

CLASSIFICATION OF BENIGN AND MALIGNANT TUMOUR USING SVM

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Abstract - Biomedical Image Processing is a growing and demanding field. It comprises of many different types of imaging methods likes CT scans, X-Ray and MRI. These techniques allow us to identify even the smallest abnormalities in the human body. The primary goal of medical imaging is to extract meaningful and accurate information from these images with the least error possible. Out of the various types of medical imaging processes available to us, MRI is the most reliable and safe. Brain tumors are the most common malignant neurologic tumors with the highest mortality and disability rate. Because of the delicate structure of the brain, the clinical use of several commonly used biopsydiagnosis is limited for brain tumors. In this project, SVM Classification is used to differentiate whether it is malignant or benign brain tumors.

Index Terms— Brain tumors, radiomics, sparse representation, tumor differentiation, molecular marker estimation.

I INTRODUCTION

The brain is an organ that serves as the center of the nervous system in all vertebrate and most invertebrate animals. The brain is located in the head, usually close to the sensory organs for senses such as vision. The brain is the most complex organ in a vertebrate's body. In a human, the cerebral cortex contains approximately 10–20 billion neurons, and the estimated number of neurons in the cerebellum is 55–70 billion. Each neuron is connected by synapses to several thousand other neurons. These neurons

communicate with one another by means of long protoplasmic fibers called axons, which carry trains of signal pulses called action potentials to distant parts of the brain or body targeting specific recipient cells

Physiologically, the function of the brain is to exert centralized control over the other organs of the body. The brain acts on the rest of the body both by generating patterns of muscle activity and by driving the secretion of chemicals called hormones. This centralized control allows rapid and coordinated responses to changes in the environment. Some basic types of responsiveness such as reflexes can be mediated by the spinal cord or peripheral ganglia, but sophisticated purposeful control of behavior based on complex sensory input requires the information integrating capabilities of a centralized brain.

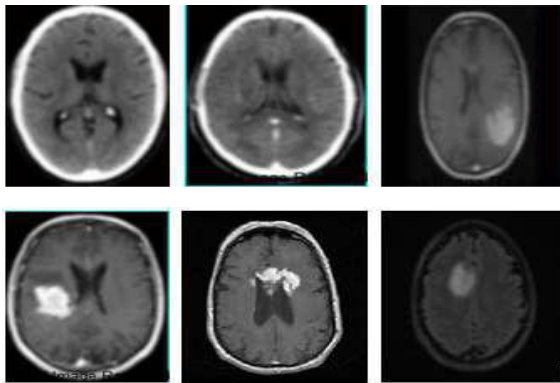
A brain tumor occurs when abnormal cells form within the brain. There are two main types of tumors: malignant or cancerous tumors and benign tumors. Cancerous tumors can be divided into primary tumors, which start within the brain, and secondary tumors, which have spread from elsewhere, known as brain metastasis tumors. All types of brain tumors may produce symptoms that vary depending on the part of the brain involved. These symptoms may include headaches, seizures, problems with vision, vomiting and mental changes. The headache is classically worse in the morning and goes away with vomiting. Other symptoms may include difficulty walking, speaking or with sensations. As the disease progresses, unconsciousness may occur.

II. BACKGROUND ON METHOD

In recent years, based on its good properties in signal representation and reconstruction, sparse representation has been widely used in image restoration feature selection object detection and image classification. The main idea of sparse representation is that natural signals can be represented sparsely over a dictionary. In general, the sparse representation model can be written as $\hat{\alpha} = \arg \min_{\alpha} \|\alpha\|_p \text{ s.t. } Dy + \alpha = y$ (1) where y is the target signal; $D = \sum_{k=1}^K d_k d_k^T$ is the sparse representation dictionary; and d is an atom. α is the sparse representation coefficient, and its estimated value $\hat{\alpha}$ contains few nonzero elements. p represents the p -norm. The regularization parameter μ is used to balance the tradeoff between fidelity and sparsity. The orthogonal matching pursuit (OMP) and least absolute shrinkage and selection operator (LASSO) methods are often used to solve. Sparse representation theory can be applied to various applications in which the symbols in have different meanings. In some applications involving image denoising and reconstruction, Equation is generally used in the representation of sparse images. Specifically, the degraded image y is first sparsely represented over dictionary D by; the original image x is then estimated as $\hat{x} \approx Dx\alpha$. In its application to feature selection, y represents a sample label set, and each row within y corresponds to a sample; on the other hand, D represents the corresponding high-dimensional sample features, and each column within D corresponds to a feature. After ranking the absolute values contained in $\hat{\alpha}$, one can select the top-ranked row as the result of feature selection. In addition, Equation (1) has also been widely used for classification. Specifically, sparse representation classification consists of two steps. First, the sparse representation model of (1) is solved, where y

denotes a testing sample; $\{x_1, \dots, x_C\}$ denotes the training sample set; C is the number of classes; and X_c is the training sample set from class c . Second, given the sparse solution $\hat{\alpha}$, the class label of y is identified via $\arg \min_c \|\hat{\alpha}_c\|_1$ (2) where $\hat{\alpha}_c$ is used to select the coefficients associated with the c -th class. These three applications of sparse representation show great potential in dealing with the three radiomics challenges presented in the introduction. For image sparse representation, some adaptive learning methods such as K -singular value decomposition (KSVD), are often employed to construct more effective dictionaries. These methods aim to learn some exclusive structure and texture information from the target images; therefore, target images can be represented more sparsely over the learned dictionary. In the classification of tumor images, when the dictionary containing the structure and texture information of the tumor image is well learned, the learned dictionary can be exploited to sparsely represent the testing tumor image. The statistical distribution of the representation coefficients effectively reflects the texture features of the tumor image; therefore, they can be used for classification. Unlike some traditional radiomics feature selection methods, such as p -value comparison and correlation analysis, which independently consider the correlation between each feature and label set to select features, sparse representation-based feature selection aims to select a group of features that are most relevant to a label set. Since it is the combination of the selected features that finally determines the class of the testing sample, sparse representation-based feature selection is more reasonable for subsequent classification. Sparse representation classification has some advantages for handling noise among samples, and it also effectively avoids over fitting. More importantly, in problems involving multi-feature fusion classification, the effective use of the

internal relationships among the coefficients of different features further improves the classification accuracy. Hence; we apply sparse representation to carry out multi-feature fusion classification in radiomics. The purpose of this paper is to present solutions to the feature extraction, feature selection, and classification challenges that radiomics confronts within a unified theoretical framework.



Database Image: In this project, Fig: 1 Input Image here database is used.

III Support Vector Machine (SVM)

Support Vector Machine” (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes very well. SVM introduced by Cortes is generally used for classification purpose. SVMs are efficient learning approaches for training classifiers based on several functions like polynomial functions, radial basis functions, neural networks etc. It is considered as a supervised learning approach that produces input-output mapping functions from a labeled training dataset. SVM has significant learning ability and hence is broadly applied in pattern recognition. SVMs are universal approximates which depend on the statistical and optimizing theory. The

SVM is particularly striking the biological analysis due to its capability to handle noise, large dataset and large input spaces.

The fundamental idea of SVM can be described as follows:

- Initially, the inputs are formulated as feature vectors
- Then, by using the kernel function, these feature vectors are mapped to separate the classes of training vector

A global hyper plane is sought by the SVM in order to separate both the classes of examples in training set and avoid over fitting. This phenomenon of SVM is more superior in comparison to other machine learning techniques which are based on artificial intelligence. The mapping of the input-output functions from a set of labeled training data set is generated by the supervised learning method called SVM.

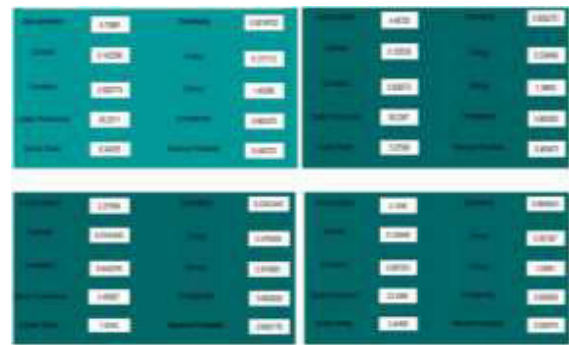


Fig 2: Feature selection and Weight Calculation

In a high dimensional feature space, SVM uses a hypothesis space of linear functions which are trained with a learning technique from optimization theory that employs a learning bias derived from statistical learning theory. In Support Vector machines, the classifier is created using a hyper-linear separating plane. It provides the ideal solution for problems which

are not linearly separated in the input space. The original input space is non-linearly transformed into a high dimensional feature space, where an optimal separating hyper plane is found and the problem is solved. A maximal margin classifier with respect to the training data is obtained when the separating planes are optimal.

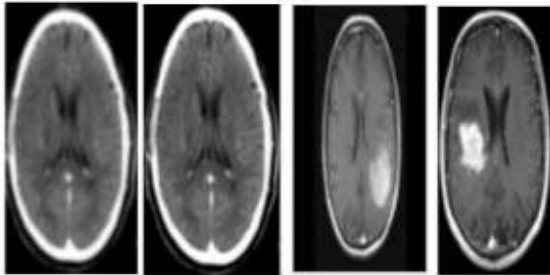


Fig :3 Pre-processing Image

IV Color Transformation Functions

First group of operations is responsible for changes and information concerning color transformation of images. Couples of functions do not change anything in the picture but they are crucial when it comes to gain information about it, without need of opening the actual object of interests. Is bw returns value 1 if the image is black white, and value 0 otherwise. Some operations have sense only when executed on binary graphic files. For example adjusting contrast, brightness or other changes, usually made on colorful pictures, would not work with black and white images. Function is gray (A), similarly to previous one, checks color map of the image. As the name suggests, this time function returns value 1 if the picture is grayscale and value 0 otherwise. It may also become useful while deciding if some operations can be performed on the file. Is RGB informs if examined file is the RGB image. These three functions are essential when it comes to deciding about changing the color map or color system. Knowing if the picture is black and white,

grayscale or RGB determines what transformations can be done to the file. There

would be no point in trying to make some changes to the image, if they are inoperative for some color models or maps. Another smaller group of functions are those responsible for picture enhancements. Im adjust adjusts image intensity values. As an additional parameter user is allowed to specify two squared brackets ranges. Pixels that do not belong to those ranges are clipped. That is how this procedure increases contrast of the input image. Other function that is responsible for contrast changes is Im contrast, which creates ready-built contrast adjustment tool. It takes opened picture as an object of contrast customization. Unfortunately, this tool works only with grayscale images.

V BLOCK DIAGRAM

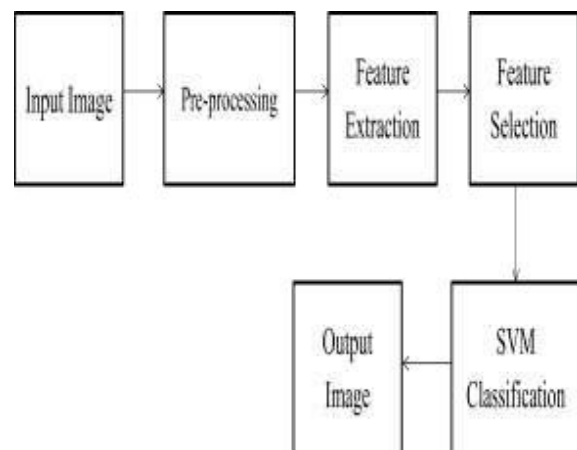


Fig: 4 Block Diagram

The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. In pre-processing, Median filter is used for the conversion of original image into gray scale image. Neighboring pixels corresponding to one object in real images have essentially the same or similar brightness value.

In feature extraction, each sub-dictionary in the feature extraction dictionary is trained from the corresponding class of images. Surf feature

extraction is used for the extraction of features. Comparing to other feature extraction, surf is very accurate for finding the features.

Among the extracted features, many are highly redundant. This high redundancy is primarily due to two aspects. In one hand, different classes of images, such as GLCM images, commonly contain some of the same texture information. On the other hand, due to the correlations between features, not all features are crucial in classification. Among the extracted features, many are highly redundant. This high redundancy is primarily due to two aspects. In one hand, different classes of images, such as GLCM images, commonly contain some of the same texture information. On the other hand, due to the correlations between features, not all features are crucial in classification.

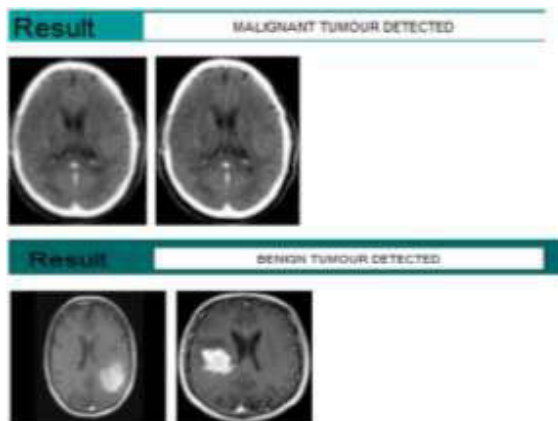


Fig :5 Output Image

An SVM classifies data by finding the best hyperplane that separates all data points of one class from those of the other class. Here binary SVM Classification is used for the classification of tumors. Binary SVM classifies the tumors as whether it is benign or malignant brain tumors. All the tumors are automatically segmented using SVM.

VI CONCLUSION & FUTURE SCOPE

This paper proposes a novel framework for the differentiation of Benign Tumor and Malignant Tumor based on SVM Classification. It is worth emphasizing that the proposed method is highly robust, due to its automatic diagnosis; manual intervention is not required at any point in the entire process. The work in this research involved using SVM with kernel function to classify Brain tumor CT images into benign and malignant. For future work, the proposed method can be applied to other types of imaging such as MRI and even can be used for segmentation and classification of tumors in other parts of body. We will also improve the classification dictionary through dictionary learning and further validate the proposed method on a larger dataset.

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