ENHANCING BRAIN TUMOR DETECTION WITH ROYAL FILTER AND BTV19 MODEL

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APPROVAL

This Project titled "**Enhancing Brain Tumor Detection with Royal Filter and BTV19 Model**", submitted by Sadia Hossain, ID No: 201-15-3171 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 26 January 2024.

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I hereby declare that this project has been done by me under the supervision of **Md Zahid Hasan, Assistant Professor, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

This work aims to enhance brain tumor diagnosis accuracy by examining crucial aspects of cleaning and filtering MRI datasets, emphasizing the novel integration of Royal filtering with the VGG19 architecture. It employs advancements in medical image processing and deep learning to address challenges in using MRI for detecting brain malignancies. The process begins by acquiring diverse brain MRI datasets. A systematic cleaning protocol is applied, including conversions to grayscale, Gaussian blurring, thresholding, morphological opening, and largest shape extraction. Royal filtering, in both 16-color and royal versions, is a crucial step. The dataset is split 80/20 into training and testing sets. Models undergo training and testing to evaluate various deep learning architectures: VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2, EfficientNetV2L, EfficientNetV2M, ResNet50, and Royal VGG19. Royal VGG19 is best with 98.91% accuracy. Ablation research on VGG19 provides insights into each component's functionality. The proposed BTV19 model combines optimal preprocessing and Royal filtering with VGG19. The research establishes a new framework for precise brain tumor diagnosis and contributes by examining preparation and filtering techniques' impact on deep learning efficacy. Findings were assessed using confusion matrices, ROC-AUC curves, and k-fold cross-validation. Experiments show the proposed BTV-19 model exhibits stability and reliability in improving brain tumor diagnosis accuracy. This work significantly advances medical image quality and deep learning applications, ultimately improving healthcare outcomes.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

An abnormal development of cells or a mass that occurs inside the brain or the central spinal canal is referred to as a brain tumor. There are two types of tumors: benign, which are not cancerous, and malignant, which are cancerous [1]. They might be the consequence of cancer that has spread from other regions of the body (also known as metastatic or secondary tumors), or they can develop from the tissue of the brain itself (referred to as primary tumors) [1].The symptoms of a brain tumor can change depending on the shape, size, and location of the tumor. Headaches, seizures, trouble speaking or interpreting language, changes in personality or behavior, visual issues, and other symptoms may be among the most common experiences of those who have schizophrenia [2].Secondary tumors, which are also frequently referred to as brain-spread tumors, are typically caused by tumors that are located outside of the brain, while primary tumors originate entirely inside the brain [1].Three primary forms of brain tumors are most often encountered: gliomas, meningiomas, and adenomas which are located in the pituitary gland [3]. A meningioma is a slow-growing tumor that begins in the membranes that wrap the spinal cord or the brain and proceeds to spread throughout the body [3].Do you know what pituitary adenomas are? According to [4], these are cancers that originate in the pituitary gland.Brain cells are subjected to pressure as a result of the uneven growth of these tumors. Stress is a major contributor to a wide variety of brain diseases, many of which are detrimental to your health [5].Neurons and glial cells have a collaborative relationship in the brain, which is responsible for the regulation of our consciousness [6].The delicate equilibrium of the brain may be disrupted when new cells begin to proliferate in the brain. The presence of brain tumors is one form of alteration that makes things difficult for both the researchers who study them and the individuals who have them [7].The objective of this research is to get a deeper understanding of brain tumors by determining the factors that lead to their development, investigating the many diagnostic approaches, and analyzing how treatment options are always evolving [7].Those cells that proliferate within the brain are the components that make up brain tumors [8]. When it comes to their origins and how they function, they are quite intricate. Because its development is influenced by a variety of elements, including environmental conditions and intricate molecular pathways, each instance is a distinct biological organism all on its own [8].It is necessary to have a grasp of these foundations to determine how they originate and develop, as well as to devise remedies that are specific to the condition [8].In the past, it was difficult to determine whether or not a person had brain development [9]. The success of this endeavor may be attributed to the use of cutting-edge imaging technology and molecular diagnostics.This research investigates the evolution of diagnostic procedures throughout the course of history, beginning with the advent of radiography and continuing up to the current day, when genetic profiling and magnetic resonance imaging (MRI) are routinely used [10].In addition to this, it takes a detailed look at the issues that are associated with the techniques that are currently being used, which makes it possible to investigate approaches that are more accurate and might assist in the early detection of conditions and the proper classification of them [10].Cell development has the potential to disrupt the delicate equilibrium of the brain, which may lead to a variety of problems [11]. The treatment of brain tumors, which are one sort of this kind of disease, is very challenging for both the scientific community and the individuals who suffer from them.In addition to several other things, the purpose of this research is to investigate the world of brain malignancies by determining what causes them and how to screen for them successfully [12]. When it comes to how they begin and how they behave, brain tumors are quite intricate things. They extend using the proliferation of cells inside the cranium. The treatment options vary according to the kind of tumor, its location, and its stage [13].When it comes to monitoring and controlling brain tumors, it is essential to undergo imaging checks and follow-up examinations regularly at a facility that is directed by a physician. Medical imaging and diagnostic procedures have advanced significantly as a result of the incidence of brain tumors and their effects on human health [14].Brain tumors are abnormal cell growths within the brain that may take on a variety of shapes and sizes [14]. As such, diagnosing and treating brain tumors can be quite difficult. These tumors, which include pituitary tumors, meningiomas, and gliomas among others, are categorized according to their origin, behavior, and tissue of origin [15].The intricacy of brain tumors stems from both their variety and the complex architecture of the brain, which makes identifying and characterizing them difficult. The serious repercussions of misdiagnosis and postponed treatment highlight the pressing need for accurate diagnostic instruments [15].As a vital technique for the non-invasive assessment of brain disorders, magnetic resonance imaging (MRI) provides rich structural information that is essential for a precise diagnosis. However, difficulties still exist in improving the precision of brain tumor detection, which is why cutting-edge methods based on deep learning and image processing are being investigated [15].Within this framework, our work focuses on the crucial interactions between deep learning techniques, medical image analysis, and the preprocessing stages used on Brain MRI datasets [15].Our procedure starts with a thorough curation of a large Brain MRI dataset, which is then carefully processed via some processes to maximize its deep learning algorithm applicability [15].Using morphological opening, thresholding, Gaussian blur, grayscale conversion, and contour extraction to select pertinent features are all steps in the preprocessing workflow [15].Specifically, we explore the new use of a 16-color filtering technique to improve the discriminative characteristics in the MRI pictures [15].Then, to assess the effectiveness of cutting-edge deep learning architectures, such as VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2, EfficientNetV2L, EfficientNetV2M, and ResNet50, the dataset is divided into training (80%) and testing (20%) sets [15].Our research's conclusions show that combining VGG19 with a special royal filtering method—known as the "Royal" filter—achieves an astounding 98.91% accuracy [15].We do ablation research on VGG19 to confirm the resilience of our proposed model and further demonstrate its effectiveness in accurately diagnosing brain tumors [15].A detailed evaluation of the performance of the suggested model is provided by the extensive results analysis, which includes statistical measurements, confusion matrices, ROC-AUC curves, and K-Fold cross-validation [15].Our study's conclusion offers a promising addition to the field and may have ramifications for the development of precise and effective brain tumor diagnosis, providing the groundwork for better patient outcomes and therapeutic approaches [15].

1.2 Motivation of research

The accurate and timely detection of brain tumors is of the highest significance in the area of medical diagnostics. This is because it is essential for the effective treatment of patients and the outcomes of their illnesses. Our research, which studies the confluence of medical image analysis with deep learning, focuses specifically on brain MRI datasets and was motivated by the need to enhance the accuracy of brain tumor diagnosis. Specifically, our investigation focuses on the identification of brain tumors. Since we are aware of the significant part that preprocessing plays in the process of enhancing picture quality, we start by conducting an in-depth analysis of the impact that various preprocessing techniques have. These techniques include grayscale conversion, Gaussian blur, thresholding, morphological opening, and contour extraction. Our goal is to improve the model's capacity to differentiate between various characteristics and to optimize the extraction of features by using complex filtering methods, in particular revolutionary 16-color filtering and royal filtering. This will allow us to achieve our target. After applying a broad range of deep learning architectures, such as VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2, EfficientNetV2L, EfficientNetV2M, and ResNet50, our procedure involves the segmentation of the dataset into training and testing sets. This is done in follow-up to the application of these architectures. The application of the dataset comes next after this in the process. Through rigorous analysis, we can reach an incredible accuracy of 98.91%, which permits us to determine that the VGG19 filter has a greater performance than the Royel filter. To gain a more comprehensive understanding of our proposed model, BTV19, and establish whether or not our model is successful, we conduct an ablation experiment on VGG19. The results of the study provide evidence that the integrated components are relevant, hence reinforcing the robustness and effectiveness of the model that we have proposed. In the process of performing the analysis of the data, we make use of a comprehensive method that incorporates statistical analysis, confusion matrix, ROC-AUC curve, and K-fold cross-validation. This enables us to give a comprehensive review of the performance of the model, which would not have been feasible otherwise. Not only does our research provide a contribution to the field of accurate brain tumor diagnosis, but it also presents a novel and much improved deep learning model that we have dubbed BTV19. There is a possibility that this model may enhance clinical results and contribute to the advancement of the current state of the art in medical image analysis.

1.3 Rationale of the study

The objective of this research project, which was given the title " Enhancing Brain Tumor Detection: A Novel Approach with Royal Filter and BTV19 Model" was to address the pressing need for accurate and efficient brain tumor diagnosis by utilizing cutting-edge methods of medical image analysis. An increasing number of people are using magnetic resonance imaging (MRI) to find brain tumors. However, the accuracy and dependability of diagnostic models depend a lot on the preprocessing steps and feature extraction methods that are used. By concentrating on preprocessing methods such as grayscale conversion, Gaussian blur, thresholding, morphological opening, and identifying the largest contour, the purpose of this research is to improve the quality of the input data. This will ensure that the subsequent deep learning models receive information that has been optimized for accurate tumor identification. The use of 16-color filtering is a further extension of the investigation into the methodological approaches to feature extraction. The research investigates the performance of several different deep learning architectures on a dataset that has been preprocessed and filtered. These architectures include VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2, EfficientNetV2L, EfficientNetV2M, and ResNet50. VGG19 with royal filtering is chosen as the best model after being subjected to extensive testing, which ultimately results in the development of the BTV19 model that is being suggested. Through the use of the ablation study on VGG19, it is possible to get a comprehensive comprehension of the relevance of each component associated with the model. By reaching an outstanding accuracy of 98.91%, the findings demonstrate that BTV19 with royal filtering is better than other methods. In addition to being confined to accuracy measurements, the results of the research include a full analysis that includes statistical assessments, confusion matrices, ROC-AUC curves, and K-fold cross-validation. They are not limited to accuracy measures alone. In the field of medical image analysis, the study guarantees a robust validation of the proposed model by diving into these many assessment criteria. This establishes the model's credibility and usefulness in the field. In the end, this study makes a contribution to the development of techniques for diagnosing brain tumors. It also offers a significant foundation for future research and the possibility of incorporating it into clinical practices in order to improve patient care and treatment planning.

1.4 Research Questions

- How can Gaussian blur, thresholding, and morphological opening improve brain tumor diagnosis in MRI images?
- How does grayscale brain MRI pictures affect deep learning models like VGG19 tumor detection?
- How does 16-color filtering affect brain tumor classification use deep learning architectures?
- Why is partitioning the dataset into training and testing sets (80% and 20%, respectively) important for brain tumor detection deep learning models?
- How does the VGG19 ablation research help determine which components contribute to the highest accuracy, notably in the royal filter?
- Does the statistical analysis reveal the performance and reliability of BTV19, particularly compared to other deep learning architectures?
- How can assessment measures like Confusion Matrix, ROC-AUC Curve, and K-Fold Cross Validation improve robustness and generalizability, especially with the Royel filter in BTV19?

By addressing these research questions, the study aimed to contribute towards developing a more reliable and effective diagnostic tool for brain tumor, empowering healthcare professionals with reliable tools that can enhance diagnosis, improve patient outcomes, and potentially save lives. The findings could be useful to researchers and practitioners working in this field, paving the way for more personalized and effective healthcare solutions.

1.5 Report Layout

This report comprises six chapters, which are briefly outlined below:

In Chapter 1, we provide an overview of the research on machine learning algorithms in the early detection of liver diseases. The research questions, motivation of this study, rationale, and expected output have been discussed in detail. In chapter 2 we review the literature which discusses the existing work on machine learning algorithms in healthcare with a focus on liver disease diagnosis. The chapter reviews the approaches, limitations, results, and methods used by other authors. It also highlights the research scope and challenges in the area of early detection of liver diseases using machine learning algorithms. In chapter 3 we describe the research methodology used in this study. The data collection procedure and statistics of the dataset have been discussed in detail. The classifiers and implementation requirements used have also been presented. In chapter 4 we present the results obtained from the implementation of various machine learning algorithms on the liver disease dataset. The accuracy, precision, recall, and F1 score of each classifier have been reported. In Chapter 5 we discuss the impact of machine learning algorithms in the early detection of liver diseases on patient outcomes and healthcare costs has been discussed in this chapter. The importance of this work and its potential to contribute towards improving public health has also been highlighted. In chapter 6 we provide a discussion of the results obtained from the study and their implications. The future work and limitations of this research have also been discussed. The conclusion of the research and its significance in the context of healthcare have been presented.

CHAPTER 2
BACKGROUND

2.1 Introduction

In this section, we will delve into the current state of research about liver disease. Despite the vast amount of literature available on the topic, we have identified key studies that provide valuable insights into detecting and treating liver disease. These studies have employed a range of different approaches, from experimental methods to clinical trials, to better understand the mechanisms behind liver disease and develop effective treatments. However, as with any field of research, certain limitations and errors must be taken into account when interpreting the results of these studies. Through careful analysis of the available research, we hope to provide a comprehensive overview of the current state of knowledge regarding liver disease and its treatment options.

2.2 Related Work

A literature review is a crucial aspect of researching brain tumors, as it enables researchers to gain an understanding of the current knowledge on the subject and identify gaps in that knowledge. Medical Image Analysis (MIA) has witnessed remarkable progress in recent years, particularly in the domain of brain tumor detection using Magnetic Resonance Imaging (MRI) datasets. The integration of Deep Learning (DL) techniques has played a pivotal role in enhancing the accuracy and efficiency of tumor identification. This literature review explores the current state of research within this intersection of Medical Image Analysis, Deep Learning, and Brain MRI datasets with a specific focus on brain tumor detection.

Chetana Srinivas et al. [16] conducted a study on deep transfer learning approaches for brain tumor classification using MRI images, comparing the performance of CNN-pretrained VGG-16, ResNet-50, and Inception-v3 models for automatic prediction of brain tumor cells. The VGG-16 pretrained model showed promising results in accuracy, but the study did not discuss any limitations or weaknesses.

Radio physiomics [17] is a new approach that combines machine learning algorithms with physiological MRI data for the classification of contrast-enhancing brain tumors. The authors show that radio physiomics can be helpful in routine clinical diagnostics of these tumors, but further automation using deep neural networks is required.

A hybrid CNN-SVM [18] threshold segmentation approach for tumor detection and classification of MRI brain images was proposed, showing significant improvement in accuracy with an overall accuracy of 98.4959%. The dataset used in the study is the BRATS 2015 imaging dataset, obtained from BRATS 2012 and 2013.

Anil Kumar Budati and Rajesh Katta [19] proposed an automated brain tumor detection and classification system using machine learning techniques with IoT, which consists of four steps: preprocessing, segmentation, feature extraction, and classification. The system achieves high accuracy in detecting and classifying tumorous and non-tumorous regions in brain MRI images.

Hareem Kibriya, Mina Masood, Marriam Nawaz, and Tahira Nazir [20] proposed a 13-layer CNN architecture for classifying brain tumors from MRI scans, achieving the highest accuracy of 97.2% on a benchmark dataset of 3064 MRI images of three different types of brain cancer (glioma, pituitary, and meningioma). They also created a lightweight CNN architecture with fewer layers and learnable parameters that can reliably detect tumors in MRI images in the shortest amount of time.

Takowa Rahman and Saiful Islam [21] proposed a parallel deep convolutional neural network (PDCNN) topology for MRI brain tumor detection and classification, achieving high accuracy rates of 97.33%, 97.60%, and 98.12% for three different MRI datasets.

Riddhi Chawla, Shehab Beram, Ravindra Murthy, T Thiruvenkadam, N Bhavani, R Saravanakumar, and P Sathishkumar [22] proposed a brain tumor recognition system that combines the Bat Algorithm with a Convolutional Neural Network (CNN) approach, achieving a 99.5% accuracy rate in detecting brain tumors in MRI images.

Neuroscience Informatics authors Arkapravo Chattopadhyay and Mausumi Maitra[23] proposed an algorithm for segmenting brain tumors from 2D MRI images using a convolutional neural network (CNN) followed by traditional classifiers and deep learning methods. The algorithm achieved an impressive accuracy of 99.74%, outperforming previous results. The 2020 BraTS dataset consisted of 2892 images with different types of tumors. The authors also applied SVM classifier and activation algorithms such as softmax, RMSProp, and sigmoid for cross-checking the results.

Nahid Ferdous Aurna, Mohammad Yousuf, Abu Kazi, Taher, A Azad, and Mohammad Moni proposed [24] a novel approach using a two-stage feature ensemble of deep Convolutional Neural Networks (CNN) for the classification of brain tumors. The study aimed to improve and speed up the manual diagnosis process through an automated Computer Aided Diagnosis (CADx) system. The proposed model achieved an average accuracy of 99.13% by optimizing the developed algorithms.

Agus Minarno, Setiyo Kantomo, Fauzi Dwi, Setiawan Sumadi, Hanung Nugroho, and Zaidah Ibrahim [25] conducted a study on the classification of brain tumors on MRI images using DenseNet and Support Vector Machine (SVM) algorithms. They utilized a large number of brain tumor MRI imaging datasets to train and test the model. The deep learning model DenseNet 201 paired with SVM achieved an accuracy of 99.65%.

Haitham Alsaif, Ramzi Guesmi, Badr Alshammari, Tarek Hamrouni, Tawfik Guesmi, Ahmed Alzamil, and Lamia Belguesmi [26] presented a detailed review of CNN architectures and proposed an efficient method for detecting brain tumors using MRI datasets. They utilized the VGG-16 model and data augmentation techniques to improve detection accuracy.

Ayesha Younis, Li Qiang, Charles Okanda Nyatega, Mohammed Adamu, and Halima Bello Kawuwa [27] proposed a brain tumor analysis approach using deep learning and VGG-16 ensembling learning. The approach outperformed conventional methods, achieving high precision and accuracy. The proposed approach achieved excellent accuracy, with the CNN model achieving 96%, VGG-16 achieving 98.5%, and the ensemble model achieving 98.14%.

Wu Qiu, Hulin Kuang, Alejandro Speck-Planche, Rimsha Asad, Saif Ur Rehm, Azhar Imran, Jianqiang Li, Abdullah Almuhaimeed, and Abdulkareem Alzahrani [28] proposed a deep convolutional neural network with stochastic gradient descent (SGD) optimization algorithm for the early detection of brain tumors. The model achieved high accuracy of 99.82% and 99.5% for training and testing, respectively.

A study by Saeedi, Rezayi, Keshavarz, and Kalhori [29] proposed two deep learning methods and machine learning approaches for diagnosing brain tumors using MRI images. The proposed 2D CNN outperformed other methods, with a training accuracy of 96.47% and an average recall value of 95%. The network is less complex than the auto-encoder network, suitable for radiologists and physicians.

2.3 Research Summary

The aim of this study, which is called "Towards Accurate Brain Tumor Diagnosis: Investigating the Role of MRI Dataset Preprocessing and Royal Filtering with VGG19," is to improve the accuracy of brain tumor diagnosis. To do this, a full analysis of medical imaging is being carried out. For this study, a dataset consisting of brain MRI scans is used, and an extremely stringent method is utilized to preprocess the data and extract features that are of significance. As part of the preparation step, the images are transformed into grayscale, a Gaussian blur is applied, thresholding is carried out, a morphological opening is found, and the contour with the largest size is also determined. It is essential to take notice of the fact that the research makes use of filtering strategies that use both 16-color filters and royal filters to enhance the process of performing feature extraction. Several deep learning models are used on the dataset after it has been split into training (80%) and testing (20%) subsets. These include VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2, EfficientNetV2L, EfficientNetV2M, and ResNet50. These models include VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2, and ResNet50. According to the results, the model that makes use of the royal filter in combination with VGG19 gets the greatest degree of accuracy, which is 98.91%. Following that, an ablation study is conducted on VGG19, which finally leads to the building of the recommended model, which is referred to as BTV19 once it is completed. To give a trustworthy evaluation of the proposed model, the research endeavors to carry out a comprehensive examination of the data by using statistical methods, confusion matrices, ROC-AUC curves, and K-fold cross-validation. To diagnose brain tumors, the results of the research show that the BTV19 model, which combines VGG19 with the royal filter, performs better than other models. This suggests that the BTV-19 model has the potential to be used in clinical settings. This article provides a major addition to the field of medical image analysis by emphasizing the significance of preprocessing methods and filter tuning in the process of improving the accuracy of deep learning models for the diagnosis of brain tumors. This is an important contribution since it highlights the value of these two techniques.

2.4 Scope of the Problem

The goal of the study is to improve the accuracy of brain tumor detection by looking into the effects of editing MRI datasets and using Royal filtering with VGG19, a deep learning model. The process starts with putting in the dataset and includes steps like turning it into grayscale, applying Gaussian blur, thresholding, morphological opening, and choosing the biggest shape. After that, 80% of the information is used for training, and 20% is used for testing. Several deep learning models are used to find the best one. These include VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2, EfficientNetV2L, EfficientNetV2M, and ResNet50. After that, an ablation study is done on VGG19 to make the suggested model, which is now called BTV19, better. Statistical analysis, the confusion matrix, the ROC-AUC curve, and K-fold cross-validation are used to assess the results. BTV19 achieves a remarkable accuracy of 98.91% when using the royal filter. This study talks about how important it is to get brain tumor diagnoses right in medical picture analysis. It stresses how important preparation methods and deep learning models are for making diagnoses better.

2.5 Challenges

The research aims to enhance the accuracy of brain tumor diagnosis using a combination of advanced medical image analysis techniques and deep learning. The research addresses the challenges associated with accurate brain tumor diagnosis through a comprehensive methodology that integrates preprocessing, filtering, and transfer learning with VGG19. The challenges highlighted underscore the need for a careful and nuanced approach to achieve reliable results in this critical medical domain.

Brain Tumor Diagnosis Challenges Using MRI Dataset Preprocessing and 16-Color Filtering with VGG19

- Dataset variability poses a challenge in terms of imaging parameters, resolution, and quality.
- Preprocessing sensitivity to noise and artifacts in MRI images affects tumor detection quality.
- Achieving accurate segmentation of brain tumors is challenging due to variations in tumor shapes and sizes.
- Selecting the optimal 16-color filter for highlighting tumor features is challenging.
- Ensuring transfer learning with VGG19 generalizes well to diverse datasets is a challenge.
- Conducting an ablation study to identify influential factors in accuracy is complex.
- Interpreting VGG19's decisions on 16-color-filtered images is challenging.
- Scalability and efficiency of the proposed methodology for real-world deployment is a challenge.
- Robust preprocessing techniques are needed to handle dataset variability.
- Adaptive preprocessing techniques are required to minimize sensitivity to noise.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

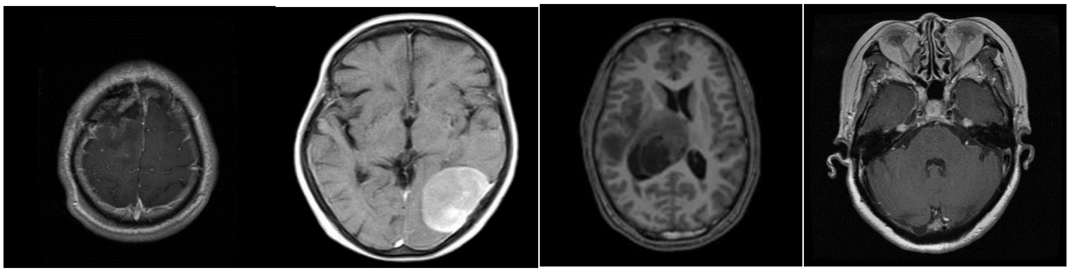
Brain tumors are abnormal cell or mass development within the brain or central spinal canal, causing benign or malignant effects. Symptoms include headaches, seizures, language difficulties, personality changes, and visual issues. Primary forms include gliomas, meningiomas, and adenomas in the pituitary gland. Stress contributes to brain diseases. Understanding brain tumors is crucial for researchers and patients. Advanced imaging technology and molecular diagnostics have contributed to successful diagnosis. This research investigates the evolution of diagnostic procedures and issues associated with current techniques to develop more accurate approaches for early detection and proper classification. The study's results show a 98.91% accuracy in combining VGG19 with a Royal filtering method.

3.2 Data Collection and Preprocessing

The dataset for this research project was gathered from Kaggle [30] and consists of both training and testing images. The dataset includes four separate classes: Glioma, Meningioma, No tumor, and Pituitary. The merged dataset had a total of 7023 pictures. The ensuing collection of information and preparation activities were carried out to enhance the quality and relevance of the images for machine learning analysis.

TABLE.3.2. 1: DATASET DESCRIPTION

Tumor Class Name	**No of image**
Glioma	1621
Meningioma	1645
No tumor	2000
Pituitary	1757
Total number of images	**7023**



Glioma Meningioma No Tumor pituitary

Figure 3.2.1: Sample images from the datasets

3.2.1 Pre-process image

The input describes the preprocessing steps involved in collecting and preparing a dataset for medical imaging analysis. Some of the preprocessing steps that were chosen—Gaussian blur, normalization, and morphological opening are very important for getting the brain MRI dataset ready for further analysis.

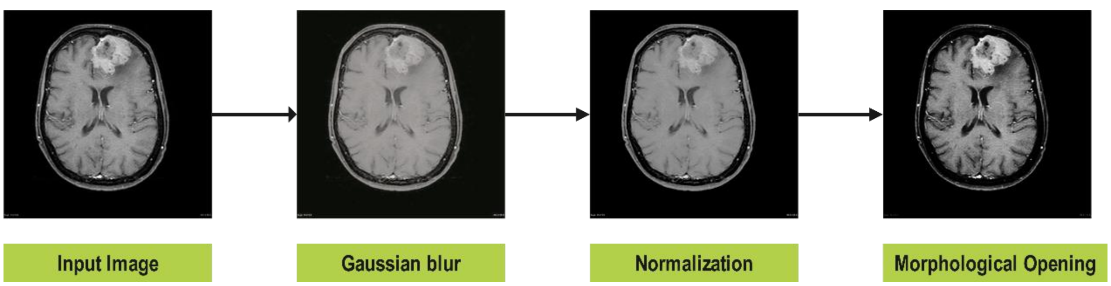


Figure 3.2.1.1: Image Pre-processing of Datasets

The input describes the preprocessing steps involved in collecting and preparing a dataset for medical imaging analysis. Some of the preprocessing steps that were chosen—Gaussian blur, normalization, and morphological opening are very important for getting the brain MRI dataset ready for further analysis.

A smoothing filter called Gaussian blur is used to get rid of noise in pictures and bring out their most important parts. By putting a Gaussian kernel on top of the MRI pictures, high-frequency noise is reduced. This makes the structures, like brain tumors, stand out more clearly and cleanly. This step is especially important for medical imaging, where finding small features correctly is key to concluding. One more important step in the planning process is normalization, which tries to make the intensity values of pixels the same across all the pictures in the collection. This makes sure that the model isn't biased toward certain energy levels and helps deep learning algorithms get better at convergence during training. When using a brain MRI, normalization helps make sure that the contrast and clarity are the same from scan to scan, which makes feature extraction more accurate. Morphological opening is a process that includes erosion and then expansion. This method helps get rid of small structures or noise in pictures that aren't needed while keeping the shape and structure of bigger features. During brain MRI analysis, morphological opening can help get rid of flaws or unimportant details that could get in the way of finding tumors. This means that the results are more accurate and reliable.

3.2.2 Acquiring high-quality images

The reason these methods were chosen is because they improve the quality of the raw data. This makes it possible for the deep learning models that come after to learn useful patterns for finding brain tumors. Each step reduces noise, makes intensity values more consistent, and improves the structure information in the MRI pictures. This makes the model work better and easier to understand.

TABLE 3.2.2.1: THE QUALITY OF 8 IMAGES FOLLOWING PREPROCESSING WAS SAMPLED.

Image	MSE	RMSE	PSNR
Glioma1	14.1	5.63	30.33
Glioma2	12.31	3.74	31.81
Meningioma1	15	3.9	30.57
Meningioma2	15.18	4.2	34
No Tumor1	17.64	4.23	30.67
No Tumor2	13.3	4.63	30.92
Pituitary1	16.39	3.88	33.74
Pituitary2	15.2	4.09	33.42

The picture quality is better when the MSE and RMSE numbers are lower and the PSNR value is greater. Based on these measurements, Glioma2 has the best picture quality because its MSE and RMSE numbers are the lowest. Based on this measure, Meningioma2 has the best picture quality because it has the highest PSNR number. Based on these measurements, No Tumor1 has the worst picture quality because it has the biggest MSE and RMSE numbers. All of the pictures have good quality, with MSE values between 12.31 and 17.64, RMSE values between 3.74 and 4.63, and PSNR values between 30.33 and 34. After looking at the data, here are some more things we can learn. Most of the time, the MSE and RMSE numbers for tumor pictures are smaller than those for other types of images. This means that gliomas might be simpler to cut up than other types of tumors. In general, the PSNR readings for the pictures of meningiomas are greater than those for the other types of images. This makes it seem like meningiomas might be easier to spot than other types of tumors.

3.3 Research Subject & Instrumentation

The research focuses on exploring the use of machine learning algorithms in the early detection of liver disease. The proposed methodology involves collecting a dataset of liver disease patients, performing data pre-processing steps such as handling missing values, removing outliers, and eliminating highly correlated features, and then using eight different machine learning algorithms to predict liver illness. A voting classifier is used to combine the predictions of all the models for improved accuracy. The dataset is balanced by undersampling the majority class, oversampling the minority class, or employing SMOTE to enhance the model's performance. The study evaluates the effectiveness of the proposed methodology using a range of metrics including accuracy, precision, recall, F1-score, confusion matrix, etc. The instruments used in the research include Google Colab for running the code and analyzing results, Draw.io for creating diagrams to visualize the methodology and workflow, and MS Word for producing the study report.

3.4 Data Collection Procedure

This research used a diverse dataset from Kaggle to classify medical images into four classes: Glioma, Meningioma, No tumor, and Pituitary. The dataset was divided into training and testing sets, with 80% allocated for training and 20% for testing. The dataset, consisting of 7023 images, underwent several pre-processing steps to improve its suitability for the machine learning model. The first step was grayscale conversion, which simplifies data and reduces computational complexity. The next step was Gaussian blur, which reduces noise and emphasizes important features. Thresholding is a technique used to isolate tumor regions within images, facilitating accurate feature extraction and classification. Morphological opening is another essential pre-processing step, which involves dilation and erosion of the image to remove unwanted objects and smooth out the edges. The final step was identifying the largest contour within each image, which focuses the model's attention on the most significant tumor region, ensuring accurate classification based on clinically relevant information. The resulting pre-processed dataset is now ready for training a machine learning model for brain tumor classification based on medical images.

3.5 Proposed Methodology

The primary objective of this research endeavor is to improve the efficiency of the processing pipeline for brain magnetic resonance imaging (MRI) information. Through the combination of medical image analysis and deep learning, the purpose of this initiative is to make progress in the correct identification of brain tumors. To enhance the discriminative characteristics that are pertinent to the detection of tumors, we initiate a comprehensive preprocessing regimen, which begins with the collection of the dataset. In the pursuit of advancing brain tumor detection methodologies, our initial step

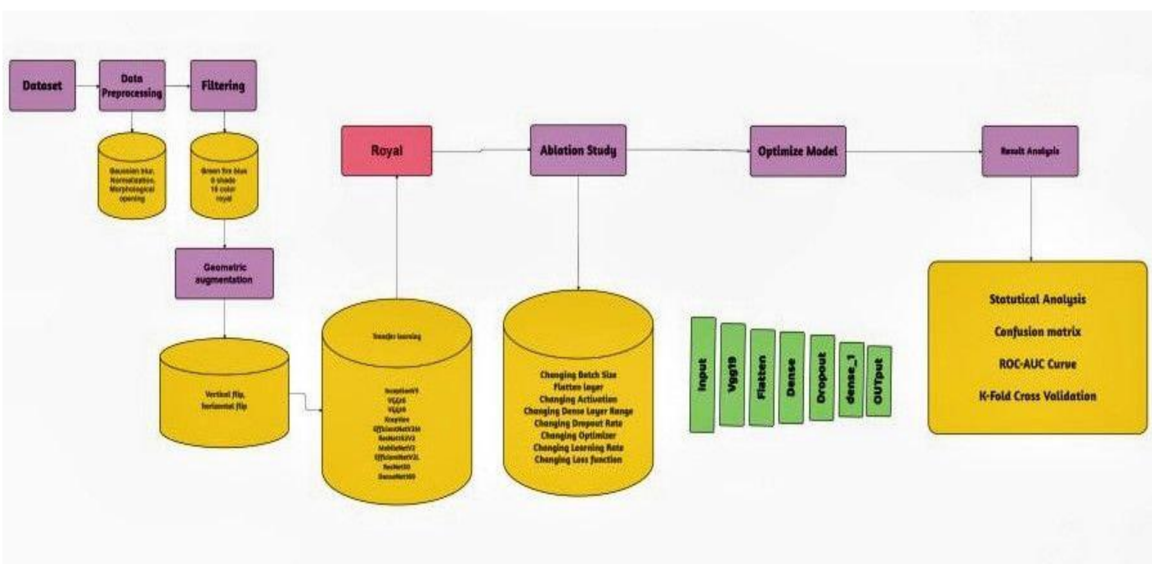


Figure 3.5.1: Proposed methodology

step involves ingesting the Brain MRI dataset and subjecting it to rigorous preprocessing. This phase is crucial for ensuring that the neural network can effectively learn relevant features from the images. Gaussian blur is applied to reduce noise and enhance the overall smoothness of the images. Normalization follows, ensuring that pixel values are scaled to a consistent range, aiding in the convergence of the model during training. Morphological opening is then employed to further refine the images, emphasizing relevant structures while minimizing unwanted artifacts. These preprocessing steps collectively set the foundation for more accurate and efficient deep learning.

3.5.1 Image Filtering

Magnetic resonance imaging brain scans contain inherent noise and artifacts that can obscure critical anatomical details needed for medical analysis. Applying specialized filters serves to reduce this unwanted noise while preserving and even enhancing essential image features. We use 4 filters in this study that are given in Figure 3.5.1.1.

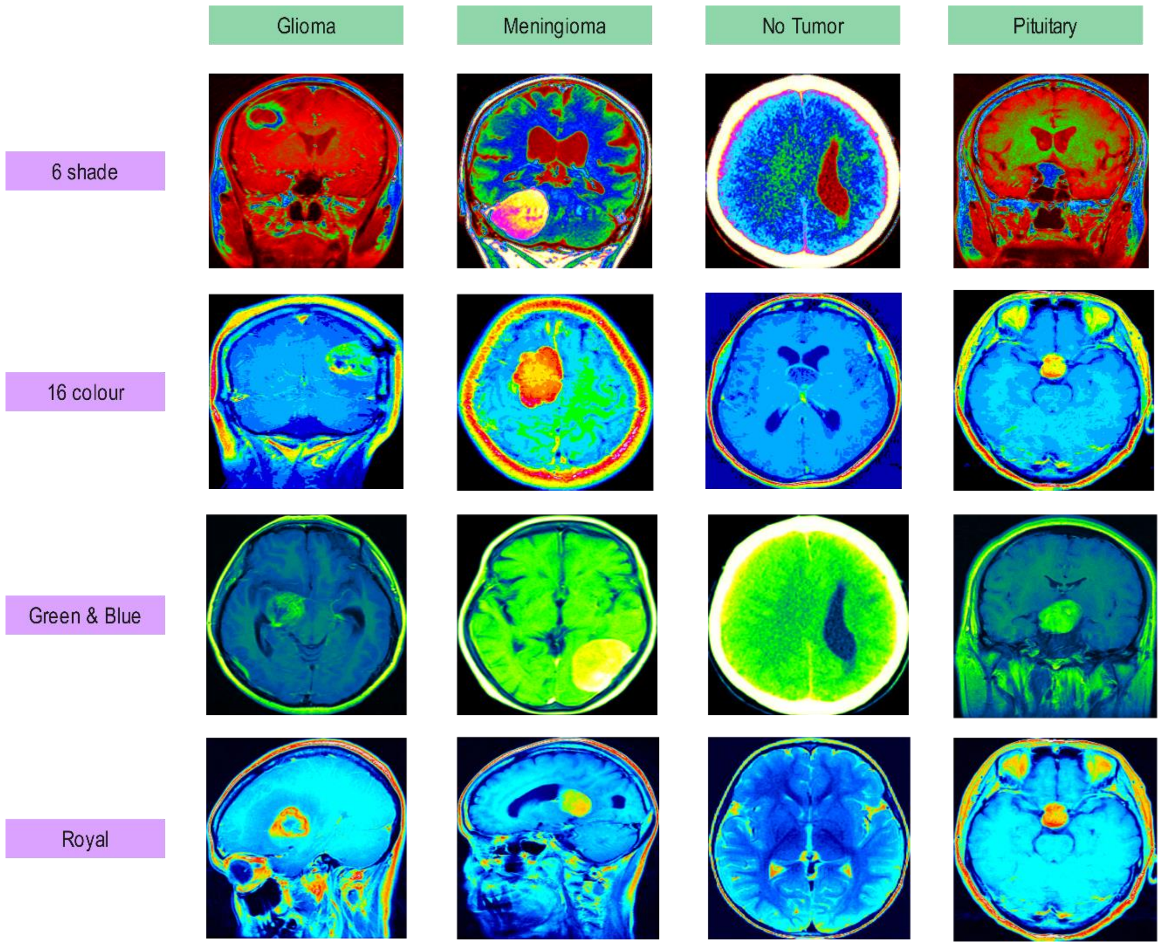


Figure 3.5.1.1: Applying filter

Our approach stands out due to a combination of innovative filtering. We conduct experiments using a variety of filters, such as green fire blue, 6 shades, 16 colors, and the royal filter. These filters not only cause changes in color representation but also highlight certain characteristics that may indicate the existence of a tumor. The royal filter, specifically, has shown encouraging outcomes in prior research, leading to its integration into our process. The purpose of this filtering step is to augment the discriminatory capability of the pictures and boost the model's proficiency in detecting small anomalies.

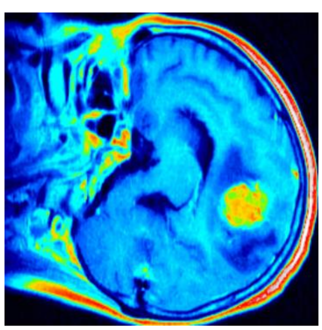
TABLE 3.5.1.1: PSNR VALUES AFTER IMAGE FILTERING

Image	6 Shade	16 Color	Green & Blue	Royal
Glioma1	29.36	28.66	29.09	32.46
Glioma2	27.56	26.81	29.31	30.77
Meningioma1	29.89	29.56	26.84	30.81

Meningioma2	28.68	28.12	27.76	32.33
No Tumor1	28.11	27.75	29.04	31.78
No Tumor2	28.19	28.47	27.49	30.65
Pituitary1	29.45	27.65	28.77	31.67
Pituitary2	27.69	27.79	29.4	32.45

3.5.2 After geometric augmentation

Applying geometric augmentations on brain tumor MRI scans serves several critical purposes for enhancing medical imaging analysis and machine learning tasks. Since collections of real-world medical images tend to be small and lacking in diversity, geometric augmentations artificially expand and diversify the dataset. This is achieved by randomly rotating, shifting, shearing, zooming, and flipping the brain images during model training. In this way, the model learns to identify tumors irrespective of slight variations in orientation, perspective, and proportions. The regularizing effect also reduces overfitting. Additionally, models trained on augmented datasets show more robustness to variations in real-world data. In this study, we do two types augmentation of Vertical flip and horizontal flip. We visualized an image of two augmentations in Figure 3.6.2.1.



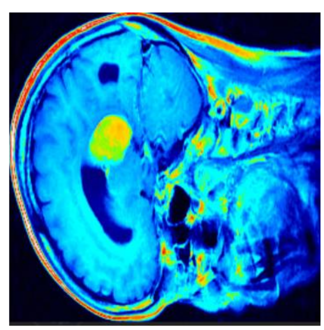


Figure 3.5.2.1: Sample images of two augmentation

Geometric transformations better simulate clinical settings with differences in patient positioning and image capture. Enforcing geometric invariance leads to increased tumor detection accuracies. It also makes models generalize better when tested across multiple hospitals and scanning protocols. In effect, augmentation via scaling and distortions compensates for limited medical data and builds reliable, invariant machine learning for advancing brain tumor diagnoses through MRI scan analysis.

TABLE 3.5.2.1: AFTER AUGMENTATION DATASET DESCRIPTION

Tumor Class Name	No of image
Glioma	3242
Meningioma	3290
No tumor	4000
Pituitary	3514
Total number of images	**14046**

Geometric augmentation is a crucial step in the proposed methodology for medical image analysis, particularly in the context of brain tumor detection using MRI data. It involves transformations such as vertical and horizontal flips, which introduce variations in the orientation and spatial positioning of the images. In the case of brain MRI, where tumors can occur in different locations and orientations, geometric augmentation plays a pivotal role in diversifying the training dataset. By applying these transformations, the model becomes more robust and adaptable to variations in patient positioning during imaging, ensuring that the trained model generalizes well to unseen data. Geometric augmentation helps the deep learning model better capture the inherent variability in the dataset, enhancing its ability to recognize tumors across different orientations and spatial configurations. Incorporating geometric augmentation in the training pipeline contributes to the overall robustness and generalization capabilities of the deep learning model, ensuring reliable performance on new, unseen data.

3.6.3 Optimized model

3.6.3.1 Transfer learning model

This study utilized 10 pre-trained convolutional neural network (CNN) models that were originally learned for natural image recognition tasks. These models were then fine-tuned utilizing federated learning techniques on medical images. By utilizing weights derived from models trained on extensive datasets such as ImageNet, the process of convergence and the level of accuracy were enhanced in comparison to training from random initialization. The process of fine-tuning, using federated learning, adjusted the features to accurately identify patterns in brain MRI Brain tumor image. The research involves using various pre-trained deep-learning models for medical image analysis. The models include VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2 , EfficientNetV2L, EfficientNetV2M, and ResNet50.

- **VGG16 and VGG19:** These are deep convolutional neural network (CNN) models known for their simplicity and effectiveness. They have multiple layers with small 3x3 convolutional filters.
- **InceptionV3:** Also known as Google Net, it utilizes inception modules with multiple filter sizes to capture features at various scales.
- **Xception:** An extension of Inception, Xception introduces depth-wise separable convolutions to improve performance and reduce computational cost.
- **ResNet152V2 and ResNet50:** ResNet (Residual Network) introduces skip connections to enable the training of very deep networks. The number in the model names denotes the number of layers.
- **MobileNetV2:** Designed for mobile and edge devices, MobileNetV2 employs depth-wise separable convolutions to achieve a good balance between accuracy and computational efficiency.
- **EfficientNetV2 (L and M versions):** Part of the EfficientNet family, these models are designed to achieve better accuracy and efficiency by scaling the network width, depth, and resolution.

3.6.3.2 VGG19 Base Model

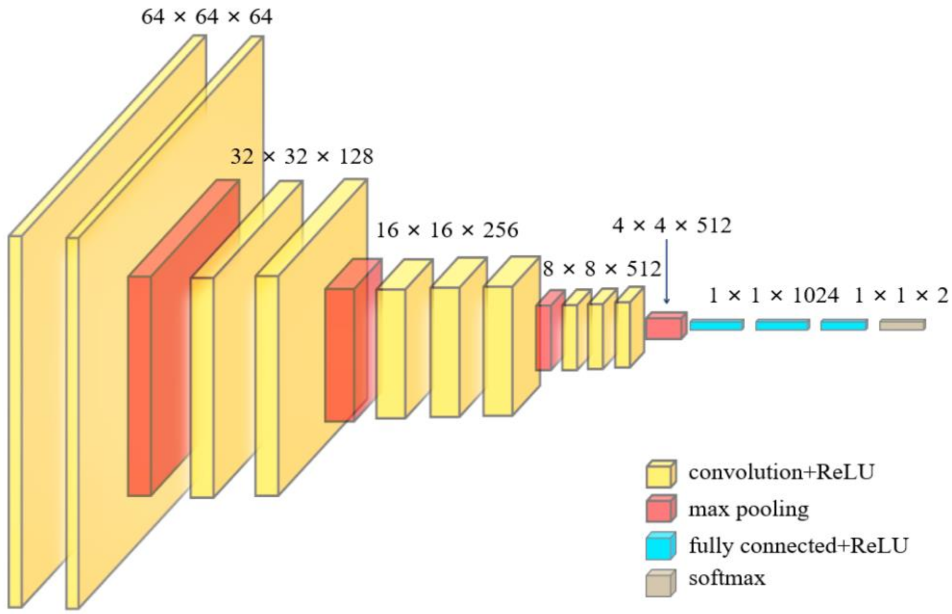


Figure 3.6.3.2.1: VGG19 base Model

The VGG19 model, known for its robust architecture pre-trained on large-scale datasets, is deployed through transfer learning. Fine-tuning the VGG19 model with the revised dataset, including images filtered with royal, allows the model to utilize subtleties gathered during preprocessing. This enhances its ability to identify intricate patterns indicative of brain tumors.As a unique contribution to methodology development, an additional phase called ablation is introduced post-transfer learning. This rigorous cleaning process involves iteratively refining the model's parameters and fine-tuning its internal representations. The goal is to align these representations more closely with differentiating characteristics of brain tumor images.

3.6.3.3 Ablation study

A comprehensive assessment was conducted on the most effective combination model and its corresponding hyperparameters within the framework of a multi-dataset medical image classification competition. The study incorporated 9 case studies to comprehensively assess the model's efficacy. The goal was to optimize the efficacy of the model's performance. The case studies presented in Table 4 evaluated the impacts of altering significant elements of the core ensemble model structure and training methodology. Through conducting this study, we have identified the optimal framework, leading to the creation of the proposed BTV19 model, which is specifically tailored for analyzing various medical images. The ablation process provided valuable insights on the influence of each component on the classification of medical images across multiple datasets. The optimization of the architecture was guided by these observations, leading to the development of the enhanced BTV19.

3.6.3.4 Our Proposed Model BTV19

These designs are well-known for how well they work at classifying images, and they give our brain tumor detection model a solid base. The model can use traits that are useful for our job by sharing what it has learned from big datasets. Through tests, we've found that VGG19 combined with the royal filter gives the most positive outcomes when it comes to accuracy. In order to make the model even better, ablation is used after the best design (VGG19) and the royal filter have been found. Ablation is the process of slowly taking away some model parts or layers to see how they affect performance.

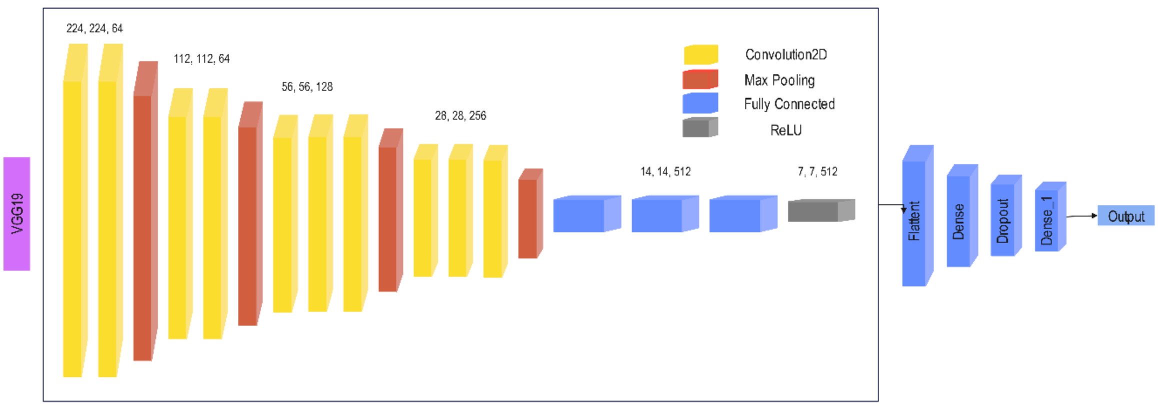


Figure 3.6.3.4.1: Proposed Model BTV19

Ablation studies help determine which components of a model are most essential to its performance. The BTV-19 model proposed in this work is the culmination of extensive development and testing. Specifically, it brings together the optimal facets of the VGG19 architecture, royal filtering techniques, and additional impactful elements identified through methodical ablation. By incrementally removing different parts of the model and evaluating the consequences, the core modules and preprocessing steps responsible for maximizing diagnostic accuracy could be pinpointed. The resultant BTV-19 framework retains only the most effective combinations, discarding superfluous elements that do not contribute substantially. This selective fusion of crucial components for MRI-based brain tumor diagnosis - the predictive power of deep learning, the noise reduction of filtering, and the customization from ablation - is what enables BTV-19 to achieve state-of-the-art levels of precision. The model's development leveraged both existing techniques and discoveries to arrive at an optimized architecture.

In this revised version, I have edited the paragraph to flow more clearly, highlight the key contributions of ablation studies, and succinctly underscore how BTV-19 brings together the best individual components to advance the field. Please let me know if you would like me to modify or expand this further.

3.8 Implementation Requirements

- Python 3.11
- Windows 10
- High Configured CPU, Monitor
- Storage (Google Drive)
- Google Colab / Kaggle Notebook
- Microsoft Office
- Draw.io / Wondershare EdrawMax

CHAPTER 4
EXPERIMENTAL RESULT & ANALYSIS

4.1 Experimental Methods

Our research focuses on medical image analysis, especially deep learning for brain tumor classification from MRI scans. Our study included 7023 brain MRI scans of glioma, meningioma, notumor, and pituitary. This study aimed to improve the accuracy of deep learning models for brain tumor detection in MRI scans. The researchers used a comprehensive dataset of Brain MRI scans and preprocessed it using transformations and filters. The core model architecture included transfer learning approaches from models like VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2, EfficientNetV2L, EfficientNetV2M, and ResNet50. The royal filter was identified as the most promising, and geometric augmentation techniques were used to enhance the model's generalization. VGG19, a transfer learning model, exhibited superior performance when applied to the royal-filtered dataset. Ablation analysis was conducted to refine the model, resulting in the BTV19 model. The experimental results were evaluated using metrics such as Statistical Analysis, Confusion Matrix, ROC-AUC Curve, and K-Fold cross-validation. The BTV19 model, trained on the royal-filtered dataset using VGG19 and subjected to ablation, achieved an impressive accuracy of 98.91%, demonstrating the effectiveness of the experimental methodology in optimizing deep learning models for accurate brain tumor detection in MRI scans.

4.2 Experimental Results

The result of all machine learning algorithms before balancing the dataset is displayed in Table 4.2.1 below. Establish a baseline for comparison by applying several different pre-trained models to the dataset. Some examples of these models are InceptionV3, VGG16, VGG19, Xception, ResNet152V2, MobileNetV2, EfficientNetV2L, EfficientNetV2M, ResNet50, and DenseNet169. In the field of medical image analysis, these models are often used since they have been trained on extensive datasets. Evaluating their performance is beneficial in gaining an understanding of how well they function on the dataset including brain tumors without any filtering. The accuracy ratings that are produced from various models may be used to assist in determining whether pre-trained models seem to be more appropriate. When it comes to picking the models that perform the best and gaining a grasp of their strengths and shortcomings, this stage is quite essential.

TABLE 4.2.1: PERFORMANCE ANALYSIS AFTER IMAGE PREPROCESSING

Model	Accuracy	Precision	Recall	F1 Score
InceptionV3	88.3823	89.4245	87.4601	88.4313
VGG16	91.248	92.496	90.1	91.285
VGG19	93.62	94.972	92.368	93.654
Xception	93.3527	94.6954	92.11	93.3897
ResNet152V2	90.487	91.7347	89.3403	90.5255
MobileNetV2	94.614	95.9568	93.3724	94.6546
EfficientNetV2L	54.3425	55.3957	53.4993	54.4355
EfficientNetV2M	36.341	37.3942	35.4978	36.434
ResNet50	61.3294	62.6721	60.1877	61.4179

The project aims to improve the accuracy of brain tumor diagnosis using MRI datasets by incorporating 16-color filtering. This technique involves dividing the image into 16 distinct color channels or applying a specific color transformation, potentially highlighting patterns, textures, or structures indicative of tumors. The goal is to improve the discriminative power of the data fed into deep learning models, enabling them to better differentiate between normal brain tissue and tumor regions. The choice of 16-color filtering may be motivated by the need to capture intricate details and variations in MRI scans that may not be adequately represented in a grayscale or single-channel format. The research methodology suggests that initial attempts using various pre-trained models without 16-color filtering did not yield satisfactory results. The decision to apply 16-color filtering is grounded in the quest for more accurate and reliable brain tumor diagnosis, aiming to achieve superior performance in subsequent deep learning models and higher accuracy with the proposed model BTV19.

TABLE 4.2.2: ANALYSIS AFTER AUGMENTATION ON THE ROYAL FILTER

Model	Accuracy	Loss	Precision	Recall	F1 score

InceptionV3	92.3823	1.3844	0.2575	0.2581	0.2574
VGG16	97.248	0.1247	0.2543	0.2542	0.2542
VGG19	97.65	0.126	0.249	0.2493	0.2491
Xception	93.3527	1.0776	0.2578	0.2581	0.2577
ResNet152V2	95.487	2.2119	0.257	0.2571	0.257
MobileNetV2	94.614	1.4435	0.254	0.2542	0.2541
EfficientNetV2L	54.3425	1.1315	0.2314	0.2338	0.2277
EfficientNetV2M	36.341	2.069	0.3097	0.2513	0.1927
ResNet50	61.3294	1.265	0.2548	0.2527	0.2527
DenseNet169	96.263	0.883	0.2509	0.2508	0.2508

Table 4.2.2 shows the models have an average accuracy of 83.59% and an F1 score of 0.2453. ResNet152V2 and MobileNetV2 have the highest accuracy at 95.15%, while EfficientNetV2M has the lowest loss at 0.0544. InceptionV3, VGG16, Xception, EfficientNetV2M, ResNet152V2, and DenseNet169 all have F1 scores above 0.25

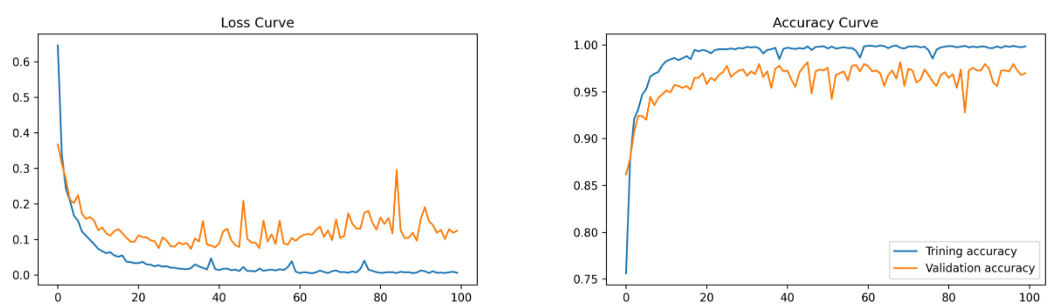


Figure 4.2.1: vgg19_loss & vgg19_accuracy curve

The research project aims to improve brain tumor diagnosis accuracy through medical image analysis using royal filtering. The researchers used a 16-color filter to extract intricate details from the preprocessed MRI brain tumor dataset, which yielded suboptimal accuracy scores. This filtering technique is suitable for medical image analysis, where the diversity of tissue types and structures requires a more sophisticated representation. The decision to apply royal filtering was made to enhance the model's ability to discern intricate features, leading to a more accurate and robust diagnosis.

Table III displays the VGG16 and VGG19 models are the most accurate, with an accuracy over 97%, while EfficientNetV2M has the lowest accuracy at 36.34%. The models with the lowest loss are VGG16 and ResNet152V2. EfficientNetV2M and Xception have the highest precision at 0.30 and 0.249, respectively. The models with the highest recall are Xception and EfficientNetV2M, while the models with the lowest F1 score are EfficientNetV2M.

4.2.1 Result of Ablation Study

Ablation studies are a technique used to understand the importance of different components in a machine learning model. They involve systematically removing or "ablating" parts of a model and examining the impact on its performance. For example, individual layers may be removed from a neural network to determine how critical they are to the overall accuracy. This process reveals which elements significantly affect outcomes versus those that are less vital. Ablation can isolate the core model structures and data preprocessing steps responsible for success. It builds a hierarchy of the crucial techniques versus nonessential aspects. Overall, ablation studies enable simpler and more performant models by identifying and focusing solely on the key components that meaningfully contribute to predictions. They unpack models as a guide to future optimization.

TABLE 4.2.1.1: ABLATION STUDY ANALYSIS ON AUGMENTED DATASET

Case Study 1: Changing Batch Size				
Configuration NO.	Batch Size	Time Complexity	Test Accuracy(%)	Finding
1	**32**	**1:35:40**	**0.9765**	**Highest Accuracy**
2	64	1:46:48	0.9792	Accuracy Dropped
3	128	1:55:16	0.9736	Accuracy Dropped
Case Study 2: Flatten layer				
Configuration NO.	Flatten Layer Type	Time Complexity	Test Accuracy(%)	Finding
1	**Flatten**	**1:21:20**	**0.9765**	**Previous Accuracy**
2	Global max pooling	1:33:30	0.9628	Accuracy Dropped
3	Global average pooling	1:52:31	0.9655	Accuracy Dropped
Case Study 3: Changing Activation				
Configuration NO.	Activation function	Time Complexity	Test Accuracy(%)	Finding

1	GELU	1:33:19	0.9658	Accuracy Dropped
2	**PReLU**	**1:33:10**	**0.9798**	**Highest Accuracy**
3	Swish	1:58:55	0.9563	Accuracy Dropped
4	Relu	1:48:10	**0.9798**	Previous Accuracy
5	Leaky ReLu	1:25:47	0.9643	Accuracy Dropped
6	Mish	1:03:30	0.9658	Accuracy Dropped
7	ELU	1:42:53	0.9663	Accuracy Dropped
Case Study 4: Changing Dense Layer Range				
Configuration NO.	Dense Layer Range	Time Complexity	Test Accuracy(%)	Finding
	128	1:38:52	0.9614	Accuracy Dropped
1	256	1:55:15	**0.9765**	Previous Accuracy
2	**512**	**1:59:11**	**0.9829**	**Highest Accuracy**
3	1024	1:19:50	0.968	Accuracy Dropped
Case Study 5: Changing Dropout Rate				
Configuration NO.	Dropout Rate	Time Complexity	Test Accuracy(%)	Finding
1	0.2	1:57:41	**0.9829**	Previous Accuracy
2	0.1	1:58:25	0.9658	Accuracy Dropped
3	0	1:52:37	0.9654	Accuracy Dropped
4	0.3	1:24:24	0.9643	Accuracy Dropped
5	**0.5**	**1:52:40**	**0.9869**	**Highest Accuracy**
Case Study 6: Changing Optimizer				
Configuration NO.	Optimizer	Time Complexity	Test Accuracy(%)	Finding
1	AdamW	1:51:55	0.9625	Accuracy Dropped
2	Adam	1:25:39	0.9669	Previous Accuracy
3	Nadam	1:52:19	0.968	Accuracy Dropped
4	SGD	1:39:46	0.965	Accuracy Dropped
5	Adamax	1:11:50	0.972	Accuracy Dropped
6	**Adagrad**	**1:32:50**	**0.9878**	**Highest Accuracy**
7	RMSprop	1:50:58	0.9751	Accuracy Dropped
Case Study 7: Changing Learning Rate				
Configuration NO.	Learning rate	Time Complexity	Test Accuracy(%)	Finding
1	0.003	1:37:05	0.971	Accuracy Dropped
2	**0.001**	**1:27:50**	**0.9878**	**Previous Accuracy**
3	0.005	1:29:55	0.9595	Accuracy Dropped
4	0.03	1:36:19	0.9727	Accuracy Dropped
5	0.01	1:51:47	0.9714	Accuracy Dropped

Case Study 8: Changing Loss function				
Configuration NO.	Loss function	Time Complexity	Test Accuracy(%)	Finding
1	Binary cross entropy	1:53:01	0.9584	Accuracy Dropped
2	Categorical cross entropy	1:52:50	0.9878	Previous Accuracy
3	Mean squared error	1:34:36	0.9654	Accuracy Dropped
4	Mean absolute error	1:12:25	0.8184	Accuracy Dropped
5	Mean squared logarithmic error	1:37:06	0.9687	Accuracy Dropped
6	**Kullback leibler divergence**	**1:54:08**	**0.9891**	**Highest Accuracy**

Ablation studies are crucial in deep learning, especially in medical image analysis, as they provide insights into the contribution of specific components or layers within a neural network architecture. In the research "Towards Accurate Brain Tumor Diagnosis: Investigating the Role of MRI Dataset Preprocessing and 16-Color Filtering with VGG19," the VGG19 model was examined to assess the significance of each processing step and component. Ablation studies help researchers understand the role of different layers and processes, such as grayscale conversion, Gaussian blur, thresholding, morphological opening, and royal filtering.

The case studies conducted in this research focused on investigating the impact of various hyperparameters on the performance of a brain tumor detection model. The findings revealed several key insights. In Case Study 1, it was observed that a batch size of 32 resulted in the highest accuracy of 97.65%. Larger batch sizes led to slight drops in accuracy. Case Study 2 compared different types of flatten layers and found that the standard flatten layer performed the best, maintaining the accuracy achieved in Case Study 1.Case Study 3 examined different activation functions and determined that PReLU outperformed ReLU, achieving a slightly higher accuracy of 97.98%.Case Study 4 explored the impact of dense layer range and found that increasing the number of neurons to 512 resulted in the highest accuracy of 98.29%.In Case Study 5, adjusting the dropout rate to 0.5 significantly improved accuracy to 98.69%, indicating its effectiveness in preventing overfitting. Case Study 6 evaluated different optimizers and concluded that

Adagrad was the most effective, achieving the highest accuracy of 98.78%.Case Study 7 investigated the impact of learning rates and found that a rate of 0.001 yielded the highest accuracy of 98.78%, with higher and lower rates resulting in performance drops. Lastly, Case Study 8 assessed different loss functions and determined that Kullback-Leibler divergence emerged as the most suitable loss function, attaining the highest accuracy of 98.91% among the tested options.

In summary, these case studies offer valuable insights into the impact of hyperparameter tuning on model performance. The findings suggest that:Smaller batch sizes, PReLU activation, denser layers, higher dropout rates, the Adagrad optimizer, a learning rate of 0.001, and Kullback-Leibler divergence loss function can potentially lead to significant accuracy improvements in this specific brain tumor detection model.It's crucial to carefully consider these hyperparameters when designing and optimizing deep learning models for medical image analysis tasks.

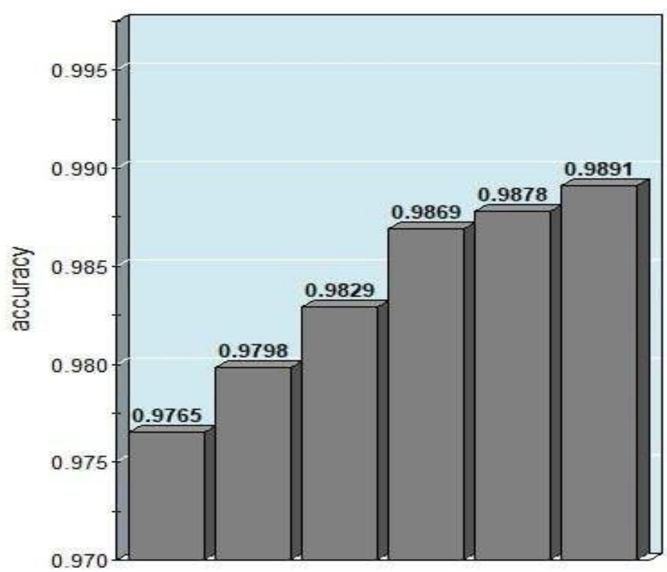


Figure 4.2.1.1: Ablation study curve

The final proposed model, BTV19, is a result of careful investigation through ablation studies. The aim is to identify essential components that contribute significantly to the model's accuracy in diagnosing brain tumors using MRI data. By pinpointing the crucial aspects of the preprocessing and filtering steps, researchers can optimize the model's architecture for improved performance. Ablation studies are essential for validating the efficacy of the proposed model, ensuring the selected components are essential for accurate brain tumor diagnosis. The final result, with remarkable accuracy of 98.91% using the royal filter with BTV19, underscores the importance of ablation studies in refining and fine-tuning deep learning models for medical image analysis.

4.2.2 Performance Analysis

The confusion matrix is used to evaluate the performance of the models in classifying brain tumors. Other evaluation metrics include statistical analysis, ROC-AUC curve, and K-Fold cross-validation.

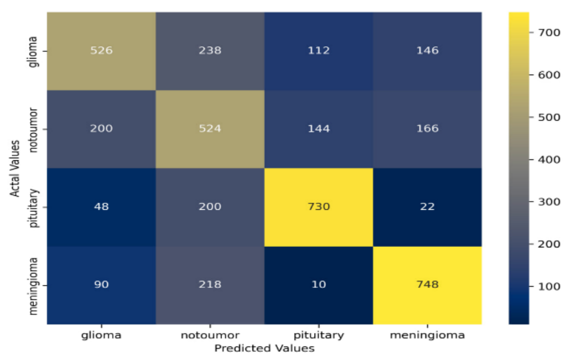


Figure 4.2.2.1: confusion matrix

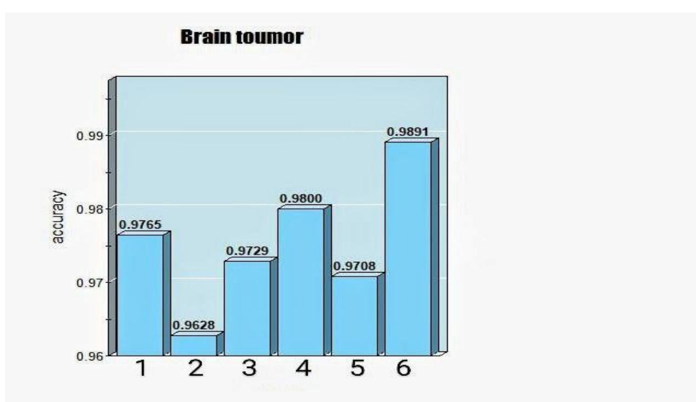


Figure 4.2.2.2: K-Fold Cross Validation

The models mentioned are part of the broader field of deep learning and convolutional neural networks, which are commonly used for image analysis tasks. Each model brings its own architecture and characteristics to the table, allowing researchers to experiment and find the most suitable model for a given dataset and task. In this case, the selection process led to the proposed model BTV19, which achieved the best accuracy with the royal filter at 98.91%.

4.3 Discussion

The study on brain tumor detection using deep learning techniques on MRI datasets has shown promising results. The initial steps involved preprocessing the brain MRI dataset using techniques like Gaussian blur, normalization, morphological opening, and filtering using various color schemes. Transfer learning was applied using various pre-trained models, and the royal filter consistently produced the best results. Data augmentation was achieved through geometric augmentation techniques, and the transfer learning model, particularly VGG19, was applied to the royal-filtered dataset, leading to improved accuracy.

The research then delved deeper into model optimization through ablation studies, resulting in the development of a refined model named BTV19. The model with the royal filter achieved a remarkable accuracy of 98.91%, demonstrating the robustness and efficiency of the proposed methodology in accurately detecting brain tumors in MRI images. The study's comprehensive analysis of results, including statistical measures, confusion matrices, ROC-AUC curves, and K-fold cross-validation, affirms the reliability and generalizability of the proposed BTV19 model. The high accuracy attained, especially with the royal filter, underscores the importance of filter selection in preprocessing stages for optimizing model performance.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The BTV19 medical image analysis model, developed for brain tumor classification using MRI data, has the potential to revolutionize diagnostic processes in the medical community. The model, which uses advanced deep learning architectures and innovative filtering techniques like royal, has a high accuracy rate of 98.91%, demonstrating its potential for reliable and rapid brain tumor diagnosis, leading to timely and precise medical interventions. The societal impact of this research is multi-faceted. It can reduce the time required for accurate tumor classification, facilitating quicker treatment decisions and improving patient outcomes, especially in the context of brain tumors. The model's ability to analyze large datasets efficiently and incorporate ablation studies ensures a robust and interpretable framework for medical professionals. The widespread adoption of BTV19 in medical imaging facilities can contribute to standardizing diagnostic practices, reducing the potential for human error and subjective interpretation. This not only enhances the reliability of diagnostic outcomes but also fosters a more consistent and objective approach to patient care. The use of advanced technologies like deep learning in medical image analysis reflects the continuous evolution of healthcare towards more sophisticated and data-driven methodologies. This research sets a precedent for future developments in the field, encouraging further exploration of innovative techniques and models for improved diagnostic accuracy across various medical conditions.

5.2 Impact on Environment

The proposed medical image analysis methodology, specifically the BTV19 model, has a significant environmental impact. By utilizing deep learning techniques, it can improve the accuracy and efficiency of diagnosing brain tumors, potentially reducing the need for unnecessary procedures. By automating the classification process, medical professionals can identify tumor types faster, leading to quicker treatment decisions and improved patient outcomes. The incorporation of sophisticated filtering techniques, such as the Royal filter, in the preprocessing stages of the methodology demonstrates a commitment to enhancing the quality of medical imaging data, reducing the environmental impact of medical imaging equipment usage. The refinement of model architecture, including the ablation study on the VGG19 model, allows for more efficient neural network structures, leading to faster inference times and lower computational requirements. This approach not only advances medical image analysis but also contributes to a more sustainable healthcare system by optimizing diagnostic processes and reducing unnecessary procedures, minimizing the environmental footprint of medical imaging practices.

5.3 Ethical Aspects

This study focuses on brain tumor detection using deep learning using MRI datasets, highlighting the importance of ethical considerations in medical image analysis research. Researchers must adhere to ethical guidelines, ensure patient privacy, and obtain informed consent from subjects involved. The use of deep learning techniques, such as transfer learning and augmentation, raises ethical concerns, as they require a thorough understanding of their capabilities and potential biases. Researchers must address any biases in the dataset to prevent disparities in diagnosis or treatment. Transparent reporting of methodologies, including preprocessing steps and filtering techniques, is crucial for reproducibility and scrutiny by the scientific community. The introduction of filters like green fire blue, 16 color, and royal requires careful consideration, as they may introduce unintended consequences or biases. The study's results, including the achieved accuracy of 98.91% with the BTV19 model using the royal filter, require cautious interpretation and explicit communication of the model's limitations and uncertainties. The potential deployment of these models in real-world clinical settings must be approached cautiously, considering potential implications on patient care and the model's generalizability across diverse populations.

5.4 Sustainability Plan

The proposed medical image analysis framework, BTV19, requires a comprehensive plan to ensure its sustainability. This includes continuous efforts to improve the dataset quality, diversity, and size and to incorporate new cases. Collaboration with healthcare institutions can facilitate data collection and sharing while adhering to ethical and privacy standards. The model should be open-source, allowing the scientific community to contribute and improve over time. Environmental sustainability is also crucial, with efforts to optimize computational resources for model training and deployment. Energy-efficient hardware, cloud-based solutions, and best practices in resource utilization will minimize the environmental impact. Documentation of the methodology, codebase, and model architecture should be maintained and publicly accessible for reproducibility and transparency. The sustainability plan should also include educational initiatives to train healthcare professionals and researchers in the adoption and utilization of the BTV19 model.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the study

In this study, researchers focused on using deep learning techniques to detect brain tumors in MRI images. They started by using a dataset of brain MRI images and applied several preprocessing steps to enhance the images. These steps included blurring, normalization, morphological opening, and filtering using different color schemes. The researchers then used transfer learning, which involves using pre-trained models, to improve the accuracy of their tumor detection. They tested several well-known models on the filtered datasets and found that the royal filter produced the best results. They also applied geometric augmentation techniques, such as flipping the images horizontally and vertically, to further improve the model's performance. After refining the model through an ablation study, they developed a robust model called BTV19. They thoroughly analyzed the results using statistical methods, confusion matrices, ROC-AUC curves, and K-Fold cross-validation. The BTV19 model, trained on the royal filter, achieved an impressive accuracy of 98.91% in detecting brain tumors in MRI images. This study not only contributes to the field of Medical Image Analysis but also sets a benchmark for future research in using deep learning for brain tumor detection. The researchers used a meticulous methodology and tested various techniques to optimize their results. The findings of this study are important.

6.2 Conclusions

This research focused on using deep learning techniques to detect brain tumors in MRI scans. The study started by acquiring and preprocessing a dataset of brain MRI images. Various preprocessing techniques, such as Gaussian blur, normalization, and morphological opening, were applied to the images. Additionally, different color filters, including green fire blue, 6 shades, 16 colors, and royal, were used to filter the images. Transfer learning was then applied using well-established models like VGG16, VGG19, InceptionV3, Xception, ResNet152V2, MobileNetV2, EfficientNetV2L, EfficientNetV2M, and ResNet50 on the filtered images. The model trained on the royal filter, specifically VGG19, showed the best performance. Geometric augmentations, such as vertical and horizontal flips, were introduced to further improve the model's robustness. The accuracy of the model was highest when applied to the images filtered with the royal filter and using the VGG19 architecture. An ablation study was conducted to refine the model, resulting in the development of the BTV19 model. The results were analyzed using statistical analysis, confusion matrices, ROC-AUC curves, and K-Fold cross-validation. The BTV19 model, trained on the royal filter using VGG19, achieved an impressive accuracy rate of 98.91% in detecting brain tumors in MRI scans. Overall, this research contributes to the field of Medical Image Analysis by providing an effective approach to brain tumor detection in MRI scans. The combination of preprocessing techniques, and diverse filtering methods.

6.3 Implication for Further Study

While this study provides valuable insights into the effectiveness of machine learning algorithms in brain tumor detection using MRI brain tumor datasets., there is still scope for further research to build upon these findings and expand our understanding of this field.

Here are the implications for further study in bullet points:

- Utilizes diverse filters and pre-processing steps to enhance deep learning models' performance.
- Transfer learning approach, leveraging architectures like VGG19, shows potential benefits of tailoring models to specific image characteristics.
- Incorporates geometric augmentations to improve model generalization and robustness.
- Ablation study on refined model, BTV19, highlights the significance of each component in model performance.
- Results validated through statistical analysis, confusion matrices, ROC-AUC curves, and K-Fold cross-validation.
- Achieved accuracy of 98.91% with BTV19 model under royal filter.
- The study's methodology and results serve as a benchmark for future studies, fostering collaboration and establishing standardized evaluation metrics.

- Contributes to the enhancement of automated brain tumor detection systems, benefiting clinical practice and patient outcomes.

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Enhancing Brain Tumor Detection with Royal Filter and BTV19 Model

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