Fine Tuned Deep Learning Model for Multi-Class Brain Tumor Detection and Classification

BY

Tonima Aslam Barsha
ID: 241-25-009

This Report Presented in Partial Fulfillment of the Requirements for
The Degree of **Masters of Science in Computer Science and Engineering**

Supervised By

Dr. Sheak Rashed Haider Noori
Professor & Head
Department of CSE
Daffodil International University

Co-Supervised By

Dr. Arif Mahmud
Associate Head
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

MAY 2025

APPROVAL

This Project/Thesis titled **"Fine Tuned Deep Learning Model for Multi-Class Brain Tumor Detection and Classification"**, submitted by **Tonima Aslam Barsha**, ID No: **241-25-009** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of **MSc. in Computer Science and Engineering** and approved as to its style and contents. The presentation has been held on **24-05-2025**.

BOARD OF EXAMINERS

Chairman

Prof. Dr. Sheak Rashed Haider Noori
Professor and Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner

Dr. Md. Zahid Hasan
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner

Dr. Naznin Sultana
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

External Examiner

Dr. Md. Zulfiker Mahmud
Professor
Department of Computer Science and Engineering
Jagannath University

DECLARATION

I hereby declare that this research has been done by me under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Dr. Sheak Rashed Haider Noori
Professor & Head
Department of CSE
Daffodil International University

Co-Supervised by:

Dr. Arif Mahmud
Associate Head
Department of CSE
Daffodil International University

Barsha

Submitted by:

Tonima Aslam Barsha
ID: 241-25-009
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First I express my heartiest thanks and gratefulness to Almighty Allah for His divine blessing which makes it possible to complete the final year project/internship successfully.

I am really grateful and wish my profound indebtedness to **Dr. Sheak Rashed Haider Noori, Professor & Head**, Department of CSE, Daffodil International University, Dhaka, deep knowledge & keen interest of my supervisor in the field of Machine Learning to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism , valuable advice ,reading many inferior drafts and correcting them at all stages have made it possible to complete this project.

I would like to express my heartiest gratitude to **Dr. Md Zahid Hasan, Associate Professor,** Department of CSE, for his kind help to finish our project and also to other faculty members and the staff of CSE department of Daffodil International University.

Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

Image processing plays a significant role in neurologists' medical diagnoses in the medical field. MRI(magnetic resonance imaging) is certainly the keystone of brain tumor imaging among all kinds of imaging, playing a crucial role in all phases of patient management, starting from medical diagnosis, through therapy preparation, to treatment reaction and reoccurrence assessment. This extensive study explores the capacity of innovative deep-learning strategies for the critical task of categorizing brain tumors from magnetic resonance imaging (MRI) scans. The methodology incorporates transfer learning, including the acquisition of a curated preprocessing with image grayscaling, data augmentation, and normalization to help with optimal model training. The research study utilizes a series of traditional machine learning approaches such as Decision Tree Classifier, Random Forest, K-Nearest Neighbors, Support Vector Machine(SVM), Logistic Regression, and Multi-Layer Perceptron (MLP), with accuracy respectively (75.5%, 81%, 76%,61%, 74%, and 61%) and sophisticated neural network architectures, with a particular concentration on the basic - CNN, Inception V3, customized - DenaseNet121, VGG16, ResNet50 designs, alongside an ingenious customized VGG16-Resnet50 hybrid model achieved accuracy respectively-(86.5%, 87%, 91%, 96.5%, 96%, and 98.5%). In order to recognize the most accurate and reliable method for clinical application each model's performance was seriously assessed based on some performance metrics, including precision, recall, F1 score, Cohen's kappa statistic, sensitivity, and specificity. In contrast, the deep learning designs displayed remarkable effectiveness on a diverse dataset of 40,000 MRI images covering four classes: glioma, meningioma, pituitary growth, and no tumor. The proposed hybrid approach demonstrated superior performance with a precision of 98.5%, outperforming the conventional machine-learning classifiers and standalone deep-learning models. This work highlights the capacity of hybrid architectures in supporting radiologists with trusted, automatic brain tumor detection systems.

.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1Introduction

Medical imaging analysis and classification are crucial for identifying anomalies in many body organs, including blood cancer [1,2], lung cancer [3-5], and brain tumors [6,7]. Furthermore, organ defects can cause tumors to proliferate. Usually, brain cells are formed by the neurogenesis process and it takes approximately six months for a new brain cell to be fully mature. However, when brain cell DNA is disrupted or particular genes malfunction due to damage, it causes unregulated growth of defective cells resulting in brain abnormalities. [8] Cancer cells found in tumors can spread to other body parts. The most common and deadly malignant tumors is one of the leading cause of death for women globally [9]. Also, brain tumors can develop at any age, but in children under 15 and adults between 85 to 89 years her, the highest risk is observed [10]. Early detection and treatment of any disease or cancer can improve survival rates and reduce the need for costly treatment for benign tumors [11]. In terms of early detection, brain tumors, which result from aberrant brain cell growth, provide a serious challenge to radiologists and neuropathologists. There are different kinds of experimental imaging techniques such as CT and MRI used for cancer/tumor diagnosis. However, MRI is safer than CT because of not expose living cells to harmful radiation [12]. MRI is especially helpful in identifying gliomas since it provides the detailed analysis of the human brain. The identification of brain tumors using MRI is a challenging and error-prone manual procedure [13]. Unusual nerve cell growth that results in a bulk is a hallmark of brain tumors. There are over 130 distinct types of tumors that can grow in the brain and central nervous system. Primary brain tumors are cancers that originate in the brain, while secondary or metastatic brain tumors can spread from other parts of the body to the brain [14]. Primary brain tumors start inside the brain itself. These tumors can develop from brain cells or they can be encased in nerve cells that surround the brain. Primary tumors can be both benign(non-cancerous) and malignant(cancerous) and those primary brain tumors can have a variety of traits [15]. The most common types of malignant brain tumors are Secondary brain tumors also known as metastatic brain tumors. It is crucial to remember that secondary brain tumors are always malignant and represent a major risk to health, whereas benign tumors usually do not move from one part of the body to another [16]. Cancer web portal statistics show over 308,102 global diagnoses per year with over 251,329 fatalities from primary brain tumors [17]. Several computer-aided techniques have been proposed to improve brain tumor diagnosis precision. Researchers have used different methods to classify brain tumor grade. Some unsupervised methods- SVM, K-means, and Logistic Regression, and some supervised models- Random Forest, Artificial Neural Networks, and Naive Bayes. Some researchers also have proposed hybrid classification models combining two deep learning models or a deep learning model with a machine learning model for brain tumor detection [18-20].

In this study, various types of methods such as data augmentation techniques and transfer learning are used to increase the generalization capacity of our models by using datasets effectively. Data preprocessing techniques solved three issues noise suppression, resolution of low contrast, and varying contrast in image dataset which helps to increase the accuracy of our model. Here, we have used both Machine learning models such as Decision Tree Classifier, MLP classifier, Random Forest Classifier, KNeighbour classifier, Logistic Regression, and SVM by using the GLCM method for feature selection and deep learning models such as CNN, DenseNet121, Inception V3, VGG16, ResNet50. We have customized those models as necessary to enhance accuracy using different techniques like layers dropout, freeze-unfreeze layers(fine-tuning), early stopping callbacks, etc. However, a hybrid model combination of two powerful CNNs "VGG16 and Resnet50" has been developed by using transfer learning. The powerful feature extraction capabilities of both (VGG16 & ResNet50) models pre-trained on ImageNet were used here. Besides, using various preprocessing techniques such as grayscaling, augmentation, rescaling, normalization, etc, and applying fine-tuning and early stopping we achieved a unique approach with high accuracy. The proposed hybrid approach can meet the critical challenges in medical imaging and improve classification performance on an imbalanced and unknown dataset. Our robust and scalable technology enables early and accurate diagnosis which ensures further medical imaging research.

Key Contributions of this study are as follows:

- We implemented a hybrid deep learning CNN model VGG16 and ResNet50 to improve feature extraction for brain tumor classification. Our data pipeline made use of data with caching, prefetching, and regulated augmentation to enhance training effectiveness and design generalization. Additionally, we used the AdamW optimizer with weight decay and incorporated callbacks such as ModelCheckpoint and ReduceLROnPlateau to enhance and support training.
- Initially, applying Grayscale for preprocessing purposes on merged dataset only represents the intensity information of the image.
- We have used several Data Augmentation techniques to increase the training dataset's size and diversity. This helps models generalize better and avoid overfitting.
- We used Normalization scales features consistently, improving training speed, model efficiency, and stability. It prevents predisposition from dominant functions and guarantees fair comparison in algorithms. Lastly, we used transfer learning techniques (Fine-tuning) & regularization strategy for better generalization.

1.2 Motivation

The motivation for this research study develops from the pushing need to enhance the accuracy and effectiveness of brain tumor detection utilizing innovative computational techniques. Brain tumors, where as benign or malignant, represent one of the most diagnostically complex and lethal conditions in contemporary medicine. To address this challenge, the research study introduces a hybrid deep learning technique that integrates the power of VGG16 and ResNet50, 2 of the most effective CNN architectures. By utilizing transfer learning, the proposed approach successfully adjusts pre-trained understanding to the specific task of tumor category, considerably improving function extraction and category accuracy even on limited datasets. This hybrid technique aims to produce a robust, scalable, and scientifically applicable tool that can support radiologists in making faster and more accurate medical diagnoses, eventually boosting client care and advancing the field of medical image analysis.

1.3 Rationale of the Study

The rationale behind this study comes from the important requirement to improve the accuracy and reliability of brain tumor classification in medical imaging. Brain growths, both secondary and primary, posture substantial obstacles for neuropathologists and radiologists, given the intricacy and range of tumor types that exist. Current diagnostic strategies, such as MRI, are important for finding brain growths however typically involve manual interpretation, which can be time-consuming and error-prone. This research aims to address these challenges by leveraging innovative artificial intelligence and deep knowing methods, particularly through the advancement of a hybrid model combining the function extraction strengths of VGG16 and ResNet50. By using transfer learning, data augmentation, and preprocessing techniques such as grayscaling, rescaling, and normalization, the research study aims to boost the generalization abilities of the model while getting rid of concerns such as noise, low contrast, and varying image contrast. The incorporation of fine-tuning and early stopping systems even more enhances the design's performance. The objective is to create a more precise, robust, and scalable system for brain tumor classification, ultimately enabling early and reliable medical diagnosis, enhancing client results, and adding to continuous improvements in medical imaging.

1.4 Research Questions

- RQ1: How effectively can a hybrid deep learning model (VGG16 + ResNet50) classify brain tumors from MRI images compared to individual models?

- RQ2: What is the impact of augmentation and preprocessing techniques (grayscaling, normalization) on model efficiency in brain tumor detection?

- RQ3: How effective is a hybrid deep learning model that integrates VGG16 and ResNet50 architectures in accurately classifying brain tumors from MRI images compared to traditional machine learning and individual deep learning models?

1.5 Research Objective

- Develop a robust, scalable deep-learning framework
- Optimize an image preprocessing pipeline
- On a balanced dataset of around 40,000 MRI images covering glioma, meningioma, pituitary tumor, and no-tumor classes.
- Perform well on Unknown & Imbalance dataset.
- Compare and benchmark the proposed model against:
  - Traditional machine learning classifiers (Decision Tree, Random Forest, K-Nearest Neighbors, SVM, Logistic Regression, MLP)
  - Standalone deep architectures (basic CNN, Inception V3, DenseNet121, VGG16, ResNet50)

1.6 Expected Output

- A hybrid deep learning model that outperforms individual CNN-based models and traditional machine learning models in brain tumor classification accuracy.
- Development of a robust VGG16-ResNet50 hybrid model for accurate classification of brain tumors from MRI images.
- Enhanced level of sensitivity, specificity, and Cohen's Kappa values, lessening misclassification dangers.
- Demonstration of the efficiency of pre-processing and augmentation in improving model generalization.
- It is anticipated that the hybrid model will outshine standalone designs such as VGG16 or ResNet50 in respect of classification accuracy, precision, recall, F1 score, and other evaluation metrics. This enhancement is expected due to the synergistic impact of integrating the spatial function extraction strength of VGG16 with the recurring learning capability of ResNet50.
- A validated, scalable, and reproducible structure for automated brain tumor detection that might help radiologists in early diagnosis.

1.7 Project Management and Finance

The research work doesn’t get fund from any individuals or organization.

1.8 Report Layout

This research paper consists of 5 chapters. The chapter 1 is for introduction, motivation and goals behind the research have been discussed in six sections.

- **Chapter 1 –** The introduction and report layout of this study (1.1 introduction; 1.2 Motivation; 1.3 Rational study; 1.4 Research Question; 1.5 Expected Outcome; 1.6 Report layout
- **Chapter 2** - The research background into four sections. (2.1 Preliminaries; 2.2 Related works; 2.3 Scope of the problem; 2.4 Challenges)

- **Chapter 3** - The details of this research experiment which divided into twelve sub-sections. (3.1 Proposed Methodology; 3.2 Data Collection Procedure; 3.2.1 Dataset Details; 3.3 Data pre-processing; 3.3.1 Data Augmentation and Normalization; 3.4 Deep Learning Models; 3.4.1 Proposed Hybrid Model (VGG16+ResNet50 3.4.2 Convolution Neural Network CNN; 3.4.3 Custom Dense121; 3.4.4 Inception V3, 3.4.5 Custom VGG16, 3.4.6 Custom ResNet50))
- **Chapter 4** – The result and discussion of that result into four sub section. (4.1 Expected Outcomes; 4.2 Experiments Result; 4.3 Compare with other platform; 4.4 Descriptive analysis of our result.)
- **Chapter 5** - Impact on society, Environment and Sustainability of our research about "Brain Tumor Detection" (5.1 Impact on Society; 5.2 Impact on Environment; 5.3 Ethical Aspects)
- **Chapter 6** – Summary of the study, recommendation and implication study (6.1 Summary of the study; 6.2 Conclusion; 6.3 Recommendation; 6.4 Implication for further research.)

CHAPTER 2
BACKGROUND

2.1 Preliminaries/Terminologies

Modern developments in health innovation have actually helped with the construction of cutting-edge systems created to recognize and classify ailments impacting brain plants. Using image processing strategies to categorize and identify the different types of conditions that affect brain cancer has actually been the subject of numerous research studies. Achieving accurate classification of brain cancer illness has been facilitated by the application of image segmentation and artificial intelligence algorithms, with an emphasis on qualities consisting of texture, color, and shape. The aforementioned advancements have made substantial strides in the domain of health illness prognosis referring to brain plants and have the capacity to essentially change farming methodologies utilized in brain growing.

2.2 Related works

In medical image classification and disease diagnosis, brain tumor detection through MRI (magnetic resonance imaging) is a crucial but challenging task in clinical practice [21].MRI has become a cornerstone by providing detailed anatomical information for precise analysis in this endeavor [22-24]. Manual interpretations of radiographic images through traditional diagnostic methods may result in subjective and inconsistent evaluations. Over the last 20 years, many approaches have been developed and evolved significantly for this crucial task [25-30].

Deep Learning Methods:

For example, The researchers of [31] presented an advanced deep learning approach for automatic microbrain tumor detection using a modified VGG19 model on diverse MMRI data. The model achieved a validation accuracy of 98.81%. The author of [32] used deep learning and machine learning approaches for MRI brain tumor detection. The features are extracted through a Gray-level co-occurrence matrix (GLCM) achieving accuracy (97.93%), sensitivity (92%), and specificity (98%) in recognizing aberrant and normal tissue from MRI images. The researchers [33] recommended building an automated, robust, intelligent, and hybrid system for the diagnosis and classifying of brain tumors. The authors proposed deep transfer learning utilizing the pre-trained Inception V3 model to refine the diagnostic process using Auto contrast enhancer and Classifier to efficiently provide improved contrast MRI images for early diagnosis and classification. The system outperforms models like AlexNet, VGG-16/19, DenseNet-201, Googlenet, and ResNet-50 achieving 98.89% accuracy. In [34] the study proposed an advanced EfficientNet-based deep learning model that also integrates Grad-CAM for visual explanations for multi-grade brain tumor classification, targeting glioma, meningioma, pituitary tumor, and non-tumor cases on MRI image data. The model achieved 98.6% accuracy with a reduced parameter count. The authors of [35] developed MobileNetv3 achieved the highest accuracy of 99.75% compared to other deep transfer learning models—ResNet152, VGG19, DenseNet169, and MobileNetv3 for brain tumor diagnosis using MRI images.

Machine Learning Methods:

The researchers of [36] in their study proposed an enhanced Fuzzy C-Means (FCM) segmentation algorithm for MRI images and developed an improved Extreme Learning Machine (ELM) classifier that achieves 98.56% accuracy, 99.14% precision, and 99.25% recall on two different datasets correspondingly. There [37] tested various machine models for brain tumor detection using around 2556 images and achieved 97.305% accuracy, 97.73% precision, 97.60% specificity, 97.04% sensitivity, and 97.41% dependability. The authors of [38] developed computer-aided diagnostic (CAD) systems that offer rapid and accurate analysis of MRI data.. CAD systems aimed at detecting brain abnormalities can significantly expedite diagnosis, facilitating timely treatment decisions. In [39] this study compares six machine learning classifiers for brain tumor detection, with Random Forest accomplishing the highest precision (98.27%) and SVC closely following (97.74%). The results highlight the capacity of these models in enhancing early medical diagnosis and treatment results.

Hybrid methods:

In the reference research paper [40] the authors proposed two deep learning models: a 23-layer CNN for a larger dataset (3064 MRI images) and a hybrid model combining VGG16 and the customer CNN to handle overfitting on a small dataset(152 images). Correspondingly, they achieved 97.8% and 100% classification accuracy. The researchers of [41] have developed a hybrid model combination of VGG16-ResNet50 that achieved exceptional performance including 99.98% accuracy, sensitivity, and F1 score. The authors of [42] explored deep learning-based multiclass classification of brain tumors and introduced a hybrid model EfficientNetB0 with Quantum Genetic Algorithms (QCA). The proposed model achieved accuracy - 98.36% and 98.25% on different datasets. The suggested approach in [43] combining a lightweight Parallel Depthwise Separable CNN (PDS CNN) with a hybrid Ridge Regression Extreme Learning Machine (RRELM) using Contrast-Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance image contrast. The hybrid RRELM achieved impressive performance—99.22% accuracy, 99.35% precision, and 99.30%. The authors tested in [44] a hybrid model for brain tumor detection. They proposed a hybrid model that integrates Adaptive Bilateral Filtering (ABF) for noise reduction, Otsu-Gannet Segmentation (OGS) for precise tumor localization, and feature extraction using GLCM combined with the Enhanced Grasshopper Optimization Algorithm (EGOA). Evaluated on multiple datasets, the proposed method achieved accuracies of up to 98.86%. The authors of [45] detected brain tumors using nine machine learning (ML) models with high-dimensional radiomic features derived from advanced and physiological MRI with accuracy (87.5%), AUROC (88.6%), and F-score (77.4%).

Prior research has developed a variety of approaches and algorithms for brain tumor detection and classification with unique drawbacks. Although deep learning techniques can directly extract features from input data requiring fixed input image sizes, expensive processing needs, and great complexity. It was a challenge in earlier studies to select an appropriate deep-learning model with optimal hyperparameters. In this study, we carefully selected optimization models with appropriate parameters and minimized pre-processing steps.

2.3 The Problem's Scope

The precise category of brain tumors from MRI scans remains a challenging job in the medical imaging domain, primarily due to the complicated nature of tumor morphology and variability in image quality. Prior research study has checked out both machine knowing (ML) and deep learning (DL) approaches for automated brain growth category. In addition, numerous deep learning models proposed in earlier works suffered from minimal generalizability due to training on small or uniform datasets. Deep learning designs such as InceptionV3, DenseNet121, and even versions of VGG often presented a compromise in between accuracy and interpretability. Another common concern in earlier research studies was the difficulty in picking optimal design architectures and hyperparameters, often leading to overfitting on imbalanced datasets. To deal with these shortcomings, the present study proposes a hybrid deep knowing design that combines VGG16 and ResNet50 architectures using transfer knowing. The model is additional supported by a robust information preprocessing pipeline that consists of grayscaling, data augmentation (e.g., rotation, turning, contrast modification), and normalization, which jointly assist alleviate problems of sound, low contrast, and image irregularity.

Crucially, the design is trained and verified on a large and well balanced dataset of 40,000 MRI images covering 4 brain tumor classes: glioma, meningioma, pituitary, and no growth. This extensive dataset makes sure better generalization than previous research studies. Prior research has actually explored both maker learning (ML) and deep learning

(DL) approaches for automated brain growth classification. To deal with these drawbacks, the present study proposes a hybrid deep learning model that combines VGG16 and ResNet50 architectures utilizing transfer knowing. Crucially, the design is trained and confirmed on a big and well balanced dataset of 40,000 MRI images covering four brain tumor classes: glioma, meningioma, pituitary, and no growth.

2.4 Challenges

The proposed hybrid deep learning model demonstrated high precision in multi-class brain growth classification, the study dealt with several significant obstacles. One major difficulty was the integration of two deep CNN architectures-- VGG16 and ResNet50-- into a single hybrid design. This procedure needed cautious architectural tuning and multiple speculative models to ensure reliable feature extraction without redundancy or training instability. Another crucial challenge was the extensive computational need. Training on a large dataset of 40,000 MRI images needed powerful GPUs and considerable memory, which may not be accessible in many scholastic or scientific institutions, particularly in resource-constrained settings. As a result, the model may not generalize well to hospital-acquired MRI scans, posing risks of domain shift. The absence of external recognition even more restricts the assessment of the model's generalization throughout different client populations and imaging protocols. These difficulties highlight the complexities of developing AI options for medical imaging and highlight the requirement for future work concentrated on design optimization, clinical recognition, and broader applicability in real-world healthcare environments.

This research study faced important challenges connected to design interpretability and data limitations. The deep learning design functions as a "black box," providing predictions without visual or explanatory insight, which undermines trust and limits clinical adoption. The lack of explainable AI strategies like Grad-CAM or SHAP makes it tough for physician to comprehend the rationale behind the design's decisions.

Furthermore, the study was confined to MRI-based image category, excluding important scientific information such as patient history, pathology, or hereditary details. This lack of multimodal combination limits the design's potential for extensive, context-aware medical diagnosis. Resolving these technical, practical, and ethical challenges-- through improved design transparency, resource optimization, clinical validation, and information combination-- is vital for transitioning the model toward real-world medical application.

CHAPTER 3

RESEARCH METHOLOGY

3.1 Proposed Methodology

The provided diagram 3.1 outlines a structured methodology for detection and classification of brain MRI using image processing and deep learning approaches.

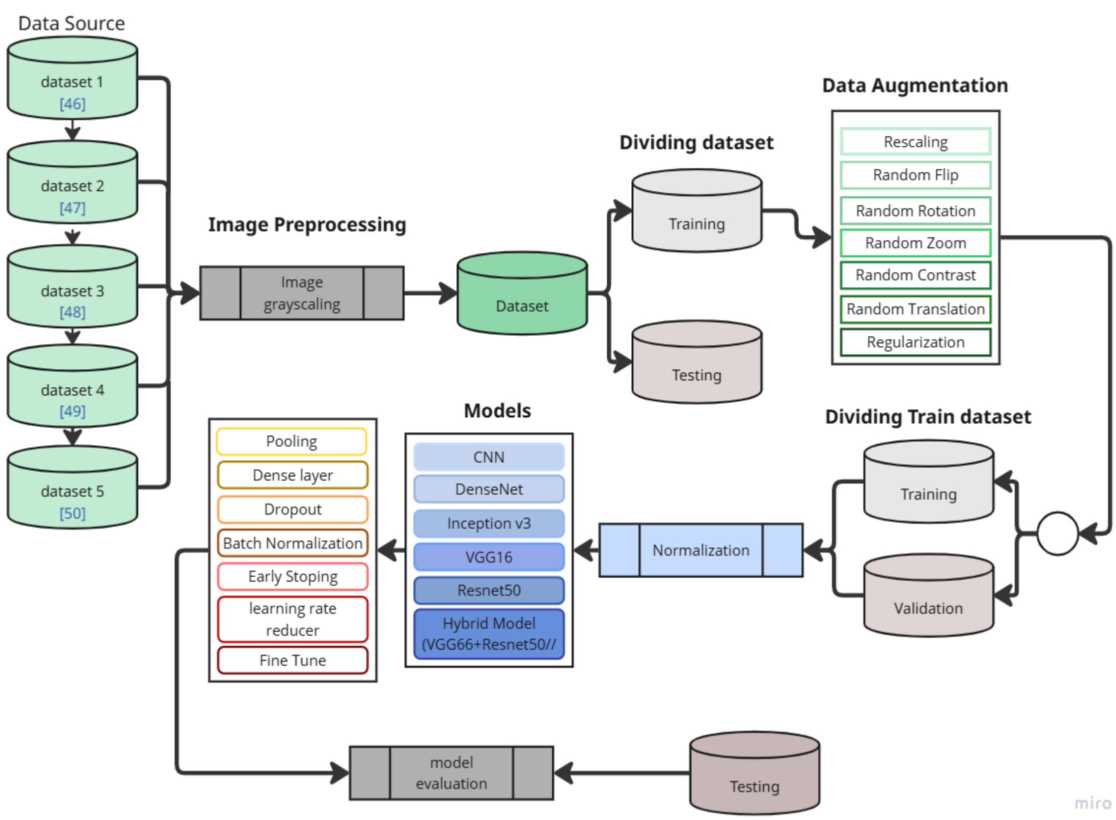


Fig 3.1: The framework of overall process to perform Brain disease prediction

This workflow describes a detailed method to brain growth category utilizing deep learning designs. It starts with the collection of 4 MRI image datasets from Kaggle, followed by preprocessing steps such as grayscaling to streamline the data. The dataset is divided into training and test sets, with extra information enhancement techniques (e.g., random rotation, zoom, and contrast) applied to increase dataset diversity and prevent overfitting. Several approaches, consisting of CNN, DenseNet121, Inception v3, VGG16, and ResNet50, are utilized for feature extraction, with a hybrid design integrating VGG16 and ResNet50 for improved efficiency. The images are normalized, and the training information is more divided into training and recognition sets for much better design evaluation. Regularization techniques- dropout, early stopping, and learning rate modification, are included to optimize the model's training process. Ultimately, the model is evaluated on the test dataset, intending for trustworthy and accurate brain tumor category. Eventually, we developed a hybrid deep learning model combining VGG16 and ResNet50 to enhance feature extraction for brain tumor classification. Our data pipeline made use of tf.data with caching, prefetching, and regulated augmentation to enhance training effectiveness and design generalization. Additionally, we used the AdamW optimizer with weight decay and incorporated callbacks such as ModelCheckpoint and ReduceLROnPlateau to enhance and support training. The result of this meticulous procedure is a collection of segmented images where the tumors are noticeably significant, assisting in simpler and more accurate identification of pathological areas. An in-depth outcome analysis follows, including a comparison with ground truth criteria to assess the model's performance on metrics such as accuracy, accuracy, recall, and the Dice coefficient. This evaluative step is not only instrumental in examining the efficacy of the segmentation design however also serves as a structure for additional improvement and research study in the realm of medical image processing.

3.2 Data Collection Procedure

The information collection procedure for this study was a fundamental action in developing a generalizable and robust deep knowing model for brain growth category. To achieve precise and extensive results, the researchers sourced MRI images from four openly accessible repositories, integrating them into a combined and substantial dataset comprising approximately 40,000 images. These images were methodically classified into 4 unique classes: glioma, meningioma, pituitary tumor, and no growth, with an equal circulation of 10,000 images per class to make sure class balance and prevent bias throughout the model training phase. This well balanced dataset is essential for training deep learning models effectively, particularly in medical imaging jobs where manipulated information can severely impact the performance and dependability of the category designs. To facilitate efficient model training and assessment, the dataset was arbitrarily split into 2 subsets, with 80% (32,004 images) designated for training and the staying 20% (7,996 images) scheduled for testing. The randomization and stratified class allocation even more enhanced the model's ability to generalize throughout varied image samples and minimize overfitting. Prior to design training, all datasets were gone through a unified pipeline that incorporated and prepared them for preprocessing, including steps like normalization, enhancement, and grayscaling. This extensive preparation made sure that each image was standardized in regards to format and quality, which is essential for high-performance knowing in convolutional neural networks. The tactical curation and preparation of this massive dataset allowed the deep knowing designs, especially the proposed VGG16-ResNet50 hybrid, to successfully identify and find out in between numerous growth types, attaining a high classification precision. In general, this careful and balanced data collection method played a critical function in the success of the proposed deep knowing framework, ensuring its dependability, scalability, and practical applicability in medical diagnostic environments.

3.2.1 Dataset details:

There we worked with around 40,000 MRI image data from four different repositories. The dataset comprises four distinct classes: Meningioma, Pituitary, Glioma, and No tumor. We have divided the dataset into 80% images for training purposes and the remaining 20% for testing with the same amount of image data. Here is a representation with the number of images for predefined classes below in Table 3.1:

Table 3.1: Dataset information (Class Distribution)

Types Of Brain Tumors	**Training (80%)**	**Test(20%)**
Meningioma	8001	1999
Pituitary	8001	1999
Glioma	8001	1999
No tumor	8001	1999
Total	**32004**	**7996**

3.3 Data (Image) Pre-processing:

The data preprocessing stage is fundamental to classifying image data with deep learning models to ensure optimal performance during the training and validation phases. In this context, we used MRI images for brain tumor detection and classification because these images provide detailed information about the brain's soft tissues. The low visual quality, noise, and low contrast of these images make it difficult to identify and localize a tumor. However, using the Keras library, we run a set of image transformations using the apply filters function before integrating the dataset into the training and testing pipeline. Initially, the datasets are merged through a unified pipeline. (fig: Image collection flow)To get intensity information of the image only, we add image grayscale preprocessing in the pipeline. It converts RGB images into grayscale and reduces color-related noise and dimensionality of images. (fig: Grayscaling image). Grayscale images contain only shades of gray varying from black(0) to white(255).

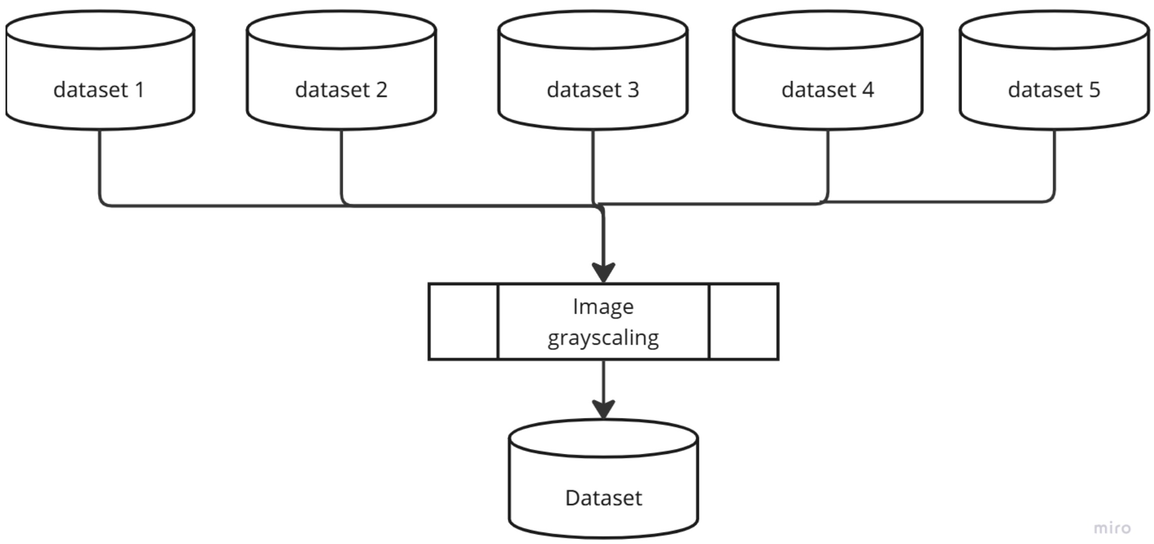


Fig 3.2: Data (image) Collection flow.

In this research study, image grayscaling played a vital function in the information preprocessing pipeline for brain tumor classification using MRI scans. Grayscaling was applied to convert RGB images into single-channel grayscale format, simplifying the data by minimizing it to intensity-based details. This change gets rid of color-related sound and decreases computational intricacy, permitting the designs to concentrate on texture and structural functions, which are more pertinent for medical imaging jobs such as growth detection. By maintaining only shades of gray ranging from black (0) to white (255), grayscaling boosts contrast and highlights subtle variations in tissue density, enhancing the model's ability to discover anomalies like brain tumors.

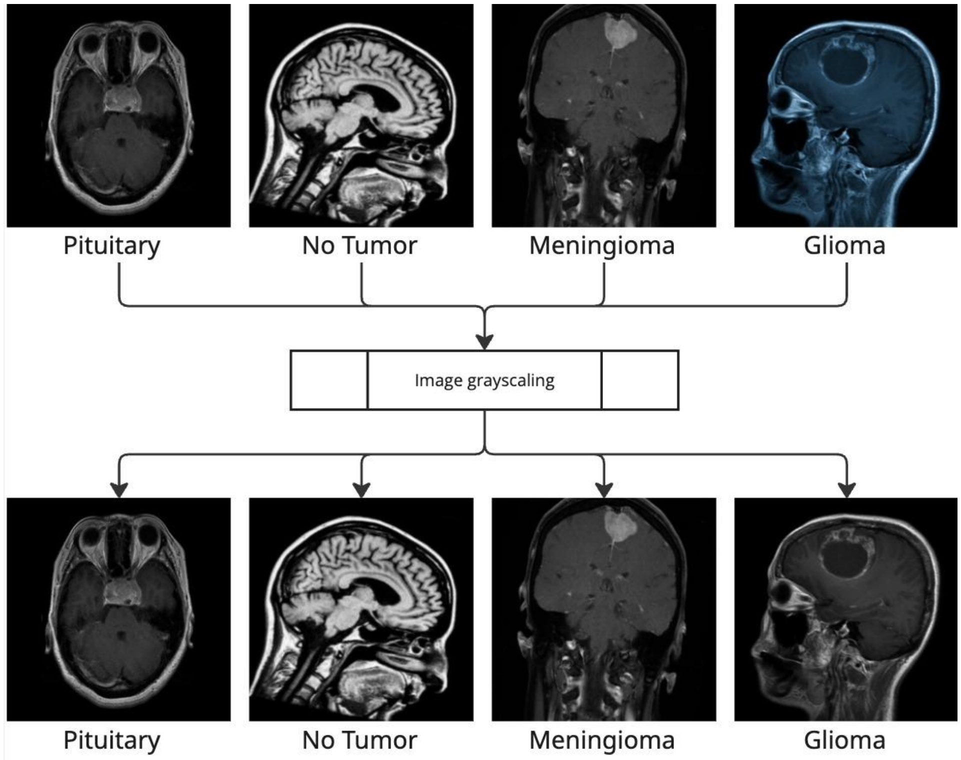


Fig 3.3: Image processing (before grayscaling & after grayscaling)

3.3.1 Data Augmentation & Normalization:

We applied a data augmentation pipeline using Keras which applies various random transformations to minimize the difficulty of improving image contrast, generalization, model accuracy, etc, and reduce overfitting. Data augmentation approach including –

- Vertical Flip
- Rotation
- Zoom
- Contrast
- Brightness variation
- Translation

In this research study, data augmentation and normalization were important preprocessing techniques used to enhance the efficiency and generalization of the deep learning designs for brain tumor classification. Information enhancement was used to the training set to artificially increase the size and diversity of the dataset, which helps avoid overfitting and enhances the model's capability to generalize throughout hidden data. Various augmentation techniques were utilized using the Keras library, including random vertical flipping, rotation, zooming, contrast modification, brightness variation, and translation. These changes introduced variability in the training images, imitating real-world conditions such as various patient orientations and lighting conditions during MRI acquisition.

To ensure the model encounters a variety of input versions during training, these augmentations are applied before normalization. We also carried out a normalization process to control complexity and encourage consistency. Normalization is a vital process to reduce the complexity resulting from the great number of pixels given the many intensity values. The size of the picture was carefully changed from the natural range of 0-255 to a normalized range of 0-1. Normalization helps stabilize and accelerate the training procedure by ensuring that the input information has a constant distribution, decreasing the risk of supremacy by high-intensity pixels and enabling the model to assemble more efficiently. Thus, simplifying the following strategies improved overall performance. Here only the training dataset is augmented but both training and validation datasets are normalized to maintain consistency.

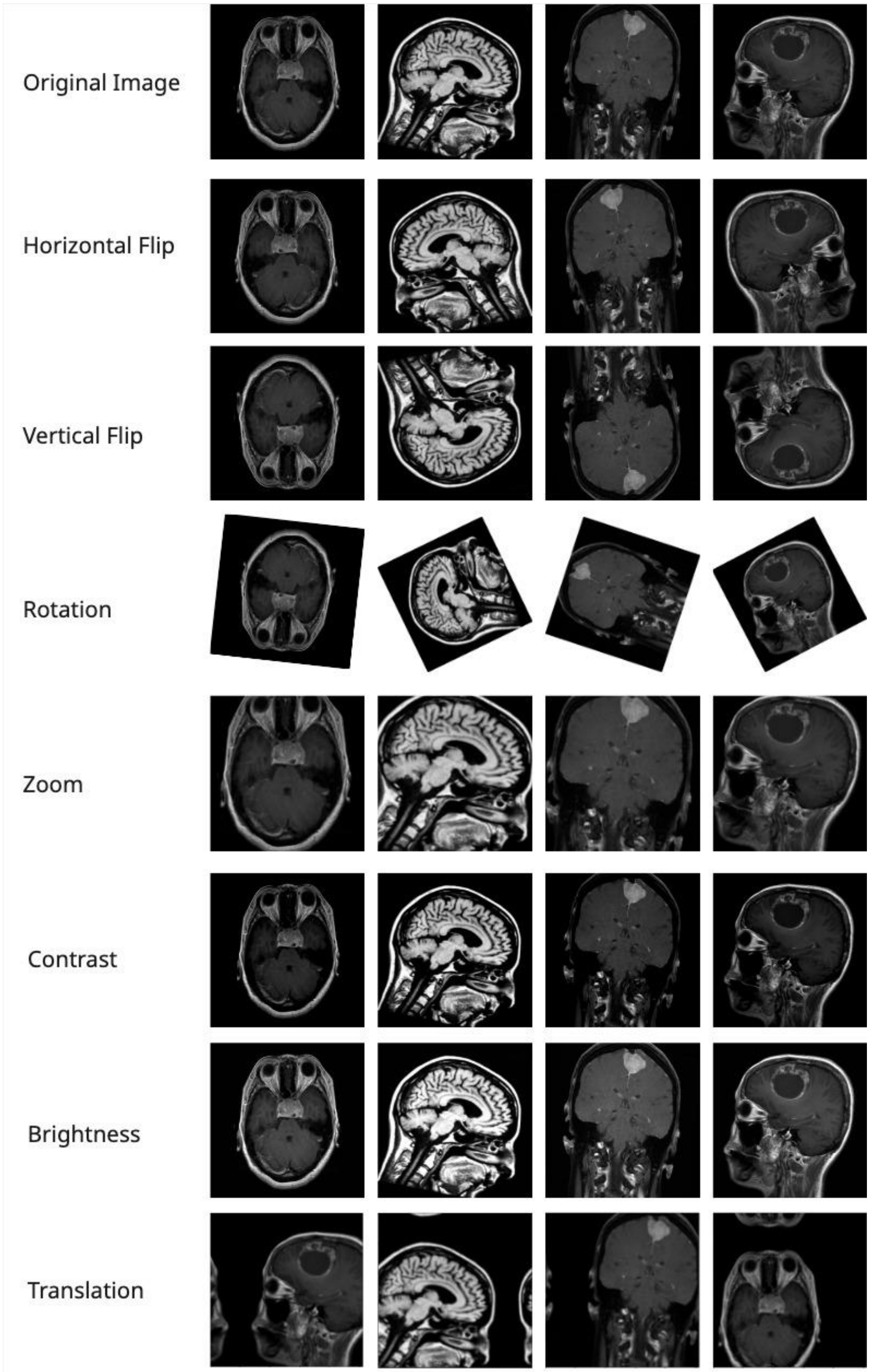


Fig. 3.4: Images of Brain MRI after Augmentation

3.4 Deep Learning Models

This research developed customized hybrid CNN model named VGG16-ResNet50 for brain tumor detection and classification with a transfer learning model.

3.4.1.Proposed Hybrid CNN (VGG16 and ResNet50) for Brain Tumor Classification

In this context, a hybrid deep learning model combining two prominent convolutional neural network architectures; VGG16 and ResNet50 is developed by using transfer learning. Both of those models are pre trained on ImageNet. The model integrates features extracted from both networks to enhance classification performance. We preprocessed the dataset by rescaling pixel values and augmented the dataset using a variety of transformations such as horizontal flipping, rotation, and zooming to enhance generalization and resizing the input images into 224×224 pixels.

Then we normalized the augmented dataset and split into training and validation sets in an 80:20 ratio. We applied fine-tuning to enhance feature learning by unfreezing the last 8 layers of VGG16 and the last 20 layers of ResNet50. We created a unified feature vector by globally averaging and concatenating the feature maps taken from both basis models and passed through a series of fully connected layers with Leaky ReLU activations, batch normalization and L2 regularization. To avoid overfitting issues we've done "Layer(L2) Regularization and Dropout". The AdamW optimizer with a rate of 0.0005 and weight decay of 1e-4 was used to construct the model. We employed EarlyStopping callbacks and ReduceLROnPlateau to improve training accuracy.

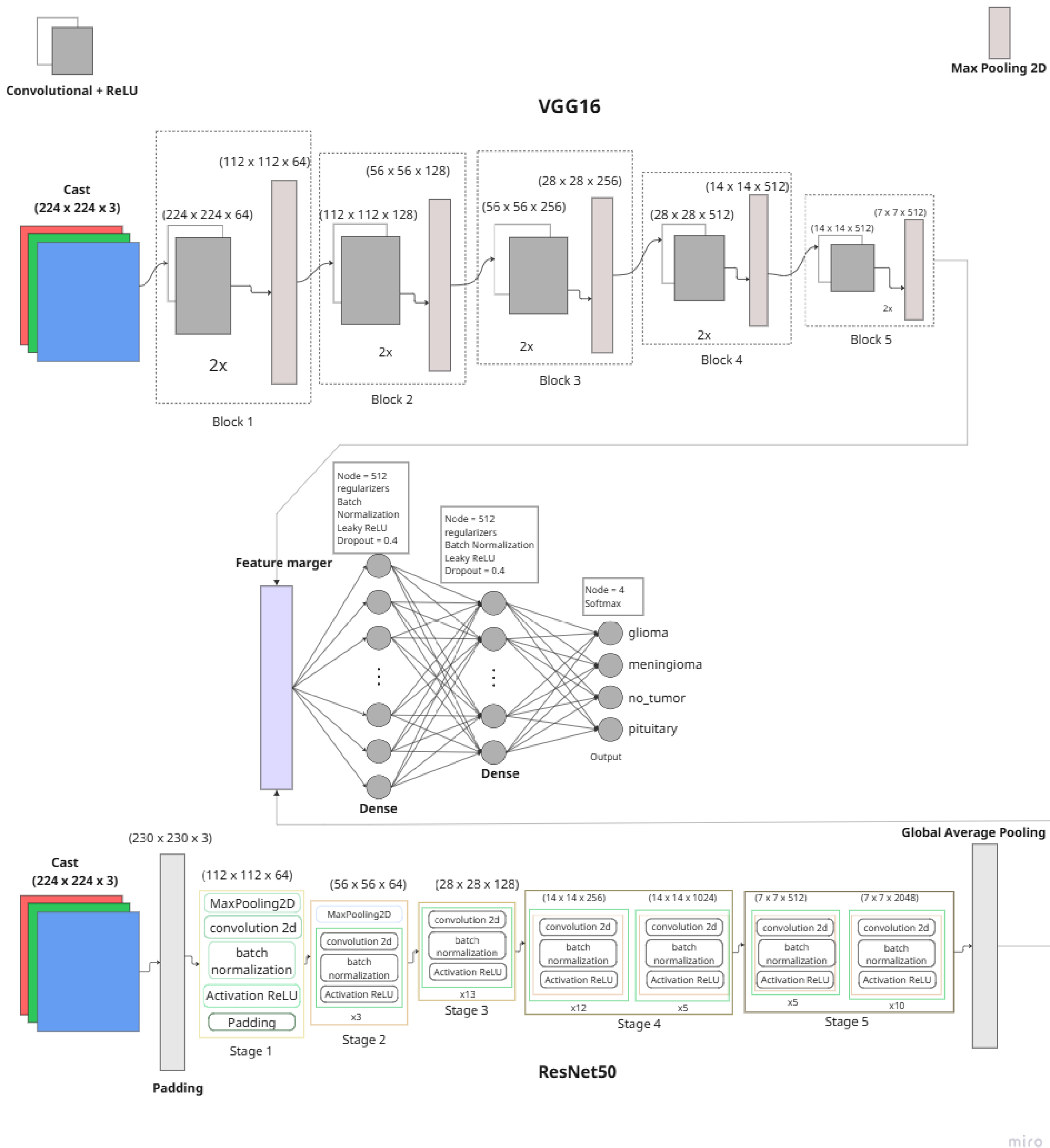


Fig. 3.6: Proposed Hybrid Model (VGG16+ResNet50) architecture

Table. 3.2: Hybrid model summary information

Architecture	Hybrid (VGG16 + ResNet50)
Batch Size	32
Number of Epochs	50
Learning Rate	3e-4
Weight decay	1e-4
Optimizer	AdamW
Total parameters	39,682,372
Trainable parameters	39,627,972
Non-trainable parameters	54,400
Model Size	151.38 MB

3.4.2. Convolution Neural Network (CNN)

A Convolution Neural Network (CNN) model was developed to classify brain tumor images. The dataset of labeled MRI images was preprocessed by resizing the (250×250) and augmented the dataset using a variety of transformations such as flipping, rotation, zoom, contrast adjustment, brightness variation and translation. The dataset was split into training (80%) and testing (20%) sets. The CNN architecture included multiple convolutional layers with increasing filter sizes (32 to 256), batch normalization, and max-pooling. A softmax-activated output layer enabled tumor class prediction. It was compiled with the Adam optimizer (learning rate = 0.0005) and trained using sparse categorical cross-entropy, balancing model complexity with regularization to optimize validation accuracy.

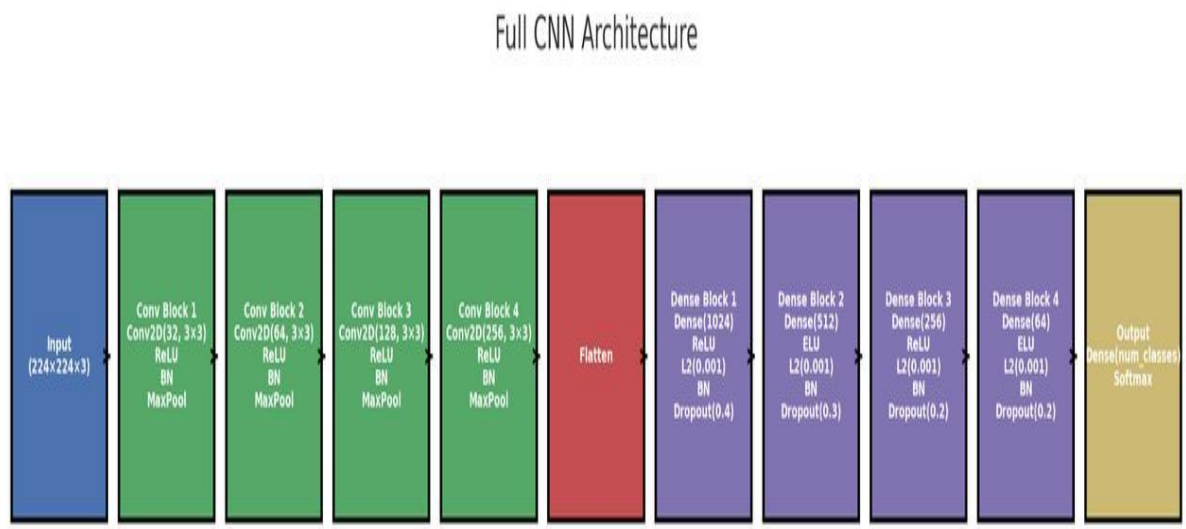


Fig. 3.6 CNN architecture

3.4.3 Custom DenseNet121

This vector is passed through a series of totally connected layers comprising 3 thick layers with 1024, 512, and 512 systems, respectively, each initialized with He normal initialization and regularized with L2 penalties to prevent overfitting. Batch normalization is applied after each dense layer to support training, and dropout layers with rates of 0.4 and 0.3 are integrated to improve generalization. The final dense layer outputs class probabilities using a softmax activation, matching the number of target classes in the dataset**.**

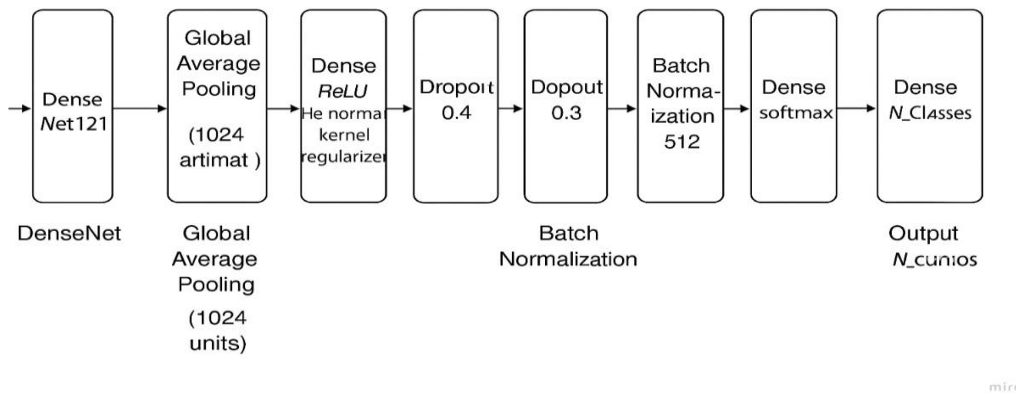


Fig. 3.7: Architecture of DenseNet121

3.4.4 Inception V3

This deep knowing model is constructed on top of the InceptionV3 architecture, pre-trained on ImageNet, and fine-tuned with additional thick layers for classification. The model outputs forecasts through a Dense layer with 4 units (matching the number of target classes) and a softmax activation for multi-class category. The model consists of 24.7 million parameters, with roughly 2.89 million trainable (generally from the included thick layers) and the rest frozen in the InceptionV3 foundation**.**

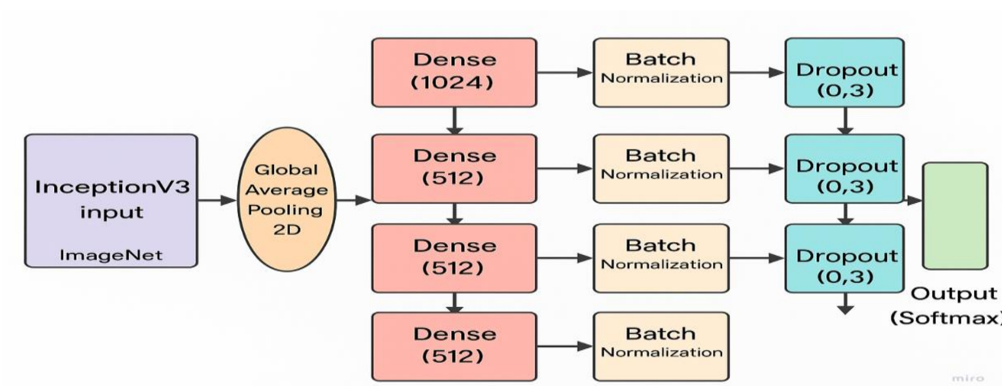


Fig. 3.8: Architecture of Inception V3

3.4.5 VGG16 based Transfer Learning:

In this study, we employed transfer learning techniques using the pre-trained model to classify brain tumor images where it exhibits notable performance to discern tumor types. A comprehensive augmentation was applied including flipping, rotation, zoom, contrast, brightness and translation) to improve generalization and resized input images into 224×224 pixels. The dataset was split into training (80%), validation (10%), and testing (10%) subsets. The VGG16 model, pre-trained on ImageNet, was used as a feature extractor with layers before Block 3 froze to retain low-level learned features. A custom classification head was added, consisting of dense layers with ReLU activation, batch normalization, and dropout for regularization. Normalization and augmentation were applied before training. The model was compiled with the Adam optimizer and a low learning rate (1e-5) to ensure stable fine-tuning.

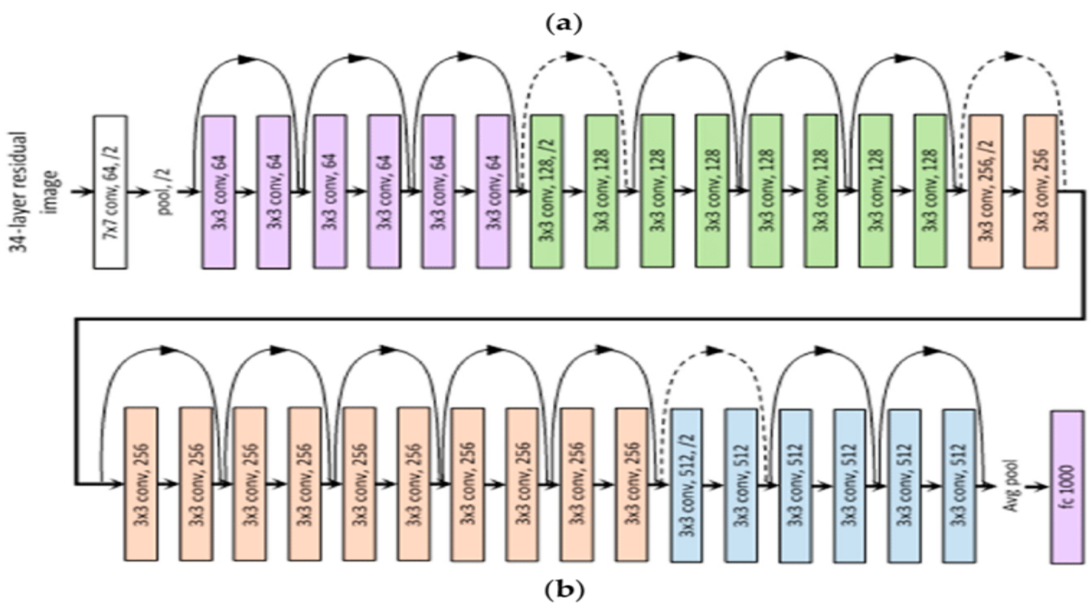


Fig. 3.9: Architecture of VGG16

3.4.6 Custom ResNet50

This work presents a custom convolutional neural network inspired by the ResNet architecture to classify brain tumor images. The dataset was preprocessed with image augmentation techniques such as random flipping, rotation, zooming, contrast, brightness, and translation. Images were then normalized and divided into training and validation sets in an 80:20 ratio. The proposed model begins with an initial convolution and max-pooling layer, followed by multiple residual blocks with increasing filter sizes (64, 128, 256, 512) to capture hierarchical features. Skip connections were implemented to improve gradient flow and reduce degradation in deeper layers. The extracted features were aggregated using global average pooling, followed by three fully connected layers with dropout for regularization. The output layer employed a softmax activation function to perform multi-class classification.

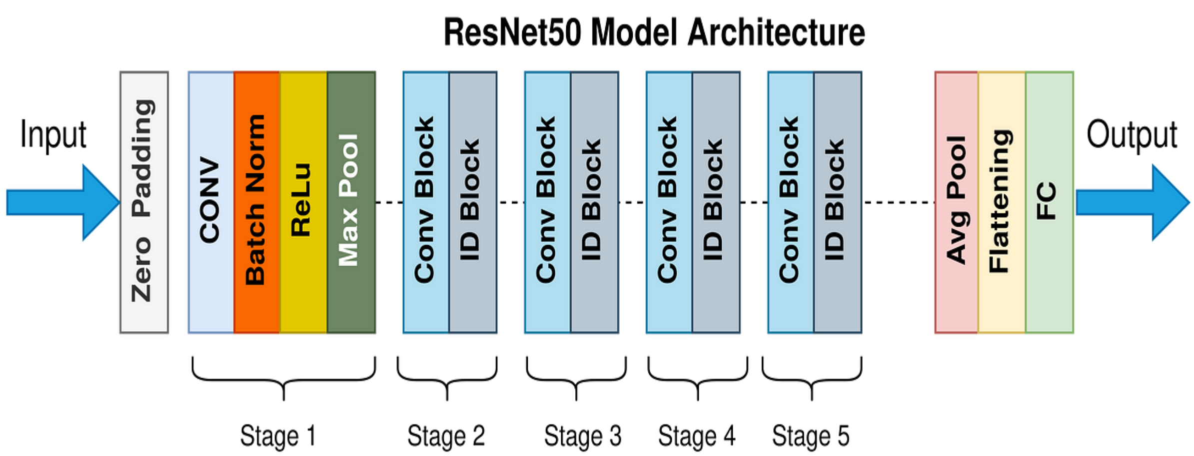


Fig. 3.10: Architecture of ResNet50

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Results of all Deep Learning models:

Here is a table of all the results together of all models used in this study. The table compares the performance of several models, consisting of CNN, DenseNet121, Inception v3, VGG16, ResNet50, and a proposed hybrid model (VGG16 + ResNet50), in categorizing brain growth types. The Hybrid Model achieved the highest accuracy of 98.5%, mastering precision and recall for all tumor types. VGG16 followed with a high accuracy of 96.5%, showing strong lead to glioma and no growth detection. ResNet50 also carried out well with 96% precision, particularly in spotting no tumor. DenseNet121 and Inception v3 achieved accuracies of 91% and 87% respectively.In general, the Hybrid Model outlines the others, using the most well balanced and accurate results throughout all tumor types.

Table 4.1: Performance comparison of all deep learning models of this study

Method	**Class**	**Precision**	**Recall**	**F1-Score**	**Cohen's Kappa**	**Sensitivity**	**Specificity**
CNN	glioma_tumor	0.84	0.94	0.89	0.83	0.94	0.93
	meningioma_tumor	0.96	0.63	0.76			
	no_tumor	0.92	0.98	0.95			
	pituitary_tumor	0.79	0.91	0.84			
Accuracy		**86.5%.**					
DenseNet	glioma_tumor	0.82	0.96	0.88	0.88	0.96	0.92
	meningioma_tumor	0.91	0.82	0.86			
	no_tumor	0.98	0.99	0.98			

121	pituitary_tumor	0.96	0.87	0.91			
Accuracy		**91%**					
Incep-tion v3	glioma_tumor	0.86	0.88	0.87	0.83	0.88	0.95
	meningioma_tumor	0.88	0.67	0.76			
	no_tumor	0.93	0.98	0.95			
	pituitary_tumor	0.82	0.96	0.89			
Accuracy		**87%**					
VGG16	glioma_tumor	0.97	0.97	0.97	0.95	0.97	0.99
	meningioma_tumor	0.99	0.95	0.97			
	no_tumor	0.95	1.00	0.97			
	pituitary_tumor	0.95	0.94	0.94			
Accuracy		**96.5%**					
Resnet 50	glioma_tumor	0.97	0.96	0.96	0.96	0.96	0.99
	meningioma_tumor	0.98	0.94	0.96			
	no_tumor	0.99	0.99	0.99			
	pituitary_tumor	0.95	0.99	0.97			
Accuracy		**96%**					
Propose d Hybrid Model (VGG66 +Resnet 50)	glioma_tumor	0.98	1.00	0.99	0.98	0.99	0.99
	meningioma_tumor	0.98	0.99	0.99			
	no_tumor	0.98	1.00	0.99			
	pituitary_tumor	1.00	0.95	0.97			
Accuracy		**98.5%**					

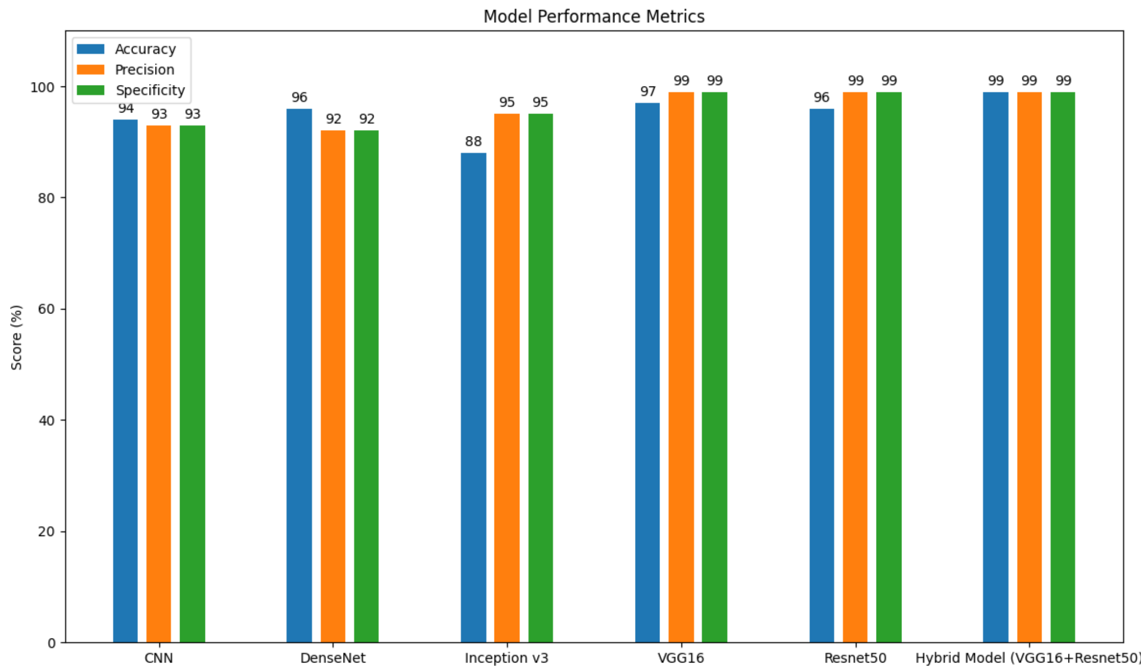


Fig 4.1: Deep Learning Model Performance metrics

4.2 Results of all Machine Learning models :

The efficiency of various machine learning classifiers for brain tumor category was assessed utilizing metrics such as accuracy, recall, F1-score, Cohen's Kappa, sensitivity, uniqueness, and total precision. Among the models evaluated, the Random Forest classifier achieved the highest precision at 81.4%, followed by K-Nearest Neighbors (76%), Decision Tree (75.5%), and MLP (73.8%). Logistic Regression and SVM showed lower performance, both with a precision of 61%. Random Forest regularly exceeded other models throughout all tumor types, showing its efficiency in handling complicated classification tasks in medical imaging.

Table. 4.2: Performance comparison of all Machine learning models of this study

Method	Class	Precision	Recall	F1-Score	Cohen's Kappa	Sensitivity	Specificity
Decison Tree Classifier	glioma_tumor	0.72	0.72	0.73	0.68	0.75	0.92
	meningioma_tumor	0.67	0.69	0.68			
	no_tumor	0.84	0.85	0.85			
	pituitary_tumor	0.78	0.75	0.77			
Accuracy		**75.5%**					
Radom forest classifier	glioma_tumor	0.80	0.79	0.79	0.75	0.81	0.93
	meningioma_tumor	0.75	0.73	0.74			
	no_tumor	0.90	0.90	0.90			
	pituitary_tumor	0.81	0.83	0.82			
Accuracy		**81.4%**					
KNN	glioma_tumor	0.71	0.73	0.73	0.68	0.76	0.92
	meningioma_tumor	0.67	0.66	0.66			
	no_tumor	0.87	0.87	0.87			
	pituitary_tumor	0.79	0.77	0.78			
Accuracy		**76%**					
MLP Classifier	glioma_tumor	0.71	0.72	0.72	0.65	0.74	0.91
	meningioma_tumor	0.64	0.60	0.61			
	no_tumor	0.83	0.83	0.83			
	pituitary_tumor	0.75	0.81	0.78			
Accuracy		**74%**					

Logistic Regression	glioma_tumor	0.56	0.63	0.60	0.47	0.61	0 .87
	meningioma_tumor	0.51	0.44	0.47			
	no_tumor	0.73	0.60	0.66			
	pituitary_tumor	0.64	0.75	0.69			
Accuracy		**61%**					
Support Vector Machine (SVM)	glioma_tumor	0.68	0.55	0.61	0.49	0.61	0.87
	meningioma_tumor	0.52	0.68	0.53			
	no_tumor	0.85	0.52	0.64			
	pituitary_tumor	0.71	0.69	0.71			
Accuracy		**61%**					

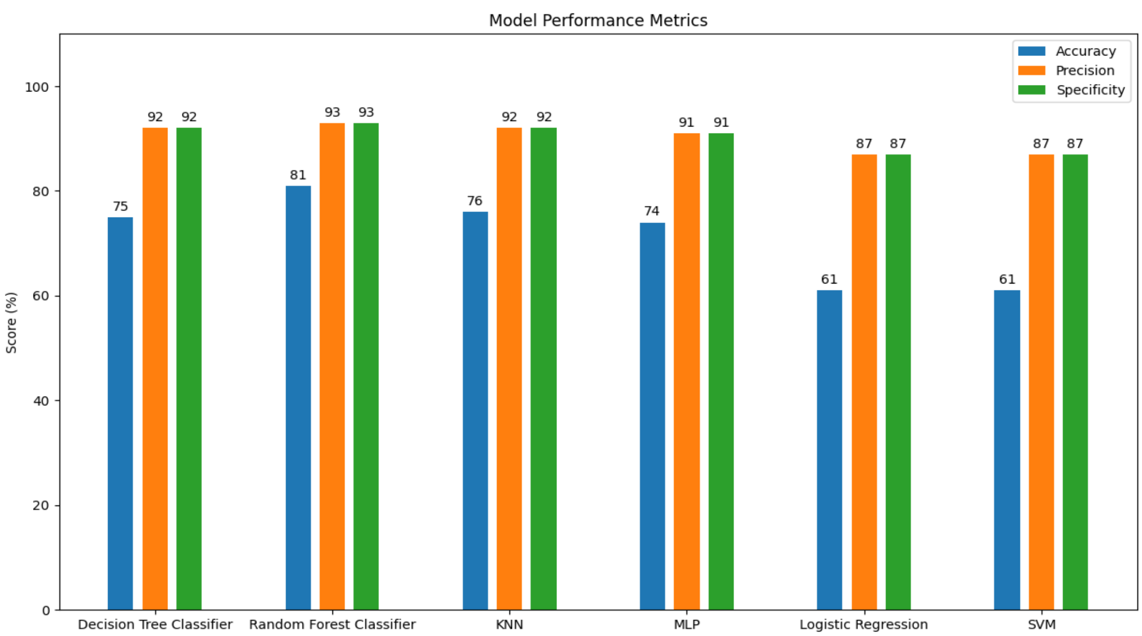


Fig 4.2: Machine Learning Model Performance metrics

4.3 Comparative Study of Experimental Results & Analysis:

Here, Table 4.3 shows accuracy comparison between deep learning and machine learning models used in this research study.

Table 4.3: Comparative table of DL and ML mode

Deep Learning Models	Accuracy	Machine Learning Models	Accuracy
CNN	86.5%	Decision Tree	75.5%
DenseNet121	91.0%	Support Vector Machine (SVM)	61.0%
Inception V3	87.0%	K-Nearest Neighbors (KNN)	76.0%
VGG16	96.5%	Multi-Layer Perceptron (MLP)	74.0%
ResNet50	96.0%	Logistic Regression	61.0%
Hybrid Model (VGG16 + ResNet50)	**98.5%**	Random Forest	81.4%

The comparative analysis of deep learning and machine learning models for brain tumor category exposes a substantial performance benefit for deep learning methods. Among all examined designs, the Hybrid Model integrating VGG16 and ResNet50 achieved the highest accuracy of 98.5%, surpassing individual deep knowing architectures like VGG16 (96.5%) and ResNet50 (96%). Standard deep knowing models such as CNN and Inception v3 demonstrated lower accuracy at 86.5% and 87%, respectively. In contrast, artificial intelligence designs displayed significantly lower precision, with Random Forest achieving the greatest among them at 81.4%, while Logistic Regression and SVM lagged at 61%.

Overall, **deep learning models, particularly the hybrid architecture**, demonstrated superior category abilities, making them more suitable for intricate medical image analysis tasks like brain tumor detection compared to traditional maker discovering algorithms. Here is a comparison of our propose hybrid deep learning model performance with other existing hybrid model's performance:

Table 4.4: Performance comparison of Proposed model with Other existing models

Model	Architecture	Dataset	Accuracy	Key Features
ResViT (2024)	Residual Vision Transformer	BraTS, Figshare, Kaggle	98.53%	CNN-ViT hybrid using self-supervised learning
FusionNet (2024)	Deep CNN + Statistical Features	BraTS	97.53%	Deep features + radiomics handcrafted features
VGG16–ResNet50 Hybrid (2024)	VGG16 + ResNet50	Not specified	99.98%	Transfer learning-based ensemble, similar to yours
MobileNetV2 + SVM (2024)	MobileNetV2 + SVM	Not specified	98.82%	Lightweight CNN + SVM, efficient and high performing
GoogleNet + SVM (2024)	GoogleNet + SVM	Kaggle MRI dataset	98.1%	Deep feature extraction combined with SVM classifier

BrainNet (2024)	Custom CNN	Not specified	97.71%	Tailored CNN outperforming some pre-trained models
Ensemble Model (2023)	CNN + LSTM	Multiple datasets	98.82%	Deep learning ensemble with temporal modeling
Res-BRNet (2022)	Residual and Regional CNN	Kaggle & Figshare	98.22%	Modified spatial and boundary-focused convolution blocks
Custom CNN (2024)	Lightweight CNN	Brain Tumor MRI Dataset	98.09%	Simpler architecture aimed at efficiency
IVX16 (2023)	VGG16 + InceptionV3 + Xception	Multiple Datasets	96.94%	Transfer learning-based multi-architecture fusion
Enhanced CNN Model (2023)	U-Net, RefineNet, SegNet	Benchmark Dataset	96.85%	Local and contextual info for segmentation and classification
EfficientNetB1 (2022)	EfficientNetB1	Custom Dataset	89.55%	Scalable and lightweight model
CapsNet (2022)	Capsule Neural Network	Custom Dataset	90.89%	Emphasizes boundary learning via capsules
Proposed Hybrid Model	**VGG16 + ResNet50**	**~40,000 MRI images**	**98.5%**	**Combines VGG16 & ResNet50, mixed precision, controlled data augmentation**

4.3 Evolution Methods

In this study, several assessment metrics were utilized to examine the performance of brain tumor classification models. Precision provides an overall measure of accuracy, while precision and recall examine how well the model identifies true growth cases and prevents incorrect alarms. The F1-score offers a balance in between precision and recall, making it suitable for imbalanced datasets. Uniqueness determines the model's ability to properly recognize non-tumor cases, and Cohen's Kappa evaluates the agreement in between predicted and real classifications beyond possibility. Together, these metrics make sure a dependable and comprehensive assessment of the proposed hybrid model's efficiency in medical diagnostics.

After classification of images then forecasted with Transfer Learning model. The evaluation is utilizes the confusion matrix like, accuracy, accuracy, recall, F1 score, Cohen's uniqueness, level of sensitivity, and kappa. True favorable (TP) values hold true in truth. False positives (FP) take place when incorrect outcomes are mislabeled. The third kind, incorrect unfavorable (FN), takes place when a correct worth is misinterpreted as unfavorable. TN and FN are the fifth and 4th options. A real negative (TN) is a positive worth misidentified as unfavorable. 4th is true negative (TN).

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad (1)$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \quad (2)$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (3)$$

$$\mathrm{F1\ Score} = 2 \times \frac{\mathrm{precision} \times \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}} \quad (4)$$

$$\text{Cohen's kappa, } \mathrm{K} = \frac{p_0 - p_e}{1 - p_e}$$

Here,

$$p_0 = \frac{TP+TN}{TP+TN+FP+FN}$$

$$p_e = \frac{(TP+FP)(TP+FN)+(FN+TN)(FP+TN)}{TP+TN+FP+FN} \tag{5}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{6}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{7}$$

4.4.1 Accuracy and Loss Curve

Figure 4.2: The image compares training and validation efficiency (accuracy and loss) throughout several deep knowing models-- CNN, Custom DenseNet121, Inception v3, Custom VGG16, Custom ResNet50, and a Hybrid model (VGG16 + ResNet50)-- used for brain tumor category. Amongst them, Custom ResNet50, Custom VGG16 and the Hybrid model demonstrate the very best efficiency, showing consistent and high precision with minimal loss and strong generalization. Inception v3 and Custom DenseNet likewise perform well, displaying steady training and recognition curves. Overall, much deeper architectures and hybrid techniques yield more trustworthy and precise outcomes for brain tumor detection jobs.

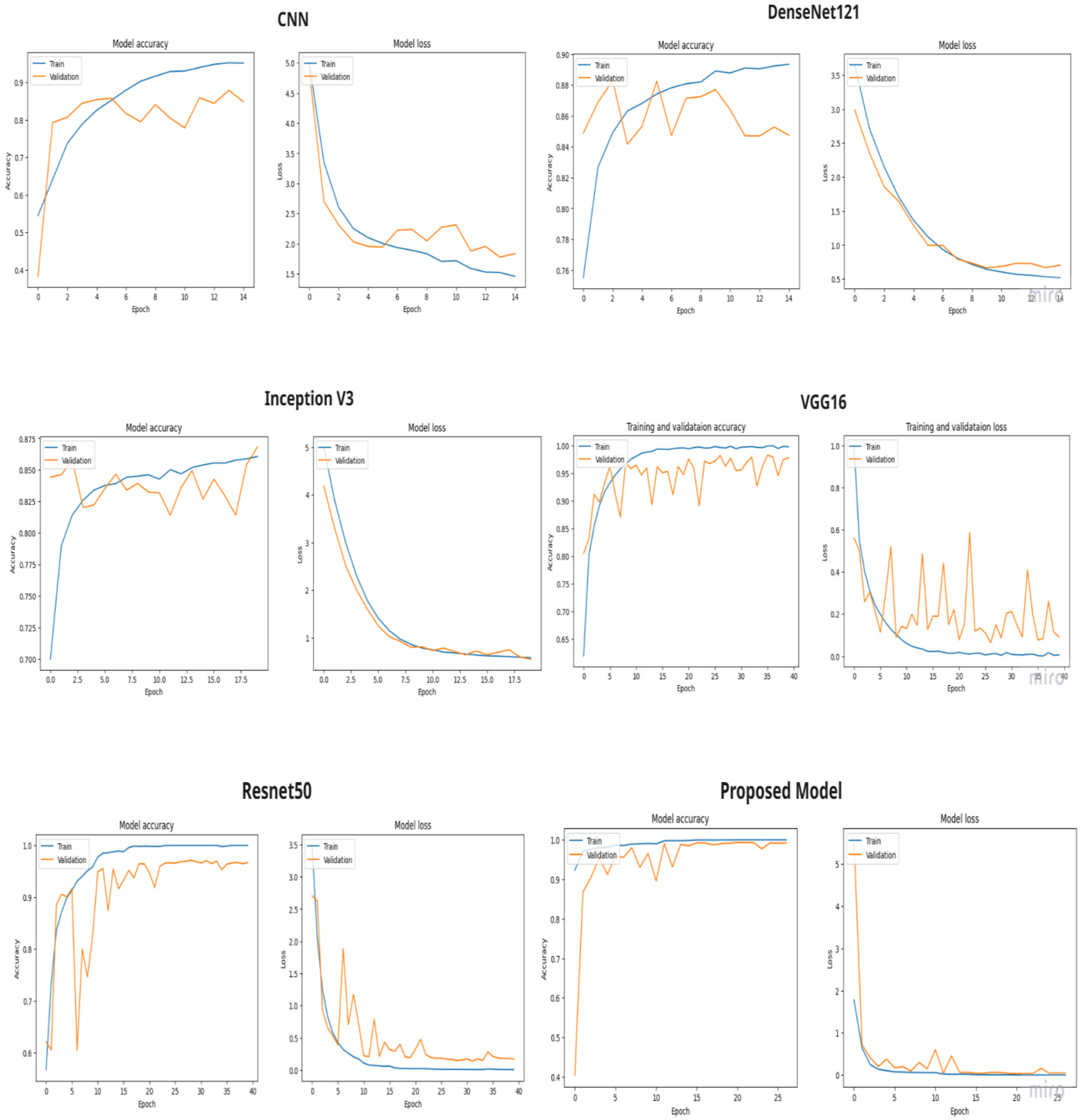
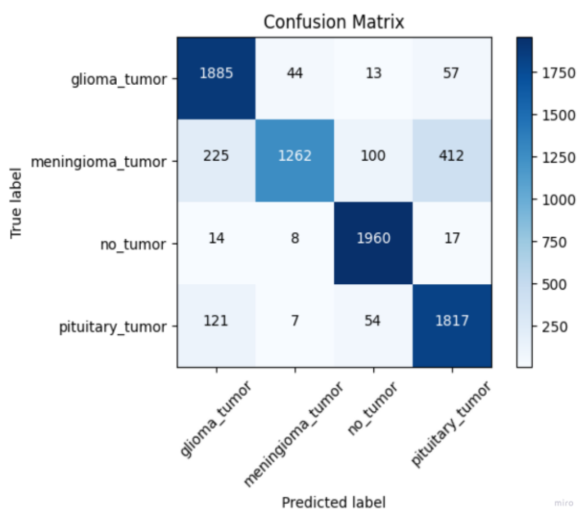


Fig 4.2. Accuracy and Loss Curve of all models.

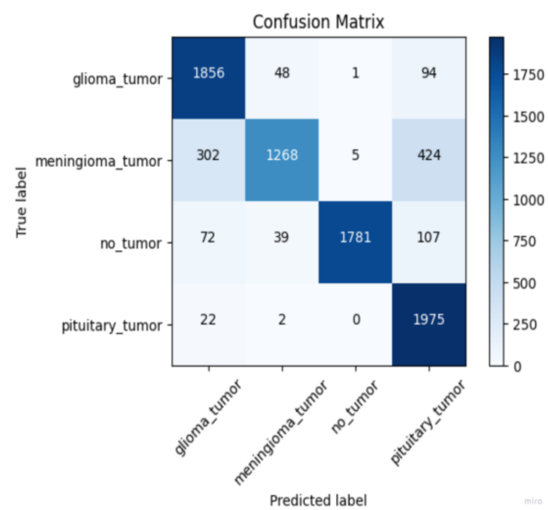
4.4.2 Confusion Matrix

Figure 4.3: The Hybrid model (VGG16 + ResNet50) and Custom ResNet50 show the highest precision throughout all growth classes, with very couple of misclassifications, particularly for the "no_tumor" and "pituitary_tumor" classes. Customized VGG16 also carries out strongly however shows slightly more confusion in between glioma and meningioma growths.

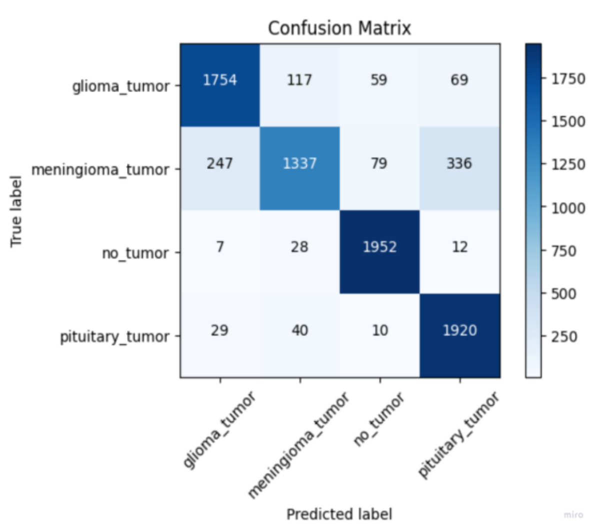
CNN



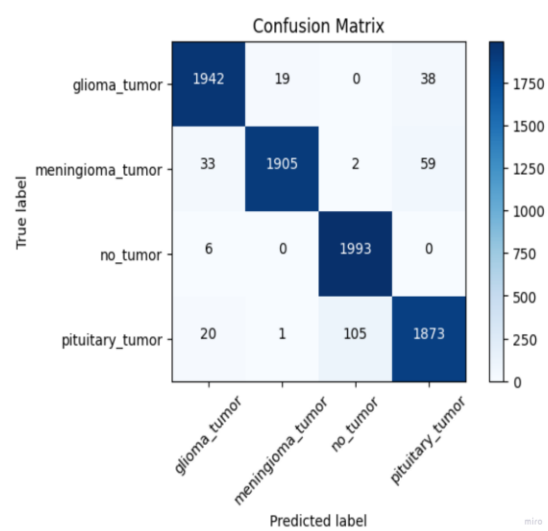
DenseNet121



Inception V3



VGG16



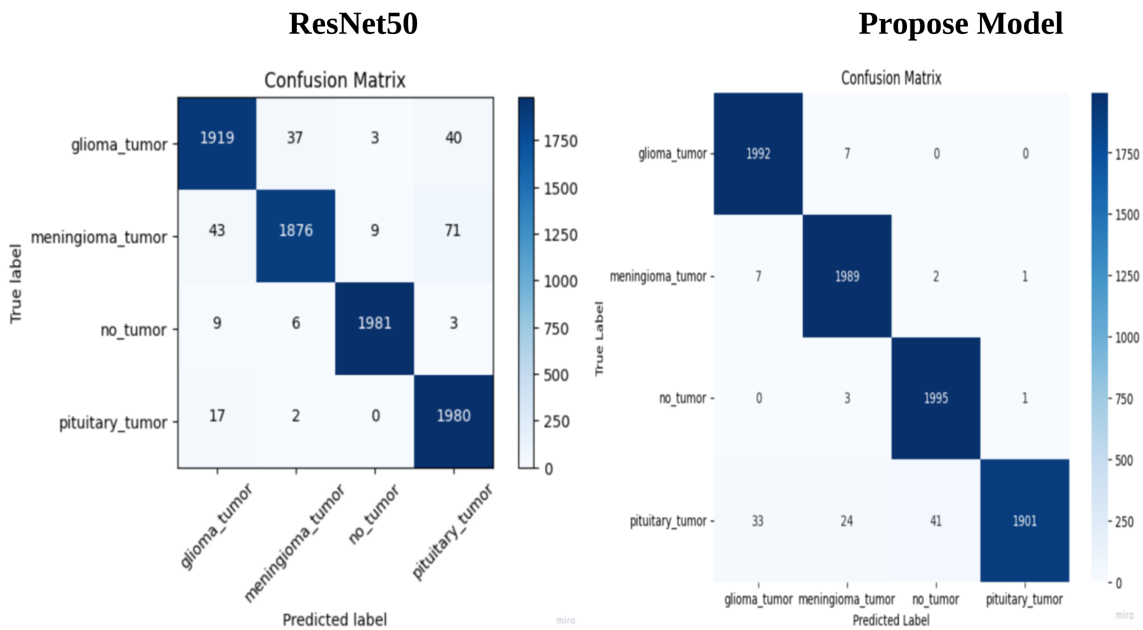
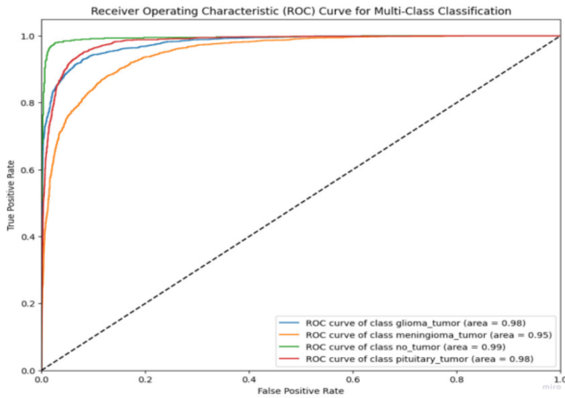


Fig 4.3. Confusion Matrix of all models

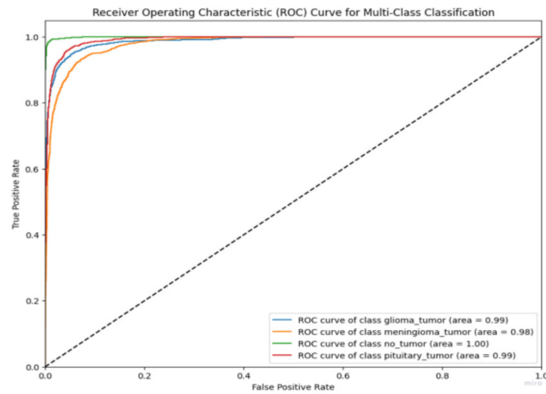
4.4.3 ROC Curve

Figure 4.4: The ROC curves provided for various models in the brain tumor category task show the comparative effectiveness of each architecture. Amongst all, the Hybrid model (VGG16 + ResNet50) and Custom ResNet50 exhibit the very best efficiency, with ROC AUC worths approaching 1.0 across all classes-- glioma, meningioma, pituitary, and no tumor-- suggesting near-perfect level of sensitivity and uniqueness. Customized VGG16 also carries out remarkably well, with consistently high curves. On the other hand, the fundamental CNN design reveals fairly lower ROC AUC ratings, showing weaker class discriminationIn general, the examination underscores that much deeper and more intricate models, especially the Hybrid and ResNet-based architectures, use superior diagnostic precision in multi-class brain growth classification.

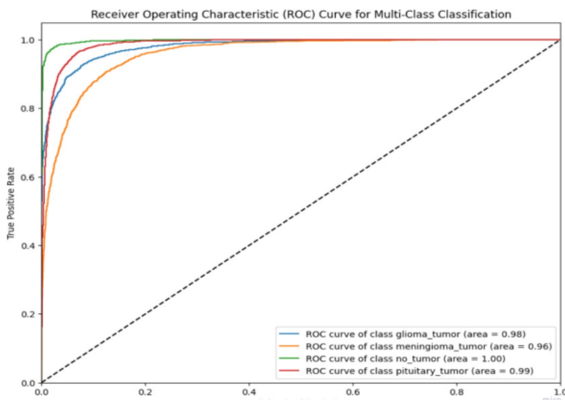
CNN



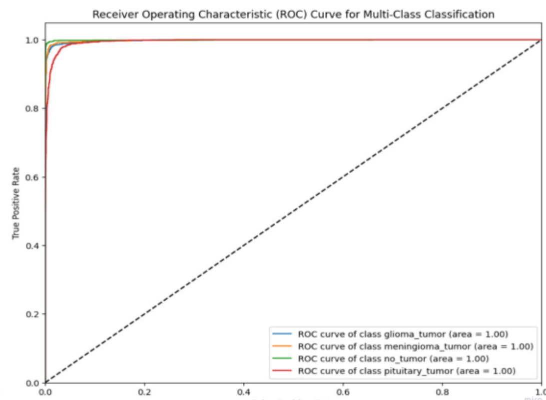
DenseNet121



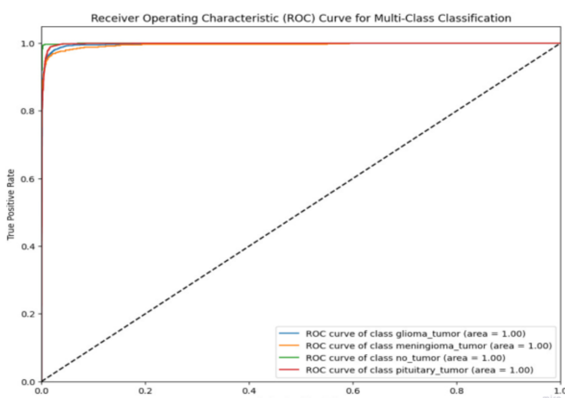
Inception V3



VGG16



ResNet50



Propose Model

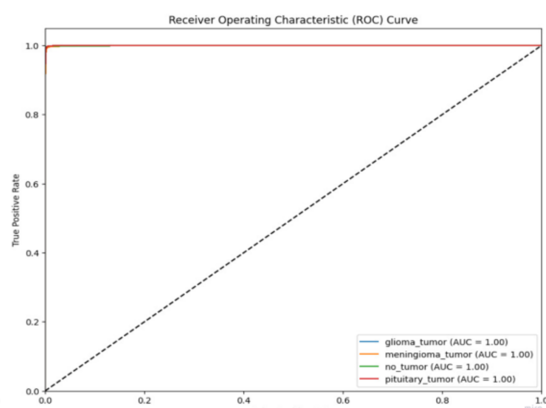


Fig 4.5. ROC curve of all models

4.5 Discussion

The findings of this research study highlight the efficiency of deep learning approaches, particularly hybrid models, in the category of brain tumors from MRI images. A detailed evaluation was performed utilizing both traditional machine learning algorithms-- such as Decision Tree Classifier, Random Forest, K-Nearest Neighbors, Support Vector Machine(SVM), Logistic Regression, and Multi-Layer Perceptron (MLP)-- and deep knowing architectures including basic- CNN, Inception V3, customized - DenseNet121, VGG16, ResNet50 approaches and eventually, a proposed hybrid model customized (VGG16+ResNet50) that incorporates both.

Amongst the conventional machine disc overing models, Random Forest accomplished the highest precision of 81.4%, followed carefully by K-Nearest Neighbors (76%) and Decision Tree (75.5%). These models had the ability to perform reasonably well however revealed restrictions in dealing with complicated feature spaces, specifically when separating between comparable growth types such as glioma and meningioma. The lower performance of SVM and Logistic Regression (both at 61% accuracy) further suggests that these models battle with the high-dimensional nature and variability of MRI image information without sophisticated feature extraction mechanisms.

In contrast, the deep knowing designs displayed substantially exceptional efficiency. VGG16 and ResNet50 accomplished accuracies of 96.5% and 96%, respectively, showing their strength in discovering deep hierarchical functions from images. The proposed hybrid design, integrating VGG16 and ResNet50, went beyond all with a precision of 98.5%. This enhancement can be attributed to the blend of complementary functions drawn out from both networks-- VGG16's strength in maintaining spatial info and ResNet50's capability to deal with much deeper architectures with residual knowing.

The hybrid model not only demonstrated remarkable accuracy but likewise achieved high values in vital assessment metrics such as precision, recall, F1-score, specificity, and Cohen's Kappa. The high Cohen's Kappa worths indicate strong arrangement between the predicted and real categories beyond opportunity, verifying the model's reliability. The elevated uniqueness and sensitivity worths suggest that the model successfully lowers both false positives and false negatives, which is necessary in medical diagnostics where misclassification can have major consequences.

The success of the hybrid deep learning model underscores the importance of leveraging numerous architectures to improve generalization and performance. The usage of grayscale image preprocessing helped in noise decrease and dimensionality management, which likely contributed to boosted design performance.

These results not just validate the effectiveness of deep learning, especially hybrid architectures, for medical image analysis but also suggest their possible for real-world clinical integration. Automated systems powered by such designs could assist radiologists in early medical diagnosis, decrease manual workload, and ultimately result in much better client outcomes. Nevertheless, additional validation with real-time clinical information and diverse imaging conditions is required before deployment in healthcare settings.

In contrast, the deep learning models displayed significantly remarkable efficiency. The proposed hybrid design, integrating VGG16 and ResNet50, surpassed all with a precision of 98.5%. The hybrid model not just showed superior accuracy however likewise attained high values in important assessment metrics such as accuracy, recall, F1-score, uniqueness, and Cohen's Kappa.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on society

The development of an accurate, automatic system for brain growth detection carries extensive implications for society, especially in the areas of healthcare accessibility, early medical diagnosis, and clinical effectiveness. Brain tumors, being among the most dangerous neurological disorders, require accurate and timely identification for effective treatment. However, access to expert radiologists and diagnostic facilities remains limited in many parts of the world-- specifically in low-resource and rural regions. The proposed hybrid deep knowing design has the possible to bridge this gap by offering a scalable, effective, and trusted diagnostic assistance system that can help doctor regardless of their geographical area or institutional capacity. From a public health viewpoint, the design promotes early detection, which can substantially increase survival rates, lower treatment costs, and improve lifestyle for clients. By assisting in quicker and more accurate classification of growth types, it likewise facilitates individualized treatment preparation, which is a foundation of contemporary accuracy medicine. The execution of AI-based diagnostic tools has the prospective to reduce the workload on medical experts, allowing radiologists to focus on complex cases and make better-informed choices. This not only improves clinical outcomes however likewise enhances overall healthcare system performance and minimizes human mistake in regular image interpretation.

In the long term, such innovations can contribute to worldwide health equity, allowing under-resourced centers and hospitals to benefit from the exact same sophisticated diagnostic capabilities as top-tier medical institutions. As AI becomes more integrated into healthcare delivery, the social perception of medical technology might move towards greater trust and approval, provided that ethical factors to consider such as personal privacy, accountability, and openness are supported.

Ultimately, this research study supports the vision of technology-assisted, patient-centered care, and leads the way for more innovations in AI-powered healthcare. It shows how deep knowing can play a critical role in equalizing access to advanced medical diagnostics, saving lives, and transforming the method society approaches critical health obstacles.

5.2 Impact on the environment

While the primary focus of this research study is on enhancing medical diagnostics through deep learning, it likewise bears environmental ramifications, particularly in the context of computational resource usage and healthcare system performance. Training deep neural networks-- especially large hybrid architectures like VGG16 and ResNet50-- can be energy-intensive, consuming significant quantities of electrical power and computational power. This adds to carbon emissions, particularly if the training is performed on infrastructure powered by non-renewable energy sources. As the demand for AI in health care grows, so too does the ecological footprint of massive design training. For that reason, addressing energy efficiency becomes an essential issue. To reduce this, the research study integrates strategies such as early stopping, dropout, and L2 regularization to lower unnecessary calculation and overfitting. In future implementations, design compression, pruning, and the usage of light-weight architectures can even more lower energy consumption. Furthermore, transitioning training and deployment to cloud platforms powered by renewable resource sources provides a sustainable alternative to conventional on-premise computing. From a more comprehensive systems perspective, the adoption of AI-based diagnostic tools can indirectly add to environmental sustainability by enhancing health care workflows. Precise early detection decreases the requirement for repeated scans and invasive treatments, lowering energy and material usage in health centers. Additionally, decreasing diagnostic errors can lessen wasteful treatments and associated resource intake, contributing to a more effective and sustainable healthcare infrastructure.

In summary, while deep knowing models present environmental difficulties due to their computational demands, this research encourages energy-aware AI practices and highlights the potential for AI to promote sustainable healthcare shipment by improving diagnostic precision and reducing systemic ineffectiveness.

5.3 Ethical Aspects

The combination of deep knowing in medical diagnosis, particularly for brain tumor detection, introduces several ethical responsibilities that should be resolved to make sure equitable and accountable implementation. Central to these is the security of client privacy and information security. This research study makes use of anonymized and openly readily available MRI datasets, any future clinical deployment must adhere to rigorous regulative structures such as the General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) to protect sensitive health info. Another critical ethical concern lies in algorithmic openness and accountability. Incorporating explainable AI (XAI) methods in future versions will be vital to ensure the design's outputs are interpretable and reasonable.

In addition, the avoidance of bias is important to promote fairness and medical safety. Training information need to be representative of diverse populations to prevent variations in efficiency across age, gender, or ethnic groups. Models trained on restricted or homogeneous datasets run the risk of producing unequal diagnostic results, thus worsening existing health injustices.

Lastly, ethical AI advancement requires human oversight and obligation for results. Automated systems should work as assistive tools rather than replacements for professional judgment. Clear standards need to be in location to define the functions of AI systems and make sure that health care professionals remain in control of diagnosis and treatment choices.

In summary, ethical considerations in this research encompass data personal privacy, algorithm openness, fairness, and human-centered accountability. Addressing these concerns is necessary not just for constructing trustworthy medical AI but also for guaranteeing safe, inclusive, and accountable integration into medical practice.

5.4 Sustainability Plan

To ensure the long-term success and practical implementation of the proposed hybrid deep learning model for brain tumor category, a comprehensive sustainability technique has actually been laid out. Technologically, the design needs to be optimized through compression and modular style to support efficient operation on varied hardware platforms, including mobile and edge gadgets. Clinically, partnership with health care organizations is essential for real-world recognition and integration with existing medical systems using standard protocols like DICOM and HL7.

Ethical and regulative compliance is a core pillar, requiring rigorous adherence to information personal privacy laws such as GDPR and HIPAA, along with continuous auditing to identify and correct algorithmic bias. Educational outreach will promote sustainability by equipping medical professionals with the understanding to effectively utilize and translate the system, while partnerships with academic organizations will cultivate continuous innovation.

Environmentally, the model's advancement need to emphasize energy-efficient practices to reduce computational overhead, supported by cloud platforms utilizing eco-friendly energy. A robust assistance community involving researchers, clinicians, and policymakers will guarantee the system evolves in positioning with medical advancements, policy modifications, and financing chances-- allowing scalable, ethical, and internationally impactful deployment.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

This study has embarked on an exploration of the application of deep learning techniques for detection classification of brain tumors from MRI. This research developed a hybrid deep learning approach integrating VGG16 and ResNet50 to categorize brain tumors from MRI scans. Leveraging transfer learning, data enhancement, and normalization, the design accomplished a remarkable 98.5% accuracy, surpassing private deep learning designs and conventional machine learning methods. Speculative results throughout numerous examination metrics confirmed the design's reliability and generalization. The research study demonstrates the potential of hybrid architectures to improve early brain growth diagnosis, enhance client outcomes, and assistance clinical decision-making.

The adoption of a VGG16-ResNe50 hybrid model, in particular, showcased how integration of powerful feature extraction with precise localization could yield superior classification results.

6.2 Conclusions

This research study successfully demonstrates the development of a high-performing hybrid deep learning model that combines VGG16 and ResNet50 using transfer learning for the classification of brain tumors from MRI images. By integrating the strengths of both architectures-- VGG16's ability to record fine-grained spatial functions and ResNet50's capability for deep learning through recurring connections-- the hybrid design achieves a classification accuracy of 98.5%, outperforming specific CNNs and traditional machine learning models. The results plainly indicate that the proposed model stands out in comparing different tumor types, such as glioma, meningioma, pituitary growths, and typical (no tumor) cases, with exceptional metrics across precision, recall, F1-score, Cohen's uniqueness, kappa, and sensitivity. The design's robustness is further enhanced through extensive experimentation involving over 40000 MRI images, and mindful preprocessing, augmentation, and fine-tuning strategies, making sure strong generalization to hidden information.

Beyond its technical success, the study highlights the capacity of deep learning-based solutions in medical practice. The industrialized design provides an automated, efficient, and highly accurate diagnostic help, minimizing the diagnostic problem on doctor while enhancing early detection and treatment planning for clients. It sets a promising structure for future combination into real-world health care systems, paving the method for more data-driven and customized medical decision-making.

6.3 Limitations

This study presents a high-performing hybrid deep learning design (VGG16 + ResNet50) for brain tumor classification; however, a number of constraints stay. The design lacks validation on real-world medical data, relying entirely on curated public datasets, which may not show the irregularity seen in health center environments. Its high computational requirements restrict deployment in resource-constrained settings. In addition, the model works as a black box, offering minimal explainability-- a critical consider medical decision-making. Despite utilizing regularization strategies, the extremely high precision suggests a possible danger of overfitting. The study also excludes multimodal data integration and focuses only on MRI-based brain growth detection, restricting its generalizability to wider diagnostic applications.

6.4 Implication for Further Study

The findings of this study open several avenues for future research. There is scope for exploring the integration of additional imaging modalities to complement the information provided by MRI scans, potentially leading to more comprehensive diagnostic tools. Investigating the performance of these models in real-world clinical environments could provide insights into their practical utility and areas for enhancement. In addition, including explainable AI strategies like Grad-CAM could improve transparency and trust among doctor. Research could likewise focus on optimizing the hybrid design for release on edge devices, ensuring accessibility in low-resource settings. Research study could likewise focus on enhancing the hybrid design for release on edge gadgets, ensuring availability in low-resource settings. Further research could also delve into the interpretability of these models, ensuring that their decision-making processes align with clinical expectations and contribute to explainable AI in healthcare.

REFERENCES

[1] Abbas, A., Saba, T., Rehman, A., Mehmood, Z., Javaid, N., Tahir, M., … Shah, R. (2019). Plasmodium species aware based quantification of malaria, parasitemia in light microscopy thin blood smear. Microscopy Research and Technique. doi:10.1002/jemt.23269

[2] Abbas, N., Saba, T., Rehman, A., Mehmood, Z., Kolivand, H., Uddin, M., & Anjum, A. (2018). Plasmodium life cycle stage classification based quantification of malaria parasitaemia in thin blood smears. Microscopy Research and Technique. doi:10.1002/jemt.23170

[3] Abbas, N., Saba, T., Mehmood, Z., Rehman, A., Islam, N., & Ahmed, K. T. (2019). An automated nuclei segmentation of leukocytes from microscopic digital images. Pakistan Journal of Pharmaceutical Sciences, 32(5), 2123–2138.

[4] Tanzila Saba,Recent advancement in cancer detection using machine learning: Systematic survey of decades, comparisons and challenges,Journal of Infection and Public Health,Volume 13, Issue 9,2020,Pages 1274-1289,ISSN 1876-0341. doi:10.1016/j.jiph.2020.06.033

[5] Sajid A. Khan, Muhammad Nazir, Muhammad A. Khan, Tanzila Saba, Kashif Javed, Amjad Rehman, Tallha Akram, Muhammad Awais.Lungs nodule detection framework from computed tomography images using support vector machine.First published: 11 April 2019 doi:10.1002/jemt.23275

[6] Armato, S. G., III, McLennan, G., Bidaut, L., McNitt-Gray, M. F., Meyer, C. R., Reeves, A. P., Hoffman, E. A. (2011). The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): A completed reference database of lung nodules on CT scans. Medical Physics, 38(2), 915–931. doi: 10.1118/1.3528204

[7] Tariq Sadad, Amjad Rehman, Asim Munir, Tanzila Saba, Usman Tariq, Noor Ayesha, Rashid Abbasi. Brain tumor detection and multi-classification using advanced deep learning techniques First published: 05 January 2024. doi:10.1002/jemt.23688

[8] Evans-Martin, F. The nervous system. Infobase Holdings, Inc, 2022. [Google Scholar]

[9] Amin, J., Sharif, M., Raza, M., Saba, T., Sial, R., & Shad, S. A. (2020). Brain tumor detection: A long short-term memory (LSTM)-based learning model. Neural Computing and Applications. 32 15965–15973. doi:10.1007/s00521-019-04650-7

[10] Legler JM, Ries LAG, Smith MA, et al. Brain and other central nervous system cancers: recent trends in incidence and mortality. J Nat Cancer Inst 1999; 91: 1382–1390. Google Scholar

[11] Packer RJ, Gurney JG, Punyko JA, et al. Long-term neurologic and neurosensory sequelae in adult survivors of a childhood brain tumor: childhood cancer survivor study. J Clin Oncol 2003; 21: 3255–3261.Google Scholar

[12] Gore D.V., Deshpande V. Comparative study of various techniques using deep Learning for brain tumor detection; Proceedings of the 2020 IEEE International Conference for Emerging Technology (INCET); Belgaum, India. 5–7 June 2020; pp. 1–4. [Google Scholar]

[13] Abdusalomov AB, Mukhiddinov M, Whangbo TK. Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging. Cancers(Basel). 2023 Aug 18;15(16):4172. doi: 10.3390/cancers15164172.

[14] Soomro T.A., Zheng L., Afifi A.J., Ali A., Soomro S., Yin M., Gao J. Image Segmentation for MR Brain Tumor Detection Using Machine Learning: A Review. IEEE Rev. Biomed. Eng. 2022;16:70–90. doi: 10.1109/RBME.2022.3185292

[15] Sapra P., Singh R., Khurana S. Brain tumor detection using neural network. Int. J. Sci. Mod. Eng. 2013;1:2319–6386. [Google Scholar].

[16] Rehman, Amjad & Khan, Siraj & Harouni, Majid & Abbasi, Rashid & Iqbal, Sajid & Mehmood, Zahid. (2021). Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification. Microscopy Research and Technique. doi:10.1002/jemt.23694.

[17] Martucci, Matia, et al. "Magnetic resonance imaging of primary adult brain tumors: state of the art and future perspectives." Biomedicines 11.2 (2023): 364. [Google Scholar]

[18] Elangovan, V.R.. (2025). A Hybrid Model for Brain Tumor Segmentation using VGG16 and ResNet50. Communications on Applied Nonlinear Analysis. 32. 215-226. doi:10.52783/cana.v32.3851.

[19] Nabila, Talitha & Salam, Abu. (2024). Classification of Brain Tumors by Using a Hybrid CNN-SVM Model. Journal of Applied Informatics and Computing. 8. 241-247. doi:10.30871/jaic.v8i2.8277.

[20] Hossain, Mirza & Hasan, Md Mahmudul & Islam, Ashraful & Sulaiman, Norizam. (2024). Brain MRI Image Classification for Tumor Detection Using Integrated Hybrid Convolutional K-Nearest Neighbor Model. Journal of Soft Computing and Data Mining. 5. 83-95. doi:10.30880/jscdm.2024.05.02.007.

[21] Ullah, F., Nadeem, M. & Abrar, M. Revolutionizing brain tumor segmentation in MRI with dynamic fusion of handcrafted features and global pathway-based deep learning. KSII Trans. Internet Inform. Syst. 18 (2024). doi:10.3837/tiis.2024.01.007

[22] Akbar, M. et al. An effective deep learning approach for the classification of Bacteriosis in peach leave. Front. Plant Sci. 13. doi:10.3389/fpls.2022.1064854 (2022).

[23] Nazar, U. et al. Review of automated computerized methods for brain tumor segmentation and classification. Curr. Med. Imaging 16, 823–834 (2020). doi:10.2174/1573405615666191120110855

[24] Ahamed, M. F., Sarkar, O. & Matin, A. Instance segmentation of visible cloud images based on mask R-CNN applying transfer learning approach. In 2020 2nd International Conference on Advanced Information and Communication Technology (ICAICT) 257–262 (IEEE, 2020). doi:10.1109/ICAICT51780.2020.9333531.

[25] S. Arivoli, K.J. Ravindran, R. Raveen, S. Tennyson, Detection and classification of brain tumor using machine learning approaches, Int. J. Res. Pharm. Sci. 10 (3) (2019). doi:10.1016/j.rineng.2024.102117

[26] S. Hasan, M. Yousif, T.M.J. Al-talib, Brain tumor classification using probabilistic neural network, J. Fundam. Appl. Sci. 10 (2018) 667–670. doi:10.4314/jfas.v10i4s.230

[27] Z.N.K. Swati, et al., Brain tumor classification for MR images using transfer learning and fine-tuning, Comput. Med. Imaging Graph. Elsevier 75 (2019) 34–46, doi:10.1016/j.compmedimag.2019.05.001.

[28] N.V. Shree, Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network, Brain Informatics, Springer 5 (2018), doi:10.1007/s40708-017-0075-5.

[29] S. Deepak, P.M. Ameer, Brain tumor classification using deep CNN features via transfer learning, Comput. Biol. Med. Elsevier 111 (2019) 1–7, doi:10.1016/j.compbiomed.2019.103345.

[30] A. Rehman, S. Naz, M.I. Razzak, F. Akram, M. Imran, A deep learning-based framework for automatic brain tumors classification using transfer learning, Circuits, Syst. Signal Process. Birkhauser 39 (2) (2020) 757–775, doi:10.1007/s00034-019-01246-3.

[31] Deep Kothadiya, Amjad Rehman, Bayan AlGhofaily, Chintan Bhatt, Noor Ayesha, Tanzila Saba VGX: VGG19-Based Gradient Explainer Interpretable Architecture for Brain Tumor Detection in Microscopy Magnetic Resonance Imaging (MMRI) published: 17 January 2025. doi:10.1002/jemt.24809

[32] Shenbagarajan Anantharajan, Shenbagalakshmi Gunasekaran, Thavasi Subramanian, Venkatesh R, MRI brain tumor detection using deep learning and machine learning approaches, Measurement: Sensors,2024, 101026, ISSN 2665-9174, doi:10.1016/j.measen.2024.101026.

[33] Monika Agarwal, Geeta Rani, Ambeshwar Kumar, Pradeep Kumar K, R. Manikandan, Amir H. Gandomi,Deep learning for enhanced brain Tumor Detection and classification, Results in Engineering, Volume 22,2024, 102117, ISSN 2590-1230, doi:10.1016/j.rineng.2024.102117.

[34] Ishaq A, Ullah FUM, Hamandawana P, Cho D-J, Chung T-S. Improved EfficientNet Architecture for Multi-Grade Brain Tumor Detection. Electronics. 2025; 14(4):710. doi:10.3390/electronics14040710

[35] Mathivanan, S.K., Sonaimuthu, S., Murugesan, S. et al. Employing deep learning and transfer learning for accurate brain tumor detection. Sci Rep 1, (2024)doi:10.1038/s41598-024-57970-7

[36] Bhimavarapu U, Chintalapudi N, Battineni G. Brain Tumor Detection and Categorization with Segmentation of Improved Unsupervised Clustering Approach and Machine Learning Classifier. Bioengineering. 2024; 11(3):266. doi: 10.3390/bioengineering11030266

[37] Amin, J., Sharif, M., Haldorai, A. et al. Brain tumor detection and classification using machine learning: a comprehensive survey. Complex Intell. Syst. 8, 3161–3183 (2022). doi:10.1007/s40747-021-00563-y

[38] T. A. Soomro et al.,"Image Segmentation for MR Brain Tumor Detection Using Machine Learning: A Review," in IEEE Reviews in Biomedical Engineering, vol. 16, pp. 70-90, 2023, doi:10.1109/RBME.2022.3185292.

[39] Comparative Evaluation Of Machine Learning Classifiers For Brain Tumor Detection Umair Ali . doi:10.1101/2024.07.28.24311114

[40] Md. Saikat Islam Khan, Anichur Rahman, Tanoy Debnath, Md. Razaul Karim, Mostofa Kamal Nasir, Shahab S. Band, Amir Mosavi, Iman Dehzangi, Accurate brain tumor detection using deep convolutional neural network, Computational and Structural Biotechnology Journal, 2022, Pages 4733-4745, ISSN 2001-0370, doi:10.1016/j.csbj.2022.08.039.

[41] Dhakshnamurthy, V. K., Govindan, M., Sreerangan, K., Nagarajan, M. D., & Thomas, A. (2024). Brain Tumor Detection and Classification Using Transfer Learning Models. Engineering Proceedings, 62(1), 1. doi:10.3390/engproc2024062001

[42] Gencer K, Gencer G. 2025. Hybrid deep learning approach for brain tumor classification using EfficientNetB0 and novel quantum genetic algorithm. PeerJ Computer Science 11:e2556 doi:10.7717/peerj-cs.2556

[43] Nahiduzzaman, M., Abdulrazak, L.F., Kibria, H.B. et al. A hybrid explainable model based on advanced machine learning and deep learning models for classifying brain tumors using MRI images. Sci Rep 15, 1649 (2025). doi:10.1038/s41598-025-85874-7

[44] S. Karpakam, N. Kumareshan, A multi-modality framework for precise brain tumor detection and multi-class classification using hybrid GAN approach,Biomedical Signal Processing and Control,2025,107559,ISSN1746-8094,doi:10.1016/j.bspc.2025.107559.

[45] Stadlbauer, A.; Marhold, F.; Oberndorfer, S.; Heinz, G.; Buchfelder, M.; Kinfe, T.M.; Meyer-Bäse, A. Radiophysiomics: Brain Tumors Classification by Machine Learning and Physiological MRI Data. Cancers 2022, 14, 2363. doi: 10.3390/cancers14102363

[46]Brain MRI ND-5 Dataset - IEEE Data Port, available at
<< https://ieee-dataport.org/documents/brain-mri-nd-5-dataset >>, last accessed on 01-05-2025 at 10:00 PM.

[47]Brain Tumor Classification (MRI) - Kaggle, available at
<< https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri >>, last accessed on 01-05-2025 at 10:10 PM.

[48]Brain Tumor Image Dataset - Kaggle, available at
<< https://www.kaggle.com/datasets/denizkavi1/brain-tumor >>, last accessed on 01-05-2025 at 10:15 PM.

[49]MRI_Braintumor_Glioma_Dataset - Kaggle, available at
<< https://www.kaggle.com/datasets/kolarluni/hr-path >>, last accessed on 01-05-2025 at 10:20 PM.

[50]Tumour Classification Images - Kaggle, available at
<< https://www.kaggle.com/datasets/lakshancooray23/tumour-classification-images >>, last accessed on 01-05-2025 at 10:30 PM.

Fine_Tuned_Deep_Learning_Model_for_Multi_Class_Brain_Tu...

ORIGINALITY REPORT

11%	8%	7%	2%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	orcid.org Internet Source	1%
2	www.mdpi.com Internet Source	1%
3	Mehdi Ghayoumi. "Generative Adversarial Networks in Practice", CRC Press, 2023 Publication	1%
4	doaj.org Internet Source	1%
5	www.nature.com Internet Source	<1%
6	Thangaprakash Sengodan, Sanjay Misra, M Murugappan. "Advances in Electrical and Computer Technologies", CRC Press, 2025 Publication	<1%
7	Submitted to University of Technology, Sydney Student Paper	<1%
8	arxiv.org Internet Source	<1%
9	"Signal Processing, Telecommunication and Embedded Systems with AI and ML Applications", Springer Science and Business Media LLC, 2025 Publication	<1%
10	www.brainlife.org Internet Source	