IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-11, Nov 2018 E-ISSN: 2347-2693

Automated MRI Brain Tumor Classification and Cancer Detection Using Support Vector Machine

M. A. Rahman[1*]

[1] Department of Computer Science and Engineering, Hamdard University Bangladesh, Munshiganj-1510, Bangladesh

[*]*Corresponding Author: himel113026@gmail.com, Tel.: +8801831825302*

Available online at: www.ijcseonline.org

Accepted: 26/Nov/2018, Published: 30/Nov/2018

***Abstract*—** this research paper proposes an automated and intelligent classification technique of Magnetic Resonance Imaging (MRI) brain images which is extremely important for medical analysis and interpretation. ECG, CT-scan and MRI images are important ways to diagnose brain diseases efficiently. An abnormal growth of cells without any purposes is called a tumor. Sometimes doctors can tell if a tumor is cancer or isn't using MRI. MRI also used to find the signs that cancer may have spread from its starting part to another part of the body. Radiologist or physician analyze tumor manually by visual inspection which is a conventional method. This may lead to error in classification while a large number of MRIs are to be analyzed. Brain cancer is the leading cause of death among people which is caused from malignant brain tumor. A benign tumor is one that does not invade nearby tissue but a malignant tumor does. The chances of survival can be increased if the tumor can be detected at its early stage. In this paper a novel method to classify brain tumors as benign (non-cancerous) or malignant (cancerous) is presented. MRI brain image database was used for training and testing. Images were filtered, skull-masked and segmented. The proposed method employed wavelet transform to extract features from several images. Principle component analysis (PCA) was applied to reduce dimensionality of features. Gray Level Co-occurrence Matrix (GLCM) based Features were selected and submitted to a kernel support vector machine (KSVM). To generalize KSVM, k-fold stratified cross validation was applied. Features were extracted from MRI images named gray scale, symmetrical and texture features. The main goal of this paper is to offer an excellent result of MRI brain tumor classification and cancer detection using SVM. Our proposed system achieved classification accuracy of 96% for RBF kernel.

***Keywords*—**Brain Tumor, Classification, MRI, K-means clustering, PCA, Wavelet, GLCM, SVM.

I. INTRODUCTION

Automated and efficient diagnosis of medical images has become very important nowadays. Automatic defects detection in MRI images is essential for many diagnostic and applications. Computer and information technology is being used in different medical areas such as cancer research, brain tumors, gastroenterology, heart diseases etc. Brain tumor refers to any mass that results from an uncontrolled and abnormal growth of cells in the brain. The level of threat is measured by combining the factors like the type of tumor, state of development, location and size. Brain tumors can be cancerous or non-cancerous depends on their property. The main purpose of this research is to segment the tumor from an MRI image, then classify it whether it is benign or malignant and after that to find a conclusion if cancer is detected or not.

MRI offers detailed information of the internal tissue constitutions of the image. For brain image segmentation, the high resolution and non-evasive MR images have a vital effect. The segmentation process includes the detachment of soft brain tissues like Gray Matter, White Matter and Cerebral Spinal Fluid etc. in the form of anatomical structures. Such regions are called pathological tissues [1]. The methodology (Fig. 4.1) contains: image pre-processing, Features extraction, Feature reduction, feature selection, training and testing the classifier.

Image pre-processing refers to the technique of getting better quality images which are important for accurate observations. But medical images are often degraded by different types of noises [2]. Median filter is an approach of removing noise. It is simple to understand and preserves brightness differences and position boundaries. Skull masking refers to the process of removing non-brain tissues like scalp, neck, eye etc. and helps to improve diagnostic and predictive accuracy [3].

Otsu's method [4], named after Nobuyuki Otsu, is used to automatically perform clustering-based image thresholding, or simply the reduction of a graylevel image to a binary image. Clustering is widely used by supervised or unsupervised learning. K-means is one of the unsupervised learning algorithms for clusters which is a segmentation

method that allocates a pixel to a class or does not [1]. Feature Extraction refers to the process of finding different quantitative measurement of medical image normally used for decision making regarding. It's a process of transforming the input dataset into the set of features [3]. PCA offers dimensionality reduction. If training sets are small then PCA can outperform LDA [5]. This method will help to reduce the computation time and complexity [3].

Gray Level Co-occurrence Matrix (GLCM) offers feature extraction of several gray scale, textural and symmetrical features [6]. GLCM helps to characterize the texture of an image by calculating how often pairs of pixel with specific values in a specified spatial relationship occur in an image. The features selected by GLCM are submitted to SVM. Classifiers like SVM, K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), Probabilistic Neural Network (PNN), Hidden Markov Model (HMM), etc. are often used for various applications.

KNN's major limitation is that it needs to compute distance of all query instance to all training samples, thus it has a high computation cost. It's accuracy severely degraded by the presence of noisy and unrelated features. PNN has a limitation that it is slower than multilayer perceptron network as classifying new classes and for the storage of model it requires more memory space.

ANN offers better classification than other with high dimensional features. But it has high computing cost, high CPU and physical memory. SVM has shown to be more accurate than other classification techniques [3]. SVM has a high accuracy, elegant mathematical tractability and direct geometric interpretation. In order to avoid overfitting, it does not need a large number of training samples [5].

Rest of the paper is organized as follows, section I contains the introduction of this paper, Section II contains the related work, Section III explains the methodology with flow chart, Section IV describes results and discussion and Section V contains conclusion and future scope.

II. RELATED WORK

Several authors proposed various techniques for MRI brain tumor classifications and abnormality detections. Ahmed Kharrat, Mohamed Ben Halima and Mounir Ben Ayed proposed a new approach for automated diagnosis. The approach contains feature extraction by 2D Wavelet Transform and Spatial Gray Level Dependence Matrix (DWT-SGLDM). Simulated Annealing was applied for feature reduction. To optimize SVM, Genetic algorithm and SVM (GA-SVM) was used in that approach [7]. D. Sridhar and IV. Murali Krishna proposed an approach for brain tumor classification. Dimensionality reduction and feature extraction were done using Discrete Cosine Transform and Classification was done using PNN [8].

Jainy Sachdeva, Vinod Kumar, Indra Gupta, Niranjan Khandelwal and Chirag Kamal Ahuja proposed a hybrid machine learning system that is based on GA and SVM. Texture and intensity features are taken as input [9]. Due to variance and complexity of tumors Classification of MRI brain image becomes difficult so that Walaa Hussein Ibrahim, Ahmed Abdel Rhman, Ahmed Osman and Yusra Ibrahim Mohamed proposed a neural network technique consisting of three stages: preprocessing, dimensionality reduction and classification. Normal or abnormal MRI brain images were classified by back propagation neural network [10]. G. Kharmega Sundararaj and V. Balamurugan proposed a system for brain tumor classification form Computer Tomography (CT) images. KNN-SVM hybrid classifier was used along with PCA and Gaussian filter. The proposed system improved accuracy with respect to other neural network based classifier [11].

Image classification is important for automated system for differentiating several abnormal brain images based on optimal feature set. Though this approach has a fast convergence rate, but it may not be useful because of its low accuracy than Artificial Intelligent (AI) techniques. Ahemd Kharrat and Karim Gasmi proposed an approach of hybrid classification for classification of brain tissues in MRI based Genetic algorithm [12]. Using spatial gray level dependence method, optical texture features were extracted from normal and tumor regions. Gabor filters are poor because of its lack of orthogonality that results into redundancy of features. Wavelet transform can represent texture easily at the suitable scale. P. John proposed a system which classifies MR brain images into normal, cancerous and non-cancerous brain tumor. A wavelet and co-occurrence matrix method based texture classification are used along with PNN for brain tumor classification [13].

III. METHODOLOGY

The proposed system consists of two phases: Image segmentation and classification. Several image processing techniques are provided for image segmentation. Classification process contains two parts: training and testing. At first the training data are given to the classifier for training. Trained data is stored in trained database.

For testing, unknown data is given input to the classifier and classification is performed. Accuracy of classification depends on the efficiency of training.

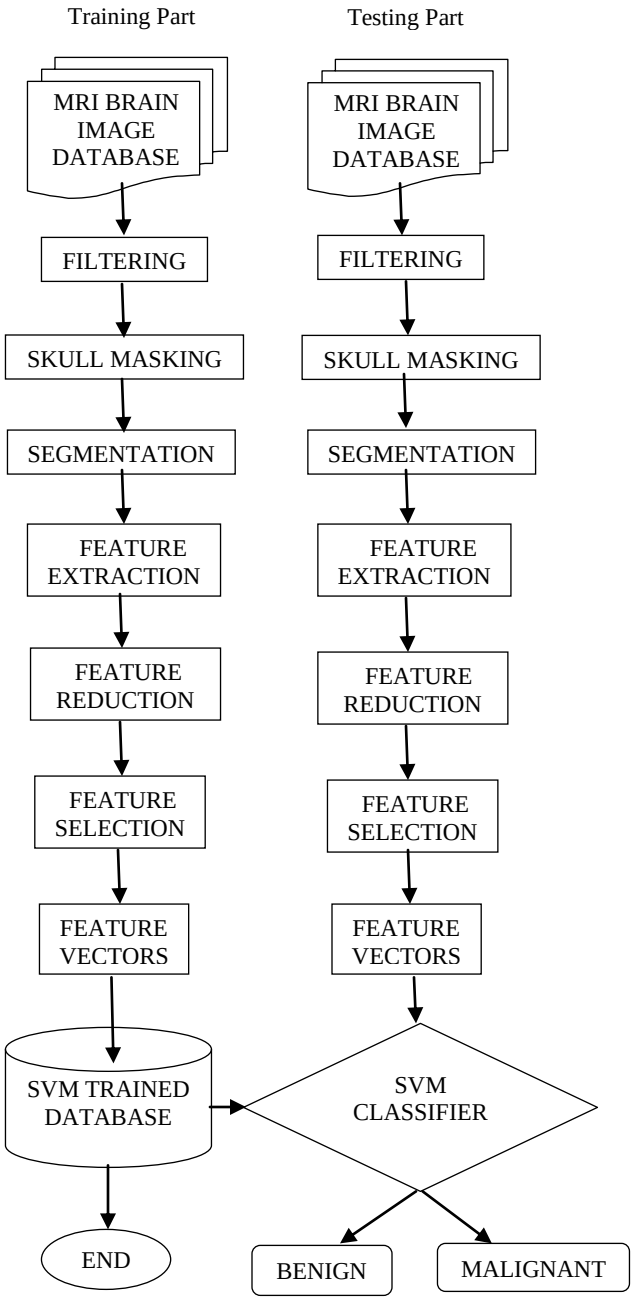

Fig. 1. Methodology system

A. MRI Image

For medical image diagnosis, MRI is one of the productive and safe methods. The most vital advantage is that it provides good contrast between various organs and tissues. It is dependent on some biologically variable parameters, proton density (PD), longitudinal relaxation time (T1) and transverse relaxation time (T2).

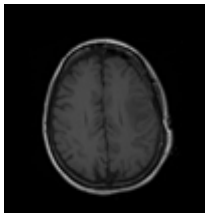

Fig. 2. Normal MRI (No Tumor)

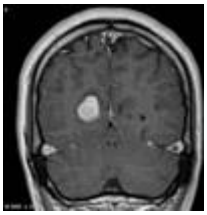

Fig. 3. Abnormal MRI (Benign Tumor)

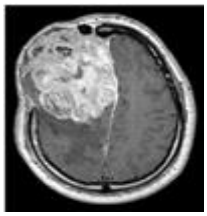

Fig. 4. Abnormal MRI (Malignant Tumor)

B. Filtering

Median filter is used to remove noise from the MRI images. Median filter is simple to understand. It preserves the brightness differences resulting in minimal blurring of regional boundaries. It also preserves the portions of boundaries in an image, making this method useful for visual examination and measurement.

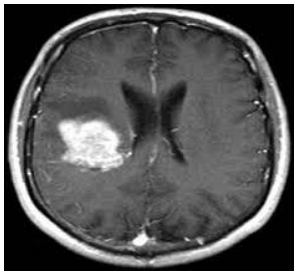

Fig. 5. Before Filtering

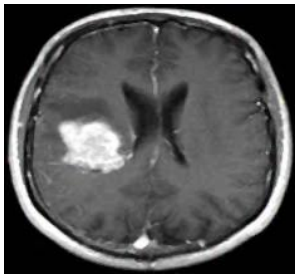

Fig. 6. After Filtering

C. Skull Masking

The process of removing non-brain tissue like scalp, skull, fat, eyes, neck, etc. from MRI brain image is called skull masking. It facilitates to improve the speed and accuracy of medical applications in terms of diagnostic and predictive procedures [14]. Two elementary morphological operations named dilation and erosion are used for skull masking. Opening refers to erosion followed by a dilation with the same structuring element.

$$A \circ B = (A \ominus B) \oplus B \quad (1)$$

Pixels on object boundaries are removed by erosion while dilation adds pixels to object's boundaries. The size and shape of the structuring element used in image processing depend on the amount of pixels added or removed from the objects. For filling in holes, region filing is used. After that image enhancement is done which is a basic image processing task to have a better subjective decision over the images. Image enhancement refers to transformation of an image f into image g using T. Values of pixels of in images named f and g are denoted by r and s . T is a transform that maps a pixel value r into pixel value s. Following expression shows that relation,

$$S = T(r) \quad (2)$$

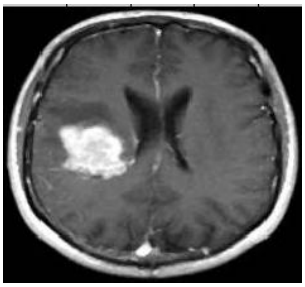

Fig. 7. Before Skull Masking

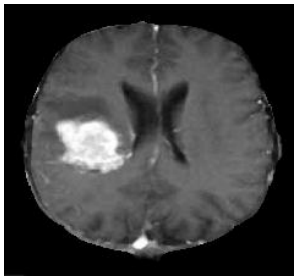

Fig. 8. After Skull Masking

D. Segmentation

Image segmentation refers to classification of an image into different groups. K-means clustering algorithm is an unsupervised algorithm and it is used to segment the interest area from the background. Otsu's method is used for clustering based image thresholding or reduction of gray level image to binary image. It is used to choose the threshold to minimize the interclass variance of the black and white pixels.

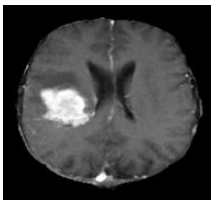

Fig. 9. Before Segmentation

Fig. 10. After Atsu's Thresholding

Fig. 11. Segmented Tumor (by k-means clustering)

E. Feature Extraction

Feature extraction is the process on the basis of which an image can be classified. It is a process to represent raw images to make decision such as pattern classification. From the tumor region of the MRI images, features can be extracted. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. In our proposed system discrete wavelet transform is used to extract features from images.

F. Feature Reduction

Immoderate number of features used for classification increases computation time and storage memory. Sometimes they make classification more complicated. It is required that the number of features are needed to be reduced to overcome the problems. PCA [5] is a proficient tool to reduce the dimensionality of a dataset which consists of a large number of interconnected variables. It is able to retain most of the variations. Steps of PCA are as follows,

- Compute the mean of the data matrix
- Subtract the mean from each image.
- Compute the covariance matrix.
- Compute the Eigen vectors and values for covariance matrix.
- Arrange the Eigen vectors according to the Eigen values and as per the threshold value.
- Compute the feature matrix (the space that required to project testing image on it.

G. Feature Selection

Feature selection is the process of finding the specific features that will be used to form feature vector later. In this proposed system Gray Level Co-occurrence Matrix (GLCM) is used to find second order statistical texture features. 22 textural features are extracted from each image [6].Three kind of features are extracted. They are as follows,

- Gray Scale
- Texture
- Symmetrical

These features certainly contain some redundancy, but the process helps to find potential by useful features.

) Gray Scale features: Some gray scale features [6] are mean, standard deviation, variance, skewness and kurtosis.

a) Mean=$\sum_{i=1}^{n}\sum_{j=1}^{n} i(C(i,j))$ (3)

b) Variance= $\sum_{i=1}^{n}\sum_{j=1}^{n}(1-\mu)^2 C(i,j)$ (4)

c) Standard Deviation= $\sqrt{Variance}$ (5)

d) Skewness=$\frac{1}{Variance^3}\sum_{x=1}^{m}\sum_{y=1}^{m}(f(x,y)-\mu)^3$ (6)

e) Kurtosis=$\frac{1}{Variance^4}\sum_{x=1}^{m}\sum_{y=1}^{n}(f(x,y)-\mu)^4$ (7)

2) Texture Features: Some textural features are extracted from each image. From each computed co-occurrence matrices, several Haralick texture descriptors can be extracted. Some texture features are,

a) Entropy− $\sum_{i=1}^{n}\sum_{j=1}^{n} C(i,j)\log(C(i,j))$ (8)

b) Dissimilarity= $\sum_{i,j=1}^{n} C(i,j)^*|(i-j)|$ (9)

a) Inverse=$\sum_{i,j=1}^{n}\frac{C(i,j)}{(i-j)^2}$ (10)

b) Energy= $\sum_{i=1}^{n}\sum_{j=1}^{n} C(i,j)^2$ (11)

c) Contrast= $\sum_{i=1}^{n}\sum_{j=1}^{n}(i,j)^2\, C(i,j)$ (12)

d) IDM= $\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{1}{1+(i-j)^2} C(i,j)$ (13)

3) Symmetrical Feature:

a) Exterior Symmetry= $\frac{\sum_{i=1}^{n}(m_i-M)^2}{n}$ (14)

H. Feature Vector

In patter recognition and machine learning, a feature vector is an n-dimensional vector of numerical features that represent some object's characteristics. In the proposed system, a feature vector is formed by using features selected by the GLCM. These features are stored in SVM trained dataset. At the time of testing, SVM classifies new MRI images on the basis of Training [15].

I. Classification with SVM

SVM is a binary classifier based on supervised learning. It gives better learning than other classifiers. SVM classifies

between two classes by constructing a hyperplane. This hyperplane exists in a high dimensional feature space which can be used for classification. SVM is based on different kernel methods. SVM can be classified into two groups.

1) Linear SVM: It is simple and its training patterns are linearly separable. A linear function is given below

$$F(x) = W^T + b \quad (15)$$

For each training sample x_i, the function yields $f(x_i) \geq 0$ for $y_i = +1$ and $f(x_i) \leq 0$ for $y_i = -1$. Training samples of two different classes are separated by the hyperplane $f(x)= W^T + b$, where w is the weight vector and it is normal to the hyperplane, b is the bias or threshold and x_i is the data point. For a given training set, there may exist many hyperplanes that make separation between two classes. But classification is performed based on the hyperplane that maximizes the separating margin between two classes. (Fig. 12).

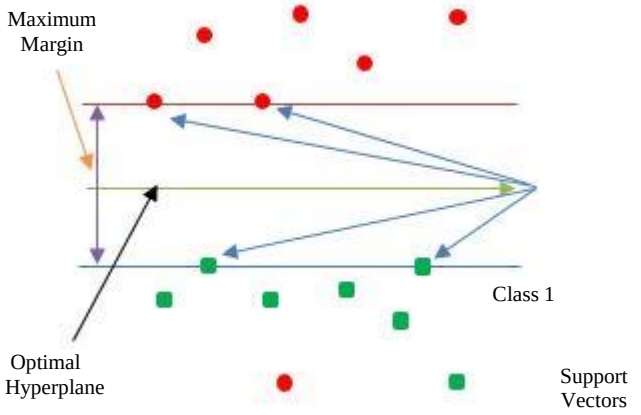

Fig. 12. Linear SVM Classification

In fig. 12, SVM classification is done where Class 2 perplane maximizes the separating margin between the two classes are indicated by data points by red circles and green squares. Support vectors are the training set's element lying on the boundary hyperplane of the two classes.

2) Non Linear SVM: When data points cannot be separated by drawing a straight line or hyperplane then nonlinear SVM classifier is used. In nonlinear SVM, a nonlinear operator is used to map the input pattern x into a higher dimensional space H, this nonlinear SVM classifier is defined as

$$f(x) = W^T \Phi(x) + b \quad (16)$$

Data which are linearly separable can be analysed with a hyperplane and the linearly non separable data are analyzed with different kernel functions as Quadratic or higher order polynomial kernel. Output of SVM with linear combination of training examples is mapped onto a high dimensional feature space through the use of kernel function as in fig. 13.

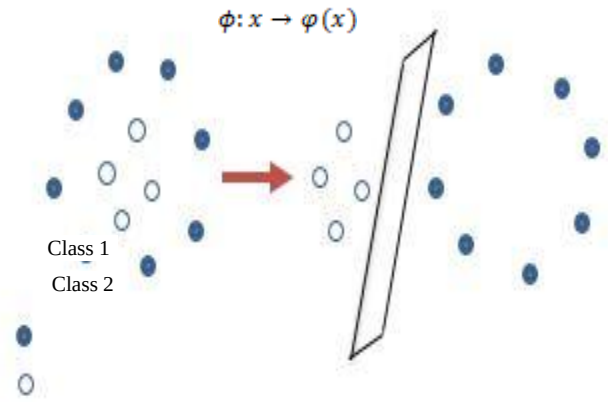

Fig. 13. Non Linear SVM Classification

J. Performance Measures

Classification result may have an error rate and on occasion may fail to identify an abnormality. It is usual to describe this accuracy rate in terms of true and false positive rate and true and false negative rate as follows are used to measure the performance of the classifier.

- True Positive Rate (TPR): Malignant (cancerous) tumor correctly identified as malignant.
- True Negative Rate (TNR): Benign (non-cancerous) tumor correctly identified as benign.
- False Positive Rate (FPR): Benign tumor incorrectly identified as malignant.
- False Negative Rate (FNR): Malignant tumor incorrectly identified as benign.

1) Error rate = (FPR+FNR)/(TPR+TNR+FPR+FNR)*100%
2) FPR = FPR/(TNR+FPR)*100%
3) Precision = TPR/(TPR+FPR)*100%
4) Sensitivity = TPR/(TPR+FNR)*100%
5) Specificity = TNR/(TNR + FPR)*100%
6) Accuracy = (TPR+TNR)/(TPR+TNR+FPR+FNR)*100%

IV. RESULTS AND DISCUSSION

Images from BRAINX database of OSIRIX DICOM image library and Dataset from Website of Harvard Medical School were used. The dataset consists of T1 weighted, T2 weighted and PET modalities MRI images and 256×256 in resolution with axial and coronal orientations. We had chosen 50 MRI image consisting 25 Benign Tumors and 25 Malignant Tumors. They were trained and stored in the SVM trained database. 200 images of MRI images containing Neoplastic Disease were stored in a testing dataset randomly and had been tested. Several pre-processing steps were implemented by the steps shown in (Fig. 14.)

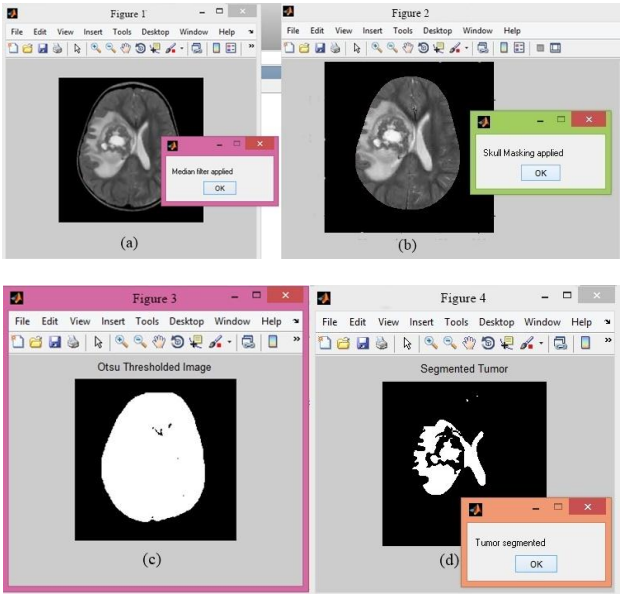

Fig. 14. (a) Median Filtering (b) Skull Masking (c) Otsu's thresholding (d) tumor segmentation by k-means clustering

The MRI brain image database was used for training and testing. After several processes i.e. feature extraction, reduction and selection, feature vectors were stored in SVM Trained Database which was applied to SVM classifier to classify. When the classifier detects a benign tumor it comes to a conclusion that cancer is not detected. If it detects a malignant tumor it shows that cancer is detected. SVM trained database was stored for future use.

Fig. 15. Classification results

Several performance measurements are evaluated in the given table I and II, and shown in Fig. 16 and 17.

TABLE 1 SVM CLASSIFIER RESULTS(1)

Sr. No.	SVM Results			
	Kernel Function	Error Rate	FPR	Precision
1	Linear	11%	12.5%	91.5%
2	Polynomial	09%	11.25%	92.5%
3	RBF	04%	3.75%	97.5%
4	Quadratic	05%	2.5%	98.2%

TABLE 2 SVM CLASSIFIER RESULTS (2)

Sr. No.	SVM Result			
	Kernel Function	Sensitivity	Specificity	Accuracy
1	Linear	90%	87.5%	86%
2	Polynomial	92.5%	89%	91%
3	RBF	95.8%	96%	96%
4	Quadratic	93.3%	97.5%	95%

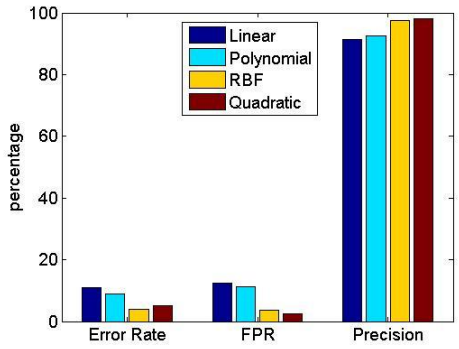

Fig. 16. Bar graph showing Error Rate, FPR and Precision

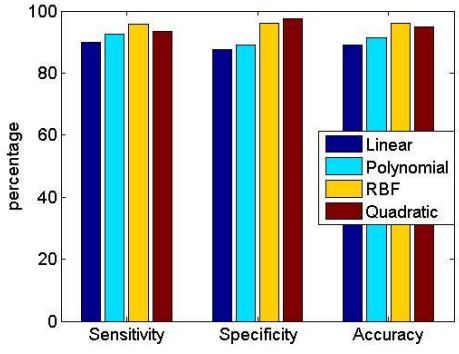

Fig. 17. Bar graph showing Sensitivity, Specificity and Accuracy

Performance of our proposed system can be compared with other systems related to the field of brain tumor classification and cancer detection. We have compared with five other systems and analysed the performance (Table III).

TABLE 3 PERFORMANCE COMPARISON

Sr. No.	Methods Used	Accuracy
1	SVM + Meta Heuristic Method	95.65%
2	Genetic Algorithm + SVM	91.7%
3	PCA + BPN	96%
4	PCA + Linear SVM	94%
5	PCA + KNN	92%
6	Our Proposed System: DWT + PCA + GLCM+ SVM	96%

V. CONCLUSION AND FUTURE SCOPE

The experimental result shows that the proposed system offers a higher accuracy rate and a low error rate. It is highly effective for classification to classify a brain tumor and detect cancer with high sensitivity, specificity and accuracy rate. The purpose is to develop the proposes system is to create a tool for discriminating two tumor classes named Benign and Malignant from MRI input and assist on decision making in clinical diagnosis and will help doctor to take or analyse in which stage of brain tumor the patient have, and does he have cancer?, or not. A hybrid classifier i.e. SVM-KNN can be proposed to increase the accuracy of the system. This Proposed method offers automatic MRI brain tumor classification and cancer detection method to increase the accuracy and decrease the diagnosis time.

REFERENCES

[1] K. B. Vaishnavee and K. Amshakala, "An automated MRI brain image segmentation and tumor detection using SOM-clustering and Proximal Support Vector Machine classifier", in IEEE International Conference on Engineering and Technology (ICETECH), pp. 1 - 6, 2015.

[2] Ketan Machhale, Hari Babu Nandpuru, Vivek Kapur and Laxmi Kosta, "MRI brain cancer classification using hybrid classifier (SVM-KNN)", in International Conference on Industrial Instrumentation and Control (ICIC), pp. 60-65, 2015.

[3] Hari Babu Nandpuru, S. S. Salankar and V. R. Bora , "MRI brain cancer classification using Support Vector Machine", in IEEE Students' Conference on Electrical, Electronics and Computer Science (SCEECS), pp. 1 - 6, 2014.

[4] Arashdeep Kaur "An Automatic Brain Tumor Extraction System Using Different Segmentation Methods" International Conference on Computational Intelligence & Communication Technology (CICT), pp. 187-191, 2016.

[5] Y. Zhang and L. Wu, "An MR Brain Images Classifier Via Principal Component Analysis and Kernel Support Vector Machine", in Progress in Electromagnetics Research(PIER) , Vol. 130, pp. 369-388, 2012.

[6] Sheweta Jain, "Brain Cancer Classification Using GLCM Based Feature Extraction in Artificial Neural Network", IJCSET, ISSN: 2229-3345, Vol. 4 No. 07 Jul 2013.

[7] Ahmed Kharrat, Mohamed Ben Halima and Mounir Ben Ayed, "MRI brain tumor classification using Support Vector Machines and meta-heuristic method", International Conference on Intelligent Systems Design and Applications (ISDA), pp. 446-451, 2015.

[8] D. Sridhar and IV. Murali Krishna "Brain Tumor Classification using Discrete Cosine Transform and Probabilistic Neural Network" International Conference on Signal Processing Image Processing & Pattern Recognition (ICSIPR), pp. 1-5, 2013.

[9] Jainy Sachdeva, Vinod Kumar, Indra Gupta; Niranjan Khandelwal and Chirag Kamal Ahuja, "Multiclass Brain Tumor Classification Using GA-SVM", pp. 182-187, 2011.

[10] Walaa Hussein Ibrahim, Ahmed AbdelRhman, Ahmed Osman and Yusra Ibrahim Mohamed "MRI brain image classification using neural networks", International Conference on Computing, Electrical and Electronics Engineering (ICCEEE), pp. 253-258, 2013.

[11] G. Kharmega Sundararaj and V. Balamurugan, "Robust classification of primary brain tumor in Computer Tomography images using K-NN and linear SVM", International Conference on Contemporary Computing and Informatics (IC3I), pp. 1315-1319, 2014.

[12] Ahmed Kharrat, KarimGasmi, et.al, "A Hybrid Approach for Automatic Classification of Brain MRI Using Genetic Algorithm and Support Vector Machine", Leonardo Journal of Sciences. pp. 71-82, 2010.

[13] P. John, "Brain Tumor classification Using Wavelet and Texture Based Neural Network", International Journal of Scientific & Engineering Research, Vol. 3, Issue 10, pp. 1-7, 2012.

[14] Janki Naik and Prof Sagar Patel, "Tumor Detection and Classification using Decision Tree in Brain MRI", IJEDR, ISSN: 2321-9939, 2013.

[15] Mr. Ajaj Khan and Ms. Nikhat Ali Syed, "Image Processing Techniques for Automatic Detection of Tumor in Human Brain Using SVM", International Journal of Advanced Research in Computer and Communication Engineering (IJARCE), Vol. 4, Issue 4, pp. 541-544, 2015.

[16] Asha Patil, Kalyani Patil, Kalpesh Lad, "*Leaf Disease detection using Image Processing Techniques*", International Journal of Scientific Research in Computer Science and Engineering, Vol.06, Issue.01, pp.33-36, 2018.

[17] Amey Samant, Sushma Kadge, "*Classification of a Retinal Disease based on Different Supervised Learning Techniques*", International Journal of Scientific Research in Network Security and Communication, Vol.5, Issue.3, pp.9-13, 2017

Authors Profile

M.. A. Rahman pursed Bachelor of Science in Computer Science and Engineering from Rajshahi University of Engineering and Technology(RUET), Bangladesh in 2016. He is currently working as Lecturer in the Department of Computer Science and Engineering under Faculty of Science, Engineering and Technology, Hamdard University Bangladesh, Bangladesh since May 2017. His main research work focuses on Image Processing, Artificial Intelligence, Bioinformatics, Routing path optimization, Enhancing battery lifetime of wireless sensor network. He has more than 1 year of teaching experience and 3 years of Research Experience.

