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Brain Tumor Type Detection Using Deep Learning

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Abstract

Brain tumor diagnosis is a complex and critical task in medical imaging. Interpreting MRI scans requires both expertise and time, making it difficult to achieve quick, accurate results consistently. In addition, doctors increasingly need systems that not only provide correct predictions but also explain how those decisions are made. However, many existing computer-aided approaches face several limitations. These include limited availability of quality data, poor performance on unseen cases, and a lack of interpretability. Because of these challenges, such systems are not always reliable for real-world clinical use. This paper presents a Hybrid Lightweight CNN Transformer model designed to automate the detection and classification of brain tumor types from MRI scans. To address the issue of class imbalance, the system uses GAN-based data augmentation, which helps generate additional training samples and improves model robustness. In addition, Grad-CAM visualisation is incorporated to make the model's predictions more interpretable, allowing medical professionals to better understand and validate the results. The model is further optimised using pruning and quantisation techniques so that it can run efficiently on low-resource devices. For practical usability, the system is deployed through a Streamlit-based interface, enabling easy access in clinical and diagnostic environments. Experimental results indicate that the proposed approach achieves better accuracy, faster inference time, and improved interpretability when compared to traditional CNN-based models. Overall, the system aims to provide a balanced solution in terms of efficiency, transparency, and usability. This makes it suitable for early brain tumor diagnosis and can assist clinicians in making timely and informed decisions.

Keywords - Brain Tumor Classification, Deep Learning, CNN Transformer Model, GAN Augmentation, Explainable AI

1. INTRODUCTION

Brain tumor detection is an important part of clinical diagnosis and treatment planning, as early identification can greatly improve patient outcomes. However, analysing Magnetic Resonance Imaging (MRI) scans manually is often time-consuming and requires significant expertise. It can also be affected by human error, especially when dealing with complex cases. Although computeraided diagnostic (CAD) systems have helped reduce this burden, many existing solutions still struggle with issues such as data imbalance, limited interpretability, and high computational requirements.

In recent years, deep learning has significantly improved the field of medical imaging. Most current approaches rely mainly on Convolutional Neural Networks (CNNs), which are effective at capturing local spatial features. However, they often fail to capture global relationships within the image. In addition, many of these models require high computational resources, making them difficult to use in real-time clinical environments. Another major concern is the lack of explainability, as medical professionals need clear reasoning behind predictions before trusting automated systems.

Despite these advancements, existing brain tumor detection systems still face several challenges:

1. Limited ability to generalise across different MRI datasets, resulting in inconsistent performance.
2. Imbalanced data distribution causes the model to favour certain tumor classes over others.
3. Lack of interpretability makes it difficult for clinicians to understand how decisions are made.
4. High computational cost, which limits usage in resource-constrained healthcare settings.

To overcome these limitations, this work proposes a Hybrid Lightweight CNN Transformer model for brain tumor classification. The model is designed to improve accuracy while also being efficient and interpretable. The main features of the proposed system are as follows:

1. GAN-based data augmentation is used to address class imbalance and improve model robustness.
2. Grad-CAM is applied to provide visual explanations, helping clinicians understand model predictions.
3. Pruning and quantisation techniques are used to optimise the model for real-time performance on low-resource devices.

The primary contribution of this research lies in developing a hybrid architecture that combines both spatial and contextual feature learning. In addition, the work focuses on improving interpretability and creating a practical deployment pipeline using a Streamlit-based interface. The overall goal is to make deep learning models more suitable for real-world clinical applications by ensuring they are accurate, transparent, and easy to use.

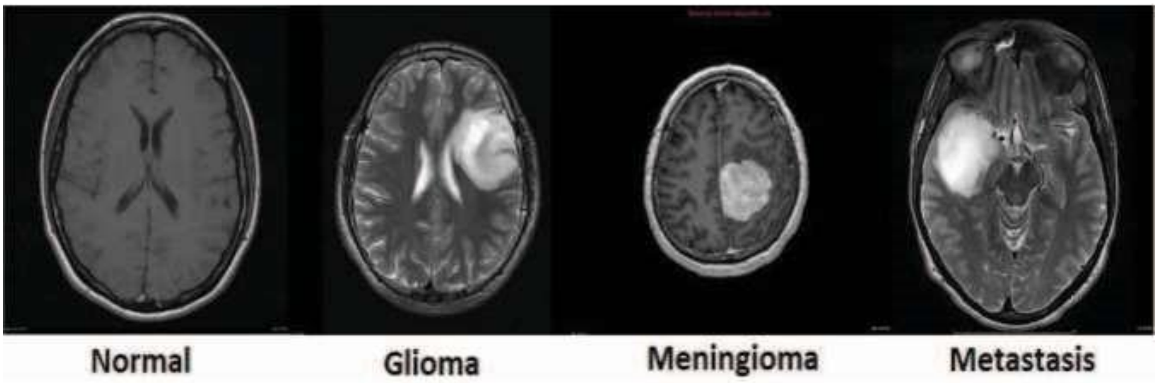

Fig.1 MRI Images showing Normal Brain and Different Types of Brain Tumors.

2. Background and Motivation

Brain tumors are among the most serious and life-threatening neurological conditions, caused by the uncontrolled growth of abnormal cells in the brain. Early and accurate detection is essential for effective treatment and better survival rates. Magnetic Resonance Imaging (MRI) is widely used for diagnosing brain tumors because it provides detailed, non-invasive images with excellent soft-tissue contrast. However, analyzing MRI scans manually can be time-consuming and depends heavily on the expertise of radiologists. In many cases, this may lead to delays or variations in diagnosis.

With the advancement of technology, deep learning has become an important tool in medical image analysis. Convolutional Neural Networks (CNNs) have shown strong performance in automatically extracting meaningful features from MRI images and often perform better than traditional image processing techniques. Even so, these models are not without limitations. They may overfit when trained on small or imbalanced datasets, struggle to generalise across different tumor types, and often lack interpretability, which is especially important in medical applications where understanding the decision process is crucial.

The motivation for this work comes from the need to design a system that is not only accurate but

also efficient and explainable. Recent developments suggest that combining CNNs with
Transformer architectures can improve performance, as Transformers are capable of capturing longrange relationships that CNNs may miss. In addition, techniques such as GAN-based data augmentation can help address class imbalance and improve model robustness. Grad-CAM visualisation further adds value by highlighting the regions of the image that influence the model's prediction, making the system more transparent for medical use.

By bringing these ideas together, this research attempts to address key limitations in existing methods. The focus is on improving diagnostic accuracy while also reducing computational requirements and enhancing interpretability. The overall goal is to develop a solution that performs well technically and is also practical for real-world clinical environments, where reliability, clarity, and speed are equally important.

3. Problem Statement and Objectives

Brain tumors are serious medical conditions that require early and accurate diagnosis for effective treatment. However, manual analysis of MRI scans is often time-consuming, requires expert knowledge, and can be affected by human error. This creates a need for an automated system that can assist in detecting and classifying different types of brain tumors more efficiently. Such a system can improve diagnostic speed, increase accuracy, and provide better support to medical professionals during clinical decision-making.

Objectives:

1. To preprocess MRI brain images to improve data quality and prepare them for effective model training.
2. To design and develop a Hybrid Lightweight CNN–Transformer model for accurate and reliable brain tumor classification.
3. To use GAN-based data augmentation techniques to handle class imbalance and enhance model performance.
4. To incorporate Grad-CAM for visual interpretability, helping medical experts understand how the model makes predictions.
5. To optimize the model using pruning and quantization so that it can run efficiently in realtime environments.
6. To deploy the system using a Streamlit-based interface, making it easily accessible for medical professionals.

4. Literature Review

Deep learning methods, especially Convolutional Neural Networks (CNNs), have been widely used for brain tumor detection and classification from MRI images. Over time, researchers have focused on improving model performance by increasing accuracy, reducing computational complexity, and enhancing interpretability. However, many existing studies tend to prioritize either accuracy or model complexity, while aspects such as explainability and real-time applicability are often not given equal importance.

In addition, various deep learning approaches such as CNNs, Residual Networks, and hybrid architectures have been applied in medical image analysis. These methods have shown promising results in extracting useful features and improving classification performance across various datasets.

Deepak et al. (2021) implemented multiple CNN architectures—AlexNet, VGG, Inception, and ResNet—for brain tumor classification using the BraTS and Kaggle MRI datasets, achieving 95– 98% accuracy. While their work demonstrated strong performance, the models were computationally intensive and unsuitable for real-time medical use. Similarly, Kamnitsas et al. (2020) proposed a 3D CNN for brain lesion segmentation, improving localization but remaining resource-heavy and lacking explainable outputs.

Comprehensive reviews by recent researchers also highlight the evolution of deep learning models for tumor detection. Transformer-based and hybrid CNN–Transformer models are gaining traction due to their ability to capture both spatial and contextual information. However, these approaches often require large datasets and high-end GPUs, limiting their accessibility in smaller clinical setups. To overcome these challenges, recent works have suggested lightweight CNNs and transfer learning, but they still lack robust explainability and cross-dataset validation.

In addition, several researchers have proposed optimization and augmentation strategies to enhance model robustness. GAN-based data augmentation has proven useful for addressing class imbalance by generating synthetic MRI samples, but concerns remain regarding data authenticity and generalization. Explainability tools like Grad-CAM have recently been integrated into CNN models to highlight tumor regions influencing predictions, yet they are rarely used as core components for model evaluation.

From these studies, a clear pattern emerges deep learning models for brain tumor classification achieve excellent accuracy in controlled environments but struggle to balance efficiency, interpretability, and clinical deployability. Few works effectively integrate explainable AI (XAI) mechanisms with high-performing CNN or hybrid architectures optimized for real-time medical use.

4.1 CNN-Based Brain Tumor Classification

Deepak et al. [1] explored various CNN architectures, including AlexNet, VGG, Inception, and ResNet, for brain tumor diagnosis. Their models achieved around 95–98% accuracy, confirming CNN's effectiveness in spatial feature extraction. However, their computational complexity limited their suitability for time-critical applications and real-time use in clinical settings.

4.2 Residual and Advanced CNN Architectures

Kamnitsas et al. [2] developed a deep residual CNN that mitigated vanishing gradient issues through skip connections, achieving 99% accuracy. While the model improved convergence and precision, it remained computationally expensive and lacked generalization across multi-centre datasets, emphasizing the need for more adaptable frameworks.

4.3 Lightweight and Efficient CNN Models

Researchers have also explored lightweight CNN architectures integrating depth-wise separable convolutions and squeeze-and-excitation blocks. Such models achieved high accuracy (≈98%) while reducing computational demand, offering promise for deployment in hospitals with limited computing resources. Although lightweight models offer several benefits, they are often tested on smaller datasets. This makes it difficult to fully assess their performance in real-world clinical settings, indicating the need for evaluation on larger and more diverse datasets.

4.4 Hybrid CNN–Transformer Approaches

Recent studies combining CNNs with Transformers show improved accuracy and contextual understanding of MRI features. These hybrid models utilize CNNs for local feature extraction and Transformers for long-range dependency modeling. Nevertheless, few have focused on optimizing these models for real-time execution or incorporating explainability through techniques like Grad-CAM.

4.5 Data Augmentation and Explainable AI Integration

Generative Adversarial Networks (GANs) have been increasingly used for data augmentation to address class imbalance in brain tumor datasets. GAN-generated images enhance model generalization by expanding minority tumor classes. Additionally, Grad-CAM has been adopted for visual interpretation of model predictions, improving transparency for medical professionals. However, both techniques are often implemented independently rather than as part of a unified, endto-end diagnostic framework.

4.6 Research Gaps Identified

Based on the reviewed literature, several gaps remain in the domain of automated brain tumor detection:

1. Most models prioritize accuracy over efficiency and interpretability.

2. Hybrid CNN–Transformer architectures have not been fully optimized for real-time clinical use.

3. GAN-based augmentation is underutilized as a systematic solution for dataset imbalance.

4. Explainability methods like Grad-CAM are rarely integrated into model design as core components.

5. Deployment-oriented optimizations such as pruning and quantization are often overlooked.

These limitations underscore the need for a hybrid, lightweight, and explainable deep learning system capable of performing accurate brain tumor detection while ensuring transparency, robustness, and real-time deployability. The present research aims to bridge these gaps through a Hybrid Lightweight CNN–Transformer model integrated with GAN-based augmentation, GradCAM explainability, and Streamlit-based deployment to support radiologists in clinical decisionmaking.

5. Proposed System / Architecture

5.1 System Overview

The proposed Brain Tumor Type Detection System is a deep learning–based diagnostic framework designed to automate the process of identifying and classifying brain tumors from MRI images. The system architecture consists of two major phases: training and testing. During the training phase, a dataset of MRI brain images is collected and pre-processed using techniques such as normalization, resizing, and noise reduction. These steps help improve image quality and ensure uniform input dimensions. After preprocessing, important spatial and contextual features are extracted using a Hybrid Lightweight CNN–Transformer model. In this architecture, the CNN focuses on capturing detailed local patterns, while the Transformer learns relationships between different regions of the image. The extracted features are then used for tumor classification, and the trained model parameters are stored for use during inference.
In the testing phase, new MRI images go through the same preprocessing and feature extraction steps. The trained model then classifies the images into tumor categories such as glioma, meningioma, or pituitary tumor. To make the predictions more understandable, Grad-CAM is used to highlight the regions of the image that influence the model's decision. This helps clinicians visually verify the results.
To further improve performance, GAN-based data augmentation is applied to handle class imbalance and enhance generalization. In addition, pruning and quantization techniques are used to optimize the model so that it can run efficiently in real-time environments. The system is integrated with a Streamlit-based interface, allowing medical professionals to easily upload MRI scans, view classification results, and analyze highlighted tumor regions.
Overall, the proposed approach provides a fast, interpretable, and reliable solution for brain tumor detection, supporting better clinical decision-making.

5.2 System Modules

1. Input Module:

Accepts MRI brain images for both training and testing. The dataset may include different tumor types such as glioma, meningioma, and pituitary tumors.

2. Preprocessing Module:

Performs image enhancement steps, including resizing, normalization, noise removal, and contrast adjustment. This ensures consistent input quality for the model.

3. Feature Extraction Module:

Uses the Hybrid CNN–Transformer architecture to extract meaningful features from MRI images. CNN captures local textures, while the Transformer identifies long-range dependencies.

4. Classification Module:

Classifies the extracted features into specific tumor categories using the trained model, ensuring accurate prediction.

5. Knowledge Base:

Stores the learned model parameters and feature representations during training. This information is later used during testing for prediction.

6. Identification Module:

Compares features from new MRI images with stored patterns to determine the tumor type.
Grad-CAM is also used here to highlight important regions influencing the decision.

7. Output Module:

Displays the final classification result along with the processed MRI image. It may also include labelled outputs showing tumor location and prediction confidence.

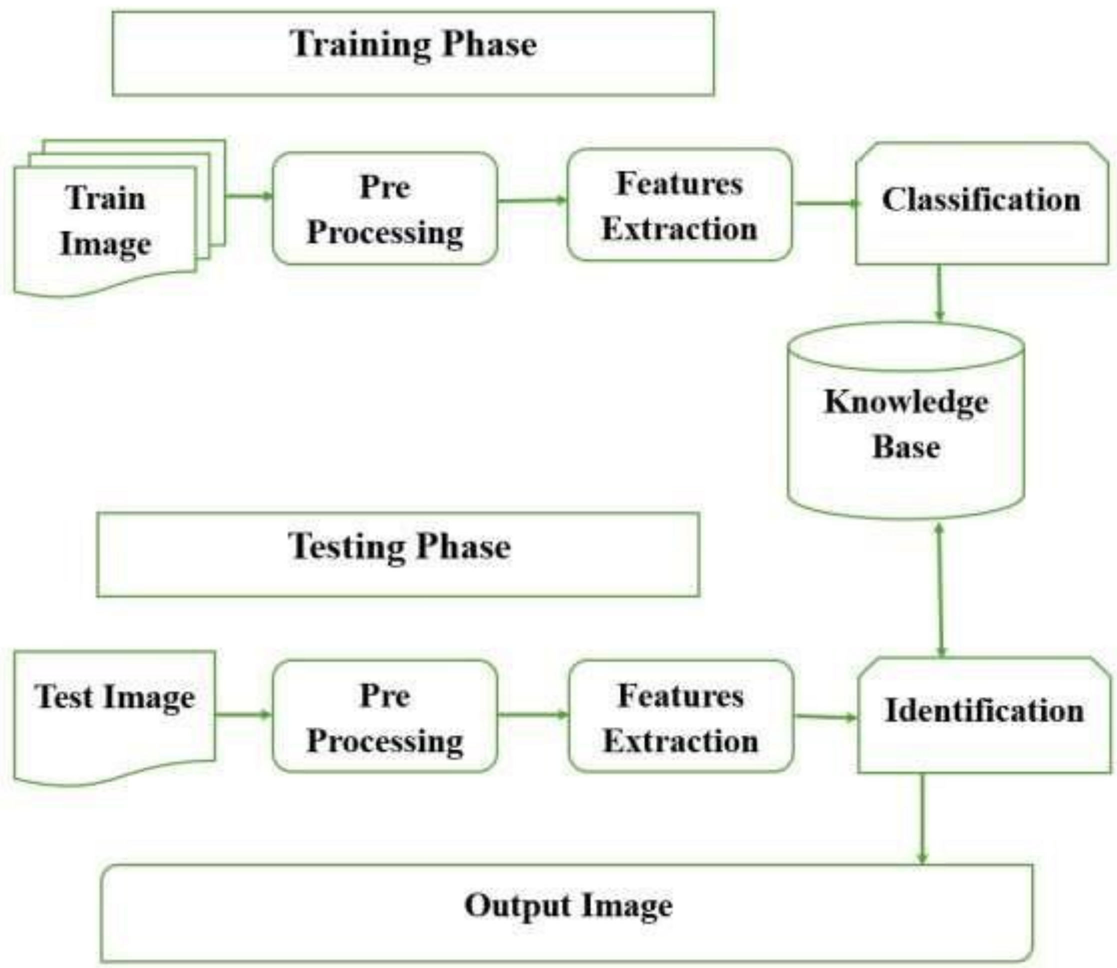

Figure 3: System Architecture

6. Tools and Implementation Scope

- **Programming:** Python, TensorFlow, Keras
- **Model Framework:** Hybrid Lightweight CNN–Transformer architecture
- **Data Augmentation:** Generative Adversarial Network (GAN) for synthetic MRI generation
- **Explainability:** Grad-CAM (Gradient-weighted Class Activation Mapping)
- **Optimization:** Model pruning and quantization for real-time deployment
- **User Interface:** Streamlit-based interactive web application
- **Development Environment:** Google Colab / Jupyter Notebook with GPU acceleration
- **Database / Storage:** Local knowledge base for model weights and extracted features
- **Deployment:** Real-time inference on standard medical systems and low-spec hardware

7. Challenges and Limitations

- Data Imbalance: Limited availability of diverse and balanced MRI datasets for all tumor types
- Computational Resources: High GPU and memory requirements during training
- Model Generalization: Performance variation across MRI datasets from different scanners or hospitals
- Explainability Depth: Grad-CAM provides visual interpretation, but not full clinical reasoning
- Processing Speed: Real-time inference may slow down on low-power or embedded systems
- Clinical Validation: Model performance requires further testing on large-scale, real-world clinical data

8. Discussion and Future Scope

The proposed Hybrid Lightweight CNN–Transformer–based Brain Tumor Detection System demonstrates a robust and efficient solution for automatic classification of brain tumors from MRI images. The combination of CNN and Transformer architectures helps the model learn both spatial and contextual features from MRI images. This improves classification performance and allows the system to generalize better across different cases. In addition, the use of GAN-based data augmentation helps address the issue of class imbalance, ensuring that the model performs more consistently across various tumor types. Grad-CAM further enhances the system by providing visual explanations, allowing clinicians to see which regions of the image influence the prediction and increasing trust in the results.

The use of pruning and quantization techniques reduces the overall computational cost, making the model suitable for deployment on standard systems as well as low-resource medical devices. The Streamlit-based interface improves usability by providing a simple yet interactive platform where radiologists can upload MRI images and easily view the classification results along with highlighted regions. Experimental results show that the model maintains a good balance between accuracy, interpretability, and efficiency, making it useful as a supportive tool in medical diagnosis. However, certain challenges remain, such as limited data diversity, variations across datasets from different institutions, and the need for large-scale real-world validation.

In the future, the system can be further improved in several ways. Expanding the dataset to include images from multiple institutions and different imaging modalities, such as MRI, CT, and PET scans, can improve robustness and reliability. Adding a tumor segmentation component may help in identifying precise tumor boundaries and assist in treatment planning. The use of federated learning can also be explored to enable collaborative training across hospitals while maintaining data privacy. Moreover, adapting the model for edge deployment using frameworks like TensorFlow Lite or ONNX can support real-time diagnosis on portable devices. Further validation in collaboration with healthcare institutions will be important to ensure the system's effectiveness in real clinical settings.

Overall, the proposed framework provides a strong base for developing an efficient and interpretable brain tumor detection system, with the potential to support future advancements in AIbased medical imaging.

With continued advancements in model optimization, dataset diversity, and clinical validation, this approach holds great potential to revolutionize AI-assisted medical imaging and support radiologists in delivering faster and more accurate diagnoses.

Conclusion

The proposed Hybrid Lightweight CNN–Transformer model provides an effective and intelligent approach for the automatic detection and classification of brain tumors from MRI images. This integration helps improve the overall accuracy and reliability of brain tumor classification when compared to conventional deep learning approaches. The use of GAN-based data augmentation addresses class imbalance and improves model robustness, while Grad-CAM provides visual explanations that make the predictions more transparent and easier to interpret. In addition, model optimization through pruning and quantization reduces computational requirements, making the system suitable for real-time use on low-resource devices.

The developed framework, along with a Streamlit-based interface, offers a practical and userfriendly tool that can assist radiologists in making quicker and more informed decisions. Experimental results indicate that the system performs efficiently and has good potential for clinical use.

In the future, the model can be further improved by using larger and more diverse datasets collected from multiple institutions. Adding a tumor segmentation component may also help in more precise localization and treatment planning. Furthermore, large-scale clinical validation will be important to ensure the reliability of the system in real-world environments.

Overall, this work presents a scalable and interpretable approach for brain tumor detection, with the potential to support healthcare professionals in early diagnosis and decision-making.

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