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Tumour semantic segmentation and SVM classification using magnetic resonance imaging data

Srilekha Boda[1], Assistant Professor[1], Department of ECE, Siddhartha Institute of Technology & Sciences, Telangana, India

Kiran Kumar Thanniru[2], Assistant Professor[2], Department of CSE, Siddhartha Institute of Technology & Sciences, Telangana, India.

Abstract:

A brain tumour is a malignant growth of abnormal cells or tissues that causes damage to the brain. Brain tumour tissue detection is extremely challenging when examining the entire brain. The key to successful treatment is early tumour discovery. In modern times, detecting and segmenting the brain-tumour area from brain MRI pictures using detection or segmentation methods has proven to be a very helpful strategy. Magnetic resonance imaging is a challenging area of image processing because of the critical importance of precision in medical diagnostics. The supplied material includes one MRI scans. Brain tumour segmentation is the process of extracting MRI pictures of the brain from normal brain tissue. Pre-processing steps for MRI scans include applying filters like median filtering and cranium removal before submitting them to a thresholding procedure using the watershed segmentation technique. The tumour area is then divided and acquired. Then, in later phases, GLCM techniques implemented in MATLAB were used to retrieve the characteristics of interest. Support vector machine (SVM) was then used to classify the pictures; the algorithm achieved an average accuracy of 93.05%. Which is significantly superior to the usual versions.

Keywords:

Keywords: MATLAB, GLCM features, SVM classification, grayscale picture, MRI, skull removal, watershed segmentation, brain tumours

INTRODUCTION

A brain tumour is an abnormal growth of cells in the brain. There are the cells that rapidly replicate, leading to an abundance of abnormal tissue. That is medical jargon for growth. Malignant cells with the potential to metastasize to the brain. Benign and dangerous brain lesions are both possible. Malignant tumours develop quickly and can travel to the brain, where they damage healthy brain cells and put strain on the brain inside the cranium, while benign tumours grow slowly and are harmless. Some of the tumour cells are not malignant, but the ones that are pose a significant risk to the patient's life. MRI scans of the brain were necessary for pinpointing the exact position, type, and amount of a patient's brain growth. Using magnetic resonance imaging (MRI), brain lesions can be isolated from the rest of the brain. The annual incidence of brain-tumour illness is. over 125,000, and the annual death rate is over 97,000, as reported by the International Agency for Research on Cancer (IARC) [2]. Obtaining accurate tumour identification findings is crucial for saving patients' lives. There are a number of methods for obtaining brain pictures, but Magnetic Resonance Imaging (MRI) stands out. In terms of analysis, a Resonance Imaging scan is superior to other screening methods, including CT scans. Since it does not emit any radioactivity, it poses no health risks to humans. The combination of a powerful magnetic field and radio signals in an MRI scanner allows for the creation of highly informative pictures [3]. Tumour size and form are revealed through picture segmentation. Intensity-based thresholding is being used with this data to separate objects based on their brightness [4]. Digital Imaging and Communications in Medicine (DICOM) [5] is used to analyse and display information about medical pictures. Segmentation is the process of breaking down a computer picture into its component components, or clusters, of images, for use in medical applications. In the first stage, called pre-processing, filters like median filtering are used to strip pictures of background noise before they undergo the main processing phase. By employing median filtering, the value of each pixel in the incoming picture is changed to match that of the centre pixel. This effect softens the picture. The cranium reduction method is then used to isolate the brain region in the MRI scans, which otherwise show only bone. The watershed segmentation approach for identifying the cancer area uses a thresholding procedure in which a minimal luminance value of images is established automatically [6, 7]. As was previously stated, the thresholding method depends on the pixel luminance levels of the incoming picture. It can be used to isolate tumours in MRI scans of the brain. The watershed method successfully separates the baritenor from the surrounding healthy tissue in

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imaging studies [8]. Different colours at the designated regions are mentioned by the watershed segmentation technique. Herein, we present a method for extracting brain tumours and calculating GLCM characteristics like contrast, correlation, energy, and uniformity [6, 7]. Median filtration is used to clean up pictures before they are used [8, 9, 10]. The region of highest luminosity, indicative of malignancy, is thenidentified [11, 12, 13]. Then, 'support vector machine' is used to categorize the pictures based on the derived GLCM characteristics. (SVM). In Part II, we detail the methods we intend to use. In part III, the MATLAB output is shown. In part IV, all the study is summarized. A powerful magnetic field and a specific frequency range are used by MRI scanning machines to create MRI pictures. It creates high-resolution photographic pictures of a or a portion of the organism. The magnetic field used to create the images in an MRI scanner is about 10,000 times greater than the magnetic field of the planet. The DICOM file of the MRI pictures that have been saved. The DICOM pictures are then converted to jpeg files for simpler editing [5].

METHODOLOGY

This part provides examples of how to separate a brain tumour from an MRI scan. Median filtration (pre-processing), thresholding, watershed segmentation, and GLCM feature extraction make up the technique for segmenting Brain tumours. MATLAB R2019a has been used to realize that exercise. The Fig. 1 flowchart illustrates this process and describes it in detail.

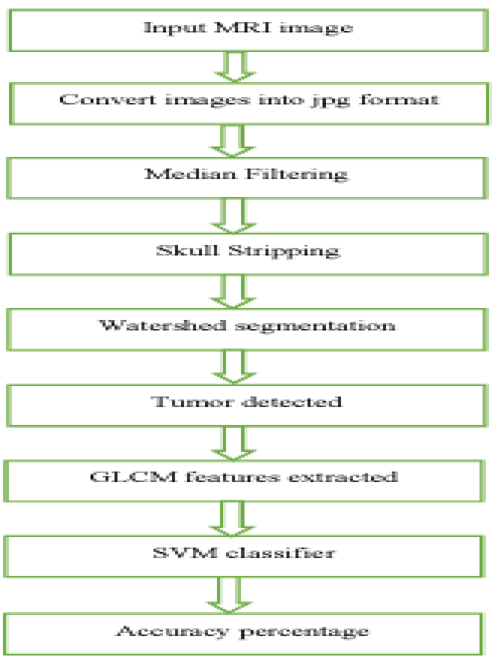

Fig. 1. Flow chart of the algorithm about brain tumour detection and

A. MRI Scan of obtained Brain Tumour Images

When dealing with MRIs, the luminance information is stored in an 8-bit picture, with values ranging from 0 (black) to 255 (white) [1]. These pictures are 512 pixels by 512 pixels in size. Grayscale pictures are a unique kind that only contain information about the luminance of the scene.

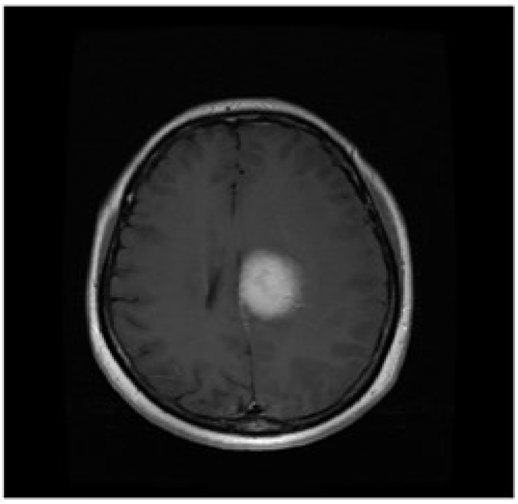

Fig. 2. The input brain tumour image

B. Median-Filtering

Median filtering is a useful technique for eliminating noise and improving the overall smoothness of a picture. After an MRI picture is captured or transferred to another device, noise can appear [11, 14, 15]. The removal of noise is the first stage in preparing a picture to increase its usability. The median filtration method averages neighbouring pixels to determine a new number for each individual pixel. Images can be altered or improved through a screening procedure. [16, 17]. To decipher the pixel numbers, one must first acquire the image's middle value. The median is then determined by taking the midpoint of the range of image luminance changes. (x, y). The median filtration algorithm is given in (1). The median filter always has a positive impact on the MRI picture. There appears to be blurring on the MRI scan. In Fig. 3 we see the final result of applying a median filter to the picture. The salt and pepper sounds can be eliminated using the median filtration method. The most common types of noise in MR pictures are Gaussian noise, Rician noise, and Rayleigh noise. The amount of the SNR can be used to determine the nature of the noise. Gaussian

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noise happens at signal-to-noise ratios (SNRs) higher than 2, and Rayleigh noise occurs as SNRs approach zero. However, here, with the aid of MATLAB 2019a, we use a median filtration method to get rid of the disturbance in the MR pictures.

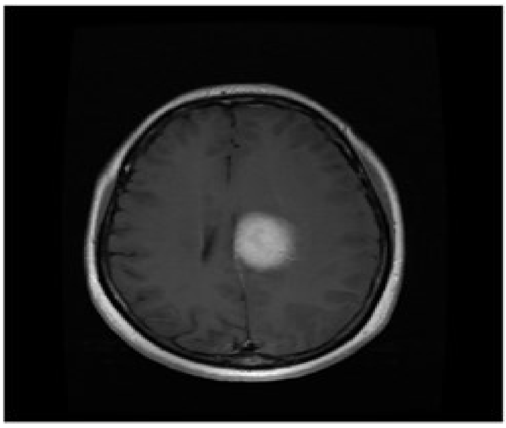

Fig. 3. Result of Median Filtering

C. Skull Stripping

These techniques use a morphological procedure involving attrition and elongation to remove the cranium area, including bones, from the raw brain MRI picture. The cranium stripping method removes the region of the MRI picture that contains the skull and bones, leaving only the brain. The success of this technique relies heavily on trial and error and the fine-tuning of picture characteristics [3]. Figure 4 depicts the cranium removal method. In order to remove the cranium, structural procedures are used. The MRI scans are then put through a binary thresholding procedure. This method makes use of attrition and elongation, two structural operations. Seed growth, superimposition, thresholding based histogram, anisotropic diffusion, cutting, and other techniques are also helpful for eliminating the cranium region.

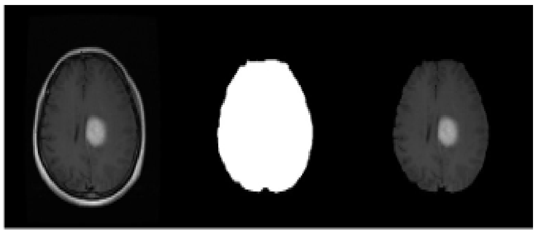

Fig. 4. Represents the result of skull removal operations.

D. Watershed segmentation of brain tumour:

An MRI image's centre and backdrop can be separated with the help of a method called watershed segmentation. After some preliminary processing, the system shows an MRI picture as an outline, defining only the pixels that are near its borders. This method aids in producing more accurate segmentation results. In addition, the segmentation process benefits greatly from this method when the image in question has sharp, well-defined margins, as these edges allow for superior separation from the rest of the picture. This article suggests a method for extracting and analysing the brain-tumour region from MRI scans of a patient's brain. The technique of segmenting watersheds is founded on the expansion of regions. After watershed segmentation, the outputs are further processed to extract the pictures' highest-intensity pixels, for which the system has previously chosen an average intensity value across all areas. The growth area has been marked off here. Grayscale pictures can be converted effectively using watershed. The purpose of this method is to separate parts of a picture that are physically near together. In the watershed segmentation method, the lowest possible luminance value of a picture is used as the cut-off. When processing an MRI picture, the luminance values of each pixel are compared to the image's cut-off value, also known as the bare minimum value.

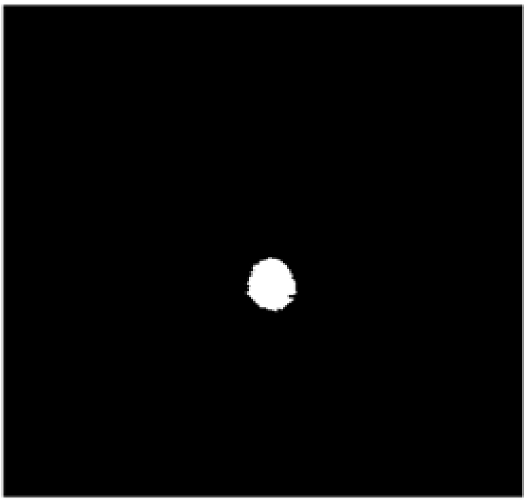

Fig. 5. Result of tumourdetected.

E. Calculation for GLCM feature extraction.

Grey Level Co-occurrence Matrix is the program used for MRI feature extraction. (GLCM). Contrast, association, energy, and uniformity are just some of the characteristics of MRI pictures that can be calculated using this method [5]. 1) Contrast, which characterizes the difference in brightness between neighbouring or contiguous cells in MRI scans.

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$$Contrast = \sum_{x,y=0}^{K-1} P_{xy}\ (x-y)^2 \qquad (2)$$

2) Correlation: It presents the relation among the pixel information of an MRI image.

$$Correlation = \sum_{x,y=0}^{K-1} P_{xy}\ \frac{(x-\mu)(y-\mu)}{\sigma^2} \qquad (3)$$

3) Energy: The energy presents the similarity among the pixels in an MRI image and define the repetitions of the pixels having same values.

$$Energy = \sum_{x,y=0}^{K-1} \left(P_{xy}\right)^2 \qquad (4)$$

4) Homogeneity: The homogeneity define the region in which the image should be textured [6].

$$Homogeneity = \sum_{x,y=0}^{K-1} -ln\left(P_{xy}\right)P_{xy} \qquad (5)$$

Pixels in these MRI pictures have x and y coordinates, and the GLCM has a dimension of (K), and the likelihood of a pixel's appearance is shown as (P). (2, 3, 4, 5).

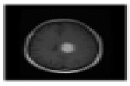
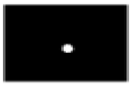
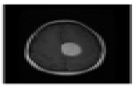
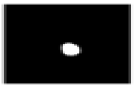
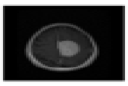
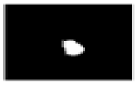
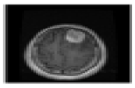
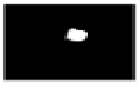
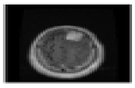
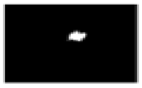
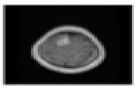
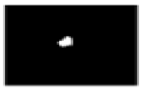
F. Classification of images using SVM classifier

The second half of this article, which focuses on categorization, is discussed now [18, 19]. While findings can be obtained using other classification methods (Convolutional Neural Networks, Artificial Neural Networks, etc.), SVM classification is used here due to its effectiveness. In this work, we compute a set of characteristics for MRI brain scans. The characteristics are dissimilarity, similarity, energy, and uniformity [7]. Methods of categorization: 1. Extraction of GLCM Features The SVM algorithm is then used to learn and evaluate the MRI dataset. Third, tumour and normal pictures from the collection are isolated from one another. Images' grey level co-occurrence matrix (GLCM) and other characteristics are computed for SVM categorization. The pictures are then sorted into categories based on the numbers it has assigned to them. Data analysis and picture clustering take place in the SVM categorization, a guided machine learning technique. Fast picture classification and processing on massive data sets are two of its many strengths. The data was trained using 36 pictures and then tested using 26. The quantity of tumorous and healthy pictures is about the same. In this machine learning approach, a judgment limit consisting of pictures from various regions has been generated using a support vector machine classifier.

EXPERIMENTAL RESULT

Using a morphological process for cranium removal and a watershed segmentation method, the suggested study has successfully located the tumour area in 36 brain MRI pictures. The process is continued by deducing contrast, association, energy, and uniformity, the four GLCM characteristics of these pictures. Then, in the second stage, a support vector machine (SVM) classification is used to assign labels to the pictures, with an average accuracy of 93.05%. A variety of SVMs (support vector machines) were employed in the suggested study to categorize the pictures into distinct classes. Below are examples of split images:

Table 1: Tumour segmentation results from someMRI images

No.	MRI Image	Tumor Segmentation
1.		
2.		
3.		
4.		
5.		
6.		

The proposed work has detected tumour region for all the images those have tumours, but some images are shown in.

this research paper. Further, all six SVM classification results are illustrated below:

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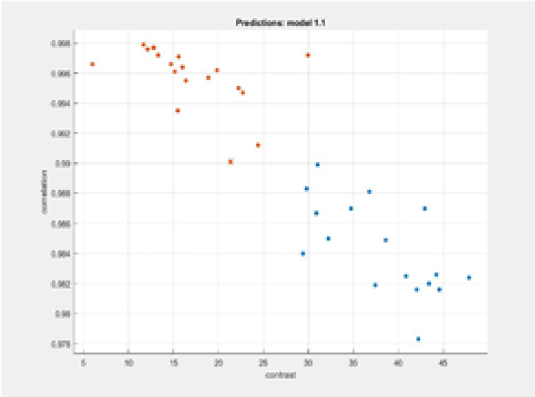

Fig. 6. Linear SVM classification of 36 images

Figures 6–11 display tumour pictures in red and typical images in blue. Using SVM, we can distinguish between 18 pictures with tumours and 18 regular ones. Class 1 pictures are considered typical, while class 2 images depict a brain growth.

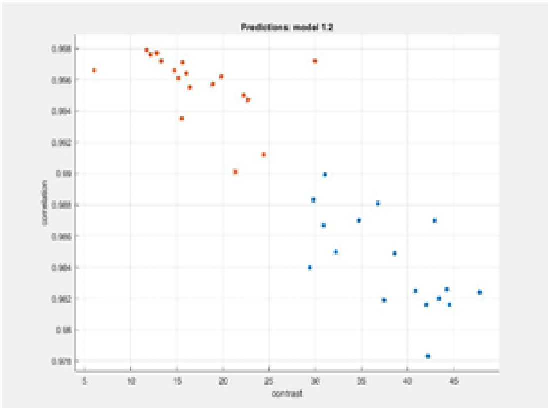

Fig. 7. Quadratic SVM classification

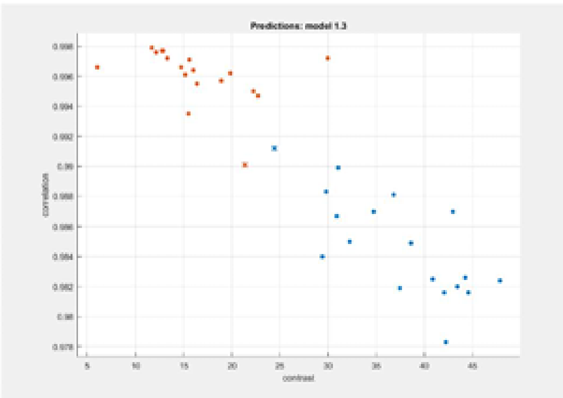

Fig. 8. Cubic SVM classification

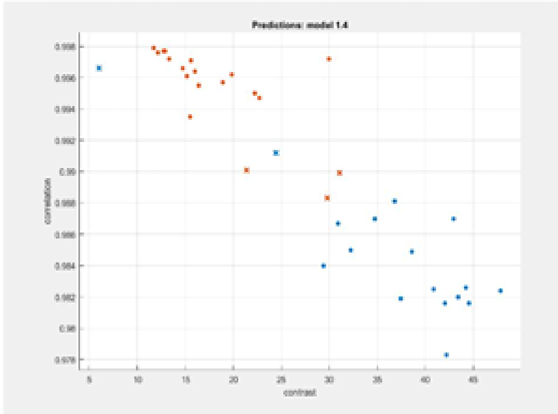

Fig. 9. Fine Gaussian SVM classification

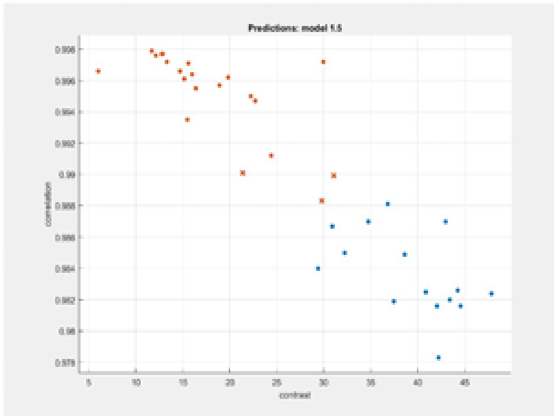

Fig. 10. Medium Gaussian SVM classification of thirty-six images

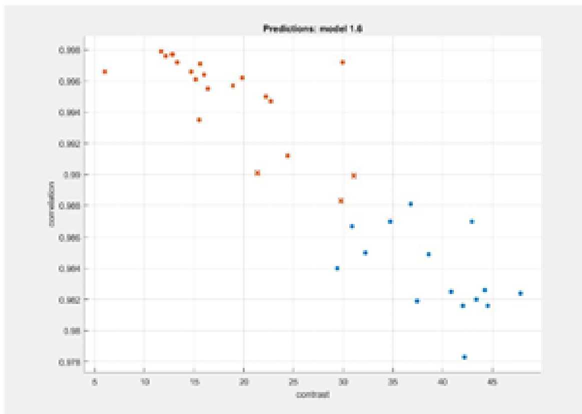

Fig. 11. Coarse Gaussian SVM classification

Table 2: SVM Classification of 36 Brain MRI Images

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No.	SVM Classifiers	Accuracy percentage
1.	Linear SVM classification	97.2%
2.	Quadratic SVM classification	97.2%
3.	Cubic SVM classification	94.4%
4.	Fine Gaussian SVM classification	86.1%
5.	Medium Gaussian SVM classification	91.7%
6.	Coarse Gaussian SVM classification	91.7%

CONCLUSIONS

The identification of brain tumours is a crucial part of medical picture analysis. Due to the presence of noise in MRI images and the fact that the cranium sometimes shares an intensity profile with the brain tumour area, the experimental findings show that median filtering and skull stripping should be performed as a pre-processing step before segmentation of the brain-tumour region. Multiple support vector machine models are used to improve precision on average. Proposed model's gained average precision is significantly higher than that of the status quo. Images' contrast, association, energy, and uniformity are among the GLCM characteristics that can be calculated. After that, a support vector machine (SVM) will be used to determine whether a picture contains a growth or not. Additional machine learning models could be implemented to increase precision, even for low-light pictures, expanding the research's potential applications.

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