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# Brain Tumor Detection using the Concept of Convolutional Neural Network

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## Abstract

This study explores the application of a Convolutional Neural Network(CNN) for the detection and classification of brain tumors using Magnetic Resonance Imaging(MRI) scans. The datasets for this research are sourced from Kaggle. The CNN model receives the training and test accuracy of 0.9876 and 0.947 respectively. Model performance was assessed using evaluation metrics such as the confusion matrix, F1 score, precision and recall. The training process was carried out over 11 epochs, with a batch size of 16 and a learning rate of 0.001. The outcome of this study display CNN's efficiency in medical imaging analysis, which contributes to the diagnosis accuracy and progress in computational healthcare.

***Keywords:*** *CNNs, Brain tumor detection, Medical imaging, deep learning, MRI Images*

## 1. Introduction

In the field of computer-aided diagnosis, the classification of medical images acts as the fundamental task for medical practitioners that assist the healthcare professionals with reliable tools to enhance the accuracy and efficiency of diagnosing diseases. A reliable and accurate scientific classification of medical imaging helps medical persons to hit and interpretation of exact problem in minimum time and cost efficiency.

In recent years, numerous automated computer-aided diagnosis (CAD) systems have been developed to assist in the identification of brain tumors, The various domains of artificial intelligence work as decision support tools to identify diseases and enhance the accuracy of medical diagnoses(M. El-kenawy et al., 2021). Several medical imaging new technologies, including X-ray, Medical Resonance Imaging (MRI), Computed

Tomography (CT), and others, play a vital role and they are the most popular techniques to accurately diagnose the tumor, and then the doctor can easily recommend the further treatment mechanism(Ayadi et al., 2021). The technique, Magnetic Resonance Imaging (MRI), is one of the most widely acceptable imaging techniques in diagnosis due to its ability to provide detailed images of internal body structures. Despite the various advantages of this imaging technique it is more challenging and time consuming process for healthcare practitioners. For this reason, automated classification systems based on deep learning techniques become a promising solution to streamline this process.

In this study, various data augmentation techniques, such as flipping, scaling, rotation, and adding Gaussian noise, are applied to the dataset. These methods help increase the diversity of the training data and enhance the resilience of machine learning models, especially those designed for tasks like image classification, object detection, and segmentation.

This study aims to develop as well as evaluate a Convolutional Neural Network(CNN) model for the classification of MRI images into two categories: positive and negative for a specific condition. CNN is one of the most important classical Multilayered Neural Network, which is applicable not only for the classification of medical image but also in computer vision(Li et al., 2024). In this concept, data augmentation techniques are applied to overcome the problems and challenges due to data availability and class imbalance that expand the dataset. This concept helps to expand the dataset's diversity and robustness.

The concept of Tensor Flow and Keras are used in the design of the CNN model architecture, which includes dense layers for classification and convolutional layers for feature extraction. In order to train, validate, and test the model, the dataset is divided into training, validation, and test sets in an 80:10:10 ratio. Furthermore, the model's performance is assessed using a variety of classification metrics, including as F1 score, accuracy, precision, and recall. Additional insights into the model's performance are obtained through the use of visualizations like the accuracy curve and confusion matrix.

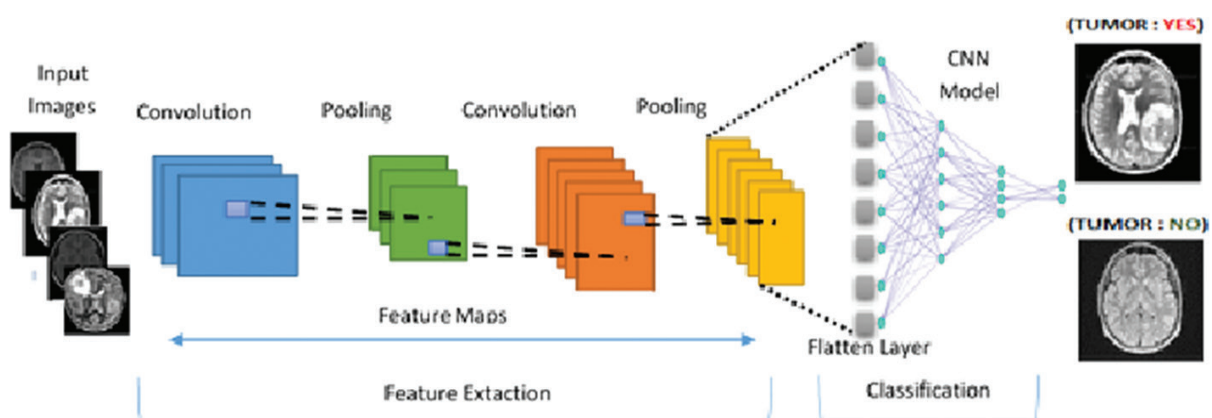



**Figure 1:** Architecture of CNN model (Lamrani et al., 2022)

## 2. Statement of the problem

The correct detection of brain tumors is actually important task which help people get the right treatment at the right time. Doctors often use an MRI scan to find a brain tumor, but sometimes it takes a long time to check them properly, and may cause mistakes. In this study, with the machine learning model, we will find a better and faster ways to spot these tumors, which will not only improve accuracy and diagnose them, but also ensure that the best care is possible for people.

## 3. Objective

The objectives of this study are listed as below:

a. Implement Convolutional Neural Networks (CNNs) for identifying and classifying brain tumors based on Magnetic Resonance Imaging (MRI) data.

b. Evaluate the performance of the model using metrics such as accuracy, recall, and F1-score, along with graphical representations.

## 4. Literature Review

A brain tumor is the result of unwanted and unexpected cell development in the central nervous system. Such problems can be easily shorted out when early and accurate detection is made otherwise it may be the root causes the serious health complications and major reason of death and, according to (Ahmed et al., 2024), it is essential to employ modern techniques , such as magnetic resonance imaging (MRI) , for the classification of brain tumors.

Typically, brain tumors arise when brain cells undergo abnormal growth and exhibit irregular behavior. Numerous studies have been conducted in the area of brain tumor detection and prevention process. Researchers (Lamrani et al., 2022) emphasized that as CNNs gained popularity, there was an increase in interest in data augmentation. Conventional techniques such as affine and elastic transformations are among the most commonly applied and effective approaches for enhancing data diversity through augmentation. These techniques involve operations such as flipping, rotating, scaling translating, introducing deformations, and modifying color properties to generate new variations of the original images. Along with benefits, there are situations in which straightforward classical operations are insufficient to solve the overfitting issue or greatly increase the accuracy of neural networks.

Data augmentation and image synthesis can greatly increase the dataset size by adding noise to images and by altering a single pixel. This approach generally makes the model more robust and less vulnerable to adversarial attacks. The authors in the paper by (Mikolajczyk & Grochowski, 2018) give the concept of various data augmentation and image synthesis algorithm.

Deep Neural Networks are multi-layered Artificial Neural Networks (ANNs) renowned for their ability to process extensive datasets effectively, particularly in pattern recognition. Out of the various deep learning models, Convolutional Neural Networks have become especially well-known due to their strong performance in applications like image classification, computer vision tasks, and natural language processing. Convolutional Neural Networks (CNNs) utilize convolutional operations across layers that include convolutional, activation, pooling, and fully connected components to extract and classify features effectively. The researchers in their study(Albawi et al., 2017)aims to elucidate CNN mechanisms and pertinent concepts while addressing factors influencing their efficiency, assuming readers possess a foundational understanding of machine learning and artificial neural networks.

The development of artificial intelligence (AI) methods has significantly transformed brain tumor detection, with magnetic resonance imaging (MRI) serving as the main tool for diagnosis. Machine learning and deep learning approaches especially convolutional neural networks (CNNs) have been widely adopted to enhance this process as well as doctors can swiftly and accurately identify abnormal tissue growth indicative of brain tumors. These algorithms offer advantages such as rapid prediction, reduced errors, and enhanced precision, facilitating informed decision-making regarding patient treatment. According to the literature (Sajjad et al., 2019), CNN model was employed to detect brain tumors, achieving impressive performance with precision and classification accuracy rates exceeding 90%, based on training and testing results. This stress the effectiveness of Convolutional Neural Network (CNNs) as a machine learning technique in the identification , categorization and demonstrating the superiority over alternative technique of brain tumors.

In (Malarvizhi et al. ,2022), researcher employed the concept of MRI-based techniques for brain tumor detection by integrating feature extraction methods with a Support Vector Machine (SVM) classifier. In order for the SVM to precisely identify the tumor's location within the brain and categorize it as either benign or malignant, the method focuses on extracting important tumor-related properties.

To segment the brain tumors, ref. (Mengqiao et al., 2017) use a deep learning algorithm. Since global and local features are an essential framework for brain image segmentation, this method makes use of them. Significant challenges in this study are overfitting and batch normalization issues, both of which limit the model's capacity to attain the desired level of accuracy.

## 5. Methodology

In this study, Brain tumor detection with the concept of MRI scans is carried out using a Convolutional Neural Network (CNN). For this , detailed workflow of the system is as:

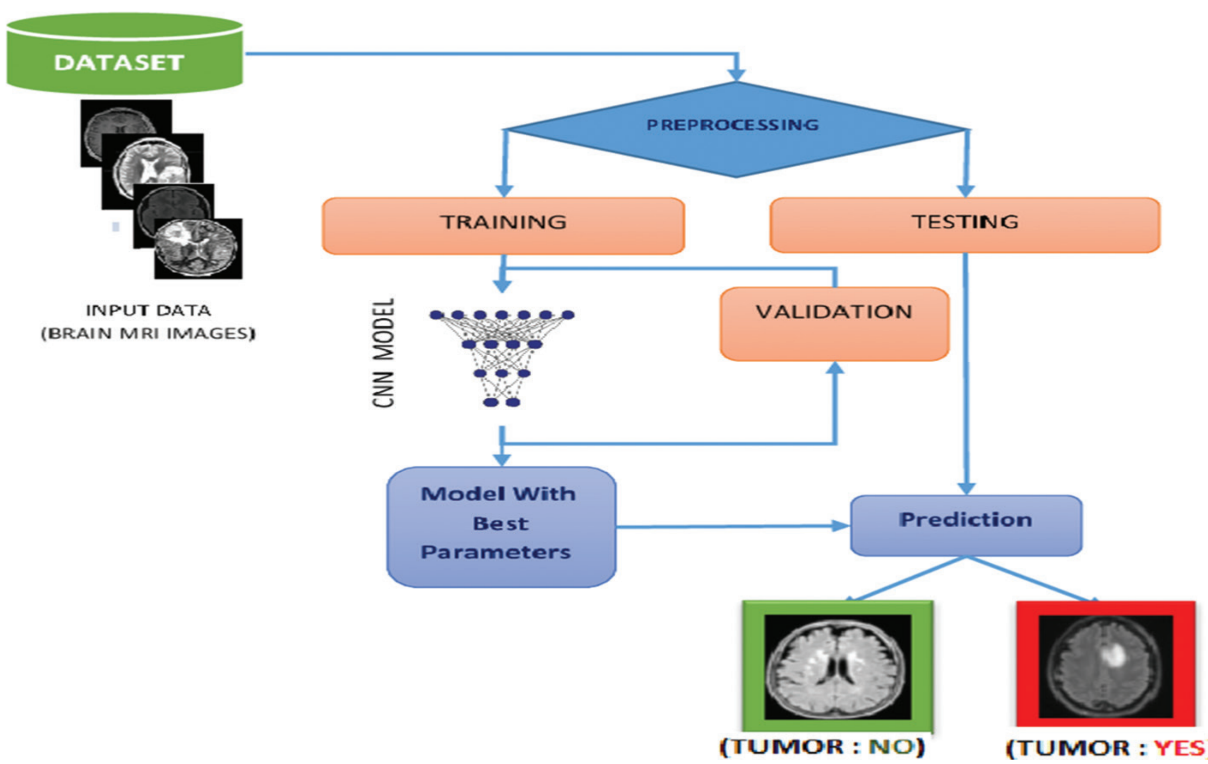



**Figure 2:** Flow diagram of working model (Lamrani et al., 2022)

*Dataset Description*

MRI images of brain are sourced from Kaggle dataset (Chakrabarty, 2019). It contains 3117 Brain MRI image in which, 1500 images are of people having brain tumors, and 1617 images are of people having no brain tumors.

*Data Preprocessing*

Data augmentation is applied during preprocessing to enhance both the dataset size and the accuracy of the model. The proposed method adds the image and saves it in the same folder, making the new dataset both original and enhanced. The total data size became 6234 images.

a. **Flipping**: The image is randomly flipped horizontally by the script. This indicates that the image's vertical axis is mirrored. The scale or ratio is not applicable here.
b. **Adding Gaussian Noise**: Gaussian noise with a mean of 0 and a standard deviation of 10 is introduced to the image to create random variations in pixel intensity. In this context, scale or ratio does not apply.
c. **Scaling**: The script randomly scales the image by a factor between 0.8 and 1.2. This means that the image can be resized to 80% to 120% of its original size while maintaining its aspect ratio.
d. **Rotation**: The script randomly rotates the image by an angle between -30 and 30 degrees around its center. This introduces variations in the orientation of objects within the image. The scale or ratio is not applicable here.
e. **Normalization**: Each pixel value in the image is scaled to a range between 0 and 1 by dividing by 255.0. This normalization helps maintain consistency across pixel values, allowing the neural network to more effectively learn patterns from the input images.

*Data Preparation*

The data is divided into distinct sets and then model will be trained, validated and tested over the different dataset, which is crucial for evaluating its performance and generalization ability. Therefore, data splitting is an important aspect of data preparation.

a. **Training Set (80%)** – It is used to enable the model to identify patterns and extract knowledge from the input features. And represented as as X_train and y_train.
b. **Validation Set (10%)** – This step is used during model development, the validation data (X_val, y_val) helps in tuning hyperparameters and preventing overfitting by evaluating model performance on unseen data.
c. **Testing Set (10%)** – This is final step, denoted as X_test and y_test, is reserved for evaluating the model's generalization ability on completely new data after training is complete.

**Table 1:** Splitting datasets

| Data | Total Number |
|---|---|
| Training data shape | 4987 |
| Validation data shape | 623 |
| Test data shape | 624 |

## 6. Configuration of CNN Model

**a. Convolutional Layers**:

I. The first convolutional layer (Conv2D) contains 20 filters, each sized 4 x 4, and uses the Rectified Linear Unit (ReLU) as its activation function. The input image sizes of 256 x 256 with RGB color are processes in this layer.

II. Subsequent convolutional layers each feature 20 filters, sized at 2x2, with ReLU activation functions.

b. **Max Pooling Layers**: A MaxPooling2D layer with a pool size of 2x2 is applied following each convolutional layer. This step reduces the spatial dimensions of the feature maps while retaining the most important features.

c. **Flatten Layer**: Post max pooling, a flatten layer (**Flatten**) is introduced. The 2D feature maps are transformed into a 1D feature vector by this layer, facilitating their integration into subsequent fully connected layers.

d. **Densely Connected Layers**: The model incorporates multiple densely connected (fully connected) layers (**Dense**). These layers' feature varying numbers of units/neurons, each utilizing ReLU activation functions.

The network's fully connected layers are structured progressively, starting with 1024 units in the first dense layer. This is followed by a reduction to 512 units in the second layer, and then further decreased to 256 units in the third. The fourth dense layer contains 128 units, and the fifth and final dense layer is compressed to 64 units, creating a streamlined architecture for efficient feature learning.

e. **Output Layer**: In accordance with the binary classification objective, the output layer (Dense) is composed of two units. It generates class probabilities using the softmax activation function.

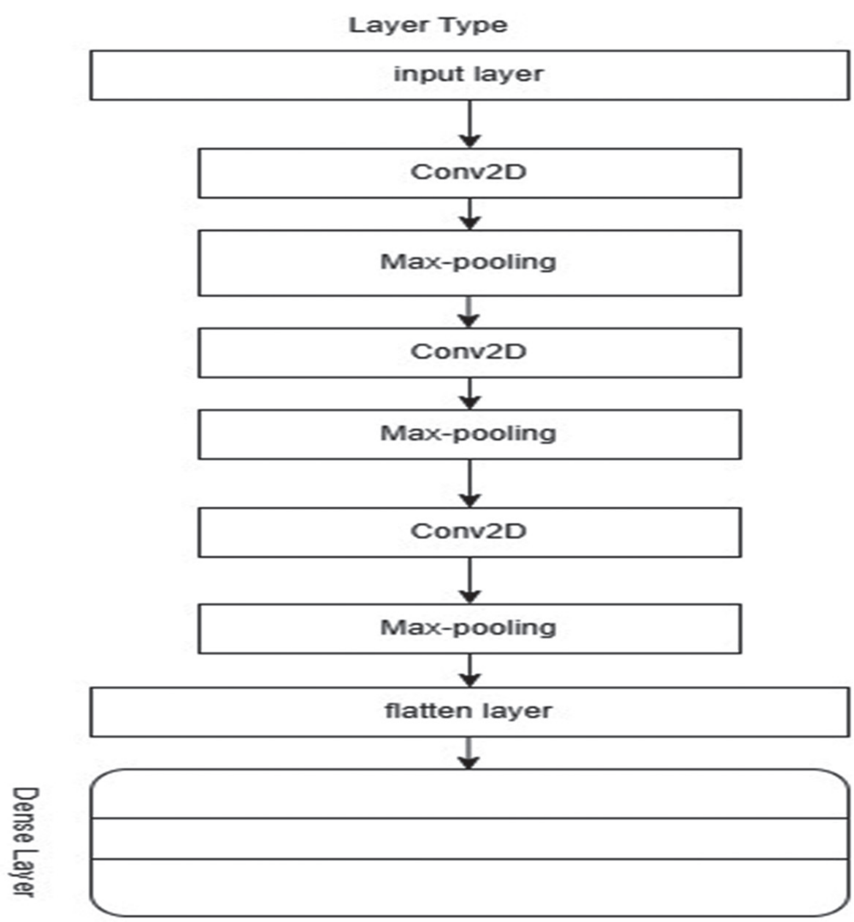



**Figure 3:** CNN Model Configuration

## 7. Performance Measurement

Performance of the model is determined not only by its accuracy but also other various factors including:

*Confusion Matrix:* It is a method for summarizing the performance of classification algorithm. When dealing with datasets that have multiple classes or imbalanced class distributions, relying solely on classification accuracy can provide a distorted view of model performance. A deeper understanding of the model's advantages and drawbacks can be obtained by computing a confusion matrix. TP, FP, FN, and TN data from the dataset.

*Accuracy:* Accuracy score refers to the proportion of correctly predicted instances out of the total number of input samples. It is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

*Precision:* Precision is defined as the proportion of true positive predictions among all instances predicted as positive. It measures how many of the predicted positive results are genuinely correct.

$$Precision = \frac{TP}{TP + FP}$$

*Recall: In classification*, recall is the ratio of True Positives to Total Actual Positives. It calculates the proportion of actual positives that are projected to be True Positives as:

$$Recall = \frac{TP}{FN + TP}$$

*F1 Score*: F1 Score, which combines Precision and Recall. It is considered as crucial evaluation indicator for binary classification. F1 score s the precision and recall's harmonic mean.

$$F1 - Score = 2 * \frac{precision * recall}{precision + recall}$$

## 8. Implementation

In this study, implementation is carried out using python and its library. Some of them are;

*Panda:* In this report panda is used to import/load the dataset as well as evaluating the nature of dataset. It is also used to remove unnecessary data and null data present in dataset.

*Sklearn:* This library is used for many propose like splitting data, train model and testing data. Sklearn library include different module for different proposed among them following are used during implementation.

a. *model_selection:*The train_test_split() method provided by this module is employed to separate the dataset into training and testing portions.
b. *Metrics:* This module is used to assess the model's effectiveness by computing performance measures such as accuracy, precision, recall, and F1 score for each individual class..

## Data and Data cleaning

Here, panda library is used for import data and data cleaning. Dataset is in csv format so read_csv() method is use to load data.

## Splitting Data

At this stage, the train_test_split function from sklearn.model_selection is used to divide the dataset into three parts: training, validation, and testing subsets. In particular, training uses 80% of the data, with the remaining 20% being split equally between testing and validation.

## Train Model

The model is trained on the training data for 8 epochs with a batch size of 16. Throughout the training process, validation data is used to track and evaluate the model's performance.

## Model Evaluation

The performance of the trained model is assessed using the test dataset to determine the final loss and accuracy values.

## 9. Result and Analysis

***Model Evaluation***

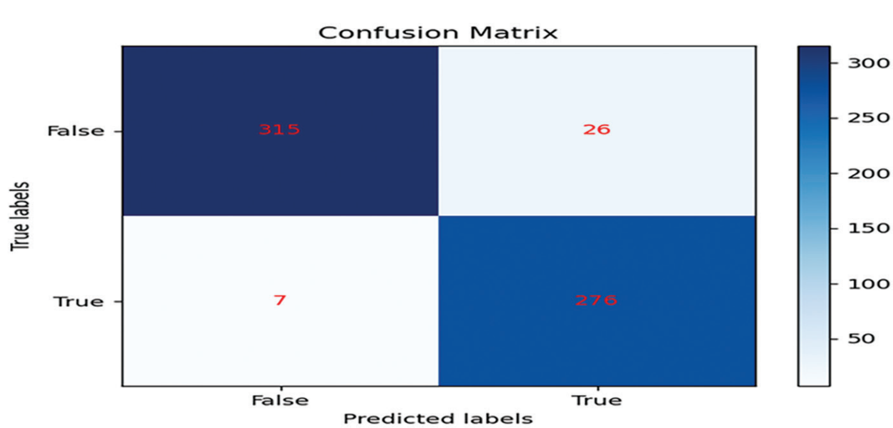
The evaluation results and training metrics after training the model for 5 epochs are as follows

Table 2: Model Evaluation

| **Training Metrics (Epoch 8):** | **Validation Metrics (Epoch 8):** | **Test Metrics:** |
|---|---|---|
| Training Loss: 0.0459 | Validation Loss: 0.1368 | Test Loss: 0.1503 |
| Training Accuracy: 0.9876 | Validation Accuracy: 0.9551 | TestAccuracy: 0.9471 |

***Confusion Matrix***

The confusion matrix of proposed model on test data images is as follows:



The confusion matrix reveals that 315 instances were correctly identified as negative (True Negatives), while 276 were accurately classified as positive (True Positives). However, 26 instances were incorrectly labeled as positive (False Positives), and 7 were mistakenly classified as negative (False Negatives).

***Evaluation Matrices***

- **Precision**=0.91390
- **Recall**= 0.97526
- **F1score** =0.943489

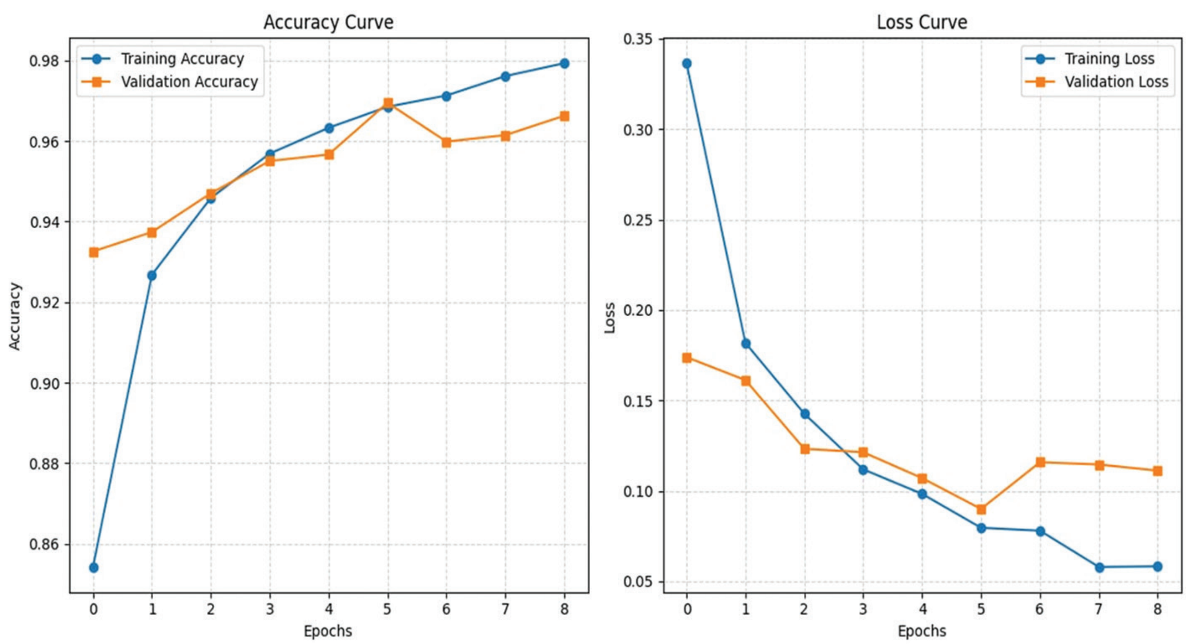



**Figure 4:** Training and Validation accuracy

## 10. Conclusion

The CNN model designed for brain tumor detection demonstrates strong performance, achieving a low test loss of 0.164 and a high accuracy of 94.55%. Its effectiveness is further supported by the confusion matrix, which reflects accurate classification of both tumor and non-tumor cases. Evaluation metrics such as precision, recall, and F1-score confirm the model's robustness, highlighting its high sensitivity and specificity. These results indicate that the CNN model holds significant promise as a dependable diagnostic tool for early brain tumor detection, potentially facilitating timely medical intervention and improving patient outcomes. Overall, the model shows potential to become a crucial component in rapid tumor identification, ensuring that patients receive appropriate treatment without delay.

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