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Brain Tumor Detection System using Deep Learning

Siddharth Ruria, Priyanshu Gautam, Aditya Raj, Garima Pandey

Abstract - This project's objectives include locating brain tumours and enhancing patient care. Tumours are abnormal cell growths, and malignant tumours are abnormal cell growths. The two types of scans, CT and MRI frequently detect infected brain tissues. Numerous more techniques are employed for the diagnosis of brain tumours, some of which include molecular testing, and positive charges imaging of blood or lymph arteries. In order to identify disease causes like tumors, this article will use various MRI pictures. This study paper's major goals are to 1) recognize irregular sample photos and 2) locate the tumor region. In order to administer the appropriate therapy, the aberrant portions of the photographs will anticipate the levels of tumours. From example photos, deep learning is utilized to identify anomalous areas. The aberrant section will be segmented in this study using VGG-16. The number of pixels that are malignant determines the extent of the contaminated area.

Keywords: Brain Tumor, Deep Learning, Machine Learning, MRI Scan, CT scan.

I. INTRODUCTION

Different cell and tissue types make up our body. The most important and unique organ in our body, the brain, is composed of unique types of tissues. The tumor is an abnormality caused by the unidentified development or expansion of tissue masses in that bodily component. The development of these anomalies in our brain causes excruciating agony. However, improvements in contemporary technology have made finding a solution for it simple. With the use of image processing, it may now be treated without having to access that bodily part [1].

Brain tumours are referred to as "intracranial neoplasms." Both deadly and benign tumours are possible. On account of their distinct textures and visual changes, tumours can be identified in standard MRI pictures. The World Health Organization (WHO) has classified deadly brain tumours into 120 different categories.

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**Correspondence Author(s)*

Siddharth Ruria*, Department of Computer Science and Engineering, Galgotias University, Greater Noida (Uttar Pradesh), India. E-mail: siddharth.20scse1010364@galgotiasuniversity.edu.in

Priyanshu Gautam, Department of Computer Science and Engineering, Galgotias University, Greater Noida (Uttar Pradesh), India. E-mail: priyanshu.20scse1010427@galgotiasuniversity.edu.in

Aditya Raj, Department of Computer Science and Engineering, Galgotias University, Greater Noida (Uttar Pradesh), India. E-mail: aditya.20scse1010429@galgotiasuniversity.edu.in

Garima Pandey, Department of Computer Science and Engineering, Galgotias University, Greater Noida (Uttar Pradesh), India. E-mail: garima.pandey@galgotiasuniversity.edu.in

Each kind of brain tumor has a different set of signs and symptoms depending on the part of the brain that is affected. Headache, momentary disorientation, nausea, varied mental illnesses, forgetfulness, loss of balance, and other symptoms are some of the signs and symptoms of brain tumours [2].

Age, exposure to various electromagnetic waves and electromagnetic radiation from various contemporary technologies, illnesses, etc. are only a few of the factors that might contribute to the growth of such anomalies in parts of the body [3]. There are only two kinds of tumors that may lead to cancer; the first develops in the brain, and the second begins in another region of the body before spreading to the brain.

Ionizing radiation, exposure to vinyl chloride, neurofibromatosis, and other elements are risk factors for brain tumours. It is possible to experience specific neurological abnormalities during therapy, including motor difficulties, hearing loss, or visual field defects [4].

Deep learning is a method that teaches computers how to respond to any circumstance like a person would. A computer model can categorise pictures, audio, and text using deep learning. Deep learning algorithms have been shown to occasionally outperform people. There are several active and well-liked neural networks created by humans. Each node is interconnected with the others, and all these nodes work together to generate neurons in various locations throughout the body [5]. The major goal of this study is to build a CNN- based system to detect brain tumours using sample MRI images. It was put to examination and contrasted with currently used classification approaches in order to ascertain the effectiveness of the recommended categorization methodology.

The goal of this study (or system) is to create a reliable and effective brain tumor detection system that will help medical professionals make an accurate diagnosis of brain tumours. We want to increase the effectiveness of brain tumor identification by utilizing deep learning as well as machine vision, which may result in early interventions, individualized treatment regimens, and better patient outcomes.

We hope to advance the area of clinical image analysis through this research and show the use of models based on deep learning for the diagnosis of brain tumours. The findings from this study (or system) might have a big impact on clinical practice and eventually help patients by making it possible to identify brain tumours quickly and accurately.

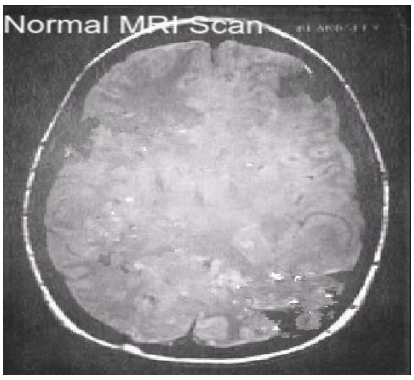

Figure 1: MRI Image

II. RELATED WORKS

The most crucial step in creating a neural learning apparatus is to classify and segment images, which is aprocess that is frequently used in diagnosis [6]. It takes a long time since numerous layers of wavelets must be trained, but this finally aids in identifying the various forms of brain tumours. White matter (WM) and grey matter (GM), normaltissues, and fluid. Gopinath R. and Somasundaram S. et al. [7] investigated several methods of image processing, particularly deep processing that recommends 3D sample pictures, for tumor diagnosis. An NN-based technique was described by Damodaran S., Raghavan D., et al. [8] using 10 photos with tumours and 10 images without tumours.

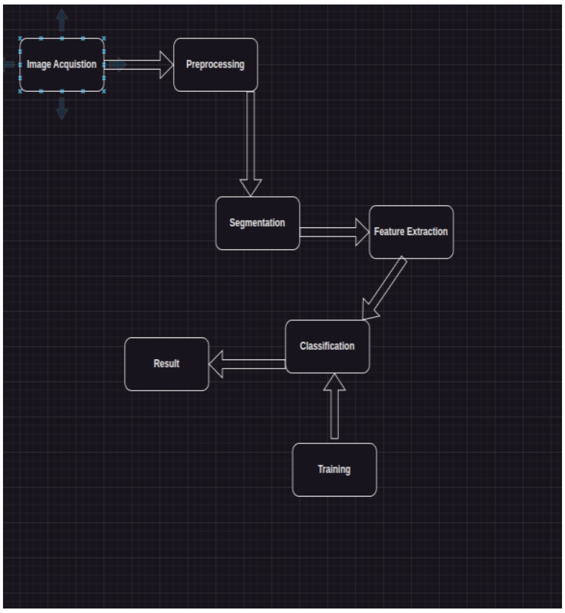

Figure 2: The Components of the Recommended System's Structure Include Picture Acquisition, Preprocessing, Feature Extraction, Segmentation, Training, and Classification

A rapid and effective data mining system was presented by [9] using an automated image processing method. According to the researchers [10], computations may be used to determine the precise position and size of tumours. Because these calculations must be done by hand, they take a lot of time. An excellent method that makes advantage of the characteristics of fragmented MRI images was provided by Xiaoya Wang, Xianying Qi, and Rui Wang et al. [11]. This approach classified photographs based on their extremely high quality, divided them based on their characteristics, etc.

III. PROPOSED METHOD

A. Image Acquisition

For the aim of doing research on brain tumor detection, many neurological imaging records are available. Computed tomography (CT) and positron emission tomography (MRI) are common methods. For the diagnosis of brain tumours, other methods involve PET scans, retinal angiograms, pelvic punctures, and molecular testing. However, their price is high. Through MRI, the water particles, waves, etc. inside of our bodies show the whole image of our body. Portable and compact MRI equipment is now being developed to avoid the difficulties of traditional scanning processes. A better degree of knowledge and detail is delivered by MRI. Here, an MRI dataset that Navneet Chakrabarty gave to Kaggle has been utilized [12]. It includes 98 photos of a normal brain and 155 images that are abnormal. "Yes" refers to photos of tumours in this dataset, and "no" to views of healthy tissue. The augmentation process is also used in this instance to increase the sample size. Maximum rotation is 10 degrees, maximum width changes are 0.1, maximum brightness changes are 0.3 to 1.0, and maximum flips are horizontal and vertical. A dataset with upgraded photos is chosen from a total of 2530 photographs. The total collection comprises of 980 conventional photos and 1550 odd photos. The acquired MRI images are typically viewed as cross-sectional slices of the brain. Radiologists or other specialized healthcare professionals review these images to assess the location, size, shape, and characteristics of the brain tumor. They analyze various imaging sequences and compare the tumor with the surrounding brain tissue to determine the nature of the tumor (e.g., benign or malignant) and develop a treatment plan. MRI is a valuable tool for brain tumor imaging due to its ability to provide detailed images without exposing the patient to ionizing radiation. It is often used in conjunction with other imaging modalities, such as CT (Computed Tomography) and PET (Positron Emission Tomography), to obtain a comprehensive evaluation of braintumors.

B. Pre-processing

Preprocessing method mostly depends on the data collecting tools, each to get the brain pictures ready for more work [13]. It has unique traits that are intrinsic. If the data being provided is 3D and is properly MRI Scanned.

Median filtering is the most efficient method for reducing noise in biological pictures. Images in the collection range in resolution. Images are assigned a size and go through a regular rotation.

Histogram equalization enhances the image quality. A contrast-constrained adaptive histogram equalization approach is used to enhance the images.

C. Image Segmentation

In order to enhance, the sample is separated into numerous sections. Because it entails isolating a specific image region from its background, this stage is crucial for feature extraction. Thresholding and morphological processes (erosion, dilation, opening) make up the fundamental stages of segment disease. At this stage, it is challenging to identify the irregularities in certain areas.

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The contrast between the tumor region and the healthy images is similar So the brain and skull may be separated using the segmentation process. The tumor lies inside this Area of Interest (AOI). An OTSU-based thresholding method results in a segmented mask that covers the skull [14]. The boundary of the area is defined via the active contour method. Additionally, the ROI can be subjected to the subsequent phase of segmentation to produce the tumor area mask. This method might not produce satisfying results with healthy photos. The features of the tumor region may be examined using this segmented image, which will help figure out the density. The selection of traits has a big influence on categorization. The characteristics imbalance, length, and irregular border are frequent [15].

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Figure 3: Used Various Threshold to Segment the Tumor Area

D. Classification

Several machine-learning techniques are used to diagnose illnesses using brain pictures. If the features are collected in a specific order, artificial neural networks can be used to categorize [16]. Each property is thought to be independent of the others according to a neural network classifier. In this case, tumor picture classification using deep learning techniques will be successful without segmentation. Convolutional neural network methods may be used to create deep neural networks. [17].

Convolutional neural networks' overall architecture is seen in Figure 6. The feature is automatically extracted using deep learning from the entire picture. This procedure is carried out by a CNN model. More feature mapping occurs as CONV layer thickness increases. When the measurement is small, it is best to begin the model. To sample a characteristic dimension, layers are accumulated downward. Fully linked layers have the ability to alter the rating of each label. To build the model, SoftMax layers employ feature and class scores.

The CNN architectural dimensions has been somewhat changed in order to train on pictures of brain tumors. Table 1 shows the modified model system.

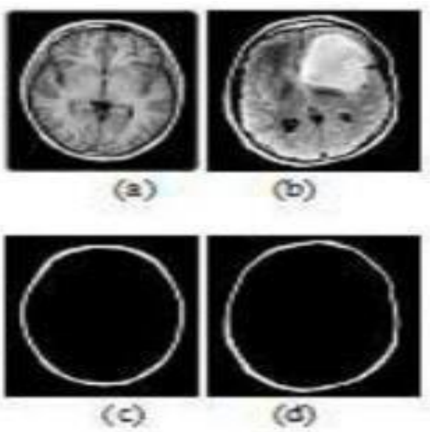

Figure 4: Classification of Skull (a) Normal Input Image (b) Irregular Input Image (c) Normal Differentiated Image (d) Irregular Differentiated Image

E. Feature Extraction

The real features of the disease might be calculated in order to illustrate the behaviour or indication of the illness.

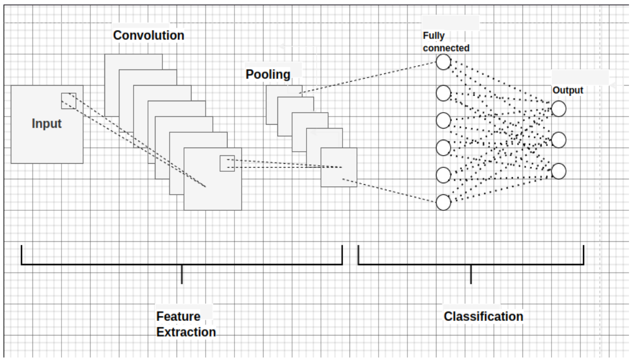

Figure 5: Common Architecture of CNN

IV. TABLE AND FIGURES

Table 1: Altered Model Architecture

Model: Brain Tumor Detection Model

Layer(type)	Output Parameter	Param #
input_1 (InputLayer)	[(None, 240, 240, 3)]	0
zero_padding2d (ZeroPadding)	(None, 244, 244, 3)	0
conv0 (Conv2D)	(None, 238, 238, 32)	4736
bn0 (BatchNormalization)	(None, 238, 238, 32)	128
relu0 (Activation)	(None, 238, 238, 32)	0
max_pool0 (MaxPooling2D)	(None, 59, 59, 32)	0
max_pool1 (MaxPooling2D)	(None, 14, 14, 32)	0
flatten (Flatten)	(None, 6772)	0
fc (Dense)	(None, 1)	6273

Total params: 11,137
Trainable params: 11, 037
Non-trainable params: 64

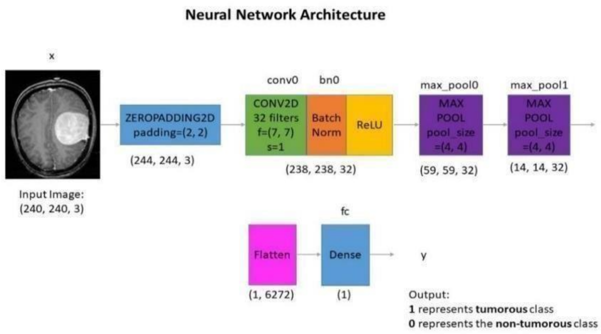

Figure 6: Graph of Neural Network Architecture

***Figure 7 Referenced from Another Study* [Research Paper link]**

For building models, Karas use the Adam optimizer and binary cross- Entropy loss. The learning rate is set at 0.001 by default. A 32-batch size spanning across 24 epochs was used in the creation of the model. For the example photos, our trained model delivers an accuracy of 95,5 percent. In images that have been identified as containing brain tumours, the tumor site is detected using a combination of multilayered thresholding, morphology methods, and contour extraction.

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$$g(x,y) = \begin{cases} 1, & f(x,y) > T \\ 0, & f(x,y) <= T \end{cases}$$

T represents the image's intensity average, spanning highest to lowest. Use a morphological open function to segment the areas into groups. The outlines of each zone are displayed, and the tumor region is situated in the section with the biggest surface area. The density of the tumor area may be calculated using the Gaussian kernel distribution.

$$f(x) = \frac{1}{n\sigma\sqrt{2\pi}} \sum_{i=0}^{n} e^{-1/2\left(\frac{x_i - x}{\sigma}\right)^2}$$

V. RESULT

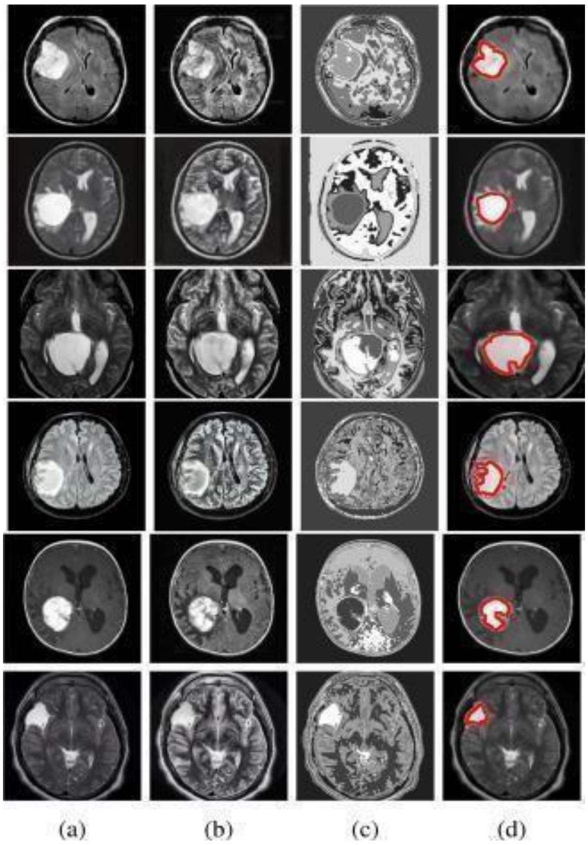

Figure 7: Results of Tumor Detection: (A) Input Image (B) Abnormality Detection (C) Tumor Region Detection (D) Tumor Mask for Density Estimation

****This is a Reference Image we have used and have Credited the Respective Owner Below** Image Credit**: (source)

The suggested system's goal is to categories malignant brain tumors from MRI scans. Kaggle dataset had 253 MRI pictures. For simulating a deep neural network, the number of data points is insufficient. As a result, 2530 photos were produced using the augmentation technique. Following cropping, the extracted images are resized to (240, 240) resolution. The model is built using the Karas framework (with Tensor Flow as the backend). To examine the system's performance, two different forms of segmentation are used at various levels. Both before and after classification, segmentation was performed. Segmentation comes after classification, according to the performance analysis, and produces superior results.

When used with typical MRI pictures, this technique runs more quickly. If abnormal images are found, segmentation is the next process that is taken. The sensitivity and specificity relationship can be seen in the ROC curve.

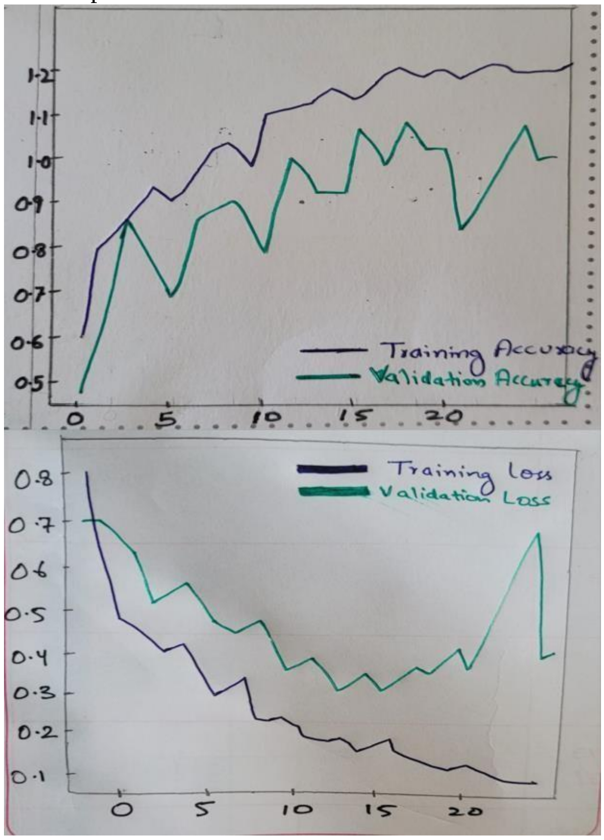

Figure 8: Graph Between the Training Data and Validation Data

	Validation set	Test set
Accuracy	91%	89%
F1 score	0.91	0.88

VI. CONCLUSION

This work presents a novel deep learning approach for the early detection of brain tumours. For a cancer to be treated effectively and quickly, early identification is essential. For use in research, the Kaggle dataset contains high-quality MRI pictures. We looked at many segmentation techniques.

Therefore, the best methods for this dataset are multilayer thresholding and OTSU thresholds. Convolutional neural networks built utilizing improved techniques allowed for an outcome that was 98% accurate. Additionally advised for use with this density estimation approach is the Gaussian distributions kernel.

A web interface might be added to this system to improve its utility. Other ailments might be found using this method. Instead of density, other variables might be evaluated for therapeutic purposes.

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Authors Contributions	All authors have equal participation in this article.

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