

CBIR Using Multi-Resolution Transform for Brain Tumour Detection and Stages Identification

H. Benjamin Fredrick David, R. Balasubramanian, A. Anbarasa Pandian

Abstract—Image retrieval is the most interesting technique which is being used today in our digital world. CBIR, commonly expanded as Content Based Image Retrieval is an image processing technique which identifies the relevant images and retrieves them based on the patterns that are extracted from the digital images. In this paper, two research works have been presented using CBIR. The first work provides an automated and interactive approach to the analysis of CBIR techniques. CBIR works on the principle of supervised machine learning which involves feature selection followed by training and testing phase applied on a classifier in order to perform prediction. By using feature extraction, the image transforms such as Contourlet, Ridgelet and Shearlet could be utilized to retrieve the texture features from the images. The features extracted are used to train and build a classifier using the classification algorithms such as Naïve Bayes, K-Nearest Neighbour and Multi-class Support Vector Machine. Further the testing phase involves prediction which predicts the new input image using the trained classifier and label them from one of the four classes namely 1- Normal brain, 2- Benign tumour, 3- Malignant tumour and 4- Severe tumour. The second research work includes developing a tool which is used for tumour stage identification using the best feature extraction and classifier identified from the first work. Finally, the tool will be used to predict tumour stage and provide suggestions based on the stage of tumour identified by the system. This paper presents these two approaches which is a contribution to the medical field for giving better retrieval performance and for tumour stages identification.

Keywords—Brain tumour detection, content based image retrieval, classification of tumours, image retrieval.

I. INTRODUCTION

AN image retrieval system is normally a computer system which is used for searching and retrieving images from a large database of digital images. Traditionally, the image retrieval techniques utilized some methods of adding metadata to the images such as captioning, keywords, or descriptions to categorize images so that retrieval can be performed based on the quality of the words used in the description [27]. Human tracking, number plate detection, human face recognition of criminal, crime prevention and traffic control are some of the fields in which there is a huge growing demand for image

retrieval. This has made the application developers to rely upon the image retrieval techniques to search and retrieve images more efficiently. There are many such systems which identify the contents of the images and such types of systems are in great demand currently [27]. CBIR technique is one among them. The CBIR systems can retrieve the similar images which are almost accurate to the original images [29]. These systems function mainly based on the concept which is purely rely upon the content of images itself rather than the metadata stored along with the image.

CBIR expanded as Content Based Image Retrieval is a procedure for retrieving the desired relevant image of our choice from a large collection of images [25]. These images are extracted on the basis of the features that are present in those images [26]. The features can be anything from colour, texture to shape feature which are used to distinguish between the other [27]. Each of these features are extracted and stored as vectors for processing in the computer system [28]. Further this system utilizes these feature vectors to particularly identify the relevant images that are relevant to the input.

CBIR is desirable because searches are made based on the metadata which are dependent on annotation quality and completeness. There might be some amount of errors present in the annotation of those images [24]. Annotation is nothing but adding metadata to the digital content. When humans manually annotate these images, entering keywords for a large database can be time consuming and will not be efficient for them to name them correctly [24]. This paper will present the CBIR system in which we have performed an analysis of the CBIR techniques using the three image transforms for feature extraction, Contourlet, Ridgelet and Shearlet Transforms, and also performed classification of the images by using the classification methods such as Naïve Bayes, k-Nearest Neighbour (k-NN) and Multi Class Support Vector Machine (Multi-SVM). This paper provides a solution to this problem using a comparative approach for retrieving the similar images related to the input brain image. Later, the stage of the brain tumour is also identified using the system developed.

II. RELATED WORK

Anitha and Murugavalli [1] have explained the texture retrieval and classification by segmenting the tumour from the skull image and finally extracting features which are then classified by two tier classifiers.

Pandian and Balasubramanian, [2] did a comparative study based on a model consisting of texture feature and it was used to detect the MRI brain tumour images. There are two parts, namely; feature extraction process and classification for the

H. Benjamin Fredrick David is a Ph.D. scholar in Department of Computer Science & Engineering, Manonmaniam Sundaranar University, Tirunelveli (phone: +91-9952806093; e-mail: benjamindavid03@gmail.com).

Dr. R. Balasubramanian is currently working as a Professor and Head of the department in the Department of Computer Science & Engineering, Manonmaniam Sundaranar University, Tirunelveli. (phone: +91-9443695573; e-mail: rbalus662002@yahoo.com)

A. Anbarasa Pandian A. is a research scholar in Department of Computer Science & Engineering, Manonmaniam Sundaranar University, Tirunelveli (phone: +91-9566543053; e-mail: anbuacc@gmail.com).

entire process.

Dong et al. [3] proposed a method for texture retrieval method which is based on the working of two successive retrieval processes. The first process is implemented using their own proposed statistical texture retrieval method which is based in Contourlet domains. The second process is basically formed using a pseudo-feedback mechanism which is based on the linear regression modelling of Shearlet sub band dependencies.

Mejia [4] explained the problem of denizing reconstructed Positron Emission Tomography (PET) images of small animals with the image transform such as Contourlet, Shearlet, Curvelet and Wavelet which is based on multi resolution approaches.

El-Dahshan et al. [5] proposed a technique for image segmentation based on the feedback pulse coupled neural network. Using the discrete wavelet transform for feature extraction and feed forward back-propagation neural network (NN) for classification, the input images are classified into normal and abnormal.

Sharma and Meghrajani [6] proposed an approach based on mathematical and morphological reconstruction for the brain tumour images being extracted from labelled brain magnetic resonance imaging (MRI) images which are affected by impulse noise.

Badran et al. [7] proposed an algorithm for computer-based method which can be used for defining any tumour region inside the brain using MRI images. A classification of brain into healthy brain or a brain having a tumour classified into benign or malignant or severe based on the MRI image.

Mosleh et al. [8] used the properties of contourlet coefficients to assign the normal distribution function to the distribution of coefficients in each sub-band. The assigned normal distribution functions are used to extract the texture feature vector at the next stage

Wu et al. [9] presented top 10 data mining algorithms identified by IEEE International conference on Data Mining. It represents the discussions on C4.5, k-Means, SVM, Apriori, EM, PageRank, AdaBoost, k NN, Naive Bayes, and CART.

Hiremath and Pujari [10] presented a paper which describes a novel framework for combining all the three i.e. colour, texture and shape information, and achieve higher retrieval efficiency.

Dubeet al. [11] proposed a methodology for CBIR of glioblastoma multiforme (GBM) and non-GBM tumours. Further, The MRI images were manually segmented for regions containing GBM lesions from 40 patients and non-GBM lesions from 20 patients.

Easley et al. [12] developed Shearlet Transform which is a new discrete multiscale directional representation. Their work combines the power of multiscale methods to capture geometry of multidimensional data and the images containing edges are represented in an optimally efficient manner.

Lu and Do [13] proposed a new contourlet construction as a solution for the problems occurred in original contourlet transform. Instead of using the Laplacian pyramid, they employed a new multiscale decomposition defined in the

frequency domain. The images produced are sharply localized in the frequency domain and while representing in spatial domain the main ridges in the image exhibit smoothness in them.

Datta et al. [14] discussed some of the key contributions in the current decade related to image retrieval and automated image annotation. They have also discussed on the challenges regarding the adaptation of existing image retrieval techniques to construct a system which can handle real-world data or open data.

Doand Vetterli [15] developed the contourlet transform for detecting contours using the Laplacian pyramid and extracting features using the directional filter bank.

Müller et al. [16] have written an article which describes the overview of available literature in the field of content-based retrieval using various types of medical images and it complements various technologies that are used in the field.

Lehmann et al. [17] developed a more suitable general structure for semantic image analysis which is efficient for CBIR systems in medical applications.

Long et al. [18] briefly addressed the various similarity measures also known as distance measures. The indexing schemes, query formation techniques and the performance evaluation of the system are also addressed by them.

Kato [19] described visual interaction mechanisms for image database systems. Query by visual example and query by subjective descriptions are two typical mechanisms for visual interactions. Naïve Bayes Classifier is designed for the case when each predictor is independent of one another within each class. But, the opposite also appears to be true in some cases. The classification is purely based on the probabilities which are mostly easy to implement and learn.

Multi-SVM Classifier [20] includes a classification model which is based on the given training set with a corresponding group vector and the test set is classified using the built classifier using a one vs. all relation for multiple classes.

III. METHODOLOGY

The CBIR system proposed for brain tumour image retrieval and stages identification retrieves similar brain tumour images of same stages. It also helps in identifying the stage of the tumour image. This paper produces a comparative analysis based on the architecture of our work given in Fig. 1. As this work is related to medical image processing, there may be noise removal processes which are to be included in the pre-processing step because of the demand in quality required when used in a medical imaging system. The noises which may be present in the images are to be considered and necessary measures are to be taken for removing the noise in the brain tumour images. In this work, such type of noises is removed by using Median filter applied on the dataset which will remove some of the noises that are present in the image before using for classification.

Our image retrieval system consists of three main components. When considering medical images, the quality of the image should be as high as possible without any loss of information or without any errors in image. Hence, the initial

step in the retrieval system is the pre-processing step in which the input images are resized and the redundant noise is removed from the images. The pre-processed images are further transformed into the frequency domain for extracting the texture features from the image as feature vectors. These feature vectors are defined in the form of a one-dimensional array which consists of the features retrieved by the feature extraction techniques. All the feature extraction techniques are given in the following sections. The extracted features are further stored in the form of feature vectors having the class names assigned and concealed as feature values. This is an iterative process until all the features are extracted and the classifier is trained using the three classification techniques. It

is essential for a classifier to be trained with all those features in order to make the classifier predict the unknown feature vectors from the input image. The classification work is performed for finding out the target class label which the input image belongs to. The retrieval part is the final part of our image retrieval system which retrieves the similar brain tumour images and the relevant images are displayed at the end. An additional work has been incorporated using the best performing classifier to predict the stage of the new input brain tumour patient image using supervised machine learning. This is done in order to give treatment suggestion to doctors based upon the tumour stage identified by the system. The individual steps and their processes are explained below.

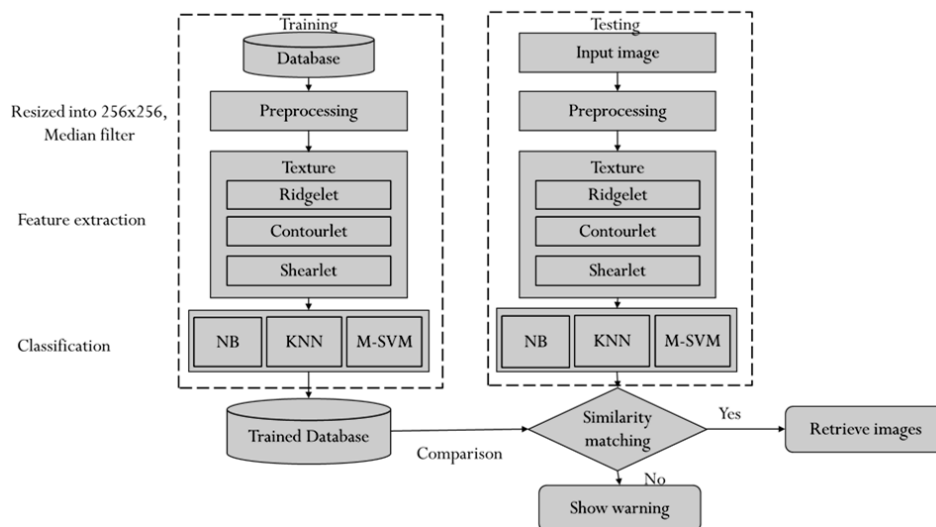


Fig. 1 Architecture of the CBIR system

A. Pre-Processing

As the images used in our system are medical images, noise removal process needs to be performed on the image in order to get clear images for the system to correctly identify the brain tumour stage from the brain tumour database. Hence the pre-processing operations are included in both training and testing in this research work. Further the image is resized to a uniform 256x256 size image. To remove the noise present in the image a median filter is also applied to the images.

B. Feature extraction

The pre-processed image is further processed through a feature extraction procedure which extracts the features that are present in the images. Feature extraction is one of the most important procedures which are used for the interpretation and indexing of images in CBIR systems. Feature extraction is performed with the image transforms in the frequency domain. Those transforms are Contourlet Transform, Ridgelet Transform and Shearlet Transform. A data structure is created for storing the features extracted by using the image transforms. The data structure for describing the feature vectors is given in Table I. Here, F_i denotes the features from the images and the X denote the class name.

TABLE I
THE 1-D STRUCTURE FOR DESCRIBING FEATURE VECTORS

The 1-D feature array	Class name
$F_0, F_1, F_2, F_3, \dots, F_n$	X

1. Ridgelet Transform

The Ridgelet feature extraction technique is best used for detecting the line discontinuities. As in terms of Wavelet, it is best used for detecting point singularities. But, in Ridgelet, the ridges around the objects are extracted as coefficients which form the energies in image for texture representation in the image. The algorithm for the Ridgelet transform [21] is given by:

1. Let i be the input image
2. The image i is transformed to Fourier Transform \mathcal{E}
3. \mathcal{E} is then converted to Radon Transform φ
4. Finally, φ is converted to 1-D Ridgelet domain ψ by using wavelet transform.

The ψ consists of features of the image in 1-D array.

2. Contourlet Transform

The Contourlet feature extraction technique is best used for detecting the contour areas around the objects and the curves.

The Low-Low information is extracted at each level and further decomposed. To be precise, the Contourlet Transform [15] captures smooth contours and edges at any orientation. It filters the noise in the texture. The Laplacian pyramid is performed in the sub bands of the images at each level and the output is sent to the directional filter banks. The implementation of Contourlet transform is comprised upon the directional filter bank. The main advantage of using this approach is that it allows the implementation with a tree-structured filter bank. A drawback of using this approach is that the occurrence of various artefacts. The Contourlet algorithm is given as follows:

1. Let $a_i[n]$ is the input image.
2. The sub-bands are extracted
3. The output after the Low Pass Stage is J band pass images $b_i[n]$, $i=1, 2, \dots, J$ (in fine to coarse manner)
4. That means the i^{th} level of the Low Pass decomposes the image $a_{i-1}[n]$ into a coarser image $a_i[n]$ and a detail image $b_i[n]$.
5. Each band pass image $b_i[n]$ is further decomposed by and l_j - level DFB into $2l_j$ band pass directional images.

$$C_{j,k}^{t_j}[n], k = 0, 1, 2 \dots 2^{t_j-1}$$

6. The directional filter bank produces the Contourlet coefficients.

3. Shearlet Transform

The Shearlet transform [12] is used for extracting the anisotropy texture features. Shearlets are frame elements which yield (nearly) optimally sparse representations. This is the latest feature extraction technique in which the representation is based on a simple yet rigorous mathematical framework which not only provides a more flexible theoretical tool for the geometric representation of multidimensional data, but is also more natural for implementations. As a result, the Shearlet approach can be associated to a multi-resolution analysis. [12] The Shearlets are well localized. They exhibit parabolic scaling and high directional sensitivity. The Shearlets are optimally sparse. The Shearlet transform extracts the anisotropy texture feature. The input image is split up into multiple sub bands and the Laplacian pyramid is applied to decompose. Then a pseudo polar grid in the angular direction is obtained. This results in the coefficients for the Shearlet features. The algorithm for Shearlet [23] is as follows.

1. Define f_0 to be the given $N \times N$ image and set $N_0 = N$. For $j = 1, 2, 3, \dots, J$ do the following:
2. Apply the Laplacian pyramid scheme to decompose f_0^{j-1} into a low-pass $\frac{N_{j-1} * N_{j-1}}{4}$ image f_0^j and a high-pass $N_{j-1} * N_{j-1}$ image f_d^j
3. Compute $\widehat{f_d^j}$ on a pseudo-polar grid and apply filtering $\widehat{\psi_2(\xi)}$ along the angular direction to obtain $\widehat{f_d^j}$.
4. Invert to obtain $\widehat{f_d^j}$

This algorithm runs in $O(N^2 \log N)$ operations.

C. Classification Methods

1. Naïve Bayes Classifier

Naive Bayes [22] is based on Bayes rule and it assumes that attributes are independent of each other. The working principle of naïve Bayes classifier is as follows:

1. Training step: By assuming predictors to be conditionally independent given for a class, the method estimates the parameters of a probability distribution known as the prior probability from the training data.
2. Prediction step: For unknown test data, the method computes the posterior probability of the dataset which is belonging to each class. The method finally classifies the test data based upon the largest posterior probability from the set

2. KNN Classifier

KNN classifier [19] is a lazy learner algorithm, which holds the entire training data in memory and then performs classification of the test data based on the training data. The Working principle of KNN classifier is given below:

1. Extract Training features of the training data set and train the classifier.
2. Extract Testing features of the testing data set.
3. Find the distance of each test sample with k -nearest training samples.
4. The distance is calculated between k elements by default using the Euclidean distance function given below which describes the distance between two points x_a and y_a . The function is given in (1):

$$d(x, y) = \sqrt{\sum_{a=1}^m (x_a - y_a)^2} \quad (1)$$

5. Assign the class label for the test sample based upon the class labels of majority of k -NN.

3. Multi-SVM Classifier

Multi-SVM classifier [20] is a combination of SVM classifier and decision tree. SVM is non-probabilistic binary linear classifier considered to be the most robust and accurate. It has an excellent theoretical foundation for its application and requires only a few samples for training, and is insensitive to the number of dimensions. SVM constructs hyper planes in multidimensional space which is used to classify dataset. The Multi-SVM is a combination of SVM classifier and a decision tree approach. The SVM classifier is classified with one vs. all classes or each class with the SVM algorithm. The SVM classifier can only classify two classes. For classifying multiple classes, we are using the multi class classifier which can classify the items into many classes. The working principle of Multi-SVM classifier is as follows:

1. Project the training data set in feature space.
2. Project the testing data set in the same features space.
3. Find a hyper plane such that it should maximize the

distance between the closest data point.

4. Separate the items and perform the same above operations for all classes till all the items are classified into separate classes.

D. Stage Identification

The stage identification process is given in Fig. 2. It takes place as an integrated module in our work and is implemented by the best feature extraction technique and the best classifier. The algorithm for the stage identification is similar to the CBIR technique. It is given below.

1. The image to be tested or to identify the tumour is given as an input.
2. The feature extraction is made with the Shearlet transform

and the feature vectors are compared with those in the Pre-processed tumour database.

3. The feature vector is classified with Multi-SVM [20] by comparing it with the dataset.
4. The input image is labelled with the class which determines the tumour stage.
5. The stage is displayed by the class which the brain tumour image belongs to.

The system is further made to provide suggestions or opinions to the doctors or the concerned persons about the treatment steps to be further taken from the relevant brain tumour.

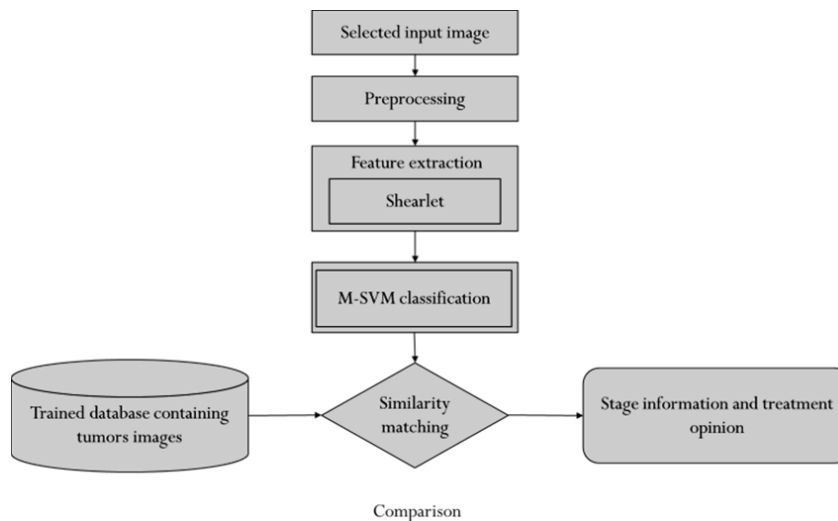


Fig. 2 Architecture for the stage identification

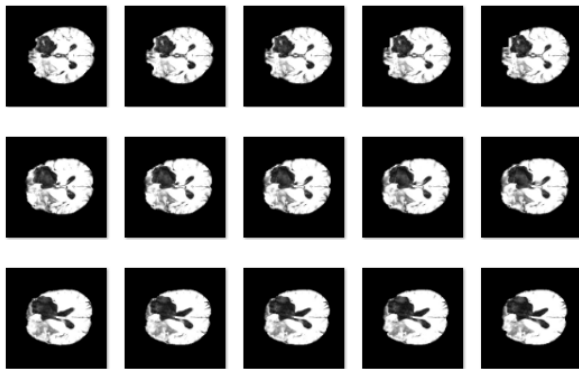


Fig. 3 Sample MRI Brain tumour images

IV. EXPERIMENTAL RESULTS

A. Dataset

The dataset for the comparison work is taken from the Brats2015 database which consists of brain tumour images of various stages. Totally there are 200 many images taken and 50 of them are normal, 50 are benign, 50 are malignant and 50 are of severe stages. The classifier is trained by giving the

labelled image features. The normal brain tumour images of patients are labelled as 1. The benign brain tumour images are labelled as 2. The malignant brain tumour images are labelled as 3. The severely affected brain tumour images of patients are labelled as 4. Some of the sample MRI brain tumour images of patients are given in Fig. 3.

B. Performance Metrics

Performance of the algorithms is evaluated by comparing different techniques of this research work. The metrics are commonly used to measure the quality of the retrieval process.

The expansions for FP, TP, FN and TN are false positive, true positive, false negative and true negative. [24] True Positives are cases in which we predicted yes and they do are true. True Negatives are cases in which we predicted no and they do are true. False Positives are cases in which we predicted yes and they do are false. True Positives are cases in which we predicted no and they do are false.

These are used in a confusion matrix which is normally a table which holds the values of true- positives, false-positives, true-negatives and to false-negatives which can be used to represent the set of test data for describing the performance of a classification mode or classifier. The process of classifying

the elements into two distinct groups on the basis of classification rule given by the person is known as Binary classification. A sample confusion matrix for binomial classification is given in Fig. 4.

n=165	Predicted:	
	NO	YES
Actual: NO	50	10
Actual: YES	5	100

Fig. 4 Confusion matrix for binomial classification

This work mainly classifies the brain tumour into four classes and known as multi class classification. In this work classifiers are compared using following metrics:

1. Sensitivity

Sensitivity of the images retrieved can be retrieved using the mathematical formula in (2):

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

2. Specificity

The specificity of the images retrieved using the CBIR in this work is mathematically given in (3):

$$\text{Specificity} = \frac{TN}{FP+TN} \quad (3)$$

3. Accuracy

Accuracy is the measure of how accurate the results are given which includes the relevant images in the CBIR. The accuracy is not alone given by any unique calculation. It gives the sum of true positive and true negative divided by the sum of all other odds. It is given in (4):

$$\text{Accuracy} = \frac{TP+TN}{(TP+FP+TN+FN)} \quad (4)$$

4 .Error rate

Error Rate is the number of percentage the error results are occurring.

$$\text{Errorrate} = 100 - \text{Accuracy} \quad (5)$$

5. Jacquard Coefficient

The Jacquard coefficient can be calculated by using:

$$\text{Jacquard Coeffieicnt} = \frac{TP}{TP+FP+FN} \quad (6)$$

6. F-measure

The F-measure can be calculated by using:

$$F - \text{measure} = \frac{2TP}{(2TP + FP + FN)} \quad (7)$$

C. Performance Evaluation

As shown in Table II, the Multi-SVM and Naïve Bayes classifiers results better results. The specificity of the Naïve Bayes is higher for Ridgelet transform. Likewise, when the sensitivity increases, the Accuracy rate also increases and resulting in the Multi-SVM classifier outperforming with 90.76% accuracy for Ridgelet transform. The Multi-SVM classifier gives higher values for the accuracy, error rate, jacquard coefficients and f-measure score for Ridgelet transform.

TABLE II
PERFORMANCE EVALUATION OF SHEARLET

Metrics	Naïve Bayes	k-NN	Multi-SVM
Sensitivity (%)	75	78.5	93.7
Specificity (%)	91.66	91.33	97.28
Accuracy (%)	87.5	89.9	97.2
Error rate (%)	12.5	10.2	2.8
Jacquard Coefficient	0.6276	0.6017	0.8136
F-measure	0.7409	0.7314	0.8721

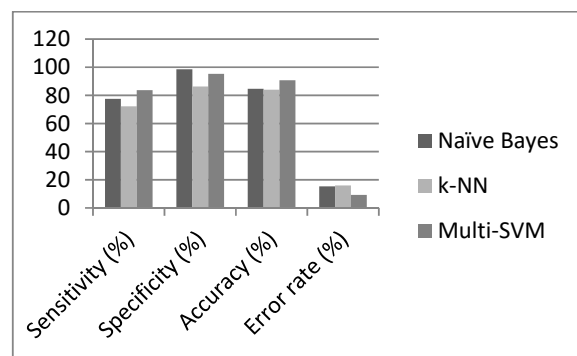


Fig. 5 Performance evaluation of Ridgelet

From Fig. 5, we can understand that the specificity of the Naïve Bayes is higher for Ridgelet transform whereas the other metrics are low. The Accuracy and Error rate of the Multi-SVM is better for Ridgelet transform.

TABLE III
PERFORMANCE EVALUATION OF RIDGELET

Metrics	Naïve Bayes	k-NN	Multi-SVM
Sensitivity (%)	77.5	72.16	83.64
Specificity (%)	98.55	86.24	95.27
Accuracy (%)	84.68	84	90.76
Error rate (%)	15.28	16	9.24
Jacquard Coefficient	0.6178	0.6327	0.7244
F-measure	0.7418	0.6947	0.8364

As shown in Table III, the Multi-SVM and Naïve Bayes classifiers perform better. The sensitivity, specificity and accuracy of the Multi-SVM are much higher for Contourlet transform when compared to the others. The Jacquard Coefficient and F-measure for Naïve Bayes are higher than the

Multi-SVM and K-NN classifier's values which are a contrast result when compared with the same classifiers for Ridgelet transform.

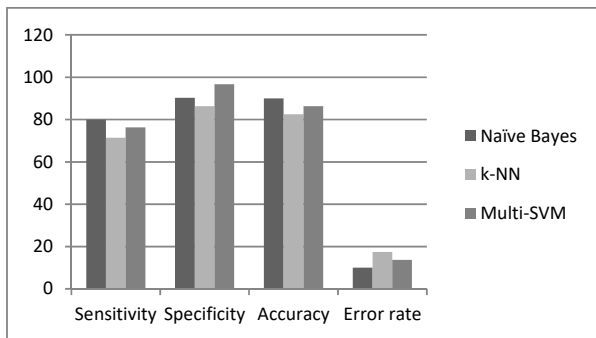


Fig. 6 Performance evaluation of Contourlet

As shown in Fig. 6, the Sensitivity, Specificity, Accuracy and Error rate are compared for Contourlet transform. As shown in Table IV, the Multi-SVM classifier gives better results when used with Shearlet Transform. The sensitivity, specificity and accuracy of the Multi class SVM are much higher than others. The Error rate produced by the Multi-SVM classifier is also very much low and only 2.8%.

TABLE IV
PERFORMANCE EVALUATION OF CONTOURLET

Metrics	Naïve Bayes	k-NN	Multi-SVM
Sensitivity (%)	80	71.42	76.32
Specificity (%)	90.33	86.32	96.71
Accuracy (%)	90	82.57	86.3
Error rate (%)	10	17.43	13.7
Jacquard Coefficient	0.6856	0.5283	0.6037
F-measure	0.7958	0.6951	0.7518

Fig. 7 gives the performance evaluation of Shearlet. The Multi-SVM is best when used with Shearlet Transform. The Multi-SVM classifier gives better F-measure and Jacquard Coefficient score for the Shearlet transform

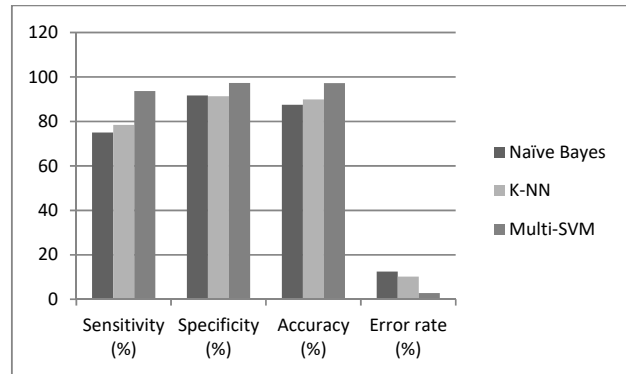


Fig. 7 Performance evaluation of Shearlet

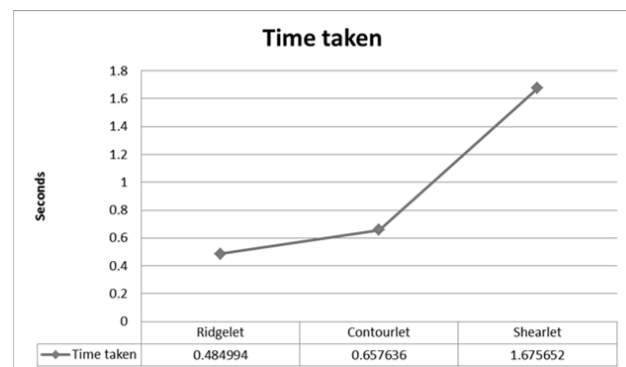


Fig. 8 Time analysis of feature extraction algorithms

The Shearlet extracts more features and thus outperforms the other two classifiers because of its ability to handle and extract more features from the images than the Ridgelet and Contourlet. But, as shown in Table V and Fig. 8, Shearlet takes more time to extract the coefficients than the others. Thus, for higher accuracy, some amount of consideration has to be made in time for accurate results.

V.SCREENSHOTS

Figs. 9-13 show screenshots of the work done in MATLAB.

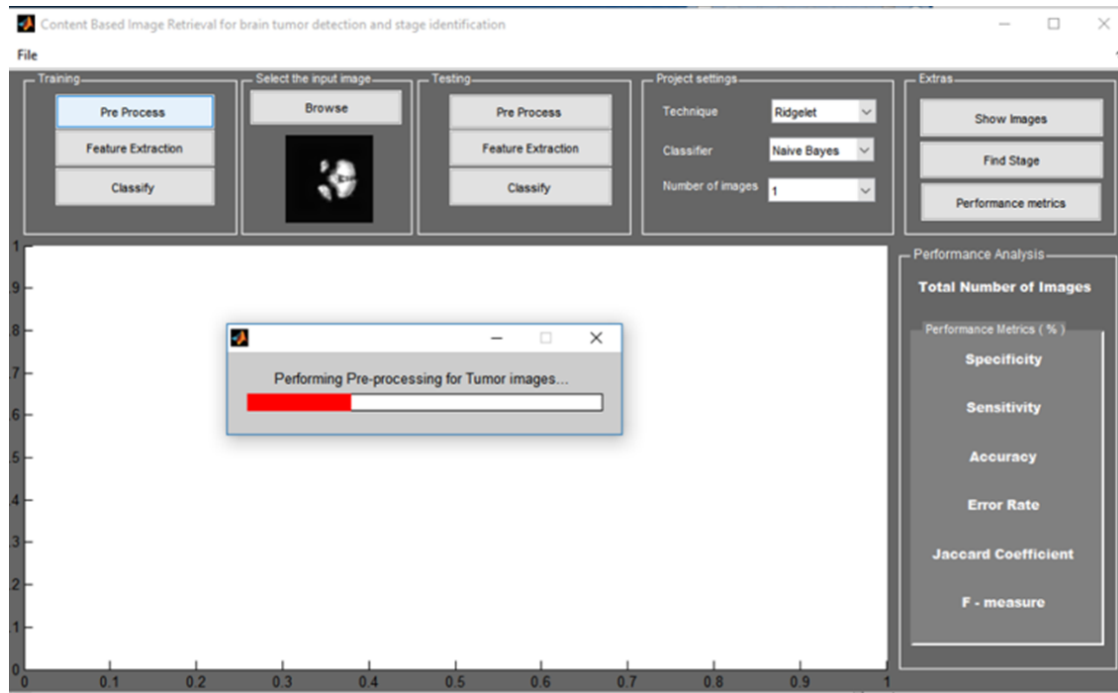


Fig. 9 Loading into our system

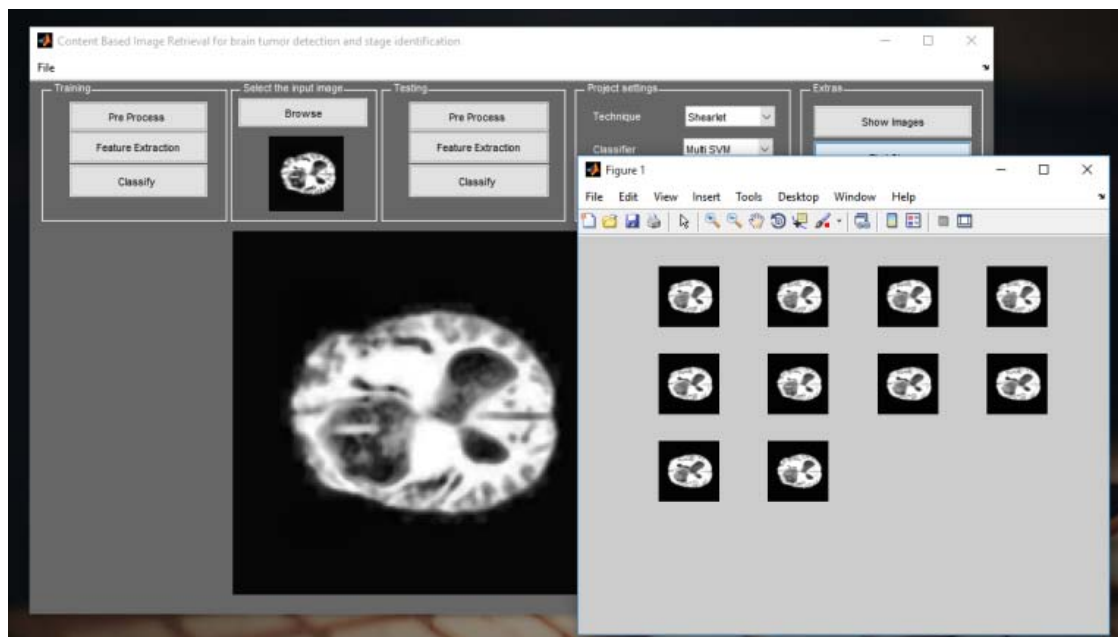


Fig. 10 Retrieval of Brain tumour images

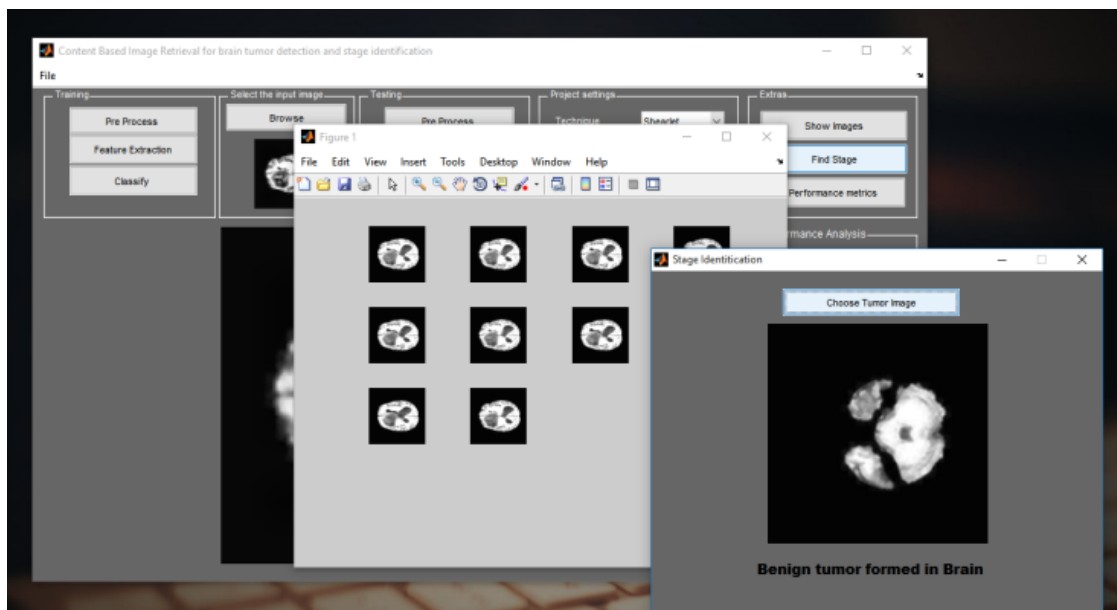


Fig. 11 Tumour stage identification

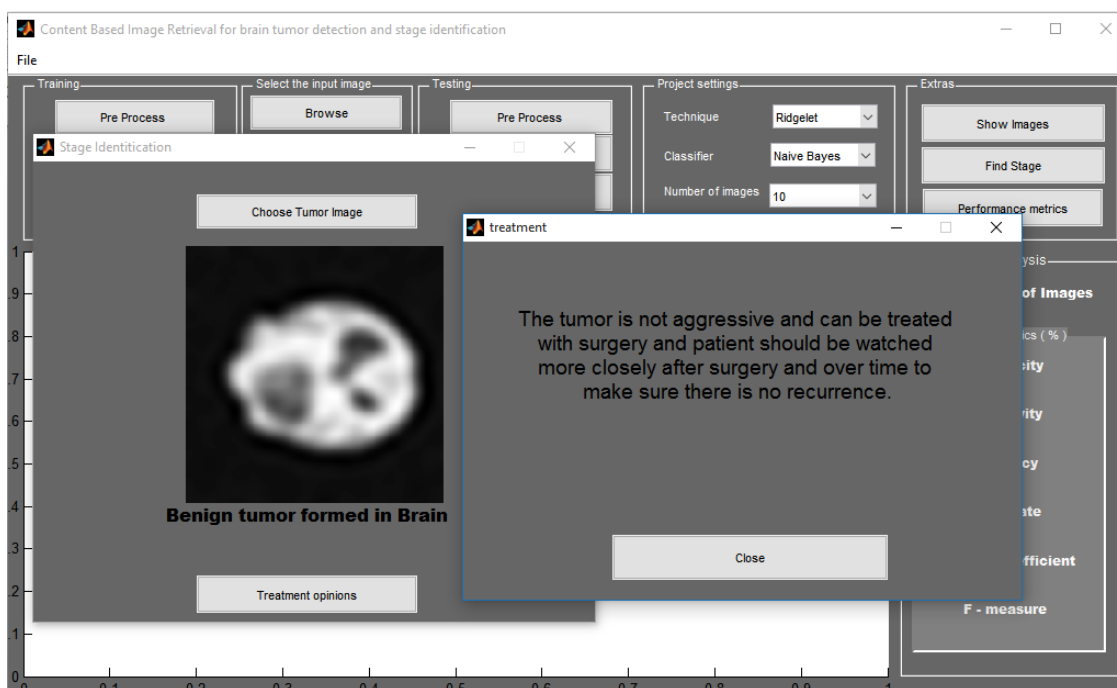


Fig. 12 Treatment opinion for the tumour identified

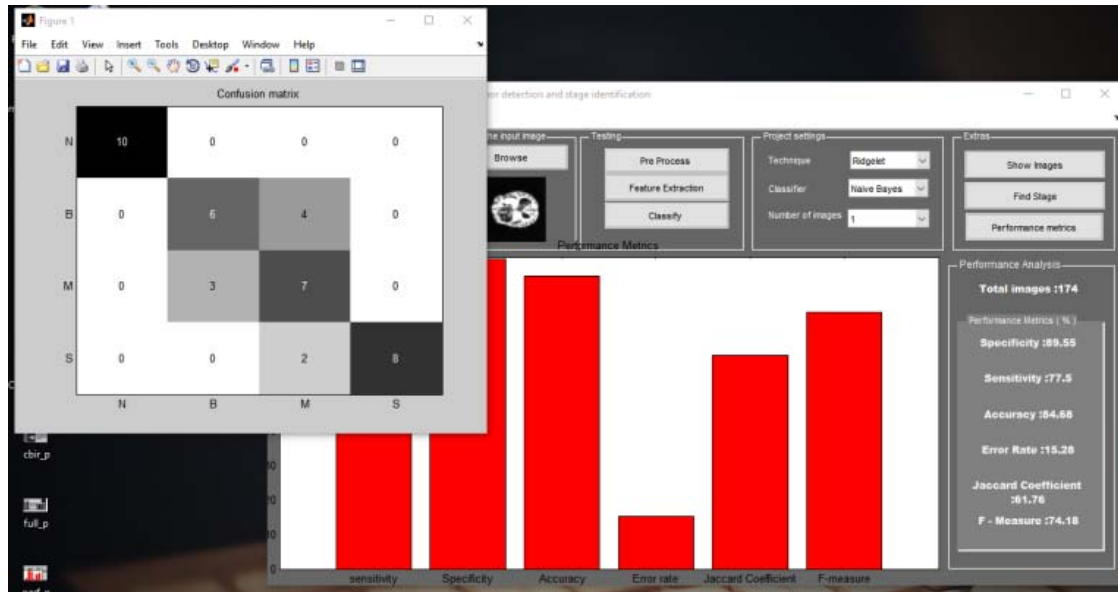


Fig. 13 Confusion matrix and Performance analysis

TABLE V
TIME ANALYSIS OF FEATURE EXTRACTION ALGORITHMS

	Ridgelet	Contourlet	Shearlet
Time taken (secs)	0.484994	0.657636	1.675652

VI. CONCLUSION

This paper produces a CBIR architecture consisting of the procedures which are required to be followed while determining the brain tumour stages and prediction of the tumour stage. Texture is a vital visual attribute which determines both the human perception and image analysis systems. This research provides a comparative approach to identify the best feature extraction technique as Shearlet transform and the best classification algorithm as Multi-SVM based on the results which provided maximum accuracy. Although the Shearlet Transform took more time for computation, it performs best when combined with Multi-SVM in CBIR. Based on the experiments conducted, Ridgelet is the fastest and the Shearlet is the slowest for feature extraction. But, shearlet provided more desirable features. An application based on the best combination is constructed for performing tumour stage identification and which is used to give medical suggestions to doctors. The future enhancement for this work can be training upon a larger dataset of brain tumour images. The extracted features can be based on both the shape and texture feature fused together in the future. The research can be further preceded such that the overall cost can be reduced by improving the efficiency of the algorithm.

REFERENCES

- [1] Anitha, V., and S. Murugavalli. "Brain tumour classification using two-tier classifier with adaptive segmentation technique." *IET Computer Vision* 10.1 (2016): 9-17.
- [2] A. Anbarasa Pandian and R. Balasubramanian, Performance Analysis of Texture Image Retrieval for Curvelet, Contourlet Transform and Local Ternary Pattern Using MRI Brain Tumour Image, *International Journal in Foundations of Computer Science & Technology (IJFCT)* Vol.5, No.6, November 2015.
- [3] Dong, Yongsheng, et al. "Texture classification and retrieval using Shearlets and linear regression." *IEEE transactions on cybernetics* 45.3 (2015): 358-369.
- [4] Mejia, Jose M., et al. "Noise reduction in small-animal PET images using a multiresolution transform." *IEEE transactions on medical imaging* 33.10 (2014): 2010-2019.
- [5] El-Dahshan, El-Sayed A., et al. "Computer-aided diagnosis of human brain tumour through MRI: A survey and a new algorithm." *Expert systems with Applications* 41.11 (2014): 5526-5545.
- [6] Sharma, Yamini, and Yogesh K. Meghrajani. "Brain tumour extraction from MRI image using mathematical morphological reconstruction." *Emerging Technology Trends in Electronics, Communication and Networking (ET2ECN)*, 2014 2nd International Conference on. IEEE, 2014.
- [7] Badran, Ehab F., Esraa Galal Mahmoud, and Nadder Hamdy. "An algorithm for detecting brain tumours in MRI images." *Computer Engineering and Systems (ICCES)*, 2010 International Conference on. IEEE, 2010.
- [8] Mosleh, Ali, Farzad Zargari, and Reza Azizi. "Texture image retrieval using contourlet transform." *Signals, Circuits and Systems*, 2009. ISSCS 2009. International Symposium on. IEEE, 2009.
- [9] Xindong Wu, Vipin Kumar, J. Ross Quinlan, Joydeep Ghosh, Qiang Yang, Hiroshi Motoda, Geoffrey J. McLachlan et al. "Top 10 algorithms in data mining", *Knowledge and Information Systems*, Vol. 14, No. 1, pp. 137, 2008.
- [10] Hiremath, P. S., and Jagadeesh Pujari. "Content based image retrieval using colour, texture and shape features." *Advanced Computing and Communications*, 2007. ADCOM 2007. International Conference on. IEEE, 2007.
- [11] Dube, Shishir, et al. "Content based image retrieval for MR image studies of brain tumours." *Engineering in Medicine and Biology Society*, 2006. EMBS'06. 28th Annual International Conference of the IEEE. IEEE, 2006.
- [12] G. R. Easley, D. Labate, L. Wang-Q, optimally sparse image representations using Shearlets, *Conference on Signals, Systems and Computers* 2006, pp. 974-978, 2006.
- [13] Lu, Yue, and Minh N. Do. "A new contourlet transform with sharp frequency localization." 2006 International Conference on Image Processing. IEEE, 2006.
- [14] Datta, Ritendra, Jia Li, and James Z. Wang. "Content-based image retrieval: approaches and trends of the new age." *Proceedings of the 7th ACM SIGMM international workshop on Multimedia information retrieval*. ACM, 2005.
- [15] Do, Minh N., and Martin Vetterli. "The contourlet transform: an

- efficient directional multiresolution image representation." IEEE Transactions on image processing 14.12 (2005): 2091-2106.
- [16] Müller, Henning, et al. "A review of content-based image retrieval systems in medical applications—clinical benefits and future directions." International journal of medical informatics 73.1 (2004): 1-23.
 - [17] Lehmann, Thomas M., et al. "Content-based image retrieval in medical applications." Methods of information in medicine 43.4 (2004): 354-361.
 - [18] Long, Fuhui, Hongjiang Zhang, and David Dagan Feng. "Fundamentals of content-based image retrieval." Multimedia Information Retrieval and Management. Springer Berlin Heidelberg, 2003. 1-26.
 - [19] Kato, Toshikazu. "Database architecture for content-based image retrieval." SPIE/IS&T 1992 symposium on electronic imaging: science and technology. International Society for Optics and Photonics, 1992.
 - [20] <http://www.mathworks.com/matlabcentral/fileexchange/33170-multi-class-support-vector-machine>
 - [21] Do, Minh N., and Martin Vetterli. "The finite ridgelet transform for image representation." IEEE Transactions on image Processing 12.1 (2003): 16-28.
 - [22] Leung, K. Ming. "Naive Bayesian classifier." Polytechnic University Department of Computer Science/Finance and Risk Engineering (2007).
 - [23] Jiuwen Zhang and Yaohua Chong. "Text localization based on the Discrete Shearlet Transform", 2013 IEEE 4th International Conference on Software Engineering and Service Science, 2013
 - [24] Kakade, Vikram M., and Ishwar A. Keche. "Review on Content Based Image Retrieval (CBIR) Technique."
 - [25] Kaur, Ramandeep, and Ashok Kumar Bathla. "Enhanced Content-Based Image Retrieval Using Cuckoo Search Algorithm." International Journal of Advanced Research in Computer science and Software Engineering (IJARCSSE), volume 4: 233-241.
 - [26] Harvey, R. J. "The extraction of features and disparities from images by a model based on the neurological organisation of the visual system." Vision research 48.11 (2008): 1297-1306.
 - [27] Deshpande, Gauri, and Megha Borse. "Image Retrieval with the use of Color and Texture Feature." International Journal of Computer Science and Information Technologies 2.3 (2011): 1018-1021.
 - [28] Bargavi, B. Saranya, and C. Santhi. "Global and local facial feature extraction using Gabor filters." International Journal of Science, Engineering and Technology Research (IJSETR) 3.4 (2014): 1020-1023.
 - [29] Chaudhari, Reshma, and A. M. Patil. "Content based image retrieval using color and shape features." International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering 1.5 (2012): 67-72.