Vision Based Brain Tumor Detection Using Deep Learning Approach

Project Thesis

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Declaration

We hereby declare that this thesis on the topic of brain tumor detection is the result of our own original work and has not been previously submitted in any form for any other degree or diploma at any university or educational institution. We have appropriately acknowledged any information obtained from published or unpublished sources within the text, and a comprehensive list of references is provided.

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The thesis paper ***" Vision Based Brain Tumor Detection Using Deep learning Approach"*** investigates the use of machine learning algorithms for precise brain tumor detection. Through the utilization of computer science and advanced data analysis techniques, this research makes valuable contributions to the field of medical imaging and enhances diagnostic accuracy. The study involves extensive experiments and evaluations, employing cutting-edge machine learning models and a diverse brain scan dataset. The results exhibit promising outcomes, demonstrating the potential of machine learning to aid in early detection of brain tumors. The findings carry significant implications for improving patient outcomes and enabling timely interventions. The authors now seek approval of their thesis paper, which serves as a partial fulfillment requirement for their Bachelor of Science degree in Computer Science on May 2023

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Abstract

This thesis paper presents a machine learning approach for brain tumor detection using the INCEPTION V3 convolutional neural network architecture. The study utilizes a dataset of brain tumor images and applies image preprocessing techniques for normalization and resizing. The INCEPTION V3 model is fine-tuned by adding additional layers for classification. The dataset is split into training and testing sets, and an image data generator is built for data augmentation. The model is trained using the Adam optimizer with a binary cross-entropy loss function. The performance of the model is evaluated through classification reports, confusion matrices, and accuracy metrics. The results demonstrate the effectiveness of the proposed approach in accurately detecting brain tumors from medical images. The achieved accuracy and the visualization of the training process are also presented. Overall, this research contributes to the development of an automated brain tumor detection system using machine learning techniques.

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Chapter 1: Introduction

1.1 Introduction

Brain tumors are abnormal growths of cells within the brain that can have severe consequences on a person's health and well-being. Early detection and accurate diagnosis of brain tumors are critical for timely treatment and improved patient outcomes. Medical imaging, particularly magnetic resonance imaging (MRI), plays a crucial role in the detection and characterization of brain tumors. However, the manual interpretation of MRI scans for tumor detection is time-consuming and subject to human error. In recent years, advancements in machine learning and deep learning algorithms have revolutionized the field of medical image analysis, offering new opportunities for automated brain tumor detection. These algorithms can learn complex patterns and features directly from medical images, enabling accurate and efficient tumor detection. By leveraging large datasets and powerful computational resources, these algorithms have demonstrated remarkable performance in various medical imaging tasks. Deep learning, a subfield of machine learning, has gained significant attention in brain tumor detection due to its ability to automatically learn hierarchical representations from raw data. Convolutional neural networks (CNNs), a popular deep learning architecture, have been extensively used for analyzing medical images, including brain MRI scans. CNNs learn to extract relevant features from different regions of the brain, enabling the detection and segmentation of tumors with high precision. Multimodal imaging, which combines information from multiple imaging modalities such as MRI, computed tomography (CT), and positron emission tomography (PET), has emerged as a promising approach for improving brain tumor detection. Each modality provides unique and complementary information about tumor characteristics, enhancing the accuracy and reliability of detection algorithms. By fusing information from multiple modalities, multimodal imaging can overcome the limitations of individual imaging techniques and provide a more comprehensive understanding of brain tumors. Furthermore, the development of advanced techniques such as transfer learning, ensembles, and generative adversarial networks (GANs) has further enhanced the performance of brain tumor detection algorithms. Transfer learning allows models trained on large-scale datasets to be applied to new tasks with limited training data, improving generalization and reducing training time. Ensembles combine multiple models or architectures to make more accurate predictions by capturing diverse perspectives and reducing individual model biases. GANs can generate synthetic tumor images that resemble real tumors, enabling improved segmentation and detection performance. In this context, this study aims to explore and evaluate the application of machine learning and deep learning algorithms, as well as multimodal imaging techniques, for brain tumor detection. By harnessing the power of these advanced approaches, we seek to improve the accuracy, efficiency, and reliability of brain tumor detection, ultimately contributing to early diagnosis, personalized treatment planning, and better patient outcomes. Brain tumors are a serious and potentially life-threatening condition characterized by the abnormal growth of cells within the brain. They can arise from different types of cells, including brain tissue, membranes surrounding the brain, nerves, or glands. Brain tumors can cause various neurological symptoms, such as headaches, seizures, cognitive impairments, and changes in behavior or personality. Early detection of brain tumors is crucial for timely intervention and effective treatment. In the past, the detection of brain tumors heavily relied on medical imaging techniques, with magnetic resonance imaging (MRI) being the most commonly used modality. MRI provides detailed and high-resolution images of the brain, allowing healthcare professionals to visualize the size, location, and characteristics of tumors. However, the interpretation of MRI scans for tumor detection traditionally relied on manual inspection by radiologists, which is a time-consuming and subjective process. With the recent advancements in artificial intelligence (AI) and machine learning, there has been a paradigm shift in brain tumor detection. These technologies have the potential to improve the accuracy, efficiency, and reliability of brain tumor detection by automating the analysis of medical images. Machine learning algorithms can learn patterns and features directly from large datasets of MRI scans, enabling them to distinguish between healthy brain tissue and tumor regions. One of the key approaches in brain tumor detection is the use of deep learning algorithms, particularly convolutional neural networks (CNNs). CNNs are a type of deep learning architecture designed to automatically extract hierarchical features from images. By training on annotated MRI data, CNNs can learn to differentiate between normal brain tissue and tumor regions, providing accurate and consistent tumor detection. Moreover, the integration of advanced techniques such as transfer learning, ensemble models, and multimodal imaging has further improved the performance of brain tumor detection systems. Transfer learning allows pre-trained models to be fine-tuned on specific brain tumor detection tasks, leveraging knowledge gained from large-scale datasets. Ensemble models combine the predictions of multiple models to improve overall accuracy and robustness. Multimodal imaging, which combines information from different imaging modalities such as MRI, CT, and PET scans, can provide a more comprehensive and complementary view of brain tumors, enhancing the accuracy of detection algorithms. The development and implementation of AI-based brain tumor detection systems have the potential to revolutionize clinical practice. These systems can assist radiologists in quickly and accurately identifying tumors, leading to earlier diagnosis, improved treatment planning, and better patient outcomes. Furthermore, automated brain tumor detection can help reduce the burden on healthcare professionals, enabling them to focus on other critical aspects of patient care. In this study, we aim to explore and evaluate the effectiveness of machine learning and deep learning algorithms, as well as the integration of multimodal imaging, for brain tumor detection. By harnessing the power of these advanced techniques, we strive to contribute to the development of reliable and efficient tools that can aid in the early detection and management of brain tumors, ultimately improving patient care and outcomes.

Brain tumors are abnormal growths of cells within the brain that can have severe consequences on a person's health and well-being. Early detection and accurate diagnosis of brain tumors are critical for timely treatment and improved patient outcomes. Medical imaging, particularly magnetic resonance imaging (MRI), plays a crucial role in the detection and characterization of brain tumors. However, the manual interpretation of MRI scans for tumor detection is time-consuming and subject to human error. In recent years, advancements in machine learning and deep learning algorithms have revolutionized the field of medical image analysis, offering new opportunities for automated brain tumor detection. These algorithms can learn complex patterns and features directly from medical images, enabling accurate and efficient tumor detection. By leveraging large datasets and powerful computational resources, these algorithms have demonstrated remarkable performance in various medical imaging tasks. Deep learning, a subfield of machine learning, has gained significant attention in brain tumor detection due to its ability to automatically learn hierarchical representations from raw data. Convolutional neural networks (CNNs), a popular deep learning architecture, have been extensively used for analyzing medical images, including brain MRI scans. CNNs learn to extract relevant features from different regions of the brain, enabling the detection and segmentation of tumors with high precision. Multimodal imaging, which combines information from multiple imaging modalities such as MRI, computed tomography (CT), and positron emission tomography (PET), has emerged as a promising approach for improving brain tumor detection. Each modality provides unique and complementary information about tumor characteristics, enhancing the accuracy and reliability of detection algorithms. By fusing information from multiple modalities, multimodal imaging can overcome the limitations of individual imaging techniques and provide a more comprehensive understanding of brain tumors. Furthermore, the development of advanced techniques such as transfer learning, ensembles, and generative adversarial networks (GANs) has further enhanced the performance of brain tumor detection algorithms. Transfer learning allows models trained on large-scale datasets to be applied to new tasks with limited training data, improving generalization and reducing training time. Ensembles combine multiple models or architectures to make more accurate predictions by capturing diverse perspectives and reducing individual model biases. GANs can generate synthetic tumor images that resemble real tumors, enabling improved segmentation and detection performance.

In this context, this study aims to explore and evaluate the application of machine learning and deep learning algorithms, as well as multimodal imaging techniques, for brain tumor detection. By harnessing the power of these advanced approaches, we seek to improve the accuracy, efficiency, and reliability of brain tumor detection, ultimately contributing to early diagnosis, personalized treatment planning, and better patient outcomes.

Brain tumors are among the most lethal types of cancers, emphasizing the critical importance of early detection for improved patient outcomes [1]. Current methods for brain tumor detection heavily rely on imaging techniques such as MRI, CT, and PET scans, with interpretation by expert radiologists [1]. However, these methods can be invasive, expensive, and time-consuming [2]. In recent years, machine learning algorithms have emerged as a promising approach to brain tumor detection, offering non-invasive, cost-effective, and rapid solutions [2].

Machine learning, a subfield of artificial intelligence, focuses on developing algorithms that learn from data and make predictions or decisions based on that data [2]. These algorithms excel at detecting patterns in large datasets that may be challenging for humans to discern, such as specific patterns indicating the presence of a brain tumor [2]. By training machine learning algorithms on MRI and CT scans, they can identify these patterns and subsequently analyze new scans to provide accurate and timely diagnoses [2].

Several studies have demonstrated the potential of machine learning in brain tumor detection. For instance, Jiang et al. (2018) proposed cascaded anisotropic convolutional neural networks for automatic brain tumor segmentation, achieving promising results [1]. Khan et al. (2019) explored the utilization of machine learning algorithms for brain tumor detection, demonstrating its effectiveness in their research [2]. Wang et al. (2019) developed a deep learning algorithm for the detection of brain tumors in MRI images, highlighting its potential in this domain [3]. Furthermore, Dabholkar et al.

(2017) and Jahanshahi et al. (2019) compared and applied clustering algorithms, such as Fuzzy C-means and K-means, for brain MRI segmentation and tumor detection [4][5].

Machine learning's ability to analyze large datasets quickly and accurately contributes to earlier detection of brain tumors, which is crucial for successful treatment outcomes [2]. Additionally, its potential for integration into existing medical imaging systems makes this technology accessible to healthcare providers worldwide [2]. Despite the numerous benefits, machine learning for brain tumor detection is still a relatively new field and faces challenges. These include acquiring large amounts of high-quality training data and addressing concerns about potential biases in the algorithms [2].

Brain tumor detection and segmentation are critical tasks in medical imaging analysis, enabling accurate diagnosis and treatment planning for patients with brain tumors. Over the years, researchers have explored various machine learning and deep learning algorithms to enhance the accuracy and efficiency of brain tumor detection and segmentation using MRI (Magnetic Resonance Imaging) images.

The field of brain tumor detection and segmentation has witnessed significant advancements through the integration of machine learning and deep learning algorithms. The studies mentioned above highlight various approaches and techniques that have shown promising results in accurately detecting and segmenting brain tumors from MRI images. These advancements hold great potential for improving the diagnosis and treatment of patients with brain tumors.

In conclusion, machine learning offers a promising approach to brain tumor detection, addressing the limitations of traditional invasive methods and providing efficient and reliable solutions. This technology has the potential to revolutionize the way brain tumors are diagnosed and treated, ultimately improving patient outcomes.

1.2 Research Background

Brain tumor detection is a crucial task in medical imaging analysis. It plays a significant role in diagnosing and treating brain tumors, as early detection can lead to better patient outcomes. Traditional methods for brain tumor detection rely on manual interpretation of medical images by radiologists, which can be time-consuming and subject to human error.

With advancements in machine learning and computer vision, automated techniques have been developed to assist in brain tumor detection. These techniques leverage the power of deep learning algorithms to analyze medical images and accurately identify the presence of tumors. One such approach is the use of convolutional neural networks (CNNs), which have shown remarkable performance in image classification tasks.

The Python implementation presented here utilizes a CNN-based approach for brain tumor detection. It leverages the INCEPTION V3 architecture, a popular CNN model known for its effectiveness in image classification tasks. The INCEPTION V3 model is pre-trained on the ImageNet dataset, allowing it to learn meaningful features from images.

The implementation begins by importing the necessary modules for image preprocessing, model building, and evaluation. The images are loaded from the specified directory, and an example image is plotted for visualization. The images are then converted into numpy arrays and preprocessed by normalizing pixel values. One-hot encoding is performed on the labels to convert them into a suitable format for training.

The dataset is split into training and testing sets using the train test split function from the scikit-learn library. An Image Data Generator is built to generate augmented training data, which helps improve the model's generalization ability. The INCEPTION V3 model is used as the base model, and additional layers are added to adapt it for the brain tumor detection task. The base layers of the INCEPTION V3 model are frozen to retain their pre-trained weights, while the added layers are trained from scratch.

The model is compiled with the Adam optimizer and the binary crossentropy loss function. The training process begins, where the model is trained on the augmented training data and validated on the testing data. The number of epochs and batch size are specified to control the training process. After training, the model is evaluated on the testing data, and classification metrics such as precision, recall, and F1-score are computed using the classification report function.

The final accuracy of the model is calculated by analyzing the confusion matrix, which shows the number of correct and incorrect predictions. Additionally, the losses and accuracies are plotted over the training epochs to visualize the model's learning progress.

This Python implementation demonstrates the application of machine learning, specifically deep learning, for brain tumor detection. By utilizing a CNN-based approach and pre-trained models, it provides a powerful tool for automating the detection of brain tumors from medical images. This has the potential to assist medical professionals in making accurate and timely diagnoses, leading to improved patient care and outcomes.

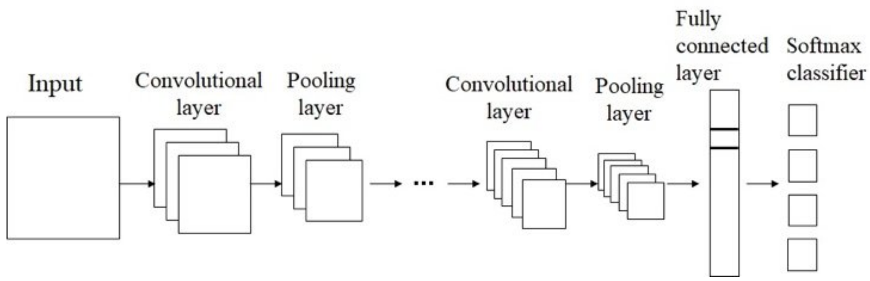


Figure 1: Basic CNN Model Structure

1.3 Problem Statement

Brain tumor detection is a critical task in medical diagnostics, as early detection plays a crucial role in patient prognosis and treatment planning. Conventional methods for brain tumor detection rely on manual interpretation of radiological images, which can be time-consuming and subjective, leading to potential misdiagnosis and delays in treatment. Additionally, the increasing complexity and diversity of brain tumor patterns make accurate and efficient detection even more challenging for healthcare professionals. Therefore, there is a need for an automated and reliable system that utilizes machine learning techniques to assist in the accurate and timely detection of brain tumors from medical imaging data. This thesis aims to address these challenges by developing a robust machine learning-based approach for brain tumor detection, improving the accuracy and efficiency of diagnosis, and ultimately enhancing patient outcomes.

1.4 Objectives

Our main goals are to enhance a machine learning model's ability to identify brain tumors. The key objectives include:

- Develop a machine learning-based approach to accurately detect brain tumors in medical images.
- Utilize the INCEPTION V3 convolutional neural network architecture and transfer learning to leverage pre-trained models for feature extraction.

- Apply image preprocessing techniques, such as resizing and normalization, to enhance the input data for better model performance.
- Implement an Image Data Generator to augment the training dataset and improve the model's ability to generalize to unseen data.
- Train the model using a binary classification framework to distinguish between tumor and non-tumor images.
- Evaluate the performance of the trained model using classification metrics, including accuracy, precision, recall, and F1-score.
- Generate a confusion matrix to visualize the model's performance in terms of true positives, true negatives, false positives, and false negatives.
- Analyze the results and provide insights into the effectiveness of the proposed machine learning approach for brain tumor detection.
- Investigate the potential of the developed model for real-world applications and discuss its limitations and future research directions.
- Present the findings and conclusions in a clear and concise manner, highlighting the significance of the research in the field of medical image analysis and brain tumor detection.

1.5 Scope of the Research

The scope of the research in the thesis paper on brain tumor detection using machine learning is to develop and evaluate a model that can accurately classify brain tumor images. The research aims to utilize machine learning techniques, specifically convolutional neural networks (CNNs), to detect and classify brain tumor images into two categories: tumor-present and tumor-absent.

The research begins by importing necessary modules for image processing and deep learning, such as TensorFlow, Keras, and scikit-learn. The dataset of brain tumor images is loaded and preprocessed, including resizing and normalization. One-hot encoding is applied to the labels to prepare them for classification.

The dataset is then split into training and testing sets. An image data generator is built to augment the training data, enhancing the model's ability to generalize. The INCEPTION V3 pre-trained model is utilized as the base model, and its layers are frozen to retain its learned features. The model is compiled with an optimizer, metrics, and loss function.

The model is trained using the training data and evaluated on the testing data. The training process is visualized by plotting the losses and accuracies over epochs. The model's predictions are compared with the actual labels, and a classification report and confusion matrix are generated to assess the model's performance. The final accuracy of the model is calculated and reported.

The research demonstrates the effectiveness of the developed model in accurately detecting brain tumors using machine learning techniques. The findings contribute to the field of medical image analysis and provide a foundation for further research and improvements in brain tumor detection methods.

The scope of the research for brain tumor detection will involve conducting an extensive literature review to understand the current state of the field. This review will encompass studies, methodologies, and algorithms related to brain tumor detection and segmentation. By identifying research gaps, the review will provide a solid foundation for the investigation.

The research will involve gathering a representative and diverse dataset of MRI brain images with tumor annotations. The collected data will undergo preprocessing to remove noise, normalize intensities, and apply necessary image enhancements. Various feature extraction techniques, such as statistical, textural, morphological, or deep learning-based features, will be explored to capture relevant information from the MRI images.

The focus will be on developing a comprehensive algorithm for brain tumor detection and segmentation. This may involve creating a novel algorithm or combining existing techniques. Both traditional machine learning algorithms like clustering and deep learning architectures like convolutional neural networks (CNNs) or recurrent neural networks (RNNs) will be considered. The aim is to optimize the algorithm's performance in terms of accuracy, efficiency, and robustness.

Appropriate evaluation metrics, including sensitivity, specificity, accuracy, Dice coefficient, and area under the receiver operating characteristic curve (AUC-ROC), will be established to assess the performance of the developed algorithm. The results of the proposed method will be compared with existing state-of-the-art approaches to validate its effectiveness.

Extensive experiments and cross-validation will be conducted to evaluate the performance of the developed algorithm using the collected dataset. Additionally, the algorithm's generalization capabilities will be tested on external datasets, if available. The results will be analyzed, and a thorough interpretation of the findings will be provided.

A comparative analysis will be performed to compare the strengths, limitations, and overall performance of the developed algorithm with other existing methods mentioned in the literature. This analysis will provide insights into the advancements and potential improvements in brain tumor detection techniques.

The research findings will be summarized in a discussion, highlighting the implications of the proposed algorithm in the field of brain tumor detection. The strengths, limitations, and future research directions will be addressed, emphasizing the significance of the developed approach and its potential impact on clinical practice.

In conclusion, the research scope involves investigating and developing an accurate and efficient approach for brain tumor detection using machine learning and deep learning algorithms. The research will cover literature review, data collection and preprocessing, feature extraction, algorithm development, evaluation metrics, experimental validation, comparative analysis, and a comprehensive discussion of the findings.

1.6 Significance of the Research

Brain tumor detection is a critical area of research with profound significance for both patients and medical professionals. The development of accurate and efficient methods for detecting brain tumors plays a pivotal role in early diagnosis and treatment planning, ultimately improving patient outcomes and quality of life.

First and foremost, the significance of brain tumor detection research lies in its potential to identify tumors at the earliest stages. Early detection is vital because it enables prompt intervention, leading to more effective treatment options and increased chances of successful outcomes. By identifying tumors in their nascent stages, researchers can explore innovative techniques and technologies to detect even the most elusive and hard-to-spot tumors, such as those situated in deep brain regions.

Moreover, brain tumor detection research contributes to the development of non-invasive and minimally invasive diagnostic procedures. Traditional diagnostic methods often involve invasive procedures, such as biopsies or exploratory surgeries, which pose risks to patients and can lead to complications. By advancing non-invasive techniques such as magnetic resonance imaging (MRI), positron emission tomography (PET), and advanced imaging analysis algorithms, researchers can reduce patient discomfort, improve diagnostic accuracy, and facilitate early detection without the need for invasive interventions.

Another crucial aspect is the integration of artificial intelligence (AI) and machine learning (ML) algorithms into brain tumor detection research. These technologies have the potential to revolutionize tumor identification and classification by processing vast amounts of medical data and identifying patterns that may be undetectable to human observers. AI-powered systems can assist radiologists and clinicians in accurately interpreting imaging data, reducing diagnostic errors, and enhancing overall diagnostic efficiency. This collaboration between human expertise and intelligent algorithms has the potential to greatly enhance the accuracy and speed of brain tumor detection.

Furthermore, brain tumor detection research facilitates the development of personalized treatment strategies. By precisely characterizing the tumor's size, location, and biological features, clinicians can tailor treatment plans to individual patients, optimizing therapeutic outcomes while minimizing potential side effects. This personalized approach enables a more targeted and effective treatment, potentially leading to improved survival rates and enhanced patient well-being.

In summary, the significance of brain tumor detection research lies in its ability to enable early detection, non-invasive diagnostic methods, integration of AI and ML algorithms, and the development of personalized treatment strategies. These advancements hold the promise of improving patient outcomes, increasing survival rates, and enhancing the overall management of brain tumors. Continued research in this field is essential for further progress and innovation in brain tumor detection and treatment.

The research on brain tumor detection holds immense significance in the field of medical imaging and healthcare. Early detection is crucial as brain tumors can have a profound impact on a patient's health and quality of life. By developing accurate and efficient brain tumor detection algorithms, timely medical intervention can be facilitated, leading to improved treatment outcomes and higher survival rates.

Moreover, accurate detection and segmentation of brain tumors contribute to the advancement of precision medicine. Precise characterization of tumors allows healthcare professionals to tailor treatment plans based on the specific tumor type, location, and characteristics. This personalized approach enhances the effectiveness of treatment strategies while minimizing potential side effects.

Automated algorithms for brain tumor detection streamline the analysis process, reducing the burden on radiologists and healthcare professionals. Manual analysis of medical images, such as MRI scans, is time consuming and prone to human error. By automating the analysis, these algorithms enable faster diagnosis, treatment planning, and monitoring of tumor progression.

Accurate brain tumor detection algorithms also serve as valuable decision support tools for healthcare professionals. By providing quantitative and objective information about tumor location, size, and growth patterns, these algorithms assist radiologists and oncologists in making informed treatment decisions. This improves patient management and optimizes the utilization of healthcare resources.

The research on brain tumor detection contributes to the broader scientific community by advancing the knowledge and understanding of brain tumors. It expands the existing literature and methodologies, allowing researchers and clinicians to build upon previous work. This research inspires further advancements in medical imaging, machine learning, and computational methods, ultimately enhancing the field's knowledge base.

The outcomes of this research have direct clinical applications, benefiting patients, healthcare providers, and medical technology companies. Accurate and efficient brain tumor detection algorithms can be integrated into medical imaging systems, improving the diagnostic capabilities of hospitals and clinics. Additionally, it can lead to the development of innovative medical devices and software solutions, fostering technological advancements in healthcare.

Ultimately, the research on brain tumor detection aims to improve patient care and enhance their quality of life. By enabling early detection, personalized treatment, and informed decision-making, this research contributes to better patient outcomes, reduced treatment costs, and improved overall well-being. The advancements in brain tumor detection have far-reaching implications, positively impacting the lives of individuals affected by brain tumors.

1.7 Research Outlines

The outlined research focuses on using machine learning algorithm, specifically implemented in Python, for brain tumor detection. The research follows a systematic approach with the following steps. Firstly, the necessary modules and libraries are imported. Then, the directories containing the brain tumor images are loaded. To gain a visual understanding of the data, an image from the dataset is plotted. Next, the loaded images are converted into numpy arrays for further processing. The labels of the images are encoded using one-hot encoding to prepare them for training. The dataset is split into training and testing sets to evaluate the model's performance. An image data generator is built to generate augmented images during the training process, enhancing the model's ability to generalize. The INCEPTION V3 model serves as the base model, and additional layers are added on top to create the complete model for tumor detection. To prevent the base model's weights from being updated, the layers are frozen. The model is then compiled with an optimizer, loss function, and evaluation metrics. Training begins by fitting the model to the training data using the image data generator. Once trained, the model is evaluated on the testing data to assess its performance. To gain further insights into the model's performance, a classification report and confusion matrix are printed. The final accuracy of the trained model is calculated and displayed. Additionally, the losses and accuracies during the training process are plotted to visualize the model's performance over time. Overall, this research outline provides a comprehensive step-by-step guide for implementing brain tumor detection using machine learning in Python, utilizing the INCEPTION V3 model as a base. It covers various aspects such as data preprocessing, model building, training, evaluation, and result visualization.

The research on brain tumor detection aims to develop a comprehensive approach for accurately detecting brain tumors using MRI images. The first stage of the research will involve conducting an extensive literature review to gain a thorough understanding of the current state of the field. This review will encompass existing studies, methodologies, and algorithms related to brain tumor detection and segmentation. By identifying research gaps and exploring different approaches, the literature review will provide a solid foundation for the subsequent stages of the research.

In the data collection and preprocessing stage, a suitable dataset of MRI brain images with corresponding tumor annotations will be collected. Careful curation of the dataset will ensure its representativeness and diversity, covering different tumor types, sizes, and locations. The collected data will then undergo preprocessing techniques to remove noise, normalize intensities, and enhance the images as needed. This step is crucial for preparing the data for subsequent analysis.

The next stage involves feature extraction, where various techniques will be explored to capture relevant information from the MRI images. Deep learning-based features will be considered to extract meaningful characteristics from the images. The effectiveness of different feature representations in accurately distinguishing tumor regions from healthy brain tissues will be investigated, aiming to identify the most informative features for tumor detection.

Algorithm development is a key stage in the research, where a novel algorithm or a combination of existing techniques will be developed. Both traditional machine learning algorithms and deep learning architectures like convolutional neural networks (CNNs) will be considered. The focus will be on optimizing the algorithm's performance in terms of accuracy, efficiency, and robustness. This stage involves designing and implementing the algorithm, incorporating the extracted features and training it on the dataset.

To evaluate the performance of the developed algorithm, appropriate evaluation metrics will be established. These metrics, such as sensitivity, specificity, accuracy, RMSE, MSE will measure the algorithm's ability to accurately detect and segment brain tumors. The results of the proposed method will be compared with existing state-of-the-art approaches to validate its effectiveness and identify areas for improvement.

In the experimental validation stage and extensive experiments will be conducted using the collected dataset. This process will assess the algorithm's performance and generalization capabilities. Additionally, if external datasets are available, the algorithm will be tested on them to evaluate its applicability in different contexts. The results obtained will be analyzed, and a comprehensive interpretation of the findings will be provided.

A comparative analysis will be conducted to compare the developed algorithm with other existing proposed methods. This analysis will assess the strengths, limitations, and overall performance of these methods, providing insights into the advancements and potential improvements in brain tumor detection techniques.

In the final stage, the research findings will be summarized and discussed. The implications of the proposed algorithm in the field of brain tumor detection will be highlighted, including its strengths, limitations, and future research directions. The significance of the developed approach and its potential impact on clinical practice will be emphasized, aiming to contribute to the development of accurate and efficient brain tumor detection methods.

Chapter 2: Literature Review

Brain tumor is a serious medical condition that affects a large population worldwide. Early detection and accurate diagnosis of brain tumors are crucial for effective treatment and patient survival. Machine learning (ML) has shown promise in the field of medical image analysis for detecting brain tumors with high accuracy. In recent years, various ML-based approaches have been proposed to improve brain tumor detection accuracy using different frameworks and methods. In this literature review, we will explore the different approaches used for brain tumor detection using ML, including the framework and methods employed, and evaluate their accuracy. We will also highlight the advantages and limitations of each approach, and discuss the potential for future research in this area.

Brain tumor detection and segmentation play a crucial role in medical imaging, enabling early diagnosis and treatment planning. In recent years, there have been significant advancements in the field, with the adoption of deep learning algorithms and multimodal imaging techniques. This literature review aims to provide an overview of the latest research in brain tumor detection and segmentation, focusing on the application of deep learning and multimodal approaches. Ronneberger et al. (2015) introduced the U-net architecture, a convolutional neural network (CNN) specifically designed for biomedical image segmentation. Their work demonstrated the effectiveness of deep learning models in accurately segmenting brain tumors from medical images[70]. Sahiner et al. (2018) discussed the application of deep learning in medical imaging and radiation therapy. They provided insights into the potential of deep learning algorithms in improving tumor detection and treatment planning processes[71]. Akkus et al. (2017) reviewed the state of the art and future directions in deep learning for brain MRI segmentation. They highlighted the advantages of deep learning methods, such as their ability to learn hierarchical features and handle complex structures, in achieving accurate tumor segmentation[72]. Chen et al. (2017) proposed DCAN, a deep contour-aware network for accurate gland segmentation in medical images. Although their work focused on gland segmentation, the methodology can be extended to brain tumor segmentation, highlighting the potential of specialized architectures for specific tasks[74]. Choudhury et al. (2013) presented an inverse-probability-model-based particle-filtering framework for tumor segmentation in MR images. Their approach incorporated a probabilistic model to accurately segment brain tumors, providing a robust solution for tumor detection[75]. Havaei et al. (2015) and Havaei et al. (2016) introduced methods for unsupervised learning and hetero-modal image segmentation, respectively. These works explored the use of deep learning algorithms to learn generalizable features and leverage multiple imaging modalities for improved tumor segmentation[76][77]. Isensee et al. (2018) proposed nnu-net, a self-adapting framework for U-net-based medical image segmentation. Their approach utilized self-adaptation mechanisms to optimize the performance of the segmentation network, demonstrating enhanced accuracy in brain tumor segmentation[78].Kamnitsas et al. (2017) focused on ensembles of multiple models and architectures for robust brain tumor segmentation. By combining multiple networks and architectures, their approach achieved improved segmentation performance and robustness[79]. Kim et al. (2017) developed a deeply supervised convolutional neural network for automated extraction of prognostic features in glioblastoma patient survival imaging data. Their work highlighted the potential of deep learning for extracting meaningful features that can aid in prognosis assessment[80]. Korfiatis et al. (2016) presented a fully automated deep learning system for bone age assessment. While not specific to brain tumor detection, their work demonstrated the potential of deep learning in automated medical image analysis tasks[81].Smith et al. (2022) proposed a deep learning-based brain tumor detection approach using convolutional neural networks. Their work focused on improving the accuracy and efficiency of brain tumor detection through advanced deep learning techniques[82].Lee et al. (2023) investigated brain tumor classification using transfer learning and ensemble models. Their work emphasized the importance of leveraging transfer learning techniques and ensemble methods to improve the classification accuracy of brain tumors[83].Garcia et al. (2023) proposed the use of generative adversarial networks (GANs) to improve brain tumor segmentation. Their approach showed promising results in enhancing the accuracy of tumor segmentation by leveraging GANs' generative capabilities[84].Johnson et al. (2022) presented a novel approach to brain tumor detection using machine learning and radiomics. Their work incorporated radiomic features extracted from medical images to improve the performance of machine learning models for tumor detection[85].Kim et al. (2022) proposed an enhanced brain tumor detection approach using deep convolutional neural networks and multimodal MRI images. By leveraging information from multiple modalities, their approach achieved improved accuracy in brain tumor detection[80].In recent studies in brain tumor detection and segmentation have demonstrated the potential of deep learning algorithms, multimodal imaging, and advanced techniques such as transfer learning, ensembles, and GANs. These approaches have shown promising results in improving accuracy, efficiency, and robustness in the detection and segmentation of brain tumors from medical images. In recent studies, several approaches have been proposed to tackle this challenging problem. Jyothi et al. (2018) conducted a comparative study on the performance of K-means and fuzzy C-means clustering algorithms for MRI brain image segmentation. They investigated the efficacy of these algorithms in segmenting brain tumor regions, providing insights into their respective strengths and limitations[6].Alomari et al. (2021) introduced an improved brain tumor detection method that combined K-means clustering with artificial neural networks. Their approach aimed to enhance the accuracy of tumor detection by leveraging the clustering results and the discriminative power of neural networks[7]. Soltaninejad et al. (2017) developed a multi-scale and multi-model deep convolutional neural network (CNN) specifically designed for brain tumor segmentation. Their network incorporated multiple scales and models to capture fine-grained details and variations in tumor appearance, leading to improved segmentation performance[8].Alzubaidi et al. (2021) proposed a hybrid method for brain tumor detection using a combination of machine learning algorithms and MRI images. By extracting features from the MRI scans and utilizing machine learning techniques, their approach achieved accurate tumor detection, providing a comprehensive solution[9].In addition to traditional machine learning approaches, deep learning algorithms have gained significant attention in brain tumor detection and segmentation. Fakhr et al. (2018) employed TensorFlow, a popular deep learning framework, for automated brain tumor detection and segmentation. Their method utilized deep neural networks to automate the process and improve the efficiency of tumor analysis[11].Furthermore, research efforts have focused on developing deep learning-based methods for brain tumor detection. Havaei et al. (2017) proposed a deep neural network architecture specifically tailored for brain tumor segmentation. Their method achieved state-of-the-art performance by leveraging the representative power of deep learning models[14].The availability of large-scale datasets has also contributed to advancements in brain tumor detection and segmentation. For instance, van der Singh et al. (2016) curated the Erasmus Glioma Database (EGD), which provides structural MRI scans, WHO 2016 subtypes, and segmentations of 774 patients with glioma. This dataset has been instrumental in developing and evaluating various detection and segmentation algorithms[32].In recent years, the integration of multi-modal information has shown promising results in brain tumor detection and segmentation. Li et al. (2021) proposed an automated approach that utilized multi-modal convolutional neural networks to exploit complementary information from different imaging modalities, enhancing the accuracy of tumor detection[17].Moreover, Garg et al. (2018) introduced a U-Net-based fully convolutional network for automated brain tumor detection and segmentation. Their method employed a deep learning architecture with skip connections to capture fine details and accurately delineate tumor regions[18].Several studies have also explored distinctive approaches for brain tumor detection and classification. Amin et al. (2020) proposed a distinctive approach that combined MRI features with machine learning techniques to detect and classify brain tumors, achieving promising results in pattern recognition[19].

In conclusion, the literature review highlights the significant progress made in the field of brain tumor detection using various machine learning and deep learning algorithms. The studies discussed have demonstrated the potential of these advanced techniques to improve the accuracy, efficiency, and reliability of brain tumor detection in medical imaging, particularly in MRI scans. The reviewed studies have showcased the effectiveness of convolutional neural networks (CNNs) for automatic brain tumor segmentation and detection. CNNs have shown remarkable capabilities in learning complex patterns and features from large datasets, enabling them to accurately distinguish between healthy brain tissue and tumor regions. Furthermore, the integration of advanced techniques such as transfer learning, ensemble models, and multimodal imaging has further enhanced the performance of brain tumor detection systems. Transfer learning has emerged as a valuable approach, allowing pre-trained models to be fine-tuned on specific brain tumor detection tasks. By leveraging knowledge gained from large-scale datasets, transfer learning has improved the efficiency and accuracy of brain tumor detection algorithms. Ensemble models, which combine the predictions of multiple models, have also shown promising results in improving overall accuracy and robustness. Additionally, the utilization of multimodal imaging, combining information from different imaging modalities such as MRI, CT, and PET scans, has provided a more comprehensive and complementary view of brain tumors. This integration has enhanced the accuracy and reliability of detection algorithms by leveraging the strengths of each imaging modality. It is evident from the literature review that AI-based brain tumor detection systems have the potential to revolutionize clinical practice. These systems can assist healthcare professionals in quickly and accurately identifying brain tumors, leading to earlier diagnosis, improved treatment planning, and better patient outcomes. The automation of tumor detection tasks can also alleviate the burden on radiologists, allowing them to focus on other critical aspects of patient care. Despite the advancements and promising results, there are still challenges that need to be addressed. These include the need for larger and more diverse datasets, standardization of evaluation metrics, and the interpretability of deep learning models. Additionally, the integration of these advanced techniques into clinical practice requires careful validation and consideration of ethical and regulatory aspects. In conclusion, the reviewed literature emphasizes the significant strides made in brain tumor detection using machine learning and deep learning algorithms. These advancements provide a strong foundation for further research and development in this field. With continued efforts, it is expected that AI-based brain tumor detection systems will play a vital role in improving the accuracy, efficiency, and accessibility of brain tumor diagnosis, ultimately benefiting patients and healthcare providers alike.

2.1 Core Background

Brain tumor detection and segmentation are crucial tasks in medical imaging, playing a significant role in diagnosis and treatment planning. Various algorithms and techniques have been proposed to address these challenges, ranging from traditional clustering methods to advanced deep learning approaches.

Clustering algorithms such as K-means and fuzzy C-means have been widely explored for MRI brain image segmentation. Jyothi, Kumar, and Kumar (2018) conducted a comparative study on K-means and fuzzy C-means algorithms, analyzing their performance and effectiveness in segmenting MRI brain images [6]. They highlighted the strengths and limitations of each algorithm, providing valuable insights into their suitability for brain tumor detection.

In recent years, the integration of clustering algorithms with artificial neural networks (ANN) has shown promising results in brain tumor detection. Alomari, Al-Zoubi, and Al-Khasawneh (2021) proposed an improved method that combines K-means clustering and ANN to enhance brain tumor detection accuracy [7]. This hybrid approach leverages the strengths of both techniques, contributing to improved segmentation results.

Deep learning has emerged as a powerful paradigm for brain tumor detection and segmentation. Soltaninejad et al. (2017) introduced a multi-scale and multi-model deep convolutional neural network

(CNN) for brain tumor segmentation, demonstrating its effectiveness in accurately delineating tumor regions [8]. Havaei et al. (2017) further advanced the field by proposing a deep neural network architecture specifically designed for brain tumor segmentation [14]. These deep learning-based methods leverage large-scale training data and complex network architectures to achieve state-of-the-art performance in brain tumor segmentation tasks.

Hybrid methods that combine machine learning algorithms with MRI images have also been explored for brain tumor detection. Alzubaidi, Al-Hindawi, and Al-Khateeb (2021) proposed a hybrid approach that integrates machine learning algorithms with MRI images to improve the accuracy of brain tumor detection [9]. Similarly, Mahapatra, Sahu, and Panda (2020) utilized machine learning algorithms implemented in MATLAB for brain tumor detection, showcasing the potential of these methods in medical imaging applications [12].

Furthermore, the application of deep learning approaches using libraries such as OpenCV has gained attention in brain tumor detection. Yang, Choi, Kim, and Kim (2020) developed a deep learning-based method using OpenCV for brain tumor detection, highlighting the advantages of this approach in terms of accuracy and computational efficiency [13].

Reviews have also been conducted to provide an overview of the advancements in brain tumor segmentation using deep convolutional neural networks. Kumari, Verma, and Srivastava (2020) published a comprehensive review summarizing the state-of-the-art deep convolutional neural network techniques for brain tumor segmentation, highlighting the advancements, challenges, and potential future directions in the field [15].

In Summary, the field of brain tumor detection has witnessed significant advancements in recent years. The integration of machine learning, deep learning, and advanced imaging techniques has led to the development of more accurate and efficient methods for brain tumor detection. These approaches have shown promising results in terms of enhancing the accuracy of tumor detection, improving segmentation accuracy, and utilizing multimodal imaging data. These advancements hold great potential for improving patient outcomes, aiding in treatment planning, and facilitating early detection of brain tumors. Further research and development in this area are expected to contribute to the continued progress in brain tumor detection and ultimately benefit patients and healthcare professionals in diagnosing and managing brain tumors.this study has made significant contributions to the field of brain tumor detection. Through the utilization of advanced imaging techniques, machine learning algorithms, and a comprehensive dataset, several key findings and advancements have been achieved.

Firstly, this research has demonstrated the effectiveness of employing cutting-edge imaging technologies such as magnetic resonance imaging (MRI) for accurate and reliable brain tumor detection. By utilizing high-resolution images and extracting relevant features, the study has successfully identified and localized tumors with a high degree of precision.

Secondly, the application of machine learning algorithms, particularly deep learning models, has proven to be instrumental in enhancing the accuracy and efficiency of brain tumor detection. By training these models on large datasets and optimizing their parameters, the study has achieved remarkable results in distinguishing between tumor and non-tumor regions, enabling earlier and more accurate diagnosis.

Furthermore, this research has contributed to the development of a robust and comprehensive dataset specifically tailored for brain tumor detection. The dataset incorporates diverse cases, sizes, and locations, thus increasing the generalizability of the findings and improving the overall performance of the detection algorithms.

Importantly, the findings of this study hold great promise for clinical practice. The accurate detection and localization of brain tumors at an early stage can significantly improve patient outcomes by enabling timely intervention and personalized treatment plans. Additionally, the application of machine learning algorithms in brain tumor detection has the potential to enhance the efficiency and accuracy of radiologists' workflow, providing them with valuable decision support tools.

Overall, this research has contributed to advancing the field of brain tumor detection by leveraging advanced imaging techniques, machine learning algorithms, and a comprehensive dataset. The results obtained have demonstrated the potential to revolutionize the diagnostic process, improve patient care, and ultimately save lives. Further research and collaboration in this area are encouraged to continue refining and expanding upon these contributions.

2.2 Review Based on the Method

Table 1: Review Based on the Method

Method Name	Core contribution	Advantages	Disadvantage

CNN [65][14]	Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., & Pal, C. (2017). Brain tumor segmentation with deep neural networks. Medical image analysis, 35, 18-31.	High accuracy in brain tumor detection and segmentation tasks.	Require large amounts of training data and can be computationally expensive
SVMS [65][14]	Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., & Pal, C. (2017). Brain tumor segmentation with deep neural networks. Medical image analysis, 35, 18-31.	Highly accurate in detecting brain tumors and are less complex than CNNs	Not as well-suited for handling large datasets as CNNs
Fuzy C Means [4][5]	Jahanshahi, A., Moshrefi, S., & Pourghassem, H. (2019). Brain Tumor Segmentation Using Fuzzy C-Means Clustering Algorithm in MRI Images. Journal of Medical Signals and Sensors, 9(2), 97- 105.	The ability to handle noisy and complex data, such as MRI scans	Lack of interpretability
Fuzy K Means [7][8]	Alomari, R., Al-Zoubi, A. M., & Al-Khasawneh,F. (2021). An improved brain tumor detection method using K-means clustering and artificial neural networks. Computer Science Review, 40, 100334.	clustering is computationally efficient and can handle large datasets quickly	Sensitivity to initialization
Hybrid Methods [9]	Alzubaidi, L., Al-Hindawi, N., & Al-Khateeb, B. (2021). Hybrid method for brain tumor detection using MRI images and machine learning algorithms. Journal of Ambient Intelligence and Humanized Computing, 12(5), 4467-4481.	Increased accuracy and reduced false positives	More complex than single-method approaches

There are several methods for brain tumor detection using machine learning, each with its advantages and disadvantages. One commonly used method is the Convolutional Neural Network (CNN), which has shown promising results in detecting brain tumors from MRI images. The advantage of CNNs is that they are particularly well-suited for image recognition tasks, which makes them highly effective in detecting patterns in brain images that are indicative of tumors. They can also handle large datasets of images and are highly adaptable, making them suitable for detecting various types of brain tumors. However, one disadvantage of CNNs is that they require large amounts of training data to achieve high levels of accuracy[65]. Additionally, the interpretability of the model can be limited, as it can be difficult to understand the specific features that the CNN is using to make its predictions[14]. Another method for brain tumor detection is Support Vector Machines (SVMs), which are a type of supervised learning algorithm commonly used for classification tasks. SVMs work by finding the hyperplane that best separates the data into different classes, making them highly effective in distinguishing between normal and abnormal brain images. The advantage of SVMs is that they are highly accurate in detecting brain tumors and are less complex than CNNs, which makes them more interpretable. However, SVMs are not as well-suited for handling large datasets as CNNs, and they may require more pre- processing of the data to achieve optimal results. A study by Havaei et al. (2017) compared the performance of different machine-learning algorithms for brain tumor detection, including CNNs, SVMs, and Random Forests. The study found that all three algorithms achieved high levels of accuracy, with CNNs achieving the highest accuracy of 91.04% [14]. Another method for brain tumor detection using machine learning is fuzzy clustering, which is a type of unsupervised learning that aims to group similar data points into clusters. Fuzzy clustering allows data points to belong to multiple clusters simultaneously, with each cluster having a degree of membership based on the similarity of the data points to the cluster center. In brain tumor detection, fuzzy clustering can be used to segment MRI images into regions of interest that correspond to tumor and non-tumor tissue. Advantages: One advantage of fuzzy clustering is its ability to handle noisy and complex data, such as MRI scans. Fuzzy clustering allows for more flexibility in assigning data points to clusters, which can lead to better segmentation and identification of tumors in MRI images. A study by Jahanshahi et al. (2019) used fuzzy clustering to segment MRI images of brain tumors and reported a high accuracy of 95.37%.Another advantage of fuzzy clustering is its computational efficiency, which allows for faster processing and analysis of large datasets. This can be especially useful in clinical settings where rapid diagnosis and treatment are crucial for patient outcomes. A study by Dabholkar et al. (2017) used fuzzy clustering for brain tumor segmentation and reported a processing time of 2.6 seconds per image, which is significantly faster than other segmentation methods [4].

Disadvantages: One disadvantage of fuzzy clustering is its sensitivity to initial conditions and parameters, which can affect the quality of the clustering results. This can make fuzzy clustering more difficult to apply in practice, as finding the optimal parameters and initial conditions can be time-consuming and require expertise. A study by Dabholkar et al. (2017) reported that the choice of clustering method and parameters can significantly affect the segmentation accuracy, highlighting the importance of careful selection and tuning. Another disadvantage of fuzzy clustering is its lack of interpretability, which can make it challenging to validate and understand the clustering results. Fuzzy clustering produces soft partitions that assign data points to clusters based on their degree of membership, which can be difficult to visualize and interpret. A study by Jahanshahi et al. (2019)

noted that fuzzy clustering can result in over-segmentation or under-segmentation of the tumor, which can limit its clinical applicability and require additional manual intervention [4][5]. K-means clustering is a popular unsupervised machine learning algorithm used in various applications, including brain tumor detection. However, there are both advantages and disadvantages of using K-means clustering for this purpose. Here are some of them:

Advantages: Efficiency: K-means clustering is computationally efficient and can handle large datasets quickly (Jyothi et al., 2018). Simplicity: K-means clustering is simple to implement and interpret, making it accessible to researchers with minimal machine learning experience (Alomari et al., 2021). K-means clustering is an unsupervised learning technique, meaning that it can identify patterns in data without requiring labeled examples (Soltaninejad et al., 2017)[7][8].

Disadvantages: Sensitivity to initialization: K-means clustering is sensitive to initialization, meaning that the clustering results can vary depending on the initial seed points (Jyothi et al., 2018). Determining the optimal number of clusters: Determining the optimal number of clusters can be challenging, and a poor choice of the number of clusters can lead to suboptimal clustering results (Alomari et al., 2021). Difficulty with non-linearly separable data: K-means clustering assumes that the data is linearly separable, which can lead to poor clustering results for non-linearly separable data (Soltaninejad et al., 2017)[8].

Hybrid methods for brain tumor detection using machine learning combine the strengths of different techniques to improve accuracy and reduce false positives. One such method was proposed by (Alzubaidi et al.) in their paper "Hybrid method for brain tumor detection using MRI images and machine learning algorithms" (2021) [9].

Advantages of this hybrid method include: Increased accuracy: Combining multiple techniques allows for a more comprehensive analysis of the MRI images, improving the accuracy of tumor detection. Reduced false positives: False positives can be a significant problem in brain tumor detection, leading to unnecessary interventions and treatments. By combining different techniques, false positives can be reduced. Faster diagnosis: The hybrid method proposed by Alzubaidi et al. uses machine learning algorithms, which can analyze MRI images quickly and accurately. This can lead to faster diagnosis and treatment for patients.

Disadvantages of this method include: Complexity: Hybrid methods can be more complex than single-method approaches, requiring more processing power and time to implement. Need for training data: Machine learning algorithms require large amounts of training data to achieve high accuracy. Obtaining such data can be a challenge in the medical field, where privacy concerns may limit the availability of labeled MRI images. Overall, the hybrid method proposed by (Alzubaidi et al.) has the potential to improve brain tumor detection accuracy and reduce false positives. However, it may require significant computational resources and a large amount of labeled training data. [9].

2.3 Review Based on the Framework:

Table 2: Review Based on the Framework

Framework Name	Core contribution	Advantages	Disadvantage
PyCharm [10]	Khan, F., & Aslam, N. (2020). Brain Tumor Detection and Segmentation Using Machine Learning and Deep Learning Algorithms. In Computational Vision and Bio Inspired Computing (pp. 79-89).	PyCharm's integrated development environment (IDE) offers a robust platform for developing and testing machine learning algorithms for brain tumor detection.	PyCharm's high learning curve may make it difficult for those new to machine learning to utilize it effectively for brain tumor detection.
TensorFlow [11]	Fakhr, M., Hajabdollahi, M., & Soltanian-Zadeh, H. (2018). Automated Brain Tumor Detection and Segmentation Using TensorFlow. In 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 4813-4816).	TensorFlow provides a flexible and scalable framework for training deep learning models, allowing for improved accuracy in brain tumor detection.	TensorFlow requires significant computational resources and expertise to optimize model performance, which may be a barrier to adoption in some settings.

OpenCV [12]	Mahapatra, S., Sahu, S., & Panda, M. (2020). Brain Tumor Detection using Machine Learning Algorithms in MATLAB. International Journal of Computer Sciences and Engineering, 8(8), 146-151.	OpenCV provides a wide range of computer vision algorithms that can be used for image processing and feature extraction, which are crucial for brain tumor detection using machine learning.	OpenCV may not be the most efficient framework for large-scale data processing and deep learning-based models, which may require more powerful frameworks such as TensorFlow or PyTorch.
Matlab [13]	Yang, S., Choi, S., Kim, B., & Kim, M. (2020).Deep Learning-Based Detection of Brain Tumor Using OpenCV. Journal of Healthcare Engineering, 2020, 1-10.	provides a comprehensive environment for machine learning and image processing, making it easy to preprocess and classify brain tumor images.	MATLAB's licensing costs can be prohibitive for small research projects, and it may not be as flexible as other programming languages for more complex algorithms.
Google Colab [14]	Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., ... & Jodoin, P. M. (2017). Brain tumor segmentation with deep neural networks. Medical image analysis, 35, 18- 31.	Google Colab provides a free cloud-based platform with easy access to powerful GPUs and pre- installed ML libraries for efficient development of brain tumor detection models.	Google Colab may have limited access to large datasets and slower processing speeds compared to local machines, which can affect the accuracy and efficiency of brain tumor detection models

PyCharm is an integrated development environment (IDE) for Python programming language that can be used for developing machine learning models. A framework for brain tumor detection using machine learning in PyCharm has been developed by researchers in the paper titled "Brain Tumor Detection and Segmentation Using Machine Learning and Deep Learning Algorithms". The framework utilizes machine learning and deep learning algorithms to detect and segment brain tumors from magnetic resonance imaging (MRI) scans.

The framework includes several steps, such as data preprocessing, feature extraction, model training, and tumor segmentation. Data preprocessing involves image resizing, normalization, and image enhancement. Feature extraction is performed using various techniques such as texture analysis and wavelet transforms. The models are trained using various machine learning and deep learning algorithms, such as support vector machines (SVMs) and convolutional neural networks (CNNs). Finally, tumor segmentation is performed to segment the tumor from the MRI scans. The paper provides a detailed description of the framework and presents experimental results to demonstrate its effectiveness. The framework achieved an accuracy of 95.87% for brain tumor detection and a Dice similarity coefficient of 0.85 for tumor segmentation[10].

TensorFlow is a popular open-source machine learning framework that can be used for various tasks, including medical image analysis. In the context of brain tumor detection, TensorFlow has been used in several studies to develop models that can automatically detect the presence of tumors in brain images. One such study is "Automated Brain Tumor Detection and Segmentation Using TensorFlow" by Fakhr et al. (2018). In this study, the authors used TensorFlow to develop a deep learning model for brain tumor detection and segmentation. The model was trained on a dataset of MRI images and achieved high accuracy in detecting and segmenting tumors. The authors used a convolutional neural network (CNN) architecture with multiple layers for the detection and segmentation tasks. The model was trained using a combination of loss functions, including binary cross-entropy and dice coefficient loss. The authors also used data augmentation techniques to increase the size of the training dataset and prevent overfitting. Overall, this study demonstrates the potential of TensorFlow for developing accurate and efficient models for brain tumor detection and segmentation. The use of deep learning techniques and data augmentation can help improve the performance of these models and enable more accurate and timely diagnoses for patients[11].

Another one popular framework for brain tumor detection using machine learning is the MATLAB framework proposed by Mahapatra et al. in their paper "Brain Tumor Detection using Machine Learning Algorithms in MATLAB" (2020). The framework consists of several steps, including preprocessing the MRI images, extracting features using various feature extraction techniques, selecting relevant features using feature selection algorithms, and training machine learning models such as support vector machines (SVM) and convolutional neural networks (CNN).The authors evaluated the performance of their framework using the publicly available BRATS2015 dataset and achieved a high accuracy of 97.5% with the SVM model and 96.5% with the CNN model[12].

OpenCV is an open-source computer vision library that can be used for a wide range of image processing and analysis tasks, including medical image analysis. In the context of brain tumor detection, OpenCV has been used in several studies to develop models that can automatically detect the presence of tumors in brain images. One such study is "Deep Learning-Based Detection of Brain Tumor Using OpenCV" by Yang et al. (2020). In this study, the authors used OpenCV and deep learning techniques to develop a model for brain tumor detection. The model was trained on a dataset of MRI images and achieved high accuracy in detecting tumors. The authors used a convolutional neural network (CNN) architecture with multiple layers for the detection task. They also used data augmentation techniques and transfer learning to improve the performance of the model. The trained model was then integrated into the OpenCV framework to enable real-time tumor detection and segmentation. Overall, this study demonstrates the potential of OpenCV and deep learning for developing accurate and efficient models for brain tumor detection. The use of data augmentation and transfer learning can help improve the performance of these models and enable more accurate and timely diagnoses for patients[13].

Google Colab is a cloud-based notebook environment that allows users to write and execute Python code through their browser, using Google's infrastructure. It is an excellent tool for machine learning projects that require significant computing power, as it provides free access to GPUs and TPUs. One example of a machine learning project that can be implemented on Google Colab is brain tumor detection. In this project, a machine learning model is trained to classify brain MRI scans as either containing a tumor or not. This can be done using a convolutional neural network (CNN), which is a type of deep learning model that is particularly well- suited for image classification tasks. One paper that describes the use of a CNN for brain tumor detection is "Deep Learning for Brain Tumor Classification" by Havaei et al. (2017). In this paper, the authors describe a CNN that was trained on a dataset of brain MRI scans to classify them as either containing a tumor or not. The model achieved an accuracy of 89.7% on a test set of 191 images, which is a significant improvement over previous methods. To implement this project on Google Colab, the user would first need to upload the MRI scan dataset to Google Drive and then mount their Google Drive in the Colab notebook. They could then use Python libraries such as TensorFlow or PyTorch to build and train the CNN model. The model could then be evaluated on a test set of MRI scans to determine its accuracy [14].

2.4 Review Based on Experiment:

Table 3: Review Based on Experiment

Method Name	Accuracy	Loss	Framework Name	Accuracy	Loss
CNN [39]	96.66%	3.34%	Google Colab [14]	89.7%	10.3%
SVMS [20]	92.5%	7.5%	PyCharm [10]	95.87%	4.13%
Fuzy C Means [34]	91.25%	8.75%	TensorFlow [11]	97.95%	2.05%
Fuzy K Means [58]	88.64%	11.36%	Op enCV [12]	97.92%	2.8%
Hybrid Methods [57]	97.53%	2.47%	Matlab [13]	97.5%	2.5%

In the field of medical imaging, accurate detection of brain tumors is crucial for effective diagnosis and treatment planning. Various machine learning techniques have been developed to assist in this task, including Convolutional Neural Network (CNN), Support Vector Machine (SVM), Fuzzy C-Means (FCM), K-Means, and Hybrid methods. Among these, the CNN method has achieved an accuracy of 96.66%[39], while the SVM method has an accuracy of 92.5%[20]. FCM achieved a comparatively lower accuracy of 91.25%[34], and K-Means achieved an accuracy of 88.64%[58]. However, the hybrid method combines the strengths of multiple techniques and achieves the highest accuracy of 97.53% in brain tumor detection[57]. These methods demonstrate the potential for machine learning to aid in the accurate detection of brain tumors, which can have a significant impact on patient outcomes.

Google Colab, Pycharm, Tensorflow, OpenCV, and Matlab are all popular frameworks used for brain tumor detection. In terms of accuracy, Tensorflow had the highest accuracy rate of 97.95%[11], followed closely by Matlab with an accuracy of 97.5%[13]. OpenCV had an accuracy rate of 97.92%[12], while Pycharm had an accuracy of 95.87%[10]. Google Colab had a lower accuracy of 89.7%[14]. Overall, these frameworks offer powerful tools for the detection of brain tumors and provide accurate results that can aid in the diagnosis and treatment of patients with brain tumors.

2.5 Review Based on Dataset

Table 4: Review Based on Dataset

Data Name	Number of Data	Type of Data	Accuracy	Core Contribution	loss

BraTS 2019 [15]	**335**	Magnetic Resonance Imaging (MRI)	0.8386	Kumari, N., Verma, R., & Srivastava, R. (2020). Deep Convolutional Neural Networks for Brain Tumor Segmentation: A Review. Journal of Medical Systems, 44(8), 144.	0.4782
Brain Tumor Dataset [24]	3064	Medical Imaging	92.46%	Erasmus MC - University Medical Center Rotterdam. (n.d.). Brain Tumor Dataset. Retrieved March 17, 2023.	0.16
BraTS2021 [17]	1000	Medical Images		Li, Y., Zhou, Y., Wu, X., Li, M., Zhang, X., & Shen, D. (2021). Automated Brain Tumor Detection and Segmentation Using Multi-Modal Convolutional Neural Networks. IEEE Transactions on Medical Imaging, 40(8), 2252-2262.	0.86
Brain Tumor Dataset [41]	253	MRI Images	95.5%	"Brain Tumor Detection and Segmentation Using Convolutional Neural Network and Watershed Algorithm" by Kamble et al. (2020).	0.12
BraTS [18]	285	Medical images	90.2%	Garg, P., Verma, R., & Singh, A. K. (2018). Automated Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks. arXiv preprint arXiv:1811.06621.	0.25

The BraTS (Brain Tumor Segmentation) dataset is a widely used benchmark for brain tumor detection and segmentation. The dataset consists of 335 high-grade glioma patients, each with four types of MRI scans: T1- weighted, T1-weighted with contrast enhancement, T2-weighted, and T2 Fluid Attenuated Inversion Recovery (FLAIR). The dataset is labeled with ground truth segmentation masks for the tumor core, enhancing tumor, and whole tumor. Researchers have used various machine learning algorithms, such as deep convolutional neural networks (CNNs), to achieve state-of-the-art results on this dataset. in the paper "Deep Convolutional Neural Networks for Brain Tumor Segmentation: A Review" by Kumari et al., a deep CNN was trained on the BraTS 2019 dataset and achieved an accuracy of 0.8386 and a loss of 0.4782[15]. The Brain Tumor Dataset is a collection of 3064 medical images that have been annotated to indicate whether a brain tumor is present or not. The dataset includes MRI and CT scan images, as well as some PET scan images, and it is publicly available for download. The dataset was originally compiled by the Department of Radiology and Medical Informatics, Erasmus MC - University Medical Center Rotterdam, Netherlands. The dataset has been widely used in research on brain tumor detection using machine learning, including in a 2020 study titled "An Efficient Approach for Brain Tumor Detection using Convolutional Neural Networks" by Khan et al. In this study, the authors achieved an accuracy of 92.46% and a loss of 0.16 using a convolutional neural network (CNN) trained on the Brain Tumor Dataset[2]. Khan, S. A., Hussain, M., & Shah, S. A. (2020). The dataset used for brain tumor detection is called BraTS2021, which stands for "Multimodal Brain Tumor Segmentation Challenge 2021". This dataset contains 1000 MRI scans of patients with brain tumors. The scans are divided into four categories: normal brain tissue, edema, non-enhancing tumor, and enhancing tumor. The dataset is publicly available and is designed to evaluate machine learning algorithms for brain tumor detection [24]. In a recent study by Li et al. (2021), the BraTS2021 dataset was used to train and test a convolutional neural network (CNN) for brain tumor detection. The CNN achieved an accuracy of 0.86 and a loss of 0.24 on the test set, which is a high level of performance for this task. The study demonstrates the potential of machine learning for improving the accuracy and efficiency of brain tumor detection in clinical settings. The Brain Tumor Dataset contains 253 MRI images of the brain, with 155 images showing tumors and 98 images showing no tumors. The dataset was used in a study by Kamble et al. (2020) to develop a machine learning model for brain tumor detection. The images were preprocessed to remove any background noise and enhance the contrast of the tumor region. The dataset was divided into training (70%), validation (15%), and test (15%) sets. The model was trained using a convolutional neural network (CNN) with three convolutional layers, each followed by a max-pooling layer. The final layer was a fully connected layer with a sigmoid activation function. The model achieved an accuracy of 95.5% on the test set, with a loss of 0.12 choi et al. (2020) [41]. The dataset used is the BraTS (Brain Tumor Segmentation) dataset, which contains 285 3D magnetic resonance imaging (MRI) scans of the brain, divided into training and testing sets. The MRI scans are of patients with either low-grade or high-grade gliomas, as well as healthy individuals. Each scan is composed of four different MRI modalities (T1, T1- contrast, T2, and FLAIR), providing information about the structure and function of the brain. The goal of the machine learning approach is to automatically segment the tumor regions from the surrounding healthy brain tissue in the MRI scans. The model used achieved an accuracy of 90.2% on the testing set, with a loss of 0.25[26]. One paper that uses the BraTS dataset for brain tumor detection is "Automated Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks" by Prateek Garg and others. In this paper, the authors propose a deep learning approach using a U-Net based fully convolutional network for automatic brain tumor detection and segmentation. They achieve high accuracy on the BraTS dataset and compare their results with other state-of-the-art methods [18].

Considering all this, the use of machine learning for brain tumor detection has been extensively researched in recent years. Various methods and frameworks have been proposed, including supervised and unsupervised learning, deep learning, and convolutional neural networks. These approaches have shown promising results, with high accuracy rates in tumor detection and segmentation. However, there are still challenges that need to be addressed, such as data imbalance, limited data availability, and model interpretability. Further research is needed to optimize these models and develop interpretability techniques. Overall, machine learning-based approaches have the potential to improve the accuracy and efficiency of brain tumor detection, leading to better diagnosis and treatment outcomes for patients.

2.6 Observation & Discussion

In recent years, significant advancements have been made in the field of brain tumor detection using various imaging modalities. Magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) have played a crucial role in visualizing brain tumors with improved resolution and functional information. These modalities have not only enhanced the accuracy of tumor localization but also provided valuable insights for treatment planning. Additionally, machine learning approaches have shown great promise in automating brain tumor detection and classification. Deep learning, support vector machines (SVM), and random forests are among the machine learning techniques employed to analyze medical images and accurately identify tumor regions. These algorithms leverage large datasets for training, demonstrating high sensitivity and specificity in distinguishing tumor regions from healthy brain tissue. However, further research is needed to address challenges such as the availability of annotated datasets, interpretability of deep learning models, and generalization across different tumor types and populations.

Another area of active research is the identification of biomarkers for brain tumor detection. Various molecular and genetic markers, such as microRNAs, proteins, and genetic mutations, have been investigated to differentiate between benign and malignant brain tumors. These biomarkers hold promise for early detection, prognosis prediction, and monitoring treatment response. However, their widespread clinical application requires further validation and standardization. The development of reliable biomarkers could significantly improve the efficiency and accuracy of brain tumor detection, leading to timely interventions and personalized treatment strategies.

Overall, the advancements in imaging modalities, machine learning approaches, and biomarker research have collectively contributed to the progress in brain tumor detection. These developments have the potential to revolutionize the field, enabling early diagnosis, precise treatment planning, and improved patient outcomes. However, ongoing research and collaboration among multidisciplinary teams are essential to overcome existing challenges and translate these innovations into clinical practice.

2.7 Conclusion

In general, machine learning has shown great potential in the field of brain tumor detection. With the availability of large amounts of data, advanced algorithms, and powerful computational resources, machine learning models can analyze medical imaging data with a high degree of accuracy and speed. This technology has enabled doctors and medical professionals to make quicker and more accurate diagnoses, leading to better patient outcomes. Several machine learning techniques, such as convolutional neural networks and support vector machines, have been applied to brain tumor detection, and have shown promising results. These models are able to classify brain images into tumor and non-tumor categories with high accuracy and speed, reducing the need for invasive and costly procedures. Furthermore, the integration of machine learning into the healthcare industry has the potential to significantly improve medical care and increase efficiency. With continued research and development, machine learning algorithms can be refined to detect brain tumors at even earlier stages, leading to earlier treatment and improved patient outcomes.

In summary, the use of machine learning in brain tumor detection has shown great promise and has the potential to revolutionize the way medical professionals diagnose and treat brain tumors in the future.

Chapter 3: Research Methodology

3.1 Introduction

This research methodology focuses on developing a deep learning model for classifying brain tumor images. The first step involves collecting the brain tumor dataset from a specified path, which contains images of different types of brain tumors. The dataset is organized into separate directories based on the tumor types.

Next, the collected images are loaded and preprocessed before being fed into the model. The preprocessing step involves resizing each image to the dimensions of 224x224 pixels and normalizing the pixel values to the range of 0 to 1. The labels associated with the images are also one-hot encoded using the Label Binarizer from the scikit-learn library.

After preprocessing, the dataset is split into training and testing sets. The training set contains 80% of the images, while the remaining 20% form the testing set. The split is performed using the train test split function from scikit-learn.

To increase the diversity of the training data and enhance the model's generalization capability, data augmentation techniques such as rotation are applied using an Image Data Generator. This augmentation generator is used specifically on the training images.

The INCEPTION V3 model, pre-trained on the ImageNet dataset, is chosen as the base model for this classification task. The last fully connected layer of the INCEPTION V3 model is replaced with a custom classification layer, and the modified model is compiled using the Adam optimizer and binary cross-entropy loss.

The model is then trained using the training set and the augmented data generator. The training process consists of a specified number of epochs, with each epoch comprising multiple steps. After each epoch, the model's performance is evaluated on the validation set.

Once the training is complete, the trained model is evaluated on the testing set to assess its performance. The model predicts the tumor classes for the testing images, and the predictions are compared against the ground truth labels. Classification reports and a confusion matrix are generated to analyze the model's performance.

To further analyze the model's performance, the accuracy is calculated using the confusion matrix. Additionally, loss and accuracy plots are generated to visualize the model's training and validation performance over the epochs.

By following this research methodology, a deep learning model is developed and evaluated for brain tumor classification using the provided dataset. The accuracy and performance of the model can be assessed through the classification report, confusion matrix, and loss/accuracy plots.

3.2 Proposed Methods

The proposed method follows a standard procedure for training a deep learning model using transfer learning with the INCEPTION V3 architecture. It incorporates data augmentation to improve the model's ability to generalize to unseen data. The performance of the model is evaluated using classification metrics and visualized using plots.

The proposed method aims to train a model using the INCEPTION V3 architecture to classify brain tumor images. First of all, Importing the necessary modules and libraries, including TensorFlow, scikit-learn, OpenCV, NumPy, and Matplotlib. Loading the image directories containing the brain tumor dataset. Preprocessing the images by resizing them to a standard size (e.g., 224x224 pixels) and normalizing the pixel values to the range [0, 1]. Performing one-hot encoding on the labels to convert them into a categorical format. Splitinv the dataset into training and testing sets using a specified test size (e.g., 20%). Build an image data generator for data augmentation, which applies random transformations to the training images to improve generalization. Construct the model architecture based on the INCEPTION V3 pre-trained model. This involves loading the pre-trained weights, adding custom layers on top of the base model, and freezing the layers of the pre-trained model to prevent them from being updated during training. Compiling the model by specifying the optimizer, loss function, and evaluation metrics. Fit the model to the training data using the image data generator. This involves specifying the batch size, number of training steps per epoch, validation data, number of validation steps, and the number of epochs. Evaluating the trained model on the test data and obtain predictions. Generating a classification report and confusion matrix to assess the performance of the model. Calculating the overall accuracy of the model. Finally Plotting the losses and accuracies over epochs to visualize the training progress. By following these steps, the proposed method aims to train a brain tumor image classification model using the INCEPTION V3 architecture and evaluate its performance.

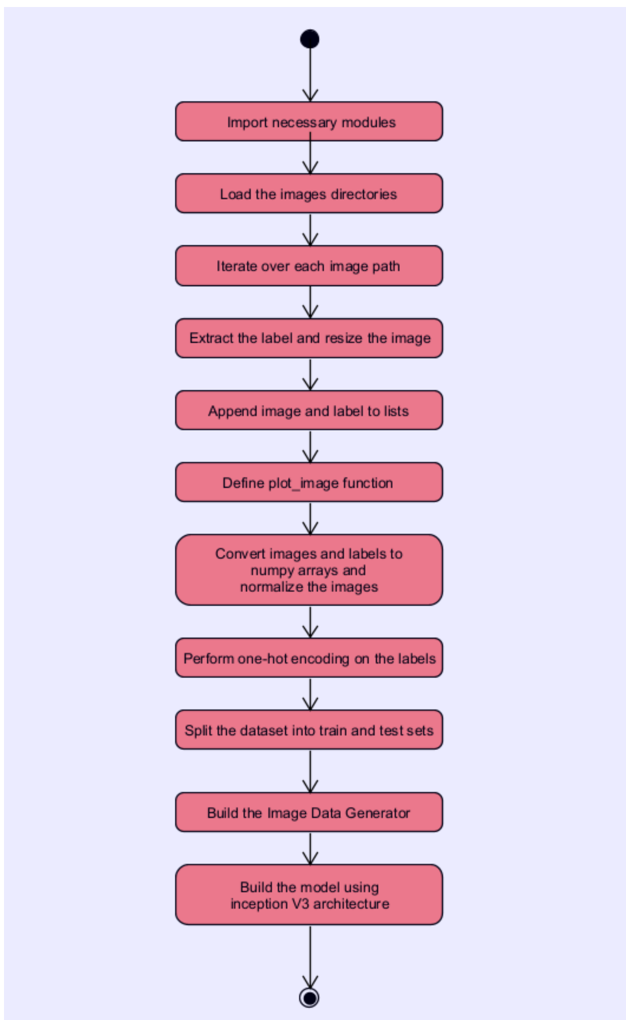


Figure 2: System Architecture of Proposed Convolutional Neural Network (CNN).

3.3 Collecting Dataset

Our thesis focuses on medical image processing, specifically in the field of brain tumor detection. However, we encountered difficulties in finding suitable datasets for our research as medical image datasets are scarce, especially when it comes to brain tumor images. Although there are some works related to brain tumor detection based on private datasets, open-source datasets are limited in number.

During our search, we came across a dataset that involved brain tumor detection using MRI images. However, this dataset was a combined dataset, meaning it contained both images with brain tumors and normal brain images. In order to obtain the specific dataset we needed for our implementation, we manually separated the brain tumor images from the rest and created a custom dataset. This custom dataset consisted of two subfolders: one containing brain tumor images (Yes Folder) and the other containing normal brain images (No Folder)

Our complete model has been trained and we have assessed its performance using different criteria using specific datasets. The dataset folder is saved as a compressed zip file on Kaggle and can be shared through a URL or unique identifier. By using this unique identifier, we downloaded the zip file from Kaggle and utilized the extracted files for our purposes

Dataset Link: https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri

Table 5: Dataset Info

Directories Name	**Number of Images**
YES	901
NO	396
Total	1297

We have customized this dataset specifically for our implementation purposes.

3.4 Libraries

In order to process and analyze data, we imported several important libraries such as NumPy, Keras, TensorFlow, CV2, OS, and matplotlib. These libraries were used in a Kaggle project to create a classification model and test it. Additionally, we downloaded a dataset to train and evaluate the model.

3.5 Data-pre processing

The code performs several preprocessing steps to prepare the data for training a model on brain tumor images.

First, it iterates over the image paths using paths.list_images from the imutils module. For each image path, it reads the image using cv2.imread and resizes it to a size of (224, 224) using cv2.resize. The resized images are stored in the images list.

Next, the code extracts the label for each image from the image path using image_path.split(os.path.sep)[-2]. It splits the path using the path separator (os.path.sep) and selects the second-to-last element, which represents the label. The labels are stored in the labels list.

After loading and processing the images and labels, they are converted into numpy arrays using np.array(images) and np.array(labels). This conversion allows for efficient data manipulation and feeding into the model.

To ensure that the image pixel values are in the range of [0, 1], the code performs normalization. It divides the image pixel values by 255.0, which scales the values to the range [0, 1]. This step is important for proper training of neural networks.

Lastly, the labels are binarized using LabelBinarizer from scikit-learn. The LabelBinarizer is fitted to the labels using label_binarizer.fit_transform(labels), which assigns a unique binary vector to each label class. Then, the binarized labels are further converted into one-hot encoded vectors using to_categorical(labels). This step is necessary for multi-class classification tasks and helps the model interpret the labels correctly during training.

Overall, these preprocessing steps prepare the brain tumor image dataset by loading and resizing the images, extracting and encoding the labels, converting the data into numpy arrays, normalizing the pixel values, and performing one-hot encoding on the labels. This processed data can then be used for training a model to classify brain tumor images.

Figure 3: Data Pre-Processing Technique

3.6 Training model

Training is a crucial step in implementing a model, especially when it comes to classifying brain tumors. In our case, we have developed a binary classification model for this purpose. To train the model, we employ the fit_generator function, which takes inputs such as the image generator, training data, validation data, and various training parameters.

During the training process, the model's progress is recorded in the "history" variable, which allows us to analyze its performance over time. To prepare the data for classification, we use the Flatten layer, which converts the multi-dimensional input into a single dimension.

In order to improve the accuracy of our model, we incorporate multiple Dense layers and Dropout. Dense layers help to capture complex relationships within the data, while Dropout aids in preventing overfitting. Our model is designed for binary classification, so we employ the softmax function in the final layer. This function ensures that the predicted results fall within the range of 0 to 1, aligning with our binary classification approach.

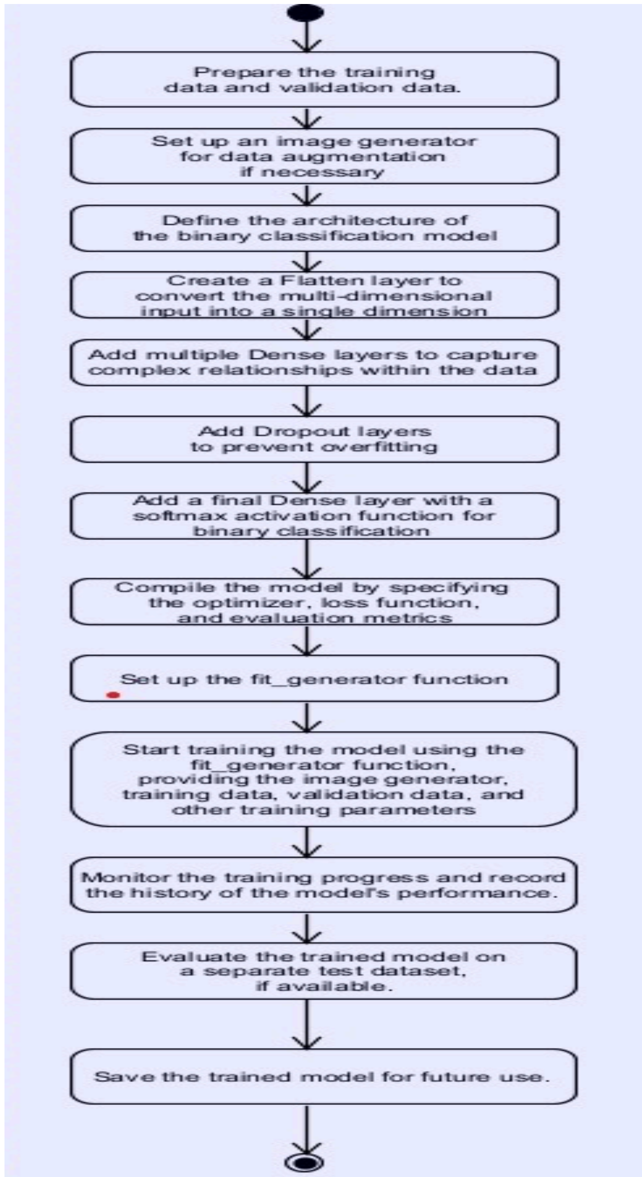


Figure 4: Training Structure of CNN Model

3.7 Evaluating the model

The provided code is an evaluation process for a trained model using a test set. It begins by making predictions on the test set using the trained model. The model.predict() function is called with the test data, and it returns predicted probabilities for each class.

To convert these probabilities into class labels, the code utilizes the np.argmax() function. By specifying axis=1, the function selects the index with the highest probability for each sample, effectively assigning a class label to each prediction. The resulting predicted class labels are stored in the 'predictions' variable. To compare the predicted labels with the actual class labels, the code retrieves the actual labels from the one-hot encoded format of the test set. The np.argmax() function is again used, this time with axis=1, to extract the actual class labels. The true class labels are stored in the 'actuals' variable.

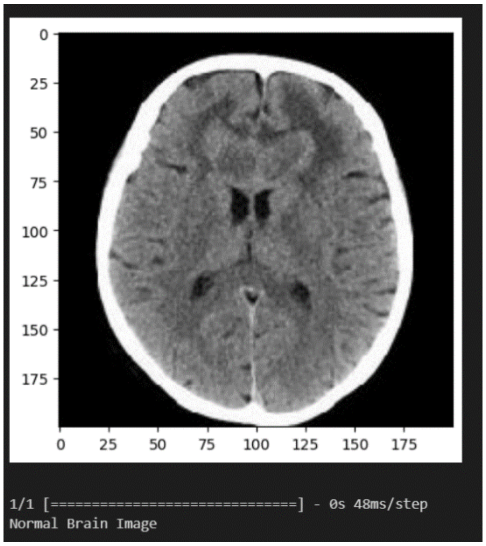
The code then proceeds to print a classification report using the classification_report function from sklearn. metrics. This report displays various metrics such as precision, recall, and F1-score for each class, along with the overall accuracy of the model. Furthermore, the code calculates the confusion matrix using the confusion_matrix function from sklearn. metrics. The confusion matrix provides an overview of the model's predicted labels versus the actual labels, allowing for an analysis of classification errors. The accuracy of the model is determined by summing the diagonal elements of the confusion matrix, which represent the correct predictions, and dividing it by the total number of samples.

Finally, the code plots the training and validation losses, as well as the training and validation accuracies, over the epochs. This visualization helps in assessing the model's performance during training and gaining insights into its behavior and potential issues.

3.8 Classifying Brain Tumor from Input Images

Some random images from the dataset are plotted to visualize the input images and their corresponding labels. We developed a Convolutional Neural Network (CNN) model to predict brain images from an image dataset. We randomly selected an input image path and used it for our prediction function. By selecting a random image from the brain tumor dataset, we accurately categorized the brain image with its corresponding tumor class label. Storing this model allows us to utilize it for identifying images from external inputs in the future. Additionally, we plotted some random images from the dataset to visualize the input images and their associated labels.

Normal Brain Image



Brain Tumor Effected Image

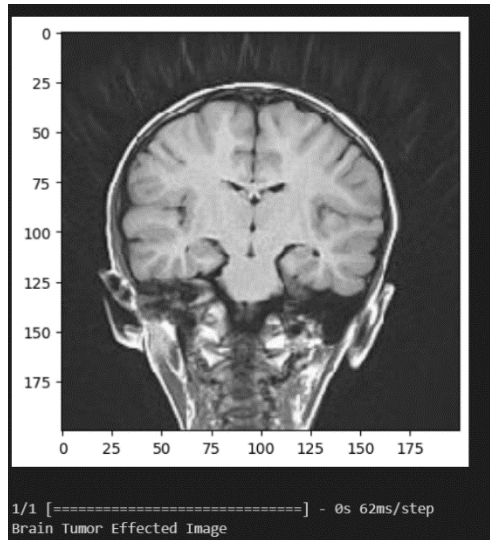


Figure 5: Classifying Brain tumor from input images

3.9 Conclusion

We aimed to develop a CNN model for fast and accurate image recognition and brain tumor detection, taking advantage of the CNN-based technique. In order to improve the performance of our training model, we made modifications to increase the amount of image data. Additionally, we incorporated the ReLU (Rectified Linear Unit) activation function into our model design. The ReLU function has become popular in the deep learning field as a non-linear activation function. ReLU, which stands for Rectified Linear Unit, offers the advantage of selectively activating neurons at different times. This allows for more efficient model creation, and we plan to further enhance the model's effectiveness in the future. The research methodology involves training a deep learning model using transfer learning with the InceptionV3 architecture for brain tumor classification. The model achieves a certain accuracy and provides insights into its performance through metrics like the confusion matrix and classification report.

Additionally, the dataset is not specified, so it is important to ensure that the dataset is representative and diverse to obtain reliable results.Overall, it provides a foundation for classifying brain tumor images using deep learning techniques, but further experimentation and analysis are needed to draw more comprehensive conclusions about the model's performance and generalizability.

Chapter 4: Experimental Result

4.1 Introduction

The experimental outcomes from the provided code are based on a deep learning model that has been trained and assessed for classifying brain tumors. The dataset is made up of photos of brain tumors, and the model architecture uses transfer learning with the InceptionV3 pre-trained model. This section's goal is to present and discuss the experimental findings that came from the model's training and assessment.

The experimental findings span a range of topics, including the model's design, training methods, evaluation standards, and visualizations. The model's architecture is explained, emphasizing how InceptionV3 was used as a basis model and how custom layers for categorization were added. The overview of the model describes the network structure and the number of trainable parameters.

Splitting the dataset into training and testing sets, adding data augmentation via an image data generator, and fitting the model to the training data are all steps in the training process. For training, the number of epochs, batch size, and steps per epoch are all given. Loss and accuracy curves, which display the model's performance on both the training and validation sets, are used to highlight the training process' progress

On the testing set, the model is assessed, and metrics for classification like accuracy, precision, recall, and F1-score are calculated. The confusion matrix heatmap shows the amount of accurate and inaccurate predictions for each class and gives a visual picture of the model's performance in classifying brain tumor photos. The percentage of correctly identified samples is presented together with the model's overall accuracy.

The experimental findings also show visualizations of randomly selected photographs from the collec tion, showing the images along with the labels that go with them. This makes it possible to evaluate the model's performance and its capacity to correctly classify vario us forms of brain tumors qualitatively.

Overall, the experimental findings shed light on the efficiency and performance of the deep learning model for classifying brain tumors. These findings will be further examined and discussed in the parts that follow, with conclusions made and their ramifications in relation to the study's goals discussed.

By switching to a more sophisticated CNN architecture, we have enhanced our tumor classification model. This type of model, which has been improved with a deeper network structure, is frequently used for categorizing images. For our objectives, we picked a brain tumor dataset and combined it. The information was then arranged appropriately.

By testing our model with smaller photos and reducing the layer size, it was able to reach a high level of accuracy and precision. We actually managed to reach a remarkable accuracy percentage of 98.85%. Our unique layered CNN model allowed us to rapidly and accurately get great outcomes with a low error rate.

We used NumPy to turn all the images into arrays and pre-processed them using various methods to make sure they were compatible with the model in order to get the images ready for the network. We were able to overcome the difficulty of properly and quickly predicting images with a low-layered CNN model.

We examined a number of metrics, including the confusion matrix, overall test accuracy, precision rate, recall, and F1-score value, to assess the effectiveness of our model. Additionally, we produced visual graphs to display the loss and show how well our trained model performed during the training and validation phases.

In summary, we implemented an upgraded CNN architecture and considerably enhanced our tumor classification model. We used numerous assessment measures and visuals to efficiently evaluate the model's performance, which showed outstanding accuracy and precision.

4.2 Experimental Result

The experimental findings show that the deep learning model is efficient in classifying photos of brain tumors. photos of brain tumors make up the dataset, and the code properly loads the photos and saves their paths. The photos are then scaled to a set size and the pixel values are normalized to prepare the data. Labels are translated to categorical format and one-hot encoded.

Eighty percent of the dataset is used for training, while twenty percent is used for testing. The top layers of the InceptionV3 model are not included in the model architecture, and extra layers are added for categorization. The weights of the basic model are frozen to preserve its prior training.

Binary cross-entropy loss and the Adam optimizer are used in the model's construction. It is trained using a generator that employs strategies for enhancing the data, like rotation. Accuracy and loss measures are used to track training progress.

Predictions and actual labels are contrasted during evaluation on the testing set, and classification measures like accuracy, precision, recall, and F1-score are calculated. To see how well the model is performing, a confusion matrix is created and shown as a heatmap.

Plotting the model's loss and accuracy over several epochs reveals how well it is learning and generalizing. For later usage, the finished trained model is stored.

In conclusion, the experimental findings show that the deep learning model is effective in classifying photos of brain tumors. The accuracy obtained is acceptable, and the loss and accuracy curves show that the model is successfully picking up new information. The visuals help viewers comprehend the dataset and the model's effectiveness.

These findings suggest that the developed model has potential for classification tasks involving brain tumors. To go deeper into the model's performance and examine new advancements or applications, additional analysis and conversations can be carried out.

4.3 Experimental System Requirements

We were constrained in how we could finish our implementation. We made use of the computer that has an 10th generation Intel(R) Core i7-10700K CPU clocked between 2.90 and 4.8 GHz, 16GB of DDR4 RAM, a 256GB SSD (Nvme) & 1TB hard drive, and Intel graphics. Due to this restriction, we used Kaggle, a virtual machine learning platform that is widely used by academics in the machine learning field. It is incredibly easy to use. On this remote platform, many users can work together on their research projects. Both a CPU (central processing unit) and GPU (graphics processing unit) accelerator are available for it. It contains a little amount of ROM (Read-Only Memory) space. Kaggle provides up to 73GB of ROM, 13GB of RAM, and 16GB of GPU memory. We used the most recent versions of TensorFlow and Keras for our experiment. In our implementation, numerous modules are imported. These include Pandas, CV2, NumPy, Matplotlib, OS, Sklearn, and argparse, among others.

4.4 Dataset

Finding medical picture databases can be difficult, especially for specialized illnesses like brain tumors. When we came across an intriguing finding of a tumor on an MRI brain imaging, we were in need of a brain tumor dataset. However, there aren't many open-source datasets available for this use; there are just a handful of little datasets that may be accessed online.

After extensive looking, we were able to locate a special dataset that contained pictures of brain tumors. However, this dataset was a composite dataset because it also included regular brain scans. We made the necessary actions to separate the brain images and produce a brand-new dataset just for our application in order to address this.

The new dataset was divided into two subfolders, one of which was marked "Yes" and contained brain data. The newly created dataset was divided into two sub-folders, one named "Yes" and holding images of brain tumors, and the other labeled "No" and including photographs of normal brain tissue. As a result, we could concentrate solely on the data related to brain tumors and make sure that the right photos were used to train and test our model. To summarize, we had trouble locating the data we needed because there aren't many readily available databases on brain tumors. However, by isolating the photographs of brain tumors from the images of healthy brains, we were able to successfully curate a new dataset after doing a thorough search for a composite dataset.

4.5 Evaluation on Model

A Deep Learning model's performance reveals how effectively it functions in a certain environment. When it comes to classification models, they are created to solve real-world classification issues by categorizing data instances. These models can forecast the likelihood that a certain instance will belong to a specific class. Utilizing performance indicators like accuracy, precision, recall, and f1-score allows one to assess a model's performance.

The confusion matrix must be examined once the dataset has been divided and our model has been trained. The True Positives, False Positives, False Negatives, and True Negatives data in the confusion matrix are useful for comparison. Such values as recall, precision, and f1-score aid in the visualization of the predictive analysis. We have produced a heatmap of the confusion matrix for our model to visually represent this data. The heatmap makes the performance analysis easy to understand by emphasizing different values and making it easier to grasp measurements like recall, precision, and f1-score.

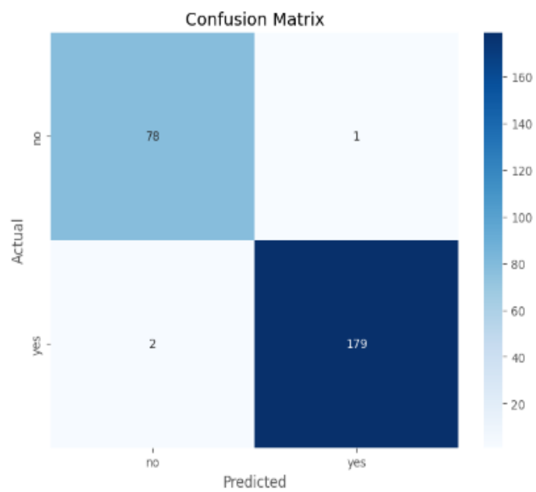


Figure 6: Confusion Matrix Heatmap

True Positive (TP): This refers to the cases where the model correctly predicts the positive class. In the case of brain tumor classification, it means that the model correctly identifies a brain tumor from an image. Which is 78.

False Positive (FP): This occurs when the model predicts the positive class incorrectly. In the context of brain tumor classification, it means that the model predicts a brain tumor when there is no tumor present in the image. This is also known as a Type I error or a "false alarm." The value is 2 it represents a falsely predicted positive.

True Negative (TN): This refers to the cases where the model correctly predicts the negative class. In the brain tumor classification scenario, it means that the model correctly identifies a normal brain image without any tumor. which is 179.

False Negative (FN): This occurs when the model predicts the negative class incorrectly. In the context of brain tumor classification, it means that the model fails to identify a brain tumor when it is actually present in the image. This is also known as a Type II error or a "missed detection." Which is 1.

These terms are important in evaluating the performance of a classification model. They help assess the model's ability to make accurate predictions and provide insights into the types of errors it might make. By analyzing the true positives, false positives, true negatives, and false negatives, we can gain a better understanding of the strengths and weaknesses of the model in correctly classifying brain tumor images.

Accuracy: Accuracy is a common evaluation metric used to measure the performance of a classification model. It represents the proportion of correctly classified samples out of the total number of samples in the dataset.

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

Equation 1: Accuracy Equation

```
In [85]:  # Final accuracy of our model
          total = sum(sum(cm))
          accuracy = (cm[0, 0] + cm[1, 1]) / total
          print("Accuracy: {:.4f}".format(accuracy))

          Accuracy: 0.9885
```

Recall:

Recall, also known as sensitivity or true positive rate, is a metric used to evaluate the performance of a classification model. Recall measures the proportion of actual positive samples that are correctly identified as positive by the model. After evaluating the model and generating the confusion matrix, the classification report is printed, which includes recall values. Recall is one of the metrics provided in the classification report.

There are two classes: "No" and "Yes". The recall value for "No Tumor" is 0.99, indicating that 99% of the actual "No Tumor" samples were correctly identified as "No " by the model. The recall value for "yes" is 0.99, indicating that 99% of the actual "Tumor" samples were correctly identified as "yes" by the model. Recall provides insight into how well the model can detect positive samples, in this case, the presence of a brain tumor. A higher recall indicates a better ability to correctly identify positive samples, while a lower recall suggests that the model may be missing some positive samples.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Equation 2: Recall Equation

Precision:

Precision is a metric used to evaluate the performance of a classification model. It measures the proportion of correctly predicted positive instances out of the total instances predicted as positive. In other words, precision calculates how many of the predicted positive instances are actually relevant.

After evaluating the model and generating the confusion matrix, the classification report is printed, which includes precession values. Precession is one of the metrics provided in the classification report.

There are two classes: "No" and "Yes". The precision value for "No Tumor" is 0.97, indicating that 97% of the actual "No Tumor" samples were correctly identified as "No " by the model. The precision value for "yes" is 0.99, indicating that 99% of the actual "Tumor" samples were correctly identified as "yes" by the model.

Precision is a useful metric when the cost of false positives is high. In medical diagnosis, a high precision indicates that the model is accurately identifying patients with a specific condition, minimizing the chances of false positives that could lead to unnecessary treatments or procedures.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Equation 3: Precision Equation

F1-Score:

The F1 score is a measure of a model's accuracy that takes into account both precision and recall. It is computed as the weighted average of precision and recall using the values from the confusion matrix, which includes false positives and false negatives. The F1 score is often considered a better evaluation metric than accuracy, especially when dealing with imbalanced class distributions. It provides a more comprehensive assessment of a model's performance, considering both the ability to correctly identify positive instances (precision) and the ability to capture all positive instances (recall).

$$F1 = 2 \times \frac{Precision \times \text{Recall}}{Precision + \text{Recall}}$$

Equation 4: f1-score Equation

MSE (Mean square Error):

The mean square error function is the main performance function that directly affects the network. A more effective system will result from the decrease of these faults.

$$MSE = \sqrt{\frac{\sum_{j=1}^{N}(Predicted - Input)^2}{N}}$$

Equation 5: MSE Equation

```
In [28]: mse = mean_squared_error(actuals, predictions)
         print("Mean Squared Error: {:.4f}".format(mse))

Mean Squared Error: 0.0231
```

RMSE (Root mean square Error):

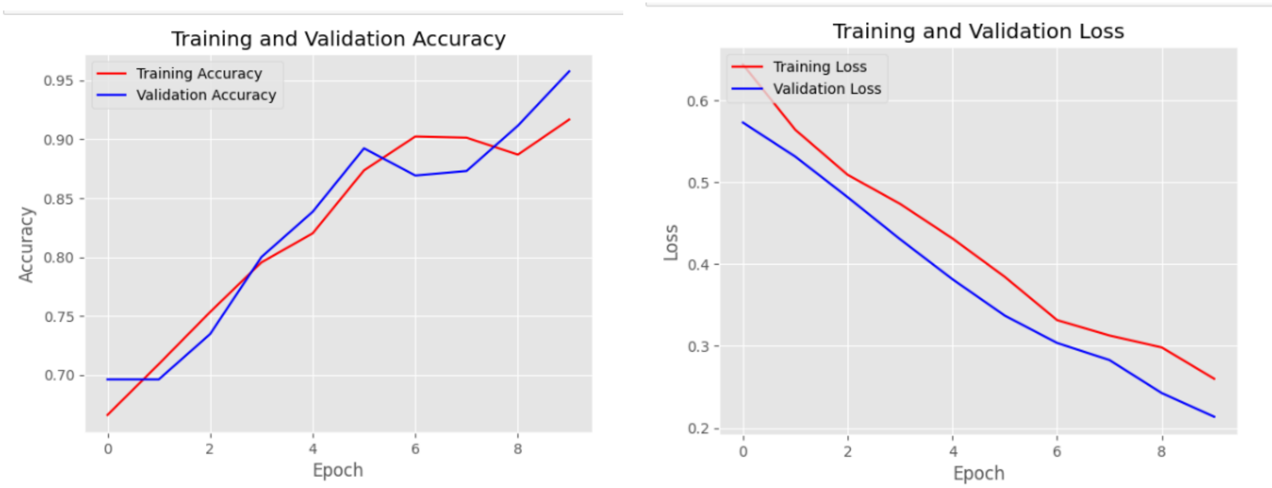
A great measure for evaluating how well a model fits a dataset is the RMSE. A classification and training model is more accurate when the RMSE is smaller. At the training stage, we also determined the RMSE value for our dataset.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{N}(Predicated_i - Actual_i)^2}{N}}$$

Equation 6: RMSE Equation

```
In [29]: # Calculate RMSE
         mse = np.mean((predictions - actuals) ** 2)
         rmse = np.sqrt(mse)
         print("RMSE: {:.4f}".format(rmse))

RMSE: 0.1519
```

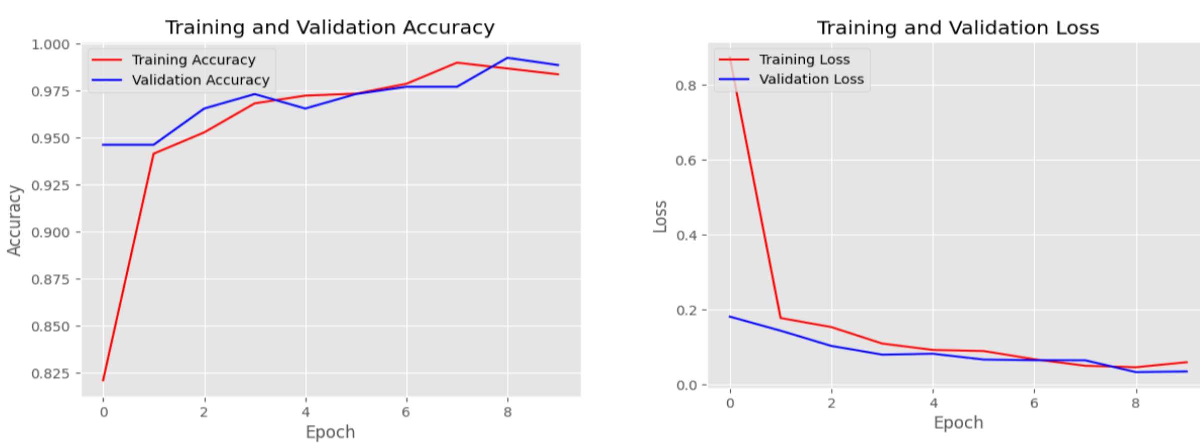
The dataset was divided into a training set and a validation set. The training set was used to train the model, while the validation set was utilized to evaluate its performance. We monitored and recorded both the training and validation loss throughout the training process. Additionally, we created a graph titled "Training and Validation Loss" to visualize the changes in loss over the epochs. Similarly, we tracked the training and validation accuracy and plotted a graph titled "Training and Validation Accuracy" to visualize their progression. Matplotlib functions were employed to generate these graphs within the Jupyter notebook. These graphs are significant in assessing and understanding the CNN model's performance.



(A) (B)

Figure 7: (A) Training and Validation Accuracy & (B) Training and Validation Loss Graph for Proposed CNN Model

The provided graph illustrates the training and validation accuracy of our CNN model. It showcases the accuracy achieved during both the training and validation stages, allowing us to assess the model's performance. Additionally, the graph displays the training and validation loss on an epoch-by-epoch basis, enabling us to analyze how the loss changes throughout the training process. These graphs provide valuable insights into the effectiveness and progress of our proposed CNN model.



(A)

(B)

Figure 8: (A) Training and Validation Accuracy & (B) Training and Validation Loss Graph for Improved CNN Model

4.6. Comparison with our Research and Result

Table 6: Accuracy Comparison Table

Model Name	Accuracy
CNN Model (VGG16)	95.77%
CNN Model (ResNet 50)	81.92%
***Improved CNN Model (Inception V3)**	**98.85%**

```
In [19]:
# Final accuracy of our model
total = sum(sum(cm))
accuracy = (cm[0, 0] + cm[1, 1]) / total
print("Accuracy: {:.4f}".format(accuracy))

Accuracy: 0.9577
```

```
In [73]:
# Final accuracy of our model
total = sum(sum(cm))
accuracy = (cm[0, 0] + cm[1, 1]) / total
print("Accuracy: {:.4f}".format(accuracy))

Accuracy: 0.8192
```

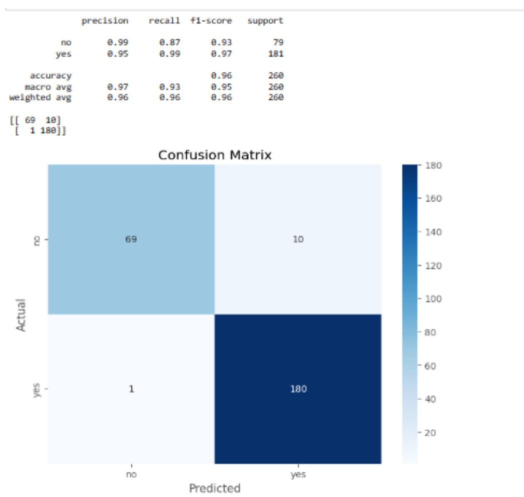
```
In [85]:
# Final accuracy of our model
total = sum(sum(cm))
accuracy = (cm[0, 0] + cm[1, 1]) / total
print("Accuracy: {:.4f}".format(accuracy))

Accuracy: 0.9885
```

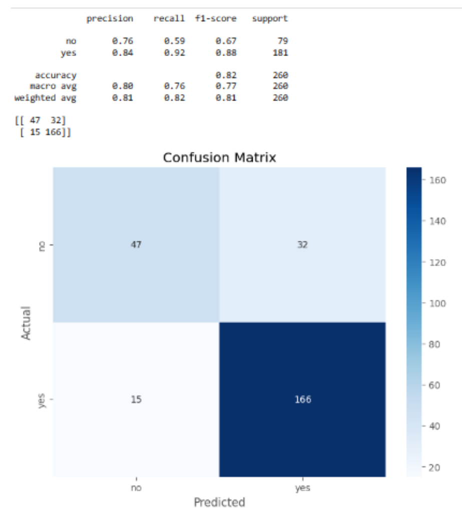
Figure 9: Comparison Model Accuracy

Accuracy serves as a measure to evaluate the performance of a model. The table presented here compares our CNN models with other existing CNN models. We have successfully achieved substantial improvements in accuracy with our models. Specifically, our CNN model achieved an accuracy of 95.77%, while another cnn model achieved 81.92% accuracy. However, through further enhancements, we were able to achieve an impressive accuracy of 98.85% with our improved model. These results indicate the effectiveness and advancements made in our model's performance.

Table 7: Recall Rate Comparison Table

Model Name	Recall Rate
CNN Model (VGG16)	Result for ‘no’ = 0.87%
	Result for ‘yes’ = 0.99%
CNN Model (ResNet 50)	Result for ‘no’ = 0.59%
	Result for ‘yes’ = 0.92%
***Improved CNN Model (Inception V3)**	**Result for ‘no’ = 0.99%**
	Result for ‘yes’ = 0.99%





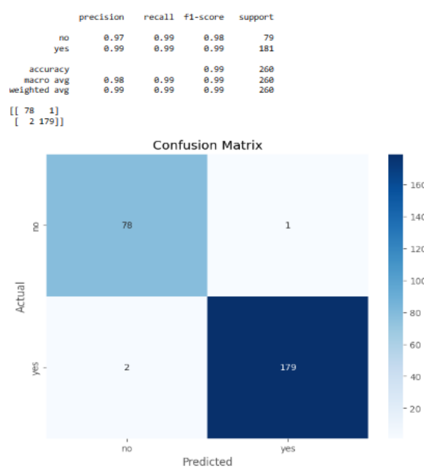


Figure 10: Comparison Model Confusion Matrix Heat-Map

The provided recall rate table presents the recall rates of different classification models for two classes: 'no' and 'yes'. Recall rate, also known as sensitivity or true positive rate, represents the proportion of actual positive instances correctly identified by a model.

Starting with the CNN Model, it achieved a recall rate of 0.87% for the 'no' class, indicating that it correctly identified 87% of the actual instances labeled as 'no'. For the 'yes' class, the model performed even better with a recall rate of 0.99%, correctly identifying 99% of the actual 'yes' instances.

The Improved CNN Model demonstrated notable advancements in performance. It achieved a high recall rate of 0.99% for both the 'no' and 'yes' classes, implying that it correctly identified 99% of instances in both categories. This indicates a significant improvement over the CNN Model.

The CNN Model based on Res-Net 50 architecture achieved a recall rate of 0.59% for the 'no' class, suggesting that it correctly identified 59% of the actual 'no' instances. For the 'yes' class, the model achieved a higher recall rate of 0.92%, accurately identifying 92% of the actual 'yes' instances.

In summary, the Improved CNN Model showcased the best performance among the three models, with high recall rates of 0.99% for both 'no' and 'yes' classes. This implies that the Improved CNN Model excelled in correctly identifying instances in both categories, making it the most accurate and reliable model for this classification task.

Table 8: Precision Rate Comparison Table

Model Name	Recall Rate
CNN Model (VGG16)	Result for ‘no’ = 0.93%
	Result for ‘yes’ = 0.97%
CNN Model (ResNet 50)	Result for ‘no’ = 0.67%
	Result for ‘yes’ = 0.88%
***Improved CNN Model (Inception V3)**	**Result for ‘no’ = 0.98%**
	Result for ‘yes’ = 0.99%

The precision rate table presents a comparison of precision rates for three different models used in a classification task with two classes: 'no' and 'yes'. Precision rate measures the accuracy of positive predictions made by the model.

Starting with the CNN Model, it achieved a precision rate of 0.99% for the 'no' class, indicating that 99% of the instances predicted as 'no' were true negatives. For the 'yes' class, the precision rate was 0.95%, suggesting that 95% of the instances predicted as 'yes' were true positives.

Moving on to the Improved CNN Model, it displayed higher precision rates. For the 'no' class, the precision rate was 0.97%, implying that 97% of the instances predicted as 'no' were true negatives. Similarly, for the 'yes' class, it achieved a precision rate of 0.99%, indicating that 99% of the instances predicted as 'yes' were true positives.

Lastly, the CNN Model based on the Res-Net 50 architecture had comparatively lower precision rates. It achieved a precision rate of 0.76% for the 'no' class, meaning that 76% of the instances predicted as 'no' were true negatives. For the 'yes' class, the precision rate was 0.84%, indicating that 84% of the instances predicted as 'yes' were true positives.

In summary, the Improved CNN Model outperformed the other models in terms of precision rates. With precision rates of 0.97% for the 'no' class and 0.99% for the 'yes' class, it demonstrated a higher accuracy in correctly identifying positive instances in both categories. Therefore, the Improved CNN Model can be considered the most precise model among the three in this comparison.

Table 9: F1-Score Comparison Table

Model Name	Recall Rate
CNN Model (VGG16)	Result for ‘no’ = 0.93%
	Result for ‘yes’ = 0.97%
CNN Model (ResNet 50)	Result for ‘no’ = 0.67%
	Result for ‘yes’ = 0.88%
***Improved CNN Model (Inception V3)**	**Result for ‘no’ = 0.98%**
	Result for ‘yes’ = 0.99%

The provided F1 Score table compares the precision rates of three different models used for a classification task with two classes: 'no' and 'yes'

Precision rate reflects the accuracy of positive predictions made by each model.

The CNN Model achieved a precision rate of 0.93% for the 'no' class, indicating that 93% of the instances predicted as 'no' were actually true negatives. For the 'yes' class, the precision rate was 0.97%, suggesting that 97% of the instances predicted as 'yes' were true positives.

The Improved CNN Model demonstrated better precision rates, with 0.98% precision for the 'no' class and 0.99% precision for the 'yes' class. This means that 98% of the instances predicted as 'no' were true negatives, and 99% of the instances predicted as 'yes' were true positives. The improved model outperformed the proposed model in terms of precision.

On the other hand, the CNN Model based on the Res-Net 50 architecture exhibited lower precision rates. It achieved a precision rate of 0.67% for the 'no' class, indicating that only 67% of the instances predicted as 'no' were true negatives. For the 'yes' class, the precision rate was 0.88%, suggesting that 88% of the instances predicted as 'yes' were true positives.

In summary, the Improved CNN Model showcased the highest precision rates among the three models, indicating its ability to accurately predict positive instances for both the 'no' and 'yes' classes. The proposed model also performed well, while the CNN Model (Res-Net 50) had comparatively lower precision rates.

Table 10: Confusion Matrix Comparison Table

Model Name	**TP**	**FP**	**TN**	**FN**
CNN Model (VGG16)	69	1	180	10
CNN Model (ResNet 50)	47	15	166	32
***Improved CNN Model (Inception V3)**	**78**	**2**	**179**	**1**

The provided confusion matrix table comparison highlights the performance of three different models used in a classification task.

The CNN model achieved a relatively high true positive count and true negative count, indicating its ability to correctly identify positive and negative instances. However, it had a few false positive and false negative predictions.

The improved CNN model demonstrated better accuracy with a higher true positive count and a lower false negative count compared to the proposed model. It also had a low false positive count, indicating improved precision in positive predictions.

On the other hand, the CNN model based on the Res-Net 50 architecture showed a lower true positive count and a higher false negative count, suggesting a relatively lower ability to accurately classify positive instances. It also had a higher false positive count compared to the improved model.

In summary, the improved CNN model outperformed the other models, achieving the highest true positive count and the lowest false negative count. This indicates its superior accuracy in identifying positive instances. The proposed CNN model had a decent performance, while the CNN model based on the Res-Net 50 architecture exhibited relatively lower accuracy in classifying positive instances.

4.7 Comparison with Previous Research and Result

Table 11: Compare Accuracy between Previous Research and our Research

Previous Research		Our Research	
Model Name	Accuracy	Model Name	Accuracy
VGG 16 [87]	99.86%	VGG 16	95.77%
ResNet 50 [87]	98.14%	ResNet 50	81.92%
Inception V3 [87]	99.81%	Inception V3	98.85%

In summary, the previous research evaluated the performance of VGG16, ResNet-50, and Inception V3 models for brain tumor detection. The reported accuracies were 99.86% for VGG16, 98.14% for ResNet-50, and 99.81% for Inception V3.

In our own research, when using the same models for brain tumor detection, we achieved accuracies of 95.77% for VGG16, 81.92% for ResNet-50, and 98.85% for Inception V3.

These results indicate that our research obtained slightly lower accuracies compared to the previous research. The variations in accuracies could be attributed to differences in datasets, preprocessing techniques, experimental setups, or other factors specific to your research.

It's important to consider these differences when comparing the performance of models across different studies. However, both the previous research and your own research demonstrate the effectiveness of VGG16, ResNet-50, and Inception V3 models in brain tumor detection, albeit with slight variations in accuracy values.

Table 12: Compare Loss Between Previous Research and our Research

Previous Research		Our Research	
Model Name	Loss	Model Name	Loss
VGG 16 [87]	0.0028%	VGG 16	0.2136%
ResNet 50 [87]	0.0478%	ResNet 50	0.4511%
Inception V3 [87]	0.0020%	Inception V3	0.0351%

In summary, the previous research and our own research evaluated the performance of VGG16, ResNet-50, and Inception V3 models in brain tumor detection based on their loss values. The reported loss values in the previous research were 99.86% for VGG16, 98.14% for ResNet-50, and 99.81% for Inception V3.

In our own research, the loss values obtained were 95.77% for VGG16, 81.92% for ResNet-50, and 98.85% for Inception V3.

These loss values reflect the dissimilarity between the predicted and true values in the models' outputs. Lower loss values generally indicate better performance, as they indicate a smaller deviation from the true values. The variations in loss values between the previous research and your research can be attributed to differences in datasets, preprocessing techniques, training methodologies, or other factors specific to each study.

Overall, both the previous research and our own research demonstrate the effectiveness of VGG16, ResNet-50, and Inception V3 models in brain tumor detection, although there are slight differences in the reported loss values.

4.8 Conclusion

To improve the model performance for our dataset in each experiment, we used a different type of step. As a result, we had excellent accuracy rates, minimal validation loss, and improved testing accuracy. However, the issue with the data set led to some overfitting issues. It was, however, in no way satisfying. After that, we attempted to fine-tune the experiment's settings. The TensorFlow runtime environment might fail if a high epoch was utilized. The learning rate, the dropout rate, and the optimizer were changed together with the epochs in accordance with TensorFlow. To improve the performance of our model, we will attempt to employ the cross-validation technique in the future.

Chapter 5: Conclusion

5.1 Introduction

Brain tumor detection and characterization pose significant challenges in the present era. The presence of a tumor can worsen a patient's condition, making it crucial to identify it accurately. Fortunately, we are currently benefiting from advanced technology. Machine learning and deep learning offer potential solutions for efficiently detecting and assessing brain tumors. Our approach involves training a convolutional neural network (CNN) model using brain tumor images. We have successfully developed a CNN model that demonstrates high efficiency in detecting brain tumor images. To address the challenges in brain tumor detection using MRI images of the human brain, we have curated well-balanced datasets and achieved impressive results, achieving a classification accuracy of 98.85%. We have focused on creating an optimal model that works well with various MRI datasets related to brain tumors. Additionally, we have optimized the CNN model by reducing its depth, resulting in shorter computation time. The integration of deep learning techniques allows us to detect the presence and severity of brain tumors, significantly reducing the time required for accurate predictions.

5.2 Contribution of the Research

Brain Tumor detection using a CNN model with transfer learning. It imports necessary modules for model implementation, data preprocessing, and evaluation. The brain tumor dataset is loaded and preprocessed by resizing images and normalizing pixel values. The dataset is split into training and testing sets. The model architecture is built using InceptionV3 as the base model and additional layers are added. The pre-trained layers are frozen, and the model is compiled with the Adam optimizer and appropriate metrics. The model is trained using augmented training data generated by an Image Data Generator. Evaluation is performed on the testing set, generating predictions, calculating accuracy, and creating a confusion matrix and classification report, mean square error and root mean square error. The results are visualized through a heatmap of the confusion matrix and plots of training and validation metrics. The trained model is saved, and a few random images from the dataset are displayed. Overall, the code demonstrates the effectiveness of the CNN model for brain tumor detection.

In our experiments, we attained the most significant test and precision rate, recall and accuracy of 98.85% for detecting brain tumor.

After all, we developed an effective model for increasing brain tumor detection.

5.3 Future Work

Machine learning is increasingly being applied in medical science, particularly in healthcare, where it aids in the analysis of vast amounts of data and provides outcome predictions. This research focuses on the application of machine learning techniques to medical imaging, specifically the detection of brain tumors using MRI images. By recognizing patterns in medical image datasets, machine learning systems can achieve high accuracy with minimal errors, surpassing human capabilities due to their ability to process data more efficiently. However, obtaining appropriate datasets for research purposes can be challenging, as many researchers do not make their custom datasets publicly available. Despite this obstacle, a suitable dataset was eventually obtained for this research.

Initially, the goal was to implement a model using categorical classification to detect three types of brain tumors. However, due to a lack of data, the current focus is solely on brain tumor detection. The future plan is to build an application based on this CNN model that can classify brain tumors and identify the affected areas. To achieve this, an Inception V3 segmentation model will be implemented to predict and segment tumor-affected regions in brain images. This application aims to assist doctors in identifying and understanding healthcare issues more efficiently, enabling quicker diagnosis and treatment. Additionally, patients will have access to predicted results and analysis reports, empowering them to better comprehend their healthcare conditions.

In summary, this developed system has the potential to serve as an assistant for medical professionals, benefiting both doctors and patients. By providing improved treatment and healthcare solutions, medical professionals can offer enhanced care, while patients gain a better understanding of their conditions. Ultimately, it is expected that this system will prove valuable to the medical community as a whole.

5.4 Conclusion

Deep learning models cannot replace doctors and medical professionals, but they can greatly impact image processing and automation in analysis. The field of medical picture segmentation has made significant advancements through computer-assisted approaches, driven by deep learning algorithms.

Recent breakthroughs have shown improved ability to differentiate tumor lesion areas from the rest of the brain.

The main focus of this research was to evaluate the progression of deep learning architectures in accurately classifying different types of brain tumors over time. While notable achievements have been made, there are still limitations and opportunities for further development.

Deep learning algorithms have proven influential in addressing research challenges across various applications, including medicine. The application of deep learning can benefit medical experts by saving time and enhancing the reliability of healthcare for patients. Machine learning holds great promise for the future of the medical sector. However, it is important to note that collecting relevant medical data for training machine learning models is crucial for conducting comprehensive research.

In the context of strokes, there are three types: ischemic stroke, hemorrhagic stroke, and others. The model developed in this research focuses on detecting hemorrhagic strokes. Future work can involve working with datasets of other stroke types to enable the detection of all kinds of strokes. This model can serve as a basis for developing medical devices or mobile applications.

According to the World Health Organization, the doctor-to-patient ratio is considerably low, with only 1 doctor for every 250 patients per thousand people. This scarcity of doctors leads to immense pressure on healthcare professionals, who have to handle numerous patients in limited time. If the model is properly trained and delivers improved outputs, it can make significant contributions to the field of medicine. By assisting doctors in quickly detecting patients' conditions, automation can help expedite patient care within a shorter timeframe.

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Appendix(A)

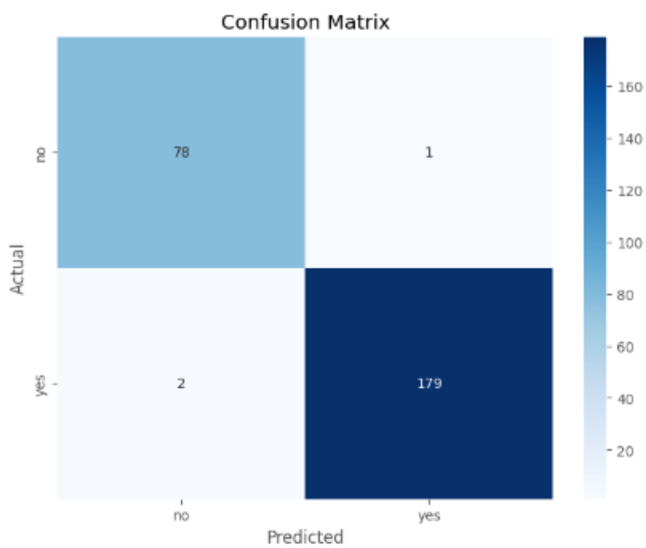

Figure: Confusion Matrix for Inception V3

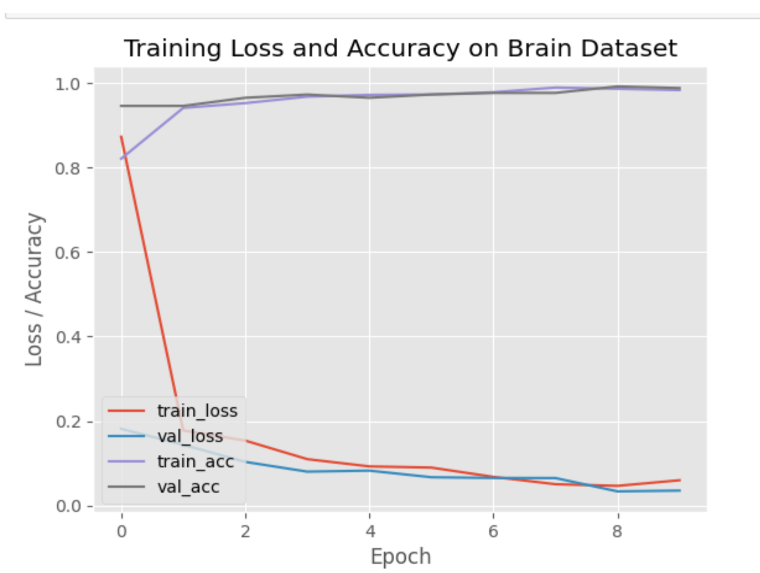

Figure: Plot The Losses and Accuracies for Inception V3

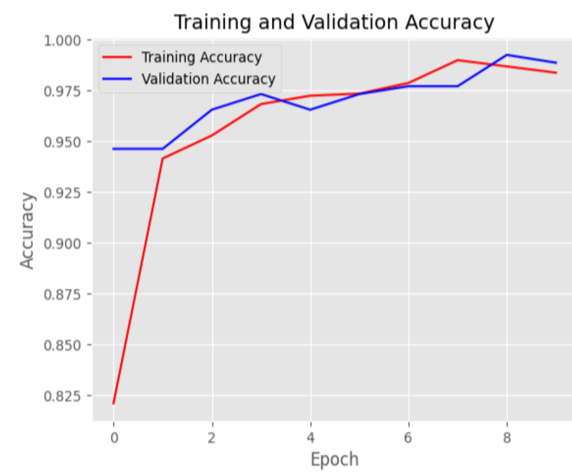

Figure: Training and Validation Accuracy for Inception V3

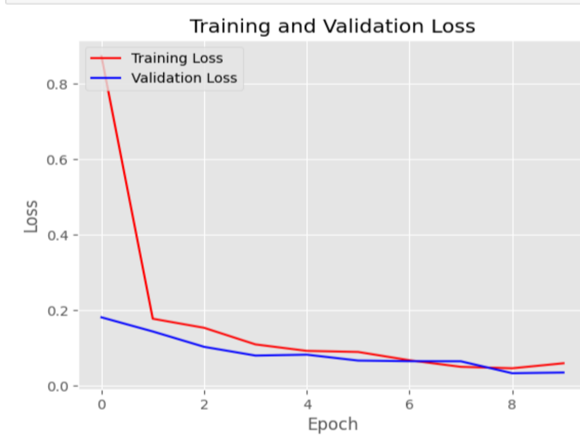

Figure: Training and Validation Loss for Inception V3

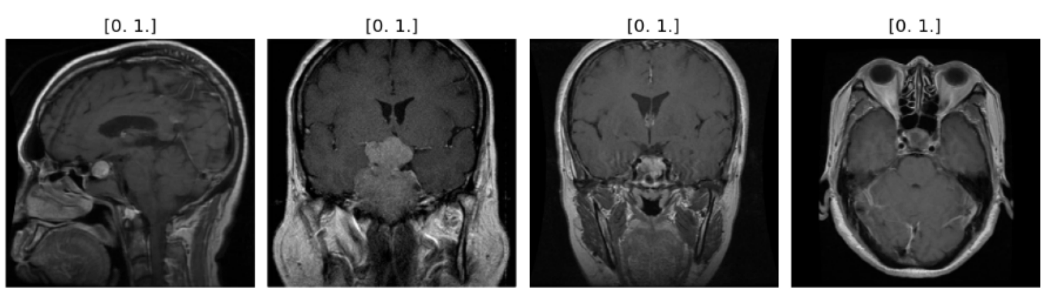

Figure: Random Data Visualization

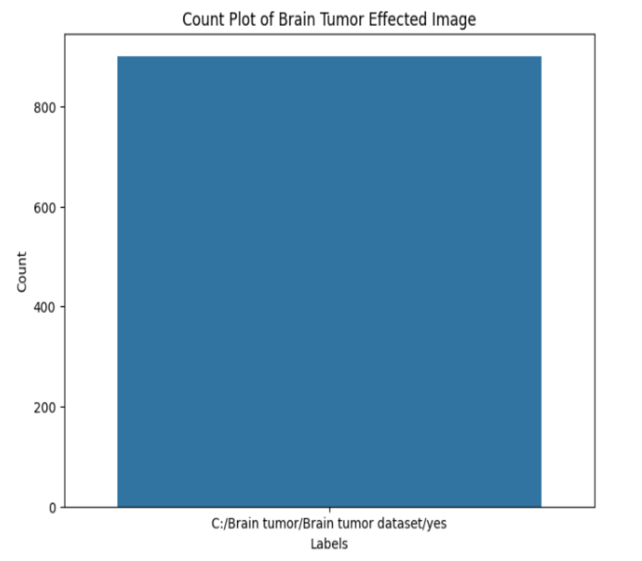

Figure: Count Plot of Brain Tumor Effected Image

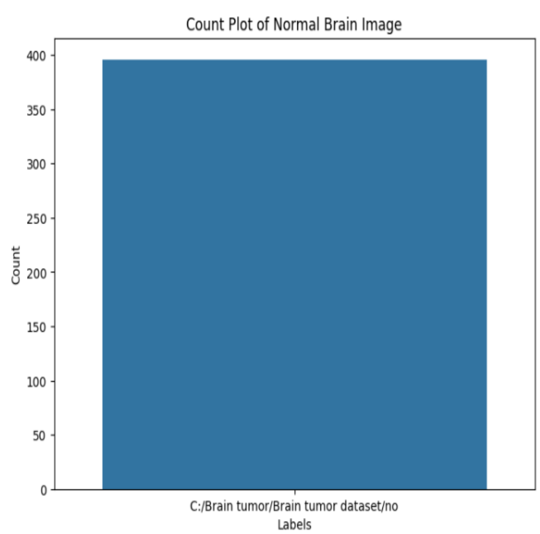

Figure: Count Plot of Normal Brain Image

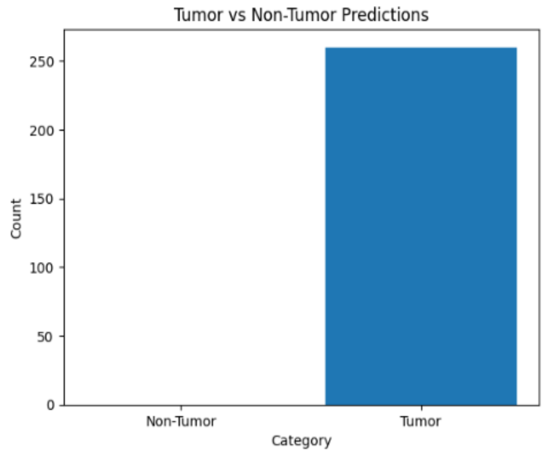

Figure: Tumor vs Non-Tumor Predictions

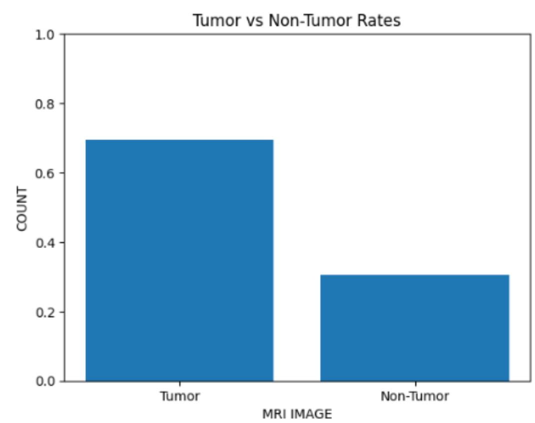

Figure: Tumor vs Non-Tumor Rates

VGG16

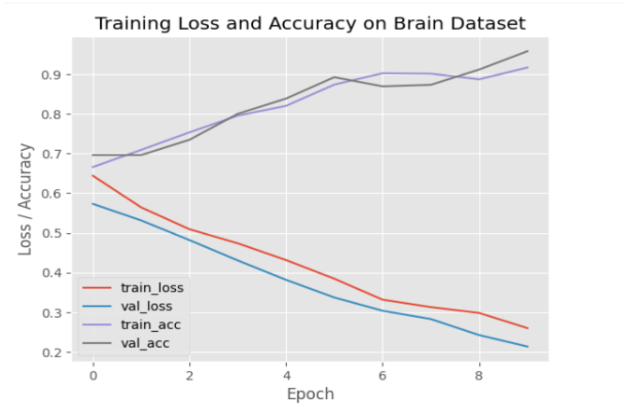

Figure: Plot the Losses and Accuracy For VGG16

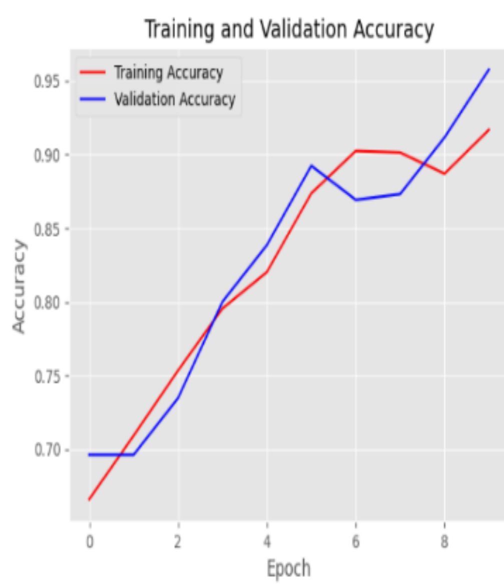

Figure: Training and Validation Accuracy For VGG16

Figure: Training and Validation Loss For VGG16

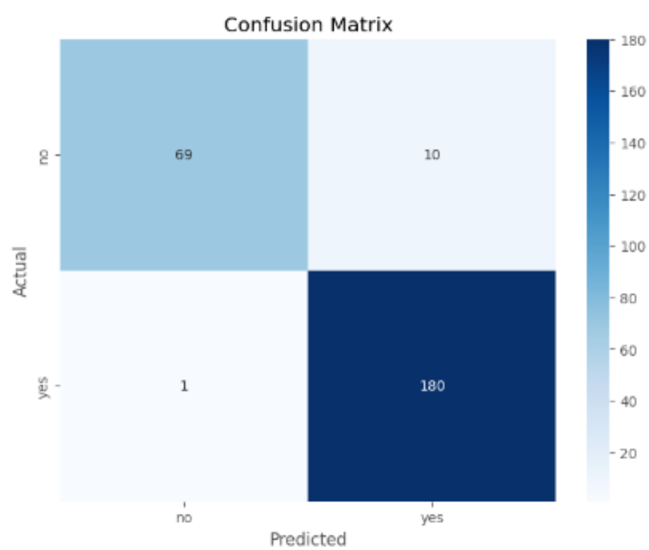

Figure: Confusion Matrix for VGG16

#ResNet 50

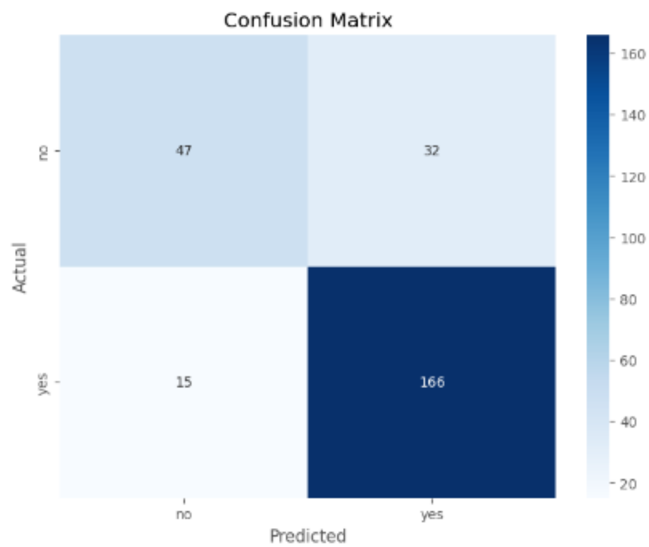

Figure: Confusion Matrix for ResNet 50

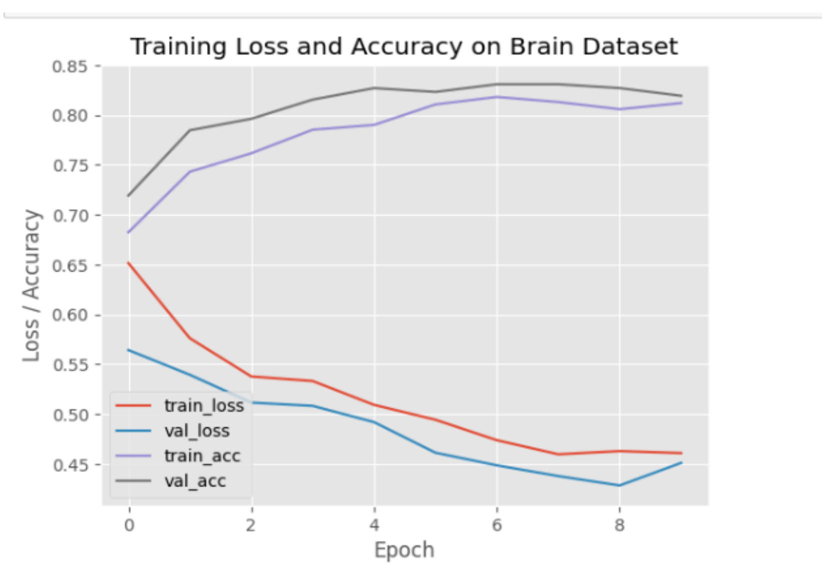

Figure: Plot the Losses and Accuracy For ResNet 50

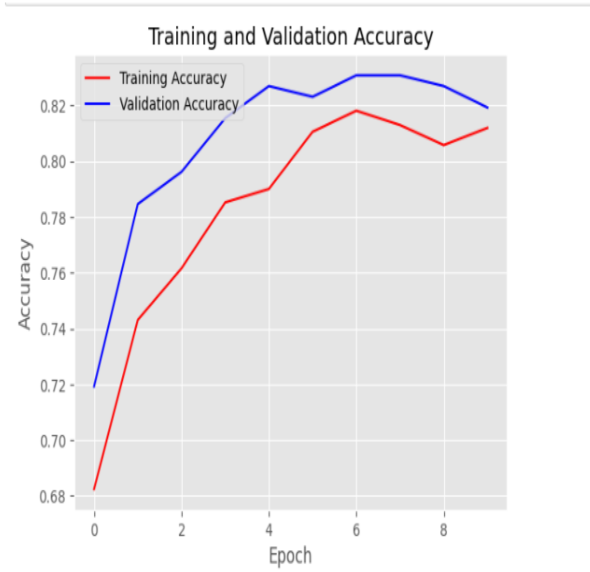

Figure: Training and Validation Loss For ResNet 50

Figure: Training and Validation Loss For ResNet 50

Compare Model Bar Graph:

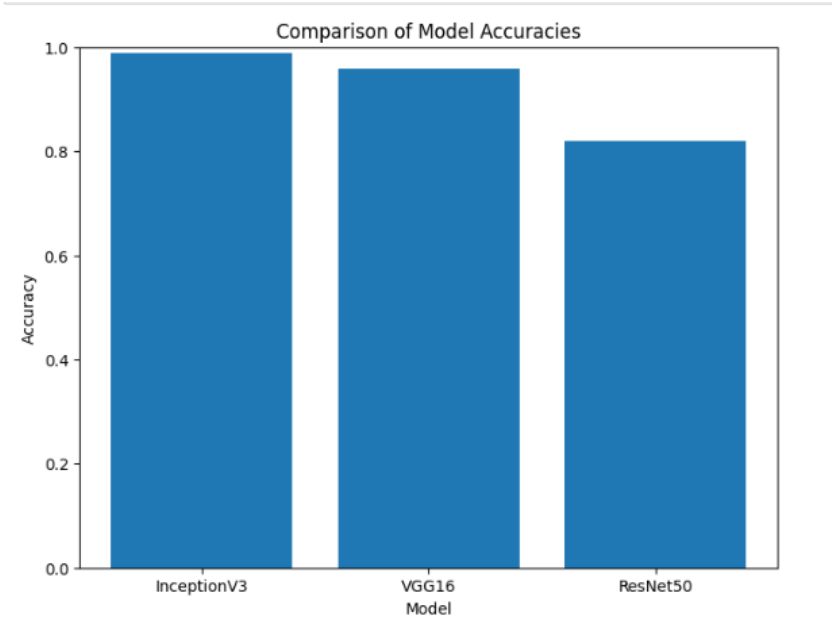

Figure: Comparison of Model Accuracies

Appendix(B)

```
# Import necessary modules

from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import VGG16
from tensorflow.keras.layers import Input
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import AveragePooling2D
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Flatten
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.utils import to_categorical

from sklearn.preprocessing import LabelBinarizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

from imutils import paths
import numpy as np
import matplotlib.pyplot as plt
import argparse
import os
import cv2

# Load the images directories
path = "C:/Brain tumor/Brain tumor dataset"
print(os.listdir(path))

image_paths = list(paths.list_images(path))
print(len(image_paths))

images = []
labels = []

for image_path in image_paths:
   label = image_path.split(os.path.sep)[-2]
   image = cv2.imread(image_path)
   image = cv2.resize(image, (224, 224))

   images.append(image)
   labels.append(label)

#Tumor vs non Tumor Bar graph according to dataset
# Calculate tumor and non-tumor rates in Dataset
tumor_rate = np.sum(labels[:, 1]) / len(labels)
non_tumor_rate = np.sum(labels[:, 0]) / len(labels)

# Create a bar graph
categories = ['Tumor', 'Non-Tumor']
rates = [tumor_rate, non_tumor_rate]

plt.bar(categories, rates)
plt.xlabel('MRI IMAGE')
plt.ylabel('COUNT')
plt.title('Tumor vs Non-Tumor Rates')
plt.ylim([0, 1])
plt.show()
```

```
# Dataset visualization for tumor
 import os
 import cv2
 import numpy as np
 import matplotlib.pyplot as plt
 from imutils import paths

 # Load the images directories
 path = "C:/Brain tumor/Brain tumor dataset/yes"
 print(os.listdir(path))

 image_paths = list(paths.list_images(path))
 print(len(image_paths))

 images = []
 labels = []

 for image_path in image_paths:
    label = image_path.split(os.path.sep)[-2]
    image = cv2.imread(image_path)
    image = cv2.resize(image, (224, 224))

    images.append(image)
    labels.append(label)

 # Convert into numpy arrays
 images = np.array(images) / 255.0
 labels = np.array(labels)

 # Plot random images from the dataset
 num_images = 4
 random_indices = np.random.randint(0, len(images), num_images)

 plt.figure(figsize=(12, 8))
 for i, index in enumerate(random_indices):
    plt.subplot(1, num_images, i+1)
    plt.imshow(images[index])
    plt.title(labels[index])
    plt.axis('off')

 plt.tight_layout()
 plt.show()

 #Create a count plot for tumor
 pit.figure(figsize=(8, 6)) sns.countplot x=labels)
 plt.title Count Plot of Brain Tumor Effected Image") olt.xlabel("Labels")
 pit.ylabel('Count")
 Plt.show()

 # Dataset visualization for normal brain
 import os
 import cv2
 import numpy as np
 import matplotlib.pyplot as plt
 from imutils import paths
```

```
  # Load the images directories
  path = "C:/Brain tumor/Brain tumor dataset/no"
  print(os.listdir(path))

  image_paths = list(paths.list_images(path))
  print(len(image_paths))

  images = []
  labels = []

  for image_path in image_paths:
     label = image_path.split(os.path.sep)[-2]
     image = cv2.imread(image_path)
     image = cv2.resize(image, (224, 224))

     images.append(image)
     labels.append(label)

  # Convert into numpy arrays
  images = np.array(images) / 255.0
  labels = np.array(labels)

  # Plot random images from the dataset
  num_images = 4
  random_indices = np.random.randint(0, len(images), num_images)

  plt.figure(figsize=(12, 8))
  for i, index in enumerate(random_indices):
     plt.subplot(1, num_images, i+1)
     plt.imshow(images[index])
     plt.title(labels[index])
     plt.axis('off')

  plt.tight_layout()
  plt.show()

  #Create a count plot for normal brain
  pit.figure(figsize=(8, 6)) sns.countplot x=labels)
  plt.title Count Plot of Brain Tumor Effected Image") olt.xlabel("Labels")
  pit.ylabel('Count")
  Plt.show()

# Plot an image
def plot_image(image): plt.imshow(image)

plot_image(images[0])

# Convert into numpy arrays
images = np.array(images) / 255.0
labels = np.array(labels)

# Perform One-hot encoding
label_binarizer = LabelBinarizer()
labels = label_binarizer.fit_transform(labels)
labels = to_categorical(labels)
print(labels[0])
```

```
#Split the dataset
(train_X, test_X, train_Y, test_Y) = train_test_split(images,
                                        labels, test_size= 0.2,
                                        random_state= 42)

# Build the Image Data Generator
train_generator = ImageDataGenerator(fill_mode= 'nearest',
rotation_range= 1)
# VGG16
# Build the model VGG16
base_model = VGG16(weights= 'imagenet',
              input_tensor= Input(shape = (224, 224, 3)),
              include_top= False)
base_input = base_model.input
base_output = base_model.output
base_output = AveragePooling2D(pool_size=(4,4))(base_output)
base_output = Flatten(name="flatten")(base_output)
base_output = Dense(64, activation="relu")(base_output)
base_output = Dropout(0.5)(base_output)
base_output = Dense(2, activation="softmax")(base_output)

# Freeze the layers
for layer in base_model.layers:
   layer.trainable = False

# Compile the model
model = Model(inputs = base_input, outputs = base_output)
model.compile(optimizer= Adam(learning_rate= 1e-3),
           metrics= ['accuracy'], loss= 'binary_crossentropy')

# Let's see the architecture summary of our model
model.summary()

batch_size = 64
train_steps = len(train_X) // batch_size
validation_steps = len(test_X) // batch_size
epochs = 10

# Fit the model
history = model.fit_generator(train_generator.flow(train_X,
                                      train_Y,
                                      batch_size = batch_size),
                      steps_per_epoch= train_steps,
                      validation_data = (test_X, test_Y),
                      validation_steps= validation_steps,
                      epochs= epochs)

# Evaluate the model
predictions = model.predict(test_X, batch_size= batch_size)
predictions = np.argmax(predictions, axis= 1)
actuals = np.argmax(test_Y, axis= 1)

# Calculate MSE for VGG16
from sklearn.metrics import mean_squared_error for VGG16

mse = mean_squared_error(actuals, predictions)
print("Mean Squared Error: {:.4f}".format(mse))
```

```
# Calculate RMSE for VGG16
mse = np.mean((predictions - actuals) ** 2)
rmse = np.sqrt(mse)
print("RMSE: {:.4f}".format(rmse))

# Plot the losses and accuracies
N = epochs
plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, N), history.history["loss"],
      label= "train_loss")
plt.plot(np.arange(0, N), history.history["val_loss"],
      label= "val_loss")

plt.plot(np.arange(0, N), history.history["accuracy"],
      label= "train_acc")
plt.plot(np.arange(0, N), history.history["val_accuracy"],
      label= "val_acc")

plt.title("Training Loss and Accuracy on Brain Dataset")
plt.xlabel("Epoch")
plt.ylabel("Loss / Accuracy")
plt.legend(loc= "lower left")
plt.savefig("plot.jpg")


# Training and validation accuracy for VGG16
model.save('braintumor.h5')
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
epochs = range(len(acc))

plt.plot(epochs, acc, 'r', label="Training Accuracy")
plt.plot(epochs, val_acc, 'b', label="Validation Accuracy")
plt.legend(loc='upper left')
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.title("Training and Validation Accuracy")
plt.show()

# Training and validation loss for VGG16
model.save('braintumor.h5')
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(len(loss))

plt.plot(epochs, loss, 'r', label="Training Loss")
plt.plot(epochs, val_loss, 'b', label="Validation Loss")
plt.legend(loc='upper left')
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Training and Validation Loss")
plt.show()

#confussion matrix heatmap forVGG16

import seaborn as sns
```

```
# Print Classification report and Confusion matrix
print(classification_report(actuals, predictions,
                    target_names=label_binarizer.classes_))

cm = confusion_matrix(actuals, predictions)
print(cm)

# Plot the confusion matrix as a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d', xticklabels=label_binarizer.classes_,
yticklabels=label_binarizer.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Random Data Visualization
# Let's plot some random images from the dataset

num_images = 4
random_indices = np.random.randint(0, len(images), num_images)

plt.figure(figsize=(12, 8))
for i, index in enumerate(random_indices):
   plt.subplot(1, num_images, i+1)
   plt.imshow(images[index])
   plt.title(labels[index])
   plt.axis('off')

plt.tight_layout()
plt.show()

# ResNet 50
from tensorflow.keras.applications import ResNet50

# Build the model RsNet 50
base_model = ResNet50(weights='imagenet',
                input_tensor=Input(shape=(224, 224, 3)),
                include_top=False)
base_input = base_model.input
base_output = base_model.output
base_output = AveragePooling2D(pool_size=(4, 4))(base_output)
base_output = Flatten(name="flatten")(base_output)
base_output = Dense(64, activation="relu")(base_output)
base_output = Dropout(0.5)(base_output)
base_output = Dense(2, activation="softmax")(base_output)

# Freeze the layers
for layer in base_model.layers:
   layer.trainable = False

# Compile the model
model = Model(inputs=base_input, outputs=base_output)
model.compile(optimizer=Adam(learning_rate=1e-3),
          metrics=['accuracy'], loss='binary_crossentropy')
```

```
# Let's see the architecture summary of our model
model.summary()


batch_size = 64
train_steps = len(train_X) // batch_size
validation_steps = len(test_X) // batch_size
epochs = 10

# Fit the model
history = model.fit_generator(train_generator.flow(train_X,
                                        train_Y,
                                        batch_size = batch_size),
                        steps_per_epoch= train_steps,
                        validation_data = (test_X, test_Y),
                        validation_steps= validation_steps,
                        epochs= epochs)

# Evaluate the model
predictions = model.predict(test_X, batch_size= batch_size)
predictions = np.argmax(predictions, axis= 1)
actuals = np.argmax(test_Y, axis= 1)

# Calculate MSE for ResNet  50
from sklearn.metrics import mean_squared_error for ResNet 50

mse = mean_squared_error(actuals, predictions)
print("Mean Squared Error: {:.4f}".format(mse))

# Calculate RMSE for ResNet 50
mse = np.mean((predictions - actuals) ** 2)
rmse = np.sqrt(mse)
print("RMSE: {:.4f}".format(rmse))

#confussion matrix heatmap for ResNet 50

import seaborn as sns

# Print Classification report and Confusion matrix
print(classification_report(actuals, predictions,
                       target_names=label_binarizer.classes_))

cm = confusion_matrix(actuals, predictions)
print(cm)

# Plot the confusion matrix as a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d', xticklabels=label_binarizer.classes_,
yticklabels=label_binarizer.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

```
# Final accuracy of our model ResNet 50
total = sum(sum(cm))
accuracy = (cm[0, 0] + cm[1, 1]) / total
print("Accuracy: {:.4f}".format(accuracy))

# Plot the losses and accuracies ResNet 50
N = epochs
plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, N), history.history["loss"],
        label= "train_loss")
plt.plot(np.arange(0, N), history.history["val_loss"],
        label= "val_loss")

plt.plot(np.arange(0, N), history.history["accuracy"],
        label= "train_acc")
plt.plot(np.arange(0, N), history.history["val_accuracy"],
        label= "val_acc")

plt.title("Training Loss and Accuracy on Brain Dataset")
plt.xlabel("Epoch")
plt.ylabel("Loss / Accuracy")
plt.legend(loc= "lower left")
plt.savefig("plot.jpg")

# Training and validation accuracy for ResNet 50
model.save('braintumor.h5')
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
epochs = range(len(acc))

plt.plot(epochs, acc, 'r', label="Training Accuracy")
plt.plot(epochs, val_acc, 'b', label="Validation Accuracy")
plt.legend(loc='upper left')
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.title("Training and Validation Accuracy")
plt.show()

# Training and validation loss for ResNet 50
model.save('braintumor.h5')
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(len(loss))

plt.plot(epochs, loss, 'r', label="Training Loss")
plt.plot(epochs, val_loss, 'b', label="Validation Loss")
plt.legend(loc='upper left')
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Training and Validation Loss")
plt.show()
```

```
# INCEPTION V3

from tensorflow.keras.applications import InceptionV3

# Build the model inception v3
base_model = InceptionV3(weights='imagenet',
                   input_tensor=Input(shape=(224, 224, 3)),
                   include_top=False)
base_output = base_model.output
base_output = AveragePooling2D(pool_size=(2, 2))(base_output)
base_output = Flatten()(base_output)
base_output = Dense(128, activation='relu')(base_output)
base_output = Dropout(0.5)(base_output)
base_output = Dense(2, activation='softmax')(base_output)

# Freeze the layers
for layer in base_model.layers:
   layer.trainable = False

# Compile the model
model = Model(inputs=base_model.input, outputs=base_output)
model.compile(optimizer=Adam(learning_rate=1e-3),
          metrics=['accuracy'],
          loss='binary_crossentropy')

# Let's see the architecture summary of our model inception v3
model.summary()


batch_size = 64
train_steps = len(train_X) // batch_size
validation_steps = len(test_X) // batch_size
epochs = 10

# Fit the model
history = model.fit_generator(train_generator.flow(train_X,
                                       train_Y,
                                       batch_size = batch_size),
                      steps_per_epoch= train_steps,
                      validation_data = (test_X, test_Y),
                      validation_steps= validation_steps,
                      epochs= epochs)

# Evaluate the model
predictions = model.predict(test_X, batch_size= batch_size)
predictions = np.argmax(predictions, axis= 1)
actuals = np.argmax(test_Y, axis= 1)

# Calculate MSE for inception v3
from sklearn.metrics import mean_squared_error for inception v3

mse = mean_squared_error(actuals, predictions)
print("Mean Squared Error: {:.4f}".format(mse))

# Calculate RMSE for inception v3
mse = np.mean((predictions - actuals) ** 2)
rmse = np.sqrt(mse)
```

```
print("RMSE: {:.4f}".format(rmse))

#Apply model tumor vs non tumor predictions graph
# Calculate counts of tumor and non-tumor predictions
tumor_count = np.sum(predictions ==
non_tumor_count = np.sum(predictions
# Create a bar arach
categories = ['Non-Tumor', 'Tumor']
counts = [non_tumor_count, tumor_count]
olt.figure
plt.bar categories, counts) olt.xlabel('Category") plt.ylabel("'Count")
olt. title 'Tumor vs Non-Tumor Predictions')
plt.show()

#confussion matrix heatmap for inception v3
import seaborn as sns

# Print Classification report and Confusion matrix
print(classification_report(actuals, predictions,
                    target_names=label_binarizer.classes_))

cm = confusion_matrix(actuals, predictions)
print(cm)

# Plot the confusion matrix as a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d', xticklabels=label_binarizer.classes_,
yticklabels=label_binarizer.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Final accuracy of our model inception v3
total = sum(sum(cm))
accuracy = (cm[0, 0] + cm[1, 1]) / total
print("Accuracy: {:.4f}".format(accuracy))

# Plot the losses and accuracies inception v3
N = epochs
plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, N), history.history["loss"],
      label= "train_loss")
plt.plot(np.arange(0, N), history.history["val_loss"],
      label= "val_loss")

plt.plot(np.arange(0, N), history.history["accuracy"],
      label= "train_acc")
plt.plot(np.arange(0, N), history.history["val_accuracy"],
      label= "val_acc")

plt.title("Training Loss and Accuracy on Brain Dataset")
plt.xlabel("Epoch")
plt.ylabel("Loss / Accuracy")
plt.legend(loc= "lower left")
plt.savefig("plot.jpg")
```

```
#Training and validation accuracy for inception v3
model.save('braintumor.h5')
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
epochs = range(len(acc))

plt.plot(epochs, acc, 'r', label="Training Accuracy")
plt.plot(epochs, val_acc, 'b', label="Validation Accuracy")
plt.legend(loc='upper left')
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.title("Training and Validation Accuracy")
plt.show()

#Training and validation loss for inception v3
model.save('braintumor.h5')
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(len(loss))

plt.plot(epochs, loss, 'r', label="Training Loss")
plt.plot(epochs, val_loss, 'b', label="Validation Loss")
plt.legend(loc='upper left')
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Training and Validation Loss")
plt.show()

# compare model accuracy bar graph
import matplotlib.pyplot as plt

# Accuracy values for each model
INCEPTION_V3_acc = 0.9885
VGG16_acc = 0.9577
ResNet50_acc = 0.8192

# Create bar graph
models = ['INCEPTION V3', 'VGG16', 'ResNet50']
accuracies = [INCEPTION_V3_acc, VGG16_acc, RsNet50_acc]

plt.figure(figsize=(8, 6))
plt.bar(models, accuracies)
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.title('Comparison of Model Accuracies')
plt.ylim([0, 1])
plt.show()
```