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Comparison of Various Classification Technique using MRI Images to Detect Malignant or Benign Tumor

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***Abstract*— The brain is the greatest imperative body part in the human body, responsible for monitoring and regulating entirely serious lifetime functions for the body and a tumor is a form of flesh formed by the buildup of anomalous cells, which keep on increasing. A brain tumor is a tumor which is moreover designed in the brain or has wandered Not at all prime cause has been recognized for the development of tumors in the brain till date. Still the death proportion of malignant brain tumors is increasing due to the circumstance that the tumor development is in the most life-threatening tissue of the body. Hereafter, it is of greatest importance to exactly detect brain tumors at primary stages to lesser the death rate.**

In this paper, we have applied a prototypical that segments images using Watershed and PSO algorithm, extracts features using DWT and PCA algorithms and finally classifies the tumors using CNN, SVM and Lazy IBK and Decision Tree algorithms with a high degree of accuracy [1].

***Index Terms*— Magnetic Resonance images (MRI), Brain tumor, Principal component analysis (PCA), discrete wavelet transform (DWT), Convolutional Neural Network (CNN), Decision Tree, Lazy IBK, and Support Vector Machine (SVM).**

I. INTRODUCTION

The human body consists of myriad number of cells. When cell growth becomes uncontrollable the extra mass of cell transforms into tumor. CT scans and MRI scans are used for identification of the malignant or benign tumor. The goal of our study is to accurately detect tumors in the brain and classify it over the means of several methods involving medical image processing, pattern analysis, and computer vision for enhancement, segmentation and organization of brain diagnosis.

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The research is expected to improve the sensitivity, specificity, and diagnostic effectiveness of brain tumor screening using industry standard simulation software tool, MATLAB. These techniques involve Pre-processing of MRI scans collected from online cancer imaging archives as well as scans obtained from several pathology labs. Images are resize and then we apply the proposed algorithms used for segmentation as well as classification [2].

II. LITERATURE REVIEW:

C. Hemsundaara Rao et al. [6] focuses in their research paper on detecting the brain tumor region with the help of preprocessing, edge detection and segmentation methods. They also used the K means clustering to improve the result of brain tumor identification by using this methodology.
Swapnil R. Telrandhe et al. [7] used the K means clustering and SVM to increase the accuracy in the Brain tumor detection after preprocessing, feature extraction method. The result is improved due to the Support vector Machine.
O. N. Pande et al. [8] developed the system on 2D MRI data which identifies the data of tumor. The Author developed the automated tool for the brain tumor detection. He used Noise removal function to remove the noise from the given MRI images. He also used the water shade segmentation to detect the brain tumor. The accuracy is improved by his proposed technology.
D. J. Hemanth et al. [9] developed the brain tumor identification system by using Fuzzy methodology. He used fuzzy clustering for the accurate brain tumor detection system used in abnormal brain image segmentation. This method gives the better accuracy in the brain tumor recognition system.
S. Koley et.al: propose the efficient work on tumor detection and segmentation of brain MRI for the purpose of determining the exact location of brain tumor using CSM based partitioned K-means clustering algorithm. CSM has attracted much attention as it has given efficient result as a self-merging algorithm compared to other merging processes and the effect of noise is also less and the probability of obtaining the exact location of tumor is more. Their approach is much simpler and computationally less complex and computation time is very less.
Laxami et.al, proposed the work on information (region of interest) in the medical image and thereby vastly improve upon the computational speed for tumor segmentation results. Significant feature points based approach for primary brain tumor segmentation was proposed. Axial slices of T1-weighted Brain [10]
J. Vijay et.al: propose the work on automated brain tumor detection by using segmentation by k-means algorithm and object classification algorithm. They identified that a well-known segmentation problem within MRI is the task of classification the tissue type which include White Matter (WM), Grey Matter (GM), Cerebrospinal Fluid (CSF) and sometimes pathological tissues like tumor. [3]

II. PROPOSED ALGORITHM

The features in the MR Images are extracted using the DWT method and further Reduction of the MR image is done by PCA. Once the features are readily extracted then the classification methods (SVM) is run so as to classify which type of tumor it is benign or malignant.

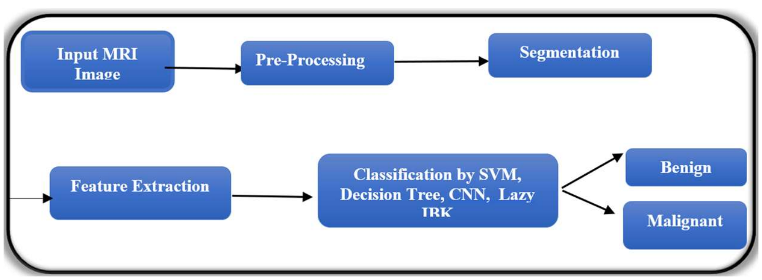


Figure 1 Stage diagram of the classification process

A. Input MRI Image

MRI scan images are obtained and these scanned images are displayed in a two-dimensional matrix having pixels as its elements. These matrices are dependent on its field of view and matrix size. Images are displayed as a grayscale image and Images are stored in Image file. The entries of a grayscale image are ranging from 0 to 255, where 0 shows total black color and 255 shows pure white color. Entries among these ranges differ in intensity from black to white [6].

B. Pre-processing Techniques

Pre-processing of MRI images is the major step in image Analysis which perform noise reduction and enhancement techniques, which are used to improve the image quality.
Noise Removal: To remove noise from the image many filters are used. Like, Laplacian, Gaussian and Median filters are used to remove salt and pepper noise from the image.

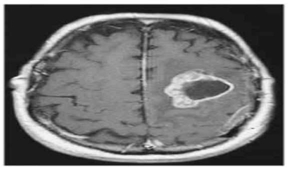


Fig 2. Original image

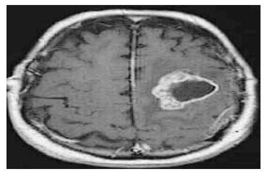


Fig 3. Laplacian Filter

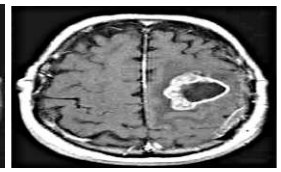


Fig 4. Gaussian Filter

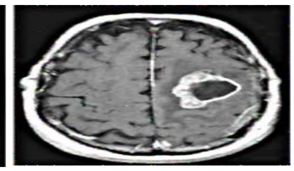


Fig 5. Median Filter

C. Segmentation

Segmentation of an image is an essential step and the most hypercritical tasks of image investigation. Its role of extracting tumor or removing tumor from an image of an image segmentation.
Image segmentation is the primary step and the most critical tasks of image analysis. In this Paper following segmentation algorithms are used to implemented segmentation:

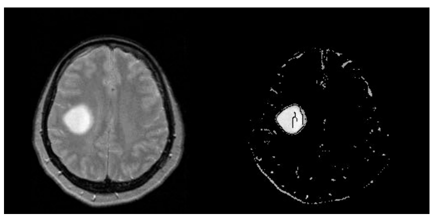


Fig 6. Canny Algorithm

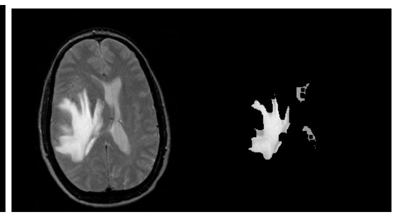


Fig 7. Otsu Algorithm

Malignant Tumor Benign Tumor

Fig 8

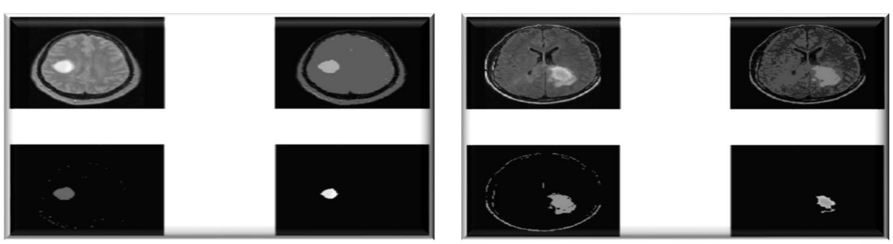


Fig 9. Particle Swarm Optimization (PSO)

Feature extraction scheme using DWT (Discrete Wavelet Transform)

The feature vector is extracted by DWT in the proposed system. The wavelet is a powerful mathematical tool for feature extraction, and will be used to extract the wavelet coefficient from MR images. Wavelets are functions that are concentrated in time as well as in frequency around certain point. The basic advantage of using the Wavelet Transform method is that it works in such a way that it gives good frequency resolution for low frequency components and high temporal resolutions for high frequency components.
A review of fundamental of wavelet decomposition is introduced as follows:

Initially the process is started by selecting a mother wavelet from 'Haar', 'Daubecheis', 'Morlet' etc. The signal is now translated into shifted and scaled versions of this mother wavelet. This analysis divides the signal into approximate and three detailed signals. The approximate sub signal shows the general trend of pixel values a detailed sub signals on the horizontal, vertical, and diagonal details [3].

Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) with Gray-Level Co-occurrence Matrix Algorithm (GLCM)

Discrete wavelet transform is a mathematical tool for analyzing signals and images by decomposing them into different frequency components extracts meaningful features from signals

The discrete wavelet transforms (DWT) is a powerful implementation of the WT using the dyadic scales and positions. The fundamentals of DWT are introduced as follows. Suppose x (t) is a square-integral function, then the continuous WT of x (t) relative to a given wavelet ψ (t) is defined as

$$W_\psi(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)\,dt \qquad (1)$$

where

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{b}\right) \qquad (2)$$

Here, the wavelet lamb (t) is calculated from the mother wavelet ψ (t) by translation and dilation: a is the dilation factor and b the translation parameter (both real positive numbers). There are several different kinds of wavelets which have gained popularity throughout the development of wavelet analysis. The most important wavelet is the Harr wavelet, which is the simplest one and often the preferred wavelet in a lot of applications [4].

GLCM: - GLCM is a widely used method for medical image analysis, classification. This method gives us information about relative position of two pixels with respect to each other.

Many features are taken for research like mean, mode, standard deviation, Kurtosis, smoothness, covariance, root mean square, variance, inverse difference movement, contract, energy, homogeneity, entropy, Skewness etc. from these features only 10 features are selected with the help of feature selection method. The values of features are mentioned

TABLE I. SHOWS THE VALUES OF EXTRACTED FEATURES

SRno	Image	Mean	Standard Deviation	Entropy	RMS	Variance	IDM	Contract	Correlation	Energy	Homogeneity
1	Y1	0.0036193	0.08974	3.58649	0.0898027	0.00799964	-0.345	0.2275	0.08469	0.748	0.930293
2	Y2	0.004937	0.08968	3.64088	0.0898027	0.00798999	2.0348	0.2392	0.07757	0.7286	0.923559
3	Y3	0.0019694	0.08979	3.66542	0.0898027	0.00797461	-0.218	0.2047	0.07729	0.7423	0.929204
4	Y4	0.0469597	0.08969	3.51706	0.0898027	0.00797428	-0.458	0.2425	0.07637	0.7517	0.931605
6	Y6	0.0043872	0.08971	3.50863	0.0898027	0.00801056	0.7465	0.2789	0.07876	0.7553	0.929843
7	Y7	0.0012945	0.08981	3.5692	0.0898027	0.00798602	-0.169	0.2022	0.08641	0.7568	0.932008
8	Y8	0.0032019	0.08976	3.12103	0.0898027	0.0080557	1.1487	0.2611	0.08214	0.7479	0.929461
9	Y9	0.0007111	0.08981	3.427	0.0898027	0.00799574	-0.288	0.2122	0.1097	0.7475	0.929829
10	Y10	0.0014765	0.0898	3.30698	0.0898027	0.00804159	0.8716	0.2464	0.120578	0.76302	0.933217

III. CLASSIFICATION

A. Support Vector Machine (SVM)

Support vector machines (SVMs) are a type of supervised learning models along with associated learning algorithms that analyze data and recognize various patterns, used for classification analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes, malignant and benign forms the output, making it a non-probabilistic binary linear classifier.

$$F(x) = w \cdot x + b$$

Where: - w is the weight vector, x is the feature vector, b is the bias or intercept term [5].

B. Lazy IBK

Instance based learning algorithms compare the new problem instances with the instances that are seen during the training of the algorithm and are stored in memory. It is different from normal algorithms, as it does not perform explicit generalizations.

It is called instance-based because it constructs hypotheses directly from the training instances themselves. As the hypothesis grows so does the hypothesis complexity.

In the worst case, a hypothesis is a list of n training items and the computational complexity of classifying a single new instance is O (n) [6].

$$\text{Argmax\_x } P(x|O) = \text{argmax\_x } \Sigma\text{\_i } \alpha (T, i) * \beta (T, i)$$

Where: P (x|O) is the posterior probability of state sequence x given observation sequence O, α (T, i) is the forward probability at time T for state i, β (T, i) is the backward probability at time T for state i

C. Convolutional Neural Networks (CNN):

The CNN algorithm is a multilayer perceptron that is the special design for identification of two-dimensional image information. It has the following layers: input layer, convolution layer, sample layer and output layer. Each neuron parameter is set to the same parameter, namely, the sharing of weights, i.e. each neuron with the same convolution kernels to DE convolution image.

$$y = f (w\text{^}T * x + b)$$

Where: y is the predicted output label, f is the activation function, w is the weight matrix, x is the input feature vector, b is the bias vector [7].

D. Decision Trees

Decision Trees (DT) is a super-vised machine learning algorithm for regression and classification and non-parametric in nature. It calculates the target value through simple piecewise decision rules applied on the features of the data. As an example, if a cosine curve has to be approximated using if-else functions then more the rules, complex will be the decision tree system and finer will be the model. The advantages of DT are its simplicity, little data preprocessing, complexity is log (training size), handles categorical data, easy to interpret the test results being a white-box model, statistical validation is possible and resistant to violations of data distribution assumptions of the model [8].

$$\boldsymbol{T}(\boldsymbol{x}) = \sum_{i=1}^{n} P(\boldsymbol{i}/\boldsymbol{x}).\ \boldsymbol{C}.\ (\boldsymbol{i})$$

Where: T(x) is the decision tree prediction for input x, p (I/x) is the probability of class I given input x, C (I) is the class label for class I, n is the number of classes.

IV. Classification and Grading

Supervise learning classifier was used for classification and grading, and grading was done based on the Statistical measures

TABLE II: Comparison of the Supervise learning Classification Models Applied for Grading via Statistical Measures

Sr. No	Supervise learning models	Accuracy
1	Support vector machine	88.7%
2	Conventional Neural Network	87.2%
3	Decision tree	99.7%
4	Lazy IBK	49.7%

IV. Confusion Matrix

Confusion matrix represents the performance of the algorithm. Where the row is the predicted class and column is the actual class or true class.

In following figure, we can see all classifier Number of the observations and comparatively Support vector machine and Decision tree gives good result.

A. Comparison of the Number of Observation Supervise Learning Classification on Q measures

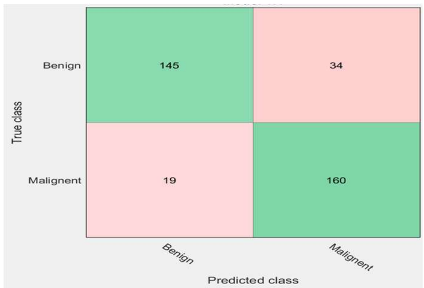


Figure 10. Confusion Matrix of CNN

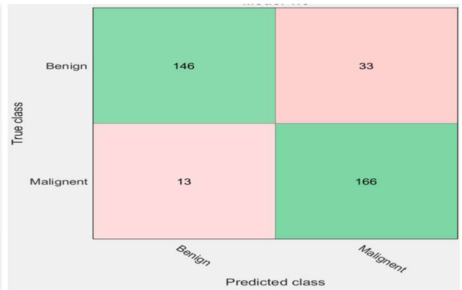


Figure 11. Confusion Matrix of SVM

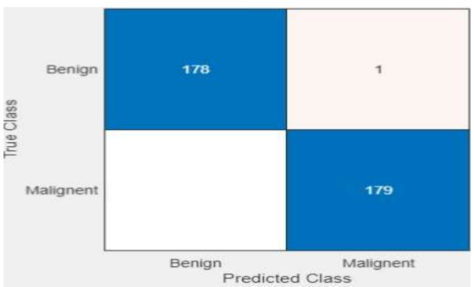


Figure 12: Confusion Matrix of Decision Tree

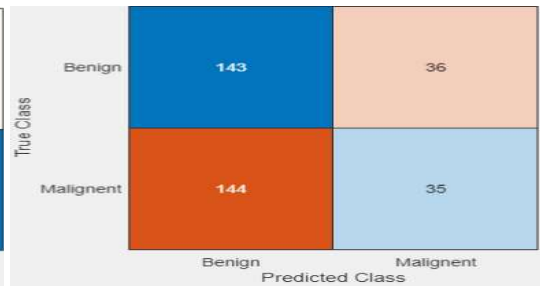


Figure 13: Confusion Matrix of Lazy IBK

True positive rates indicate the actual positive value correctly identified and false negative rate is the condition in which the test result is positive in negative condition.

The fig SVM and Decision Tree indicates that the True Positive Rate good both in the Predicted and True Class of the data is predicted correctly, in SVM shows the 6 % and in Decision tree shows the 7% in the false negative rate.

B. Comparison of the True Positive Rate and False Positive Rate Supervise Learning Classification Model on Statistical Measures

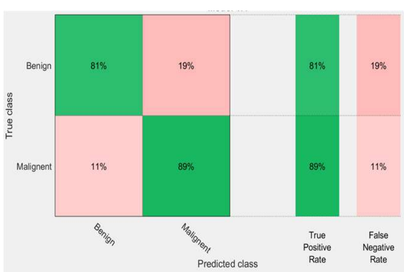


Figure 10: True Positive Rate and False Positive Rate CNN

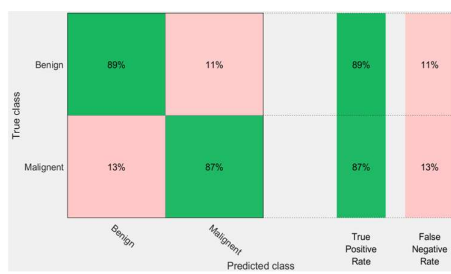


Figure 11: True Positive Rate and False Positive Rate SVM

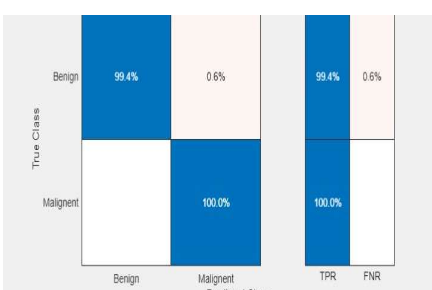


Fig12: True Positive Rate and False Positive Rate Decision Tree

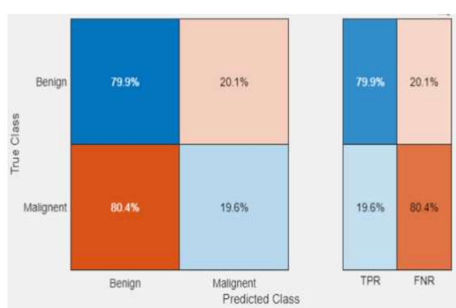


Fig 13: True Positive Rate and False Positive Rate Lazy IBK

Number of correctly classified positive value divided by the number of positive classified samples and the results unmatched are classified as negative when computation is done with Positive Predictive Value.

C. Comparison of the Positive Predictive Values False Discovery Rate Supervise Learning Classification Mode on Statistical Measures

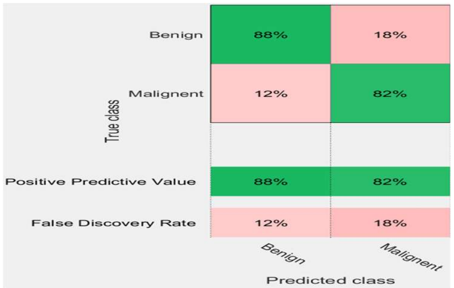


Figure 14: Positive Predictive Values False Discovery Rate CNN

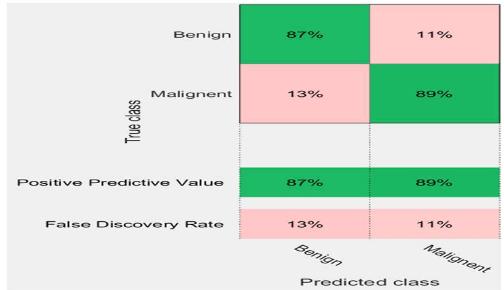
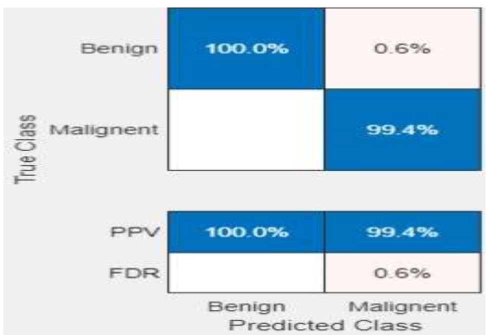


Figure 15: Positive Predictive Values False Discovery Rate SVM



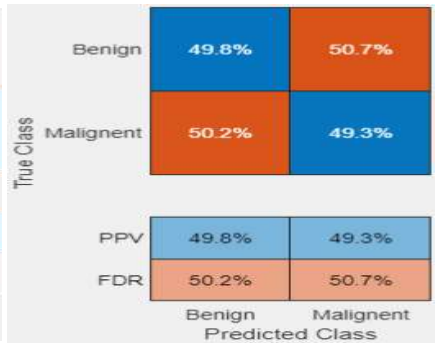


Figure 17: Positive Predictive Values False Discovery Rate Decision Tree Figure 18: Positive Predictive Values False Discovery Rate Lazy IBK

V. Overall Result Calculation

Following table shows the overall result, while classification and grading Brain Tumor is classified as Malignant and Benign Tumor.

TABLE III: OVERALL RESULTS

Reno.	Technique	Result
1.	Decision Tree classifier	99.7%
2.	Statistical Technique	99%
3.	Confusion Matrix	99%
Overall Result		99%

VI. Conclusion

Abnormal growth of tissue in the brain which affect the normal functioning of the brain is considered a brain tumor. The main goal of medical image processing is to identify accurate and meaningful information using algorithms with minimum error possible. Brain tumor detection and classification through MRI images is categorizes into two section i.e. feature extraction and image classification. It can be concluded that the algorithms and the parameters used in the proposed system are all meant to increase the efficiency of the system by achieving better results.

Features extracted by using GLCM method help to increase efficiency as minute details of tumor by using various features can be extracted. Of the various classification methods studied, it was experimentally found that the convolution neural networks give the best classification accuracy. Accuracy and reliability are of utmost importance in tumor diagnosis, as a patient’s life depends on the results predicted by the system. Thus, the proposed methodology helps in increasing the accuracy and obtaining the desired results [21].

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