BRAIN TUMOR CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

A Major Project Report Submitted in Partial
fulfilment of the Requirements for the
Degree of

Bachelor of Technology
in
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By

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to the

COMPUTER SCIENCE AND ENGINEERING DEPARTMENT
MOTILAL NEHRU NATIONAL INSTITUTE OF TECHNOLOGY
ALLAHABAD PRAYAGRAJ **May, 2025**

UNDERTAKING

We declare that the work presented in this report titled "Brain Tumor Classification using Convolution Neural Network", submitted to the Computer Science and Engineering Department, Motilal Nehru National Institute of Technology Allahabad, Prayagraj, for the award of the Bachelor of Technology degree in Computer Science & Engineering, is our original work. We have not plagiarized or submitted the same work for the award of any other degree. In case this undertaking is found incorrect, we accept that our degree may be unconditionally withdrawn.

Sattwik Jana, 20214154
May, 2025

CERTIFICATE

Certified that the work contained in the report titled
“Brain Tumor Classification using Convolution Neural Network”
by Sattwik Jana (20214154), has been carried out under my supervision and that this work has not been submitted elsewhere for a degree. It is deemed to be an authentic and original piece of work.

Dr. Saugata Roy
Computer Science and
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Allahabad May 2025

Abstract

Brain tumor detection poses a significant challenge in the field of medical imag- ing, particularly in the diagnosis and treatment of neurological disorders. The pres- ence of brain tumors can have severe implications on a patient’s health and require prompt and accurate identification for effective medical intervention. In many cases, the manual interpretation of medical images, such as MRI scans, by radiologists is time-consuming and subject to human error, leading to delays in diagnosis and treatment planning.

This study aims to address these challenges by developing a brain tumor de- tection algorithm using a deep learning convolutional neural network (CNN). The objective is to leverage the power of deep learning to automate the process of tumor detection, thereby reducing reliance on human expertise and enhancing the efficiency of diagnosis.

The findings of this study demonstrate that the developed CNN model effectively learns and extracts relevant features from input MRI images, enabling accurate de- tection and localization of brain tumors. Through rigorous evaluation and validation on independent datasets, the algorithm achieves a high accuracy of 95.80% in 10 epochs in identifying tumor presence and distinguishing between different tumor types.

Contents

Chapter 1

Introduction

A brain tumor represents an abnormal mass or growth of cells in the brain, existing within the confined space of the skull. This condition can lead to serious complications due to increased intracranial pressure and potential brain damage. Tumors can be benign (noncancerous) or malignant (cancerous), and their early detection and accurate classification are critical for effective treatment planning, underscoring the importance of advancements in medical imaging.

Deep learning, particularly in the realm of healthcare, has brought significant improvements in diagnosing various conditions, including brain tumors. The World Health Organization emphasizes the importance of accurate brain tumor diagnosis, which includes detecting the presence of a tumor, pinpointing its location, and classifying its type and grade.

This project deals with such a system, which uses computerized procedures to de- tect tumor blocks and classify the type of tumor using Convolution Neural Network Algorithm for MRI images of different patients. Different types of image processing techniques like image segmentation, image enhancement and feature extraction are used for the brain tumor detection in the MRI images of the cancer-affected pa- tients. Detecting Brain tumor using Image Processing techniques its involves the four stages is Image Pre-Processing, Image segmentation, Feature Extraction, and Classification. Image processing and neural network techniques are used for improve the performance of detecting and classifying brain tumor in MRI images .

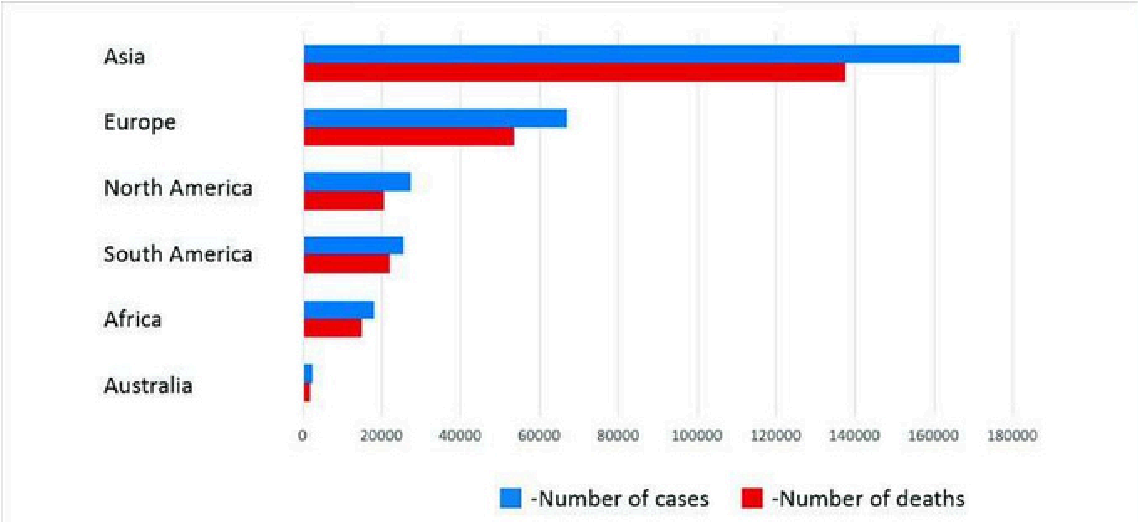


Fig.1 : Brain Tumor Cases and Deaths per Continent

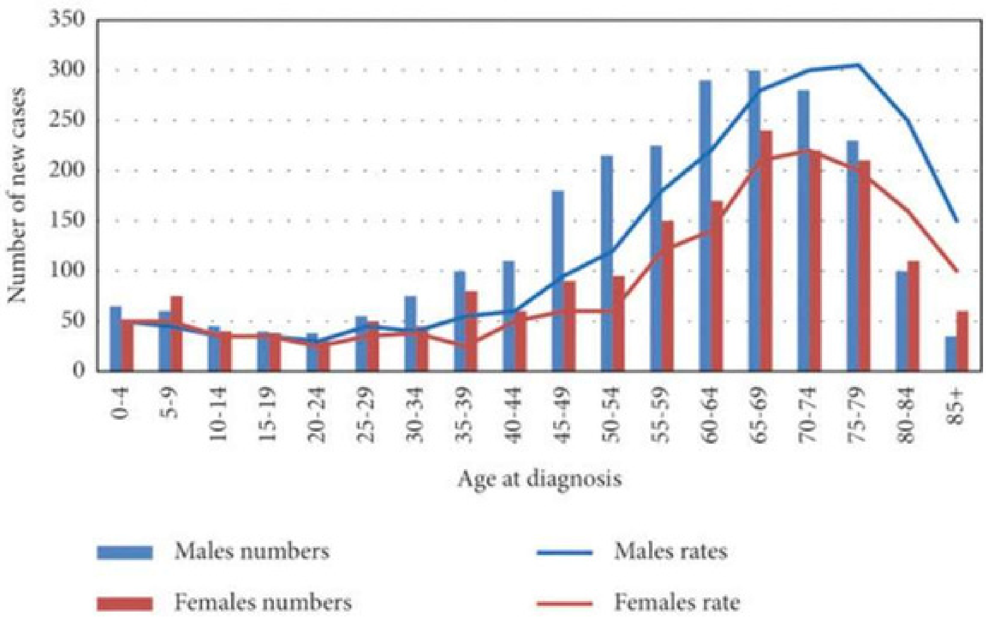


Fig. 2 : Brain Tumor Cases Age distribution

1.1 Motivation

Brain tumors are a significant health concern worldwide, with potentially life-threatening consequences. Developing an accurate and reliable detection model can contribute to early diagnosis and intervention, ultimately improving patient outcomes and quality of life.

The symptom having of brain tumor depends on the location, size and type of the tumor. It occurs when the tumor compressing the surrounding cells and gives out pressure. Besides, it is also occurring when the tumor blocks the fluid that flows throughout the brain. The common symptoms are having headache, nausea and vomiting, and having problem in balancing and walking. Brain tumor can be detected by the diagnostic imaging modalities such as CT scan and MRI. Both of the modalities have advantages in detecting depending on the location type and the purpose of examination needed. In this paper, we prefer to use the MRI images because it is easy to examine and gives out accurate calcification and foreign mass location

The MRI is the most regularly utilized strategy for imaging brain tumors and the identification of its vicinity. The conventional technique for CT and MR image classification and detection of tumor cells remains largely supported for the human reviewing apart from different other methods. MR images are mainly used because they are non-destructive and non-ionizing. MR imaging offers high-definition pictures that are extensively utilized in discovering brain tumors.

1.2 Problem and Idea

The Global Brain Tumor Mortality Report (2020) highlights. Here are some key findings and points from the report:

- A significant increase in brain tumor-related deaths globally in 2020.
- Regional differences in mortality rates due to factors like healthcare access and socioeconomic status.
- Variations in mortality across age groups and genders.

- The profound impact on quality of life for patients and families.
- The substantial economic burden on healthcare systems and society.

Urgent need for research, early detection, innovative treatments, and supportive care. The report calls for collaborative action to address brain tumor mortality's complex challenges and reduce its burden

Idea

In order to address this challenge, we have proposed the development of a Python-based machine learning model that utilizes image processing and deep learning techniques to accurately classify the conditions into various different types of brain tumor conditions. Subsequent chapters we will delve into the specifics of this model, providing a more detailed explanation of its methodology and imple- mentation.

Chapter 2 Overview of Existing Work

In this chapter we shall discuss some of the works that have already been done in the field of Brain Tumor Detection.

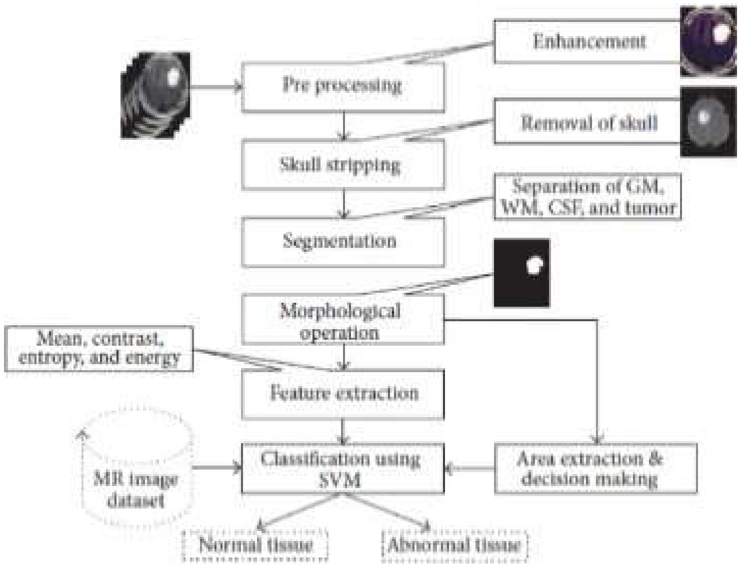


Fig. 3: Workflow

1. Image Preprocessing :

   • As input for this system is MRI, scanned image and it contain noise. Therefore, our first aim is to remove noise from input image. As explained in system flow we are using high pass filter for noise removal and preprocessing

2. Segmentation :

   • A Region growing is the simple region-based image segmentation technique. It is also classified as a pixel based image segmentation technique since it is involve the selection of initial seed points

3. Morphological operation :

   • The morphological operation is used for the extraction of boundary areas of the brain images. This operation is only rearranging the relative order of pixel value, not mathematical value, so it is suitable for only binary images. Dilation and erosion is basic operation of morphology. Dilation is add pixels to the boundary region of the object, while erosion is remove the pixels from the boundary region of the objects.

4. Feature Extraction :

   • The feature extraction is used for edge detection of the images. It is the process of collecting higher level information of image such as shape, texture, color, and contrast.

5. Connected component labeling :

   • After recognizing connected components of an image, every set of connected pixels having same gray-level values are assigned the same unique region label.

6. Tumor Identification :

   • In this phase, we are having dataset previously collected brain MRIs from which we are extracting features. Knowledge base is created for comparison.

Chapter 3

Methods and Model used

3.1 Dataset

The dataset comprises a total of 7023 human brain MRI images, categorized into four distinct classes. The dataset focuses on brain tumors and their classification. The four classes are as follows:

Glioma : Cancerous brain tumors in glial cells.

Meningioma : Non-cancerous tumors originating from the meninges.

No Tumor : Normal brain scans without detectable tumors.

Pituitary : Tumors affecting the pituitary gland, which can be cancerous or non-cancerous.

Advancing the development of machine learning models for tumor classification is crucial for driving progress in the field of neurology and making a significant impact on the lives of individuals.

These models have the potential to enhance medical research, improve diagnostic accuracy, and contribute to effective treatment strategies for various types of tumors. By leveraging machine learning techniques, we can significantly aid in the advancement of neurology and ultimately improve healthcare outcomes for people affected by tumor .

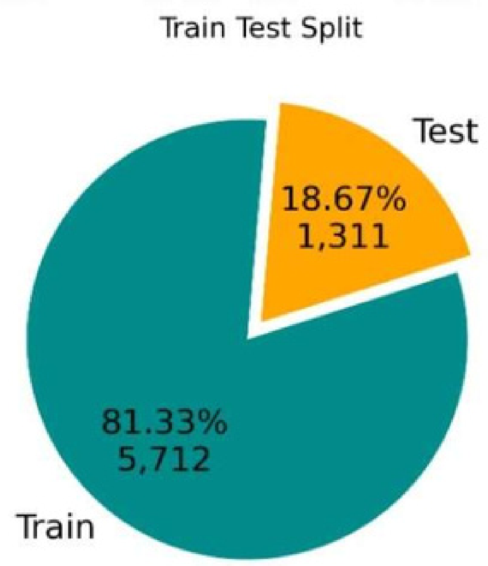


Fig. 4 : Composition of the dataset

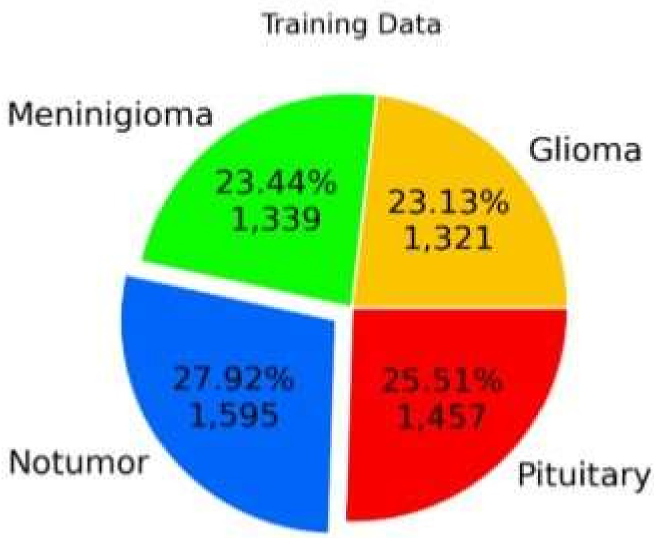


Fig. 5 : Composition of training dataset

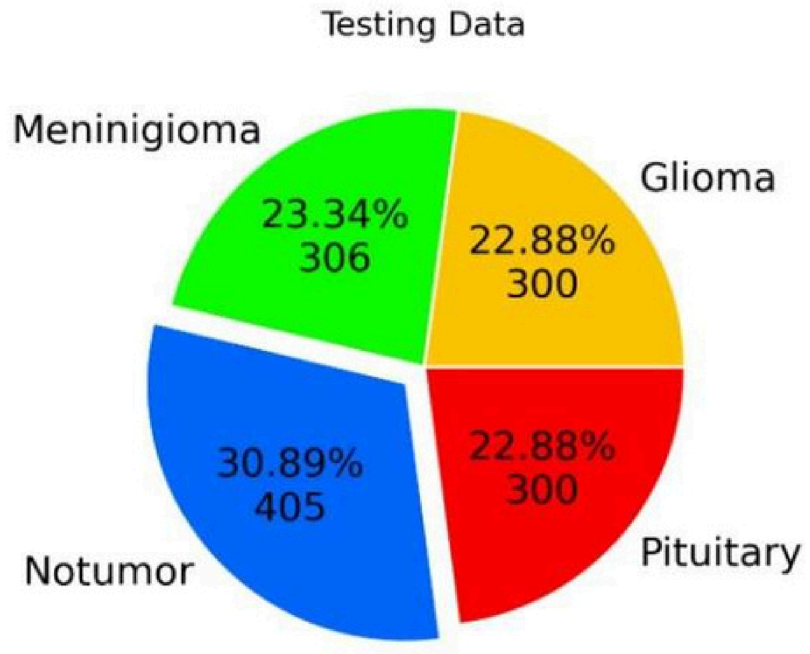


Fig. 6 : Composition of testing dataset

3.2 Model Description

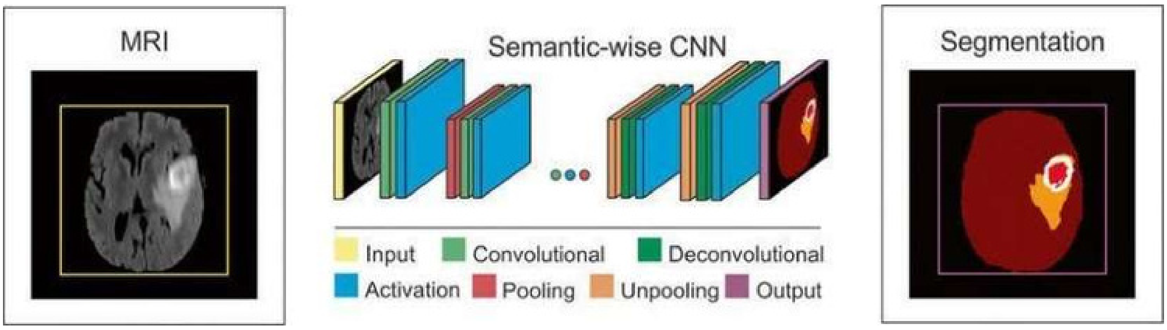


Fig. 7: Working of CNN model for brain tumor detection

- Layer of CNN model: :
  - o Convolution 2D
  - o MAX Poolig2D
  - o Dropout
  - o Flatten
  - o Dense
  - o Activation
- Convolution 2D: In the Convolution 2D extract the featured from input image. It given the output in matrix form.
- MAX Poolig2D:In the MAX polling 2D it take the largest element from rectified feature map
- Dropout:Dropout is randomly selected neurons are ignored during training feature map
- Flatten: Flatten feed output into fully connected layer. It gives data in list form feature map

- Dense: A Linear operation in which every input is connected to every output by weight. It followed by nonlinear activation function

- Activation: Activating the output from the convolutional layer is achieved through the Rectified Linear Unit (ReLU) activation function. This function selectively activates non-negative neurons, enhancing computational efficiency in contrast to the sigmoid and tanh functions.

- Optimizer: Optimizer in machine learning refers to an algorithm that modifies the parameters of a model to minimize the differences between predicted and actual output.

It is a key component of the training process and is used to update the model's parameters to minimize the loss function.

There are several types of optimizers, such as Stochastic Gradient Descent, Adagrad, Adam, and RMSprop.

- Adam optimizer: It is a popular stochastic gradient descent optimization algorithm utilized in machine learning due to its efficient, low memory requirements, and ability to handle large datasets.

It is an amalgamation of two other optimization algorithms, Adagrad and RMSprop, that offer better performance and quicker convergence

Computationally efficient.

Little memory requirement.

The Adam optimizer adapts the learning rate for each weight of the model by calculating the first and second moments of the gradients.

Layer (type)	Output Shape	Param
conv2d (Conv2D)	(None, 164, 164, 64)	1,664
max_pooling2d (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_1 (Conv2D)	(None, 50, 50, 64)	102,464
max_pooling2d_1 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_2 (Conv2D)	(None, 13, 13, 128)	131,200
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
conv2d_3 (Conv2D)	(None, 3, 3, 128)	262,272
max_pooling2d_3 (MaxPooling2D)	(None, 1, 1, 128)	0
flatten (Flatten)	(None, 128)	0
dense (Dense)	(None, 512)	66,048
dense_1 (Dense)	(None, 4)	2,052

Fig. 8 : CNN Layers Breakdown

3.3 Project Implementation

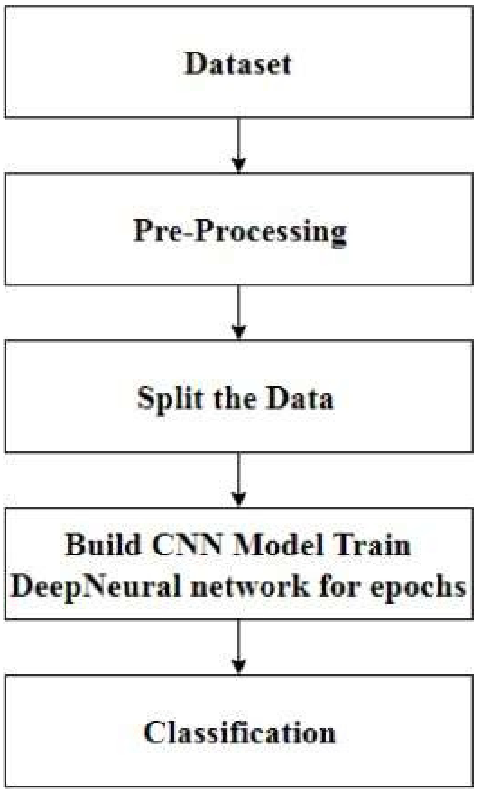


Fig. 9 : Proposed work flow of brain tumor detection

3.3.1 Program Flow

- Imports and Setup: This section includes importing necessary libraries and setting up the environment, including checking for GPU availability and updating data visualization settings.

- Data Processing: his section involves loading and preprocessing the dataset, including splitting it into training and testing sets, preparing the data with appropriate labels and transformations, and printing out dataset information.

- Data Visualization: This part visualizes the dataset distribution and provides a function to display sample images.

• Training Setup: Here, the training data is augmented and normalized, and the model architecture is defined using Convolutional and Dense layers. The model is compiled with an Adam optimizer and categorical cross-entropy loss..

• Model Evaluation: The trained model is evaluated using the test dataset, and metrics such as accuracy, precision, recall, and F1-score are calculated. Confusion matrix and misclassified tumor images are also plotted.

• Testing on New Data: Lastly, the model is tested on new brain tumor images, and predictions are made and displayed alongside true labels.

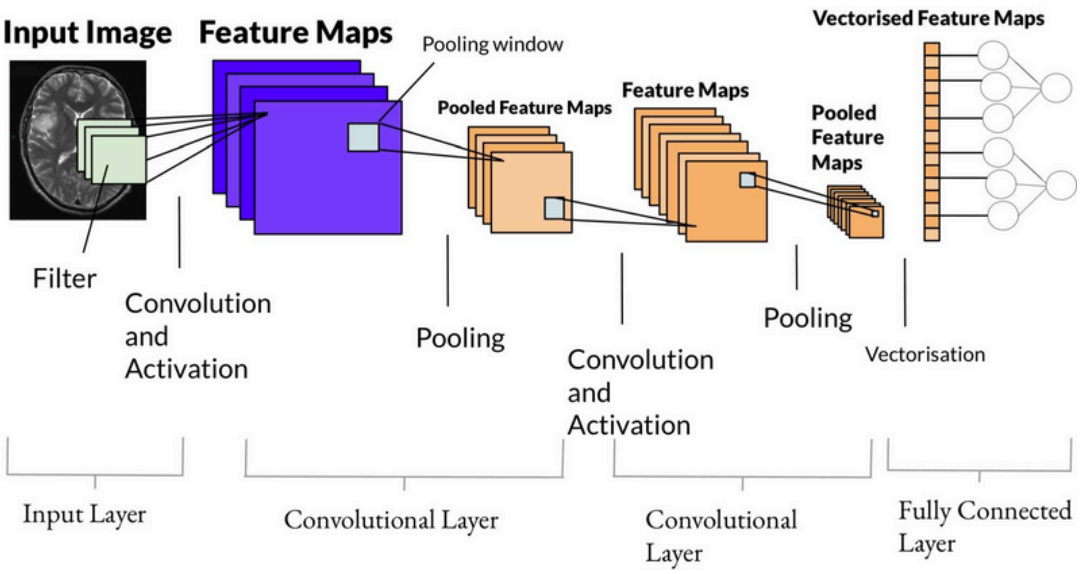


Fig. 10 : Visual Workflow

Chapter 4

Experimental Setup & Result Analysis

4.1 Tools and Technologies Used

• Python: Python is a high-level, interpreted, interactive and object-oriented scripting language. Python is designed to be highly readable. It was created by Guido van Rossum during 1985- 1990[3]. Python is dynamically-typed and garbage-collected. Python's source code is also available under the GNU General Public License (GPL), which is free to download. We are using the Python code for the processing because Python is widely used in image pro- cessing, machine learning and AI-driven projects, including simplicity and con- sistency, flexibility, access to powerful AI and machine learning (ML) libraries and frameworks, platform independence, and large communities.

• TensorFlow: TensorFlow is an open-source machine learning framework developed by Google, widely employed for various tasks in artificial intelligence and deep learning. It offers a comprehensive suite of tools and functionalities for building, training, and deploying machine learning models, particularly focusing on neural networks. TensorFlow is highly regarded for its flexibility, scalability, and efficiency, making it a top choice for researchers and practitioners alike.

Key features of TensorFlow include its robust computational graph abstrac- tion, which enables users to define complex mathematical operations as a graph of nodes, and its automatic differentiation capabilities for efficient gradient computation during training.

Moreover, TensorFlow provides seamless integration with specialized hardware accelerators such as GPUs and TPUs (Tensor Processing Units), optimizing performance for large-scale machine learning workloads. Its high-level APIs, including TensorFlow Keras, facilitate rapid prototyping and development of machine learning models with minimal boilerplate code.

• NumPy: NumPy is a Python library that offers numerical computing and provides efficient and convenient array manipulation and mathematical oper- ations. It stands for Numerical Python. NumPy provides a multidimensional array object and a set of functions to operate on these arrays, making it easy to perform mathematical operations on large amounts of data quickly and ef- ficiently. Python's NumPy module is crucial for scientific computing and data processing.

4.2 Result Analysis

After training the model, the maximum accuracy in 10 epochs turned out to be 95.80%. Following are the detailed results out of each epoch.

- **Accuracy:**

Accuracy measures how well a machine learning model can correctly predict or classify a given set of data. It is calculated as the ratio of the number of correct predictions to the total number of predictions made by the model.

$$\text{Accuracy} = \frac{\text{Correctly predicted samples}}{\text{Total samples}}$$

- **Precision:**

Precision is the percentage of true positive predictions.

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

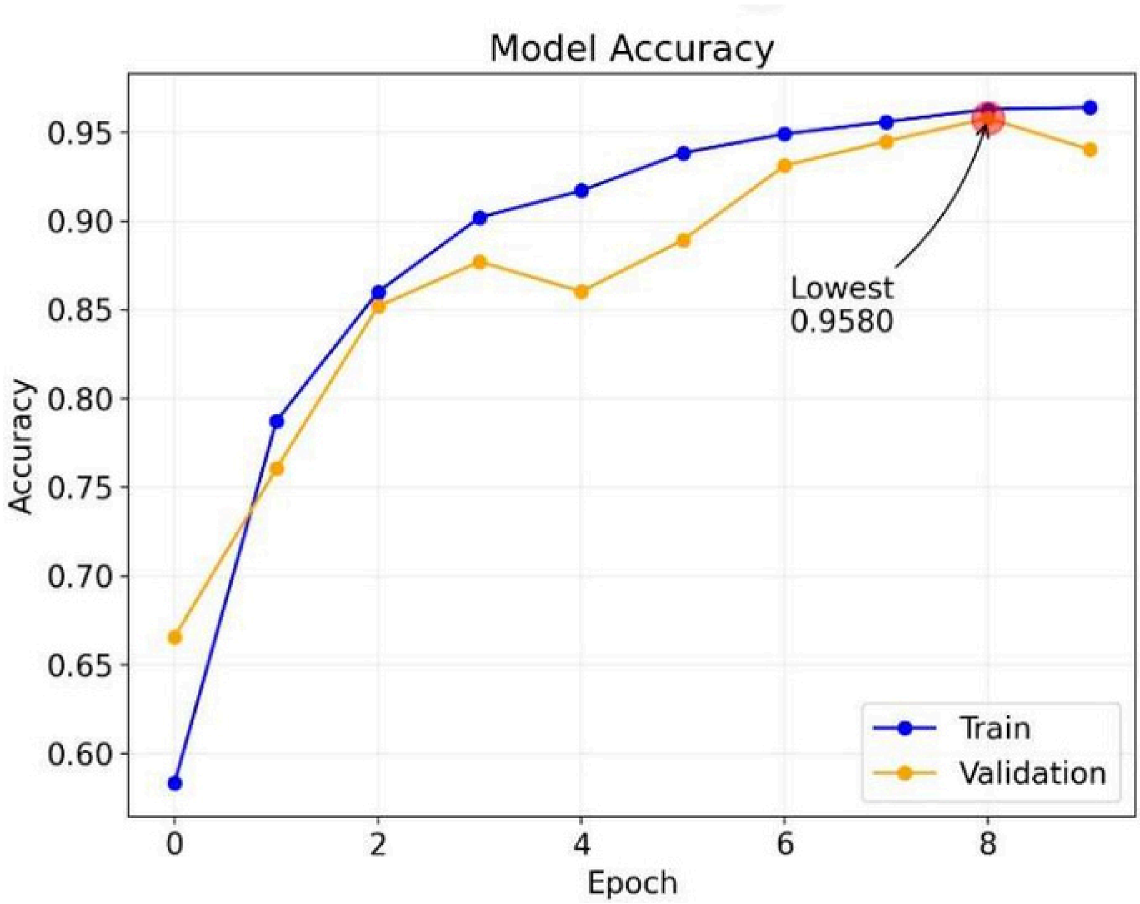
- **Recall:**

Recall calculates the percentage of true positive predictions out of all actual positive cases in the data.

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

- **Accuracy & Loss:**

Following are the loss and accuracy curves per epoch:



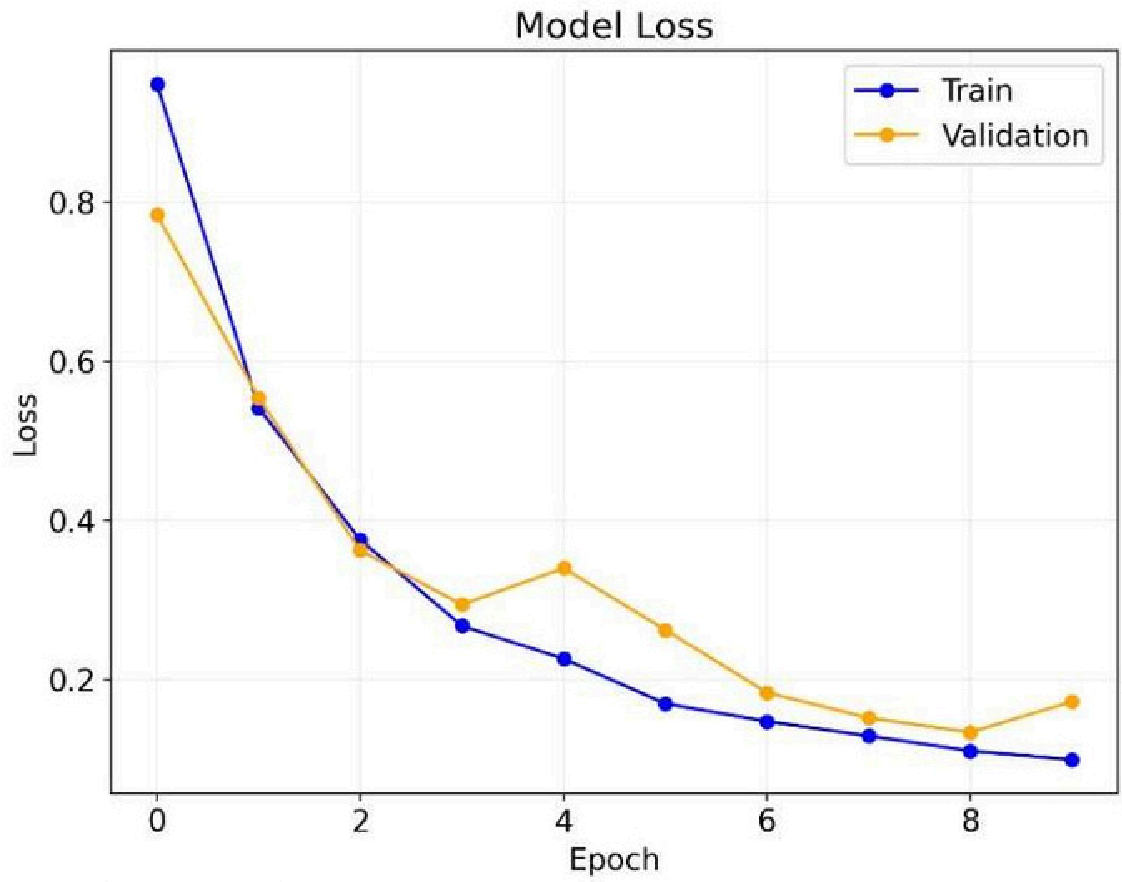
GRAPH 1- Accuracy vs Epoch (Reference - model trained)

```
Class-wise metrics:
Class: Glioma
Precision: 0.9855
Recall: 0.9067
F1-Score: 0.9444

Class: Meninigioma
Precision: 0.9049
Recall: 0.9641
F1-Score: 0.9335

Class: Notumor
Precision: 0.9584
Recall: 0.9679
F1-Score: 0.9631
```

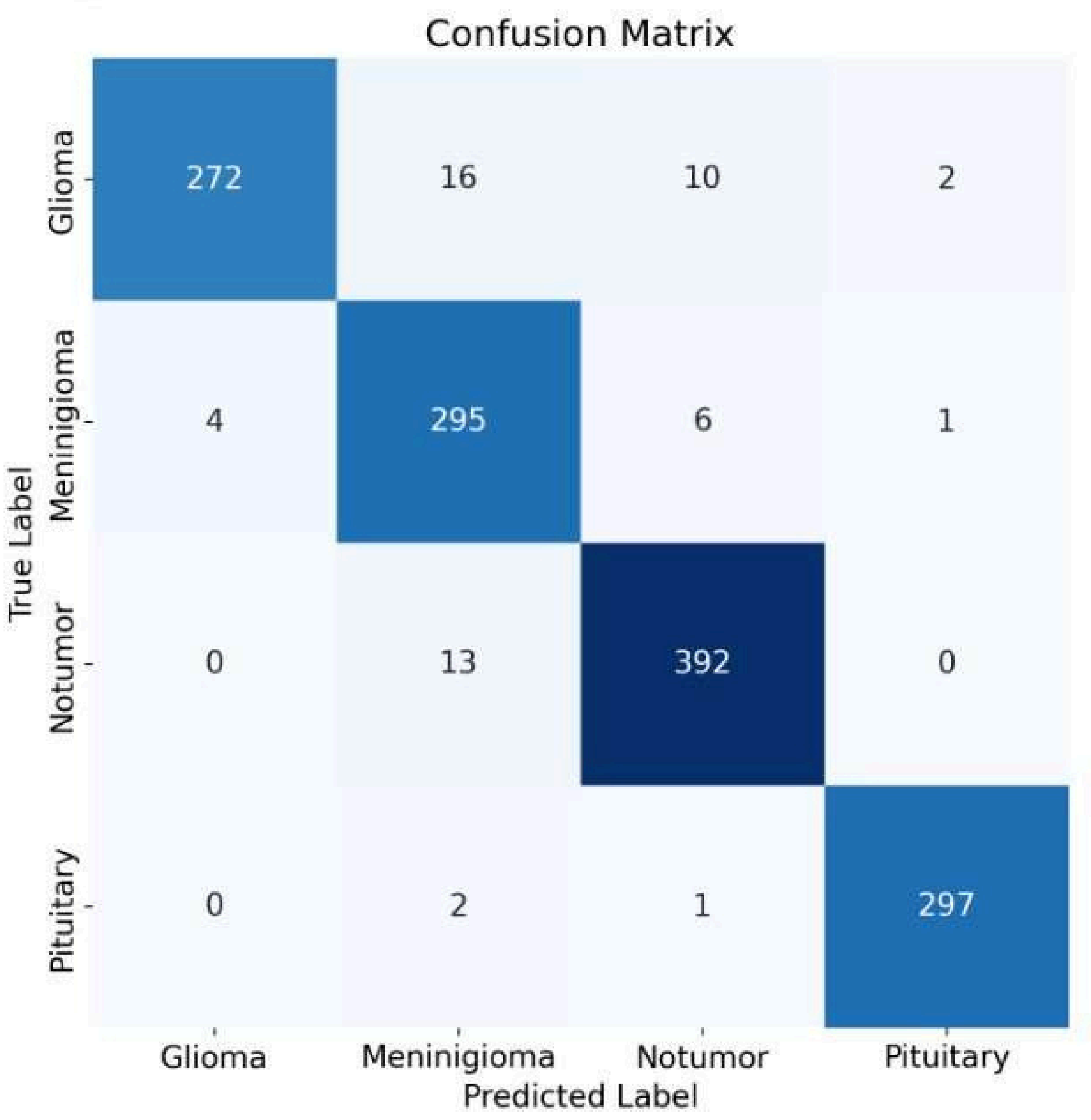
Metrics for tumor types



GRAPH 2- Loss vs Epoch (Reference - Model trained)

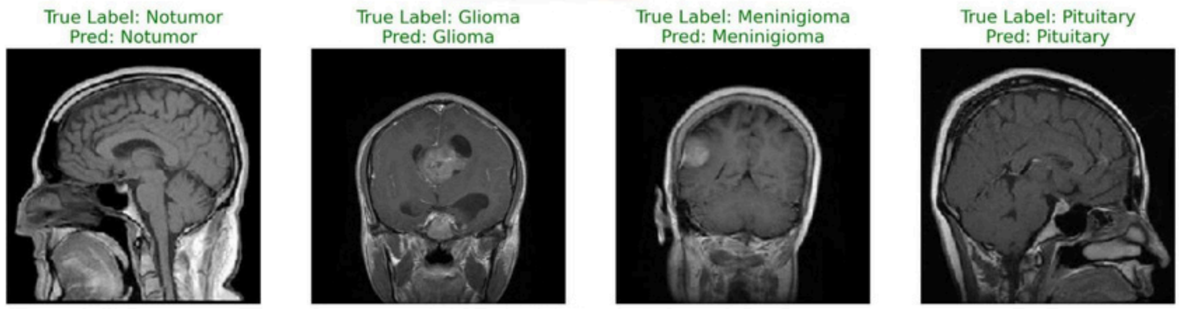
Confusion Matrix:

Confusion Matrix: A confusion matrix is a tool in machine learning to measure the performance of a classification model. It’s a table that shows the true positive, true negative, false positive, and false negative values for each class in the model. These values are used to calculate metrics like accuracy, precision, recall, and F1 score. The confusion matrix for test data is as below:

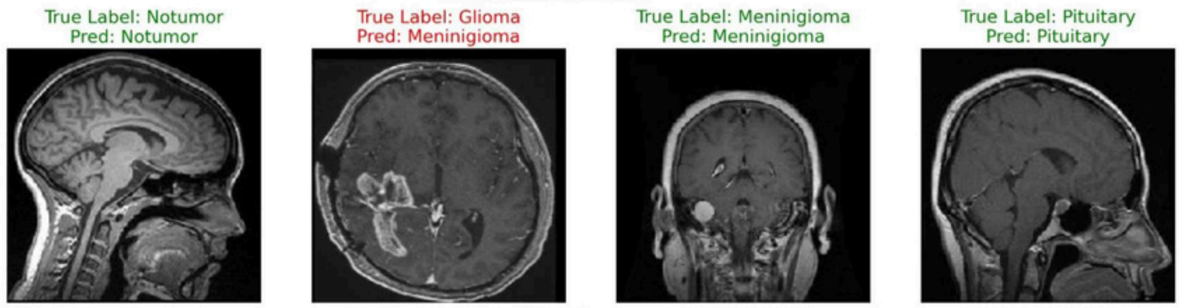


Reference-(model trained)

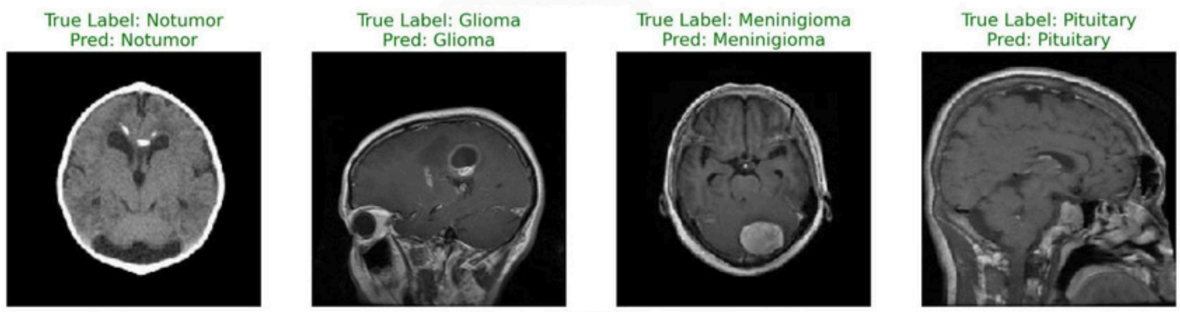
4.3 Output



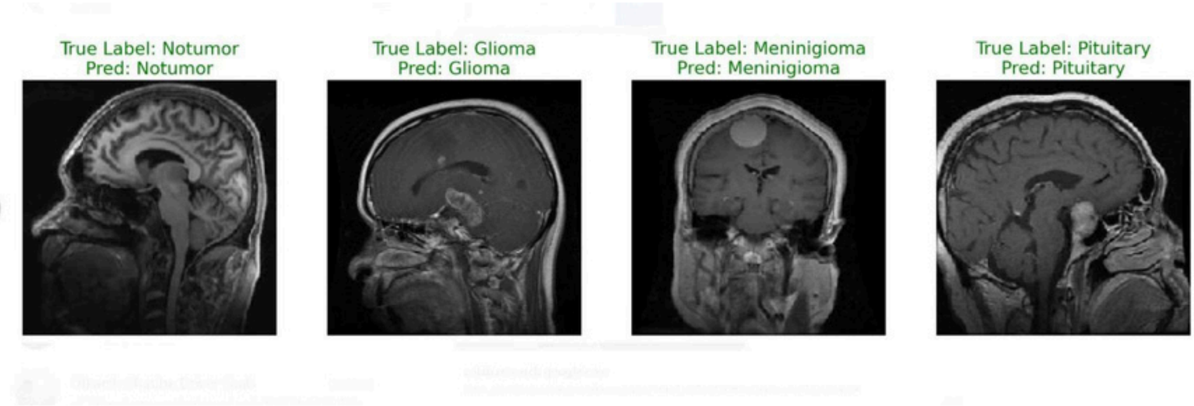
Sample Output 1



Sample Output 2



Sample Output 3



Sample Output 4

Chapter 5 Conclusion & Future Scope

5.1 Conclusion

The study shows that the pre-trained convolutional neural network model supporting 4 layers , achieved the test accuracy of 95.80% after 10 epochs when classifying the different types of brain tumors. The Adam optimizer, ReLU as an activation layer, and binary cross-entropy were used for this model.

The model exhibited good processing time and accuracy, suggesting its feasibility for real-world applications and potential for future expansion.

In the realm of development, perfection is often elusive, and every task, no matter how well-executed, harbors potential for further improvement. Even as we strive for excellence in this application, we acknowledge that there are avenues for refinement and enhancement waiting to be explored. Throughout this journey, We have garnered invaluable insights and acquired a wealth of knowledge about the development field, underscoring the iterative nature of progress and the endless opportunities for learning and growth.

5.2 Future Work

As our project nears completion, it is crucial to look into its potential future developments and advancements. The project has several aspects that could be further improved in the future.

1. Enhancing Model Accuracy: Developing more sophisticated CNN architectures or incorporating advanced techniques such as transfer learning to improve the accuracy of brain tumor detection.

   Extending the model to accurately classify and differentiate between various types of brain tumors, including rare or complex subtypes.

2. Integration with Medical Robotics: Exploring integration with medical robotics technology to create a semi-automated or fully automated system for brain tumor detection and surgical assistance.

   Incorporating robotic tools for precise tumor localization, biopsy, and minimally invasive surgery based on the CNN's detection results.

3. Extension to Mobile Applications: Extending the brain tumor detection system to mobile applications to empower healthcare professionals and patients with on-the-go access to diagnostic tools and information.

   Developing user-friendly interfaces and decision support systems within mobile apps to facilitate early detection, patient education, and communication with healthcare providers.

4. Scaling Up and Deployment: Scaling up the project to cover larger geographic regions or healthcare facilities to improve access to advanced brain tumor detection technology.

   Collaborating with hospitals, research institutions, and healthcare providers to deploy the CNN-based brain tumor detection system in clinical settings and integrate it into routine medical practice.

By taking these future aspects into account, the project can continue to progress and remain pertinent in the dynamic field of machine learning. Moreover, it can provide opportunities for collaborations and partnerships with other researchers and organization.

Chapter 6

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