# BRAIN TUMOR CLASSIFICATION USING DEEP LEARNING

## A CONVOLUTIONAL NEURAL NETWORK APPROACH FOR MULTI-CLASS MRI CLASSIFICATION

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FINAL MODEL ACCURACY (TEST SET): 98%

## THE PROBLEM:

- Manual analysis of brain MRIs is a specialized, time-consuming, and subjective task.
- Early and accurate diagnosis is critical for patient outcomes.

## PROJECT OBJECTIVES:

- To develop an Artificial Intelligence model to automatically classify brain MRIs.
- To accurately distinguish between four categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor.
- To build and validate a high-performance Convolutional Neural Network (CNN) for this task.

# DATASET: THE FOUNDATION OF OUR MODEL

- Over 7,023 total MRI images 4569 trained contrast-enhanced MRI images.
- Validated: 1143 and Tested: 1311 Images across four classes.

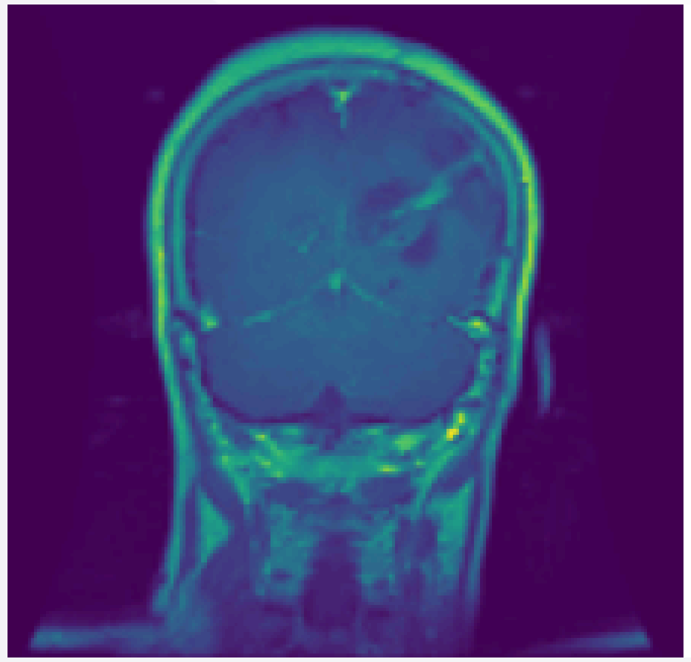
DATASET LINK

## Tools and Technologies:

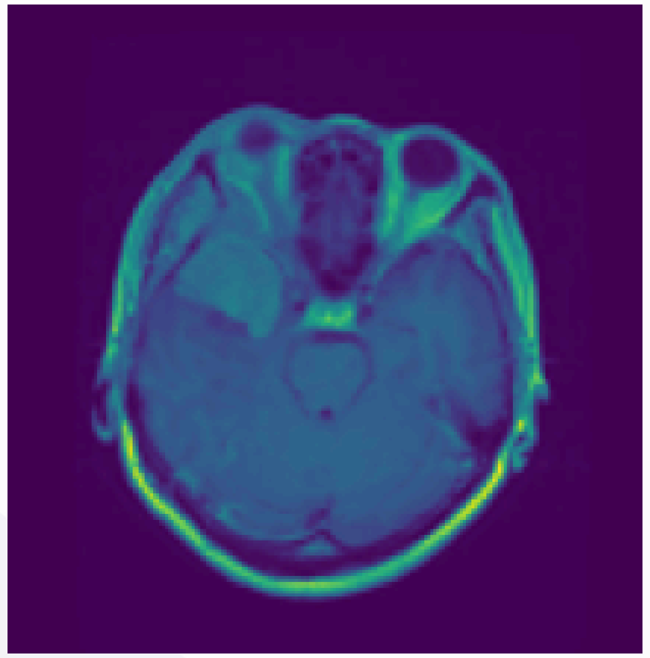
- **Deep Learning: TensorFlow/Keras** for model building.
- **Model: VGG16** (Transfer Learning) for feature extraction.
- **Environment: Google Colab** for development and GPU access.
- **Language:** Python for all scripting.
- **Data/Metrics: NumPy, Pandas, Scikit-learn** for numerical handling, data processing, and evaluation metrics (Confusion Matrix, ROC/AUC).
- **Visualization:** Matplotlib/Seaborn for generating all graphs.

## EXPLORATORY DATA ANALYSIS: VISUALIZING THE DATA

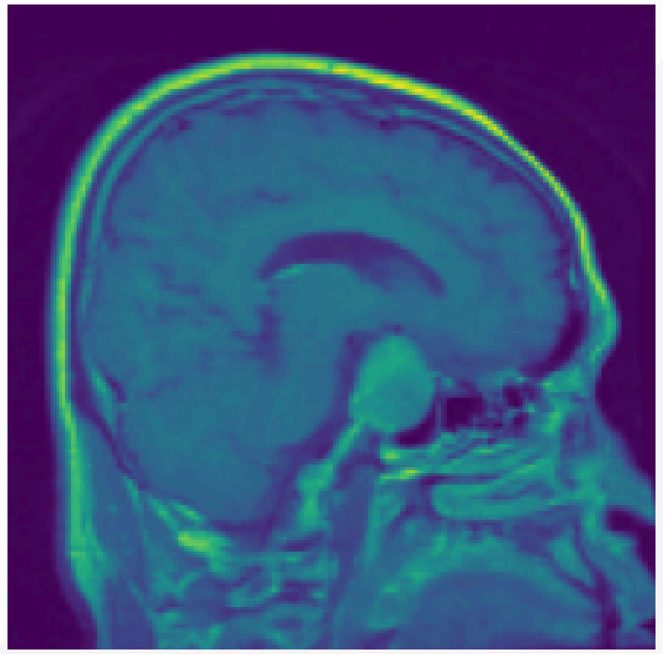
# A VISUAL INSPECTION OF THE FOUR DISTINCT CLASSES.



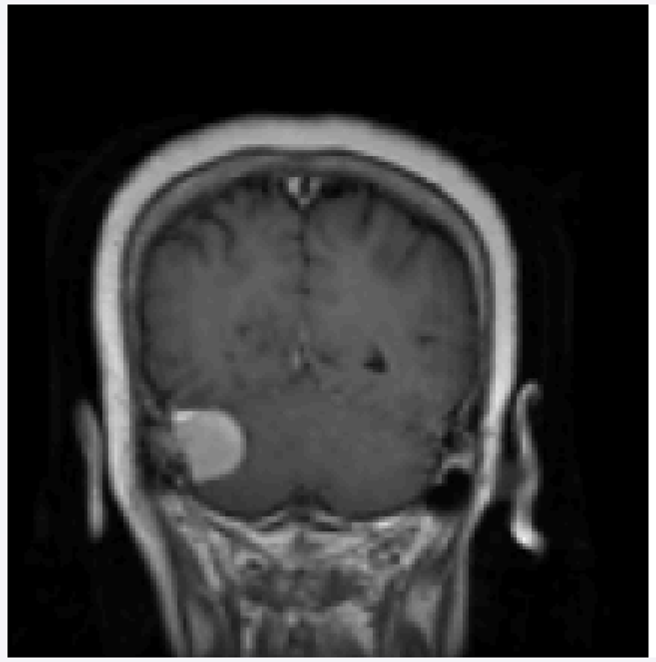
GLIOMA



MENINGIOMA



PITUITARY



NO TUMOR

# METHODOLOGIES

**Pre-processing:**

1. All images resized to 224x224 pixels (VGG16 standard input size).
2. Pixel values normalized from [0-255] to [0-1] range.

**Augmentation (Critical for medical data):** Used random brightness/contrast adjustments during training to prevent overfitting and enhance generalization.

**Architecture:**

1. VGG16 Base: Loaded weights trained on the massive ImageNet dataset.
2. Fine-Tuning: The last four convolutional layers of VGG16 were unfrozen and trained, allowing the model to adapt general features to specific MRI patterns.
3. Custom Head: Added layers for classification: Global Average Pooling, Dropout (0.5), Dense (256), Batch Normalization, and a Final Dense (4 neurons) layer with Softmax activation.

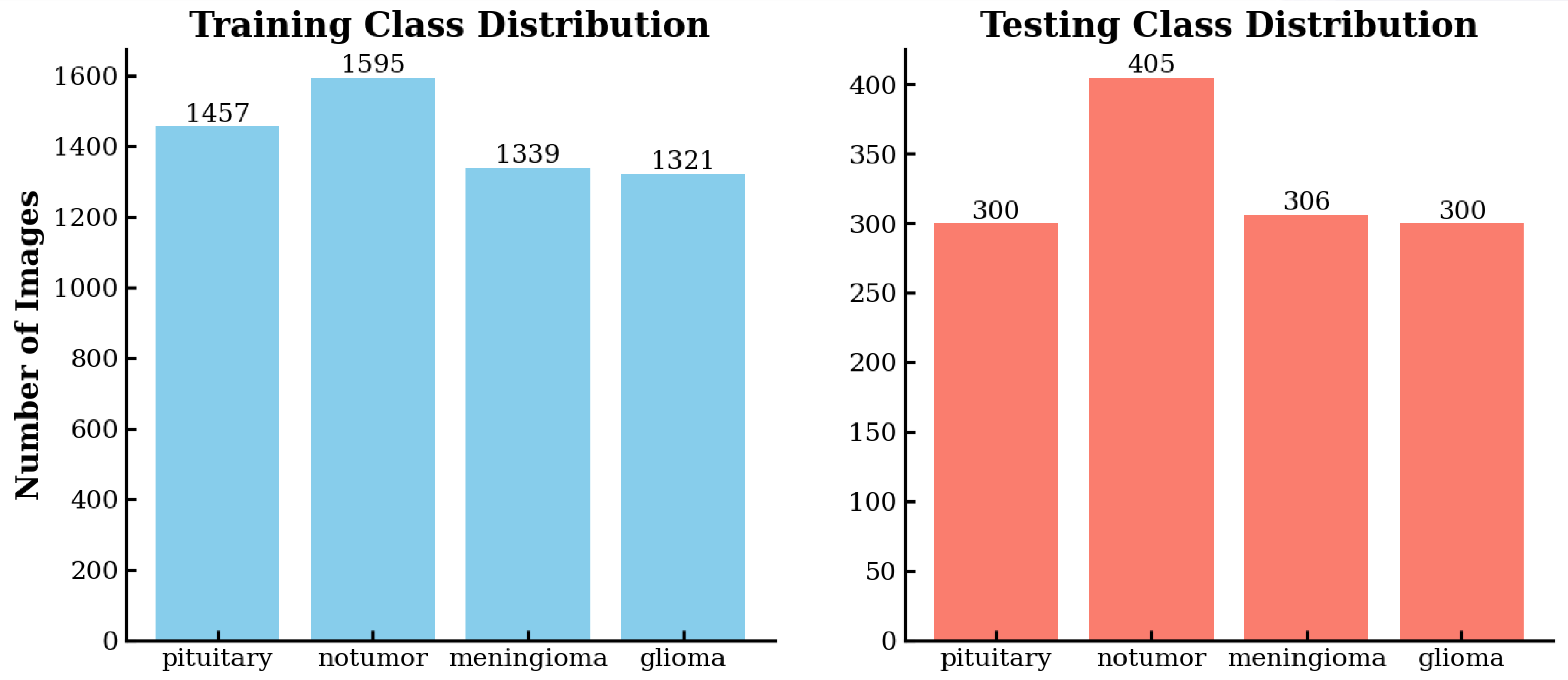
# TRAINING PARAMETERS

## KEY PARAMETERS:

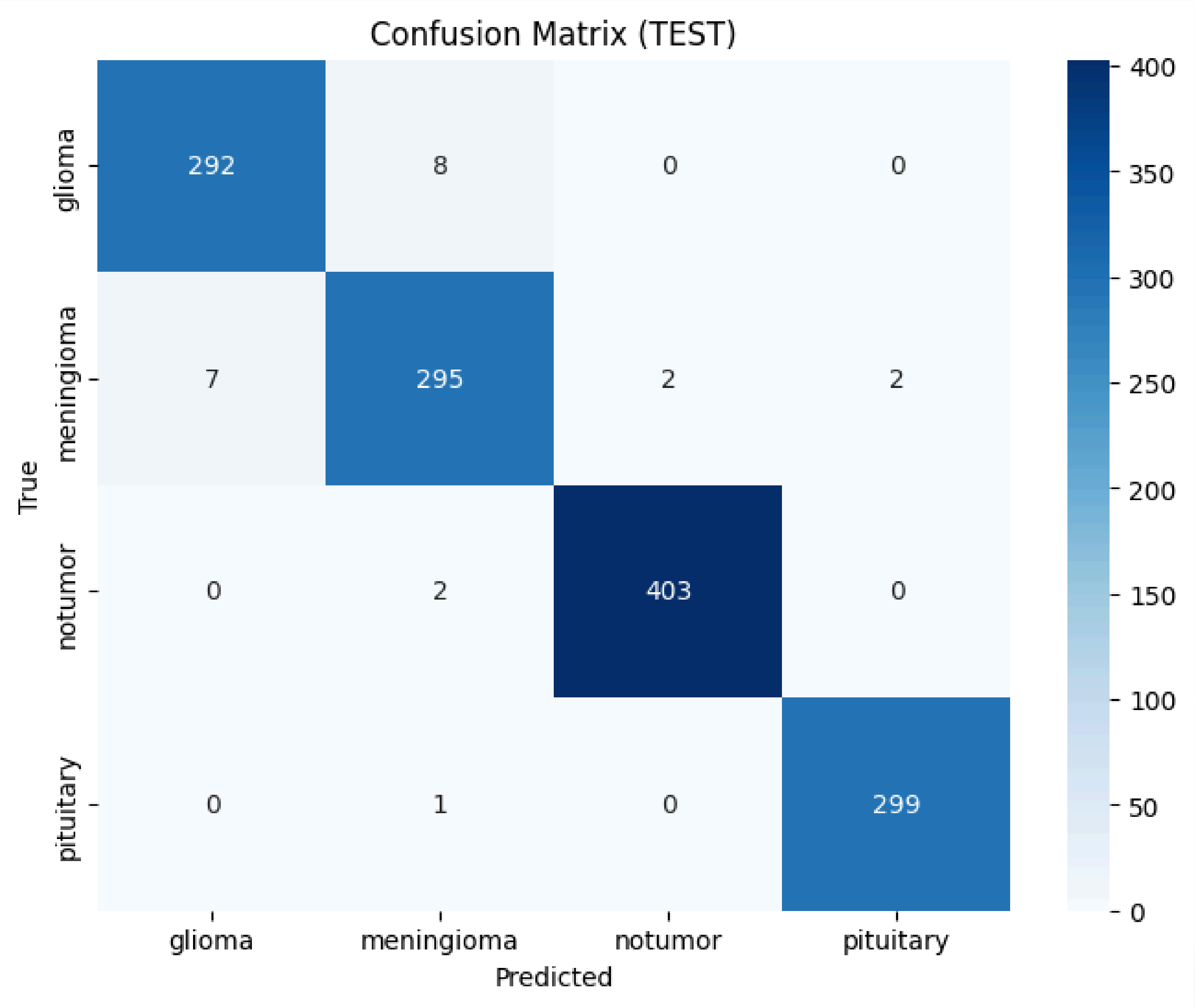
- **Optimizer:** Adam (Learning Rate: 0.0001)
- **Loss Function:** Sparse Categorical Crossentropy
- **Batch Size:** 32
- **Epochs:** 25 (with Early Stopping)
- Both training and validation loss converged to near-zero values, confirming the model successfully learned the distinction between the four classes.
- **Regularization:** Used **Dropout** (**0.5 and 0.3**) and **Batch Normalization** to ensure the model generalizes well and avoids overfitting.
- **Callbacks: Early Stopping** (patience 10) and **ReduceLROnPlateau** were used to optimize training time and stability.

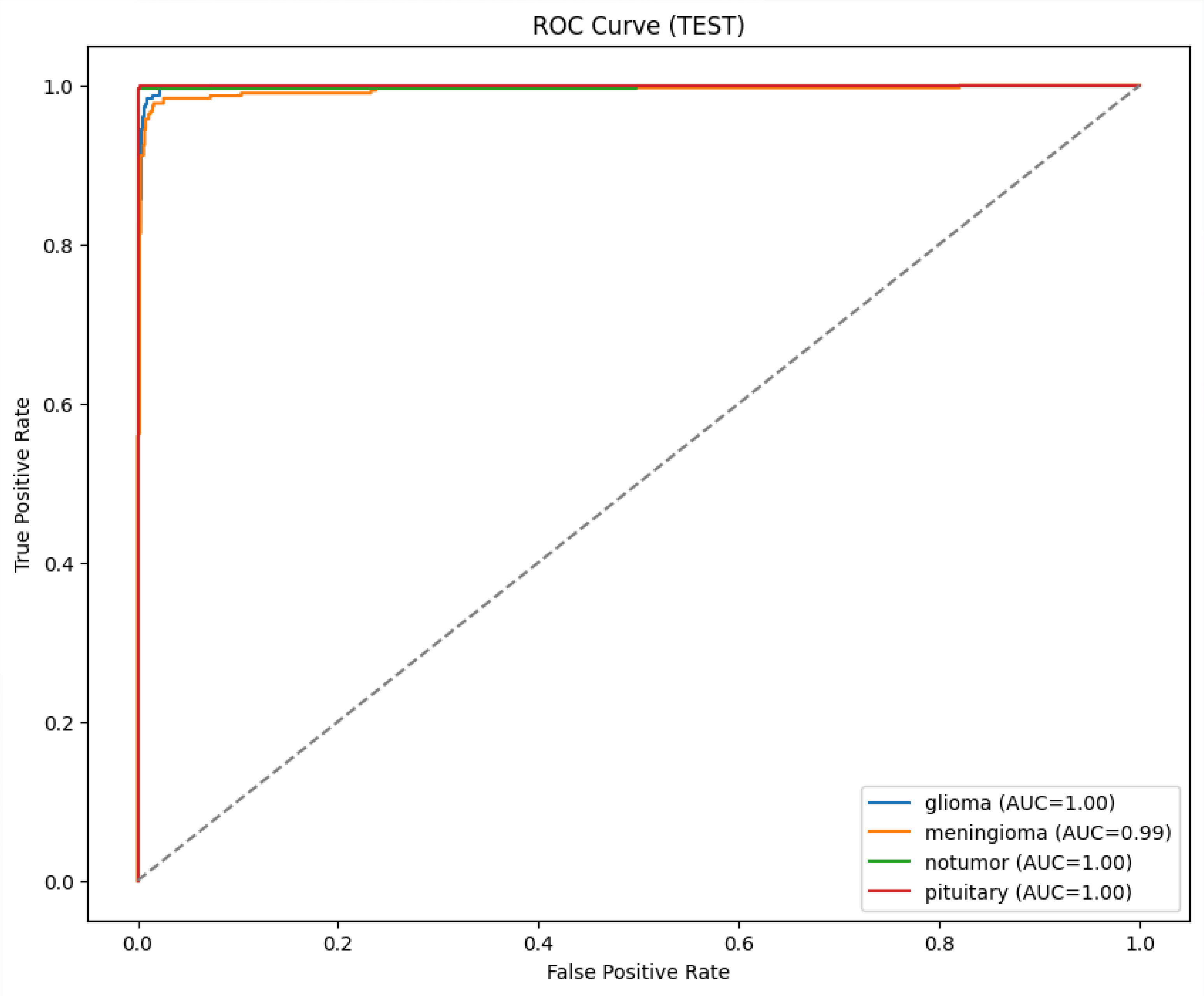
# EXPLORATORY DATA ANALYSIS: CLASS BALANCE

## THE BAR CHART SHOWING THE COUNT FOR EACH OF THE 4 CLASSES.



# ACCURACY& ERROR MINIMIZATION



# FINAL PERFORMANCE ON THE TEST SET

- Overall Metrics:
- Overall Accuracy: 0.98 (98%)
- Macro/Weighted Average F1-Score: 0.98
- Per-Class Strength: The model achieved 1.00 Precision/Recall for 'notumor' and close to perfect scores for the other three tumor types.

Classification Report (TEST):

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| glioma | 0.98 | 0.97 | 0.97 | 300 |
| meningioma | 0.96 | 0.96 | 0.96 | 306 |
| notumor | 1.00 | 1.00 | 1.00 | 405 |
| pituitary | 0.99 | 1.00 | 1.00 | 300 |
| accuracy | | | 0.98 | 1311 |
| macro avg | 0.98 | 0.98 | 0.98 | 1311 |
| weighted avg | 0.98 | 0.98 | 0.98 | 1311 |

# OBSERVATIONS AND RESULTS

- **Observations:** The 22 misclassified images often show complex, non-standard tumor shapes or poor image contrast.
- **Classification & ANN:** Successfully developed and evaluated a deep learning classification model (**VGG16 CNN**).
- **Pre-processing:** Implemented data normalization and augmentation for high-quality input.
- **Application & Evaluation:** Built a robust ML application, achieving a high-level outcome on a real-world problem.

# APPLICATION & GUI: REAL-TIME DIAGNOSTIC SUPPORT

- **Deployment Platform:** The final model is deployed using **Streamlit**, which creates an interactive, user-friendly web application (GUI).
- **The Model's Role:** The app loads the trained **VGG16 model** (final_clean.keras) to serve as the core prediction engine.
- **User Interaction:** The user simply **uploads an MRI image** via the web interface.
- **Real-Time Processing:** The system automatically performs necessary pre-processing (resizing to **224x224** and normalization) before feeding the image to the model.
- **Result Output:** The GUI instantly displays the **Predicted Tumor Class** (e.g., glioma), the model's **Confidence Score** (e.g., 99.2%), and the full probability breakdown for all four tumor types.
- **Practical Use:** This application functions as an effective **Clinical Decision Support System,** providing doctors with a fast, objective "second opinion" to enhance diagnostic accuracy and speed.

# CONCLUSION & LIMITATIONS

- **Conclusion:** The VGG16 Transfer Learning model achieved state-of-the-art performance with 98% overall accuracy in multi-class brain tumor detection.

- **Limitations:**

1. Model performance is dependent on the quality of MRI scans.
2. The model performs classification but does not provide localization (segmentation) of the tumor, which is a next logical step.

# FUTURE ENHANCEMENTS

- **Technical Future Work:**

1. Integration of Segmentation: Modify the model to perform instance segmentation (identifying the exact boundaries of the tumor).
2. Alternative Architectures: Test newer models like EfficientNet or ResNet to push the accuracy to 99%+.

- **Deployment:** Finalize the Flask UI deployment for clinical demonstration and testing.

# THANK YOU.