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Brain Tumor MRI Segmentation and Classification Using Ensemble Classifier

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Abstract---Brain tumor is a group of tissue that is prearranged by a slow addition of irregular cells. It occurs when cell get abnormal formation within the brain. Recently it is becoming a major cause of death of many people. The seriousness of brain tumor is very big among all the variety of cancers, so to save a life immediate detection and proper treatment to be done. Detection of these cells is a difficult problem, because of the formation of the tumor cells. It is very essential to compare brain tumor from the MRI treatment. It is very difficult to have vision about the abnormal structures of human brain using simple imaging techniques. Ensemble methods have been called the most influential development in Data Mining and Machine Learning in the past decade. They combine multiple models into one usually more accurate than the best of its components. Ensemble methods combine the procedure of neural network, extreme learning machine (ELM) and support vector machine classifiers. The proposed system consists of manifold phases. Preprocessing, segmentation, feature extraction, and classification. At initially preprocessing is performed by using filtering algorithm. Secondly segmentation is performed by using clustering algorithm. Thirdly feature extraction is performed by Gray Level Co-Occurrence Matrix (GLCM). Automatic brain tumor stage is performed by using ensemble classification. This phase classifies brain images into tumor and non-tumors using Feed Forwarded Artificial neural network based classifier. Experiments have exposed that the method was more robust to initialization, faster and accurate.

Keywords-- Ensemble classifiers, GLCM, ELM, SVM, Feed Forward Artificial Neural Network and Fuzzy C-means Clustering.

I. INTRODUCTION

In recent times, the introduction of information technology and e-health care system in the medical field helps clinical experts to provide better health care to the patient. Brain tumors affect the humans badly, because of the abnormal growth of cells within the brain. It can disrupt proper brain function and be life-threatening. Two types of brain tumors have been identified as benigntumors and malignanttumors. Benign tumors are less harmful than malignant tumors as malignant are fast developing and harmful while benign are slow growing and less harmful. The various types of medical imaging technologies based on noninvasive approach like; MRI, CT scan, Ultrasound, SPECT, PET and X-ray [1]. When compared to other medical imaging techniques, Magnetic Resonance Imaging (MRI) is majorly used and it provides greater contrast images of the brain and cancerous tissues.

Therefore, brain tumor identification can be done through MRI images [2]. This paper focuses on the identification of brain tumor using image processing techniques. The detection of a brain tumor at an early stage is a key issue for providing improved treatment. Once a brain tumor is clinically suspected, radiological evaluation is required to determine its location, its size, and impact on the surrounding areas. On the basis of this information the best therapy, surgery, radiation, or chemotherapy, is decided. 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 [3]. As a result, the study of brain tumors using imaging modalities has gained importance in the radiology department. In this paper the brain tumor identification is done by an image processing.

In this paper, there are four process are done to identify the brain tumors. The first process is pre processing the image data from the collection of database using median filtering, second stage is segmentation using Fuzzy C-means Clustering Algorithm [4], third stage is feature extraction using Gray Level Co- Occurrence Matrix (GLCM), [5] and the fourth stage is classification using ensemble classifiers is the combination of neural network, Extreme Learning Machine (ELM) and Support Vector Machine classifier (SVM). This will be discussed briefly in this following section.

II. LITERATURE REVIEW

Saleck et al [4] introduced a new approach using FCM algorithm, in order to extract the mass from region-of interested (ROI). The proposed method aims at avoiding problematic of the estimation of the cluster number in FCM by selecting as input data, the set of pixels which are able to provide us the information required to perform the mass segmentation by fixing two clusters only. The Gray Level Occurrence Matrix (GLCM) is used to extract the texture features for getting the optimal threshold, which separate between selected set and the other sets of the pixels that influences on the mass boundary accuracy. The performance of the proposed method is evaluated by specificity, sensitivity and accuracy.

Bhima and Jagan [6] demonstrated the superior accuracy for brain tumor detection in compared to the presented methodologies. Also the major identified bottleneck of the recent research outcomes are limited to detection of brain tumor and the overall analyses of internal structure of the brain is mostly ignored being one of the most important factor for disorder detection.

Vrji and Jayakumari [7] improved brain tumor approximation after a manual segmentation procedure and 2D & 3D visualization for surgical planning and assessing tumor.

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thetumor identification, the investigations has been made for the potential use of MRI data for improving brain tumor shape approximation. In Preprocessing and Enhancement stage, medical image is converted into standard formatted image. Segmentation subdivides an image into its constituent regions or objects.

Rashid et al [8] investigated the chosen brain MRI image and a method is targeted for more clear view of the location attacked by tumor. An MRI abnormal brain images as input in the introduced method, Anisotropic filtering for noise removal, SVM classifier for segmentation and morphological operations for separating the affected area from normal one are the key stages if the presented method. Attaining clear MRI images of the brain are the base of this method. The classification of the intensities of the pixels on the filtered image identifies the tumor.

Sudharani et al [9] the present paper proposed the c1assification and identification scores of brain tumor by using k-NN algorithm which is based on training of k. In this work Manhattan metric has applied and calculated the distance ofthe c1assifier. The algorithm has been implemented using the Lab View.

Vidyarthi, A., &Mittal[10] proposed a hybrid model which identifies the region of interest using fused results of threshold segmentation and morphological operations. Initially, an abnormal brain MR image is processed with Otsu threshold based segmentation and morphological operations like erosion. Further, both the segmented resultant images are fused with the original MR image to preserve the background and correctly identification of the tumor region.

Li et al [11] proposed framework employs local binary patterns (LBPs) to extract local image features, such as edges, corners, and spots. Two levels of fusion (i.e., feature-level fusion and decision-level fusion) are applied to the extracted LBP features along with global Gabor features and original spectral features, where feature-level fusion involves concatenation of multiple features before the pattern classification process while decision-level fusion performs on probability outputs of each individual classification pipeline and soft-decision fusion rule is adopted to merge results from the classifier ensemble. Moreover, the efficient extreme learning machine with a very simple structure is employed as the classifier.

Dhanaseely et al [12] presented and investigated two different architectures in this work. The cascade architecture (CASNN) and feed forward neural architecture (FFNN) are investigated. The feature extraction is performed using principal component analysis (PCA) as it reduces the computational burden.

For a given database the features are extracted using PCA. The Olivetti Research Lab (ORL) database is used.The extracted features are divided into training set and testing set. The training data set is used to train both the neural network architectures. Both are tested extensively using testing data.

Liu and Liu [13] proposed an algorithm of HV microscopic image feature extraction and recognition using gray level co-occurrence matrix (GLCM) in order to effectively extract the feature information of human viruses (HV) microscopic images. Firstly, 20 pieces of microscopic images of human virus are obtained by using GLCM, and then the four texture feature parameters, entropy, energy inertia moment and correlation are extracted utilizing the GLCM, and then HV image recognition is carried out.

Parveen and Singh [14] proposed a new hybrid technique based on the support vector machine (SVM) and fuzzy c-means for brain tumor classification.

The purposed algorithm is a combination of support vector machine (SVM) and fuzzy c-means, a hybrid technique for prediction of brain tumor. In this algorithm the image is enhanced using enhancement techniques such as contrast improvement, and mid-range stretch. Double thresholding and morphological operations are used for skull striping. Fuzzy c-means (FCM) clustering is used for the segmentation of the image to detect the suspicious region in brain MRI image.

Grey level run length matrix (GLRLM) is used for extraction of feature from the brain image, after which SVM technique is applied to classify the brain MRI images, which provide accurate and more effective result for classification of brain MRI images.

AmasyaliandErsoy [15] proposed ensemble classifier in order to improve the accuracy and execution time. Classification accuracy and execution time are two important parameters in the selection of classification algorithms.

In these experiments, 12 different ensemble algorithms, and 11 single classifiers are compared according to their accuracies and train/test time over 36 datasets. The results show that Rotation Forest has the highest accuracy. However, when accuracy and execution time are considered together, Random Forest and Random Committees can be the best choices.

III. PROPOSED METHODOLOGY

The proposed work is mainly focused on the identification of brain tumor to reduce the death rate. The identification of brain tumor is done by MRI segmentation and by using Ensemble Classifiers. The proposed methodology consists of four stages.

The first stage is pre-processing by using filtering algorithm, the second stage is Segmentation is done by clustering algorithm, third process is feature extraction which is done by Gray – Level Co-occurrence Matrix(GLCM) [40] and the fourth stage of work is Classification by using Ensemble classifier which is a combiner process of neural network, Extreme Learning Machine (ELM) and Support Vector Machine (SVM) and here an automatic brain tumor stage by ensemble classifier by forwarded Artificial Neural Network.

Image segmentation is an essential preprocessing trend in a complicated and composite image dealing algorithm in Brain magnetic resonance imaging (MRI). Segmentation plays a fine role in the medical image segmentation. The overview of proposed methodology is shown in figure 1.

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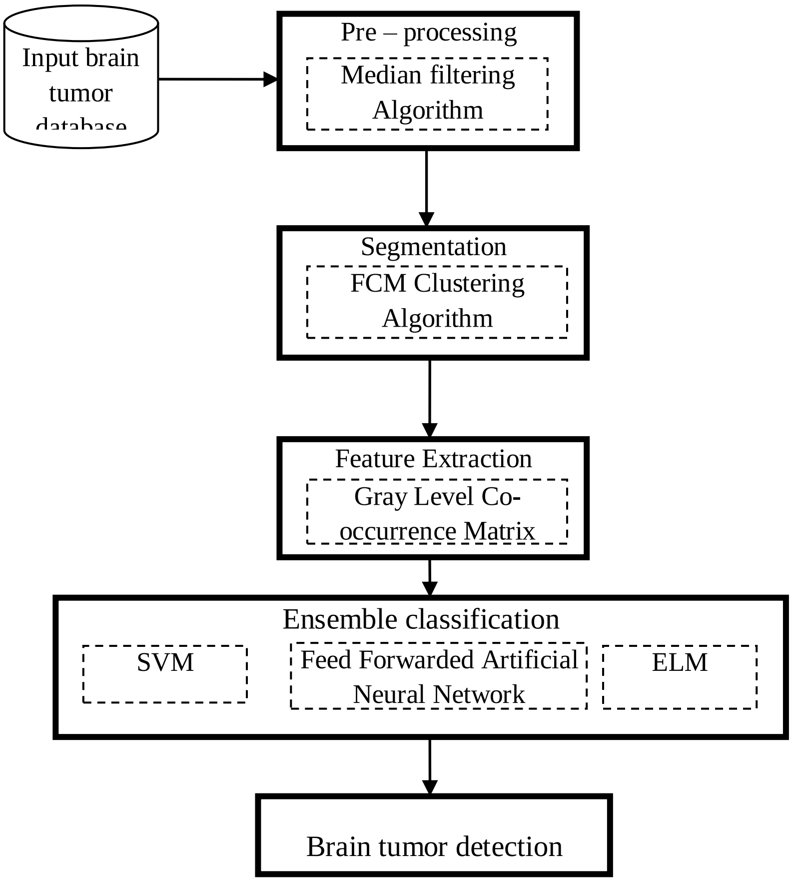

Figure 1:Overview of Proposed Methodology

3.1. Pre-Processing

It is very difficult to process an image. Before any image is processed, it is very significant to remove unnecessary items it may hold. After removing unnecessary artifacts, the image can be processed successfully. The initial step of image processing is Image Pre-Processing [16].Pre-Processing involves processes like conversion to grayscale image, noise removal and image reconstruction. Conversion to grey scale image is the most common pre-processing practice [17]. After the image is converted to grayscale, then remove excess noise using different filtering methods.

Median Filter This most common technique which used for noise elimination. It is a 'non-linear' filtering technique. This is used to eliminate 'Salt and Pepper noise' form the grayscale image [18]. Median filter is based on average value of pixels. The advantages of median filter are efficient in reducing Salt and Pepper noise and Speckle noise. Also, the edges and boundaries are preserved. The main disadvantages are complexity and time consumption as compared to mean filter. [19]

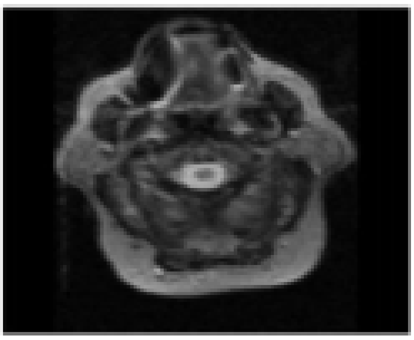

Figure 2: Median filter

In our proposed work we are going to use median filter for less computation complexity and better smoothing of images. However, it is better in preserving useful detail in the image than the mean filter. Like the mean filter, the median filter considers each pixel in the image and replaces it with the median of the neighborhood pixel values. The median filter has two main advantages over the mean filter [20]:

- It is a more robust estimation than the mean. A single unrepresentative pixel in a neighborhood will not affect the median significantly.
- It does not create new unrealistic pixel values, since the median must actually be the value of one of the pixels in the neighborhood.

3.2. Segmentation

Segmentation of images is important as large numbers of images are generated during the scan and it is unlikely for clinical experts to manually divide these images in a reasonable time. Image segmentation refers to segregation of given image into multiple non-overlapping regions. Segmentation represents the image into sets of pixels that are more significant and easier for analysis. It is applied to approximately locate the boundaries or objects in an image and the resulting segments collectively cover the complete image [21]. The segmentation algorithms works on one of the two basic characteristics of image intensity; similarity and discontinuity [22].

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Segmentation has a significant part in clinical diagnosis and can be useful in pre-surgical planning and computer assisted surgery.

Therefore, numerous segmentation techniques are available which can be used widely, such as threshold based segmentation, histogram based methods, region-based (region growing, splitting and merging methods), edge-based and clustering methods (expectation maximization, k-means, FCM and mean shift) [23]-[25].

Clustering methods are most promising technique for processing the medical images. Cluster analysis can be set out as a pre-processing stage for other methods, namely classifiers that would then run on selected clusters [26].

Therefore in our system, we have used clustering segmentation techniques for diagnosis of tumor and calculating tumor area in MRI images.

Fuzzy C – means algorithm is used for proposed work which divide the set of pixels X= {x1, x2, . . .,xN} into C fuzzy clusters where each point has a degree of belonging to clusters. It allows a point to belong to more than one cluster as per its membership value. It is an iterative process for minimizing objective function, related to fuzzy membership set U of cluster centers C:

$$j = \sum_{i=1}^{N} \sum_{j=i}^{C} u_{ij}^{m} (x_i - c_j)^2 \quad (1)$$

Where, uij is the membership table, m is a cluster fuzziness factor and (xi – cj) is Euclidean distance. The data points nearer to center of cluster have highest degree of membership than the points on edge [27].

FCM initially guess the cluster centers and assigns every point a membership grade for each clusters. Then, it moves the cluster center to right location by iteratively updating the centers within a data set.

The membership defines the fuzziness of an image and also defines information contained in an image. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k-1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (2)$$

$$c_j = \frac{\sum_{i-1}^{N} u_{ij}^{m} x_i}{\sum_{i-1}^{N} u_{ij}^{m}} \quad (3)$$

This iteration will stop when $max_{ij} \left\{ \left| u_{ij}^{(k+1)} - u_{ij}^{k} \right| \right\} < \varepsilon$, where **ε** is a termination criterion between 0 and 1, whereas *k* are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m. The algorithm is composed of the following steps:

1. *Initialize U=[u_{ij}] matrix, $U^{(0)}$*
2. *At k-step: calculate the centers vectors $C^{(k)}$=[c_j] with $U^{(k)}$*

$$c_j = \frac{\sum_{i-1}^{N} u_{ij}^{m} x_i}{\sum_{i-1}^{N} u_{ij}^{m}}$$

Update $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k-1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}$$

3. *If || $U^{(k+1)}$ - $U^{(k)}$||< ξ then STOP; otherwise return to step 2.*

3.3. Feature Extraction

Feature extraction [28] is an important step in the construction of any pattern classification and aims at the extraction of the relevant information that characterizes each class. In this process relevant features are extracted from objects/ alphabets to form feature vectors. These feature vectors are then used by classifiers to recognize the input unit with target output unit.

It becomes easier for the classifier to classify between different classes by looking at these features as it allows fairly easy to distinguish. Feature extraction is the process to retrieve the most important data from the raw data. In our work feature extraction is based on GLCM will be briefly discussed in this following section [40].

Gray-level co-occurrence matrix (GLCM) [5] is the statistical method of examining the textures that considers the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.

The gray co matrix function in MATLAB creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j.

By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (i, j) in the resultant GLCM is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image.

Feature Extraction is helpful in identifying brain tumor where is exactly located and helps in predicting next stage. Transforming the input data into the set of features is called feature extraction [29].

In this paper we're extracting some features by using GLCM [27] and Gabor are: Contrast, Correlation, Homogeneity, Entropy, Energy, Shape, Color, Texture and Intensity.

Contrast: Contrast is defined as the separation between the darkest and brightest area

$$\text{Contrast} = \sum_{ij=0}^{n-1} P_{ij} (i-j)^2 \quad (4)$$

Correlation: Correlation is computed into what is known as the correlation coefficient, which ranges between -1 and +1.

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$$\text{Correlation} = \sum_{ij=0}^{n-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (5)$$

Homogeneity: Homogeneity is defined as the quality or state of being homogeneous

$$\text{Homogeneity} = \sum_{ij=0}^{n-1} \frac{P_{ij}}{1+(i-j)^2} \quad (6)$$

Entropy: Entropy is a measure of the uncertainty in a random variable.

$$\text{Entropy} = \sum_{ij=0}^{N-1} -\ln(P_{ij})P_{ij} \quad (7)$$

Energy: It provides the sum of squared elements in the GLCM .Also known as the uniformity or the angular second moment.

$$\text{Energy} = \sum_{ij=0}^{N-1} (P_{ij})^2 \quad (8)$$

Shape: The term shape is commonly used to refer to the geometric properties of an object or its external boundary, as opposed to other properties such as color, texture, material composition.

Color:Color is a component of light which is separated when it is reflected off of an object. Colors can be identified numerically by their coordinates.

Intensity: Intensity is a purity or strength of color.

Texture: It is the visual characteristic of a surface. For example, a surface can be rough or smooth.

3.4. Classification

Classification is used to classify each item in a set of data into one of predefined set of classes or groups. In other words, classification is an important technique used widely to differentiate normal and tumor brain images.

The data analysis task classification is where a model or classifier is constructed to predict categorical labels (the class label attributes).

Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data. In this proposed work the classification is done by the combined process of three different algorithms is known as ensemble classification.

Ensemble Classification

Ensemble based methods have recently enjoyed great attention [30] due to their reported superiority over single method based system generalization performance [31], [32].

The aim of classification is to combine multiple models (classifiers or features) to solve particular problems [33].

Ensemble methods can be divided into a number of categories, such as ensemble classifiers [34]; ensemble features [35]; and ensemble feature and classifiers [36]. To demonstrate the full and practical importance of using a multiple classifier system, an analogy can be made with decision making in everyday life.

When making an important decision, an expert is likely to ask opinions from several other experts before the final decision is made. In such a situation, the final decision is made by combining the individual decisions of several experts.

The idea behind all ensemble based systems is that if individual classifiers or features are diverse, then they can make different errors, and combining these models can reduce the error through averaging. Ensemble learning is primarily used to improve classification or prediction performance, where a single model does not have these capabilities, especially in dealing with multiclass problems.

In the work classification consist of three work they are support vector machine classifier, Extreme learning Machine and Feed Forwarded Artificial Neural Network.

This phase classifies brain images into tumor and non-tumors using Feed Forwarded Artificial neural network based classifier.

Support Vector Machine (SVM)

SVMs are set of related supervised learning methods used for classification and regression [37]. They belong to a family of generalized linear classification.

A special property of SVM is, SVM simultaneously minimize the empirical classification error and maximize the geometric margin. So SVM called Maximum Margin Classifiers. SVM is based on the Structural risk Minimization (SRM). SVM map input vector to a higher dimensional space where a maximal separating hyper plane is constructed.

Two parallel hyper planes are constructed on each side of the hyper plane that separate the data. The separating hyper plane is the hyper plane that maximizes the distance between the two parallel hyper planes.

An assumption is made that the larger the margin or distance between these parallel hyper planes the better the generalization error of the classifier will be [37].We consider data points of the form {(x1, y1), (x2, y2), (x3, y3), (xn, yn)}.

Where yn=1 / -1, a constant denoting the class to which that point xn belongs. n = number of sample. Each x n is p-dimensional real vector.

The scaling is important to guard against variable (attributes) with larger variance. To view this Training data, by means of the dividing (or separating) hyper plane,this takes

$$w \cdot x + b = o \quad (9)$$

Where b is scalar and w is p-dimensional Vector. The vector w points perpendicular to the separating hyper plane. Adding the offset parameter b allows us to increase the margin. Absent of b, the hyper plane is forced to pass through the origin, restricting the solution.

As with the interest in the maximum margin, we are interested in SVM and the parallel hyper planes. Parallel hyper planes can be described by equation

$$w.x + b = 1 \quad (10)$$

w.x + b = -1 If the training data are linearly separable, we can select these hyper planes so that there are no points between them and then try to maximize their distance. By geometry, we find the distance between the hyper planes is $2 / |w|$. So we want to minimize $|w|$.

To excite data points, we need to ensure that for all I either $w.\ xi - b \geq 1$ or $w.\ xi - b \leq -1$ this can be written as yi

$$(w.\ xi - b) \geq 1,\ 1 \leq i \leq n \quad (11)$$

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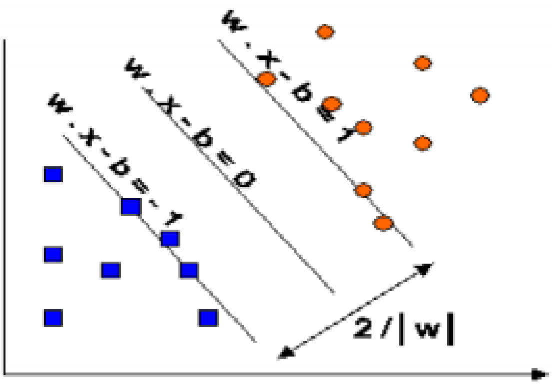

Figure 3: Maximum margin hyper planes for a SVM trained with samples from two classes

SVMs fall into the intersection of two research areas: kernel methods [39], and large margin classifiers. SVM has been applied to feature selection, time series analysis, reconstruction of a chaotic system, and non-linear principal components. Further advances in these areas are to be expected in the near future. SVMs and related methods are also being increasingly applied to real world data mining.

Extreme Learning Machine

Extreme Learning Machine (ELM) is a single hidden layer feed forward neural network (SLFNN) which randomly selects input weights and hidden neuron biases without training. The outputs weights are analytically are analytically determined using the norm least-square solution and Moore-Penrose inverse of a general linear system, thus allowing a significant training time reduction. The activation function like sine, Gaussian, sigmoid etc., can be chosen for hidden neuron layer and linear activation functions for the output neurons .The SLFNN evaluated here uses additive neuron design instead of kernel based [39], hence random parameter selection. SLFNs are considered as a linear system. The aim of the approach is to generate high resolution images from inputs with low-resolution. In the training process, the input was extracted from the image features. Furthermore, the high frequency components that were taken from the original images with high-resolution were utilized as the target values. Then, ELM learns a model that is capable of mapping the interpolated image and imposing it on the high frequency components. Once training is done, the learned model can predict the high-frequency components using low resolution images [36].

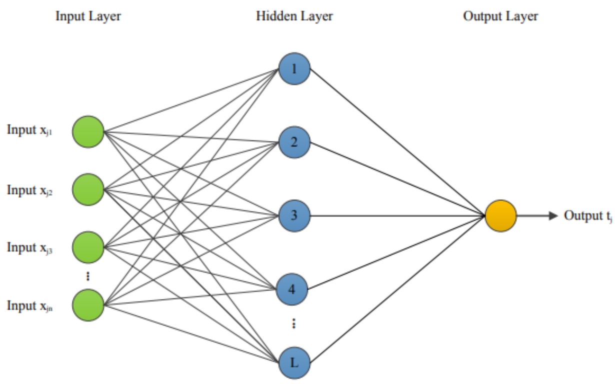

Figure 4: Overview of ELM

Feed Forwarded Neural Network

In more practical terms neural networks are nonlinear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in Data. Using neural networks as a tool, data warehousing firms are harvesting information from datasets in the process known as data mining.

The difference between these data warehouses and an ordinary database is that there is actual manipulation and cross-fertilization of the data helping users makes more informed decisions.

Feed forward Neural Network One of the simplest feed forward neural networks (FFNN) [38], such as in Figure 5, consists of three layers: an input layer, hidden layer and output layer. In each layer there are one or more Processing Elements (PEs). PEs is meant to simulate the neurons in the brain and this is why they are often referred to as neurons or nodes.

PE receives inputs from either the outside world or the previous layer. There are connections between the PEs in each layer that have a weight (parameter) associated with them. This weight is adjusted during training. Information only travels in the forward direction through the network - there are no feedback loops.

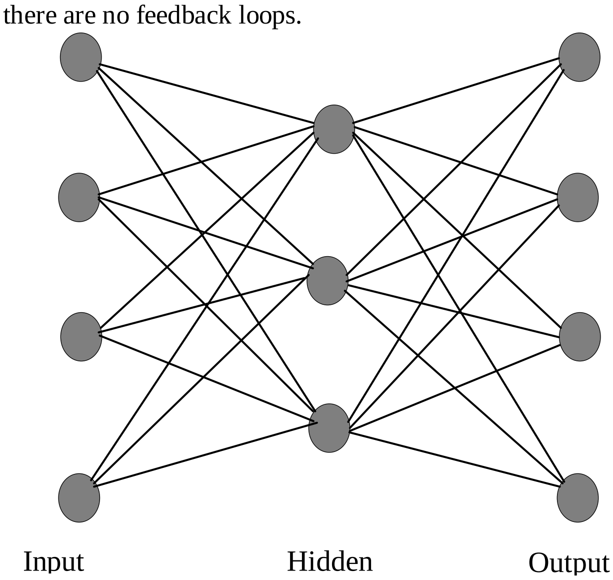

Figure 5: FIFO in Neural Networks

IV. RESULT AND DISCUSSION

In this section we are going to discuss the result of various classification techniques. The comparison of existing classifiers like Feed Forward Artificial Neural Network (FFANN), Ensemble Learning Machine (ELM) and Support Vector Machine (SVM) and proposed Ensemble classifier results are discussed briefly in this section. Comparison will be takes place with of accuracy, precision, F1 Score and Sensitivity with the image pixel of 30,000.

A. Accuracy

Table 1 illustrates the comparison of various classifier techniques with accuracy.

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$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{Positive + Negative}$$

Table1. Comparison between various techniqueswith accuracy

CLASSIFIER TECHNIQUE	ACCURACY (%)
Feed Forward Artificial Neural Network	84.33
Extreme Learning Machine	86.00
Support Vector Machine	89.67
Ensemble Classifier	91.17

It is very clear from table 1 and figure 6, the accuracy for ensemble classifier is 91.17% whereas FFANN, ELM and SVM have an accuracy of 84.33%, 86% and 89.67% respectively with the image pixel of 30,000. The proposed Ensemble classifier has a higher accuracy when compared with all other classifiers.

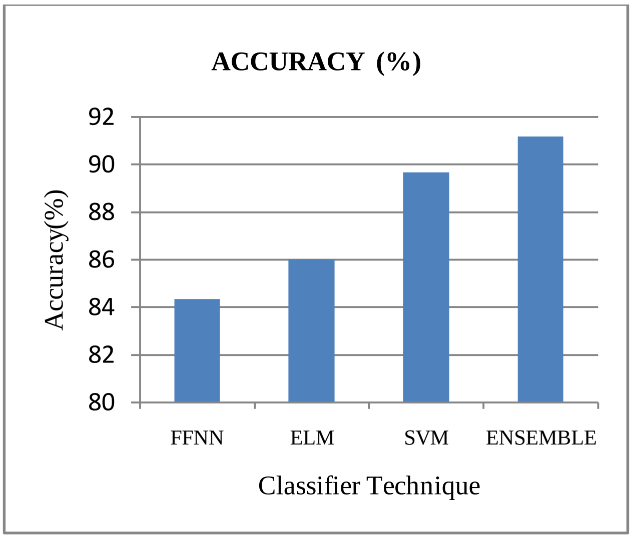

Figure 6: Comparison between various techniques with accuracy

B. Precision

Table 2 illustrates the comparison of various classifier techniques with precision.

$$\text{Precision or Positive Predictive Value} = \frac{True\ Positive}{False\ Positive + True\ Negative}$$

Table 2.Comparison between various techniques with precision

CLASSIFIER TECHNIQUE	PRECISION (%)
Feed Forward Artificial Neural Network	89.41
Extreme Learning Machine	90.20
Support Vector Machine	92.99
Ensemble Classifier	94.17

It is very clear from table 2 and figure 7, the precision for ensemble classifier is 94.17% whereas FFANN, ELM and SVM have precision of 89.41%, 90.20% and 92.99% respectively with the image pixel of 30,000. The proposed Ensemble classifier has a higher precision when compared with all other classifiers.

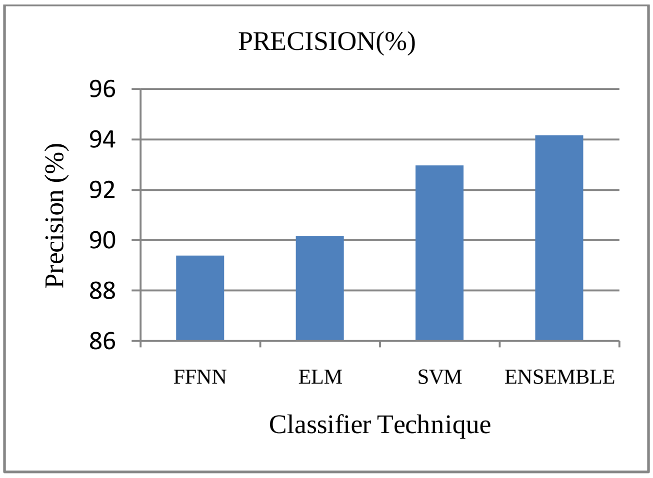

Figure 7: Comparison between various techniques with precision

C. Sensitivity

Table 3 illustrates the comparison of various classifier techniques with Sensitivity.

$$\text{Sensitivity or True Positive Rate} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Table 3:Comparison between various techniques with Sensitivity

CLASSIFIER TECHNIQUE	SENSITIVITY (%)
Feed Forward Artificial Neural Network	91.94
Extreme Learning Machine	93.12
Support Vector Machine	94.83
Ensemble Classifier	95.47

It is very clear from table 3 and figure 8, the precision for ensemble classifier is 95.47% whereas FFANN, ELM and SVM have sensitivity of 91.94%, 93.12% and 94.83% respectively with the image pixel of 30,000. The proposed Ensemble classifier has a higher sensitivity when compared with all other classifiers.

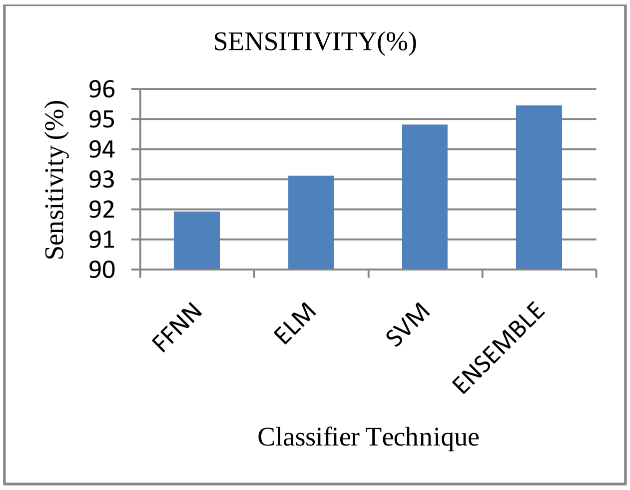

Figure 8: Comparison between various techniques with Sensitivity

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D. F1 Score

Table 4 illustrates the comparison of various classifier techniques with F1 Score.

$$\text{F1 Score} = \frac{2\,True\,Positive}{2\,True\,Positive + False\,Positive + False\,Negative}$$

Table 4.Comparison between various techniques with F1 Score

CLASSIFIER TECHNIQUE	F1 SCORE (%)
Feed Forward Artificial Neural Network	90.66
Extreme Learning Machine	91.63
Support Vector Machine	93.90
Ensemble Classifier	94.81

It is very clear from table 4 and figure 9, the F1 score for ensemble classifier is 94.81% whereas FFANN, ELM and SVM have F1 score of 90.99%, 91.63% and 93.90% respectively with the image pixel of 30,000. The proposed Ensemble classifier has an higher F1 score when compared with all other classifiers.

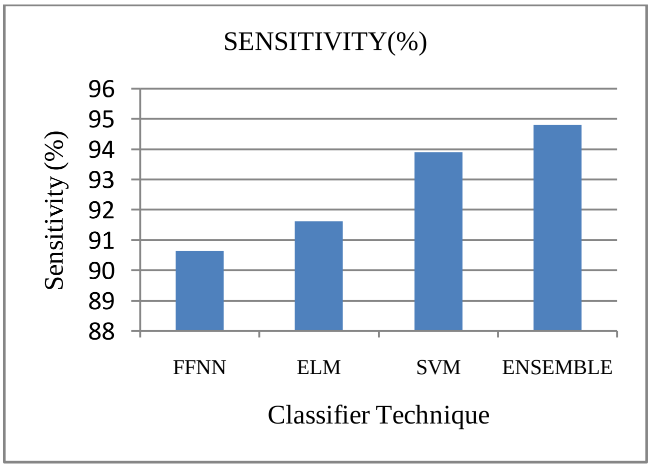

Figure 9: Comparison between various techniques with F1 Score

We have a very detailed discussion in this section on various classifier techniques and came to know that our proposed Ensemble classifier has best Accuracy, Precision, Sensitivity and F1 Score as compared with other classifier technique like FFANN, ELM and SVM.

V. CONCLUSION

In this work, brain tumor is identified by an image processing techniques. This identification required various processes like pre-processing using filter algorithm, segmentation using clustering algorithm, feature extraction using Gray level co-occurrence matrix and ensemble classification.

The ensemble classifier is finally classified the tumor and non-tumor region. Ensemble classifier plays an important role in our work. Ensemble classifier is the combination of different individual or separate classifiers. In our work the ensemble classifier is made up of combined classifiers of feed forward artificial neural network, extreme learning machine and support vector machine classifier. Here the ensemble have an high accuracy and less execution time and it is very efficient when compared to all other classifier techniques as we discussed in this paper. The comparison results are shown in this paper and concluded that the proposed ensemble classifier is best with various aspects.

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