BRAIN TUMOR DETECTION BASED ON MRI SCAN IMAGES

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FACULTY OF INFORMATION SCIENCE & TECHNOLOGY

MULTIMEDIA UNIVERSITY

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DECLARATION

I hereby declare that the work have been done by myself and no portion of the work contained in this thesis has been submitted in support of any application for any other degree or qualification of this or any other university or institute of learning.

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ABSTRACT

This Final Year Project explores the development of a Convolutional Neural Network (CNN) for the detection of brain tumors using MRI scan images. The project is divided into two phases, with the first phase focusing on establishing a theoretical framework and planning the implementation strategy. This includes a comprehensive review of current methodologies in brain tumor detection, selection of tools and technologies, and outlining the proposed CNN architecture. The dataset, sourced from Kaggle, includes various categories of MRI images, which are preprocessed using techniques like grayscale conversion, resizing, and noise reduction. The project aims to contribute significantly to the medical imaging field by enhancing the accuracy and efficiency of brain tumor detection through advanced deep learning techniques. The second phase, which will be the focus of future work, will involve the actual coding, training, and testing of the CNN model.

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LIST OF ABBREVIATIONS/ SYMBOLS

AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
BAT	BAT Algorithm
CNN	Convolutional Neural Network
CRF	Conditional Random Field
CV	Computer Vision
FC	Fully Connected
FCM	Fuzzy C-Means
FSS	Fish School Search
FYP	Final Year Project
GA	Genetic Algorithm
GPU	Graphics Processing Unit
GBC	Gradient Boosting Classifier
HOG	Histogram of Oriented Gradients
KNN	K-Nearest Neighbors
MICCAI	Medical Image Computing and Computer-Assisted Intervention
MMU	Multimedia University
MRI	Magnetic Resonance Imaging
mAP	Mean Average Precision
MSE	Mean Squared Error
NLM	Non-Local Means
OpenCV	Open Source Computer Vision Library
PCA	Principal Component Analysis
PSNR	Peak Signal-to-Noise Ratio

PSO	Particle Swarm Optimization
ReLU	Rectified Linear Unit
RF	Random Forest
RSNA	Radiological Society of North America
SGD	Stochastic Gradient Descent
SGDM	Stochastic Gradient Descent with Momentum
SVM	Support Vector Machine
SSIM	Structural Similarity Index
TPU	Tensor Processing Unit
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
VGG	Visual Geometry Group Network
YOLO	You Only Look Once

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CHAPTER 1

INTRODUCTION

1.1 Overview

This project is focusing on the development of a machine learning or deep learning model for detecting brain tumors through MRI scans to utilized the power of deep learning in the realm of medical field. The project is structured to develop a robust and high accuracy system for detecting brain tumors. Besides, I will address the challenges in image quality and standardization in MRI scans. The overarching goal is to enhance diagnostic procedures, reduce human error, and help medical specialist to have better treatment strategies on brain tumor cases.

1.2 Problem Statement

Magnetic Resonance Imaging (MRI) plays a pivotal role in diagnosing tumors, yet variability in image quality and the absence of standardized preprocessing methods hinder accurate analysis. To address these challenges, this research aims to develop a comprehensive framework that standardizes and enhances MRI scan images, followed by the design of a robust deep learning model for tumor classification.

1.2.1 Inconsistencies in Image Quality

Noise in MRI scans related to brain tumor detection is a result of irregularities in image quality, which are frequently ascribed to patient movement and distortions in the magnetic field. Unwanted changes in pixel intensity, or "image noise," can mask important information and make it more difficult to detect brain tumor. Preprocessing, which applies picture enhancement algorithms and noise reduction approaches, is essential to reducing these difficulties. Good preprocessing techniques can reduce the effect of inconsistent image quality, improving MRI scan overall clarity and making the later stages of automated brain tumor diagnosis easier. By addressing issues related to noise and image quality inconsistencies through preprocessing, the automated system becomes more robust and capable of providing accurate and reliable results, laying the foundation for improved healthcare outcomes in the detection of brain tumors.

1.2.2 Manual Limitations

The reliance on human review of MRI scans reveals the manual limitations in the existing brain tumor identification procedure. Because of the complex structure of the brain and the wide range of tumor characteristics, the manual technique is not only time-consuming but also prone to error. It can be difficult for medical personnel to recognise and understand tiny anomalies in the scans, which could cause diagnosis to be missed or delayed. Medical workers' capacity is further stressed by the resource-intensive nature of the manual review process, which makes it harder for them to effectively handle other important responsibilities. Therefore, it is imperative to go over these manual constraints and implement an automated system that can improve brain tumor detection's precision and efficiency.

1.2.3 Lack of systematic and universal evaluation

The lack of standardized evaluation metrics and comprehensive validation procedures poses a significant obstacle to objectively assess the performance of image preprocessing frameworks and deep learning models in tumor classification. This deficiency inhibits the ability to compare, validate, and generalize the outcomes of different methodologies. Consequently, the translation of research advancements into clinical practice is hindered, impeding the widespread adoption of efficient and reliable solutions. Addressing this problem is essential for establishing a robust foundation in brain tumor detection methodologies, facilitating consistent performance evaluation, and promoting the seamless integration of advanced technologies into the realm of medical diagnostics.

1.3 Objectives

The project has three main objectives that are meant to advance the science of brain tumor detection by combining deep learning model and image processing techniques. The objectives are listed below and will be discussed.

- To develop an image preprocessing framework to standardize and enhance the quality of MRI scan images.
- To design a deep learning model for tumor classification.
- To evaluate the performance of the framework.

1.3.1 Develop an image preprocessing framework to standardize and enhance the quality of MRI scan images

The development of an image preprocessing framework is essential to resolving the issues arising from the intrinsic variability in the image quality of MRI scans. Through sophisticated preprocessing methods, the initiative seeks to standardize and enhance the quality of these images, laying a solid foundation for subsequent automated brain tumor detection.

1.3.2 Design a deep learning model for tumor classification

In order to accurately classify MRI scan images into tumor and non-tumor classes, the second goal of designing a deep learning model for tumor classification is to automate the detection process. An important factor to evaluate is how well this model fits the complexity of brain architecture and varies in tumor features.

1.3.3 Evaluate the performance of the framework

The project's goal is to evaluate the performance of deep learning model and the image preprocessing framework perform. To enable the smooth incorporation of these developments into medical diagnostics, this review entails the creation of standardised metrics, cross-validation processes, and a thorough assessment of clinical application.

1.4 Project Scope

- Designing and implementing a machine learning/deep learning model tailored for brain tumor detection.
- Processing and standardizing MRI scan images for model training and testing.

- Experimentation with various deep learning techniques to optimize model performance.
- Evaluation of the model using standard metrics to ensure accuracy and reliability.
- Investigating the model's applicability and potential integration into medical diagnostic processes.

1.5 Report Organisation

The report is organized into several chapters, each addressing a critical component of the project:

- Chapter 1: Introduction, outlining the motivation, objectives, and scope of the project.
- Chapter 2: Literature Review, discussing existing methods and technologies in brain tumor detection, machine learning and deep learning applications.
- Chapter 3: Methodology, detailing the chosen methodologies for developing the CNN model.
- Chapter 4: Implementation Design, describing the data acquisition, preprocessing steps, model architecture, and evaluation metrics.
- Chapter 5: Conclusion and Future Work, summarizing the findings and suggesting directions for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter will provide a thorough examination of the current literature and existing research on the detection of brain tumors. I will explore various methods and techniques, including traditional approaches, advanced computational models and useful techniques like SVM, CNN, ANN, PCA, RF, GA and so on. The focus will be on understanding how these methodologies contribute to the accuracy, efficiency, and reliability of detecting brain tumors. The literature review will also highlight the role of MRI in providing high-resolution, multi-dimensional images, which are crucial for precise tumor detection and diagnosis. This chapter aims to lay a foundation for understanding the complexities and challenges in brain tumor detection and the potential of innovative technologies to transform diagnostic processes.

2.2 Image Type

The imaging modality employed in this experiment is Magnetic Resonance Imaging (MRI) pictures. MRI, or magnetic resonance imaging, is a diagnostic technique that utilizes a strong magnetic field and radio waves to generate highly detailed images of the internal structures of the brain. This technology is particularly effective in identifying and highlighting abnormalities, such as tumors, for medical experts. The reasons of MRI are chosen among so many images type is because of MRI provides high-resolution, multi-dimensional scans that help determine the location, size, and features of brain tumors. With its accuracy, medical specialists are able to plan an efficient and suitable surgical procedures and therapies, which greatly improves patient outcomes and prognoses.

2.3 Noise

(Raj & Singh, 2021) The presence of irregular noises, high-intensity pixels, and undesirable background pixels in medical MRI pictures might significantly impair the accuracy of tumor detection and categorization. The distortion occurs in the amplitude of the radio signal level, whereas the noise in the test pixel is mostly caused by uneven attenuation of sensor signals, leading to random fluctuations in pixel intensity. The objective of the noise removal method is to restore the distorted image and return the patient's image to its original state. (Ramasamy,J., Doshi, R., & Hiran, K. K., 2022) In order to achieve a better experiment result, filtering method will be implemented to remove any noise in the MRI images.

2.4 Filtering Methods

(SVS College of Engineering et al., n.d.) discussed about the filtering methods such as Gaussian filtering and Weiner Filtering used them in removal of voice in this paper. Besides, they had made a comparison between them and also Median filtering. The reason of using these filtering methods is because they are efficient to reduce MSE(Mean-square error) and increase the value of PSNR(Peak signal-to-noise ratio). The Gaussian filter is a type of spatial linear filter that is commonly employed to eliminate Speckle noise in MRI pictures. Gaussian filter is commonly employed in the preprocessing stage to eliminate noise and improve the visibility of various structures at varying scales. MSE and PSNR have been measured and used for evaluating the performance of filtering methods. The lower MSE the better; The greater PSNR the better. The Table 2.1 has shown the evaluation for the mentioned filtering methods.

IMAGES	Filters for Removal of Noise					
	GAUSSIAN FILTER		WEINER FILTER		MEDIAN FILTER	
	PSNR	*MSE*	*PSNR*	*MSE*	*PSNR*	*MSE*
IMG1	47.4891	1.1592	49.7057	0.4374	41.6062	4.4922
IMG2	59.7756	0.0685	55.8416	0.1694	58.2849	0.0965
IMG3	57.9902	0.1033	51.7219	0.6958	52.6918	0.3499

Table 2.1: Filter Evaluation.

According to Table 2.1, the Gaussian Filter had the highest Peak Signal-to-Noise Ratio (PSNR) of 59.7756 and the lowest Mean Squared Error (MSE) of 0.0685 when compared to the Weiner Filter and Median Filter. This indicates that the Gaussian Filter performed better in removing noise from the MRI images utilized in this work.

Besides, they performed the mentioned filtering methods on 3 different images respectively and conducted a table. Table 2.2 shows the Structural Similarity Index(SSIM) values of the 3 images after filtering.

IMAGES	GAUSSIAN	MEDIAN	WEINER
IMG1	0.9993	0.9962	0.9960
IMG2	0.9998	0.9993	0.9986
IMG2	0.9996	0.9974	0.9965

Table 2.2: SSIM Values of Filtered Images.

SSIM is a metric used to measure the similarity between processed images and reference images. A higher SSIM value means better image quality.

In practical terms:

- When SSIM is equal to 1: The images are identical.
- When SSIM is near to 1: The images are very similar.

- When SSIM is near to 0: The images are dissimilar.

From Table 2.2, the filtered images using Gaussian Filter achieved the highest SSIM values and prove its effectiveness in the utilized dataset of this research paper.

(Ramasamy et al., 2022) implemented a method named non-local means(NLM) while doing pre-processing step to the MRI images of the utilized dataset in their research. This method works well for image denoising by fine tuning each pixel's value by adding the weighted total of the values of the surrounding pixels. This method has been used for a certain of time and shows its effectiveness. The research findings suggest that the NLM method surpasses other techniques in effectively reducing noise and preserving the integrity of edges.

2.5 Deep Learning in brain tumor detection

(Benkrama & Hemdani, 2023) suggested a convolutional neural network (CNN) strategy that utilizes Apache Spark to autonomously classify MRI images of brain tumors. This work integrated the principles of big data and image processing. The architecture of the suggested CNN model in this paper is depicted in Figure 2.1.

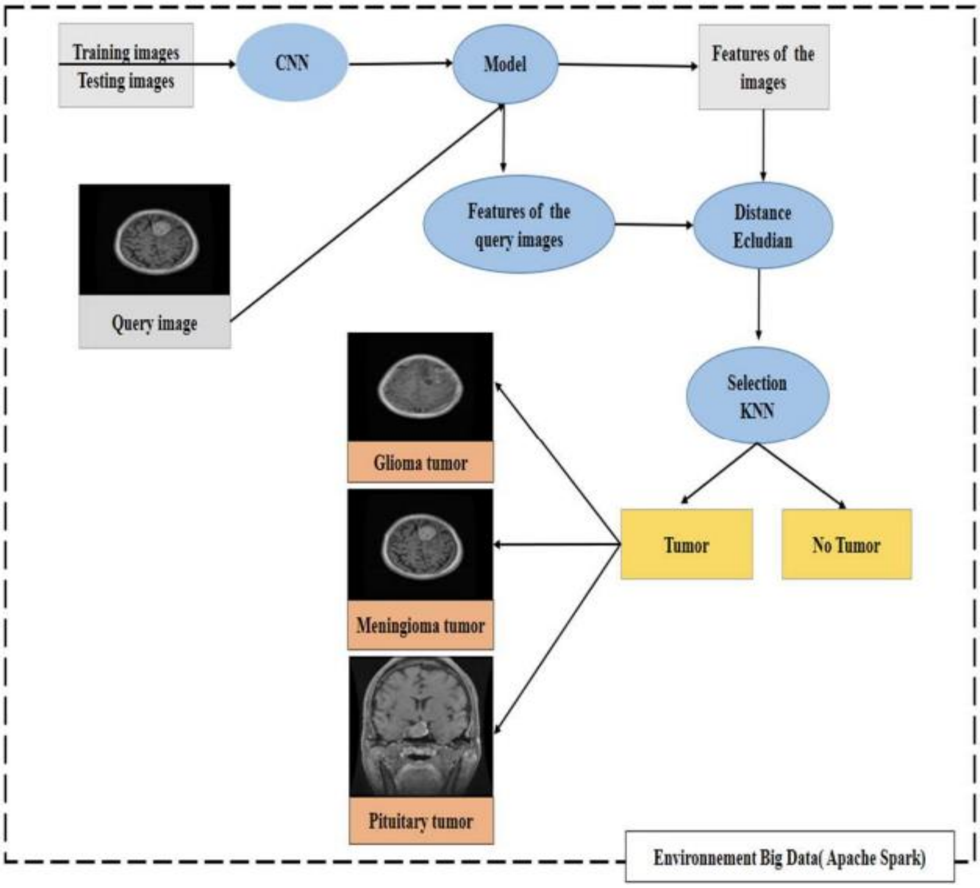

Figure 2.1: General architecture of CNN model (Benkrama & Hemdani, 2023)

This paper utilizes the EfficientNetb1 CNN model due to its superior accuracy, efficient performance, reduced time requirements, and lowered standards. The EfficientNetb1 model is utilized for the implementation of network architectures that are capable of operating at several scales and including multiple networks. The EfficientNetb1 model can extract profound characteristics from the MRI images. In addition, the researchers utilized the Epoch as the variable in the experiment. Increasing the number of epochs in this experiment should result in higher accuracy, given each epoch involves training on the entire dataset. The Figure 2.2 displays the topology of EfficientNetb1.

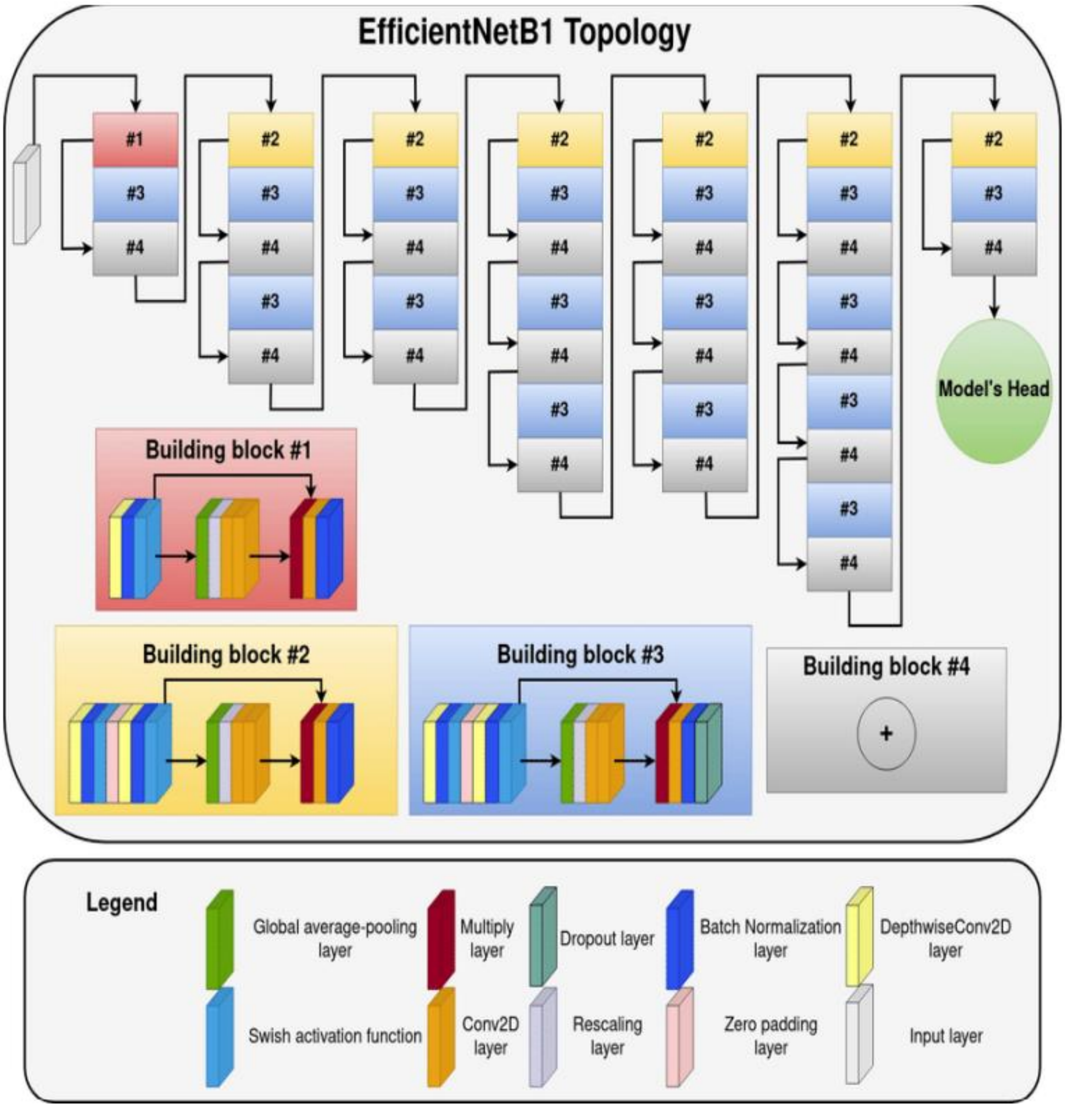

Figure 2.2 : EfficientNetb1 topology.

In results, they achieved 97% of accuracy by using Epoch 15. Lastly, a comparison between their proposed approach results and proposed approach by others. Model CNN-LTSM(Long Short-Term Memory) is 92%, Model CNN, EfficientNetB0, Resnet is 95.95% which is greater than the proposed approach in this paper. Meanwhile, this comparison has shown that Efficient Net's accuracy was the biggest and the best.

(Tang & Teoh, 2023) examine the utilization of ResNet18, CapsNet, and GoogLeNet architectures on a dataset of 3064 T-1 weighted CE-MRI images acquired via Figshare. The authors employ scaling and data augmentation tactics to enhance the resilience of their models. The chosen optimization strategy for classification is

Stochastic Gradient Descent with Momentum (SGDM). The research emphasizes the advantages of utilizing deep learning techniques, specifically ResNet18, for automatic feature extraction. These techniques outperform traditional methods by achieving higher recognition accuracies. The research acknowledges a potential restriction, specifically highlighting the possibility of overfitting in deep neural networks. This is more likely to happen when the networks are large or when they are trained on little samples. Overfitting can potentially hinder the model's ability to effectively generalize to new and untested data.

The study conducted by (Dipu, N. M., Shohan, S. A., & A Salam, K. M. ,2021) explores various deep learning techniques to accurately detect brain cancers. The algorithms that were studied include YOLO V5, YOLO V3 Pytorch, YOLO V4 Darknet, Scaled YOLO V4, YOLO V4 Tiny, Faster-RCNN, and Detectron2. Performing shrinking and converting DICOM images to JPG format, along with additional preprocessing techniques, and utilizing the "Brain-Tumor-Progression" dataset from The Cancer Imaging Archive (TCIA).

(Nagarjuna College of Engineering and Technology et al., n.d.) centers on the utilization of CNN in the categorization and type of brain cancers. Setting the picture size, label binarization, grayscale conversion, thresholding, erosion, dilation, contour extraction, normalization, and data augmentation are some of the critical image processing pipeline processes that are included in the study. There are 2,123 MRI pictures in the dataset that was used for the study, which was retrieved via Figshare. The preprocessing procedures are designed to improve the data's quality and diversity so that CNN training works well. The activation function, Rectified Linear Unit (ReLU) has been utilized in the research and Adam is the optimization approach used.

(Mahajan & Chavan, 2023) present a study about on the use of CNN for multiclass brain tumor diagnosis with magnetic resonance imaging (MRI). The study uses a Kaggle dataset and resizes it as a preprocessing step. Rectified Linear Unit (ReLU) activation functions are used in the construction of the CNN model. The research highlights the CNN's effectiveness even in situations where training datasets are scarce, emphasizing the model's capacity to function well with a tiny amount of training data.

(Sri Eshwar College of Engineering & Institute of Electrical and Electronics Engineers, n.d.) investigate the application of region-based CNN (R-CNNs) to MRI brain tumor detection and classification. The min-max approach is used to normalize the images as part of the preprocessing procedure. The study's dataset was gathered by Jun Cheng and colleagues. Stochastic Gradient Descent (SGD) is the optimization algorithm used. According to the research, the R-CNN model can effectively identify and categorize various tumor kinds in MRI pictures. Nonetheless, "low accuracy" is mentioned, although the precise accuracy levels are not given. This implies that although the R-CNN model is effective in classifying and detecting tumors, there might be restrictions on reaching high accuracy.

(Hu, H., Li, X., Yao, W., & Yao, Z., 2021) presents a novel model for automated brain tumor identification and classification that blends YOLO (You Only Look Once) and Convolutional Neural Network (CNN) architectures. Preprocessing methods like color differential and cropping are used into the model to improve the input data and concentrate on pertinent areas. The study investigates the possibilities of this hybrid CNN-YOLO model using a dataset that is accessible on GitHub. The study does point out that using enhancement techniques lowers accuracy, indicating a trade-off between preprocessing gains and the system's overall effectiveness in detecting and classifying brain tumors.

Author	Dataset	Method	Performance
(Benkrama , et al., 2023)	Kaggle dataset 3264 MRI images	CNN-LSTM	Accuracy:92%
(Tang , et al., 2023)	(CNN)3064 T-1 weighted CE-MRI images from Figshare	ResNet18	Accuracy: 0.8833
		CapsNet	Accuracy:0.8475
		GoogLeNet	Accuracy: 0.8667
(Dipu et al., 2021)	Brain-Tumor-Progression dataset provided by The Cancer Imaging	YOLO V3 PyTorch	mAP@5Score: 84.30% f1-score: 82.40%
		YOLO V4 Darknet	mAP@5Score: 88.71% f1-score: 90.00%
		YOLO V4-Tiny	mAP@5Score: 88.99%

	Archive (TCIA)+A3:M3		f1-score: 89%
		Scaled-YOLO V4	mAP@5Score: 89.77% f1-score: 86.18%
		YOLO V5	mAP@5Score: 95.07% f1-score: 90.46%
		Faster R-CNN Tensorflow	mAP@5Score: 85.63% f1-score: 83.94%
		Detectron2	mAP@5Score: 91.51% f1-score: 82.39%
(Nagarjuna College of Engineering and Technology et al., n.d.)	Figshare which consists of 2,123 images of MRI	KNN	Accuracy: 85.18%
		Decision Tree	Accuracy: 65.88%
		Random Forest	Accuracy: 69.65%
		CNN	Accuracy: 92.62%
(Mahajan , et al., 2023)	Kaggle	CNN	Accuracy: 88%
(Sri Eshwar College of Engineering & Institute of Electrical and Electronics Engineers, n.d.)	MRI Image dataset collected by Jun Cheng et al.	R-CNN	Accuracy: 77.60%
(Hu et al., 2021)	GitHub	CNN-YOLO	Accuracy: 63%
		VGG19	Accuracy:76.396%
		AlexNet	Accuracy:74.365%
		GoogLeNet	Accuracy:75.381%
		ResNet50	Accuracy:76.904%

Table 2.3 : Summary Table of Existing Deep Learning Approaches.

2.6 Machine Learning

(Saraswathi & Gupta, n.d.) explains an algorithm for classifying tumors in the brain using brain MRI data. The suggested method combines Principal Component Analysis (PCA) and Random Forest (RF) to handle feature extraction and classification. For research objectives, the study uses textural features such the Gray

Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP). The method depends on using PCA to simplify the feature space and Random Forest to provide reliable classification. One method the author suggests to avoid the problem of overfitting, which is a common problem in machine learning models, is to use a random subset of features. The study also observes that the size of the Random Forest decision tree and the classification time have a favourable link.

(Ramasamy et al., 2022) detects brain cancers in medical pictures by combining a variety of machine learning algorithms with feature extraction using the Histogram of Oriented Gradients (HOG). Relevant features were extracted by preprocessing methods including thresholding, Histogram of Oriented Gradients (HOG), and Non-Local Means (NLM) denoising in the study. We made use of the Kaggle dataset. Machine learning techniques including Support Vector Machine (SVM), XG Boost, Random Forest, Gaussian Naive Bayes, and Decision Tree are used in this work. The research acknowledges the usefulness of HOG as a preliminary measure and proposes its use for feature extraction in brain cancer diagnosis.

(SCAD College of Engineering and Technology & Institute of Electrical and Electronics Engineers, n.d.) presents a unique algorithm for brain tumor detection. CNN, genetic algorithms(GA), SVM, and conditional random fields (CRF) are all used in the process. A number of data preparation techniques, including cleaning, transformation, integration, resizing, and reduction, are used in the study. UCI datasets are used to conduct experiments. The suggested method is a multifaceted way to improve brain tumor identification that combines CNN, SVM, GA, and CRF. Notably, the study makes use of many preprocessing methods to deal with issues linked to data. The research discovered that CNN-based methods performed better in spite of these attempts.

(Sree et al., 2022) focuses on applying machine learning (ML) techniques to the detection of brain tumor. The approach uses preprocessing techniques to apply resizing, cropping, and normalization to MRI data that is obtained from Kaggle. The detection and classification model performs better overall when common preprocessing methods like cropping and normalizing are used. Although the research offers a useful approach for brain tumor identification, the breadth of knowledge may be constrained by the lack of particular details regarding the ML algorithms employed and their comparative evaluation.

(Joshi & Suthaharan, 2020) presents pixel-level feature space modelling as a unique method for brain tumor detection. The study uses binary image segmentation methods in conjunction with machine learning algorithms, including Random Forest (RF), Artificial Neural Network (ANN), and Support Vector Machine (SVM). The BraTS 2015 dataset, which provides Ground Truth (GT) for precise model training and validation, is the foundation of the methodology. The study highlights how crucial a reference frame is to the procedure and shows how heavily it depends on selection and availability.

Author	Dataset	Method	Performance
(Saraswathi & Gupta, n.d.)	-	PCA-RF	Accuracy: 85.56%.
(Ramasamy et al., 2022)	Kaggle	Random Forest	Accuracy:83%
		Decision Tree	Accuracy:72%
		Gaussian Naive Bayes	Accuracy:62%
		XG Boost	Accuracy:80%
		SVM	Accuracy:84%
(SCAD College of Engineering and Technology & Institute of Electrical and Electronics Engineers, n.d.)	UCI datasets	Conditional Random Field(CRF)	Accuracy: 89%
		SVM	Accuracy: 84.5%
		Genetic Algorithm (GA)	Accuracy: 83.64%
		CNN	Accuracy: 91%
(Sree et al., 2022)	Kaggle	ML based	Accuracy:88.79%
(Joshi & Suthaharan, 2020)	Ground Truth: BraTS 2015 dataset	RF	Accuracy:92%
		ANN	Accuracy:90%
		SVM	Accuracy: 88%

Table 2.4 : Summary Table of Existing Machine Learning Approaches.

2.7 Hybrid Learning

In order to attribute to the medical field, (Duvvuri, K., Kanisettypalli, H., & Jayan, S., 2022)investigates a CNN model and a hybrid model(CNN-SVM) that combined CNN and SVM for the purpose of detecting brain tumors. This study discussed the application of the sigmoid activation function in combination with the Adam optimizer. Besides, the researchers utilized a dataset obtained from Kaggle in the experiment. The study emphasizes the effectiveness of the models, especially when applied to a bigger dataset, indicating their ability to improve brain tumor identification.

According to (Raj & Singh, 2021), a unique hybrid method for the diagnosis of brain tumors combines Support Vector Machines (SVM) with the Fish School Search Algorithm (FSSA). This research endeavors to tackle obstacles in medical image processing, namely in the areas of noise reduction and skull stripping—two essential procedures that enhance the precision of brain tumor identification. The experimental dataset is obtained from Kaggle. The FSSA-based segmentation technique is incorporated into the hybrid approach, emphasizing its importance in improving the segmentation process. The two most important preprocessing procedures are skull stripping and noise reduction, which improve picture quality and, in turn, increase the accuracy of tumor detection.

(Ramachandran, R., Senthil, R., Mukunthan, M. A., Kanimozhiraman, & Balasubramanian, D., 2023). presented a hybrid model for the detection and classification of brain tumors. The machine learning and deep learning algorithms have utilized in this research. They have implemented and made a comparison between SVM, RBNN, ANN, and a hybrid model combining fuzzy C-means and convolutional neural network named FCM-CNN. They combined HIS linear decomposition algorithms with the mentioned algorithms and significantly reduces the computational cost. Besides, super pixel segmentation also has been implemented to the dataset to ` the process of detection and classification.

(Mallampati, B., Ishaq, A., Rustam, F., Kuthala, V., Alfarhood, S., & Ashraf, I., 2023)presents a novel method for the identification of brain tumors. The suggested approach combines a Hybrid Machine Learning Model (HM) that combines a gradient boosting (GBC) and K-Nearest Neighbors (KNN) with 3D-UNet Segmentation Features.

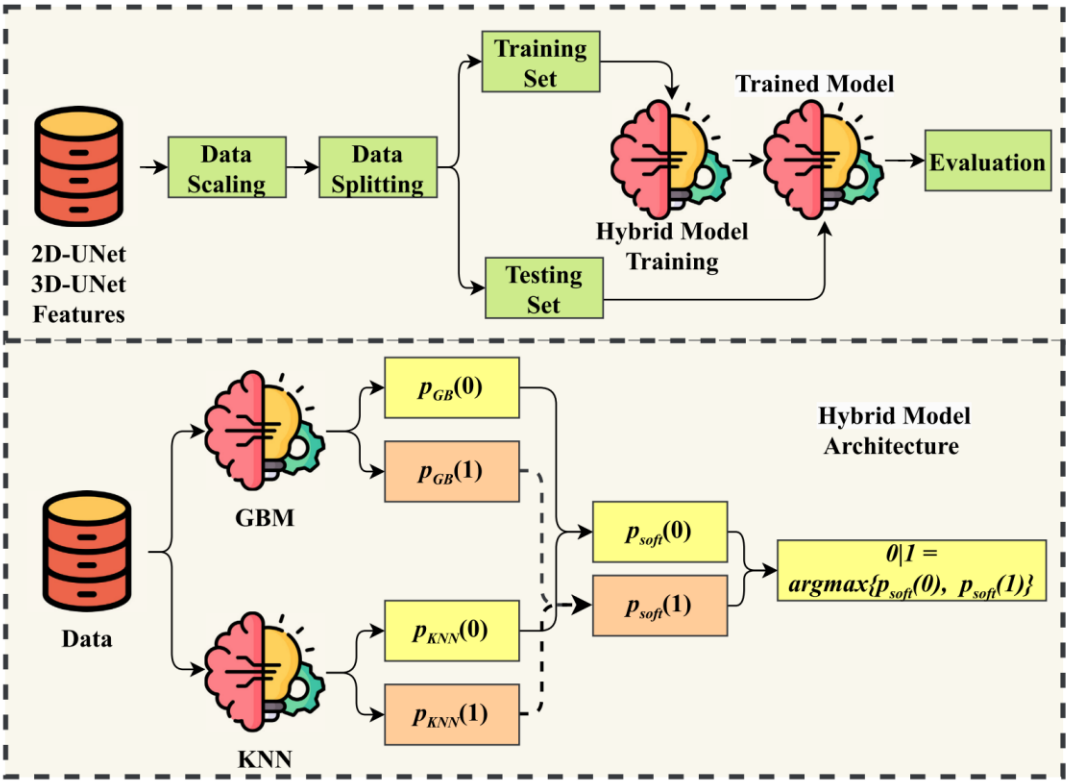

Figure 2.3 : Methodology of combination of KNN and GBM. (Mallampati et al., 2023)

Figure 2.3 shows how overview of their methodology. They use soft voting in Hybrid model to combine the predictions from KNN and GBM to allows leveraging the strengths of both models and improves the overall classification performance by considering the probability scores instead of relying solely on final class predictions. The 'RSNA-MICCAI Brain Tumor Classification' dataset is used in the study's experiments. In order to improve and enhance the image quality, some feature extractions have been utilized such as GLCM, GLSZM, and GLDM.

(Dharshini, S., Geetha, S., Arya, S., Mekala, N., Reshma, R., & Sasirekha, S. P., 2023) discussed how BAT algorithms helps Convolutional Neural Networks (CNN)to increase the efficiency and accuracy of detecting brain tumors. The suggested technique entails reducing noise and adverse effects from pictures, obtaining age-related data, and mapping tumor boundaries and contours for diagnostic purposes.

While the BAT algorithm enhances CNN performance, the CNN is trained to recognize patterns suggestive of malignancies. The goal of this hybrid technique is to improve brain tumor diagnostic speed and accuracy.

Author	Dataset	Method	Performance
(Duvvuri et al., 2022)	Kaggle	CNN	Accuracy: 88.47%
		CNN-SVM	Accuracy:92.96
(Raj, et al., 2021)	Kaggle	Fssa based SVM	Accuracy: 94.57%
		K-Mean Clustering	Accuracy: 76%
		Pso Algorithm	Accuracy: 81.3%
		MCSO	Accuracy: 84.1%
(Ramachandran et al., 2023)	-	SVM	Accuracy:87.12%
		RBNN	Accuracy: 89.15%
		ANN	Accuracy: 90.32%
		FCM-CNN	Accuracy: 94.55%
(Mallampati et al., 2023)	RSNA-MICCAI Brain Tumor Classification	HM(KNN+GBC)+3D-Unet Segmentation Features	Accuracy:71.1%
(Dharshini et al., 2023)	Self-collected from hospital	CNN-BAT	-

Table 2.5 : Summary Table of Existing Hybrid Learning Approaches.

CHAPTER 3

Methodology

3.1 Overview

This chapter outlines the methodology employed in this research to create a machine learning/deep learning model for the detection of brain tumors using MRI scan pictures. I employ a methodical and organized framework, specifically the Waterfall model, to oversee and track each aspect and stage of the project. The technique includes an examination of the Waterfall model, as well as the software and programming languages that will be used in the development process.

3.2 Waterfall model

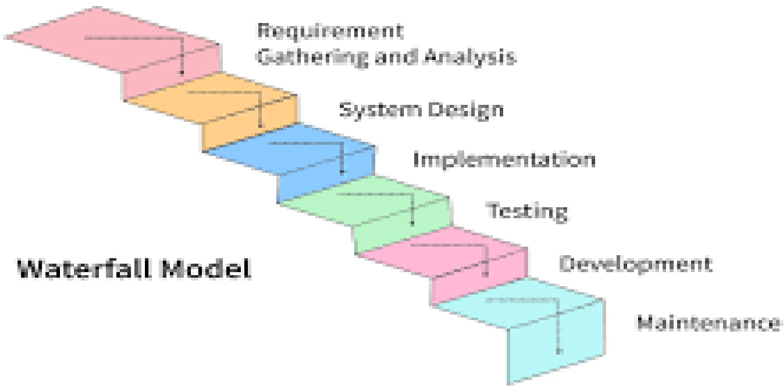

Figure 3.1 : Illustration of Waterfall Model.

The Waterfall model is good for its systematic and linear approach and has been meticulously chosen for this project due to its suitability in managing complex development processes of brain tumor detection. This model is characterized by its distinct, sequential stages, where each phase must be completed before proceeding to the next, ensuring a structured progression of the project.

The key phases in the Waterfall model for this project include:

- Requirements Analysis
    - This initial phase involves a comprehensive analysis to define the specific requirements for the proposed model.
    - I will conduct a detailed study of brain tumor types, characteristics, and how they manifest in MRI images.
    - The output of this phase is a well-defined requirement document, outlining the objectives, expected functionalities, and performance criteria for the proposed model.

- System Design:
    - In this phase, the overall system architecture is planned.
    - The data processing pipeline, from image preprocessing to data augmentation strategies, is also architected.
    - This phase results in a comprehensive system design document that serves as a blueprint for implementation.

- Implementation:
    - This phase is where the actual coding and development of the CNN model occur.
    - Utilizing the selected programming languages (like Python) and tools (such as TensorFlow or Keras), the model as per the design document is coded.
    - Data preprocessing scripts are developed to transform raw MRI images into a suitable format for model training.
    - This phase is iterative and may cycle back to design for modifications if needed.

- Testing
    - Post-implementation, the model undergoes rigorous testing to ensure its accuracy and reliability in detecting brain tumors.
    - The model is also tested with different sets of data to evaluate its performance under various scenarios.

- Maintenance

- The final stage involves the maintenance of the proposed model.
- This includes updating the model based on user feedback, performance evaluations, and advancements in the field.
- Regular checks and updates are necessary to ensure the model's relevance and accuracy over time.

3.3 Software requirement

3.3.1 Google Colab

Figure 3.2 : Logo of Google Colab.

The major development environment is Google Colab. It gives users free access to strong computational resources, such as GPUs and TPUs, which are necessary for deep learning model training, via a cloud-based platform. Additionally, Google Colab and Google Drive interact easily, making effective data management and storage possible. Code authoring, execution, and sharing are made easier by its Jupyter notebook interface, which also makes it an adaptable tool for team development.

3.3.2 Anaconda

Anaconda is utilized as the primary Python distribution for this project, offering a comprehensive suite of scientific libraries and tools. Its package management and environment management systems allow for a streamlined setup of different Python environments that ensure consistency and reproducibility of the project's computational environment across various stages.

3.3.3 Kaggle

Kaggle's computing environment is employed, particularly for its powerful cloud-based capabilities and access to high-performance GPUs such as GPU T4x2, GPU P100 and TPU VMv3-8. These GPUs are crucial for accelerating the computation-intensive tasks involved in training deep learning models, significantly reducing training time and enabling more complex model experiments. Additionally, Kaggle provides a vast repository of datasets and a community-driven platform for exploring and utilizing these datasets for model training.

3.4 Programming language

3.4.1 Python

Figure 3.3 : Logo of Python.

Python is a popular choice in the fields of machine learning and data science because of its adaptability and simplicity. It provides an extensive ecosystem of frameworks and libraries, including TensorFlow and Keras, which are essential for developing and refining deep learning models. Python's simple syntax and simplicity of reading make it possible to design applications quickly and maintain them easily.

3.4.2 Open CV

Figure 3.4 : Logo of OpenCV.

For OpenCV (Open Source Computer Vision Library) is utilized for image processing tasks. It is a comprehensive library specifically designed for computer vision, offering a wide array of functions to manipulate and process images. OpenCV is critical in the preprocessing stages, such as in image resizing, cropping, and enhancement, preparing the MRI data for the proposed model.

3.4.3 Tensorflow

TensorFlow is the core framework for developing the convolutional neural network (CNN) used in this project. As a flexible and comprehensive library for machine learning and deep learning, TensorFlow supports both the design and training of complex neural network architectures with efficient computation, leveraging both CPUs and GPUs. Its extensive library of tools and pre-built functions allows for efficient implementation of neural networks, which is critical for handling the intricate patterns and large data volumes associated with MRI images.

3.5 Models

3 critical architectures used in the detection of brain tumors from MRI images: ResNet50, Inception V3, and a traditional Convolutional Neural Network (CNN). Each architecture has unique characteristics that make it suitable for deep learning tasks involving image recognition and classification.

3.5.1 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of neural network that is specifically designed for processing and analyzing visual data. A conventional CNN design typically consists of three primary types of layers: convolutional layers, pooling layers, and fully connected layers. Regarding the detection of brain tumors:

- Convolutional layers utilize diverse filters to process the input and generate feature maps that effectively capture crucial characteristics such as edges and textures.
- Pooling layers, usually implemented as max pooling, decrease the spatial dimensions (width, height) of the input volume for the subsequent convolutional layer. This reduction in parameters and computation within the network aids in the management of overfitting.
- The fully connected layers analyze the characteristics generated by the convolutional and pooling layers in order to categorize images into categories such as 'tumor' or 'no tumor'. The output layer commonly employs a softmax activation function to yield the probabilities associated with each class.

3.5.2 ResNet50

ResNet50 is renowned for its deep network architecture which utilizes residual learning to facilitate training deeper models without the risk of vanishing gradients. The key component of ResNet50 is the residual block that uses skip connections, or shortcuts, to jump over some layers. These connections enable the model to acquire an identity function, guaranteeing that the upper levels will achieve at least the same level of performance as the lower layers. This capability is particularly beneficial in medical imaging, where precision in feature extraction across many layers can significantly enhance tumor detection.

3.5.3 Inception V3

Inception V3 is an advanced CNN architecture that improves on its predecessors through optimizations such as factorized convolutions and expanded the receptive field. The model is composed of both symmetric and asymmetric components, which include convolutions, average pooling, max pooling, concatenations, dropouts, and fully linked layers. Each block has filters of different sizes operating at the same level, which allows the network to capture information at various scales. The inclusion of auxiliary classifiers acts as regularizers, and the use of batch normalization accelerates the training process. For brain tumor detection, Inception V3's ability to capture complex patterns and subtle nuances in medical images makes it highly effective.

3.6 Gantt chart

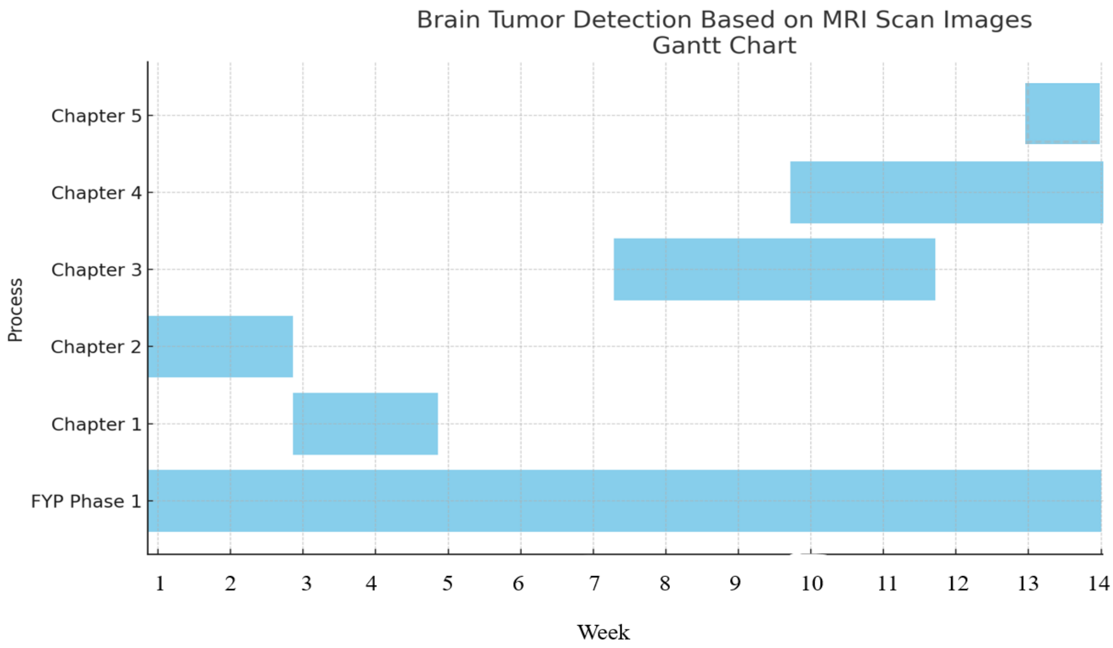

Figure 3.5: Gantt Chart of this FYP Phase 1.

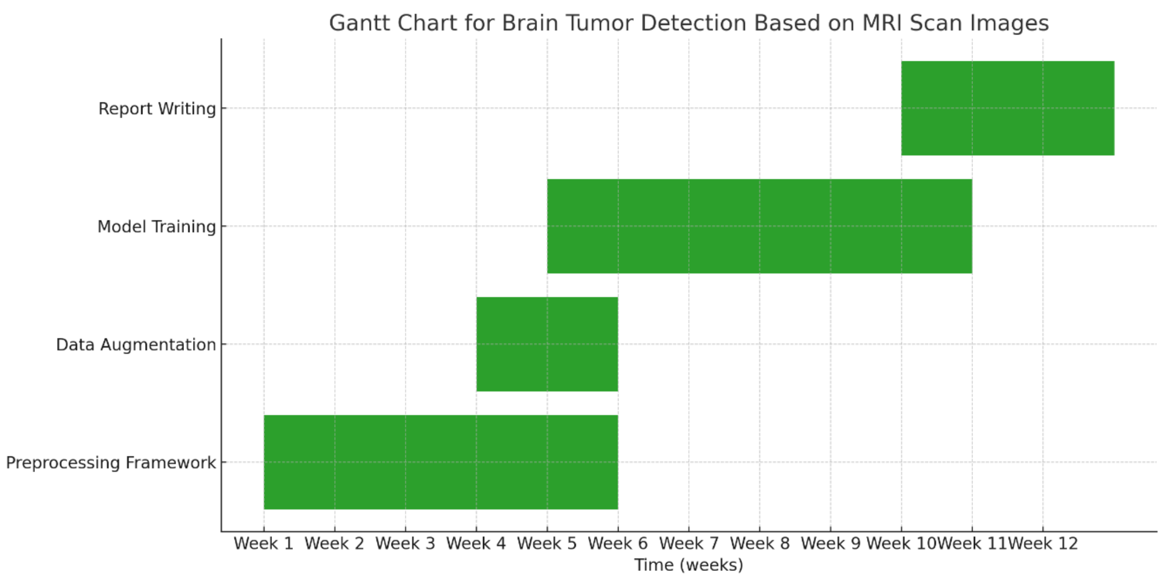

Figure 3.6: Gantt Chart of this FYP Phase 2.

CHAPTER 4

IMPLEMENTATION DESIGN

4.1 Overview

This chapter delves into the architecture and operational mechanics of a CNN developed specifically for the detection of brain tumors from MRI images. After meticulous preprocessing, detailed in subsequent sections, the MRI images undergo a sophisticated analysis by the CNN, which is engineered to discern critical features distinguishing normal from tumorous brain tissues effectively.

Central to this process is the CNN architecture, which integrates several layers each designed to perform complex image data analysis. The culmination of this layered processing is a binary classification system, categorizing images into 'Yes Tumor' or 'No Tumor'. This dichotomous output is pivotal, providing clear, actionable insights that are crucial for informed decision-making.

In order to assess the effectiveness and dependability of the CNN, I employ crucial assessment measures including accuracy, precision, recall, and the F1-score. The focus is on reducing both false positives and false negatives to improve the usefulness of the model in clinical settings, guaranteeing that it passes the rigorous requirements necessary for medical diagnostic purposes.

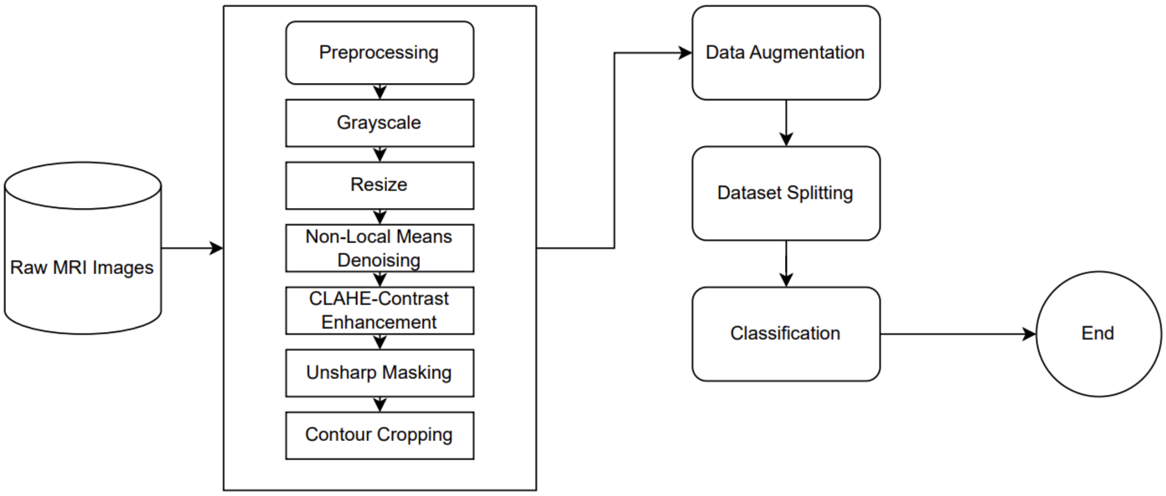

Figure 4.1: Architecture of Proposed Preprocessing Framework.

4.2 Data Acquisition

The dataset that utilized in this research is a combination of two publicly accessible datasets from Kaggle to compile a comprehensive collection of human brain MRI images. This dataset is specifically tailored to support the detection of brain tumors through deep learning models. The initial dataset comprises 155 MRI images that exhibit brain tumors and 98 MRI images without brain tumors, leading to an imbalance that could potentially bias the model towards predicting the presence of tumors. To address this issue and ensure a balanced dataset, which is crucial for unbiased model training and accurate performance evaluation, an additional 57 MRI images without brain tumors were incorporated. This adjustment brings the total to 310 images, evenly distributed across the two categories:

Number and types of images:

- No Tumor: 155 images

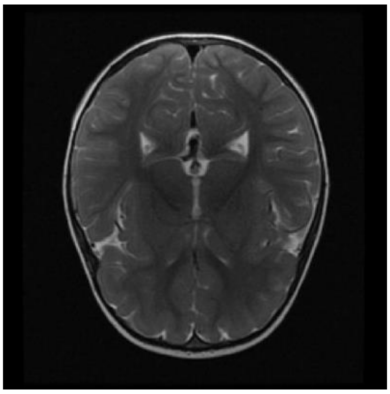

Figure 4.2 : Brain MRI Scan Images – No Tumor.

Representing a reference class, the non-tumor category consists of images from the compiled dataset. The normal brain in an MRI scan typically shows a well-defined and symmetrical structure. Normal brain tissue has uniform intensity and is free from irregularities or abnormal growths. These images offer a baseline for understanding normal brain anatomy and serve as a crucial component for comparative analysis.

- Yes Tumor: 155 images

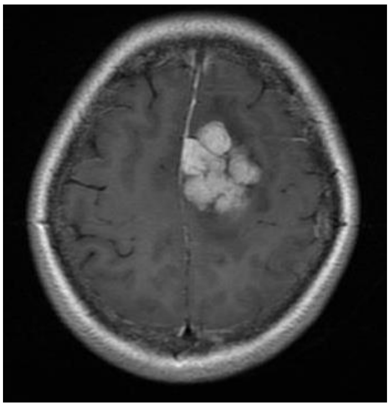

Figure 4.3 : Brain MRI Scan Images – Yes Tumor.

Meningiomas are tumors that arise from the meninges, the protective layers covering the brain and spinal cord. They typically appear as contrast-enhancing lesions, meaning they can be highlighted with contrast agents in the MRI images. Meningiomas are generally slow-growing and may have a characteristic dural tail, a tapering extension adjacent to the tumor.

4.3 Simulation of Real World Dataset

In this study, Gaussian noise has been deliberately added to the dataset of brain tumor MRI images to mimic the real-world challenges frequently encountered in clinical settings. Factors such as mechanical limitations of MRI scanners, and electronic noise inherently present in medical imaging can introduce artifacts that significantly impact the quality and interpretability of the scans. By incorporating Gaussian noise, the dataset not only simulates these real-world imperfections but also provides a basis for a critical comparative analysis. This approach allows us to assess the effectiveness of the preprocessing techniques in enhancing model accuracy by directly comparing the performance on the noised dataset versus the preprocessed dataset.

4.4 Preprocessing Framework

In the realm of brain tumor detection using deep learning, data preprocessing is a critical step that directly influences the performance and especially the accuracy of the model. This preprocessing framework involves several key techniques to refine MRI images for effective analysis. Initially, I will convert the MRI images to grayscale, simplifying the multi-channel data while retaining essential structural details. This is followed by resizing the images to a uniform dimension of 512x512 pixels, ensuring consistency across the dataset. Next, I employ brain region cropping using thresholding, edge detection, and contour detection to focus exclusively on relevant areas. To enhance image quality, I will apply histogram equalization for contrast enhancement and Gaussian blur for noise reduction. Data augmentation techniques, including adjustments in brightness and contrast, horizontal flipping, and random rotation, are implemented to increase the robustness of the model. Finally, normalization is performed by standardizing pixel values based on the dataset's mean and standard deviation, fostering stable and efficient model training. These preprocessing steps are fundamental in transforming raw MRI scans into a format that is optimally suited for the subsequent CNN analysis.

4.4.1 Convert image to Grayscale format

Converting images to grayscale is an essential initial step in computer vision and image processing. Brain MRI scans are typically acquired as multi-channel images, often containing information in three colour channels (Red, Green, Blue). However, for many image processing and analysis tasks related to brain imaging, the intricate details captured in colour might not be necessary. By converting these MRI images to grayscale, I retain essential structural information while simplifying the data representation. This transformation simplifies the image to a single channel, where pixel intensities represent shades of gray.

4.4.2 Image Resizing

Due to the varying sizes of the images in the dataset, the next step is to resize all images to a uniform dimension. This standardization is essential for subsequent processing stages and for feeding data into our deep learning model. After a meticulous evaluation of the dataset, I have decided on a standard size of 256x256 pixels, striking a balance between retaining essential details and ensuring computational efficiency.

4.4.3 Non-Local Means Denoising

The denoising step, Non-Local Means Denoising is employed to remove the artificial noise added previously as well as any inherent noise in the original images. This method is effective in preserving important features like edges and textures while reducing noise, which is vital for maintaining the diagnostic quality of the images.

4.4.4 CLAHE Contrast Enhancement

Contrast enhancement through CLAHE (Contrast Limited Adaptive Histogram Equalization) adjusts the pixel values to enhance the contrast of the images. This technique is particularly useful for medical images, as it improves the visibility of subtle features within the tissue, which can be crucial for detecting small or early-stage tumors.

4.4.5 Unsharp Masking

Applying unsharp masking is the final step to enhance the clarity of the images. This technique sharpens the image by emphasizing the edges, making it easier to distinguish between different tissues and anomalies. It involves enhancing the contrast around the edges, which helps in highlighting potential areas of interest like tumor boundaries.

4.4.6 Brain Region Cropping

In order to remove the unnecessary region in the MRI images and highlights the interest information, some OpenCV techniques are utilized to isolate the brain region in each MRI images. This involves:

- Image Preparation: Each image in the array is first ensured to be a numpy array of type ‘uint8’.
- Blurring (cv2.GaussianBlur): Reduces image noise and detail by smoothing the image to enhance the effectiveness of the thresholding step that follows.
- Thresholding (cv2.threshold): Simplify the image to just the essential parts that are significantly different from the background in terms of intensity
- Erosion (cv2.erode) and Dilation (cv2.dilate): Remove small white noises and detach small objects from the background and restore the object size and to connect disjoint objects, to enhance the main features in the image.
- Contour Detection(cv2.findContours): Retrieves the contours as a list, each representing a continuous 'edge' based on the thresholded binary image.
- Contour Selection and Cropping: Largest contour is identified using the max function with (cv2.contourArea) as the key. A bounding rectangle is computed for this largest contour (cv2.boundingRect), which provides the coordinates for cropping. The cropping coordinates are adjusted by an (add_pixels_value) to give some padding around the contour. This helps in not cutting off parts of the main feature. The image is then cropped to these dimensions. If no contours are detected, the original image is used instead.

- Resizing: The cropped image is resized to a target size, typically making it uniform across all processed images, which is essential for maintaining consistency in input size for any machine learning model training.

This function is useful in preprocessing steps where focusing on the key features of an image directly affects the outcome of analytical models. The area of interest needs to be isolated from the surrounding noise. By cropping to the most significant contour, the function ensures that models are not distracted by irrelevant data, potentially improving both the performance and accuracy of diagnostic tools.

4.4.7 Dataset Splitting

The dataset containing preprocessed MRI images is carefully separated to enable efficient model training, validation, and testing. At first, the dataset is divided into two separate segments: 70% of the data is assigned for training, and the remaining 30% is temporarily held aside for later segmentation into validation and test sets. This stratification guarantees that the allocation of classes (tumor and no tumor) remains uniform across all datasets, which is essential for preserving the accuracy of model evaluations.

The temporary dataset is subsequently partitioned into validation and test sets, with each set comprising 15% of the original dataset. The purpose of this division is to guarantee that throughout the last stages of model training and subsequent evaluations, both validation and testing can depend on separate, impartial data samples, offering a precise assessment of the model's performance under varying circumstances.

4.4.8 Data Augmentation

Given the complexity and variability inherent in medical imaging data, particularly with MRI scans, data augmentation is employed exclusively on the training dataset. This process involves artificially expanding the dataset using various transformations, thereby helping to prevent overfitting and improving the model's generalization capabilities. The transformations include:

- Normalization (rescale=1./255): Scales pixel values from a range of 0-255 to 0-1. This is crucial for model training efficiency as it helps with faster convergence.
- Random Rotations (rotation_range=15): Rotates images within a range of +/- 15 degrees, allowing the model to learn to recognize objects regardless of their orientation.
- Random Horizontal Shifts (width_shift_range=0.05): Shifts images horizontally by up to 5% of their width, simulating scenarios where objects aren't perfectly centered.
- Random Vertical Shifts (height_shift_range=0.05): Shifts images vertically by up to 5% of their height, adding robustness against vertical displacements in object positioning.
- Shear Transformations (shear_range=0.05): Shears images by 5%, altering their geometry to mimic the effect of different viewing angles or object distortions.
- Random Zoom (zoom_range=0.05): Zooms into or out of images by 5%, helping the model to detect features at various scales and improve its accuracy in size variation of objects.
- Brightness Adjustment (brightness_range=[0.5, 1.5]): Adjusts image brightness between 50% and 150% of the original levels, which trains the model to perform well under different lighting conditions.
- Horizontal Flipping (horizontal_flip=True): Mirrors images horizontally, doubling the dataset diversity and helping the model to learn patterns that are orientation-independent.
- Vertical Flipping (vertical_flip=True): Mirrors images vertically, further increasing data variety and aiding in the model's understanding of patterns in different orientations.
- Fill Mode (fill_mode='nearest'): Fills new pixels in transformed images using the nearest existing pixel values, maintaining the integrity of the image data after augmentation.

These augmentation settings collectively enhance the training dataset, ensuring that the neural network learns to generalize from a varied and realistically modified set of images. This approach significantly increases the model's ability to adapt to the variations it will encounter in real-world diagnostic settings, thereby improving its diagnostic accuracy and reliability.

4.5 Proposed model 1

This chapter describes the development of a sophisticated CNN model leveraging the InceptionV3 architecture, specifically adapted for the detection of brain tumors from MRI images. The model incorporates advanced features such as a custom GrayToRGB conversion layer and trainable depths within the InceptionV3 framework to enhance diagnostic accuracy.

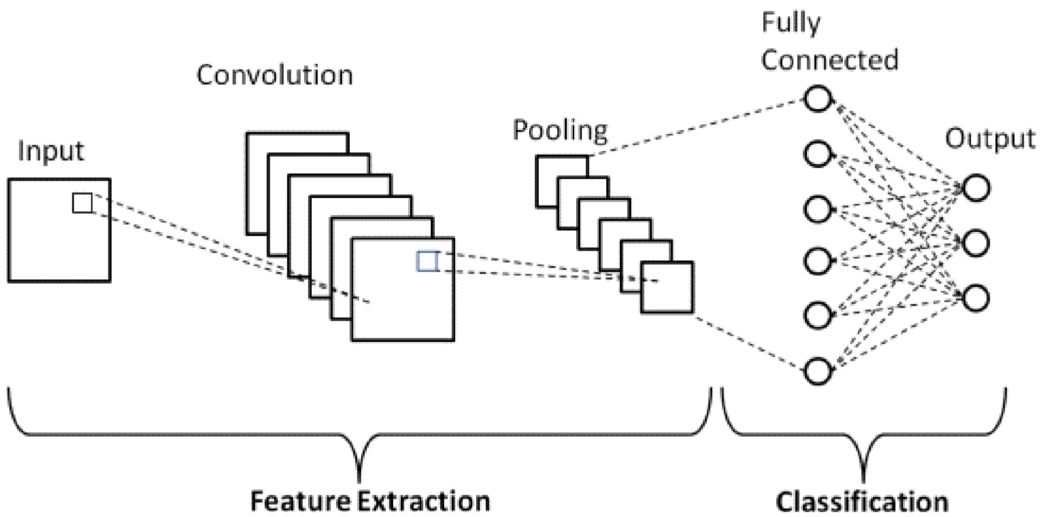

Figure 4.4: Architecture of Proposed CNN Model.

4.5.1.1 Input Layer

The foundation of the model is the Input Layer, configured to accept single-channel grayscale MRI images with a resolution of 256x256 pixels. This layer serves as the gateway for processing MRI data, ensuring that all subsequent operations are tailored to the unique characteristics of medical imaging.

4.5.1.2 GrayToRGB Conversion Layer

Following the input, the GrayToRGB layer plays a crucial role by converting grayscale images into a three-channel RGB format. This conversion is essential as it allows the subsequent InceptionV3 base model to process the image data more effectively, leveraging the complex patterns that the InceptionV3 architecture is renowned for handling.

4.5.1.3 InceptionV3 Base Model

At the core of my architecture is the modified InceptionV3 base model, equipped with pretrained ImageNet weights and customized by removing the top layers to focus on feature extraction rather than classification. The adaptability of the last 50 layers is particularly crucial, as these layers have been made trainable to fine-tune the model specifically for detecting nuances in brain tumors from MRI scans.

4.5.1.4 Global Average Pooling

The Global Average Pooling layer is used in the InceptionV3 model to simplify the output by compressing the feature maps. This compression helps to make the output more manageable without sacrificing important spatial information. As a result, the features retrieved from the model are preserved effectively.

4.5.1.5 Dense and Dropout Layers

The network includes two dense layers, each followed by batch normalization and a dropout layer. The first dense layer has 512 neurons, and the second has 256, both utilizing ReLU activation functions. These layers are designed to process and refine the features extracted by the InceptionV3 base. The inclusion of dropout, set at a rate of 0.5, helps prevent overfitting by randomly omitting a portion of the feature detectors on each iteration, ensuring that the model generalizes well to new, unseen data.

- ReLU (Rectified Linear Unit)

  The ReLU activation function will be used in every convolutional layer. The ReLU activation function is selected due to its high efficiency and efficacy in introducing non-linearity, which allows the neural network to effectively learn complicated patterns. The method operates by zeroing out any negative pixel values in the feature map, resulting in accelerated training and enhanced capacity of the network to acquire a wide range of features. The mathematical representation of the Rectified Linear Unit (ReLU) function is:

$$ReLU(x) = \max(0, x)$$

- x is the input to the function.
- The function outputs x if x is greater than 0, else it outputs 0.

4.5.1.6 Output Layer

The culmination of the model is the Output Layer, which uses a sigmoid activation function to deliver the final classification—indicating the presence or absence of a tumor. This binary classification is crucial for providing clear, actionable outputs that can directly inform medical decisions.

4.5.1.7 Optimization and Loss Function

The Adam optimizer is selected for its adaptive learning rate capabilities, which is particularly beneficial for managing the sparse gradients that are common in deep learning models used for image classification. This optimizer is well-suited to our needs, providing efficient convergence by adjusting learning rates based on the computation of first and second moments of the gradients.

4.5.1.8 Loss Function

The selection of the Binary Cross-Entropy loss function is based on the fact that the classification problem is binary in nature, namely distinguishing between the presence or absence of a tumor. This function is optimal because it measures the precision of the predictions by assigning a numerical value to the accuracy, where the output falls within the range of 0 to 1. It increases the loss as the prediction probability diverges from the true label. It is especially efficient for the kind of intricate decision-making needed in medical diagnostics.

4.5.1.9 Early Stopping

To avoid overfitting and minimize unnecessary computation, early stopping is implemented. It monitors 'val_loss' with a patience of 10 epochs, halting training if there’s no improvement in validation loss over these epochs. This mechanism ensures the model retains only the most effective parameters, reverting to the best-performing iteration if subsequent epochs fail to deliver improvements.

4.5.1.10 Batch Normalization

This process is applied following each activation function within the dense layers, normalizing the inputs by re-centering and re-scaling them based on the batch's mean and variance. It addresses internal covariate shift, stabilizing the network by ensuring consistent layer input distributions throughout training, thereby accelerating convergence.

4.5.1.11 Batch Size and Epochs

The model training is structured with a batch size of 32 and is initially set to run for up to 20 epochs. This setup balances computational efficiency and performance, allowing for effective learning and optimization based on the model's response during validation.

4.5.1.12 Model Checkpointing

Checkpointing is utilized to save the model configuration that achieves the highest accuracy on the validation dataset. This approach preserves the best-performing model throughout the training process, safeguarding against performance degradation in later epochs.

4.5.1.13 Learning Rate

The learning rate is set at 0.0001 to foster steady convergence without overshooting the loss function's minimum. To adapt to training dynamics, adjustments might be made, potentially implementing learning rate schedules or adaptive learning rate techniques like Learning Rate Annealing. This strategy helps in fine-tuning the learning rate decrementally as the model training progresses, aiding in optimal convergence and model stability.

4.6 Proposed model 2

Furthermore, I delves into the sophisticated design of a Convolutional Neural Network (CNN) that I have developed, utilizing the InceptionV3 architecture enhanced for high-precision medical imaging—specifically, the detection of brain tumors from MRI images. The model is meticulously structured with advanced features, custom layers, and specific training strategies to achieve optimal diagnostic accuracy.

4.6.1.1 Input Layer

The initial layer of the model handles the input of MRI images. Configured to accept grayscale images with a resolution of 256x256 pixels, this layer ensures that all image data is suitably formatted for the subsequent processing layers.

4.6.1.2 GrayToRGB Conversion Layer

This custom layer is critical for adapting grayscale MRI inputs into a three-channel RGB format, which is necessary for the following InceptionV3 layers. This adaptation allows the model to leverage the pre-trained capabilities of the InceptionV3 architecture more effectively.

4.6.1.3 InceptionV3 Base Model

The InceptionV3 Base Model, renowned for its deep and complex architecture that excels in image recognition, is integrated without its top layers (include_top=False) to focus on feature extraction tailored for brain tumor detection. All layers of the InceptionV3 model are set as trainable, enabling comprehensive fine-tuning on brain MRI images to capture subtle pathological features.

4.6.1.4 Global Average Pooling

Following the InceptionV3 base, this layer reduces the dimensionality of the data, condensing feature maps into more manageable forms without losing essential spatial information, thus aiding the robustness of feature extraction.

4.6.1.5 Dense and Dropout Layers

The network incorporates two dense layers with 512 and 256 neurons, respectively, each followed by batch normalization and a high dropout rate of 0.7. These layers are designed to refine the extracted features further and help in mitigating the risk of overfitting through the random deactivation of neurons.

4.6.1.6 Output Layer

The model concludes with an output layer that employs a sigmoid activation function. This layer classifies the processed features into two categories—'tumor' or 'no tumor'—providing a binary classification that is crucial for medical diagnostics.

4.6.1.7 Optimization and Loss Function

The Adam optimizer is chosen for its ability to adaptively adjust the learning rate, which is especially advantageous for handling the sparse gradients that are frequently encountered in deep learning models employed for image categorization. This optimizer is highly suitable for our requirements as it achieves efficient convergence by dynamically modifying learning rates based on the calculation of both the first and second moments of the gradients.

4.6.1.8 Loss Function

The Binary Cross-Entropy loss function is selected because of the binary character of the classification problem, which involves distinguishing between the presence or absence of a tumor. This function is optimal because it measures the precision of the predictions by assigning a numerical value to the accuracy, where the predicted probability falls within the range of 0 to 1. The loss increases as the predicted probability deviates further from the real label. It is especially efficient for the kind of intricate decision-making needed in medical diagnostics.

4.6.1.9 Regularization

Both dense layers utilize L2 regularization, which introduces a penalty equivalent to the square of the coefficients' magnitude to the loss function. This technique aids in mitigating overfitting by inhibiting the development of excessively intricate models during the training process.

4.6.1.10 Early Stopping

To avoid overfitting and minimize unnecessary computation, early stopping is implemented. It monitors 'val_loss' with a patience of 10 epochs, halting training if there’s no improvement in validation loss over these epochs. This mechanism ensures the model retains only the most effective parameters, reverting to the best-performing iteration if subsequent epochs fail to deliver improvements.

4.6.1.11 Batch Normalization

This process is applied following each activation function within the dense layers, normalizing the inputs by re-centering and re-scaling them based on the batch's mean and variance. It addresses internal covariate shift, stabilizing the network by ensuring consistent layer input distributions throughout training, thereby accelerating convergence.

4.6.1.12 Batch Size and Epochs

Training utilizes a batch size of 32 and is planned for up to 20 epochs. This configuration balances computational efficiency with performance, allowing for effective learning and model optimization based on ongoing validation results.

4.6.1.13 Model Checkpointing

Checkpointing is utilized to save the model configuration that achieves the highest accuracy on the validation dataset. This approach preserves the best-performing model throughout the training process, safeguarding against performance degradation in later epochs.

4.6.1.14 Learning Rate

The learning rate is set at 0.0001 to foster steady convergence without overshooting the loss function's minimum. To adapt to training dynamics, adjustments might be made, potentially implementing learning rate schedules or adaptive learning rate techniques like Learning Rate Annealing. This strategy helps in fine-tuning the learning rate decrementally as the model training progresses, aiding in optimal convergence and model stability.

4.7 Evaluation metrics

- True Positive (TP):

  Definition: The number of instances correctly predicted as positive by the model.

  In the context of brain tumor detection, this represents the number of actual tumor cases correctly identified by the model.

- True Negative (TN):

  Definition: The number of instances correctly predicted as negative by the model.

  In brain tumor detection, this corresponds to the number of instances correctly identified as non-tumor cases.

- False Positive (FP) :

  Definition: The number of instances wrongly predicted as positive by the model when they are actually negative.

  In the context of brain tumor detection, this represents the number of cases where the model incorrectly indicates the presence of a tumor.

- False Negative (FN) :

  Definition: The number of instances wrongly predicted as negative by the model when they are actually positive.

  For brain tumor detection, this corresponds to cases where the model fails to identify an actual tumor.

4.7.1 Accuracy

This metric provides an overall effectiveness of the model. However, it might be misleading in cases of imbalanced datasets where one class dominates. It's calculated as the ratio of the sum of true positive and true negative predictions to the total number of predictions. The formula is:

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

4.7.2 Precision

Precision is crucial in medical diagnostics as it reflects the reliability of positive predictions. It's especially important in scenarios where false positives carry significant consequences. Precision is the ratio of true positive predictions to the total number of positive predictions (both true and false). The formula is:

$$Precision = \frac{TP}{TP+FP}$$

4.7.3 Recall(Sensitivity)

This metric measures the model's ability to correctly identify positive instances among all actual positive instances. High recall is vital in medical applications to ensure all potential issues are flagged. The formula is:

$$Recall(Sensitivity) = \frac{TP}{TP + FN}$$

4.7.4 F1 Score

The F1 Score is a mathematical measure that combines precision and recall by taking their harmonic mean. It offers a unified metric that takes into account both false positives and false negatives. It is especially beneficial in datasets that have an unequal distribution of data points. The equation is:

$$F1Score = \frac{2xPrecisionxRecall}{PrecisionxRecall}$$

4.7.5 Confusion Matrix

The matrix is a tabular depiction that shows the quantities of true positives, false positives, true negatives, and false negatives. It aids in comprehending the model's efficacy in distinguishing across classes.

4.7.6 Peak Signal-to-Noise Ratio (PSNR)

PSNR is widely used to measure the quality of reconstruction of lossy compression codecs. It is a good indicator of the absolute fidelity of an image compressed and then reconstructed relative to its original version. The PSNR is typically expressed in terms of the logarithmic decibel scale and is calculated using the following formula:

$$PSNR = 20 \times \log_{10} \frac{MAX_I}{\sqrt{MSE}}$$

Where:

- MAX_I represents the highest achievable pixel value in the image. For example, if the image has a sample depth of 8 bits, the corresponding value would be 255.
- MSE (Mean Squared Error) is computed between the original and the reconstructed image.

4.7.7 Structural Similarity Index (SSIM)

SSIM is employed to quantify the resemblance between two images. The SSIM index is a comprehensive statistic that measures picture quality by comparing it to a reference image that is uncompressed or free from distortion. SSIM is specifically developed to enhance conventional techniques such as PSNR and MSE, which have demonstrated inconsistency with human visual perception.

4.8 Chapter Summary

This chapter outlines the comprehensive strategy and detailed plan implemented to develop a robust CNN capable of identifying brain tumors from MRI scans. From the careful selection and preprocessing of the dataset to the precise configuration and optimization of the CNN architecture, every step is meticulously designed to achieve exceptional accuracy and reliability in tumor detection. The model integrates advanced deep learning techniques and is specifically fine-tuned to handle the complexities of medical imaging data. Through stringent evaluation metrics, the model's capability to learn effectively from training data and generalize to new, unseen datasets is rigorously tested. This is essential in medical diagnostics, where the accuracy of detection can significantly impact patient outcomes. In essence, this chapter sets the stage for the subsequent phases of model development and evaluation. It serves as a detailed manual, explaining the methods and considerations involved in creating a potent and effective tool for the detection of brain tumors.

CHAPTER 5

Experimental Results

5.1 Overview

This chapter evaluated the how well is the preprocessing frame increase PSNR and SSIM to enhance the image quality. Besides, a procedures of evaluation metrics will be performed to evaluate the proposed model1, proposed model2 along with the comparison models, CNN and ResNet50.

5.2 Evaluation of Preprocessing Framework

This section evaluates the preprocessing framework developed for enhancing MRI images used in the detection of brain tumors. The effectiveness of the preprocessing techniques is quantitatively assessed using two well-established image quality metrics: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). These metrics are crucial for determining how well the preprocessing methods improve image quality relative to the original scans, which directly impacts the accuracy and reliability of subsequent tumor detection by the CNN model.

5.2.1 Peak Signal-to-Noise Ratio (PSNR) & Structural Similarity Index (SSIM)

5.2.1.1 Example evaluation on 'Yes Tumor' data

For the MRI images labeled 'Yes Tumor', the preprocessing framework significantly enhanced image clarity and contrast. As indicated by the PSNR and SSIM metrics:

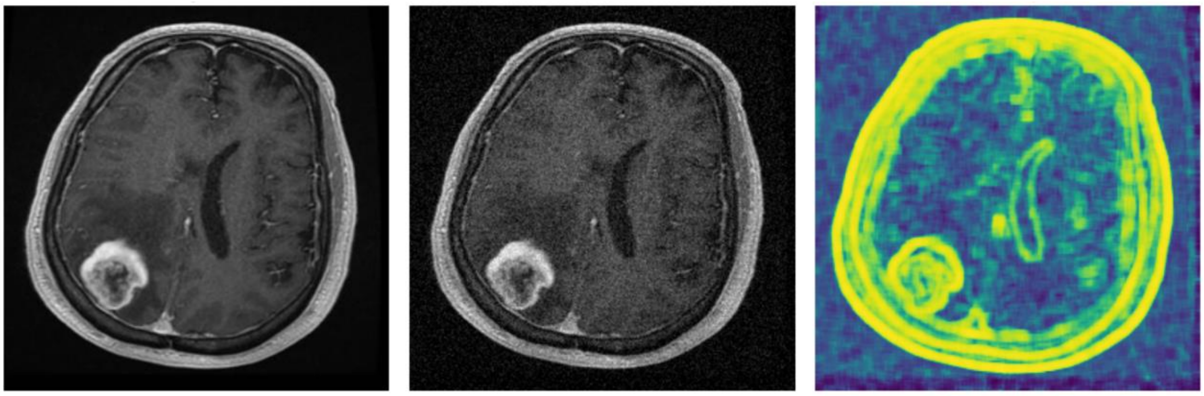

Figure 5.1: Original vs Noised of 'Yes Tumor' data.

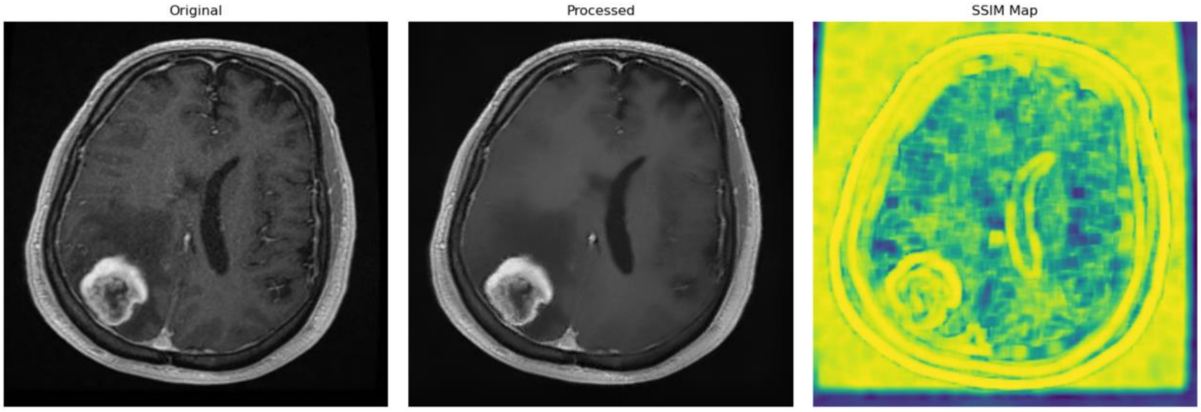

Figure 5.2:Original vs Processed of 'Yes Tumor' data.

- PSNR: The Peak Signal-to-Noise Ratio between the original and processed 'Yes Tumor' images increased to 38.98, up from 25.28 when compared with the noised images. This substantial improvement signifies a reduction in noise and an enhancement in image quality, which is essential for accurately identifying tumor regions within the brain.

- SSIM: The Structural Similarity Index also showed remarkable improvement. The SSIM value between the original and processed 'Yes Tumor' images rose to 0.84 from an initial 0.54. This increase demonstrates a better preservation of structural content and texture, which are critical for medical diagnostic applications where detail recognition is paramount.

5.2.1.2 Example evaluation on 'No Tumor' data

In the case of 'No Tumor' MRI images, the preprocessing steps also led to noticeable improvements in both metrics:

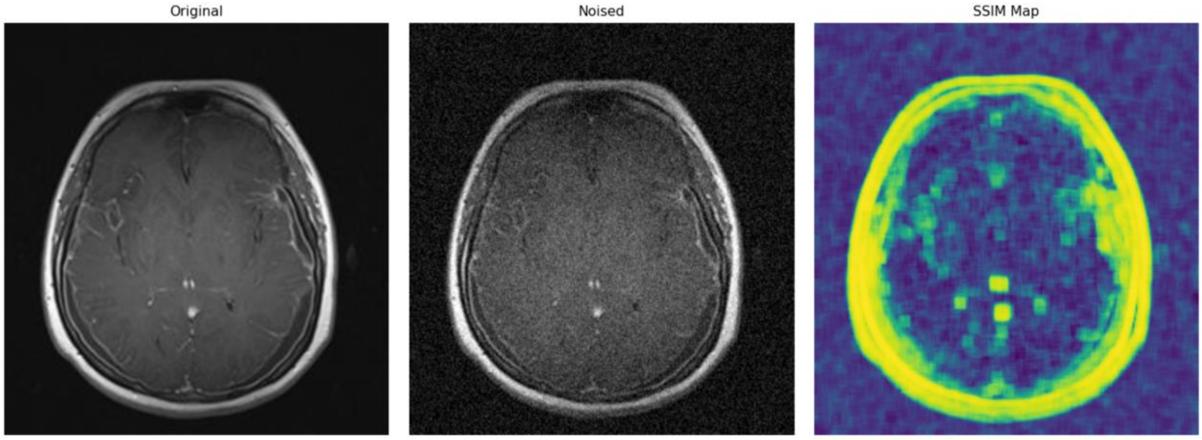

Figure 5.3: Original vs Noised of 'No Tumor' data.

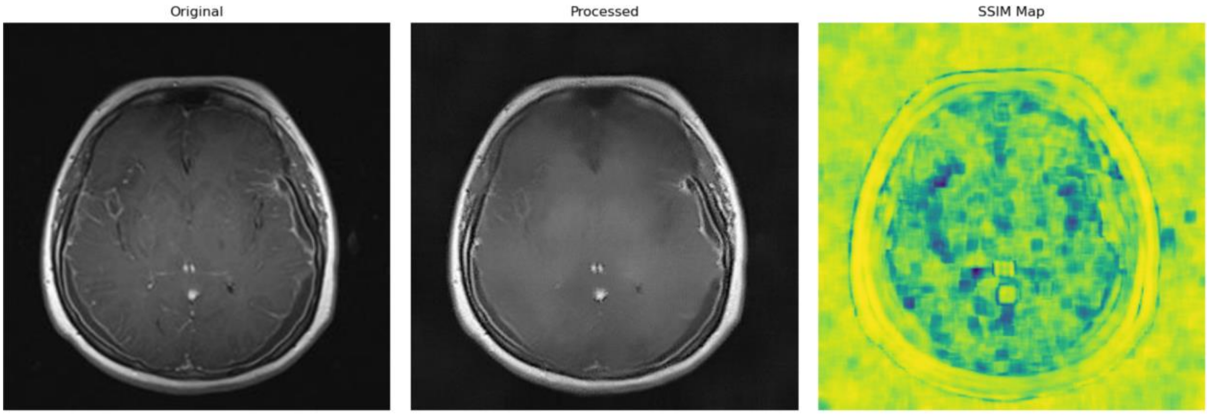

Figure 5.4: Original vs Processed of 'No Tumor' data.

- PSNR: There was an increase in PSNR to 25.95 from 24.91, indicating a moderate enhancement in the overall image quality by reducing noise and increasing signal clarity.

- SSIM: The SSIM improved to 0.87 from 0.42. This significant jump highlights the efficacy of the preprocessing framework in maintaining structural integrity and improving the visual quality, crucial for ensuring that non-tumorous areas are accurately identified and not misclassified.

Image Category	Metric	Original vs Noised	Original vs Processed
Yes Tumor	PSNR	25.28	38.98

	SSIM	**0.54**	**0.84**
No Tumor	**PSNR**	**24.91**	**25.95**
	SSIM	**0.42**	**0.87**

Overall, the preprocessing framework proves to be highly effective in enhancing the diagnostic quality of MRI images. By significantly improving both PSNR and SSIM, the framework ensures that images are not only clearer and less noisy but also maintain their essential structural characteristics. This dual enhancement is crucial for both detecting the presence of tumors and confirming their absence, thereby supporting more accurate and reliable medical evaluations. The results underscore the value of sophisticated image preprocessing in medical imaging contexts, particularly in improving the outcomes of automated analysis and aiding clinical decision-making.

5.3 Models Performance Evaluation

This section delves into a comprehensive evaluation of various machine learning models applied in the detection of brain tumors using MRI scan images. The analysis encompasses both a standard dataset and one subjected to artificial noise, examining how each model performs under different conditions. The models evaluated include ResNet50, a basic CNN model, and two proposed models, which are specifically designed to handle the complexities of medical image processing more effectively. This evaluation aims to discern the robustness, accuracy, and reliability of each model across various metrics such as accuracy, precision, recall, and F1-score. The insights gained are pivotal for understanding the potential real-world applications of these models in clinical settings, where accuracy in detecting tumors can significantly impact patient outcomes.

The comparison involves assessing models on two types of datasets: one that has been preprocessed to enhance image quality and another that incorporates noise to simulate more challenging diagnostic environments. This approach helps in highlighting the models' ability to not only detect tumors with high accuracy but also their resilience against degradation in image quality, which is common in clinical scenarios.

5.3.1 Models Performance on Noised Dataset

Models	Category	Accuracy	Precision	Recall	F1-Score
ResNet50	No Tumor	55.32	0.56	0.58	0.57
	Yes Tumor		0.55	0.52	0.53
CNN Model	No Tumor	59.57	0.58	0.75	0.65
	Yes Tumor		0.62	0.43	0.51
Proposed Model 1	No Tumor	82.98	0.94	0.71	0.81
	Yes Tumor		0.76	0.96	0.85
Proposed Model 2	No Tumor	91.49	0.92	0.92	0.92
	Yes Tumor		0.91	0.91	0.91

Table 5.1: Models Performance on Noised Dataset.

- ResNet50: Exhibits relatively lower performance on the noised dataset, with accuracy peaking around 55.32%. The model shows nearly balanced precision and recall for 'No Tumor' and 'Yes Tumor' categories, but both metrics hover just above 0.55, reflecting a moderate ability to distinguish between the two conditions under challenging conditions with added noise.

- CNN Model: Shows modest improvements in distinguishing 'No Tumor' cases with an accuracy of 59.57%, showcasing better recall in 'No Tumor' cases at 0.75. However, the performance drops significantly in 'Yes Tumor' cases, particularly in recall (0.43), indicating difficulty in consistently identifying true tumor cases amidst noise.

- Proposed Model 1: Performs robustly even with noised images, achieving 82.98% accuracy. It shows high precision (0.94) in 'No Tumor' cases and excellent recall (0.96) in 'Yes Tumor' cases, demonstrating strong capabilities in both detecting the absence of tumors and correctly identifying tumor presence despite the noise.

- Proposed Model 2: Delivers the highest performance among the evaluated models on the noised dataset, with an impressive accuracy of 91.49%. This model maintains high precision and recall across both categories, almost mirroring its performance on the preprocessed dataset. This consistency underscores its effectiveness and reliability in noisy clinical environments.

5.3.2 Models Performance on Preprocessed Dataset

Models	Category	Accuracy	Precision	Recall	F1-Score
ResNet50	No Tumor	0.617	0.62	0.62	0.62
	Yes Tumor		0.61	0.61	0.61
CNN Model	No Tumor	0.720	0.69	0.75	0.72
	Yes Tumor		0.71	0.65	0.68
Proposed Model 1	No Tumor	0.893	0.91	0.88	0.89
	Yes Tumor		0.88	0.91	0.89
Proposed Model 2	No Tumor	0.936	0.96	0.92	0.94
	Yes Tumor		0.92	0.96	0.94

Table 5.2: Models Performance on Preprocessed Dataset.

- ResNet50: Shows the lowest overall performance among the models tested, with an accuracy just over 61%. Both precision and recall for detecting tumors are at 0.61, indicating a balanced yet moderate ability to identify and accurately classify tumor cases.

- CNN Model: Exhibits moderate performance with an overall accuracy of 72%. This model shows a slightly better precision for non-tumor cases compared to tumor cases, indicating a slightly better performance in correctly identifying non-tumor instances.

- Proposed Model 1: Achieves a high level of accuracy at approximately 89.3%. This model demonstrates high effectiveness in both recognizing and classifying tumor images correctly, with precision and recall for tumor detection both above 88%.

- Proposed Model 2: Delivers the best performance among the models evaluated, with an impressive accuracy near 93.6%. It shows excellent precision and recall rates, particularly in tumor detection, which is critical for medical diagnostic applications where false negatives can have severe implications.

5.3.3 Confusion Matrix, Accuracy Graph and Train/Validation Lose Graph

5.3.3.1 Resnet50

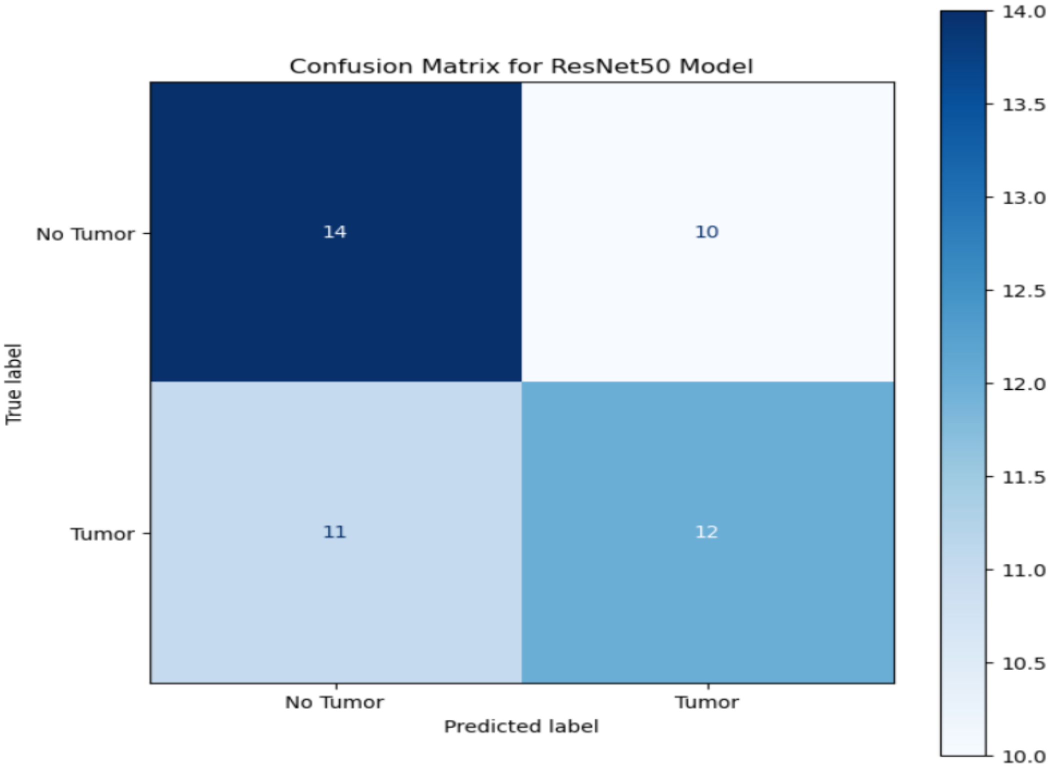

Figure 5.5: Confusion Matrix of ResNet50 in noised dataset.

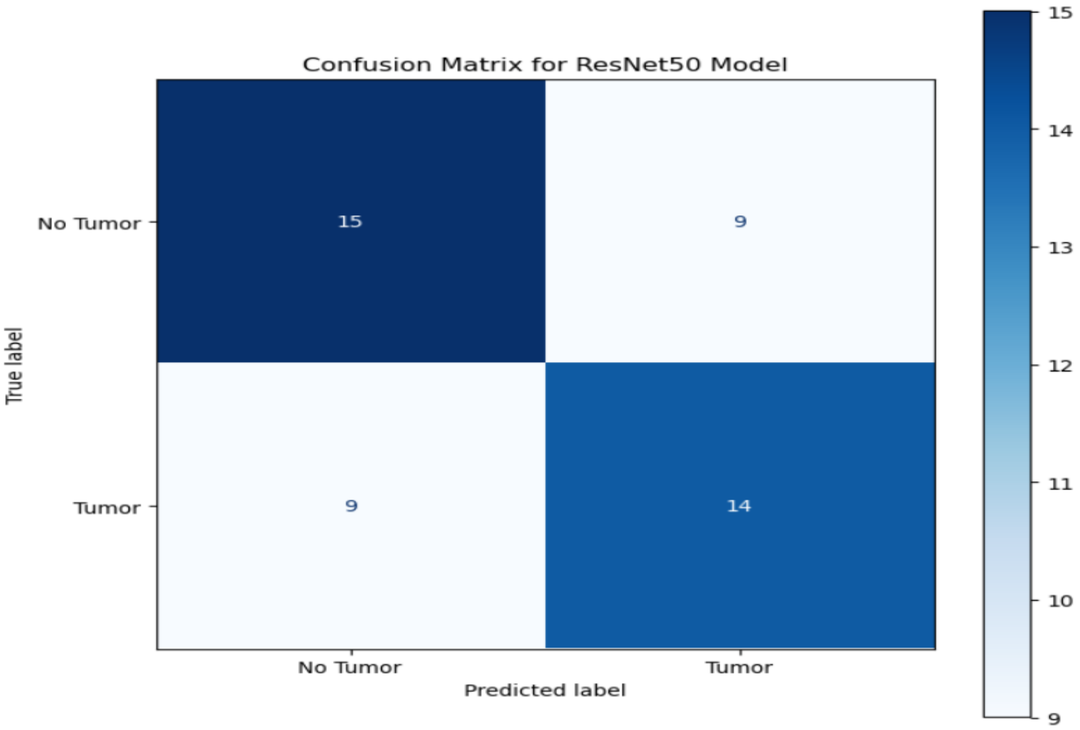

Figure 5.6: Confusion Matrix of ResNet50 in preprocessed dataset.

5.3.3.2 CNN Model

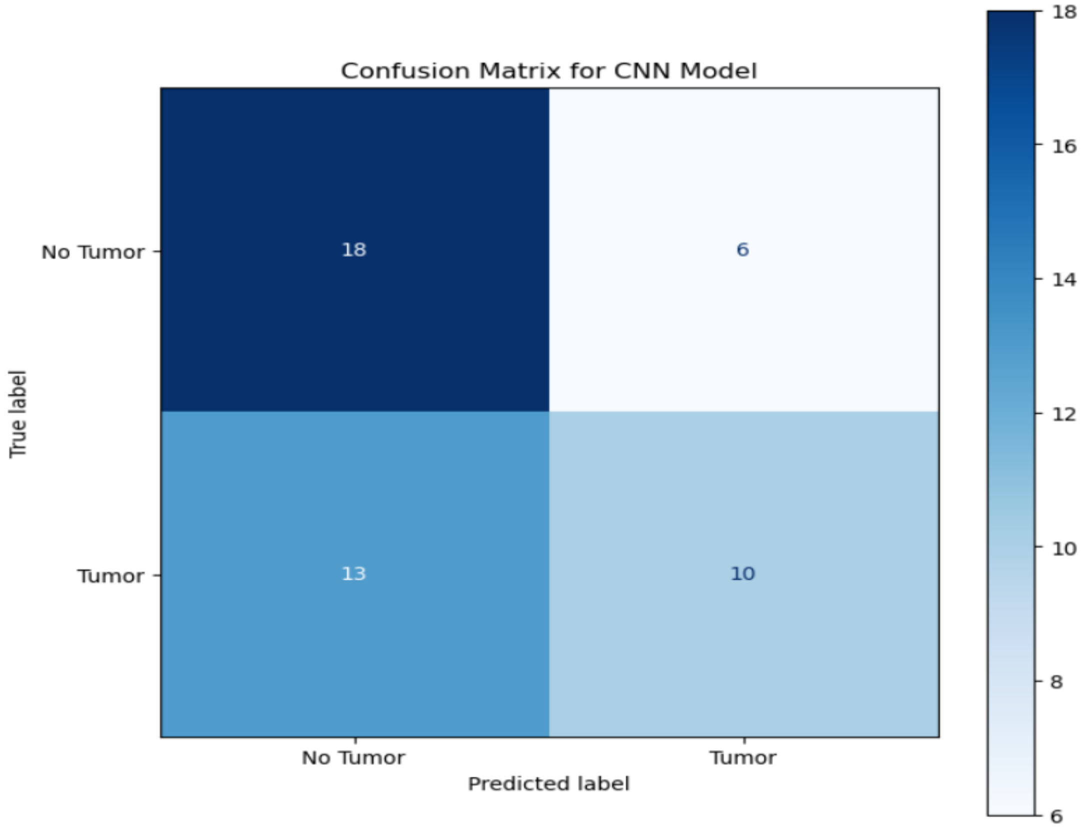

Figure 5.7: Confusion Matrix of CNN model in noised dataset.

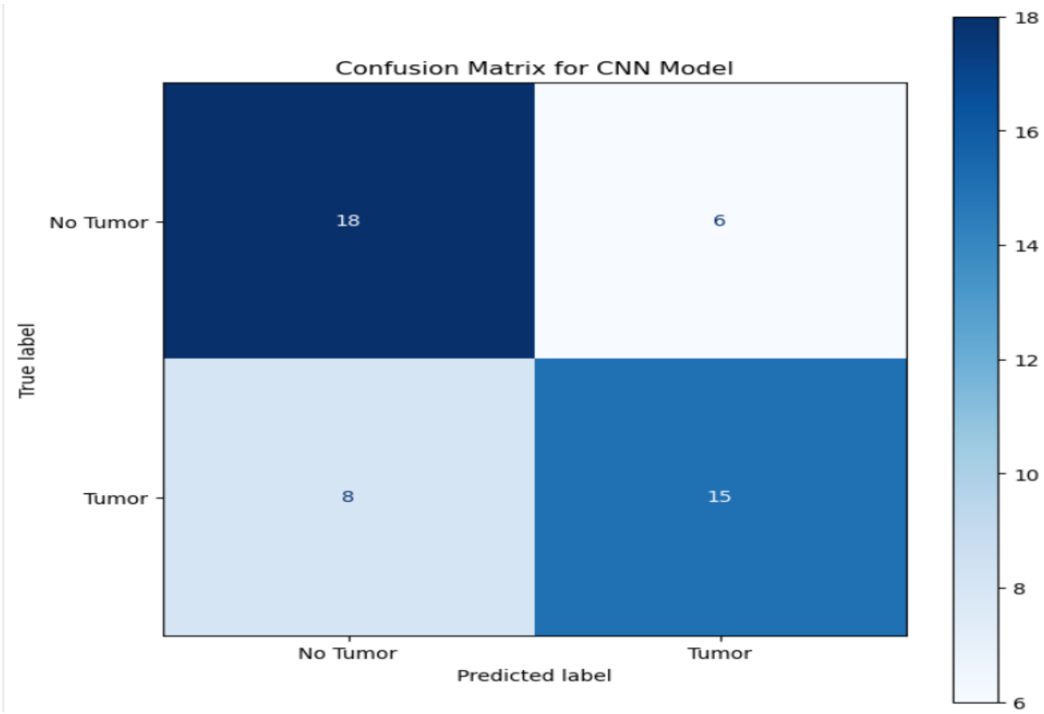

Figure 5.8: Confusion Matrix of CNN model in preprocessed dataset.

5.3.3.3 Proposed Model1

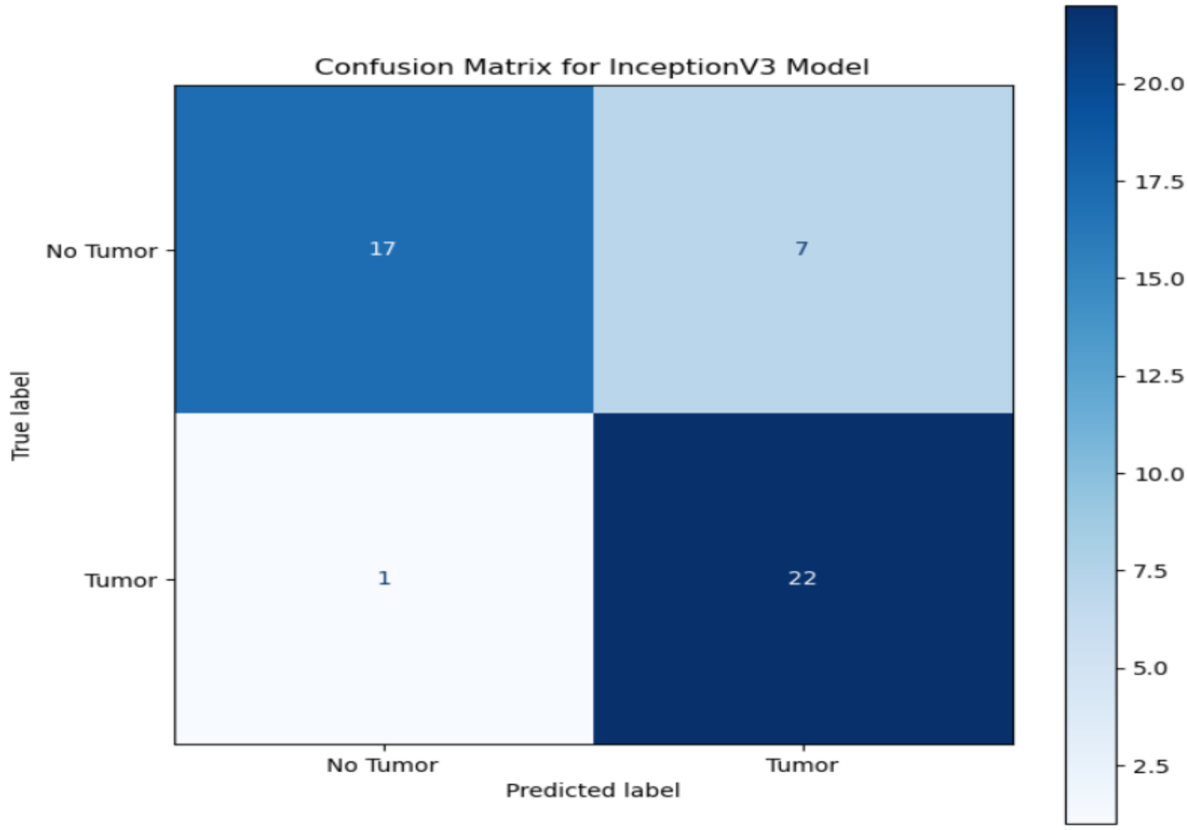

Figure 5.9: Confusion Matrix of Proposed Model1 in noised dataset.

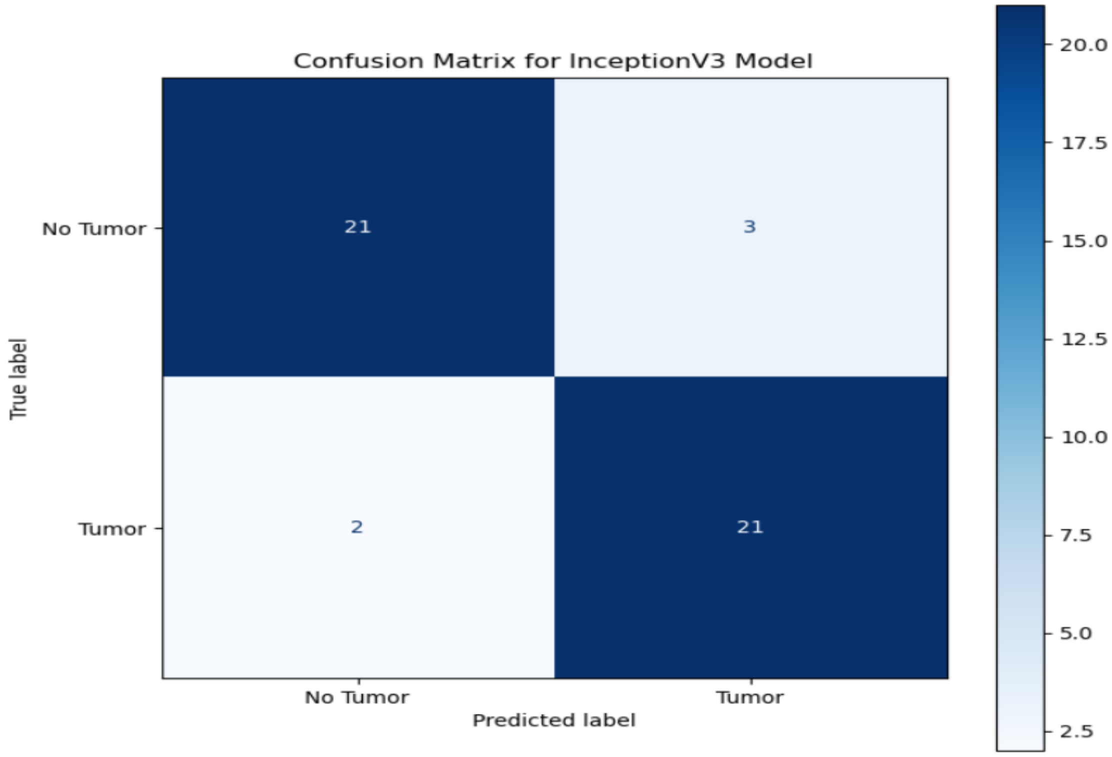

Figure 5.10: Confusion Matrix of Proposed Model1 in preprocessed dataset.

5.3.3.4 Proposed Model2

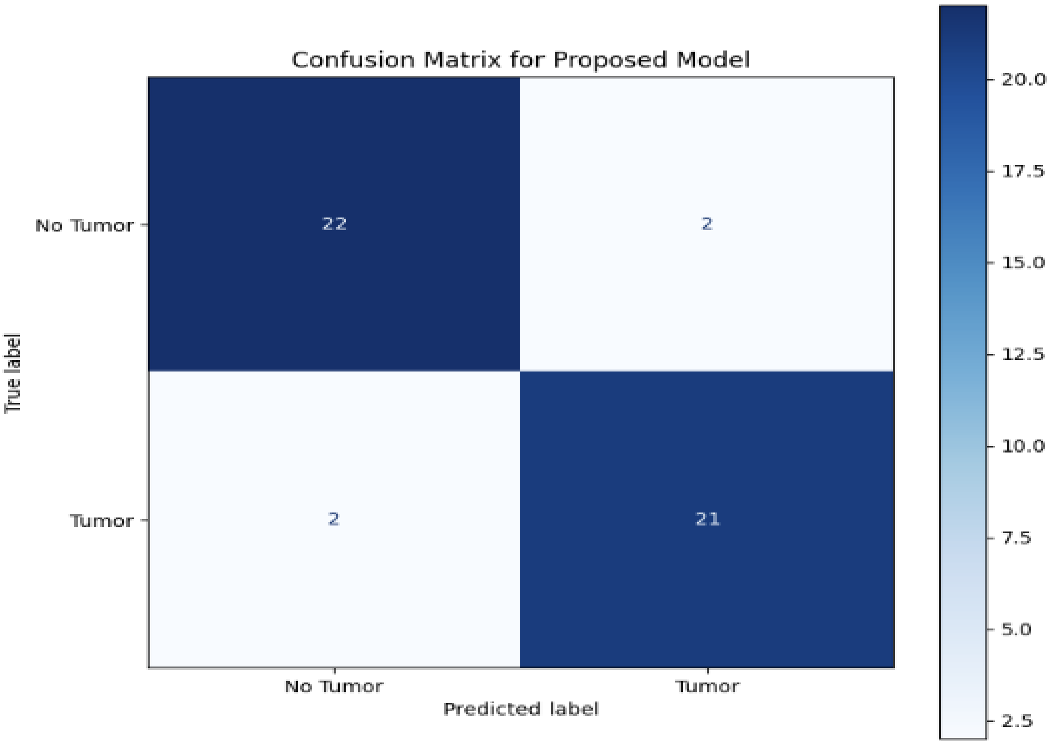

Figure 5.11: Confusion Matrix of Proposed Model2 in noised dataset.

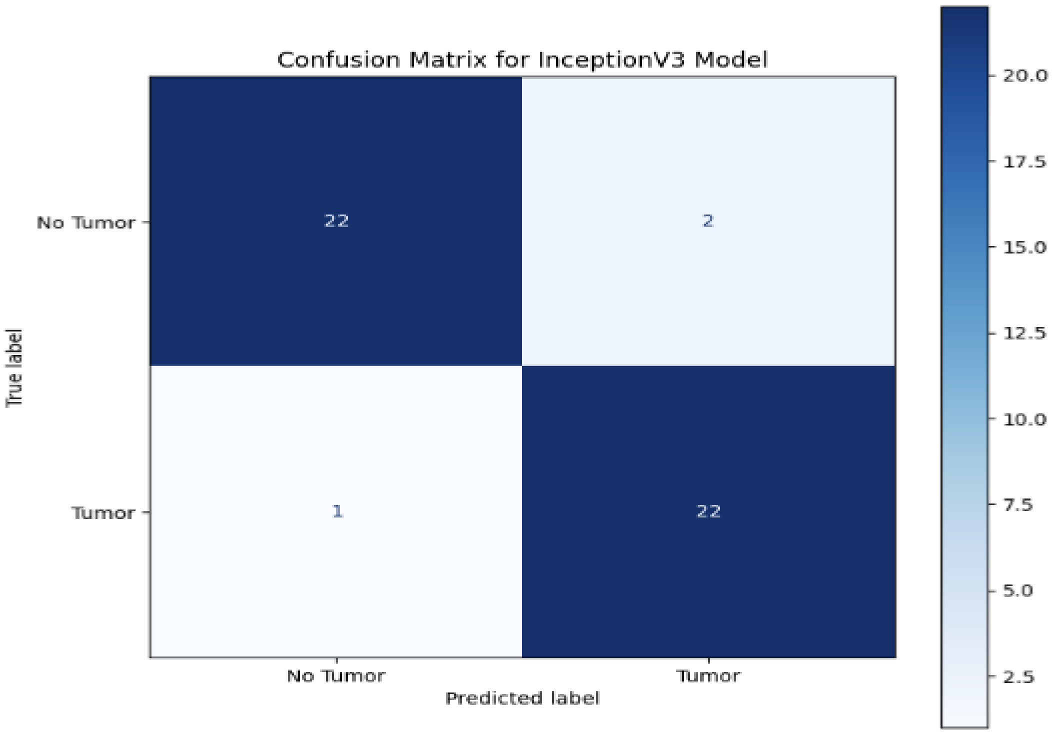

Figure 5.12: Confusion Matrix of Proposed Model2 in preprocessed dataset.

5.3.4 Summary for Models Performance

The evaluation of the models on both preprocessed and noised datasets highlights significant variances in their ability to handle different types of image qualities. Proposed Model 2 consistently outperforms the other models across all metrics, demonstrating superior robustness and accuracy, making it particularly valuable in clinical settings where precision is critical. Proposed Model 1 also shows promising results, particularly in recognizing 'Yes Tumor' cases in noisy images, which is essential for effective diagnosis.

On the other hand, both the ResNet50 and CNN models show considerable drops in performance on the noised dataset compared to the preprocessed one, especially in identifying tumor cases, which could lead to higher false negative rates. This underscores the importance of using more sophisticated or tailored models like Proposed Model 2 for critical medical imaging tasks, where the cost of misdiagnosis can be high.

These findings suggest that while traditional models like ResNet50 and CNN can be effective under controlled conditions, advanced models with specific enhancements (as seen in Proposed Models 1 and 2) are necessary to maintain high diagnostic performance in real-world, noisy environments.

CHAPTER 6

Conclusion

6.1 Conclusion

This paper has extensively explored the performance of various deep learning models for the task of detecting brain tumors from MRI images. Throughout the study, models were tested on both preprocessed and noised datasets to assess their robustness and diagnostic accuracy in realistic clinical settings. The comparative analysis focused on traditional models such as ResNet50 and CNN, as well as two proposed models that were specially designed and optimized for this task.

Key Findings:

- Performance Variability: The study highlighted significant variability in model performance, with Proposed Model 2 consistently outperforming all other models across various metrics such as accuracy, precision, recall, and F1-score. This model proved exceptionally reliable, demonstrating its potential for deployment in clinical environments where high accuracy is critical.

- Impact of Noise: The models' performances were notably different on noised versus preprocessed datasets. Traditional models like ResNet50 and CNN struggled with the noised data, indicating a potential risk of higher false negative rates in real-world applications. In contrast, Proposed Model 1 and especially Proposed Model 2 exhibited robustness to noise, maintaining high levels of accuracy and diagnostic reliability.

- Advantages of Advanced Modeling: The superior performance of the proposed models underscores the benefits of using advanced deep learning techniques and customized architectures for medical imaging tasks. These models effectively leveraged complex patterns in the data, enhancing their ability to distinguish between tumorous and non-tumorous regions even in challenging imaging conditions.

- Preprocessing Effectiveness: The preprocessing techniques employed significantly improved the quality of MRI images, as evidenced by the improved PSNR and SSIM metrics. This enhancement was crucial for maximizing the performance of the deep learning models by reducing noise and improving image clarity, which are vital for accurate tumor detection.

In conclusion, the research conducted provides a substantial contribution to the field of medical imaging, particularly in the application of deep learning for brain tumor detection from MRI images. The findings advocate for the adoption of advanced deep learning models in clinical practices, highlighting their capability to enhance diagnostic accuracy and reduce the likelihood of misdiagnosis. This study not only demonstrates the potential of such models in improving patient outcomes but also emphasizes the importance of continuous innovation and adaptation in the rapidly evolving field of medical technology.

6.2 Suggestions on Future Work1

6.2.1 Data Expansion

Incorporating a larger and more diverse dataset can enhance the model's ability to generalize and perform accurately across different patient demographics and imaging conditions.

6.2.2 Model Optimization

Exploring advanced neural network architectures or fine-tuning existing models can yield improvements in accuracy and efficiency.

6.2.3 User Interface Development

Creating a user-friendly interface for the model can facilitate its adoption by healthcare professionals, allowing for seamless integration into their workflow.

6.2.4 Suggestions on Future Work 2

Looking forward, the study opens several avenues for further research. First, exploring additional advanced deep learning architectures and training strategies could potentially yield even better results. Second, implementing and testing these models in a real-world clinical setting would provide more insights into their practical effectiveness and user acceptance. Finally, integrating these models into a comprehensive diagnostic system that includes other forms of data, such as patient history and genetic markers, could enhance the overall accuracy and reliability of brain tumor diagnoses.

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