposed Model				
Cross-Validated NGBoost Classifier	98.54%	0.9917	0.9302	0.0146
Baseline Model				
Gradient Boost	97.37%	0.97	0.89	0.03
AdaBoost	98.18%	0.982	0.92	0.02
Random Forest	97.98%	0.98	0.92	0.02
Extra Trees	94.13%	0.94	0.72	0.06

Table 3: Performance Summary of Ensemble Techniques

Conclusion

Use of ensemble ML techniques was utilized in this paper that identifies patients with brain abnormalities. This research has been carried out to point out the feasibility of using ML techniques that predicts brain tumors with promising efficiency and lowest error rate. NGBoost algorithm with 5-fold stratified cross-validation is proposed as classifier model. It automatically detects patients with brain tumors. The proposed method is compared against ensemble based baseline classifiers such as AdaBoost, Gradient Boost, Random Forest and Extra Trees Classifier. An accuracy of 98.54%, f1-score of 0.9917, kappa statistics score of 0.9302 and MSE of 0.0146 obtained by the proposed model.

Declarations

CONFLICT OF INTERESTS

Authors have declared that no conflicts of interests exist.

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Figures

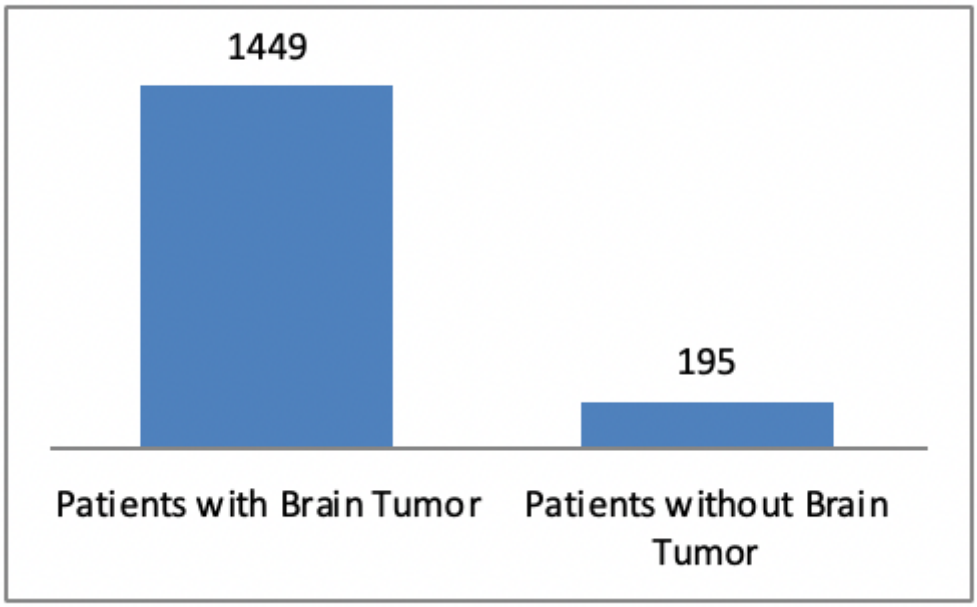

Figure 1

Distribution of brain tumor patients in the dataset

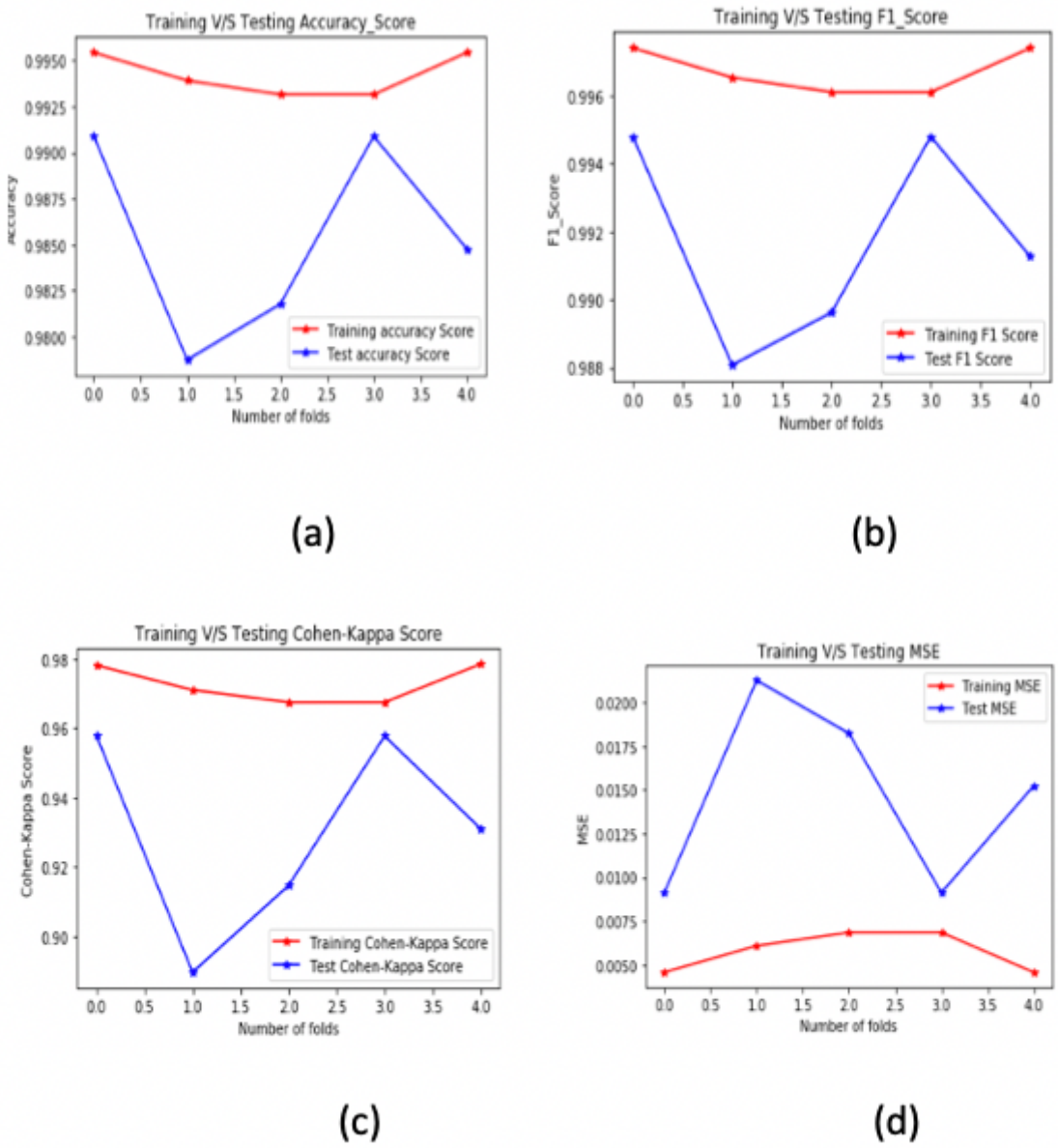

Figure 2

Score obtained during each fold of proposed classifier

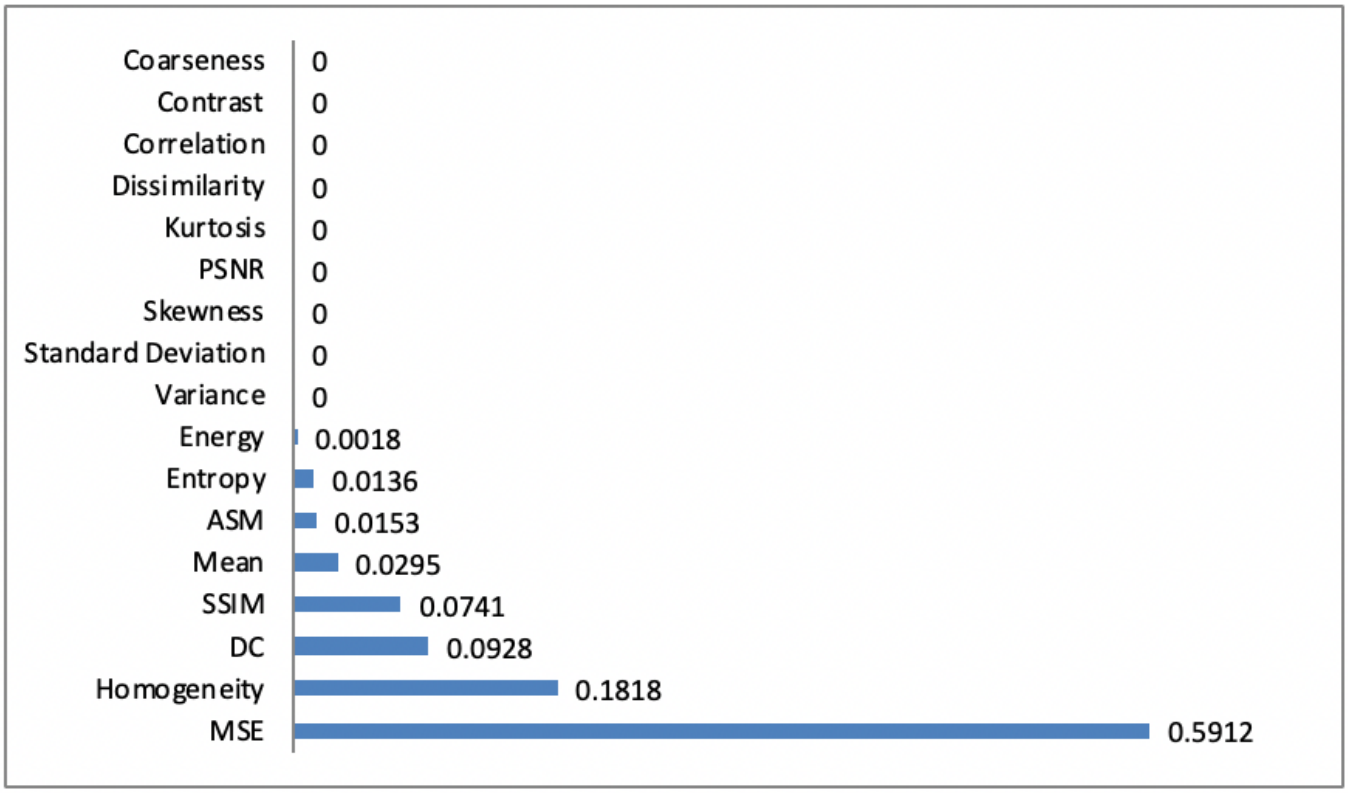

Figure 3

Feature Importance Ranking obtained from Cross-Validated NGBoost Classifier