SRM University – AP, Andhra Pradesh

Bachelor of Technology

In

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School of Engineering and Sciences

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ABSTRACT

This project focuses on the automatic classification of brain tumors using deep learning methods applied to MRI images. The Brain Tumor MRI Dataset (Kaggle) consisting of thousands of labeled MRI scans is used for analysis and model development. The goal is to classify images into four tumor categories: Glioma, Meningioma, Pituitary, and No Tumor. Extensive preprocessing, resizing, normalization, and augmentation are applied to improve image quality and model performance.

To establish strong baselines, a Custom Convolutional Neural Network (CNN) is trained to learn image features and classify tumor types. Additionally, a more advanced Transfer Learning approach using VGG16 is applied, as pre-trained CNNs can better capture spatial patterns and structural variations in MRI scans. Exploratory data analysis includes visual inspection of tumor images, class distributions, and augmentation effects.

Models are evaluated using Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. Overall, this project demonstrates a scalable deep learning pipeline capable of automatically classifying brain tumor types from MRI scans, supporting improved diagnostic processes and reducing the workload for medical professionals.

INTRODUCTION

Brain tumors pose a significant challenge in clinical diagnosis due to the complex structure of the brain and the wide variation in tumor appearance across MRI scans. Accurate, early diagnosis is crucial to improve treatment outcomes and survival rates. Traditionally, radiologists manually interpret MRI scans, which requires extensive expertise, is time-consuming, and may lead to variations between observers.

Deep learning offers a powerful alternative by automatically learning high-level visual features, identifying abnormal tissue patterns, and providing consistent predictions. This project aims to develop an end-to-end deep learning pipeline using the Brain Tumor MRI Dataset, enabling accurate classification of tumors into four categories.

The system uses image preprocessing methods, Convolutional Neural Networks, and transfer learning to enhance predictive performance. The final pipeline not only automates tumor detection but also provides interpretable evaluation metrics useful for medical decision-making.

SYSTEM DESIGN

The system architecture consists of several logical components:

i. Data Loading and Cleaning

MRI images are loaded from Training and Testing directories. Images are inspected for size inconsistencies, and filenames are standardized. Duplicates and corrupted images are removed where necessary.

ii. Image Preprocessing

Before training, images undergo:

- Resizing to 150×150 pixels
- Normalization (scaling pixel values between 0–1)
- Augmentation (rotation, zoom, horizontal flip) to expand dataset variation

iii. Feature Extraction

Two approaches are used:

- **Custom CNN:** Learns features directly from MRI scans
- **VGG16:** Uses pre-trained convolutional filters to extract advanced spatial features

iv. Data Splitting

Dataset is divided into:

- 70% Training
- 15% Validation
- 15%Testing
  Ensuring balanced distribution across tumor categories.

v. Model Training

Models are trained using categorical cross-entropy loss, Adam optimizer, and early stopping for stabilization.

vi. Model Evaluation

Predictions are analyzed using performance metrics and confusion matrices to understand class-wise accuracy.

vii. User Prediction Module

Allows uploading a single MRI scan and outputs the predicted tumor category.

IMPLEMENTATION

Data Preprocessing

- Import dataset using Google Colab
- Resize and normalize images
- Apply augmentation for robustness

Model 1: Custom CNN

The custom CNN architecture includes:

- Convolution layers for spatial pattern detection
- MaxPooling layers to reduce dimensionality
- Dropout layers to prevent overfitting
- Dense layer for classification into four categories

Model 2: VGG16 Transfer Learning

- Pre-trained VGG16 model with frozen convolution layers
- Custom dense layers added for classification
- Utilizes powerful pre-learned filters for feature-rich MRI analysis

Evaluation Metrics

Both models are evaluated based on:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix visualization

Prediction Module

Users can upload an MRI image, and the trained model predicts the tumor type in real-time.

RESULTS

The deep learning system achieved strong performance across all tumor categories.

- Custom CNN provided a solid baseline accuracy
- VGG16 showed significantly improved classification due to advanced feature extraction

Evaluation reports highlight correct identification of tumor patterns and strong generalization on unseen images. Confusion matrices further reveal which tumor classes are more distinguishable and where misclassifications occur.

MRI sample predictions confirm the model's capability to differentiate between tumor types with high reliability.

PERFORMANCE

• The custom CNN achieved competitive accuracy and served as a strong baseline.
• The VGG16 transfer learning model outperformed the custom CNN by leveraging pre-trained filters, leading to higher accuracy and better feature understanding.
• Precision, recall, and F1-scores show strong balance across all classes.
• Confusion matrix results demonstrate robust performance, especially for Glioma and Meningioma classifications.

CONCLUSION

This project successfully implements a complete deep learning pipeline for brain tumor classification using MRI scans. Through preprocessing, CNN-based feature extraction, and model training, the system is capable of accurately identifying tumor categories. VGG16 provided superior performance through advanced visual feature extraction techniques.

The project highlights the potential of AI in medical imaging to support radiologists, improve diagnostic accuracy, and enable faster decision-making.

FUTURE ENHANCEMENTS

Implement Grad-CAM visualizations to highlight tumor regions for interpretability.
• Train deeper models or transformer-based architectures for improved accuracy.
• Expand dataset with multi-modal MRI sequences (T1, T2, Flair).
• Deploy the system using a web interface or mobile app for real-world use.
• Add segmentation modules to detect tumor boundaries, not just classification.