BRAIN TUMER DETECTION USING IMAGE PROCESSING

BY

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled “Brain Tumor Detection Using Image Processing”, submitted by MD: Emam Shafi 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 26-01-2024.

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DECLARATION

I hereby declare that this project has been done by me under the supervision of **Mr. Saiful Islam, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University**. I 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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Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

This academic paper presents a novel method for identifying brain tumors by utilizing sophisticated (CNN) architectures. This so many hard detect brain tumor cell for a doctor. So, our main goal is to detect brain tumor very easily. So that patient can get treatment at the right time. Transfer learning involves using pre-train models, such as EfficientNet, ResNet-50, MobileNet and InceptionV3. The results of the experiments show encouraging levels of accuracy for the suggested approach. EfficientNet exhibited remarkable performance, achieving impeccable accuracy at a success rate of 93%. Inception v3 attained an accuracy rate of 92%. MobileNet achieved an outstanding accuracy rate of 91%. ResNet-50 demonstrated marginally reduced accuracy levels, achieving 61%. They remained effective in identifying brain tumors, each in their own way. Here I used some image preprocessing technique like Image Scaling, Crop, Blur, Gaussian Noise, Salt Pepper, Color Juttering. This technique help improve accuracy. The system is developed using GoogleColab.

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CHAPTER 1

Introduction

1.1 Introduction

A brain tumor is an abnormal mass that develops inside the brain and can affect the surrounding brain tissues or the skull. Tumors in the brain are categorized into two types: malignant (cancerous) and benign (non-cancerous). These tumors grow irregularly within the brain and can exert pressure, leading to various brain disorders. In the United States, it was estimated that nearly 0.7 million people were living with brain tumors in 2019, and approximately 0.86 million cases were diagnosed. Among these cases, 60,800 were classified as benign and 26,170 as malignant. The survival rate for patients with malignant brain tumors in the US is 35% [7]. High-quality MRI images of brain tumors are crucial for clinical diagnosis and treatment decision-making for patients. Manual classification of brain tumors from MRI scans, especially when tumors exhibit similar structures or features, is a complex and difficult task. It often relies on the availability and experience of radiologists to accurately recognize and diagnose brain tumors. Automated classification presents a promising solution to this challenge by using algorithms to classify brain tumor MRI images with minimal human intervention, reducing reliance on specific expertise in the field. This automated approach can enhance efficiency and consistency in diagnosing brain tumors from MRI scans.

Tumors represent one of the most serious and aggressive disorders, leading to a high mortality rate. Therefore, preparing for recovery is essential to enhance quality of life. Typically, various imaging techniques like CT, MRI, and ultrasound are used to assess tumors in different parts of the body such as the brain, lungs, liver, breast, and prostate. This work specifically utilizes MRI to detect brain lesions. A brain tumor is described as an abnormal mass of cells growing within the brain, resulting from uncontrolled proliferation of cells from different brain components like glial cells, nerves, lymphatic tissue, and others. Brain MRI is crucial for tumor diagnosis and monitoring progression, providing more detailed information compared to CT or ultrasound. This study introduces a new neural method for classifying brain tumors using MR images, utilizing a dataset of brain MRIs with various tumor types. Key steps of the system include preprocessing to simplify image size and extract relevant features.

1.2 Motivation

Advancing medical diagnostics using cutting-edge technology is an ongoing effort driven by the goal of improving patient care and global health outcomes. Brain tumors are a major concern in the realm of respiratory diseases, necessitating prompt and precise diagnosis for successful treatment. The title "Brain Tumor Detection Using Image Processing" underscores a strong dedication to employing advanced methods to tackle this issue. Transfer learning, a concept within artificial intelligence, is crucial as it allows the model to utilize knowledge from different tasks and apply it to brain tumor detection. (CNN) framework, renowned its proficiency in photo analysis, serves as the foundation of this technological effort.

This research thoroughly examines detection and segmentation techniques to accurately identify brain tumors and delineate the affected areas. By offering a comprehensive understanding essential for personalized medical treatments, the study aims to discover the most effective strategies. This will significantly advance brain tumor diagnostics and improve the global standard of healthcare.

1.3 Rational of the Study

The purpose of conducting the study on "Brain Tumor Detection Using Image Processing" is to tackle important challenges in medical imaging and the diagnosis of respiratory diseases. Brain tumors are a major health issue worldwide, requiring prompt and accurate detection for proper treatment and management. By using transfer learning, a key technique in artificial intelligence, the study aims to utilize existing knowledge from different tasks to improve the model's capability in identifying brain tumor patterns in medical images. Furthermore, the application of deep convolutional neural networks (CNNs) enhances the study's potential due to their proven efficiency in image analysis.

This research is driven by both detection and a comparative analysis of detection and segmentation methods. Grasping the subtleties of these techniques is vital for a deep understanding of the spatial scope and complexities of brain tumor-affected areas. By extensively investigating both detection and segmentation, the study seeks to highlight the strengths and weaknesses of each method, offering valuable insights to the scientific community. This comparative analysis is crucial for improving current diagnostic tools and promoting the creation of more accurate and dependable systems. The study ultimately aims to establish a foundation for advancements in brain tumor diagnostics, significantly improving the precision and speed of identification and segmentation processes. With deepening our understanding of the optimal use of transfer learning and deep CNNs in this context, the research aspires to contribute both to academic discussions and practical healthcare applications, where enhanced diagnostics can directly improve patient outcomes and overall public health.

1.4 Research Questions

- How can Brain Tumor Data corpus be categorized?
- How many categories does this dataset contain?
- How does transfer learning improve the accuracy and efficiency of detecting brain tumors in medical imaging?
- How does the segmentation method enhance pneumonia detection, and what understanding does it offer about the spatial distribution and features of regions affected by pneumonia?

1.5 Expected Output

This study focuses on identifying different types of brain tumors and categorizing them into four groups: Glioma, Meningioma, Pituitary, and No Tumor. The main aim is to develop a robust deep learning method for classifying brain tumor types. To achieve this goal, three Convolutional Neural Network (CNN) models, along with the InceptionV3 model, were employed in the research. The objective is to leverage these models to accurately classify brain tumor images into the specified categories, aiding in effective diagnosis and treatment planning.

1.6 Project Management and Finance

Ensuring effective oversight is essential for the success and long-term viability of the proposed research on "Brain Tumor Detection Using Image Processing". These elements play a pivotal role in coordinating various tasks and allocating resources efficiently. In terms of project management, meticulous planning and coordination will be essential throughout the research process. Tasks like data collection, model development, training, and evaluation are encompassed within this scope. We will formulate a comprehensive project plan to delineate essential milestones, allocate resources efficiently, and establish clear timelines. This methodical strategy aims to streamline workflow and facilitate the research team's efficient pursuit of objectives. Simultaneously, robust financial management is critical to the project's viability. Budget planning will be meticulously structured to encompass costs associated with equipment, computational resources, and potential research partnerships. Developing a clear and fair financial strategy will enhance how resources are used while ensuring fiscal accountability. By integrating effective project management and financial oversight, The research team will have the authority to handle the intricacies of the study adeptly. This method guarantees that resources assigned will support research goals, promoting smooth advancement toward project objectives and enhancing the influence of research results.

1.7 Report layout

The paper is organized into the following sections:

- Chapter 2: Investigates existing literature, performs a comparative analysis, and examines the range of issues and difficulties.
- Chapter 3: The emphasis is on Research approach, offering an overview of the dataset and detailing the planned model.
- Chapter 4: Analyzes the results obtained from the research.
- Chapter 5: Analyzes how the categorization of Brain Tumer affects

CHAPTER 2

Background

2.1 Preliminaries/Terminologies

To ensure comprehensive grasp fundamental principles and methodologies applied in the study on "Brain Tumor Detection Using Image Processing," it is crucial to first define key terms and concepts. Transfer learning, a pivotal concept in artificial intelligence, serves as the foundation of this research, enabling the model to utilize knowledge from unrelated tasks to improve brain tumor detection.

2.2 Related Works

Dahab, D. A. et.al showed that Automated Brain Tumor Detection and Identification Using Image Processing and Probabilistic Neural Network Techniques [1]. This paper utilizes altered image segmentation methods to identify brain tumors within MRI scans. Additionally, it introduces an adapted Probabilistic Neural Network (PNN) model, employing learning vector quantization (LVQ), combined with image and data analysis and manipulation techniques, to automate the classification of brain tumors using MRI scans. Effectively managing brain tumor classification in MRI images achieves a 100% accuracy rate when the spread value is set to 1. These findings also assert that the LVQ-based PNN system proposed reduces processing time by around 79% compared to conventional PNN methods, showcasing significant promise in in-vivo brain tumor detection and identification.

Sharma, K. et.al introduced. Automated identification of flaws in medical imaging has emerged as a significant area in various diagnostic medical applications [2]. The automated detection of tumors in Magnetic Resonance Imaging (MRI) is particularly critical as it furnishes vital information about abnormal tissues, essential for treatment planning. The suggested project consists of three main components: initial preprocessing is conducted on brain MRI images, texture characteristics are derived utilizing the Gray Level Co-occurrence Matrix (GLCM), and subsequently, The dataset comprises 212 brain MR images, and for data classification, we utilized the Multi-Layer Perceptron and Naïve Bayes algorithms, achieving high accuracies of 98.6% and 91.6%, respectively. It's likely that augmenting the dataset size and incorporating intensity-based features alongside texture-based features could further enhance accuracy.

Nagaraj, M. P. et.al showed that Programmed Multi-Classification of Brain Tumor Images Using Deep Neural Network [3]. Detecting brain tumors plays a crucial role in assessing their severity and determining appropriate treatment strategies based on their grades. Despite the widespread use of MRI due to its superior image quality and lack of exposure to cosmic radiation, deep learning (DL) has emerged as a promising approach, particularly in tasks like classification and segmentation. This article proposes a DL framework based on Convolutional Neural Networks (CNNs) to identify different types of brain tumors by leveraging publicly available datasets. One dataset distinguishes between Meningioma, Glioma, and Pituitary tumors, while another dataset categorizes tumors into Grade II, Grade III, and Grade IV.

Methil, A. S. et.al showed that Brain Tumor Detection Using Deep Learning and Image Processing [4]. Detecting brain tumors poses a significant challenge within the realm of medical image processing due to the diverse nature of the images. This difficulty arises from the varying shapes and textures of brain tumors, making the detection task inherently complex. Tumors may manifest in various sites, and their location often hints at the type of cells instigating their growth, thereby facilitating subsequent diagnosis. Detecting brain tumors can pose challenges due to ubiquitous issues in digital images, such as illumination inconsistencies, which can exacerbate the process. Histogram equalization and opening were utilized prior to applying a convolutional neural network (CNN) in the study. Additionally, the paper explores various other image preprocessing methods beyond those chosen for training, examining their effects on the dataset. The experimental analysis was conducted on a dataset featuring tumors of diverse shapes, sizes, textures, and locations. The CNN was employed for classification tasks, achieving a remarkable recall rate of 98.55% on the training set and 99.73% on the validation set, demonstrating strong performance.

Ural, B. et.al introduced that A Computer Based Brain Tumor Detection Approach with Advanced Image Processing and Probabilistic Neural Network Methods [5]. The demand for automation in tumor detection is increasing due to a potential shortage of experienced radiologists. This research introduces a computer-based method for detecting brain tumors in MRI scans. In this research, initially, a unique clustering method is applied to MRI images. Subsequently, tumor regions are accurately identified through the application of thresholding and level-set segmentation techniques. Following this, automatic classification and analysis of brain tumors are conducted using the acquired tumor regions employing the PNN method. In the experimental phase, 25 neuro images are utilized for system optimization, while an additional. Corso algorithm provide lowest accuracy. Which is 62% to 69%. This algorithm used weighted aggregation approach. The highest accuracy provide Varma algorithm. That is 93%. That Algorithm used SVM approach.

Sharma, P. et.al showed that Application of Edge Detection for Brain Tumor Detection [6]. Brain tumors originate from irregular and unregulated cell division within the brain. When the growth exceeds 50%, recovery becomes unlikely for the patient. Hence, swift and precise detection of brain tumors is imperative. The aim of this paper is to present a proficient algorithm designed for identifying the boundaries of brain tumors. MRI scans display gray and white matter, with tumor regions exhibiting higher intensity. Initially, noise filters are employed to eliminate noise, followed by enhancement techniques applied to the brain MRI scan. Subsequently, basic morphological operations are utilized to isolate the tumor-affected region. Finally, verification of the detected region is conducted using watershed segmentation. Approximately 43% of brain and central nervous system tumors are diagnosed in males, while roughly 57% are diagnosed in females.

Hemanth, G. et.al Introduced that Design and Implementing Brain Tumor Detection Using Machine Learning Approach [7]. The detection of brain tumors has become a common concern in healthcare. A brain tumor is characterized as an abnormal mass of tissue where cells multiply rapidly and uncontrollably. Image segmentation techniques are utilized to isolate the abnormal tumor area within the brain. Particularly in MRI scans, segmenting brain tissue is crucial for identifying the presence and boundaries of brain tumors. The study investigates a range of risk factors identified in brain tumor surveillance systems. Additionally, the proposed approach ensures significant efficacy and accuracy in detecting, classifying, and segmenting brain tumors. To achieve this level of precision, automated or semi-automated methods are essential. The research introduces an automatic segmentation technique utilizing Convolutional Neural Networks (CNN), employing small 3 x 3 kernels. Through this method, both segmentation and classification tasks are successfully executed. CNN, a machine learning technique, represents an advancement from traditional Neural Networks (NN), featuring layered structures for result classification. Here are some techniques used like Conditional Random Field (CRF), Support Victor Machine (SVM), Genetic Algorithm (GA), and Convolutional Neural Network (CNN). CNN provides highest Precision, that is 91% and GA techniques provides lowest accuracy that is 83.64%. If dataset was large, it might be more reliable.

Borole, V. Y. et.al showed that Image Processing Techniques for Brain Tumor Detection: A Review [8]. MRI imaging is crucial in the analysis, diagnosis, and planning of treatment for brain tumors. It assists doctors in understanding the progression of brain tumors. Detecting brain tumors using MRI images is challenging due to the brain's intricate structure. A brain tumor is characterized by abnormal cell growth in the brain. MRI images provide superior differentiation of various soft tissues in the human body compared to CT, ultrasound, and X-ray. Techniques such as filtering, contrast enhancement, and edge detection, as well as post-processing methods like histogram analysis, thresholding, segmentation, and morphological operations, are available in MATLAB for processing MRI images to detect brain tumors. Preprocessed images undergo post-processing procedures such as thresholding, histogram analysis, segmentation, and morphological operations to enhance their quality.

Sobhaninia et.al, proposed a novel method for CNN to automatically classify the most popular brain tumour forms, i.e., Pituitary, Glioma, Meningioma. They utilized a LinkNet network for tumor segmentation, employing 2100 images for training the network[9]. Twenty percent of these images were set aside for validation, while the remaining data were used for testing. Experimental tests of the network demonstrated a dice score of 0.73 for a single network and 0.79 when using multiple networks. Notably, in sagittal images, this approach achieved a relatively high segmentation score for tumors. Sagittal images are advantageous for tumor detection because they exclude detailed information about other organs, making tumors more prominent and easier to identify compared to other types of images.

Nilakshi Devi et al. work focused on automatic brain tumor detection and classification of grades of astrocytoma [10]. The approach involves using GLCM (Gray-Level Co-occurrence Matrix) for extracting features, followed by the application of an artificial neural network (ANN) for tumor detection. The subsequent step focuses on the classification of astrocytoma using a Radial Basis Function Network (RBFN). This classification task involves differentiating between Grade I, Grade II, Grade III, and Grade IV types of images based on the characteristics extracted from the tumors.

Mustafa, Ikhlas qader et al. paper focused on brain tumor classification using statistical features and back propagation of neural network [11]. For feature extraction, the Discrete Wavelet Transform (DWT) and Gabor filter techniques are employed. These methods help extract relevant features from images. Subsequently, the extracted features are used for the classification of three types of brain tumors: Meningioma, Glioma, and Pituitary tumors. To perform the classification task, a Backpropagation Neural Network (BPNN) is utilized. The BPNN is a type of artificial neural network that uses supervised learning and backpropagation of errors to classify input data into different categories or classes. In this context, the BPNN is trained to distinguish between the specific types of brain tumors based on the extracted features from the DWT and Gabor-filtered images. This approach aims to automate and improve the accuracy of brain tumor classification using advanced image processing and machine learning techniques.

Lichi Zhang, Han Zhang et al. worked on malignant brain tumor classification using random forest method [12]. Individual characteristics such as age, gender, and tumor size are considered on a per-subject basis, while features like intensity histogram and Haar-like descriptors are extracted from image patches. These extracted features are then utilized to train a random forest classifier, which achieved an accuracy of 59.88% in classification.

Sehgal, Aastha et al. work represented for automatic brain tumor segmentation and extraction in MR image. The brain tumor detection method described is entirely automated [13]. The experiment utilized the BraTS dataset. The process involved several stages of image processing. Initially, in the Preprocessing stage, noise was eliminated and MRI brain images were enhanced using mathematical operations or modification techniques. Firstly, the MRI images underwent N3 correction using the N3 algorithm to eliminate bias field. The segmentation of tumors was performed using the Fuzzy C Means technique. Tumor region extraction involved assessing Area and Circularity, with the Dice coefficient calculated for evaluation.

Gupta, Sheifali, et al. By Brain magnetic resonance images were segmented using image processing techniques [14]. Astrocytoma's were classified as either low-grade or high-grade using the k-NN classifier. The classification results were assessed based on three evaluation parameters:

accuracy, sensitivity, and specificity. The dataset used was collected from BraTS and consisted of magnetic resonance images (MRI). Shape-based features were extracted as part of the feature extraction process. The KNN classifier was employed for clustering classification, categorizing brain tumor images into low-grade or high-grade.

Anjali Joshi, V. Charan, Shanti et al. paper focuses on the classification of malignant and benign brain tumors using a two-stage segmentation method for MRI images [15]. This method involves the use of Gabor filter and contour level set segmentation techniques. The contour level set method helps in detecting different regions within the image, particularly aiding in the extraction of brain tumor parts. This extraction is crucial for subsequent feature extraction methods such as analyzing the size, shape, and density of the tumor. The evaluation of this work is based on analyzing the pixel values of tumor tissues, which typically exhibit higher values compared to normal tissues. For calculating shape features, the area and shape matrix of the tumor are considered. If the metric value derived from these features is 1, it indicates a benign tumor. Conversely, if the shape matrix value is higher than 1, it suggests a malignant tumor.

Table 2.2.1: Related Work Table of My Thesis

Study	**Image type**	**CNN Model**	**Accuracy**
Dahab, D. A. et.al (2012)	Brain Tumor	Probabilistic Neural Network (PNN)	Accuracy 79%
Sharma, K. et.al(2014)	brain MRI images	deep Convolutional Neural Network (CNN)	Accuracy 91.6% and 98.6%
Sehgal, Aastha et al.(2016)	MRI images	Convolutional Neural Network (CNN)	N/A
Ural, B. et.al(2018)	brain MRI images	Probabilistic Neural Network (PNN)	Accuracy 69%
Hemanth, G. et.al(2019)	brain MRI images	deep Convolutional Neural Network (CNN)	Accuracy 91%
Sobhaninia et.al(2018)	MRI images	Convolutional Neural Network (CNN)	Accuracy 73%

Lichi Zhang et.al(2018)	Brain images	Convolutional Neural Network (CNN)	Accuracy 59.88%
V. Charan, Shanti et al.(2015)	Brain Tumor	deep ConvolutionalNeural Network(CNN)	N/A
Gupta, Sheifali, et al.(2016)	MRI images	Convolutional Neural Network (CNN)	N/A
Methil, A. S. et.al(2021)	Brain Tumor	Convolutional Neural Network (CNN)	Accuracy 99.73%
Mustafa, Ikhlas qader et al.(2018)	brain MRI images	Convolutional Neural Network (CNN)	N/A
Nilakshi Devi et al.(2016)	MRI images	artificial neural network (ANN)	N/A

2.3 Comparative Analysis and Summary

The comparative Assessment conducted in this study on "Brain Tumor Detection Using Image Processing" is vital for understanding the nuanced distinctions and collaborations among different methodologies. The research systematically evaluates how transfer learning and deep Convolutional Neural Networks (CNNs) contribute to brain tumor detection, comparing them with traditional methods and advanced segmentation techniques. Through rigorous experimentation and detailed result analysis, the study unveils insights into the advantages and drawbacks of each method, offering a thorough comprehension of their roles in enhancing diagnostic procedures.

The study extensively explores detection and segmentation methods, examining how these techniques enhance the precision and effectiveness of identifying brain tumors. By analyzing results from various approaches, the research provides valuable insights to help practitioners and researchers choose optimal strategies for their particular requirements. Crucially, it emphasizes not only differences but also the potential synergy between detection and segmentation, advancing our comprehension of the spatial patterns and attributes of brain tumor-affected areas.

In this research, a comparative analysis was conducted to evaluate the effectiveness of transfer learning and deep convolutional neural networks (CNNs) in detecting brain tumors. The study provides a comprehensive perspective by examining both traditional and modern techniques, emphasizing the importance of a holistic approach in medical diagnostics. The findings not only deepen our understanding of brain tumor detection but also offer practical insights for improving current diagnostic methods. This comparative analysis forms a robust foundation for subsequent chapters, facilitating discussions on societal impact, recommendations, and implications for future research. Various machine learning and deep learning models, such as Naive Bayes Classifier, K-Nearest Neighbors (KNN), CNN, ResNet50, VGG16, AlexNet, and GoogLeNet, have been employed in comparison to other relevant studies for brain tumor detection.

2.3.1 Naive Bayes Classifier:

The Naïve Bayes algorithm is recognized as a significant tool for rapidly developing machine learning models to predict outcomes. It functions based on probabilities, classifying data in a probabilistic manner. Common applications of Naïve Bayes include spam filtering, article classification, face recognition, and weather prediction. The term "Naïve Bayes" comprises two components: and that Represented by:

Naïve: subject "naive" in Naïve Bayes originates from the algorithm's treats each attribute independently. Thus, a brain tumer could be recognized as a yellow, oval-shaped. This method enables each characteristic to contribute individually to identifying the brain tumer, without accounting for interactions among them.

Bayes: The core principle behind the Naïve Bayes algorithm is Bayes' theorem, which is why the algorithm is named after Bayes. Bayes' theorem is a mathematical concept used to calculate the probability of an event based on prior knowledge of conditions related to the event. In the context of the Naïve Bayes algorithm, Bayes' theorem is applied to make predictions or classifications by assessing the probability of specific features or characteristics.

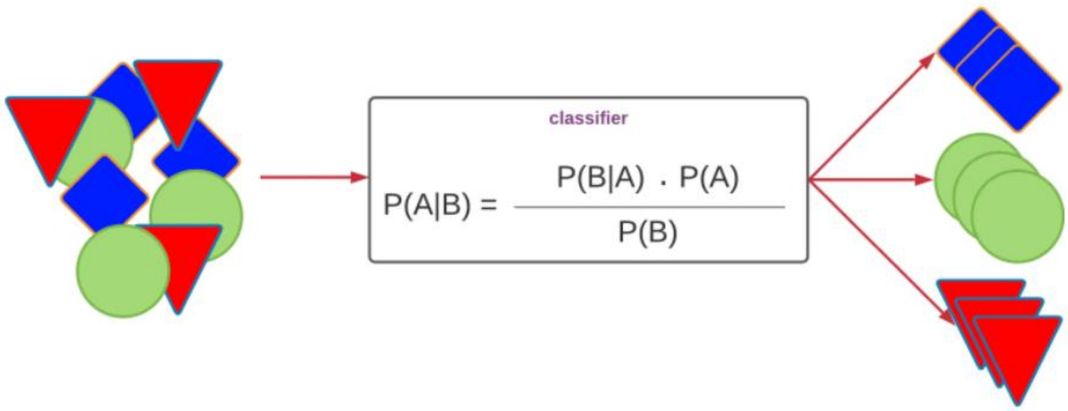

Figure 2.3.1: Naïve Bayes Classifier [17]

2.3.2 K-Nearest Neighbor (KNN):

K-Nearest Neighbors (K-NN) works labeled data, that both current with current instance are comparable. That matches categories based on proximity in feature space. By utilizing all playing document and assessing same, k-nn effectively categorizes enter. That method allows Quick and definite classification of update info goto appropriate Classes.

- Select importance with K: Decide on counter nearest (K) to use for classification.
- Identify the K nearest neighbors by finding those with the shortest Euclidean distances to the new data point.
- Count the categories of neighboring data points: Identify how many data points fall into each category (class) within the K nearest neighbors.
- Assign Category to New Observation: Assign the new data point to the category (class) that appears most frequently among the K nearest neighbors.
- Develop K-NN Model: Through this process, establish a K-NN model that can be used for classifying new data points based on their proximity to existing labeled data.\

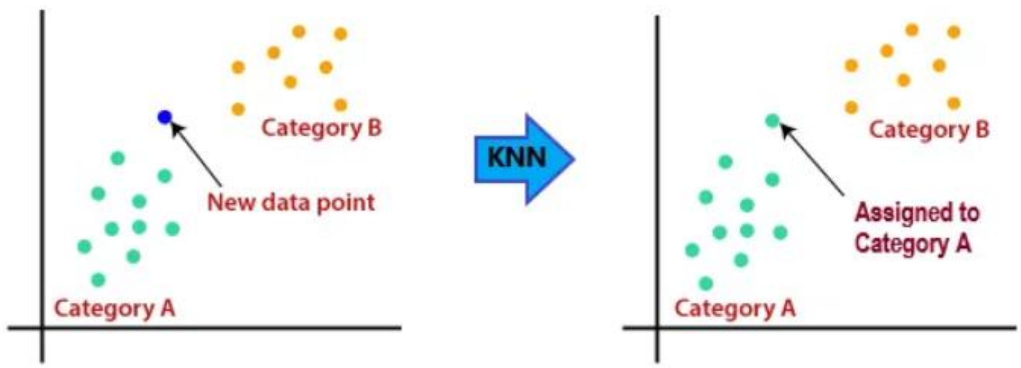

Figure 2.3.2: K-NN Algorithm [18]

2.3.3 Convolutional Neural network (CNN):

The CNN is a specialized specifically analyzing picture and info. It abstracts to drawing employ convolutional layers as their fundamental component. In these layers, input data is processed using learnable filters (kernels) that perform elementwise operations, to extract. This process generates

typically hundreds or thousands of layers, enabling them to detect a wide range of convolutional varying, progressively extracting distinctive characteristics to accurately recognize the image.

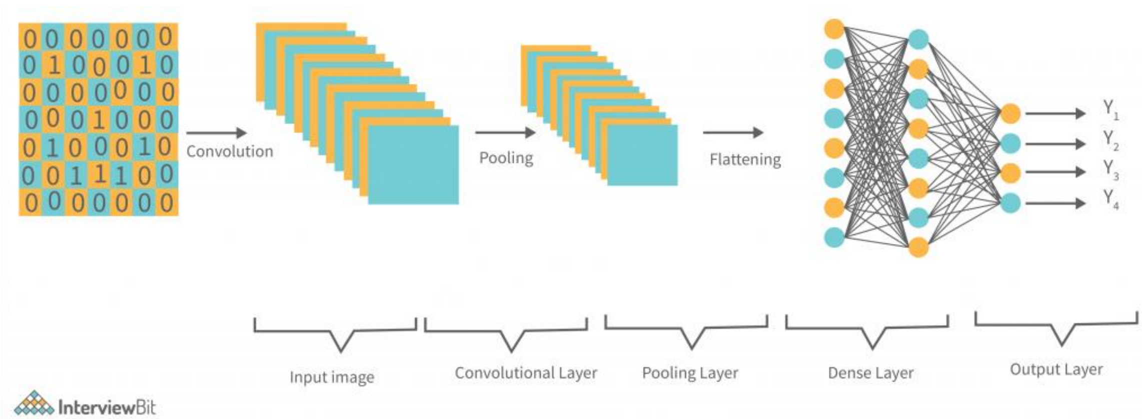

Figure 2.3.3: Basic CNN Architecture [18]

2.3.4 ResNet50:

It hat 48 convolutional layers, supplemented by a distinctive characteristic of ResNet-50 is its utilization of bottleneck building blocks, commonly known as "bottlenecks." These bottlenecks incorporate 1x1 convolutions to reduce the number of parameters and matrix multiplications. This strategic design enhances the model's efficiency while maintaining high performance levels overall.

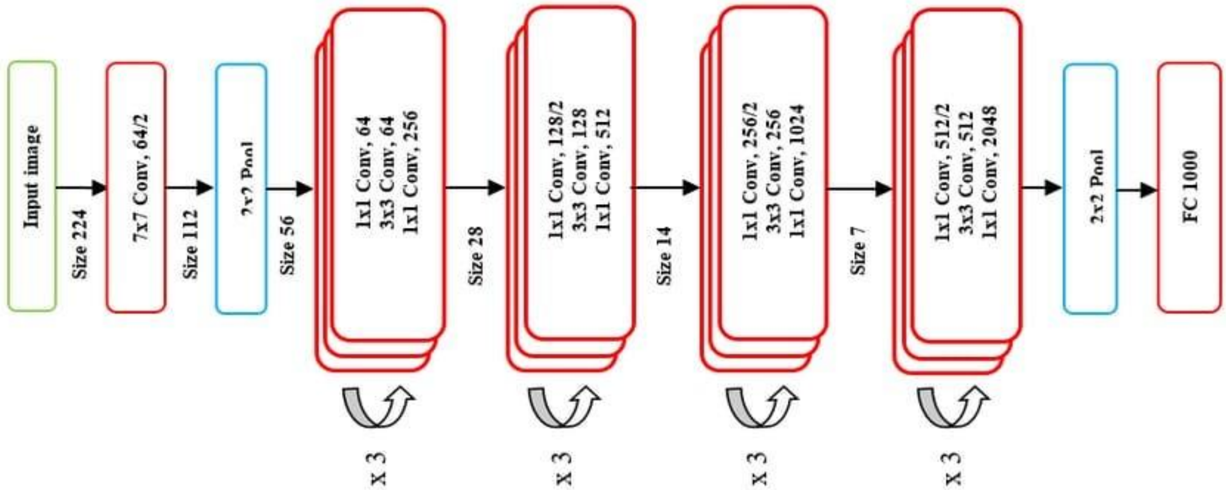

Figure 2.3.4: ResNet50 Model Architecture [19]

2.3.5 VGG16:

The VGG model, developed by the VGG group, has gained widespread recognition and serves standard like because of its exceptional performance.

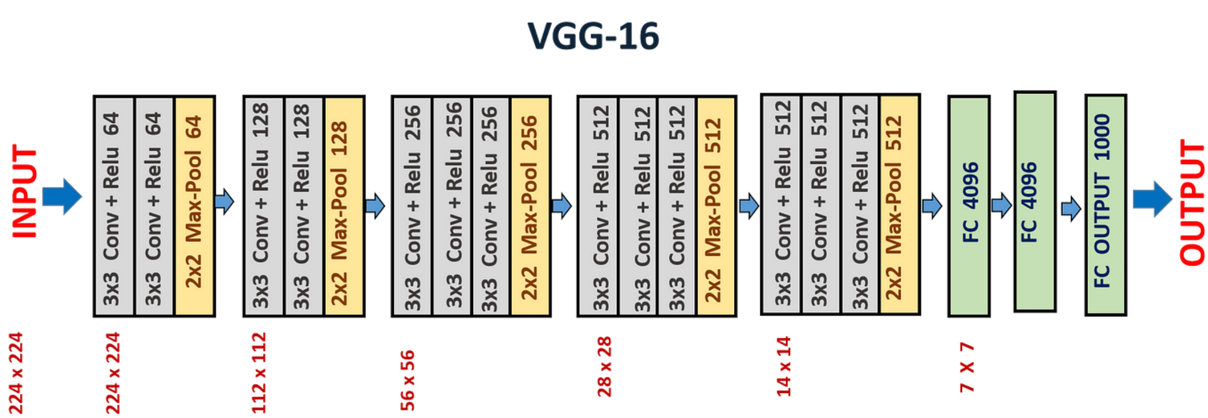

Figure 2.3.5: VGG16 Model Architecture [19]

2.3.6 AlexNet:

AlexNet made significant breakthrough showcasing notable decrease rates prior leading models. It achieved a 15% error rate, marking a substantial improvement from the previous 26%. AlexNet's architecture includes five convolutional layers, each followed by maximum pooling layers, and incorporates used throughout network to mitigate the vanishing gradient problem and enhance training effectiveness. The model employs various convolutional filter sizes, ranging from common sizes like 3x3 to larger ones such as 5x5 and 11x11. This diversity enables AlexNet to capture diverse. By integrating and a range of, AlexNet achieved exceptional, significantly advancing the field of deep learning for image recognition tasks.

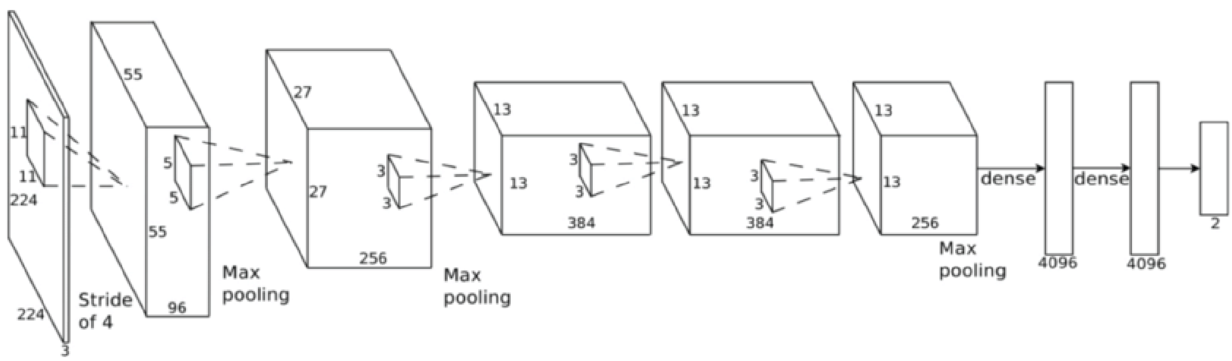

Figure 2.3.6: AlexNet Model Architecture [20]

To increase the effective size of the training set and address overfitting, AlexNet utilizes data augmentation techniques and a dropout approach. These strategies help improve the model's generalization performance by exposing it to diverse variations of the training data and reducing reliance on specific individual neurons during training.

The success of AlexNet highlighted the effectiveness of deep learning techniques in computer vision, sparking greater interest and advancement in the field. Additionally, AlexNet played a significant role in promoting the adoption of Graphics Processing Units (GPUs) for training deep learning networks. GPUs excel at performing parallel computations, making them well-suited for the intensive matrix operations involved in training large neural networks like AlexNet. As a result, the use of GPUs has become standard practice in accelerating the training and deployment of deep learning models across various domains.

2.3.7 GoogLeNet:

Google researchers that significantly impacted the field with its Inception module. This module integrates multiple parallel convolutional layers with varying filter sizes, followed by a pooling layer and concatenated outputs. By processing multiple receptive field sizes simultaneously, the module enhances feature learning's efficiency and expressiveness.

GoogLeNet also includes auxiliary classifiers at intermediate layers, which serve two main purposes. The design principles of this network have profoundly leading to deeper and more accurate models in computer vision tasks.

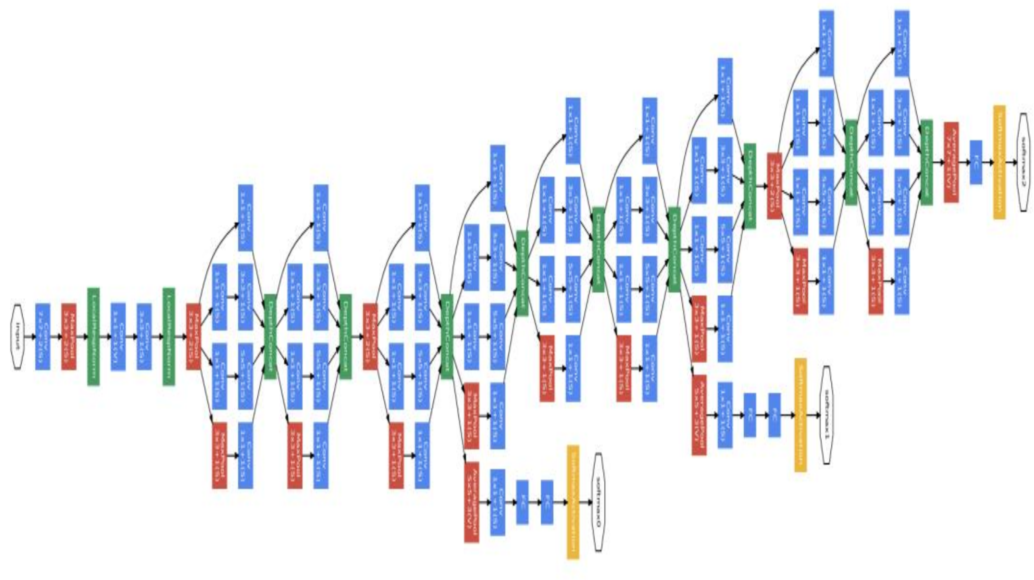

Figure 2.3.7: GoogLeNet Model Architecture [25]

fundamental principles of like LeNet initially demonstrated successful deep learning applications , however exceeds highlight. However, exceeds highlighting progress in convolutional cnn design and architecture.

2.4 Scope of the Problem

The study on "Brain Tumor Detection Using Image Processing" delves into a critical area of medical diagnostics, focusing on the challenges and advancements in detecting brain tumors. Brain tumors pose significant health risks, necessitating accurate and prompt detection for effective treatment. The research goes beyond conventional detection methods, which may have limitations in sensitivity, specificity, and overall diagnostic precision. A key aspect of this investigation involves exploring transfer learning, an emerging concept in artificial intelligence, to improve brain tumor detection capabilities. Transfer learning allows the model to apply knowledge from unrelated tasks, potentially enhancing its ability to interpret complex images of brain tumors. Furthermore, integrating deep Convolutional Neural Networks (CNNs) enhances the complexity and sophistication of the approach, as CNNs excel in extracting intricate patterns and features from visual data. The study also includes a comparative examination of various detection and segmentation methods, seeking to comprehend their strengths, limitations, and potential synergies. Thorough diagnostics necessitate a nuanced grasp of the spatial distribution and characteristics of brain tumor-affected areas, which conventional methods may struggle to deliver. The research seeks to provide insights that enhance diagnostic approaches beyond traditional techniques. Ultimately, the research addresses challenges in brain tumor detection, explores innovative methods such as transfer learning and deep convolutional neural networks (CNNs), and conducts a comparative assessment of detection and segmentation techniques. By addressing these aspects, the study aims to refine diagnostic approaches and enhance our capacity to address the impact of brain tumors on public health.

CHAPTER 3

Research Methodology

3.1 Research Subject and Instrumentation

My Brain Tumor Determination Using Image Processing. I conducted this research by utilizing Google Colab for programming purposes. For image augmentation, resizing tasks and image preprocessing task I employed Jupyter Notebook.

3.1.1 Methodology

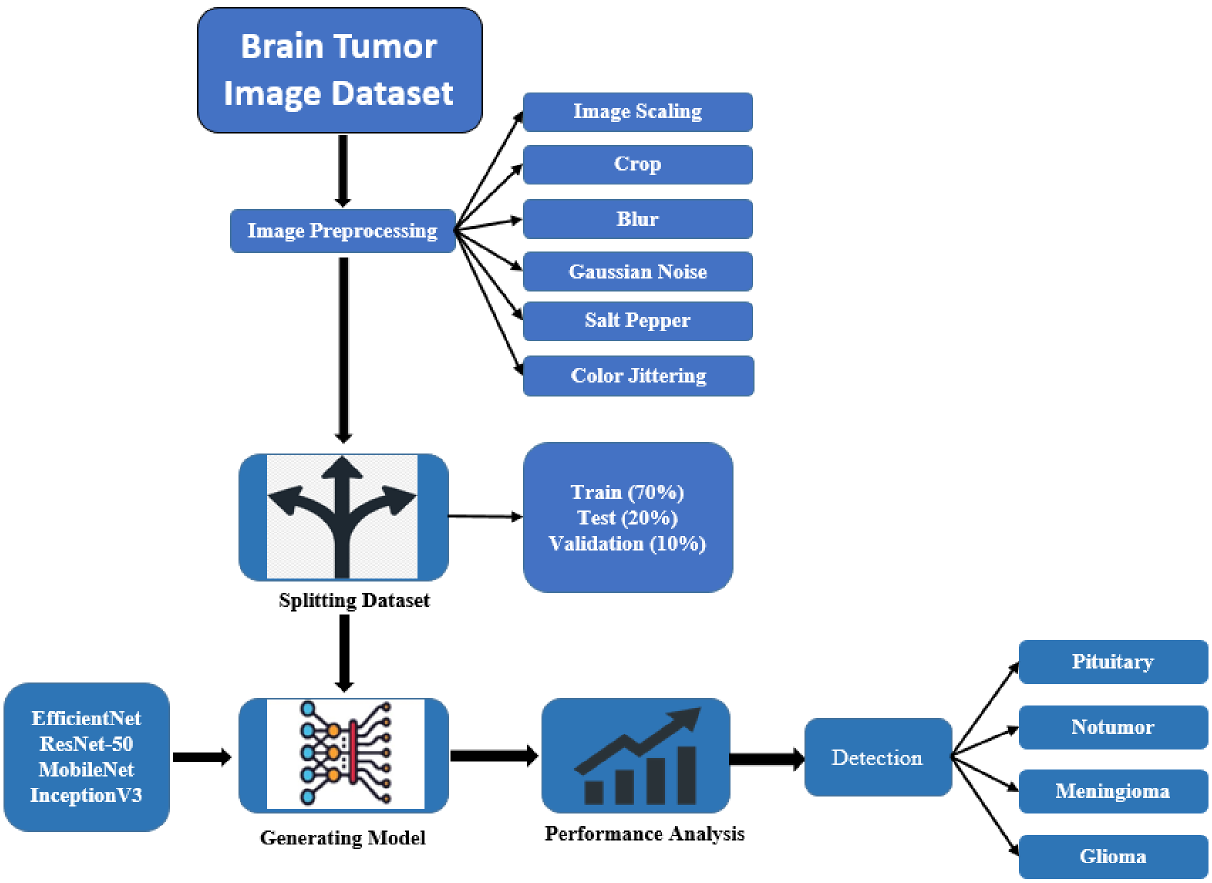

Fig. 3.1.1: Methodology of Brain Tumor Detection

Fig. 3.1.1 present the methodology of Brain Tumor Detection. Here we can see that, we use some preprocessing techniques. There are Image Scaling, Crop, Blur, Caussian Noise, Salt Pepper and Color Jittering. After that I splited all of data into train (70%), test(20%) and validation (10%) and finally I used some model like EfficientNet, ResNet-50, MobileNet, InceptionV3.

3.2 Data Collection Procedure

Mainly I downloaded the for brain tumor detection research. I have seen many datasets for brain tumor detection in kaggle, I downloaded the best dataset among them. The dataset I downloaded has 4 classes, there are Pituitary, Notumor, Meningioma, Glioma. Pituitary class has 1757 data, Notumor class has 2000 data, Meningioma class has 1645 data and Glioma class has 1621 data. So total amount of data is 7023.

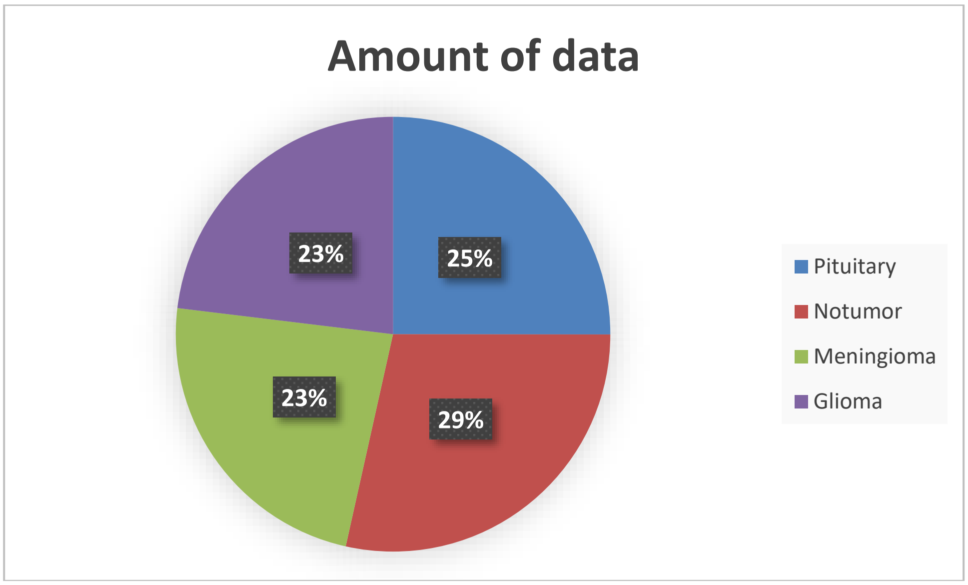

Fig. 3.2 Classes of Dataset

Fig. 3.2 show that Pituitary class has 25% data, it means 1757 data out of 7023. Notumor class has 29% data it means 2000 data out of 7023. Meningioma class has 23% data it means 1645 out of 7023 and Glioma class has 23% data it means 1621 out of 7023.

3.3 Data Preprocessing

First of all I applied some preprocessing technique for data preprocessing like Image Scaling, Crop, Blur, Gaussian Noise, Salt Pepper, Color Jittering. The platform I used for preprocessing the dataset is google colab. After that I splited all of data into Train, Test and validation. Train dataset has 70%, Test dataset has 20% and Validation dataset has 10%.

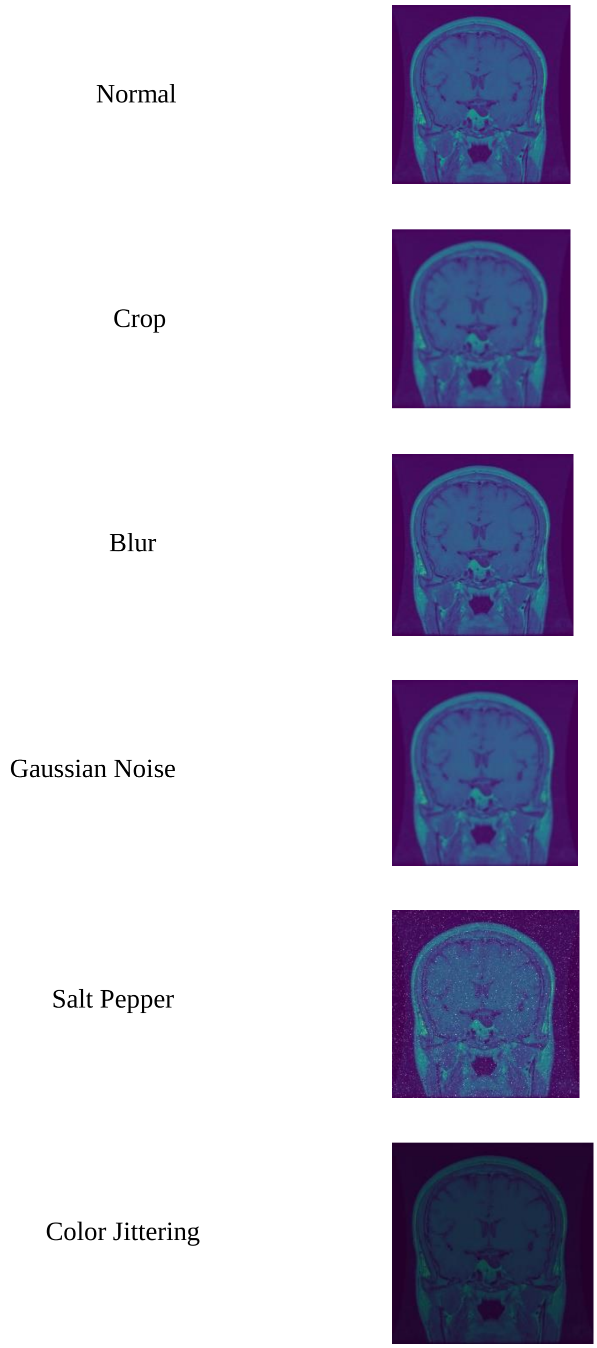

Fig. 3.3: Processed Images

Fig 3.3 show that Normal and some preprocessed images

- **Image Scaling:** A fundamental concept in image processing is image scaling and applied in various applications. Scaling the images while maintaining the aspect ratio. This can be done by enlarging and compressing the image.

- **Crop:** We will use crop preprocessing technique to remove unnecessary. Its process focuses on key features and improves model efficiency. Crops speed up training and enhance generalization by removing noise and reducing data dimensionality.
- **Blur:** We applied filters to our picture datasets using the Blur preprocessing approach to reduce high frequency noise in order to obtain smoother images. This approach aids models in identifying significant patterns by removing unimportant information.
- **Gaussian Noise:** The statistical noise known as Gaussian noise follows the normal distribution, often known as the Gaussian distribution. This kind of noise is routinely added to pictures at the pre-processing stage in order to mimic real-world changes, boost model resilience, and enhance the performance of machine learning models, especially deep learning models.
- **Salt Pepper:** Salt and pepper noise is a common type of noise that can harm digital photographs. The black and white specks that randomly emerge across the image and mimic salt and pepper grains are what give the image its name.
- **Color Jittering:** Color jittering is a common technique in picture pre-processing for deep learning. It comprises introducing controlled adjustments to an image's color channels to broaden the diversity of training data and enhance the model's ability to generalize to different lighting settings and color variances.

Table 3.3: Dataset Description

Dataset Category	Class	Train	Test	Validation
Brain Tumor Image Dataset	Pituitary	1230	351	176
	Notumor	1400	400	200
	Meningioma	1152	329	164
	Glioma	1135	324	162
	Total	4917	1404	702

Table 3.3 describe that my total class has 4. There are Pituitary, Notumor, Meningioma and Glioma, I splited all data into Train, Test and Validation. For Training purpose Pituitary class has 1230 images, Notumor class has 1400 images, Meningioma class has 1152 images and Glioma class has 1135 images. So For training purpose total images are 4917. For Testing purpose Pituitary class has 351 images, Notumor class has 400 images, Meningioma class has 329 images and Glioma class has 324 images. So For testing purpose total images are 1404. For Validation purpose Pituitary class has 176 images, Notumor class has 200 images, Meningioma class has 164 images and Glioma class has 162 images. So For training purpose total images are 702. And finally total amount of data is 7023.

3.4 Proposed Methodology/ Applied Mechanism

Proposed this research paper are CNN model like EfficientNet, ResNet-50, MobileNet, InceptionV3.

MobileNet, a computer vision model created by Google and available as open-source, is designed for training classifiers. It utilizes depthwise convolutions to significantly reduce the number of parameters compared to other networks, resulting in the development of a lightweight deep neural network. MobileNet is Tensorflow's first model tailored for mobile-centric computer vision tasks. It employs depthwise separable convolutions to notably decrease the parameter count compared to networks using standard convolutions with the same depth, thereby producing lightweight deep neural networks.

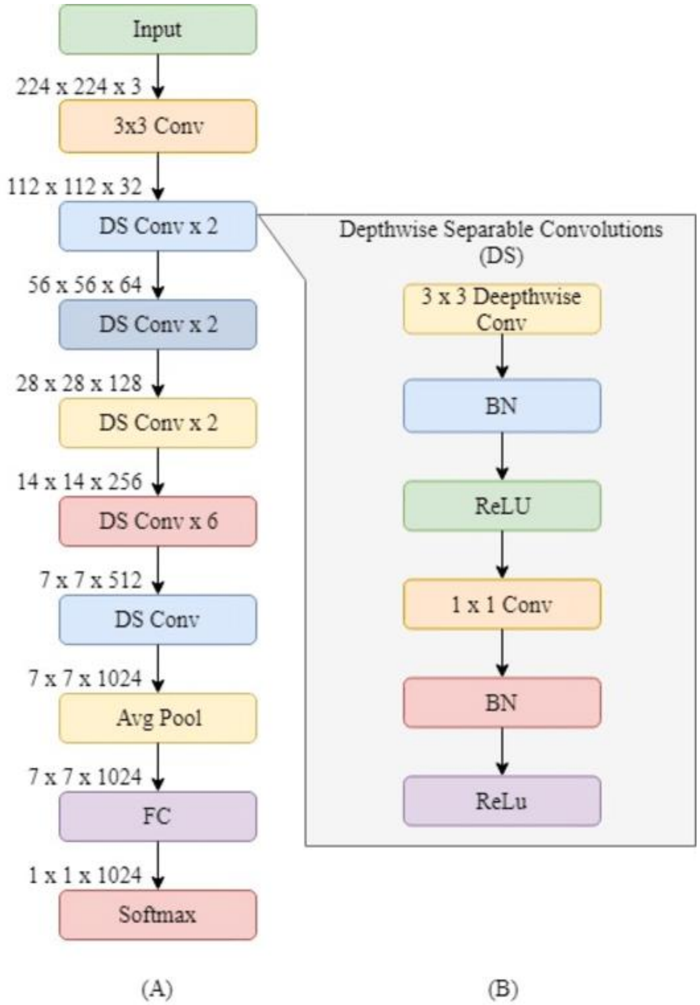

Fig. 3.4.1: MobileNet Architecture [22]

A depthwise separable convolution is created by amalgamating two separate operations.

1. Deptwise Convolution
2. Pointwise Convolution

Depthwise convolution involves using a separate convolutional filter for each input channel, contrasting with traditional 2D convolution that spans all input channels. While conventional convolution blends channels in output generation, depthwise convolutions preserve the independence of each channel.

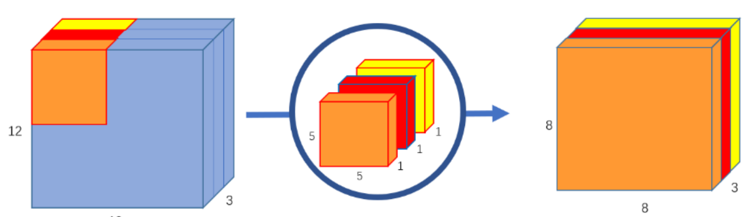

Fig. 3.4.2: Deptwise Convolution [23]

Pointwise Convolution utilizes a 1x1 kernel to systematically handle each point in the input. This kernel has a depth matching the number of channels in the input image. When used alongside depthwise convolutions, it plays a key role in forming a more efficient convolutional method called depthwise-separable convolutions.

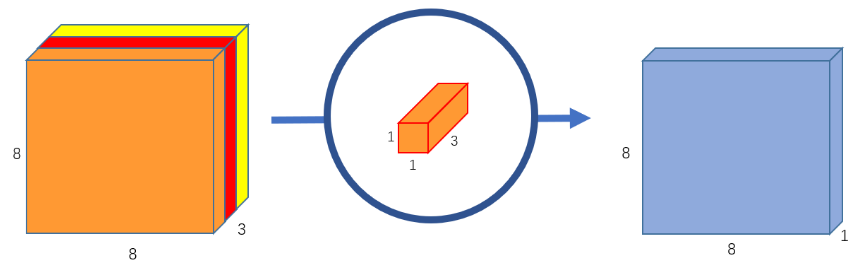

Fig. 3.4.3: Pointwise Convolution [23]

The accuracy for MobileNet is 91%.

ResNet-50 is composed of 50 layers, including 48 layers, one MaxPool layer, and one average pool layer. Residual neural networks, which belong to the category of artificial neural networks (ANN), are structured by assembling residual blocks. I got the least accuracy from this ResNet-50 model. The accuracy for this is 61%.

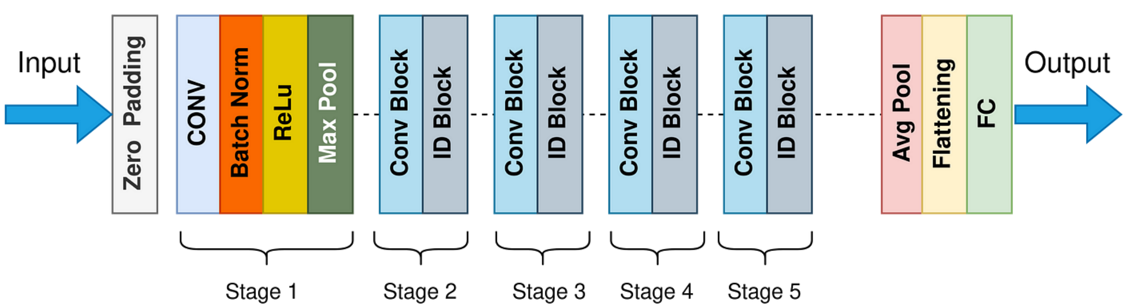

Fig. 3.4.4: Architecture of ResNet-50 [25]

I utilized InceptionV3, a pre-trained model boasting 48 layers, for image classification. This model exceeds both InceptionV1 and InceptionV2 in terms of depth. Its functionality revolves around sequentially processing blocks, where the output of one feeds into the next. These blocks are known as inception blocks. By default, InceptionV3 processes images in RGB format with dimensions of 299 x 299, extracting features from the image in a block-by-block fashion. The accuracy attained by InceptionV3 reaches 92%.

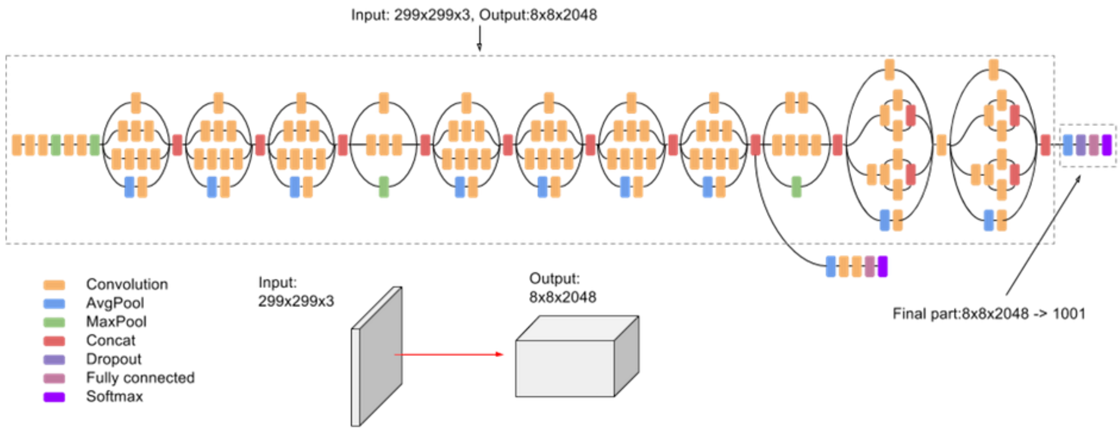

Fig. 3.4.5: Architecture of InceptionV3 [27]

I also used a model called EfficientNet. EfficientNet employs Mobile Inverted Bottleneck (MBConv) layers, blending depth-wise separable convolutions with inverted residual blocks. Moreover, the architecture incorporates Squeeze-and-Excitation (SE) optimization to augment the model's effectiveness. EfficientNet employs a convolutional neural network framework grounded in the principle of "compound scaling." This strategy tackles the enduring challenge of balancing model size, precision, and computational effectiveness. Compound scaling involves adjusting three key aspects of a neural network—width, depth, and resolution—in tandem to achieve optimal performance.

- **Width:** Width scaling pertains to adjusting the number of channels within each layer of the neural network. Boosting the width allows the model to encompass more intricate patterns and characteristics, consequently enhancing its accuracy. Conversely, diminishing the width produces a lighter model, ideal for settings with limited resources.
- **Depth:** Depth scaling refers to the overall count of layers within the network. More layers in a model enable the capture of complex data representations, yet they require greater computational resources. Conversely, models with fewer layers are computationally economical but might compromise on accuracy.
- **Resolution:** Resolution scaling entails modifying the dimensions of the input image. Increasing the resolution can yield enhanced detail, possibly improving overall performance. Nevertheless, this enhancement comes at the cost of increased memory and computational demands. Conversely, decreasing the resolution conserves resources but might result in a reduction of intricate details.

I got the most accuracy from this EfficientNet model. Accuracy is 93%.

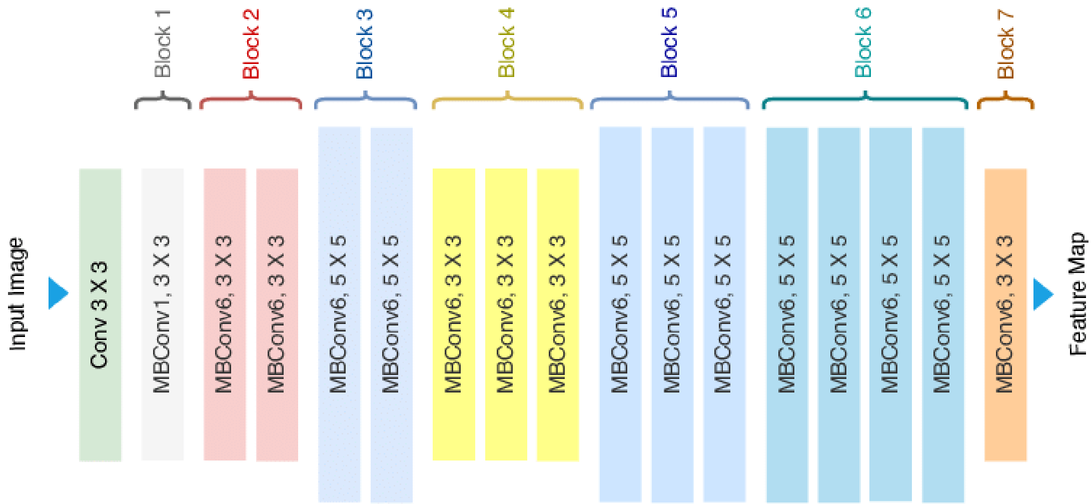

Fig. 3.4.6: Architecture of EfficientNet [29]

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

Extensive research carried out on brain tumor detection and classification to estimate tumor lifespan. This investigation utilized Customized MobileNet, ResNet50, InceptionV3, and EfficientNet models trained with a dataset over 10 epochs. Below are visualizations

For MobileNet:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 mobilenetv2_1.00_224 (Func  (None, 7, 7, 1280)        2257984
 tional)

 flatten (Flatten)           (None, 62720)             0

 dropout (Dropout)           (None, 62720)             0

 dense (Dense)               (None, 1024)              64226304

 dense_1 (Dense)             (None, 512)               524800

 dense_2 (Dense)             (None, 4)                 2052

=================================================================
Total params: 67011140 (255.63 MB)
Trainable params: 64753156 (247.01 MB)
Non-trainable params: 2257984 (8.61 MB)
_________________________________________________________________
```

Figure 4.1: Model Summary of MobileNet

Figure 4.1 The MobileNet model summary shows it has a total of 67,011,140 parameters. It achieves an accuracy of 91%. Below is the graph depicting its accuracy and loss.

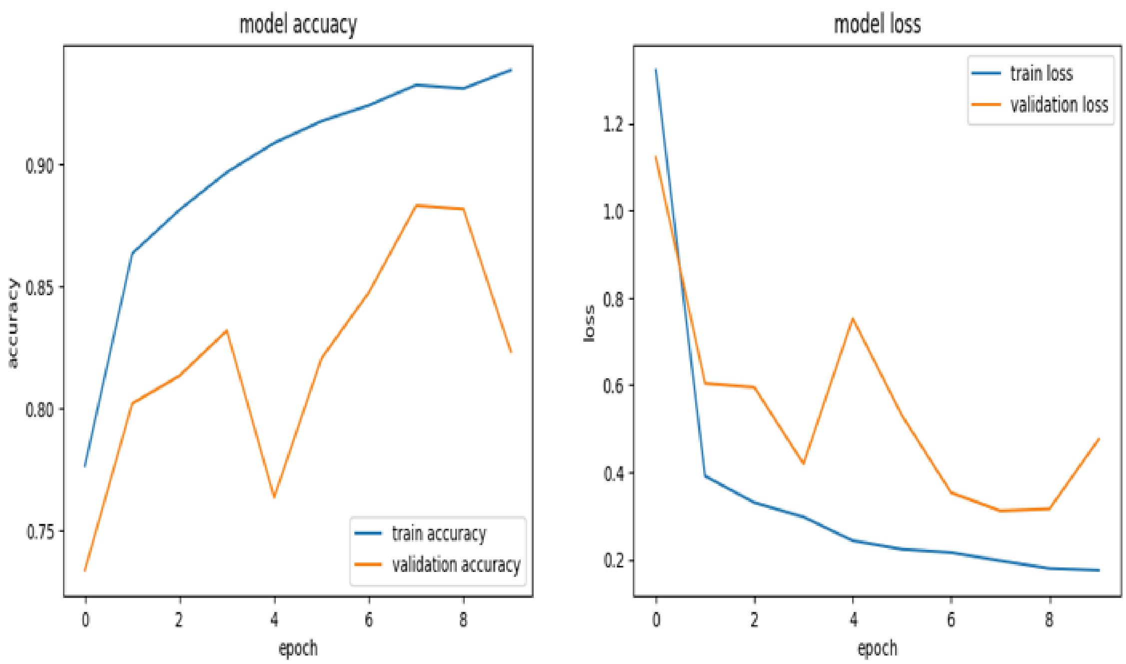

Figure 4.1.1: Accuracy and Loss graph of MobileNet

The charts showing, as well as MobileNet,

demonstrate how well the model performed throughout the training.

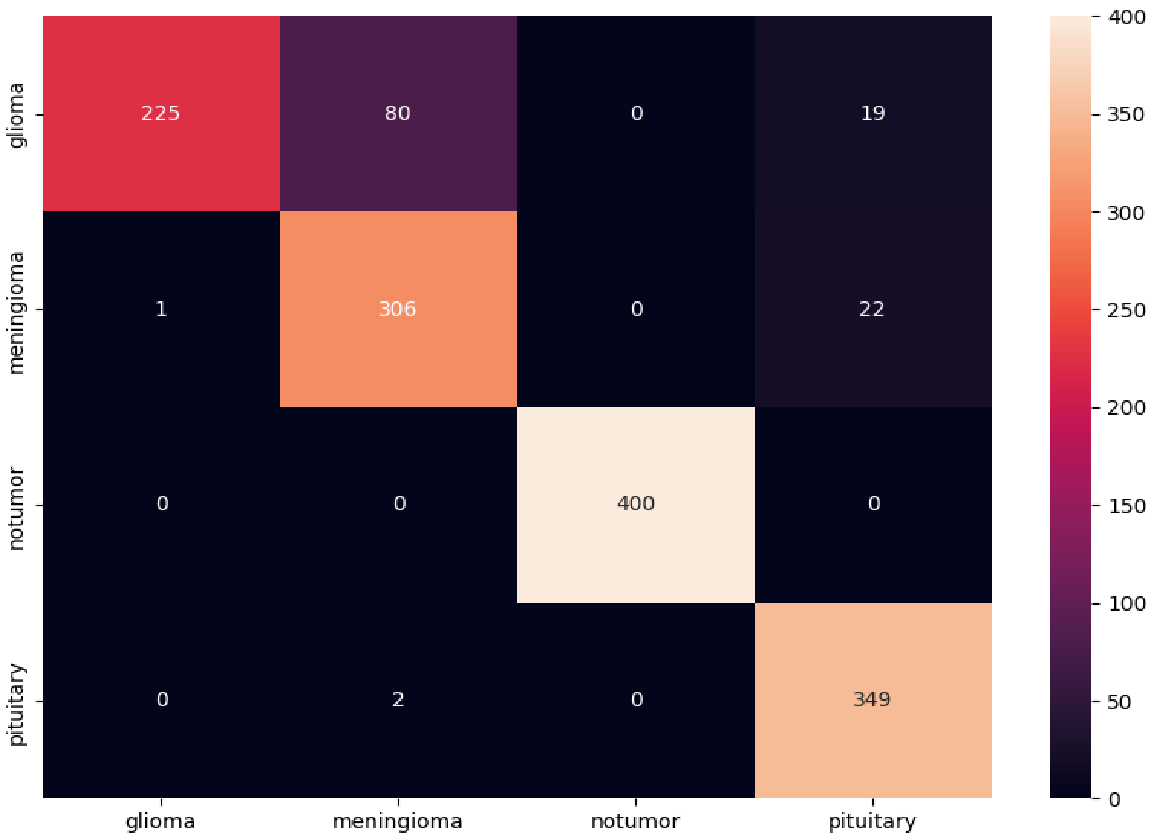

Figure 4.1.2: Confusion Matrix of MobileNet

For ResNet50:

The model has 67,011,140 parameters in total. It achieves an accuracy of 61%. Below is a graph illustrating

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 mobilenetv2_1.00_224 (Func  (None, 7, 7, 1280)        2257984
 tional)

 flatten (Flatten)           (None, 62720)             0

 dropout (Dropout)           (None, 62720)             0

 dense (Dense)               (None, 1024)              64226304

 dense_1 (Dense)             (None, 512)               524800

 dense_2 (Dense)             (None, 4)                 2052

=================================================================
Total params: 67011140 (255.63 MB)
Trainable params: 64753156 (247.01 MB)
Non-trainable params: 2257984 (8.61 MB)
_________________________________________________________________
```

Figure: 4.1.3: Model summary of ResNet50

charts illustrating metrics for ResNet50, visually represent how well the model performed during training.

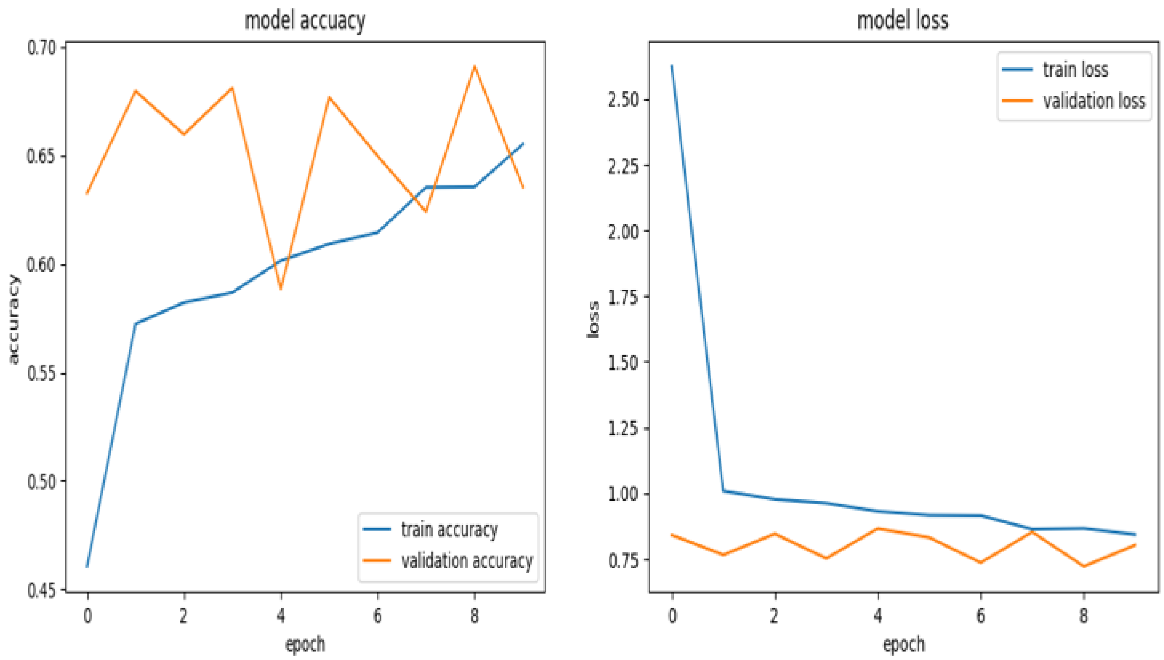

Figure 4.1.4: Accuracy and loss graph of ResNet50

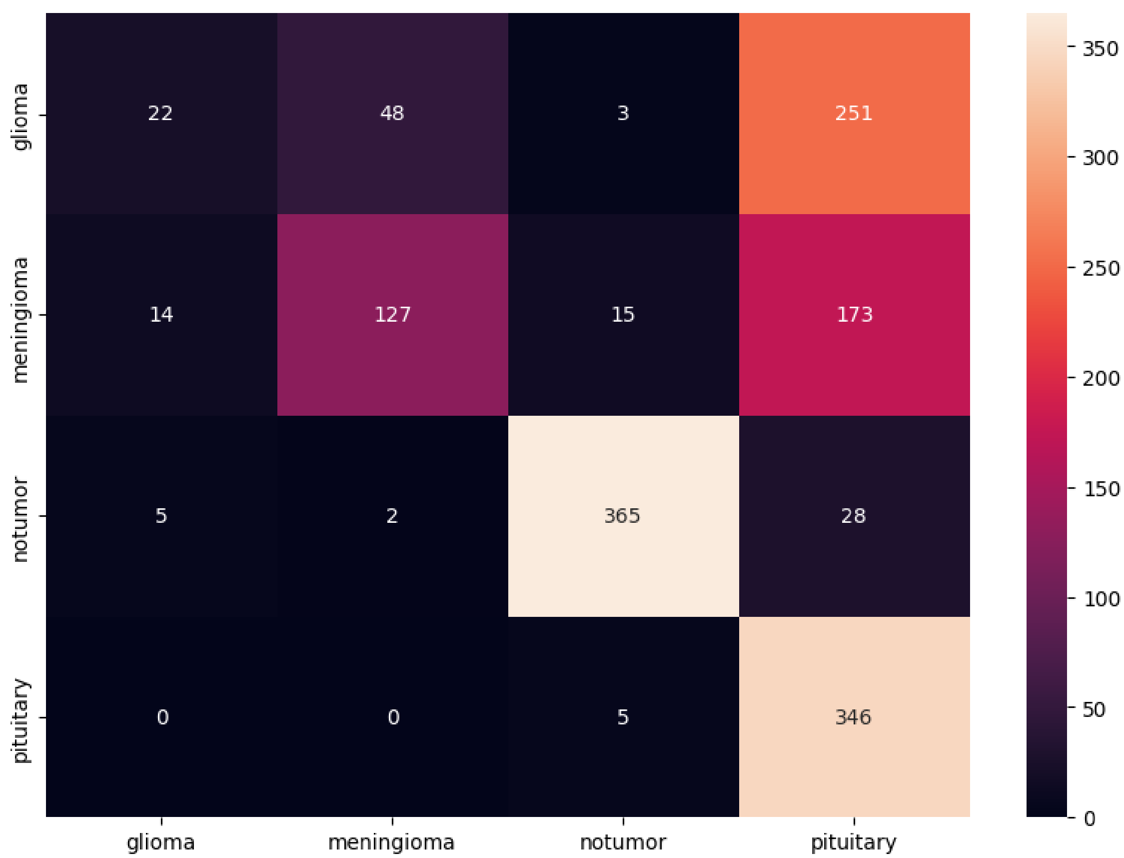

Figure 4.1.5: Confusion Matrix of ResNet50

For InceptionV3:

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inception_v3 (Functional)   (None, 5, 5, 2048)        21802784

 flatten (Flatten)           (None, 51200)             0

 dropout (Dropout)           (None, 51200)             0

 dense (Dense)               (None, 1024)              52429824

 dense_1 (Dense)             (None, 512)               524800

 dense_2 (Dense)             (None, 4)                 2052

=================================================================
Total params: 74759460 (285.18 MB)
Trainable params: 52956676 (202.01 MB)
Non-trainable params: 21802784 (83.17 MB)
_________________________________________________________________
```

Figure 4.1.6: Model summary of InceptionV3

Figure 4.1.3 presents, revealing a parameter count of 74,759,460. This model attains an accuracy rate of 92%. Below, you will find the graphical representations of both accuracy and loss metrics for this model.

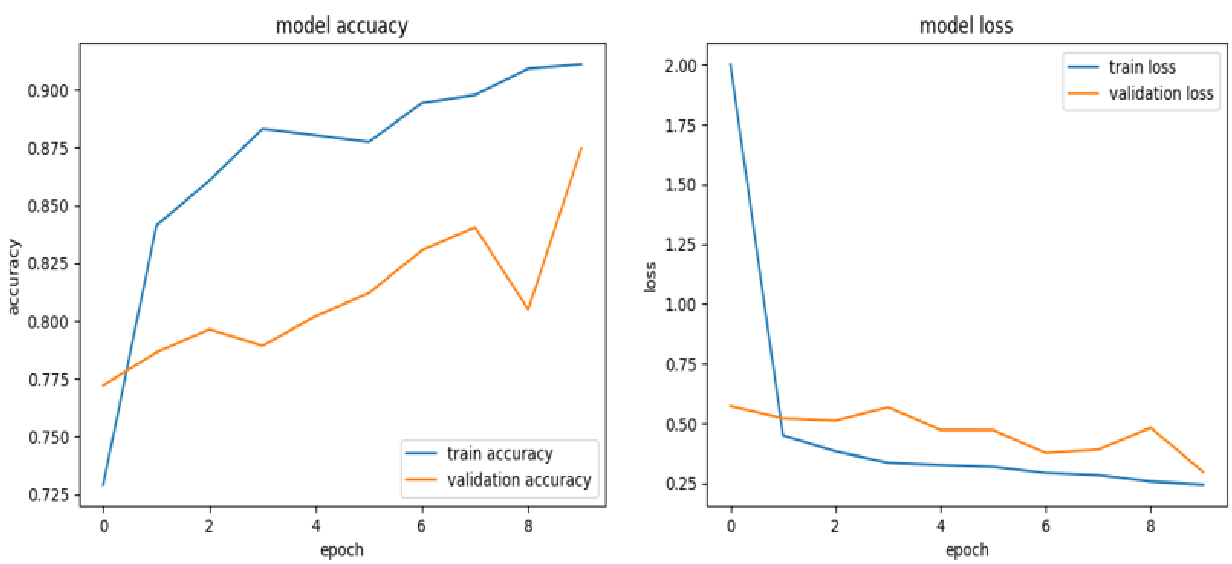

Figure 4.1.7: Accuracy and loss graph of InceptionV3

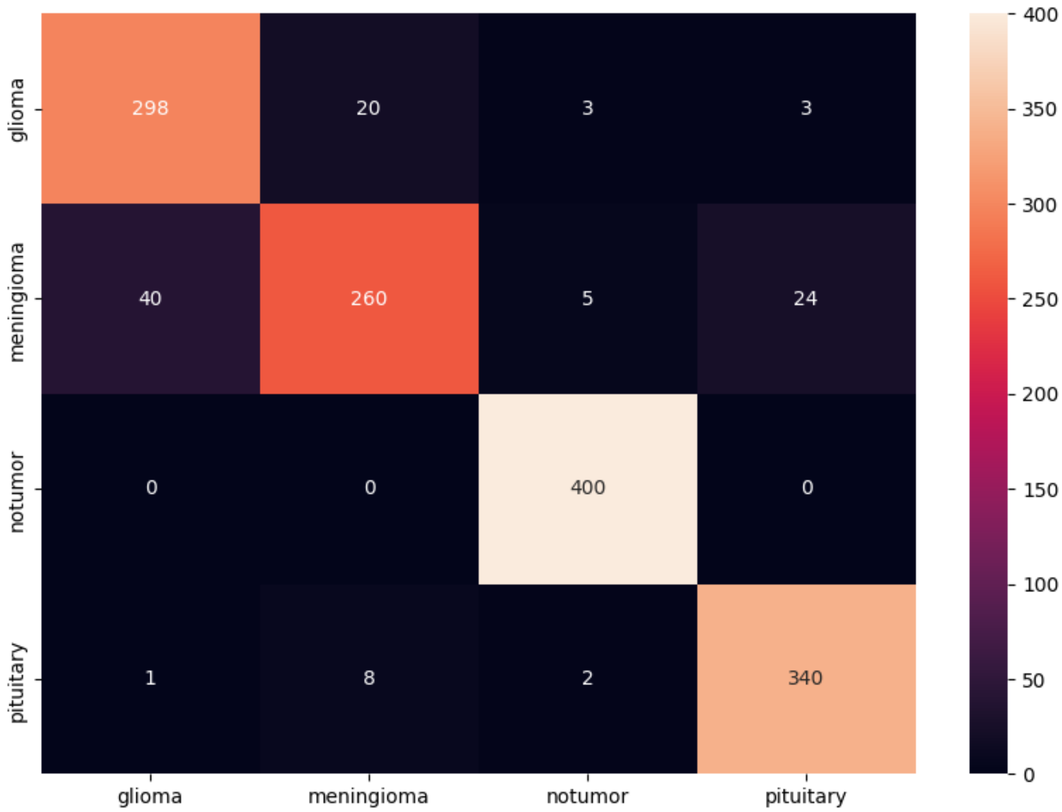

Figure 4.1.8: Confusion Matrix of InceptionV3

For EfficientNet:

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb0 (Functional  (None, 7, 7, 1280)        4049571
 )

 flatten (Flatten)           (None, 62720)             0

 dropout_1 (Dropout)         (None, 62720)             0

 dense_1 (Dense)             (None, 1024)              64226304

 dense_2 (Dense)             (None, 512)               524800

 dense_3 (Dense)             (None, 4)                 2052

=================================================================
Total params: 68802727 (262.46 MB)
Trainable params: 64753156 (247.01 MB)
Non-trainable params: 4049571 (15.45 MB)
_________________________________________________________________
```

Figure: 4.1.9: Model summary of EfficientNet

Model comprise a of 68,802.727 parameters , 93% refer provide

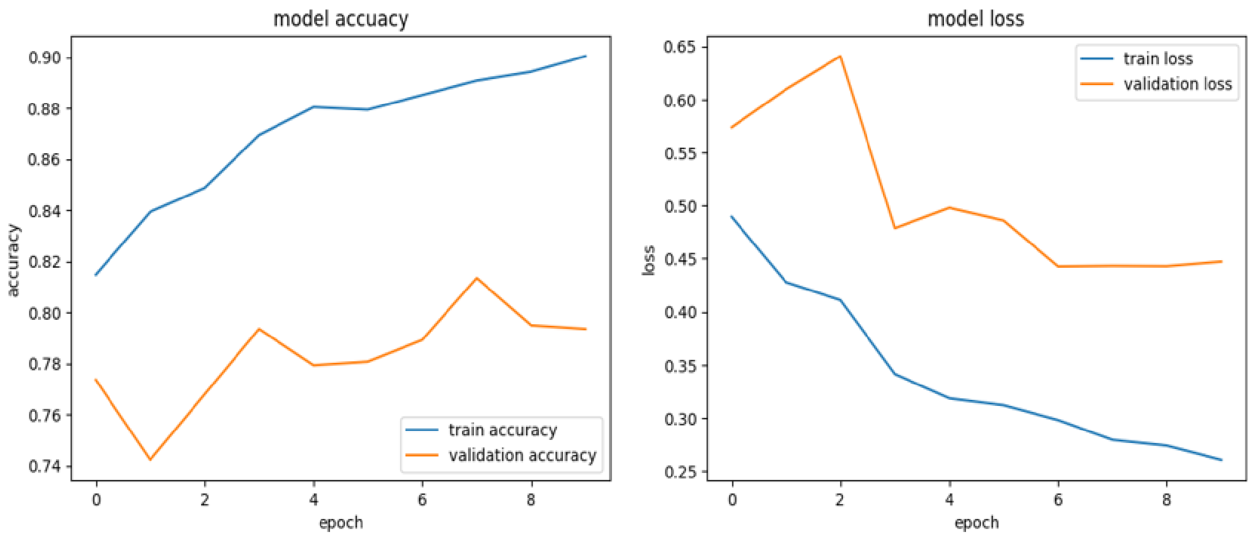

Figure 4.1.10: Accuracy and loss graph of EfficientNet

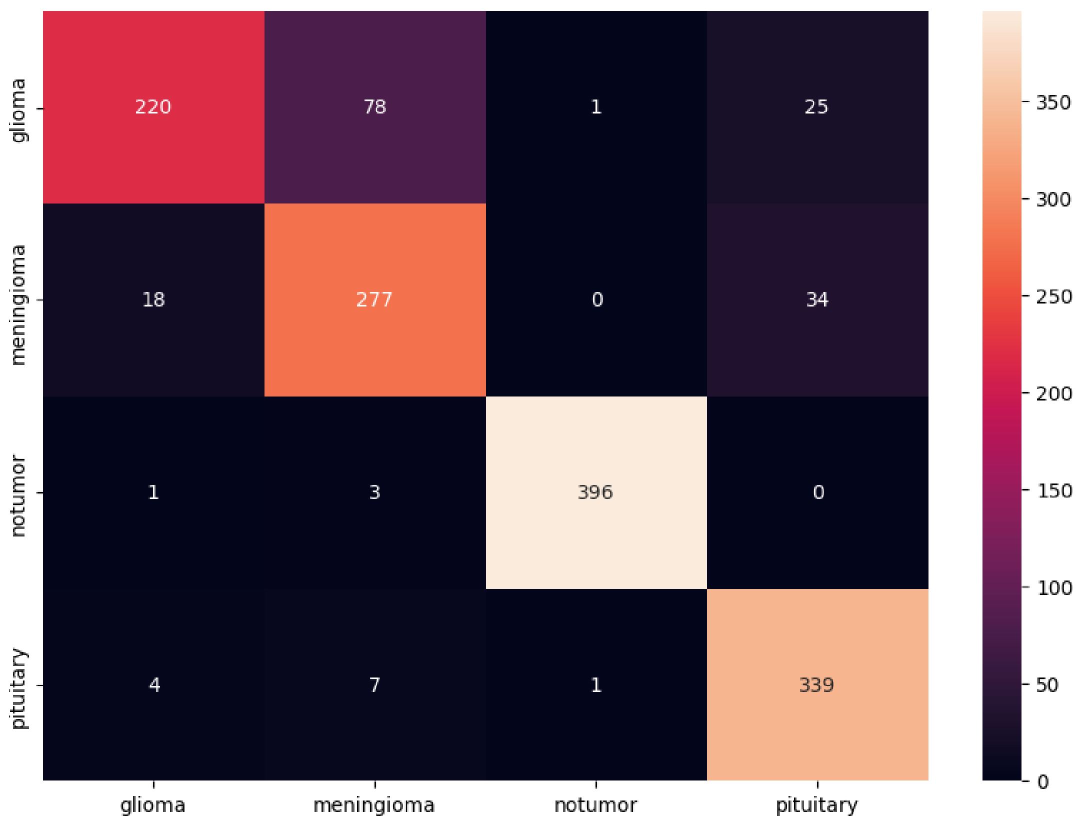

Figure 4.1.11: Confusion Matrix of EfficientNet

It's essential to monitor these graphs continuously during training to evaluate how well the model is performing. detecting potential issues like overfitting, and making informed decisions about adjusting hyperparameters or determining when to conclude training for achieving optimal results.

Table 4.1: Result summary table

Dataset	Model	Accuracy(%)
Brain Tumor Dataset	ResNet50	61%
	MobileNet	91%
	InceptionV3	92%
	EfficientNet	93%

4.2 Discussion

I used modified MobileNet, InceptionV3, EfficientNet. underwent customizations to their layers, resulting in varying accuracy percentages. Below, you'll find a line graph depicting these percentage variations.

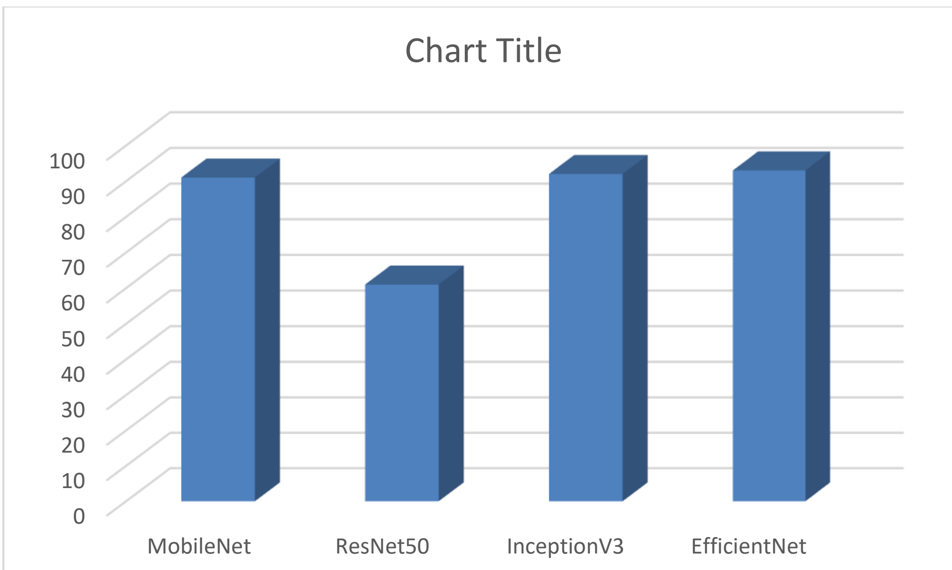

Figure 4.2: Percentage line graph

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

The utilization of image processing for brain tumor detection holds considerable potential to bring about meaningful societal impacts across various fronts.

Detecting brain tumors early is essential for better treatment results and patient prognosis. Employing image-processing methods can aid in the early identification of tumors, facilitating prompt medical intervention and treatment strategizing. Detecting brain tumors manually in medical images may lead to inaccuracies and subjective judgments. Utilizing image-processing algorithms can improve detection precision by automating the procedure and diminishing the need for human interpretation. Detecting brain tumors promptly can result in better distribution of healthcare resources and decreased treatment expenses. Early identification of tumors may necessitate less invasive and less expensive treatment methods, potentially minimizing costs compared to treating advanced-stage tumors.

5.2 Impact on Environment

The application of image processing methods for brain tumor detection could yield numerous beneficial effects on the environment. Conventional approaches to detecting brain tumors typically require invasive techniques like biopsies or surgeries, demanding substantial resources like operating rooms, medical tools, and supplies. Employing non-invasive imaging methods such as MRI or CT scans, along with advanced image processing algorithms, can diminish the demand for these resources, thus minimizing the environmental impact.

Invasive medical techniques such as biopsies or surgeries often require the application of various chemicals for sterilization, anesthesia, and tissue preservation. If not managed correctly, these chemicals pose risks to the environment. Emphasizing imaging-based detection approaches can limit the need for such chemicals, leading to decreased environmental pollution.

Invasive medical procedures frequently produce medical refuse, such as single-use medical tools, tainted substances, and biological specimens. Transitioning to non-invasive detection techniques reliant on imaging can mitigate the production of medical waste, resulting in decreased waste management needs and a lighter.

5.3 Ethical Aspects

Certainly, paramount in all medical research and technological advancements, such as the utilization of image processing for brain tumor detection. Here are several ethical dimensions you should contemplate within your thesis manuscript:

Ensure that brain tumor detection algorithms prioritize accuracy and reliability to prevent misdiagnosis or errors such as false positives or negatives. It's ethically imperative to guarantee that these technologies don't jeopardize patient well-being through inaccuracies. It's crucial to contemplate the future impacts of brain tumor detection technologies on patients, healthcare systems, and society overall. Ethical foresight is necessary to predict and tackle any unforeseen consequences that may arise. Ensure transparency is upheld at every stage of the research journey, spanning from the creation of algorithms to their implementation in clinical environments. Those involved in research and development must take responsibility for the effectiveness and results of brain tumor detection systems.

5.4 Sustainability Plan

Developing a sustainability strategy for brain tumor detection requires taking into account a range of elements, including environmental ramifications, financial viability, societal significance, and lasting efficiency. Here's a systematic method:

Offer training courses tailored to healthcare professionals, focusing on the most recent developments in techniques for detecting brain tumors. Provide educational programs aimed at increasing public understanding regarding the significance of early identification and management of brain tumors. Dedicate resources to continuous research and development aimed at improving the precision and effectiveness of techniques for detecting brain tumors. Choose eco-friendly materials for producing detection devices to minimize both waste and pollution.

CHAPTER 6

CONCLUSION, LIMITATION & FUTURE SCOPE

6.1 Conclusion

Brain tumors are a serious health concern that can have a significant effect on quality of a life. Every year many people are affected by this but they cannot get proper treatment for the lack of an identified tumor. That's why we are creating a deep-learning model to identify Brain tumor types. In that model, we use four transfer learning models (MobileNet, InceptionV3, ResNet-10, and EfficientNet). To pick the most appropriate transfer learning model for brain tumor class classification, the accuracy of these four transfer learning models was differentiated. The results show that the performance of the EfficientNet model is much higher than that of the four CNN models. In our model, the EfficientNet model gives 93 % accuracy. This model can identify all four types of Brain tumors perfectly. In spite of these advances, there is at rest much work to be done to fully understand and identify brain tumors more efficiently. Further research is needed to improve our understanding to identify brain tumors.

6.2 Limitation & Future Scope

Transfer learning techniques demonstrated superior performance over traditional classifiers in this study for multi-class classification. Despite a significant weakness in the study involving substantial leakage of real medical data, the dataset used to train the recommended model is considered sufficient. In the near future, there will be access to large volumes of raw medical effectiveness suggested real-time medical data. However, the proposed approach in this study consistently achieved correct classification of brain tumor types in the majority of tests. It is feasible to ensure accuracy and improvement of the suggested fine-tuned Vision Transformer model across all diagnostic domains, notwithstanding a few minor flaws.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
Brain Tumor Detection Using Image Processing

Student ID: 201-15-3353

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **Brain Tumor detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently individually interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data Preprocessing techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like EfficientNet, MobileNet, ResNet-50 and InceptionV3, enhancing pneumonia detection accuracy in Brain Tumor images, crucial for computer-aided diagnosis.	**Page no:** [26-30] **Section:** [3.2] **Page no:** [1-7] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing CNN model.	**Page no:** [30] **Section:** [3.2(B)] **Page no:** [33]

					Section: [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance Brain Tumor detection using image processing, showcasing a comprehensive understanding of current methodologies.	**Page no:** [5-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in brain tumor detection, including limitations of traditional methods and the complexities of integrating deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [23-24] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing brain tumor detection amidst multiple potential approaches.	**Page no:** [36-57] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting medical diagnostics in respiratory diseases like brain tumor, contributing to advancements in public health and healthcare practices which indicates **EP-4**.	**Page no:** [16-24] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in medical diagnostics which ensures **EP-7**.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, CNN frameworks, annotated datasets, and ensuring ethical considerations are upheld is crucial for conducting systematic research and advancing brain tumor detection using transfer learning and deep convolutional neural networks (CNNs).	**Page no:** [33-35] **Section:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This project contributes to society by improving healthcare through advanced brain tumor detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [58-61] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in brain tumor detection through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [7-10] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [13] **Section:** [1.6]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Page no:** [60] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [26-34, 37-55] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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