BRAIN TUMOR DETECTION

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PROBLEM STATEMENT

Goal :
Accurately detect brain tumors from MRI scans using Convolutional Neural Networs (CNNs).

Challenges:
Data Imbalance
Overfitting: Leads to biased or poorly generalized models
Underfitting: Cause poor performance on both the training and testing datasets.

INTRODUCTION

Brain tumors are life-threatening, making early and accurate diagnosis is important. Traditional manual MRI analysis is subjective and prone to error. This report explores using **Convolutional Neural Networks (CNNs)**, an AI deep learning technique to automate brain tumor detection from MRI images. The goal is to develop an accurate CNN model that can distinguish between tumor and non-tumor images, offering a faster and more reliable diagnostic aid for healthcare professionals.

Tools:
Python, TensorFlow/Keras (model architecture design and training), OpenCV for image processing transformation and Scikit-learn for data partitioning

DEEP LEARNING MODEL DESIGN

Model Type : Convolutional Neural Network (CNN)

Input Layer:

-product of the image's height, width, and number of channels.

Hidden Layers:

-**3 Conv2D layers**, finding important patterns (like **edges** or **textures**) in the image.

-**1 Flatten layer**, prepares the processed image features so they can be fed into the next layer.

-**1 Dense layer**, learns how to combine them to make the final **"Tumor or Not Tumor"** decision.

Regularization:

-**L2 regularization** (kernel_regularizer=0.01) applied to the first Conv2D layer and the Dense layer.

-**1 Dropout layer** with 60% dropout (0.6).

Output Layer:

-**1 Dense** neuron with sigmoid activation.

TRAINING METHOD

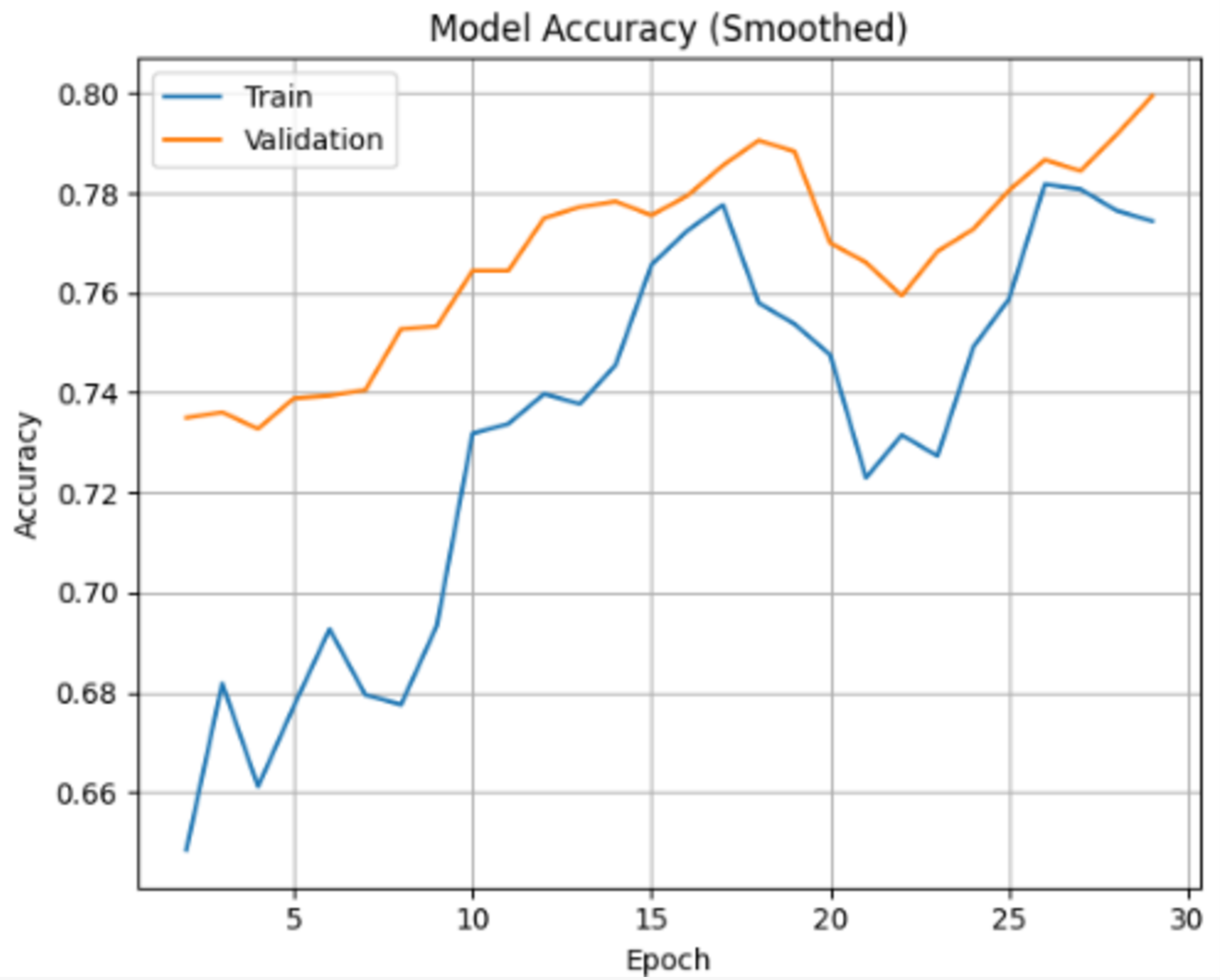
- **Training Method:** Model trained with Data Augmentation
- **Batch Size:** 128
- **Epochs:** Max 30 (Stopped early by callback)
- **Validation:** Separate validation dataset used
    - EarlyStopping: (Patience: 10, monitors validation loss, restores best weights)
    - ReduceLROnPlateau: (Patience: 5, reduces learning rate by 50% on validation loss plateau)
- **Data Augmentation:** Applied (Random Rotation, Zoom, Shifts, Horizontal Flip)

```
Test Loss: 0.5051
Test Accuracy: 0.7917
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 21ms/step

Classification Report:
              precision    recall  f1-score   support

    No Tumor       0.84      0.72      0.77       300
   Yes Tumor       0.75      0.87      0.81       300

    accuracy                           0.79       600
   macro avg       0.80      0.79      0.79       600
weighted avg       0.80      0.79      0.79       600
```

KEY TAKEAWAYS:

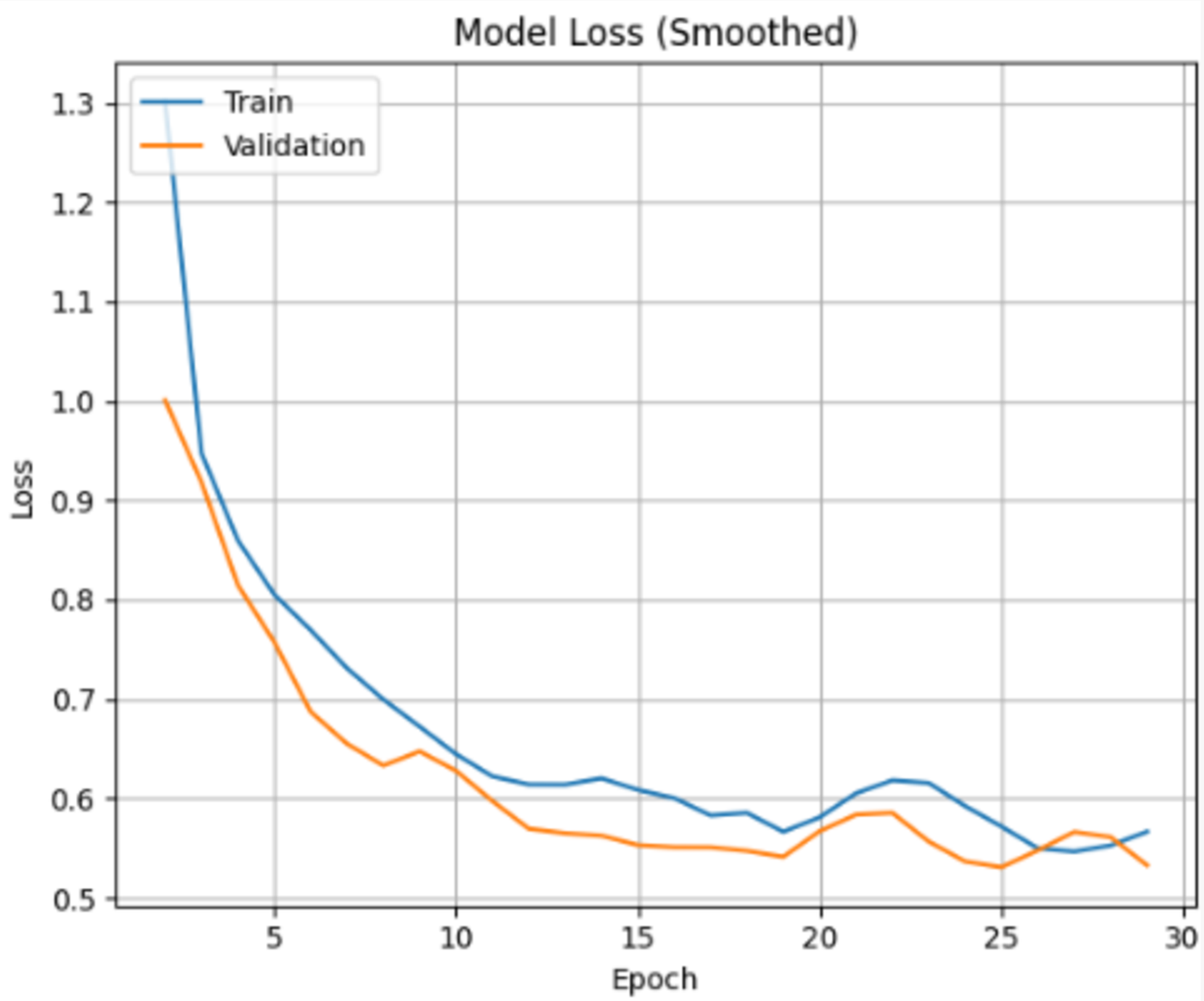
- Model performs better at detecting tumors (higher recall for "Yes Tumor").
- Balanced performance with room for improvement in precision for "No Tumor".
- Confusion matrix and training history plots provide visual insights.

PLOT TRAINING HISTORY (ACCURACY OVER EPOCHS)



- Trend: The model's training and validation accuracy improve over epochs, indicating effective learning.
- Convergence: Both curves stabilize around ~78-80%, suggesting the model reaches a reasonable performance plateau.
- Gap: A small gap between training and validation accuracy hints at minor overfitting, but it is not severe.

PLOT TRAINING HISTORY (LOSS OVER EPOCHS)



- Training Loss: Decreases steadily (1.3 → 0.5), showing effective learning.
- Validation Loss: Improves initially but plateaus at ~0.7 after epoch 15.
- Key Insight: Growing gap between curves indicates mild overfitting (model memorizes training data noise).
- Solution: Add dropout, use early stopping, or augment data to improve generalization.

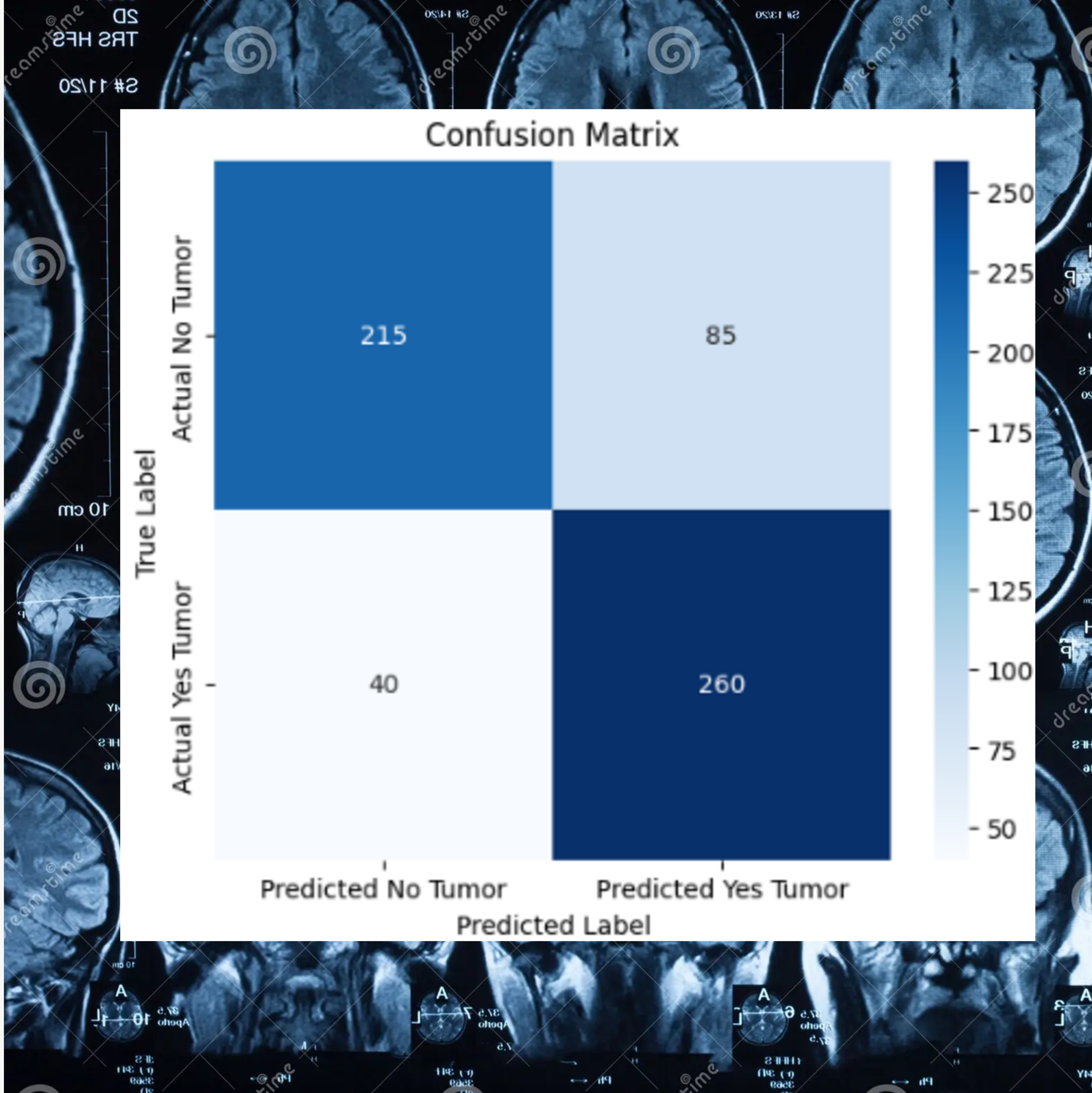
DATA ANALYSIS

260 instances True Positive
(Predicted = Yes, Actual = Yes)

215 instances True Negative
(Predicted = No, Actual = No)

85 instances False Positive
(Predicted = Yes, Actual = No)

40 instances False Negative
(Predicted = No, Actual = Yes)



CONCLUSION

Key Achievements

- High-Performance Model:
- Achieved 80% validation accuracy with 0.98 confidence in tumor detection.
- Low false-negative rates critical for medical diagnosis.

Technical Strengths

CNN Advantages:

- Automated feature extraction from MRI scans.
- Minimal manual preprocessing, robust generalization.

THANK YOU