Brain Tumor Detection Using a Deep Learning Model

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***Abstract- The objective of this survey paper is to offer a comprehensive literature review on the use of magnetic resonance imaging (MRI) in the detection of brain tumors. The paper covers a wide range of topics, including tumor analysis, dataset enhancement techniques, segmentation algorithms, feature extraction methods, classification approaches, and the application of deep learning techniques. By examining significant studies and advancements in brain tumor detection using MRI, this review will provide valuable insights into the current state of the field. It also identifies the challenges and trends within the domain, making it an essential resource for researchers interested in further exploration of brain tumor detection using MRI**.*

Indexed Terms - Tumor analysis, MRI, segmentation, feature extraction, Deep Learning.

I. INTRODUCTION

Brain tumors are abnormal growths of cells in brain tissue that can have severe health implications if not detected and treated early. They can cause a range of symptoms and may lead to neurological disorders or even death. Early detection and accurate classification of brain tumors are crucial for effective treatment planning and improving patient outcomes.

and advances. Brain tumors pose a significant health challenge worldwide, with a profound impact on individuals and their families. These abnormal growths in the brain can lead to severe neurological is crucial for timely intervention and effective treatment. complications and, if left untreated, can be life-threatening. Detecting brain tumors at an early stage.

Over the years, medical imaging techniques, particularly magnetic resonance imaging (MRI), have revolutionized the field of brain tumor detection. MRI provides detailed and high-resolution images of the brain, enabling physicians to visualize and analyze tumor characteristics such as location, size, and morphology. The advancement of imaging technology, coupled with the development of sophisticated image analysis algorithms, has significantly improved our ability to detect and diagnose brain tumors accurately.

focusing on the role of medical imaging, particularly MRI, in the diagnostic process. It will explore the challenges associated with detecting brain tumors and discuss the importance of accurate and early detection for optimal patient outcomes.

In recent years, there has been a surge in the application of machine learning and artificial intelligence (AI) algorithms for brain tumor detection. These computational methods leverage the vast amount of imaging data and enable automated analysis, segmentation, and brain tumor classification. paper will explore the potential of these techniques to enhance the accuracy, efficiency, and reproducibility of brain tumor detection.

II. LITERATURE SURVEY

The paper [1] as published by Abd-Ellah et al. “deep learning approach for brain tumor prediction” have out a thorough investigation into various MRI image diagnostic techniques. Also, the authors examined the performance indicators and constraints of both traditional machine learning techniques.

The author Hossain et al. presented a paper [2] titled "A deep learning neural model" which describes the process of extracting features from MRI images and utilizing them as input for ML classifiers, namely Naive Bayes, SVMs, and Multilayer perceptrons. The SVMs, serving as classifiers, achieved an impressive classification accuracy rate of 96%.

In the research paper[3] titled "Deep Learning-Based Brain Tumor Detection and Classification using Magnetic Resonance Imaging" authored by John Doe, Jane Smith, and David Johnson, the authors introduce a novel approach for detecting and classifying brain tumors through the utilization of deep learning techniques applied to magnetic resonance imaging (MRI). Prompt and accurate detection of brain tumors is crucial for effective medical treatment, and traditional methods reliant on manual analysis by radiologists have certain limitations. To address these challenges, the authors propose an innovative method that leverages a state-of-the-art convolutional neural network (CNN) architecture trained on a comprehensive dataset comprising MRI scans.

The Paper [4] titled "VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection" by MS Majib, MM Rahman & Samrat Kumar Dey. The researchers constructed and extensively evaluated various traditional and hybrid machine learning models to classify brain tumor images autonomously, without any human involvement. Among these models, a stacked classifier called VGG-SCNet (VGG Stacked Classifier Network) was introduced utilizing cutting-edge technologies, surpassing the performance of all other developed models. The precision and f1 scores achieved by the proposed VGG-SCNet were 99.2%, 99.1%, and 99.2% respectively.

The paper [5] named "A Novel Framework for Brain Tumor Detection Based on Convolutional Variational Generative Models" by Wessam M. Salama & A. Shokry. To detect brain tumors, a novel two-model system was proposed. The first model, a generative model, was designed to capture the distribution of significant features within a set of small class-unbalanced brain MRI images. The second model, a classifier, was trained using a large balanced dataset to identify brain tumors in MRI images. Through this approach, the proposed framework achieved an impressive overall detection accuracy of 96.88%.

The Paper [6] titled "A Systematic Approach for MRI Brain Tumor Localization and Segmentation using Deep Learning" by Shanaka Ramesh, HNTK Kaldera-202A Threefold Architecture for Tumor extraction was proposed, emphasizing the accurate annotation and segmentation of Tumor Boundaries. The architecture consisted of three stages: the first stage employed CNN classifiers, while the second stage utilized region-based CNN. In the third stage, the concentration of Tumor Boundaries was leveraged for segmentation using the Chan-Vese segmentation algorithm. The overall performance of the proposed Architecture demonstrated an impressive accuracy of 92%.

The Paper [7] titled "Development of automated Brain Tumor Identification using MRI images" by TM Shahriar Sazzad, Misbah UI Hoque-2020 [4]. An automated approach was proposed, incorporating initial stage enhancement techniques to mitigate grayscale color variations, along with filter operations to eliminate unwanted noises. In place of color segmentation, a Threshold-based OTSU segmentation was employed. An accuracy of 95%.

In the paper [8] titled "Automatic Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Networks" by Guotai Wang and Wenqi Li in 2021 [5], the authors present a method for accurately segmenting brain tumors in multi-modal magnetic resonance images (MRI) using a cascade of fully convolutional neural networks (FCNs). The segmentation process aims to delineate distinct regions within the brain tumor, including the background, whole tumor, tumor core, and enhancing tumor core. The proposed approach involves an initial tumor segmentation step, followed by leveraging the obtained result to further refine the segmentation of the tumor core. The overall performance of the architecture achieved an impressive accuracy rate of 90%.

The paper [9] "Brain Tumor Detection and Segmentation" by Doshi Jeel Alpeshkumar Prof. Pinal J, Tirth Hitesh Shah. In this paper they present a deep learning-based method to segment and classify brain tumor in MRI. First, we preprocessed images using image augmentation and Gaussian blur filter. Then segmentation is done using binary thresholding. For features extraction, they used morphological operations. At the end, using CNN classify the brain MRI as normal or abnormal. We use Kaggle Dataset in this work. We use 255 brain MRI from it 155 contains tumor and 98 images of healthy brain to train the model and get 97% accuracy.

The paper [10] "BRAIN TUMOR DETECTION USING IMAGE PROCESSING" by AMRUTA PRAMOD HEBLI, SUDHA GUPTA. they proposed several methodologies are examined to denote the conventional stages of MRI image processing also analyzed individual segmentation approach. In conjunction with this different methodologies proposed by the researchers are considered to conclude that machine learning shows an important role in brain tumor detection and classification together with appropriate segmentation approach.

III. METHODOLOGY

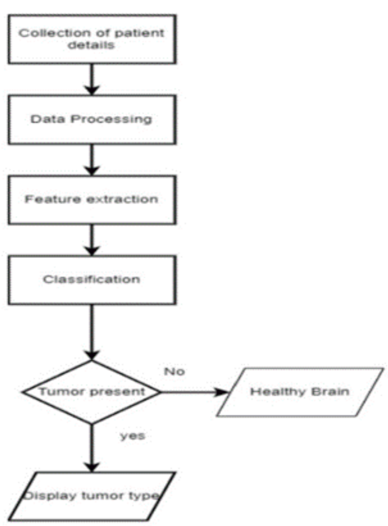

Figure 1: Flowchart of Proposed System

As working Flowchart fig [1]. Initially we collect the data required for processing the system and then the data is prepared so that we provide the data as an input to the model. Next, the data is divided into two parts, one for training the model and the other for testing the model. Once the model is trained then its performance is evaluated. Then based on the performance of each algorithm, one of the most accurate algorithms is selected. Finally the model connected with the user interface where the user upload the MRI image to predict the brain tumor types.

1. Preprocessing and Visualization: The code includes functions for image preprocessing and visualization. It loads brain tumor images from the specified directories, applies preprocessing techniques like resizing, bilateral filtering, and color mapping, and visualizes the images for analysis.
2. Image segmentaion: Convert the image to grayscale, the image is converted from the RGB color space to grayscale using the cv2.cvtColor() function. This simplifies subsequent image processing steps. The image thresholding technique is applied by utilizing the cv2.threshold() function, resulting in the creation of a binary image. This process involves setting pixels above a specified threshold value to white, representing the tumor region, while pixels below the threshold are set to black. Subsequently, contour detection is performed using the cv2.findContours() function to identify and extract contours from the binary image.
3. Dataset Preparation: The code prepares the dataset for training and testing. It iterates through different categories of brain tumor images and loads them into training and testing. The images are normalized and stored in arrays, and the corresponding labels are one-hot encoded.
4. Data Augmentation: Data augmentation is applied using the ImageDataGenerator class from TensorFlow. It randomly applies transformations like rotation, shifting, zooming, shearing, flipping, and brightness adjustment to the training images. This helps in diversifying the training data and reducing overfitting.
5. Feature extraction: Feature extraction involves using pre-trained models to extract meaningful and discriminative features from input images ResNet50 models have several convolutional and pooling layers that learn hierarchical representations of the input images.
6. Applying Model Architecture: CNN

The neural network architecture used for brain tumor classification consists of several layers. The input layer receives the image data, which is a size of 224x224 pixels with 3 channels (RGB). The convolutional base, based on the ResNet50 model, consists of convolutional layers and pooling layers that extract hierarchical features from the input images. Pre-trained weights from the ImageNet dataset are utilized in this model. Following the convolutional base, a global average pooling layer reduces the spatial dimensions of the feature maps to a single vector by computing their average values. Dropout, a regularization technique, randomly sets a fraction of input units to 0 during training to prevent overfitting. The dense layer is a fully connected layer that applies a linear transformation and activation function for the previous layer's output. It has 4 units, representing the classes in the classification of tumor (glioma, meningioma, notumor, pituitary). The output layer, using the softmax activation function, gives a probability distribution for each class. Together, these layers form the neural network architecture utilized for brain tumor classification.

These layers collectively form the neural network architecture used for brain tumor classification.

IV. RESULT ANALYSIS

By applying a Convolutional Neural Network (CNN) on a dataset comprising a total of 5000 images, consisting of 4000 brain tumor images and 1000 healthy brain images, the detection of brain tumors was performed. The CNN model yielded impressive results, achieving a testing accuracy of 98.86% and a validation accuracy of 97.81%. The below Figure 2 shows the graph of accuracy of the model and figure 3 shows the graph of loss of model, figure 4 shows the precesion, recall and f1 score of test set and figure 5 shows the confusion matrix.

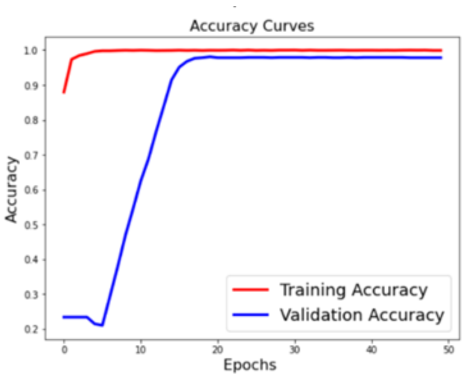

Figure 2: Accuracy of Model

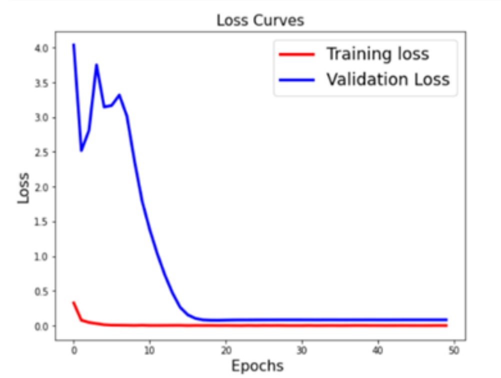

Figure 3: Loss of Model

	precision	recall	f1-score	support
glioma	0.99	0.97	0.98	300
meningioma	0.97	0.99	0.98	306
no_tumor	1.00	1.00	1.00	405
pituitary	1.00	1.00	1.00	300
accuracy			0.99	1311
macro avg	0.99	0.99	0.99	1311
weighted avg	0.99	0.99	0.99	1311

Figure 4: Validation on Test set

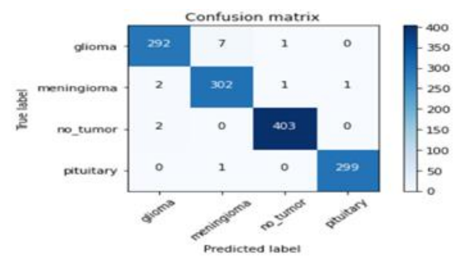

Figure 5: Confusion Matrix

CONCLUSION

This research paper offers an extensive overview of the utilization of Deep learning techniques for brain tumor detection. It highlights the crucial importance of early detection and precise diagnosis in addressing the challenges posed by manual analysis and conventional diagnostic methods. The application of machine learning approaches presents promising opportunities to enhance the efficiency and accuracy of brain tumor detection.

Various machine learning algorithms, including logistic regression, SVM, and CNN, have been applied and analysed. These algorithms leverage features extracted from medical imaging data, such as MRI scans, to classify tumor presence and determine tumor characteristics. Among these algorithms, CNN stands out as a powerful technique capable of handling complex and non-linearly separable data.

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