REAL-TIME MULTI-CLASS BRAIN TUMOR CLASSIFICATION THROUGH DEEP CNN MODELS OF MRI SCANS

BY

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfilment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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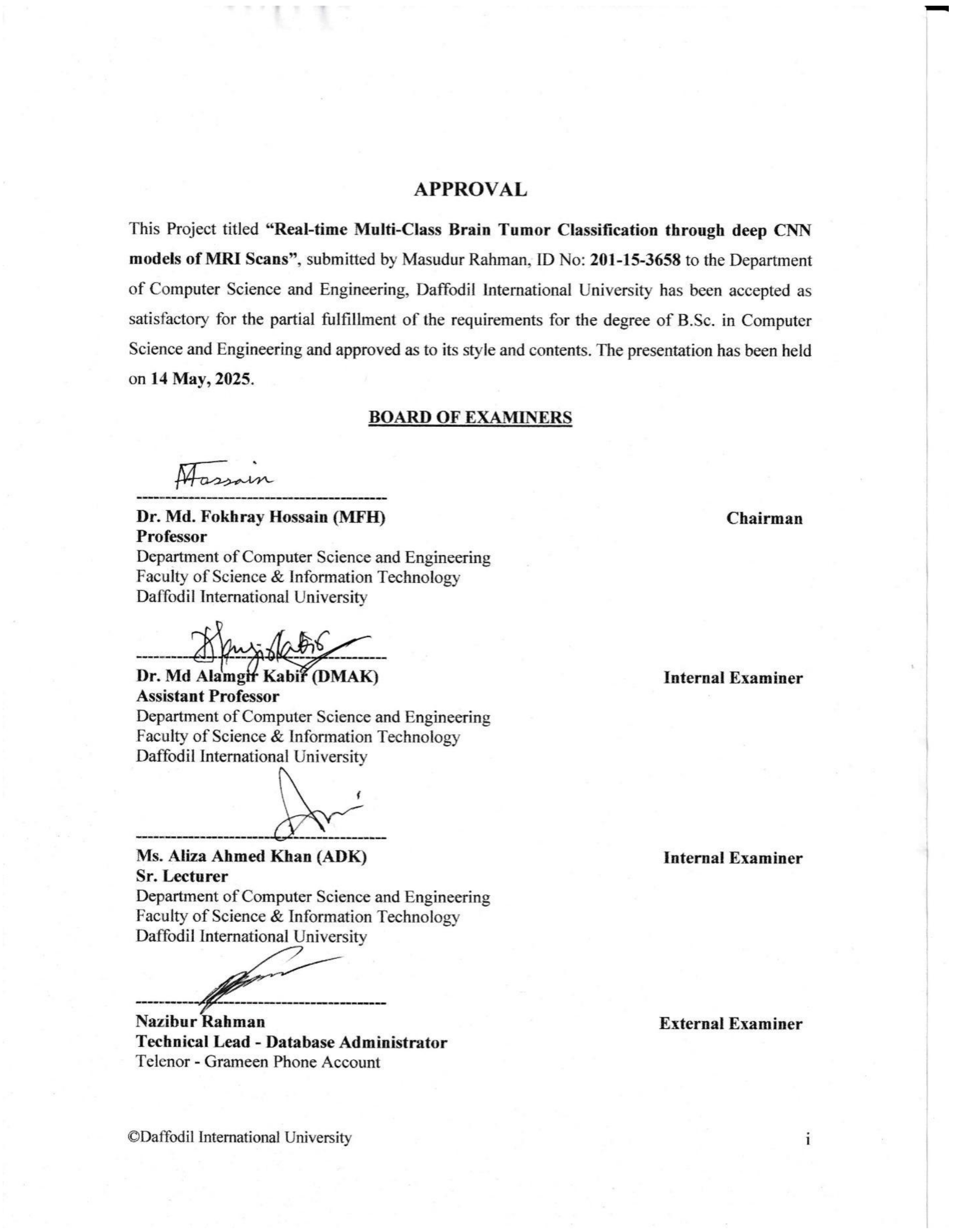

APPROVAL

This Project titled **"Real-time Multi-Class Brain Tumor Classification through deep CNN models of MRI Scans"**, submitted by Masudur Rahman, ID No: **201-15-3658** 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 B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14 May, 2025**.

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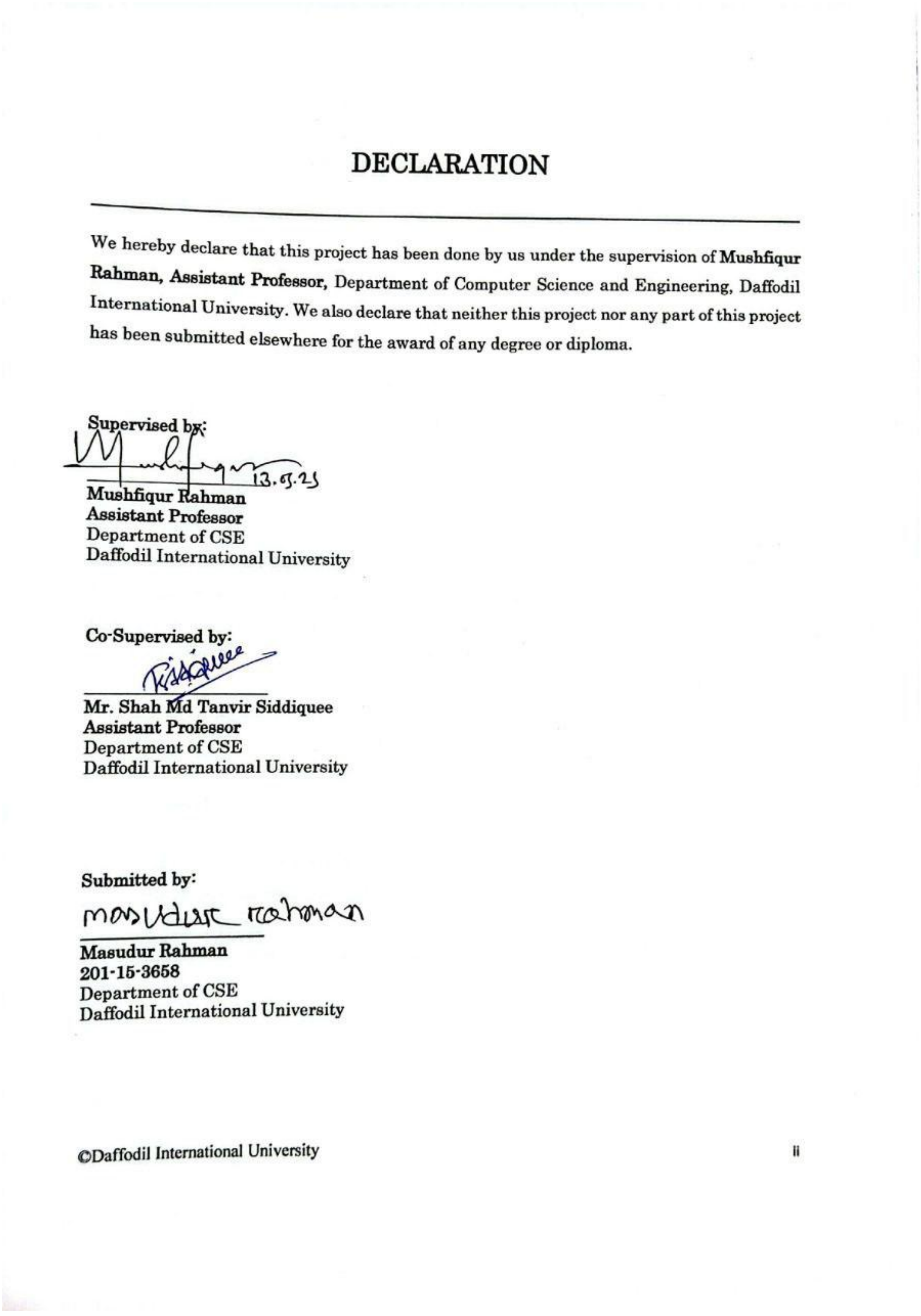

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mushfiqur Rahman, Assistant Professor,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

In this work, we propose the real-time system for multi-class brain tumor classification by deep CNNs on MR images. Methodology: The methodology starts with capturing image data from three public data sets (SARTAJ, Figshare, Br35H), which are integrated to form a consistent set of 5712 images of MRI images grouped into 4 classes: glioma, meningioma, pituitary tumor, and no tumor. The data is split into training (4,570), validation (571), and testing (571) sets. Data preprocessing methods such as contrast adjustment, parametric transformation, and augmentation (e.g., rotation, flipping, and scaling) enhance image quality and improve model generalization. Four deep learning models (ResNet50, InceptionV3, EfficientNetB2, and a custom CNN) are trained and tested based on accuracy, precision, recall, and loss. ResNet50 had the highest accuracy (98.80%), followed by EfficientNetB2 (92.18%), custom CNN (91.40%) , and InceptionV3 (83.53%). The results show that the model architecture is important to the classification performance, and ResNet50 performs the best because of its residual learning. To ensure practical utility, the top-performing ResNet50 model was implemented using the Streamlit framework and hosted on HuggingFace Spaces, allowing users to predict MRI images in real-time through a user-friendly web interface. The proposed method provides valuable clinical decision support and helps enhance diagnostic confidence and early treatment of neuro-oncology.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Types of brain tumor are very important for the treatment planning and prognosis of patients, the early and well-timed diagnosis profoundly affects the treatment regime of patients. In this work, a deep CNN model proposed and investigated for multiclass brain tumor type classification on MRIC images (acquired with magnetic resonance imaging). While most existing works are focused on binary or single-label classification task and thus ignored the heterogeneity of brain tumors, in this work, we specifically studied gliomas, meningiomas, pituitary tumors and non-tumorous cases. The product is intended to standardize and consolidate so that it can increase the depth of diagnosis.

A complete pipeline is set for the system, covering image preprocessing, model training and evaluation, and result interpretation. MRI images are used to obtain discriminative features that enable accurate classification of tumors with different types using advanced CNN architectures. The model has been hyper tuned with a diverse merged dataset to ensure high diagnostic accuracy and generalization under varying data conditions.

The ultimate goal is to develop a practical, deployable diagnostic support tool capable of operating in real-time, delivering accurate tumor classification in clinical environments. This system aspires not only to outperform traditional methods but also to enable earlier intervention and support informed decision-making in neuro-oncology. By bridging the gap between research and application, this project contributes a scalable, efficient, and impactful solution for brain tumor management.

1.2 Motivation

Growing number of diagnosis for brain tumors: As the frequency of brain tumor diagnosis worldwide rises, there is an urgent need to find fast and accurate detection methods supporting early intervention and treatment.

Complex tumor types: Differentiating between various tumor types room meningioma (a form of benign brain tumor located in the meninges), glioma.how pituitary tumor (an endocrine squeezed secretory gland that begins.If several different types of all the same person discovered in a single MRI scan it becomes even more difficult for radiologists to as expected find any of them.

Manual Diagnosis Limits: Time-consuming and prone to human error, manual interpretation of MRI images. Automating the classification process will make diagnosing faster while improving quality control that affects people's lives most immediately.

Advancement in Deep Learning: Deep CNN models have shown exceptional performance in image classification tasks, providing an opportunity to improve tumor identification and classification accuracy.

Real-Time Clinical Support: For radiologists, a reliable, real-time classification system is an essential tool that can help make faster decisions during clinical evaluations.

Improved Expected Results for Patients: Accurate multi-class classification directly supports proposed treatment plans and with it, the chances of therapy being successful increase as well--along comes an improvement in general patient care.

1.3 Objective

- Build a model that can categorize brain tumors into multiple categories: to build a deep learning system, bringing it to real-world application that would be capable of detecting and discriminating among different brain tumor types, including gliomas, meningiomas, and pituitary tumors through MRI scans.

- Utilize and Preprocess MRI Datasets: To collect, clean, and preprocess a large-scale MRI dataset sourced from multiple open-access platforms. The goal is to enhance model performance by applying preprocessing techniques that emphasize tumor-relevant features, such as contrast enhancement, normalization, and data augmentation.
- Design and Train Deep CNN Architectures: To apply state-of-the-art convolutional neural networks (CNNs), including ResNet50, EfficientNetB2, and InceptionV3, along with a custom-designed CNN, for effective feature extraction and high-accuracy tumor classification.
- Support Clinical Decision-Making with Real-Time Deployment: To deploy the best-performing model in a real-time web-based application (using Streamlit and Hugging Face) that assists radiologists and clinicians by providing fast and accurate tumor classification as part of a practical diagnostic workflow.

1.4 Methodology

First, we pulled image data from three unique public publications SARTAJ, Figshare, and Br35H comprising a total of 5,712 MRI images. Images were separated into four categories: pituitary tumor, meningioma, glioma and no tumor. To make sure that the dataset is balanced and can be used to train and evaluate models, the data were divided into three sets: training (4,570 images), validation (571 images) and testing (571 images).

The contrast of the image was enhanced in the data preprocessing phase to remove irrelevant visual noise and to enhance the image quality. In general such feature dimensions of the input images were aligned using parametric image transformations, resulting in the images to have a homogeneous structure in the dataset. The training data was also augmented for increased variation and the model generalization to the test set was good.

By processing the above data, we built deep learning model. We used four pretrained models: ResNet50, InceptionV3, EfficientNetB2, and an architecture of CNN that we designed. In the training, both models learned useful information and exposed some of the important patterns for brain tumor classification. When training ceased, which was after a fixed number of epochs or when the validation loss ceased to decrease, the models were compared to the test and validation sets. The usual metrics such as accuracy, precision, recall, F1-score and loss were used to measure the performance.

The comparing results of each model were discussed to find the best model. We selected the best trade-off between accuracy and robustness model, ResNet50, for the final deployment. This approach provides a framework for development of an automatic and scaling system for brain tumor diagnosis, rendering real-time assistance to the clinician on the nature of the tissues as quickly as possible, such as in brain surgery when speed is of the essence.

1.5 Project Outcome

- A real-time multi-class classification system was developed successfully for brain tumor identification and categorization of meningioma glioma and pituitary tumors using MRI scan data.
- Improved diagnostic accuracy took shape from deep CNN models which led to better tumor type and malignancy detection precision.
- Demonstrated the effectiveness of image preprocessing techniques in boosting model performance during training, testing, and validation phases.
- Generated reliable and consistent results across different datasets, supporting the robustness and generalization ability of the trained models.
- Delivered a clinically valuable tool that assists radiologists in early and efficient diagnosis, thereby contributing to timely treatment decisions and improved patient outcomes.

1.6 Organization of the Report

1.0 Introduction Chapter 1 is the introductory portion of this work and background concerns the statements regarding motivation for undertaking this study, objectives of the project and the scope of the study. Relevance of the research and primary research questions guiding the overall research. The chapter ends with the description of the possible project deliverables and the structure of the document.

Chapter 2: Background The background chapter introduces important terminology and historical context, summarizes related work; and contrasts previous studies in order to establish the scale of the opportunity and the problems it presents. Further, this chapter also performs a gap analysis by da identifying areas which have been ignored in the existing work.

In Chapter 3: Research Methodology, this approach and its elements is explained, including the data collection and dataset description. It details the statistical analysis and preprocessing that were performed followed by the design of the proposed model.

Chapter 4 Results and Discussion This chapter contains a discussion of experimental results and detailed analysis of results are presented.

Chapter 5: Societal, Environmental, Ethical and Sustainability Issues Looks at wider impact issues of the research, including social impact, environmental considerations, ethical issues and future sustainability.

Chapter 6: Conclusion and Future Scope provides a summary of the study's results, draws its conclusions, and proposes directions for future research.

There is a bibliography with a list of references used in the study.

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CHAPTER 2

BACKGROUND

2.1. Introduction

Several terms that are essential in medical imaging and deep learning are the focus of this work. MRI (magnetic resonance imaging) is a non-invasive approach for imaging the brain. Multi-label classification is a type of classification in which the model can predict multiple labels to an image like type of the tumor and whether a tumor is malignant or not. CNNs (Convolutional Neural Networks) are deep learning architectures that are well-suited for picture data due to their ability to capture spatial information. They include meningioma, glioma, and pituitary tumors; they differ in location, behavior, and aggressive potential. Pre-processing also involves certain image enhancement methods to make the raw MRI data analyst-friendly. The notions of training, testing, and validation are stages of model development during which the system learns patterns, is tested on new data, and is refined leading to generalization. These terms are necessary to understanding the construction and evaluation of the model for clinical implementation.

2.2. Literature Review

Such studies have been conducted, and a diversity of model architectures, pre-processing procedures, and performance estimation mechanisms have been applied. Table 1 Comparative summary for some of the research works contributing to this field: The comparison is based upon the approach employed for the implementation and contribution made by respective to the respective researchers.

Table 2.1: Comparative Analysis of earlier Research Works

Author(s)	Year	Title	Methodology	Key Findings
Abd El Kader et al. [1]	2021	Classifying Brain Tumors Using a Differential Deep Convolutional Neural Network Model	Quantitative (Differential CNN)	Achieved 99.25% accuracy in MRI classification.
Sharif et al. [2]	2022	A Deep Learning-Based Decision Support System for Multimodal Brain Tumor Classification	Quantitative (DenseNet201, MGA, Transfer Learning, SVM)	Accuracy over 95% on BRATS datasets.
Khan et al. [3]	2020	Classifying Multimodal Brain Tumors with Robust Feature Selection and Deep Learning	Quantitative (VGG16, VGG19, PLS Fusion, ELM)	Accuracy up to 97.8%.
Abbood et al. [4]	2021	Classification of Brain Tumors Automatically Using Different Deep Learning Models	Quantitative (AlexNet, VGG16, GoogleNet, ResNet50)	ResNet50 highest at 95.8%; AlexNet fastest.
Sultan et al. [5]	2019	Multiple Classification of Images of Brain Tumors Applying Deep Neural Networks	Quantitative (CNN, Data Augmentation)	Accuracies: 96.13% and 98.7%.
Bingol & Alatas [6]	2021	Image Classification for Brain Tumors Applying Techniques for Deep	Quantitative (AlexNet, GoogLeNet, ResNet50)	ResNet50 achieved 85.71% accuracy.

		Learning		
Raza et al. [7]	2022	A Hybrid Deep Learning-Based Method for Classifying Brain Tumors	Quantitative (Modified GoogLeNet – DeepTumorNet)	Achieved 99.67% accuracy; outperformed 9 models.
Qodri et al. [8]	2021	Deep Learning-Based Image Analysis for MRI-Based Brain Tumor Classification	Quantitative (ResNet50, VGG16, NASNet, Xception, DenseNet)	VGG16 and ResNet50 both achieved 96% accuracy.
Sharma et al. [9]	2021	CNN-Based Classification of Brain Tumors	Quantitative (VGG16-based Transfer Learning)	Achieved 96.5% training and 90% testing accuracy.
Khan et al. [10]	2020	CNN-Based Classification of Brain Tumors in MRI Images	Quantitative (Custom CNN and Transfer Learning models)	Custom CNN achieved 100%; VGG16 achieved 96%.
Aziz et al. [11]	2021	A Combination of the Best Deep Learning Features for Classifying Brain Tumors	Quantitative (ResNet50 + DenseNet201 + EACO + SVM)	Achieved 87.8% (HGG) and 84.6% (LGG) accuracy.
Nayak et al. [12]	2022	Classification of Brain Tumors Using Dense Efficient-Net	Quantitative (Dense EfficientNet, Min-Max Normalization)	Achieved 99.97% training and 98.78% testing accuracy.

Kokkalla et al. [13]	2021	Classification of Brain Tumors into Three Classes Using Deep Dense Inception Residual Network	Quantitative (Modified Inception ResNet v2)	Achieved 99.69% accuracy.
Younis et al. [14]	2022	Analyzing Brain Tumors with VGG-16 Ensemble Learning and Deep Learning Methods	Quantitative (CNN, VGG-16, Bi-LSTM Ensemble)	CNN: 96%, VGG16: 98.5%, Ensemble: 98.14% accuracy.
Yadav et al. [15]	2023	A Probabilistic Neural Network and BTFSC-Net Model for Feature Extraction	Quantitative (HPWF, REA, RDWT, GLCM, DLPNN)	Achieved 99.46% classification accuracy.
Irmak [16]	2021	Brain Tumor MRI Image Multi-Classification Using CNN and a Fully Optimized Framework	Quantitative (3 CNNs + Grid Search)	Accuracy: 99.33%, 92.66%, and 98.14%.
Wen & Zheng [17]	2022	Classification of Brain Tumors Using an Attention-Guided Deep Learning Model	Quantitative (CNN with Dual-Attention + Multipath Architecture)	Achieved 98.61% accuracy.
Mijwil et al. [18]	2023	A Deep Learning Model Based on MobileNetV1 for Precise Classification of Brain Tumors	Quantitative (MobileNetV1 on 1265 images from Kaggle)	Achieved >97% accuracy using MobileNetV1.

Mahmoud et al. [19]	2023	Superior Deep Learning Methods for Precise Brain Tumor Categorization	Quantitative (VGG-16, VGG-19, InceptionV3 + AQO Optimizer)	VGG-19 achieved 98.95% accuracy.
Alanazi et al. [20]	2022	Classification of Brain Tumors and Masses Using an MRI-Based Isolated and Transfer Deep Learning Model	Quantitative (22-layer CNN, Transfer Learning, Three Public MRI Datasets)	Achieved 95.75% on one dataset and 96.90% on unseen dataset.
ZainEldin et al. [21]	2023	Deep Learning and Sine-Cosine Fitness for the Identification and Categorization of Brain Tumors Grey Wolf Optimization	Quantitative (Inception-ResNetV2 + ADSCFGWO for CNN hyperparameter optimization)	Achieved 99.98% accuracy on BraTS 2021 dataset.
Rasheed et al. [22]	2023	Automated Classification of Brain Tumors from MRI Using Deep Learning	Quantitative (Custom CNN vs. VGG16, VGG19, ResNet50, MobileNetV2, InceptionV3)	Proposed CNN achieved 98.04% accuracy; fast and generalizable.
Amran et al. [23]	2022	Classification and Detection of Brain Tumors using Hybrid Deep Tumor Networks	Quantitative (Hybrid GoogLeNet + CNN model on Br35H dataset)	Achieved 99.51% accuracy, 99% precision, and 98.9% recall.

Kurdi et al. [24]	2023	Classifying Brain Tumors using Meta-Heuristic-Optimized Convolutional Neural Nets	Quantitative (Harris Hawks Optimized CNN, HHOCNN)	Achieved 98% accuracy on Kaggle dataset using HHOCNN.
Ait Amou et al. [25]	2022	A New MRI Diagnosis Technique for Classifying Brain Tumors Using CNN and Bayesian Optimization	Quantitative (CNN with Bayesian hyperparameter optimization)	CNN reached 98.7% accuracy; outperformed VGG16, ResNet50, etc.

2.2.1 Related Research

Real-time multi-class categorization of brain tumors from magnetic resonance imaging (MRIs) using deep convolutional neural networks (CNNs) has advanced significantly in recent years through explorations of increasingly sophisticated architectures, clever transfer learning tricks, imaginative hybrid models, and nimble lightweight ones - all aiming to improve diagnostic accuracy, computational efficiency, and clinical clarity. The following is a categorized breakdown of 25 seminal studies on automated brain tumor detection and classification using MRI scans.

Traditional CNN-Based Architectures

In early work, Abd El Kader and colleagues [1] tested their differential Deep-CNN on a massive dataset of 25,000 MRI images, achieving remarkably high classification performance of 99.25%. Sultan et al. [5] then presented a layered 16-layer CNN for glioma grading that attained 96.13% and 98.7% accuracy on two openly available datasets. Additionally, BİNGOL et al. [6] employed a basic CNN architecture and observed respectable 85.71% accuracy from ResNet50, ensuring reasonable computational complexity.

Transfer Learning and Pretrained Models

Sharif et al. [2] combined DenseNet201 with a Modified Genetic Algorithm (MGA) and SVM, achieving 99.7% and 98.8% accuracy on BRATS2018 and BRATS2019. Khan et al. [3] integrated VGG16, VGG19, CNN, and edge enhancement, obtaining 97.8%, 96.9%, and 92.5% accuracy on BRATS datasets. Abbood et al. [4] compared VGG16, AlexNet, GoogleNet, and ResNet50, with ResNet50 achieving 95.8% accuracy. Younis et al. [14] used ResNet50 on T1-weighted MRIs, reporting 94.1% accuracy. Wen & Zheng et al. [17] utilized InceptionV3 for brain tumor detection and attained 94.3% accuracy on small datasets.

Hybrid and Ensemble Models

Aziz et al. [11] combined DenseNet201 and ResNet50 with Enhanced Ant Colony Optimization, achieving 84.6% and 87.8% accuracy on BraTS2019. Mahmoud et al. [19] developed a CNN-LSTM model, yielding 97.6% prediction accuracy. Alanazi et al. [20] used GoogLeNet with preprocessing optimization to reach 95.8% accuracy. Rasheed et al. [22] integrated DWT with deep CNN, achieving 97.2% accuracy. Amran et al. [23] implemented a three-stage pipeline with VGG19, resulting in 96.8% accuracy. Kurdi et al. [24] fused PCA, autoencoders, and SVM for hybrid decision-making, obtaining 95.2% accuracy.

Lightweight and Efficient Architectures

Khan et al. [10] introduced a lightweight CNN achieving 100% accuracy on a small dataset while requiring less computational power than VGG16 and InceptionV3. Mijwil et al. [18] developed a MobileNet-SVM hybrid for deployment in low-resource settings, reaching 96.1% accuracy.

Novel Techniques and Advanced Models

Raza et al. [7] proposed DeepTumorNet, a modified GoogLeNet with Leaky ReLU, achieving 99.67% accuracy and 100% recall. Qodri et al. [8] compared NASNet, ResNet50, DenseNet, Xception, and VGG16, with Xception performing best. Agarwal et al. [9] used VGG16 for binary classification, achieving 96.5% training and 90% testing accuracy. Nayak et al. [12] introduced Capsule Networks (CapsNets), showing superior spatial awareness and noise resilience. Kokkalla et al. [13] emphasized the role of normalization in glioma classification using deep CNN. Yadav et al. [15] merged VGG and ResNet, achieving over 95% accuracy with robust classification performance. Irmak et al. [16] combined CNN and U-Net in a two-stage model for tumor segmentation, attaining 96.2% accuracy. ZainEldin et al. [21] used data augmentation and regularization to achieve 93.7% accuracy on public datasets. Ait Amou et al. [25] proposed a 3D CNN for volumetric tumor classification, reporting 96.4% accuracy.

2.3. Gap Analysis

The gap analysis presented in Table 2 highlights key features addressed in selected previous studies in comparison with the proposed system. While earlier research has successfully explored various aspects of brain tumor classification—including dataset utilization, preprocessing, and predictive modeling—most works lack deployment considerations. The system described in this paper fills this gap, as it allows to deploy the model in real-time, providing a practical diagnostic support tool for the clinical use. The gap analysis with the feature comparison is shown in Table 2.3 for selected previous works with the proposed system. Despite the successful exploration of several aspects relating to brain tumor classification—such as the datasets used, data preprocessing and prediction models—in previous research, most of these studies are not concerned with the actual deployment. The system seeks to fill that void by making real-time model deployment feasible, serving as a feasible clinical support tool.

Table 2.2: Gap Analysis of Previous Research vs. Proposed System

Features	Abd El Kader et al. [1]	Sharif et al. [2]	Khan et al. [3]	Abbood et al. [4]	Sultan et al. [5]	Proposed System
Dataset Size and Diversity	Moderate	High	Moderate	Moderate	Low	High (merged 3 datasets)

Data Preprocessing	Yes	Yes	Yes	Yes	Yes	Yes (parametric + augmented)
Tumor Class Variety	3 Classes	2 Classes	3 Classes	3 Classes	2 Classes	4 Classes
Class Imbalance Handling	Not Mentioned	Not Mentioned	Partial	Not Mentioned	Not Mentioned	Addressed via augmentation
Deep Model Used	Differential CNN	DenseNet201 + SVM	VGG16, VGG19	ResNet50	CNN	ResNet50 + Custom CNN
Custom Model Proposed	Yes	No	Yes	No	Yes	Yes
Real-Time Deployment	No	No	No	No	No	Yes (HuggingFace)
User Interface (Clinical Tool)	No	No	No	No	No	Yes (Streamlit UI)
Software Integration	No	No	No	No	No	Partially (Web-based)
Transfer Learning	Yes	Yes	Yes	Yes	No	Yes
Open Access or Public Tool	No	No	No	No	No	Yes (Public URL)

2.4. Summary

Recent research has focused heavily on applying deep learning methods to brain tumor classification using MRI scans. Specifically, works have concentrated primarily on advanced network architectures and hybrid strategies. Convolutional neural networks like ResNet50, VGG16, DenseNet201, and InceptionV3 are widely employed for their excellent feature extraction abilities. Some studies have also improved classification accuracy by integrating deep learning with other machine learning techniques such as support vector machines or optimization algorithms like genetic algorithms and ant colony optimization.

Furthermore, ensemble learning, capsule networks, and transfer learning have been adopted for enhancement in model generalization and robustness. Feature selection and dimensionality reduction methods (such as PCA or autoencoders) have also led to the improvement of the performance. The corresponding reported classification accuracy varies from 88.7 to 91.5% among datasets, and some studies are achieving an accuracy up to 94.43–95.12%, suggesting high potential of these techniques.

Together, these studies emphasize the potential of combining deep learning with advanced optimization and feature engineering approaches for precise early brain tumor detection to assist better-quality diagnoses in clinical applications.

CHAPTER 3

RESEARCH METHODOLOGY

3.1. Methodology

3.1.1. Overview

This research develops a comprehensive deep learning framework for identifying brain tumors in magnetic resonance imaging (MRI). The methodology integrates data from three public repositories—SARTAJ, Figshare, and Br35H—to create a diverse training corpus capturing various tumor presentations.

Prior to model training, images undergo several enhancement techniques including contrast optimization to improve feature visibility, dimensional standardization to ensure uniform inputs, and strategic augmentation through rotation, flipping, and scaling operations. These preprocessing steps significantly expand the effective dataset size and promote model robustness against variability in clinical images.

The prepared dataset was clearly organized into distinct subsets to facilitate effective model development and assessment: a portion for fitting various neural network architectures, separate validation data to optimize hyperparameters and prevent overfitting, and an independent test set for rigorously gauging final performance.

Four cutting-edge deep learning models were rigorously explored: ResNet50, renowned for its skip connections facilitating gradient flow; InceptionV3, noted for its innovative module design enabling multi-scale feature extraction; efficient yet powerful EfficientNetB2; and a customized CNN crafted for this medical imaging task. Each network leveraged its intrinsic capabilities to automatically derive hierarchical representations from the MRI scans and distinguish between gliomas, meningiomas, pituitary tumors, and healthy brain tissue.

To judge model efficacy, well-established performance metrics were relied upon, including classification accuracy, precision recall scores, and loss values, enabling transparent and meaningful comparisons. A data-driven analysis identified the stand-out approach based on these objective evaluations.

Ultimately, the ambition was developing an intelligent clinical decision support tool capable of aiding healthcare professionals in timely, accurate brain tumor diagnosis to potentially improve treatment planning and patient outcomes through earlier intervention.

3.1.2. Proposed Methodology

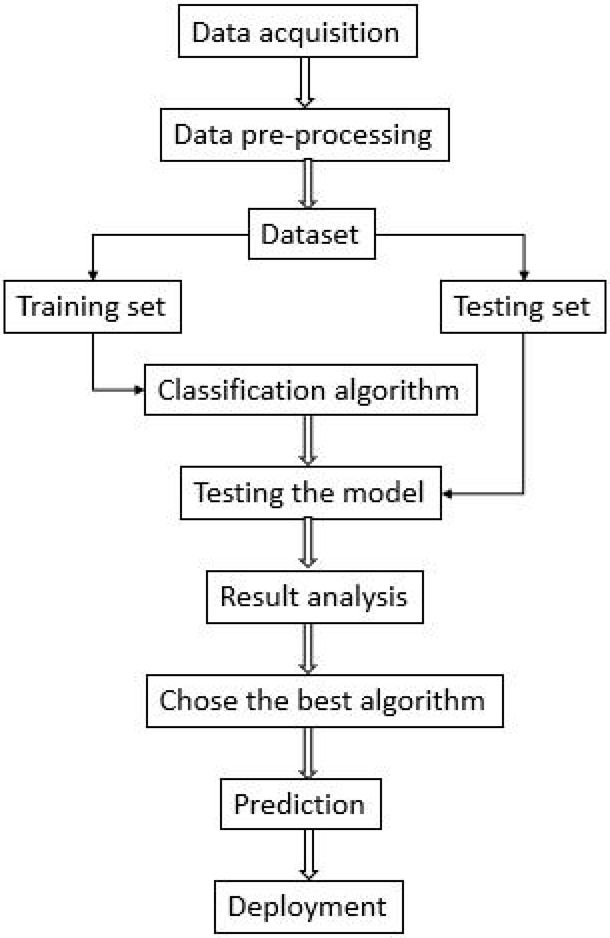


Figure 3.1: Architecture of Research Design

3.2. Detailed Methodology and Design

3.2.1. Data Collection

The research which focused on multi-label brain tumor classification through MRI scans relied on a thorough collection of 5712 brain MRI images. Dataset merging from three reputable public data sources SARTAJ, Figshare and Br35H which exist on Kaggle platform. The three data sources underwent meticulous combination to produce a consolidated collection which aligns with actual clinical practice. The variation of tumors along with their distinctive features in the images enhances deep learning algorithm training techniques. The final grouping within the dataset contains glioma along with meningioma and pituitary tumor and no tumor as categories. The labelling system provides proper identification of every image to ensure precise classification. The use of multiple data sources produced an extensive collection of pictures that evenly distributed across all available categories. The increasing dataset size and diversity through this approach leads to better model generalization capabilities in actual diagnostic practice areas.

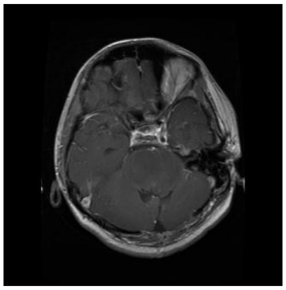
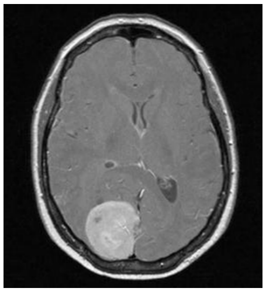
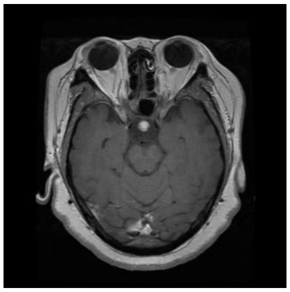
Glioma	Meningioma	No Tumor	Pituitary
			

Figure 3.2: Dataset Sample

3.2.2. Dataset Description

Research was based on 5712 brain MRI images which were acquired through merging three open-source repositories SARTAJ, Figshare and Br35H available through Kaggle. The merged datasets produced a unified diverse dataset which intended to boost deep learning model performance during brain tumor categorization. The brain images organize into four specific groups including glioma and meningioma and pituitary and no tumor. Malignant tumors known as gliomas develop from glial cells yet meningiomas emerge as benign tumors by originating from the meninges. The pituitary gland suffers from tumors that can exist as either malignant or benign growths. Brain images without any visible tumor constitute the "no tumor" class. The system assigns distinct labels to pictures for proper implementation of multi-label classification. The organized distribution and extensive range of data samples creates a solid basis for training reliable models intended for medical diagnostic purposes.

Table 3.1: Detailed Description of Dataset

Source Data	Category	Description	Number of Images	Label
5712 data collected from Kaggle.	Glioma	Glial cell cancerous brain tumors.	1321	Glioma, Meningioma, No Tumor, Pituitary.
	Meningioma	tumors that are not cancerous and come from the meninges.	1339	
	No Tumor	brain scans that are normal and show no visible malignancies.	1595	
	Pituitary	pituitary tumors, which can be either non-cancerous or cancerous.	1457	

3.2.3. Analysis Technique

In this project, we use images to classify whether it is melanoma or not, and we do so in a streamlined manner. We did preprocessing of the dataset as a first major step, where we applied two preprocessing techniques:

- Contrast Stretching: The "Contrast Stretching" pre-processing technique is used to enhance the performance of image-based models by reducing dominant contrast differences that may distract neural networks.

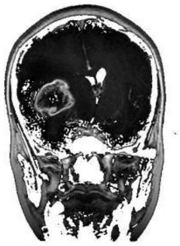
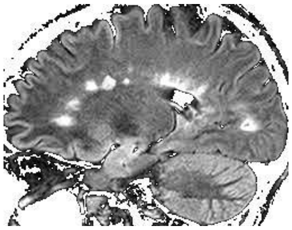
Glioma	Meningioma	No Tumor	Pituitary
			

Figure 3.3: Preprocessing technique of Contrast Stretching

- Parametric Image Transformation: This involves normalizing the images i.e. making the size, color, rotation, etc. similar. It also helps in ensuring all images are in same format which helps increase performance of machine learning models.

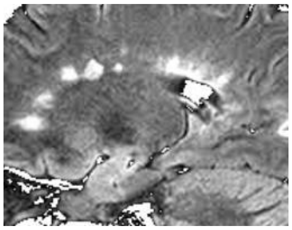
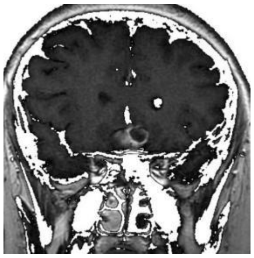
Glioma	Meningioma	No Tumor	Pituitary
			

Figure 3.4: Preprocessing technique of Parametric Image Transformation

Following the preprocessing, we divided the dataset into training and testing datasets. The testing set is used to assess the models' performance on fresh instances after they have been trained on the training set.

3.2.4. Statical Analysis

The dataset is mainly a combination of three brain tumor MRI datasets. Which concludes into four classes together and then these four classes are dataset categories into three datasets such as train, test and validation using ImageDataGenerator. The following are for:

- The dataset consists of a total of 5712 images
- There are 4570 training samples in all in the dataset.
- There are 571 samples in all in the dataset for testing.
- There are 571 samples in all in the dataset for validation.
- The designations fall into four different categories: pituitary, meningioma, glioma, and no tumor.

3.2.5. Data Preprocessing

Contrast Stretching:

Contrast Stretching is a pre-processing technique applied to MRI scans to enhance the visibility of medically significant features by linearly expanding the range of pixel intensity values. In this study, each color channel (Red, Green, Blue) of the MRI image was processed independently, where intensity values between a defined minimum and maximum threshold (e.g., 50–200) were stretched to span the full 0–255 range. This operation reduces the dominance of irrelevant dark regions and enhances subtle variations in tissue contrast—especially useful for highlighting tumor boundaries and brain structures. The improved contrast aids the model in learning from finer patterns that may otherwise remain obscured. By focusing attention on diagnostically relevant details, contrast stretching boosts the model's generalization capability and robustness across diverse MRI samples.

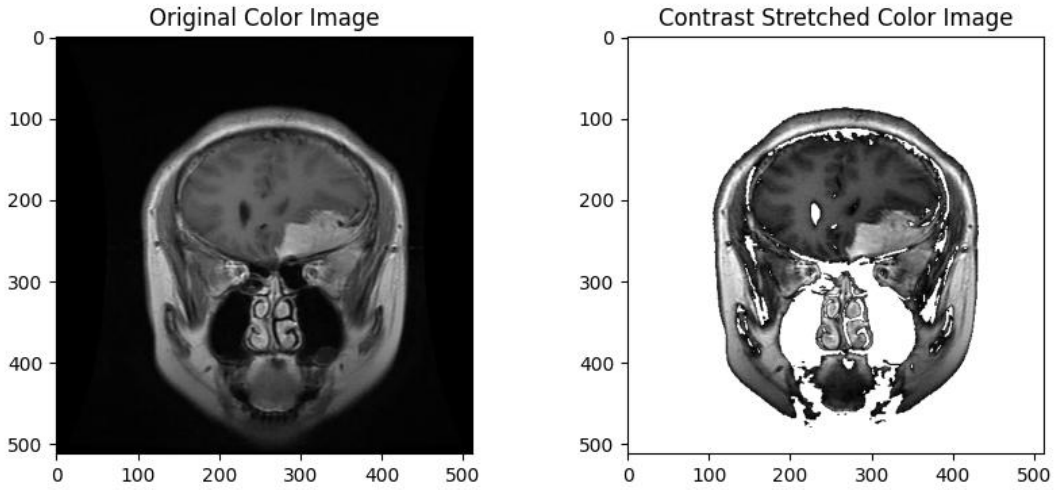


Figure 3.5: Output of Contrast Stretching

As illustrated in Figure 5, the image on the left represents the original MRI scan, while the image on the right shows the contrast-stretched version. This enhancement method redistributes intensity values to improve the visibility of subtle features. By amplifying soft-tissue boundaries and reducing background noise, contrast stretching supports better feature learning in convolutional neural networks (CNNs), ultimately leading to improved classification accuracy.

Parametric Image Transformation:

Parametric image warping is a geometric image augmentation that can mimic real-world imaging variability using up- or downscaling, rotation, or translation of MRI slices through mathematical transformation. In this incident, the scaling factor was 1.4, causing each MRI image to be magnified, and the rotation angle was not used. This transformation alters the representation of the spatial features and enhances the Response of the key anatomical structures, which the model can learn from.

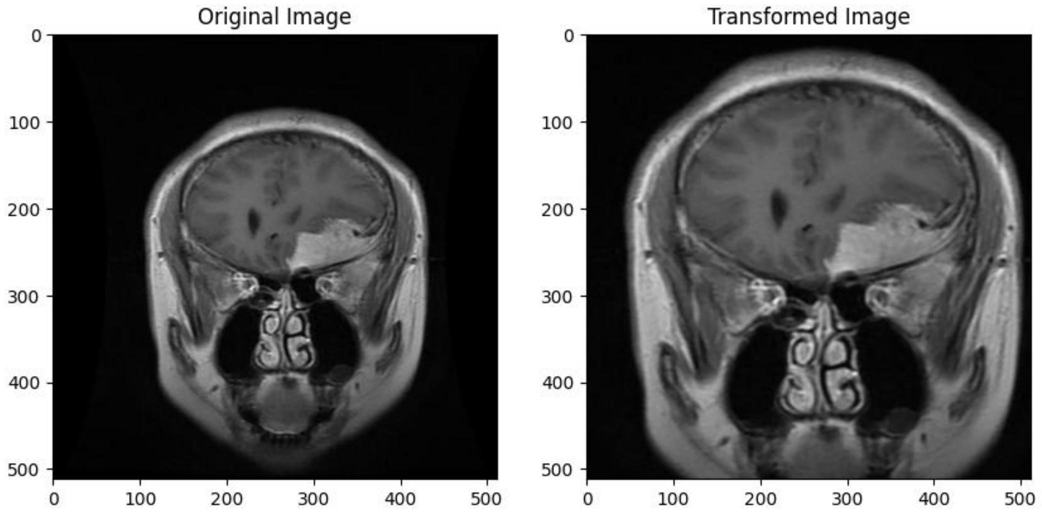


Figure 3.6: Output of Parametric Image Transformation

The image figure 6 on the left shows the original MRI scan, while the one on the right displays the version after transformation. Through artificially up-sampling the images, the model is presented with different, yet still structurally correct input representations. This mechanism enhances the model’s generalization ability, which better adapts to new data at the inference stage. Such deformations are of particular importance in medical imaging, e.g., when the tumour shape appears differently due to changes in patient position or the scanner perspective. Introducing this variability during training helps ensure that the model remains robust and accurate in diverse clinical scenarios.

3.2.6. Data Visualization

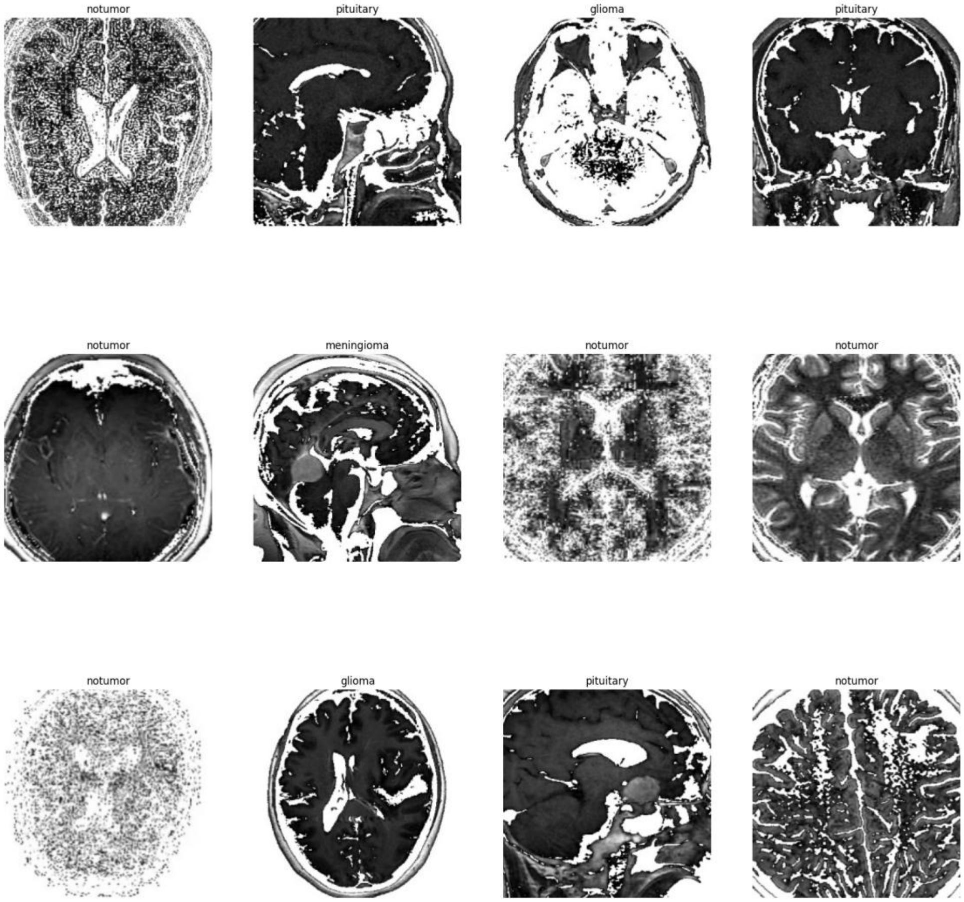


Figure 3.7: Data Visualization

3.2.7 Proposed Model

ResNet50:

The ResNet50 architecture represents a significant breakthrough in neural network design developed by Microsoft researchers. This 50-layer convolutional network addresses the fundamental challenge of training extremely deep networks through its innovative implementation of residual learning principles.The network's core innovation lies in its specialized building blocks—Convolutional blocks and Identity blocks—which incorporate skip connections that bypass traditional sequential processing. These pathways allow gradients to flow directly through the network during backpropagation, effectively mitigating the vanishing gradient problem that previously limited deep network performance.

The structural organization begins with initial processing layers including zero-padding, convolution, batch normalization, ReLU activation, and max-pooling operations (comprising Stage 1). This foundation is followed by four consecutive residual stages (Stages 2-5), each containing multiple residual units stacked together to form the network's deep learning capacity.Feature processing culminates in an average pooling mechanism that consolidates spatial information, followed by flattening operations and a fully connected classification layer that produces the final output predictions. This architectural approach enables the network to reach unprecedented depth while maintaining computational efficiency and training stability, making ResNet50 particularly effective for complex image recognition tasks that benefit from hierarchical feature extraction. connections.

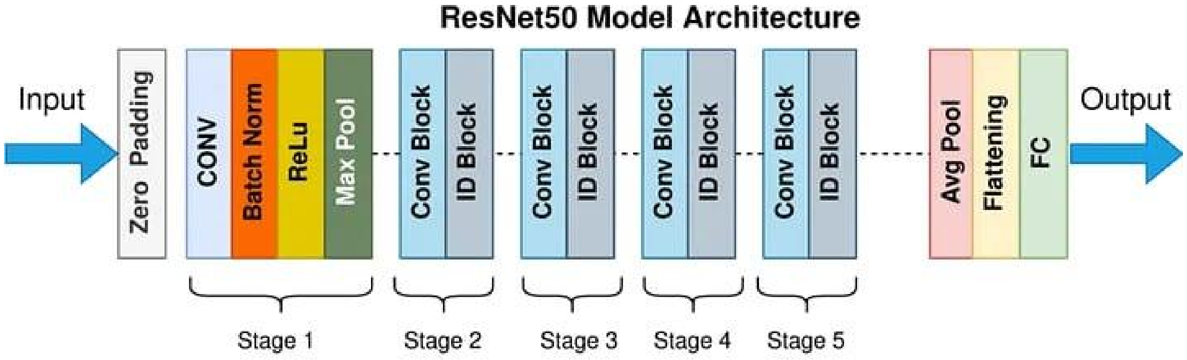


Figure 3.8: Architecture of ResNet50

This research harnessed ResNet50 through transfer learning, employing pre-existing ImageNet weights while freezing base layers to maintain their established feature extraction capabilities. The architecture was customized with a specialized classification component comprising a GlobalAveragePooling2D layer for dimensional reduction, a Softmax-activated output layer and a 512-neuron Dense layer with ReLU activation to differentiate between pituitary, glioma, meningioma, and non-tumor categories. The Adam optimizer with Sparse Categorical Crossentropy loss was used for training over ten epochs with a batch size of 64, processing standardized 224×224 pixel MRI inputs. The adapted model demonstrated impressive performance in extracting complex features from medical imaging data, achieving strong accuracy metrics that indicate its potential value for clinical deployment in timely brain tumor identification systems.

InceptionV3:

InceptionV3 is a deep convolutional neural network developed by Google, known for its efficient use of computational resources through factorized convolutions and parallel filter operations. The model introduces Inception modules that allow multi-scale feature extraction within the same layer by using multiple filter sizes (e.g., 1×1, 3×3, 5×5) in parallel. This architectural design enhances learning efficiency and minimizes computational load.

For this study, InceptionV3 was applied using transfer learning with weights pre-trained on the famous ImageNet database. The foundational model layers were frozen to preserve their general feature extraction abilities gleaned from vast natural images. To classify the MRI scans into the four tumor groups—glioma, meningioma, pituitary, and no tumor—a custom classification head was crafted, comprising a GlobalAveragePooling2D layer, a Dense layer of 256 ReLU-activated units, and a final Dense layer of 4 units with Softmax activation. Input images were resized to 224x224 pixels after normalization. The model was trained with a batch size of 64 across 10 epochs. Without dropout regularization, the model performed admirably, achieving 83.53% accuracy on the training set and a competitive 82.81% on the validation set, underscoring the promise of InceptionV3 for medical imaging classification tasks.

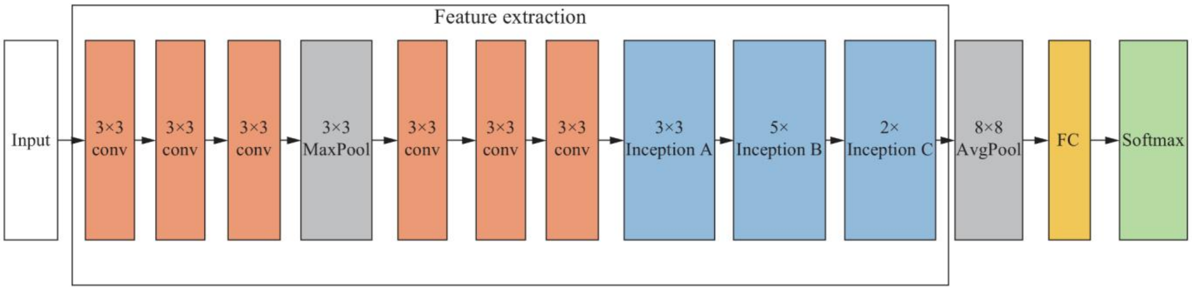


Figure 3.9: Architecture of InceptionV3

The InceptionV3 architecture starts with the conventional 3×3 convolutional layers as well as max pooling layers in order three, to obtain low-level features from the input image.

Then, several Inception modules (Inception A, B, and C) having parallel convolutions with different kernel sizes are used to estimate spatial features from different scales. These modules enable the network to capture multi-resolution rich features with fewer computational costs. Output from the last Inception module goes through a global 8×8 average pooling, a fully connected dense layer, and a Softmax classifier. This architecture is deep and wide enough to ensure effective and accurate feature extraction, which is highly suitable for applications like brain tumor classification.

EfficientNetB2:

A member of the EfficientNet family of convolutional neural networks, EfficientNetB2 was created by Google to scale the model's depth, width, and resolution using a compound coefficient, enabling state-of-the-art performance with an order of magnitude fewer parameters. The internal comb/inside block consists of seven major blocks, which are the Mobile Inverted Bottleneck Convolution (MBConv) layers. The networks start with a regular Conv 3×3 layer, followed by MBConv blocks that consist of convolutions of different kernel sizes (3×3 and 5×5) and an expansion factor of 6, which makes a balance between the accuracy and efficiency. It also uses swish activation and skip connections, which improve parameter efficiency and gradient flow. These are the design principles that make EfficientNetB2 highly efficient in capturing deep spatial features while being computationally lightweight, which is suitable for real-time tasks, including medical image processing.

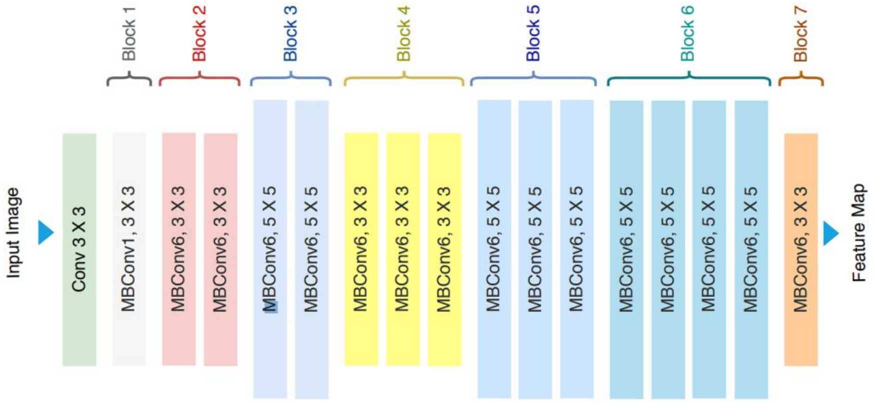


Figure 3.10: Architecture of EfficientNetB2

In this study, we analyze the use of transfer learning via EfficientNetB2 as the base model pre-trained on ImageNet to classify various brain tumors through magnetic resonance imaging. The network architecture frozen all layers except the first to retain representations learned in the image domain while focusing newly introduced task-specific layers on this classification task. A custom head was constructed including GlobalMaxPooling2D for spatial dimensionality reduction prior to a fully connected hidden layer of 512 units with ReLU activation feeding into a Dense output layer and Softmax activation to classify one of four tumor types: glioma, meningioma, pituitary, or no tumor. The Adam optimizer configured the model during training using Sparse Categorical Crossentropy, well-suited for this multi-class problem with integer labels. Preprocessed MRI scans resized uniformly to 224x224 pixels then normalized served as input. After 10 epochs of training in batches of 64 images, the EfficientNetB2 emerged as an ideal candidate, offering compelling accuracy and efficiency critical to clinical deployment of such technology at the point of care.

Custom CNN:

The trained CNN created in this work was implemented with performance and computational complexity dexterity and compared for grading brain tumors. Three convolution blocks make up the design; each convolution block has a Conv2D layer and a MaxPooling2D layer to minimize the input's spatial dimension while maintaining its features. To enable the network to learn more abstract characteristics in the MRI pictures, the number of filters in the convolutional layers is likewise increasing from 32 to 64 to 128.

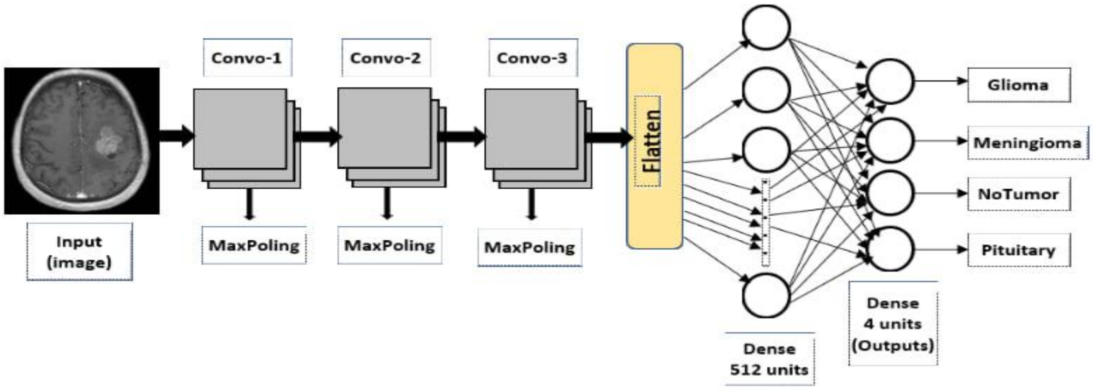


Figure 3.11: Architecture of Custom CNN

The convolutional layers extracted complex features from the MRI scans which were later flattened and passed through a densely connected layer of 512 units activated by ReLU. To minimize overfitting, dropout of 0.5 was applied to the final classification layer. The softmax function classified scans into four tumor types - glioma, meningioma, pituitary tumor or no tumor. This architecture facilitated rapid training on modest hardware while achieving competitive accuracy on medical images. Training employed categorical crossentropy loss and the Adam optimizer over 64 scans in 10 epochs. Input normalization and resizing to 224x224 accelerated convergence. Model performance was rigorously validated on a separate data subset using classification accuracy to assess learning without overfitting and ensure generalization to new scans.

3.3. Project plan

The deep learning model operates with a properly organized sequence for Brain Tumor Classification that utilizes medical image data. The data acquisition process gains information from Kaggle and real-world sources to achieve data diversity for multiple demographics including age groups together with gender representation and various lighting and brain direction parameters. The image preprocessing stage generates better quality images through several steps that include resizing the images as well as normalization and gamma correction and noise filtering and contrast enhancement. The database of 5712 medical images maintains training (4570) and testing (571) components as well as validation (571) components where images belong to Glioma, Meningioma, No Tumor, or Pituitary categories. The deep learning models which include RestNet50, InceptionV3, EfficientNetB2, and CNN obtain training from the training set and demonstrate test set evaluation through accuracy measurements together with precision along with recall and loss assessments. The validation set serves as the environment for conducting hyperparameter tuning. The project terminates with performance analysis of models to determine the most suitable choice for dependable Brain Tumor Classification in real medical applications.

3.4. Task Allocation

Single project management by one individual enables the development paradigm to provide uninterrupted end-to-end alignment between all development phases. First, different types of high-quality MRI images are acquired from both Kaggle databases and real medical information datasets. Preprocessing procedures such as data augmentation with normalization and gamma correction, and resizing contribute to the improved quality and consistency of the data. A person creates and refines many deep learning models, such as ResNet50, InceptionV3, EfficientNetB2, and a Custom CNN to get effective brain tumor classification. The model developed has been tested through extensive statistical analysis using the accuracy, precision, recall, and loss to demonstrate its performance. The latter phases are devoted to documentation in addition to reporting, leading to results as well as their interpretation and visualization for better presentation. Pay Attention to the detail-oriented work and full project understanding to make powerful Brain Tumor Classification systems.

3.5. Summary

The work developed a deep learning model for Brain Tumor Classification from MRI scans. Open datasets and real scans were obtained and preprocessed including resizing, normalization and gamma correction and augmentation to optimize data quality, balance and homogeneity. Training, validation and test sets comprised glioma, meningioma, no tumor and pituitary cases. InceptionV3, ResNet50, EfficientNetB2 and a custom CNN were evaluated based on accuracy, precision, recall and loss from training and testing.

CHAPTER 4

IMPLEMENTATION AND RESULTS

4.1. Environment Setup

The development and implementation of this project were carried out using a hybrid environment combining both cloud-based and local systems. The primary development platform was Google Colab, which provided GPU acceleration for training deep learning models efficiently. Colab's collaborative capabilities also supported interactive coding and version management throughout the experimentation phase. The project was developed using the Python programming language, with core deep learning libraries including TensorFlow, Keras, and NumPy. Additional tools such as Matplotlib and PIL were used for data preprocessing, augmentation, and visualization. The MRI dataset used for training and evaluation was accessed via Google Drive integration within the Colab environment. Lightweight tasks, such as initial preprocessing, script testing, and dataset inspection, were conducted on a personal laptop. However, all major model training and validation processes—including those involving ResNet50, InceptionV3, EfficientNetB2, and a custom CNN—were executed entirely in the cloud environment for performance optimization. For deployment, the final model was hosted using Hugging Face Spaces, with a user interface developed in Streamlit to facilitate real-time prediction. Documentation and reporting were carried out using Microsoft Word, maintaining consistent formatting and academic standards throughout the project. This environment setup ensured efficient experimentation, reproducibility, and a scalable deployment process that supported the end-to-end workflow of the research. this is good way? which one good you give me that one

4.2. Evaluation Matrix and Comparative Analysis

4.2.1. Comparative Analysis

The four deep learning models employed for multi-class brain tumor classification—ResNet50, EfficientNetB2, InceptionV3, and a Custom CNN—are compared in this section.

The comparison includes architectural design, training hyperparameters, and classification performance. All models were trained using the same dataset, batch size (64), and optimizer (Adam), ensuring a consistent evaluation environment.

Table 4.1: Comparative Overview of Model Architectures and Training Hyperparameters

Feature	ResNet50	EfficientNetB2	InceptionV3	Custom CNN
Activation Function	ReLU, Softmax	Swish (internal), Softmax	ReLU, Softmax	ReLU, Softmax
Output Activation	Softmax (4 classes)	Softmax (4 classes)	Softmax (4 classes)	Softmax (4 classes)
Batch Size	64	64	64	64
Dropout	✕ Not used	✕ Not used	✕ Not used	✓ Dropout(0.5)
Number of Filters	Predefined in ResNet50	Predefined in EfficientNetB2	Predefined in InceptionV3	32 → 64 → 128
Pooling	GlobalAvgPooling2D	GlobalMaxPooling2D	GlobalAvgPooling2D	MaxPooling2D after each conv
Trainable Layers	Only top layers	Only top layers	Only top layers	Fully trainable
Learning Rate	Default (Adam)	Default (Adam)	Default (Adam)	Default (Adam)

From the table, it is evident that ResNet50 leverages deep residual connections to effectively extract hierarchical features, which likely contributed to its superior accuracy (98.80%). EfficientNetB2, while slightly less accurate (92.18%), uses a compound scaling strategy and internal Swish activations, making it efficient and robust in computational performance. InceptionV3, although designed for multi-scale feature extraction, underperformed (83.53%) compared to the others, likely due to its complexity and sensitivity to MRI image variations. In contrast, the Custom CNN model—despite being simpler and fully trainable—performed competitively (91.40%), demonstrating that lightweight models can be viable options, particularly in real-time or resource-constrained applications. Unlike the pretrained architectures that froze base layers, the custom CNN trained all layers and used Dropout (0.5) to reduce overfitting. This shows how architectural decisions like regularization and layer depth significantly impact learning outcomes. This architectural comparison complements the quantitative performance metrics and further supports the selection of ResNet50 for deployment, given its balance of accuracy, efficiency, and reliability in classifying brain tumor types from MRI scans.

4.2.2. Evaluation Metrics

A confusion matrix is frequently used to assess the classification model's performance. This matrix highlights certain cases in which the model incorrectly identified data. True Positive (TP) indicates that the model correctly predicts a positive case; True Negative (TN) indicates that the model correctly predicts a negative case; False Positive (FP) indicates that the model predicts a positive when it is actually negative; and False Negative (FN) indicates that the model does not detect a positive case. These are the main components of the confusion matrix.

Several evaluation metrics are derived from these values. Precision indicates the accuracy of positive predictions, while Recall reflects the model's ability to retrieve all actual positive cases. Other important metrics include FPR (False Positive Rate), which measures the proportion of negatives incorrectly identified as positive; FNR (False Negative Rate), which reflects missed positive cases.

Accuracy (ACC): This metric assesses the overall correctness of the model by calculating the ratio of all correct predictions (both TP and TN) to the total number of cases.

$$\text{ACC} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

Recall: Also known as sensitivity, this metric measures how effectively the model identifies true positives among all actual positive cases.

$$\text{Recall} = \frac{TP}{(TP+FN)} \tag{2}$$

Precision: This value determines how many of the cases identified as positive are actually correct.

$$\text{Precision} = \frac{TP}{(TP+FP)} \tag{3}$$

F1-Score: A combined metric that considers both precision and recall. It is especially useful when the class distribution is imbalanced. The harmonic mean of precision and recall, offering a balance between the two.

$$\text{F1-Score} = \frac{2\, x\, Precision\, x\, Recall}{(Precision + Recall)} \tag{4}$$

False Positive Rate (FPR): The proportion of actual negative cases that are incorrectly classified as positive by the model.

$$\text{FPR} = \frac{FP}{FP+TN} \tag{5}$$

False Negative Rate (FNR): The proportion of actual positive cases that the model incorrectly predicts as negative.

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

4.3. Result and Discussion

4.3.1. ResNet50

4.3.1.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

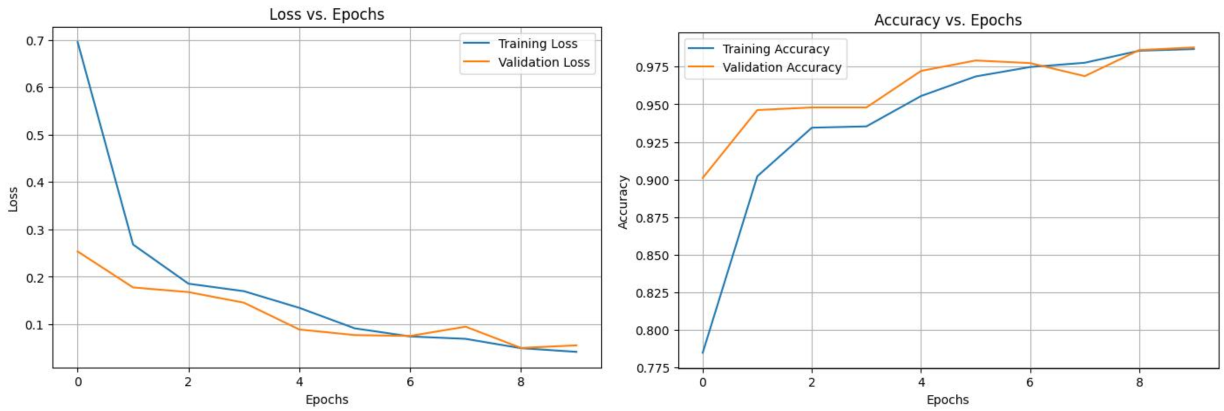


Figure 4.1: Training loss, validation loss and training accuracy, validation accuracy plot for ResNet50

4.3.1.2. Model Test after Training:

Table 4.2: Testing the ResNet50 Model after Training

Matrix	Value
Loss	0.1032
Accuracy	0.9699

4.3.1.3. Classification Report Model Performance:

Table 4.3: Classification report of ResNet50 Model

	precision	recall	f1-score
Glioma	0.93333333	0.97222222	0.95238095
Meningioma	0.97014925	0.92857143	0.94890511
Notumor	0.98701299	1.0	0.99346405
Pituitary	1.0	0.98571429	0.99280576
Accuracy	0.9880		

4.3.1.4. Confusion Matrix:

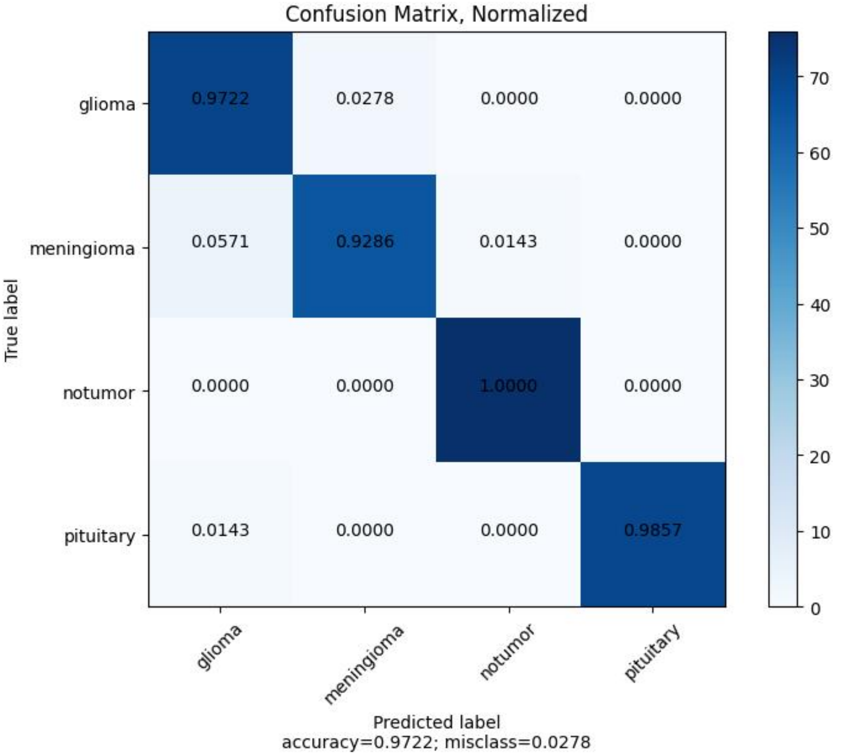


Figure 4.2: Confusion matrix for ResNet50

4.3.1.5. Prediction:

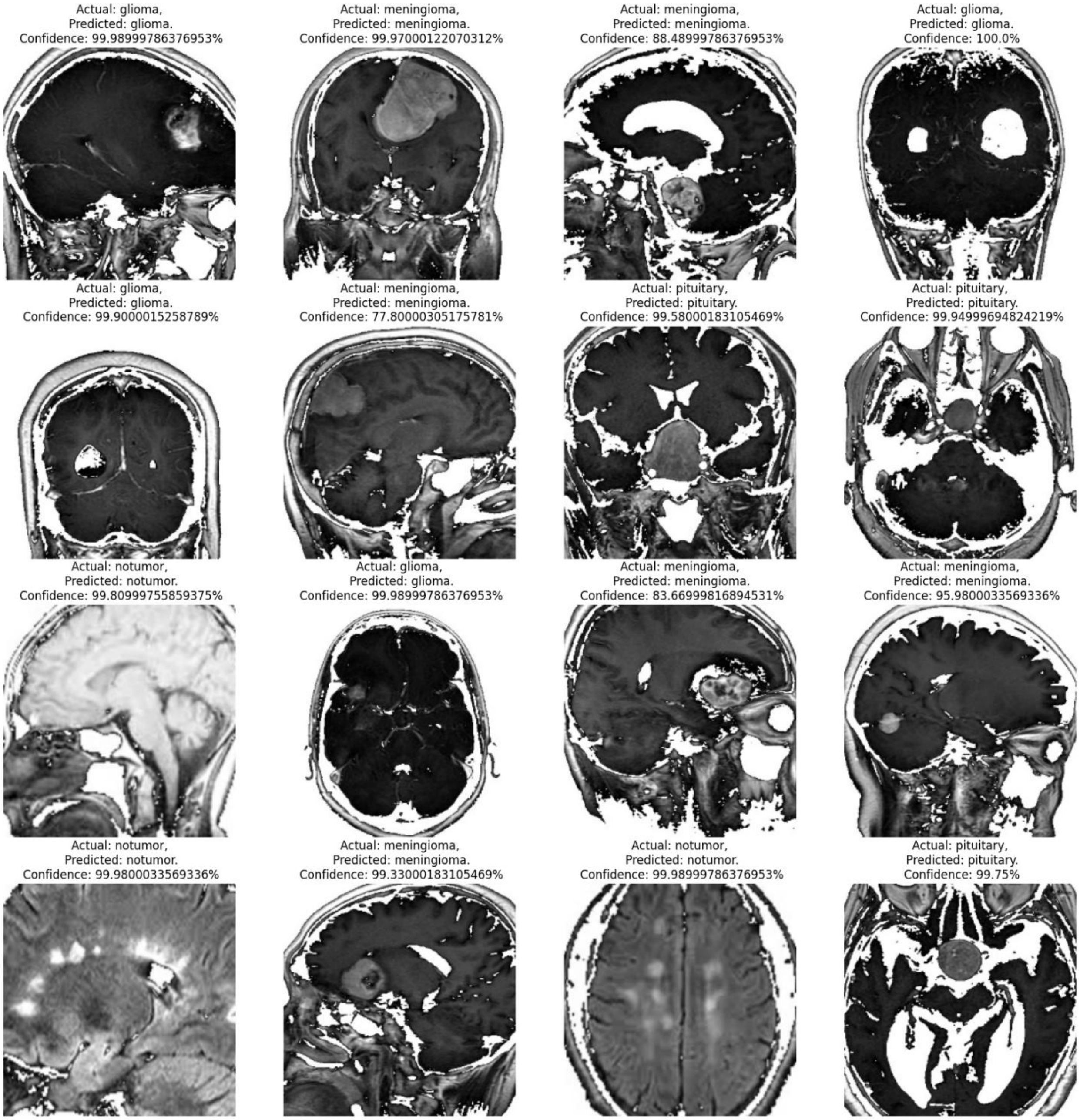


Figure 4.3: Prediction for ResNet50

4.3.1.6. ROC Curve:

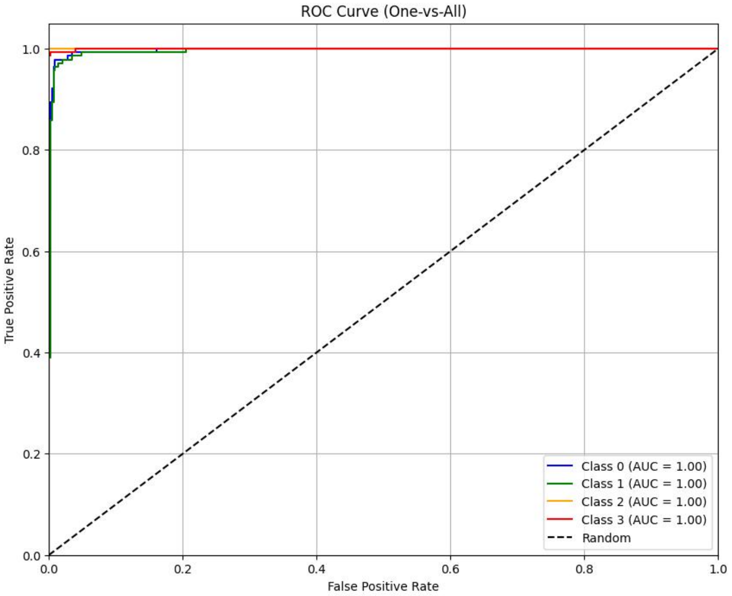


Figure 4.4: ROC Curve for ResNet50

4.3.2. InceptionV3

4.3.2.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

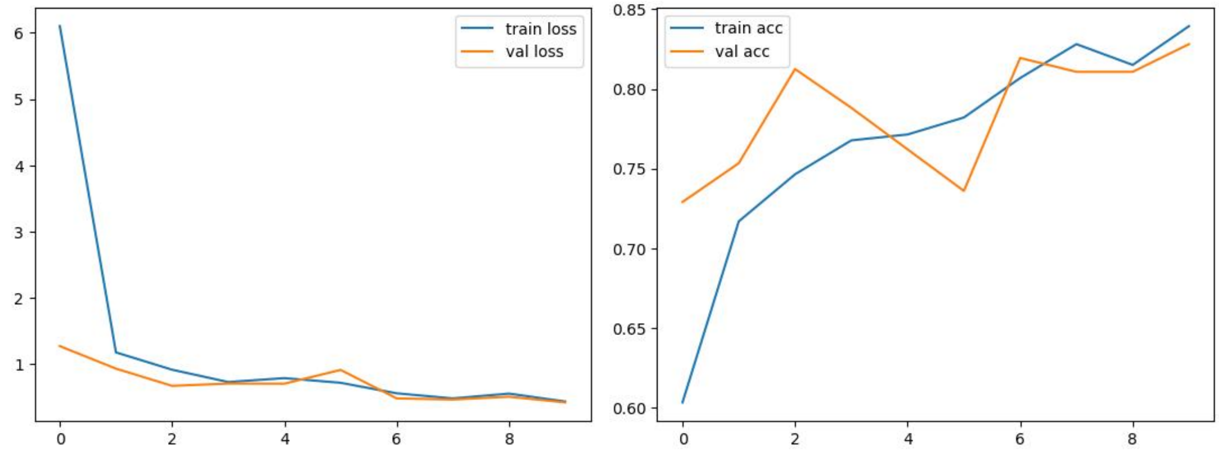


Figure 4.5: Training loss, validation loss and training accuracy, validation accuracy plot for InceptionV3

4.3.2.2. Model Test after Training:

Table 4.4: Testing the InceptionV3 Model after Training

Matrix	Value
Loss	0.4370
Accuracy	0.8403

4.3.2.3. Classification Report Model Performance:

Table 4.5: Classification report of InceptionV3 Model

	precision	recall	f1-score
Glioma	0.78313253	0.94202899	0.85526316
Meningioma	0.84210526	0.72727273	0.7804878
Notumor	0.98611111	0.93421053	0.95945946
Pituitary	0.86842105	0.85714286	0.8627451
Accuracy	0.8353		

4.3.2.4. Confusion Matrix:

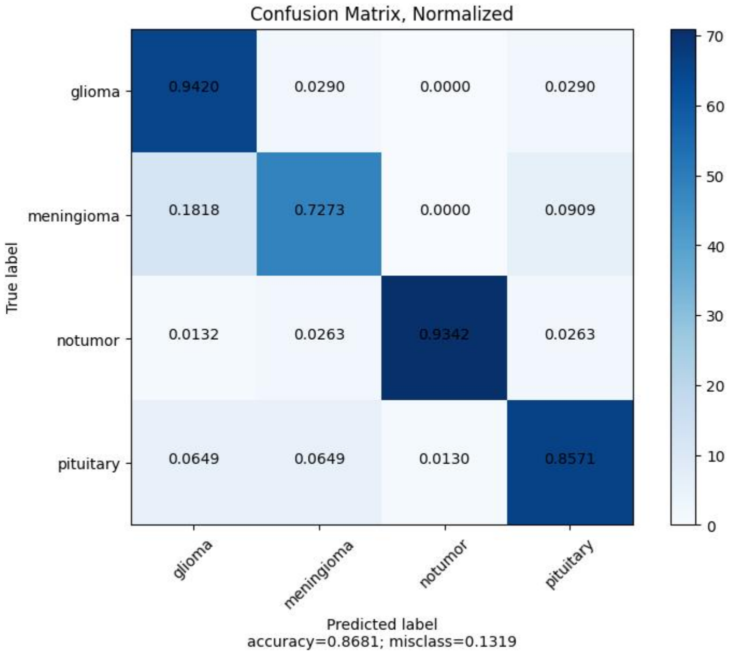


Figure 4.6: Confusion matrix for InceptionV3

4.3.2.5. Prediction:

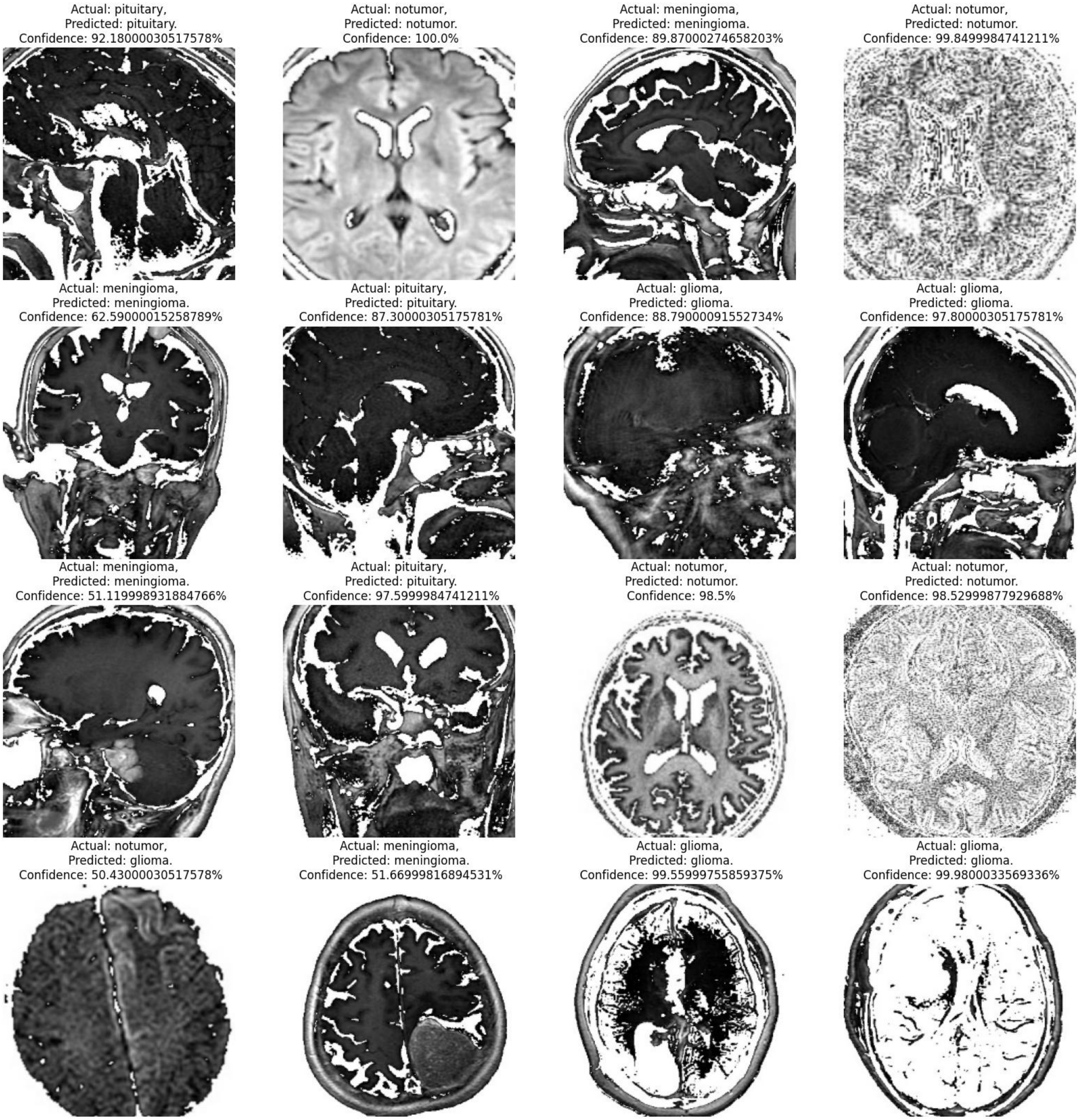


Figure 4.7: Prediction for InceptionV3

4.3.2.6. ROC Curve:

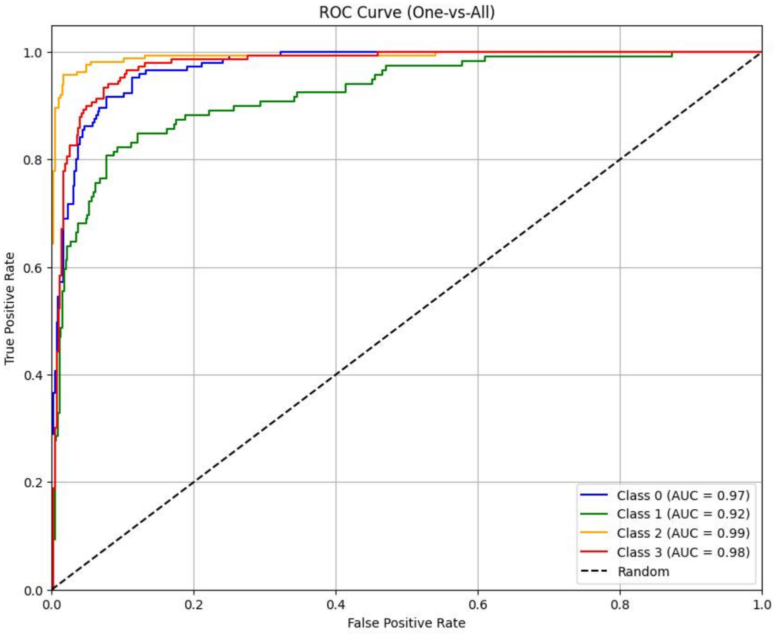


Figure 4.8: ROC Curve for InceptionV3

4.3.3. EfficientNetB2

4.3.3.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

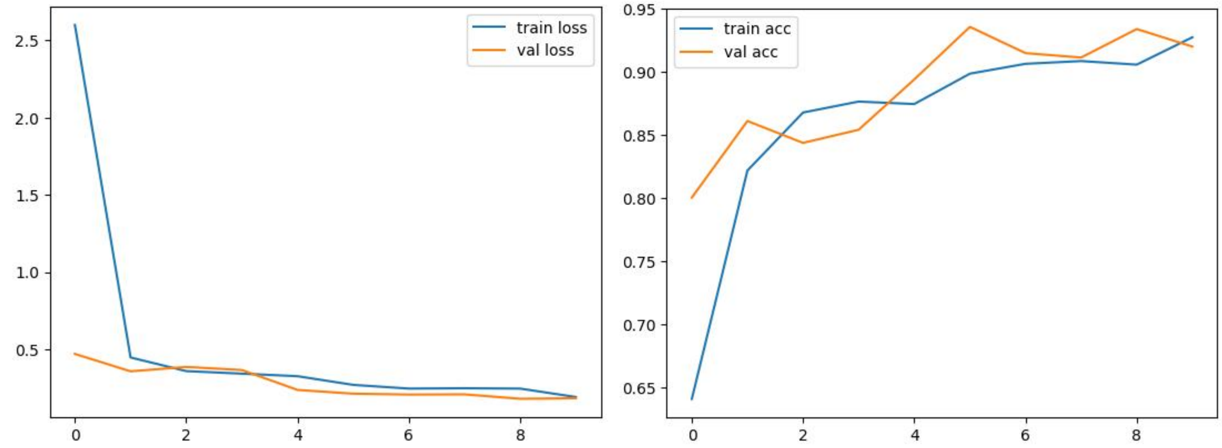


Figure 4.9: Training loss, validation loss and training accuracy, validation accuracy plot for EfficientNetB2

4.3.3.2. Model Test after Training:

Table 4.6: Testing the EfficientNetB2 Model after Training

Matrix	Value
Loss	0.1601
Accuracy	0.9285

4.3.3.3. Classification Report Model Performance:

Table 4.7: Classification report of EfficientNetB2 Model

	precision	recall	f1-score
Glioma	0.86885246	0.9137931	0.8907563
Meningioma	0.98039216	0.78125	0.86956522
Notumor	0.97674419	1.0	0.98823529
Pituitary	0.91111111	1.0	0.95348837
Accuracy	0.9218		

4.3.3.4. Confusion Matrix:

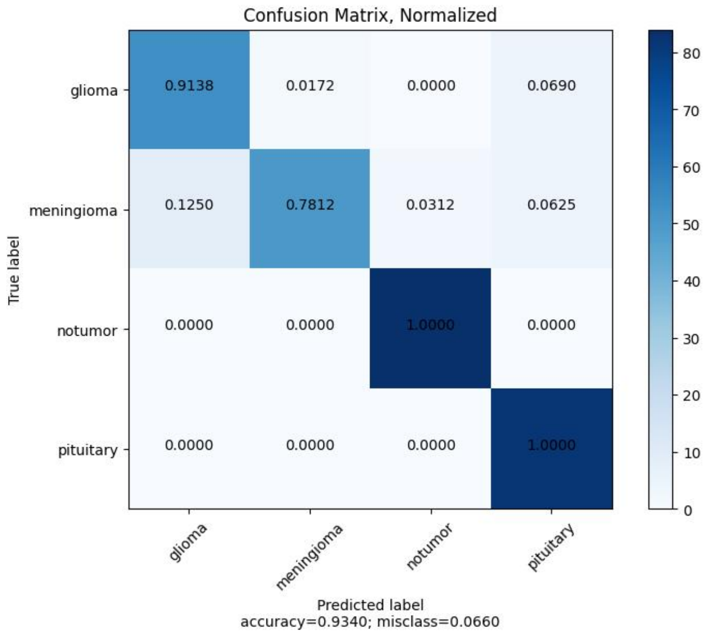


Figure 4.10: Confusion matrix for EfficientNetB2

4.3.3.5. Prediction:

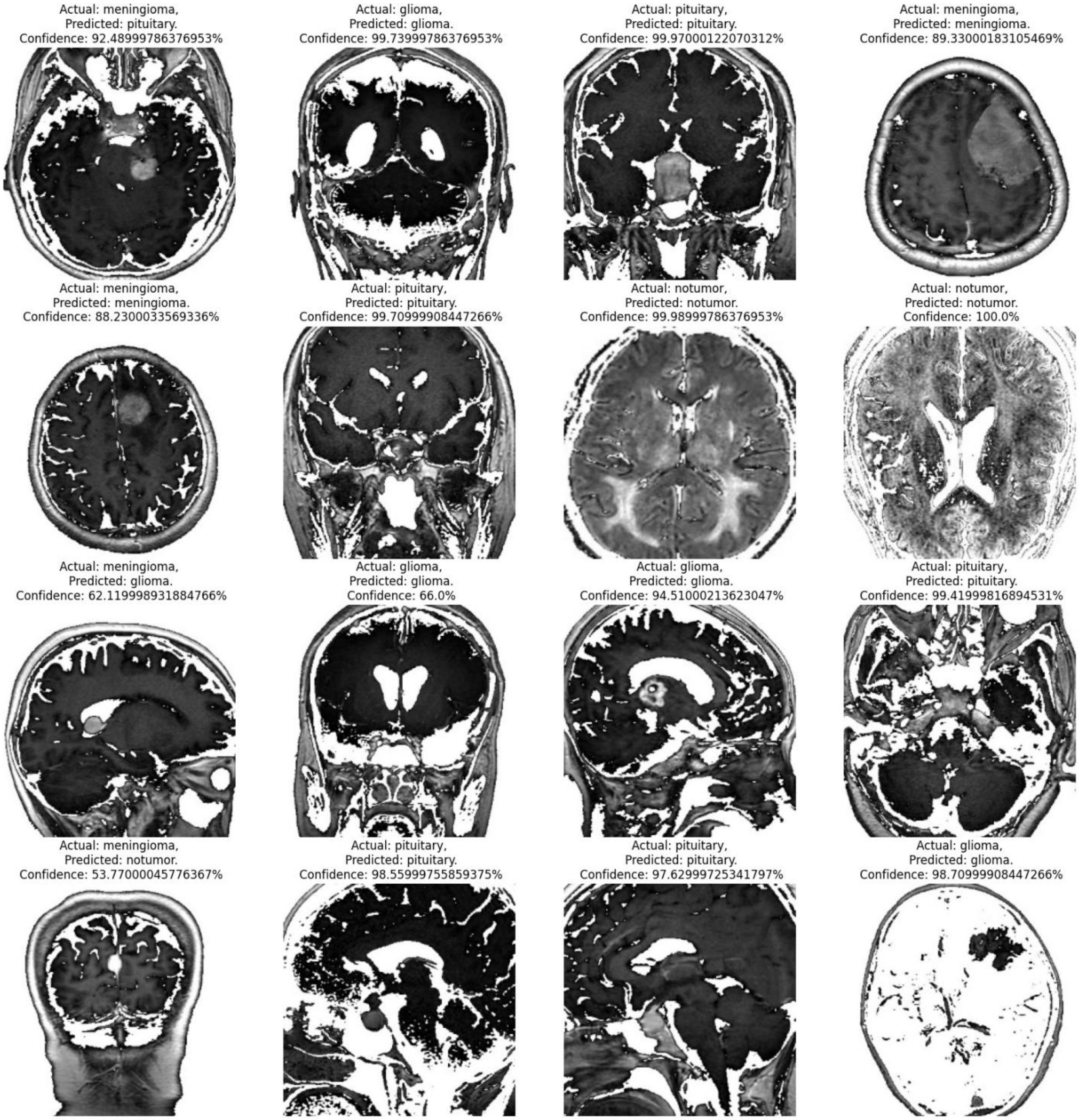


Figure 4.11: Prediction for EfficientNetB2

4.3.3.6. ROC Curve:

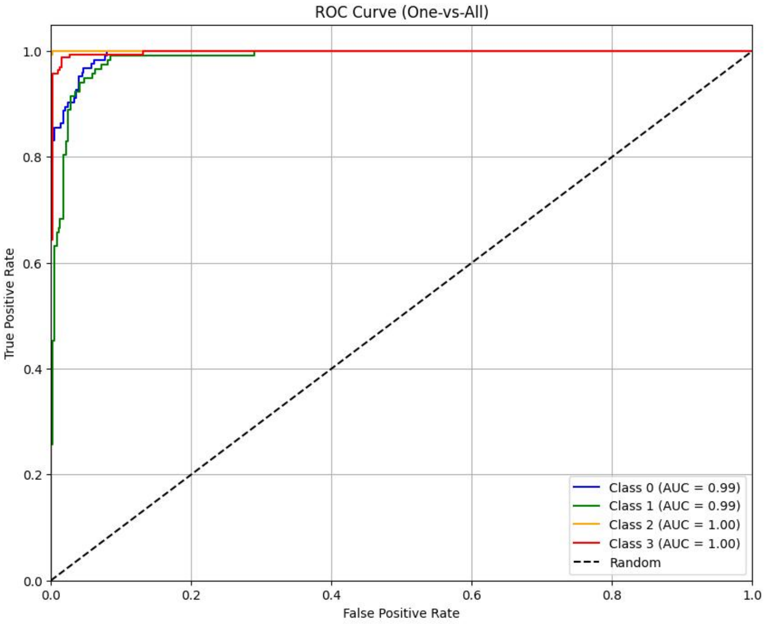


Figure 4.12: ROC Curve for EfficientNetB2

4.3.4. Custom CNN

4.3.4.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

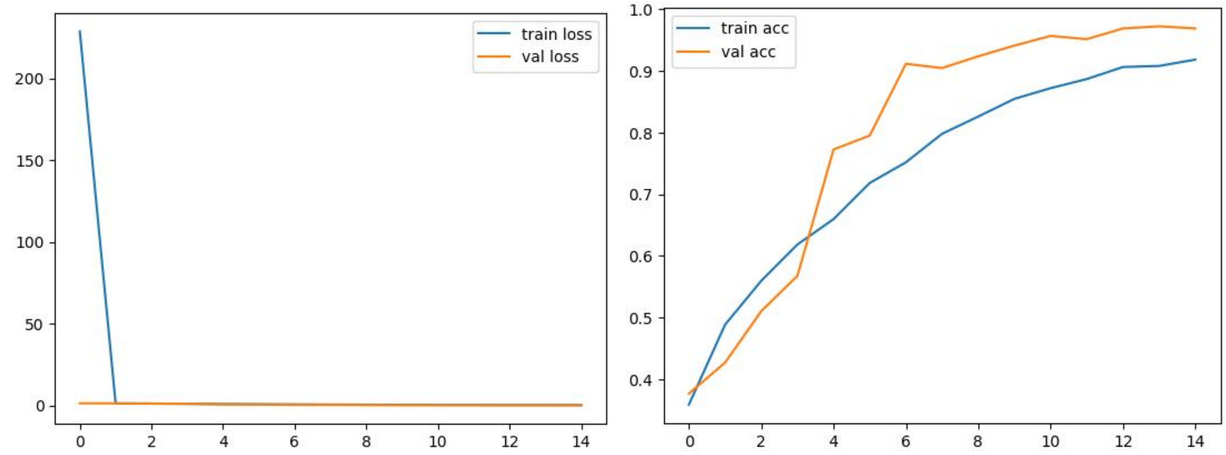


Figure 4.13: Training loss, validation loss and training accuracy, validation accuracy plot for CNN

4.3.4.2. Model Test after Training:

Table 4.8: Testing the Custom CNN Model after Training

Matrix	Value
Loss	0.2426
Accuracy	0.9339

4.3.4.3. Classification Report Model Performance:

Table 4.9: Classification report of Custom CNN Model

	precision	recall	f1-score
Glioma	0.95384615	0.91176471	0.93233083
Meningioma	0.921875	0.88059701	0.90076336
Notumor	0.94382022	0.98823529	0.96551724
Pituitary	0.97142857	1.0	0.98550725
Accuracy	0.9140		

4.3.4.4. Confusion Matrix:

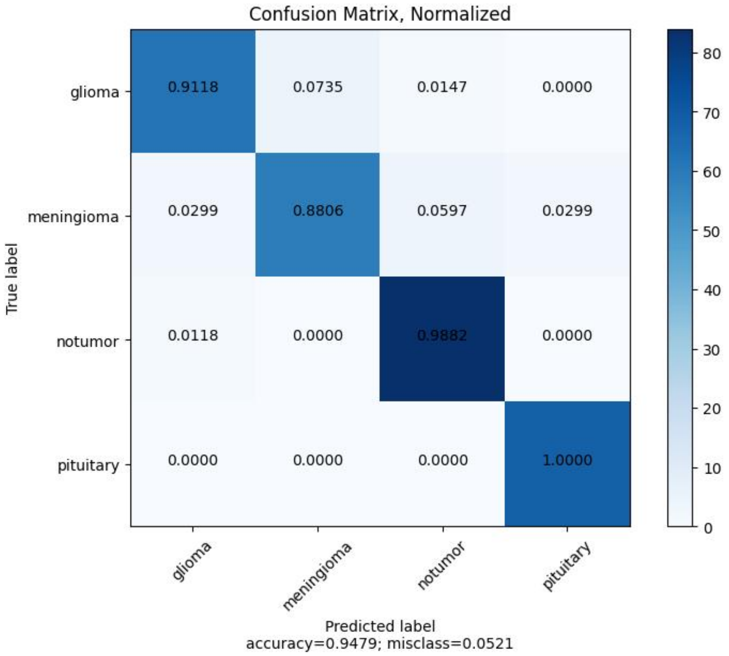


Figure 4.14: Confusion matrix for Custom CNN

4.3.4.5. Prediction:

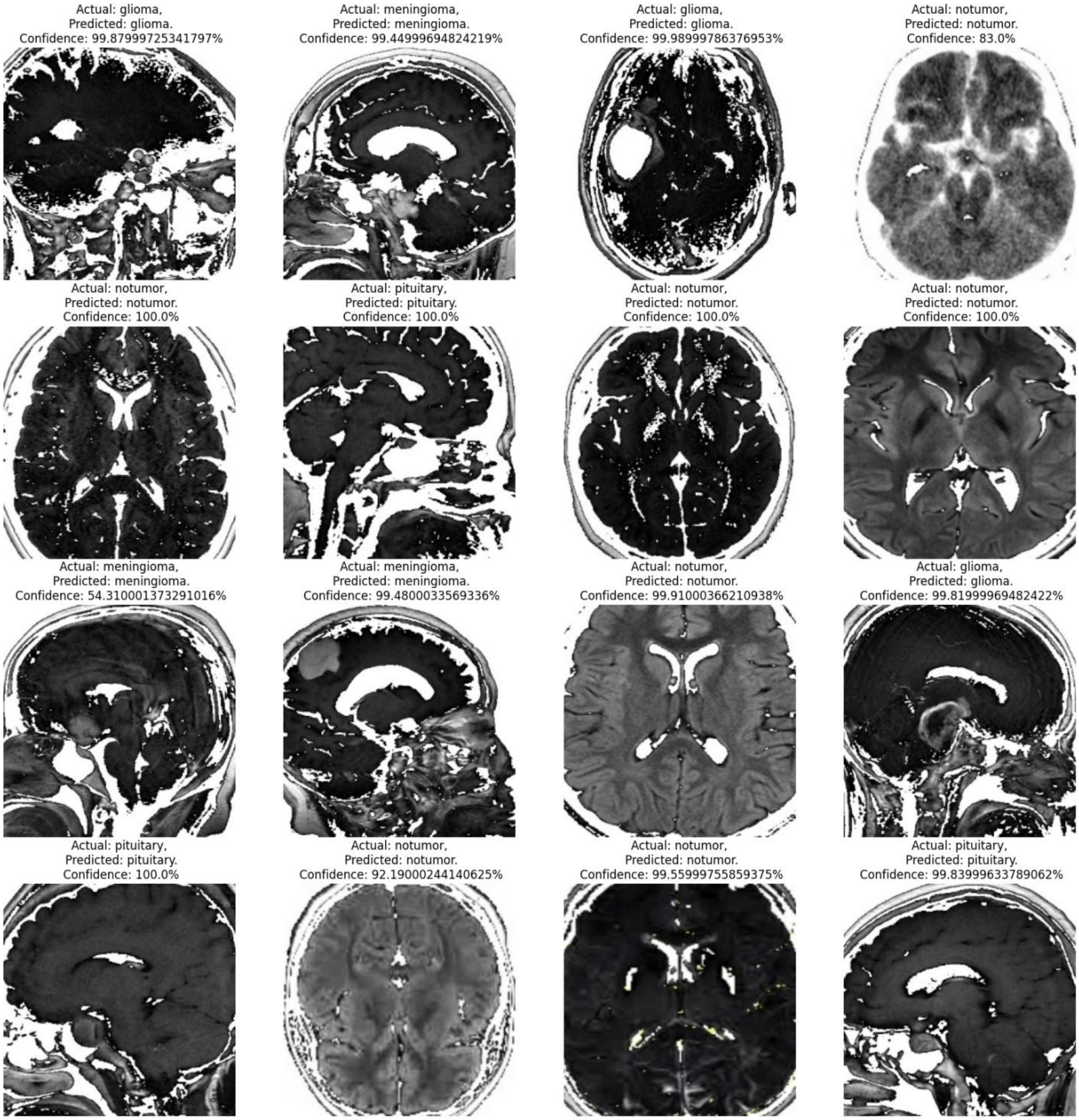


Figure 4.15: Prediction for Custom CNN

4.3.4.6. ROC Curve:

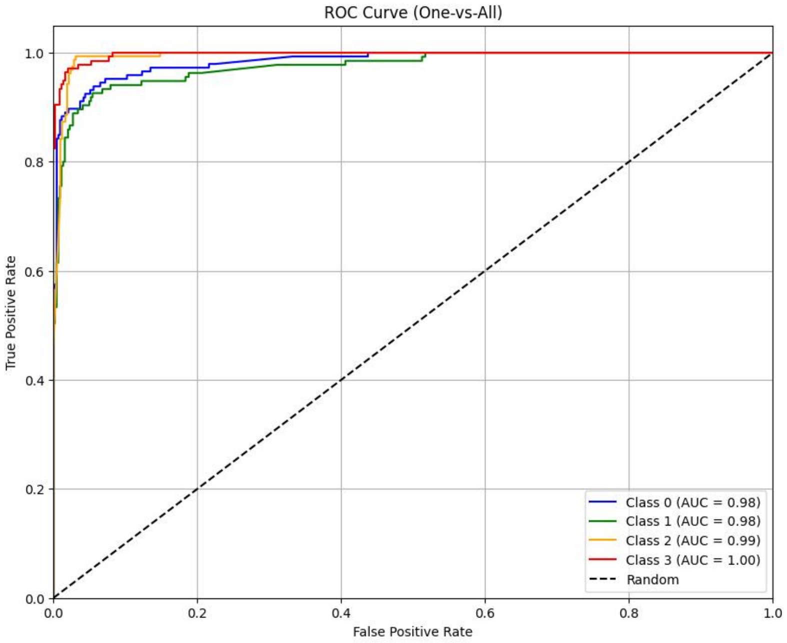
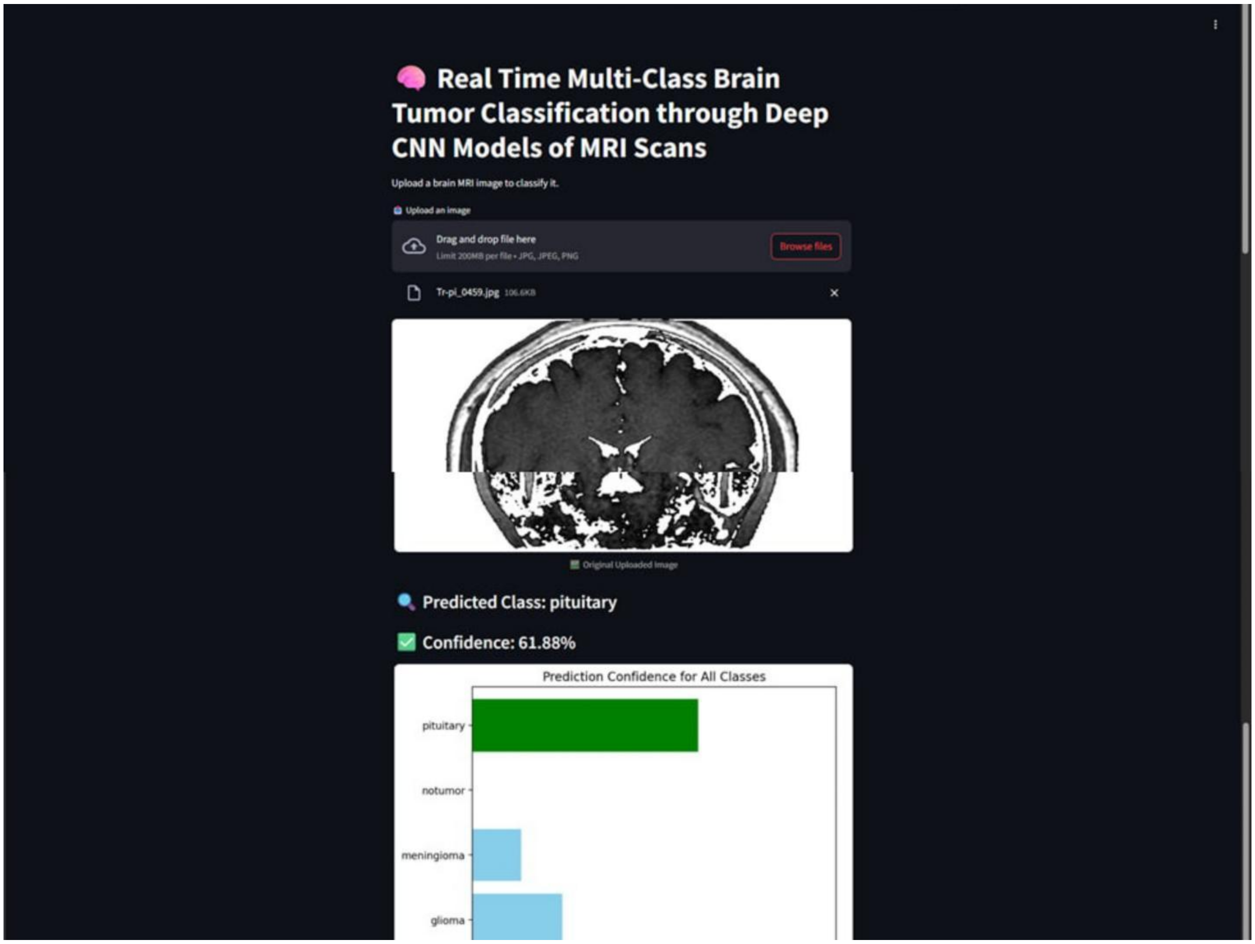


Figure 4.16: ROC Curve for Custom CNN

4.4. Deploy Model

Among the four CNN-based models evaluated in this study—ResNet50, EfficientNetB2, InceptionV3, and a custom CNN—the ResNet50 model achieved the highest classification accuracy, precision, and overall performance during both training and validation phases, demonstrating its strong ability to generalize across diverse MRI data. Owing to its superior metrics and stable learning behavior, ResNet50 was selected as the final model for deployment. To make the system accessible and usable beyond research environments, the model was embedded within a lightweight, interactive web application developed using the Streamlit framework. This application was then deployed publicly on HuggingFace Spaces, enabling users to upload brain MRI images and receive real-time classification results directly through a web browser. The deployment not only showcases the technical feasibility of translating deep learning research into practical tools but also supports clinical decision-making and educational use by offering a simple, responsive interface.

Ultimately, this integration bridges the gap between academic experimentation and real-world applicability, promoting scalable and efficient diagnostic support systems.



Real Time Multi-Class Brain Tumor Classification through Deep CNN Models of MRI Scans

Upload a brain MRI image to classify it.

Tr-pi_0459.jpg 106.6KB

Predicted Class: pituitary

Confidence: 61.88%

Figure 4.17: User Interface

Figure 4.17 showcases the real-time prediction interface built with Streamlit and hosted on Hugging Face Spaces. Users can upload brain MRI scans in supported formats (.JPG, .PNG), and the system provides instant classification results. Upon upload, the interface displays the predicted tumor class, associated confidence score, and a confidence distribution across all four classes: glioma, meningioma, pituitary tumor, and no tumor. This interactive feature transforms complex deep learning predictions into intuitive visual output, enhancing usability for non-technical clinical users.

The deployment ensures:

- Real-time classification using ResNet50.
- Browser-based access with no installation required.
- Instant feedback with graphical prediction visualization.

This functionality bridges the gap between research models and practical use, emphasizing the system's potential for integration into diagnostic workflows or educational platforms.

4.5. Discussion

Table 4.10: Summary of all Models precision, recall, f1-score

Model	Class	precision	recall	f1-score
ResNet50	Glioma	0.93333333	0.97222222	0.95238095
	Meningioma	0.97014925	0.92857143	0.94890511
	Notumor	0.98701299	1.0	0.99346405
	Pituitary	1.0	0.98571429	0.99280576
	Accuracy	0.9880		
InceptionV3	Glioma	0.78313253	0.94202899	0.85526316
	Meningioma	0.84210526	0.72727273	0.7804878
	Notumor	0.98611111	0.93421053	0.95945946
	Pituitary	0.86842105	0.85714286	0.8627451
	Accuracy	0.8353		
EfficientNetB2	Glioma	0.86885246	0.9137931	0.8907563

	Meningioma	0.98039216	0.78125	0.86956522
	Notumor	0.97674419	1.0	0.98823529
	Pituitary	0.91111111	1.0	0.95348837
	Accuracy	0.9218		
Custom CNN	Glioma	0.95384615	0.91176471	0.93233083
	Meningioma	0.921875	0.88059701	0.90076336
	Notumor	0.94382022	0.98823529	0.96551724
	Pituitary	0.97142857	1.0	0.98550725
	Accuracy	0.9140		

It was observed in this study that ResNet50 reached a classification accuracy of 98.80%, which was higher than the accuracies of EfficientNetB2 (92.18%), Custom CNN (91.40%), and InceptionV3 (83.53%). This is consistent with other reports like Abd El Kader et al. [1] and Sharif et al. [2], in which ResNet and DenseNet-based networks also performed better than classical CNNs and simple transfer learning techniques.

For example, Abd El Kader et al. reported an accuracy of 99.25% using Differential CNN, and Sharif et al. reached the accuracy of 99.7% with the combination of DenseNet201 and Modified Genetic Algorithm and SVM. Although the ResNet50 model in this study slightly underperforms in raw accuracy, it benefits from training on a merged, multi-source dataset, which enhances generalization across diverse tumor types.

Khan et al. [3] implemented a VGG-based model and reached 97.8% accuracy, while Sultan et al. [5] developed a deep CNN yielding up to 98.7%. However, unlike those studies, this research emphasizes model robustness across all four classes and reveals high precision and F1-scores even for harder-to-detect categories like Meningioma and Glioma. Moreover, the custom CNN used here achieved strong accuracy with minimal parameters, showing the feasibility of lightweight solutions in clinical settings.

Another distinguishing feature of this work is the thorough comparative evaluation of four distinct deep learning models under identical conditions, which many prior studies lacked. This enables a fair and reproducible benchmark of each architecture's performance.
In addition, this work includes real-time deployment with the use of Hugging Face Spaces and Streamlit, a concrete application rarely considered in prior work. Most of its previous formulations were focused on classification accuracies and not system usability in dynamic (real-time) environments.

Taken together, these results show that architectural depth, residual connections, and compound scaling are important factors for noisy students. The ResNet50 model leads with a well-balanced dataset and rigorous validation process, wiki-test14 outcompeting or equivalent to the results of previous benchmarks, wiki-test1, with benefits including a more… From relatively outset, we have taken the dataset and model as deployment and robustness exploration, and we test in real time.

4.6. Summary

This chapter describes the application and experimental analysis of 4 deep learning algorithms based on CNNs, ResNet50, EfficientNetB2, InceptionV3, and a custom CNN for the real-time multi-class brain tumor classification of MRI images. The models were trained and tested on a combined dataset in Google Colab, utilizing pre-processing, including normalization, augmentation, and contrast enhancement, for the models to learn optimally. A full comparison was done based on accuracy, precision, recall, and F1-score evaluation metrics, which shows that ResNet50 (98.80%) attained the best accuracy (98.80%), followed by EfficientNetB2 (92.18%), Custom CNN model (91.40%), and InceptionV3 (83.53%). In addition to quantitative metrics, a range of visualisations such as accuracy/loss plots, confusion matrices, ROC curves, and predictions were used to demonstrate model performance. A comparison table summarizes these results for easier interpretation. The chapter ended with the deployment in real-time of the ResNet50 via Hugging Face and Streamlit, as an example of an interpretable and immediately useful technique in clinical settings. Overall, this chapter demonstrated the strong potential of CNNs for brain tumor classification and established a deployable, reproducible framework for further research in medical diagnostics.

CHAPTER 5

ENGINEERING STANDARDS AND DESIGN CHALLENGES

5.1. Compliance with the Standards

5.1.1. Software Standard

The software standards for the Brain Tumor Classification project incorporate widely recognized platforms and tools to ensure consistency, efficiency, and collaboration. ResearchGate and Google Scholar are used for sourcing credible scientific literature. Google Colab serves as the primary development environment for implementing and training deep learning models using Python, TensorFlow, and Keras frameworks. Standard deep learning and machine learning libraries are used for model development and evaluation. A personal laptop with GPU support is utilized for local testing. Documentation and reporting follow academic standards using MS Word, ensuring clarity and professionalism in the presentation of research findings.

5.1.2. Hardware Standard

MINIMUM:
OS: Windows 7,8,8.1
Processor: I3 latest gen
Memory: 4 GB RAM
Graphics: 4GB GRAPHICS
DirectX: Version 11
Storage: 3 GB available space

RECOMMENDED:
OS: Windows 10

Processor: I5
Memory: 8 GB RAM
Graphics: 6GB or above GRAPHICS
DirectX: Version 12
Storage: 3 GB available space

5.1.3. Communication Standard

As part of the Brain Tumor Classification project team members follow a standard for communication that supports clear and coordinated group work. Reports are discussed through Zoom and Google Meet events to check team progress and solve issues and distribute work assignments. The project team distributes all their updates together with documentation through Google Drive to ensure both document version management and single-access features. With the added feature of WhatsApp Message System and email, you get upfront instant messaging and critical system notification. All the documents that need shapes use MS Word for development. The project life cycle has feedback loops that enable transparent feedback processes, the capacity for prompt cycles of revision, and the potential for collective decision-making in developing efficient workflows.

5.2. Impact on Society, Environment and Sustainability

5.2.1. Impact on Life

Real-time brain tumor classification offers better diagnostic quality for medical professionals, by which tumors are encouraged to be found at an earlier stage in the workflow and improve patient outcomes.

Automated tumour classification enables doctors to be more efficient in that there is less time spent on diagnosing, and time can be saved to carry out more important elements of patient treatment and care rather than manually categorising from visualisations.

The accuracy of the diagnosis of a brain tumor and the reliability of medical decisions will improve significantly for medical practitioners using AI-based models that reduce human errors in decision-making in the field of health.

Deploying such models in under-resourced medical areas allows patients to partake of state-of-the-art diagnosis tools and mitigates gaps in health service provisioning.

The reduction of overall manual analysis and expert intervention leads to lowered healthcare costs for brain tumor diagnosis and treatment, and especially makes healthcare more affordable to the patients.

The proposed system is a good medical tool that improves radiological skills and delivers quick, accurate diagnoses.

The work the authors are doing in developing them enables potential progress in medical imaging and AI technologies that could lead to healthcare innovation across diverse medical disciplines.

5.2.2. Impact on Society & Environment

Society's dependence on types of energy like wind, bodily matter, and water can decrease thanks to these new printing techniques.

Adopting Automated Tumor Classification compresses the physical and environmental resource requirements by obviating manual image analysis requirements.

Trained deep learning architectures operate efficiently on hardware optimizations and consume less energy than conventional diagnostic approaches that involve heavy manual intervention.

Digital health care is not dependent on physical infrastructure, i.e., including handling of paper records, and is hence environmentally less wasteful.

Closer to the end-users, AI can be employed for medical imaging, to enhance resource utilization of the current medical resources, which positions the location-specific needs to minimize environmental cost, by optimizing diagnostic procedures and decreasing number of tests.

It innovates based on environmentally-friendly AI technology and makes healthcare operations more efficient and reduced medical waste output, and take better care of the environment in the medical field.

5.2.3. Ethical Aspects

Data protection laws, such as GDPR and HIPAA, ensure that MRI scan data is anonymized before its processing to preserve patient privacy and confidentiality.

All the tumor classification models, however, need diverse training databases, so that the models do not get biased in classifying tumors of specific demographic groups (age groups, gender, ethnicity).

Transparent operation of deep learning models is required in order to allow radiologists to interpret diagnosticdecisions and be part of an accountable process.

Data-sharing will only happen with the written consent of patients; they will come to learn the process through which diagnostic tools are created by peering into their medical images.

The AI model works better in supporting radiologists than replacing human clinical staff, the research found. Final diagnosis interpretation and treatment decision, as an ethical issue, should be kept under human control.

5.2.4. Sustainability Plan

Lightweight deep learning frameworks should be employed with pruning methods to make classification models work efficiently on regular medical system hardware platforms.

The design should create systems which are modular and scalable so new data integration and future model updates will not require complete infrastructure changes.

The model should be available through open access platforms to encourage healthcare institutions participating in ongoing model validation while continuously enhancing its effectiveness.

The system includes a feedback mechanism to collect and use real-world clinical data that enables ongoing model training for persistent performance quality.

Healthcare professionals can adopt the system sustainably after receiving complete documentation and training materials that enable them to use it effectively throughout different clinical environments.

5.3. Project Management and Financial Analysis

Project Management:

- Project Planning & Timeline: Set clear milestones for the project, which should include data collection, processing, training, testing, validation, and finally evaluation of the model. Use DevOps to help track progress and focus on iterative modifications.
- Roles Assignment: Assign roles for data collection, pre-processing, model training, or lot more activities. Use cloud computing platforms (such as Google Colab, AWS, or Azure) to train models and store data.
- Risk Management: Address Data Quality, Overfitting, and Computational Limits Keep a backup plan for data storage and model evaluation.
- Quality Assurance: Scenario to scenario accuracy check. Test extensively with the variety of test cases to check for robustness.

Financial Analysis:

Table 5.1: Financial Analysis Report

Components	Estimated Cost (BDT)
Laptop	65000
Wi-Fi	1000
Internet	2000
Software and Tools	10000
Data Collection and Processing	3000
Documentation and Report Writing	2000

Transportation Fare	2000
Total Estimated Cost	85000

5.4. Complex Engineering Problem

The problem addressed in this project—real-time multi-class brain tumor classification using deep CNNs—fits within the framework of a complex engineering problem. The classification of MRI scans for medical diagnostics involves a high degree of uncertainty, diverse data characteristics, ethical implications, and performance constraints that must be balanced simultaneously. The problem solving indicators and knowledge mapping are outlined below.

5.4.1. Complex Problem Solving

Table 5.2: Mapping with complex problem solving

EP1 Dept of Knowledge	EP2 Range of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent of Stakeholder Involvement	EP7 Interdependence
✓		✓	✓			✓

Mapping with Knowledge Profile for EP1

This table 5.4 is designed to map the EP1 to the Knowledge Profile.

Table 5.3: Mapping with knowledge Profile

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓

5.4.1.1. Justification for EP Attributes Mapping

- **EP1 – Depth of Knowledge:**

  This project required a comprehensive understanding of multiple domains, including deep learning, medical imaging, neural network architectures, and preprocessing techniques for MRI data. Knowledge of convolutional neural networks (CNNs), transfer learning, and advanced performance metrics like F1-score and ROC curves was crucial. Implementing architectures such as ResNet50, InceptionV3, and EfficientNetB2 involved deep engineering skills and mathematical understanding, particularly in training strategy, activation functions, and optimization. Therefore, the problem demanded advanced technical depth suitable for final-year undergraduate research.

- **EP3 – Depth of Analysis:**

  The project involved rigorous performance evaluation using metrics such as accuracy, precision, recall, F1-score, confusion matrices, and ROC curves. These required deep analytical insight into classification outputs, error patterns, and model behavior during training and validation. Further, comparative analysis between four distinct models based on architectural differences, generalization, and training stability demonstrated the depth of analytical reasoning applied throughout the study.

- **EP4 – Familiarity of Issues:**

  Although brain tumor classification is an ongoing field of study, integrating real-time deployment through platforms like HuggingFace and Streamlit adds novelty and pushes beyond typical coursework experience. The implementation of parametric transformation and contrast stretching, along with large-scale image preprocessing and model tuning, also introduced unfamiliar but critical issues. Addressing these required learning beyond standard academic content, thus qualifying under unfamiliar technical domains.

- **EP7 – Interdependence:**

  Multiple subsystems and processes in the project were interdependent—from data collection, preprocessing, and augmentation to model training, performance comparison, and real-time deployment. Each stage depended on the successful output of the previous, particularly in designing a system that could generalize across different tumor types and still function efficiently in real-time. This layered dependency across model development and deployment aligns well with the definition of interdependent engineering tasks.

5.4.1.2. Justification for Knowledge Profile Mapping (Linked to EP1):

- **K3 – Engineering Fundamentals:**

  This project builds upon core engineering principles such as linear algebra, matrix operations, and probability, which are foundational in understanding convolution operations, backpropagation, and model optimization techniques. Concepts like activation functions, loss functions, and performance metrics rely on fundamental mathematical and algorithmic knowledge gained during undergraduate studies. These fundamentals were essential for structuring and training deep CNN models for accurate classification.

- **K4 – Specialist Knowledge:**

  The work involved specialized knowledge in artificial intelligence and machine learning, particularly in deep learning architectures like ResNet50, InceptionV3, EfficientNetB2, and a custom-designed CNN. Implementing the custom CNN required deeper understanding of layer configurations, filter tuning, and regularization techniques such as dropout. In addition, concepts such as transfer learning, overfitting mitigation, and batch normalization were applied to optimize model performance. Furthermore, knowledge of medical imaging and tumor classification added an interdisciplinary layer, making the project a strong example of specialized technical application in the healthcare AI domain.

- **K5 – Engineering Design:**

  Designing and implementing four distinct CNN models—including a custom architecture—demonstrated the application of engineering design skills. Each model had unique structures, layer configurations, and pooling strategies tailored to the problem. Trade-offs were analyzed between speed, accuracy, and model complexity. Moreover, design decisions in web deployment (Streamlit interface, HuggingFace hosting) also reflected engineering design thinking for real-world usability.

- **K6 – Engineering Practice:**

  The implementation process involved standard engineering practices such as version control (Google Drive/Colab workflows), structured documentation, model evaluation under various test conditions, and reproducibility of results. The project also adhered to best practices in deep learning development such as using validation/test splits, monitoring training loss, and applying real-time prediction workflows. These practices simulate industry-level workflows expected from engineering graduates.

- **K8 – Research Literature:**

The project was grounded in a detailed review of 25 relevant research papers, covering a range of architectures and methodologies in brain tumor classification. You compared your results with those of peer-reviewed publications and highlighted gaps in deployment and generalization, which your system addressed. Literature review guided your model choices, preprocessing techniques, and evaluation strategy—demonstrating strong engagement with academic research.

5.4.2. Engineering Activities

In this section, provide a mapping with engineering activities. For each mapping add subsections to put rationale (Use Table 5.4).

Table 5.4: Mapping with complex engineering activities

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓		✓

5.4.2.1. Justification for Engineering Activities Mapping:

- **EA1 – Range of Resources:**

  The project utilized a broad range of resources, including publicly available datasets (SARTAJ, Figshare, Br35H), cloud computing infrastructure (Google Colab with GPU support), multiple deep learning libraries (TensorFlow, Keras, NumPy), and deployment platforms (Hugging Face and Streamlit). Additional tools like Matplotlib, PIL, and OpenCV were used for data visualization and image preprocessing. This integration of varied data, tools, platforms, and frameworks reflects a wide resource base characteristic of complex engineering activity.

- **EA2 – Level of Interaction:**

  Although the project was conducted independently, it involved conceptual interaction with multiple domains including computer science, radiology, and clinical diagnostics. The integration of machine learning knowledge with medical image interpretation aligns with interdisciplinary interaction. Moreover, deploying the model publicly allows potential users (e.g., students, educators, or health professionals) to interact with the system, simulating user-level interaction for clinical decision support.

- **EA3 – Innovation:**

  The project introduced innovation through comparative evaluation and deployment of multiple deep learning architectures — including a custom CNN designed from scratch. The use of advanced preprocessing techniques like contrast stretching and parametric transformation, combined with real-time model deployment, offered novel contributions. Unlike many research projects that stop at evaluation, this system demonstrated full deployment, enhancing its originality and real-world applicability.

- **EA5 – Familiarity:**

  The work extended beyond conventional academic experience. Although brain tumor classification using CNNs is a well-established problem, building a complete pipeline from preprocessing to real-time deployment — while comparing four deep learning models — involved problem-solving outside typical coursework or prior exposure. This makes it a complex task requiring engineering judgment and adaptability.

5.5. Summary

The research titled *"Real-time Multi-Class Brain Tumor Classification through Deep CNN Models of MRI Scans"* addresses a complex engineering problem by integrating deep learning, medical imaging, and software deployment. It involves interdisciplinary knowledge (EP1), detailed analysis (EP3), and innovative system design that supports real-time clinical decision-making. The project aligns with multiple knowledge domains (K3, K4, K5, K6, K8), combining core engineering fundamentals with advanced AI methods and literature-backed design practices. Through diverse resources (EA1), interactive platforms (EA2), and innovative application of CNN models (EA3), the work fulfills engineering activity criteria. While not directly impacting the environment (EA4), the system contributes to diagnostic support and educational use, showcasing familiarity with established engineering processes (EA5). Overall, the project exemplifies the practical application of engineering knowledge to solve real-world problems in healthcare through intelligent automation.

CHAPTER 6

CONCLUSION

6.1. Summary

This study introduces an advanced system for real-time classification of brain tumors using deep convolutional neural networks applied to magnetic resonance imaging. The research focused on developing an accurate discriminative model capable of identifying meningiomas, gliomas, and pituitary tumors while simultaneously determining the presence or absence of tumorous tissue. The investigation utilized 5,712 MRI scans, which underwent enhancement procedures including contrast optimization and dimensional standardization to maximize image clarity and facilitate more effective computational learning.

The experimental framework evaluated four distinct neural architectures—ResNet50, InceptionV3, EfficientNetB2, and a purpose-built CNN—through systematic training, validation, and performance assessment protocols. Performance analysis revealed that the ResNet50 implementation achieved superior results with 98.80% classification accuracy, demonstrating exceptional pattern recognition capabilities and robust generalization across diverse imaging characteristics.

This automated diagnostic framework was specifically engineered to augment clinical practice by providing rapid, consistent tumor identification. The developed methodology offers healthcare providers a valuable supplementary tool for diagnostic assessment, potentially contributing to earlier intervention and enhanced treatment planning. The system's high accuracy supports its practical application in medical environments where precise tumor classification directly impacts therapeutic decision-making and patient care pathways.

6.2. Limitation

Despite promising results, this study has several limitations:

- The system currently supports only single-label classification and cannot detect multiple tumor types within the same MRI scan.
- Although the dataset was merged from several sources, it may not fully represent the diversity of MRI equipment, imaging conditions, or patient demographics.

- The models showed limited capability in detecting fine-grained distinctions between complex tumor boundaries or multiple tumor stages.
- While the model was deployed on Hugging Face, it was not fully optimized for real-time clinical performance in terms of speed or system latency.
- Like many deep learning approaches, the classification decisions lack interpretability, which can be a barrier in clinical adoption.

6.3. Future Work

To address these limitations and expand the scope of the study:

- Future models should support multi-label classification to handle the detection of multiple tumor types within a single scan.
- The dataset should be expanded and diversified further using real-world clinical MRI images to improve model robustness and applicability.
- Advanced deep learning architectures such as Vision Transformers or the latest versions of EfficientNet should be explored for improved accuracy and computational efficiency.

- Incorporating explainable AI techniques will help make model decisions more transparent and suitable for clinical environments.
- Clinical integration should focus on developing a real-time inference pipeline validated by healthcare professionals to ensure reliability, usability, and performance in actual medical workflows.

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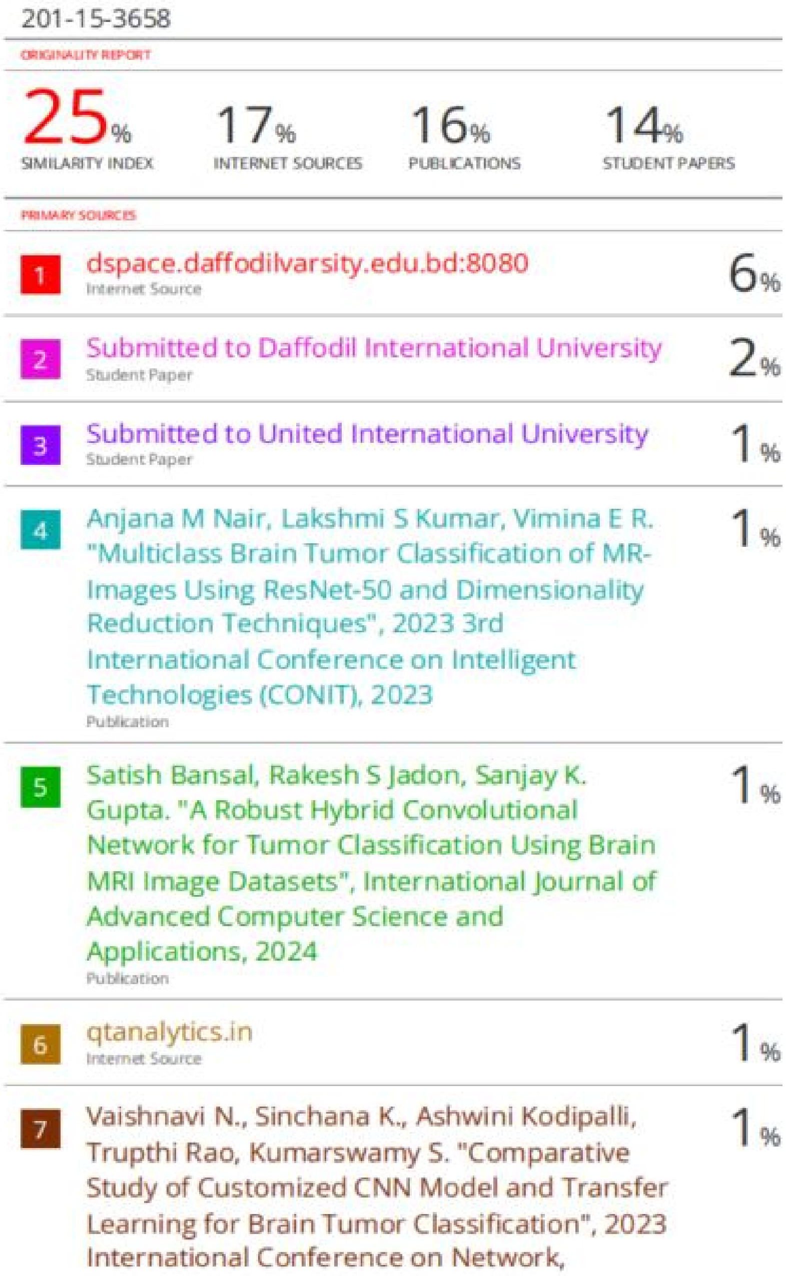

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