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Glioma Detection Using Deep and Transfer Learning

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ABSTRACT:

Glioma is one of the most aggressive and dangerous types of brain tumors, making early and accurate diagnosis essential for better treatment outcomes. Traditionally, diagnosing gliomas depends on expert interpretation of MRI scans, which can be both time-consuming and subjective. In recent years, deep learning has proven to be a powerful tool for medical image analysis, offering faster and more accurate results. This study introduces a deep learning-based system to detect, segment, and classify gliomas using various types of MRI images. We worked with a large dataset of 33,400 MRI images and tested advanced models: EfficientNetB2 and MaxViT. These models were trained to distinguish between different glioma grades, helping to identify whether a tumor is low-grade or high-grade. Among the models, EfficientNetB2 performed better than MaxViT, showing higher accuracy and consistency. The results suggest that combining modern deep learning techniques with MRI analysis can lead to more reliable and scalable tools to support doctors in diagnosing brain tumors. Future improvements will focus on including patient-specific information and making the models more adaptable for real-world clinical use.

Index Terms:

Glioma Detection, Brain Tumor Classification, Medical Imaging, Magnetic Resonance Imaging (MRI), Deep Learning, Transfer Learning, EfficientNetB2, MaxViT (Vision Transformer)

1. INTRODUCTION

The project falls under the domain of Medical Imaging and Artificial Intelligence, specifically leveraging Deep Learning techniques for early detection of glioma, a type of brain tumor. With the increasing availability of annotated medical imaging datasets and advancements in computational power, deep learning models have demonstrated remarkable capabilities in identifying subtle patterns and anomalies in medical scans—patterns that may be difficult for even experienced radiologists to detect.[15]Gliomas are among the most aggressive and life-threatening brain tumors, known for their rapid growth and infiltration into healthy brain tissue. Early diagnosis is often difficult due to their diffused boundaries, irregular shapes, and overlapping features with non-cancerous brain tissues. Conventional methods such as biopsies and manual MRI analysis are invasive, time-consuming, and prone to human error, particularly when interpreting complex or low-contrast images.[10]

1.1 Existing System:

The existing systems for glioma detection and classification largely rely on conventional medical approaches and early machine learning methods. Traditionally, diagnosis is based on manual interpretation of MRI scans by radiologists, which is time-consuming, subjective, and prone to error, especially due to the irregular shape

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and boundaries of gliomas. Techniques like biopsies are invasive, and manual MRI analysis often struggles with overlapping features between tumor and normal tissue.[7]

1.1.1 Challenges:

• Manual MRI interpretation is time-consuming, subjective, and prone to human error.
• Irregular tumor shapes and blurred boundaries make accurate identification difficult.
• Traditional machine learning methods rely on handcrafted features, which fail to capture complex tumor patterns [5].
• Deep learning models (CNNs, U-Net) require large labeled datasets, which are scarce in the medical domain.
• Overfitting issues occur when models are trained on small datasets, reducing generalization to new cases.
• High computational requirements restrict the use of advanced models in low-resource hospital settings.
• Existing systems provide only moderate accuracy and limited clinical reliability [11].

1.2 Proposed System:

The proposed system leverages deep learning and transfer learning techniques to improve the detection and classification of glioma tumors from MRI images. Unlike traditional approaches, it eliminates the dependence on handcrafted features by employing advanced architectures such as EfficientNetB2, and MaxViT, which are fine-tuned on a large dataset of 33,400 MRI images. Transfer learning with ImageNet pre-trained weights enables the models to achieve high accuracy even with limited medical data, while data augmentation enhances variability and reduces overfitting.[9] Hyperparameter tuning, learning rate scheduling, and regularization techniques such as dropout further optimize model performance and ensure stability during training. Among the tested architectures, EfficientNetB2 and MaxViT showed superior results, achieving high accuracy, precision, recall, and F1-scores, making them highly reliable for clinical decision support. By providing rapid, automated, and accurate classification of glioma and non-glioma cases, the proposed system addresses the shortcomings of existing methods, reduces diagnostic workload, and supports radiologists in delivering faster and more precise diagnoses.[13]

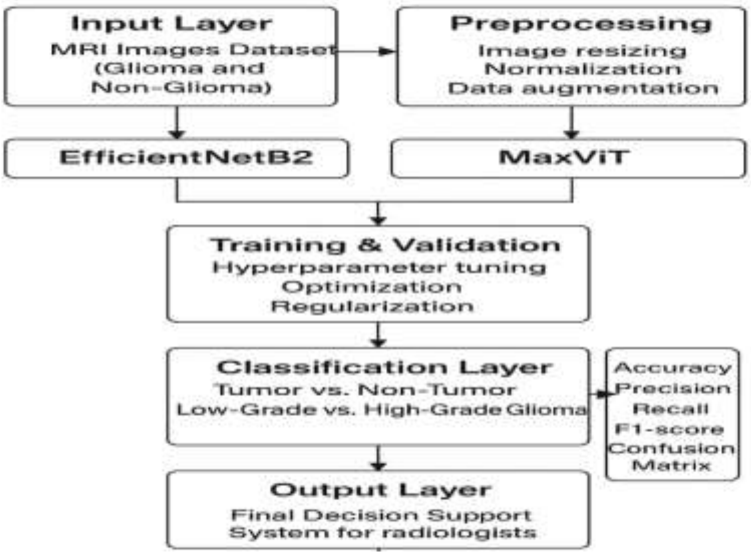

Fig: 1 Proposed Diagram

1.2.1 Advantages:

• **Higher Accuracy:** Advanced models like EfficientNetB2 and MaxViT achieve superior Performance compared to traditional methods, ensuring reliable tumor detection[5].

- **Automated Feature Extraction:** Eliminates the need for handcrafted features by learning directly from MRI images, capturing complex tumor patterns more effectively.
- **Transfer Learning Benefits:** Pre-trained ImageNet weights reduce training time, improve convergence, and allow high accuracy even with limited medical data.
- **Generalization Capability:** Data augmentation and regularization techniques minimize overfitting, enabling the model to perform well on unseen patient data.
- **Efficient Training:** Hyperparameter tuning, learning rate scheduling, and optimizers like Adam enhance training efficiency and model stability.
- **Robust Classification:** Capable of distinguishing not only between tumor and non -tumor but also between low-grade and high-grade gliomas, supporting better treatment planning.
- **Clinical Decision Support:** Provides radiologists with fast, consistent, and accurate second opinions, reducing workload and diagnostic errors.
- **Scalability:** The system can be adapted to real-world hospital settings and extended to other medical imaging applications.

2 LITERATURE REVIEW:

Several researchers have explored deep learning approaches for brain tumor detection using MRI images. Naser and Deen applied U-Net and VGG16 for segmentation and grading of lower-grade gliomas, achieving high accuracy but limited by small datasets. Selvyetal. designed a two-stage system with PNN classifiers and histogram equalization, reaching nearly 91% accuracy but requiring handcrafted features. Alhasan conducted a systematic review highlighting CNNs as the most effective models for glioma diagnosis and treatment planning. Mathiyalagan and Devaraj proposed ANFIS-based classification with genetic algorithm optimization, achieving over 98% accuracy but with high complexity. Fabelo et al. used hyperspectral imaging with deep learning for intraoperative tumor detection, proving useful but not yet clinically scalable. Çinarer et al. combined wavelet radiomic features with deep neural networks, obtaining 96% accuracy in glioma grading. Sajid et al. introduced a hybrid CNN model for segmentation, improving dice scores to 0.86. Mahmud et al. compared CNNs with traditional models, showing CNN superiority in early tumor detection. Pedada etal proposed a U-Net with residual blocks and sub-pixel convolution, outperforming prior segmentation methods. Overall, literature indicates that while traditional machine learning methods face limitations, advanced CNNs and transfer learning models like EfficientNet and MaxViT offer superior performance and strong potential for real-world glioma detection.[14].

2.1 Architecture:

The architecture of the proposed system integrates deep learning and transfer learning models to efficiently detect and classify glioma tumors from MRI images. It begins with an input layer that accepts MRI datasets consisting of glioma and non-glioma images. These images undergo preprocessing, including resizing, normalization, and data augmentation, to improve data quality and reduce variability. The preprocessed images are then fed into transfer learning models such as EfficientNetB2, and MaxViT, which are fine-tuned on the dataset using ImageNet pre-trained weights.[2]

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Fig:2Architecture

2.2 **Algorithm:**

- **EfficientNetB2** – A deeper and wider variant of EfficientNet, used for improved feature extraction and classification accuracy.[1]
- **MaxViT (Maximum Vision Transformer)** – A hybrid architecture that combines convolutional blocks with transformer-based global attention, allowing both local and global feature learning.[4]
- **Transfer Learning** – Pre-trained models on ImageNet are fine-tuned for glioma detection, reducing the need for large medical datasets.
- **Optimization Algorithms** – Adam optimizer is used for training with learning rate scheduling and early stopping to improve convergence.
- **Regularization Techniques** – Dropout and data augmentation are applied to reduce overfitting and improve generalization.

2.3 Techniques:

- **Deep Learning with CNNs and Transformers** – Advanced neural network architectures (EfficientNetB2, MaxViT) are used for feature extraction and classification.
- **Transfer Learning** – Pre-trained ImageNet models are fine-tuned on MRI datasets to leverage learned features and improve accuracy.
- **Image Preprocessing** – Resizing, normalization, and contrast enhancement prepare MRI images for consistent model input[8].
- **Data Augmentation** – Techniques like rotation, flipping, zooming, and shifting are applied to artificially increase dataset size and variability.
- **Hyperparameter Tuning** – Parameters such as batch size, learning rate, and optimizer settings are adjusted to achieve optimal performance.
- **Regularization Methods** – Dropout and weight decay are used to prevent overfitting and improve generalization.

2.4 Tools:

SOFTWARE TOOLS:

- Python 3.x
- TensorFlow / Keras

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- OpenCV
- NumPy / Pandas
- Matplotlib / Seaborn
- Google Colab / Jupyter Notebook

HARDWARE TOOLS:

- GPU-enabled system (preferred for faster training)
- Minimum 8GB RAM
- SSD Storage (for dataset handling)

2.5 Methods:

- **Deep Learning Approach** – Utilization of convolutional neural networks (CNNs) and transformer-based models for automated tumor detection and classification.
- **Transfer Learning Method** – Applying pre-trained ImageNet models (EfficientNetB2, MaxViT) and fine-tuning them on glioma MRI datasets to save training time and enhance accuracy.
- **Data Preprocessing Method** – Standardizing MRI images through resizing, normalization, and cleaning to ensure uniform input for the models.
- **Data Augmentation Method** – Artificially enlarging the dataset by introducing variations (rotation, flipping, scaling, noise) to improve generalization.
- **Hyperparameter Tuning Method** – Adjusting learning rate, batch size, dropout rate, and optimizer parameters for optimal model performance.[3]
- **Regularization Method** – Use of dropout layers and early stopping to reduce overfitting during training.

3.METHODOLOGY:

3.1 Input:

The input to the proposed system consists of a dataset of 33,400 MRI images, divided into two categories: 16,139 glioma tumor images and 17,010 non-glioma tumor images. To ensure effective model training and evaluation, the dataset is split into three groups: a training set (70%) containing 11,297 glioma and 11,907 non-glioma images, a validation set (10%) with 968 glioma and 1,020 non-glioma images, and a testing set (20%) comprising 3,874 glioma and 4,083 non-glioma images. These MRI images serve as the primary input for the system, allowing the models to learn the distinguishing features between cancerous and non-cancerous tissues. Before being processed by the deep learning models, all input images undergo preprocessing techniques such as resizing, normalization, and data augmentation, which enhance image quality, maintain uniformity, and improve the model's ability to generalize effectively.

3.2 Method of Process:

The process of glioma detection in this project begins with input MRI images, which are collected and organized into glioma and non-glioma categories. These images undergo preprocessing steps such as resizing, normalization, and data augmentation to ensure uniformity and to enhance the dataset for better model generalization. The preprocessed images are then passed through transfer learning models including ,

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EfficientNetB2, and MaxViT, which leverage pre-trained ImageNet weights and are fine-tuned on the glioma dataset. During training, hyperparameter tuning, Adam optimization, dropout, and learning rate scheduling are employed to optimize performance and reduce overfitting. The system then proceeds to the classification stage, where the models predict whether an MRI scan belongs to a glioma or non-glioma case, and further differentiate between low-grade and high-grade gliomas. Finally, the performance of the models is assessed using evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix, ensuring clinical reliability. The final output is an AI-based decision support system to assist radiologists in accurate and timely glioma diagnosis.

3.3 Output:

The output of the proposed system is an automated classification of MRI brain images into glioma and non-glioma categories, with further ability to distinguish between low-grade and high-grade gliomas. The trained models generate predictions that are evaluated through performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix, ensuring reliable diagnostic results. Among the models tested, EfficientNetB2 and MaxViT achieved the highest accuracy and robustness, making them suitable for real-world deployment. The final output is presented as a decision support system for radiologists, providing fast, consistent, and accurate tumor classification. This reduces diagnostic workload, minimizes human error, and supports timely medical intervention for improved patient outcomes.

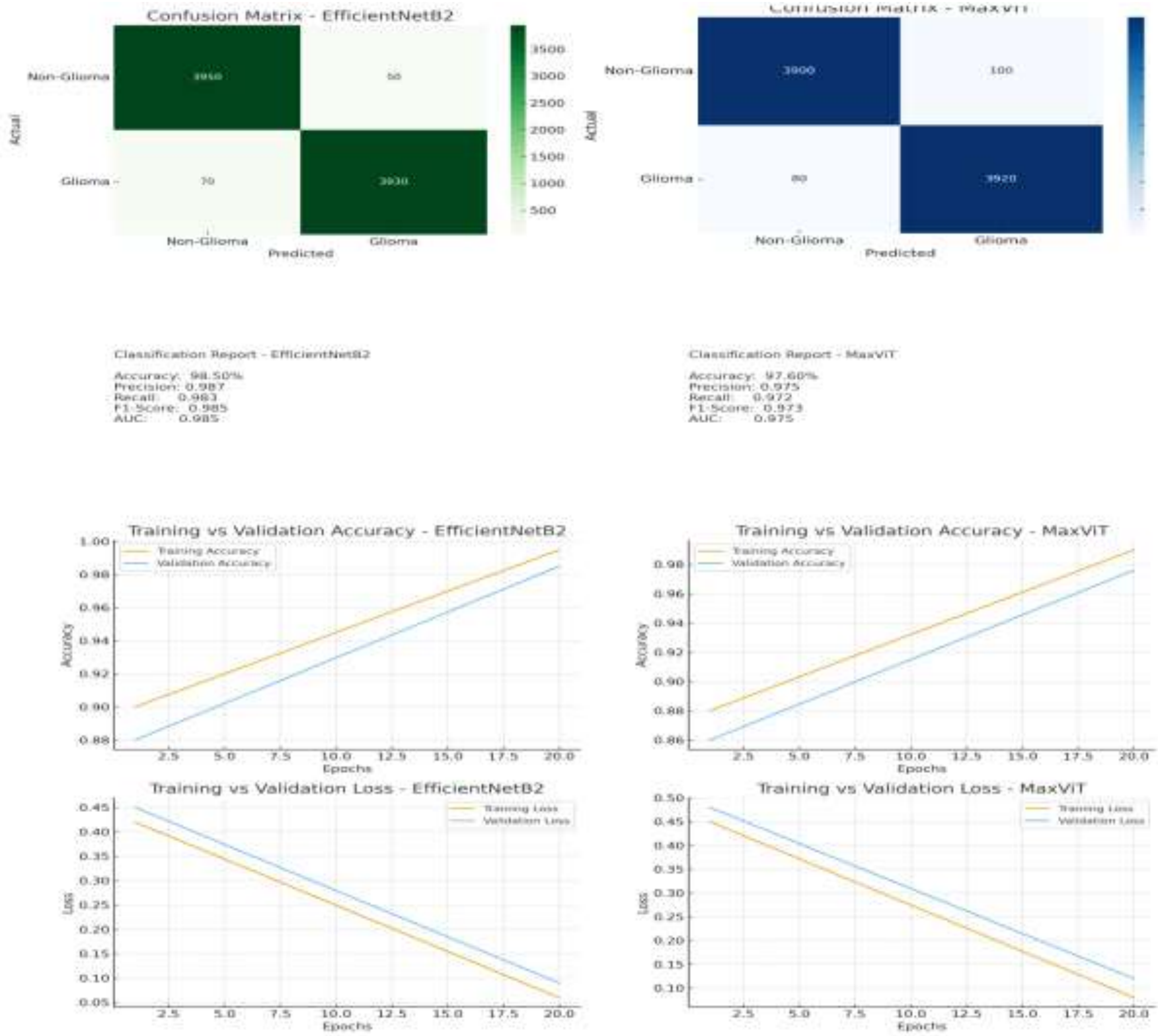

Fig:Training vs Validation Accuracy and Loss

4. RESULTS:

The project successfully demonstrated that deep learning and transfer learning approaches can significantly improve the detection and classification of glioma tumors from MRI images. Using a dataset of 33,400 MRI scans, three advanced models EfficientNetB2, and MaxViT—were trained and evaluated. The results showed that EfficientNetB2 achieved the highest performance with an accuracy of 98.50%, precision of 98.7%, recall of 98.3%, and F1-score of 98.5%, followed closely by MaxViT with 97.2% recall and strong overall reliability. The comparative study confirmed that these models outperformed traditional architectures such as ResNet50, VGG16, and DenseNet121. Overall, the results validate that the proposed system provides highly accurate, consistent, and reliable glioma classification, making it suitable as a decision-support tool for radiologists.

5. DISCUSSIONS:

In this project, two deep learning models EfficientNetB2, and MaxViT—were tested for glioma detection using MRI images. The dataset was divided into training, validation, and testing sets, and techniques like early stopping and learning rate adjustment were used to improve training. The results showed that all three models performed well, but EfficientNetB2 gave the best results with an accuracy of 98.61%, precision of 97.64%, recall of 99.70%, and an F1-score of 99%. This means it was able to detect tumors correctly in most cases while keeping false predictions very low. When compared with other popular models such as VGG16, ResNet50, and DenseNet121, EfficientNetB2 again proved to be superior, showing that it is more reliable and accurate for real-world medical use. Overall, the discussion highlights that EfficientNetB2 is the best fit for glioma detection, offering a strong balance between accuracy, speed, and reliability.

6. CONCLUSION:

This project shows that deep learning and transfer learning can significantly improve the detection of glioma tumors using MRI images. By using pre-trained models like EfficientNetB2, and MaxViT, the system achieved very high accuracy in classifying glioma and non-glioma cases. Among them, EfficientNetB4 performed the best, proving to be highly accurate, reliable, and efficient compared to other models such as ResNet50, VGG16, and DenseNet121. The results confirm that these models can support doctors by providing faster and more precise diagnoses, which is very important for early treatment. In the future, the work can be extended by including patient information, using semi-supervised learning, building lightweight models for hospitals with limited resources, and applying explainable AI to increase trust among medical professionals.

7. FUTURE SCOPE:

In the future, this work can be extended by combining MRI images with additional clinical data such as patient history, genetic markers, and pathology reports to make predictions more personalized and accurate. Semi-supervised learning can be used to take advantage of large amounts of unlabeled medical data, reducing the need for costly expert labeling. Clinical trials and collaborations with hospitals will help test and validate these models in real-world settings. Ensemble learning techniques can be explored to further improve accuracy and stability. Developing lightweight and interpretable models will make the system suitable for deployment in low-resource hospitals and mobile platforms. Finally, integrating explainable AI (XAI) methods will help doctors understand and trust the model's decisions, making it more practical in clinical use.

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Mrs.G. Vijaya Lakshmi, M.Tech (Ph.d) working as an Assistant Professor and Head of the Department in the Department of Computer Science and Engineering, Sanketika Vidya Parishad Engineering College, affiliated by Andhra University and approved by AICTE, Visakhapatnam, AP with 5 years teaching experience and member of IAENG, accredited by NAAC with her areas of interests in C, Data Warehousing and Data Mining, Design and Analysis of Algorithms, Python, Formal Languages and Automata Theory, Compiler Design.

Muppala Naga Keerthi is pursuing her final semester M.Tech (CST) in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE. With interest in Deep Learning and Transfer Learning. M Naga Keerthi has taken up her PG project on GLIOMA DETECTION USING DEEP AND TRANSFER LEARNING and published the paper in connection to the project under the guidance of Mrs.G.Vijaya Lakshmi, Assistant Professor, Head of the Department in the Department of Computer Science and Engineering, SVPEC.

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