BRAIN TUMOR VISION AI

AI - Powered Deep Learning System for Brain Tumor Prediction and Classification Using MRI Images

Ai

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Problem Statement

Brain tumor detection from MRI scans is slow and requires expert radiologists.
Manual diagnosis may cause delays, variation, and human error.

Common dataset issues in MRI classification:

- Class imbalance
- Incorrect train–test splits
- Mixed data distributions
- Unclean/noisy validation images

👉 **How to automatically detect and classify types of brain tumors using AI & deep learning with high accuracy, reliability, and clinical usefulness?**

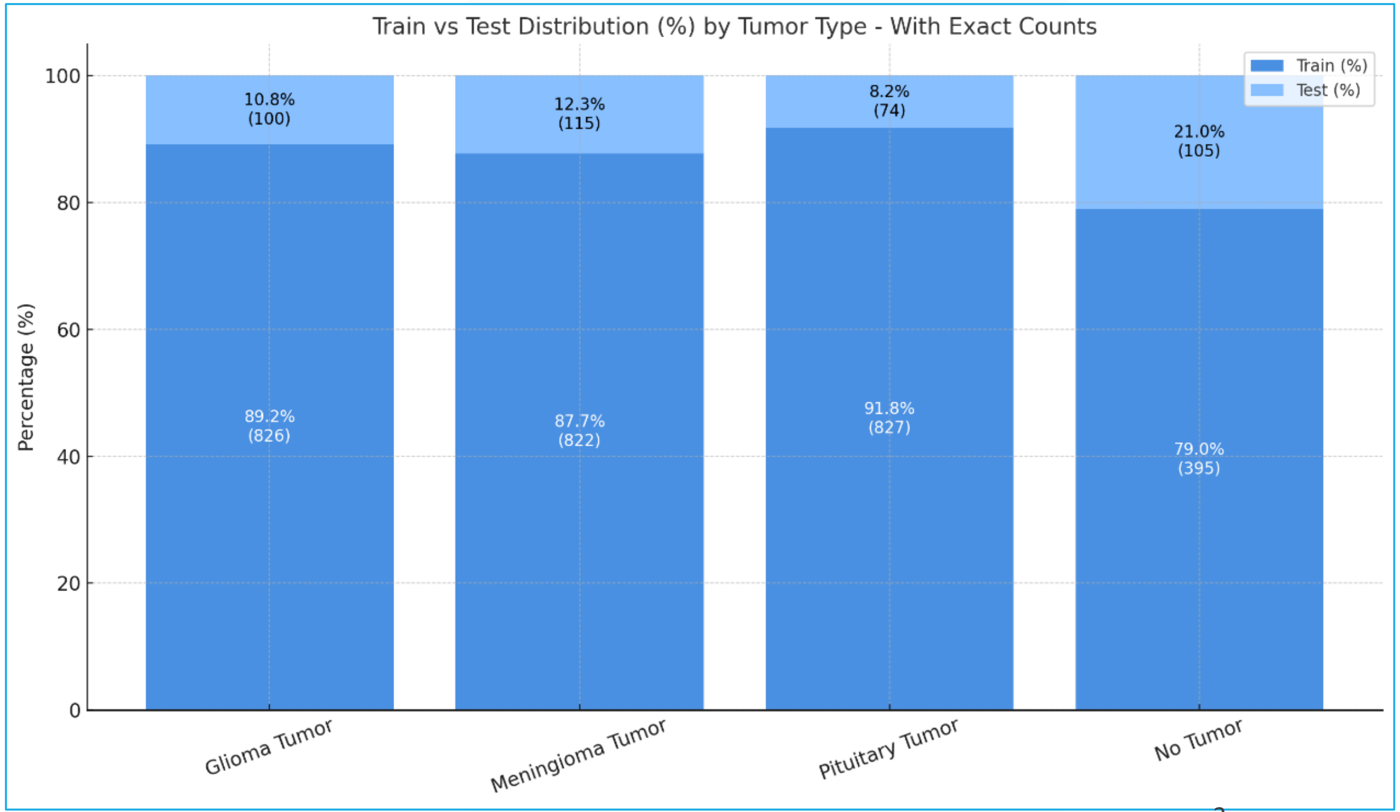
Dataset Preparation

Kaggle Dataset: A publicly available Brain MRI Tumor Dataset was downloaded from Kaggle: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset

Brain Tumor MRI Dataset Summary (Kaggle)

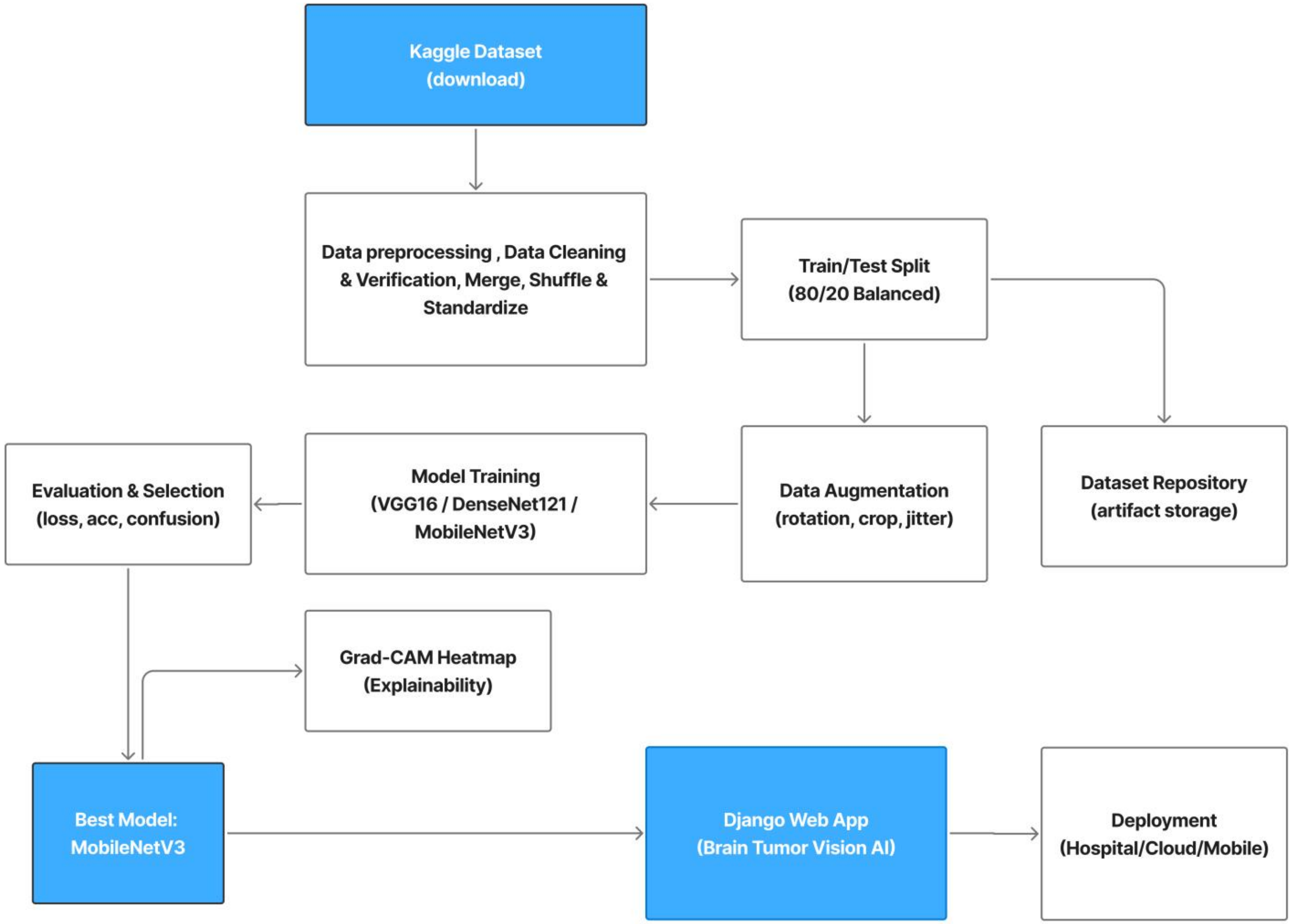
Tumor Type	Train Images	Test Images	Total Images
Glioma Tumor	826	100	**926**
Meningioma Tumor	822	115	**937**
Pituitary Tumor	827	74	**901**
No Tumor	395	105	**500**
Total	**2870**	**394**	**3264**

MRI Dataset Train–Test Distribution by Tumor Type



System Architecture and methodology workflow

Brain Tumor Vision AI



Data Preprocessing

The initial Kaggle MRI dataset was **highly imbalanced**

- ## Before dataset imbalanced

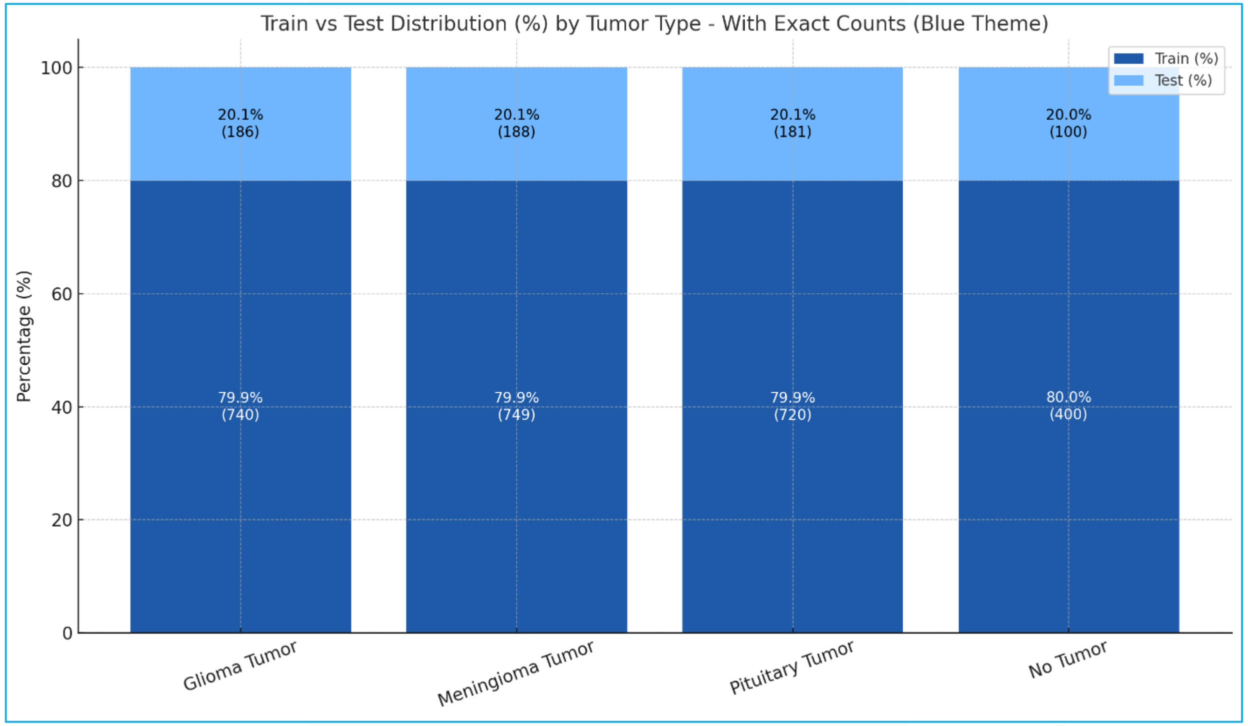
- Overfitting with unstable validation accuracy
- High training accuracy but low validation accuracy (46–78%)
- Validation images had a different distribution from training images
- Uneven or incorrect train–test splits
- Significant class imbalance across tumor categories

- ## After dataset balanced

- All MRI images were **verified, cleaned, and standardized**
- Original **train and test folders were merged** to ensure uniform distribution
- The full dataset was **shuffled** to remove ordering bias
- A new **balanced 80/20 train–test split** was generated
- Class imbalance and distribution mismatches were fully corrected

Balanced dataset

Tumor class	Train (80%)	Test (20%)	Total
Glioma Tumor	740	186	926
Meningioma Tumor	749	188	937
Pituitary Tumor	720	181	901
No Tumor	400	100	500
TOTAL	2609	655	3264



Model Selection & Training

Convolutional Neural Networks (CNNs) were selected for this project because they are the state-of-the-art architecture for medical image analysis.

Three widely used CNN architectures were evaluated

Model	Reason for Selection
VGG16	Classical deep CNN architecture, well-known for strong feature extraction and baseline benchmarking.
DenseNet121	Efficient gradient flow, dense layer connectivity, and high feature reuse-often achieves strong performance on medical datasets.
MobileNetV3-Large	Lightweight, fast, optimized for real-time inference, and ideal for deployment on CPU/GPU environments.

Each model was trained using:

- **Transfer Learning** with pretrained ImageNet weights
- **Data augmentation** (rotation, cropping, jitter, flips) to improve robustness
- **Selective fine-tuning** of the deeper layers
- **Cross-entropy loss + Adam optimizer**
- **Early stopping and best-model checkpointing**

- Model performance was evaluated using:
- **Training loss**
- **Validation loss**
- **Validation accuracy**
- **Generalization behavior across epochs**

Model Comparison

Model Performance Summary (VGG16, DenseNet121 and MobileNetV3)

Model	Dataset Condition	Best Validation Accuracy	Best Validation Loss	Notes
VGG16	Original (Imbalanced)	71.32%	15.19	Heavy, slow on CPU, high overfitting, weak generalization
DenseNet121	Original (Imbalanced)	70.56%	1.0570	High-capacity but sensitive to imbalance; requires clean data
MobileNetV3-Large (Before Fix)	Imbalanced Dataset	78.93%	0.6159	Good architecture but limited by dataset mismatch
MobileNetV3-Large (After Balanced Dataset)	Balanced + Shuffled Dataset	**95.11%**	0.2096	Best model: fast, stable, high accuracy, no overfitting, strong generalization
Grad-CAM	Balanced + Shuffled Dataset			Shows tumor region

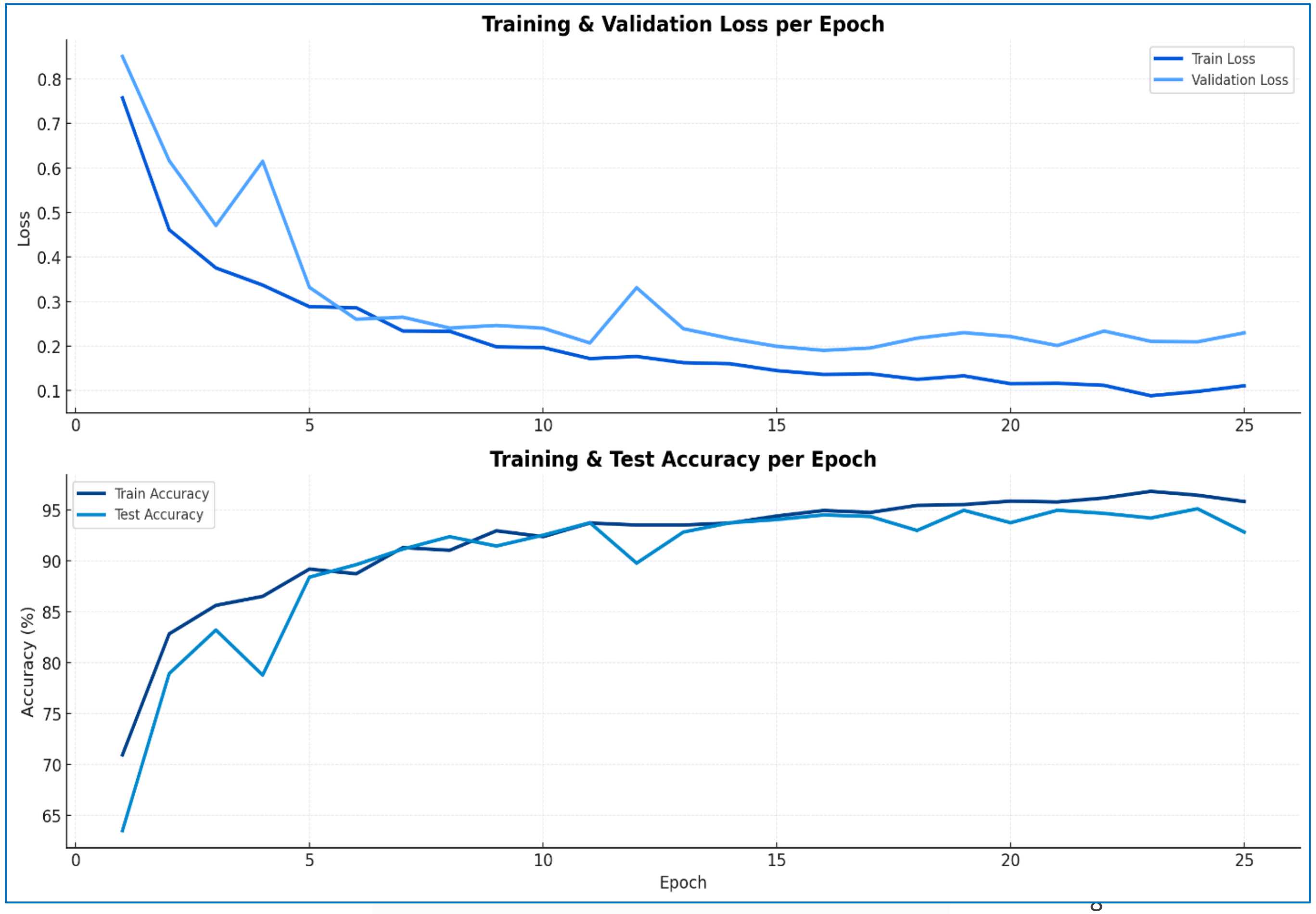
Model Comparison

MobileNetV3 Performance: Both losses and a consistent rise in accuracy, indicating stable learning, minimal overfitting, and strong generalization.

MobileNetV3 Performance Comparison – Before vs After Dataset Balancing

Metric	Before (Imbalanced Dataset)	After (Balanced Dataset)	Improvement
Best Train Epoch	22	**24**	
Train Loss	0.5038	**0.0980**	↓ Major improvement
Train Accuracy	83.51%	**96.44%**	↑ +12.93%
Validation Loss	0.6159	**0.2096**	↓ Stronger generalization
Validation Accuracy	78.93%	**95.11%**	↑ +16.18%
Generalization	Poor - Overfitting	Excellent - Balanced learning	Dramatic improvement
Dataset Quality	Unbalanced & mismatched	Clean, shuffled, balanced	Fixed distribution

Training & Validation Loss and Accuracy Curves for MobileNetV3-Large



Conclusion & Deployment

This project successfully developed **Brain Tumor Vision AI**, an end-to-end deep-learning system capable of accurately detecting and classifying brain tumors from MRI scans with **95.11% accuracy** using MobileNetV3-Large. Dataset balancing and preprocessing were key to high performance. Grad-CAM enabled clinical interpretability

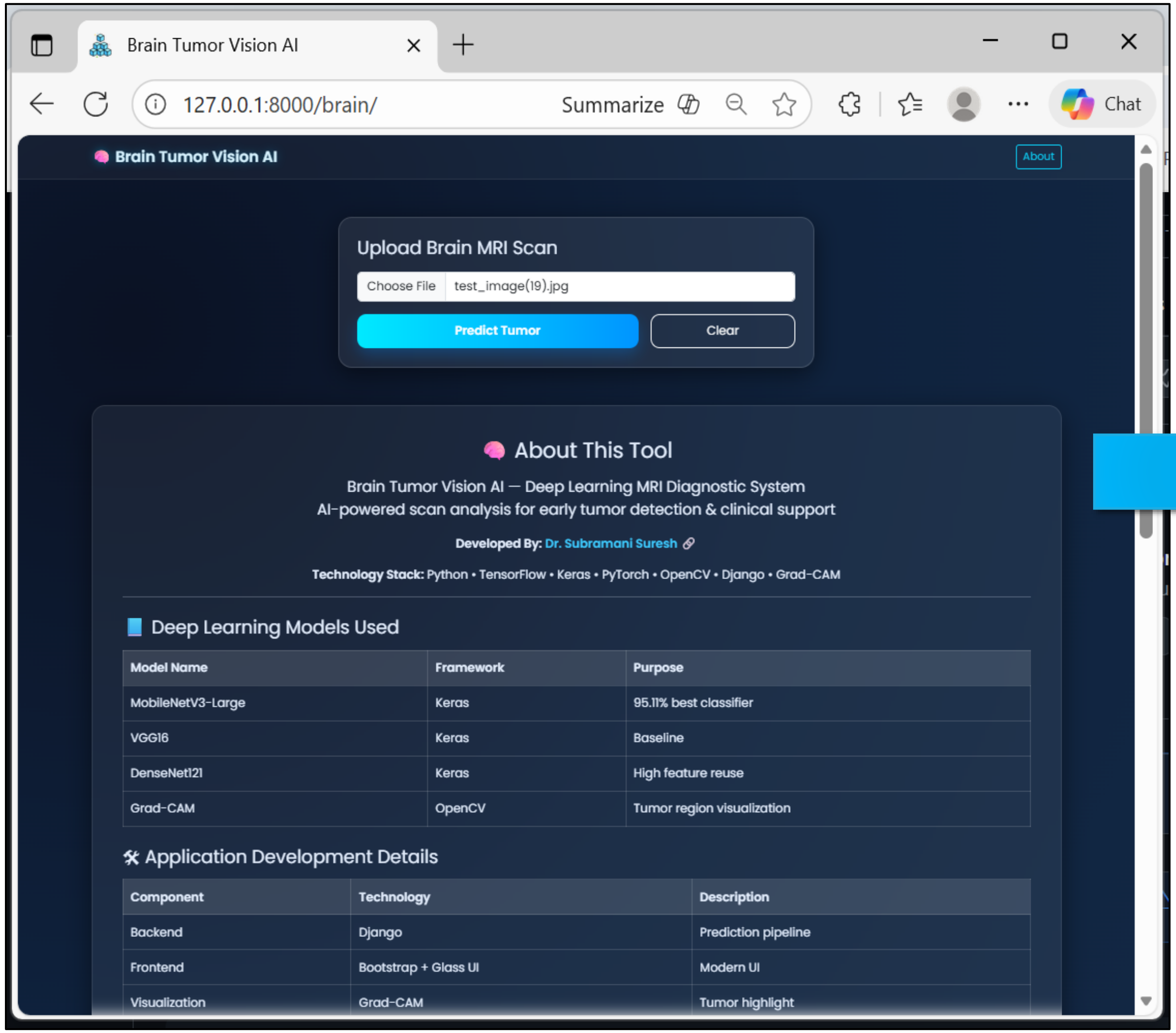
Deployment:
✓ Django Web Application
✓ MRI Upload → Preprocess → Predict → Heatmap
✓ Fast, accurate, explainable diagnostic support tool

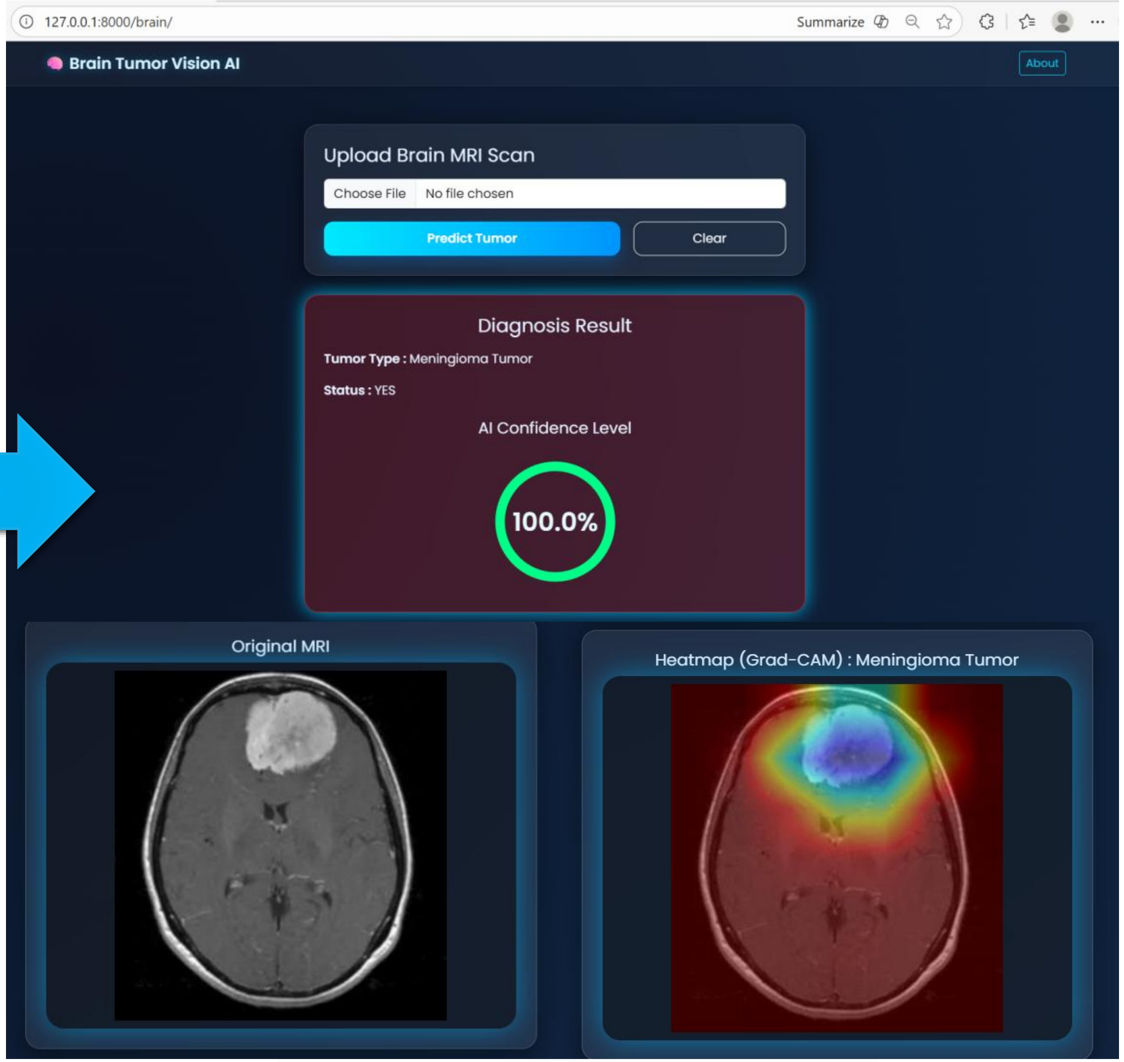
Final Output Example:
•**Tumor / No-Tumor detection**
•**Predicted Class** (Glioma, Meningioma, Pituitary, No Tumor)
•**Ai Confidence Score**
• **Grad-CAM heatmap:** highlight suspected tumor regions

Tech Stack

Component	Technology	Description
Backend / API	Django (Python)	Handles image upload, processing, and inference
Frontend	HTML, CSS, Bootstrap	Clean and responsive UI
Model Integration	PyTorch	Loads best MobileNetV3 model for prediction
Visualization	Grad-CAM + OpenCV	Generates heatmaps for interpretability
Deployment	Django Web Application	Runs on CPU/GPU; suitable for labs and hospitals

Brain Tumor Vision AI - Result





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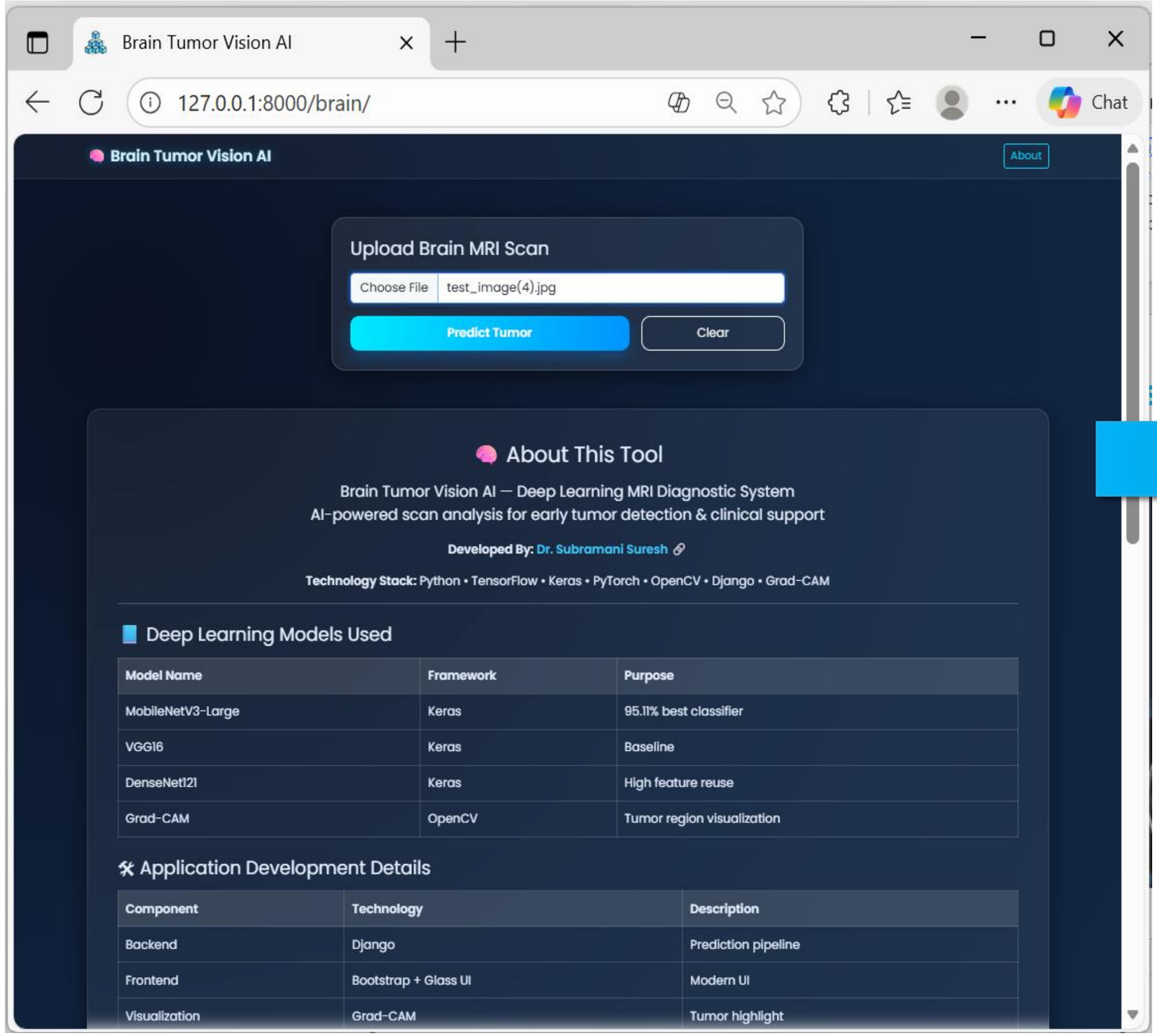

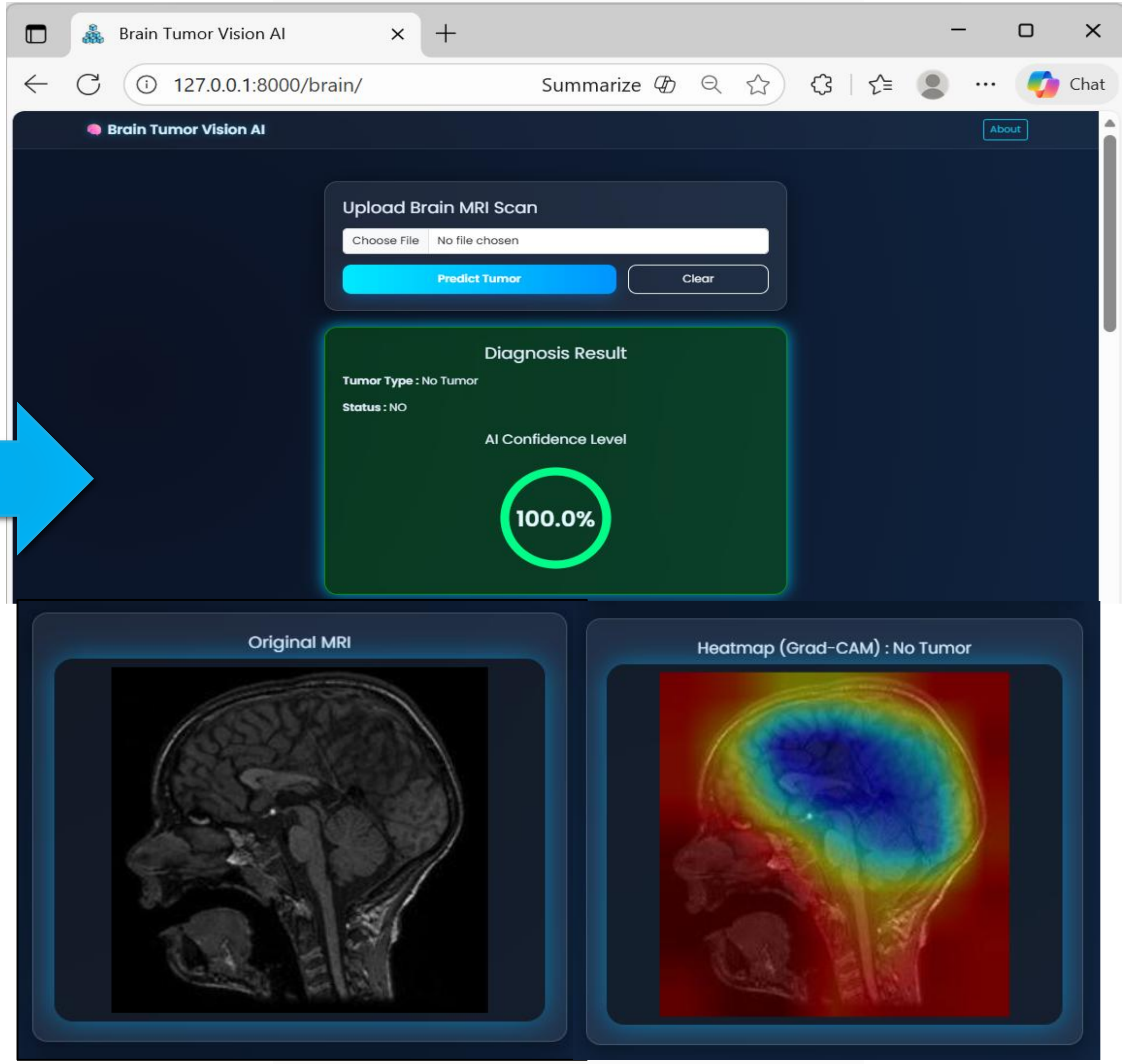

Thank You

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