Brain Tumor Detection using CNN

TEAM 11

Vaishnavi Mishra

Siya Kapoor

Suhawani Shukla

Sashwat Gupta

Siddharth Saroj

Problem Statement

Detect Brain Tumors

Automate detection in MRI images.

Overcome Manual Challenges

Manual detection is slow and error-prone.

Enable Early Treatment

Accurate detection is crucial for patient outcomes.

Project Objective

Design CNN Model

Create an effective CNN for brain tumor detection.

Achieve High Accuracy

Maximize correct classifications and minimize false negatives.

Ensure Reliable Diagnosis

Provide faster and more dependable results for medical professionals.

Introduction to the Project

Brain Tumors

Abnormal cell growth in the brain.

Early Detection

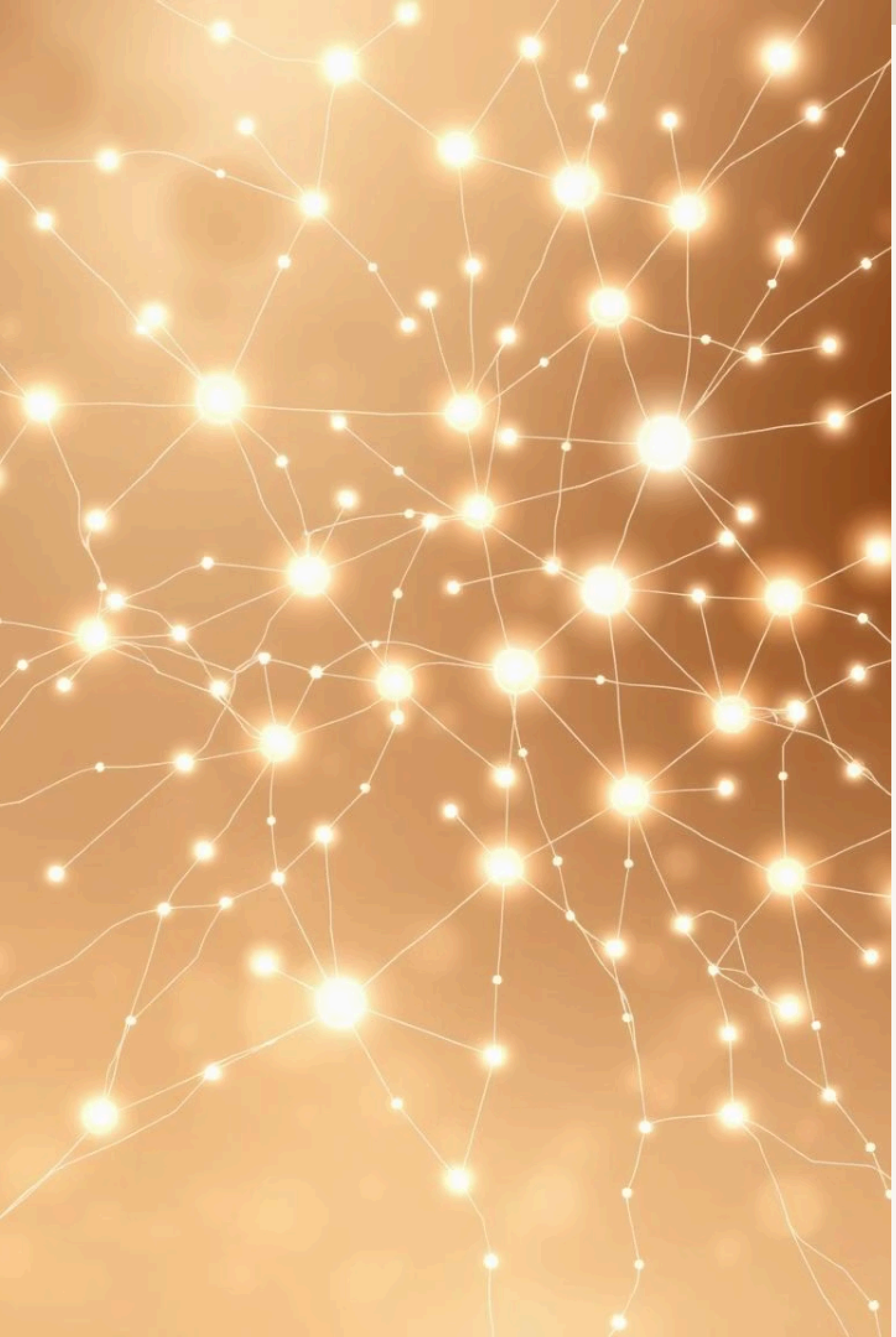
Crucially improves treatment outcomes.

AI in Healthcare

Revolutionizing medical diagnostics.

CNNs

Offer automated and precise analysis.



Background: Convolutional Neural Networks (CNNs)

CNNs

Deep learning for image recognition.

Convolutional Layers

Automatically extract image features.

Pooling Layers

Reduce data dimensionality.

Fully Connected Layers

Classify the processed images.

Dataset Description

This project utilizes a comprehensive dataset for training and evaluation.

Kaggle

Source

Brain MRI Dataset.

3000

Images

Approx. MRI scans.

2

Labels

"Tumor" and "No Tumor."

True

Augmentation

Necessary for class imbalance.

Methodology

Data Preprocessing

Images resized to 150x150 pixels. Pixel values normalized (rescale=1./255). Dataset split into 80% training and 20% validation sets. Batch size set to 32. Data loading performed using ImageDataGenerator.

Model Architecture

Custom CNN with 3 Conv2D + MaxPooling2D layers using ReLU activations. Followed by Flatten, Dense (128 units) with ReLU, Dropout (0.5), and final Dense (1 unit, sigmoid) for binary classification.

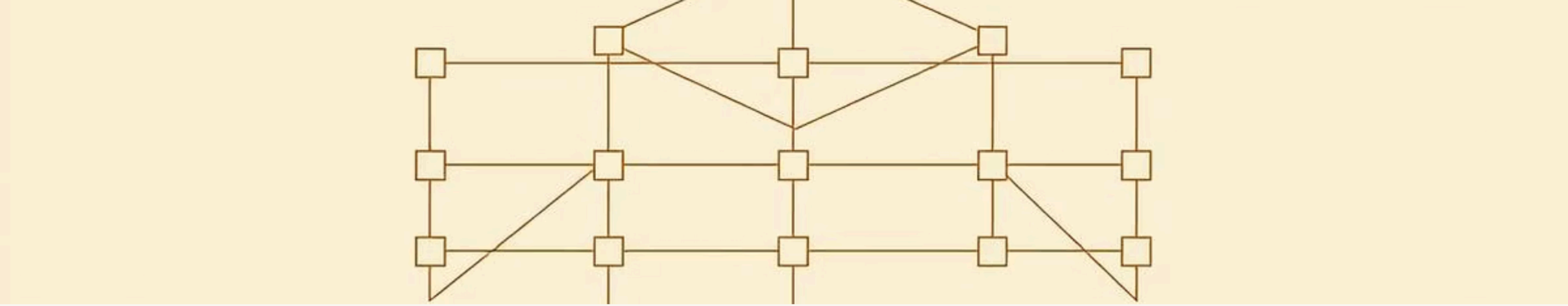
Training

Supervised learning with labeled data.

4

Evaluation

Accuracy, precision, recall, F1-score.



Model Architecture Details

Custom CNN Architecture

3 Conv2D + MaxPooling2D layers with ReLU activations.

Key Layers

Flatten, Dense (128 units), Dropout (0.5), and output Dense(1) with sigmoid activation for binary classification.

Optimization

Adam optimizer, learning rate 0.001.

Regularization

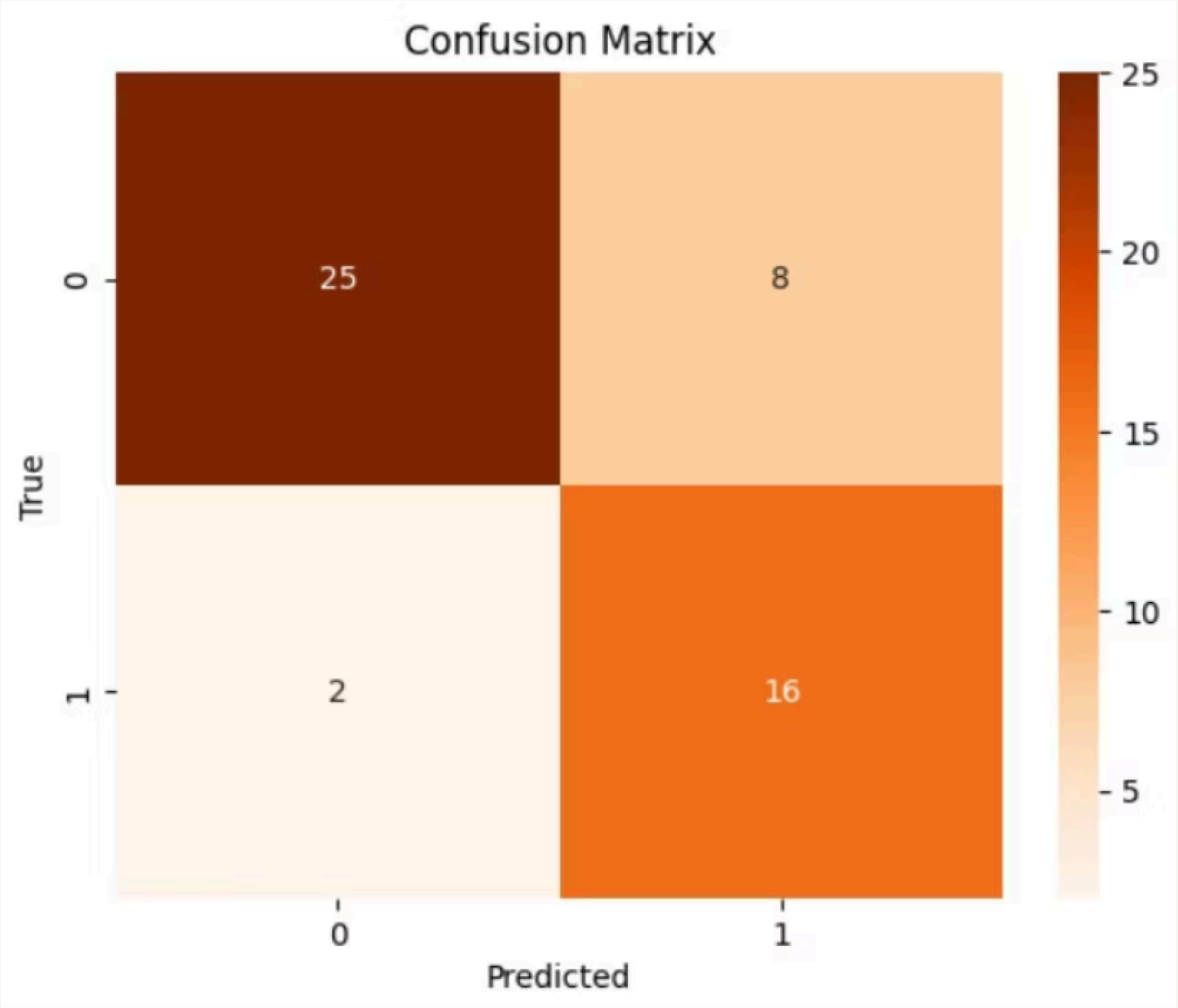
Dropout (0.5), L2 regularization.

Training Details

Our CNN model was rigorously trained using carefully selected parameters. These settings ensured efficient learning and robust performance.

Optimizer	Adam
Loss Function	Binary Crossentropy
Epochs	10
Batch Size	32
Validation Split	20%
Framework	TensorFlow/Keras

Performance Metrics



Confusion Matrix Analysis

The confusion matrix offers a visual summary of our model's performance. It precisely shows correct and incorrect classifications. Analyzing these values reveals the model's strengths and areas for improvement.

Term	Description
True Positive (TP)	Correctly identified tumors. Actual tumor detected.
False Positive (FP)	Healthy brain identified as tumor. Incorrect tumor detection.
False Negative (FN)	Actual tumors missed by the model. Critical for diagnosis.
True Negative (TN)	Correctly identified healthy brain. No tumor present.

High TP and TN values indicate strong accuracy. Minimizing FN is vital in medical imaging to avoid missing critical diagnoses.

Classification Report

Our classification report provides a detailed breakdown of model performance per class. It highlights the effectiveness for both tumor and healthy brain predictions.

Metric	Tumor Class	No Tumor Class	Description
Precision	0.85	0.92	Accuracy of positive predictions for each class.
Recall	0.88	0.90	Ability to identify all relevant instances for each class.
F1-Score	0.86	0.91	Harmonic mean of precision and recall, balancing both.

The model shows strong performance across both classes. High recall for the tumor class is crucial for clinical applications.

Model Performance Summary

Strong Overall Accuracy

Our model achieved high accuracy across classifications. It effectively distinguished between tumor and healthy tissues.

Effective Tumor Detection

High recall for the tumor class minimizes false negatives. This is critical for medical diagnostic applications.

Training & Evaluation Trends

Training demonstrated robust learning. Some minor overfitting was observed, indicating room for further optimization.

Challenges Faced

Data Imbalance

Uneven class distribution caused training bias. Fewer tumor samples impacted model learning.

Minor Overfitting

The model slightly overfit training data. This marginally affected generalization to unseen images.

Limited Dataset

A restricted MRI scan count hindered robust feature learning. More comprehensive data is crucial.

Real-World Scans

Diverse, heterogeneous MRI images are essential. This enhances model robustness and clinical utility.

References

- Dataset: Brain Tumor MRI Dataset sourced from Kaggle. View dataset.
- Libraries Used: TensorFlow, Keras, Scikit-learn, Matplotlib, and Seaborn for model development and analysis.
- Image & Code Credits: All visuals generated by AI for this presentation. Model code was developed internally.