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IDENTITY THE EXTRACT BRAIN TUMOR VOLUME USING EDGE DETECTION ALGORITHM USING DEEP LEARNING MODELS

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ABSTRACT:
Brain tumours are a potentially fatal condition characterized by the abnormal development of tissues within the brain. According to the cell types present in a tumour, it can be divided into benign and malignant categories. Benign tumours are noncancerous and possess a rudimentary size and shape. In addition, malignant tumours are considered cancerous and lack clearly defined borders. So many imaging techniques for interior body evaluation and analysis have been introduced by modern technology. Edge detection methods are implemented to diagnose numerous diseases due to their superior accuracy and quality compared to other methods. Utilizing standard approaches to diagnose brain cancers utilizing MRI and identifying their characteristics is challenging due to the complexity of the brain. Hence, image processing methods can be utilized to automatically and effectively detect and extract features from brain tumours. This work proposes a five-step approach for identifying and features extracted of brain cancers, including preprocessing, skull stripping, detecting tumours in axial, coronal, and sagittal planes, determining tumour location, and features extraction. Effectively identifying a brain tumour and its characteristics will be facilitated by the study's findings for physicians and medical technicians.
Keywords: brain tumer,edge detection ,image segmentation,

INTRODUCTION:

The brain is one of the body's most complex systems due to the variety of daily obstacles it must face. The abnormal growth pattern caused by uncontrolled cell division is what makes brain tumours so hazardous. The group of cells will alter the behaviour of brain activity, so compromising the healthy cell. But, only skilled neurosurgeons are now able to manually separate and evaluate intrinsic MRI imaging of brain tumours, a laborious and time-consuming operation. Digitally processing MRI scans is an essential aspect of the field. Therapeutic radiologists routinely use X-rays to assess the progression of tumours. Both children and adults can develop a brain tumour [1]. Tumors frequently cause a high concentration of cerebral fluid throughout the brain stem. Normal brain function is disrupted by a malignant tumour within the skull. Tumors may be a cause of cancer, the second leading cause of death worldwide (responsible for around 15% of all deaths) [2]. The NCI anticipates that there will be 22,070 new cases of brain cancer and associated diseases of the central and peripheral nervous systems in the United States in 2009. In 2013, the American Brain Tumor Association (ABTA) documented 63,930 new cases of brain tumours in their initial stages [3]. Figure 1 depicts a malignant brain tumour. There is currently no simple approach for determining the cause of brain tumours. Nonetheless, radiation contamination during imaging techniques such as MRIs, X-rays, and CT scans remains an issue. Nevertheless, radiation contamination during magnetic resonance imaging [4], computed tomography (CT), and x-rays can result in severe convulsions and lasting brain damage. Brain tumours are characterised by severe seizures, loss of consciousness, brain function, neurological disorders, numbness, speech difficulties, hormone abnormalities, and changes in personality. The most current conventional method of diagnosis relies on human experience from the perspective of choice in the MRI scan, which raises the probability of erroneous identification and recognition of a cerebrum tumour. This technique utilised Digital Image Processing (DIP) to facilitate the detection of tumours. Medical image segmentation played a key role in the research since segmenting brain illness images accurately brought new challenges. Radiologists conduct visual examinations using diagnostic imaging instruments such as CT and MRI scans. MRI imaging is being used to investigate the brain's structure, tumour size, and tumour location [6]. Imaging is necessary for an accurate diagnosis of brain cancer. Tendon MRIs frequently reveal iso or hypo tensive patterns. When the building's components are referred to as sides, there are sudden variations in the building's grey tones. Images with varied shades of grey assist edge identification techniques in transforming images into edges. The optimization map goes beyond merely altering the physical properties of the source image. The MRI pictures analysed by the radiologists revealed details such as the location of the tumour, a straightforward procedure for diagnosing it, and how to prepare for surgical operation [7]. Brain tumours in Figure 1 represent a vitiated section of the cerebrum. [Kumar S, et al .2022]

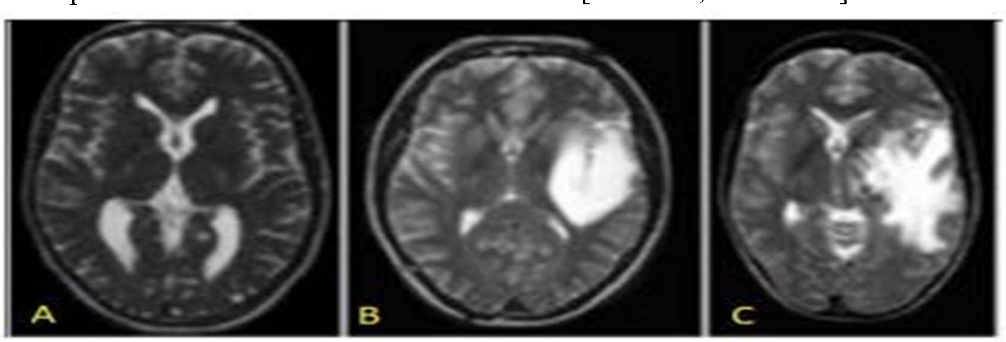

Figure 1: (a) Normal Brain, b) Benign Tumor, c) Malignant Tumor.

Using a strong magnetic field and radio waves, magnetic resonance imaging (MRI) reveals the concealed organ. Patients are not exposed to hazardous quantities of ionising radiation during magnetic resonance imaging (MRI) [8]. A significant advantage of MRI scanning is that it does not employ ionising radiation. As a result of developments in computer vision algorithms, MRI scans may now be analysed more precisely. The processing of brain images is crucial for medical diagnostics and therapies [9]. The ability to generate images that reveal the inner workings of the human body makes it possible to identify cures. The processing of medical images is beneficial for both patients and professionals. Correct; one of the most common purposes for optical computer vision applications is to refine images using a range of techniques. Using image processing to diagnose brain tumours has been a standard practise for decades. Researchers have discovered a variety of semiautomatic methods for detecting brain tumours, as well as a number of impulsive computer vision methods. Unfortunately, the majority of them do not provide useful and accurate results [10] because to the prevalence of noise and poor, dissimilar images in medical imaging. Due to the intricacy of the brain, effectively detecting and segmenting brain tumours in their early stages is difficult. Regarding cancer, edoema, and decomposing tissue, this diagnostic instrument is necessary. Normal brain stems are quickly harmed by cancer, resulting in edoema, increased pressure on brain areas, and increased skull pressure. Personalization streams are currently led by mathematical models, and numerous arithmetic trends are used to store patient data [11].

LITERATURE SURVEY:

Before the widespread adoption of deep learning systems, computer vision researchers produced a number of unique and moderately effective brain tumour detection approaches. Early classification approaches need the identification of meaningful features for the intended classification target by domain experts. Using statistical analysis or a technique based on deep learning, these designs are then used to evaluate individual differences (Arya Sharma). Recent usage of MRI in informatic computer vision by Islam et al. [12] With Magnetic Resonance Imaging (MRI), malignancies of the cerebrum can be rapidly identified and localised. We propose to classify cerebrum scans into eight categories, with seven representing distinct, many tumour types and one representing a healthy cerebrum. Validation of the univariate approach used for the suggested categorization strategy. The segmentation of brain tumours has attracted considerable attention in recent medical imaging investigations [13]; Joshi et al. Monitoring and recovery are only possible with quantitative disease modelling measurements. MR is common in the initial periods. The condition makes it more difficult to detect brain disorders such as cerebral infarction, brain tumours, and infection. Backpropagation of the neutrals order procedure is employed by Deepak et al. to describe a way for the ordering of MRI images [5]. The method is created using image improvement, registration, nature identification, and isolation techniques. In the segmentation process, morphological methods and threshold values are taken into account. The Neural Network (NN) backpropagation technique is used to evaluate them. 3 Kumar S, et al. OPEN ACCESS Freely accessible online J Tumor Res, Vol. 8 No. 2 1000165 training images and experiments to identify the presence of a cerebellar tumour. [10] Sasikala et al. discover a new technique for autonomous tumour identification using a deep neural network to detect glioblastoma. It employs a final layer that employs rapid segmentation, which takes between 24 seconds to 3 minutes for the entire lungs region. [11] Kiranmayee et al.

devised a strategy for detecting brain cancers that combined training and testing. The functionality of the proposed algorithm has been proven through the development of a blueprint application. The prototype's results indicate that emotionally supportive networks can be linked with pharmacological services to increase service quality. Arya et al.
[12] claimed that histogram-based, watershed, SVM-based, and MRF segmentation can be implemented as a module to achieve improved accuracy and a reduced error rate. Demirhan et al. consider partitioning methods for MRI classification of cerebrum malignancies. SWT, LVQ, and grey matter [3] are used to study CSF, edoema, WM, and GM. The average similarity between grey matter, cerebrospinal fluid, edoema, and white matter was 0.87 percent,
0.96 percent, 0.77 percent, and 0.91 percent, respectively. Aneja et al. [1] employ the FCM and partitioning technique, which works in conjunction with the FCM cluster to combat image noise. The segmentation value is determined by the cosine similarity parameters, the latency, and the converging regression coefficient of 0.537 percent. Kunam, et al. Apriori k-means grouping, k-nearest neighbour classification, fp tree-based association collecting, and random forest are statistical methods used to study such operations employing internal and external evaluation techniques [6]. In connection with the experiment reported in this study, the following techniques are implemented: There are three main ways to data mining, each with its own set of algorithms. In nearly all circumstances, the interface has an overhead of less than 10%. Each of the four statistical approach methods produces an excellent act of equivalence. If a decision tree construction method materialises, spectacular execution will require a variety of strategic shifts. A tumour was discovered by Siar et al. using a Deep Convolutional Neural Network (DCNN) [10]. The DCNN was the initial location where images were discovered. The classification accuracy of the Softmax Fully Connected (SFC) plate used to classify the images was 98.67 percent. The Convolution Neural Network's (CNN) precision is 97.34 percent when using RBF grasses and 94.24 percent when using DT analysis.

Proposed Methodology

Brain tumour detection can be one of the most difficult challenges in medical image processing. Brain tumours come in a range of shapes and textures, which makes the detection process complex. Many cell types contribute to the creation of brain tumours, and these cells can provide information about the tumor's origin, severity, and rarity. The location of a tumour can reveal information about the type of cells responsible for its development, thereby aiding in its diagnosis. The difficulty of diagnosing brain tumours may be exacerbated by the inherent limitations of nearly all digital pictures, such as lighting concerns.

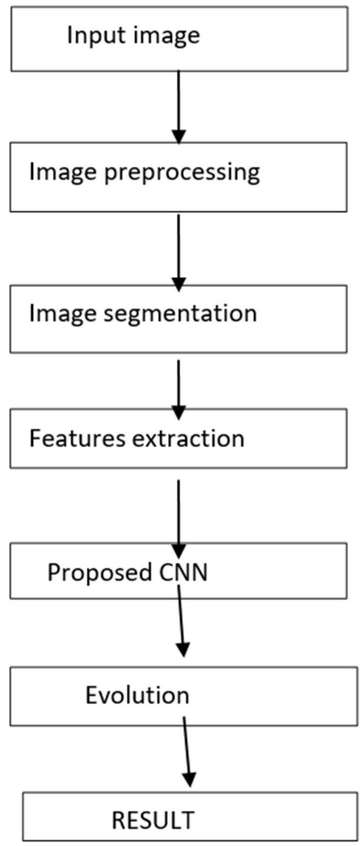

Figure 2: methdology

Dataset Collection

Early diagnosis and classification of brain tumours is a crucial topic of research in the field of medical imaging, as it aids in the selection of the most effective treatment strategy to preserve patients' lives. The UCI repository was leveraged to collect the training and testing datasets. It is comprised of 250 brain MRI images. There could be 150 photos of tumours and 100 photographs of normal tissue. The images come in various sizes and formats. This collection features photographs of brain x-rays taken from people diagnosed with a brain tumour. The growth within a confined space that causes problems in brain tumours may be benign or malignant. During the growth of malignant or benign tumours, the skull pressure may have grown, and as a result, brain injury could have occurred. For brain MRI categorization, the suggested methodology is adaptable to a variety of classification methods. This article use CNN-based multitask classification to classify the brain tumour as normal or abnormal. Using a CNN-based model, brain tumour segmentation can be used to determine the location of a brain tumour.

Image Preprocessing

It's possible that errors occurred during the segmentation and classification operations as a result of the dataset's varying sizes and possible presence of background noise. Hence, MRI image preprocessing has been utilised to reduce noise, and the picture can then be converted into a grayscale format suited for categorization and segmentation applications. In the proposed method, a grayscale image format with a fixed size of 256x256 pixels has been utilised.

Enhancing gaussian blur can be used to reduce background noise in a photograph. A high pass filter is used to sharpen the image for efficient feature extraction
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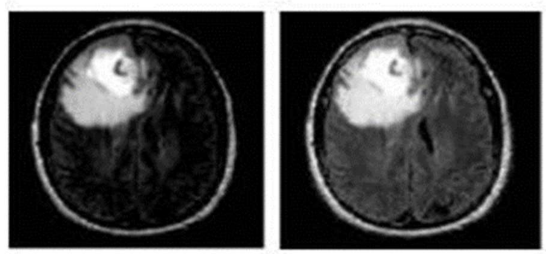

Figure 3. Raw images and preprocessed image

Each pixel in a binary image source has just two values, 0 and 1, which correspond to black and white. There are 256 distinct grey colours in a greyscale image because each pixel contains a specific number of evidence sources, most often eight per pixel. Original impressions are converted to grayscale photos using Figure 4's Scale 0.7.

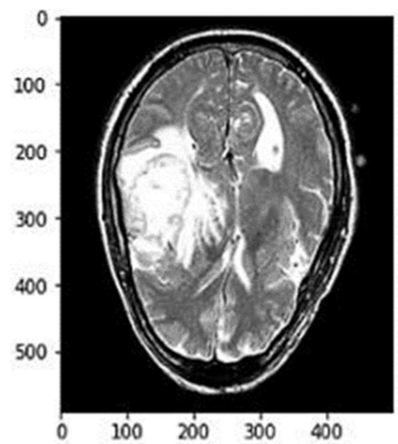

Figure 4 :Gray image

MRI pictures are changed to the shape (240, 240,3) during preprocessing since images are obtained from several sources. As a result, the dataset contains images of varying sizes and each MRI image must be in the same format in order to be used as input for the neural network (NN). Lastly, range normalisation will be employed to scale pixel values to the 0-1 range.

IMAGE SEGMENTAION:

Image segmentation is the process of splitting a digital photo into subgroups known as image segments, therefore reducing the image's complexity and allowing for further analysis or analysis of each image segment. Segmentation plays a crucial role in medical imaging, since it enables physicians to quickly and accurately identify potential cancerous characteristics in pictures.

Below are some commonly used image segmentation methods.

Edge-Based Segmentation:

Edge-based segmentation is a common image processing approach that recognises the edges of distinct image objects. Using information from the image's edges, it assists in locating features of linked items. Edge detection aids in removing redundant data from photos, hence lowering their size and facilitating analysis.

Edge-based segmentation methods recognise edges based on differences in contrast, texture, hue, and saturation. Using edge chains made up of individual edges, they can precisely depict the boundaries of objects in a picture.

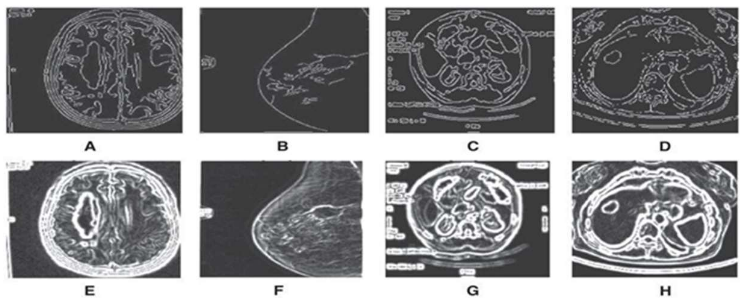

Figure 5:Edge detection

Threshold-Based Segmentation

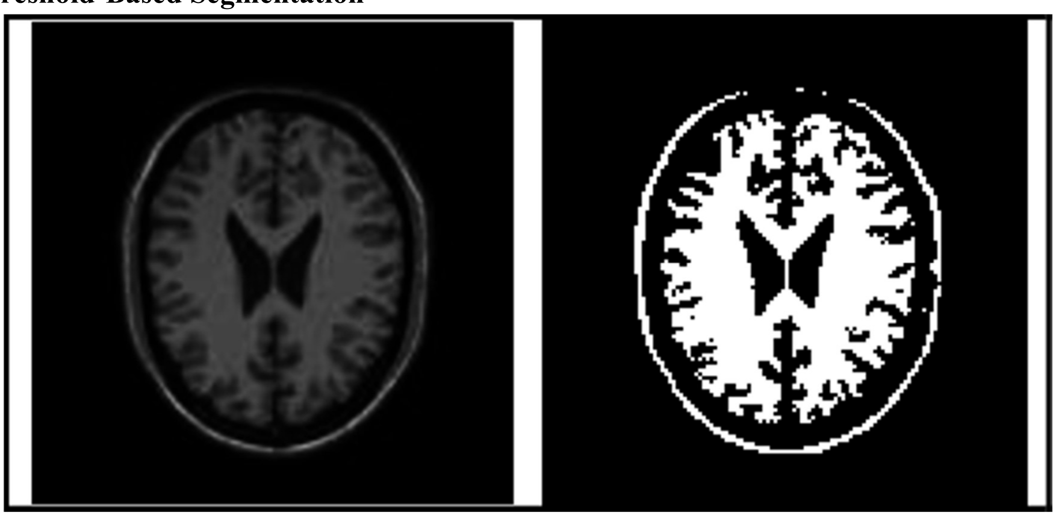

Figure 6: Threshold-Based Segmentation

The simplest technique for segmenting a picture is called thresholding, and it divides the image into regions based on the intensity of the pixels in comparison to a threshold. It works well for distinguishing between foreground and background items with significantly different intensities.

In low-noise photos, the threshold value T can be used as a constant. A dynamic threshold can be used in various situations. Thresholding takes a grayscale image and separates it into a binary image based on its relationship to the threshold value T

Region-Based Segmentation

To do region-based segmentation, a picture is first broken up into groups of pixels that share comparable features. The programme finds each zone by looking for a certain cluster of pixels around a given seed. After locating the seed locations, the algorithm can expand a region by adding new pixels or contract it by merging it with neighbouring regions.

Cluster-Based Segmentation

Clustering algorithms aid in the discovery of previously unknown information in images by using unsupervised classification techniques. They help people see more clearly by separating out details like patterns and colours. The programme separates data pieces and groups them together into clusters, dividing pictures into clusters of pixels with comparable features.

5. Watershed Segmentation

Grayscale images can undergo changes, or watersheds. Algorithms used for watershed segmentation analyse photographs like topographic maps, with the brightness of each pixels representing the terrain's elevation (height). The method identifies ridge and basin lines, which denote the transition zones between watersheds. Pixels of the same grey value are clustered together and the image is partitioned into different sections.

Among the many significant applications of the watershed method is medical image processing. When applied to an MRI image, for instance, it can help differentiate between lighter and darker areas, which can aid in the diagnosing process.

Feature Extraction

It's the step in which relevant aspects of an image are identified and made available for analysis. For most image and computer vision problems, this is a crucial first step. The diagnosis for the tumour is made after the extraction of signs. Factors such as the image's dimensions, its shape, its composition, and its placement are all considered throughout the extraction process. In this process, we take a particular input image and pull out its distinctive characteristics. These details are used in the image analysis process to pinpoint the tumor's location.

CNN ARCHITECUTRE:

CNN Is Used to Classify Images This research begins with detecting the ROI in MRI images before describing proposed brain tumour classification studies. Using an image edge detecting method, a brain tumour can then be cropped. Next, data augmentation approach is leveraged for taken training data size improvement. Hence, a basic CNN network is utilised to efficiently classify the brain tumour in the MRI picture. Figure 7 depicts the overall procedure of the CNN approach.

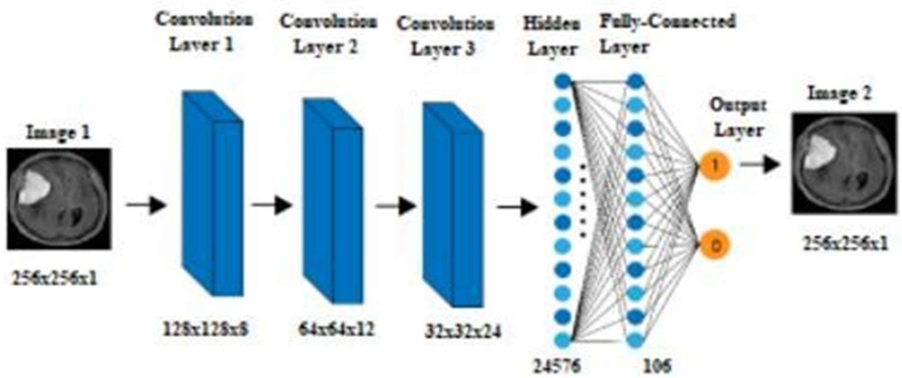

Figure 7.CNN ARCHUTECTURE

Proposed Algorithm

Step 1: Get brain MRI scan images from the repository.

Step 2: Using medical image analysis, analyse the collected images and delete any that do not belong using noise using some filter methods.

Step 3: The tumour is segmented using a box defined by a CNN algorithm. Step 4: Classifying the input photos using a neural network.

Step 5: Using the catalogued photos, predict the presence or absence of a tumour.

Early segmentation and analysis are essential for establishing the presence of a tumour. Because to the complex anatomy of the brain, brain MRI tumour detection has long been an intriguing topic. As a result, several image- based techniques have been employed to detect objects, and recent advances in deep learning have considerably improved object recognition performance. Consequently, the results suggest that the suggested model is capable of categorising brain tumours for a number of applications; also, the results demonstrate that erroneous categorization will necessitate adequate preprocessing and data augmentation.

Result and Discussion:

Metrices evaluation :

Using training and validation data to generate accuracy and loss graphs [30], the dataset is divided into 70% training, 15% validation, and 15% test sets. Using the weighted average of precision, a categorization report is generated. Precision, also known as a Positive Predictive value (PPP), is a phrase used to indicate the capacity to remember information. Sensitivity, also known as Recall, is another often employed metric for segmentation precision. Both are based on the two-by-two Confusion matrix (in the case of binary classification). Below is a calculation of precision:

$$Precision = \frac{calculating color of input images}{compared\ with\ normal\ brain\ image\ of\ color\ values} \quad (1)$$

Recall:

The recall is measured by comparing the values of correctly identified pixel values of the output of brain image results with a healthy image of brain tumour.

$$recall = \frac{Values of correctly analyzed pixel shape of brian tumor}{Total shape of pixel value analyzed in brain tumor} \quad (2)$$

Important considerations include feature extraction, categorization, and brain tumour identification in an input image. The optimum image classification algorithms must have a high level of recall with accurate tumour or non- tumor image analysis outcomes by anyone.

F-Measure:

In the final step of image categorization and analysis of brain tumor/nontumor data, the F-measure is generated with precision and recall that can be disheartened.

$$F - Measure = \frac{2(precision X recall)}{precision + recall}$$

Metrics	Proposed method	Fuzzy Clustering (%)	KMeans (%)
Precision	90.23	88.8	88.2
Recall	90.9	87.9	88.3
FMeasure	91.03	84.32	87.4

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