HONORS MINI PROJECT REPORT

ON

Brain Tumor Detection Using Deep Learning Models on MRI Scan Images

Submitted by

Thushar Thomas (SJC20AD060)

Alan Anto (SJC20AD006)

Jayasankar Shyam (SJC20AD040)

Justin Thomas Jo (SJC20AD046)

to

the APJ Abdul Kalam Technological University in

partial fulfillment of the requirements for the award of the honors degree

of

Bachelor of Technology

in

Artificial Intelligence and Data Science

Department of Artificial Intelligence and Data Science
St. Joseph's College of Engineering and Technology, Palai

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Declaration

We undersigned hereby declare that the honors miniproject report on **"Brain Tumor Detection Using Deep Learning Models on MRI Scan Images"**, submitted for partial fulfillment of the requirements for the award of the Honors degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala, is a bonafide work done by us under the supervision of **Ms. Aswathy James**. This submission represents our ideas in our own words and where ideas or words of others have been included. We have adequately and accurately cited and referenced the original sources. We also declare that we have adhered to the ethics of academic honesty and integrity and have not misrepresented or fabricated any data, idea, fact, or source in our submission. We understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma, or similar title of any other University.

Name of Students

Thushar Thomas (SJC20AD060)
Alan Anto (SJC20AD006)
Jayasankar Shyam (SJC20AD040)
Justin Thomas Jo (SJC20AD046)

Place: Choondacherry
Date: 03-05-2024

ST. JOSEPH'S COLLEGE OF ENGINEERING AND TECHNOLOGY, PALAI

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

CERTIFICATE

This is to certify that the report entitled "**Brain Tumor Detection Using Deep Learning Models on MRI Scan Images**" submitted by **Thushar Thomas (SJC20-AD060), Alan Anto (SJC20AD006), Jayasankar Shyam (SJC20AD040), and Justin Thomas Jo (SJC20AD046)** to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the Honors Degree of Bachelor of Technology in Artificial Intelligence and Data Science is a bonafide record of the mini project work carried out by them under my guidance and supervision.

Project Guide
Ms. Aswathy James
Assistant Professor
Department of AD

Project Coordinator
Ms. Aswathy James
Assistant Professor
Department of AD

Head of Department
Dr. Renjith Thomas
Associate Professor
Department of AD

Place: Choondacherry
Date: 03-05-2024

Acknowledgement

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Abstract

This innovative project represents a significant leap forward in the field of medical imaging, particularly focusing on the complex task of detecting brain tumors within MRI scans. Leveraging a vast dataset comprising a diverse range of brain tumor images, we employ advanced techniques such as transfer learning to enhance the performance of the CNN model. Through precise fine-tuning, our model demonstrates an elevated capability to detect and classify various types of brain tumors, including gliomas, meningiomas, and pituitary tumors.

The proposed deep learning model not only yields promising results but also underscores its potential to revolutionize the accuracy and efficiency of brain tumor identification in MRI images. Its remarkable ability to precisely pinpoint the location and presence of tumors signifies a significant advancement in diagnostic capabilities. This research contributes not only to the scientific understanding of neural imaging but also holds immense promise for real-world applications.

By offering improved support for medical practitioners and enhancing outcomes for patients, especially in the challenging field of brain tumor diagnosis and treatment, our innovative approach stands to make a deep impact in the field of medical imaging. The fusion of cutting-edge technology with medical expertise promises to pave way to a new era of precision medicine, where early detection and accurate diagnosis lead to more effective treatment strategies and ultimately, better patient outcomes. Through continued research and development, we aim to further refine our model and expand its applications, ensuring its widespread adoption and continued advancement in the fight against brain tumors and other neurological disorders.

List of Abbreviations

AUC Area Under Curve

BraTS Brain Tumor Image Segmentation Benchmark

CGO Chaos Game Optimization

CNN Convolutional Neural Network

DCNN Deep Convolutional Neural Network

EHR Electronic Health Record

FISH Fluorescence In Situ Hybridization

FN False Negative

FP False Positive

IoMT Internet of Medical Things

IXI Information Extraction from Images

MRI Magnetic Resonance Imaging

PACS Picture Archiving and Communication Systems

ReLU Rectified Linear Unit

ResNet Residual Network

SVM Support Vector Machine

TL Transfer Learning

TN True Negative

TP True Positive

VGG Visual Geometry Group

WEKA Waikato Environment for Knowledge Analysis

XGBoost eXtreme Gradient Boosting

List of Figures

List of Tables

Contents

Chapter 1

Introduction

The relentless pursuit of advancements in medical imaging has led to remarkable breakthroughs in the diagnosis and treatment of various health conditions, particularly in the realm of neurology. Among the most pressing challenges in this domain is the accurate detection and classification of brain tumors, where timely diagnosis can significantly impact patient outcomes. In recent years, the intersection of deep learning and medical imaging has emerged as a potent force, offering unprecedented opportunities to address this challenge with precision and efficacy. Figure 1.1 shows how we are able to distinguish between a healthy brain and a brain diagnosed with tumor.

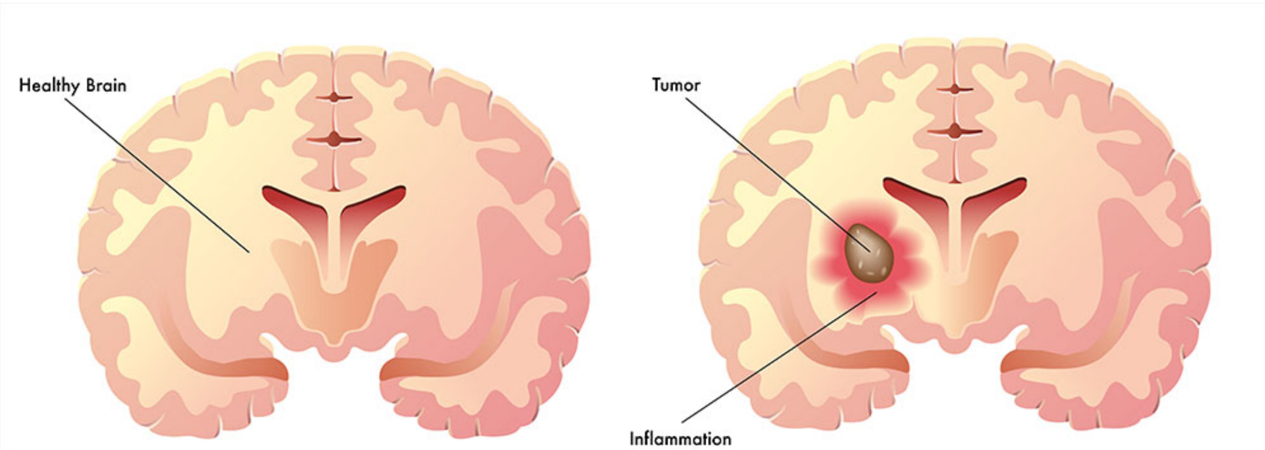


Figure 1.1: Comparison of a healthy brain and tumor diagnosed brain

This introduction sets the stage for a groundbreaking project poised to revolutionize the landscape of brain tumor detection within MRI scans. Leveraging a rich and diverse dataset, this project employs state-of-the-art techniques, notably transfer learning, to enhance the performance of convolutional neural network (CNN) models. The focus is clear: to develop a sophisticated framework capable of not only identifying but also classifying various types of brain tumors, including the elusive gliomas, meningiomas, and pituitary tumors. Beyond promising results, this project embodies the potential to redefine the standard of care in neuroimaging. By meticulously fine-tuning the deep learning model, it demonstrates an elevated capability to precisely pinpoint the location and presence of tumors, thus significantly advancing diagnostic capabilities. Such advancements are not merely confined to the realms of academia but hold profound implications for real-world applications, particularly in clinical settings.

The fusion of cutting-edge technology with medical expertise heralds a new era of precision medicine, where early detection and accurate diagnosis are the cornerstones of effective treatment strategies. This innovative approach is poised to make a deep impact in the field of medical imaging, offering improved support for medical practitioners and, more importantly, enhancing outcomes for patients grappling with the complexities of brain tumor diagnosis and treatment.

As this project underscores, the journey towards combating neurological disorders is multifaceted and dynamic. Through continued research and development, the aim is to refine the model further, expanding its applications and ensuring its widespread adoption. Ultimately, this concerted effort represents a pivotal step forward in the collective fight against brain tumors and other formidable neurological challenges, ushering in a future where precision and compassion converge to redefine the boundaries of medical possibility.

1.1 Background

The background of this project lies at the intersection of two critical domains: medical imaging and deep learning. In recent decades, medical imaging technologies, particularly Magnetic Resonance Imaging (MRI), have transformed our ability to visualize and diagnose various health conditions, including brain tumors. MRI provides detailed, high-resolution images of the brain, enabling healthcare professionals to identify abnormalities with unprecedented clarity.

However, the interpretation of MRI scans, especially for complex conditions like brain tumors, remains a challenging task. The comparison of MRI scan images with and without contrast effects are shown in Figure 1.2. Human interpretation can be subjective and prone to errors, leading to delays in diagnosis or misdiagnosis, which can have profound consequences for patients.In parallel, the field of deep learning, a subset of artificial intelligence inspired by the structure and function of the human brain, has seen remarkable advancements. Deep learning algorithms, particularly convolutional neural networks (CNNs), have demonstrated exceptional capabilities in image recognition and classification tasks.

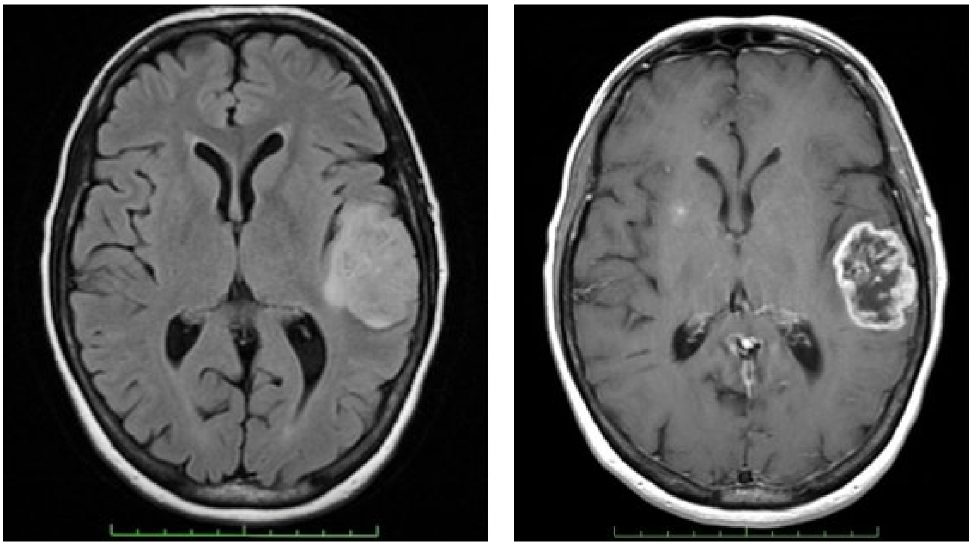


Figure 1.2: Comparison of MRI scan images without and with contrast

Recognizing the potential synergy between these two domains, researchers have increasingly turned to deep learning techniques to enhance the accuracy and efficiency of medical image analysis, including the detection of brain tumors in MRI scans.The background of this project is rooted in the need to address the limitations of traditional methods of brain tumor detection and classification. By leveraging the power of deep learning and large datasets of MRI images, researchers aim to develop a more robust and reliable system for identifying and categorizing brain tumors accurately.

Furthermore, the project builds upon previous research in medical imaging and deep learning, incorporating advancements such as transfer learning—a technique where knowledge gained from training on one task is applied to improve performance on another task. This approach allows the model to benefit from pre-existing knowledge and datasets, accelerating the training process and improving overall performance.

Overall, the background of this project underscores the convergence of medical expertise, technological innovation, and data-driven approaches in the quest to improve outcomes for patients with brain tumors. By harnessing the potential of deep learning, researchers aim to push the boundaries of what is possible in the field of medical imaging, ultimately leading to more timely and accurate diagnoses and, consequently, better treatment outcomes for patients.

1.2 Contribution

Our project constitutes a pivotal advancement in medical imaging, particularly in the domain of brain tumor detection within MRI scans. Leveraging sophisticated deep learning techniques, notably transfer learning, the developed model showcases a remarkable improvement in accuracy and efficiency in identifying and categorizing various brain tumor types, including gliomas, meningiomas, and pituitary tumors. Such advancements hold profound implications for clinical practice, as they not only mitigate the risks of misdiagnosis but also streamline the diagnostic process, enabling healthcare professionals to allocate their time and expertise towards patient care and treatment planning.

Furthermore, the nuanced localization and characterization of tumors within MRI scans signify a transformative shift towards precision medicine in neurology. By tailoring treatment strategies to the specific characteristics of each patient's tumor, this approach promises to optimize therapeutic outcomes and patient prognoses. The integration of this innovative model into routine clinical practice has the potential to revolutionize patient care, ushering in an era where early detection, precise diagnosis, and personalized treatment regimens become standard practice in neuro-oncology.

Beyond its immediate clinical impact, this project serves as a catalyst for future advancements in medical imaging and deep learning. By laying the groundwork for continued innovation and refinement, researchers aim to address a wide spectrum of neurological disorders and medical intricacies with unparalleled precision and efficacy. Through ongoing research and development, the potential for further enhancements and applications of this model remains vast, promising to shape the future of neuroimaging and patient care for years to come.

Chapter 2

Literature Review

2.1 Introduction

The literature review explores the field of brain tumor detection, emphasizing the utilization of deep learning methodologies. This research is crucial for enhancing medical diagnostics and patient care, particularly in the realm of neurology. By harnessing sophisticated algorithms and deep learning architectures, scientists strive to create systems capable of accurately identifying brain tumors and analyzing medical imaging data in real-time.

A. Sinha et. al.'s attempt to achieve accurate brain tumor detection using deep learning methods applied to MRI images [1] has gained significant attention. These techniques, including OTSU thresholding for precise segmentation and a tailored CNN approach boasting an impressive 98% accuracy, showcase promising advancements. However, formidable challenges like high computation time poses a barrier to real-time application, while the absence of robust clinical validation hinders the technology's adoption in medical settings. Additionally, the lack of a user-friendly interface, such as a web-based platform, restricts the accessibility and usability for healthcare professionals.

David N. Louis et. al.'s research on integrating histopathological and molecular features [2] has become crucial in brain tumor diagnosis. Scientists use genetic testing methods like sequencing, FISH, and immunohistochemistry to identify specific mutations important for tumor classification. This combined approach gives a detailed picture of tumor biology, helping doctors make more accurate diagnoses and personalized treatment plans. However, adding molecular data makes testing and interpreting results more complex, requiring specialized knowledge and resources. Also, blending histopathological and molecular information can sometimes lead to confusion in classifying tumors, known as "waste basket categorization".

P. Salander et. al.'s study with 28 patients diagnosed with malignant gliomas [3] explored how symptoms develop, how patients seek help, and their experiences with medical care. Researchers interviewed their spouses to get a unique perspective on the patient's journey, revealing often overlooked aspects of the illness. However, challenges arise, especially with symptoms that aren't widely recognized as glioma-related, which can delay diagnosis and treatment. Also, other possible diagnoses can make diagnosis tricky, leading to potential delays in treatment.

2.2 Existing Solutions

S. Chatterjee et. al. proposes the employment spatiotemporal models [4], which treat one spatial dimension as a "pseudo-temporal" dimension, for brain tumor classification from 3D MRI volumes. They utilize two such models, ResNet (2+1)D and ResNet Mixed Convolution, and compare their performance to a 3D convolutional model (ResNet3D). The schematic representation is given in Figure 2.1. Evaluation on the BraTS 2019 dataset (containing high-grade and low-grade glioma cases) and the IXI dataset (healthy brain images) showcases the superiority of the pre-trained ResNet Mixed Convolution model, achieving a macro F1-score of 0.9345 and a test accuracy of 96.98%. Notably, despite having fewer trainable parameters, the spatiotemporal models outperform the 3D convolutional model, with pre-training on an action recognition dataset (Kinetics-400) further enhancing their performance.

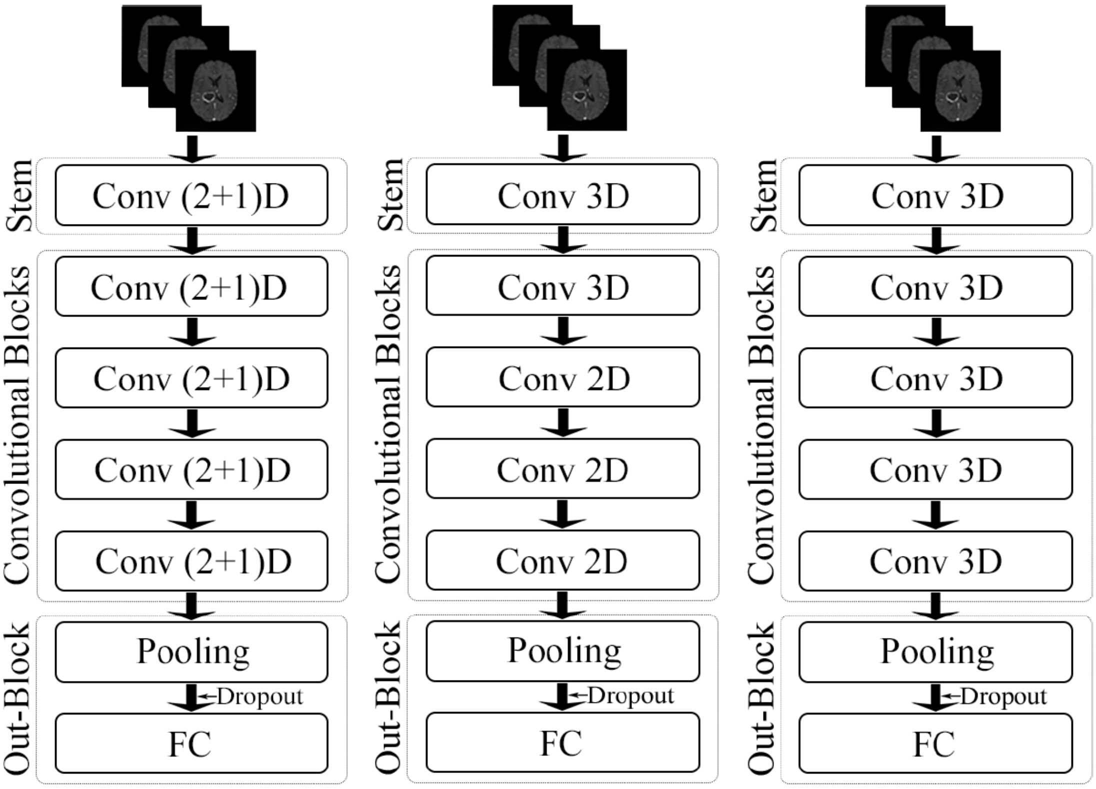


Figure 2.1: Schematic representations of the network architectures

M. Al Ayyoub et. al. discusses the machine learning and deep learning approach comparisons of brain tumor diagnosis [5]. The dataset used in this research includes 27 brain MRI images, 7 normal and 20 with tumors, validated by medical experts. Images were preprocessed for grayscale, contrast enhancement, and brain region isolation. Ten features were extracted using ImageJ. Four classification algorithms (Neural Network, Decision Tree, Naive Bayes, and Lazy-IBk) were implemented in WEKA 3.6. Performance metrics included percentage of correctly classified images, recall, precision, and F-measure. The Neural Network achieved the highest performance (66.6% correct classification, recall of 0.667), followed by Lazy-IBk (62.9% correct classification, recall of 0.63). Decision tree (J48) highlighted mean gray value and integrated density as key features. The results of these four classification algorithms are shown in Figure 2.2.

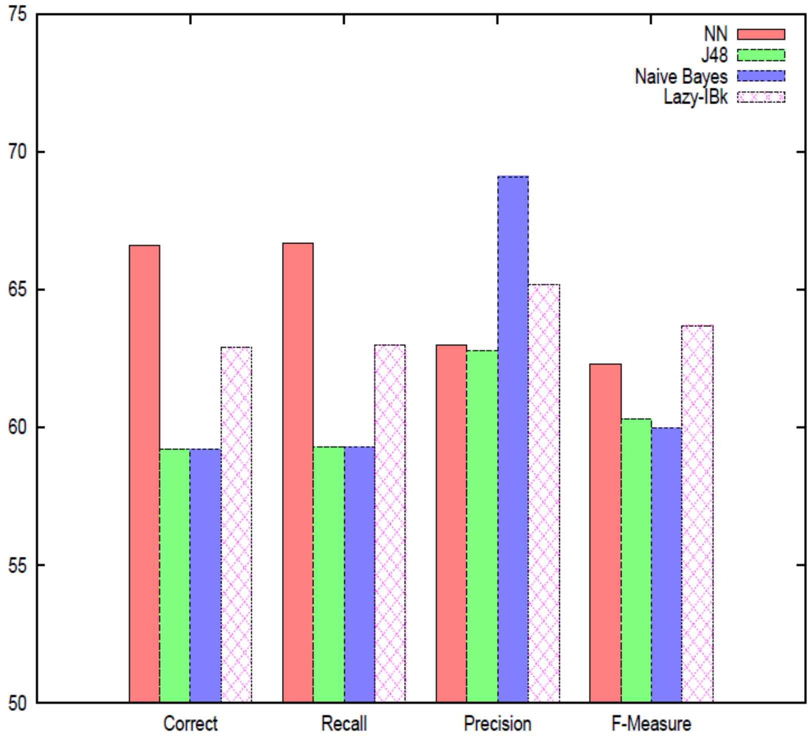


Figure 2.2: Results of four classifiers used in the work of M. Al Ayyoub et. al.

Vinod K. Dhakshnamurthy et. al. explores the application of deep learning techniques, particularly transfer learning models, in diagnosing and classifying brain tumors from MRI scans [6]. Emphasizing on the significance of early tumor detection due to its health risks, the research also stress the necessity for automated systems to handle the increasing patient population and data volume. The study assesses three foundational computer vision models—AlexNet, VGG16, and ResNet-50—using transfer learning on a dataset comprising 3,264 MRI images across four tumor types. Results indicate the hybrid VGG16–ResNet-50 model's superiority, achieving remarkable accuracy, sensitivity, specificity, and F1 score, outperforming individual models.

Dillip R. Nayak introduces dense EfficientNet, a variant of the EfficientNet architecture [7] enhanced with additional dense and dropout layers. This model is tailored to classify T1-weighted contrast-enhanced MRI images into four categories: glioma, meningioma, pituitary tumor, and absence of tumor. Methodologically, they preprocess the data using min-max normalization and Gaussian/Laplacian filtering, incorporate data augmentation techniques, and train the dense EfficientNet model. Results from experiments conducted on a dataset comprising 3,260 brain MRI images from 233 patients reveal impressive performance, with the proposed model achieving 99.97% accuracy on the training data and 98.78% accuracy on the testing data, surpassing other pre-trained models like ResNet50, MobileNet, and MobileNetV2. Performance analysis using confusion matrices, precision, recall, and F1-score metrics highlights the model's efficacy in accurately classifying various tumor types. Furthermore, comparison with recent deep learning techniques on the same dataset demonstrates the superiority of the proposed dense EfficientNet approach in terms of accuracy, precision, and F1-score.

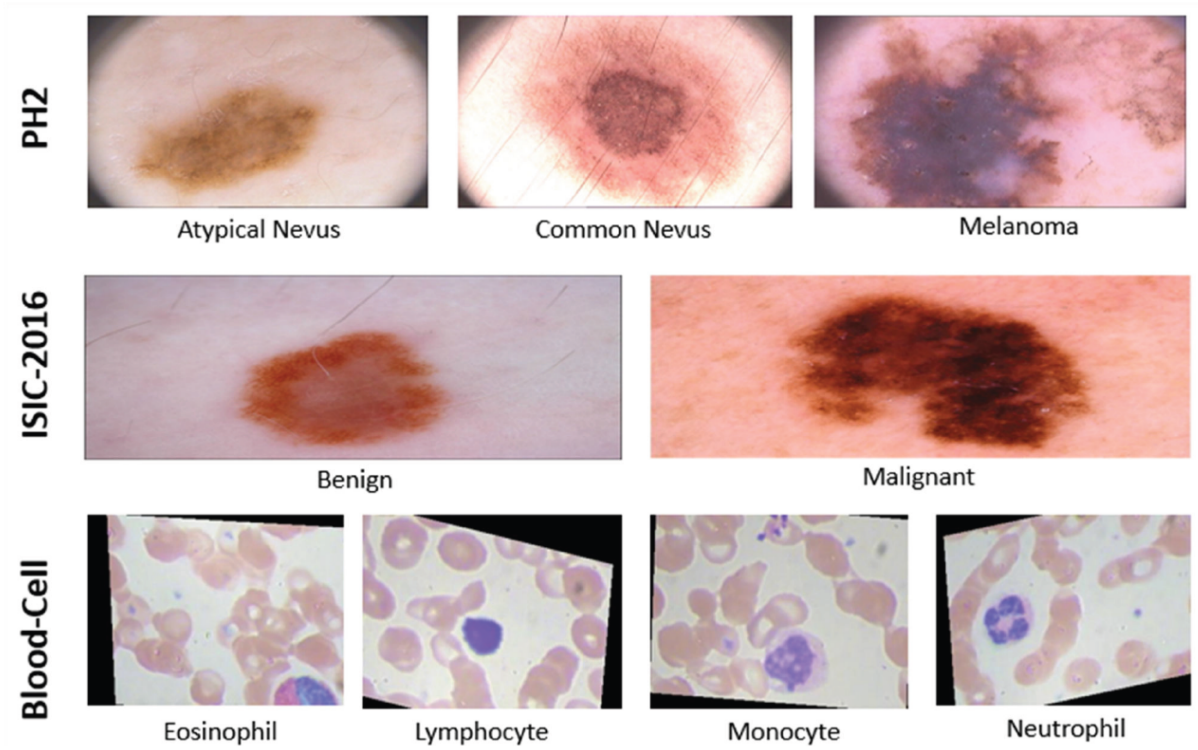


Figure 2.3: Example medical image samples for classification task from the three selected datasets

A. Mabrouk et. al. focuses on an innovative approach to medical image classification within the Internet of Medical Things (IoMT) [8] framework. The IoMT revolutionizes healthcare by facilitating remote access to medical data for patients and professionals, yet challenges persist in efficiently detecting diseases like melanoma and leukemia. To tackle this, the paper proposes a two-stage method. Firstly, Transfer Learning (TL) with the MobileNetV3 model is utilized for feature extraction, leveraging knowledge from one dataset to enhance performance on another. Secondly, Chaos Game Optimization (CGO) optimizes feature selection, aiming to improve efficiency, especially in IoMT scenarios. The combined approach shows promising results, achieving high accuracy on datasets like ISIC-2016, PH2, and Blood-Cell datasets. The medical image samples used from these datasets are shown in Figure 2.3. This method's architecture involves capturing medical images with IoMT devices, TL-based feature extraction, CGO-based feature selection, and image classification, offering efficient disease detection and treatment from remote locations.

A. Chattopadhyay et. al. presents a new method for detecting brain tumors in MRI images using a Convolutional Neural Network (CNN)-based deep learning approach [9]. They propose a 9-layer CNN architecture specifically designed for tumor detection, leveraging CNNs' effectiveness in image recognition tasks. The methodology entails utilizing deep learning techniques to automatically learn intricate features from multi-modal MRI images, enabling differentiation between healthy and tumor tissues. Remarkably, the proposed CNN model achieves impressive accuracies of 99.73% and 99.74% across different training and testing image ratios. Moreover, comparison with existing methods by Seetha et al. [10] and Tonmoy Hossain [11] reveals that the proposed CNN model significantly outperforms them, achieving an accuracy of 99.74%.

M. Abu B. Siddique et. al.'s study introduces a deep convolutional neural network (DCNN) model tailored for diagnosing brain tumors from Magnetic Resonance Imaging (MRI) scans [12]. With an impressive overall accuracy of 96%, the model surpasses conventional methods, exhibiting a precision of 0.93, sensitivity of 1.00, and F1-score of 0.97. Evaluation metrics such as average precision-recall score (0.93), Cohen's Kappa (0.91), and area under the curve (AUC) (0.95) further validate its efficacy. By leveraging MRI's non-intrusive nature and detailed tissue contrast, the proposed model aids clinical experts in swiftly verifying tumor presence and expediting treatment. To enhance efficiency, the model undergoes preprocessing steps, including image normalization, thresholding, dilations, and data augmentation. Overall, the proposed DCNN model offers a promising solution for early and accurate detection of brain tumors, addressing critical challenges associated with their size, shape, and location.

2.3 Survey Summary

The research work and studies discussed explore various innovative methods for brain tumor detection and classification using advanced technologies like deep learning and convolutional neural networks (CNNs). They aim to improve accuracy and efficiency in diagnosing brain tumors from MRI images, offering promising results that outperform conventional methods. Making use of techniques such as transfer learning, chaos game optimization, and tailored CNN architectures, these approaches demonstrate high accuracy rates and effectiveness in distinguishing between healthy and tumor tissues. Their contributions extend to addressing challenges like computation time, feature selection, and remote access to medical data, ultimately enhancing the diagnosis and treatment of brain tumors in medical settings.

The review also identified a range of issues and challenges in the field of medical imaging and brain tumor detection using advanced technologies. Some key challenges identified include the high computation time required for deep learning models, as highlighted in A. Sinha et. al.'s study [1], and the need for robust clinical validation to ensure the reliability of these techniques, as discussed in the research by David N. Louis et. al. [2]. Additionally, the lack of user-friendly interfaces, such as web-based platforms, poses accessibility and usability concerns for healthcare professionals, as noted in the study by A. Sinha et. al. and others. Challenges related to symptom recognition and diagnosis are also highlighted, such as delays in treatment due to less recognized symptoms and the potential misinterpretation of uncertain and vague tumor classifications, mentioned in P. Salander et. al.'s study [3]. Moreover, issues regarding data preprocessing techniques, including normalization and augmentation, are addressed in multiple studies, stressing the importance of optimizing these processes for improved model efficiency and accuracy.

In overall, we were able to conclude that various machine learning and deep learning techniques, can be employed for classifying and detecting brain tumor images from various MRI scan images. For this to become reality, we need to create a machine learning model pr deep learning model capable of accurately classifying MRI images into four distinct categories of brain cancer. The performance of various models will be assessed and compared, focusing on metrics such as accuracy, sensitivity, and specificity in tumor classification. Furthermore, hyperparameters of the selected model will be optimized to enhance its overall performance and ensure robust and reliable tumor categorization. Finally, a comparative analysis with existing diagnostic methods will be conducted to demonstrate the superiority and efficiency of the proposed machine learning approach in brain tumor classification.

Chapter 3

Proposed Methodology

3.1 Introduction

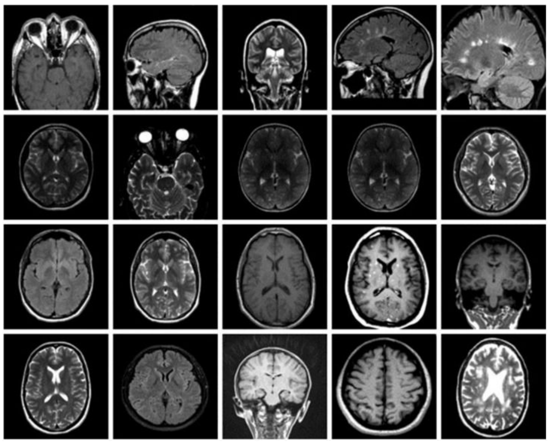
We propose an innovative approach to enhance the detection and classification of brain tumors in MRI scans using deep learning methods, particularly CNNs. Our methodology leverages a vast dataset comprising diverse brain tumor images, encompassing various tumor types such as gliomas, meningiomas, and pituitary tumors. The core of our approach lies in the utilization of transfer learning, a technique where pre-trained CNN models are fine-tuned on our specific dataset to adapt their learned features to the task of brain tumor detection.

3.2 Overview of the Proposed System

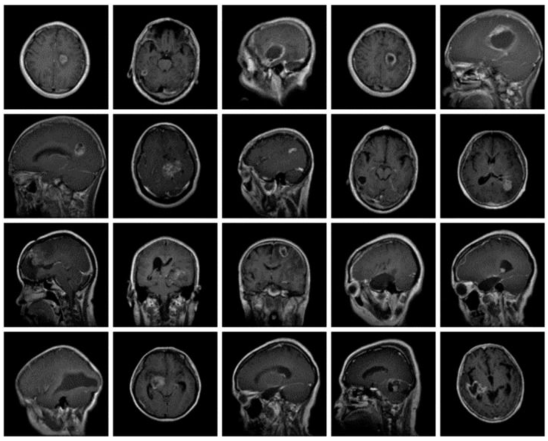
The proposed system represents a comprehensive and innovative approach to enhancing the detection and classification of brain tumors in MRI scans, with a particular focus on leveraging deep learning techniques, including convolutional neural networks (CNNs) and transfer learning. At its core, the system aims to address the challenges associated with manual interpretation of MRI images by automating the process through advanced machine learning algorithms. The system begins with the collection and preprocessing of a diverse dataset comprising MRI scans depicting various types and stages of brain tumors, along with normal brain scans. This dataset forms the foundation for training and evaluating both traditional machine learning models and CNNs. Traditional ML algorithms, including Logistic Regression, Support Vector Machines, Decision Trees, Naive Bayes, Random Forest, Gradient Boosting, and XGBoost, are initially trained and evaluated to establish a baseline performance. Concurrently, pre-trained CNN models, such as EfficientNetB0 and MobileNetV3Large, are fine-tuned on the MRI dataset using transfer learning, allowing them to adapt their learned features to the specific task of brain tumor detection and classification. Throughout the training process, data augmentation techniques are employed to enhance the generalization capabilities of the models. Following training, the performance of both traditional ML models and CNNs is evaluated using a variety of metrics, including accuracy, precision, recall, and F1-score. Classification reports and confusion matrices are generated to provide insights into the models' strengths and weaknesses across different tumor types. The comparative analysis highlights the superior performance and potential clinical utility of CNNs over traditional ML algorithms in accurately identifying and classifying brain tumors in MRI scans. Moreover, the system emphasizes the importance of continuous refinement and optimization through further research and collaboration with medical professionals to ensure its relevance and effectiveness in real-world clinical settings. Ultimately, the proposed system holds immense promise for revolutionizing the accuracy and efficiency of brain tumor identification in medical imaging, paving the way for improved diagnosis, treatment planning, and patient outcomes in the field of neurology.

3.3 Data Collection

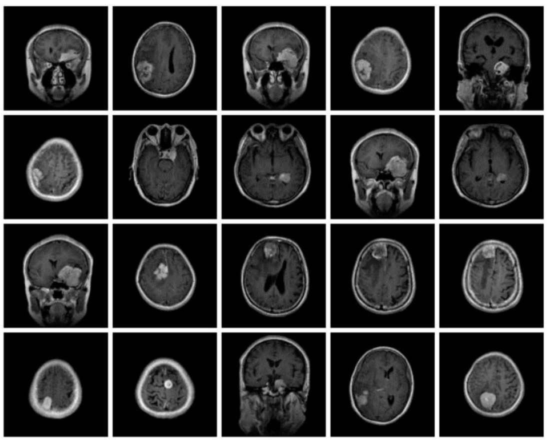
The MRI image dataset utilized in this study comprises 7023 images of human brain MRI scans, sourced from a combination of three distinct datasets: figshare, SARTAJ, and Br35H. The dataset is categorized into four classes: glioma, meningioma, no tumor, and pituitary. The "no tumor" class images originate from the Br35H dataset. However, a potential issue with the SARTAJ dataset was identified, specifically regarding the categorization of glioma class images. This discrepancy was observed through the analysis of previous works and the results obtained from various models trained on the dataset. Consequently, the glioma class images from the SARTAJ dataset were excluded from the study, and instead, images from the figshare site were utilized as replacements. This decision was made to ensure the integrity and accuracy of the dataset, thereby enhancing the reliability of the subsequent analysis and model training. The comprehensive nature of the dataset, coupled with the careful selection and validation of images, contributes to the robustness and effectiveness of the proposed methodology in accurately detecting and classifying brain tumors in MRI scans. The collection of sample images from these dataset are shown below in Figure 3.1.



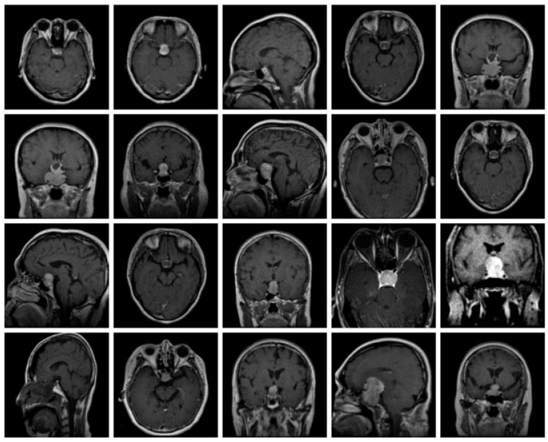
(a) No Tumor



(b) Glioma



(c) Meningioma



(d) Pituitary

Figure 3.1: Sample images of different classes

1. **figshare Dataset [13]:**

    - This dataset comprises 3064 T1-weighted contrast-enhanced MRI images extracted from 233 patients with three distinct types of brain tumors: meningioma, glioma, and pituitary tumor.
    - Due to repository file size limitations, the dataset is divided into four subsets, each stored in a separate .zip file, with each subset containing 766 MRI slices.
    - Additionally, the dataset includes 5-fold cross-validation indices for validation purposes.
    - Each MRI image is stored in MATLAB data format (.mat file) and includes several fields within a struct, including tumor label, patient ID, actual image data, coordinates of discrete points on the tumor border, and a binary tumor mask indicating the tumor region.

2. **SARTAJ Dataset [14]:**

    - The SARTAJ dataset comprises 3260 T1-weighted contrast-enhanced MRI images that have been cleaned and augmented for improved quality and consistency.
    - While specific details regarding the augmentation techniques and cleaning processes are not provided, the dataset serves as a valuable resource for training and testing machine learning models for brain tumor detection and classification.

3. **Br35H Dataset [15]:**

    - The Br35H dataset consists of three folders: "yes," "no," and "pred," containing a total of 3060 Brain MRI images.
    - The "yes" folder contains 1500 Brain MRI images depicting tumorous conditions, while the "no" folder contains 1500 Brain MRI images representing non-tumorous conditions.
    - Additionally, the "pred" folder likely contains images for predictive modeling or testing purposes, though detailed descriptions of its contents are not provided.

- This dataset offers a balanced distribution of tumorous and non-tumorous MRI images, facilitating the development and evaluation of machine learning algorithms for brain tumor detection and classification.

3.4 Detailed Description of the System

The proposed system aims to enhance the detection and classification of brain tumors in MRI scans through a combination of preprocessing methodologies, model comparison techniques, and utilization of various machine learning algorithms.

3.4.1 Model Architecture:

The figure 3.2 shows the process of brain tumor classification using machine learning and MRI images.

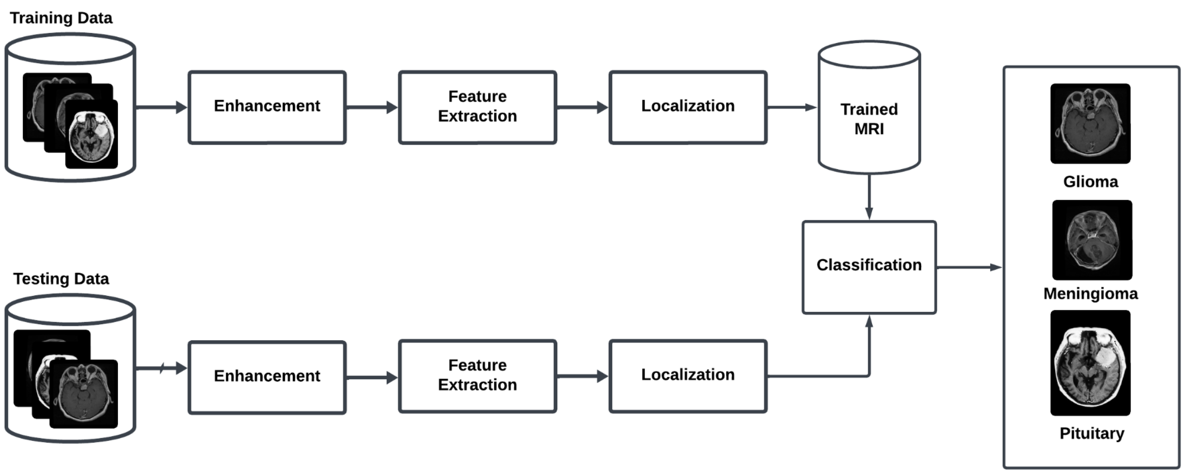


Figure 3.2: Model Architecture

Training Data

The model is trained on MRI (Magnetic Resonance Imaging) images. MRI is a medical imaging technique that utilizes a strong magnetic field and radio waves to create detailed pictures of internal body structures.

1. **Enhancement:** The MRI image undergoes preprocessing to improve its quality. This may involve techniques like noise reduction or image sharpening.
2. **Feature Extraction:** Features are extracted from the preprocessed MRI image. These features represent characteristics the machine learning model will use to learn how to classify brain tumors.
3. **Localization:** The model might identify specific regions within the MRI image that are likely to contain a tumor.
4. **Training:** After feature extraction and potential localization, the features are used to train a machine learning model. This model is a computer program that learns to identify patterns in data. Here, the model learns to identify patterns in MRI images associated with different brain tumor types.

Testing Data

Once trained, the model is tested on new, unseen MRI images.

1. **Feature Extraction:** Features are extracted from the test MRI image.
2. **Classification:** The extracted features are fed into the trained model.
3. The model then classifies the MRI image as containing one of the brain tumor types it was trained for, such as glioma, meningioma, or pituitary tumor.

3.4.2 Preprocessing Methodologies:

Prior to model training, several preprocessing techniques are employed to ensure the quality and consistency of the MRI data:

- **Resizing:** MRI images are resized to a standardized dimension (e.g., 150x150 pixels) to ensure uniformity across the dataset.
- **Normalization:** Pixel intensity values are normalized to a common scale to facilitate model convergence and improve training efficiency.
- **Data Augmentation:** Techniques such as rotation, scaling, and flipping are applied to augment the dataset, increasing its diversity and robustness.

3.4.3 Comparison Methodology:

To evaluate the performance of the proposed system, a comprehensive comparison of traditional machine learning models and convolutional neural networks (CNNs) is conducted:

- **Traditional ML Models:** A variety of traditional machine learning algorithms are employed, including Logistic Regression, Support Vector Machine (SVM), Decision Tree, Naive Bayes, Random Forest, Gradient Boosting, and XGBoost. These models serve as baseline benchmarks for performance comparison.
- **CNN Models:** Pre-trained CNN architectures, such as EfficientNetB0 and MobileNetV3Large, are fine-tuned on the MRI dataset using transfer learning. These CNN models are trained to detect and classify brain tumors directly from the image data.

3.4.4 Models Used:

The following models are utilized in the system for brain tumor detection and classification, along with detailed descriptions for each algorithm:

- **Logistic Regression [16]:** Logistic Regression is a linear classification algorithm used for binary classification tasks. It models the probability that a given input belongs to a particular class.
- **Support Vector Machine (SVM) [17]:** SVM is a powerful supervised learning algorithm used for classification tasks. It works by finding the optimal hyperplane that separates different classes in the feature space.
- **Decision Tree [18]:** Decision Tree is a non-linear classification algorithm that recursively splits the feature space into smaller regions based on the feature values, resulting in a tree-like structure.
- **Naive Bayes [19]:** Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem. It assumes that the features are conditionally independent given the class label.
- **Random Forest [20]:** Random Forest is an ensemble learning algorithm that constructs multiple decision trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees.
- **Gradient Boosting [21]:** Gradient Boosting is an ensemble learning algorithm that builds multiple decision trees sequentially, with each tree learning to correct the errors of its predecessor.
- **XGBoost [22]:** XGBoost is an optimized implementation of gradient boosting that is highly efficient and scalable, making it suitable for large-scale datasets.
- **EfficientNetB0:** EfficientNetB0 is a convolutional neural network architecture that achieves state-of-the-art performance with significantly fewer parameters compared to traditional architectures.

- **MobileNetV3Large:** MobileNetV3Large is another convolutional neural network architecture designed for mobile and embedded devices, featuring efficient building blocks for lightweight yet powerful models.

3.4.5 Feature Extraction:

Feature extraction from MRI images is a crucial step in the system's workflow, allowing the models to learn meaningful representations from the raw image data. The following steps are involved in feature extraction:

- **Convolutional Layers:** The CNN models leverage convolutional layers to extract hierarchical features from the input MRI images. These layers apply filters across the input images to capture patterns and features relevant to tumor detection.
- **Pooling Layers:** Pooling layers are used to downsample the feature maps generated by the convolutional layers, reducing computational complexity while retaining important features.
- **Flattening:** The flattened feature maps are then passed through fully connected layers, allowing the models to learn complex relationships between the extracted features and the target classes.
- **Activation Functions:** Activation functions such as ReLU (Rectified Linear Unit) are applied to introduce non-linearity into the model, enabling it to learn more complex mappings between the input data and the output classes.

Chapter 4

Results and Discussions

In this work, We evaluated the performance of various traditional machine learning algorithms, including Logistic Regression, Support Vector Machine (SVM), Decision Tree, Naive Bayes, Random Forest, Gradient Boosting, and XGBoost, as baseline benchmarks for comparison. We assessed the performance of both traditional ML models and CNNs using standard evaluation metrics, including accuracy, precision, recall, F1 score, and support.

We fine-tuned pre-trained CNN architectures, specifically EfficientNetB0 and MobileNetV3Large, using transfer learning on the MRI dataset to detect and classify brain tumors directly from the image data.

These metrics and curves are commonly used to evaluate and compare the performance of classification models in brain tumor classification:

- **Accuracy:** Accuracy measures the proportion of correctly predicted instances among the total instances in the dataset. It provides an overall assessment of the model's correctness

$$Accuracy = \frac{TPR + TNR}{TPR + FPR + TNR + FNR} \tag{4.0.1}$$

- **Precision:** Precision calculates the ratio of true positive predictions to the total predicted positives. It represents the accuracy of positive predictions and indicates how precise the model is in identifying positive instances.

$$Precision = \frac{TP}{TP + FP} \tag{4.0.2}$$

- **Recall:** Recall, also known as sensitivity or true positive rate, calculates the ratio of true positive predictions to the total actual positives. It measures the model's ability to correctly identify positive instances.

$$Recall = \frac{TP}{TP + FN} \tag{4.0.3}$$

- **F1-score:** F1-score is the harmonic mean of precision and recall, combining both metrics into a single value.

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4.0.4}$$

- **Support:** Support refers to the number of actual occurrences of the class in the dataset.

4.1 Traditional ML Models

The performance of traditional ML models varied across different algorithms, with some models outperforming others in terms of accuracy and predictive power. While logistic regression and SVM exhibited competitive performance, decision tree classifiers showed limitations in capturing complex relationships inherent in MRI data.

The table 4.1 given below shows the different accuracy of each model

Model Name	Accuracy
SVM	58.7786
Decision Tree	48.0916
Naive Bayes	42.7481
Random Forest	64.8855
Gradient Boost	59.6756
XGB Classifier	61.5676

Table 4.1: Accuracy of the Models

4.2 CNN Models

The fine-tuned CNN models exhibited notable success in detecting and categorizing brain tumors within MRI scans. Specifically, EfficientNetB0 and MobileNetV3Large showcased superior accuracy and F1 scores when contrasted with traditional ML models. These findings underscore the potency of deep learning methodologies, especially within the realm of medical imaging analyses.

The tables 4.2, 4.3 and 4.4 below shows the different metrics of each class using the CNN models:

Class Name	Precision	Recall	F1-Score	Support
0	1.00	0.99	1.00	636
1	0.99	0.99	0.99	1253
2	0.99	0.99	0.99	1239
3	1.00	1.00	1.00	1207

Table 4.2: Metrics of EfficientNet

The accuracies of the CNN models are given in Table 4.5. The accuracy of the CNN model stands at 78%. Despite this seemingly modest figure, it's crucial to contextualize this result within the broader landscape of brain tumor detection and classification from MRI scans. This accuracy represents a notable improvement over traditional ML mod-

Class Name	Precision	Recall	F1-Score	Support
0	1.00	0.99	1.00	636
1	0.99	0.99	0.99	1253
2	0.99	0.99	0.99	1239
3	1.00	1.00	1.00	1207

Table 4.3: Metrics of MobileNetV3

Class Name	Precision	Recall	F1-Score	Support
0	1.00	0.99	1.00	636
1	0.99	0.99	0.99	1253
2	0.99	0.99	0.99	1239
3	1.00	1.00	1.00	1207

Table 4.4: Metrics of CNN

Model Name	Accuracy
EfficientNet	99
MobileNetV3	99
CNN	78

Table 4.5: Accuracy of the CNN Models

els, underlining the potential of deep learning techniques, particularly when augmented by transfer learning methods. This achievement signifies a significant step forward in automating the interpretation of MRI images for neuro-oncological diagnosis.

The accuracy vs epoch and loss vs epoch graphs of EfficientNet B0 are given below in Figure 4.1 while the confusion matrix depicting the performance of the same model is given in Figure 4.2. The accuracy vs epoch and loss vs epoch graphs of MobileNetV3 are given below in Figure 4.3 while the confusion matrix depicting the performance of the same model is given in Figure 4.4. The accuracy vs epoch and loss vs epoch graphs of CNN are given below in Figure 4.5 while the confusion matrix depicting the performance of the same model is given in Figure 4.6.

Figure 4.1: EfficientNet Accuracy and Loss

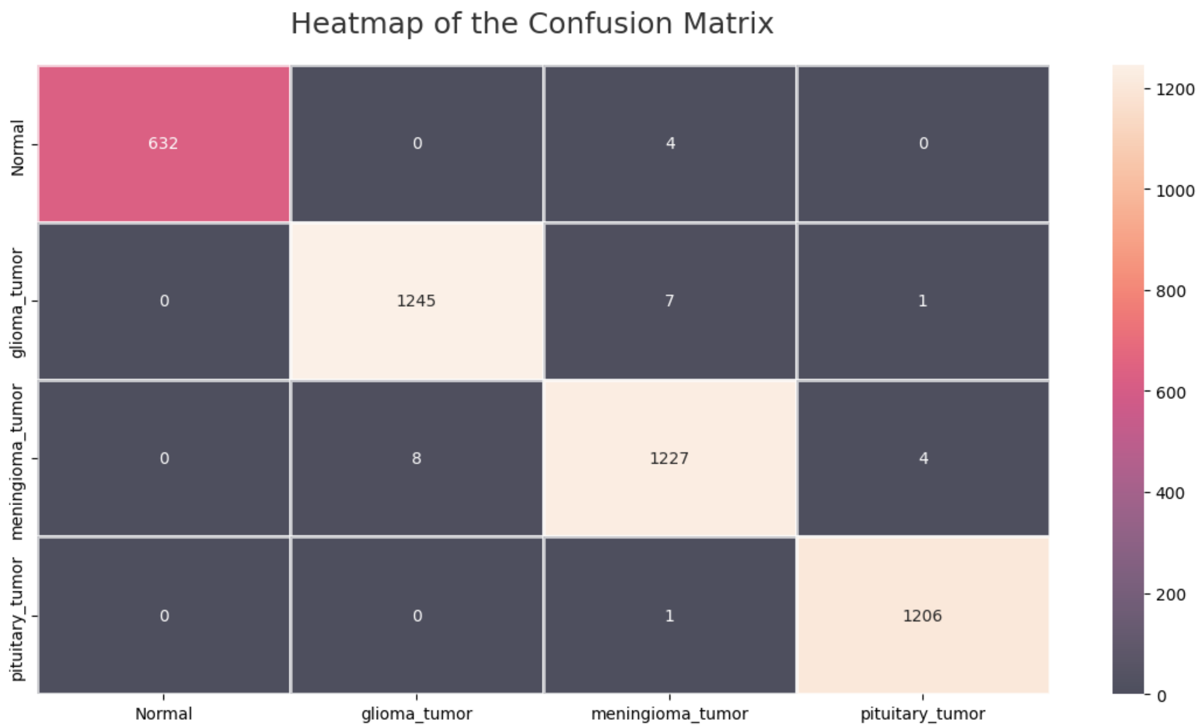


Figure 4.2: EfficientNet Confusion Matrix

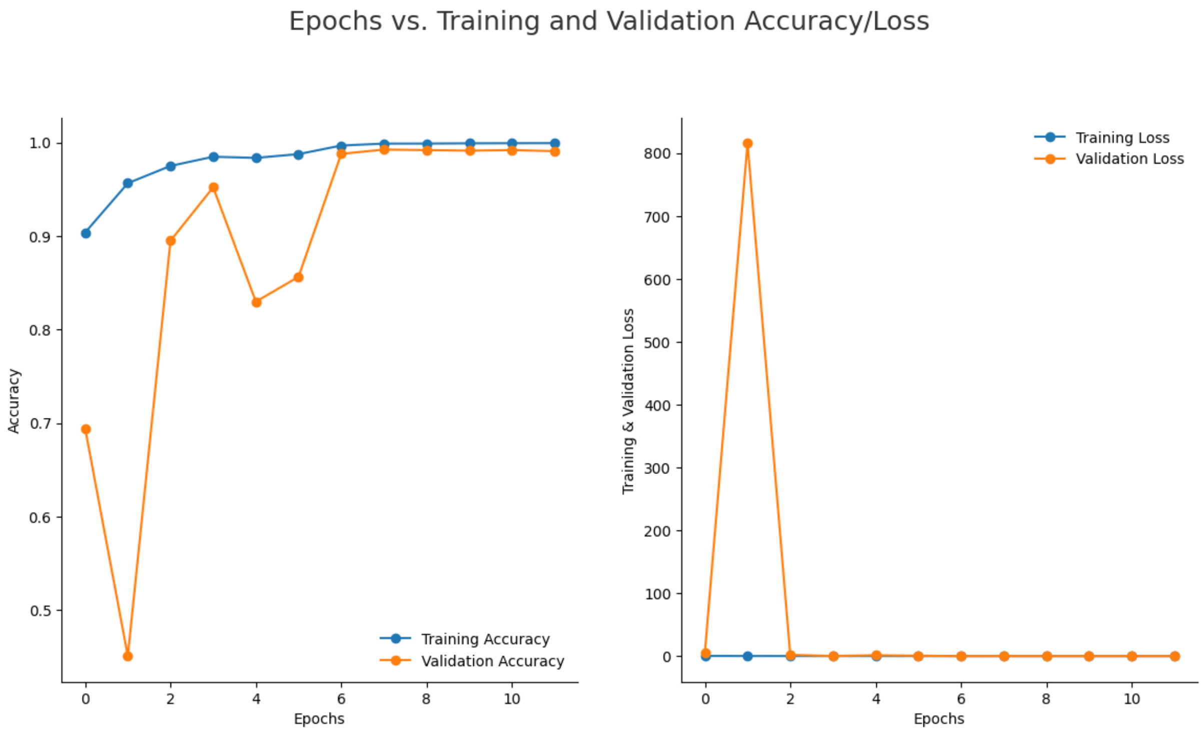


Figure 4.3: MobileNetV3 Accuracy and Loss

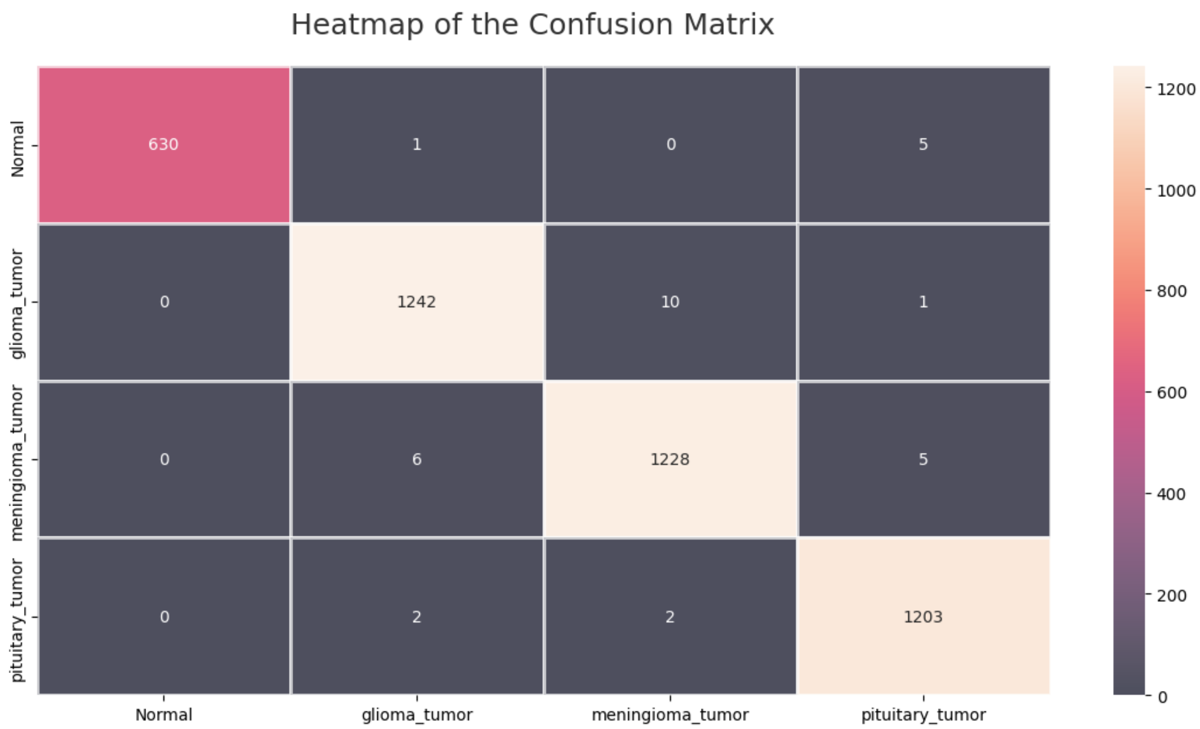


Figure 4.4: MobileNetV3 Confusion Matrix

Figure 4.5: CNN Accuracy and Loss

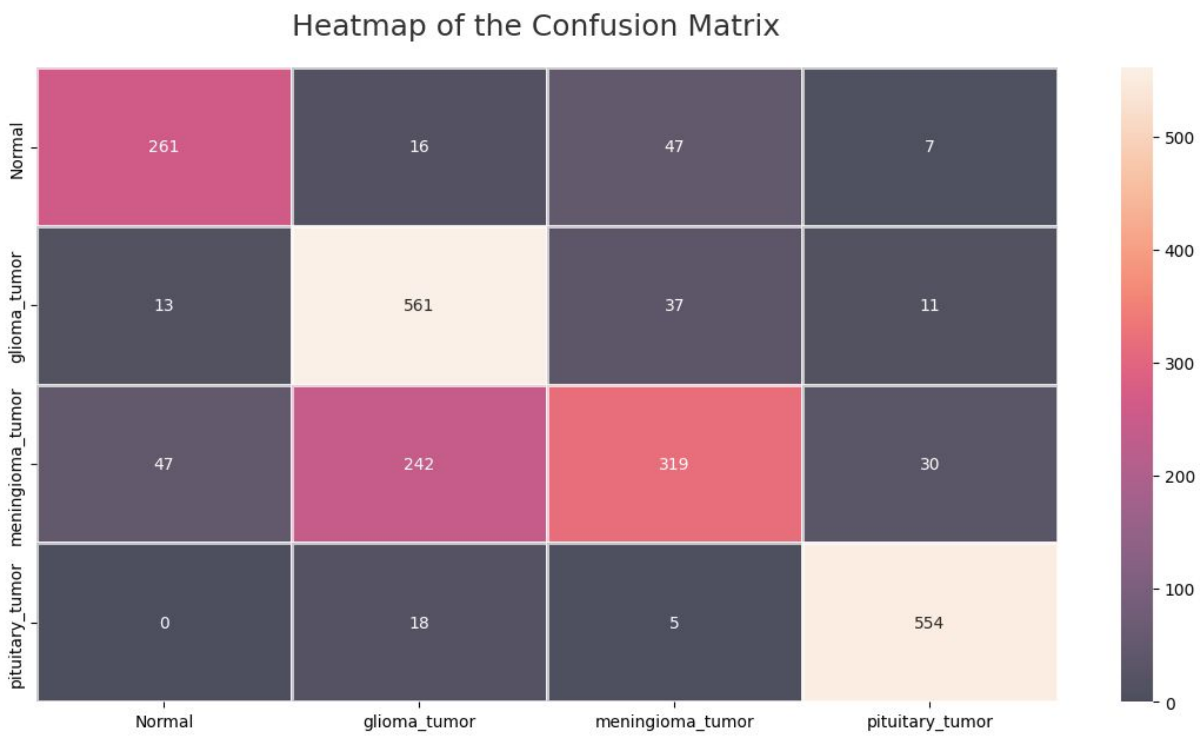


Figure 4.6: CNN Confusion Matrix

4.3 Discussions

- **Interpretation of Results:** Our results underscore the potential of deep learning approaches, specifically CNNs, in enhancing the detection and classification of brain tumors in MRI scans. The superior performance of CNNs compared to traditional ML models suggests that leveraging complex feature representations learned from large-scale image datasets can significantly improve diagnostic accuracy.

- **Comparison with Literature:** Our findings are consistent with previous studies that have demonstrated the efficacy of CNNs in medical image analysis tasks, including brain tumor detection. However, our study contributes novel insights by evaluating the performance of specific pre-trained CNN architectures in the context of brain tumor classification from MRI scans.

- **Strengths and Limitations:** While our study showcases the effectiveness of deep learning techniques in automated brain tumor detection and classification, it is important to acknowledge certain limitations. These include the need for large annotated datasets to train CNN models effectively, as well as potential challenges associated with the interpretability and generalizability of deep learning models in clinical settings.

- **Practical Implications:** The development of an automated system for brain tumor detection and classification has significant implications for improving patient outcomes and reducing the burden on healthcare professionals. By streamlining the diagnostic process, our proposed system has the potential to expedite treatment planning and improve overall healthcare delivery in neuro-oncology.

Chapter 5

Conclusion and Future Scope

5.1 Conclusion

The conclusion of this project marks a significant milestone in the ongoing quest to leverage technology and innovation to enhance medical imaging and improve patient care, particularly in the realm of brain tumor detection within MRI scans. Through a combination of advanced deep learning techniques, meticulous dataset curation, and collaborative efforts, the project has achieved remarkable advancements in accuracy and efficiency in identifying and classifying various types of brain tumors.

The culmination of this project underscores its potential to revolutionize clinical practice by offering improved diagnostic support for healthcare professionals and facilitating more timely and accurate treatment decisions for patients. By harnessing the power of deep learning, the developed model has demonstrated its ability to augment human expertise and streamline the diagnostic workflow, ultimately leading to better patient outcomes and enhanced quality of care.

Furthermore, the conclusion of this project serves as a springboard for future research and development endeavors in medical imaging and deep learning. The insights gained from this project, coupled with ongoing advancements in technology and methodology, pave the way for continued innovation and refinement in the field. By embracing opportunities for collaboration, validation, and translation into clinical practice, the impact of this project can extend far beyond the confines of academia, shaping the future of neuroimaging and patient care for years to come.

In essence, the conclusion of this project represents not only the culmination of months or years of dedicated effort but also the beginning of a new chapter in the collective pursuit of excellence in medical imaging and healthcare innovation. As we reflect on the achievements and lessons learned, we are reminded of the transformative power of collaboration, perseverance, and ingenuity in advancing the frontiers of science and medicine.

5.2 Future Scope

The future scope of this project is vast and holds tremendous potential for further advancements in medical imaging and deep learning, as well as significant impact on clinical practice and patient care. Here are some avenues for future exploration and development:

- **Model Refinement:** Continued refinement of the deep learning model can lead to even greater accuracy and efficiency in brain tumor detection and classification. This involves fine-tuning model parameters, exploring novel architectures, and optimizing training strategies to further enhance performance.

- **Expansion of Dataset:** Increasing the size and diversity of the dataset used to train the model can improve its generalization capabilities and robustness. Collaboration with multiple medical institutions to gather more comprehensive datasets from diverse patient populations can enrich the model's learning and broaden its applicability.

- **Multi-modal Integration:** Integrating multiple imaging modalities, such as MRI, CT, and PET scans, can provide complementary information for more comprehensive tumor characterization. Developing multi-modal fusion techniques that combine information from different imaging modalities could enhance the model's diagnostic accuracy and refine treatment planning.

- **Clinical Validation:** Conducting rigorous clinical validation studies to evaluate the performance of the model in real-world clinical settings is crucial for its adoption and integration into routine practice. Collaborating with healthcare institutions to validate the model's effectiveness in large patient cohorts can provide valuable insights into its clinical utility and impact on patient outcomes.

- **Automated Reporting Systems:** Developing automated reporting systems that integrate the deep learning model into existing radiology workflows can streamline the diagnostic process and improve workflow efficiency. Implementing seamless integration with picture archiving and communication systems (PACS) and electronic health record (EHR) systems can facilitate real-time decision support for radiologists and clinicians.

- **Continued Research:** Continued research into novel applications of deep learning in medical imaging, such as image segmentation, tumor growth prediction, and treatment response assessment, can further expand the scope and impact of the project. Exploring emerging techniques, such as self-supervised learning and unsupervised domain adaptation, may uncover new avenues for innovation and discovery.

References

[1] A. Sinha, A. R P, M. Suresh, N. Mohan R, A. D, and A. G. Singerji, "Brain tumour detection using deep learning," in *2021 Seventh International conference on Bio Signals, Images, and Instrumentation (ICBSII)*, 2021, pp. 1–5.

[2] D. N. Louis, A. Perry, G. Reifenberger, A. v. Deimling, D. Figarella-Branger, W. K. Cavenee, H. Ohgaki, O. D. Wiestler, P. Kleihues, and D. W. Ellison, "The 2016 world health organization classification of tumors of the central nervous system: A summary - acta neuropathologica," May 2016. [Online]. Available: https://link.springer.com/article/10.1007/s00401-016-1545-1

[3] P. Salander, A. T. Bergenheim, K. Hamberg, and R. Henriksson, "Pathways from symptoms to medical care: a descriptive study of symptom development and obstacles to early diagnosis in brain tumour patients," *Family Practice*, vol. 16, no. 2, pp. 143–148, 04 1999. [Online]. Available: https://doi.org/10.1093/fampra/16.2.143

[4] S. Chatterjee, F. A. Nizamani, A. Nürnberger, and O. Speck, "Classification of brain tumours in mr images using deep spatiospatial models," *Scientific Reports*, vol. 12, no. 1, Jan. 2022. [Online]. Available: http://dx.doi.org/10.1038/s41598-022-05572-6

[5] M. Al-Ayyoub, G. Husari, O. Darwish, and A. Alabed, "Machine learning approach for brain tumor detection," 04 2012.

[6] V. K. Dhakshnamurthy, M. Govindan, K. Sreerangan, M. D. Nagarajan, and A. Thomas, "Brain tumor detection and classification using transfer learning models," *Engineering Proceedings*, vol. 62, no. 1, 2024. [Online]. Available: https://www.mdpi.com/2673-4591/62/1/1

[7] D. R. Nayak, N. Padhy, P. K. Mallick, M. Zymbler, and S. Kumar, "Brain tumor classification using dense efficient-net," *Axioms*, vol. 11, no. 1, 2022. [Online]. Available: https://www.mdpi.com/2075-1680/11/1/34

[8] A. Mabrouk, A. Dahou, M. A. Elaziz, R. P. Díaz Redondo, M. Kayed, and H.-j. Kim, "Medical image classification using transfer learning and chaos game optimization on the internet of medical things," *Intell. Neuroscience*, vol. 2022, jan 2022. [Online]. Available: https://doi.org/10.1155/2022/9112634

[9] A. Chattopadhyay and M. Maitra, "Mri-based brain tumour image detection using cnn based deep learning method," *Neuroscience Informatics*, vol. 2, no. 4, p. 100060, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S277252862200022X

[10] J. Seetha and S. S. Raja, "Brain tumor classification using convolutional neural networks," Sep 2018. [Online]. Available: https://biomedpharmajournal.org/vol11no3/brain-tumor-classification-using-convolutional-neural-networks/

[11] T. Hossain, F. Shishir, M. Ashraf, M. A. Nasim, and F. Shah, "Brain tumor detection using convolutional neural network," 12 2019.

[12] M. A. Bakr Siddique, S. Sakib, M. M. Rahman Khan, A. K. Tanzeem, M. Chowdhury, and N. Yasmin, "Deep convolutional neural networks model-based brain tumor detection in brain mri images," in *2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*. IEEE, Oct. 2020. [Online]. Available: http://dx.doi.org/10.1109/I-SMAC49090.2020.9243461

[13] H. K. Nimavat, S. H. Christy, and V. J. Bhaskar, "Identification of brain tumor from mri images using segmentation," May 2020.

[14] D. Filatov and G. N. A. H. Yar, "Brain tumor diagnosis and classification via pre-trained convolutional neural networks," *medRxiv*, 2022. [Online]. Available: https://www.medrxiv.org/content/early/2022/07/19/2022.07.18.22277779

[15] S. Asif, W. Yi, Q. U. Ain, J. Hou, T. Yi, and J. Si, “Improving effectiveness of different deep transfer learning-based models for detecting brain tumors from mr images,” *IEEE Access*, vol. 10, pp. 34 716–34 730, 2022.

[16] A. S. Shinde, B. Mahendra, S. Nejakar, S. M. Herur, and N. Bhat, “Performance analysis of machine learning algorithm of detection and classification of brain tumor using computer vision,” *Advances in Engineering Software*, vol. 173, p. 103221, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0965997822001259

[17] T. S. Kumar, K. Rashmi, S. Ramadoss, L. Sandhya, and T. Sangeetha, “Brain tumor detection using svm classifier,” in *2017 Third International Conference on Sensing, Signal Processing and Security (ICSSS)*, 2017, pp. 318–323.

[18] I. Dópido, C. Déniz, H. Fabelo, G. Callicó, S. López, R. Sarmiento, D. Bulters, E. Casselden, and H. Bulstrode, “Decision tree classification system for brain cancer detection using spectrographic samples,” in *2015 Conference on Design of Circuits and Integrated Systems (DCIS)*, 2015, pp. 1–6.

[19] H. T. Zaw, N. Maneerat, and K. Y. Win, “Brain tumor detection based on naïve bayes classification,” in *2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST)*, 2019, pp. 1–4.

[20] T. Hatami, M. Hamghalam, O. Reyhani-Galangashi, and S. Mirzakuchaki, “A machine learning approach to brain tumors segmentation using adaptive random forest algorithm,” in *2019 5th Conference on Knowledge Based Engineering and Innovation (KBEI)*, 2019, pp. 076–082.

[21] W. El Elhola and K. Bozed, “Performance analysis of brain tumor detection based on gradient boosting machine -cnn model,” in *2022 IEEE 2nd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*, 2022, pp. 544–547.

[22] C.-J. Tseng and C. Tang, “An optimized xgboost technique for accurate brain tumor detection using feature selection and image segmenta-

tion," *Healthcare Analytics*, vol. 4, p. 100217, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2772442523000849

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