A Novel Ensemble Machine Learning Models for Classification of Brain Tumors from MRI

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Abstract:

The categorization of brain tumors is crucial for accurate clinical diagnosis and treatment. We offer a strategy for classifying brain tumors using an ensemble of deep characteristics and machine learning classifiers in this paper. Several clinical imaging applications now use automated anomaly detection. Since verification and information about the tissues that need therapy and treatment, computerized identification of a brain tumor by Magnetic resonating imaging (MRI) is essential. The conventional method for detecting any abnormality in magnetic resonance brain imaging needs a doctor's verification, that takes a long time. To improve the death rate, automated classification methods will be required in the future. To improve brain tumor classification accuracy and performance, a variety of machine learning methods are increasingly being explored. The diversity and heterogeneity of brain malignancies make MRI inspection difficult. Using magnetic resonance imaging, ensemble machine learning models would accurately detect and classify brain tumor cells. Random forest ensemble model outperforms other machine learning algorithms including support vector machine (SVM), decision tree, and gradient boosting, especially for large datasets, according to experimental results.

Keywords: Brain Tumor, Ensemble Learning, Gradient Boosting, Machine Learning, MRI, Random Forest, Support Vector Machine.

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1 Introduction

The nervous system sends sensory data and the actions that go with it to all parts of the body [1–3]. The brain and spinal cord work together to help the above happen. The brain is a massive and complicated organ in the human body that governs the whole nervous system and comprises roughly 100 billion nerve cells [4]. The origin of this major organ is in the nervous system's center. It governs a wide range of bodily activities, including our ability to move, feel emotions, and think. An unusual growing cell in the brain that may be cancerous is called a brain tumor.

Rickman Godlee performed the first known resection of a primary brain tumor in 1884, and the tumor was detected. A neurological test is used to detect a brain tumor in today's world [5]. Any anomaly in the brain could be an indication of a brain tumor. Computerized anomaly detection is increasing in popularity in several fields. It is also utilized in clinical imaging applications employing machine learning methods. These algorithms are vital in detecting brain tumors in MRI because they utilize images and provide relevant details about abnormal brain structures, that is important in selecting therapy.

Image processing is now one of the most widely used tools for diagnosing and showing various disorders. In addition, cancer cases are on the rise across the globe. Unregulated cell growth results in lumps, which can progress to a brain tumor known as glioblastoma. There are two types of tumors: benign and malignant. Benign tumors have a covering over them and spread throughout the body. it will affect the functioning of the nervous system [6].

Effective treatments for brain tumors vary according to the tumor's size, location, and type. Neurosurgery is currently very popular treatment for brain tumors because there is no

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deleterious consequences in brain [7]. Medical imaging technologies such as CT, PET, and MRI can be used to examine the human body's internal state. A non-invasive and non-ionizing imaging method, MRI is the only one that can provide valuable two-dimension and three-dimension image of brain tumor with different size and location [8].

Previously, doctors used to diagnose the development of unregulated cells by visually watching the image, but the results were not always correct. However, as time passes, other medical facilities emerge, allowing exact results to be obtained. MRI (Magnetic resonance imaging) is a broad approach method of image analysis that examines the internal structure of the human body. This method of imaging is also employed in the detection of brain cancers [9].

Automated classification of brain tumors has been the subject of several investigations. But there are various problem arises due to the shape, texture, size, and color fluctuations, when using typical machine learning (ML) techniques, the solution is limited in its ability to be robust since features are handcrafted. Whereas the techniques based on novel ensemble machine learning model automatically extract useful elements that work noticeably better for users.

Annotated data is needed for machine learning training, but obtaining it is challenging. Therefore, we developed a Novel Ensemble machine learning model that uses pre-trained features and machine learning classifiers to distinguish between normal and pathological brain MRI.

Recent research shows that automated disease detection and diagnosis based on medical records may be a better option to present approaches, as it improves accuracy and saves time for the radiologist. The therapeutic management of brain tumors could be improved if machine learning algorithms can accurately represent tumors. It would relieve clinicians from the burden of manually depicting tumors. There are various classification methods for the image data [22].

The structure of this study is as follows: Section 2 explains an overview of relevant literature. Section 3 contains the dataset description. Section 4 explains the algorithms used in this study. Section 5 illustrates the procedures and methods. Section 6 summarizes the results and conclusions.

2 Overview of Related Work

Table 1 shows several ways of brain MRI classification using traditional machine learning and deep learning algorithms.

Traditional machine learning techniques include pre-processing, feature extraction, feature reduction, and classification. Feature extraction is essential in traditional Machine learning since it improves accuracy of classification. Feature extraction comes in two forms. There are two types of feature extraction: low-level characteristics, such as texture and intensity, and high-level features such as gray level co-occurrence matrix, wavelet transform, Gabor feature, and shape.

Selvaraj et al. [10] used least square support vector machine (SVM) to categorize conventional and pathological brain MRI. John et al. [11] used gray level co-occurrence matrix and isolated wavelet transformations to classify tumors.

Ullah et al. [12] Color moments (CM) were used to lower the coefficient of level-3 decomposition, and ultimately feed-forward neural network was used to distinguish natural and unusual brain MRI.

Y. Zhang et al. [19] suggested a hybrid approach to classify MRI. The proposed solution used discrete wavelet transform to obtain important components from MRI then used principal component analysis to reduce subspace.

Second-level features include fisher vectors, SIFT, and bag-of-words (BoW). Researchers uses BoW for image retrieval and segmentation. For example, mammography density classification [13], X-ray information extraction and classification on disease [14], and brain tumor data extraction [15].

The brain tumor was retrieved by fisher vector by Cheng et al. [16] developed the feature transformation, fisher vector, and statistical features on a limited scale that ignores geospatial data. Thus, the traditional ML technique has two major issues at the feature extraction phase. The concentration is on all the aspects of parameters. Second, traditional machine learning focuses on constructed characteristics, that require significant previous information like cancer in an image and are prone to mistakes. Thus, combining high-level and low-level characteristics without handmade characteristics is critical.

Farooqui et al. [17] analyzed three machine learning models for early detection of breast cancer using a unique dataset and found that Random Forests worked the best.

Table 1. Overview of Brain Tumor Classification Methods

Author	Types of Solution	Classification methods	Objective	Dataset	Feature Extraction Methods	Accuracy
Ullah et al., 2020	Traditional Machine Learning-based Solutions	Feed Forward Network	Classification of brain MRI into normal and abnormal	71 MRI	Deep Wavelets transform	
Rajan and Sundar.2019		SVM	Tumor detection and segmentation	41 MRI	Modified Gray Level Cooccurrences Matrix (GLCM)	98.45%
Preethi and Aishwarya, 2019		Deep Neural network	Categorization of tumor and non-tumor images	25 MRI	GLCM and Wavelet transform	99,50%
Francisco et al., 2021	Novel Approach of deep learning-based solutions	Convolutional neural network (CNN)	Brain Tumor classification	3060 MRI	CNN	97.32%
Ahmet and Mohammad, 2020		CNN	Identification and classification of brain tumor	255 MRI	CNN	97.22%
Hemanth et al., 2019		CNN with Learning model	Classification into healthy and unhealthy brain images	240 MRI	CNN	93.87%

3 Dataset Description

We execute different tests using publicly available brain MRI datasets for the categorization of brain tumors. The Kaggle website has been used to download the initial set of brain MR images [18]. The Central nervous system images data set contains several image recordings of brain MRI scans collected from various perspectives. It has 254 images and is regularly utilized for tumor diagnosis due to its validity and lack of duplication. It is divided into Tumor Present and Not present. During processing, the images should be scaled the dimensions.

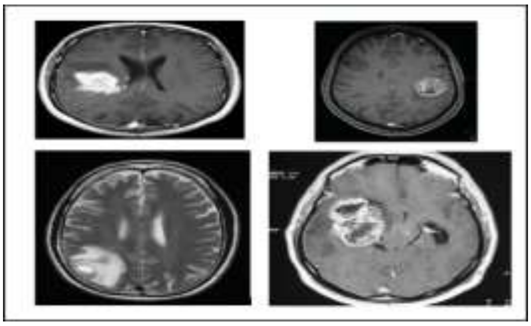

Figure 1. Sample Images of tumor

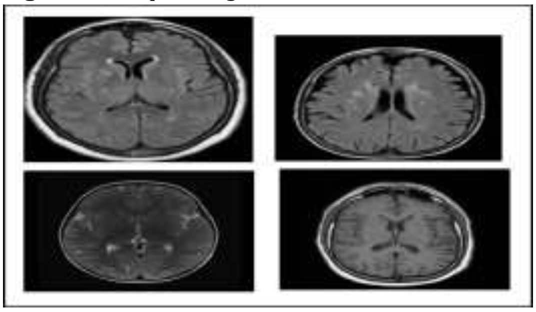

Figure 2. Sample Images of non-tumor

4 Machine Learning Methods

The Support Vector Machine (SVM) is a classification machine learning model that employs a supervised learning approach. In 1992, Boser, Guyon, and Vapnik announced the Support Vector Machine (SVM) at COLT-92. One of the most often used classification and regression techniques is the usage of support vector machines. The SVM's aim is to determine the smartest decision boundary for classification sets of data in an n-dimensional environment into multiple, valid groups. The hyperplane is the decision boundary that has the highest accuracy.

Researchers have applied classification model systems [20]. Classification methods in machine learning can handle large amounts of data. It can classify learning based on the training sets and class labels [21]. Applying classification techniques, decision tree algorithm will be employed for regression and classification problems. The internal nodes represent the dataset's characteristics, while the branches represent decision rules. Two types of nodes used in the decision tree one for decision and one for the result.

Random Forests use ensemble learning to enhance accuracy and solve complicated problems. Random Forest, as the name implies, uses several decision trees on different data sets. Instead of dependent on a single decision tree, the method can aggregate the predicted outputs from several trees. The technique significantly reduces generalization error. High-dimensional data modelling can benefit from the random forest's ability to manage incomplete data, as well as consistent, categorical data. Data augmentation can be avoided by random forest's bootstrapping and aggregation method, therefore there is no need to prune the trees.

Gradient Boosting uses prediction model for classification, like Random Forest. Gradient Boosting, unlike Random Forests, produces classification model one at a time by enhancing the performance of previously lower branches. Gradient boosting will produce a high accuracy and create precise predictions if variables are properly set.

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5 Proposed Procedure and Methodology

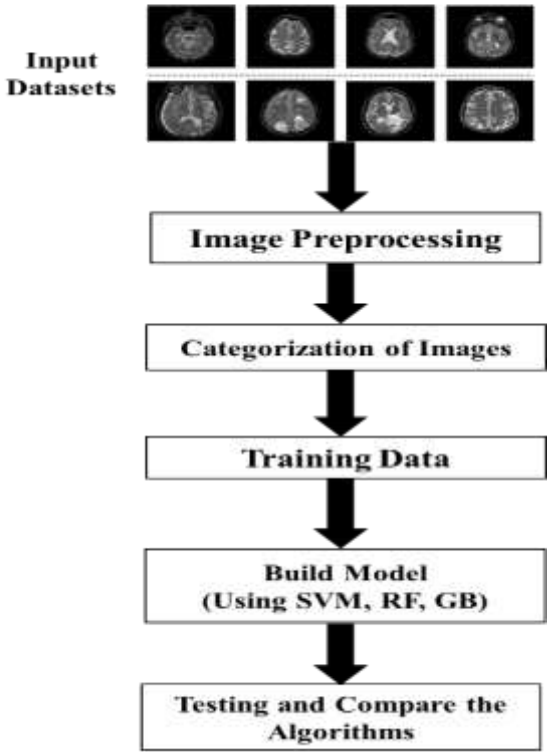

Figure 3. Proposed Model for the Brain Tumor Classification

A. Image Preprocessing

An abnormal cell size in the brain could be malignant or non-cancerous. Tumors are caused by abnormal cell development in the brain and can be deadly. Early and proper detection of all such illnesses will help the patient's recovery. Firstly, we collected the images. Image pre-processing is the process of arranging images for use in model training and prediction. This includes scaling, rotating, and color adjustment. We pre-processed the images into grayscale because descriptor is typically extracted using grayscale representations. Using grayscale instead of color images improves the process and decreases processing demands.

B. Categorization of Images

During the training phase, we run a high risk of overfitting the model to train the dataset. That illustration, the model can learn a very specific function that works well on current training data but not on new images. That indicates the model isn't learning properly and is simply remembering the training data. This suggests that the model will have difficulty with new images it hasn't seen before. The train, validation, and testing divides help to stop overfitting. we categorize the data 80% train data and 20% test data.

C. Training and Build Model

After image pre-processing and splitting the dataset into such an 80:20 ratio, then trained the SVM, Random Forest, Decision Trees, and Gradient Boosting models. We subsequently performed K-fold cross-validation (K=12) to repeat and evaluate the training phase. After the training of the image test the model for the different algorithms and compare the result and find the best algorithm that gives the accurate result.

6 Results & Conclusion

The Confusion matrix is used to describe the classifier performance, that were of vital significance. Whenever comparing to other metrics like accuracy, it provides a clear description of how the classification is functioning. It's possible for accuracy to deliver inaccurate findings in cases where there are unequal observations for a single class or numerous classes in datasets. The results of all the classifications in the matrices are shown in the following table 2.

Table 2. Results of Confusion Matrix

ML Classifiers	FP (False Positive)	TP (True Positive)	FN (False Negative)	TN (True Negative)
SVM	9	45	10	15
Random Forest	5	48	3	20
Decision Trees	15	37	10	22
Gradient Boosting	10	41	9	23

Table 3. Accuracy, F1 Score, Matthews Correlation Coefficient, Precision, Sensitivity, Specificity of the Proposed Model

Performance Matrices	SVM	Random Forest	Decision Tree	Gradient Boosting
Sensitivity	81.82%	**92.31%**	78.72%	82.00%
Specificity	62.50%	**89.29%**	59.46%	69.70%
Precision	83.33%	**94.12%**	71.15%	80.39%
Accuracy	75.95%	**91.25%**	70.24%	71.88%
F1 Score	82.57%	**93.20%**	74.75%	30.30%
Matthews Correlation Coefficient	43.82%	**80.90%**	39.03%	19.61%

Random Forest is the best classifier for the proposed model. Figure 4. explains performance matrices with the help of the boxplot that shows the variation in the accuracy of each ML classifiers. SVM use it to estimate start probabilities, while random forests use it to choose characteristics. Due to the importance of the random variable, the classification offers significant variability.

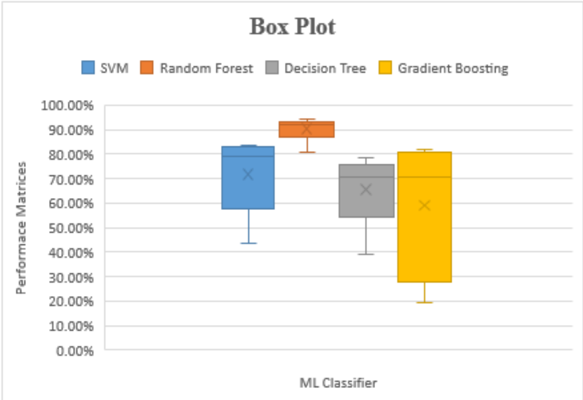

Figure 4. Boxplot of the Performance Matrices of the ML Classifiers

Using cross-validation, machine learning models are evaluated against a dataset. K-Folding simulation has been performed k=12 for cross-validation. The dataset is distributed into 12 groups. Figure 5. shows the accuracy of classifiers cross validation with K=12.

Table 4. Performance Matrices of ML Classifiers Pre and Post Cross Validation

Performance Metrics	SVM	Random Forest	Decision Tree	Gradient Boosting
Accuracy before K-Fold	75.95%	91.25%	70.24%	71.88%
Accuracy after K-Fold	76.28%	95.76%	73.45%	76.38%

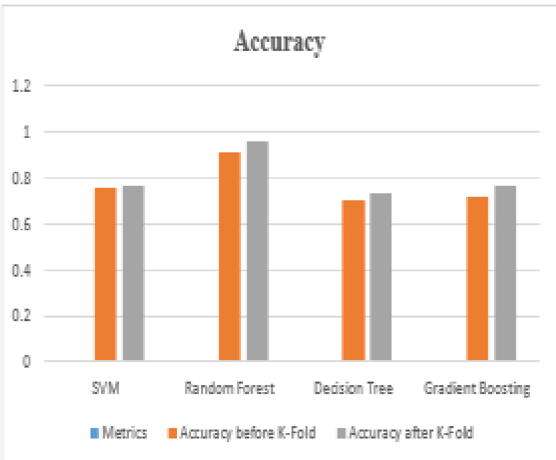

Figure 5. Accuracy of the ML Classifiers pre and post cross validation

Figure 5 shows that, when we use cross-validation, there is a less overfitting and good result. Overfitting is not reduced by 12 cross validations; rather, it delivers a more accurate estimate, with less overfitting. Consequently, we may conclude that the Random Forest ensemble model outperformed the other models in our analysis. I trained my model on 255 images, but the accuracy will be improved even more by taking some more samples and other techniques. Figure 6 and 7 shows the relationship between the random forest and decision tree, SVM and decision tree respectively. That explains the random forest is better than the others to achieve the goal. Figure 8 shows the graphical representation of the overall performance of the multiple values.

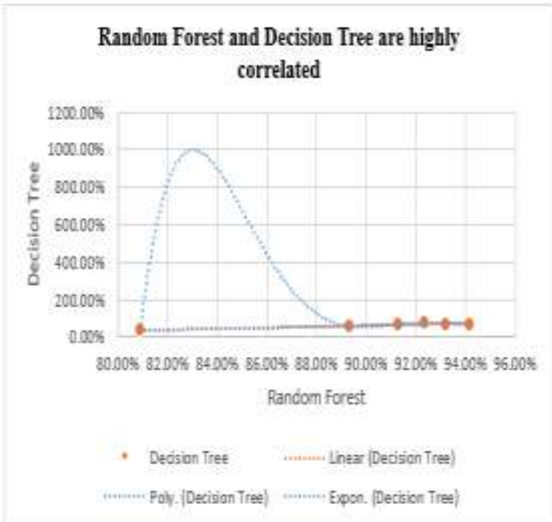

Figure 6. Relationship between the random forest and decision tree

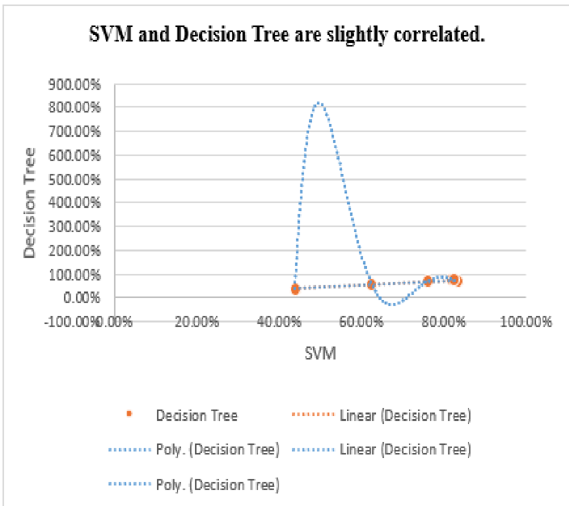

Figure 7. Relationship between the SVM and decision tree

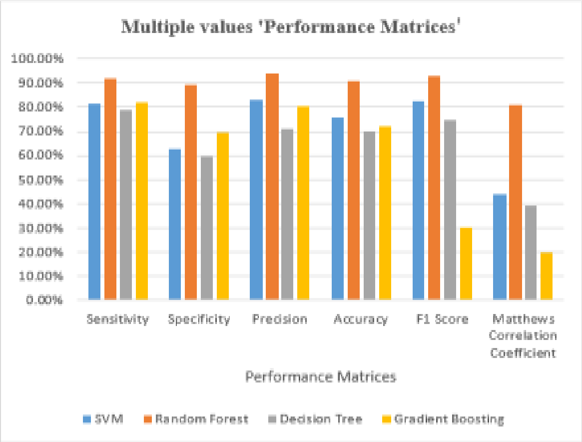

Figure 8: Overall performance matrix of the multiple values

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