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Brain Tumor Detection System using Deep Learning

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Abstract - The objectives of this project 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 additional techniques are employed for the diagnosis of brain tumours, some of which include molecular testing and positron emission tomography (PET) imaging of blood or lymphatic vessels. To identify disease causes, such as tumours, this article will utilise various MRI images. This study paper's primary objectives are to (1) identify irregular sample photos and (2) locate the tumour region. To administer the appropriate therapy, the aberrant portions of the photographs will indicate 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 the VGG-16 model. The number of malignant pixels determines the extent of the contaminated area.

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

I. INTRODUCTION

Different cell and tissue types make up our body. The most critical and unique organ in our body, the brain, is composed of distinctive kinds of tissues. The tumour is an abnormality caused by the uncontrolled development or expansion of tissue masses in a 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. Due to their distinct textures and visual changes, tumours can be identified in standard MRI images. The World Health Organization (WHO) has classified deadly brain tumours into 120 different categories.

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Each type of brain tumour has a unique set of signs and symptoms, depending on the part of the brain 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 tumours 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.

Ionising 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 outperform people occasionally. There are several active and well-liked neural networks that humans have created. Each node is interconnected with the others, and all these nodes work together to generate neurons in various locations throughout the body [5]. The primary goal of this study is to develop a CNN-based system for detecting brain tumours using sample MRI images. It was subjected to examination and compared with currently used classification approaches to assess the effectiveness of the recommended categorisation methodology.

The goal of this study (or system) is to develop a reliable and effective brain tumour detection system that will assist medical professionals in making accurate diagnoses of brain tumours. We aim to enhance the effectiveness of brain tumour identification by leveraging deep learning and machine vision, which may lead to earlier interventions, more personalised treatment regimens, and improved patient outcomes.

We aim to advance the field of clinical image analysis through this research and demonstrate the application of models based on deep learning for the diagnosis of brain tumours. The findings from this study (or system) may have a significant impact on clinical practice and ultimately benefit patients by enabling the quick and accurate identification of brain tumours.

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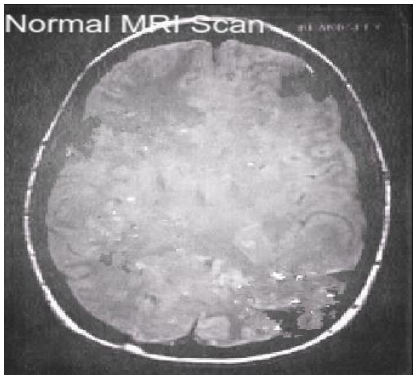

Figure 1: MRI Image

II. RELATED WORKS

The most crucial step in creating a neural learning apparatus is to classify and segment images, which is a process that is frequently used in diagnosis [6]. It takes a long time, as numerous layers of wavelets must be trained, but this ultimately aids in identifying the various forms of brain tumours. White matter (WM) and grey matter (GM) are normal tissues, and cerebrospinal fluid. Gopinath R. and Somasundaram S. et al. [7] investigated several methods of image processing, intense 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.

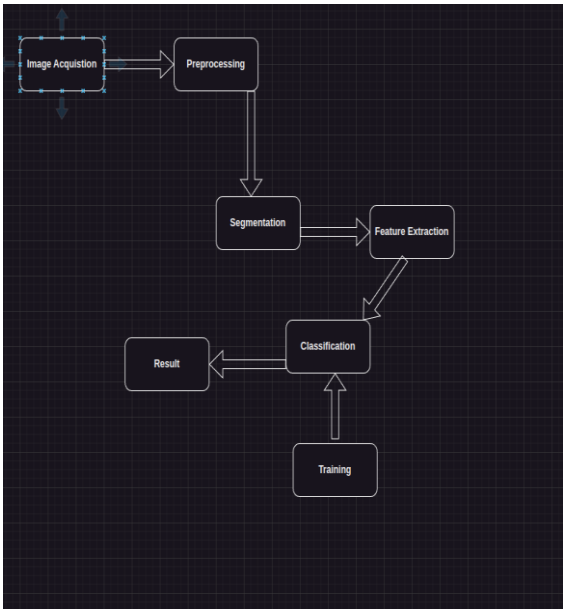

Figure 2: The Components of the Recommended System's Structure Include Picture Acquisition, Preprocessing, Feature Extraction, Segmentation, Training, and Classification

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 performed manually, they require a significant amount 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 exceptionally high quality, dividing them by their characteristics, etc.

III. PROPOSED METHOD

A. Image Acquisition

To research brain tumour detection, numerous neurological imaging records are available. Computed tomography (CT) and positron emission tomography (PET) are standard 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, and other internal structures inside our bodies form a complete image of our body. Portable and compact MRI equipment is being developed to overcome the challenges of traditional scanning processes. MRI delivers a better degree of knowledge and detail. Here, an MRI dataset that Navneet Chakrabarty gave to Kaggle has been utilized [12]. It includes 98 photos of a normal brain and 155 abnormal images. "Yes" refers to pictures 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 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 analyse various imaging sequences and compare the tumour with the surrounding brain tissue to determine the nature of the tumour (e.g., benign or malignant) and develop a personalised treatment plan. MRI is a valuable tool for brain tumour imaging due to its ability to provide detailed images without exposing the patient to ionising 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 brain tumours.

B. Pre-processing

Preprocessing method primarily depends on the data collecting tools, each of which gets 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 equalisation approach is employed to enhance the images.

C. Image Segmentation

To enhance the sample, it 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, and opening) comprise the fundamental stages of segmenting disease. At this stage, it is challenging to identify the irregularities in certain areas.

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The contrast between the tumour region and the healthy images is similar; therefore, the brain and skull may be separated using the segmentation process. The tumour 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 tumour area mask. This method may not yield satisfactory results with healthy photos. The features of the tumour region can be examined using this segmented image, which will help determine the density. The selection of traits has a significant influence on categorization. The characteristics imbalance, length, and irregular border are frequent [15].

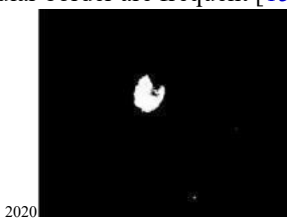

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Figure 3: Used Various Thresholds to Segment the Tumour Area

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 considered independent of the others by a neural network classifier. In this case, tumour picture classification using deep learning techniques will be successful without segmentation. Convolutional neural network methods may be used to create deep neural networks. [17][18].

The overall architecture of convolutional neural networks is illustrated 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 the thickness of the CONV layer increases. When the measurement is small, it is best to begin with the model. To sample a characteristic dimension, layers are accumulated from the bottom upward. Fully linked layers can alter the rating of each label. To build the model, SoftMax layers employ feature and class scores.

The CNN architectural dimensions have been slightly modified to train on images of brain tumours. Table 1 shows the modified model system.

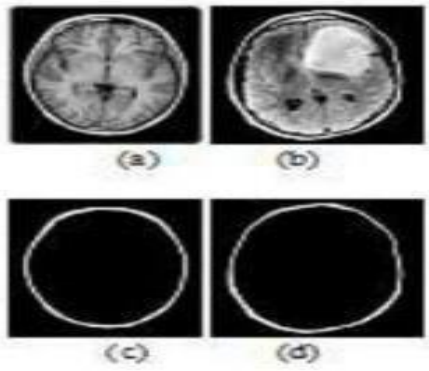

Figure 4: Classification of Skull (a) Normal Input Image, (b) Irregular Input Image, (c) Normal Differentiated Image, (d) Irregular Differentiated Image

E. Feature Extraction

The real features of the disease can be calculated to illustrate the behaviour or indication of the illness.

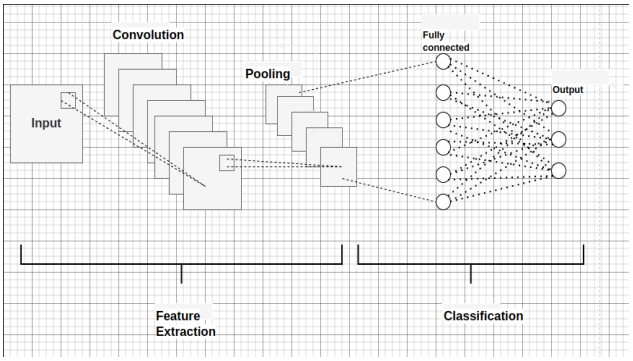

Figure 5: Common Architecture of CNN

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

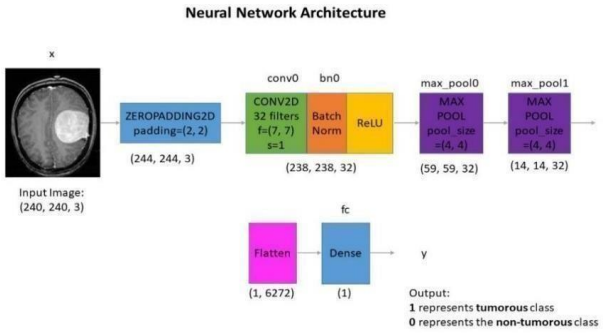

Figure 6: Graph of Neural Network Architecture

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

For building models, Karas uses the Adam optimiser 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 achieves an accuracy of 95.5%. In images identified as containing brain tumours, the tumour site is detected using a combination of multilayered thresholding, morphological 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 from highest to lowest. Use a morphological open function to segment the areas into groups. The outlines of each zone are displayed, and the tumour region is located in the section with the largest surface area. The density of the tumour 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

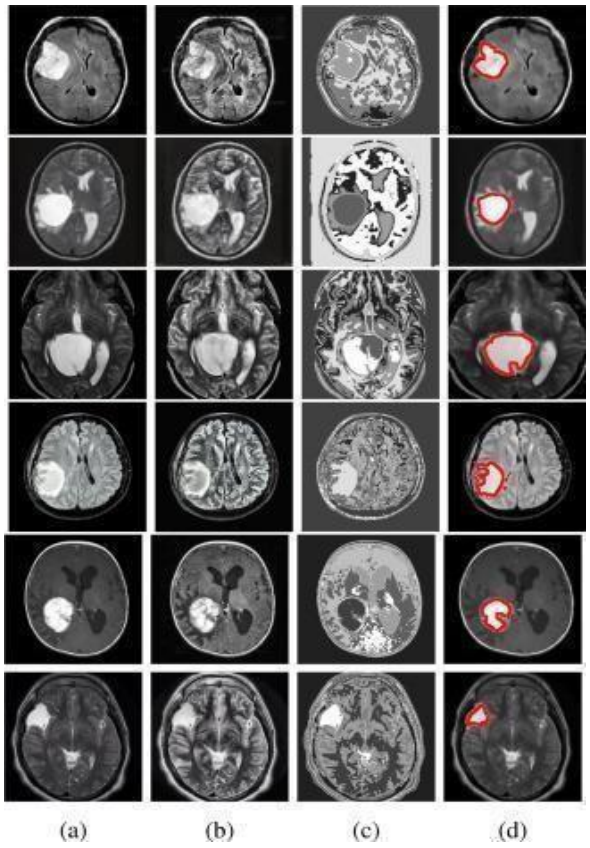

Figure 7: Results of Tumor Detection: (A) Input Image, (B) Abnormality Detection, (C) Tumor Region Detection, (D) Tumor Mask for Density Estimation

****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 categorise malignant brain tumours from MRI scans. The Kaggle dataset consisted of 253 MRI images. 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 follows classification, according to performance analysis, and yields superior results.

When used in conjunction with typical MRI images, this technique runs more quickly. If abnormal photos are found, the following process is taken. The relationship between sensitivity and specificity is evident in the ROC curve.

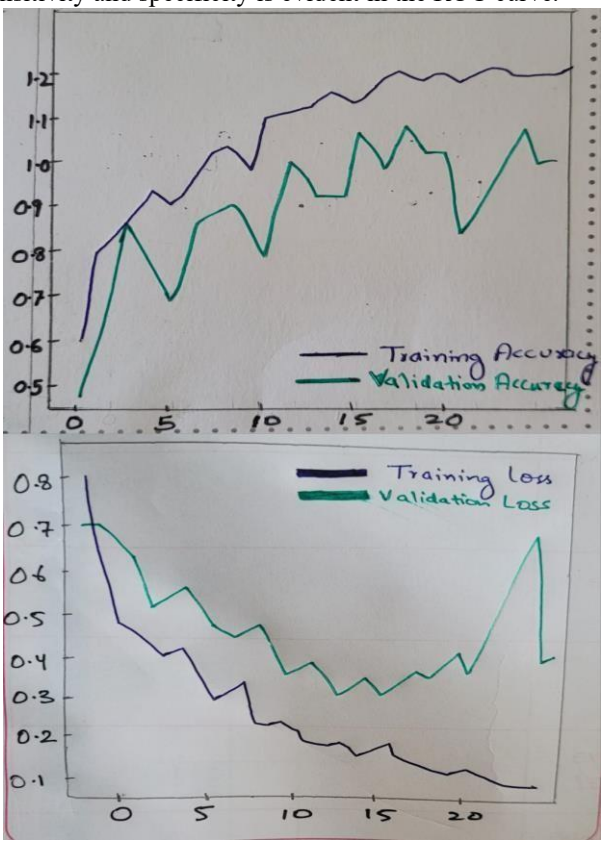

Figure 8: Graph Between the Training Data and Validation Data

	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 research purposes, the Kaggle dataset features high-quality MRI images. We looked at many segmentation techniques.

Therefore, the most effective methods for this dataset are multilayer thresholding and Otsu thresholds. Convolutional neural networks built using improved techniques yielded an accuracy rate of 98%. Additionally, the Gaussian distribution is advised for use with this density estimation approach.

A web interface could be added to this system to enhance its usability and accessibility. 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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