Brain Tumor Detection using Deep Learning

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OUTLINE

INTRODUCTION

- Brain tumors are life-threatening and require early detection for effective treatment.
- Manual diagnosis from MRI scans is time-consuming and prone to errors.
- Deep Learning offers a powerful solution through automated image analysis.
- Convolutional Neural Networks (CNNs) are especially effective for medical imaging.
- This project focuses on detecting brain tumors from MRI images using CNNs.

DEEP LEARNING

Deep Learning is a subset of machine learning that uses artificial neural networks with multiple layers to learn and extract complex patterns from large datasets. It mimics the way the human brain processes information, making it especially powerful for tasks like image recognition, speech processing, and natural language understanding. Deep learning models automatically learn features from raw data, reducing the need for manual feature engineering.

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a type of deep learning model designed for image processing tasks. They use layers like convolution, pooling, and activation functions to automatically extract features such as edges, textures, and shapes from images. CNNs are highly effective in identifying patterns and have become the standard for tasks like object detection and medical image classification.

APPLICATIONS

- Early Detection of Brain Tumors: Assists doctors in diagnosing brain tumors quickly and accurately from MRI scans.
- Medical Decision Support: Acts as a second opinion to support radiologists in clinical decision-making.
- Automated Screening: Enables large-scale, automated screening in hospitals and diagnostic labs.
- Telemedicine: Useful in remote healthcare systems where specialist availability is limited.
- Research and Training: Helps in medical research and training of radiology students using AI-assisted diagnosis.

CHALLENGES

- Limited availability of high-quality, labeled medical image datasets.
- Variations in MRI image formats, angles, and lighting.
- Overfitting due to small dataset sizes.
- High computational resources required for model training.
- Difficulty in distinguishing between tumor and non-tumor tissues in complex cases.

PROBLEM STATEMENT

To develop an accurate and efficient deep learning model using Convolutional Neural Networks (CNNs) that can automatically detect brain tumors from MRI images, reducing the reliance on manual analysis and improving early diagnosis.

OBJECTIVES

- To build a CNN model capable of classifying MRI images as tumor or no tumor.
- To improve diagnostic accuracy and reduce human error.
- To automate the brain tumor detection process using image classification.
- To evaluate model performance using accuracy, loss, and confusion matrix.
- To contribute towards AI-assisted healthcare solutions.

DATASET

- **Type**: MRI (Magnetic Resonance Imaging) brain scan images
- **Categories**:

  Tumor – MRI images showing presence of a brain tumor

  No Tumor – MRI images showing a healthy brain
- **Format**: Image files (likely JPEG/PNG)
- **Preprocessing Done**:

  Resized all images to a uniform size (e.g., 150x150 pixels)

  Normalized pixel values (scaling between 0 and 1)

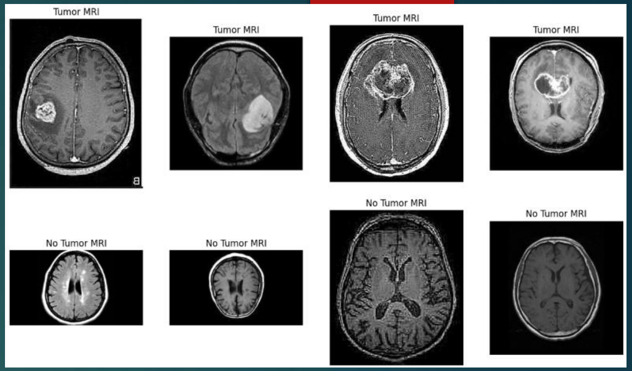
  Labeled images for binary classification (1 for tumor, 0 for no tumor)
- **Splitting**: Dataset is divided into training, validation, and testing sets for model evaluation
- **Usage**: Used to train and test a CNN model for binary image classification

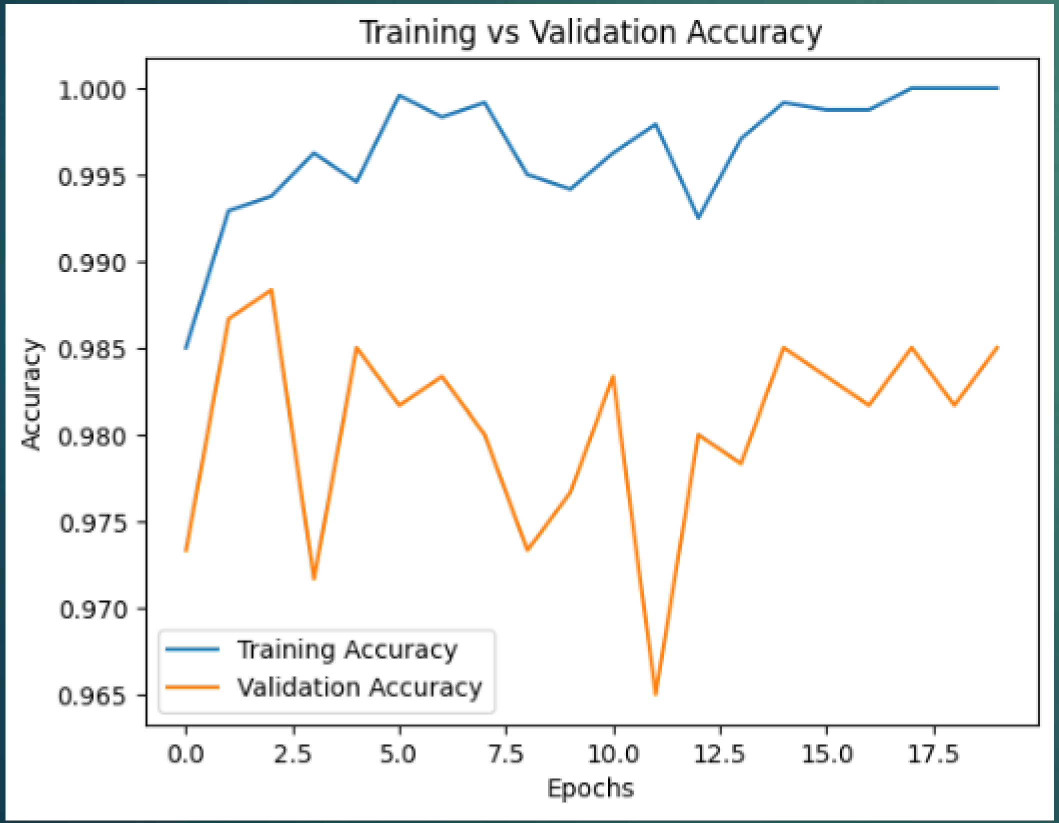
```python
import os

# Define dataset paths in Google Colab
tumor_dir = "/content/Dataset/yes"
no_tumor_dir = "/content/Dataset/no"

# Count images
num_tumor = len(os.listdir(tumor_dir))
num_no_tumor = len(os.listdir(no_tumor_dir))

print(f"Number of Tumor images: {num_tumor}")
print(f"Number of No-Tumor images: {num_no_tumor}")
```

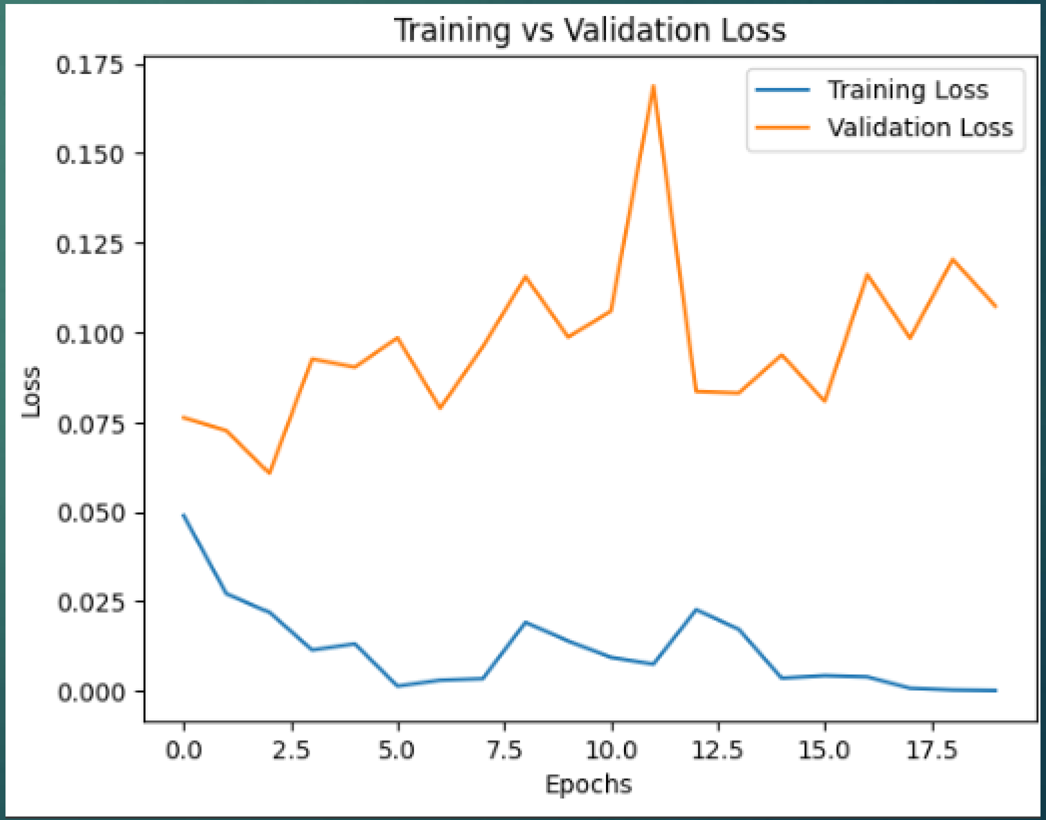
```
Number of Tumor images: 1500
Number of No-Tumor images: 1500
```

ACCURACY

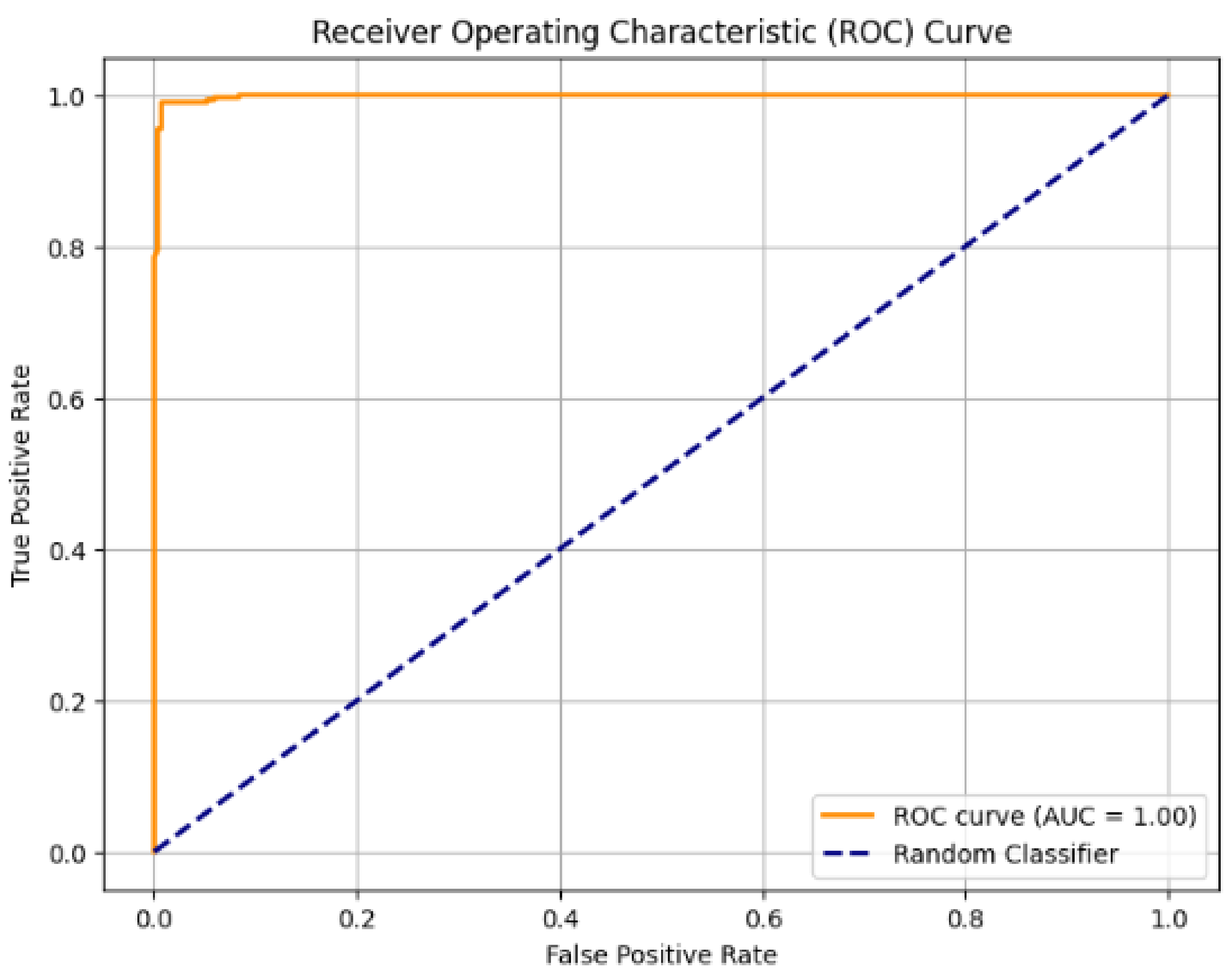
The CNN model achieved a high training accuracy of **100%** and a validation accuracy of up to **98.67%** over 20 epochs, demonstrating strong performance in detecting brain tumors from MRI images.

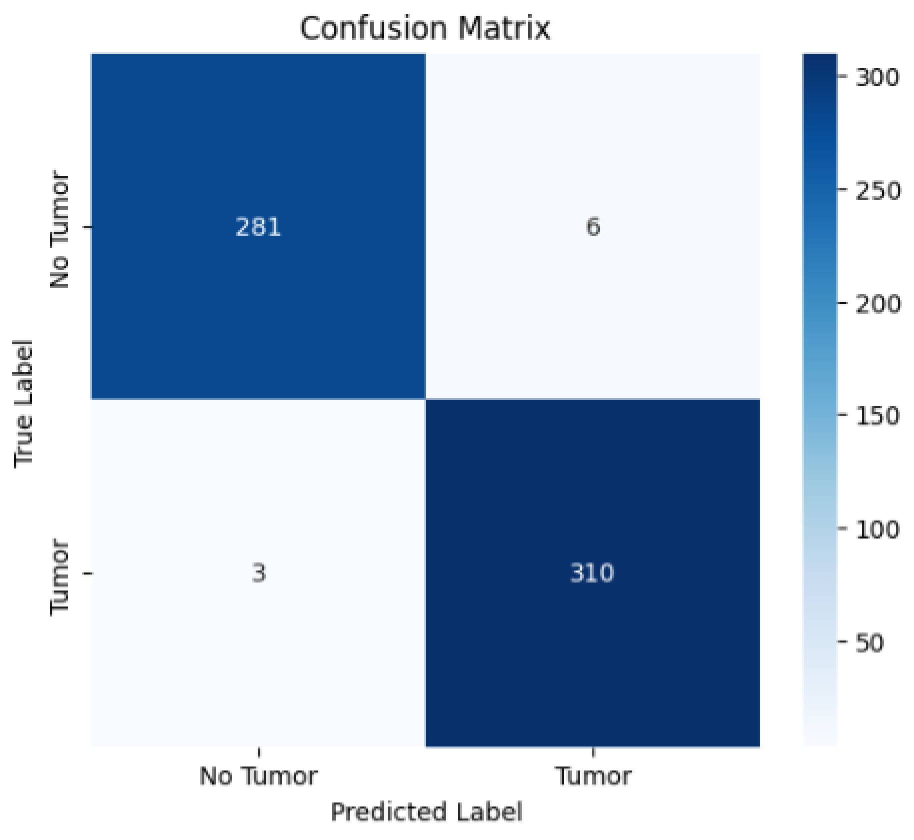






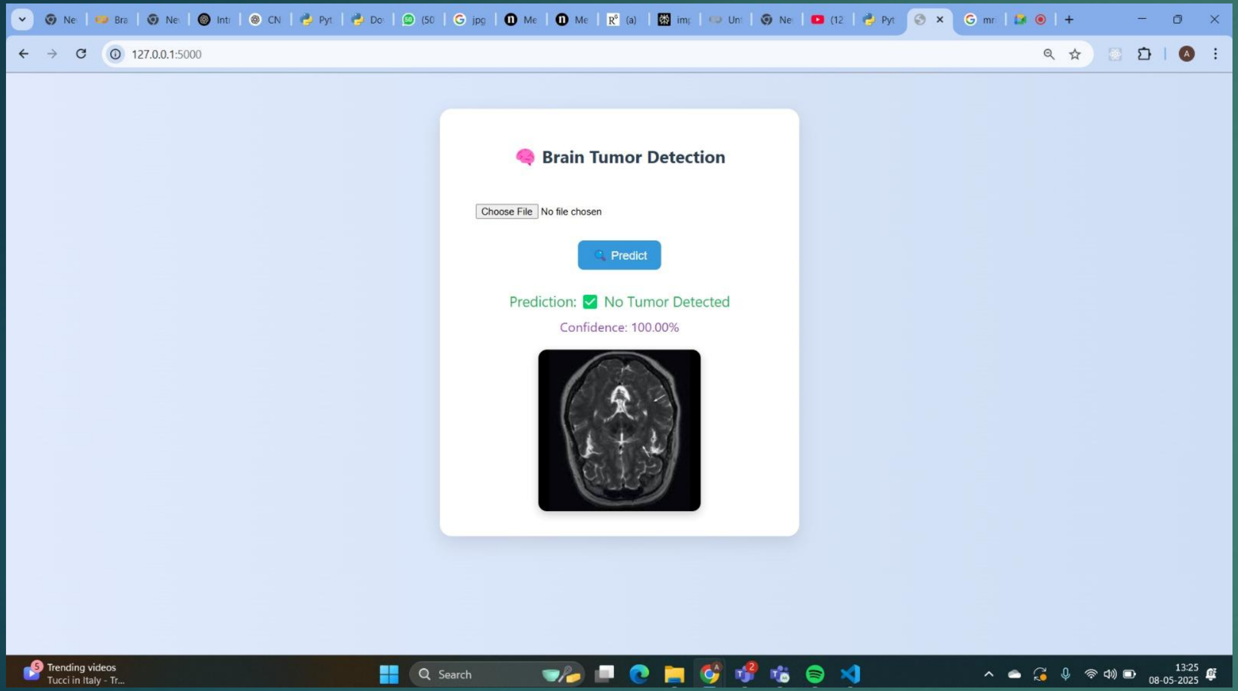
ACCURACY

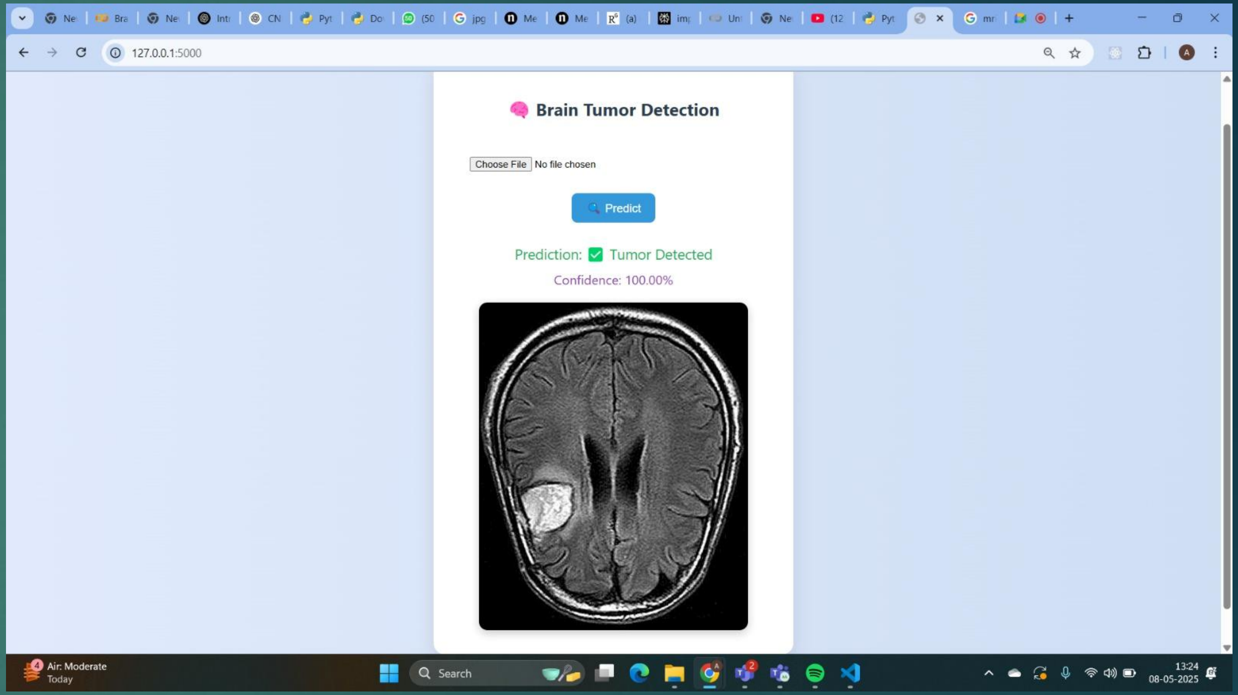





```
Classification Report:
              precision    recall  f1-score   support

    No Tumor       0.99      0.98      0.98       287
       Tumor       0.98      0.99      0.99       313

    accuracy                           0.98       600
   macro avg       0.99      0.98      0.98       600
weighted avg       0.99      0.98      0.98       600
```

SAMPLES


127.0.0.1:5000
Brain Tumor Detection
Choose File No file chosen
Predict
Prediction: No Tumor Detected
Confidence: 100.00%
Search
13:25
08-05-2025


127.0.0.1:5000
Brain Tumor Detection
Choose File No file chosen
Predict
Prediction: Tumor Detected
Confidence: 100.00%
Air: Moderate
Today
Search
13:24
08-05-2025

LIMITATIONS

- Model accuracy may decrease with low-quality or unclear MRI scans.
- Limited dataset size can lead to overfitting and reduced generalization.
- Cannot differentiate between different types of brain tumors.
- Performance may vary across MRI machines and imaging conditions.
- Requires high computational resources for training and tuning deep models

FUTURE SCOPE

- Expand the model to classify different tumor types (e.g., glioma, meningioma).
- Train on larger and more diverse datasets for improved accuracy.
- Integrate with real-time hospital MRI systems for live detection.
- Deploy as a mobile or web application for easy access by doctors.
- Use advanced models like ResNet, EfficientNet, or attention-based networks.

CONCLUSION

This project demonstrates the effectiveness of using deep learning, specifically Convolutional Neural Networks (CNNs), for brain tumor detection from MRI images. The model shows promising accuracy in classifying images as tumor or no tumor, contributing to faster and more reliable diagnoses. With further improvements and real-world integration, this approach has the potential to significantly aid in early tumor detection and better patient outcomes.