Automated Brain Tumor Classification Using MRI Images

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ABSTRACT

Early diagnosis and treatment of brain tumors depend on their identification and classification. Manual MRI interpretation is laborious and prone to mistakes. In order to categorize MRI scans into four groups glioma, meningioma, pituitary tumor, and no tumor this study employs a deep learning technique using the ResNet152V2 model. Compared to conventional CNNs, the model is more efficient in extracting important features. Its 96% accuracy with data augmentation provided a quick and dependable automated system. Transfer learning preserved good accuracy while cutting down on computational expense and training time. The system provides robustness, reduces human error, and may be incorporated into clinical processes to assist radiologists and enhance patient care results. It has been validated on benchmark datasets.

Keywords : **ResNet152v2, CNNs, tumor, Augmentation, Deep-learning**

I.INTRODUCTION

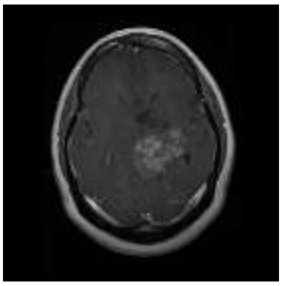
The process of manually identifying brain tumors from MRI data is laborious and error-prone. In order to overcome these obstacles, this research suggests an automated categorization system that makes use of the deep learning model ResNet152V2.

Glioma, Meningioma, Pituitary Tumor, and No Tumor are the four categories into which the system is intended to classify MRI brain pictures. Prior to training the ResNet152V2 model, MRI data must be gathered, preprocessed, and enhanced. Metrics like accuracy are then used to assess the system's performance.

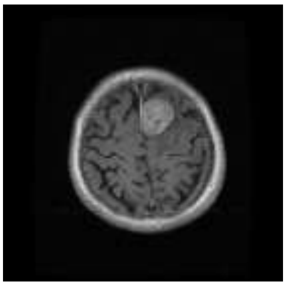
The goal of this project is to give radiologists and physicians a quick, dependable, and scalable tool. It can increase access to prompt medical care, lessen the workload for medical providers, and improve diagnostic accuracy especially in distant places. In order to save lives by early discovery, this is an essential step.

Problem Statement: Brain tumor detection is challenging due to complex brain structures and similar tumor appearances.Manual MRI diagnosis is slow, error prone, and reliant on radiologist expertise, while traditional machine learning lacks generalization. An automated system using deep learning, especially ResNet152V2 with transfer learning, can accurately classify tumors (glioma, meningioma, pituitary, or no tumor), improve diagnostic reliability, and support early treatment.

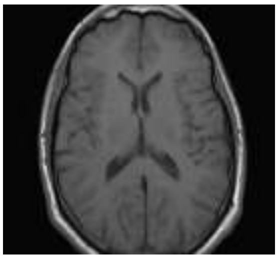
Objectives: An automated system is built to classify brain tumors (Glioma, Meningioma, Pituitary, and No Tumor) using MRI images with ResNet152V2.
Images are preprocessed through resizing, normalization, and augmentation to improve accuracy.The model's performance is evaluated using accuracy, precision, recall, and F1-score.
Comparisons with other models such as ResNet50, Xception, and CNN are carried out.Results show that ResNet152V2 performs better and provides more reliable classification.



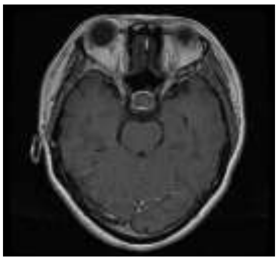
Glioma tumor



Meningioma tumor



No tumor



Pituitary tumor

Fig 1: Sample Images of 4 Tumor Types

Fig 1 Presents sample MRI Brain scan images used for the classification of brain tumors. Glioma Tumor this image represents an MRI scan of a brain affected by a glioma tumor. Gliomas are type of tumor that occurs in the glial cells of the brain. Meningioma Tumor- Meningiomas originate in the meninges, the membranes that surround the brain . No Tumor- this MRI image depicts a healthy brain with no visible tumors. Pituitary Tumor- this usually located at the base of the brain, in the region of the pituitary gland.

II.RELATED WORK

[1] F. M. Salama and A. Shokry, 2022, A novel framework for brain tumor detection using convolutional variational generative models; Proposed: Variational generative models for tumor detection; Drawback: Requires large data; not robust for rare tumor types.

[2] M. M. Zahoor and S. H. Khan, 2022, Brain tumor MRI classification using a novel deep residual and regional CNN; Proposed: Deep residual + regional CNN hybrid; Drawback: High computational cost; limited generalization.

[3] Fatma Taher, Mohamed R. Shoaib, 2022, Efficient framework for brain tumor detection using deep learning (BRAIN-TUMOR-net); Proposed: Custom CNN architecture for tumor detection; Drawback: Dataset diversity limited; performance varies on unseen data.

[4] Alsubai, Khan, Alqahtan, 2022, Ensemble deep learning for brain tumor detection (CNN-LSTM hybrid); Proposed: CNN + LSTM hybrid for MRI feature extraction; Drawback: Training is complex; longer processing time.

[5] H. ZainEldin et al., 2023, Brain tumor detection and classification using deep learning ; Proposed: Grey wolf optimization integrated with deep learning; Drawback: Sensitive to hyperparameter tuning; moderate accuracy gain.

[6] M. I. Mahmud et al., 2023, A deep analysis of brain tumor detection from MR images using deep learning networks; Proposed: Comparative analysis of DL networks for detection; Drawback: Focused only on small-scale datasets.

[7] A. M. Mostafa et al., 2023, Brain tumor segmentation using deep learning on MRI images; Proposed: CNN-based segmentation on MRI; Drawback: Lower precision for overlapping tumor boundaries.

[8] F. Ullah et al., 2023, Brain tumor segmentation from MRI images using hand crafted convolutional neural network; Proposed: Handcrafted CNN features for segmentation; Drawback: Less effective compared to transfer learning models.

[9] H. Sun, 2023, Brain tumor image segmentation based on improved feature pyramid networks (FPN) convolutional neural network; Proposed: Improved FPN with CNN for segmentation; Drawback: Performance depends on resolution of MRI images.

[10] M. Srivastava et al., 2024, Brain tumor detection using a deep CNN model; Proposed: Deep CNN for tumor classification; Drawback: Model overfits on small datasets.

[11] D. M. Zahoor et al., 2024, Brain tumor MRI classification using a novel deep residual and regional CNN; Proposed: Residual CNN with region-level features; Drawback: Complex architecture, requires GPU resources.

[12] M. K. Abd-Ellah et al., 2024, Automatic brain-tumor diagnosis using cascaded deep learning; Proposed: Cascaded CNN pipeline for automated diagnosis; Drawback: Limited interpretability of predictions.

III. METHODOLOGY

The suggested system's layered and modular design ensures dependability, scalability, and clarity. The project's main goal is to employ deep learning to automate the classification of brain tumors, and the main model is ResNet152V2.

3.1 Requirement Analysis:

In this initial stage, the focus is on understanding and collecting all the needs of the system. It involves carefully documenting these requirements and reviewing them to ensure they are clear, complete, and accurate. This phase also helps identify constraints, dependencies, and priorities, forming the foundation for the entire development process.

3.2 System Design:

Once the requirements are well-defined, they are transformed into a structured blueprint for the software. This phase concentrates on designing algorithms, selecting appropriate data structures, and defining the overall architecture to guide development. Additionally, it includes creating detailed diagrams and models to visualize system workflows and interactions.

3.3 Coding:

Here, developers bring the design to life by writing the actual code. This phase converts the specifications into a functional software system that can be executed and tested. Proper coding standards, version control, and documentation are also maintained to ensure long-term maintainability and collaboration.

3.4 Implementation:

During implementation, the system components are assembled, deployed, and delivered, along with supporting materials such as user manuals, libraries, and executable files. This stage also involves initial setup, configuration, and ensuring that all modules integrate smoothly for real-world use.

3.5 Testing:

Testing ensures that all integrated modules work correctly and the system fulfills the intended requirements. It involves identifying defects and verifying the functionality, reliability, and performance of the software. Various testing methods, including unit, integration, and system testing, are applied to ensure robustness and user satisfaction.

3.6 Maintenance:

Maintenance is an ongoing phase where the system is updated to accommodate evolving user needs, adapt to changes in the environment, fix previously undetected issues, and enhance performance and efficiency over time. It also involves monitoring system usage, providing technical support, and implementing incremental improvements for sustained reliability.

ARCHITECTURE DIAGRAM

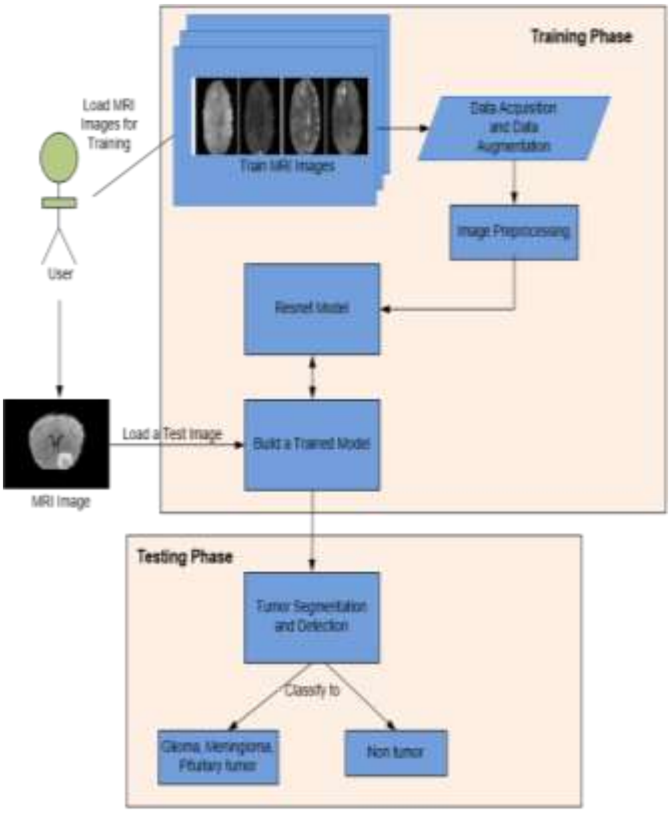


Fig: 2 System Architecture

Glioma, meningioma, pituitary tumor, and no tumor MRI scans gathered from databases such as BraTS and Kaggle are used by the automated brain tumor classification system. Preprocessing (resizing to 224×224, normalizing, and enhancing contrast) and augmentation (rotation, flipping, scaling, and noise addition) are used to increase the diversity of the images during the training phase. Features including tumor forms, textures, and intensity patterns are extracted by the ResNet152V2 model, a 152-layer deep CNN with residual connections that was pretrained on ImageNet and refined on MRI data. By reducing prediction errors through iterative weight adjustments, a trained model for precise categorization is produced. In order to provide quick, automated, and accurate diagnosis, the trained model preprocesses and analyzes unseen MRI data during the testing phase. It then segments and detects cancers, classifying them as gliomas, meningiomas, pituitary tumors, or no tumor.

IV. APPLIED TECHNOLOGY

To guarantee precise picture processing, deep learning model training, and real-time prediction through a web interface, the Brain Tumor Classification project combines a number of technologies. These technologies are used to build an automated brain tumor detection system that is reliable, scalable, and easy to use.

4.1 Python

The main programming language used for deep learning and data processing.
Use in Project: Uses Flask web app backend, training, assessment, augmentation, and preprocessing for the ResNet152V2 model.
Python's simplicity and extensive library support make it ideal for rapid prototyping and integration of machine learning workflows. Its versatility allows seamless connection between data processing, model training, and web deployment.

4.2 Anaconda Spyder IDE

The goal is to provide Python developers with an Integrated Development Environment.
Use in the Project: Creating, evaluating, and debugging Python scripts for data management and model development.
It simplifies package management and environment setup, enabling smooth handling of dependencies and Python libraries. Spyder's interactive console and visualization tools enhance workflow efficiency.

4.3 Keras & TensorFlow

Deep learning libraries for neural network construction and training are the goal.
Use in Project: Model training, transfer learning, and the ResNet152V2 architecture are implemented.
They provide high-level APIs for building complex models efficiently while offering GPU acceleration for faster computations. Their compatibility ensures smooth experimentation and model scalability.

4.4 OpenCV

Goal: Image processing library for computer vision.
Use in Project: Manages MRI image augmentation, normalization, scaling, and preprocessing.
OpenCV allows advanced image transformations and feature extraction, crucial for enhancing model performance. It supports seamless integration with Python-based deep learning pipelines.

4.5 Flask

The goal is to provide a web framework for implementing Python applications.
Use in Project: Provides a web interface through which users can upload MRI scans and view predictions for the trained model.
Flask enables lightweight, scalable web development and facilitates integration of machine learning models into interactive applications. It supports REST APIs and smooth client-server communication.

4.6 MRI Datasets (Kaggle, BraTS)

MRI images with labels are provided for model testing and training.
Use in Project: Provides a range of excellent photos for the four-class classification of tumors.
High-quality, annotated datasets ensure accurate model learning and validation. Diverse datasets also improve generalization across different patient scans.

4.7 Hardware with GPU Capabilities

The goal is to speed up the training of deep learning models.
Use in Project: Facilitates effective processing of huge MRI datasets and cuts down on training time.
GPUs allow parallel computation, which is essential for deep learning tasks involving large networks like ResNet152V2. This significantly reduces experimentation and iteration cycles.

4.8 Linux/Windows OS

Goal: Development and deployment operating environment.
Use in Project: Guarantees web apps, libraries, and scripts run steadily and are compatible.
Using these OS platforms ensures cross-platform support, system stability, and the ability to leverage hardware optimizations for faster processing.

V. RESULTS

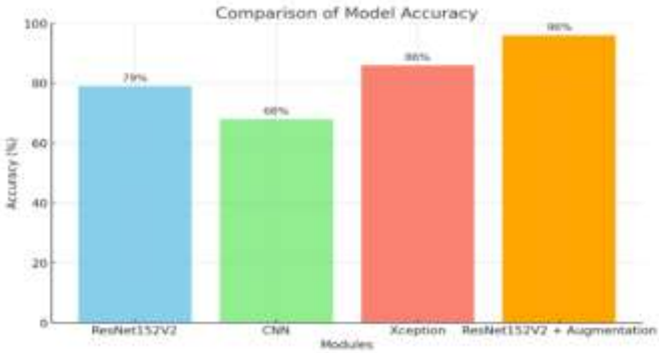


Fig: 3 Comparison Bar Chart

Table:1 comparison Table

Sl.No	Module name	Accuracy
1	ResNet152V2 model	79%
2	CNN module	68%
3	Xception module	86%
4	ResNet152V2 model with data augmentation	96%

In this , we tested different deep learning models for classifying brain tumors: a basic CNN, Xception, & ResNet152V2. The CNN model was simple and had low accuracy. Xception did better but still wasn't the best. ResNet152V2 without augmentation gave about 79% accuracy.When we added data augmentation and trained it, its accuracy improved to 96%. This shows that ResNet152V2 with augmentation performed the best and is very effective for brain tumor classification.

Fig:4 Welcome Page

Fig:5 Upload Page

Fig:6 Prediction Page

The Welcome Page of the Brain Tumor Classification system welcomes users with an easy-to-use interface that makes it simple to register or log in. By providing a username and password, new users can create an account on the Register Page, guaranteeing secure access. Returning users can access the system by entering their credentials in a straightforward and secure manner using the Login Page. The Dashboard acts as the main hub following login, including the ability to submit MRI scans and view prior findings. Users can submit brain MRI images using the Upload Page, which also provides guidance on appropriate image format and quality. Lastly, the Prediction Page provides a quick and easy diagnosis experience by displaying the classification results: Glioma, Meningioma, Pituitary Tumor, or No Tumor along with visual highlights of tumor locations.

VI. CONCLUSION

In this work, a deep learning–based framework for brain tumor detection and classification from MRI scans was developed using the ResNet152V2 model with transfer learning. The primary objective was to design an automated system that achieves high accuracy while reducing reliance on manual interpretation. The proposed model effectively classified MRI scans into four categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor. Leveraging the 152-layer ResNet152V2 architecture with transfer learning addressed vanishing gradient issues and enabled efficient extraction of tumor-specific features, thereby improving accuracy and training efficiency with limited data. Rather than replacing medical professionals, the system functions as a decision-support tool, enhancing diagnostic precision and accelerating the overall process. The results demonstrate that the proposed framework holds significant potential for reliable automated brain tumor analysis and integration into clinical workflows.

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