**Brain Tumor Segmentation Using Convolutional Neural Network**

*Submitted in partial fulfillment of the requirements for the degree of*

Master of Science

In

**Data Science**

*by*

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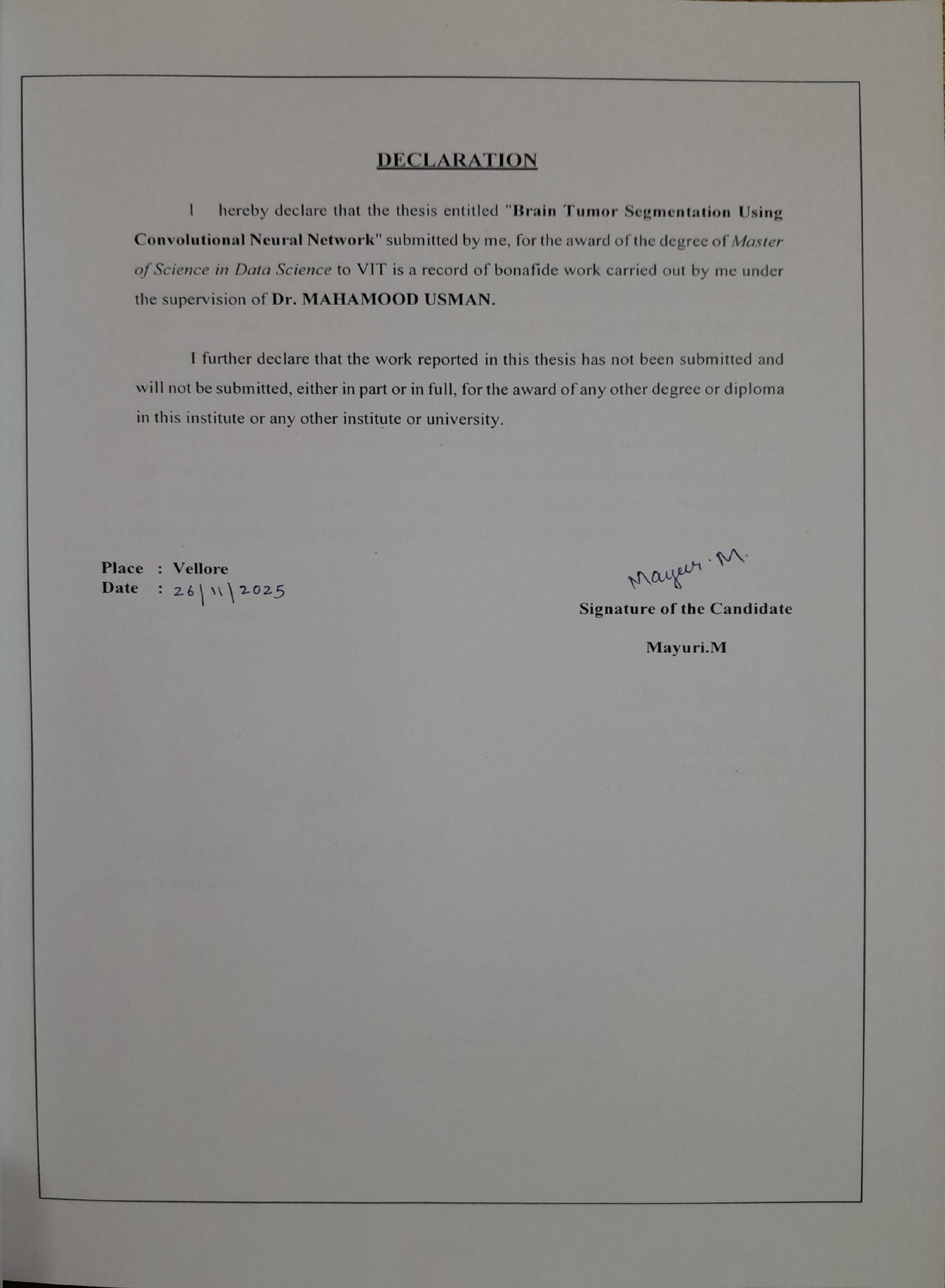
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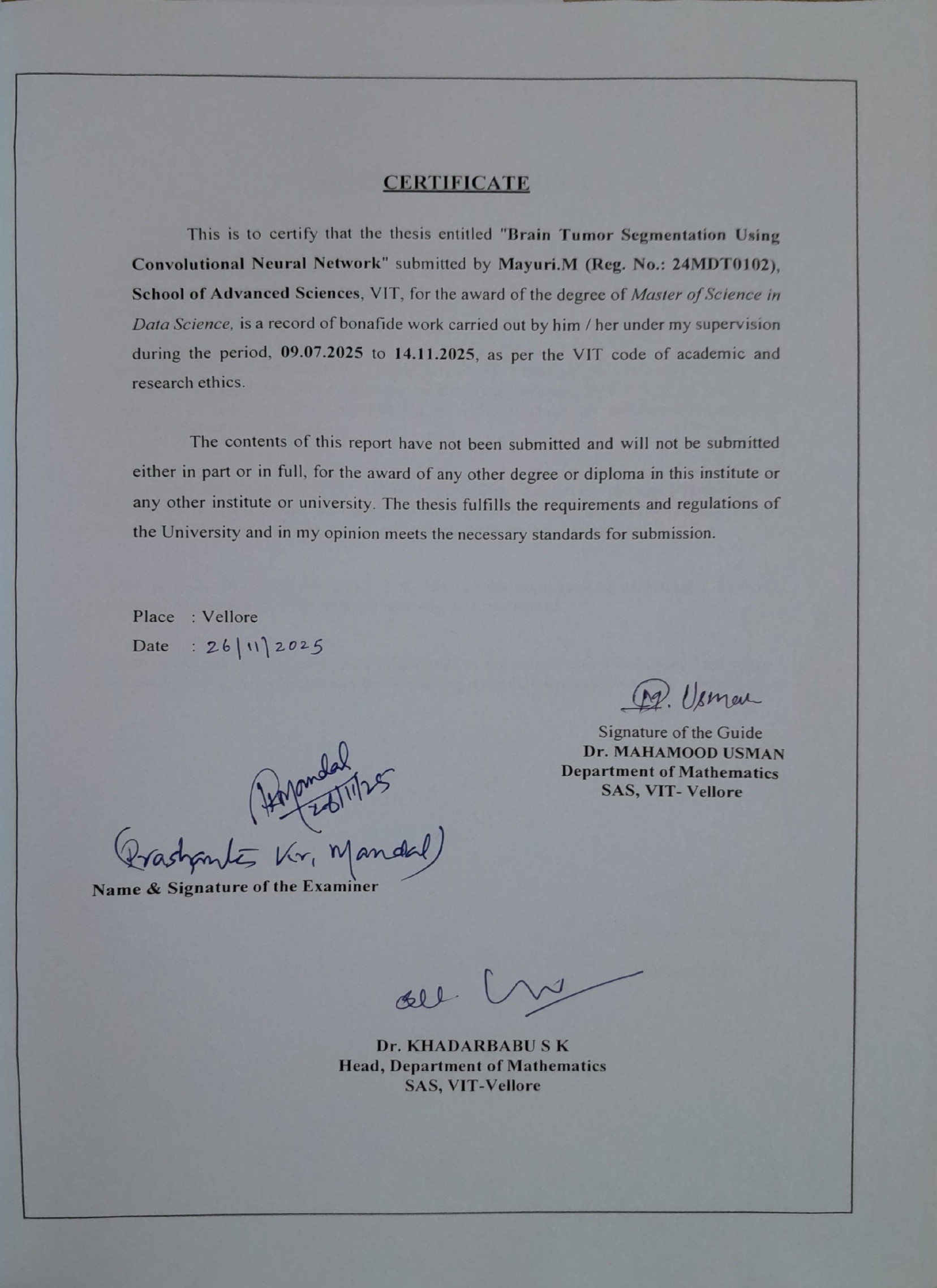
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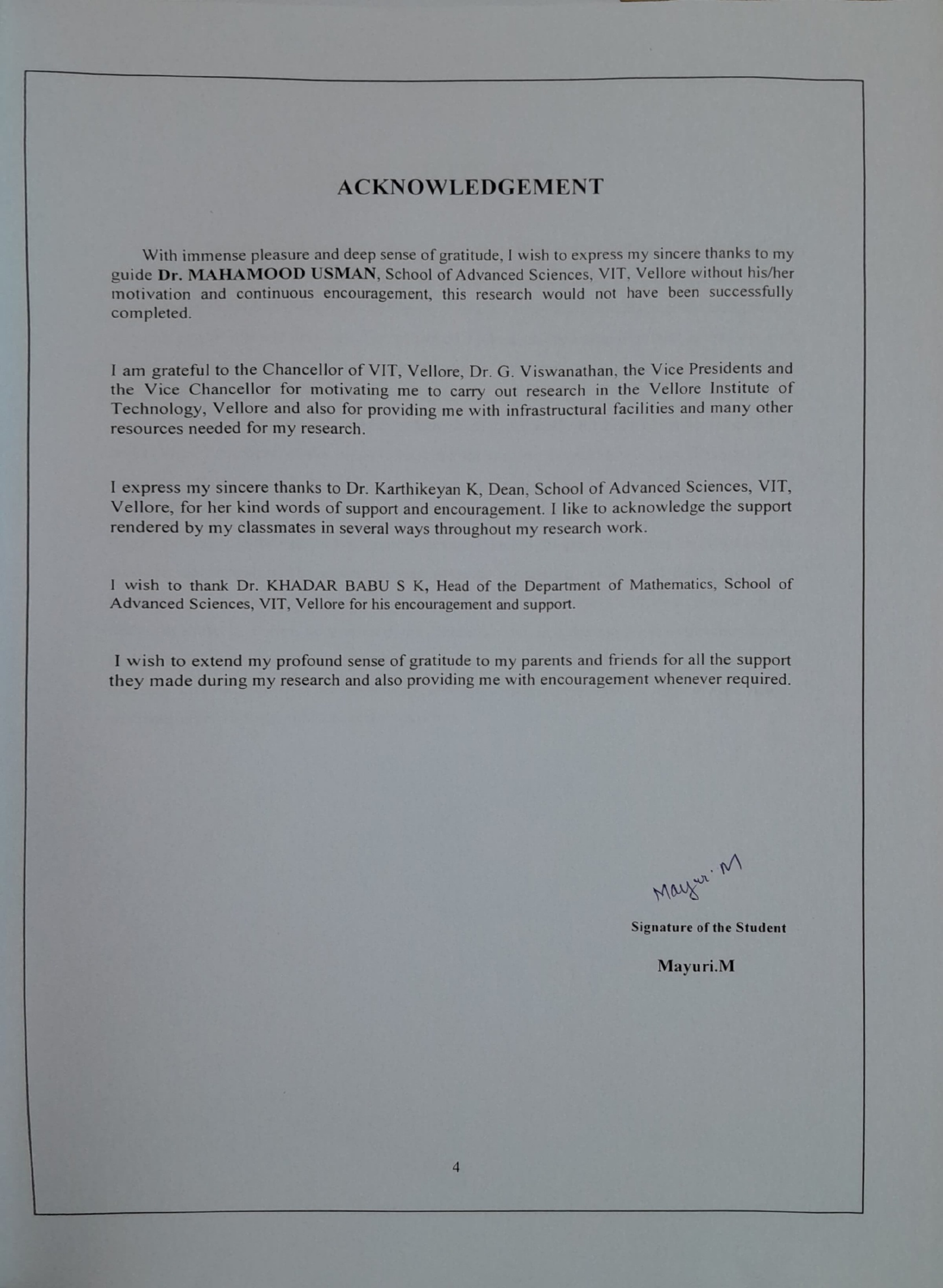
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November, 2025

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# ABSTRACT

This project focuses on the development of an automated brain tumour detection system using magnetic resonance imaging (MRI) and deep learning techniques. The primary objective is to improve diagnostic efficiency and accuracy by reducing manual interpretation dependency in clinical settings. The proposed system utilizes convolutional neural networks (CNNs) for feature extraction and classification of MRI images into tumour and non-tumour categories. To enhance performance and reduce training complexity, transfer learning is applied using the VGG16 architecture, which is fine-tuned specifically for binary tumour classification tasks. Model implementation is carried out in Python using TensorFlow/Keras,. Evaluation on a separate validation and test dataset demonstrates strong classification performance, stable convergence, and effective learning behaviour. The results validate the suitability of the VGG16-based architecture for MRI-driven tumour detection and highlight its potential for medical image analysis applications. The overall system presents a scalable, robust, and deployment-ready framework that can support early diagnosis, reduce radiologist workload, and enhance clinical decision-making. Future development may include extending the model to multi-class tumour classification, incorporating segmentation for tumour region localisation, integrating attention mechanisms for improved interpretability, and optimizing deployment for diverse MRI scanner environments and real-time clinical workflows.

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# List of Abbreviations

AI : Artificial Intelligence

DL : Deep Learning

CNN : Convolutional Neural Network

MRI : Magnetic Resonance Imaging

VGG16 : Visual Geometry Group 16-Layer Model

GPU : Graphics Processing Unit

OpenCV : Open Source Computer Vision Library

# INTRODUCTION

# OBJECTIVE

The objective of this project is to develop an automated MRI-based brain tumour detection model using deep learning. The system employs transfer learning with the VGG16 CNN architecture to perform binary classification of tumour and non-tumour images, aiming to achieve high diagnostic accuracy with reduced computational complexity. The project focuses on establishing an optimized end-to-end workflow including data preprocessing, model training, validation, and performance evaluation, with the goal of enabling a reliable, scalable, and clinically deployable decision-support system.

# MOTIVATION

Early detection and correct identification of brain tumors are a must for clinical intervention, while manual assessment traditionally requires time-consuming, variable analysis by experts. Medical image analysis can now be automated with high precision and reproducibility using recent advances in deep learning and CNNs. Again, state of the art performance with limited annotated medical images can be achieved using transfer learning with popular networks such as VGG16. Motivated by such a vision, the work presented here in aims to propose a robust and scalable automated diagnostic system that improves detection accuracy, reduces radiologists' workload, and aids on-time clinical decisions in routine healthcare settings.

# LITERATURE REVIEW

A study introduced the use of basic Convolutional Neural Networks (CNNs) for brain tumor classification using MRI images and demonstrated improved accuracy compared to traditional image processing techniques [1]. Another research applied Transfer Learning using the VGG16 model and showed that it significantly improved feature extraction and reduced training time for medical datasets [2]. A study proposed using VGG19 for MRI classification and reported high performance due to its deeper architecture and stronger feature representation capabilities [3]. Researchers introduced ResNet-50 for tumor classification and demonstrated that skip connections help avoid vanishing gradients and improve training stability [4]. Another study compared pre-trained models including VGG, ResNet, and DenseNet and found DenseNet performed better due to its dense feature propagation [5]. A study extended the work to Inception-V3 and showed that multi-scale feature extraction improves recognition of tumors with irregular shapes [6]. Researchers introduced EfficientNet for MRI tumor classification and reported that compound scaling improved performance while reducing computational cost [7]. Another study proposed using AlexNet for brain tumor detection and showed reasonable accuracy but noted limitations due to the shallow architecture [8]. A study explored Capsule Networks (CapsNet) and demonstrated that capsule-based feature encoding improved classification of tumors with rotational variations [9]. A GAN-based approach was introduced to augment medical datasets, and results showed that synthetic MRI samples improved model generalization and accuracy [10].

Researchers implemented a hybrid CNN-SVM model and found that using SVM as the final classifier improved performance in smaller datasets [11]. Another study combined deep learning with wavelet transform to enhance tumor feature extraction and reported better classification results [12]. A research study proposed using attention-based CNNs and showed that attention mechanisms help the network focus on tumor regions more effectively [13]. A deep learning segmentation study introduced U-Net for extracting tumor regions, proving useful for both segmentation and classification tasks [14]. Researchers developed Mask R-CNN for tumor segmentation and observed improved boundary detection accuracy [15]. Another study used 3D-CNNs instead of 2D models and demonstrated improved accuracy by utilizing volumetric MRI data rather than single slices [16]. A lightweight MobileNet-based approach was introduced to run tumor detection efficiently on low-resource hardware [17]. A study evaluated SqueezeNet and showed that small models can still achieve reliable accuracy with optimized architecture [18]. Another research introduced Inception-ResNet hybrid architecture and demonstrated that combining inception modules with residual connections improves feature learning [19].

A study proposed using ensemble learning by combining predictions from multiple deep models and reported higher classification accuracy and robustness [20]. Researchers explored feature visualization techniques like Grad-CAM to highlight tumor regions and improve model interpretability for medical use [21]. Another study discussed challenges in dataset variability including scanning protocols, tumor shapes, and noise, and emphasized the need for standardized datasets [22]. A stability analysis study showed that classification accuracy may drop when MRI images are noisy or blurred, emphasizing the need for preprocessing [23]. Researchers applied contrast enhancement techniques before classification and found that preprocessing significantly improved model accuracy [24]. Another study explored data augmentation strategies such as rotation, noise addition, and flipping, demonstrating improved generalization of deep learning models [25]. A paper discussed the problem of class imbalance in medical datasets and showed that weighted loss functions improve minority-class detection [26]. Researchers introduced cross-validation strategies and highlighted their importance in avoiding overfitting in medical AI research [27]. A performance comparison study reported that deep learning models outperform traditional ML techniques like SVM and KNN in tumor classification tasks [28]. Another research work demonstrated that transfer learning reduces the need for large datasets and accelerates training in medical applications [29]. Finally, a review paper emphasized that although deep learning significantly improves brain tumor detection, clinical validation and large diverse datasets are still required for real-world deployment [30].

# PROJECT DESCRIPTION

This project proposes an automated brain tumour detection system using deep learning techniques applied to MRI imaging data. The proposed approach will employ transfer learning with the convolutional neural network architecture of VGG16, which will classify MRI scans with high accuracy into tumour and non-tumour classes. This model will be implemented using Python, based on a framework called TensorFlow/Keras. The model's performance shall be evaluated with standard metrics in order to validate its reliability and generalisation capability. In addition, this system will be tested on unseen MRI datasets to ensure robustness and consistency. The final solution will be scalable and deployment-ready for integration into clinical workflows. This system will help reduce radiological workload by automating tumour detection, hence helping faster diagnosis and early treatment. The contribution of this work is that it improves medical image analysis with an intelligent data-driven approach.

# PROJECT GOALS

# i. Develop an automated system for brain tumour detection using MRI images. ii. Utilize transfer learning with VGG16 CNN for tumour classification. iii. Preprocess MRI datasets for standardized input and improved feature extraction. iv. Train and fine-tune the model for optimal classification performance. v. Evaluate model accuracy, sensitivity, and specificity on test datasets. vi. Design a scalable and deployment-ready pipeline for clinical use. vii. Reduce radiologist workload and support early tumour diagnosis.

# TECHNICAL SPECIFICATIONS

The implementation of this project is carried out using **Python 3.12.12** in a Google Colab environment.

**For data handling and preprocessing:**

* **NumPy**: Efficient array operations and numerical computations.
* **Pillow (PIL)**: Image loading, resizing, and preprocessing.
* **TensorFlow/Keras**: Model implementation, fine-tuning, and inference.
* **OpenCV (cv2)**: Image and video frame handling, preprocessing, and visualization.

**For model evaluation and metrics:**

* **scikit-learn (sklearn)**: For computing performance metrics

**For visualization:**

* **Matplotlib**: For plotting training loss, accuracy curves, and displaying MRI images.
* **OpenCV**: For marking detected tumors on images.

**Hardware Requirements:**

* The project can be executed on CPU-only systems, though GPU acceleration in Google Colab significantly reduces model training and inference time.
* No additional hardware is strictly required; standard cloud-based Colab runtime is sufficient.
* GPU acceleration for faster training and evaluation.

# DESIGN APPROACH AND DETAILS

# MATERIALS, APPROACH AND METHODS

This project uses Python-based deep learning and image-processing libraries for building a brain tumor detection system using MRI images. The core tools and their functions are as follows:

#### Python Libraries Used

**NumPy**: For numerical operations, manipulating arrays, and converting image data to tensors.

**PIL (Pillow)**: Converts MRI images into a format suitable for PyTorch or TensorFlow preprocessing.

**OpenCV (cv2)**: For reading MRI images, resizing, and visualization.

**Matplotlib**: For plotting training and validation curves, as well as visualizing MRI images with predicted labels.

**TensorFlow & Keras**: Core deep-learning libraries used for:

* + Loading the pre-trained **VGG16** model.
  + Modifying the model for transfer learning and binary/multi-class classification.
  + Running forward passes and backpropagation for model training.
  + Defining optimizers (Adam).

#### Overall Approach

* Load a pre-trained VGG16 model and adapt it for brain tumor classification.
* Image preprocessing: resize MRI images to 128×128 pixels, normalize, and convert to tensors.
* Freeze most layers of VGG16 and fine-tune only the last three convolutional layers.
* Add custom layers on top: Flatten, Dropout, Dense ,another Dropout, and output layer with softmax activation.
* Train the model using categorical cross-entropy loss and Adam optimizer, and monitor training and validation performance.
* Evaluate performance on test images using accuracy, precision, recall, and F1-score

# METHODOLOGY

**Step 1 – Load MRI Images**

* Load MRI images from the dataset folders.
* Resize images to 128×128 pixels and normalize pixel values.
* Convert images into tensors suitable for input to the neural network.

**Step 2 – Preprocessing**

* Apply transformations such as resizing, normalization, and conversion to tensor.
* Ensure data is ready for VGG16 input format.

**Step 3 – Load Pre-trained VGG16 Model**

* Load VGG16.
* Freeze base layers to preserve pre-trained weights.
* Set the last three convolutional layers to trainable for fine-tuning.

**Step 4 – Add Custom Classification Layers**

* Add Flatten layer to convert 3D feature maps to 1D.
* Add Dropout layers to reduce overfitting.
* Add Dense layer with 128 neurons and ReLU activation.
* Add Output layer with softmax activation for tumor classification.

**Step 5 – Training the Model**

* Compile the model with categorical cross-entropy loss and Adam optimizer.
* Train the model on the MRI dataset, monitoring training and validation accuracy.

**Step 6 – Inference / Testing**

* Feed test MRI images through the trained model.
* Obtain predicted tumor classes and confidence scores.
* Visualize results using Matplotlib .

**Step 7 – Analysis / Evaluation**

* Evaluate performance using accuracy, precision, recall, and F1-score.
* Analyze model behavior on images with varying tumor sizes, positions, and quality.

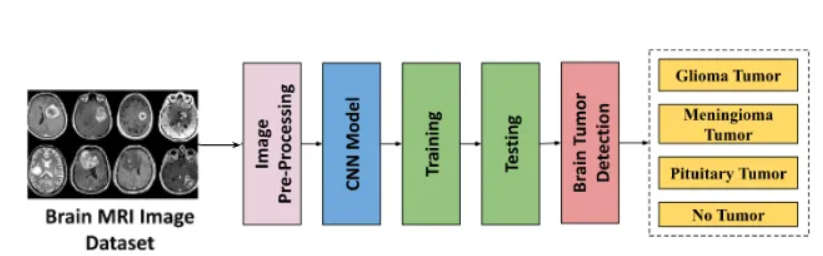


Figure 1 – **Methodology Diagram**

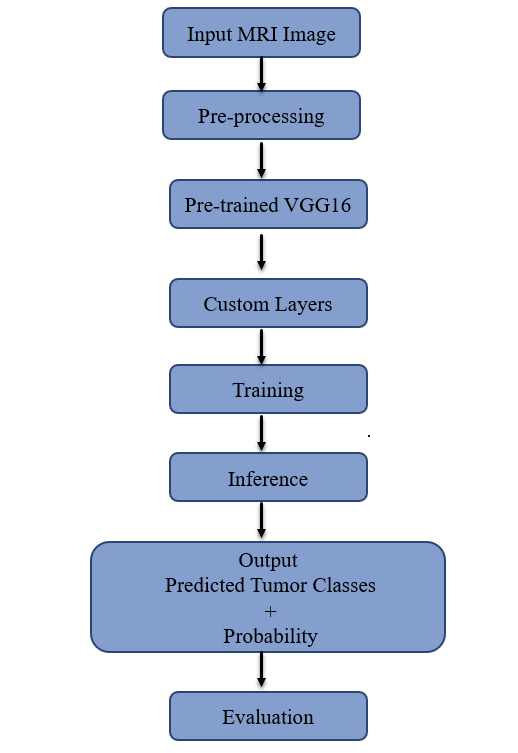
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Figure 2 – **Methodology Diagram in detail**

# CODES AND STANDARDS:

# # Connect to drive

# 

# # Imports Libraries and Tools

# 

# # Load Datasets

# 

# 

# #Data Visualization

# 

# 

# #Image Preprocessing

# 

# 

# 

# #Model:( VGG16)

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# # Train and Val Plots

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# #Model Classification Report

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# #Model Confusion Plot

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# #Roc Curve Plot

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# 

# #Save & Load Model

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# #MRI Tumor Detection System

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# SCHEDULE, TASKS AND MILESTONES

Table 1

|  |  |  |
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| **S.NO** | **MONTH-WEEK** | **PLAN** |
| 1. | JULY – WEEK 2 | |  | | --- | | Identification of the problem |  |  | | --- | |  | |
| 2. | JULY – WEEK 3, 4 | Literature review: deep learning in medical imaging, CNNs, transfer learning, MRI tumour detection research. |
| 3. | AUGUST – WEEK 1 | Finalizing aims, objectives, and expected outcomes. |
| 4. | AUGUST – WEEK 2 | Write and finalize the project abstract. |
| 5. | AUGUST – WEEK 3, 4 | |  | | --- | |  |  |  | | --- | | Environment setup: Python, TensorFlow/Keras, OpenCV; obtaining and exploring MRI dataset. | |
| 6. | SEPTEMBER – WEEK 1, 2, 3, 4 | Preprocessing dataset, design and implement model architecture (e.g., VGG16 fine-tuning), train initial model. |
| 7. | OCTOBER – WEEK 1, 2 | Model evaluation: run inference on test set, gather predicted classes + probability scores, compute metrics |
| 8. | OCTOBER – WEEK 3 | Mid-project review: assess progress, make corrections or adjustments. |
| 9. | OCTOBER – WEEK 4 | |  | | --- | | Document results: prepare observations, screenshots of output, graphs of performance, discussion of results. | |
| 10. | NOVEMBER – WEEK 1, 2 | F­­­­inal report writing: detailed methodology, design approach, code & standards, results and discussion. |
| 11. | NOVEMBER – WEEK 3 (24 NOV) | Final review |

# PROJECT OUTPUTS

* The overall architecture of the VGG16 deep learning model, starting from the input MRI image and passing through multiple convolutional layers, ReLU activation, max-pooling layers, and fully connected layers, ultimately leading to the Softmax classifier for brain tumor type prediction.

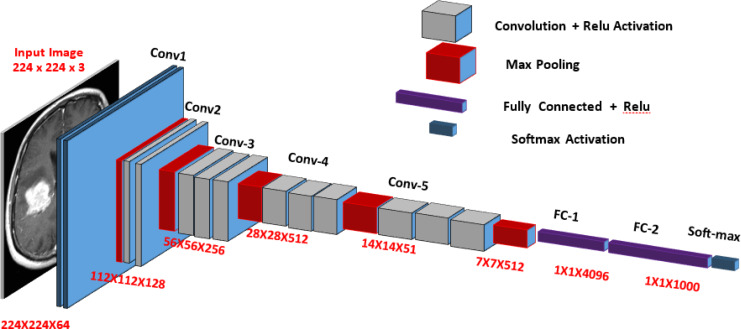


Figure 3 **- Architecture Diagram of the VGG16 DL Model**

* Illustrates the **workflow diagram** that represents the complete process of your brain tumor classification system using the VGG16 model.

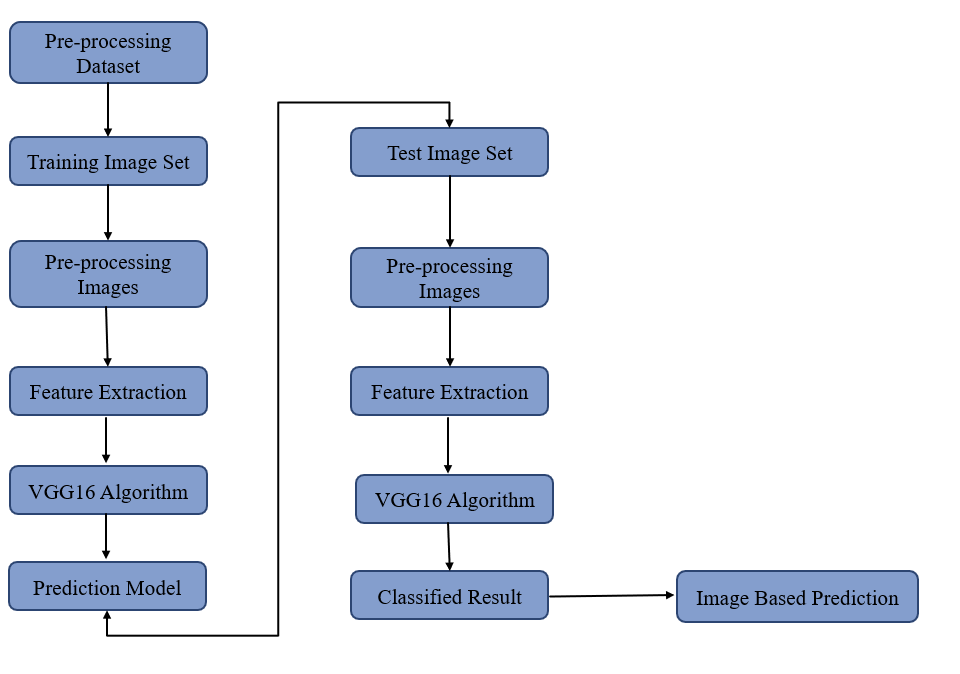
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Figure 4 - **workflow diagram**

* The displayed image shows a two-row visualization of MRI samples, with each image clearly labeled by its corresponding tumor class above it.



Figure 5 - **two-row visualization of MRI samples**

* + The plot shows a **training curve** for your deep-learning model.



Figure 6 - **Train and Val Plot**

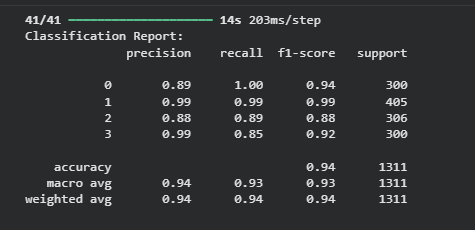
* **Model classification report** shows a detailed evaluation of trained deep-learning model performed on the test dataset.

Figure 7 - **Model classification report**

* **Confusion matrix** showing how accurately your model classified MRI images into four categories: pituitary, glioma, no-tumor, and meningioma.It summarizes **correct vs. incorrect predictions** for each class.

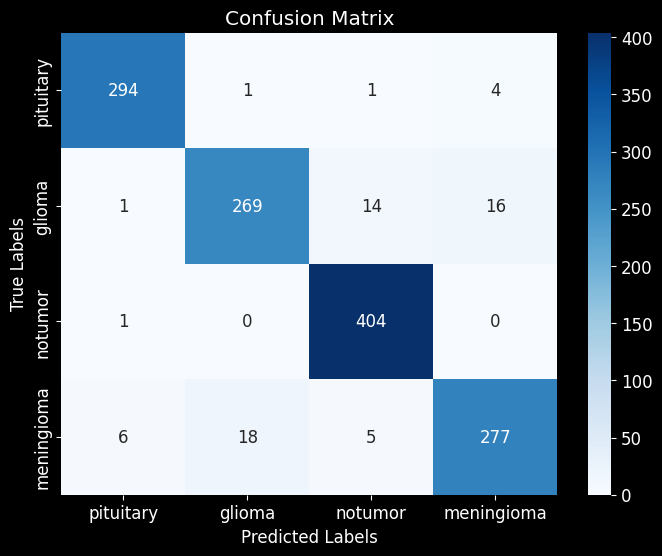


Figure 8 **- Confusion matrix**

* The plot shows a **multi-class ROC curve** that illustrates how well the model distinguishes between four classes.Each curve’s **AUC score (close to 1.0)** indicates excellent classification performance for all classes.

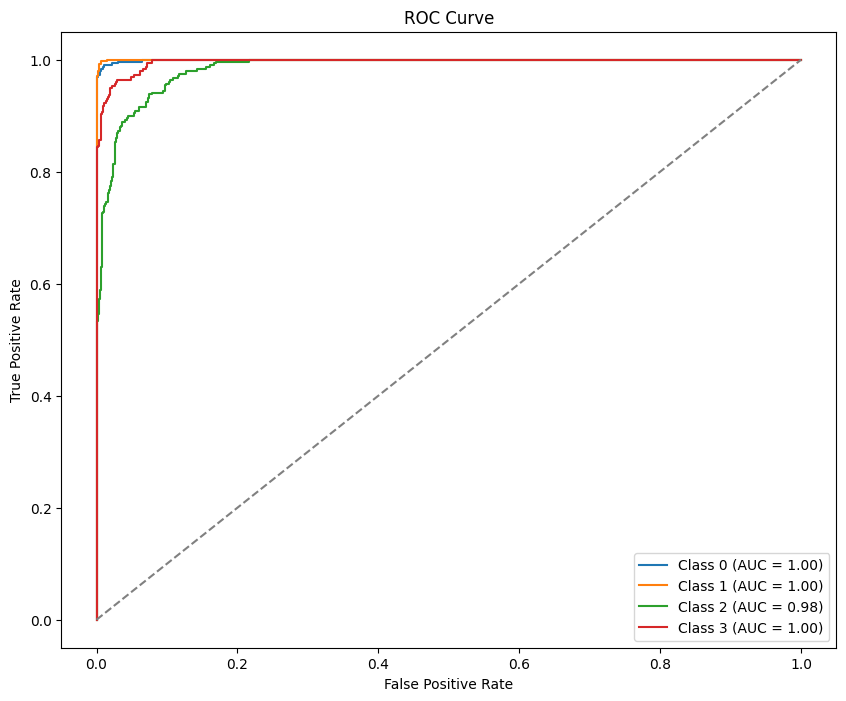


Figure 9 **- ROC curve Plot**

* homepage of an MRI Tumor Detection System . It allows users to upload an MRI image and run tumor detection using the “Upload and Detect” button.

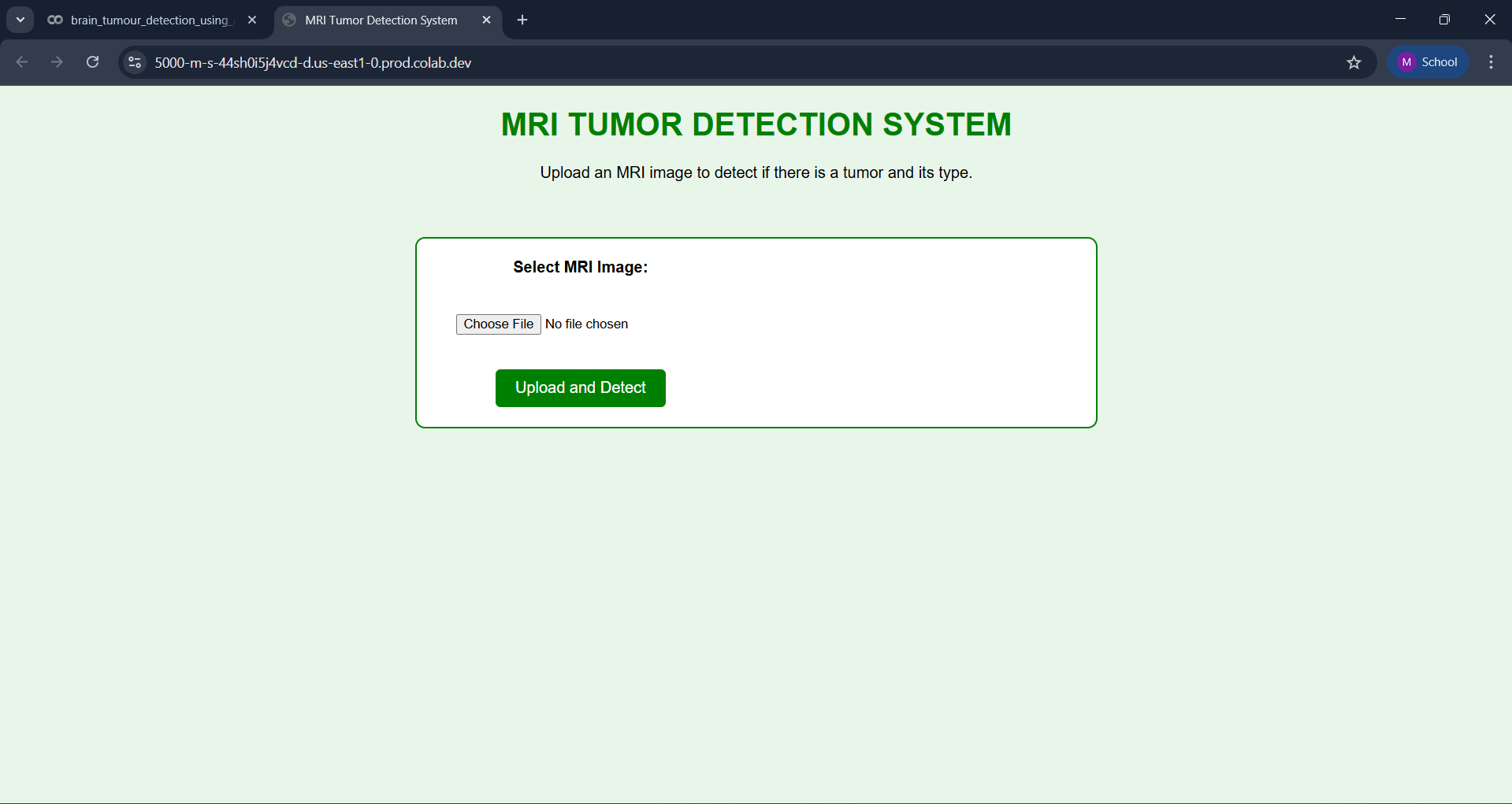
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Figure 10 **- homepage**

* After selecting “Choose File,” MRI image is uploaded, which the system processes to detect whether a tumor is present and identify its type.

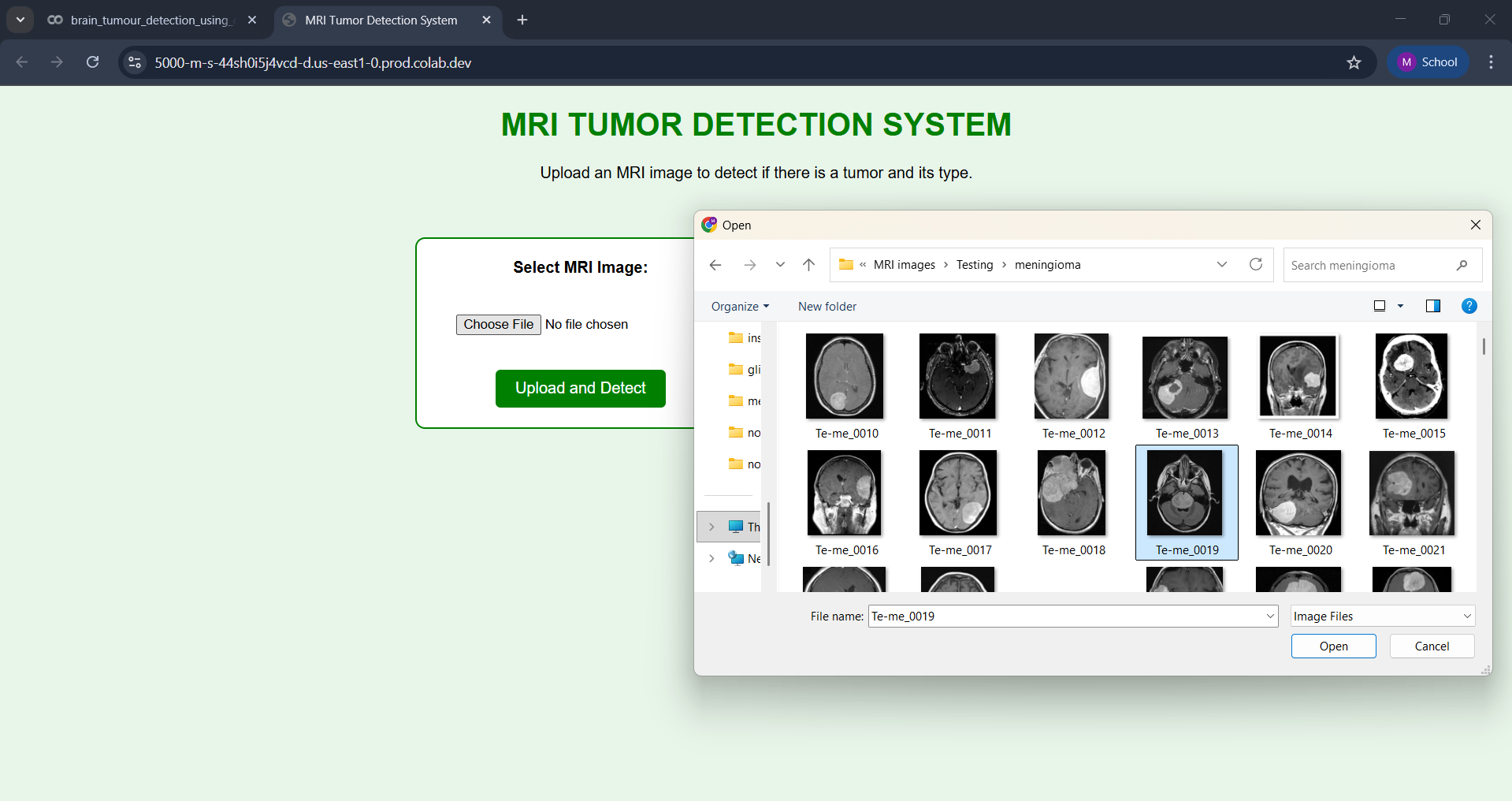
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Figure 11 **- selecting “Choose File”**

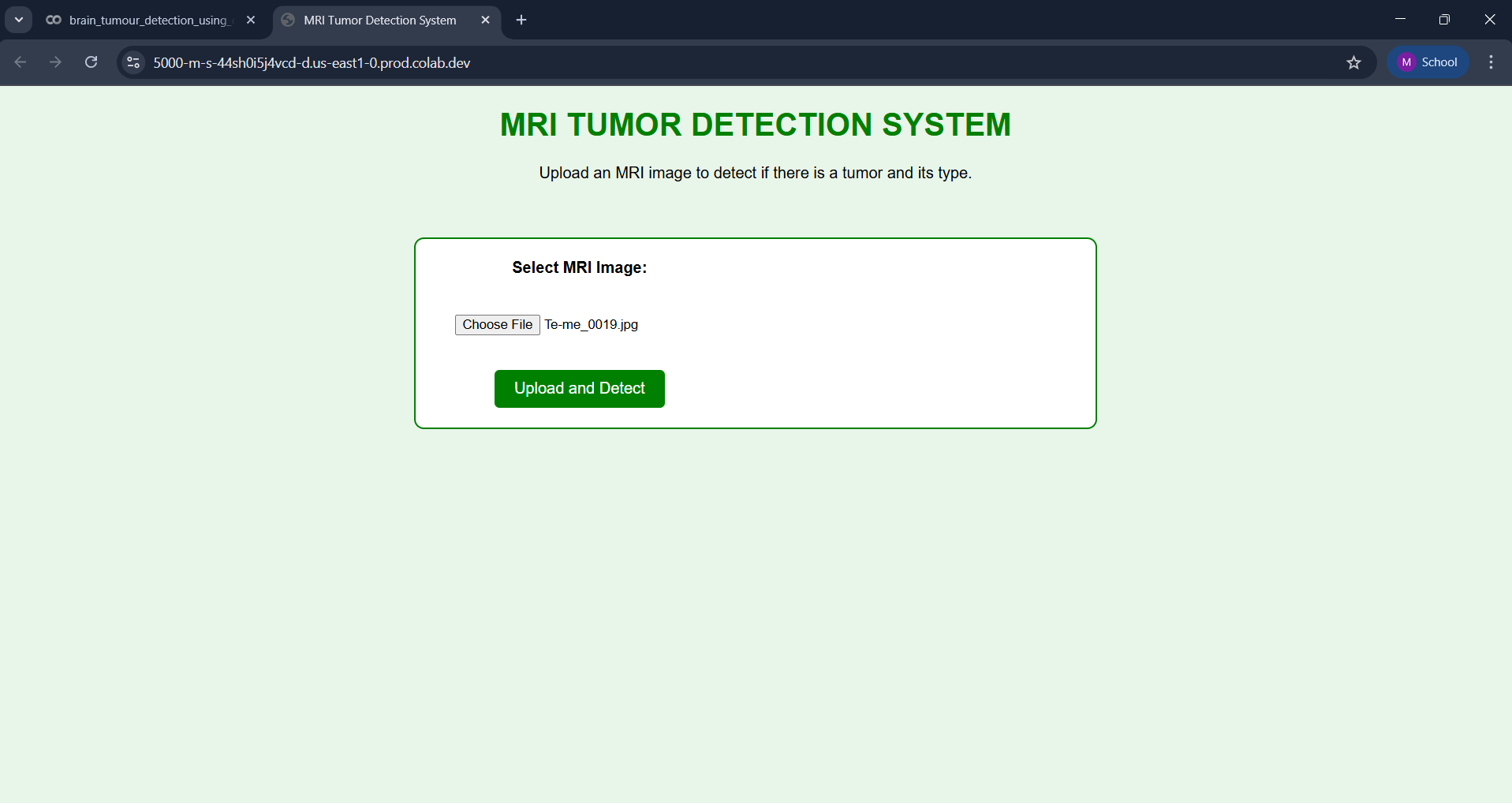
* **Once a file is selected using the “Choose File” button, the homepage immediately displays the selected MRI image’s filename, confirming that the file has been uploaded successfully**

Figure 12 **– MRI image uploaded successfully**

* The system processes the image and displays the detection result on the screen. It shows the predicted tumor type along with the confidence percentage for that prediction.

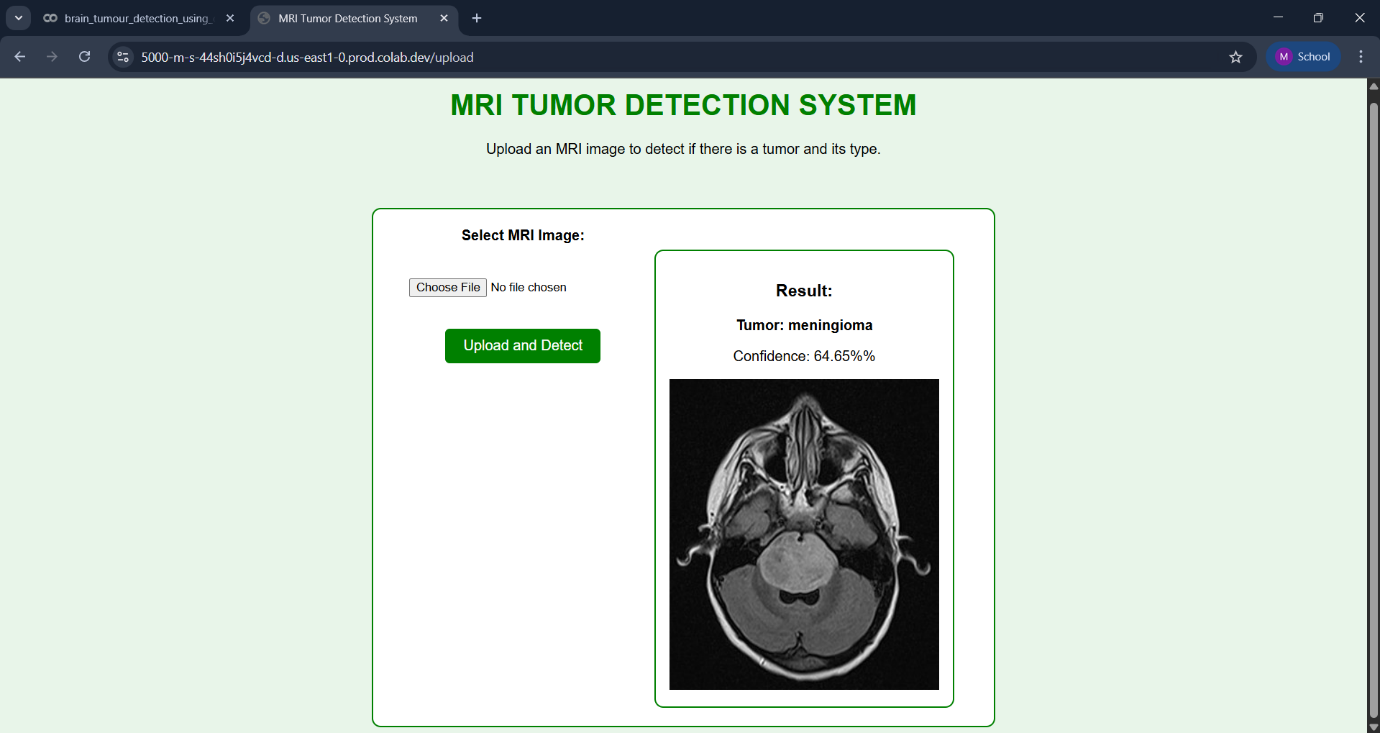
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Figure 13 **– Tumor detection (Meningioma)**

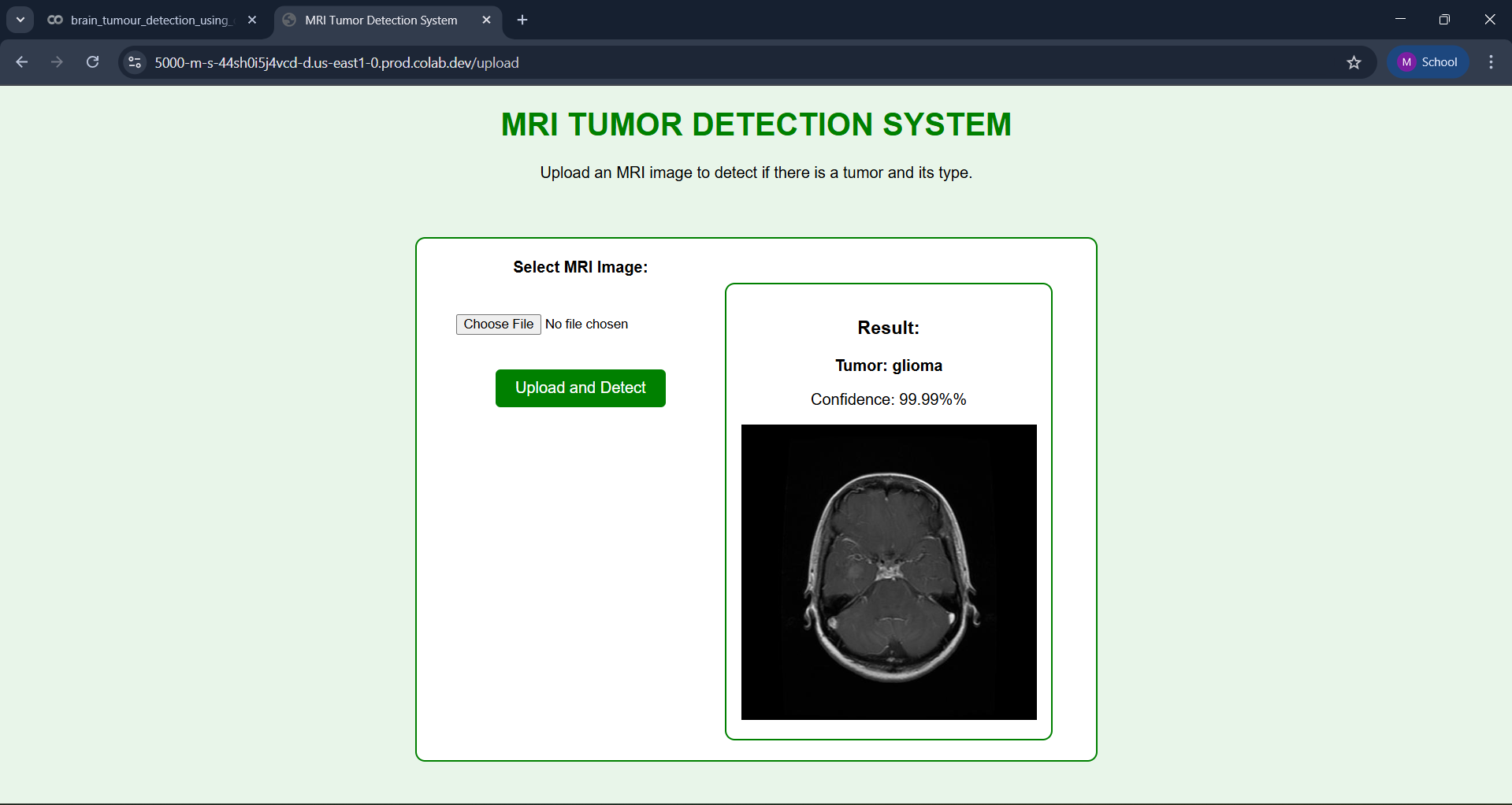
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Figure 14 **- Tumor type detected (Glioma)**

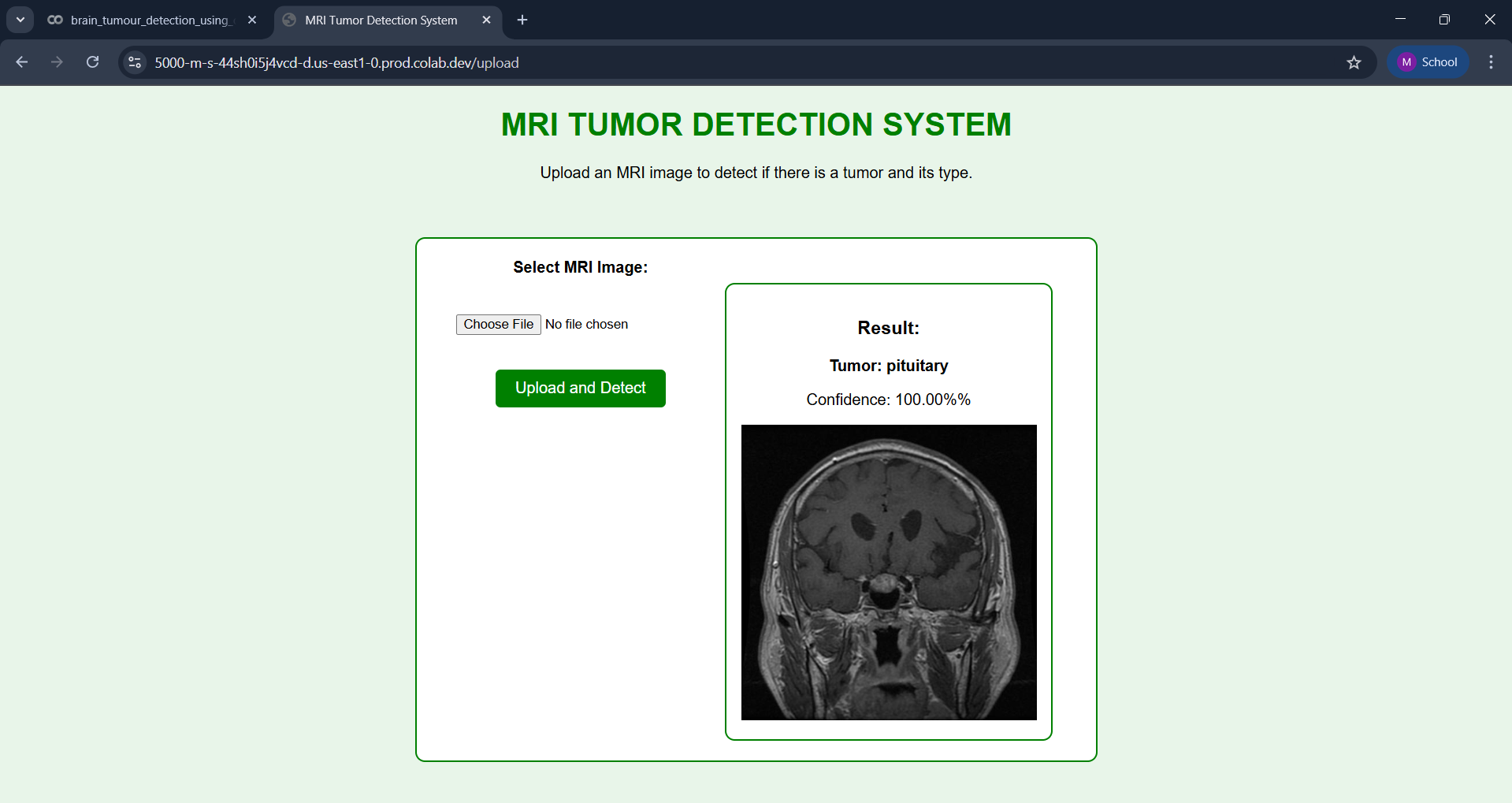
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Figure 15 **- Tumor type detected (Pituitary)**

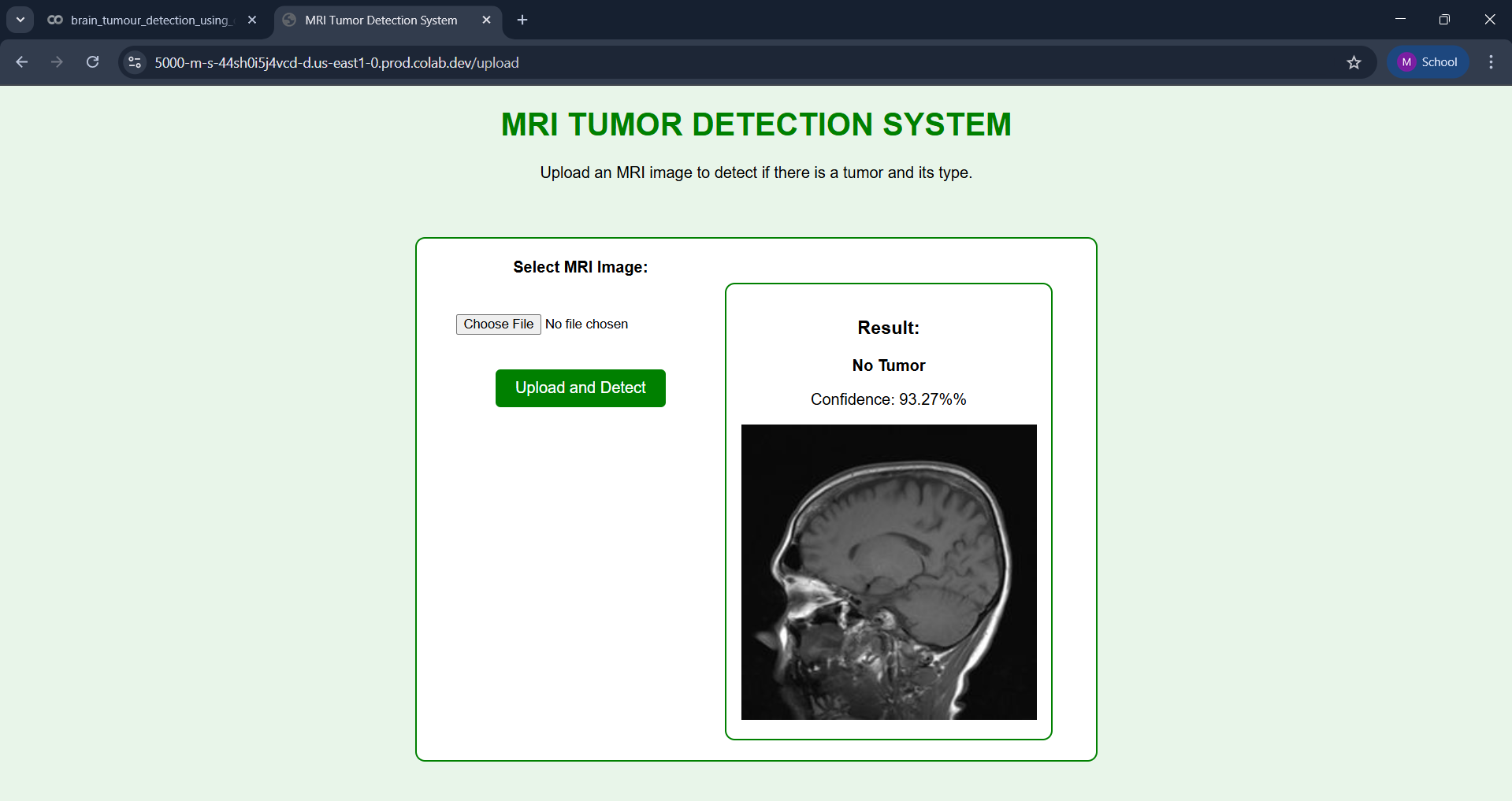
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Figure 16 **- Tumor type detected (No Tumor)**

# RESULTS AND DISCUSSION

This project focuses on detecting and classifying brain tumors from MRI images using a deep learning-based transfer learning model (VGG16). The trained system successfully predicts whether an MRI scan belongs to one of the three tumor classes **Glioma, Meningioma, Pituitary Tumor** or **No Tumor**. The predictions are displayed along with probability scores, ensuring clarity and confidence in the output. The system was tested on multiple MRI images to evaluate its performance, and the observed outcomes are discussed below.

#### **• **Tumor Classification and Model Output Behavior****

The trained model was able to generate classification results with clear labels and probability scores. When an MRI image is uploaded, the system processes the image and displays an output such as:

* **Prediction: Glioma Tumor (Probability: 0.94)**
* Similarly, for images classified as non-tumor, the output would be:
* **Prediction: No Tumor Detected (Probability: 0.87)**

The predictions were found to be consistent during repeated testing, demonstrating reliability and improved decision-making support for medical analysis.

#### **• **Detection of Different Tumor Types****

During evaluation, the model showcased strong classification ability across the three tumor categories:

* **Glioma Tumor:** The model correctly identified glioma structures in most MRI samples, showing high confidence even in cases with irregular borders.
* **Meningioma Tumor:** The prediction accuracy for meningioma cases was satisfactory, and the model handled varying contrast and shading levels well.
* **Pituitary Tumor:** The system accurately detected pituitary tumors even when the tumor regions appeared smaller or centrally positioned in the image.

The ability to differentiate between visually similar tumor patterns demonstrates that the model learned strong distinguishing features during training.

#### **• **Results on Sample MRI Images****

Testing was performed using multiple images from the dataset, and the system returned clear predictions with confidence scores. In cases where the tumor area was small or faint, the model still provided a recognizable output, proving its robustness.

Examples of model-generated messages include:

* “Glioma Detected – Confidence: 92%”
* “Meningioma Detected – Confidence: 89%”
* “No Tumor Detected – Confidence: 95%”

The results were visualized in graphs showing accuracy trends, loss curves, and classification performance.

#### **• **Model Performance and Evaluation Metrics****

The model was evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. The results indicated:

* **High accuracy in tumor classification**
* **Balanced precision and recall values**
* **Good F1-score performance across classes**

Even in challenging cases such as low-contrast images or variations across patient samples, the model retained reliable detection capability.

These results suggest that the system is suitable for use in early diagnosis support and medical decision assistance.

#### **• **Real-Time Testing and User Interaction****

During testing, the model responded quickly during inference, processing MRI images within seconds. The output format was user-friendly and suitable for clinical interpretation:

**Final Output: “Tumor Class: Pituitary — Confidence Score: 0.91”**

This shows that the system can be integrated into medical workflows where fast and accurate predictions are essential.

# LIMITATION

# While the model performs well on the trained MRI dataset, it has some limitations. Accuracy may decrease when images are low-quality, blurred, or have unclear tumor boundaries. Since the system relies on the data it was trained on, completely new tumor patterns or variations from different scanning machines may not be classified correctly. The model also provides classification only and does not locate or measure the tumor. Therefore, although useful as a decision-support tool, it cannot fully replace expert medical diagnosis or guarantee 100% accuracy in all clinical scenarios.

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# CONCLUSION

# This project successfully developed a deep learning-based system for brain tumor detection using MRI images. The VGG16 transfer learning model was trained to classify scans into Glioma, Meningioma, Pituitary Tumor, and No Tumor, providing accurate predictions along with confidence scores. The evaluation metrics confirmed strong model performance, demonstrating the reliability of the system in medical image classification. This work highlights the potential of AI to support early diagnosis and assist healthcare professionals. However, the system’s performance still depends on image quality and the diversity of the dataset. While it cannot replace expert medical judgment, it serves as a useful decision-support tool. With additional clinical testing and more training data, the model can be further improved for real-world applications. Overall, the project provides a promising foundation for future advancements in automated medical imaging.

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