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Implementation of Classification System for Brain Tumor using DWT

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ABTRACT

Image processing techniques have been widely used in medical imaging research. These techniques are useful for visualizing, enhancements segmentation and many such operations which are useful for processing medical images with MRI. An abnormal growth of cells are arises a brain tumor, that have proliferated in an uncontrolled manner. When the normal cells undergo death or get repaired by own, they either get injured or grow old. Most of the Research work shows in accurate detection of brain tumors, that are People affected to die. This paper depicts a novel framework for brain tumor classification based on Discrete Wavelet Transform (DWT) features are extracted from the brain MRI images, which signify the important texture features of tumor tissue. The experiments are carried out using BRATS dataset, considering three classes viz (Normal, Astrocytomas and Meaningiomas) and the extracted features are modeled by Support Vector Machines (SVM),k-Nearest Neighbor (k-NN) and Decision Tree (DT) for classifying tumor types. In the experimental results, k-NN exhibit effectiveness of the proposed method with an overall accuracy rate of 85.45%, this outperforms the SVM and DT classifiers.

Key words MRI, DWT, SVM, K-NN, DT, Astrocytomas, Meaningiomas, BRATS.

1. INTRODUCTION

A mass of tissue that originates by a gradual growth of abnormal cells is called a tumor. Usually, in our body the cells get aged, die and then they are replaced by newly born cells. But in the case of cancers and tumors, this cycle gets interrupted a leads to the formation, of tumors have been categorized into primary and secondary areas. When the tumors emanate from the tissues of the brain itself, they are said to be primary tumors. Secondary brain tumors are those tumors that are caused from cancer that arises from another part of the body. Magnetic Resonance imaging (MRI) is an advanced medical imaging technique primarily used in radiology to visualize high resolution images of the parts, structure and functions of the body. It provides detailed images of the body in any plane. MRI, scientists can visualize both surface and deep structures with a high degree of anatomical detail, and they can detect the occurrence of minute changes in these structures over time. In the earliest days, the technique was referred to as nuclear magnetic resonance imaging (NMRI). However, as the word nuclear was associated in the public mind as ionizing radiation exposure it is now simply referred to as MRI. MR images can also be used to track the size of a brain tumor as it responds (or doesn't) to treatment. A reliable method for classifying the tumor would clearly be a useful tool. MRI scan can be used as an accurate method for detecting tumor from human brain. . Figure 1(a), (b) shows the T2 weighted Magnetic Resonance image database considered for the implementation of feature extraction and classification. The collected T2 weighted Magnetic Resonance images are Categorized into two distinct classes as normal, abnormal brain tumors.

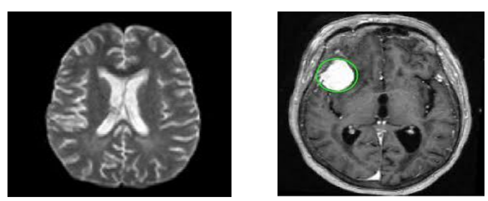
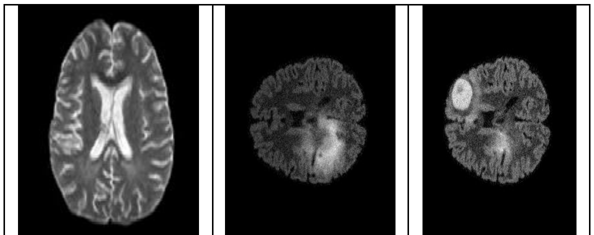


Figure1: A Magnetic Resonance Imaging (MRI) of the brain

The images are in a standard format usable in digital imaging and communication for medicine (DICOM). This is the standard format for all medical images. It was developed by the National Electronic Manufactures Association (NEMA). This standard format is mainly used for storing, printing and transmitting information in medical imaging. Many diagnostic imaging techniques can be performed for early detection of brain tumors such as Computed Tomography (CT), Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI).

Compared to all other imaging techniques, MRI is more efficient in brain tumor detection and identification, mainly due to the high contrast of soft tissues, high spatial resolution and since it does not produce any harmful radiation, and is a non invasive technique. Fig. 2(a),(b) and (c) shows the Magnetic Resonance Image (MRI) from BRATS database is categorized into three distinct classes as normal, Astrocytomas and Meaningiomas brain and it is considered for the implementation of DWT feature extraction and classification.



(a) Normal **(b) Astrocytomas** **(c) Meaningiomas**

Figure 2: MRI of the normal and abnormal images of the brain

1.1 Outline of the work

This paper deals with brain tumor classification, which aims to identify the brain tumor types as normal or abnormal from the brain MRI images. The proposed approach is evaluated using BRATS 2014 dataset. Thus, the DWT features are extracted from the MRI image as a feature set. The extracted features are modeled by SVM, k-NN and Decision tree classifiers for training and testing. The rest of the paper is structured as follows. Section 2 reviews related work. Section 3 provides an overview of the proposed approach. Section 4 describes the proposed feature extraction method and experimental results evaluating its performance on BRATS dataset are presented in Section 5. Finally, Section 6 concludes the paper.

2. RELATED WORK

From the literature survey, initially, it can be concluded that, various research works have been performed in classifying MR brain images into normal and abnormal [1], [2]. R. J. Ramteke, Khachane Monali Y[5] proposed a method for automatic classification of medical images in two classes Normal and Abnormal based on image features and automatic abnormality detection. KNN classifier is used for classifying image. K-Nearest Neighbour (K-NN) classification technique is the simplest technique conceptually and computationally that provides good classification accuracy. The K-NN algorithm is based on a distance function and a voting function in k-Nearest Neighbours, the metric employed is the Euclidean distance. SVM have high approximation capability and much faster convergence. KNN was chosen for classification purpose after verifying its classification accuracy with SVM. Normal Classified image displayed as resultant normal image. Abnormal classified image is passed to the next phase for further processing. Khushboo Singh, SatyaVerma[8] proposed advanced classification techniques based on Support Vector Machines (SVM) are proposed and applied to brain image classification using features derived.

Priyanka, BalwinderSingh [3] focused on survey of well-known brain tumor detection algorithms that have been proposed so far to detect the location of the tumor. The main concentration is on those techniques which use image segmentation to detect brain tumor. Image segmentation is the process of partitioning a digital image into multiple segments. R. J. Ramteke, KhachaneMonali Y [4] proposed a method for automatic classification of medical images in two classes Normal and Abnormal based on image features and automatic abnormality detection. KNN classifier is used for classifying image. K-Nearest Neighbour (K-NN) classification technique is the simplest technique conceptually and computationally that provides good classification accuracy. Khushboo Singh, SatyaVerma [5] proposed sophisticated classification techniques based on Support Vector Machines (SVM) are proposed and applied to brain image classification using features derived. Shweta Jain [6] classifies the type of tumor using Artificial Neural Network (ANN) in MRI images of different patients with Astrocytomas type of brain tumor. The extraction of texture features in the detected tumor has been achieved by using Gray Level Co-occurrence Matrix (GLCM). Statistical texture analysis techniques are constantly being refined by researchers and the range of applications is increasing [7], [8], [9]. Gray level co-occurrence matrix method is considered to be one of the important texture analysis techniques used for obtaining statistical properties for further classification, which is employed in this research work. Probabilistic Neural Network is found to be superior over other conventional neural networks such as Support Vector Machine and Back propagation Neural Network in terms of its accuracy in classifying brain tumors [10]. Hence a wavelet and co occurrence matrix method based texture feature extraction and Probabilistic Neural Network for classification has been used in this method of brain tumor classification.

3. PROPOSED APPROACH

The general overview of the proposed approach is illustrated in Fig. 3. This approach uses the standard benchmark Brain Research and Analysis in Tissues (BRATS) tumor dataset [11] for the experiments. The input tumor images are smoothed by median filter. It is necessary to pre-process all the tumor images for robust feature extraction and classification. Then BRATS dataset divided into three classes (normal, Astrocytomas and Meaningiomas) for feature extraction process. The extracted features are modeled using SVM, k-NN and Decision tree for classification.

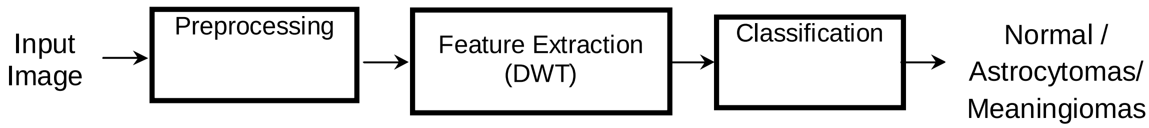


Figure 3: Block diagram of the Proposed Approach

4. FEATURE EXTRACTION

The extraction of discriminative feature is most essential and vital problem with brain tumor.

4.1. DWT for Tumor Classification

Discrete wavelet transform is a popular method in signal processing and has been used in various research fields. The main feature of DWT is the multi scale representation of a function. By using the wavelets, a given image can be analyzed at various levels of resolution. DWT converts an input series x_0, x_1, .., x_m, into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length *n/2* each) as given below.

$$H_i = \sum_{m=0}^{k=1} x_{2i} - m^S m\ (Z) \tag{1}$$

$$L_i = \sum_{m=0}^{k=1} x_{2i} - m^t m\ (Z) \tag{2}$$

where s_m *(Z)* and t_m *(Z)* are called wavelet filters, *k* is the length of the filter, and *i = 0,..., [n/2] − 1*. Such transformation is applied recursively on the low-pass series until the desired number of iterations is reached. In frequency domain, when the

MRI image is decomposed using two dimensional wavelet transform, four sub region [12]. These regions are: one low-frequency region LL (approximate component), and three high-frequency regions, namely LH (horizontal component), HL (vertical component), and HH (diagonal component), respectively. The LL image is generated by two continuous low-pass filters; HL is filtered by a high-pass filter first and a low-pass filter later; LH is created using a low-pass filter followed by a high-pass filter; HH is generated by two successive high-pass filters. Subsequent levels of decomposition follow the same procedure by decomposing the LL sub image of the previous level. Since the LL part contains most important information and discards the effect of noises and irrelevant parts, the LL part is adopted for further analysis. In the proposed work,

4.2 Support Vector Machine for Classification

Support Vector Machine (SVM) [13] is based on the principle of structural risk minimization (SRM). Support vector machines can be used for pattern classification and nonlinear regression. It constructs a linear model to estimate the decision function using non-linear class boundaries based on support vectors. If the data are linearly separable, SVM trains linear machines for an optimal hyperplane that separates the data without error and into the maximum distance between the hyperplane and the closest training points. The training points that are closest to the optimal separating hyperplane are called support vectors. Fig. 4 shows the architecture of SVM. SVM maps the input patterns into a higher dimensional feature space through some nonlinear mapping chosen a priori. A linear decision surface is then constructed in this high dimensional feature space. Thus, SVM is a linear classifier in the parameter space, but it becomes a nonlinear classifier as a result of the nonlinear mapping of the space of the input patterns into the high dimensional feature space.

4.2.1 SVM Principle:

Support vector machine (SVM) can be used for classifying the obtained data [14]. SVM are a set of related supervised learning methods used for classification and regression and they belong to a family of generalized linear classifiers. A feature vector (termed as pattern) is denoted by $x=(x_1, x_2,\ldots, x_n)$ and its class label by y such that $y = \{+1,-1\}$. Therefore, consider the problem of separating the set of n-training patterns belonging to two classes,

$$(x_i, y_i),\ x_i \in R^n,\ y = \{+1,-1\},\ i = 1,2,....,n \tag{3}$$

A decision function *g(x)* can correctly classify an input pattern *x* that is not necessarily from the training set.

discriminant function is of the form:

$$g\ (x)\ =\ w^t x\ +\ b \tag{4}$$

such that $g(x_i) \geq 0$ for y_i = +1 and $g(x_i)$ < 0 for y_i = −1. In other words, training samples from the two different classes are separated by the hyperplane *g(x)*

4.2.2 SVM for Linearly Separable Data

A linear SVM is used to classify data sets which are linearly separable. The SVM linear classifier tries to maximize the margin between the separating hyperplane and the patterns lying on the maximal margins called support vectors. Such a hyperplane with maximum margin is called maximum margin hyperplane [14]. In case of linear SVM, the

$= w^t x + b = 0$. SVM finds the hyperplane that causes the largest separation between the decision function values from the two classes. Now the total width between two margins is $2/w^t w$, which is to be maximized. Mathematically, this hyperplane can be found by minimizing the following cost function:

$$J(w) = \frac{1}{2} w^t w \quad (5)$$

Subject to separability constraints

$$\begin{gathered} g(x_i) \geq +1 \;\; for \;\; y_i = +1 \\ or \\ g(x_i) \leq -1 \;\; for \;\; y_i = -1 \end{gathered} \quad (6)$$

Equivalently, these constraints can be re-written more compactly as

$$y_i (w^t x_i + b) \geq 1; \; i = 1, 2, ..., n \quad (7)$$

For the linearly separable case, the decision rules defined by an optimal hyperplane separating the binary decision classes are given in the following equation in terms of the support vectors:

$$Y = sign\left(\sum_{i=1}^{i=N_s} y_i \alpha_i (x, x_i) + b \right) \quad (8)$$

where Y is the outcome, y_i is the class value of the training example x_i, and represents the inner product. The vector corresponds to an input and the vectors x_i, $i = 1, . . . ,N_s$, are the support vectors. In Eq. (8), b and α_i are parameters that determine the hyper plane.

4.2.3 SVM for linearly non-separable data:

For non-linearly separable data, it maps the data in the input space into a high dimension space $x \in \mathbb{R}^I \rightarrow \Phi(x) \in \mathbb{R}^H$ with kernel function $\Phi(x)$, to find the separating hyper plane.

4.3 *k*-Nearest Neighbour for Classification

The k-NN classifier ranks the test formula's neighbors among the training vectors and uses the category labels of the *k* most similar neighbors to predict categories of the test formula [15], [16]. In traditional *k*-NN, the value *k* is fixed and usually determined experimentally. If the *k* is too large, big classes (a lot of members in the class) may dominate small ones. Incorrect categories may be assigned for multi-label classification. In the opposite, if *k* is too small, the advantages of this algorithm to make use of many experts will not be presented. Moreover, in multi-label classification, the test formula may not be assigned to all categories. It should be in *k*-NN algorithm, the most popular on similarity, *i.e.*, cosine similarity, which can be calculated by the dot product between these two vectors. In case both vectors are normalized into the unit length, the value of similarity of the two vectors is in the range of 0 and 1.

$$C(f_t) = \arg\max \sum_{f_j \in kNN} z(f_j, c_k) \quad (9)$$

When the *k* nearest neighbors is set, several strategies could be taken to predict the category of a test formula. Two strategies that are widely used are listed as follows. Where f_l is a test formula f_j is one of the neighbors (*k*-NN) in the training set, $z(f_j , c_k)$. 0,1 indicates whether f_j belongs to class c_k in the set of classes C, and sim (f_l, f_j) is the similarity function between f_l and f_j . For single-label classification, the above equation means that the prediction will be a category that has the largest number of members in the *k* nearest neighbors. The Eq. (13) expresses that the category which has maximal sum of similarity (score), will be assigned. This strategy is thought to be more useful and is more widely used.

$$C(f_t) = \arg\max_{ck \in C} \sum_{f_j \in kNN} sim(f_l, f_j)\, z(f_j, c_k) \quad (10)$$

4.4 Decision Tree for Classification

Decision tree is one of the preparatory learning algorithms that construct a classification tree to classify the data [17] and decision tree represents rules. The classification tree is made by recursive partitioning of feature space based on a training set. A decision tree is visual representation of a problem. A decision tree helps to decompose a complex problem into smaller and more manageable undertakings. Decision tree is a common and intuitive approach to classify a pattern through sequence of questions in which the next question depends upon the answer to current question. Decision tree analysis is a formal, structured approach to make decisions. It is based on the "divide and conquer" strategy.

There are two common issues for construction of decision trees [18]:

(a) Growth of the tree to accurately categorize the training dataset, and
(b) The pruning stage, whereby superfluous nodes and branches are removed in order to improve classification accuracy.

A decision tree is in the form of a tree structure, where each node is either:

1. A leaf node - indicates the value of the target class of examples, or
2. A decision node - specifies some test to be

carried out on a single attribute-value, with two or more than two branches and each branch has a sub-tree.

Decision trees are the commonly used method for pattern classification. Decision tree is a common and intuitive approach to classify a pattern through sequence of questions in which the next question depends upon the answer to the current question. A decision tree is a visual representation of a problem. A decision tree helps to decompose a complex problem into smaller, more manageable undertakings. This allows the decision makers to make smaller determinations along the way to achieve the optimal overall decision. Decision tree analysis is a formal, structured approach to make decisions.

5. EXPERIMENTAL RESULTS

In this section, the proposed method is evaluated using BRATS tumor dataset. The experiments are carried out in MATLAB 2013a in Windows 7 Operating System on a computer with Intel Xeon Processor 2.40 GHz with 4 GB RAM. The obtained DWT features are fed to supervised classifiers such as SVM, K-NN and Decision tree to develop the model for each class, and these models are used to test the performance of the proposed features.

5.1 BRATS Dataset

Multimodal Brain Tumor Image Segmentation (BRATS) is a large dataset of brain tumor MR scans in which the relevant tumor structures have been delineated. In this work, 200 images are taken for evaluation is shown in the Fig. 5. For conducting the experiments, 120 images are taken as training samples and the remaining 80 images are considered fortesting

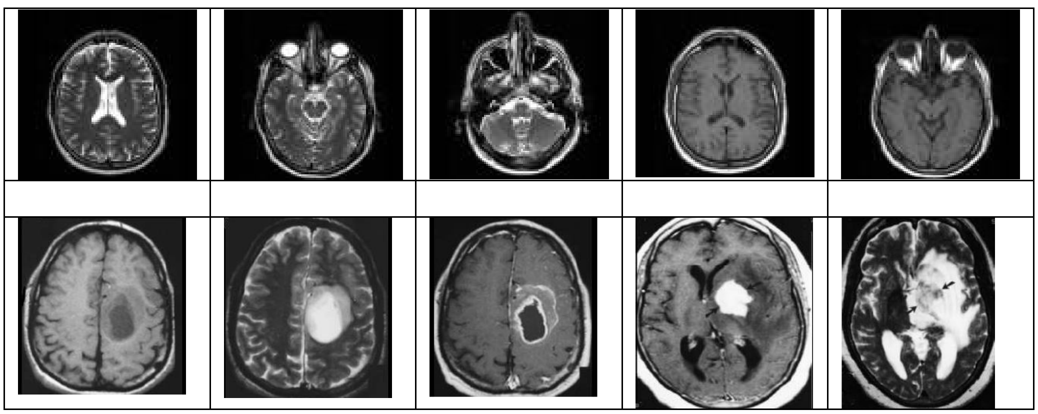


Fig. 5: Sample brain MRI images of the BRATS dataset: Normal (top row) and Abnormal (bottom row)

5.2 Quantitative Evaluation

An efficient study of performance measure for classification tasks is presented in [19]. Precision (P), Recall (R) and F-measure (F) are the commonly used evaluation metrics and these measures are used to evaluate the performance of the proposed method. These measures provide the best perspective on classifiers performance for classification. Table 2 shows confusion matrix for classification.

Table 2: Confusion matrix for classification.

	Predicted Outcomes	
	Positive	Negative
Positive`	TP	FN
Negative`	FP	TN

The confusion matrix contains information about actual and predicted classifications done by a classification system, where, TP and TN are the number of true positive and true negative predictions for the particular class. FN and FP are the number of false negative and false positive for the particular class. The classification widely uses Precision, Recall and F-measure, which do not detect changes in TN when all other matrix entries remain the same. The precision (P) is calculated as in (14). The Recall (R) or Sensitivity is calculated as in (15).

$$\text{Precision (P)} = \frac{TP}{TP+FP} \tag{14}$$

$$\text{Recall (R)} = \frac{TP}{TP+FN} \tag{15}$$

$$\text{F-Measure (F)} = 2 \times \frac{P \times R}{P + R} \qquad (16)$$

$$\text{Accuracy (A)} = \frac{TP + TN}{TP + FP + TN + FN} \qquad (17)$$

Precision and Recall do not depend on TN, but only on the correct labeling of positive examples (TP) and the incorrect labeling of examples (FP and FN). These measures provide the most excellent perspective on classifier performance for brain tumor classification. The F-measure is a combined measure of precision and recall metrics and it is calculated as in (16). The Accuracy is calculated as in (17).

5.3 Results obtained with SVM

The confusion matrices of the SVM classifier on BRATS dataset is shown in Table 3, where diagonal of the table shows that accurate responses of tumor types.

The average recognition rate of SVM is 78.61%. In SVM, the normal class is classified well, where as in Astrocytomas class is confused with Meaningiomas class and vice versa. Thus, it needs further attention.

Classifiers	Precision	Recall	F-measure
SVM	66.67	66.67	66.52
K-NN	**84.31**	**88.89**	**83.08**
Decision Tree	78.52	81.48	78.17

Table 3: Confusion matrix for SVM

	Normal	**Astrocytomas**	**Meaningiomas**
Normal	**100**	0.0	0.0
Astrocytomas	0.0	**66.67**	33.33
Meaningiomas	0.0	30.83	**69.17**

5.4 Results obtained with k-NN

The confusion matrices of the k-NN classifier on BRATS dataset is shown in Table 4, where diagonal of the table shows that accurate responses of tumor types. The average recognition rate of k-NN is 88.89%. In k-NN, the normal and Meaningiomas classes are classified well and good, where as the Astrocytomas class is confused with Meaningiomas class as 33.33%.

Table 4: Confusion matrix for KNN

	Normal	**Astrocytomas**	**Meaningiomas**
Normal	**100**	0.0	0.0
Astrocytomas	0.0	**66.67**	33.33
Meaningiomas	0.0	0.0	**100**

5.5 Results obtained with Decision Tree

The confusion matrices of the Decision Tree classifier on BRATS dataset is shown in Table 5, where diagonal of the table shows that accurate responses of tumor types. The average recognition rate of DT is 81.48%. In DT, the normal class is classified well, where as the Astrocytomas and Meaningiomas class are confused respectively. Thus, it needs further attention.

Table 5: Confusion matrix for Decision Tree

	Normal	**Astrocytomas**	**Meaningiomas**
Normal	**100**	0.0	0.0
Astrocytomas	0.0	**66.67**	33.33
Meaningiomas	0.0	22.22	**77.78**

The quantitative evaluation results are tabulated in Table 6, which shows that the proposed approach has a higher precision, recall and F-measure for the k-NN classifier on BRATS dataset, when compared to SVM and DT classifiers. The overall performance of the proposed method with various classifiers on BRATS dataset is shown in Fig. 7.

Table 6: Performance measure of the BRATS dataset on SVM, k-NN and DT classifiers

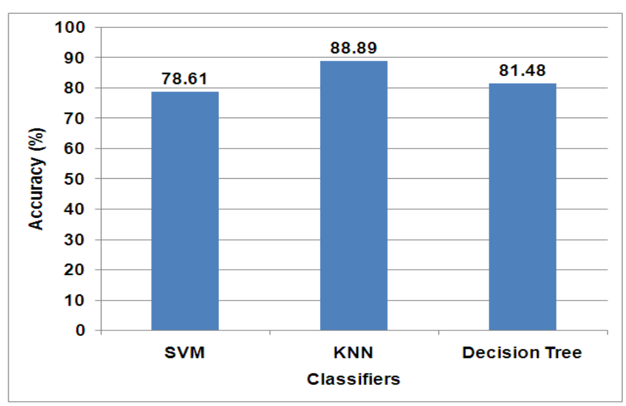


Fig 7: Overall accuracy obtained for BRATS dataset on SVM, k-NN and DT classifiers

6. CONCLUSION AND FUTURE WORK

An automated intelligent classification technique is proposed which caters the need for classification of image. This paper presents an efficient method of classifying MR brain images into normal and abnormal tumor, using a SVM, k-NN and Decision Tree. This paper presents a method called Discrete Wavelet Transform (DWT) features is extracted from the brain MRI images, which signify the important texture features of tumor tissue and gives very promising results in classifying MR images. From the experimental results, it is observed that k-NN shows a classification accuracy of 88.89%, and demonstrated that the proposed feature method performs well and achieved good recognition results for tumor classification. It is observed from the experiments that the system could not distinguish Astrocytomas class with high accuracy and is of future interest.

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