BRAIN TUMOR CLASSIFICATION & SEGMENTATION USING CNN

Presented by Adarsh P

INTRODUCTION

- Brain tumors are **serious** and **life-threatening conditions**.
- Early detection is key to improving **survival** and **treatment outcomes**.
- AI enables faster and more **accurate tumor detection**.
- **CNNs** analyze MRI scans to classify brain tumors **effectively**.
- This technology enhances diagnostic **precision** and supports timely **medical intervention**.

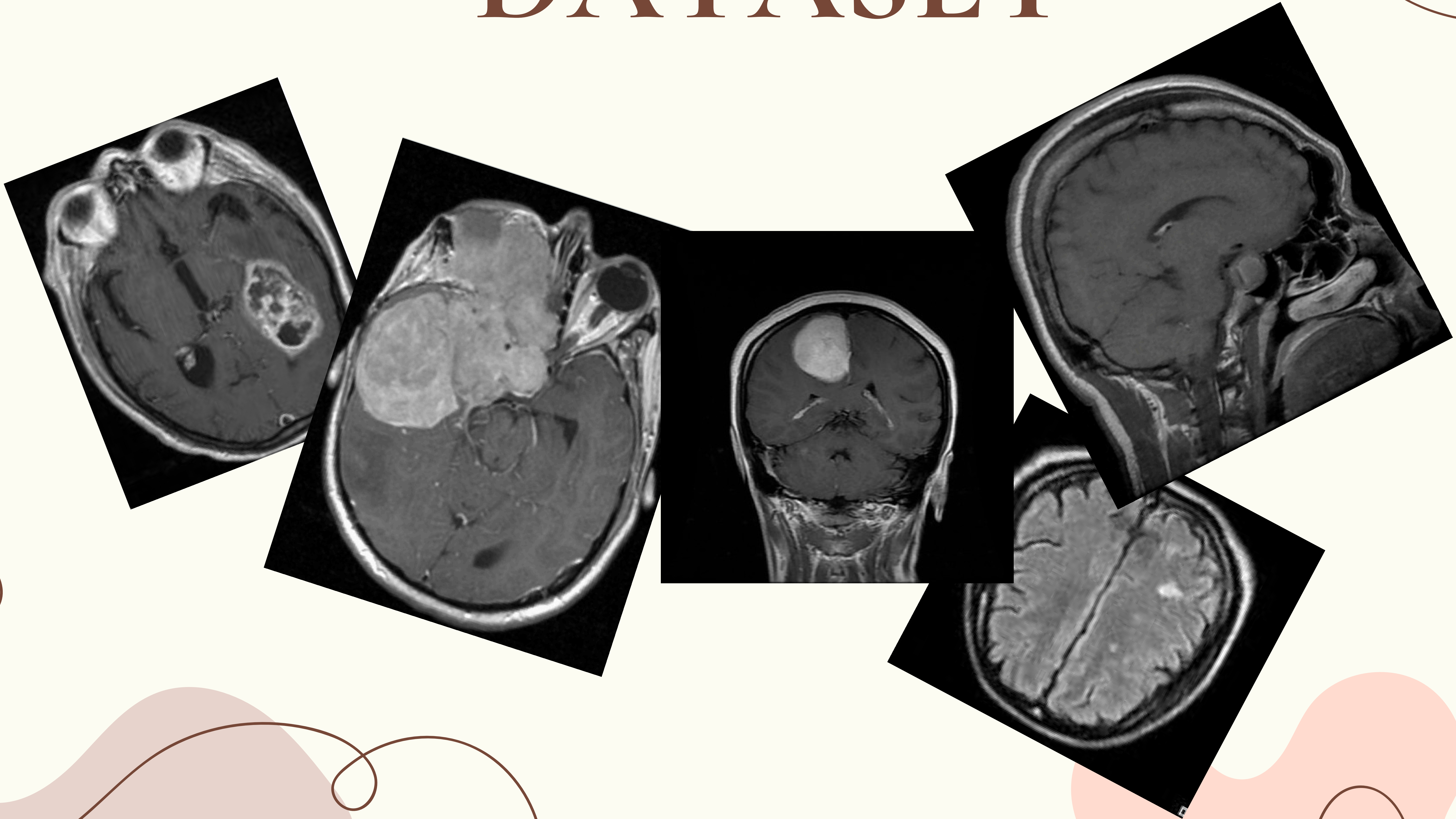
GOALS

- Develop a **robust** and **accurate CNN** model for brain tumor classification.
- **Classify different types of brain tumors** from MRI scans.
- Apply **K-Means clustering** for effective tumor **segmentation**.
- Enhance MRI image analysis to improve **diagnostic insights**.
- Support **early detection** and **aid** in medical diagnosis through AI.

DATASET

- ***Dataset is downloaded from :***
  https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset
- The Brain Tumor MRI Dataset, comprises 7,023 MRI images categorized into four classes: glioma, meningioma, no tumor, and pituitary.
- Need to do Augmentation , and to resize images to a single size

DATASET



METHODOLOGY

- **Step 1: Data Collection** - Gather MRI scan images from publicly available datasets.
- **Step 2: Data Preprocessing** - Perform image **normalization, augmentation,** and **resizing** to ensure uniform input data.
- **Step 3: Model Development** - Implement a **CNN** for tumor classification.
- **Step 4: Segmentation** - Apply **K-Means clustering** to highlight tumor regions within the MRI images.

METHODOLOGY

- **Step 5: Training & Validation** - Split data into **training** and **validation** sets, tune **hyperparameters**, and optimize the model.
- **Step 6: Testing & Evaluation** - Use **accuracy, precision, recall,** and **F1-score** to assess model performance.
- **Step 7: Deployment** - Integrate the trained model into a **Flask**-based web application where users can upload MRI scans and receive results.

END-TO-END PIPELINE REPRESENTATION

User Uploads MRI Scan

Preprocessing

CNN Model for Classification

K-Means Segmentation

Output Tumor Type & Segmented Image

Provide Next Steps & Lifestyle Guidance

MODEL SELECTION & IMPLEMENTATION

- **Algorithms Used: CNN for classification, K-Means for segmentation.**
- **Justification:** CNNs effectively analyze **medical images**, while K-Means helps in **tumor segmentation**. CNNs handle complex patterns, and K-Means provides region-based clustering.

EVALUATION

1. Accuracy

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

where:

- **TP** = True Positives (correctly predicted tumors)
- **TN** = True Negatives (correctly predicted non-tumor cases)
- **FP** = False Positives (incorrectly predicted tumors)
- **FN** = False Negatives (missed tumors)

2. Loss (Categorical Cross-Entropy Loss for Multi-Class Classification)

For a CNN model classifying brain tumors into multiple categories, cross-entropy loss is commonly used:

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where:

- y_i is the actual class label (1 for correct class, 0 otherwise)
- $\hat{y}_i$ is the predicted probability for class i
- N is the number of classes

3. Precision

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

Measures how many of the predicted tumor cases are actually tumors.

4. Recall (Sensitivity)

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

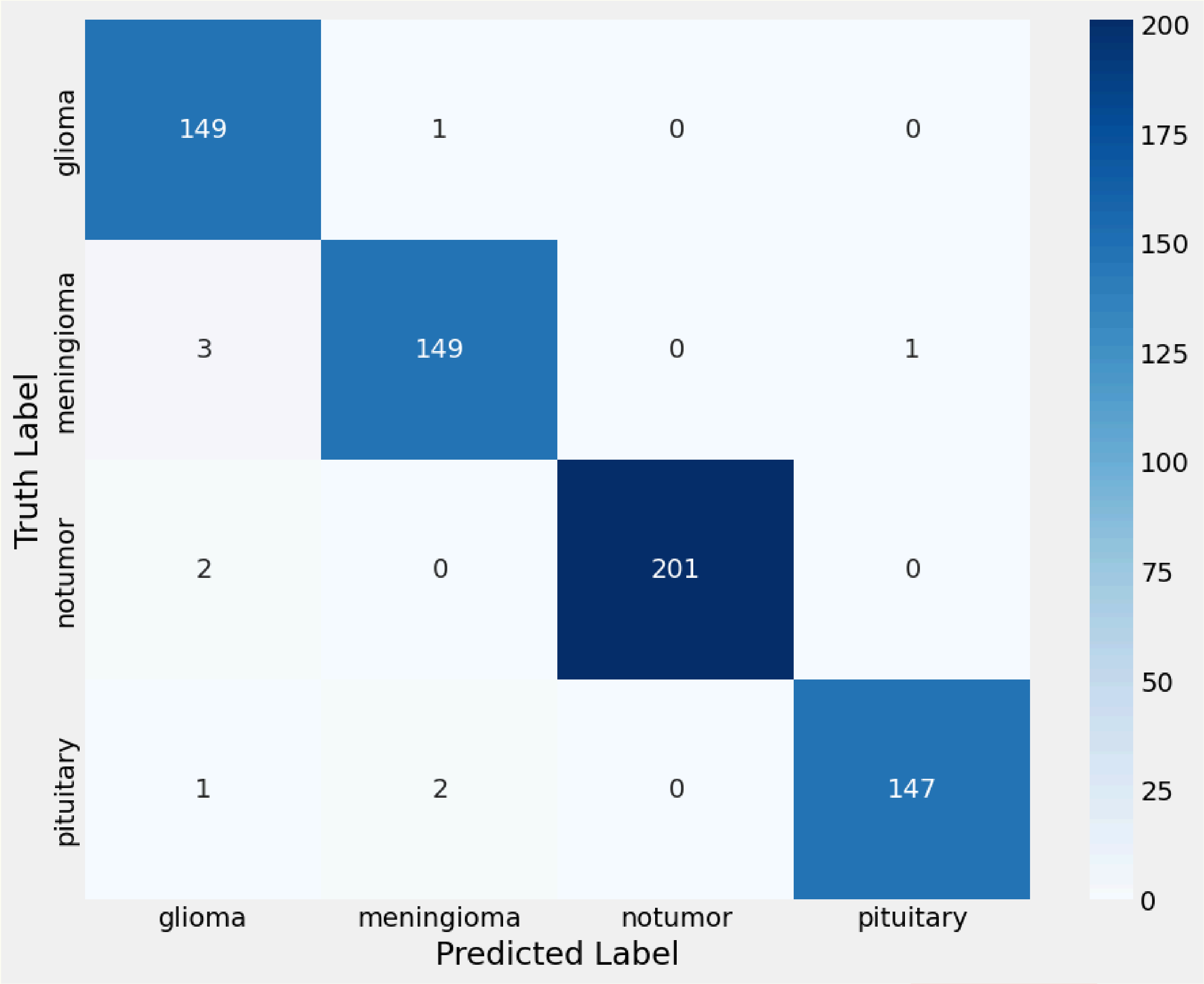
Measures how many actual tumors were correctly detected.

RESULTS

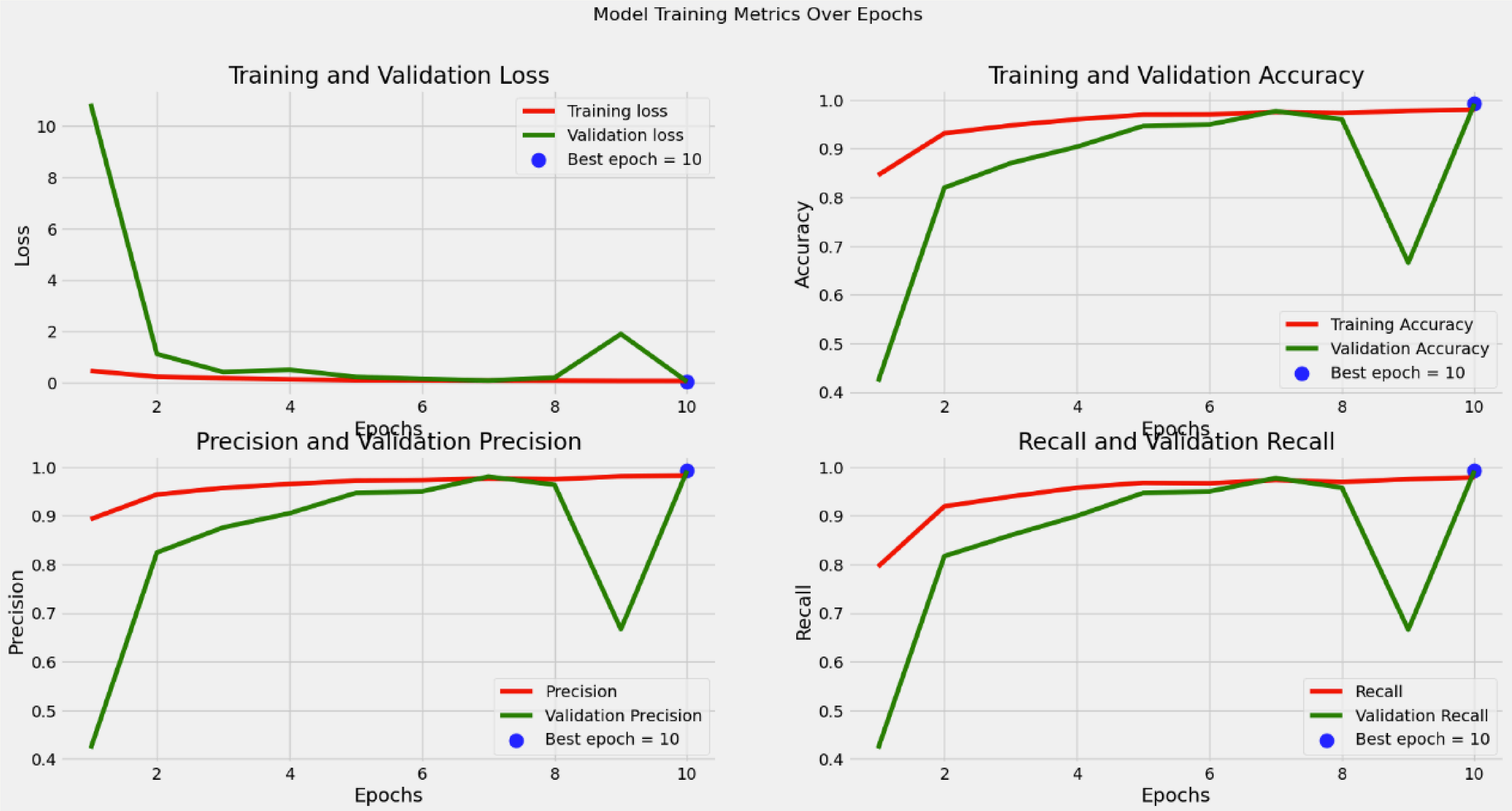
- Accuracy: 0.9830
- Loss: 0.0650
- Precision: 0.9843
- Recall: 0.9823

EVALUATION & RESULTS

Confusion Matrix



LOSS, ACCURACY, PRECISION AND RECALL

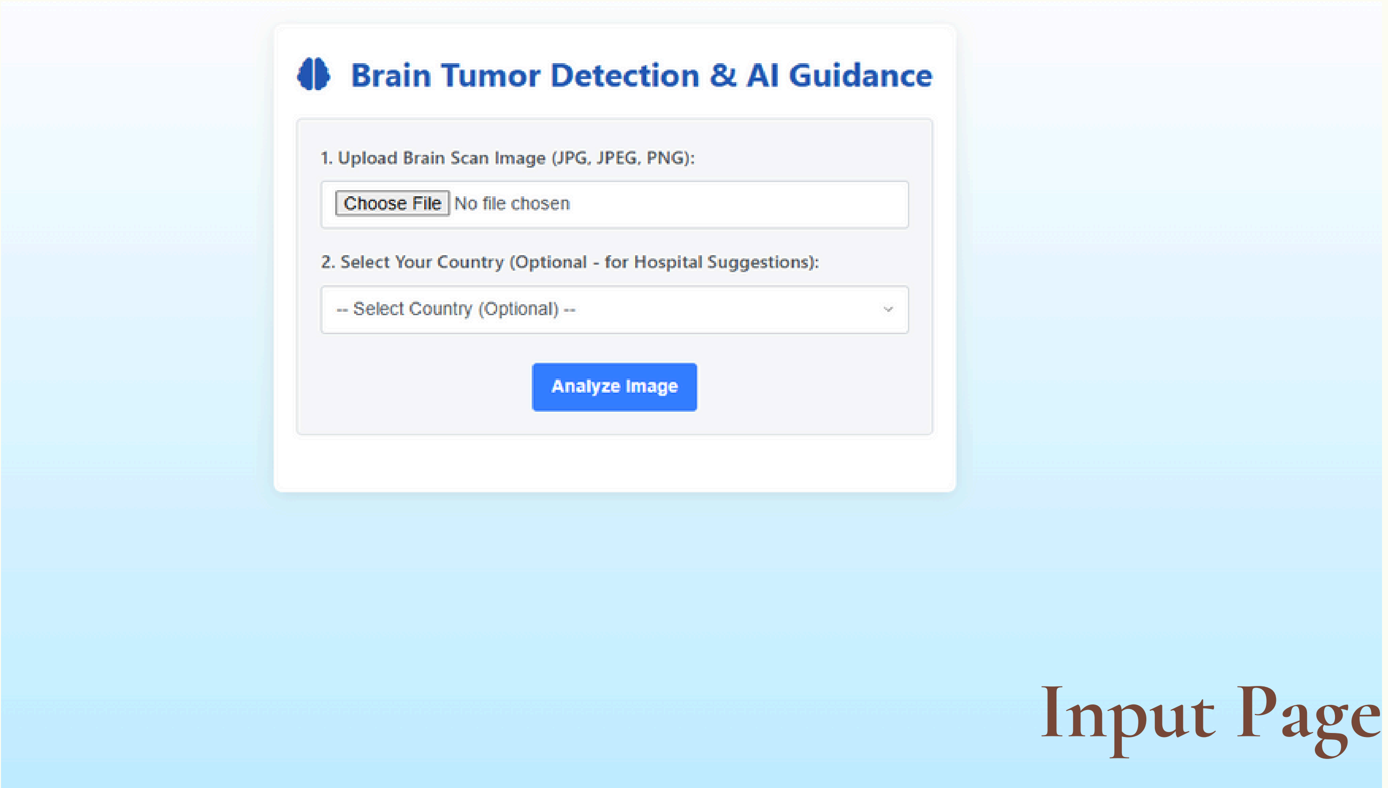


Model Training Metrics Over Epochs

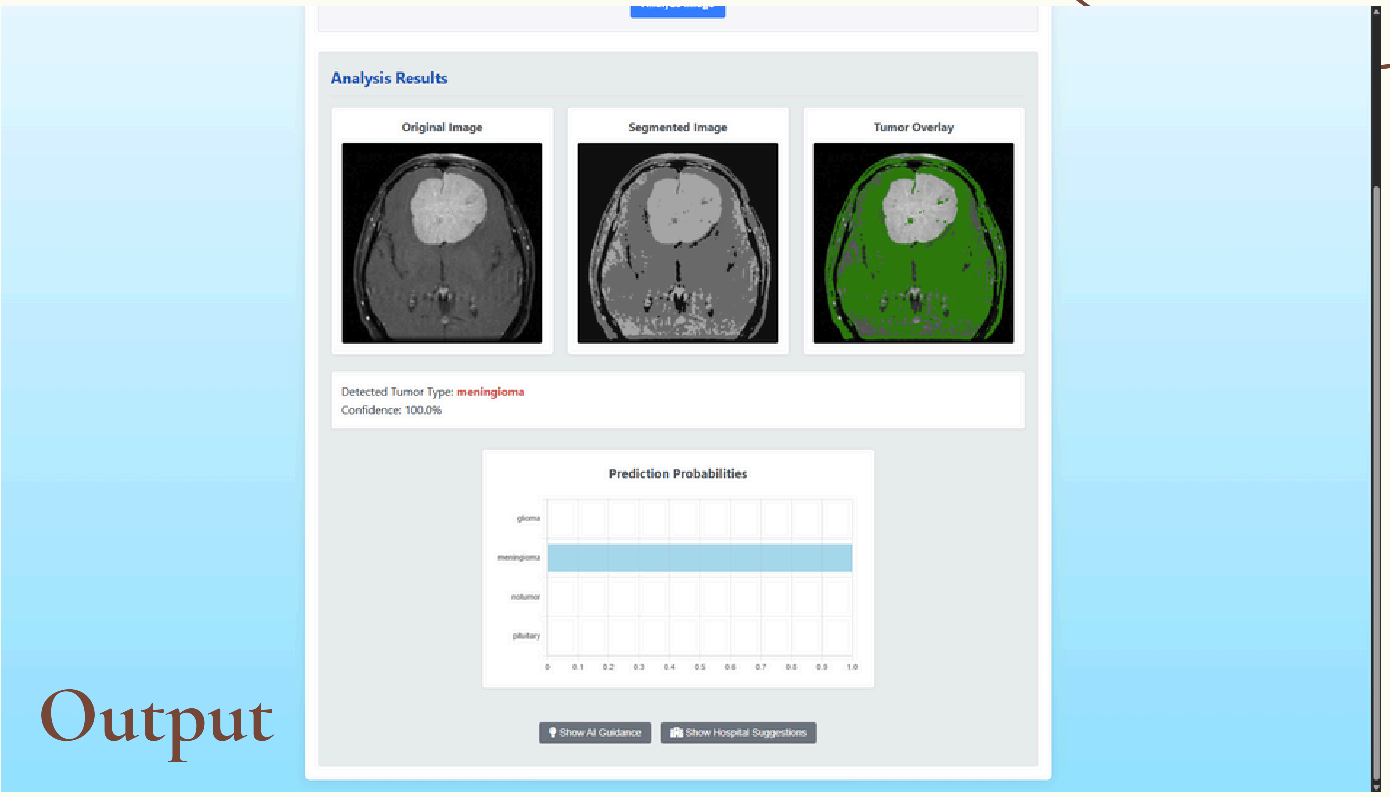
DEPLOYMENT

- Platform: Flask-based web application for easy accessibility.
- Tools: Flask (backend framework), TensorFlow (deep learning model), OpenCV (image processing), Matplotlib (visualization).

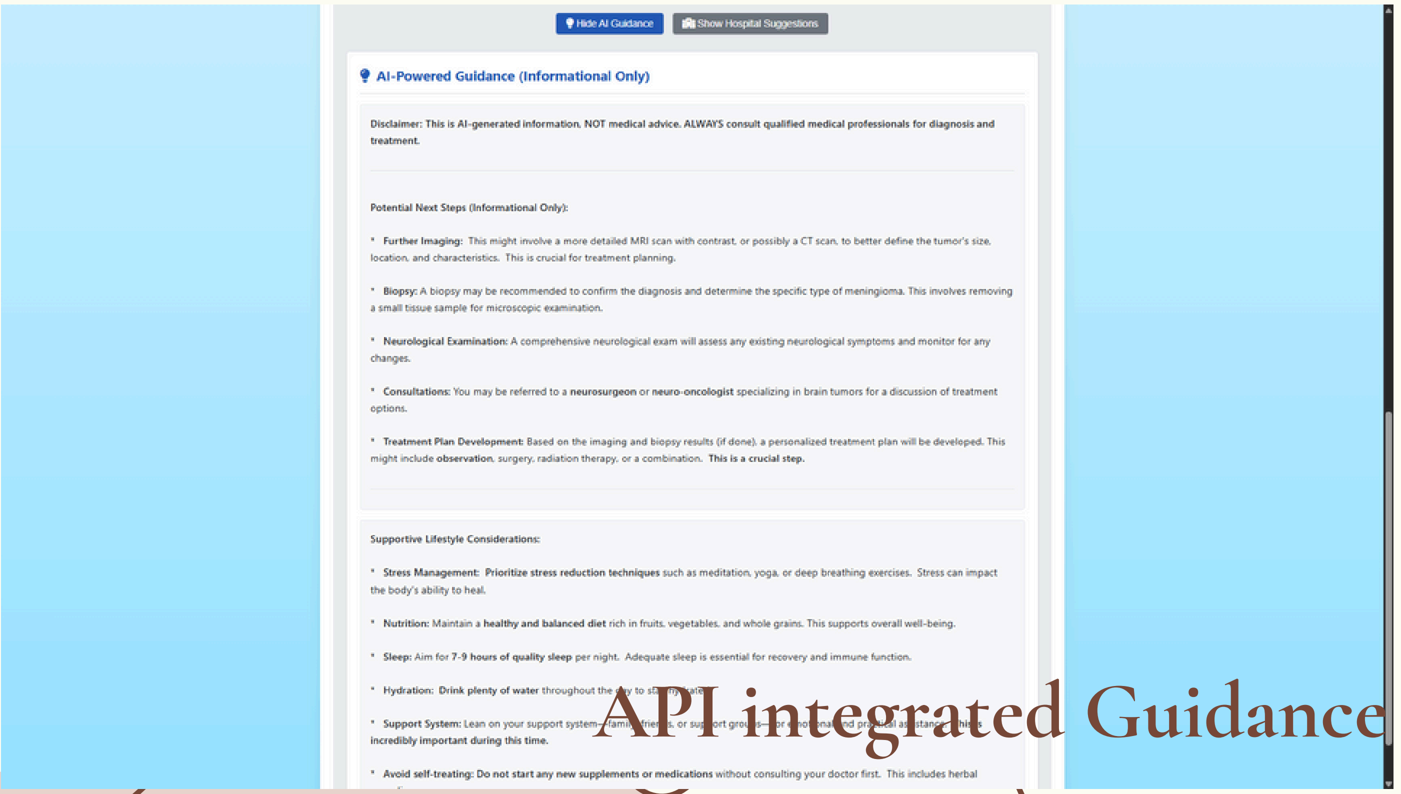
FINAL UI



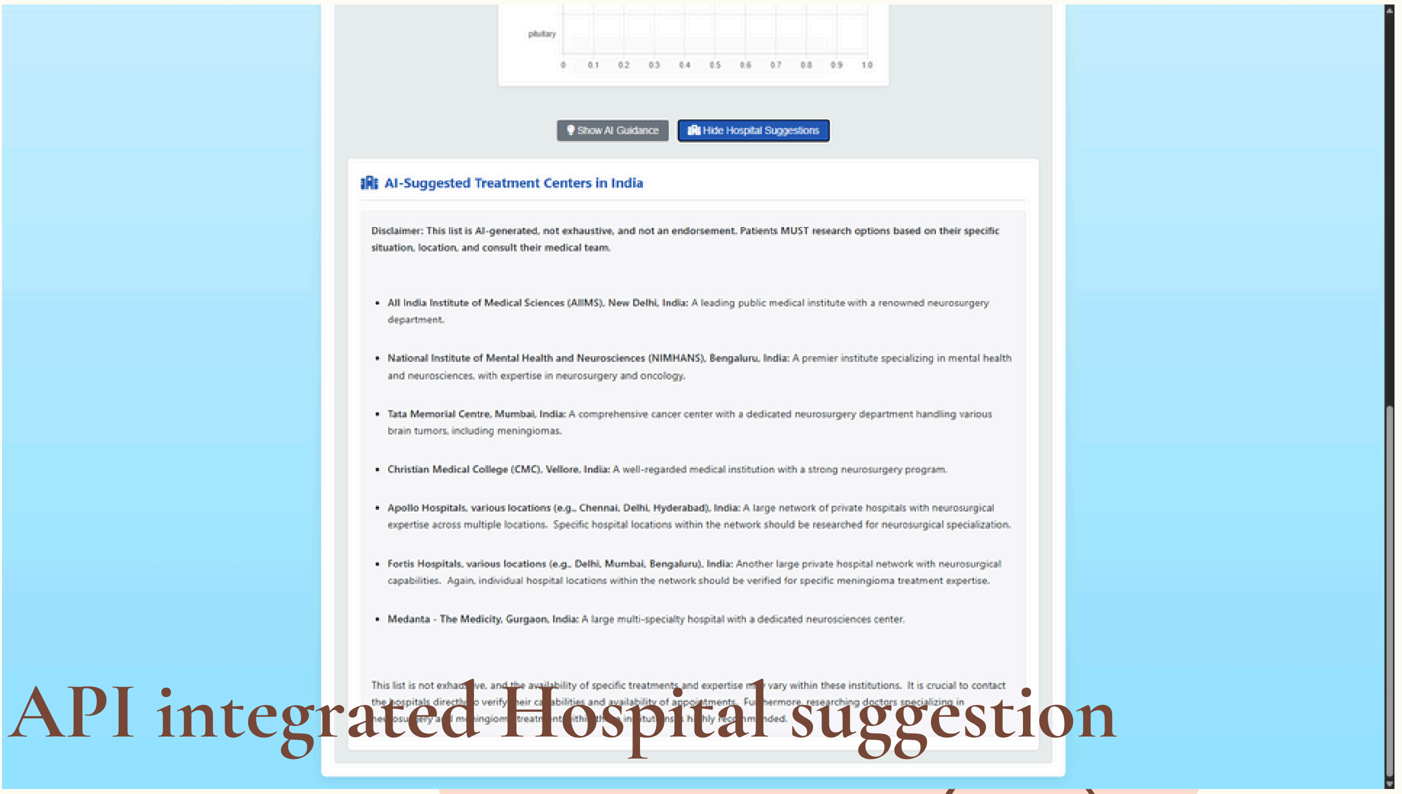
Input Page



Output



API integrated Guidance



API integrated Hospital suggestion

CHALLENGES & LIMITATIONS

Challenges

- Variations in image resolution and contrast affect model performance.
- Obtaining large amounts of labeled MRI images is difficult.

Limitations

- Model accuracy depends on dataset quality.
- Noisy or imbalanced datasets can reduce generalization.

Trade-offs

- Higher accuracy often requires a more complex model.
- Complex models demand more computational resources, making deployment challenging.

CONCLUSION & FUTURE WORK

- AI-driven brain tumor classification enhances early diagnosis and supports medical professionals.
- CNNs and K-Means segmentation enable accurate tumor identification and visualization.
- Future improvements will refine the dataset and optimize model performance.
- Expanding deployment options will increase accessibility and real-world impact.

SCOPE FOR IMPROVEMENT

- Using a dataset containing only brain MRIs can enhance model training performance.
- Removing the skull from images improves segmentation clarity and accuracy.
- Accounting for variations in MRI machines and scan types can improve model generalization.
- Access to diverse MRI scans ensures better accuracy and broader compatibility.

FUTURE ENHANCEMENTS

- Deploy the model as an application or website for wider accessibility.
- Improve the model to support all types of MRI scans and classifications.
- Expand the dataset to include diverse MRI scans for various diseases.
- Enhance model adaptability for better real-world medical applications.

REFERENCES & ACKNOWLEDGMENTS

- Kaggle : https://www.kaggle.com/code/yousefmohamed20/brain-tumor-mri-accuracy-99
- TENSORFLOW : https://www.tensorflow.org/
- YouTube : https://youtu.be/juJYmc4vrWU?si=GVgc7fFfFerngg3z
- Google Scholar : https://www.mdpi.com/2075-1729/13/2/349

THANK YOU