NED University of Engineering and Technology

Artificial Intelligence & Expert Sytems (CT-361)

PROJECT: *AL Powered Brain Tumor Detection System*

GROUP MEMBERS:

1. *Anum Mateen(CR-22002)*
2. *Mehak Ejaz (CR-22001)*
3. *Ayesha Majid(CR-22026)*
4. *Hafsa Usma (CR-22003)*

PROJECT PROPOSAL

Title: *Brain Tumor Detection using Convolutional Neural Networks (CNN)*

GROUP MEMBERS AND CONTRIBUTIONS

Member	Focus	Type
Mehak	Intro + Data Org + EDA + Augmentation	Mostly writing + light code
Ayesha	Preprocessing + image loading + splitting	Moderate code work
Anum	Model building + training + metrics	Heaviest coding
Hafsa	Deployment (Streamlit), Tools, Report Wrap-Up	Interface + integration work

Course: Artificial Intelligence & Expert Systems (CT-377)

Institution: NED University of Engineering & Technology

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1. Introduction

Brain tumors are a critical health issue, and their early diagnosis is vital for improving patient outcomes. Traditional diagnosis methods, such as biopsies and manual analysis of MRI scans, are time-consuming, expensive, and sometimes risky due to their invasive nature.

With the advent of artificial intelligence in medical imaging, automated diagnostic tools can enhance the speed and accuracy of tumor detection. This project proposes the development of a brain tumor detection system using **Convolutional Neural Networks (CNNs)**, a deep learning architecture known for its efficacy in image classification tasks.

2. Objective

The primary goal of this project is to:

- Develop a CNN-based model capable of detecting and classifying brain tumors in MRI or CT images.
- Utilize public datasets for model training and evaluation.
- Implement transfer learning using pre-trained models to enhance performance.
- Deploy the trained model as a **Streamlit web application** for real-time predictions.

3. Literature Review

CNNs have demonstrated superior performance over traditional machine learning techniques in the medical domain due to their ability to extract spatial features directly from raw images. Research has shown success using architectures like **VGG16**, **ResNet**, and **EfficientNet** for tumor classification.

Challenges in existing literature include small dataset sizes, class imbalances, and image noise. However, data augmentation and preprocessing have been effective in mitigating these issues. Our project builds upon these findings and adapts them to create a scalable and accessible solution.

4. Methodology

4.1 Data Collection

MRI and CT scan images were sourced from public repositories such as **Kaggle** and **The Cancer Imaging Archive (TCIA)**. Images are labeled as “Tumor” or “No Tumor”.

4.2 Data Preprocessing

- Images were resized (128x128 or 224x224).
- Pixel values normalized to [0,1].
- Labels encoded (Tumor = 1, No Tumor = 0).
- Dataset split into training (70%), validation (20%), and testing (10%) sets.

4.3 Data Augmentation

To combat overfitting and enhance model generalization, we applied:

- Rotation
- Flipping (horizontal & vertical)
- Brightness and contrast adjustments
- Random cropping and padding

4.4 Model Building

We designed a CNN with the following structure:

- **Input layer**: Accepts standardized MRI images.
- **Convolutional & Pooling layers**: Extract key features.
- **Fully connected layers**: Perform classification.
- **Output layer**: Sigmoid for binary classification.

Popular pre-trained models like **ResNet50** and **VGG16** were also used through **transfer learning**, improving performance and reducing training time.

4.5 Training and Optimization

- Layers of pre-trained models were **frozen** initially.
- Later layers were **fine-tuned** for tumor-specific features.
- Loss function: Binary Crossentropy
- Optimizer: Adam

5. Implementation Tools

- **Programming Language:** Python
- **Libraries:** TensorFlow/Keras, NumPy, Pandas, OpenCV, Matplotlib, Seaborn
- **Visualization:** matplotlib.pyplot, ggplot style
- **Application Framework:** Streamlit (for GUI)

6. Results and Evaluation

- **Validation Accuracy:** 65.26%

- **Testing Accuracy:** 66.77%
- **Validation Loss:** 0.6172
- **Testing Loss:** 0.6082

These results demonstrate the model's potential as a supplementary diagnostic tool. Further improvements can be made by integrating larger datasets and advanced architectures.

7. Deliverables

- A fully functional CNN-based model for tumor classification.
- A Streamlit web application for real-time MRI analysis.
- Evaluation metrics and visualizations.
- Final project report and code documentation.

8. Conclusion

This project highlights the feasibility of AI-powered diagnostic tools in healthcare. Using CNNs, we achieved promising results in brain tumor classification from MRI scans. The integration of a web interface via Streamlit makes the solution accessible and user-friendly for potential real-world use.

9. Future Work/Recommendations/Extensions

- Incorporate multi-class classification (e.g., tumor types).
- Deploy the system on cloud platforms.
- Collaborate with healthcare professionals for validation.
- Apply Explainable AI (XAI) techniques for interpretability.