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Identification And Classification Of Brain Tumor Images Using Efficient Classifier

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Abstract:- The main objective of this study is to propose a model for finding brain tumor. Failing to detect the tumor in its prior stage will increases the chance of losing a life. So the identification and treatment for the tumor in its prior stages become vital to save the life of a human being. This work uses the Magnetic Resonance Image (MRI) images to identify and classify the benign and malign type brain tumors. Low pass filter is applied to preprocess the MRI image that removes the unwanted background structures at the same time keeps the important portions sharpened. Watershed segmentation method is used for segmenting the tumor affected area independently. The statistical feature extraction method Gray Level Co-occurrence Matrix (GLCM) is applied to take out the imperative features from the segmented tumor. The feature selection is performed using Recursive Feature Elimination- Particle Swarm Optimization (RFE-PSO) method. Ensemble Support Vector Machine (SVM) is applied to classify the tumors into harmless and harmful from the medical image.

Keywords: Magnetic Resonance Imaging, Low pass Filter, Watershed segmentation, GLCM, RFE-PSO, Ensemble SVM.

I. INTRODUCTION

A tumor is an accumulation of tissue that is formed by the expansion of abnormal cells. This is one of the reasons that cause the deadliest diseases that root to death. Prime tumors originate in the brain. Prime tumors are harmless in its nature. The harmful tumor starts in one part of the body and spread to the brain. Mining the medical images for classification involves the extraction of models, abnormalities and patterns from the voluminous data. Proposing a model for classification [3] task encourages the introduction of innovative models and helps in decision making process. The prime objective of mining medical images is to fetch out the best accuracy from the model and to understand about the affected regions and its progression. Methods like textural extraction, fuzzy theory, wavlets and neural network have been used for classification. In this work a method is projected for the discovery and classification of tumors in to normal and abnormal one. The medical image is first segmented through the watershed segmentation [19] method. The Features from the medical image are extracted by GLCM [1] method. The selection of minimal sub set of feature is done through Ensemble SVM classifier [1] is used for the final classification.

II. RELATED WORKS

Mustafa R Ishmael, Ikhlas abdel-Qader proposed a framework for brain tumor classification. This method extracts the statistical features [1] of the MRI image and incorporates the neural network algorithms. The tumor can be segmented by means of manual/machine interactions. Feature selection is performed by 2D discrete wavelet transform and 2D gabor filter technique. A completely transformed feature set is generated by using the said feature selection method. In this work for the purpose of classification task a back back propagation neural network [18] is applied. 3,064 sets of T1 subjective tumor type images are of three kinds namely Meningioma, Glioma and pituitary are taken for training and testing purpose.

Varuna shree, T.N.R Kumar proposed a technique that concentrates on noise removal technique and the feature extraction done by the GLCM [1] features. The segmentation process uses DWT based region growing segmentation technique [5] to improve the performance in classification. Classification task is done through the probabilistic [2] neural network to find the results.

H.N.T.K Kaldera, Shanka Ramesh Gunasekara introduced to classify the brain tumor images with the help of the convolutional neural network [10]. The introduced technique also uses Faster R-CNN for segmenting the tumor region. The segmented tumor regions are checked with the ground truth and manual analysis by a neurologist.

Mahmoud Khaled Abd-Ellah, Ali Ismail awad proposed a two phased multi model analysis system for brain tumor discovery and localization. In this work the introduced system classifies the tumor type by preprocessing, feature extraction using a [10] convolutional neural network. The classification is done through the error correcting output code support vector machine. The first phase is used to identify the brain tumor type into normal and abnormal. The second phase of this system designed using a five layer section based convolutional neural network [10] to confine the tumor within the abnormal MRI image.

Monika, Deepti proposed a noise removal and skull removal for preprocessing task. The feature extraction step uses the GLCM method [1]. Feature reduction technique uses Rough set theory and Particle Swarm optimization [14]. Classification and performance of this system evaluated through SVM, Naïve Bayes and Rusboost classifier.

D.Bhuvana and P.Bagavathi sivakumar performed the detection and classification of tumor with the use of Probabilistic neural network [2] in their work. In the first stage they used anisotropic filtering method to remove the irrelevant features from the image. By applying this filter method the image is sharpened to extract the features. In the

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next stage by using Fuzzy C-Means segmentation [6] method they extracted the tumor region. In the next stage they applied the Probabilistic neural network for classification. The brain image has been classified into two categories. They are harmless and harmful brain.

III. PROPOSED METHODOLOGY

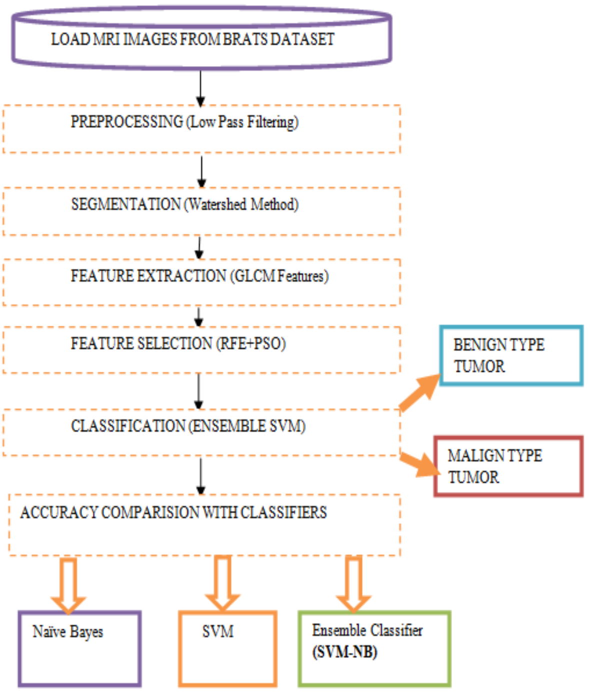

Fig1: Proposed Methodology

IV. PRE PROCESSING

The Preprocessing technique is applied on the medical image to enhance the quality of the image by smoothing. This process reduces the noise and reconstructs the medical image to improve the image features for additional processing. The pre processing operations [16] are required before the data analysis and extraction of information from the image. The Low pass filter is applied on the medical image to improve the image value by decreasing the background noise and conserve the edge points of the image [12]. This task makes the detection and interpretation of the image easier.

A. Low pass Filter

A Low pass filter can be used to make an image appear sharper. This filter keeps the finer details of the image. As MRI images are hard to understand and infer, it is necessary to improve the quality of the image and performs the feature extraction [2] stage easier and consistent one. The excess amount of tissue around the tumor region will prevent the accurate detection. The low pass filter used is used to is improve the image and tumor difference.

In this work a capable filter was applied on the image that keeps the tumor regions at the same time suppressing the irrelevant image features.

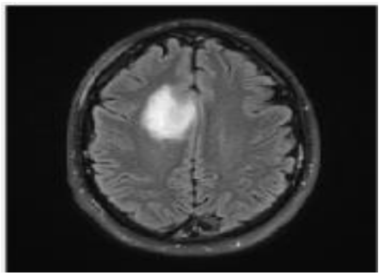

Fig 2: ROI of an Image

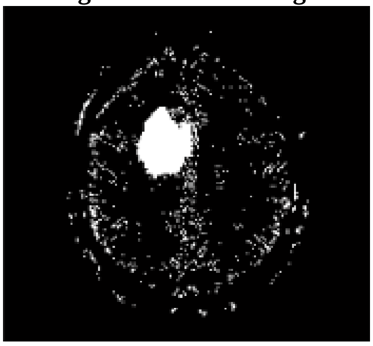

Fig3: ROI after Preprocessing

The MRI image after applying the low pass filter above shows the tumor region preserved and it also removes the unwanted structures of the medical image [4]. This task makes the tumor detection step easier.

V. SEGMENTATION USING WATERSHED SEGMENTATION METHOD

The medical image can be divided in to partition called segments. Processing the entire image is not a good practice since it takes more effort for classification. So extraction of important segments from the image makes the image processing task quicker. The simplified representation of the image is very meaningful and helpful to analyze the problem behind the image. This can be achieved through the segmentation methodology.

A. Watershed Segmentations

A transformation defined on a grayscale image is named as watershed [5]. The watershed transformation is a region based method that reads the image it works on like a map, with the clarity of each point representing its tallness, and finds the lines that run along the tops of ridges. This method is primarily used for segmentation purpose. It effectively combines elements from both the discontinuity and correspondence method based on points, lines and edges.

B. Methods to Implement Watershed Approach

Distance Transform Approach

A Methodology used in connection with the watershed transform for segmentation [9] is the distance transform. In this method the distance from each pixel to the nearest non-zero valued pixel is taken for the measurement.

Gradient Method

Before applying the watershed transformation over the segmented tumor image a gray scale image is preprocessed with the help of the gradient magnitude. [4].The original character of the gradient magnitude image is to conserve the higher pixel values beside object limits and poorer pixel values or else. Along the object edges water shed transforms results in water ridge.

Marker Controlled Method

The watershed transformed gradient image will result in over segmentation issue due to noise factor. It means the generation of more number of segmented regions. This problem can be addressed and resolved by using the idea of marker. A marker is the related constituent of an image. Two different types of markers are used with watershed segmentation method. The internal markers are used in connection with objects and the external markers are used in connection with the external parts of the boundary. This is the strong and flexible method [9] for segmenting the objects with closed contours, where the ridges represent the boundary areas. The boundaries of the watershed regions are arranged as ridges after the application of segmentation process. This procedure separates each object from the neighbors.

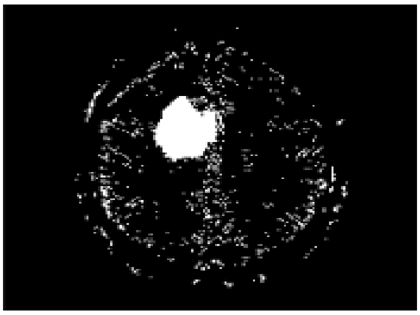

Fig4: Preprocessed Image

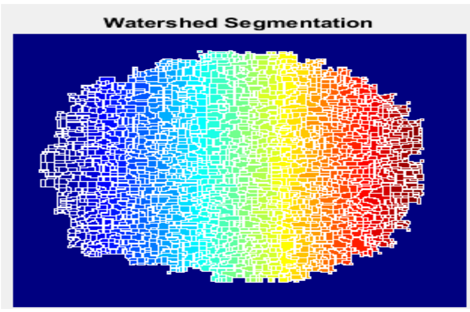

Fig5: Watershed Segmented Image

VI. FEATURE EXTRACTION USING GLCM FEATURES

Feature extraction phase reduces the attributes to a level. This is the process to transform the actual attributes. The working speed and effectiveness of the learning algorithm is improved through this feature extraction technique. The approaches similar to shape based approach, intensity based approach, template based approach and texture based approach [15] are followed for extracting vital features from the medical image. This method is implemented to mine the important features from the image that represents the various classes in classification. Classifier takes different features as input from the image and assigns them to the class that they represent.

A. GLCM Features (Gray Level Co-occurrence Matrix)

The drawing out of image features can be done through the popular statistical method known as GLCM [12]. The spatial relationship between the pixels in the Gray-level co-occurrence matrix is measured in this process. The pixel is defined as the pixel of interest and the pixel to its horizontally adjacent position is taken for defining the spatial relationship measure [18]. The specification of relationship among other pixels can be represented in the resulting GLCM as the computation of amount of times that the pixel with value I occurred in the relationship to a pixel with value J in the input image. The significant features out of the image were extracted from the segmented image and analyzed in [15] various magnitude.

From the segmented image the following image features were extracted: Contrast, Correlation, Cluster shade, Cluster prominence, Difference variance, Difference Entropy, Energy, Entropy, Inertia, Inverse difference moment, Sum average, Sum variance, Sum entropy and Variance.

Homogeneity measurement can be done by this feature. It is also known as consistency or angular succeeding moment.

Energy: $E=\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} p(i,j)^2$ (1)

It measures the intensity variation between the neighbor pixel and the reference pixel.

Contrast = $\sum_{n=0}^{Ng-1} n^2 \ \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} p(i,j)^2$ …(2)

The measure between the reference pixel and its related neighbor pixel is calculated by Correlation.

Corr = $\frac{1}{\sigma_X\sigma_Y}\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i,j).\,p(i,j)^2-\mu_x\mu_y$ (3)

$\sigma_x\ \sigma_y$ - standard deviation of $p_x\ p_y$

$\mu_x\ \mu_y$ – mean of $p_x\ p_y$

Variance: $\boldsymbol{\sigma}^2=\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i-\mu)^2.p(i,j)$ …(4)

Inverse Difference Moment: The local homogeneity of an image is calculated through IDM.

Inverse Difference Moment = $\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}\frac{1}{1+(i-j)^2}\,p(i,j)$ …(5)

Sum average: $\mu=\sum_{i=0}^{2(Ng-1)} i\,.p_{X+Y}(i)$ …(6)

Sum variance: $\sigma=\sum_{i=0}^{2(Ng-1)}(i-SE)^2.p_{X+Y}(i)$ …(7)

Sum entropy: $SE=-\sum_{i=0}^{(Ng-1)} p_{X+Y}(i).\log p_{X+Y}(i)$ …(8)

Entropy: $E=-\sum_{i=0}^{(Ng-1)}\sum_{j=0}^{(Ng-1)} p(i,j).\log p(i,j)$ …(9)

Difference variance: DV = Variance of $p_{(X-Y)}$ (10)

Difference entropy: DE = $-\sum_{i=0}^{(Ng-1)} p_{(X-Y)}(i)\log p_{(X-Y)}(i)$ …(11)

Inertia: $I=\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i-j)^2.p(i,j)$ 12)

Cluster shade: CS = $\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i+j-\mu_X\mu_Y)^3.p(i,j)$ …(13)

Cluster Prominance:

$P=\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i+j-\mu_X\mu_Y)^4.p(i,j)$ …(14)

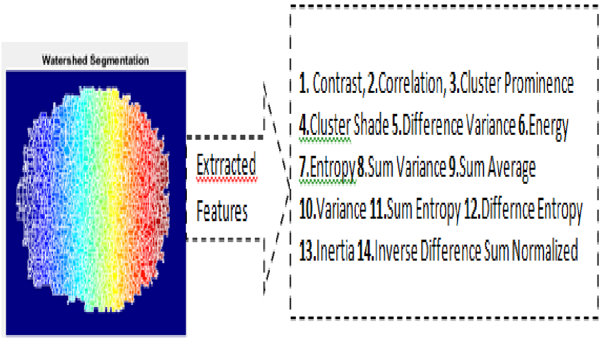

Fig6: Watershed Segmented Image Fig7: Statistical Features Extracted from the MRI Image

Table1: GLCM Features and their values of a segmented image.

Feature No	Statistical Name of selected Feature	Feature Value
1	Contrast	1.885
2	Correlation	0.1897
3	Cluster prominence	42.8652
4	Cluster shade	4.6543
5	Difference variance	1.7870
6	Energy	0.3356
7	Entropy	2.6786
8	Sum average	56.3242
9	Variance	12.2340
10	Sum variance	16.1323
11	Sum entroypy	165.6542
12	Difference entropy	1.8898
13	Inertia	0.2456
14	Inverse difference sum normalized	0.3563

VII. FEATURE SELECTION (RFE-PSO ALGORITHM)

A. Recursive Feature Elimination – Particle Swarm Optimization.

The best possible subset of features from the original feature set is extracted according to certain conditions by means of feature selection process. The reduction in the amount of data input to the classification algorithm induces the classification algorithm to be trained faster. This technique selects fewer features by eliminating the redundant and repetitive features from the feature space [13]. This technique generalizes the data in a better way. Feature selection methodology provides simpler results to interpret quickly.

RFE-PSO Algorithm

Input: The number of loops in RFE
γ – The Threshold value for the inconsistency rate
D – Selected Data set with N features

Intialize: List $L_{REF} = L_{PSO} = \{\}$
$L_{REF} = L_{REF} = L\ (D, \gamma, no)$
For each $S' \epsilon L_{REF}$
$S = PSO\ (S', D)$
$L_{PSO} = append(S, L_{PSO})$

Output: S mi

Recursive Feature Elimination method presents a rigorous way to determine the important features before even supplied to the classification task. This technique works based on the sizes and the iteration count. This method follows the working principle of random forest. It also includes the k-fold validation. It selects the top n variables out of N for the classification task. The outcome of this subset is then supplied to PSO feature selection algorithm [14] for further refinement.

The PSO procedure to find the optimal subset is as follows

Do
For RFE particles each product
The suitability value from the subset is considered
If the suitability value is better than the best fitness value (pBest) in the history
Set current value as the new pBest
End

Choose the particle with the best suitability value of all the particles as the gBest
For each product from the RFE particle
Measure the particle velocity according to the velocity values
Revise the particle location according to the position values
End

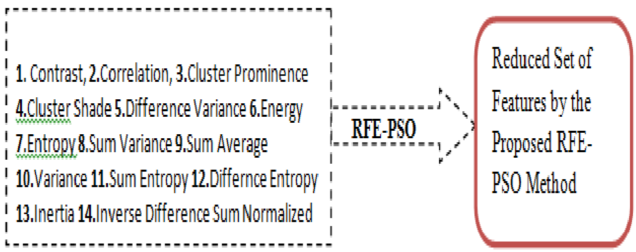

Fig8: Feature Reduction using RFE-PSO Method Fig9: Reduced Feature Set

VIII. CLASSIFICATION USING ENSEMBLE SVM

The Ensemble SVM is used to classify a brain tumor in an MRI image according to its propinquity to the most significant training vector. This technique was developed to overcome the pitfalls of single SVM and consolidating their strengths. The Ensemble of support vector machine incorporates the ensemble features of the classifier to achieve better performance.

A. Naïve Bayes Classification

A family of simple probabilistic classifier is the basic working idea behind the working principle of Naïve bayes classification method. The number of features of a model is very large in numbers then this classification [2] method can be applied. A particular MRI image is assigned to a class based on image classification process.

$$C^* = \arg\max_c \ p(c|d) \qquad (15)$$

The fundamental model can be evolved on the basis of the bayes theorem using the conditional probability as

$$p(c|d) = \frac{p(c)p(d|c)}{p(d)} \qquad (16)$$

The choice of p(d) is purely based on C*. To calculate the expression p(d |c), it is break down by the Naïve base as assuming the fi's are conditionally independent given d's class as in the subsequent equations.

$$p_{NB}(c|d) := \frac{p(c)\ (\prod_{i=1}^{m} p(f_i|c)^{n_i(d)})}{p(d)} \ \ldots \qquad (17)$$

The total number of features defined by the term m and feature vector is defined using the term fi. The significant relative frequency estimation is done through p(c) and p(fi|c).

B. Support Vector Machine

The introduction of the Support Vector Machine Classifier to this world has happened in the late 1990's. This Classifier has been applied very effectively in the field of engineering and technology.SVM follows the linear classifier method to classify data samples into two distinct categories [3].

Given training vectors in two classes Xi ϵR^n , i=1,2……L and an indicator vector Yi ϵ R^L. such that Yi ϵ {1,-1},C

The primal optimal solution can be derived from

$$min_{w,b\xi} \frac{1}{2}\ \omega^T \omega + \ C\ \sum_{i=1}^{l} \xi_i \qquad \ldots(18)$$

Subject to $\quad y_i(\omega^T \phi(x_i) + \ b) \ \geq \ 1 - \xi_i)$

Where $\quad \xi_i \ \geq \ i = 1, \ldots, l$

The (Xi) maps Xi in to a superior dimensional space and C >0 is the regularization parameter. The high dimensionality of the vector variable w, we solve this situation by means of the dual problems

$$min_\alpha \frac{1}{2}\ \alpha^T Q \alpha \ - \ e^T \alpha \qquad (19)$$

Subject to $Y^T \alpha = 0$, $\quad \leq \alpha_i \leq C$, i = 1,…,L

Where e=[1….L]^T is the vector of all samples, Q is an L by L positive semi-definite matrix,

Q_{ij} – $y_i y_j$ K(Xi,Xj), and K(Xi,Xj) $-\emptyset(x_i)^T \emptyset(x_j)$is the kernel function.

The optimal w satisfies

$$\omega \ = \ \sum_{i=1}^{l} y_i \alpha_i \emptyset(x_i) \qquad \ldots(20)$$

And the final decision function is

$$sgn(\omega^T \emptyset(x) + b) = \ sgn\ (\sum_{i-1}^{L} y_i \alpha_i K(x_i, x) + b) \quad (21)$$

C. Support Vector Machine Procedure

Probability of selecting Optimal set is $Prob_j$ and the Threshold value for the FSP $_{(REF\text{-}PSO)}$ is derived from the REF-PSO.

$D_{testdata}$ = Collection of Test Data

FSP = Feature Set Pattern of the Test Data

FSP $_{(REF\text{-}PSO)}$ = Feature Set Pattern derived out of Combined Feature Selection Method

Buff $_{set}$ = Buffer set for collecting Results

SVM_{outj}, = Output Collected from the SVM Classifier.

$Prob_j$ = Probability value for the Collected Output Pattern

```
R-Set SVM = { }
      For Each FSP in Dtestdata
            S-Buff set = 0
         For Each FSP (REF-PSO) ϵ FSP
           Pass(REF-PSO) To Classifier SVM [Output SVMoutj, Probj ]
            If | (Probj) | > FSP-TH(REF-PSO)
              If SVMoutj <> "Positive"
                 Probj = -(Probj)
              S-Buff set = Buff set + Probj
  R-Set SVM = R-Set SVM U {SVMoutj, Probj}  [SVMoutj = "Positive" if Buff set > 0
                                             SVMoutj = "Negative" if Buff set < 0 ]
```

D. Naïve Bayes Classification Procedure

```
R-Set NB = { }
      For Each FSP in Dtestdata
         Buff set = 0
     For Each FSP (REF-PSO) ϵ FSP
       Pass(REF-PSO) To Classifier NB [ Probj ]
         Buff set : {1 for Positive , 0 for negative}
         Buff set = S-Buff set + Buff set
```

IX. ENSEMBLE PROCEDURE FOR SVM-NB AS FOLLOWS

1. Identify the common results produced by both the SVM and NB classifier.

ResultSet = R-Set $_{SVM}$ ∩ R-Set $_{NB}$ = { For each x ϵ R-Set $_{SVM}$ {SVM $_{outj}$ }and

For each x R-Set $_{NB}$ {NB $_{outj}$ }

2. Find out the result difference between the SVM and NB classifier.

R-Set $_{SVM}$ {SVM $_{outj}$ }Δ R-Set $_{NB}$ {NB $_{outj}$ }

3. Find out the coefficient difference between for our proposed methodology

Diff = R-Set $_{SVM}$ (prob) + { $\log_{10}$|R-Set $_{NB}$ (prob)| }

4. Find out the average of all the coefficient differences

Result-Set = Results U R-Set $_{SVM}$ if Diff < average

Result-Set = Results U R-Set $_{NB}$ if Diff > average

Final results obtained through the Result-Set.

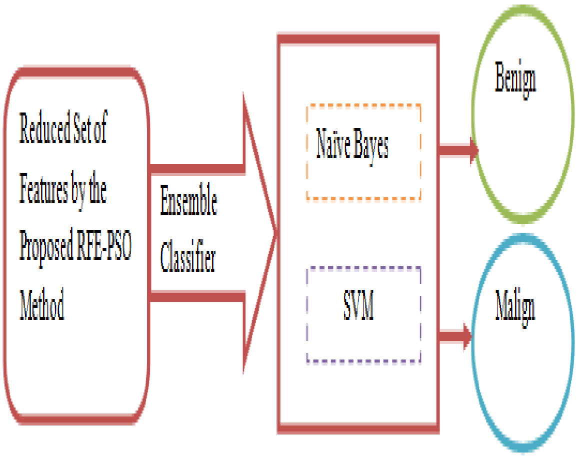

Fig10: Classification using NB-SVM Ensemble Classifier

X. RESULTS AND ANALYSIS

MRI Image Dataset Description: The data set used in this work is BRATS. The BRATS brain tumor data set contains 110 T1-subjective contrast-enhanced images with three different types of brain tumor category.

Experimental results

Ensemble Classifier methodology is used to classify the brain images into benign and malign. This Classifier successfully classifies the normal and abnormal brain. The combination of Naïve Bayes and Support Vector Machine classifier is known as the Ensemble Classifier. The accuracy level achieved through this method is 98.41%. Precision and Sensitivity parameters are analyzed for the MRI images.

Table 2: Confusion matrix measures

Disesase(Positive)	Disease(Negative)	Total No's
True Positive (TP=62)	False Positive (FP=0)	Test Positive (62)
False Negative (FN=1)	True Negative (TN=2)	Test Negative (3)
T disease (63)	T non-disease (2)	Total = 65

Table 3: Accuracy Comparison on Classifiers

Naïve Bayes	SVM	Ensemble SVM
87.69	95.67	98.46

Table 4: Performance Measures of the Classifier

Classifier Name	Accuracy	Precision	Sensitivity
Naïve Bayes	87.69	96.49	90.16
SVM	95	100	95
Ensemble SVM	98.46	100	98.41

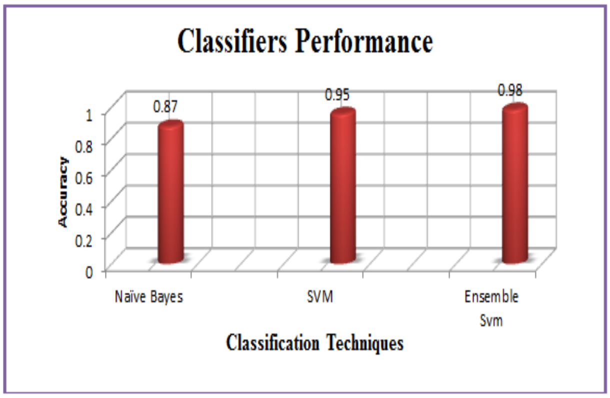

Fig11: Performance Comparison of Classifiers

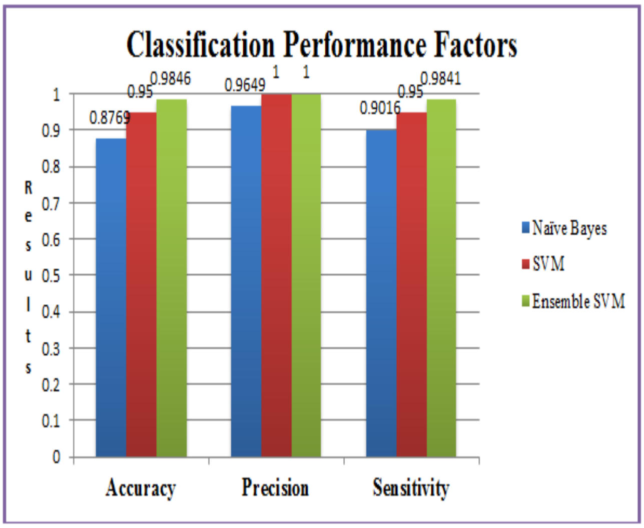

Fig12: Performance Metrics Comparison for the Classifiers

XI. CONCLUSIONS

Many researchers committed their substantial time to detect and classify the brain tumor over the past years. The detection and prediction of brain tumor in its premature phase by the physician will assist the patients to take preventive steps to extent their life span. An efficient classifier is proposed to classify the ordinary and abnormal brain in this study. Low pass filtering is applied to smoothen the MRI image for further analysis task. An effective Watershed segmentation method is applied then to segment the affected brain area separately. From the segmented medical image GLCM [4] statistical features are extracted for the next phase. RFE-PSO approach is followed to select the best possible set of features for the final phase of classification. The classification task designating a brain into normal or abnormal brain is done through the Ensemble SVM classifier [17].

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