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Multi-Level Brain Tumor Detection and Classification

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Abstract: The frenzied growth of abnormal cells in the brain, identified as brain tumor has disastrous consequence on human health and often proves fatal. However tumor detected at prompt stage could provide the patient few more years of life through proper treatment and surgical procedures, but the detection at the late stage results in a casualty. In the recent past there has been lot of prominence on medical imaging procedures to uncover human health hazards and thereby providing assistance for the surgeons to diagnose accurately. In this paper a multi-level brain tumor detection and classification system is proposed to detect the tumor from the MRI scanned images and in an event of tumor is detected, it is classified as per its severity. Tetrolet transform based feature extraction and support vector machine based classification have been used to detect the tumor and classify those detected tumors into low-grade (benign) and high-grade (malignant) categories. 10-fold cross validation experiments have been conducted to find the effectiveness of the method. The results of the proposed method have been compared with the results obtained using tetrolet transform and k-nearest neighbor classifier. From the receiver operating characteristics and confusion matrix it is evident that SVM classifier outperformed in comparison with KNN classifier in terms of accuracy. The results demonstrated an accuracy level of 98.8% for detection of tumor and 96.2% for classification of tumors into low-grade and high-grade types for brain MRI images downloaded from repository of molecular brain neoplasia database.

Keywords: Magnetic Resonance Imaging (MRI), Tetrolet Transform (TT), Support Vector Machine (SVM) classifier, K-Nearest Neighbor (KNN) classifier, Repository of Molecular Brain Neoplasia Database (RMBND), Receiver Operating Characteristics (ROC) and confusion matrix.

1. INTRODUCTION

Brain tumor is a type of health hazard that causes serious threat to human life as it refers to uncontrolled growth of abnormal cells. Brain tumor can be benign (non-cancerous or malignant (cancerous). Benign tumors have a distinct border, do not spread and very slow growing in nature and malignant tumors are metastatic in nature as they invade to the surrounding tissues and spread to other parts of the body resulting serious health conditions. The brain tumors are also classified as primary brain tumors and metastatic brain tumors. Primary brain tumors originate in the brain, whereas the metastatic brain tumors originate in different body organs and metastases to the brain. Primary brain tumors are of benign or malignant type, whereas metastatic tumors are always malignant. Because of the metastatic nature the malignant tumors do not have a distinct border and have a bizarre appearance. Presence of even benign tumor in the brain results in serious health related issues as the space in the intracranial cavity very much limited. Normally initiation of tumor in the brain results in symptoms but sometimes brain tumors can be asymptomatic and only shows up when a brain scan is taken for some other health related issues. Primary brain tumors are classified into four grades that reflect the degree of malignancy; grades I and II are considered low-grade slowest-growing and least malignant tumors; whereas grade III and IV tumors are of high-grade that grows at a moderate rate and fastest rate respectively [1].

Several imaging methods are used to screen brain tumor, but Magnetic Resonance Imaging (MRI) is popularly used to detect and classify the brain tumors. MRI is used as a valuable tool in the clinical and surgical environment because of its characteristics like superior soft tissue differentiation, high spatial resolution and contrast, but visual evaluation and examination of MRI images by radiologists is subjective by its nature and is time consuming and prone to errors or omissions [2]. Over the decade several researchers have extensively studied and contributed significantly to this area. A few of those are reviewed here.

A computer aided system for multiclass classification of brain tumors is proposed in [3]. Features are extracted from discrete wavelet transformation (DWT) using Haar wavelets and reduced by Principal Component Analysis. The classification is carried out using SVM classifier for multi class data to classify tumors into different classes based on its' presence in different parts of the brain. A modified image segmentation technique to detect brain tumor from MRI scan images is proposed in [4]. Probabilistic Neural Network (PNN) model based Learning Vector Quantization (LVQ) technique is used to carry out an automated brain tumor classification. Performance analysis is carried out to measure the training performance, classification accuracy and computational time. An automatic brain tumor detection and localization of brain tumor in magnetic resonance imaging is proposed in [5]. The tumor detection and localization system was able to accurately detect and localize brain tumor in magnetic resonance images. Gray Level Co-occurrence Matrix (GLCM) based feature extraction and Support Vector Machine (SVM) based classification is performed in [6]. Fourteen features were extracted from the MRI image and selected by forward selection and backward elimination process for detection and classification of brain tumor. Sensitivity of 91.52%, Specificity of 67.74% and Accuracy of 83.33% are reported. Automated classification of brain tumor grades using Back Propagation Network are proposed in [7]. Features of tumor grades are extracted using Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRM). Selection of optimal features are done using fuzzy entropy measure and classified using the three different (Forward Neural Network, Multilayer Perceptron and Back Propagation Network) classifiers. Back Propagation Network resulted highest classification accuracy of 96.7% for the classification of brain tumors according to their grades.

In this paper, a novel multilevel brain tumor detection and classification system is proposed in single step based on tetrolet transform and SVM classifier. The organization of rest of the paper is as follows. The methods and constituents involved for the detection and classification using the proposed multilevel architecture for brain tumor diagnosis is presented in section 2. Section 3 describes the proposed feature extraction method. The quantitative and qualitative results are presented and discussed in section 4. Conclusion is provided in the last section.

2. METHODS AND CONSTITUENTS

In this section, a detailed study on tetrolet transform and support vector machine classifier is carried out. The details of brain magnetic resonance images dataset that have been used in this work is also provided.

2.1. Tetrolet Transform

Decomposition of a two-dimensional classical Haar wavelet leads to a special tetromino partition [8]. Tetrominoes are shapes formed from a union of four unit squares, each connected by edges, not at their corners [9]. The low-pass filter and the high-pass filters in the Haar filter bank are just taken by averaging the sum and averaging the differences of each four pixel values which are then arranged in a 2×2 square. The tetrolet filter bank algorithm is implemented as below.

The input image is defined by $a^0 = (a[i, j])_{i, j=0}^{N-1}$ with $N = 2^J$, $J \in \mathbb{N}$. Then J − 1 levels of the tetrolet transform is applied. In the r^{th}-level, $r = 1, ..., J - 1$ the following computations are carried out.

1. The low-pass image a^{r-1} is divided into in to blocks $Q_{i,j}$ of size 4×4, where, $i, j = 0, 1, 2, ..., \frac{N}{r^r} - 1$.

2. In each block $Q_{i,j}$, 117 admissible tetromino coverings i.e., $c = 1, ..., 117$ are considered. For each tiling c Haar wavelet transform is applied to the four tetromino subsets $I_s^{(c)}$, $s = 0, 1, 2, 3$. For each tiling c four low-pass coefficients and 12 tetrolet coefficients is obtained. In block $Q_{i,j}$ the pixel averages for every admissible tetromino configuration $c = 1, ..., 117$ is computed by equation (1).

$$a^{r,(c)} = (a^{r,(c)}[z])_{s=0}^{3} \text{ with } a^{r,(c)}[s] = \sum_{(m,n) \in I_s^{(c)}} \in [0, L(m, n)]\, a^{r-1}[m, n] \tag{1}$$

and the three high-pass parts for $l = 1, 2, 3$ is computed by equation (2).

$$w_l^{r,(c)} = (w_l^{r,(c)}[s])_{s=0}^{3} \text{ with } w_l^{r,(c)}[s] = \sum_{(m,n) \in I_s^{(c)}} \in [l, L(m, n)]\, a^{r-1}[m, n] \tag{2}$$

where the coefficients $\in [l, L(m, n)]$ are given in Equation (3) and where L is the bijective mapping relating the four index pairs (m, n) of $I_s^{(c)}$ with the values 0, 1, 2, and 3 in descending order. Using one-dimensional indexing $J(m, n)$ the smallest index is identified with the value 0, while the largest with 3.

$$W(\in[l, L(m, n)])_{l, L(m,n)=0}^{3} = \frac{1}{2}\begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & 1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix} \tag{3}$$

Choosing the covering c^* such that the l^1-norm of the 12 tetrolet coefficients becomes minimal is given by Equation (4).

$$c^* = \arg\min_c \sum_{l=1}^{3} w_l^{r,(c)} = \arg\min_c \sum_{l=1}^{3}\sum_{s=0}^{3} \left| w_l^{r,(c)}[s] \right| \tag{4}$$

For each block $Q_{i,j}$ an optimal tetrolet decomposition $[a^{r,c^*}, w_1^{r,c^*}, w_2^{r,c^*}, w_3^{r,c^*}]$ is obtained using this process.

3. The further levels of the tetrolet decomposition are carried out by rearranging the entries of the vectors $a^{r,(c)}$, and $w_l^{r,(c^*)}$ into 2×2 matrices using a reshape function R given by Equation (5). In similar way equation (6) is computed for $l = 1, 2, 3$.

$$a^r_{|Q_{i,j}} = R(a^{r,(c^*)}) = \begin{pmatrix} a^{r,(c^*)}[0] & a^{r,(c^*)}[2] \\ a^{r,(c^*)}[1] & a^{r,(c^*)}[3] \end{pmatrix} \tag{5}$$

$$w^r_{l|Q_{i,j}} = \mathrm{R}(w_l^{r,(c^*)}) \tag{6}$$

The suitable arrangement of low-pass values are required for representation in the next level. In this work fifth level of decomposition is carried out and for each tetromino sub-bands statistical features like mean, standard deviation, and variance are computed and extracted.

2.2. SVM Based Classification

SVM classifier is the most efficient algorithm, which utilize the concept of kernel substitution and are known as kernel methods. The training set of instance-label pairs are given as (x_i, y_i); $i = 1 \ldots l$ where $x_i \in \mathrm{R}^n$ and $y \in \{1, -1\}^l$, the Support Vector Machines (SVM) [10, 11] require the solution for the optimization problem, i.e., the SVM intends to minimize an error function given in Equation 2.7 with the following constraints given in equation (2.8)

$$\min_{w, b, \xi} \frac{1}{2} \mathcal{W}^{\mathrm{T}} + \mathcal{C} \sum_{i=1}^{l} \xi_i \tag{7}$$

$$y_i(w^{\mathrm{T}} \phi(x_i) + b) \geq 1 - \xi_i \text{ with } \xi_i \geq 0 \tag{8}$$

The training vectors x_i is mapped into a higher dimensional space by the function ϕ and subsequently SVM finds a linear separating hyper-plane with the maximal margin in this higher dimensional space. $c > 0$, is the penalty parameter of the error term. Also $\mathrm{K}(x_i, x_j) \equiv \phi(x_i)^{\mathrm{T}}\phi(xj)$ is known as the kernel function. By reducing the error function, the SVM learns the extracted feature set x_i effectively in order to categorize the normal or abnormal that are analogous to the training set.

From the training data, the SVM classifier learns about the class in which the normal or tumor is present. Once the SVM is trained, it can classify any brain MR image dataset in the similar manner. In the classification phase, the selected features that are used in the training process to train the SVM classifier are extracted for testing the brain MRI image. The features set is given to the trained SVM for classifying the given brain MR image.

2.3. Image Dataset

The proposed multilevel brain tumor detection and classification system is evaluated using the magnetic resonance brain tumor images from Rembrandt database [12, 13]. Rembrandt database contains pre-surgical magnetic resonance multi-sequence images from 130 REMBRANDT patients. The magnetic images are available in DICOM format in the database, which are converted into jpeg format and stored in a local database for further processing using the proposed method. A total of 100 normal, 50 low grade and 50 high grade tumor MR images are used for this work. To train the classifier, 60% of images in each category are used. The remaining 40% of cases are tested by the classifier. Hereafter the total 200 images will be referred to as database. The number of images selected for the analysis is given in Table 1.

Table 1
Number of images selected for this study

Cases	*Number of Brain MR images*
Normal	100
Tumor Low Grade	50
Tumor High Grade	50

3. FEATURES EXTRACTION

Tetrolet transform is used to extract the features where the textural properties can be viewed in multi scale. Before extracting the features from the Tetromino sub-band, the images are freed from noises such as background information and labels. In preprocessing, bi-cubic interpolation is employed to reduce the spatial resolution of the image. Border correction procedure is applied to remove the non-x-ray film region by replacing the gray intensities to zero along the four sides of the images. The labeling such as patient data is removed by applying morphological dilation. The flow chart of the multilevel brain tumor detection and classification system is shown in Figure 1.

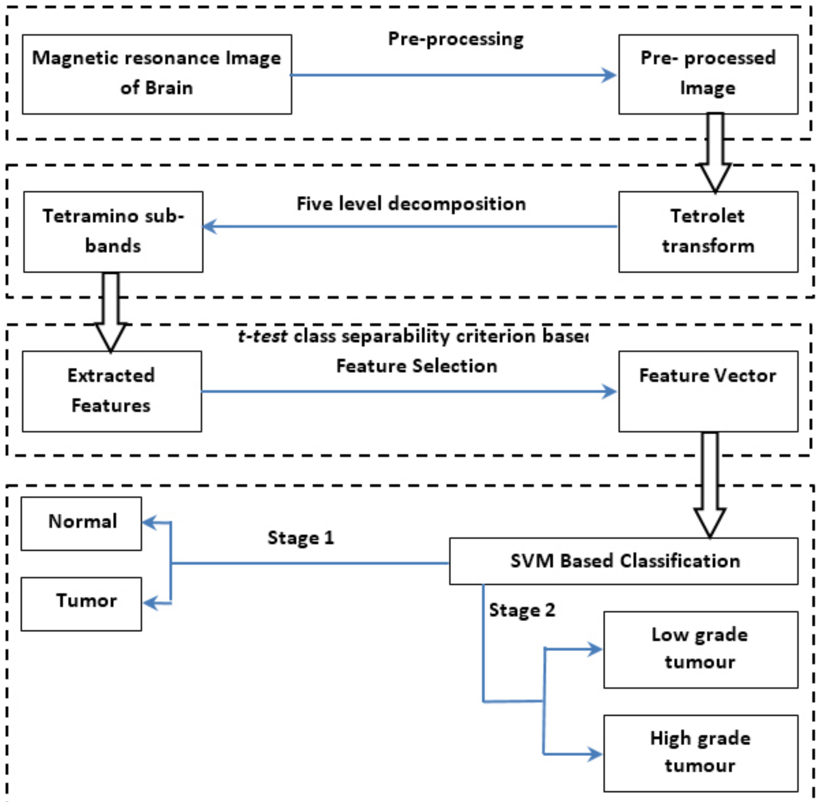


Figure 1: Flow chart for brain tumor detection and classification

After preprocessing the brain MRI image is decomposed using tetrolet transform. Statistical features such as mean, standard deviation, and variance for each tetromino sub band is computed and extracted. These extracted features comprised of a feature vector is used to train the SVM classifier. In the first stage the brain tumor MRI images are classified as normal and tumor categories. In the second stage the tumor images are classified as low grade or high grade. 10-fold cross validation experiments are conducted to determine the effectiveness of the proposed multilevel brain tumor detection and classification system. Region of convergence plots shows that the SVM classifier produces high level accuracy which the features extracted from fifth level of tetrolet transformation decomposition.

4. RESULTS AND DISCUSSIONS

In this study, brain tumor is detected and classified using a multilevel architecture using Tetrolet transform. In each layer, the classification steps are carried out by SVM classifier. The classifier in the first level helps to determine whether the given brain MRI image is having tumor or not. If the output of the first level classifier is tumor then the second level classifier is triggered and tested for type of abnormalities in terms of low grade or high grade for the input brain MRI image. From the database 60% images are used to train the classifier and 40% images are used for testing. To evaluate the complete system performance, 10-fold cross-validation experiments are conducted. A comparative analysis is done by using the feature vector for classifying using KNN classifier. Results demonstrated that the SVM classifier outperformed in terms of classification accuracy in comparison with the KNN classifier in both the levels. The classification accuracy, sensitivity and specificity at each level of the tetrolet transform decomposition for the first level by classifying with SVM and KNN classifiers are computed and given in Table 2 (a) and (b) respectively.

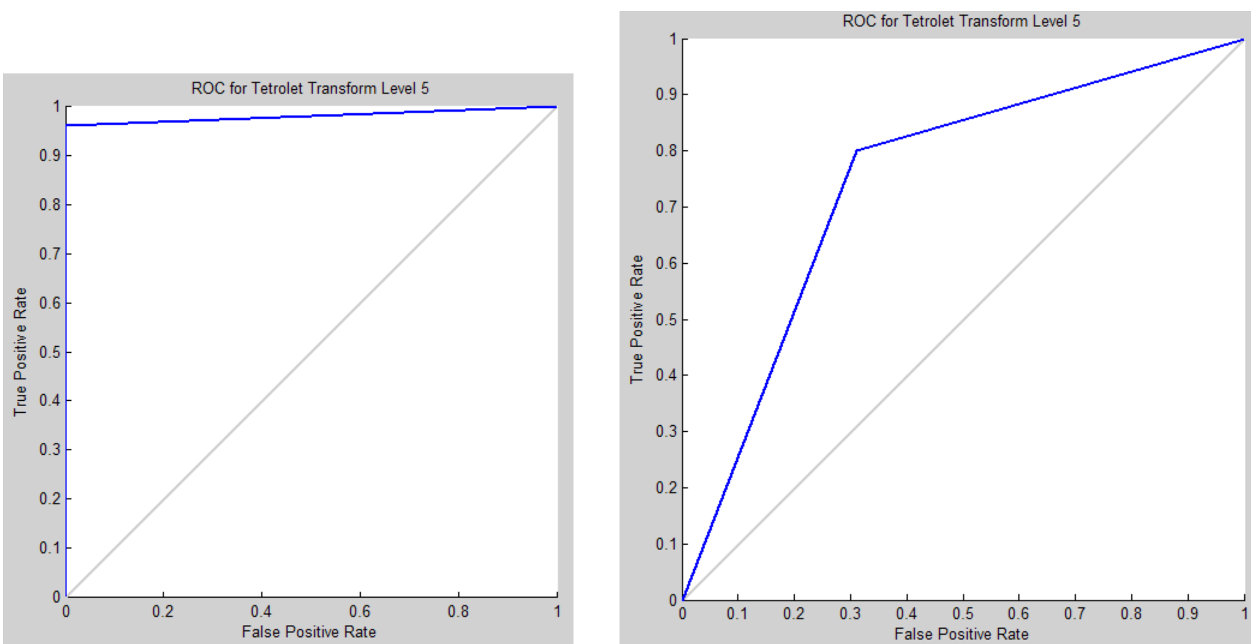
Table 2
(a) SVM Classifier Performance

Classifier	*SVM Classifier based Performance*					
Decomposition Level of TT	*1st Level*	*2nd Level*	*3rd Level*	*4th Level*	*5th Level*	*6th Level*
Accuracy	0.73	0.795	0.875	0.92	0.98	0.88
Sensitivity	0.78	0.82	0.88	0.87	0.96	0.76
Specificity	0.68	0.77	0.87	0.97	1	1

Table 2
(b) KNN Classifier Performance

Classifier	*KNN Classifier based Performance*					
Decomposition Level of TT	*1st Level*	*2nd Level*	*3rd Level*	*4th Level*	*5th Level*	*6th Level*
Accuracy	0.8	0.805	0.805	0.79	0.745	0.75
Sensitivity	0.86	0.85	0.84	0.87	0.8	0.78
Specificity	0.74	0.76	0.77	0.71	0.69	0.72

From the Tables 4.1 (a) and (b), it can be observed that maximum classification accuracy of 98% is obtained by extracting the statistical features from 5th level tetrolet transform decomposition level and classifying with SVM classifier. For the first level the classification is to detection whether a given image is normal or tumor. The receiver operating characteristics curves for fifth level of tetrolet transform decomposition level for the SVM and KNN classifiers is shown in Figure 4.1 (a) and (b) respectively.



(a) **(b)**

Figure 2: ROC Curves for first level of detection as normal or tumor from brain MRI Images with 5th level of tetrolet transform decomposition (a) Using SVM Classifier (b) Using KNN Classifier

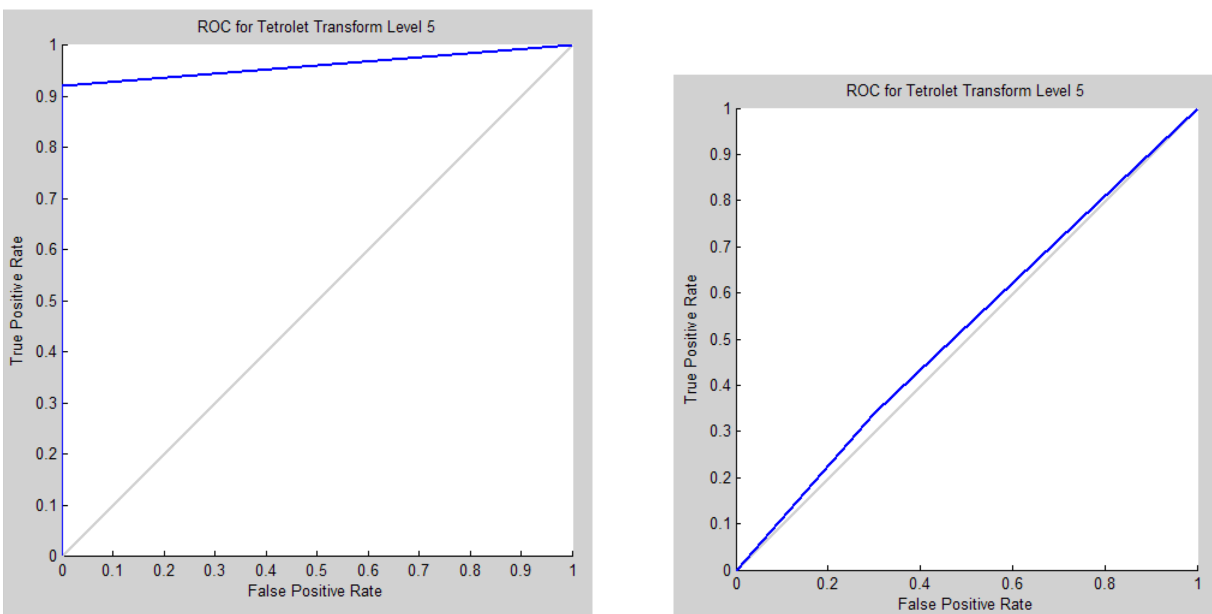
If tumor is detected in the first stage, then the second stage classification system will be triggered. The same set of statistical features are extracted and classified by SVM and KNN classifiers to give the severity of tumor (low grade or high grade). The classification accuracy, sensitivity and specificity at each level of the tetrolet transform decomposition for the first level by classifying with SVM and KNN classifiers are computed and given in Table 3 (a) and (b) respectively.

Table 3
(a) Performance of SVM Classifier in second stage

Classifier	*SVM Classifier based Performance*					
Decomposition Level of TT	*1st Level*	*2nd Level*	*3rd Level*	*4th Level*	*5th Level*	*6th Level*
Accuracy	0.8	0.82	0.86	0.93	0.96	0.87
Sensitivity	0.92	0.88	0.96	0.94	0.92	0.92
Specificity	0.68	0.76	0.76	0.92	1	0.82

Table 3
(b) Performance of KNN Classifier in second stage

Classifier	*KNN Classifier based Performance*					
Decomposition Level of TT	*1st Level*	*2nd Level*	*3rd Level*	*4th Level*	*5th Level*	*6th Level*
Accuracy	0.5	0.48	0.58	0.54	0.52	0.51
Sensitivity	0.34	0.26	0.38	0.36	0.34	0.32
Specificity	0.72	0.7	0.78	0.72	0.7	0.7



(a) **(b)**

Figure 3: ROC Curves for second level of detection as low grade tumor or high grade tumor from detected tumor brain MRI Images from the first stage with 5th level of tetrolet transform decomposition (a) Using SVM Classifier (b) Using KNN Classifier

From the Tables 3 (a) and (b), it can be seen that maximum classification accuracy of 96% is obtained by extracting the statistical features from 5th level tetrolet transform decomposition level and classifying with SVM classifier. For the second level the classification is to classify the severity of a given image in terms of low grade tumor or high grade tumor. The receiver operating characteristics curves for fifth level of tetrolet transform decomposition level for the SVM and KNN classifiers is shown in Figure 3 (a) and (b) respectively.

5. CONCLUSION

In this research, Tetrolet transform based feature extraction is carried out. The extracted features forming a feature vector are used to detect tumor from a given brain MRI image using SVM classifier in the first level. If the result of first level detection is tumor, then the second level classifier is triggered to give the severity of the detected tumor as low grade or high grade. The 200 (100 normal and 50 low grade tumor and 50 high grade tumor) brain MR images downloaded from Rembrandt database. The downloaded DICOM format images are converted into jpeg format and stored in a local database. The images were preprocessed and decomposed up to sixth level of decomposition using Tetrolet transform for feature extraction. From the experiments conducted it is clear that SVM classifier was able to produce an accuracy level of 98% in the first level and 96% in the second level. To compare the performance, KNN classifier was also used with the extracted feature sets for detection and classification of tumor. It is observed SVM classifier has outperformed the KNN classifier in terms of accuracy. 10-fold cross validation method was used for verify the classifier performance.

REFERENCES

[1] Samir Kumar Bandyopadhyay *et al,* Detection of Brain Tumor-A Proposed Method, Journal of Global Research in Computer Science 2 (1), January 2011, 56-64.

[2] Chinnu A, MRI Brain Tumor Classification Using SVM and Histogram Based Image Segmentation, (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 6 (2), 2015, 1505-1508.

[3] Akhanda Nand Pathak and Ramesh Kumar Sunkaria, Multiclass Brain Tumor Classification using SVM, International Journal of Computer Applications (0975 – 8887), Volume 97 – No. 23, July 2014.

[4] Dina Aboul Dahab *et al,* Automated Brain Tumor Detection and Identification Using Image Processing and Probabilistic Neural Network Techniques, International Journal of Image Processing and Visual Communication, ISSN 2319-1724 : Volume (Online) 1 , Issue 2 , October 2012.

[5] Ed-Edily Mohd. Azhari *et al,* Brain Tumor Detection And Localization in Magnetic Resonance Imaging, International Journal of Information Technology Convergence and Services (IJITCS) Vol. 4, No. 1, February 2014, DOI:10.5121/ ijitcs.2014.4101.

[6] Bhavana Ghotekar and K. J. Mahajan, Brain Tumor Detection and Classification using SVM, National Conference on Innovative Trends in Science and Engineering (NC-ITSE'16) ISSN: 2321-8169, Volume: 4 Issue: 7, pp. 180 – 182.

[7] B.Sudha, *et al,* Classification of Brain Tumor Grades using Neural Network, Proceedings of the World Congress on Engineering, 2014, Vol. I, WCE 2014, July 2 - 4, 2014, London, U.K.

[8] Jens Krommweh, "Tetrolet transform: A new adaptive Haar wavelet algorithm for sparse image representation," Journal of Visual Communication and Image Representation, Vol. 21, No. 4, pp. 364–374, May 2010.

[9] S. W. Golomb, Polyominoes, Princeton University Press, 1994.

[10] Boser B. E, Guyon I, and Vapnik V, "A training algorithm for optimal margin classifiers", In Proceedings of the Fifth Annual Workshop on Computational Learning Theory, ACM Press, 1992, pp. 144-152.

[11] Cortes C and Vapnik V, "Support-vector network", Machine Learning, 1995, Vol. 20, pp. 273-297.

[12] Scarpace, Lisa, Flanders, Adam E., Jain, Rajan, Mikkelsen, Tom, & Andrews, David W. (2015). Data from REMBRANDT. The Cancer Imaging Archive. http://doi.org/10.7937/K9/ TCIA.2015.588OZUZB.

[13] Clark K, Vendt B, Smith K, Freymann J, Kirby J, Koppel P, Moore S, Phillips S, Maffitt D, Pringle M, Tarbox L, Prior F. The Cancer Imaging Archive (TCIA): Maintaining and Operating a Public Information Repository, Journal of Digital Imaging, Volume 26, Number 6, December, 2013, pp 1045-1057.