ISSN 2347 - 3983
Volume 7, No. 12 December 2019
International Journal of Emerging Trends in Engineering Research
Available Online at http://www.warse.org/IJETER/static/pdf/file/ijeter297122019.pdf
https://doi.org/10.30534/ijeter/2019/297122019

MRI Brain Cancer Diagnosis Approach Using Gabor Filter and Support Vector Machine

Amal Fouad[1], Hossam M. Moftah[2] , Hesham A. Hefny[3],
[1] Faculty of Computers and Information, Beni Suef University, Egypt, amalfouad@fcis.bsu.edu.eg
[2] Faculty of Computers and Information, Beni Suef University, Egypt, hmmoftah@hotmail.com
[3]Faculty of Graduate Studies for Statistical Research, Cairo University, hehefny@ieee.org

ABSTRACT

Feature extraction is a very important and crucial stage in recognition system. It has been widely used in object recognition, image content analysis and many other applications. Feature extraction is the best way/method to recognize images in the field of medical images. However, the selection of proper feature extraction method is equally important because the classifier output depends on the input features.

This study proposes an image classification methodology that automatically classifies human brain magnetic resonance (MR) images. The proposed method consists of four main stages: preprocessing, feature extraction, feature reduction and classification, followed by evaluation. The first stage starts with noise reduction in MR images. In the second stage, the features related to MR images are obtained using Gabor filter. In the third stage, the features of MR images are reduced to the more essential features using kernel linear discriminator analysis (KLDA). In the last stage, the classification stage, two classifiers have been developed to classify subjects as normal or abnormal MRI human images. Whereas the first classifier is based on Support Vector Machine (SVM), the second classifier is based on K-Nearest Neighbor (KNN) on Euclidean distance. Classification accuracies are 100% and 96.3% for SVM and KNN classifiers respectively. The result shows that the proposed methodologies are robust and effective compared with other existing technologies in classification of MRI tumor brain.

Key words: Gabor filter, medical images, kernel discriminator analysis.

1. INTRODUCTION

In medical diagnostic application, early defect detection is a crucial task as it provides critical insight into diagnosis. Manual inspection of those images is a tedious job as the amount of data and minute details are hard to recognize by the human. Hence, automating those techniques is crucial. Magnetic Resonance imaging (MRI) is one of those reliable imaging techniques on which medical diagnosis is based upon.

MRI is an imaging technology based on the phenomenon of Nuclear Magnetic Resonance which produces three-dimensional anatomical images without the use of ionizing radiation. MRI is useful for scanning and detecting abnormalities in body's soft tissues structure such as cartilage tissue and soft organs like brain. MRI is the best choice in imaging modalities for studying brain owing to its high tissue contrast and detail [1].

In this paper, we are proposing a method which can be utilized to make tumor detection easier. MRI deals with the complicated problem of brain tumor detection. Due to its complexity and variance, getting better accuracy is a challenge.

The remainder of this paper is organized as follows. Section 2 gives a brief background of materials. The proposed method is presented in Section 3. Section 4 shows the experimental work carried and discusses the obtained results. Section 5 concludes the paper recommendations for future research.

2. LITERATURE SURVEY

In [2], Gabor filter is designed in a new approach by incorporating feature selection, i.e. filter selection, into filter bank design process. By the means of filter selection, a compact Gabor filter bank that requires reduced computations could be obtained. Gabor filter bank produces low-dimensional pattern representations in the feature space with improved sample-to-feature ratio. As a direct result, classification performance is improved to be 98.24%.

In [3], palm print is a piece of texture and applies texture-based feature extraction techniques to palm print authentication. A 2-D Gabor filter is used to obtain texture information and two palm print images are compared in terms of their hamming distance. The experimental results illustrate the effectiveness of the proposed method.

In [4], feature extraction method is described for optical character recognition (OCR) system. For feature extraction, word images, which are machine printed images, have been scanned. Features are extracted from the scanned images using Discrete Cosine Transform (DCT) and Gabor filter.

DCT provide 100 features of scanned images in zig-zag method and Gobor provides 189 features for scanned images. The result of the classification stage totally depends on the features of images.

In [5], Gabor feature extraction algorithm is improved to obtain the accurate position of the eyes and mouth in extract features process. Using Sobel edge detection technology determines the position of the nose and extracts the feature points. Gabor filter is applied at each characteristic point. The Gabor feature is extracted in low dimension, and good robustness. The experimental results achieve 96% accuracy.
In another study [6], the authors used Gray Level Co-occurrence Matrix (GLCM) as texture feature extraction, and geometrical features are also extracted. Wrapper based Particle Swarm Optimization (PSO) is used to select the best feature and to optimize the parameters of Support Vector Machine (SVM). Then, test image is subjected to SVM with RBF kernel for classification of image into Normal or Tumor. Classification accuracy of the proposed Wrapper PSO with SVM method is 98%, which is better when compared to GA with SVM.

In [7], Adaboost classifier is used for brain tumor classification. The texture features were extracted by using GLCM technique. Twenty two features were extracted from an MRI. For the classification purpose, the results achieved maximum accuracy in that system, which is 89.90%.

3. THE PROPOSED APPROACH

In medical imaging there is a massive amount of information; however, but it is not possible to access or make use of this information if it is efficiently organized to extract the semantics. Classification of semantic images represents a hard problem. In image analysis and pattern recognition community, each image is mapped into a set of numerical or symbolic attributes called features. Image classification is given a semantically well-defined image set by mapping from feature space to image classes.

The proposed approach involves processing of MR images affected by brain tumor for the detection and classification of human brain tumors. Image processing techniques, such as preprocessing, are used to enhance the tumor image to be more clarify. Feature extraction method is then used for extracting features from the MR image. Features are extracted using Gabor filter. Features reduction stage is coming after feature extraction by using KLDA. The last stage is the classification stage, SVM as a classifier detects the MR brain image is normal or abnormal image. The general structure of the proposed MR brain images classification approach is shown in Figure 1.

3.1 Preprocessing

One of the main goals of image processing is to retrieve required information from the given image in a way that will not affect the other features of that image [8]. Enhancement or de-noising of an image is the most important step required to clarify it. After removing noise from an image and applying the enhancement, the system can perform any operation on that image.

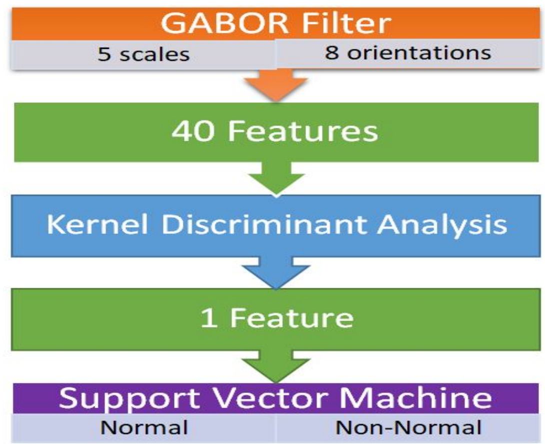


Figure 1: The proposed approach for Classifying MR Images

The image enhancement can be contrast enhancement, noise removal or details (e.g. edges) sharpening, in order to make the analysis easier, both of The image enhancement and noise removal are great potential in image analysis. Contrast enhancement can be achieved by, for example, histogram equalization, where the intensities are distributed over the histogram. Noise can be removed with different filters. Whereas a mean filter reduces the noise, it has the disadvantage that the sharpness of edges is lost. A nonlinear filter that can be used for specific types of noise, such as salt and pepper noise, is the median filter, and it further has the advantage of preserving edges [9] .

In the present study, a 5*5 median filter has been applied on the original image, and it proved the best accuracy during the classification; other than the original image, mean, contrast, and the Histogram equalization. After preprocessing, we have applied the Gabor filter bank to extract the intrinsic features [10].

3.2 Feature extraction

During diagnosis of brain, acquisition of data is quite sophisticated; it is very difficult to perform classification without dimensionality reduction. The process of collection of higher level information of an image, like texture, color, shape and contrast, is called Feature Extraction. Feature Extraction involves reducing original data set by measuring certain properties that distinguish one input pattern from another [6]. Using the appropriate transformation, certain characteristics or features of any image are identified, which are then used for evaluation that image.

Feature vector is an N dimensional vector; each element of which specifies some measurement of objects. Feature space is the N dimensional mathematical space spanned by feature vector used in classification problem. Training data is a collection of feature vector used to build a classifier. Testing data is a collection of feature vector used to test the performance of a classifier [11].

Texture features are used for recognition and interpretation measured from a group of pixels or the image as whole. Texture features are used, either directly or indirectly, in many applications, such as Classification (i.e. determining the class or category to which an observed feature belongs), and Segmentation (i.e. partitioning any image into different meaningful regions). In applying texture analysis methods, MRI is preferred when it is related to brain diseases [1, 7, and 12].

In this context, features or attributes are specific properties or characteristics extracted from the images in order to learn and recognize the tumor and non-tumor textures. This study focuses only on textural features. Textural features materialize the di□erences between the tumor and non-tumor textures.

3.2.1 Gabor features

Inspired by the multi-channel operation of the Human Visual System (HVS) for interpreting texture, research has been focused on using a multi-channel approach based on Gabor filtering to mimic the operation of HVS for identifying different texture regions. In this paper, we employ this multi-channel approach in order to gain insight into the potential of this methodology in solving the texture image problem.

A model for the HVS interpretation of texture has been based on multi-channel filtering of narrow bands. Simple cells in the visual cortex were found to be sensitive to different channels of combinations of various spatial frequencies and orientations. Since texture repetition can be characterized by its spatial frequency, and directionality by its orientation, then we can fit the HVS model into a methodology that uses multi-channel filtering at different spatial-frequencies and orientation for texture analysis.

The multi-channel filtering approach is essentially a multi-resolution decomposition process, which is similar to wavelet analysis. Since John Daugman proposed to use a Gabor filter in image analysis tasks in 1988 [13], wide experience of its application has been obtained. The Gabor filter is used in face recognition, fingerprints and iris recognition [14], texture analysis [15, 16], medical informatics [17], defects detection [2,18], video stream analysis [19, 20], image segmentation [21], texture descriptor designing [3,22], and robot vision [23, 24].

Gabor filter has received considerable attention, and has emerged as one of the most popular approaches to texture feature extraction, it has a great importance of optimal localization in both spatial and frequency domains. Gabor filter-based feature extractor is a Gabor filter bank consisting of filters with different frequencies and orientations [2].

A Gabor filter kernel is a product of the Fourier basis element and the Gaussian filter. Due to the Fourier basis, the filter becomes sensitive to specific image components of the spatial frequency and orientation. The Gaussian filter is needed for spatial localization of the filter. In this respect, the convolution with the Gabor filter is similar to windowed Fourier transform. The following equations illustrate the Gabor filter, G(x, y), where (x, y) represent a pixel coordinates in the diagram θ, λ, φ, σ. The parameters are shown in Table 1.

Complex

$$G(x, y;\lambda,\theta,\psi,\sigma,\gamma)=exp\left(\frac{x'+\gamma^2 y'^2}{2\sigma^2}\right) exp\left(i\left(2\pi\frac{x'}{\lambda}+\psi\right)\right) \quad (1)$$

Real

$$G(x, y;\lambda,\theta,\psi,\sigma,\gamma)=exp\left(\frac{x'+\gamma^2 y'^2}{2\sigma^2}\right) cos\left(2\pi\frac{x'}{\lambda}+\psi\right) \quad (2)$$

Imaginary

$$G(x, y;\lambda,\theta,\psi,\sigma,\gamma)=exp\left(\frac{x'+\gamma^2 y'^2}{2\sigma^2}\right) sin\left(2\pi\frac{x'}{\lambda}+\psi\right) \quad (3)$$

Where

$$x' = x\cos\theta + y\sin\theta \quad (4)$$

And

$$y' = -x\sin\theta + y\cos\theta \quad (5)$$

Table 1: Data of θ, λ, φ, σ.

Parameters	Symbol	Set value
direction	θ	$\left\{0,\frac{\pi}{8},\frac{2\pi}{8},\frac{3\pi}{8},\frac{4\pi}{8},\frac{5\pi}{8},\frac{6\pi}{8},\frac{7\pi}{8}\right\}$
wavelength	λ	$\left\{4,4\sqrt{2},8,8\sqrt{2},16\right\}$
phase	ϕ	$\left\{0,\frac{\pi}{2}\right\}$
Gauss radius	σ	$\sigma=\lambda$

Based on the Gabor function, principle and design theory of filter Direction, θ: represents the direction of parallel stripes in the Gabor function. Wavelength λ: in image processing, it is a pixel, there is a certain range of needs less than 1/5 the size of the image, and the minimum is 2. Phase ϕ: is in the range of -180 degrees to 180 degrees. The center-off function is obtained at 90 degrees; whereas, the center-on function is obtained at 0 degrees. Gauss radius σ: represents the standard deviation of Gaussian factor in the Gaussian's function used in Gabor transform, σ=λ. A set of filters, consisting of 5 different spatial frequencies and 8 different directions, which make up 40 different filters, is used, as shown in figure 2. The figure shows the characteristics of different features after filtering [5].

3.3 Feature reduction scheme using KLDA

Since some features are redundant, or of little importance, feature reduction is one of the crucial factors that influence the classification accuracy rate. The best feature among the extracted features is selected by discarding some redundant features can achieve better performance. An efficient and precise feature selection technique eliminates irrelevant, noisy and redundant data.

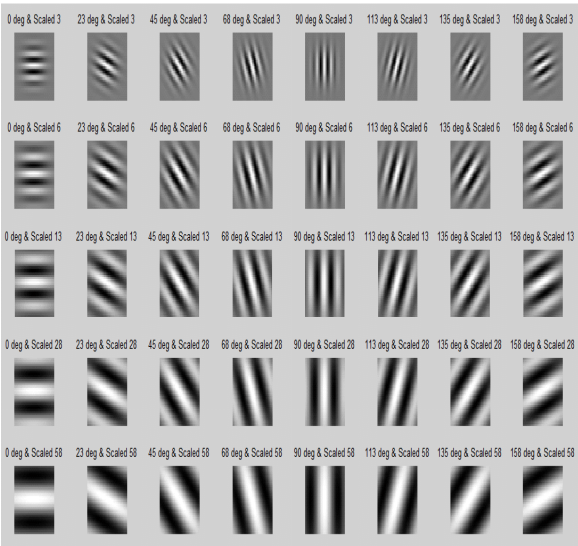


Figure 2: 5 different spatial frequencies and 8 different directions for Gabor filters bank.

For most pattern recognition problems, selecting an appropriate representation to extract the most significant features is crucially important. Linear Discriminant Analysis (LDA) [25,26 ,27], which seeks to find a linear transformation by maximizing the between-class variance and minimizing the within-class variance, has proved to be a suitable technique for discriminating different pattern classes. However, both the PCA and LDA are linear techniques which may be less efficient when severe non-linearity is involved. To extract the nonlinear discriminant features, Kernel Discriminant Analysis (KDA), a nonlinear discriminating method based on kernel techniques, was developed [28].

LDA is a traditional statistical method that has proved successful in linear classification problems. The procedure is based on an eigenvalue resolution and gives an exact solution of the maximum of the inertia. However, this method has proved inefficient in a nonlinear problem [26, 27].

LDA selects a set of those features whose linear combination generates the mean with highest difference between the preferred classes in order to separate them. In order to reduce over-fitting, LDA tries to map input data to a lower-dimensional space, which results in separating classes with higher accuracy. It basically finds the component axes that separate the multiple classes with maximum distance [25, 26].

Kernel has generalized LDA to nonlinear problems and developed LDA for mapping the input space into a high-dimensional feature space with linear properties. In the new space, one can solve the problem in a classical way, such as the LDA method. The main idea is to map the input space into a convenient feature space in which variables are nonlinearly related to the input space [29].

3.3.1. Kernel Discriminant Analysis

The principle of KDA can be illustrated in figure 2. Owing to the severe non-linearity, it is difficult to directly compute the discriminating features between the two classes of patterns in the original input space (left). By defining a non-linear mapping from the input space to a high-dimensional feature space (right), one might expect to obtain a linearly separable distribution in the feature space. Then, LDA, the linear technique, can be performed in the feature space to extract the most significant discriminating features. However, the computation may be problematic or even impossible in the feature space, owing to its high dimensionality. By introducing a kernel function which corresponds to the non-linear mapping, all the computation can conveniently be carried out in the input space. The problem can be finally solved as an Eigen-decomposition problem like PCA, LDA and KPCA.

Through a kernel function, data from different classes are implicitly mapped from an input space to a kernel-induced feature space. The LDA is then performed in the kernel-induced feature space to find an optimal direction. It increases the separation between different classes. The kernel mapping is often nonlinear, and the dimensionality of the induced feature space can be very high or even infinite [29].

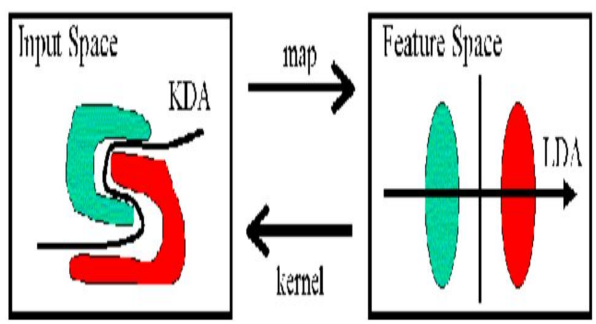


Figure 3: Kernel Discriminant Analysis.

3.4 Classification

Image pattern recognition is an important area in digital image processing. An efficient pattern recognition algorithm should be able to provide correct recognition at a reduced computational time.

Classification is a process in which a given test sample is assigned a class on the basis of knowledge gained by the classifier during training. Its task is to assign an input pattern represented by a vector to one of many specified classes.

SVM is a data classification technique initially proposed in [28]. The SVM classification model is generated from the training process with the training data. The main concept of SVM is using hyper-planes for defining decision boundaries that separate between data points of different classes. Optimal hyper-plane is the hyper-plane with the maximum margin of gap separating two classes, where the margin is the sum of the distances from the hyper-plane to the closest data points of each of the two classes. These closest data points are called Support Vectors (SVs).

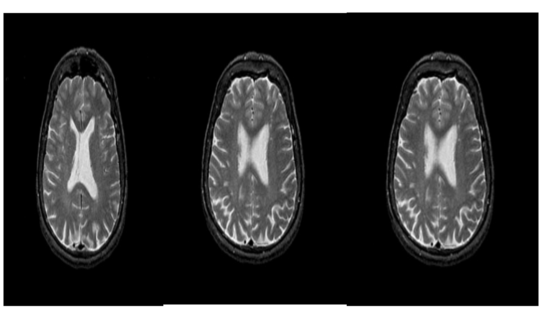
After Optimization, the global best feature is fed to the SVM classifier for training. Later on, classification of testing data is executed based on the trained model. In this paper, SVM and KNN classifiers are used for the classification of brain MR images into healthy brain, or tumor brain.

4 EXPERIMENTAL RESULTS AND DISCUSSIONS

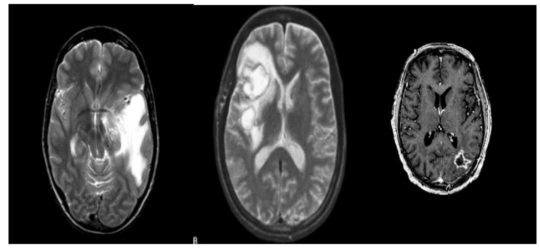
The experiments were carried out on the platform of core i7 with 3 GHz main frequency and 6 G memory; running under Windows 8 64 bit operating system. The algorithms were developed by Matlab 2018a (The Math works). The programs can be run or tested on any computer platforms where Matlab is available. This runnable version can be run by using Matlab programming languages on an environment of 64 bit.

4.1 Dataset

MR images are categorized into normal images for healthy individuals, and abnormal images containing different types of tumors. The features of our data are as follows: Format: JPEG File size: 18–25 kb, Dimensions: 256 * 256, Plane: axial, and Weight: T2-weighted. The data was obtained from the Website of Harvard Medical School [30]. Ninety-five (fifty-five images are abnormal and forty images are normal) images were obtained. Some samples of the MRI database have been displayed in figure 4.



(A)



(B)

Figure 4: Samples of brain MRIs. (A) samples of normal brain. (B) samples of abnormal brain.

4.2 Feature extraction

A Gabor filter responds to edges and texture changes. A filter that responds to a particular feature, it means that the filter has a distinguishing value at the spatial location of that feature (when it is dealing with applying convolution kernels in spatial domain). The same holds for other domains, such as frequency domains, as well.

Gabor features are calculated at 5 scales and 8 orientations which convolve each filter with the image to get 40 features (8*5=40). The different representations (response matrices) of the same image give a feature vector. So, feature vector may consist of Local Energy, Mean Amplitude, Phase Amplitude or Orientation whose local has maximum Energy.

In the present study, mean amplitude is explored and it rendered good results. Mean Amplitude equals the sum of absolute values of each matrix value from a response matrix. One matrix could be appended to the other to create a [1x40] feature matrix for one image and thus create a [nx40] vector for n images for further training purpose.in our methodology, we worked on mean amplitude and got good enough results.

4.3 Feature reduction by using KLDA

KLDA is used to further reduce the dimensions of the features; so each image having 40 feature values is reduced to only one feature values. KLDA uses the kernel trick to implicitly map the feature vectors into a kernel-induced feature space. This one feature is used in classification process. Thus, the feature values are used in classification process. Classification is performed using two machine learning techniques, namely: Knn and SVM.

4.5. Classification

In this study, SVM is adopted with three kernel functions. These kerenel functions are compared according to their classification accuracy for tumor grade identification. The adopted kernel functions are:

- Linear kernel function:

  $$K(x_i,x_j)=x_i.x_j$$

- Polynomial kernel function :

$$K(x_i,xj)=(1+x_i.x_j)^d$$

- Radial Basis Function (RBF) kernel:
  - $exp\frac{|||xi-xj||^2}{2\sigma^2}$

4.6 Classification evaluation

The proposed features set is extracted from all MRI slices of a particular tumor patient, for all the cases considered, because individual slices do not give proper information about a tumor's grade. The extracted features set is given as input to classifier and the results obtained are assessed in terms of the following parameters:

$$Accuracy=\frac{TP+TN}{TP+FP+TN+FN}*100 \quad (6)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (7)$$

$$Specificity = \frac{TN}{FP+TN} \quad (8)$$

Where

- TP is true positive.
- FP is false positive.
- TN is true negative.
- FN is false negative.

These parameters are calculated from confusion matrix as illustrated in figure (5).

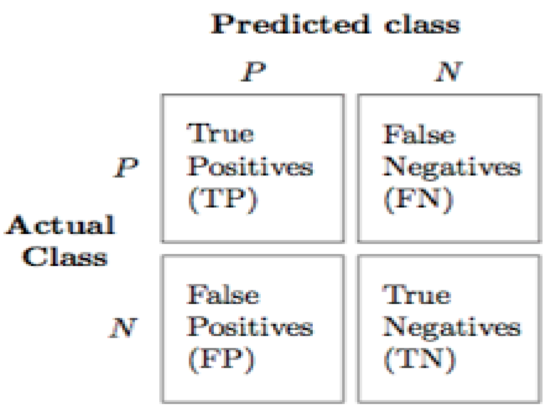


Figure 5: confusion matrix

Table 2: The classifiers results

The classifier	The accuracy
Knn	96.3%
SVM(Linear)	91.7%
SVM(Polynomial)	96.3%
SVM(RBF)	100%

The results obtained from different classifier using proposed classifiers are shown in Table 2. As the results show, SVM classifier with radial basis function (RBF) kernel produced maximum accuracy of 100%, which is much higher when compared to that obtained from linear and polynomial kernels, 93% and 96% respectively. SVM (RBF) accuracy is higher than that obtained from K nearest neighbor (knn) 96%. This clearly shows that SVM with RBF kernel performs much better as compared to other classifiers for the proposed feature set. Sensitivity gives fraction of positives that are correctly detected and specificity gives fraction of negatives that are correctly detected. As observed from the results in Table 2, for sensitivity, a maximum value of 1 is obtained using SVM with RBF kernel from the proposed model, which is the highest among all the classifiers considered in this study.

To clarify the performance of a binary classifier system in graphically display, the Receiver operating characteristic (ROC) curve is used in this paper. ROC is generated by plotting the true positives rate on the Y axis and the false positives rate on the X axis [31]. It is a useful tool to depict relative trade-offs between benefits (true positives) and costs (false positives).

Figure 6 displays the improvement results in an of ROC area of SVM (rbf) kernel was better than other kernels of SVM classifiers and KNN also. KDA-SVM (rbf) has effective capability to detect the tumor brain with accuracy 100%, so plotting its ROC curve has valuable presentation to compared with classifiers.

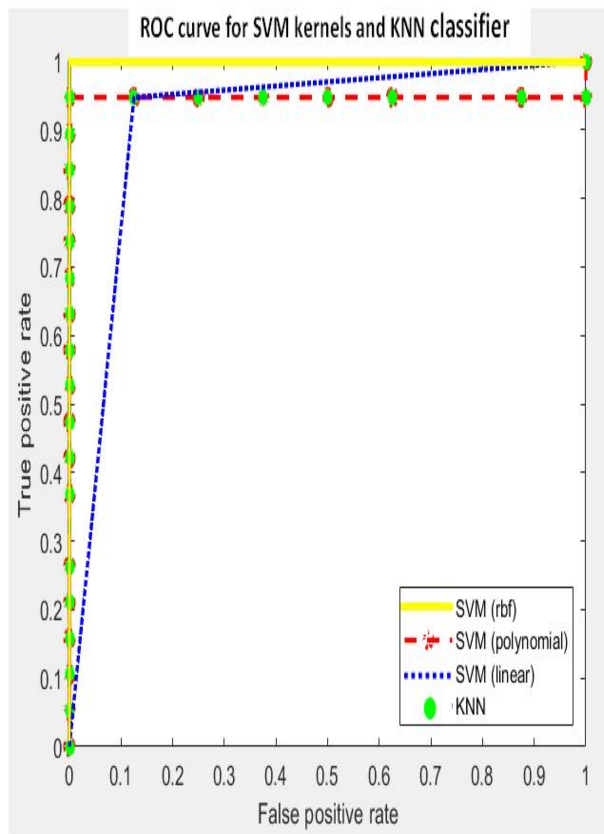


Figure 6: ROC curve for the SVM with different kernel functions and KNN classifier

5 CONCLUSION

In this study, we have presented a new approach to Gabor filter for texture feature extraction followed by KLD for feature selection. Feature extraction process, we can obtain a compact Gabor filters bank that demands reduced computations. More importantly, the compact Gabor filters bank produces low-dimensional pattern representations in the feature space. In feature selection, KLD plays a vital role by elimination the 40 feature values to be only one feature. This feature has the ability of distinguishing between two classes. As a direct result, improved classification performance can be achieved. For the classification purpose, SVM classifier is used and the maximum accuracy achieved by the proposed system is 100%. Among all the classifiers considered, a maximum accuracy of 100% is achieved from SVM classifier with RBF kernel.

The proposed tumor diagnosis approach can assist doctors in early detection of brain tumor and in planning its treatment. Since the proposed model is tested on a small dataset, it is recommended that future research focuses on testing proposed method on large dataset of tumor images to identify robustness of extracted features set.

REFERENCES

1. G. Grover , J. Tognarelli , M. Crossey, I. Cox, S. Taylor-robinson, **Magnetic resonance imaging: principles and techniques: lessons for clinicians**. Journal of clinical and experimental hepatology, Vol. 4, No. 3, pp. 570-578, August 2015. https://doi.org/10.1016/j.jceh.2015.08.001
2. L. Weitao , M. Kezhi , Z. Hong ,C. Tianyou ,selection of gabor filters for improved texture feature extraction, image processing (icip), in *Proc*. 2010 17th ieee international conference on, october 2010.
3. K. Wai, D. Zhang, W.Li , **Palmprint feature extraction using 2-d gabor filters**, Pattern recognition society, Elsevier, Vol. 36 ,No. 10 , pp. 2339-2347, October 2003.
4. S. Dhiman, L. Gurpreet, **Performance comparison of Gurmukhi script: k-NN classifier with DCT and Gabor filter,** International journal of research in computer applications and robotics, Vol. 8, No. 5, pp. 0976-5697, April 2017.
5. Y. Hao, L. Zhang, D. Zhang ,**The fusion of Gabor feature and sparse representation for face recognition**, Journal of computers ,Vol. 28, No. 2, pp. 1991-1599, January 2017.
6. P. Verma, N. Naiyar, B. Shrikant. B. Je, **Detection of brain tumor in MR images using multi-objective particle swarm optimization with support vector machine classifier with rbf kernel**" International research journal of engineering and technology (irjet), Vol. 4, No. 5, pp. 1346-1352, May 2017.
7. A. Minz , C. Mahobiya , **MR Image classification using adaboost for brain tumor type,** in *Proc*. 2017 IEEE 7th International Advance Computing Conference (IACC) , pp. 701-705, January 2017.
8. I. Bashir , A. Majeed , O. Khursheed , **image restoration and the various restoration techniques used in the field of digital image processing**, international journal of computer science and mobile computing, june- 2017.
9. S. Morillas, C. Jordán ,J. Alberto , **Smoothing vs. Sharpening of colour images: together or separated**, Applied mathematics and nonlinear sciences, Vol. 2 ,No. 1, pp. 299-316, Jun 2017. https://doi.org/10.21042/AMNS.2017.1.00025
10. E. El-dahshan, M. mahmoud,M. Bassiouni, **Computational intelligence techniques for human brain MRI classification**, Vol. 2 ,No. 1 , pp. 132-148, Wiley, 2018.
11. S. Christopher, B. Toby, **Fundamentals of digital image processing: fundamentals of digital image processing: a practical approach with examples in matlab,** 2011wiley , SN. 1119957001.
12. M. Malathi, P. Sinthia, **MRI brain tumour segmentation using hybrid clustering and classification by back propagation algorithm**, J Asian Pacific journal of cancer prevention: APJCP, Vol. 19 ,No. 11 ,pp. 3257,2018.
13. K. Salabat, H. Muhammad, A. Hatim, B. George**, A comparison of different Gabor feature extraction approaches for mass classification in mammography**. Multimedia Tools and Applications, Vol.76, No.1, pp. 33-57, 2017.
14. F. He, Y. liu,X. Zhu, **Multiple local feature representations and their fusion based on an SVM model for iris recognition using optimized gabor filters**. EURASIP Journal on Advances in Signal Processing Vol. 19 ,No. 11,pp. 1687-6180, 2014.
15. R. Jenssen,T. Eltoft, **Independent component analy- sis for texture segmentation**. Pattern recognition, Vol. 36, No. 10, pp. 2301-2315, 2003.
16. C. Sagiv, N. Sochen,Y. Zeevi, , **Integrated active contours for texture segmentation**. Ieee transactions on image processing, Vol. 15, No. 6, 2006.
17. D. Sommen, F. Zinger, S. Schoon, **Supportive automatic annotation of early esophageal cancer using local Gabor and color features**. Neurocomputing, Vol. 144, pp. 92-106, 2014. https://doi.org/10.1016/j.neucom.2014.02.066
18. M. Hanmandlu, D. Choudhury, D. Dash, **Detection of defects in fabrics using topothesy fractal dimension features**. Signal, Image and video processing, Vol. 9, No.7, pp. 1521-1530, 2015.
19. V. Santhaseelan, V. Asari, **Utilizing local phase information to remove rain from video**. International journal of computer vision, Vol.112, No.1, pp. 71-89, 2015.
20. D. Wagenaar, W. Krista, **Automated video analysis of animal movements using gabor orientation filters.** Neuroinformatics, Vol. 8, No. 1, pp. 33-42, 2010.

https://doi.org/10.1007/s12021-010-9062-1

21. Y. Yang, Y. Wang, Y. Wang, J. Zhang, **LS-SVM based image segmentation using color and texture information**. Journal of visual communication and image representation ,Vol. 23, No. 7, pp. 1095-1112, 2012.
22. T. Ahonen, M. Pietikinen, I**mage description using joint distribution of filter bank responses**. Pattern recognition letters, Vol. 30, No. 4, pp.368-376 2009.
23. L. Baunegaard, P.Karl, J.Jeppe, **A Two-level real-time vision ma- chine combining coarse- and fine-grained parallelism**. Journal of real-time image processing, Vol. 5, No. 4, pp. 291-304, 2010.
24. K. Shimonomura, T. kushima, T. Yagi, **Binocular robot vision emulating disparity computation in the primary visual cortex**, Neural networks, Vol. 21, No. 2-3, pp. 291-304, 2008.
25. A. Fisher, A. Ronald ,**The statistical utilization of multiple measurement**. Annals of eugenics, Vol. 8, No. 4, pp. 376-386, 1938.
26. K. Fukunaga. **Introduction to statistical pattern recognitiion**. Academic press, Elsevier, 1972.
27. D. Swets, J. Weng ,**Using discriminant eigenfeatures for image retrieval.** Ieee transactions on pattern analysis and machine intelligence, Vol.18, No. 8, pp. 831-836, 1996. https://doi.org/10.1109/34.531802
28. **V.** Vladimir. **The nature of statistical learning theory**. Springer science & business media, 2013.
29. L. Yongmin,G. Shaogang , L. ,**Recognising trajectories of facial identities using kernel discriminant analysis**. Image and Vision Computing,Vol.21 ,No. 13-14, pp. 1077-1086, 2003.
30. Harvard medical school, web: data available at http://med.harvard.edu/aanlib. Accessed May, 2018.
31. Elbedwehy, M. Nagy, M Elsayed ghoneim, H. Aboul Ella, and A taher. "**A computational knowledge representation model for cognitive computers**, Vol. 25, No. 7-8, pp. 1517-1534, 2014. https://doi.org/10.1007/s00521-014-1614-0