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MRI Based Detection of Brain Tumor using Advanced Image Processing Techniques

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Abstract: Brain tumor detection is essential for early diagnosis and treatment planning for patients. In recent years, image processing algorithms have evolved into practical instruments for automatic and trustworthy tumor diagnosis from medical imaging data. This study presents a novel method for image processing-based brain tumor detection. The suggested method employs a number of preprocessing steps to lower noise and enhance the clarity of brain images. Included are contrast enhancement, noise reduction, and image scaling. After preprocessing, the brain region is separated from the background using image segmentation methods, which also help to isolate potential tumor spots. To extract important properties from the segmented brain areas for tumor identification, several feature extraction techniques are applied. These criteria capture important characteristics of the tumor, like form, texture, and intensity variations. Following feature retrieval, a classifier is trained to differentiate between tumor and non-tumor regions. To evaluate the effectiveness of the recommended method, experiments are conducted with a collection of brain images that includes both tumor and non-tumor cases. The results demonstrate the excellent accuracy and efficiency of the suggested approach for brain tumor detection. The benefits of the proposed strategy in terms of computing efficiency and detection accuracy are shown through comparisons with current methods. All things considered, the proposed image-based brain tumor detection system holds great potential to assist medical practitioners in the early detection of brain cancers. It can lead to better patient outcomes by enabling prompt intervention and customized care.

Keywords: *Brain tumor, tumor detection, image processings, canny edge detection*

1. Introduction

Using magnetic resonance imaging for medical diagnosis Because the outcome is vital for patient care, the prediction algorithms' robustness and accuracy are highly significant. One of the most important steps in the planning of surgery and treatment is brain tumor segmentation. However, brain tumor imaging segmentation is now mostly done manually in clinical practice. Manual brain tumor delineation is challenging and operator-dependent, in addition to being time-consuming. Low-level procedures are quick and easily adjustable; examples include thresholding, edge detection, and morphological approaches. Nonetheless, the effectiveness of these techniques for tumor segmentation is largely dependent on the discernible variations in intensity between the tumor and non-tumor regions.

The region-growing and watershed techniques are straightforward and reliably yield entire borders. Unfortunately, the sensitivity of these two approaches to noise is a common issue with the intensity-based strategy. Moreover, because edema produces weak and diffused edges, the majority of intensity-based techniques have a tendency to over segment tumors. Unsupervised learning techniques like fuzzy clustering and k-means have become more and more popular in recent years for brain tumor segmentation. The fuzzy approach is a very potent tool for medical image processing since it acknowledges that medical images are inherently hazy. Moreover, the fuzzy approach can capture pixel proximity in the same objective region without a training phase. Nevertheless, the majority of fuzzy techniques perform badly when segmenting non-enhanced tumors and are only successful for hyper-intensity tumors. These circumstances arise from the fact that these fuzzy approaches frequently employ intensity-based pre- or post-processing techniques, like morphological operations and thresholding.

The method of supervised classification learning is widely applied in tumor segmentation. Trained classifiers are able to predict the label of every voxel in a testing volume by extracting discriminative information from the training set. The spatial relationship between the current and surrounding voxels is not taken into account by traditional classification algorithms, which instead group each voxel into distinct groups. An output that is globally optimized may not be obtained by this method. Typically, to address this problem, a regularization phase is combined with a classification algorithm. Regularization can be achieved by using a random field spatial prior (MRF/CRF) or by modeling the boundary.

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Previous studies have gotten good segmentation results without using posthoc regularization by using context-aware spatial data and the probabilities generated by tissue-specific Gaussian mixture models as inputs for classifiers.

2. Related Work

According to authors from 2023, brain cancer is a rare growth of extra nerve cells inside the brain that impairs brain function. Numerous lives have been lost as a result of it. Time is needed for the proper cure and timely discovery of this disease in order to save people from it. The process of identifying cancer-affected brain cells is laborious and time-consuming. However, a significant obstacle in the field of image processing is the time and precision needed to identify brain tumors. This study suggests a brand-new, precise, and enhanced method for identifying brain tumors. The preprocessing, segmentation, feature extraction, optimization, and detection processes are all followed by the system. A compound filter, or composition filter, is used in preprocessing systems. Image segmentation is accomplished using threshold and histogram algorithms. Feature extraction is done using the grey level co-occurrence matrix (GLCM). Here, the optimized convolution neural network (CNN) technique is used to choose the best features by the application of whale and grey wolf optimizations. CNN classifier is utilized in the detection of brain tumors.[1] Using metrics for accuracy, precision, and recall, this system evaluates its performance against another contemporary optimization method and asserts its superiority. The programming language Python is used to construct this system. This refined technique has a 98.9% accuracy rate in detecting brain tumors.

Authors reported in 2023 that the brain's unchecked and fast cell development is what causes cancer. It may prove lethal if left untreated in the early stages. Accurate segmentation and classification remain a difficulty despite many noteworthy efforts and promising results. The differences in cancer position, structure, and proportions make brain cancer detection extremely difficult. This study's primary goal is to provide researchers with extensive literature on the use of magnetic resonance imaging (MR) to detect brain tumors. This study suggested multiple methods for detecting tumors, including brain cancer, using statistical image processing and artificial intelligence approaches. An assessment matrix for a certain system employing particular systems and dataset kinds is also displayed in this study. The morphology of brain malignancies, available data sets, augmentation techniques, component extraction, and classification of Deep Learning (DL), Transfer Learning (TL), and Machine Learning (ML) models are also covered in this work. Lastly, our study gathers all pertinent information for the identification and comprehension of tumors, including their advantages, disadvantages, developments, and future trends.

The goal of artificial intelligence (AI) is to build machines that function and behave like humans. Apart from pattern recognition, planning, and problem-solving, artificial intelligence-based computer operations encompass additional tasks. Machine learning makes use of a collection of algorithms known as "deep learning." Deep learning is applied to develop brain cancer classification and detection models using magnetic resonance imaging (MRI). This makes it possible to identify brain tumors quickly and easily. Most brain illnesses are caused by abnormal brain cell growth, which can damage the brain's architecture and eventually lead to malignant brain cancer.

Early detection of brain tumors and prompt treatment after diagnosis could reduce the death rate. In this work, we propose an architecture of convolutional neural networks (CNNs) for the effective identification of brain tumors using magnetic resonance imaging.In [3] Additionally, this article compares the suggested architecture with a number of models, including ResNet-50, VGG16, and Inception V3. Several parameters, including accuracy, recall, loss, and area under the curve (AUC), were taken into consideration in order to assess the models' performance. Using these criteria to compare several models with our proposed model, we were able to determine that the suggested model outperformed the others.

We discovered that the CNN model had 93.3% accuracy, 98.43% AUC, 91.19% recall, and 0.25 loss using a dataset of 3264 MR images. Comparing the suggested model to the other models allows us to conclude that it is dependable for the early identification of various brain tumors.

One of the most deadly and serious diseases in the world today is brain cancer. In an infected person's brain, it manifests as irregular and out-of-control cells. If glioblastomas are not detected early, over 60% of them develop into big tumors. Although there is a wealth of useful material on cancer diagnosis, overall performance could be enhanced. The medical field has made extensive use of machine learning (ML)-based methods for early disease diagnosis.[4] The performance of the brain cancer detection procedure may be enhanced by the application of machine learning approaches in conjunction with enhanced image-guided technologies. This article presents a brain cancer detection method based on machine learning. Support vector machines with adaptive backpropagation neural networks (ABPNNs).

The ABPNN and SVM results are fused using fuzzy logic. The BRATS dataset is used in the development of the suggested method. The ABPNN model demonstrated 98.67% accuracy during the training phase and 96.72% accuracy during the testing phase, according to experimental results. In contrast, the SVM model achieved accuracy levels of 98.48% and 97.70% in both the training and testing stages. The overall accuracy of the suggested technique achieves 98.79% and 97.81% for the training and testing phases, respectively, after utilizing fuzzy logic for decision-based fusion. A comparison with current methods demonstrates how superior the suggested method is.

The brain's aberrant cell proliferation gave rise to brain tumors. There are two categories of medical imaging devices: brain tumors are commonly scanned with MRI and CT scanners. The internal organs of the brain can be scanned with MRI pictures. Brain tumors can be classified as either benign or malignant. A brain tumor classified as benign is curable, while a brain tumor classified as malignant is incurable. There are two varieties of malignant brain tumors: gliomas and astrocytomas[5]. A radiologist diagnosing and identifying a brain tumor by traditional methods. Delays and errors are far too common. Imaging technicians cannot manually identify and segment the vast amount of brain tumour images that neurosurgeons produce.

3. Proposed System Architecture

Figure 1 depicts the suggested system design. Preprocessing is done on the input MRI images of brain tumors to reduce noise and boost picture intensity. Following picture preprocessing, the edges of the images are detected using the clever edge detection technique. The input images are then segmented using a Gaussian filter. To extract relevant features from segmented images for classification, use the segmentation feature extraction process. In order to determine whether or not the input images are tumor images, the LIMC classifier is finally used.

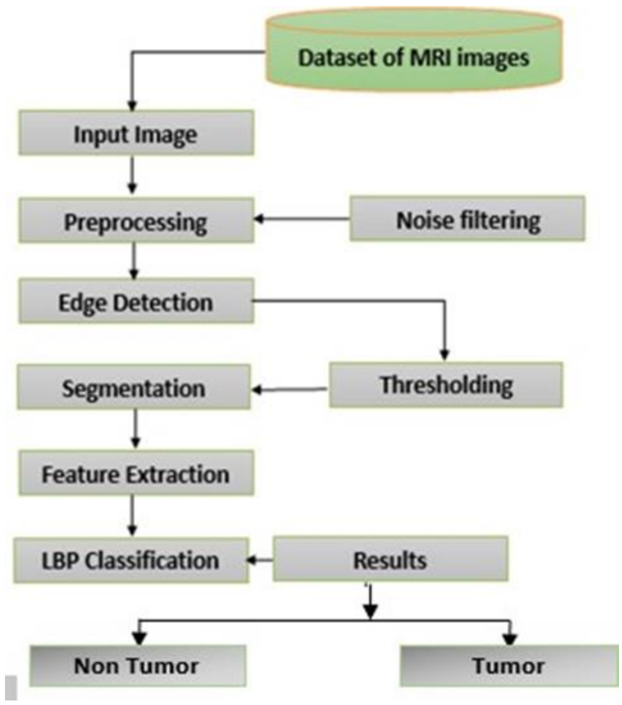

Fig. 1. Block Diagram.

3.1 Image preprocessing using Gaussian Filters

The following list outlines the different types of graphics published

This is the action taken before the primary image processing task. Here the objective is to finish a few basic tasks so that the generated image is better suited for the task at hand. In this case, it might mean lowering noise and boosting contrast. As a result, Fig. 4 displays the outcome.

3.2 Calculating the Threshold

An integrated function that use a grayscaled image to compute the threshold is used to determine it. The filtered image that was acquired in the earlier stages is largely used to compute the threshold. The limit for recognizing brain lesions in an MRI image is calculated using the threshold. Fig. 5 displays the outcome of the threshold calculation.

3.3 Edge detection

A method for identifying edges that denote a grayscale image's boundary based on comparable intensity levels is called "canny edge detection." Before doing this, a color image (i.e., an RGB image) is transformed to a grayscale image if needed for easy brain tumor identification. You can see this in Fig. 6.

3.4 Contour

To acquire the image's contoured borders for improved results in later phases, the greyscale image is converted into a binary image and overlaid with the greyscale image. Based on the plateaus and ridges of the brain lesions, contouring is done to better understand them. Fig. 7 shows the outcomes of this procedure.

3.5 Segmentation

In order to analyze the grayscale image of the brain and locate lesions and tumors, this stage involves segmenting the image. It improves image quality by working on the filtered image produced by Gaussian filtering. The goal is to identify anomalies in the brain in order to design treatments and make diagnoses. Fig. 8 shows how this procedure turned out.

3.6 Patch Segmentation

To provide a thorough analysis, the image is separated into four quadrants following segmentation. As a result of this division, malignancies can be identified with more precision because each quadrant can be carefully examined for anomalies. Figure 9 displays the outcome of this procedure.

3.7 Feature Extraction

Our approach uses the Local Binary Patterns (LBP) technique to extract the brain image's numerical elements. These characteristics help to identify brain tumors in the given grayscale picture. The 261 features that each patch segment produced by the prior method yields are essential for analyzing and determining whether brain tumors are present. The features that were retrieved are shown in Fig 10.

3.8 Classification

Using training and testing sets, segmented images are classified using the LIPC method. This method uses a machine learning technique called the LIPC algorithm to distinguish between MRI pictures that include tumors and those that do not. It is essential to our effort since it helps us identify and classify tumorous and non-tumorous photos accurately using patterns we've learned. The finished product is shown in Fig 11.

4 Results and Discussion

Hospitals are the source of the used dataset. Figure 2 displays a sample of the dataset.

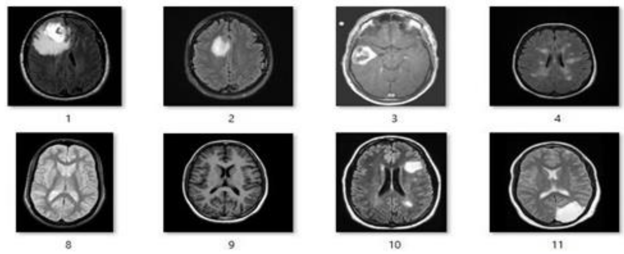

Fig 2. MRI Scans of Brain

Figure 3 displays the result of the Gaussian filter, which is used to reduce noise and enhance the intensity of the input images.Prior to processing

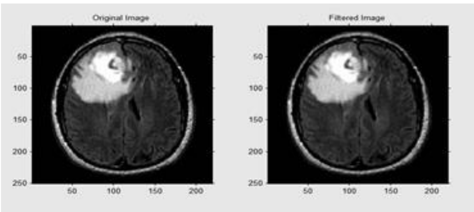

Fig 3. Image after applying gaussian filter

The Threshold Calculation for the preprocessed images is shown in figure 4**.**

Fig 4: Threshold value after calculation

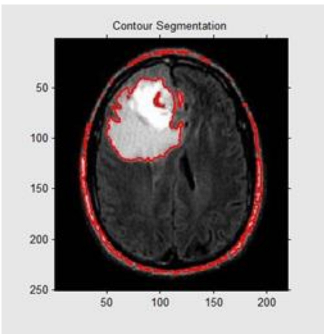

Fig 5 : Canny edge detection

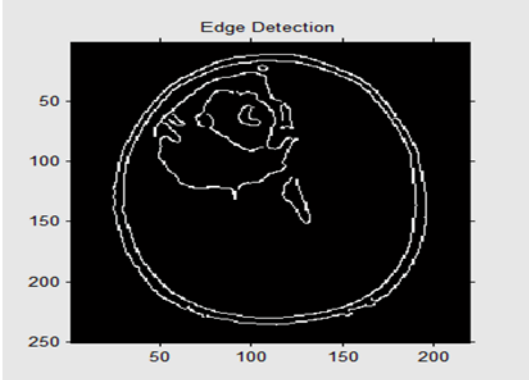

Fig 6: Contoured image

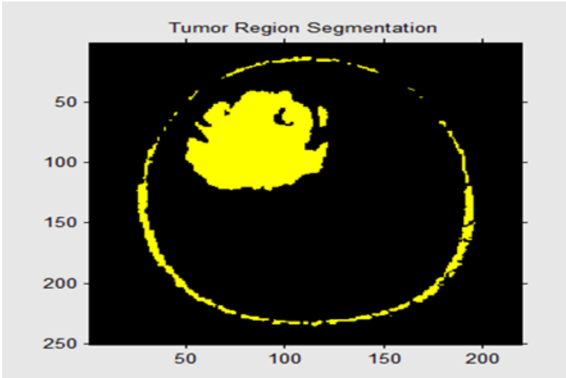

Fig 7: Segmentation of the tumor region

After threshold calculation canny edge detection algorithm is applied to detect the edge and sample output is shown in figure 5. The contour and segmented images are shown in figures 6 and 7 respectively.

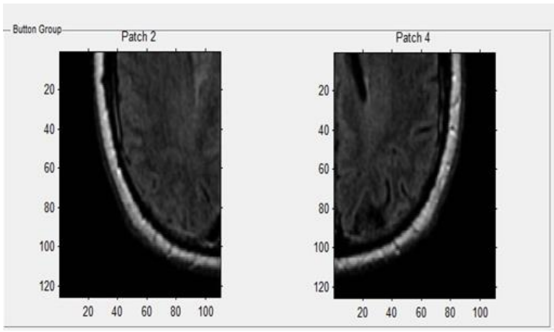

Fig 8: Splitting of filtered image

Patch Segmentation outcome is shown in figure 8.After segmentation features extraction technique is applied and extracted features are shown in figure 9.

	1	2	3	4
1	44928	175	222	281
2	36709	155	165	213
3	44583	119	226	267
4	35623	180	200	276

Fig 9: Features extracted

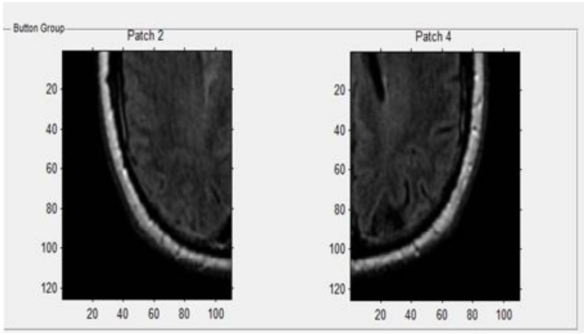

Fig 8: Splitting of filtered image

Equations

i. The equation we used to apply the gaussian filter for the 2D image is as shown below:

$G(x, y) = (1/(2 * \pi * \sigma^2))* \exp(-(x^2 + y^2)/(2 * \sigma^2))$ --------- 1

ii. The LBP algorithm calculates a binary code for each pixel in an image based on its local neighbourhood. The equation for LBP calculation used is:

$LBP(x\_c, y\_c) = \sum(g\_p * 2^p)$ *for* $p = 0$ *to* $P – 1$ 2

where (x_c, y_c) represents the central pixel coordinates, g_p is the binary value (0 or 1) of the p^{th} neighbouring pixel, and P is the total number of neighbours in the defined neighbourhood

iii. The equations used for the canny edge detection are as follows. Let Gx and Gy represent the gradients in the x and y directions, respectively:

The gradient magnitude (G) can be calculated as:

$G = \sqrt{(Gx^2 + Gy^2)}$ 3

The gradient direction (θ) can be calculated as:

$\theta = atan2(Gy, Gx)$ 4

Conclusion

image processing methods are essential for the identification of brain tumors. Generally, the procedure entails processes like segmenting grayscale images, analyzing the brain image, and using filters like Gaussian filtering. Tumors and lesions can be recognized by analyzing the photos and extracting pertinent features. These methods help with precise tumor categorization, size prediction, and location. All things considered, image processing makes it possible to have better diagnostic tools, helps with treatment planning, and advances the identification of brain tumors and medical results.

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Author contributions

Meghana G R: Conceptualization, Methodology, Software, Field study **A. Sasi Kumar:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Chandru Jathar:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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