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Classification And Performance Evaluation Of Brain MRI Images Using Machine Learning Algorithms

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Abstract: Digital image processing can help medical expertise in detection and classify the tumour in normal and abnormal type. This paper focus on classifiers as support vector machine, k-nearest neighbour and neural network for classification and confusion matrix for performance evaluation of brain MRI tumour and non-tumour images .Among different segmentation techniques, Otsu's thresholding method is adopted for segmentation purpose. Gray level co-occurrence matrix (GLCM) is used for the feature extraction. In this study ,classification methods gives desired output in terms of confusion matrix parameters which can be used for evaluating performance of the classifier in terms of accuracy ,sensitivity, precision and F1 score.

***IndexTerms* - artificial neural network (ANN) , confusion matrix , feature extraction, gray level co-occurrence matrix (GLCM), image segmentation, receiver operating characteristic (ROC).**

I. INTRODUCTION

The nervous system consists of the neurons and glial cells, which together form the nerves, ganglia and gray matter which in turn form the brain and related structures. The brain serves many aspects of communication and controls various systems and functions. Brain, being the sensitive and master organ in the body, is equally susceptible to any kind of infections and other disorders of varying intensity, such as brain cancer, tumours, alzheimer's disease, alcoholism, amnesia, altitude sickness, autism, epilepsy, and so on. Each of these conditions adversely affects the functions of brain. A brain tumour can be diagnosed by a neurosurgeon or a neurologist. The only reliable way to accurately diagnose a brain tumour is to examine a sample of a tumour under a microscope, which is the biopsy procedure. Digital image processing using image segmentation can help medical expertise in detection and classify the tumour in normal and abnormal type.

Tumour grade is the description of a tumour based on how abnormal the tumour cells and the tumour tissue look under a microscope. It is an indicator of how quickly a tumour is likely to grow and spread. Grading systems differ depending on the type of cancer. In general, tumours are graded as 1, 2, 3, or 4, depending on the amount of abnormality. In Grade 1 tumours, the tumour cells and the organization of the tumour tissue appear close to normal. These tumours tend to grow and spread slowly. In contrast, the cells and tissue of Grade 3 and Grade 4 tumours do not look like normal cells and tissue. Grade 3 and Grade 4 tumours tend to grow rapidly and spread faster than tumours with a lower grade. Brain tumours are of different types and can be dangerous at times, and glioma is the most common type of non permanent or treatable tumour. Glioma can be classified into two types, namely High-Grade Gliomas (HGG) and Low-Grade Gliomas (LGG). LGG is a slow-spreading tumour, while HGG is a rapidly growing tumour, which explains why HGG is a fatal disease. People who are diagnosed with HGG and who are aged between 20–44 years have a survival rate of 19% with treatment after 14 months of diagnosis , based on are survey of the central nervous system (CNS) on a Canadian population from 2009–2013. Figure 1 shows the distribution of survival rates between different types of brain tumours.

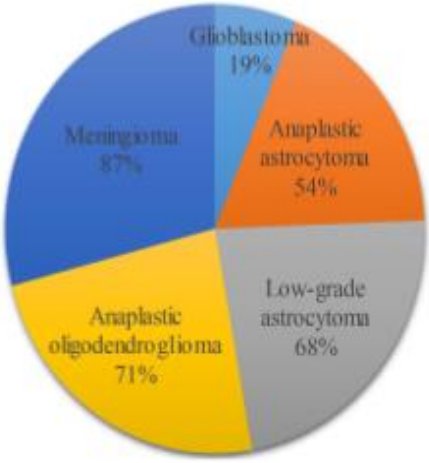

Figure 1: the distribution of survival rates between different types of brain tumours

Brain tumour treatment options depend on the type of brain tumour you have, as well as its size and location. Adult brain tumours occur typically between the ages of 40 and 60 years. An additional 150,000 individuals are diagnosed with brain tumours each year. The cure rate for most brain tumours is significantly lower when compared to other types of cancer. Brain tumours are diagnosed, based on medical history, physical examination and various specialised Tests.

II. Literature Survey

There are different research works that were carried out in past and contributed to this field of brain tumour detection. So many approaches are developed for the detection of brain tumour which were played important role to carry out this work.

Suhartono, Phong Thanh Nguyen, K. Shankar, Wahidah Hashim, Andino Maseleno suggested brain tumour segmentation and classification using KNN algorithm . A comparative analysis has been also performed for various methods. [3]

Mr. T. Sathies Kumar K. Rashmi Sreevidhya Ramadoss have worked on brain tumour detection using SVM Classifier. They also compare the accuracy of different classifiers as SVM and neural network in classification learner app. [4]

Nikita V. Chavan B.D. Jadhav P.M. Patil attempt to detect and classification of brain tumours in benign stage using K-nearest neighbour (K -NN) classifiers. The overall recognition rate or classification accuracy is achieved up to 96.15%. [7]

S.S. Dharun Raj, S. Hariharan , proposed the method which is intended to distinguish between normal and brain tumour (benign or malign). Different wavelet transforms and support vector machines are used in the identification and classification of MRI brain tumours. [9]

Komal Sharma, Akwinder Kaur, & Shruti Gujral reviewed various approaches enlightening the advantages and disadvantages of different methods to detect the brain tumour from MRI images. [10]

S.H.Lavate, Rutuja Bhasme, Amit Gore, Tejas Deshmukh proposed an algorithm for the detection of brain tumour using Otsu's segmentation method and support vector machine is used for classifying images in this paper. [11]

III. Proposed Methodology

In this work, we proposed an efficient and simple algorithm for the detection of brain tumour and analyzed the texture parameters for the normal MRI image and the tumour detected MRI image. The main modules are pre-processing, computing segmentation through Otsu's thresholding algorithm followed by feature extraction through grey level co- occurrence matrix (GLCM).The proposed algorithm contains two main phases, training and testing phases. The first phase of working in the proposed system is training phase .In this phase, the known MRI images are first processed through different image processing steps such as image pre-processing ,segmentation and then textural features are extracted using Gray Level Co-occurrence Matrix (GLCM) .The features extracted are used in the training phase. They help in successful classification of unknown images. In the training phase, known data represent the nature whether it is a normal or abnormal, to teach and train the classifier. In the testing phase , the unknown MRI image samples are first segmented and then computation of textural features using Gray Level Co-occurrence Matrix for each input MRI image is done. The obtained GLCM features are given as an input to classifiers as support vector machine (SVM), k nearest neighbour (KNN) and artificial neural network (ANN). The decision to classify the MRI of the brain as tumour or non-tumour is completed by support vector machine (SVM), k-nearest neighbour and artificial neural network classifier. The proposed system uses the discrete wavelet transform (DWT) coefficients as feature vector and principal component analysis (PCA) is used for dimensionality reduction. Confusion Matrix and Receiver operating characrteristic (ROC) are used as important tools in evaluating performance of the classifiers in the proposed method .

Figure 2 shows steps of proposed methodology.

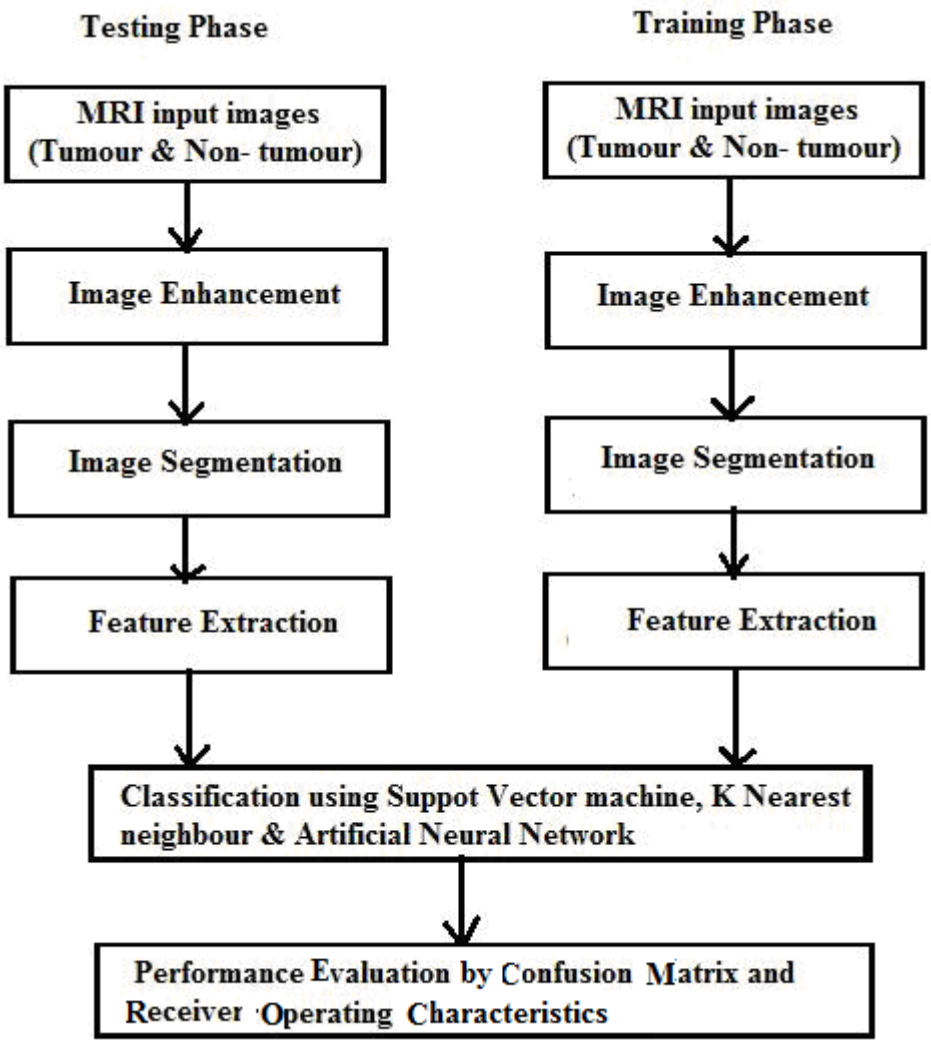

Figure 2: steps of proposed methodology

3.1 Image Enhancement

The main things that comes under the image enhancement are

- Highlighting the edges
- Improving the brightness and contrast
- De-blurring and sharpening
- Removing of the noise

3.2 Image Segmentation

It is dividing the image in to different sub images , one of the difficult tasks in the image processing, which includes,

- lines, different types of shapes in an image , finding the circles ,
- identifying tumours, different objects ,detections in an image

Here in this work segmentation plays a predominant role for the detection of tumour present in the human brain.

3.2.1 Otsu's Thresholding

Image thresholding is used to binarize the image based on pixel intensities. The input to such thresholding algorithm is usually a grayscale image and a threshold. The output is a binary image. Image thresholding is used in many applications as a pre-processing step. A problem with simple thresholding is that you have to manually specify the threshold value. We can manually check how good a threshold is by trying different values but it is tedious .The Otsu's technique named after its creator Nobuyuki Otsu is a good example of auto thresholding .This method was proposed by N. Otsu in 1975 and has been in fashion. Matlab uses graythresh function that computes a global threshold that can be used to convert an intensity image to a binary image.

level = graythresh(I)

It computes a global threshold (level) that can be used to convert an intensity image to a binary image. Level is a normalized intensity value that lies in the range [0, 1]. Function graythresh uses Otsu's method, which chooses the threshold to minimize the intraclass variance of the thresholded black and white pixels.

3.3 Principal Component Analysis (PCA)

Principal component analysis is one of the most successful and widely used techniques that have been used in image recognition and compression. The purpose of using PCA is to reduce the large dimensionality of the extracted features. Instead of incorporating all of the features, a feature selection is performed using PCA as a preprocessing step to ignore the redundant features. The feature selection is based on the statistical information, hence only the most informative features extracted from the MRI images are utilized in this process. These selected features are called principal components (PC). PC retains the greatest amount of variation in the samples. The variance of reconstructed data is preserved. This principal components lead to efficient classification algorithm utilizing supervisory learning. Using a system of feature reduction based on a principal component analysis on the feature leads to an efficient classification algorithm utilizing supervised learning approach. So, the main intention of using PCA in this approach is dimensionality reduction which leads to more efficient and accurate classifier. The proposed system uses the Discrete Wavelet Transform (DWT) coefficients as feature vector and PCA is used for dimensionality reduction. The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficient from MRI images.

3.4 Feature Extraction

The gray-level co-occurrence matrix (GLCM), a frequency matrix, is a useful method for enhancing details and is frequently used as an aid for interpretation of an image. The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. The GLCM indicates the frequency of a pair of pixels that are at exactly the same distance and direction of the displacement vector. From this principal, it computes the relationships of pixel intensity to the intensity of its neighbouring pixels which are based on hypothesis that the same gray level configuration is repeated in a texture and pixels that are close together tend to be more related than pixels that are far away from each other.

3.4.1 Independent Features

- Mean: It gives the contribution of individual pixel intensity for the entire image.
- Variance: It is used to find how each pixel varies from the neighbouring pixel.
- Standard Deviation: It measures the deviation of measured values or the data from its mean.
- Skewness: It measures of symmetry, or more precisely, the lack of symmetry.
- Kurtosis: It describes the peakiness e.g., a frequency distribution.

The above features are first order features which rely only on the values of individual pixels in the image, and do not express their relationship to other image pixels.

3.4.2 Second order features or texture features

- Contrast: It is the difference in luminance or colour across the image.
- Correlation: Correlation is the process of moving a filter mask often referred to as kernel over the image and computing the sum of products at each location.
- Energy: It is the rate of change in the colour/brightness/magnitude of the pixels over local areas.
- Homogeneity: Homogeneity expresses how similar certain elements (pixels) of the image are.
- Entropy: It is a statistical measure of randomness that can be used to characterize the texture of the image.
- ASM (Angular second moment): It is a measure of textural uniformity of an image.
- Dissimilarity: It is a numerical measure of how different two data objects are.
- Coarseness: It describes the roughness/harshness of a texture.

3.5 Image Classification

Image classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules. In this work, different classifiers used are support vector machine, k-nearest neighbour and artificial neural network classifiers.

3.5.1 Support Vector Machine Classifier

This classifier is a machine learning that gives computers the ability to learn without performing programming. Classifier is used to determine whether the given image is normal or abnormal. SVM is a binary classification method in which two classes for input data. For normal, we take '0' whereas for abnormal we take '1'. We use the parameters from feature extraction. Two functions from MATLAB are used as svmtrain and svmclassify.

3.5.2 K-Nearest Neighbour Classifier

KNN stands for K-nearest neighbour, which is a classification technique .Given a sample of images and their classes already known. We can take an image as input and find the k-nearest neighbours to the input image. The k-nearest neighbours are found out based on a 'distance' metric which can be changed depending upon the data. The value of k can also be changed. Now depending upon the k-nearest neighbours, we classify the input image. We can use KNN for a single image if we already have the dataset of sample images for different classes. If we only have one image and nothing else, then we cannot use KNN. Matlab uses knnclassify function to classify data.

3.5.3 Artificial Neural Network Classifier

Neural networks are very rapid and precise due to the fact that the completion of training, the processing, optimization and time consuming calculations are no more needed. The generation of outputs of the network is straight forward from the provided inputs. There are different types of neural networks used to classify inputs into a set of target categories.

3.6 Performance Evaluation

Performance evaluation can be achieved by the confusion matrix parameters and receiver operating characteristic curves (ROC).

3.6.1 Confusion Matrix

The confusion matrix consists of four basic characteristics (numbers) that are used to define the measurement metrics of the classifier. These four numbers are:

- TP (True Positive): TP represents the number of patients who have been properly classified to have malignant nodes, meaning they have the disease.

- TN (True Negative): TN represents the number of correctly classified patients who are healthy.
- FP (False Positive): FP represents the number of misclassified patients with the disease but actually they are healthy. FP is also known as a *Type I error*.
- FN (False Negative): FN represents the number of patients misclassified as healthy but actually they are suffering from the disease. FN is also known as a *Type II error*.

Figure 3 shows confusion matrix for two classes

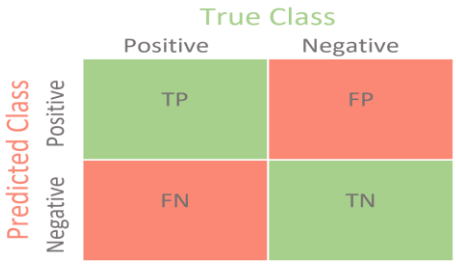

Figure 3: confusion matrix for two classes

3.6.2 Performance Metrics

Performance metrics of an algorithm are accuracy, precision, recall, and F1 score, which are calculated on the basis of the TP, TN, FP, and FN.

- **Accuracy:** Accuracy is a general measure of the model performance. Accuracy of an algorithm is represented as the ratio of correctly classified patients (TP+TN) to the total number of patients (TP+TN+FP+FN).

$$\text{Accuracy} = (TP+TN) / (TP+FP+FN+TN)$$

- **Precision:** Precision measures the accuracy of predicted positive outcome. Precision of an algorithm is represented as the ratio of correctly classified patients with the disease (TP) to the total patients predicted to have the disease (TP+FP).

$$\text{Precision} = (TP) / (TP+FP)$$

- **Recall:** It measures the proportion of actual positives that the model correctly classifies. Recall is defined as the ratio of correctly classified diseased patients (TP) divided by total number of patients who have actually the disease. The perception behind recall is how many patients have been classified as having the disease. Recall is also called as sensitivity.

$$\text{Recall} = (TP) / (TP+FN)$$

- **The F1 score:** It states the equilibrium between the precision and the recall. It is also known as the F Measure. It is a measure of a model's accuracy on a dataset. It is defined as the harmonic mean between precision and recall. It is used as a statistical measure to rate performance. A perfect model has an F1-score of 1.

$$\text{F1-score} = 2 *(\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$$

3.6.3 Receiver Operating Characteristic Curves (ROC Curve)

This is an important tool for evaluating the performance .They are most commonly used for binary classification problems .The ROC curve shows the relationship between the true positive rate (TPR) and the false positive rate (FPR). The TPR is the rate at which the classifier predicts "positive" for observations that are "positive." The FPR is the rate at which the classifier predicts "positive" for observations that are actually "negative." A perfect classifier will have a TPR of 1 and an FPR of 0.

IV. RESULTS :

4.1 SVM & KNN

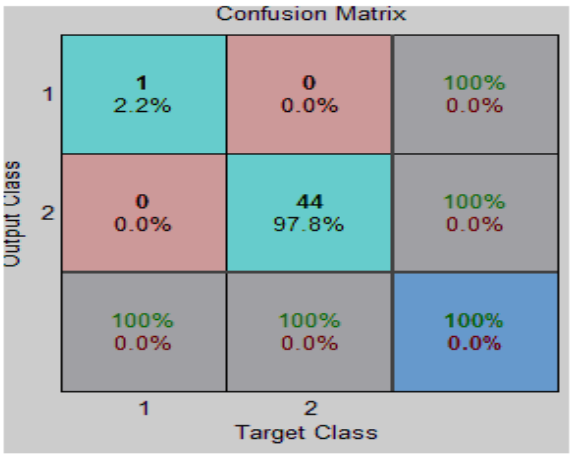

Figure 4: confusion matrix for SVM classifier

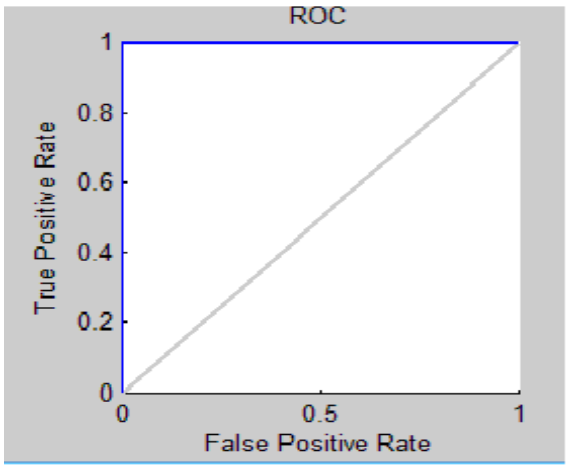

Figure 5 : receiver operating characteristic for KNN classifier

4.2 Implementation Of Different Neural Networks

4.2.1 Two-Layer Feed-Forward Neural Network (FFNN)

In pattern recognition problems, the neural network pattern recognition tool will help to select data, create and train a network, and evaluate its performance using mean square error and confusion matrices. A two-layer feed-forward network, with sigmoid hidden and output neurons can classify vectors arbitrarily well, given enough neurons in its hidden layer. Dataset for input and targets are chosen from workspace variables. In next step training, validation and test data is chosen. Training samples are presented to the network during training, and the network is adjusted according to its error. Validation samples are used to measure network generalization, and to halt training when generalization stops improving. Testing samples have no effect on training and so provide an independent measure of network performance during and after training. Then set the dimensions of the self organizing map's output layer. Figure 6 shows setting diamensions of self organizing map's output layer.

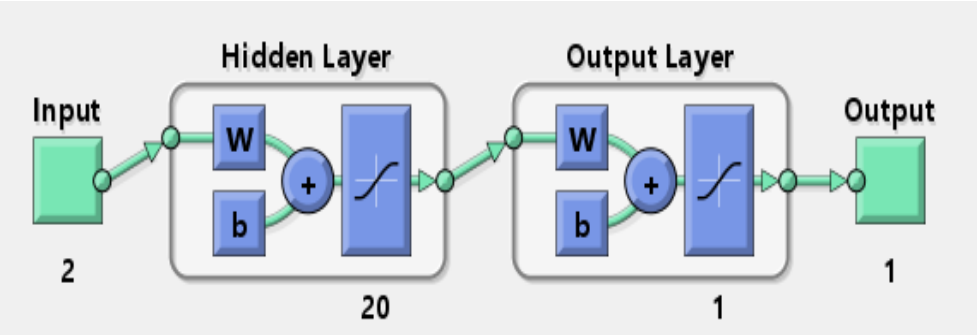

Figure 6 : setting diamensions of self organizing map's output layer.

Train the network to classify inputs according to targets. The network will be trained with scaled conjugate gradient (SCG) back propagation. Training multiple times will generate different results due to different initial conditions and sampling. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

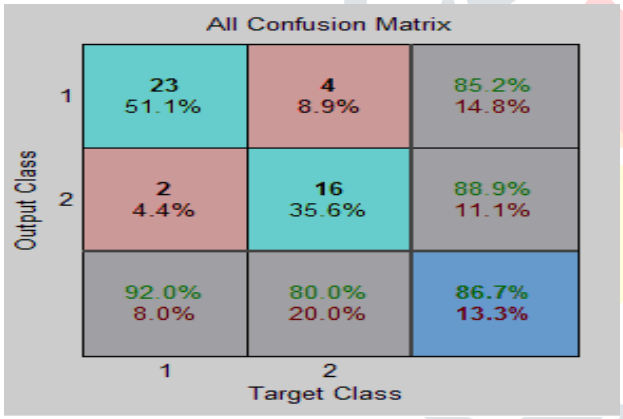

Figure 7: confusion matrix and for FFNN classifier

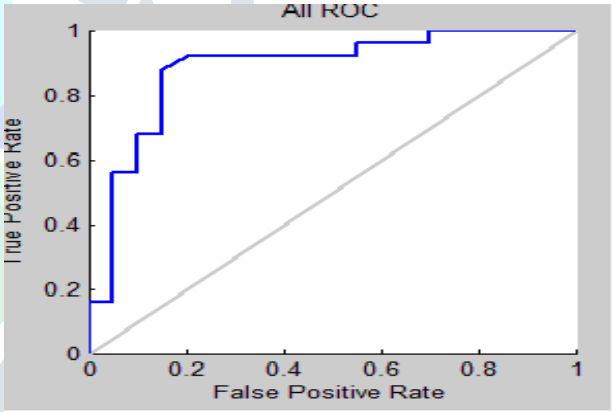

Figure 8 : receiver operating characteristic for FFNN

4.2.2 Radial Basis Function Network (RBF)

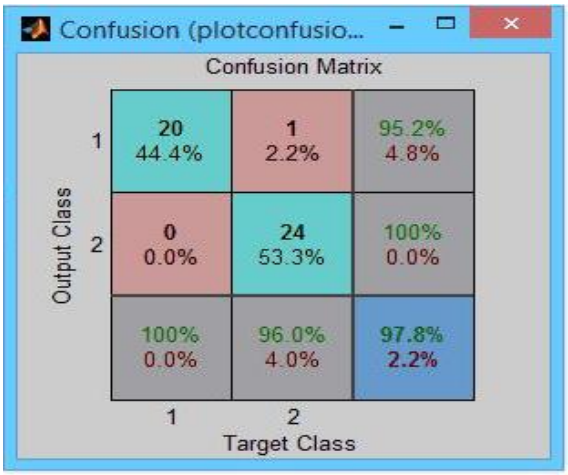

Figure 9 : confusion matrix for RBF network

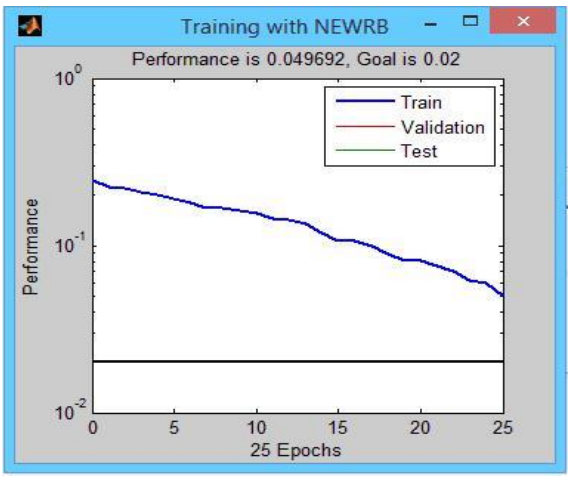

Figure 10 : performance plot for RBF Network

4.2.3 Learning Vector Quantization Network (LVQ)

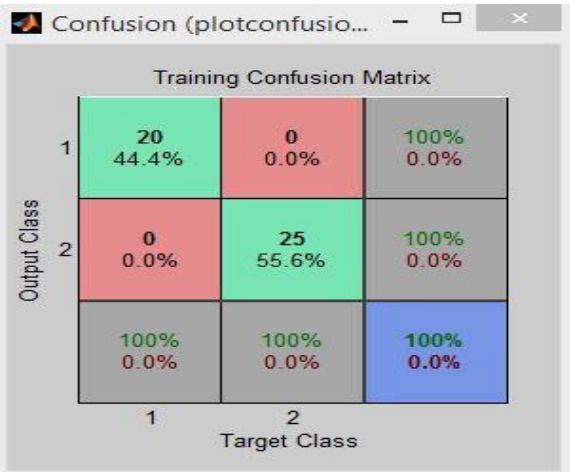

Figure 11 : confusion matrix for LVQ network

Performance of different classifiers are evaluated using confusion matrix and ROC curve .Figure 4,5,7 and 8 shows confusion matrix and ROC curve for the SVM ,KNN and FFNN respectively. The shape of ROC curves in figure 5 and figure 8 shows the good performances of respective model. Figure 9 and figure 10 shows confusion matrix and performance plot for RBF network. Hundred percent accuracy obtained from figure 11 for LVQ network. The values TP, TN, FP, FN obtained in confusion matrix are used in computing performance matrix parameters as accuracy ,precision ,recall and f1 score for each classifier. Table 1 shows confusion matrix parameters and performance metrics for different classifiers which highlight on accuracy, precision, recall and f1 score .

Table 1: Confusion Matrix Parameters And Performance Metrics For Different Classifiers

S.NO.	Classifier	TP	FP	TN	FN	Accuracy	Precision	Recall	F1 Score
1	SVM	44	0	1	0	100	100	100	1
2	KNN	44	0	0	1	97.8	100	97.8	0.99
3	FFNN	16	4	23	2	86.7	80	88.9	0.84
4	RBF	24	1	20	0	97.8	96	96	0.96
5	LVQ	25	0	20	0	100	100	100	1

V. CONCLUSION

In this work, we worked on efficient algorithm for the detection of brain tumour and analyzed the texture features for the normal MRI images and the tumour detected MRI images. This algorithm reduces the steps of the previously proposed algorithms for the brain tumour detection, gives good results for tumour classification. The analysis of texture features is carried out using the result obtained by confusion matrix in terms of accuracy, precision, recall and F1 score for the classifiers as SVM, KNN and ANN classifiers as FFNN, RBF and LVQ. Among different classifiers used here, SVM gives result with 100 percent accuracy. Also among different ANN classifiers used, LVQ gives accuracy to 100%. Also ROC curve shows good performances for all the classifiers. The work can be extended to find different grades of the tumour. Thus we can adopt the same algorithm for multiple classes. Also the procedure can be repeated in the detection of lung cancer , breast cancer etc.

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