Brain Tumor Detection with Convolutional Neural Network

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Abstract

The brain is the command center of our nervous system, which enables thoughts, memories, movements, and emotions. In other words, it is the most important organ in the human body. The human brain is very vulnerable to tumors, as merely growing old can be the cause of a tumor. Furthermore, the effects of a tumor can be fatal to a person because, as the tumor grows inside the brain, it can deform the structure of the brain and cause several diseases, the most fatal being cancer in the brain. Hence, to prevent such severe diseases, early detection of tumors is critical for a patient's treatment. Moreover, modern technology has emerged to excellent heights, as MRI scans and CT scans can detect brain tumor regions. However, to accurately detect where the tumor is situated, a team of doctors is still needed to this day. Therefore, we have planned to use convolutional neural Networks to develop a faster and inexpensive method to detect tumors from MRI images in the early stages. Moreover, we plan to develop a system where our proposed CNN model will be able to detect tumors as well as identify three types of tumors, which are glioma, meningioma and pituitary tumors. Also, if there are no tumors, the system should be able to detect them too. To develop our proposed model, we have used data pre-processing techniques with a combination of gray scaling, One encoding, and CLAHE. Also, we have used a dataset of 6484 MRI images, segmenting them by testing and training. To compare and analyze our proposed model's performance, we have tested and trained seven pre-trained models with the same dataset. The models are Vgg16, Vgg19, ResNet50, InceptionV3, DenseNet-121, EfficientNetB0, MobileNet and we received the following testing accuracy accordingly: 93.37%, 92.42%, 75.38%, 91.48%, 94.89%, 23.30% and 96.02%. However, the testing accuracy of our proposed model surpassed all the other pre-trained models, as it gained 98.11% accuracy in testing. In conclusion, we have aimed to build a CNN model that exceeds all the other CNN models in terms of overall performance, which is why we have integrated a sufficient amount of parameters to handle any unfavorable situations; however, the parameters are set in such a way that the overall system does not clutter and remains lightweight.

Keywords: Brain Tumor, CNN, accuracy, MRI, Deep learning, Machine learning, Tumor Detection, Neural Network, Gray Scaling, One hot encoding, Clahe, Vgg16, Vgg19, Inception V3, DenseNet-121, EfficientNetB0, MobileNet

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Dedication

A dedication is a heartfelt expression of gratitude and connection from the author to another individual. It serves as a poignant reminder of the bonds we share and the appreciation we hold for those who have played a significant role in our creative journey. Whether occupying a single line or spanning several, the dedication encapsulates the profound impact that individuals can have on our lives and work. It stands as a testament to the power of human connection and the enduring value of showing appreciation for those who inspire and support us on our creative path.This project is dedicated to the countless individuals who have served as a wellspring of inspiration. From mentors who shared their wisdom to friends who offered unwavering support, and from the great minds whose ideas sparked our imagination to the everyday heroes who embody resilience and determination, it is to each and every one of you that we extend our deepest gratitude. Your stories, your insights, and your unwavering belief in the power of innovation have fueled our journey and made this project possible. This dedication is a small token of our appreciation for the inspiration you have provided, and a promise to carry forward the torch of creativity and excellence that you have ignited in us.

Nomenclature

CNN - Convolutional Neural Network
ACNN - Artificial Convolutional Neural Network
R-CNN - Regional Convolutional Neural Network
Vgg16 - Visual Geometry Group 16
Vgg19 - Visual Geometry Group 19
ML - Machine Learning
CAD - Computer Aided Diagnosis
ReLU - Rectified Linear Unit
SGD - Stochastic Gradient Descent
PPV - Positive Predictive Value
NPV - Negative Predictive Value
MCC - Matthews Correlation Coefficient
VOTT - Visual Object Tagging Tool
ROIs - Regions of Interest
RPN - Regional Proposal Network
NMS - Non-maximum Suppression
E2E - End to End
MRI - Magnetic Resonance Image
CT - Computed Tomography
FNN - Fully Connected Layer

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Chapter 1

Introduction

Tumors can have an impact on the brain, and they can target a specific area of the brain. This kills cells in that area simultaneously and flawlessly, resulting in brain damage. The level of the damage and the danger it poses are determined by the size of the tumor mass and the afflicted brain region. Generally speaking, the human body's senses, organs, blood, and nerve cells are all connected to the brain. Any brain damage will disturb the body's customary functioning, making it unstable. As we discuss instability, we are discussing a person's consciousness, physiological balance, organ function, and mind, all of which can affect their health and physical state. In the brain, certain cell types stop proliferating and regenerating at a certain age, and certain neuronal types are incapable of doing so. When a tumor grows in sensitive parts of the tear, such as those that govern the five perceptions of vision, taste, touch, smell, and hearing, one of the senses is gone. If the person is fortunate enough to detect the tumor early on, the medical role is surgery or radiotherapy. It cannot be assured that these operations will result in complete tumor recovery.[20] In some cases, paralysis of one of the extremities, memory loss, or sensory loss in one of the five perceptions has happened. Not to mention that the cancer cells thrived on brain tissue that had been surgically or radiologically removed. Because we're discussing tumor-related disorders, it's worth highlighting that brain tumors can be fatal in some cases. One of these situations is the tumor's delayed detection. The consequences of the tumor spreading and feeding on additional brain cells are disastrous for the person's health and life and may result in death.[10] An accurate picture of a brain tumor serve a significant part in clinical medical diagnosis and in making treatment decisions for patients. A radiologist's availability and expertise in correctly identifying and diagnosing brain tumors are crucial for the complicated and challenging process of manually classifying brain tumors from MR images with comparable structures or characteristics. Automated classification might be a workable solution to this issue by categorizing brain tumor MR images with the least amount of human skill interference in the related sector. For an amateur, using standard machine learning techniques in this setting is a formidable obstacle. Even though very few techniques have been put into practice because of several inherent constraints, deep learning algorithms—in particular, CNN—have shown extraordinary performance in bioinformatics. CNN, or ConvNet as it is commonly called, is a deep machine-learning method for image analysis. By using data mining techniques, we may extract meaningful and interesting patterns and correlations from the data. Brain tumor prevention and early diagnosis are achieved by the effective application of machine learning (ML) and data mining techniques. This investigation made use of a CNN-based classifier available on Kaggle that uses the dataset's classification principle. Three consecutive 2D convolution layers, each with two 2x2 kernels, comprise the structure of the model. The database images were split into 80% and 20% segments, respectively, to form the training and validation sets.

1.1 Contribution:

In this research paper, we analyzed Brain tumor MRI images and classified them into four classes, where three are disease classes; glioma, meningioma, and pituitary, as well as a class if there are no tumors to be detected. Furthermore, we propose a sequential convolutional Neural Network which is best suited for identifying these three diseases, especially in the absence of no tumor. To illustrate, the following demonstrates the core contributions of this paper:

- Our research will bring in a new sequential CNN model architecture that outperforms all the other pre-trained models (Vgg16, Vgg19, ResNet50, InceptionV3, DenseNet-121, EfficientNetB0, and MobilNet) experimented in our papers as well as all the other previous works done on this same dataset.

- In contrast to all the previous pre-trained models used in our study work, we developed a lightweight model. Additionally, because it is lightweight in comparison to other models, it decreases training time complexity and yields more accurate results.

- We established an 18-layer model architecture that contains a convolutional 2D layer, max pooling layer, batch normalization layer, flatten layer, dense layer, and dropout layer, where we used the Adam optimization function while setting the initial learning rate to 0.00001. Moreover, we calculated the loss function using categorical cross-entropy.

- Our main motive is to develop a CNN model that surpasses other CNN models and pre-trained models that have worked on the same dataset. Additionally, we aim to develop a model that outperforms other models in terms of time complexity and accuracy. Lastly, by fine-tuning our model through trial and error basis, we achieved 98% testing accuracy.

1.2 Research Problem

With an emphasis on improving brain tumor detection, the project seeks to transform the field of medical diagnostics by utilizing state-of-the-art technologies. Innovations in this area have the potential to significantly improve patient outcomes since it is a crucial frontier. A subclass of deep learning models known as convolutional neural networks (CNNs) has shown great promise in improving the detection of brain tumors because of its powerful tools and exceptional image analysis skills.[3] The main goal is to highlight how artificial neural networks—in particular, CNNs have the potential to revolutionize medical diagnosis. Compared to conventional techniques, these models can significantly improve brain tumor identification accuracy, speed, and consistency. Their exceptional capacity to interpret complicated medical imaging data's many patterns and features enables the identification of minute abnormalities that frequently escape human observers.

This research project employs a multimodal approach that includes fine-tuning CNN architectures designed especially for brain tumor detection, massive training on a variety of large-scale datasets, and the development of interpretable models that provide information about the decision-making process. Furthermore, the integration of CNN-based systems into clinical workflows holds the promise of expediting the diagnostic process, mitigating subjectivity, and expediting treatment planning. This, in turn, enhances the overall quality of patient care.[25]

At its core, the broader vision of this research is to establish CNNs as transformative technology in the broader field of medical imaging and diagnostic analysis, extending beyond brain tumor detection. These capabilities have the potential to significantly enhance diagnostic precision and efficiency, resulting in improved patient outcomes, potential lives saved, and a reduced burden on healthcare systems. This research sets the stage for a paradigm shift in medical diagnostics, paving the way for advancements in diverse medical disciplines.

1.3 Research Objective

• This research tries to aid in the development of an entirely automated framework capable of acquiring MRI images of the patient's brain without human intervention, ensuring consistency and efficiency in the imaging process.[24]
• To implement advanced image processing algorithms to enhance the quality of acquired MRI images, including noise reduction, contrast enhancement, and artifact remova,to increase tumor detection's precision.[23]
• To investigate and develop robust and reliable segmentation algorithms specifically designed for autonomous detection of brain tumors, capable of accurately identifying and isolating tumor regions within the acquired MRI images.[14]
• To explore and extract a comprehensive set of relevant features from the segmented tumor regions using computer vision techniques, including shape characteristics, texture information, intensity statistics, and other relevant image-based features, to ensure the accurate classification of tumor and non-tumor regions.[7]
• To train the machine learning models using a huge and varied collection of photos with labels for brain tumors, including a range of tumor kinds, sizes, and locations, to ensure the system can accurately detect tumors across different patient cases and generalize well to unseen data.[16]
• To integrate post-processing techniques, such as morphological operations, spatial filtering, or statistical analysis, into the autonomous detection system to refine the classification results and minimize false positives or false negatives.[22]

Chapter 2

Literature Review

The successful treatment of brain tumors is strongly reliant on early and accurate detection. Early detection not only allows for better medical interventions, but it can also save lives. The combination of CAD and biomedical information science has significantly advanced neuro-oncology research in the last few years. Techniques based on deep learning, such as Convolutional Neural Networks (CNNs), are becoming known as reliable tools for processing medical images, data, and information, overtaking traditional manual diagnosis approaches that are vulnerable to human mistakes and tedious. This study introduces a unique method for classifying MRI scans as "TUMOR DETECTED" or "TUMOR NOT DETECTED" using a deep neural network, particularly a CNN. The model has a mean accuracy score of 96.08% and an F1 score of 97.3, indicating its effectiveness in the early detection of brain cancers. In numerous instances, the CNN-based approach beats human expertise, having an accuracy percentage of 96.08. Such a degree of accuracy is important for preliminary and accurate tumor identification. The model reduces the possibility of human error in manual diagnosis. This improves the consistency and dependability of the data, resulting in more confident medical decisions. Machine learning models could potentially scaled and implemented in several healthcare applications, allowing the benefits of accurate brain tumor diagnosis to be extended to a larger population. Machine learning models, such as CNNs, rely heavily on data quality and the number of ample information. Inadequate or biased data can result in erroneous outcomes. Implementing and fine-tuning deep learning models can be difficult and time-consuming. Deep neural network training frequently necessitates a large amount of processing power. Since deep learning models are often seen as "black boxes," it can be complicated to understand how they make decisions. In crucial medical applications, this lack of transparency can be problematic. While the model performs admirably on the current dataset, its potential to generalize to new and different patient populations and imaging settings may necessitate more validation and testing.[6] In conclusion, this study shows that deep learning, particularly CNNs, has a significant potential for early detection of brain cancers using MRI scans. The suggested model, with its amazing accuracy rate and strong performance, presents a promising answer to the essential challenge of prompt diagnosis in neuro-oncology. Despite their benefits, the use of such models in clinical practice should be done with caution, taking into account aspects such as data quality, model interpretability, and the need for additional validation. As machine learning advances, it has the potential to revolutionize medical diagnostics, potentially saving lives through early disease identification and intervention. In the future, sophisticated techniques such as neutrosophical principles may be used to improve brain tumor detection and therapy.

In the article (Brain Tumor Detection Using Artificial Convolutional Neural Networks), the issue of identifying brain cancers from MRI (Magnetic Resonance Imaging) pictures is discussed. The research attempts to develop an Artificial Convolutional Neural Network (ACNN) that can precisely identify MRI pictures as either displaying the existence of a tumor or not since brain cancers can be lethal if not identified in a timely manner. The researchers utilized a dataset made up of brain MRI pictures that they downloaded from Kaggle. 253 photos made up the dataset's initial 253, of which 155 showed brains with malignancies and 98 showed healthy brains. This dataset was increased by the use of data augmentation, producing 14 times more photos.[13]
The primary methodology applied in this study is Artificial Convolutional Neural Network (ACNN). Convolutional, Maxpool, Fully Connected, Dropout, and activation functions like ReLU and Softmax are all components of the ACNN architecture. Convolutional blocks in various arrangements and with various filter sizes were examined. Rotations and filters were utilized as data augmentation techniques to provide more training data. The ACNN's test and validation accuracy were both 88.25% and 96.7%, respectively. For certain specific test instances, the accuracy in identifying brain tumors was 99.99%. The authors also mentioned incidences of misdiagnosis, mainly because some brain parts in MRI pictures seemed to be tumor cells. The accuracy of the ACNN was increased through data augmentation and picture preprocessing. However, the study acknowledged and addressed a significant problem with MRI-based brain tumor detection: the possibility of misclassification. This problem arises because some brain structures and tumor cells might appear visually identical in MRI imaging, which can result in false positives or false negatives. In summary, this study emphasizes the crucial role that data preprocessing and augmentation play in improving how well ACNNs identify brain tumors. The authors took a substantial step towards the creation of a potent tool for early and accurate brain tumor identification, which might have important ramifications for healthcare and patient outcomes, by painstakingly fine-tuning their model and utilizing an expanded dataset.

This abstract discusses the significance of using automated techniques with MRI images for early and accurate brain tumor detection. It reviews 20 research papers published between 2000 and 2020, focusing on two key challenges: Image Restoration and Enhancement.[15] The abstract addresses the application of Convolutional Neural Networks (CNNs) for image classification and error correction. The model is implemented in Python and TensorFlow. It highlights the importance of quantitative analysis in assessing brain tumors' characteristics like shape, texture, and signal intensity for high accuracy. The introduction provides context about brain tumors, their impact on brain function, and their prevalence, including a mention of increasing global incidence. The related work section summarizes previous research in brain tumor detection using neural networks and deep learning techniques.
In essence, the abstract emphasizes the significance of brain tumor identification

using automated magnetic resonance imaging (MRI), outlines key challenges and references prior research.
In this section, several methodologies for improving brain tumor detection by applying MRI images are discussed. Kiranmayee et al. proposed an algorithm involving training and testing, demonstrating the potential of support networks to enhance healthcare services. Arya et al. conducted a study of image pre-processing and segmentation methods, aiming to improve accuracy and reduce errors in brain tumor detection. Demiharan et al. introduced segmentation techniques to categorize distinct parts of the brain, achieving satisfactory results in differentiating cerebrospinal fluid, edema, white matter, and gray matter. Aneja et al.presented a fuzzy clustering means approach and segmentation algorithm to handle noisy images effectively. Udhaya et al.investigated data mining algorithms to enhance detection accuracy, achieving promising results. Teshnehlab et al. used Convolutional Neural Networks (CNNs) for tumor detection, demonstrating high classification accuracy.
The methodology section outlines the brain tumor detection process using CNN models. It includes stages such as image preprocessing (cropping, transforming, and normalization), segmentation (thresholding, region growing, and watershed algorithms), feature extraction, image classification, feature optimization, and classification using CNN architecture. Furthermore, it mentions the Brain Tumor Dataset, which combines various datasets and includes MRI images categorized into "yes" (tumorous), "no" (non-tumorous), and "prediction" classes. The section also briefly discusses the challenges of brain tumor detection, particularly in older individuals, and the importance of early detection due to the limitations of MRI, CT scan, and X-ray imaging in identifying small tumors.

The topic of classifying brain tumor grades using MRI images is addressed in the publication "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms". To obtain high accuracy in brain tumor classification, the authors describe a unique approach that blends genetic algorithms (GAs) with convolutional neural networks (CNNs). The research presents two case studies: the first shows how to categorize Glioma grades with an accuracy of 90.9%, and the second shows how to classify various brain tumor types with an accuracy of 94.2%. These findings suggest the possibility of accurate categorization of different kinds of brain cancers and non-invasive early brain tumor detection. The study used a variety of datasets, including the IXI dataset, cancer imaging archive datasets, TCGA-LGG dataset, REMBRANDT dataset, TCGA-GBM data collection, a dataset from the neurosurgery department of a Tehran hospital, which included 989 axial images for training and testing, as well as 8000 glioma MR and 8000 normal MR images overall.[4] The suggested method outperforms existing methodologies, and the CNN structures are tuned using genetic algorithms to obtain high classification accuracy. The study also highlights how the suggested approach might help doctors identify brain cancers early on and shows how applicable it is to various brain MRI datasets. Finally, the suggested models as well as processes are evaluated using several methodologies, including the confusion matrix. The results verify the strategy's ability to accurately categorize brain tumor classes and formats. Anaraki et al. (2018) stated a comprehensive overview of the datasets, CNN models, genetic algorithms, and the outcomes of experiments. This explanation provides valuable context for understanding the possible applications of the suggested MRI image-based tumor identification technique.

This study addresses a critical medical image processing topic: segmentation. Errors may occur during manual classification, especially when handling large volumes of data. Because brain tumors may take many different shapes and often resemble regular tissue, it can be challenging to identify them from images. Using a fuzzy C-Means clustering algorithm, convolutional neural networks (CNN), and conventional classifiers, the authors provided a technique for identifying brain tumors from 2D MRI. The research blends classic machine learning classifiers with deep learning approaches to provide a comprehensive solution for segmenting brain tumors. The CNN obtained an outstanding 97.87% accuracy, illustrating the utility of deep learning in medical image segmentation. The work employs a real-time dataset with a variety of tumor features, making it more relevant to real-world circumstances. The usage of various MRI modalities (T1, T2, FLAIR) is mentioned in the paper, reflecting the complexity of real medical data. In the medical world, this research has significance since early detection of brain tumors is essential to improving medical outcomes and patient survival. CNN models can be computationally expensive, necessitating a large amount of CPU power. While the study specifies a real-time dataset, the size of the dataset is not indicated, which may have an impact on the generalizability of the conclusions.The report briefly acknowledges the difficulties associated with ill-defined tumor boundaries but does not go into detail about the approaches employed to overcome this issue.The publication compares its findings to those of earlier studies but does not give a thorough comparison with cutting-edge methods, restricting the context for its contributions.[12] This work describes a complete strategy for brain tumor segmentation that combines classic machine learning classifiers with deep learning using CNNs. The statistics demonstrate a high level of accuracy, particularly with CNN achieving 97.87%. While the work offers advantages like employing a real-time dataset and addressing a clinically significant topic, it also has constraints like computational complexity and dataset size. More research and a more complete comparative examination could increase its contributions to medical image processing systems.

The research project (Tumor Detection in the Brain using Faster R-CNN) explored the timely identification of brain tumors, a key element in optimal treatment results, to solve a significant healthcare concern. Early brain tumor detection can dramatically enhance patient prognosis.[9] The work used a mix of cutting-edge image processing methods and deep learning models to thoroughly address this issue. 50 brain MRI pictures from trustworthy websites like www.sciencesource.com and www.radiologyassistant.nl made up the dataset used in this study. The study looked at four different kinds of brain tumors within this dataset: benign-slow-growing tumors, cancerous tumors, glial-astrocytic tumors, and astrocytoma-low-grade tumors. This variety of tumor types made it possible to evaluate the suggested strategy thoroughly.
The use of cutting-edge models and methodologies was essential to the study process. The Visual Object Tagging Tool (VOTT) helped to facilitate preprocessing using Camshift method. Camshift is well known for processing image data quickly and precisely. VOTT played a key role in configuring the dataset for training, by categorizing images into positive, negative, and training sets and marking bounding

box values and class labels. Actually, the AlexNet model worked here as the essential architecture, while the R-CNN algorithm was its core. Using transfer learning, the model was able to increase its performance by exploiting past information. A crucial step in tumor diagnosis was the establishment of a Region Proposal Network (RPN) and the prospective creation of ROIs in the brain pictures. The invention of RPN was incredibly creative, combining the advantages of object recognition methods with the strength of deep learning. To enhance ROI (Regions of Interest) selection and ensure precise tumor detection, Non-Maximum Suppression (NMS) was applied. It was crucial to use NMS to identify high-confidence regions of interest while avoiding overlapping areas. This method significantly improved the tumor detection rate. The study's demonstration of the viability of its suggested strategy used an Intel Core 2 Duo computer with 4 GB of RAM running Windows. The 4-stage training strategy was outperformed, impressively, by the E2E training method. That refers to End-to-End methodology. For all four tumor classes—malignant, benign, glial, and astrocytoma—E2E training consistently attained astounding bounding box score accuracy rates of over 99%. The excellent level of accuracy shows how effective the proposed approach is! Surprisingly, the study's focus wasn't just on finding brain tumors. It expanded its methodology to the field of stomach cancer detection and produced findings that were as impressive. The study achieved an accuracy rate of over 99% using E2E training. The adaptability and promise of the suggested technique are highlighted by this extension. In conclusion, by utilizing cutting-edge models and methods, this research study offered a thorough and creative approach for the early diagnosis of brain cancers. It demonstrated exceptionally high levels of accuracy in both the diagnosis of stomach cancer and brain tumors. Through early illness diagnosis, this research shows enormous promise for improving healthcare outcomes.

The focus of the study (A Novel Data Augmentation-Based Brain Tumor Detection Using Convolutional Neural Network) is on brain tumor identification using CNNs as it examines similar publications in the area of medical picture interpretation. The usefulness of CNNs in recognizing and categorizing brain cancers has been shown in a number of studies. Techniques for enhancing existing datasets with new data are emphasized, and examples of enhanced findings are shown. LeNet, AlexNet, GoogleNet, ResNet, VGGNet, DenseNet, SqueezeNet, and MobileNet are only a few of the CNN architectures included in the paper's overview. Each architecture is succinctly explained, setting the stage for the technique that follows. The deep CNN architecture utilized for brain tumor identification is explained in the methods section. The VGG-16 model is highlighted, with information on its setup and structure provided. The backpropagation method and the significance of the best parameter values are also covered in the study. An organized method of model construction is demonstrated through the presentation of the CNN architecture, data pretreatment techniques, and strategies for model augmentation. The authors used a dataset with 253 brain MRI scans that was divided into instances with and without tumors. By using data augmentation methods including flipping, rotating, and translating, the dataset size was increased, enhancing model generalization. Statistics on dataset size before and after augmentation are provided in the study.[2]
The findings section describes the training and evaluation of the VGG-16 model

on the larger dataset. Metrics including accuracy, precision, recall, and F1-score are used in model assessment. A comparison with different machine learning models demonstrates that the VGG-16 model performs better in terms of performance measures. The paper's conclusion summarizes the value of data augmentation in enhancing CNN models' performance, especially when datasets are scarce. It emphasizes how accurate and successful the proposed VGG-16 model is at identifying brain cancers. It is recommended that future studies investigate more complex systems and a wider range of datasets. The essay concludes with some enlightening information regarding the usage of CNNs and deep learning in general for brain tumor diagnosis. It addresses the issue of incomplete data through data augmentation and demonstrates promising outcomes, underscoring the potential of these techniques in medical image analysis.

Using information from magnetic resonance imaging (MRI), the authors of this study created a Convolutional Neural Network (CNN) model for the purpose of identifying and categorizing brain tumors.[17] A significant public health concern is brain cancers, which are mostly detected by magnetic resonance imaging (MRI). Since the development of artificial intelligence tools, brain tumor diagnosis accuracy, and efficiency have been improved by the application of machine learning and deep learning algorithms. The proposed CNN model outperformed existing models and approaches with an outstanding 96% accuracy rate. This level of precision is critical in medical imaging for establishing correct diagnosis. Ma- chine learning models, particularly CNNs, are noted for their predictability. Brain tumor prediction can greatly shorten the time required for diagnosis and treatment preparation. Human errors in manual analysis can be reduced by using automated detection methods. The CNN model proved its capacity to effectively categorize MRI images while minimizing false positives and false negatives. The model's precision was 97.93%, suggesting its ability to reliably detect true positive cases of brain tumors. Medical imaging requires high precision to minimize unneeded treatments or procedures. CNN models may be trained on larger datasets, which may improve their performance even more as more data becomes available. Because of their scalability, they are suitable for future applications. The study used a dataset of 3000 MRI scans, which, while large, may still be deemed small for deep learning applications. A larger dataset could improve the model's performance even more. Deep learning models, such as CNNs, necessitate substantial computer resources, particularly powerful GPUs. This can be a problem for institutions that have restricted access to such resources. Due to privacy concerns and data protection requirements, access to medical imaging data might be difficult. The acquisition of big and diverse datasets might be a hurdle to the development and testing of such models. The suggested CNN model for brain tumor detection and classification based on MRI scans produced outstanding results, with a 96% accuracy rate. It provides quick forecasts, fewer errors, and high precision, making it a promising tool for supporting medical professionals in brain tumor identification. While this study sheds light on the capabilities of CNNs in medical imaging, more research with larger datasets and more diverse cases is required to validate and develop the model. Overall, the application of deep learning methods, such as CNNs, offers great potential to improve patient outcomes by increasing the precision and speed of medical diagnosis.

This paper focuses on the automated brain tumors may be classified using Convolutional Neural Networks (CNNs), specifically utilizing a pre-trained VGG16 model through transfer learning. The primary goal is to accurately differentiate between tumorous and non-tumorous brain MRI scans. Brain cancer, categorized as benign or malignant, poses challenges in diagnosis and treatment. The study em- ploys various methods, including SOM Clustering, Kmean clustering, Fuzzy C-mean technique, SVM, Deep Neural Network (DNN), and CNN, to extract and segment cancer. The emphasis is on MRI imaging for tumor detection, as it provides detailed information about brain structure. MRI relies on nuclear magnetic resonance, particularly hydrogen atoms, to generate detectable radiofrequency signals. The paper reviews related works in brain tumor imaging and segmentation, highlighting the significance of methods applicable to standard protocols for medical imaging. The proposed CNN-based approach achieves promising results, with a 96.5% training accuracy and 90% testing accuracy, showcasing its effectiveness compared to state-of-the-art methods. This study proposes a CNN-based approach for brain tumor classification using a pre-trained VGG16 model with transfer learning. The CNN architecture involves input, convolution, ReLU, pooling, and fully connected layers. The methodology consists of data pre-processing, augmentation, and training with a focus on VGG16 as a fixed feature extractor.[1] The algorithm involves importing libraries, image pre-processing, data augmentation using ”ImageDataGenerator,” applying transfer learning with VGG16 weights, adding dense layers with Sigmoid activation, compiling the model, and training. The results indicate the utilization of MRI images from diverse sources. The proposed classification of the brain tumor model utilizes transfer learning with the VGG16 architecture, eliminating the need for a separate feature extraction step. The CNN-based approach demonstrates low computation time, reduced complexity, and high accuracy (96.5% training, 90% testing) compared to traditional methods like SVM. The study suggests potential enhancements through larger datasets and improved preprocessing techniques for future improvements in accuracy and performance.

This research provides a multiscale convolutional neural network (CNN) based deep learning model for brain tumor segmentation and classification.[8] Drawing inspiration from the Human Visual System, the proposed model processes input MRI pictures at three different spatial scales. It doesn’t require preprocessing, in contrast to earlier research, to eliminate sections of the skull or vertebral column. On a dataset of 3064 slices from 233 patients, the model outperforms deep learning and standard machine learning techniques with a high accuracy of 97.3% in tumor classification. The CNN design employs a sliding window approach and has three processing routes for various scales. The collection includes sagittal, coronal, and axial views of T1-CE MRI scans showing meningiomas, gliomas, and pituitary tumors. The study presents a thorough comparison with current approaches and emphasizes the usefulness of the suggested model in both segmentation and classification. This research provides a multi-scale convolutional neural network (CNN)-based, totally automated brain tumor segmentation and classification approach. The suggested strategy outperforms existing approaches with high accuracy (0.973) in tumor classification on a T1-weighted contrast-enhanced MRI dataset. Overfitting can be avoided by using data augmentation. The CNN architecture utilizes three processing pathways for different scales and successfully segments meningioma, glioma, and pituitary tumors. The technique has outstanding segmentation ability, as shown by its average Dice index of 0.828, sensitivity of 0.940, and pttas value of 97.3%. However, it does not exclude parts of the skull and spinal column. Future research will examine how the suggested CNN may be used for segmentation in different domains of study.

The difficult challenge of classifying brain tumors The domain of medical imaging processing is addressed by Ozyurt et al. in their study "Brain tumor detection based on Convolutional Neural neural network with neutrosophic expert maximum fuzzy sure entropy". The research offers a hybrid technique called Neutrosophic Expert Maximum Fuzzy-Sure Entropy Set-Convolutional Neural Network (NS-EMFSE-CNN) that attempts to identify benign or malignant tumor locations segregated from brain pictures. The authors combine the potent feature extraction powers of Convolutional neural networks (CNN) with the Neutrosophy technique for picture segmentation.[19] They accomplish great classification performance and do away with the requirement for human feature extraction in the process. The Cancer Genome Atlas Glioblastoma Multiforme (TCGA-GBM) dataset, which is publicly available to researchers studying brain malignancies, is used in this study. Realistic tumor region segmentation is achieved by using T1-weighted post-contrast (T1-gadolinium (Gd)) sequence pictures, which are part of the dataset. The suggested NS-EMFSE-CNN approach uses the NS-EMFSE technology to segment images of brain tumors. Next, features are extracted using CNN architectures like Alexnet. The obtained features are then classified using K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) classifiers.Based on the experimental data, the proposed approach has an average success rate of 95.62% in differentiating between benign and malignant brain tumors. This work increases the categorization of brain tumors and provides a workable approach to accurate and efficient brain tumor detection by fusing the benefits of Neutrosophy with CNN.

In the original study, "Detection of brain tumors from MRI images based on deep learning using a hybrid model of CNN and NADE," authored by Hashemzehi et al., the researchers address the primary challenge of consistently detecting brain tumors from MRI images. In the setting of tiny and imbalanced datasets, the research addresses the need for both reliable classification techniques and accurate brain tumor identification. The researchers used a dataset of 3064 T1-weighted, contrast-enhanced MRI images to achieve this. Three distinct types of brain cancer were depicted in these images: pituitary tumors, gliomas, and meningiomas. This diverse and representative dataset allowed for a full examination and training of the proposed model.[11]This novel strategy uses NADE for distribution estimation to overcome short datasets and uneven class distributions while using CNN's feature extraction capabilities. These two models were combined to provide a reliable brain tumor classification method. The hybrid CNN-NADE model classified brain tumor MR images with 95% accuracy, promising study results. This finding understates the effectiveness of the proposed technique in overcoming limited datasets and differential class 13 distributions. The study's conclusions show how deep learning methods, especially hybrid models, may be used to tackle challenging classification problems and have great potential in the area of medical imaging. All things considered, the study makes a major contribution to the development of MRI image-based brain tumor identification.

Chapter 3

Work Plan

Our research will make use of brain tumor photos that we have collected from the source [26]. Pre-processing involves lowering image noise and enhancing the quality of the input photos. Then we applied augmentation by setting fill modes such as shear range, zoom range, horizontal flip, and validation split. GRAYSCALING is the first stage of pre-processing. It is employed to gauge the amount of light seen in a picture. After that, Moving further, we proceed to the scale step, which involves reducing the input image's pixel count. CLAHE is the final stage of pre-processing. In essence, it intensifies contrast in the picture to make it more distinct. The following step, rapid encoding, is then carried out. The One hot encoding is frequently used to preprocess categorical features for machine learning models. In this particular encoding method, for each potential category, a fresh binary feature is generated. The feature of each sample that corresponds to its initial category is assigned the value 1. Furthermore, we are using a convolutional neural network in the methods section (CNN). Utilizing convolution neural network algorithms, we can categorize our images of the different types of brain tumors.

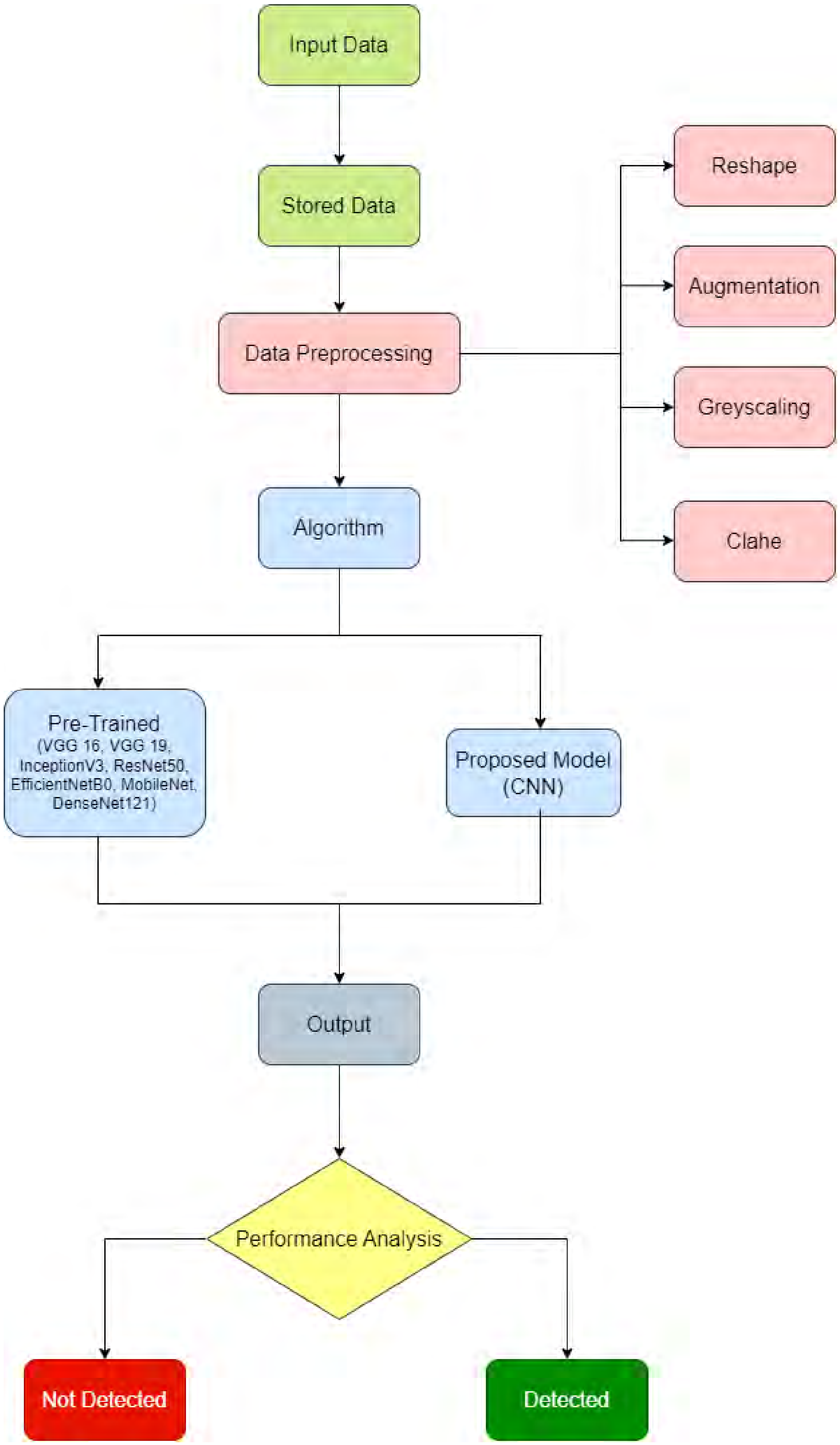


Figure 3.1: Work Flow Diagram

Chapter 4

Description of the Dataset

4.1 Proposed Methodology :

Tumor images of the brain that we have gathered from the source [26] will be used for our research. Pre-processing is the next step we take after gathering the data. Pre-processing involves lowering image noise and enhancing the quality of the input photos. We also applied augmentation by setting fill modes such as shear range, zoom range, horizontal flip, and validation split. Grayscaling is phase one of pre-processing. It is employed to gauge the amount of light existing in a picture. After that, we proceed to the scale step, which involves reducing the input image's pixel count. CLAHE is the final stage of pre-processing. In essence, it intensifies the contrast in the picture to make it more distinct. Next, we go to our next step, One Hot Encoding is a well-liked method for getting categorical data ready for machine learning models. With this encoding approach, a new binary feature is created for each potential category, and the feature of each sample that corresponds to its original category is assigned a value of 1. We also employ a convolutional neural network (CNN) in the methods section. Convolution neural network techniques allow us to classify our photographs of various types of brain tumors.[5]

4.2 Data Analysis :

We acquired our dataset from Kaggle[26], a reputable source for diverse datasets. The dataset primarily comprises images, serving as our invaluable input data. Our approach to gathering and preprocessing this data is delineated succinctly below. Our dataset procurement involved meticulous selection and curation of images, ensuring their relevance and quality. Kaggle's repository provided us with a robust foundation, offering a diverse array of images vital for our research. Subsequently, we embarked on a comprehensive data preprocessing journey. This crucial step involved refining the acquired images to enhance their suitability for analysis. We meticulously cleaned and standardized the data, rectifying any inconsistencies or anomalies. Furthermore, we conducted data augmentation, enriching our dataset by generating additional variations of the images. This process bolstered the robustness of our input data, enabling our models to generalize effectively.

4.3 Input Data :

Here, we'll go over the strategies we'll employ to accomplish our goal. We will initially make use of the brain tumor images, which contain labeled pictures. Deep learning frameworks favor using a lot of high-quality photos for model testing and training. Data thinking can be used to create a solid website. This will increase the accuracy and rate of the classification and picture differentiation processes. Applying slight adjustments to the existing dataset enables the creation of artificial images by manipulating factors such as orientation, brightness, scale, position, and more. It is easy to increase the forecast accuracy of the model without making significant changes to the model itself. In our experiment, we'll employ 6484 photographs total. This dataset includes files on various types of human brain tumors, namely,glioma, meningioma, notumor, and pituitary. So that the end user may more easily configure any model using this data, the folders are divided into two super-folders: Training and Testing.

4.4 Data Sample :

Below are images of different brain tumor of human body. The pictures display images of the different tumors. If this is the case, photographs of the different tumors with a variety of alterations in the region will be impacted, and vice versa.

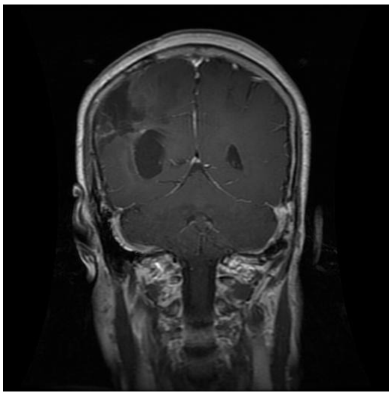
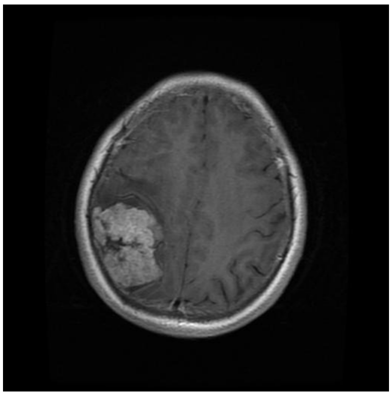
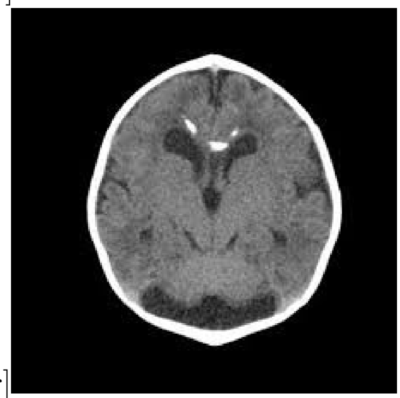
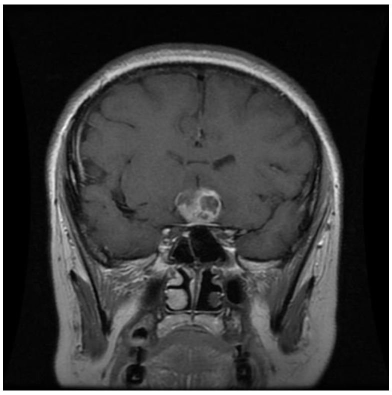
[Glioma]

[Meningioma]

[Notumor]

[pituitary]


Figure 4.1: Data Sample

4.5 Data Preprocessing :

Before using the data in the Convolutional Neural Network (CNN) method, preparing the data is a crucial stage in the process. The factors that don't help the CNN model perform better or be more accurate are eliminated using this procedure. That being said, this stage enables us to apply any required adjustments to the raw data to enhance the CNN model's performance and yield more accurate results. For ours proposed system, detecting brain tumors by images, we initially split our image dataset of brain CT images consisting of both normal and intracranial hemorrhage images in separate folders separated into two sections. 1. Training dataset and 2. Validation dataset. We put 80% of the images into the training dataset which is precisely 5284 images and the rest of 20% images went to the validation dataset which is 1200 images to be precise. Furthermore, we have applied some transformations to our training batch of data. This transformation comprises setting the pictures' sizes, batch magnitude, rescaling, rotation, magnifying, and horizontal flip.

Convolutional Neural Network(CNN):- Proposed Model

- Image size: 128x128
- Batch magnitude: 32
- Recalling size: 1/255.0
- Magnifying range:0.2
- Horizontal reversal: True

Pre-trained Models:- Vgg16, Vgg19, Inceptionv3, Resnet50

- Image size: 128x128
- Batch magnitude: 32
- Recalling size: 1/255.0
- Magnifying range: 0.2
- Horizontal Reversal: True

We have utilized the "categorical cross-entropy" class hierarchy since the categorization result, in this case, falls under the glioma, meningioma, no tumor, and pituitary categories. We used the same picture and batch size for our test dataset. We also maintained the distinctive cross-entropy class class hierarchy.

Chapter 5

Proposed Model Implementation

5.1 Model Architecture Using CNN :

By employing the method of deep learning, computers may be trained to mimic human behavior. It is a form of machine learning that employs a three-layer neural network. A computer model acquires knowledge through the process of text, audio, or picture categorization. The training of models involves the utilization of multilayer neural network structures and substantial amounts of labeled data. Every algorithm in the hierarchy applies a nonlinear transformation to its input data before generating a statistical model as the output. Convolutional neural networks are widely used in deep learning to analyze visual input. The central processing unit (CPU) is responsible for the majority of the computations and serves as the primary component of a convolutional neural network (CNN). Upon advancing through its processing phases, the CNN successfully detects and localizes the intended item by recognizing its bigger characteristics or forms.

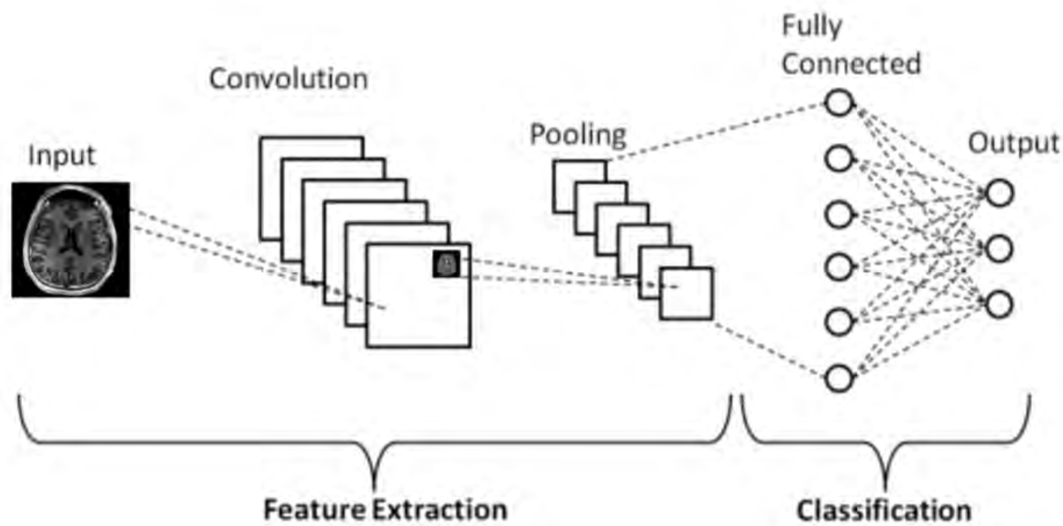


Figure 5.1: Working Process of CNN

5.2 Proposed CNN Model

Convolutional Neural Networks (CNNs), also known as ConvNets, are a type of neural network particularly intended to process data in a grid-like fashion, such as for image processing. A digital image is a visual representation of data that is encoded in binary format. The entity is composed of a consecutive series of discrete visual components referred to as pixels. The proposed methodology employs a multi-layered deep convolutional neural network (CNN) model to discern between authentic and counterfeit images. A CNN model has three layers: a fully connected (FC) layer, a convolutional layer, and a pooling layer. Now, we will go into the precise details of each layer.

5.2.1 Convulation Layer :

A CNN's convolutional layer is one of its most important parts. During the training process, one must understand all of the parameters for these filters, also known as kernels. The size of filters is often smaller than the image they are intended to improve. This layer employs kernel filters to extract pertinent information from the convolutionally processed input pictures. With smaller constant values, the kernel filters resemble the input pictures. Convolution of an image using many filters can be used to achieve edge detection, blurring, and sharpening. We built this CNN model using the Conv2D layer in the convolutional layer. Six Conv 2D layers in all were used to build the model.

5.2.2 Batch Normalization :

For deep learning, especially in neural networks, batch normalization is a technique that can help speed up convergence and increase training stability. It does this by normalizing the neuron activations in each layer across a small subset of training data.By deducting the mean and dividing by the standard deviation of the data in the current mini-batch, the input to a layer is normalized during training. The model is then able to learn the ideal scale and mean for each feature by applying shifts and scales to the normalized data using learnable parameters, such as beta and gamma. The activation function of the layer is then applied to the transformed and normalized data.

5.2.3 Max Pooling Layer :

In the context of convolutional neural networks, pooling layers are positioned after the convolutional layer. Pooling is employed to reduce the number of extracted features and, as a result, the trainable parameters, hence enhancing computational efficiency. The pooling filter controls the extent to which the pooling approach summarizes the range. If the filter's settings are set to 2 by 2, then the summary section will also have a size of 2 by 2. In addition to the existing levels, we may identify a total of six layers in this context.

5.2.4 Fully Connected Layer :

Feed forward neural networks make up the entirety of this layer. The layers that follow the last few in the network's design are known as Fully Connected Layers, or CNN. The output of the last pooling or convolutional layer is then flattened before being sent as the input to the fully connected layer. The following layers are present in this model:

- **Flatten Layer :** Following the usage of the fourth BatchNormalization layer, a single flattened layer will be applied. Ultimately, this is good news for the network as a whole.
- **Dense Layer :** Three thick layers comprise this model in addition to the flattening layer. Each and every neuron in this layer receives the outputs from layers prior.
- **Dropout Layer :** This model has two dropout layers. After first dense layer we used out first dropout layer which has a parameter of 0.5 and we used our second dropout layer with same parameter after the second dense layer.

5.3 Proposed Model Summary :

Many times, the total number of ”learnable” (if such a concept exists) components for a filter is defined as the number of parameters in a given layer. For the suggested system, we divided the dataset into train and test data and then created a sequential CNN model using the Keras neural network framework. To evaluate the accuracy of the model, this was done. A total of eighteen layers make up our model. We incorporated four batch normalization layers and four 2D convolutional layers in total. In addition, four max pooling layers were incorporated. Next, we applied three layers of thick paint and 3 dropout layers followed by one layer of flattening. In the end, we were able to precisely gather 1,438,852 trainable parameters and 704 non-trainable parameters that the model used to train the images.

Layer	Output Shape	Param#
conv2d_(Conv2D)	None,126,126,32	896
max_pooling2d_(MaxPooling2D)	None,63,63,32	0
batch_normalization_(BatchNormalization)	None,63,63,32	128
conv2d_1(Conv2D)	None,61,61,64	18496
max_pooling2d_1(MaxPooling2D)	None,30,30,64	0
batch_normalization_1(BatchNormalization)	None,30,30,64	256
conv2d_2(Conv2D)	None,28,28,128	73856
max_pooling2d_2(MaxPooling2D)	None,14,14,128	0
batch_normalization_2(BatchNormalization)	None,14,14,128	512
conv2d_3(Conv2D)	None,12,12,128	147584
max_pooling2d_3(MaxPooling2D)	None,6,6,128	0
batch_normalization_3(BatchNormalization)	None,6,6,128	512
flatten_(Flatten)	None,4608	0
dense_(Dense)	None,256	1179904
dropout_(Dropout)	None,256	0
dense_1(Dense)	None,64	16448
dropout_1(Dropout)	None,64	0
dense_2(Dense)	None,4	260
Total params:		1,438,852
Trainable params:		1,438,148
Non-trainable params:		704

Table 5.1: Table of proposed CNN model

For our proposed system, we have used four layers of 2D convolutional layers. To align with the dimensions of our input photos, we specified an input size of 128 by 128 for the first layer. As We had set up our kernel as 32 for this layer and used 'relu' activation. It gave us an output shape (126,126,32).

The formula for output size in the Convolution layer:
$W_out = (1)W - k + 2pS + 1$

For the second and third layers, we increased our kernels to 64,128 and 128. It gave output shapes (61,61,64), (28,28,128), and (12,12,128) respectively.

5.4 Pre-Trained Model

5.4.1 VGG 16:

ConvNets, a kind of artificial neural network, are occasionally called convolutional neural networks. A convolutional neural network consists of an input layer, an output layer, and many hidden layers. The makers of the model evaluated the networks and employed a design that utilized small (3 x 3) convolution filters to increase the depth, showcasing a significant improvement over earlier cutting-edge configurations. The depth was expanded to around 138 trainable parameters by expanding it to 16–19 weight layers. The VGG16 algorithm can accurately identify and classify objects in photographs with a precision of 92.7. It is capable of categorizing 1000 photos into 1000 unique categories. The "16" in VGG16 denotes the presence of 16 layers that possess weights. The "sixteen" in VGG16 represents the presence of sixteen layers with assigned weights. VGG16 consists of a total of twenty-one layers, which comprise sixteen convolutional layers, five Max Pooling layers, and three dense layers. However, it only has sixteen weight layers, which are the levels where the parameters are learned. Instead of having a lot of hyper-parameters, VGG16 is known for its focus on convolution layers with a 3x3 filter and stride 1. The architecture as a whole follows a sequential arrangement of the convolution and max pool layers. The soft-max layer is the final layer in the network architecture.

5.4.2 VGG 19

The VGG-19 model, a member of the Visual Geometry Group (VGG) series, is a convolutional neural network (CNN) notable for its depth and simplicity in architecture, designed primarily for image classification tasks. Comprising 16 convolutional layers followed by 3 fully connected layers, it utilizes 3x3 convolutional filters with a stride of 1 and 2x2 max-pooling layers with a stride of 2. The regulated architecture provides a coherent and readily comprehensible framework, which has led to its extensive acceptance and use as a reference point in the domain of deep learning. The model's nested configuration of convolutional layers afterward max-pooling layers enables the gradual extraction of intricate picture characteristics. Through the process of layering and increasing the depth, the neural network acquires knowledge and depicts visual patterns seen in photos. The VGG-19's uniform architecture, characterized by tiny filter sizes and a steady stride, enables the extraction of features at various scales while preserving spatial details. The VGG-19 model has become an influential model in the field of image recognition and categorization owing to its architectural efficiency, capacity to capture rich hierarchical representations, and computational complexity resulting from its depth and factor count.

5.4.3 Resnet-50

The initial design of the ResNet model was the ResNet-34 architecture, which is comprised of 34 layers that are assigned weights. It showed a new way to increase the number of convolutional layers in a CNN without having to deal with the vanishing gradient problem by using the idea of shortcut connections. Each convolutional layer in the standard network utilizes a 3×3 filter. The 34-layer ResNet can achieve 3.6 billion FLOPs. On the other hand, a smaller 18-layer ResNet can create 1.8

billion FLOPs. The ResNet architecture abides by two key principles. The size of the output feature map determines how many filters are present in each layer. The architecture of ResNet-50 is taken from the original ResNet-34 model, with one significant deviation. The architectural element of the 50-layer ResNet is intentionally meant to function as a bottleneck. A bottleneck residual block reduces the number of parameters and matrix multiplications by employing 1×1 convolutions, which are also known as bottlenecks. This significantly accelerates the training process for each layer. Instead of utilizing a dual-layer approach, it utilizes a tri-layer stack.

5.4.4 MobileNet

Google has released its MobileNet computer vision model as open-source. Its purpose is to be utilized for the training of classifiers. Through the use of depthwise convolutions, this technique effectively reduces the parameter count of the neural network, resulting in a lightweight deep neural network in contrast to other networks. MobileNet is the name of Tensorflow's initial mobile computer vision model. Compared to other networks that use traditional convolutions and have the same depth, this network utilizes depth-wise separable convolutions to significantly decrease the number of parameters. The result of this is the creation of lightweight, deep neural networks. Google has released open-source software for MobileNet-class convolutional neural networks (CNNs), which are ideal for constructing highly efficient and fast classifiers. The user's text is a reference to a source or citation. MobileNets are models designed to have low power consumption and low latency. They are specifically tailored to meet the resource needs of particular use cases. They can be utilized as a basis for segmentation, embedding, detection, and classification.

5.4.5 InceptionV3

The Inception v3 model has achieved accuracy values of 78.1% on the ImageNet dataset. The model is the result of several ideas that various researchers have developed over time. The paper titled "Rethinking the Inception Architecture for Computer Vision" by Szegedy et al. provided the basis for this work. The model comprises convolutions, average pooling, max pooling, concatenations, dropouts, and fully connected layers, as well as various symmetric and asymmetric building blocks. The model extensively utilizes batch normalization, which is implemented on activation inputs. The softmax function is utilized for loss computation. Before image recognition, the model must undergo training using a substantial dataset of annotated photographs. An extensively used dataset is ImageNet. One million images have bounding boxes that provide a more precise location for the listed things. Each cloud-based TPU device is connected to a host and consists of eight CPU cores. Once hosts get data from the file system or local memory, they perform necessary preprocessing on the data before transmitting it to the TPU cores. The host performs three distinct steps of data handling, namely: 1) storage; 2) preprocessing; and 3) transfer. Optimal performance can only be achieved when the system is in a state of equilibrium. The host will constrain the execution if the host CPU takes longer than the TPU to complete the three data handling phases. The processing speed of input data is now the only factor limiting Inception v3's implementation. Upon reception from the LE system, pictures undergo preprocessing and decoding.

There are several choices for preprocessing steps, ranging from basic to complex. The preprocessing stage will be a restriction on the training pipeline if we use the most sophisticated preparation processes.

5.4.6 EfficientNetB0

Using a compound coefficient, EfficientNet is a convolutional neural network design and scaling technique that equally scales all dimensions of depth, breadth, and resolution. The EfficientNet scaling approach evenly increases network breadth, depth, and resolution using a set of preset scaling coefficients, in contrast to standard practice, which scales these elements arbitrarily. The number of channels in each layer of the neural network is referred to as width scaling. The model's accuracy increases when the breadth is increased because it can capture more intricate patterns and characteristics. The total number of layers in the network is relevant to depth scaling. Although deeper models can capture more complex data representations, they also require more processing power. Resolution scaling involves adjusting the input image's size. Higher-resolution images provide more detailed information, potentially leading to better performance. However, they also require more memory and computational power. EfficientNet's ability to balance all three aspects using a principled method is one of its strongest points. The researchers conduct a methodical grid search to identify the ideal compromise between breadth, depth, and resolution, starting from a baseline model. A baseline model is used as the beginning point of the procedure. Usually, a decently large neural network that functions well on a particular task, this baseline model may not be tuned for computing efficiency. Next, a user-defined parameter called a compound coefficient is inserted, which determines the amount by which the neural network's dimensions should be scaled. It is one scalar variable that scales the model's breadth, depth, and resolution evenly.

5.4.7 DenseNet121:

As convolutional neural networks (CNNs) increase in complexity, they begin to encounter problems. This occurs due to the potential loss of information during transmission across the extensive pathway between the input and output layers, including the gradient in the opposite direction. Densely Connected Convolutional Networks, often known as DenseNets, represent the upcoming advancement in deep convolutional network technology. DenseNets optimizes the network's capacity by recycling features instead of relying on complex and extensive designs for representation. Due to the absence of the requirement to train duplicate feature maps, DenseNets have a reduced parameter count compared to a conventional CNN of the same dimensions. Furthermore, several iterations of ResNets have shown that numerous layers are redundant and may be removed. DenseNet layers are highly restricted and consist of just a small number of extra feature maps. Training more complex networks with several layers posed significant issues due to the gradients and information flow outlined above. DenseNets effectively tackle this issue by allowing each layer to directly access the gradients from both the original input image and the loss function. Concatenation combines the input volume and the outputs of the two identical operations in each dense layer inside each dense block to improve the network's collective knowledge.

Chapter 6

Performance Analysis

6.1 Performance Analysis

Confirming the innovative technical solutions that have been applied to improve performance is the aim of performance analysis. This helps us find new approaches and enhance existing ones by providing a comprehensive survey of the whole task and highlighting the advantages and disadvantages of certain employment. It may also be applied to evaluate the merits and faults of other people. Performance analysis, movement analysis, strategic and operational evaluation, and data collection are the three most crucial factors.

6.2 Performance Parameter

The suggested network is compared with this model's training dataset based on many variables. Among these parameters are batch size, epoch, learning rate, optimizer, and callbacks. Before training can begin, the dataset must be fully preprocessed. The transfer learning approach allows its settings to be changed before training begins. Before initiating the machine learning process, the user has the option to choose between pre-trained models and proposed CNN models. Subsequently, the directory that encompasses both sets of recently generated categories is imported, contingent upon the magnitude of the first layer of data. The gradient-based optimizer, known as "Adam," focuses on fresh predictions of instances with comparatively low relevance. This technique may be improved upon for randomized goal functions. The "Adam" optimizer is utilized because it is easy to build, efficient, has low memory consumption, and is impervious to changes in size along the diagonal gradient. This enables the technique to be applied in scenarios involving large volumes of data and/or parameter values. For the bespoke model, we utilized 32 batches and 60 epochs, while for the pre-trained models, we used 60 epochs. We used "categorical Cross Entropy" in the part about the loss.

Parameter	18-Layer proposed Model	Pre-trained model
Training Data	80%	80%
Testing Data	20	20
Batch Size	32	32
Target Size	128x128	128x128
Epoch	60	60
Execution Environment	GPU	GPU
Optimizer	Adam	Adam
Loss Function	Categorical	Categorical
Class Mode	Categorical	Categorical

Table 6.1: Performance Parameter Table.

6.3 Performance of Proposed Model

We made the decision to assess 6484 tumor images in total, which were split into four categories: glioma, meningioma, no tumor, and pituitary. The model we had suggested was found to be accurate 97.35 percent of the time in the end. The accuracy and loss results from training and testing are shown in the table below.

Training Accuracy	Training Loss	Testing Accuracy	Testing Loss
98.82%	3.61%	98.11%	5.60%

Table 6.2: Result of proposed model.

The suggested 18-layer model's training and testing accuracy, which are 98.82% and 98.11%, respectively, are displayed in the table. Testing data show a 3.61% loss for the model, whereas training data show a 5.60% loss.

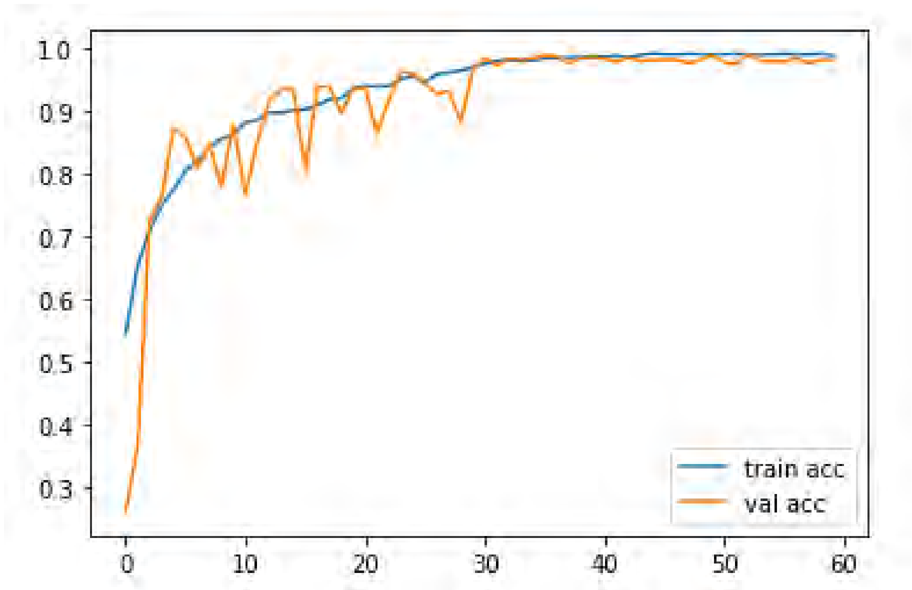


Figure 6.1: Graph of training and testing accuracy of proposed model

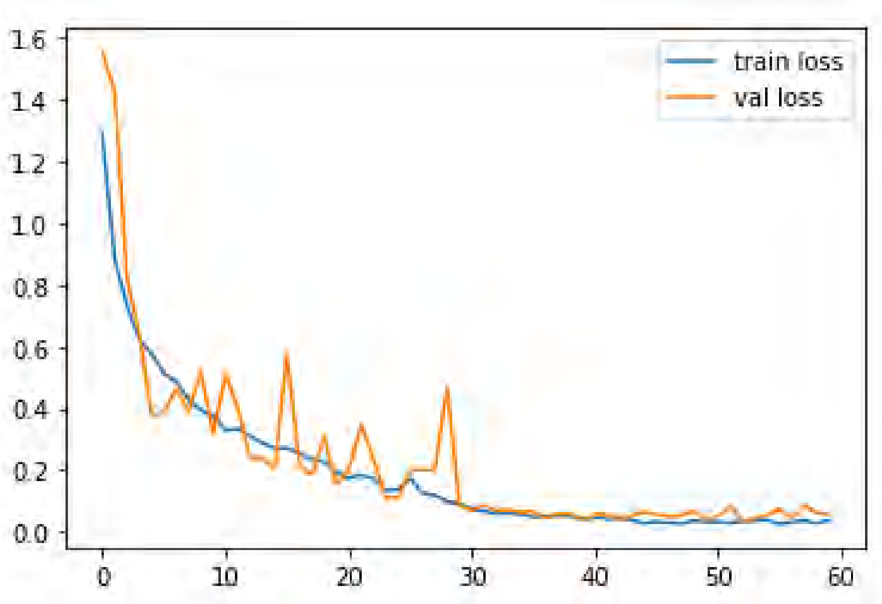


Figure 6.2: Graph of training and testing loss of proposed model

6.3.1 Performance of proposed Model with other Data-set:

The initial data set that we used is comparatively small in size which is why we wanted to be sure if our model faces a drop in performance thus, we trained our proposed model on another bigger data set and examined the performance. Moreover, the data set we used from Kaegle is the biggest data set related to Brain tumor MRI images that we could find.[27] Hence, we applied the same architecture of our model to the data set "Retinal OCT Images(optical coherence tomography)". Furthermore, the results we received after working on the same data set are as follows:

Training Accuracy	Training Loss	Testing Accuracy	Testing Loss	Epochs
96.76%	9.34%	98.14%	8.89%	80

Table 6.3: Result of proposed model on other Dataset.

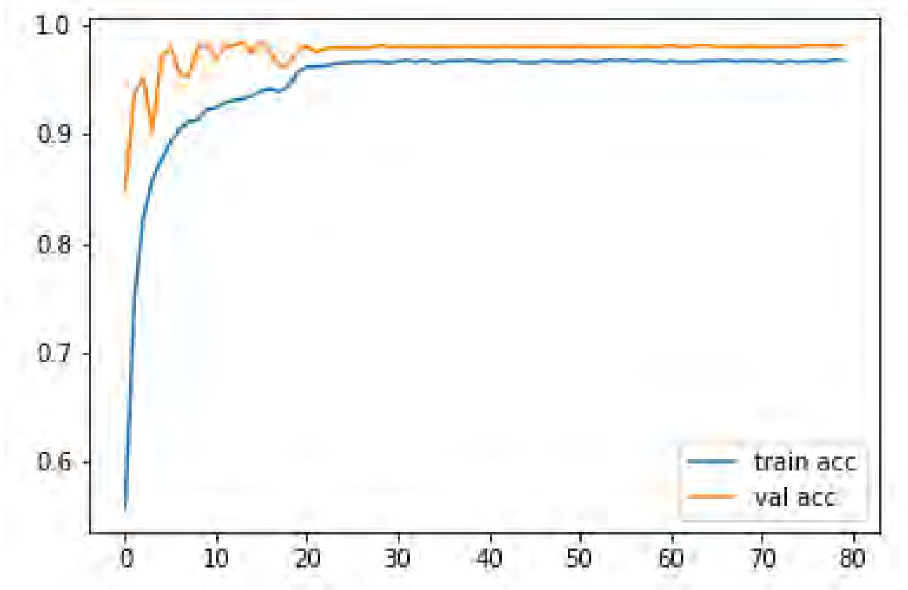


Figure 6.3: Graph of training and testing accuracy of CNN on other Dataset

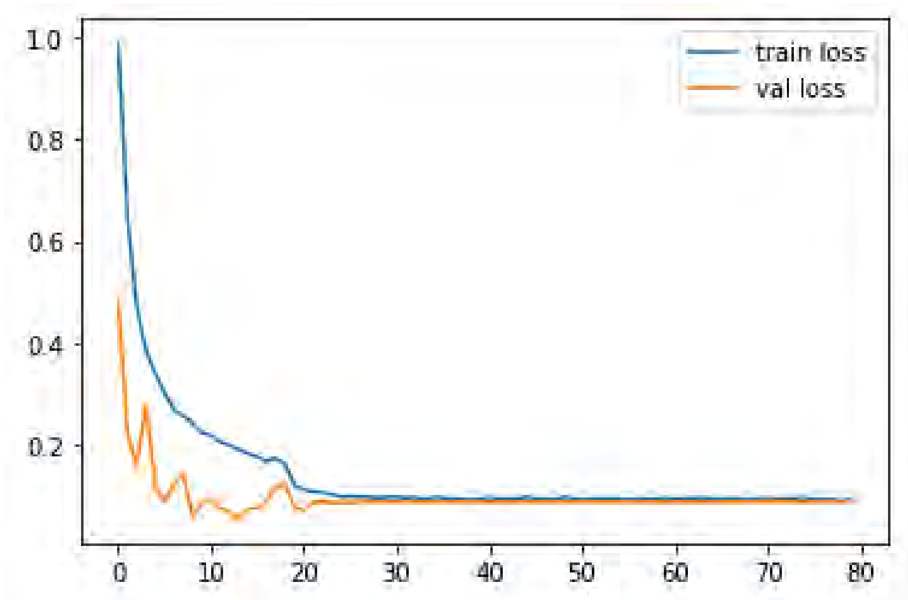


Figure 6.4: Graph of training and testing loss of CNN on other Dataset

6.4 Performance of Pre-trained Model

6.4.1 Vgg16 :

Using the Vgg16 model, a training accuracy of 93.90% and a testing accuracy of 93.37% were both attained. This figure displays the vgg16 training graph, and figure displays the vgg16 validation graph. We can infer from the figure that training accuracy improves over time.

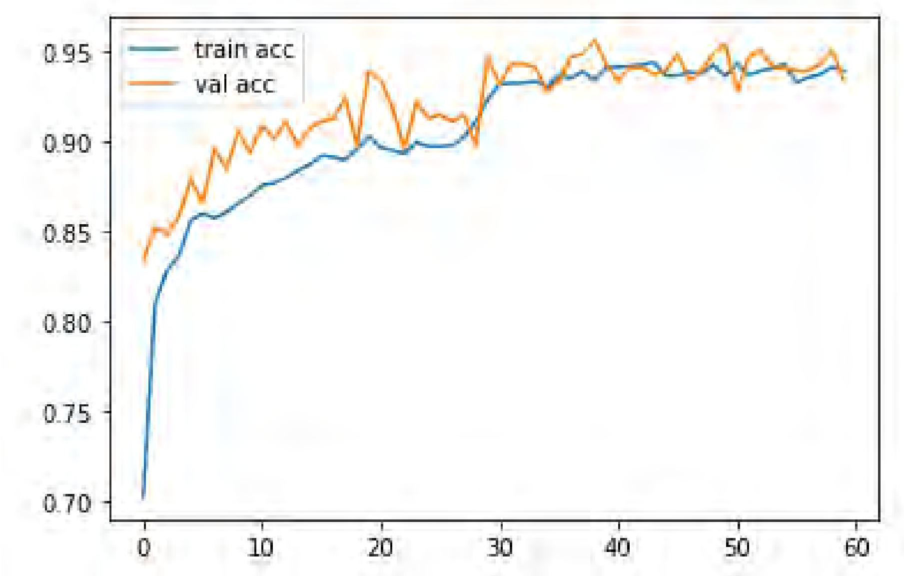


Figure 6.5: Graph of training and testing accuracy of VGG16 model

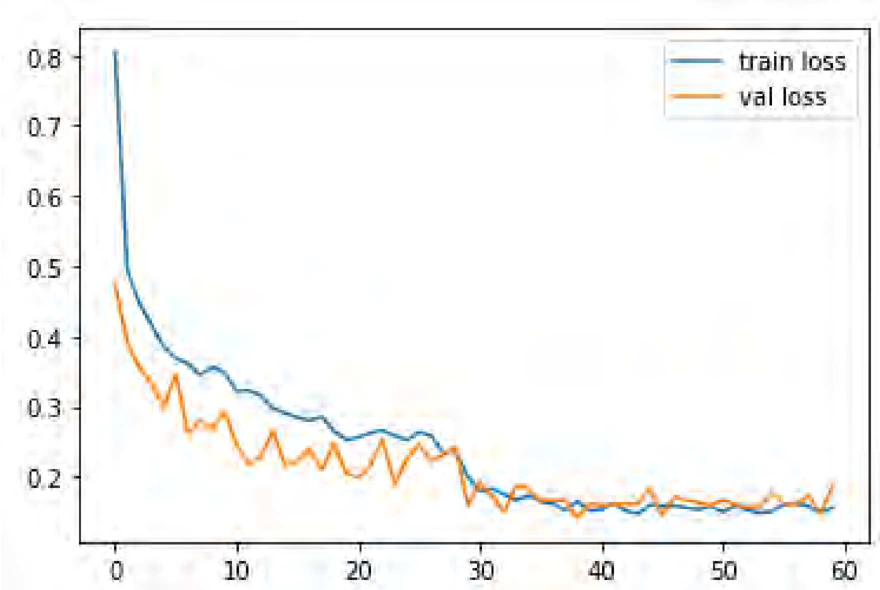


Figure 6.6: Graph of training and testing loss of VGG16 model

6.4.2 Vgg19 :

Using the Vgg19 model, a training accuracy of 85.93% and testing accuracy of 86.93% were both attained. This figure displays the vgg19 training graph, and figure displays the vgg19 validation graph. We can infer from the figure that training accuracy improves over time.

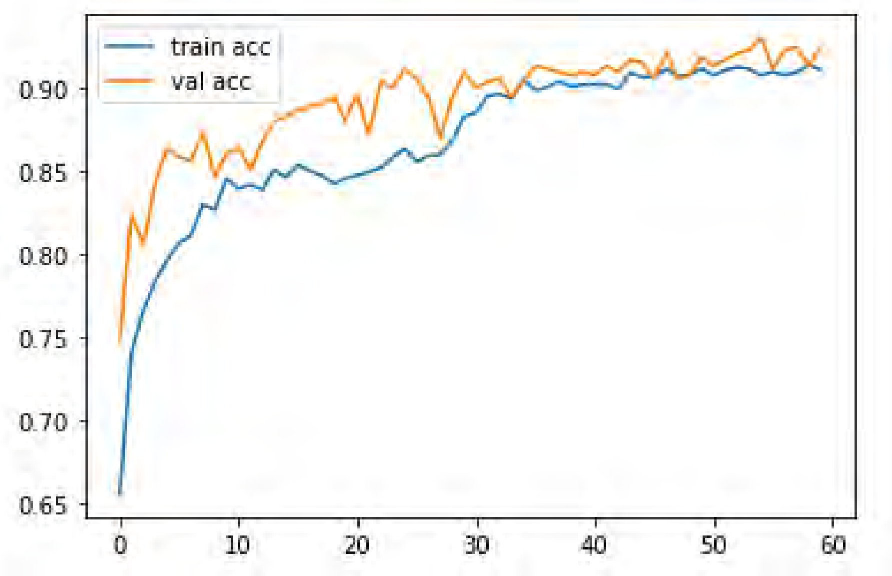


Figure 6.7: Graph of training and testing accuracy of VGG19 model

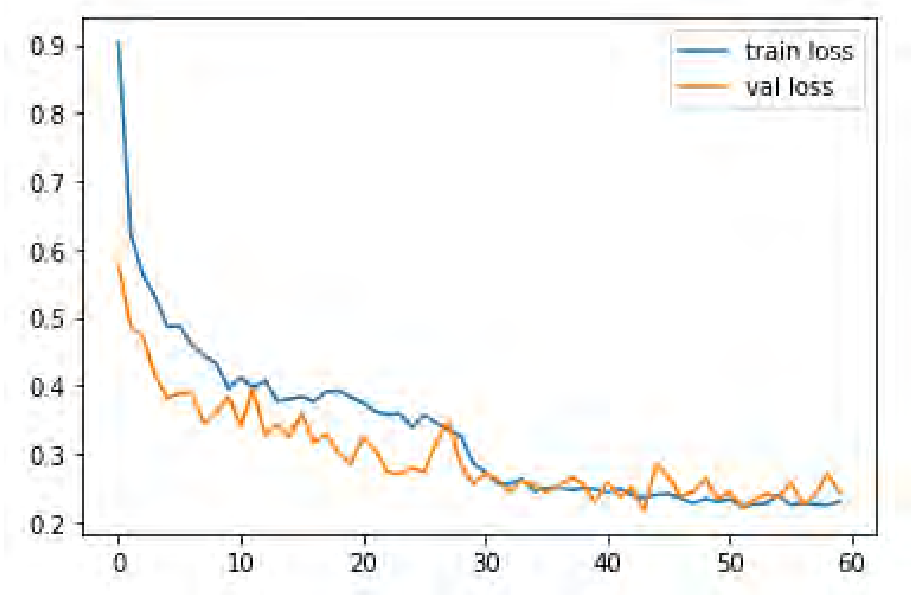


Figure 6.8: Graph of training and testing loss of VGG19 model

6.4.3 Resent50 :

Using the Resnet50 model, a training accuracy of 68.86% and a testing accuracy of 75.38% were both attained. This figure displays the Resnet50 training graph, and the figure displays the Resnet50 validation graph. We can infer from the figure that training accuracy improves over time.

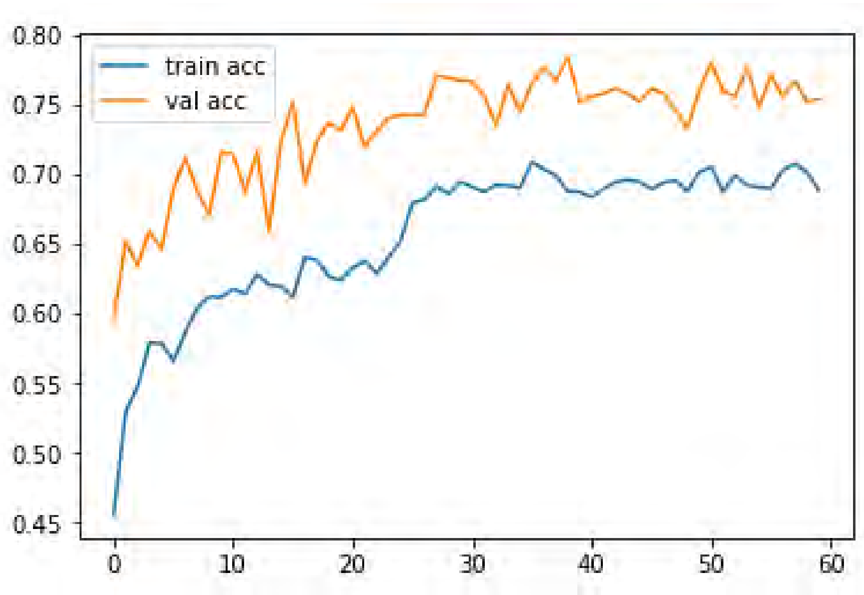


Figure 6.9: Graph of training and testing accuracy of Resnet50 model

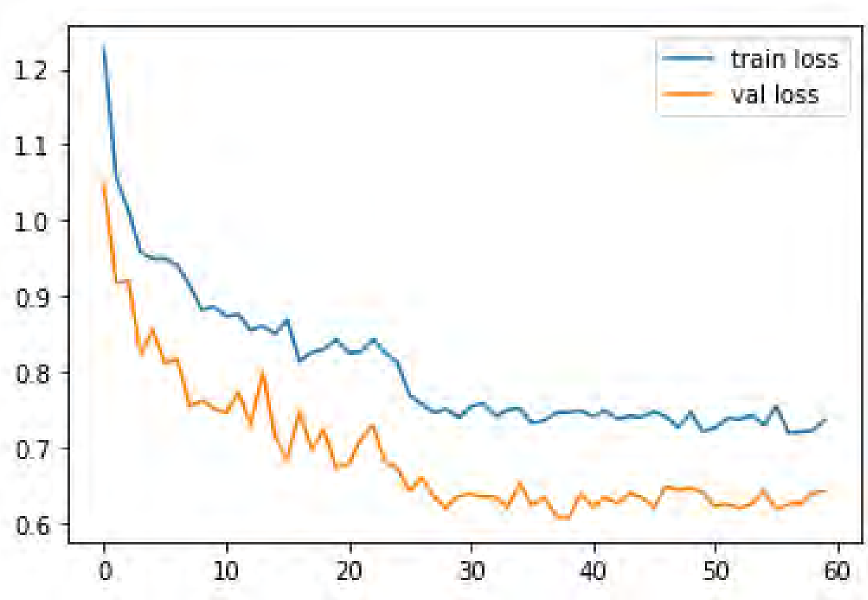


Figure 6.10: Graph of training and testing loss of Resnet50 model

6.4.4 Inceptionv3:

Using the Inceptionv3 model, a training accuracy of 89.05% and a testing accuracy of 91.48% were both attained. This figure displays the inceptionv3 training graph, and the figure displays the inceptionv3 validation graph. We can infer from the figure that training accuracy improves over time.

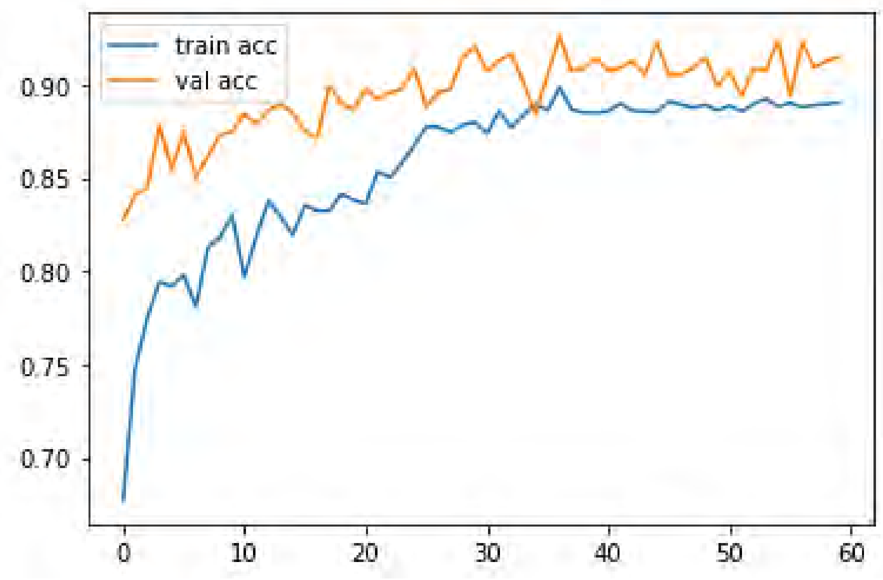


Figure 6.11: Graph of training and testing accuracy of Inceptionv3 model

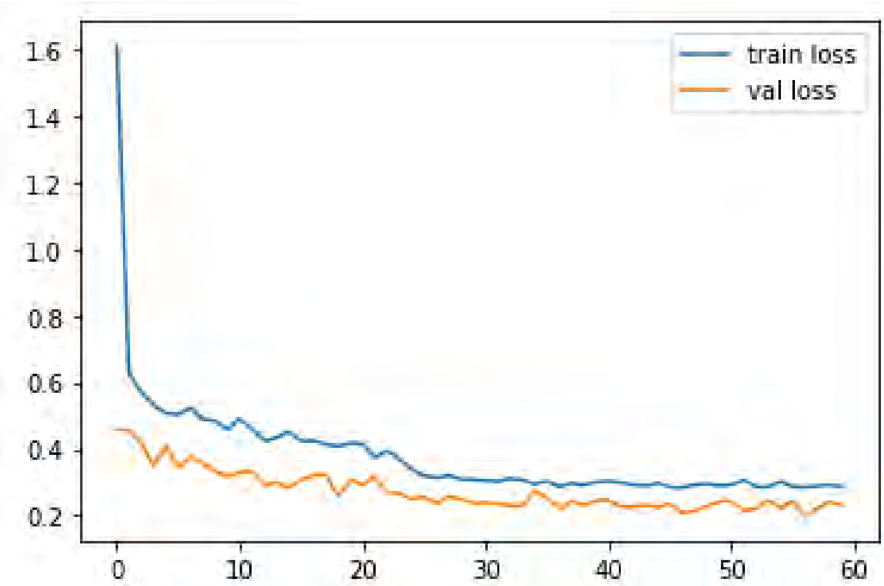


Figure 6.12: Graph of training and testing loss of Inceptionv3 model

6.4.5 DenseNet121:

The Densenet model achieved a training accuracy of 93.29% and a testing accuracy of 94.89%. The training loss is 16.90 and the testing loss is 13.22% This graph depicts the DenseNet training graph, while this graph depicts the DenseNet validation graph. The graph shows that training accuracy improves with time.

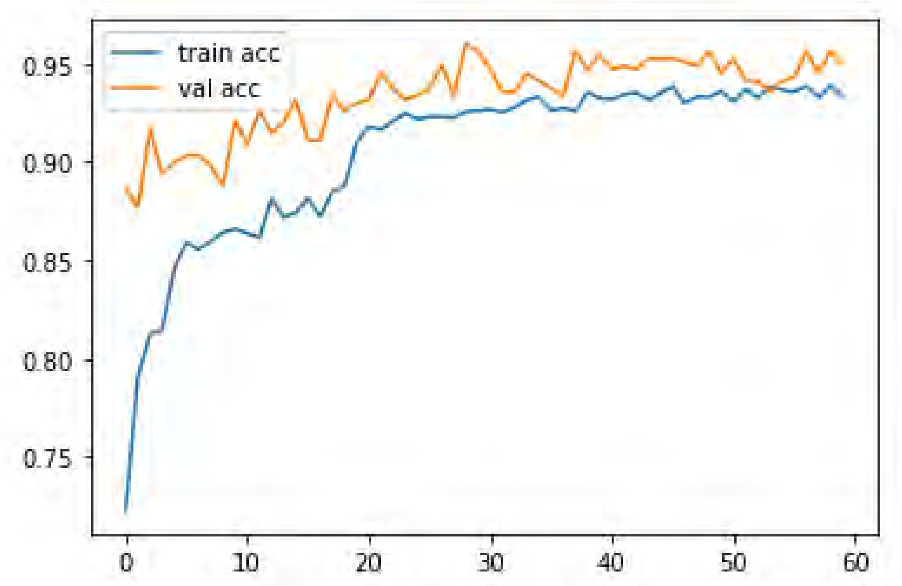


Figure 6.13: Graph of training and testing accuracy of DenseNet-121 model

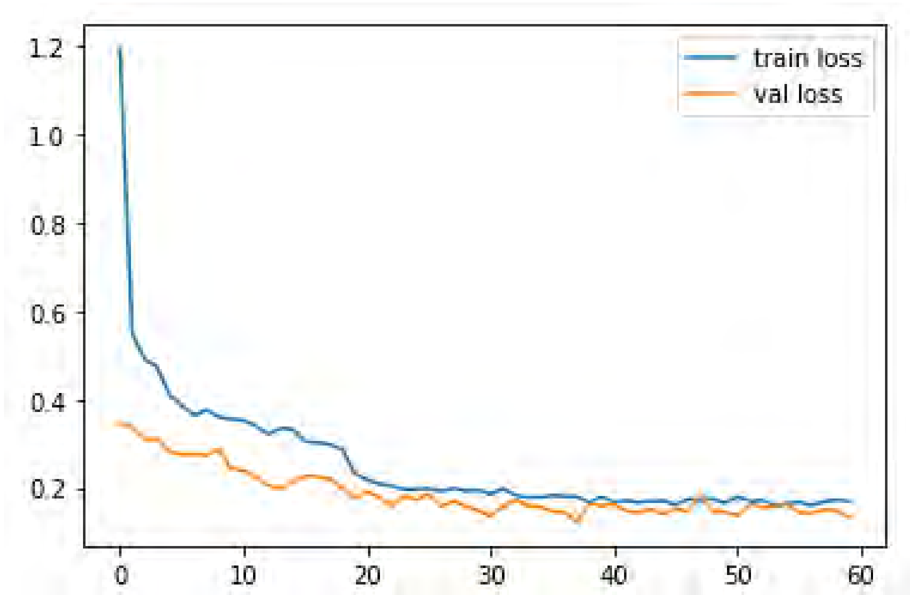


Figure 6.14: Graph of training and testing loss of DenseNet-121 model

6.4.6 EfficientNetB0:

The efficient model achieved a training accuracy of 25.19% and a testing accuracy of 23.30%. This figure shows the EfficientB0 training graph, while this figure shows the EfficientB0 validation graph. The graph suggests that training accuracy improves with time.

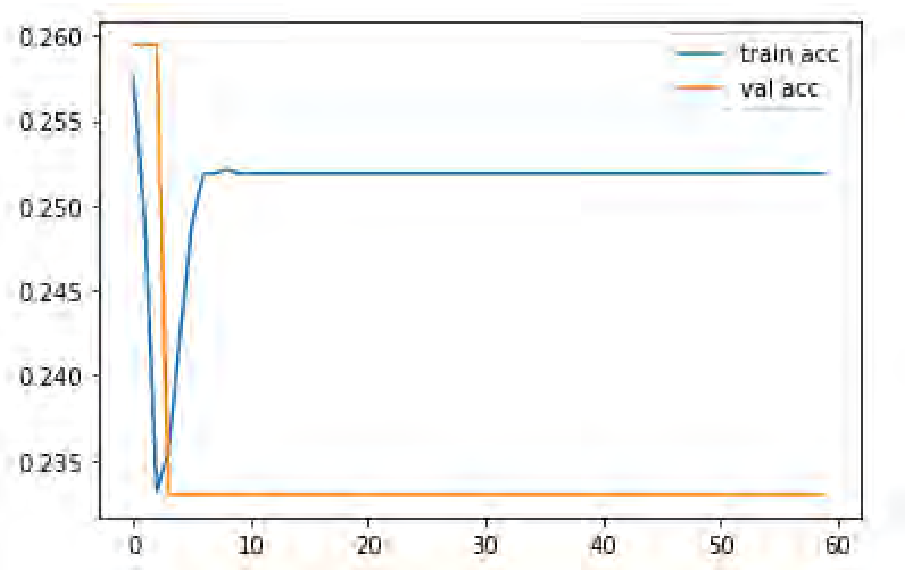


Figure 6.15: Graph of training and testing accuracy of EfficientNetB0 model

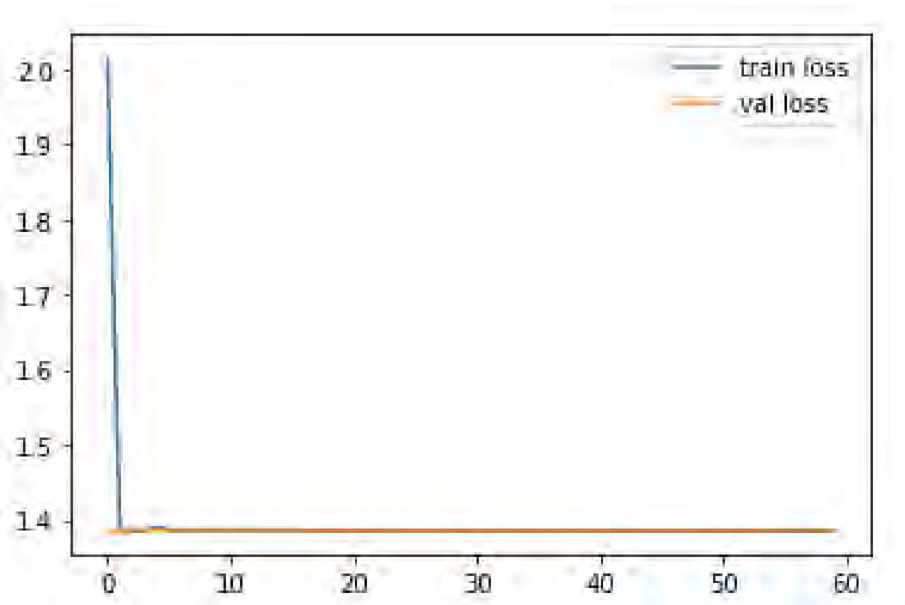


Figure 6.16: Graph of training and testing loss of EfficientNetB0 model

6.4.7 MobileNet:

The MobileNet model attained a training precision of 96.91% and a testing accuracy of 96.02%. The training loss is 7.59% and the testing loss is 11.51% The MobileNet training graph is shown in the figure, and the MobileNet validation graph is shown in the figure. The graph indicates that training accuracy improves over time.

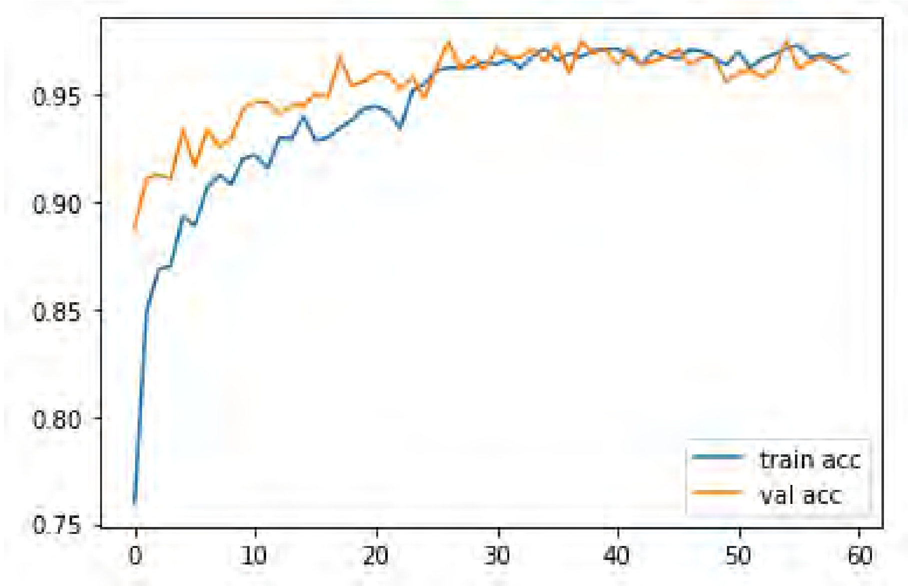


Figure 6.17: Graph of training and testing accuracy of MobileNet model

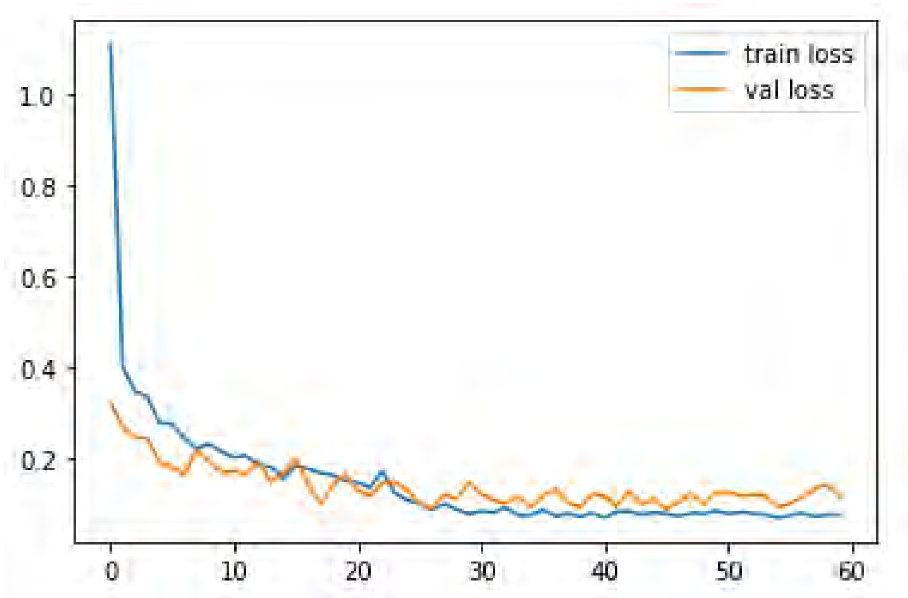


Figure 6.18: Graph of training and testing loss of MobileNet model

6.5 Performance Matrix:

6.5.1 Proposed CNN Model:

The provided classification report contains precision, recall, and F1-score metrics classification problems involving many classes along with four classes: glioma, meningioma, no tumor, and pituitary. The interpretation of the confusion matrix relies on these measures. The confusion matrix is a tabular representation that provides a comprehensive overview of the performance of a classification model. In a multiclass scenario, the confusion matrix represents the real class for each row and the expected class for each column.

- **True Positives (TP):**
  - Glioma: 288
  - Meningioma: 291
  - Notumor: 300
  - Pituitary: 297
- **False Positives (FP):**
  - Glioma: 0
  - Meningioma: 9
  - Notumor: 0
  - Pituitary: 3
- **False Negatives (FN):**
  - Glioma: 12
  - Meningioma: 9
  - Notumor: 0
  - Pituitary: 3
- **True Negatives (TN):**
  - Glioma: 900
  - Meningioma: 900
  - Notumor: 900
  - Pituitary: 897
- **Precision:** The proportion of accurately predicted positive observations to all anticipated positives is known as precision.
  - Glioma: 1.00 (288 / (288 + 0))
  - Meningioma: 0.96 (291 / (291 + 9))
  - Notumor: 0.97 (300 / (300 + 0))
  - Pituitary: 0.99 (297 / (297 + 3))

- **Recall (Sensitivity):** The ratio of accurately anticipated positive observations to all observations made during the actual class is known as recall.
  - Glioma: 0.96 (288 / (288 + 12))
  - Meningioma: 0.97 (291 / (291 + 9))
  - Notumor: 1.00 (300 / (300 + 0))
  - Pituitary: 0.99 (297 / (297 + 3))
- **F1-score:** F1-score is the harmonic mean of precision and recall.
  - Glioma: 0.98
  - Meningioma: 0.96
  - Notumor: 0.98
  - Pituitary: 0.99
- **Accuracy:** The overall accuracy of the model is 0.98 (1200 correct predictions out of 1200 total instances). The confusion matrix and metrics indicate that the model has high performance across all classes with an overall accuracy of 98%.

	precision	recall	f1-score	support
glioma	0.99	0.88	0.93	300
meningioma	0.91	0.92	0.91	300
notumor	1.00	1.00	1.00	300
pituitary	0.90	1.00	0.95	300
accuracy			0.95	1200
macro avg	0.95	0.95	0.95	1200
weighted avg	0.95	0.95	0.95	1200

Figure 6.19: F1 score of Proposed CNN model

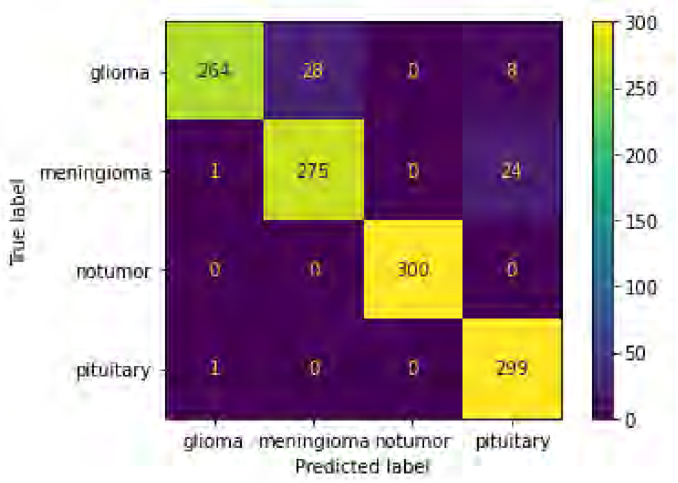


Figure 6.20: Confusion Matrix of Proposed CNN model

The metrics provided in the table are Sensitivity, Precision, and Specificity for each class (No Tumor, Meningioma, Glioma, Pituitary). Let's interpret them:

- **Sensitivity (True Positive Rate):** the percentage of true positive cases that the model accurately anticipated.
  - Glioma: 1.000 (100% of actual Glioma cases were correctly predicted as Glioma)
  - Meningioma: 0.970 (97% of actual Meningioma cases were correctly predicted as Meningioma)
  - No Tumor: 0.960 (96% of actual No Tumor cases were correctly predicted as No Tumor)
  - Pituitary: 0.990 (99% of actual Pituitary cases were correctly predicted as Pituitary)
- **Precision (Positive Predictive Value):** The proportion of predicted positive instances that are actually positive.
  - Glioma: 0.970 (97% of predicted Glioma cases were actually Glioma)
  - Meningioma: 0.960 (96% of predicted Meningioma cases were actually Meningioma)
  - Notumor: 1.000 (100% of predicted No Tumor cases were actually No Tumor)
  - Pituitary: 0.990 (99% of predicted Pituitary cases were actually Pituitary)
- **Specificity (True Negative Rate):** The percentage of real negative instances accurately predicted by the prototype.
  - Glioma: 0.999 (99.9% of actual Glioma cases were correctly predicted as not Glioma)

  - Meningioma: 0.989 (98.9% of actual Meningioma cases were correctly predicted as not Meningioma)
  - Notumor: 0.986 (98.6% of actual cases of No Tumor were correctly predicted as not No Tumor)
  - Pituitary: 0.998 (99.8% of actual Pituitary cases were correctly predicted as not Pituitary)

  These metrics provide an all-inclusive view, indicating how well each class's model performed, considering aspects like sensitivity, precision, and specificity.

- **Class Glioma:**ROC AUC OvR (One vs Rest): 0.9987.
  This indicates The model's capacity to differentiate between Glioma and all other classes. A value close to 1.0 suggests excellent performance.

- **Class Meningioma:** ROC AUC OvR (One vs Rest): 0.9979.
  This score represents the model's ability to discriminate between Meningioma and the remaining classes. A value close to 1.0 indicates strong performance.

- **Class No Tumor:** ROC AUC OvR (One vs Rest): 0.9999.
  The ROC AUC for the No Tumor class suggests very high discriminatory power, with a value close to 1.0.

- **Class Pituitary:** ROC AUC OvR (One vs Rest): 0.9998.
  This high ROC AUC value suggests that the model can distinguish between Pituitary and other classes.

- **Average ROC AUC OvR:** 0.9991.
  This is the average ROC AUC total score for every class. It provides an overall evaluation of the model's functionality in distinguishing between different classes. In summary, the ROC AUC scores are exceptionally high for each class, and the average ROC AUC indicates strong overall performance in the multi-class classification task.

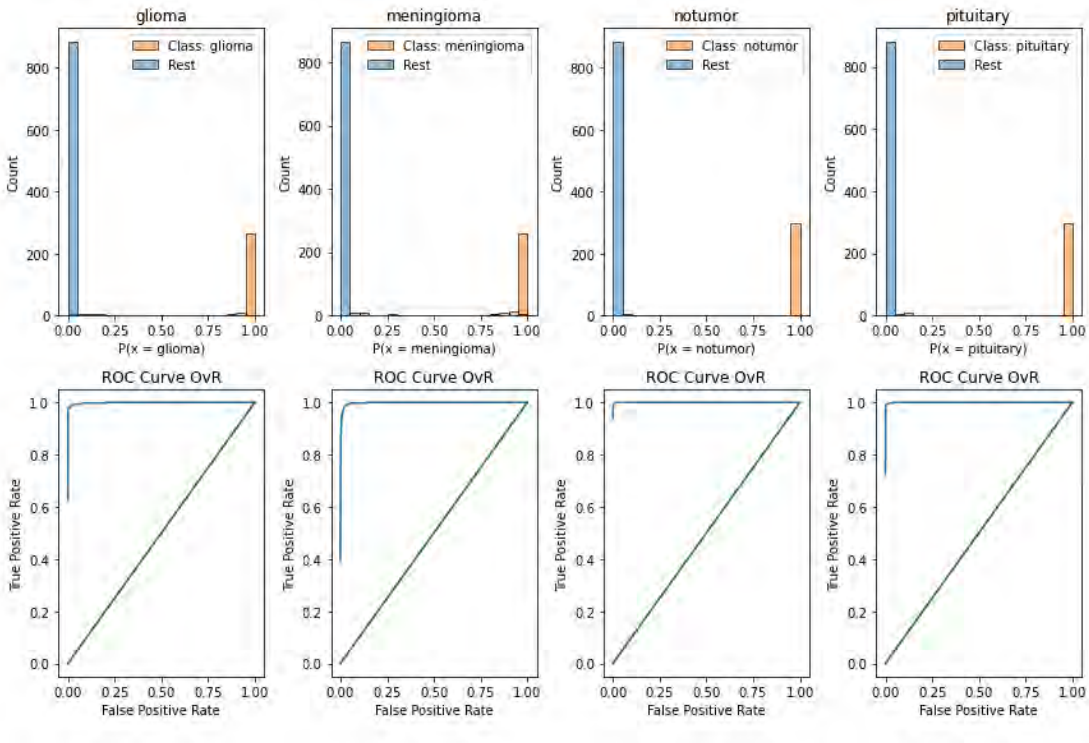


Figure 6.21: ROC Curves of Proposed CNN Model.

6.5.2 Pre-trained Models:

- **VGG16:** we shared the confusion matrix and precision, recall, and f1 score of every four classifiers for better understanding in the figure below:-

	precision	recall	f1-score	support
glioma	0.96	0.82	0.89	300
meningioma	0.85	0.86	0.85	300
notumor	0.96	1.00	0.98	300
pituitary	0.90	0.98	0.94	300
accuracy			0.91	1200
macro avg	0.92	0.91	0.91	1200
weighted avg	0.92	0.91	0.91	1200

Figure 6.22: F1 score of Vgg16 model

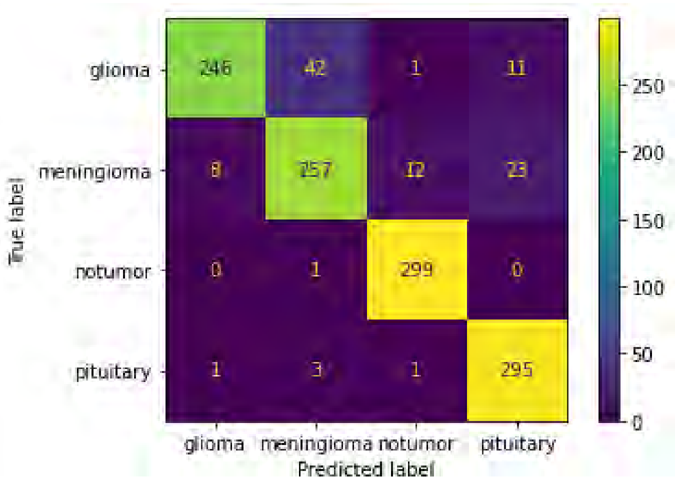


Figure 6.23: Confusion Matrix of Vgg16 model

- **VGG19:** we shared the confusion matrix and precision, recall, and f-1score of all four Classifiers for better understanding in the figure below:-

	precision	recall	f1-score	support
glioma	0.97	0.76	0.85	300
meningioma	0.82	0.83	0.82	300
notumor	0.93	1.00	0.96	300
pituitary	0.88	0.99	0.93	300
accuracy			0.89	1200
macro avg	0.90	0.89	0.89	1200
weighted avg	0.90	0.89	0.89	1200

Figure 6.24: F1 score and Confusion Matrix of Vgg19 model

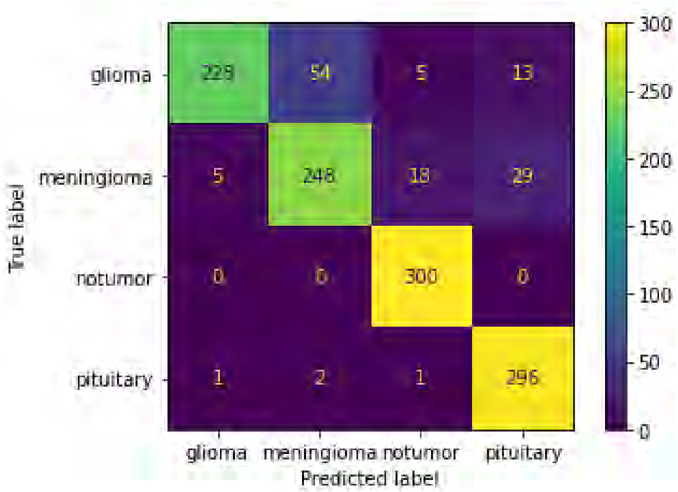


Figure 6.25: F1 score and Confusion Matrix of Vgg19 model

- **ResNet50:** We shared the confusion matrix and precision, recall, and f1score of all four Classifiers for better understanding in the figure below:-

	precision	recall	f1-score	support
glioma	0.82	0.54	0.65	300
meningioma	0.61	0.53	0.57	300
notumor	0.74	0.99	0.85	300
pituitary	0.77	0.87	0.82	300
accuracy			0.73	1200
macro avg	0.74	0.73	0.72	1200
weighted avg	0.74	0.73	0.72	1200

Figure 6.26: F1 score and Confusion Matrix of ResNet50 model

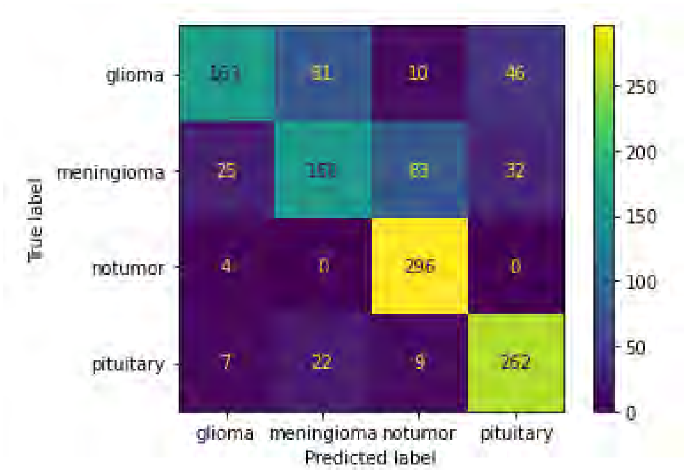


Figure 6.27: F1 score and Confusion Matrix of ResNet50 model

- **InceptionV3:** We shared the confusion matrix and precision, recall, and f-1 score of all four Classifiers for better understanding in the figure below:-

	precision	recall	f1-score	support
glioma	0.93	0.81	0.87	300
meningioma	0.83	0.83	0.83	300
notumor	0.97	0.99	0.98	300
pituitary	0.87	0.96	0.91	300
accuracy			0.90	1200
macro avg	0.90	0.90	0.90	1200
weighted avg	0.90	0.90	0.90	1200

Figure 6.28: F1 score and Confusion Matrix of inceptionV3 model

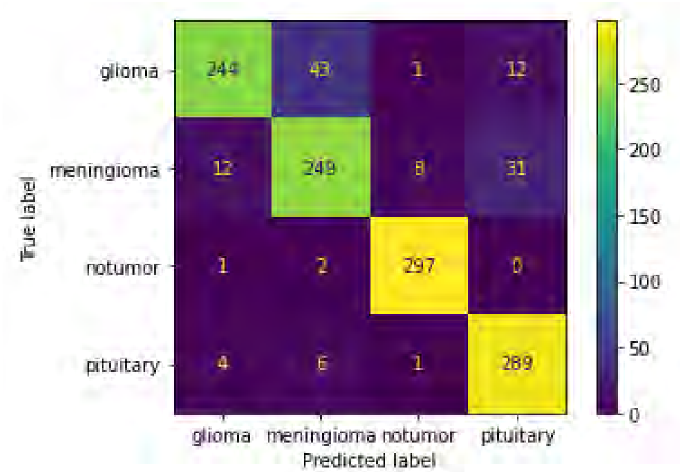


Figure 6.29: F1 score and Confusion Matrix of inceptionV3 model

- **DenseNet121:** We shared the confusion matrix and precision, recall, and f-1 score of all four Classifiers for better understanding in the figure below:-

	precision	recall	f1-score	support
glioma	0.97	0.86	0.91	300
meningioma	0.88	0.80	0.84	300
notumor	0.96	1.00	0.98	300
pituitary	0.84	0.99	0.91	300
accuracy			0.91	1200
macro avg	0.91	0.91	0.91	1200
weighted avg	0.91	0.91	0.91	1200

Figure 6.30: F1 score and Confusion Matrix of DenseNet-121 model

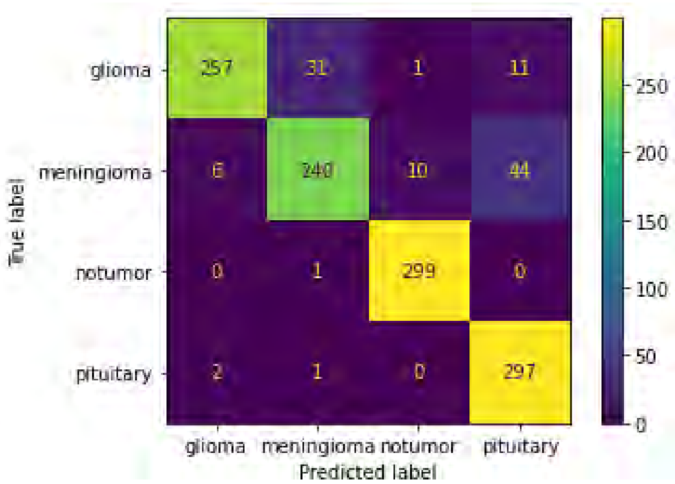


Figure 6.31: F1 score and Confusion Matrix of DenseNet-121 model

- **EfficientNet B0:** We shared the confusion matrix and precision, recall, and f-1 score of all four Classifiers for better understanding in the figure below:-

	precision	recall	f1-score	support
glioma	0.00	0.00	0.00	300
meningioma	0.25	1.00	0.40	300
notumor	0.00	0.00	0.00	300
pituitary	0.00	0.00	0.00	300
accuracy			0.25	1200
macro avg	0.06	0.25	0.10	1200
weighted avg	0.06	0.25	0.10	1200

Figure 6.32: F1 score of EfficientNetB0 model

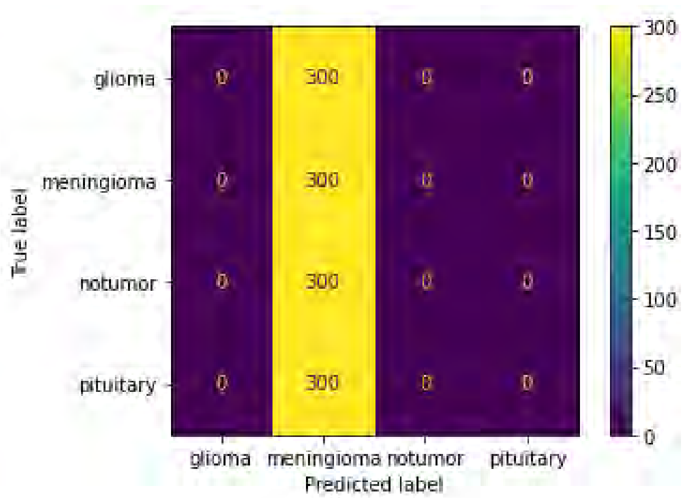


Figure 6.33: Confusion Matrix of EfficientNetB0 model

- **MobileNet:** We shared the confusion matrix and precision, recall, and f-1 score of all four Classifiers for better understanding in the figure below:-

	precision	recall	f1-score	support
glioma	0.99	0.88	0.93	300
meningioma	0.91	0.92	0.91	300
notumor	1.00	1.00	1.00	300
pituitary	0.90	1.00	0.95	300
accuracy			0.95	1200
macro avg	0.95	0.95	0.95	1200
weighted avg	0.95	0.95	0.95	1200

Figure 6.34: F1 score of MobileNet model

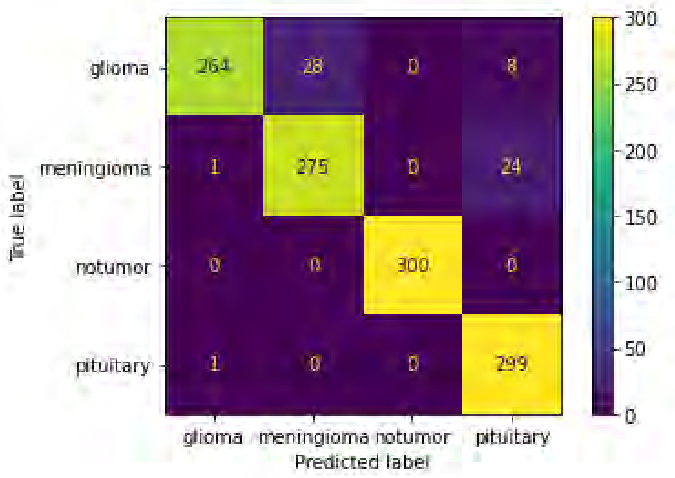


Figure 6.35: Confusion Matrix of MobileNet model

6.6 Compare and Analysis :

This study uses the following seven pre-trained models: ResNet50, Vgg16, Vgg19, Inception V3, EfficientNetBO, Desnet121, and MobileNet.Additionally, a comparison of the two groups' performances suggests an 18-layer CNN model and seven pre-trained models are provided. The data presented in the table demonstrate The models presented in the table outperform the current models by a large margin. A bar graph illustrating the CNN models' accuracy is shown in Figure alongside the proposed model and previously trained models. The proposed model produced a 98.11 percent training accuracy, which is the highest result that could have been obtained.Vgg16 had 93.90 percent training accuracy.Vgg19 had 91.90 percent training accuracy.Resnet50 had a 68.86 percent training accuracy.InceptionV3 had 89.05 training accuracy.DenseNet-121 had 93.29 percent training accuracy.EfficientNetB0 had 25.19 percent training accuracy.MobileNet had 96.91 percent training accuracy. Furthermore, the following is the testing accuracy of the seven pre-trained models: Vgg16 93.37%, Vgg19 92.42%, Resnet50 75.38%, InceptionV3 91.48%, DenseNet-121 94.89%, EfficientNetB0 23.30%, MobileNet 96.02%. We can see that different models' abilities to detect the disease vary when using the same dataset. On the other hand, The suggested model attained the maximum achievable testing outcome, which was 98.11 percent. Based on the experimental results displayed in the chart, it may be inferred that the personalized CNN models perform better than other previously trained CNN models. In short, the proposed 18-layer CNN model seems to be outperforming all the other pre-trained models by a good margin.

For a better understanding and comparison of the results of all the models the following is a bar graph of all the results obtained from our experiments:

Architecture	Training Accuracy	Testing Accuracy
Proposed CNN	98.82%	98.11%
Vgg16	93.90%	93.37%
Vgg19	91.06%	92.42%
Resnet50	68.86%	75.38%
InceptionV3	89.05%	91.48%
DenseNet-121	93.29%	94.89%
EfficientNetB0	25.19%	23.30%
MobileNet	96.91%	96.02%

Table 6.4: Performance of all Table.

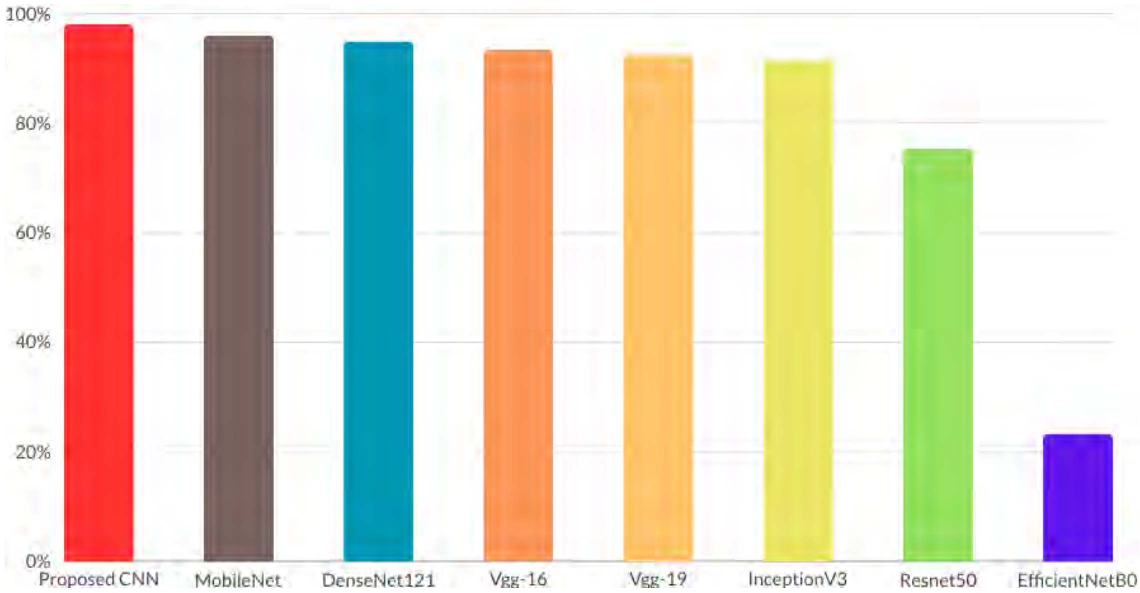


Figure 6.36: Bar chart of all model's accuracy

Based on the experimental results displayed in the chart, we may draw the conclusion that the proposed CNN models perform better than other previously trained CNN models. An example of a graph showing CNN model accuracy is presented in the figure.

Chapter 7

Conclusion

The use of computer vision technologies to improve brain tumor identification was the subject of this thesis study, which focused on several different areas including image processing, segmentation, feature extraction, and machine learning. The key findings underscore the tremendous potential of computer vision in advancing the accuracy and efficiency of brain tumor diagnosis, particularly when it comes to early detection. Looking ahead, it is advised that more study explores investigating approaches like multimodal imaging integration to use the strength of several data sources as they relate to deep learning techniques. Priorities should also be put aside for addressing issues with processing complicated medical datasets and data shortages.[18] Furthermore, research should place a strong emphasis on enhancing the interpretability of machine learning models in the context of medical diagnosis, ensuring that these models can provide insights that are comprehensible to healthcare professionals. This in turn can greatly enhance both the general standard of healthcare and patient outcomes. Computer vision is a crucial subject of study with broad ramifications in the fields of healthcare and medical imaging because it has the potential to help patients and medical professionals alike by enabling earlier detection and more precise treatment of brain tumors. [21]

7.1 Future Work:

Our primary objective will be to enhance the caliber of technology in the global healthcare industry. Furthermore, we will develop a tailored model that demonstrates a satisfactory level of accuracy in identifying brain cancers. In the present day, characterized by advanced technology, databases are constantly being enhanced with vast amounts of global data. The quantity will progressively rise daily, while the precision will continue to improve. Nevertheless, our model can swiftly and accurately identify tumors, resulting in a groundbreaking transformation in the medical field. Finally, we are planning to make a model with the weight of all the pre-trained models implemented in our experiments where we are aiming to make the model architecture as lightweight as possible as well.

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