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Diagnosis of Brain Tumor from MRI Images Using Machine Learning

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ABSTRACT

The brain is the regulatory unit in the human body. It controls the functions such as memory, vision, hearing, knowledge, personality, problem-solving, etc. The main reason for brain tumors is the abandoned progress of brain cells. Many health organizations have recognized brain tumors as the second foremost dispute that causes a large number of human deaths all around the world. Identification of brain tumors at a premature stage offers an opportunity for effective medical treatment. The use of Magnetic Resonance Imaging images has been recognized as more detailed and more consistent images when compared to Computed Tomography images. There are various techniques to detect brain tumors or neoplasms. The most competent and effective algorithms are discussed in this paper after studying a number of appropriate research papers. Preprocessing brain images, segmenting them, feature extraction, clustering, and detection of the tumor are the methodologies in most research.

1. INTRODUCTION

An uncontrolled, unnatural growth and division of the cells in the body is said to be cancer. Whereas brain tumor is an Occurrence of a mass or unnatural cell growth and division in the brain tissue, but it is not common in general, they are considered the most lethal cancers.

In enhancing the treatment possibilities, early analysis of the gliomas plays a significant part. Computed Tomography (CT), Single-Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS), and Magnetic Resonance Imaging (MRI) are the Medical Imaging techniques, which give the significant details regarding the shape, size, location and metabolism of brain tumors assisting in diagnosis. A combination of these approaches gives the maximum details about the brain tumors, because of its good soft-tissue contrast and wide availability MRI is considered the standard technique.

The fields like medical sciences, microscopy, astronomy, computer vision, geology, and many other fields are the multidisciplinary area of Digital image processing. Among various scientific and medical research, medical imaging is one of the most significant phases, which gives computerized medical image segmentation and computer-aided design. Specifically, they provide the enhanced planning and accuracy of surgical procedures with the help of human-machine intervention. To give efficient diagnostic tools in the medical field, this process brings the therapeutic plan and the development of imaging instruments. Various medical instruments were brought-in to generate the sectional views of the human anatomy. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) were the two major non-invasive techniques and make used for imaging the human body. For examining the human anatomy, MRI is used as a medical diagnostic tool and it works based on Nuclear Magnetic Resonance (NMR), to give enough properties of materials. Bloch and Purcell in the 1940s [5, 5], established the NMR. The following author Paul Lautenberg, Ray Damadian, and Peter Mansfield start to make use of the principles of NMR in MRI as an imaging modality for the head, spine, and body, in the year 1970. Then, MRI generates images of high spatial resolution with good soft-tissue contrast, which is very useful for the detection of diseases.

The primary issue here is diagnosing the brain tumor, the great challenge faced here is detecting the exact location of the tumor part, so make use of Image mining techniques, to detect the exact tumor cells by undergoing various processes. It assists in recovering the appropriate details and discloses the image patterns which are important from the given dataset. The important issue here is identifying the brain tumor in the very early stages to give proper treatment. The most suitable therapy, radiation, surgery, or chemotherapy can be decided, according to this information. As a result, it is evident that the chances of survival of a tumor-infected patient can be increased significantly if the tumor is detected accurately in its early stage.

Effectively classifying the brain tumor cells, every phase explained above undergoes severe complications. Following complications are found and widely solved in the current research.

Pre-Processing is a tedious process, which eliminates the unnecessary items, after removing the images that were processed successfully. To undergo this, the initial step is Image pre-processing [4]. Pre-Processing entails processes like conversion to a grayscale image, noise removal, and image reconstruction. Transforming to the greyscale image is the most common pre-processing practice [1]. Excess noise is removed with the help of various filtering methods after the image is transformed into grayscale. After the collection of the images from the database for achieving an effective result, eliminating the noise becomes an important process. Current schemes experience serious defects in removing the noises.

Segmentation: It is a significant process huge images were produced while scanning and it is suspected for clinical experts manually classify these images in a reasonable time. In clinical diagnosis, it has an important part which helps in pre-surgical planning and computer-assisted surgery.

Feature Extraction: Here, each and every character is represented by a feature vector that is likely to become its identity. Its targets extracting the features, which maximizes the identification rate with the least number of elements and for generating the identical feature set for several instances of the same symbol. For further diagnosis, current feature extraction schemes failed to choose the essential features.

Classification: It classifies every item in a set of data into one of a predefined set of classes or groups. This technique is widely utilized to distinguish the normal and tumor brain images. Accurately predicting the target class for each case in the data, is the primary target of classification, it classifies the brain images into tumor and non-tumor. The current schemes don't focus on the effective classification of MRI images, so our proposed work, focuses much on this phase.

Our work focuses on an effective approach for brain tumor segmentation and classification with the help of MRI with novel machine learning schemes, which are designed for effective classification and quick diagnosis of tumor patients.

Brain Tumor MR Image Segmentation and Classification with the help of one of the machine learning algorithms.

2. Related Work

It should observe that biomedical images are extensively used for many purposes in these existing medical cases. In medical science, these images play a vital role. The use case like MRI-Magnetic Resonance Imaging captures the information on the internal structure of the human brain and is also used to picture other parts of the body. MRI data are analyzed manually by medical experts in brain tumor and it is a difficult and cumbersome process. The edge detection idea is used here, to generate the high-definition images. Here, mainly review the existing systems, identify the problems in it and assist it in proceeding the further research effectively to design an effective approach for brain tumor segmentation and classification using MRI with novel machine learning schemes.

P. Gokila Brindha et. al. (2021), proposed assures to be highly efficient and precise for brain tumor detection, classification, and segmentation. To achieve this precise automatic or semiautomatic methods are needed. The research proposes an automatic segmentation method that relies upon CNN (Convolution Neural Networks), determining small 3 x 3 kernels. By incorporating this single technique, segmentation and classification is accomplished [1].

Lotlikar V. S. et. al. (2021), presented an exhaustive study of techniques such as preprocessing, machine learning, and deep learning that have been adopted in the last 15 years and based on it to present a detailed comparative analysis. The challenges encountered by researchers in the past for tumor detection have been discussed along with the future scopes that can be taken by the researchers as the future work. Clinical challenges that are encountered have also been discussed, which are missing in existing review articles [2].

S. Grampurohit, V et. al. (2020) Proposed Deep learning models like the convolutional neural network (CNN) model and VGG-16 architecture (built from scratch) to detect the tumor region in the scanned brain images. Considered Brain MRI images of 253 patients, out of which 155 MRI images are tumorous and 98 of them are non-tumorous. The study presents a comparative study of the outcomes of the CNN model and VGG-16 architecture used [3].

Amin, J. et. al. (2021), presented the study of all important aspects and the latest work done so far with their limitations and challenges. It will be helpful for the researchers to develop an understanding of doing new research in a short time and correct direction. The deep learning methods have contributed significantly but still require a generic technique. These methods provided better results when training and testing are performed on similar acquisition characteristics (intensity range and resolution); however, a slight variation in the training and testing images directly affects the robustness of the methods. Research can be conducted to detect brain tumors more accurately, using real patient data from any medium (different image acquisition (scanners) [4].

Subhashis Banerjee et. al. (2019), proposed novel ConvNet models, which are trained from scratch, on MRI patches, slices, and multi-planar volumetric slices. The suitability of transfer learning for the task is next studied by applying two existing ConvNets models (VGGNet and ResNet) trained on the ImageNet dataset, through fine-tuning of the last few layers. Leave-one-patient-out (LOPO) testing and testing on the holdout dataset are used to evaluate the performance of the ConvNets. Results demonstrate that the proposed ConvNets achieve better accuracy in all cases where the model is trained on the multi-planar volumetric dataset. Unlike conventional models, it obtains a testing accuracy of 95% for the low/high-grade glioma classification problem. A score of 97% is generated for the classification of LGG with/without 1p/19q codeletion, without any additional effort towards extraction and selection of features [5].

The pre-processing approaches for MRI brain scans were proposed by Poornachandra and Naveena [6], which is an initial and essential step to yield better segmentation of gliomas (brain tumors). Deep Learning is accomplished in recent days by state-of-the-art, which results in Medical Imaging. The proper awareness of the researchers in this field generates better segmentation results and supports the proper diagnosis of brain tumors and assists in the treatment planning for the patients affected with a brain tumor [6].

Tumor identification is an important research topic, which faces various disputes it works according to the brain MR image, which segments the tumor contour and it has many unwanted details. The intensity inhomogeneities cause difficulties in image segmentation. Pre-processing prior to a region-based active contour model with modification of the Region Scalable Fitting method was proposed by Setyawan Widyarto et al., [7], for image segmentation. In local regions, a Region-based active contour model draws upon intensity information. The 2D-sigmoid function at tumor boundary is enforced in pre-processing, which is the image enhancement process. The contrasts in the brain MRI image for pre-processing steps were improved by 2D-sigmoid function. Enhanced pixel value, F(x, y), is the `S' shape function of intensity I (x, y) of the image at the point (x, y), the width of the gradient magnitude around the brain image (α) and gradient magnitude around brain image (β). An experimental result proves the desirable MRF method with respect to computation efficiency [7].

An appropriate method to find threshold values using standard deviation was proposed by Manisha et al., [8] to acquire the intensity map. The average intensity of the pixels is computed through this. And at last, this computed average intensity is considered the threshold value to segment the tumor from the original MRI images. The greater value of intensity is set to 255 and less value is assigned to 0 and this segment abnormal region is tumor. A Sobel edge detector is utilized to recognize the border of the tumor region. The proposed work's output enhances the efficacy and accuracy of the detection of brain tumors.

For clinical application and scientific research, Automatic segmentation of brain tissues from MRI is of great importance. Recent advancements in super voxel-level examine robust segmentation of brain tissues by exploring the inherent information between various features, which is extracted on the super voxels. The challenges still remain in clustering uncertainties imposed by the heterogeneity of tissues and the redundancy of the MRI features, within this prevalent framework. A robust discriminative segmentation method was proposed by Youyong Kong et al., [9], to manage the aforementioned two challenges from the information-theoretic learning. The major target of the method is to simultaneously choose the informative feature and to minimize the uncertainties of super voxel assignment for discriminative brain tissue segmentation.

The effectiveness and efficiency of the proposed approach and experiments on two brain MRI datasets were checked. For brain tumor segmentation systems, the Extraction of relevant features is a significant one. Improved feature extraction component is proposed by Shang-Ling Jui et al., [10], to enhance the brain tumor segmentation accuracy, which takes the merits of the correlation among the intracranial structure deformation and the compression resulting from brain tumor growth. The component measures lateral ventricular (LaV) deformation in volumetric magnetic resonance images, and make use of the 3D nonrigid registration and deformation modeling techniques. By checking the location of the extracted LaV deformation feature data and enforcing the features on brain tumor segmentation with widely utilized classification algorithms. The author computes the proposed component qualitatively and quantitatively with promising results on 11 datasets comprising real and simulated patient images.

Figure 1: Summary of Related Work

Preprocessing Segmentation	Features	Classification	Dataset	Accuracy
Image resizing and enhancement	GLCM, CNN	SVM	Local-Iraqi center of research.	99.30%
Morphological operation, pixel subtraction, Maximum entropy threshold segmentation	Morphological Intensity	Naive Bayes	REMBRANDT	94%
Single Image Super-Resolution for image enhancement Segmentation-Maximum fuzzy entropy(MFE)	ResNet deep features	SVM	TCIA	95%
Min-max normalization, Resize 224*224	GoogleNet deep features	SVM, KNN	CE-MRI	SVM-97.8%KNN-98%
Median filter GA segmentation	GLCM	SVM	Harvard Medical Dataset	91.23%
OTSU BinarizationK-means clustering	DWT	SVM	BRATS 2013, BRATS 2017, Midas	99%
Skull stripping-BSE Gaussian filtering, K-Means segmentation	GLCM, Intensity, shape	SVM	Local, AANLIB and RIDER	98%
Image enhancement-DSR-AD, OTSU segmentation	Tamura, LBP, GLCM, Gabor, Shape	SVM	Local	98%
Image enhancement-DSR-AD, Global adaptive segmentation	RLCP	Naive Bayes	Local-JMCD, BRATS	96%
Median filter noise removal, Threshold-based segmentation	GLCM	Adaboost	Public dataset	89.90%
Wiener filtering Histogram based segmentation	GLCM	G-K Fuzzysystem	-	95%

It is clear that segmentation and classification result remains a crucial concern for most of the cases, according to the above survey. There are several problems with existing segmentation and classification schemes and most of the available solutions aren't sufficient for practical applications. Furthermore, still, image segmentation results weren't efficient with the current requirements. Though machine learning schemes give some solutions, still a lot of enhancements were important to give better results. This chapter clearly examines the current systems relevant to our research and assists in gaining knowledge for our further research.

III. PROPOSED METHODOLOGY

The three methods are used for feature extraction and brain tumer detection, machine learning approaches are used in this work. The focus is on extracting features using python and image processing libraries and using machine learning algorithms for prediction. Our implementation is divided into three parts. The first part is image pre-processing, Feature extraction, and leaf disease detection. For brain tumor detection, inbuilt methods available in the python library are used. Once the tumor is detected, the region of interest and important tumor features are extracted from it. There are various features that can be used for brain tumor detection. The entire working process of the presented method is shown in Figure 1. The presented model consists of a series of processes which are discussed below.

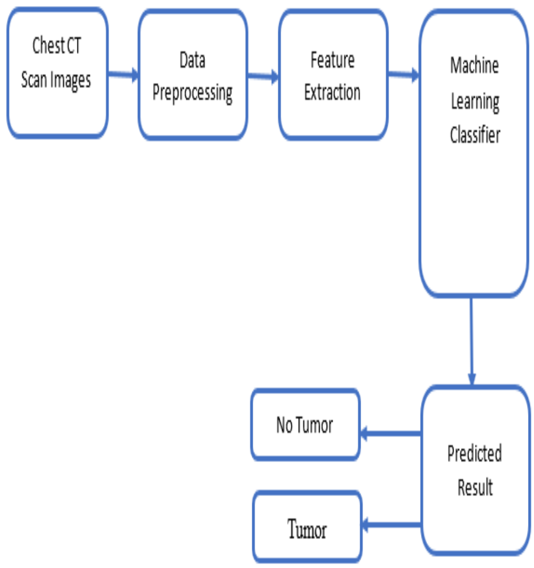

Figure 1: proposed methodology of system

A. Image Acquisition

The image data that was used for this problem is brain MRI images for brain tumor detection. It consists of MRI scans of two classes:

No - No Tumor, encoded as 0

Yes - Tumor encoded as 1

All images are in one folder with yes and no subfolders. I will split the data into train, Val, and test folders which makes it easier to work with the same dimension of images.

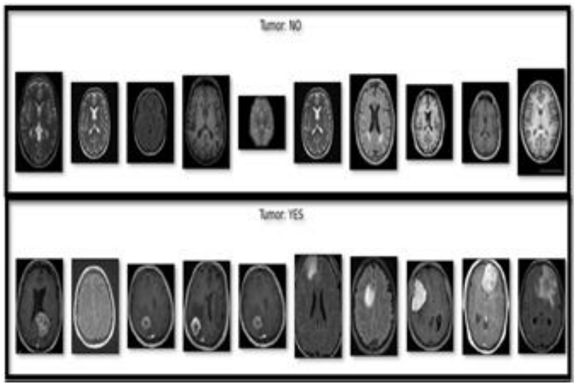

Figure 2: Online Kaggle dataset

B. Preprocessing

Preprocessing is required because it provides an improvement in image data which reinforces a number of the image features which are important for further processing.

Data labeling

The images of brain tumor have been labeled as ‗1' and the images with no brain tumor as ‗0'.

Image pre-processing: The images have been read in the grayscale (2D). To build a classifier using ML algorithms all the images have been converted into the same dimension. So, each image has been resized into 200*200 pixels.

For instance, the original image as shown in Fig. 8 has a dimension of 630*630 pixels. Its dimension has been transformed into 200*200 pixels. Similarly, each and every image in the dataset has been converted into a dimension of 200*200 pixels.

C. Segmentation

Brain tumor segmentation is the process of separating the tumor from normal brain tissues; in clinical routine, it provides useful information for diagnosis and treatment planning. However, it's still a challenging task thanks to the irregular form and confusing boundaries of tumors. Tumor cells thermally represent a heat source; their temperature is high compared to normal brain cells. The aim of this research will present the thermal information of brain tumors often wanting to reduce false positive and false negative results of segmentation performed in MRI images.

D. Feature Extraction

image-based features: the extraction of features based on the image data, potentially including intensity features, texture features, histogram-based features, and shape-based features.

E. Classification

Machine learning algorithms are used for the classification of MR brain images either as normal or abnormal.

Machine Learning Classifier

The classifier is used to classify brain tumor on test images. To classify feature data into a given number of classes, in this study used the machine learning technique. In this project, the ensemble bagging classifier is used to train the leaf disease images. Classifier takes a set of images, creates a trained model, and predicts for each input image belongs to which of the disease categories of leaf image classes.

Support Vector Machine (SVM): One of the best methods for classifying any image or pattern is SVM. SVM is used to split a set of images into two various classes. The classification is done by finding the hyper-plane that differentiates the two classes very well as given in Fig. 3.

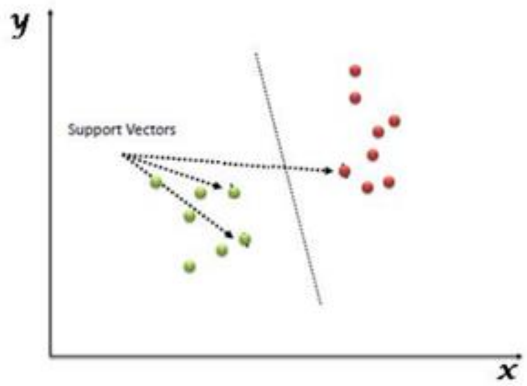

Figure 3: Classification using SVM

It builds a hyperplane based on a kernel function (K). As shown in Figue.1, feature vectors on the left side of the hyperplane belong to class -1 and the feature vectors on the right side of the hyperplane belong to class +1.

1. To detect an object in an image the features of the image have to be fed to a recognition system which in this work is SVM.

2. Stored the features of slices of every image of HG and LG sub folders of training data folder to feed them to SVM.

3. Created a .mat file which has the labels for the images indicating ‘a tumour’ or ‘no tumour’

K-nearest neighbor (kNN): KNN is a simple classification method that works well for real-time applications The training procedure is very easy and its sample includes class labels and a set of tuples interrelated with that. This algorithm works for a random number of the module. The distance function is used by the KNN classification model for mapping the samples with classes. In order to calculate distance among the assumed test illustration X with that existing samples y1,y2…yk, the Classification process of KNN is used. The nearest neighbor around the test instance is identified and depending on the selection of neighbors, the majority neighborhood lecture is allotted to the test samples. The distance function is applied between the samples using the Euclidean method or Manhattan method or the Minkowski method. These methods are employed when the values are continuous. Depends on the number of neighbors that the sample X probability is assigning. The probability of assigning a sample X to that of class C is based on the number of neighbors considered, denoted as K.

The k-nearest neighbor algorithm is a supervised classifier in machine learning algorithm used for pattern recognition and non-parametric method. Like other algorithms in machine learning, k-NN algorithm also consists of two stages namely (i) training stage (ii) testing stage. In the training stage, stored data points in n space and points used to define attributes with a corresponding class. Whereas in the testing phase, calculated the distance between new extracted features and features from training data. The Euclidean distance is used to calculate distance between the training and testing stored data and the formula is given below [20].

$$(a, b) = \sqrt{\sum_{i=1}^{m} (a_i - b_i)^2}$$

In this algorithm defines the k-closest training and set images feature as zero and the remaining tumor part is set as one, so that it can be classified. In the k-NN algorithm, class membership decides the output by classifying the images whether the tumor (Tumor and No Tumar) is present or not, the k-nearest neighbor algorithm is as follows:

- Select the k values and it is mostly based on past available data.
- Define a Euclidean distance measurement to calculate distance.

- In the training stage, consist of the training dataset, coherent class, and no of the training set.
- In the testing stage calculate the distance between the new feature and the training set.
- If the result is not suitable or appropriate then change the value of k and continue the process still obtain the suitable result.

Random Forest: The Random Forest (RF) classifier is used to classify the source brain MR image into either tumor image or nontumor image. This RF classifier used a weighted voting technique to classify the brain images for severity diagnosis. The RF classifier classifies the images based on the training and testing features. In this classification, "T" is the total number of trees in the forest, and S is the training set that constitutes the features that are extracted from tumor and nontumor brain MR images.

The classification result is a binary value which may be either zero or one. The "zero" classification result is generated if the source test brain image belongs to the nontumor image. The "one" classification result is generated if the source test brain image belongs to tumor image. Further, morphological operations are applied to the classified tumor image to segment the abnormal tumor.

The Working process can be explained in the below steps

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

Step-3: Choose the number N for the decision trees that you want to build.

Step-4: Repeat Step 1 & 2.

Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority of votes.

Decision Tree: A decision tree is a set of simple rules. Decision trees [9] are also nonparametric because they do not require any assumptions about the distribution of the variables in each class. Every interior node contains a decision criterion depending only on one feature. For the first split into two parts, the feature with the highest relevance is used. This procedure is recursively repeated for each subset until no more splitting is possible. It is followed from a root to a leaf node the decision tree corresponds to a rule-based classifier. An advantage of decision tree classifiers is their simple structure, which allows for interpretation (the most important features are near the root node) and visualization. A decision tree is built from a training set, which consists of objects, each of which is completely described by a set of attributes and a class label. The class that is associated with the leaf is the output of the tree. A tree misclassifies the image if the class label output by the tree does not match the class label. The proportion of images correctly classified by the tree is called accuracy.

Many algorithms are proposed for learning decision tree from a given dataset, but commonly, ID3 algorithm is preferred due to its simplicity for implementation [21]-[22]. ID3 algorithm is a top-down greedy search of possible branches, and it uses information gain and entropy to build the tree.

The H(Y) Shannon entropy of a random discrete variable Y with possible Y1, Y2 ⋯ :Yn and probability mass function P(Y) is defined as in

$$H(Y) = -\sum_{i=1}^{n} P(y_i)\, log_2\, P(y_i)$$

Entropy is equal to zero for a completely homogeneous dataset, and entropy is equal to one of the datasets equally divided. A branch with entropy of more than one needs splitting

Naive Bayes: The Naïve Bayes algorithm is an effective method of text classification. It works on a large training sample set and gives an accurate result. It is a probabilistic classifier based on the Bayes theorem with an independent assumption that assumes the presence of particular features of a class is unrelated to the presence of other features. A naive Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem (from Bayesian statistics) with strong (naive) independence assumptions. A more descriptive term for the underlying probability model would be "independent feature model". In simple terms, a naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. The morphological scanning technique will scan the image and the technique of naïve Bayes is applied which marks the tumor in the image. The classifier that includes all independent attributes when the value of the class variable is given is known as the Naïve Bayes classifier. Conditional independence is another name for this classifier and it is known to be the easiest form of a Bayesian network [9].

This theorem can be expressed mathematically as:

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

Here in the above equation A and B are the events and P(B)? 0. Mostly, here annoying to treasure the probability of the event A, hence given that always the event B is true. Event B is also labelled as evidence. The prior of A has P(A) i.e. (the prior probability, i.e. Probability of event before indication is seen). The indication is continuously an attribute value of a strange occurrence (here, it is event B). P(A|B) is a posteriori probability of B, i.e., probability of event after indication is seen. Now, based on our above dataset, Bayes theorem in the following way

$$P(y|X) = \frac{p(X|y)\,P(y)}{P(x)}$$

where, here the class variable is y and the vector i.e featured is X i.e dependent (of size n) where:

$X = (x1, x2, \ldots\ldots, xn)$

Just to clear, an example of a feature vector and corresponding class variable.

X = (Secondary Tumor, Lungs, Cough, Self care)

y = Yes

So essentially, P(X|y) here incomes, the probability of "Occurrence of tumor" given that the conditions are "tumor is secondary", "origination is lungs", "symptom is cough" and "treatment is self-care".

V. Result Analysis

In the previous chapter, discussed the proposed system and implementation of our thesis. This study demonstrated how the collected dataset, dataset description, visualization, and algorithms were used. Now discuss the results obtained from experiments upon the implementation of this system. Divided the dataset into two parts the training and testing dataset. This section shows the outcome of the training and testing dataset. As mentioned, before used five machine learning algorithms. First, trained the dataset with these five algorithms and then built a model. Then, tested the dataset in this model. If the test set accuracy is near to train set accuracy, then conclude that built a good model.

In this research work, an image classification and recognition system, called the machine learning model, was developed for brain tumor detection. The study proposed five categories of classification models, namely, Support Vector Machine (SVM), K-nearest neighbor (kNN), Random Forest, Decision Tree, and Naive Bayes classifiers. All the machine learning models were built using the MRI brain tumor image enhancement algorithm, segmentation, feature selection, and then leaf image classification for tumor detection.

A. Performance Metrics

This section presents the experimental results and performance metrics for different models. Accuracy is one of the common performance metrics. It is the measure of all the correctly identified cases. It is mostly used when all the classes are equally important. Accuracy is the proportion of correctly classified examples to the total number of examples, while the error rate is incorrectly classified instead of correctly.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP is True-positive, TN is True-negative, FP is False-positive and FN is False-negative. The Seven models have yielded different accuracy scores, which are displayed in table 2.

Table 2: Accuracy Score of Machine Learning Models

Sr. No	Classifiers	Accuracy
1	Support Vector Machine (SVM)	76.47
2	K-nearest neighbor (kNN)	68.62
3	Random Forest	86.27
4	Decision Tree	59.00
5	Naive Bayes	75.00

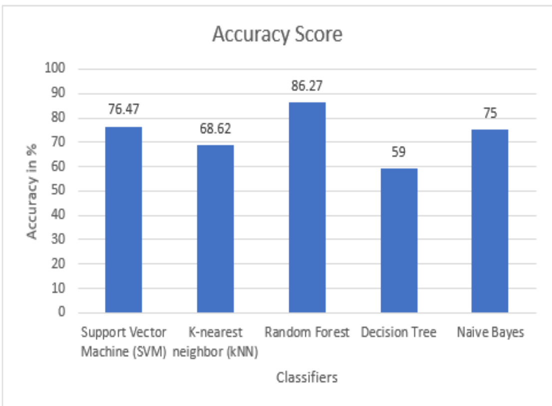

Figure 4: Graphical representation of Accuracy of various classifiers

Figure 4 shows the graphical representation of the accuracy of various machine learning classifiers. It is found that Random Forest classifiers achieve a high accuracy which is 86.27%.

B. Confusion Matrix

This matrix is one of the best methods that evaluating IDS. It depends on several measurements to determine the performance of the model where each column in this matrix represents the expected class while each row represents the actual class. The performance of the classifier is evaluated by calculating the number of the expected records correctly and the number of records classified incorrectly. Table 4 shows the four basic elements that determine the content of the matrix will be presented as follows:

Table 3: Layout of Confusion Matrix

Actual		Predicate Class	
		Positive	Negative
Class	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

C. Confusion Matrix and AUC Graph of Classifiers

12	3
9	27

Figure 5: Confusion Matrix of SVM

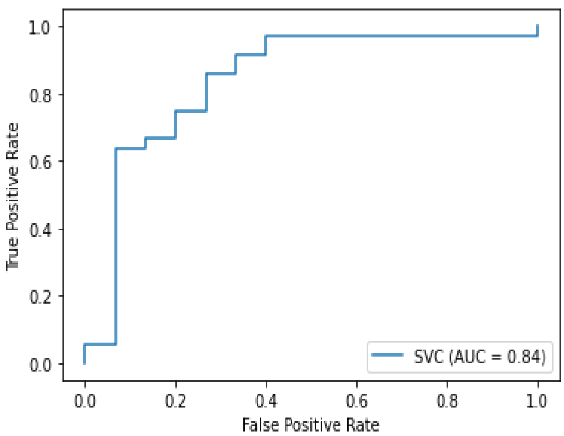

Figure 6: AUC Graph of SVM

13	2
14	22

Figure 7: Confusion Matrix of KNN

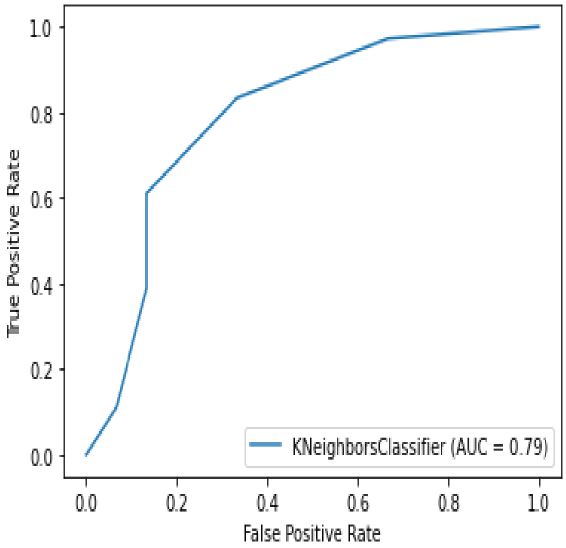

Figure 8: AUC Graph of KNN

12	3
4	32

Figure 9: Confusion Matrix of Random Forest

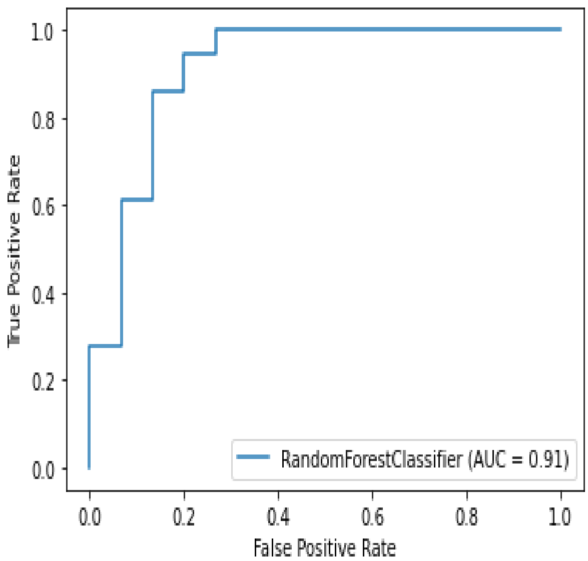

Figure 10: AUC Graph of Random Forest

7	8
10	26

Figure 11: Confusion Matrix of Decision Tree

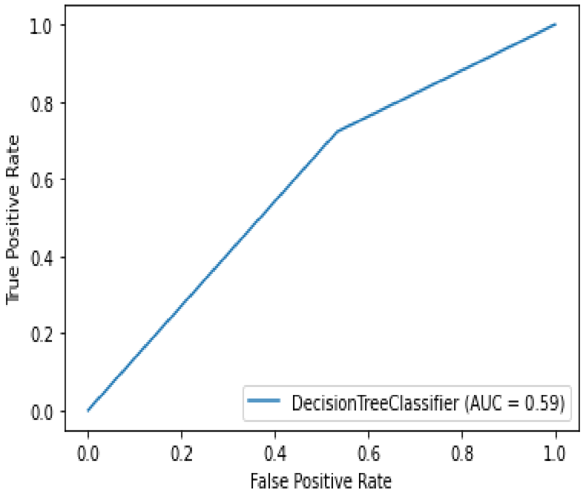

Figure 12: AUC Graph of Decision Tree

13	2
14	22

Figure 13: Confusion Matrix of Naïve Bayes

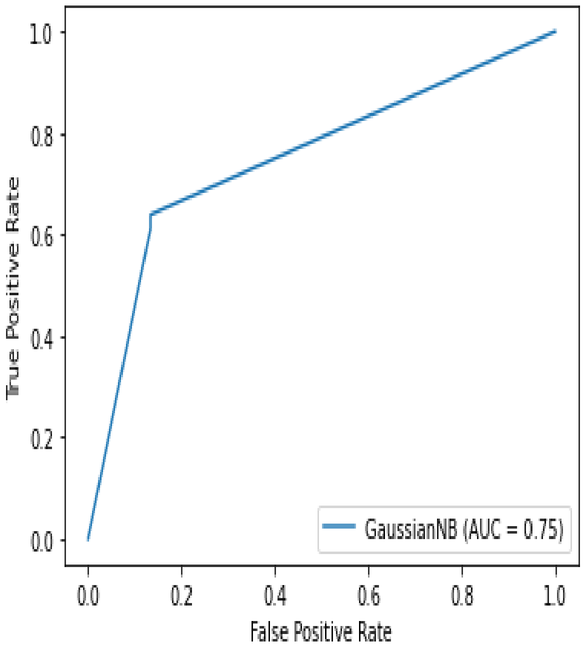

Figure 14: AUC Graph of Naïve Bayes

Conclusion And Future Scope

High-resolution Magnetic resonance imaging (MRI) has become the most popular imaging technique for technicians and doctors. MRI plays a vital role in the acquisition of brain images in the study of biomedical imaging. Due to the involute structure and variations in images, "segmentation" of "image from the magnetic resonance images" has become a "consequential", arduous and challenging task. Further, because of the intricate mathematical calculations and higher computational time requisites, the relegation of encephalon tumor from MR images becomes arduous. Algorithms for analyzing and classifying medical images have gained a great level of attention recently. The experiments present in this work show that after preprocessing MRI images, the neural network classification algorithm was the best.

Much higher accuracy can be achieved by gaining a better dataset with high-resolution images taken directly from the MRI scanner. Moreover, classifier random forest techniques can be used to raise the accuracy even higher and reach a level that will allow this tool to be a significant asset to any medical facility dealing with brain tumors.

In the Future, Various other functionalities like predicting the stage of the tumor, and possible medications suggestion can also be added. and also, Various types of filtering methods can be implemented for pre-processing of MR brain images. Particle Swarm Optimization (PSO) or Genetic Algorithm (GA) – based optimization techniques can be incorporated into the adaptive connected component pixel segmentation method. Further, different "advanced textures" feature selections can be measured for the classification of brain tumors. "Morphological reconstruction" and "membership filtering techniques" can also be utilized for large datasets of magnetic resonance images in case of segmentation.

Conflict Of Interest

The authors declare that they have no conflict of interest.

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