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Brain tumors classification using machine learning and GLCM

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ABSTRACT - Medical imaging field getting its importance with increase in the need of automated and efficient diagnosis in a short period of time. Other than, medical image retrieval system is to provide a tool for radiologists to retrieve the images similar to query image in content.. Classification is an important part in retrieval system in order to distinguish between normal patients and those who have the possibility of having abnormalities or tumor. In this paper, we have obtained the feature related to MRI images using discrete wavelet transformation. An advanced kernel based techniques such as Support Vector Machine (SVM) for the classification of volume of MRI data as normal and abnormal will be deployed. 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. Processing an image is a complicated task. Before any image can be processed, it is important to remove any unwanted artifacts it may hold. Only then can the image be processed successfully. Processing a medical image involves two main steps. The first is the pre-processing of the image. This involves performing operations like noise reduction and filtering so that the image is suitable for the next step. The second step is to perform segmentation and morphological operations

Keyword : Tumor ,Segmentation, Kernel, *SVM, MRI,, Classification, Wave, Feature Extraction*

I. INTRODUCTION

In image processing, images convey the information where input image is processed to get output also an image. In today's world, the images used are in digital format. In recent times, the introduction of information technology and e-healthcare system in medical field helps clinical experts to provide better health care for patients. This study reveals the problem segmentation of abnormal and normal tissues from MRI images using gray-level co-occurrence matrix (GLCM) feature extraction classifier. The brain tumor is an abnormal growth of uncontrolled cancerous tissues in the brain. A brain tumor can be benign and malignant. The benign tumor has uniformity structures and contains non-active cancer cells. The malignant tumor has non-uniformity structures and contains active cancer cells that spread all over parts. Most recent classifications of brain tumors build on the 1926 work of Bailey and Cushing.[2] This classification named tumors after the cell type in the developing embryo/fetus or adult which the tumors cells most resembled histologically. The cell of origin of the majority of brain tumors is unknown as no pre-malignant states are recognized, as is the case in some epithelial tumors forms. In some tumors, cells may be so atypical that it is difficult to compare them with any normal cell type—hence the use of terms such as glioblastoma. Many unsound or illogical terms have remained in the classifications, as once established in a complex medical setting they are difficult to change. In this paper the terminology and definitions of the World Health Organization classification of 2000 will be exclusively used.[1] There are more than 120 entities in this classification and here we will concentrate on those that most frequently occur in adults and children. These are the pilocytic astrocytomas, ependymomas, and medulloblastomas in children, and the diffuse astrocytic tumours (including astrocytoma, anaplastic astrocytomas, and glioblastomas), oligodendrogliomas, and meningiomas in adults.Tumours of the central nervous system often have a wide morphological spectrum and classification is dependent on the recognition of areas with the characteristic histology for a particular tumour type. Immunocytochemical methods may be required to demonstrate the expression by the tumour cells of an

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antigen typically expressed by a particular cell type and thus to assist in classification.

Unfortunately there are no antibodies that unequivocally identify the different tumour types. The presence or absence of an antigen only adds a further piece of information helping to indicate the tumour type. In our proposed technique, predominantly the input glioblastomas (both low and high grade) pictured in MRI image is pre-processed to annihilate the noise and images. By their very nature, these tumors can appear make the image prone for the repose of the process; the anywhere in the brain and have almost any kind of shape, Wiener filter is subjugated in the preprocessing stage. size and contrast. These reasons motivate our exploration Subsequently, the pre-processed image is crumbled by of a machine learning solution that exploits a flexible, high the modified region growing technique. In the segmentation process, the tentative texture features are present work, a method based on multidimensional confiscated and accorded to the neural network for mathematical morphology is used to classify brain training. In the final stage, the image is classified as a tissues for multimodality MRI comprising 4 modalities, tumor or normal tissue with the succor of the trained allowing for tumor image segmentation and classification.

II. REVIEW OF LITERATURE:

T Kesavamurthy et al.[1] The importance of medical imaging cannot be emphasized enough in this era of ever increasing speed of computation algorithm and it has brought importance to develop systems that can processes and generate very accurate results very fast. The various scanning techniques have incarnated as an inevitable tool for the doctors to help them in diagnosis. The algorithm and methodology that we propose will enable the easy and faultless identification of abnormalities present in the scanned region. This will allow for the further speeding of the diagnosis, also it will be of great help to the patients, neurophysicians and internees of radiology .

Dr.S.Thamarai Selvi et al. [4] Magnetic resonance (MR) imaging has been playing an important role in neuroscience research for studying brain images. The classifications of brain MRI data as normal and abnormal are important to prune the normal patient and to consider only those have the possibility of having abnormalities or tumor. Classification of MRI data along with skull in MR images results in reduction of efficiency to a great extent. Thus the removal of skull is done prior to classification. The statistical and gray level co-occurrence features are extracted from MR images before and after skull removed images. An advanced kernel based techniques such as support vector machine (SVM) and relevance vector machine (RVM) for the classification of volume of MRI data as normal and abnormal are deployed. Validation is done with stratified Holdout approach. The results are compared with radiologist results and performance measures such as sensitivity, specificity, and correspondence ratio for skull stripping and classification accuracy are calculated.

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[3] we propose a novel method using wavelets as input to neural networkself-organizing maps and support vector machine for classification of magnetic resonance (MR) images of the human brain. The proposed method classifies MR brain images as either normal or abnormal. We have tested the proposed approach using a dataset of 52 MR brain images. Good classification percentage of more than 94% was achieved using the neural network self-organizing maps (SOM) and 98% from support vector machine. We observed that the classification rate is high for a support vector machine classifier compared to self-organizing map-based approach

N.R.Jaganathan et al.[5] The Image Algebra [10] forms a solid theoretical foundation to implement computer vision andv image processing algorithms. With the use of very efficient and reliable high-level computer languages such as C/C++, Fortran 90, and Java, innumerable image processing and machine vision algorithms have been written and optimized. All this code written and compiled has become a powerful tool available for researchers, scientists and engineers, which further accelerated the investigation process and incremented the accuracy of the final results.

III. PROPOSED METHODOLOGY

Technique-

A. Input Datasets- MRI Data The input data set consists of axial, T2 FLAIR weighted, 256 x 256 pixels. These images were taken from original patient from Advanced Medical

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and Dentist Institute, in Bertam, Pulau Pinang, Malaysia. The determination of normal and abnormal brain image is referred at the symmetry that it is exhibits in the axial and coronal images [7]. Asymmetry in an axial MR brain image strongly indicates abnormality. Hence symmetry in axial MR images is an important feature that needs to be considered in deciding whether the MR image at hand is of a normal or an abnormal brain. A normal and an abnormal T2-weighted MR image are shown in Figure 1a and b, respectively. The lack of symmetry in an abnormal brain MR image is clearly seen in Figure 1. b. Asymmetry beyond a certain degree is a sure indication of the diseased brain and this has been exploited in our work for an initial classification at a gross leve automating the whole welding process. Metal Inert Gas welding is one of the most widely used processes in industry. The input parameters play a very significant role in determining the quality of a welded joint. In fact, weld geometry directly affects the complexity of weld schedules and thereby the construction and manufacturing costs of steel structures and mechanical devices. Therefore, these parameters affecting the arc and welding should be estimated and their changing conditions during process must be known before in order to obtain optimum results Upload sample image for segmentation. Before segmentation we have filtered image.

Image Dataset

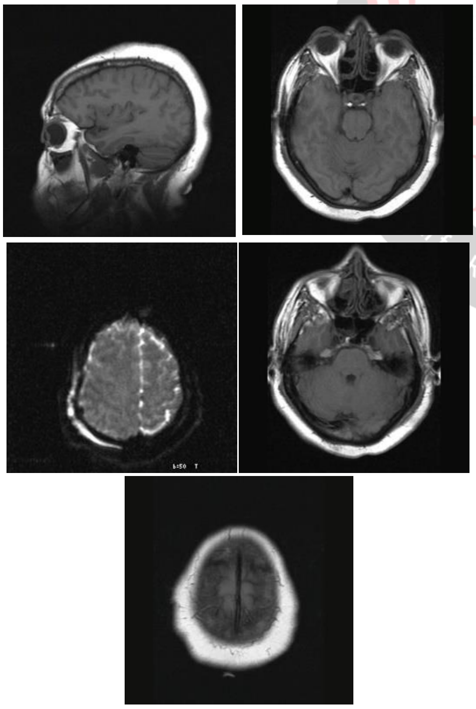


Fig 1. Brain tumor image dataset

Preprocessing

The preprocessing step improves the standard of the brain tumor MR images and makes these images suited for future processing by clinical experts or imaging modalities. It also helps in improving parameters of MR images. The parameters includes improvement in signal-to-noise ratio, enhancement in visual appearance of MR images, the removal of irrelevant noise and background of undesired parts, smoothing regions of inner part, maintaining relevant edges .

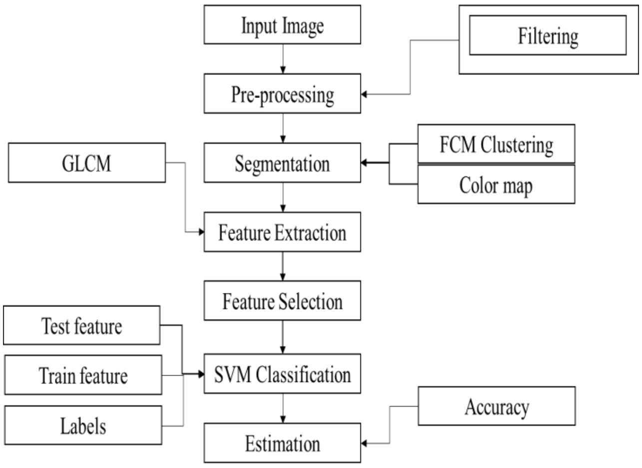


Fig.2 Block Diagram of the proposed system

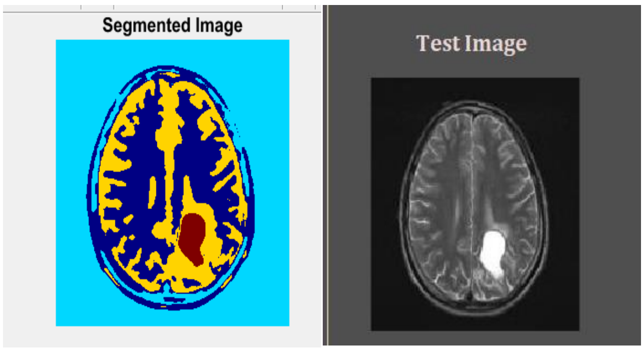
IV. RESULT AND DISCUSSION

Image Segmentation

The process of splitting an image into multiple parts is known as segmentation. It creates various sets of pixels within the same image. Segmenting an image makes it easier for us to further analyze and extract meaningful information from it. It is also described as “The process of labeling each pixel in an image such that they share the same characteristics”. The process results in pixels sharing a common property.

The paper uses Segmentation based on Algorithm. These are algorithms that are based on natural selection and evolution. These belong to a subclass of an evolutionary algorithm, as it uses evolutionary techniques and natural selection to solve optimization problems. It works on a heuristic and an iterative model.Thresholding is also a very popular and straightforward segmentation technique in use.

It creates a binary segmented image from a greyscale image. All it does is replace the pixel with a black pixel at a certain point if the intensity at that point is less than a certain intensity or replace it a with a white pixel if the intensity is more than that.



Input Image **Output Image**

Fig.3 Segmentation Process

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1.1 Feature Extraction

Gray-levl co-occurrence matrix (GLCM) is the statistical method of examining the textures that considers the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. We extracting features from MRI image Homogeneity, Correlation, Energy, Entropy.

Energy broaches the reverberation of pixel pairs of an image.

$$\text{ASM} = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} P_{ij}^2$$

Correlation is a measure linear dependancy of gray level values in co-occurrence matrices.it is a two dimentional frequency histogram in which discrete pixel pairs are accribed to each other on the basis of a specific,predifined displacement vector.

$$\text{Correlation} = \frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i,j)p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$$

Homogeneity is inversely proportional to contrast at constant energy whereas it is inversely proportional to energy.

$$\text{IDM} = \frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} P_{ij}}{1+(i-j)^2}$$

Entropy is a evaluate of non-unifomity in the image based on the probability of Co-occurrence values,it also signposts the complexity of the image.

$$\text{ENTROPY} = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} -P_{ij} * logP_{ij} \quad ...3$$

1.2 Classification

SVM Kernel

In machine learning, **kernel methods** are a class of algorithms for pattern analysis, whose best known member is the support vector machine (SVM). The general task of pattern analysis is to find and study general types of relations (for example clusters, rankings, principal components, correlations, classifications) in datasets.

The kernel function is a mathematical trick that allows the SVM to perform a 'two-dimensional' classification of a set of originally one-dimensional data.

Linear Kernel Function: Linear kernel function is commonly described. in fact do not have any kernel, you just have "normal" dot product, thus in 2d your decision boundary is always line.

Polynomial Kernel Function: The polynomial kernel function is directional, i.e. the output depends on the direction of the two vectors in low dimensional space. This is due to the dot product in the kernel. The magnitude of the output is also dependent on the magnitude of the vector.

$$k(\mathbf{x_i},\mathbf{x_j}) = (\mathbf{x_i}\cdot\mathbf{x_j}+1)^d$$

where d is the degree of the polynomial.

Radial Basis Function: Radial basis function is one of the most popular kernel functions. It adds a "bump" around each data point.

It is a general-purpose kernel; used when there is no prior knowledge about the data.

$$k(\mathbf{x_i},\mathbf{x_j}) = \exp(-\gamma\|\mathbf{x_i}-\mathbf{x_j}\|^2)$$

1.3 Evaluation Parameter

1. Recall

Recall can be defined as the ratio of the total number of correctly classified positive examples divide to the total number of positive examples. High Recall indicates the class is correctly recognized (small number of FN).

$$\textit{Recall} = \frac{TP}{TP + FN}$$

Recall=TP / (TP + FN)

2. Precision

To get the value of precision we divide the total number of correctly classified positive examples by the total number of predicted positive examples. High Precision indicates an example labeled as positive is indeed positive (small number of FP).

$$\textit{Precision} = \frac{TP}{TP + FP}$$

Precision = TP / (TP + FP)

3. F Measure

Since we have two measures (Precision and Recall) it helps to have a measurement that represents both of them. We calculate an F-measure which uses Harmonic Mean in place of Arithmetic Mean as it punishes the extreme values more.

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$$F - measure = \frac{2*Recall*Precision}{Recall + Precision}$$

Fmeasure= (2*Recall*Precision)/ (Recall+Presision)

4. Accuracy

Accuracy = (TP + TN) / (TP + TN + FP + FN)

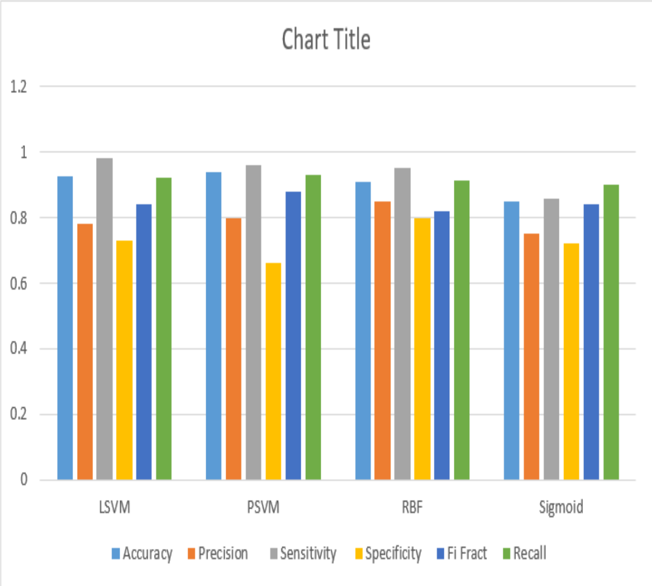

Fig.4 Comparative analyses graph of various method

Algo	Accuracy	Precision	Sensitivity	Specificity	Fi Fract	Recall
LSVM	0.925	0.78	0.98	0.73	0.84	0.92
PSVM	0.94	0.80	0.96	0.66	0.88	0.93
RBF	0.91	0.85	0.95	0.80	0.82	0.915
Sigmoid	0.85	0.75	0.86	0.72	0.84	0.9

Table 1: Detection accuracy of the proposed approach in testing data set

V. 5. CONCLUSIONS

In this methodology, we have fostered a striking tumor revealing technique by maneuvering kernel ascertained SVM. The propositioned outlook encompasses of preprocessing, segmentation, feature extraction and classification. In a preprocessing step, the noise is jettisoned and to instigate the image appropriate for the ensuing stages. In segmentation stage, the neoplasm regions are dissected over region growing method. In feature extraction, certain explicit feature will be extorted by manipulating texture as well from intensity.

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