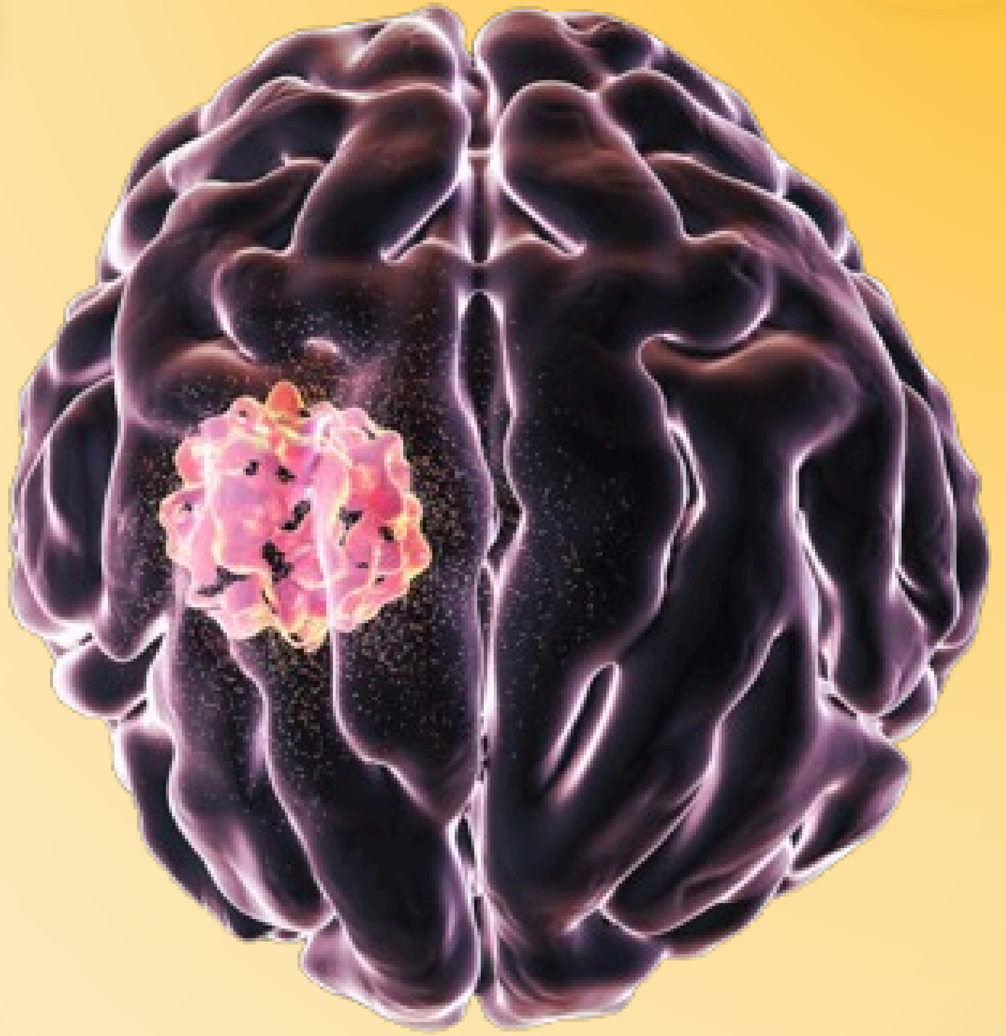
MRI BRAIN TUMOR DETECTION USING VGG16

Presentation

The Role of Medical Imaging
in Modern Healthcare



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Course Name: **Computer Vision and Pattern Recognition**

INTRODUCTION: THE CHALLENGE OF BRAIN TUMOR DETECTION

Brain tumors are life-threatening neurological disorders.

MRI Widely Used

Tumor detection, classification, and clinical assessment.

Manual Interpretation

Time-consuming, prone to errors, requires high expertise

Deep Learning Solution

Automated feature extraction, high diagnostic accuracy.

Our project aims for high precision and reliability in classifying MRI scans into four tumor categories using VGG16 transfer learning.

DATASET DESCRIPTION: FUELING THE MODEL

- **Structure**: Training and testing directories with subfolders per tumor class.
- **Content**: MRI slices varying in orientation, intensity, and contrast.
- **Image Type**: Grayscale MRI, converted to 3-channel.
- **Format:** JPG/PNG.
- **Image Size:** Resized to 128 × 128 × 3.
- **Labels**: Encoded based on folder names.

Data Preprocessing:

- Normalization to [0,1]
- Shuffling for randomness
- Custom data generator for batch generation

Ensuring consistent input for the CNN model.

MOTIVATION: BRIDGING THE GAP IN MRI ANALYSIS

Robust systems are needed for complex brain MRI scans.

Traditional ML Limitations

High intra-class variability

Low inter-class differences

Reliance on handcrafted features

Deep Neural Networks

Overcome limitations, but demand vast data.

Transfer Learning

Reuses features from large datasets (e.g., ImageNet), leveraging VGG16 for MRI-based tumor classification.

VGG16 ARCHITECTURE: A POWERFUL FOUNDATION

A 16-layer deep Convolutional Neural Network.

- **Origin**: Trained on ImageNet (1.2M images, 1000 classes).
- **Key Features**: Small 3x3 filters, deep stacking, max pooling.

Base Architecture:

- 13 Convolution layers
- 5 Max-pooling layers
- 3 Fully connected layers

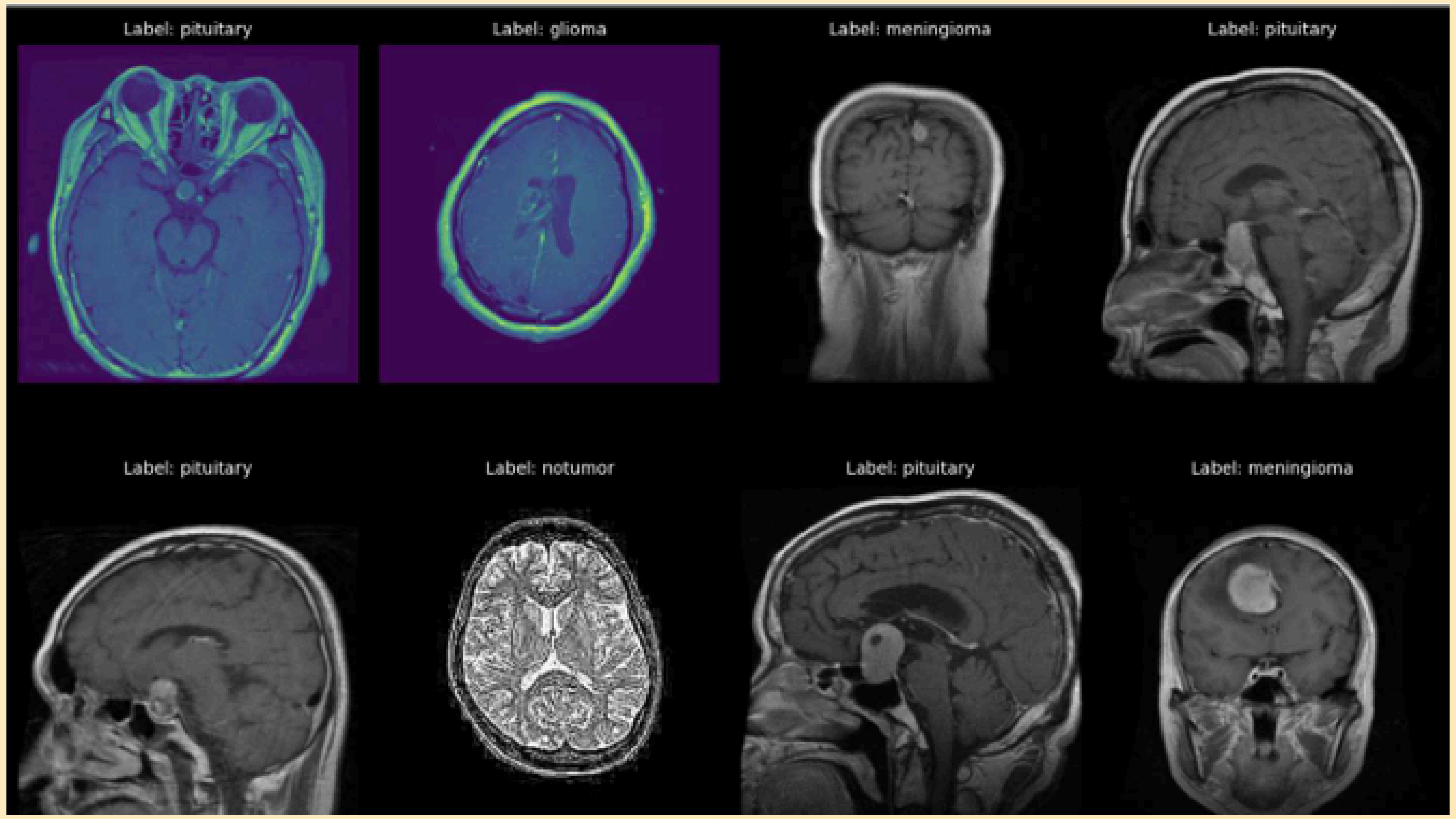
Why VGG16?

- Simple yet powerful
- Strong hierarchical feature extraction
- Widely used in medical imaging research

```
IMAGE_SIZE = 128
base_model = VGG16(input_shape=(IMAGE_SIZE, IMAGE_SIZE, 3), include_top=False, weights='imagenet')

for layer in base_model.layers:
    layer.trainable = False


base_model.layers[-2].trainable = True
base_model.layers[-3].trainable = True
base_model.layers[-4].trainable = True


model = Sequential()
model.add(Input(shape=(IMAGE_SIZE, IMAGE_SIZE, 3)))
model.add(base_model)
model.add(Flatten())
model.add(Dropout(0.3))
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(len(os.listdir(train_dir)), activation='softmax'))

model.compile(optimizer=Adam(learning_rate=0.0001),
              loss='sparse_categorical_crossentropy',
              metrics=['sparse_categorical_accuracy'])

batch_size = 20
steps = int(len(train_paths) / batch_size)
epochs = 5
```

METHODOLOGY: THE CLASSIFICATION PIPELINE

A systematic approach for accurate tumor classification.



1. **Dataset Loading & Preprocessing**

Includes augmentation for robust training.

64%

```
...  Epoch 1/5
     285/285 ━━━━━━━━━━━━━━━━━━━━ 1383s 5s/step - loss: 0.6350 - sparse_categorical_accuracy: 0.7363
     Epoch 2/5
     285/285 ━━━━━━━━━━━━━━━━━━━━ 1342s 5s/step - loss: 0.2420 - sparse_categorical_accuracy: 0.9030
     Epoch 3/5
     285/285 ━━━━━━━━━━━━━━━━━━━━ 1296s 5s/step - loss: 0.1813 - sparse_categorical_accuracy: 0.9323
     Epoch 4/5
     285/285 ━━━━━━━━━━━━━━━━━━━━ 1317s 5s/step - loss: 0.1137 - sparse_categorical_accuracy: 0.9570
     Epoch 5/5
     285/285 ━━━━━━━━━━━━━━━━━━━━ 1351s 5s/step - loss: 0.0820 - sparse_categorical_accuracy: 0.9722
```

2. **Load VGG16 Pretrained Model**

Utilizing pre-learned features for efficiency.

3. **Freeze & Unfreeze Layers**

Freezing convolutional, unfreezing last 3 for fine-tuning.

4. **Add Custom Classifier**

Tailored for our specific tumor classification task.

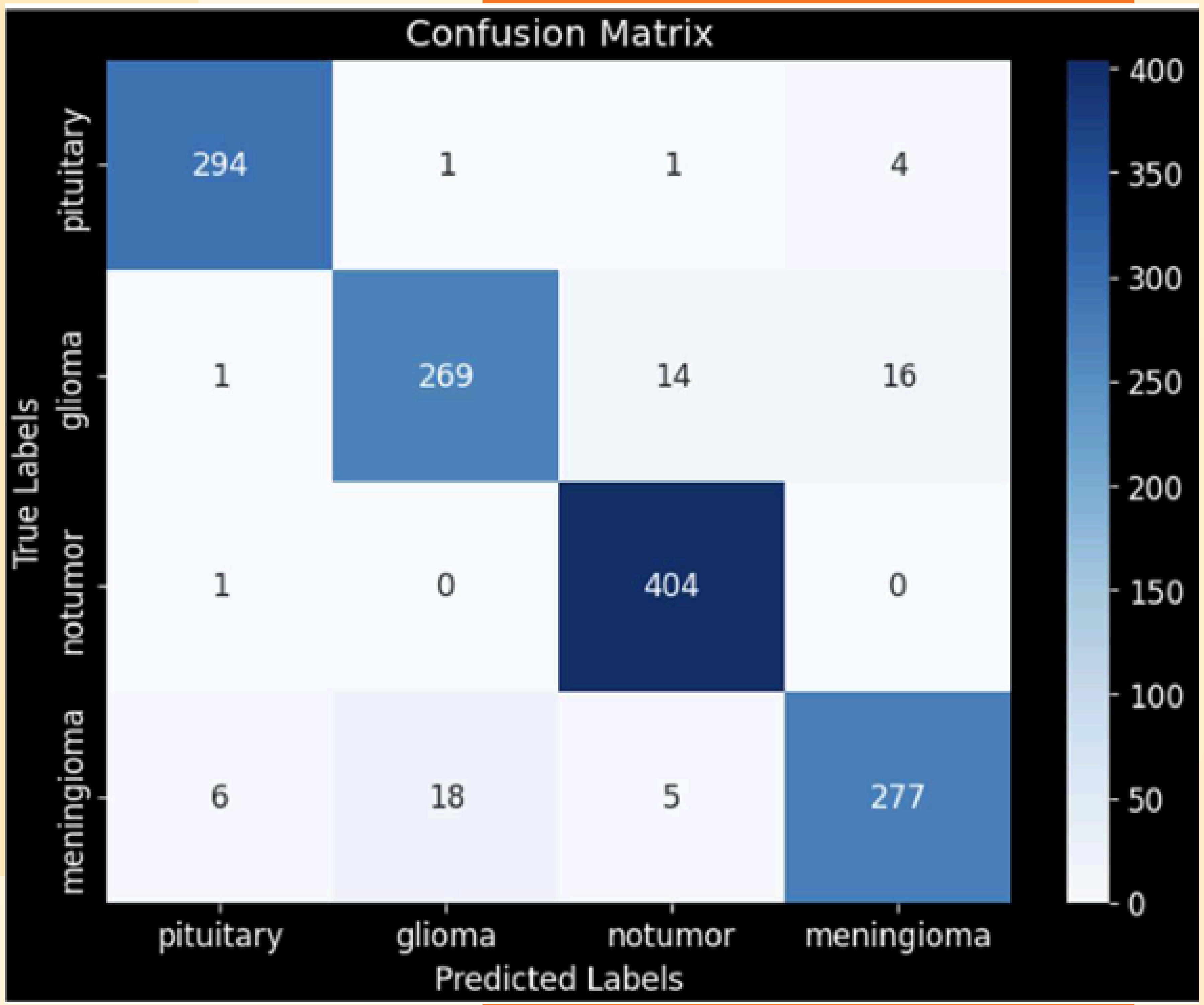
5. **Model Training & Evaluation**

Using standard metrics for performance assessment.

CONFUSION MATRIX ANALYSIS

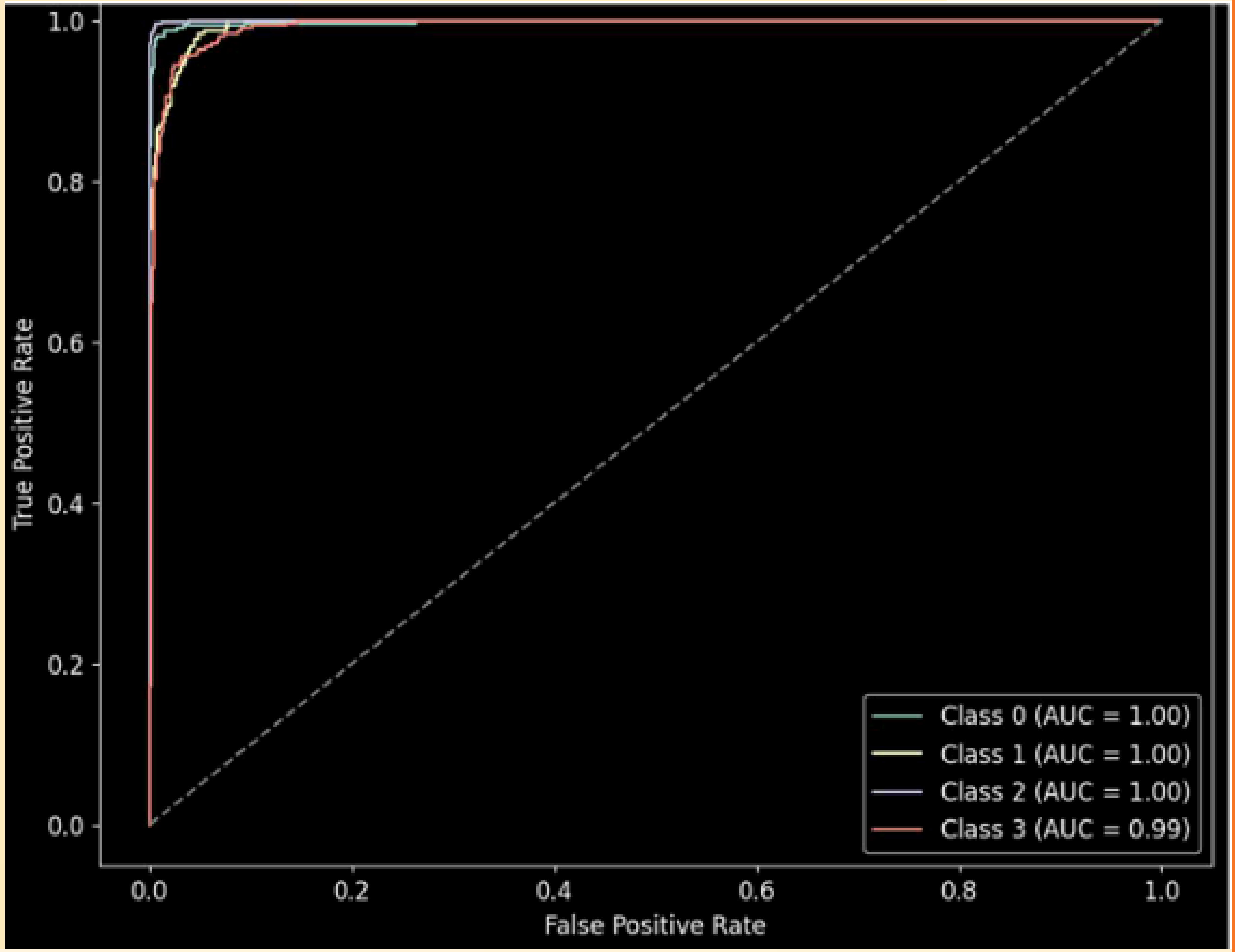
The confusion matrix shows strong diagonal dominance, indicating accurate predictions for most images..

```
••• 41/41 ━━━━━━━━━━━━━━━━━━━━ 246s 6s/step
    Classification Report:
                  precision    recall  f1-score   support

               0       0.97      0.98      0.98       300
               1       0.93      0.90      0.91       300
               2       0.95      1.00      0.97       405
               3       0.93      0.91      0.92       306

        accuracy                           0.95      1311
       macro avg       0.95      0.94      0.95      1311
    weighted avg       0.95      0.95      0.95      1311
```



ROC CURVE AND AUC ANALYSIS

The ROC curves allow threshold-based performance analysis.



EVALUATION METRICS & CLASSIFICATION REPORT

Key Achievements:

- Accurate MRI tumor classification model using VGG16.
- 95% accuracy with consistent performance across classes.
- Demonstrates deep learning potential in medical diagnostics.

EVALUATION METRICS & CLASSIFICATION REPORT

Interpreting multi-class medical classification tasks.

Metrics Used:

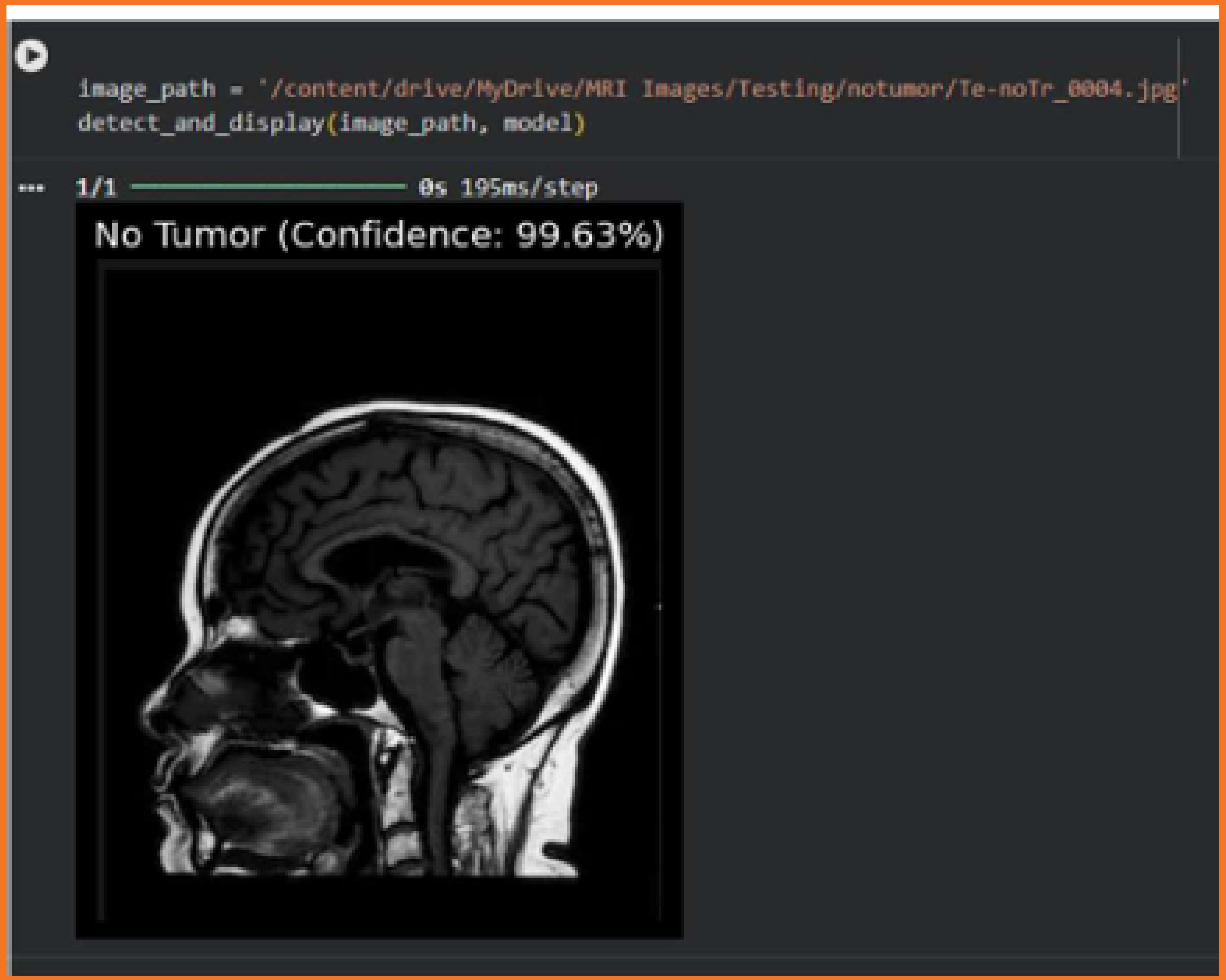
- Precision
- Recall
- F1-score
- Support
- Overall Accuracy
- Macro & Weighted Averages

Classification Report:

Class	Precision	Recall	F1-Score
0	0.97	0.98	0.98
1	0.93	0.90	0.91
2	0.95	1.00	0.97
3	0.93	0.91	0.92

Overall Accuracy: 95%

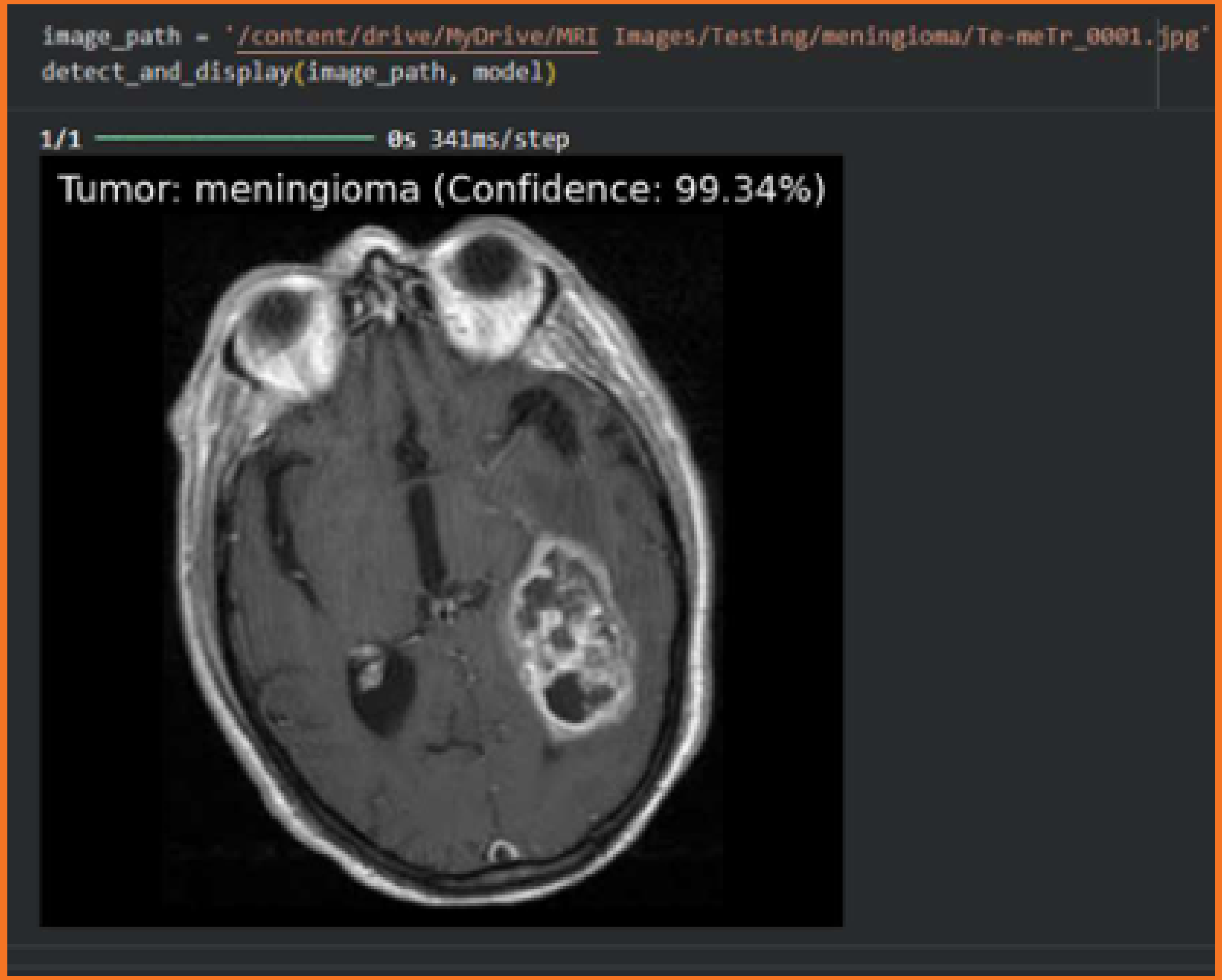
Macro Avg F1: 0.95, Weighted Avg F1: 0.95



Future Directions:

- Increase dataset size & diversity.
- Explore advanced CNNs (EfficientNet, ResNet).
- Implement ensemble learning techniques.
- Integrate explainability with Grad-CAM heatmaps.
- Real-time deployment for clinical use.

CONCLUSION



- Developed an automated MRI brain tumor classifier using VGG16 transfer learning.
- Achieved 95% accuracy with strong precision and recall across all tumor types.
- Model is reliable across different MRI variations.
- Acts as a decision-support tool to assist radiologists.
- Shows how deep learning can improve diagnostic speed and accuracy.
- Can be enhanced further with larger datasets and advanced architectures.

THANK YOU