Brain Tumor Detection Using Convolutional Neural Network

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Abstract— **Magnetic resonance imaging (MRI) scans are commonly employed in the field of medical science for the identification of brain tumors, some of which can be life-threatening. Therefore, it is essential to differentiate between benign and malignant tumors to initiate prompt treatment. The conventional method for brain tumor detection involves manual analysis by radiologists and doctors, which can sometimes be a time-consuming process. To expedite and improve this process, machine learning techniques, such as Convolutional Neural Networks (CNNs), can be leveraged to automatically detect brain tumors by training on a substantial dataset. This technological advancement holds great promise in revolutionizing the medical field.**

Keywords— Brain tumor, Magnetic resonance imaging (MRI),Deep convolutional neural networks (DCNN), Feature extraction, Medical imaging.

I. Introduction

Medical imaging techniques are employed to explore the interior of the human body to diagnoses. Among the most challenging and potentially rewarding aspects of Image Processing lies in the realm of medical image classification. Identifying tumors or detecting cancer ranks as one of the most prevalent challenges in categorizing medical images. In recent times, medical professionals have been adopting more sophisticated technologies to locate tumors in a less invasive manner. Computed Tomography (CT) and Medical Reasoning Imaging (MRI) scans stand as practical methods for assessing abnormalities in various body regions. With the growing demand for quick and unbiased analysis of extensive medical data, there has been a significant surge of interest in MRI-based medical image processing for brain tumor examinations. The assessment of such a diverse array of image formats necessitates the utilization of advanced computational quantification and visualization software. Consequently, automated diagnosis of brain tumors from MRI scans assumes pivotal importance in this context, as it obviates the necessity for human data processing[1].

II. RELATED WORKS

Sivaramakrishnan And Dr. M. Karnan "A Novel Based Approach for Extraction Of Brain Tumor In MRI Images Using Soft Computing Techniques," International Journal Of Advanced Research In Computer And Communication Engineering, Vol. 2, Issue 4, April 2013. A. Sivaramakrishnan et al. (2013)**.**The Fuzzy approach clustering algorithm and histogram equalization were used to create an image that portrayed the location of the brain tumour creatively and accurately. Primary factor assessment can be used to decompose images and shrink the wavelet coefficient. The predicted FCM clustering technique successfully removed the tumour from the MR images.

In 2017 Sankari Ali, and S. Vigneshwari. "Automatic tumor segmentation using convolutional neural networks." A. Sankari and S. Vigneshwari [19] has proposed a Convolutional Neural Network (CNN) segmentation, which principally based on the brain tumor classification method. The proposed work used the non-linearity activation feature that's a leaky rectified linear unit (LReLU). They primarily focused on necessary capabilities, which include mean and entropy of the image and analyzed that the CNN algorithm is working higher for representing the complicated and minute capabilities of brain tumor tissues present in the MR Images.

In (2018) Varuna Shree, N., Kumar, T.N.R. Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network. Kumar and Varuna Shree [22] proposed work for the detection tumor region using discrete wavelength transforms (DWT). This work consists of three phases, namely an image enhancement using filtering technique, gray-level co-incidence matrix (GLCM) feature extraction of tumor in addition to DWT based tumor location developing segmentation. It is used to improve overall performance and reduce complexity. The denoised accompanied by the aid of morphological filtering operations which put off the noises that can be even shaped subsequent segmentation technique. The PNN classifier is to use for classifying the abnormality, which is trained by different datasets, and the accuracy is measured within the detection of tumor region of mind MR images.

In Devkota, B. & Alsadoon, Abeer & Prasad, P.W.C. & Singh, A.K. & Elchouemi, A. (2018). Image Segmentation for Early-Stage Brain Tumor Detection using Mathematical Morphological Reconstruction. B. Devkota et al. [4] have proposed that a computer-aided detection (CAD) approach is used to spot abnormal tissues via Morphological operations. Amongst all different segmentation approaches existing, the morphological opening and closing operations are preferred since it takes less processing time with the utmost efficiency in drawing tumor areas with the least faults.

Aryan Methil, 2021 he suggested brain tumor detection using deep learning and image processing in this conference article. He trains the model using a dataset of 3762 photos that he divided into multiple subsets. He shifted 20 percent width to the left or right and 20 percent height to the top or bottom by resizing all photos to 150X150 pixels and rotating them between -30 and +30 degrees. To train and validate, divide the dataset into two parts: 70% and 30%. All of the work was completed using the ResNet 101v2 CNN model. Transfer learning was also crucial there, with a sufficient accuracy of 97 percent, 98.55 percent for training recall, and 99.73 percent validation.

III. PROBLEM STATEMENT

The project's objective is to implement an accurate and timely detection of brain tumors using medical imaging remains a critical challenge in healthcare. Conventional methods often lack the precision and speed required for early diagnosis and treatment. This thesis aims to address this issue by developing and implementing a Convolutional Neural Network (CNN)-based approach that leverages multimodal brain imaging data for enhanced brain tumor detection.

VI. OBJECTIVE

In brief, Convolutional Neural Networks (CNNs) are a vital technique for extracting geographical and temporal information from datasets necessary for diagnostic purposes. CNNs specialize in handling image datasets, relying on a convolution process between kernels and input images to extract features, a fundamental concept common to all neural networks. The iterative updating of weights matrices in neural networks allows them to learn. In a CNN, these kernel values serve as model weights and are gradually optimized through backpropagation and gradient descent, which involves calculating derivatives of the loss function with respect to weights and biases and updating them to minimize the loss.CNNs often incorporate convolutional layers with pooling layers, and multiple such layer pairs can be linked. Dense layers and dropout layers are employed in the final learning stages to address overfitting concerns. The ultimate output layer performs the classification task, featuring one neuron for binary classification or multiple neurons for multi-class classification[2]. Capsule networks, a neural network variant that can capture spatial information and the likelihood of objects appearing in images, have gained popularity and are increasingly utilized in recent research.

V. UNDERLYING RESEARCH

A. BRAIN TUMOR

A brain tumor is an accumulation of unusual cells within the brain that coalesce to create a mass. Your brain is shielded by a rigid skull, and any enlargement in this confined space can lead to complications. These growths can be categorized as either cancerous (malignant) or noncancerous (benign). As both benign and malignant tumors grow, they can elevate the pressure inside the skull, potentially resulting in significant brain damage and even fatality.

Fig.1. Brain Tumor [1].

Primary and secondary brain growths are differentiated in a similar manner. Primary brain growths originate within the brain itself and are often benign. In contrast, secondary brain growths, also referred to as metastatic brain growths, occur when cancer cells from another part of the body, such as the lungs or bones, migrate to the brain. While benign brain growths can cause various issues, they are generally not harmful as they tend to develop slowly and seldom metastasize to other areas of the body. They typically have well-defined boundaries, making surgical removal easier, and they rarely recur after removal. In contrast, malignant brain growths are cancerous, grow rapidly, and can spread to other parts of the brain or the central nervous system, presenting a significant and potentially life-threatening danger.

B. BRAIN TUMOR DIAGNOSIS

Diagnosing a brain tumor involves a combination of physical tests and a review of your medical history. The physical examination includes a thorough neurological assessment, where your doctor checks the health of your cranial nerves that extend from your brain. An ophthalmoscope is used to examine the inside of your eyes, allowing your doctor to assess how your pupils react to light and detect any eye abnormalities that may result from increased cranial pressure. Doctor may also evaluate: Muscle strength, Coordination, Memory, Mathematical reasoning ability. Following the physical examination, your doctor may recommend further tests as needed[3].

C. CT scan of the head

CT scan of the head provides a more detailed image of your body compared to an X-ray scan. This can be done with or without contrast. When contrast is used in a head CT scan, a special dye is employed to enhance the visibility of specific structures, such as blood vessels, for medical professionals.

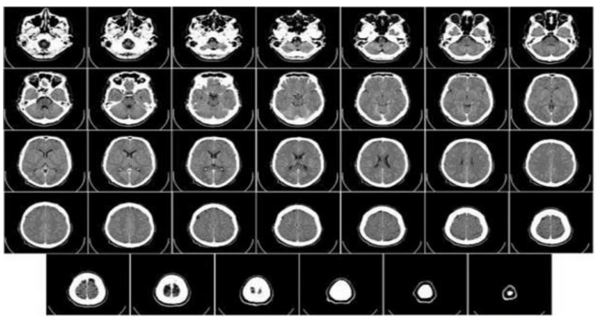


Fig.2. Various Image of CT scan [2].

D. MRI scan of the brain

A distinct dye can be employed in a head MRI to assist your physician in identifying abnormalities. An MRI, unlike a CT scan, avoids radiation and often generates more intricate brain images.

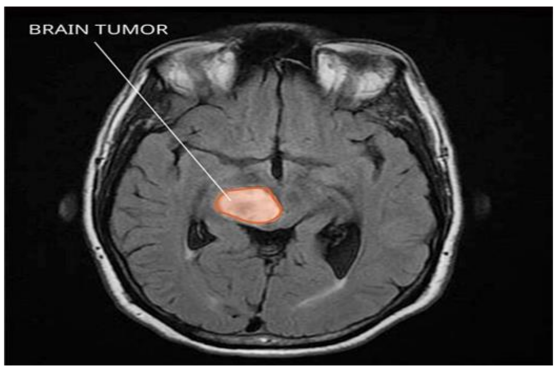


Fig.3. MRI Image [3].

VI. METHODOLOGY

In this paper, For the hardware requirements include an AMD Ryzen 5 3600 processor, 16GB of RAM, and a 64-bit Windows 10 operating system. The software used is Python 3.6, and Anaconda was employed to manage packages for scientific computing.The dataset was obtained from Kaggle, containing 1500 images for 'YES,' 1500 images for 'NO,' 826 images for 'Benign,' and 247 images for 'Malignant' tumors. Data augmentation techniques like grayscale conversion, reflection, Gaussian blur, and others were used to enhance the dataset. Pre-processing involved rescaling, noise reduction, and using the 'Adam' optimizer and 'ReLu' activation function.Segmentation techniques such as the watershed algorithm were used to separate tumor regions from images. Feature extraction involved extracting quantitative parameters from the images, and a sequential model was used for classification[4].The software tools employed included TensorFlow, Keras, NumPy, Matplotlib, and the 'Adam' optimizer. The activation functions used were softmax and ReLu, which helped with model efficiency and interpretation of results.

VII. IMAGE CLASSIFICATION BY CNN

A Convolutional Neural Network (ConvNet or CNN) is a deep learning system designed for image analysis and classification. Unlike traditional classification methods, ConvNets require minimal preprocessing and have the ability to learn important features and patterns from the data during training.The design of a ConvNet is inspired by the structure of the human visual cortex. It is composed of layers of interconnected neurons, with each neuron responding to a specific area of the input image known as its receptive field. These neurons collectively cover the entire visual field. In the context of our brain tumor detection and classification study, we employed a Convolutional Neural Network architecture. Convolutional neural networks are particularly well-suited for tasks like image categorization, image processing, and facial recognition. They work by analyzing the RGB layers of an image in a three-dimensional structure. Unlike traditional methods, ConvNets process one image at a time, extracting important features and using them to categorize the image.The key components of a ConvNet include: Input Layer: This layer takes the raw pixel values of the input image.Convolutional Layer: The first layer that extracts features from the input image. It uses mathematical operations with filters or kernels to generate feature maps, allowing operations like edge detection, blur, and sharpening. Activation Layer: It produces a single output based on the weighted sum of inputs. Pooling Layer: When dealing with large images, pooling layers reduce the number of parameters and dimensionality while preserving essential information. Types of pooling include Max Pooling, Average Pooling, and Sum Pooling. Fully Connected Layer: The feature map matrix is flattened into a vector and fed into this layer, similar to a traditional neural network[5]. Fully connected layers use these features to classify input images into different classes.Dropout Layer: This layer prevents network nodes from over-reliance on each other.

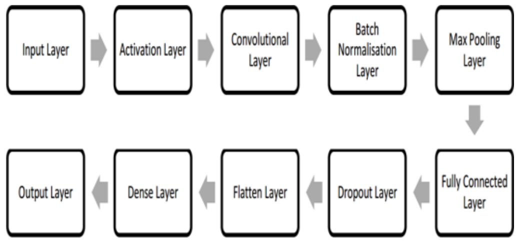


Fig. 4. CNN Layers [4].

In summary, Convolutional Neural Networks are a powerful tool for tasks like image analysis and classification, particularly when dealing with complex visual data like medical images for tumor detection and classification. They can automatically learn and extract meaningful features from the input, making them highly effective for a wide range of applications.

VIII. PROPOSED STRATEGY

The following steps are described in the study as the approach for building Brain Tumor Using Deep Learning:

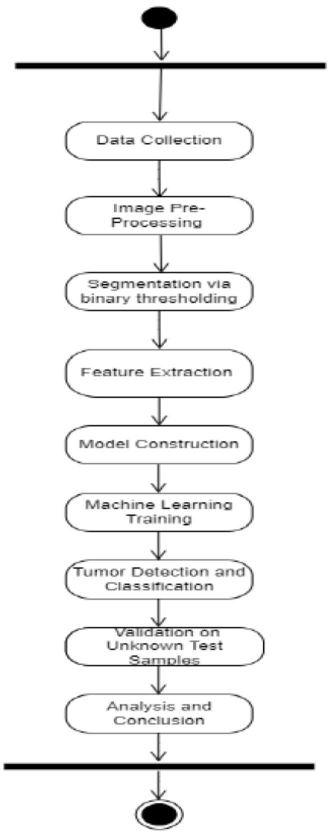


Fig. 5. Flowchart of Methodology [3].

IX. PERFORMANCE IMPROVENENT

A. TRAINING AND TESTING

The "Train/Test" technique is a method to assess your model's accuracy. It involves splitting your dataset into two parts: a training set (80% of the data) and a testing set (20% of the data). The training set is used to build and train the model, while the testing set is used to evaluate its accuracy.

In this process, we used variables like 'x_train' and 'y_train' for training and 'x_test' and 'y_test' for testing. The batch size, which determines how many samples are processed before updating the model's parameters, was set to 16. The test size was 20%, and the training size was 80%, with a random state of zero. The 'verbose' option was set to one, which provides an animated progress bar for visualization.The 'verbose' option aids in making regular expressions more visually organized and readable. Setting it to 0 makes it silent, while setting it to 1 displays an animated progress bar to track the process.In short, the Train/Test technique involves dividing your data into training and testing sets for model evaluation. 'x_train' and 'y_train' are used for training, 'x_test' and 'y_test' for testing, and the 'verbose' option helps in visualizing the process.

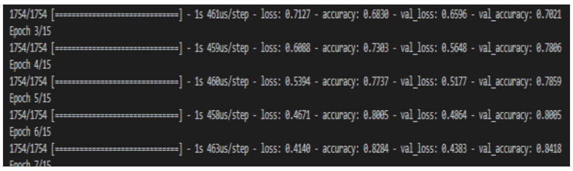


Fig. 6. Verbose Progress Bar

The number of epochs, in this case, was set to 15, and it's a crucial hyperparameter that determines how many times the learning algorithm processes the entire training dataset. During each epoch, the algorithm allows each sample in the training dataset to update the internal model parameters at once. An epoch can consist of one or more batches, with some methods like batch gradient descent processing only one batch per epoch. The evaluation of the model's performance is based on metrics like accuracy and loss, which are derived from the predictions made on the test data. Accuracy is often presented as a percentage and measures how many predictions match the actual values. It's a binary metric for individual samples (true or false). Accuracy is typically monitored during training, but the accuracy of the final model is usually emphasized. Loss, on the other hand, provides a more nuanced perspective than accuracy. It's also known as a cost function and assesses the likelihood or uncertainty of a prediction by quantifying how much it deviates from the actual value. This nuanced approach to evaluating the model's performance considers the degree of error in predictions.

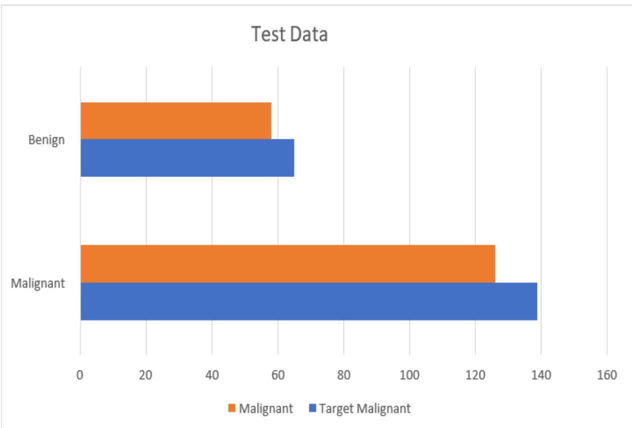


Fig. 7. Test Data Result

X. IMPLEMENTATION RESULTS AND ANALYSIS

A. Train and Validate the Model:

A machine learning model is fine-tuned using a loss function that assesses its performance by counting mistakes on both the training and validation data. The loss value reflects how well or poorly the model is doing after each optimization step. To gauge the model's performance in an understandable way, we use an accuracy metric, which is typically expressed as a percentage after determining the model's parameters[6]. This metric quantifies how closely the model's predictions match the actual data.

Plot the Accuracy Graph:

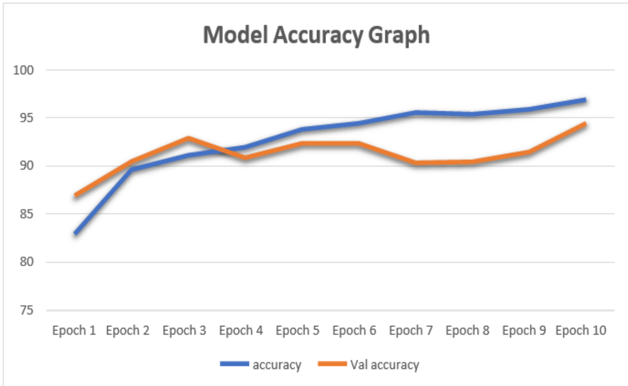


Fig. 8. Accuracy of trained model

For example, we achieved a 98% accuracy in identifying the presence of a brain tumor in MRI images. Moreover, when the system identifies a tumor in an MRI scan, it can further classify it as either Malignant or Benign with an accuracy rate of 93%.

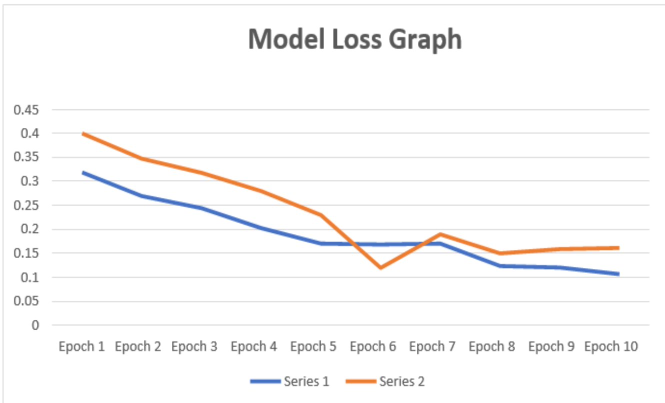
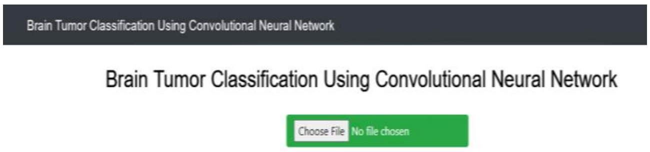


Fig. 9. Loss of trained model

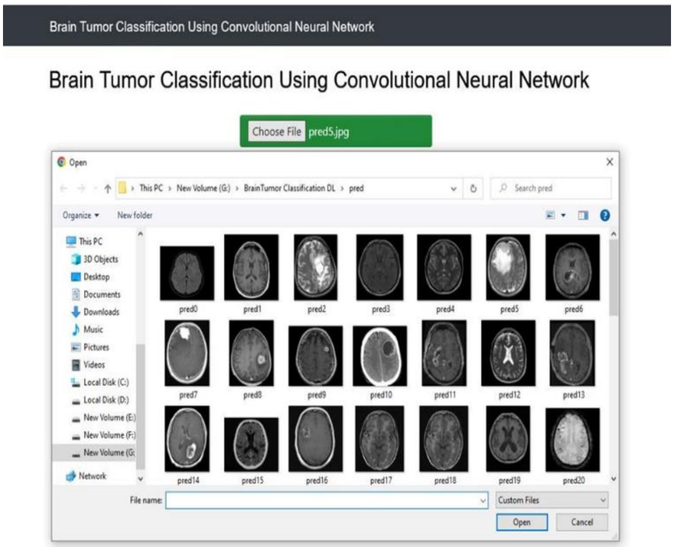
During our search for brain tumor MRI datasets, we encountered numerous options. We ultimately decided to utilize the Kaggle dataset for our thesis. However, when it came to classifying tumors as malignant or benign, we faced a scarcity of appropriately categorized MRI images. Even online, we couldn't find a sufficient number of categorized brain tumor MRI scans[7]. We recognized the importance of a substantial dataset to enhance our machine learning model's accuracy. This was a significant hurdle we had to overcome during the development process.

XI. BUILDING A GRAPHICAL USER INTERFACE (GUI)

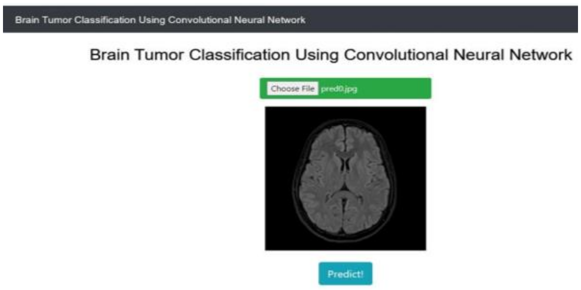
We've developed a web application to help users detect and classify tumors in MRI images. This application is built using Flask, a lightweight Python web framework, which makes it easy to create web apps quickly with just one Python file. Flask provides essential tools for web development and is beginner-friendly. It's also extendable and doesn't require complex boilerplate code or specific directory structures.In tensorflow.python.keras.preprocessing library to import and analyze the MRI images.
Additionally, we utilize the flask.templating package, which includes the render_template method in Flask. This method is used to generate output based on a template file using the Jinja2 engine, and the template file is typically located in the "templates" folder of the application. We also make use of the werkzeug.secure_filename function to ensure secure handling of filenames, which can then be safely stored or used in a conventional file system.



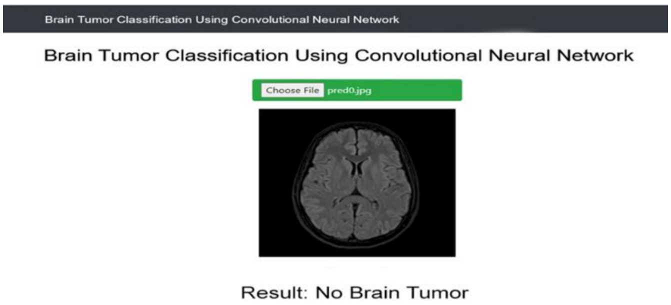
After that, we choose one image from the dataset.



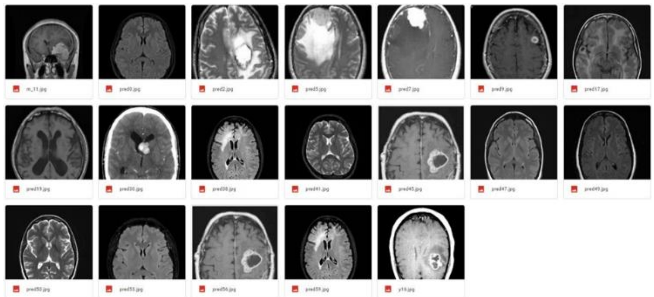
After that, we place it in the upload box.

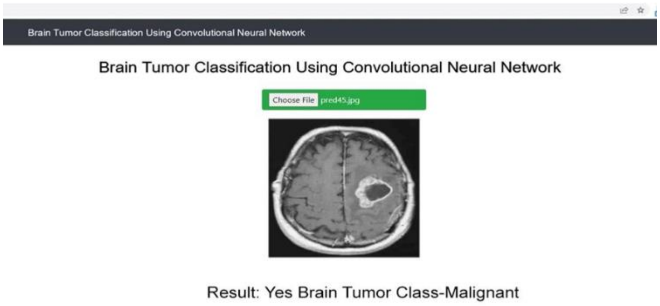


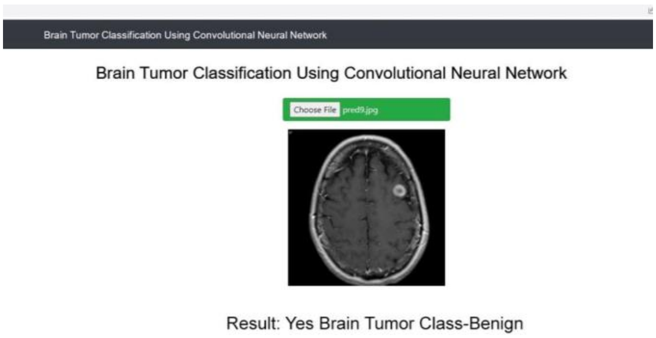
When users access our web app, they can submit MRI images and receive the results of tumor detection and classification. The web app's interface allows users to interact with it and obtain the necessary information.After that, we choose one image from the dataset. After that, we place it in the upload box. If it predicts, it will then respond.

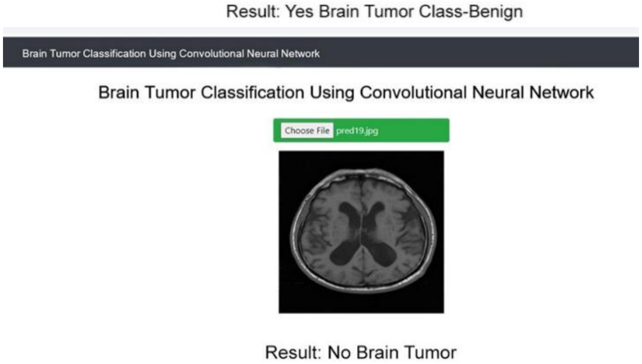


We uploaded some images like these and got the result like these.









XII. DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

XIV. CONCLUSION

In this research, we focus on the detection of brain tumors using MRI scans. We've harnessed a Kaggle dataset as the foundation for our research. After meticulously preprocessing the dataset, we've implemented a sequential model for our analysis. Our toolkit includes various libraries like cv2, os, tensorflow, keras, PIL, numpy, sklearn, and others. These libraries, in conjunction with our training data (x_train and y_train), facilitate the model's training process. We've chosen ReLU as the activation function and Adam as the optimizer, with the model being trained over 15 epochs. To evaluate its performance, we've used x_test and y_test, reserving 80% for training and 20% for testing. Following the training and testing phases, we've developed a web application to enhance user-friendliness.

This application relies on the Flask library to create a user interface that enables individuals to upload images from their smartphones. The web application promptly assesses these images to determine the presence of a tumor. If a tumor is detected, it is further classified as malignant or benign. The online app boasts an impressive 98% accuracy rate in tumor detection and a 93% accuracy rate in tumor classification, based on the model's predictions[15].

However, our ability to categorize brain tumors is currently constrained by the limited dataset. In our future endeavors, we aspire to collaborate with the V16 model and implement the ResNet architecture to diversify our results. This will enable us to make more meaningful comparisons and discern any discrepancies in the outcomes.

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