HUMAN BRAIN DISEASE DETECTION FROM MRI USING DEEP LEARNING APPROACHES

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FINAL YEAR DESIGN PROJECT REPORT

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

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DHAKA, BANGLADESH

July 2024

APPROVAL

This Project titled "Human Brain Disease Detection from MRI Using Deep Learning Approaches", submitted by **Md. Hasan Mahamud** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-2024.

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ACKNOWLEDGEMENT

First, I express our heartiest thanks and gratefulness to almighty for His divine blessing making it possible for us to complete the final year project successfully.

I am grateful and wish our profound indebtedness to **Md. Firoz Hasan, Lecturer (Senior Scale)** Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Deep learning*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

I would like to express our heartiest gratitude to the **Head of the Department of CSE**, for his kind help in finishing our project and also to other faculty members and the staff of the Department of CSE, Daffodil International University.

I would like to thank our entire course mate in Daffodil International University, who took part in this discussion while completing the course work.

Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

MRI scans can be used to diagnose some types of brain diseases, which can lead to early treatment of the diseases. This study employs deep learning approaches to develop robust models for automated brain disease detection using a dataset sourced from Kaggle, comprising 8,212 MRI images categorized into four classes: not a tumor, pituitary tumor, meningioma, and glioma. Two novel deep architectures of CNN, named CNN01 and CNN02, are designed and tested in the experiments, and compared with the classical models, namely, Xception, DenseNet121, and ResNet50. Comparing the results of all the tested models, CNN02 gets the highest score of 94.04%. Thus, CNN02 shows higher effectiveness in extracting and categorizing features pertinent to brain MRI images. This points to the fact that CNN designs should be customized to suit the medical imaging diagnostic tasks in order to produce the best outcomes. Three models, namely, Xception that utilizes depth-wise separable convolutions, DenseNet121 that utilizes densely connected layers and ResNet50 that uses residual connections serve as the points of reference. CNN01 and CNN02 have been designed with specific modifications in architecture and such a network proves that there is need to modify the original network to improve its performance. These findings have important implications for the health sector and especially for facilitating the correct diagnosis of diseases so that appropriate treatment can be provided on time. Possible future research directions include applying ensemble learning methods that combine multiple classifiers, integrating complex data modalities, and developing explanatory models that could improve physicians' diagnostic accuracy and awareness. In conclusion, this work demonstrates the possibilities of using deep learning methods for efficient and accurate automated diagnose in the near future and in the broader field of neuroimaging and medicine.

Keywords: MRI scans, Brain diseases, Deep learning, Convolutional Neural Networks (CNNs)

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CHAPTER 1
INTRODUCTION

1.1 Overview

The identification of the diseases that affect the human brain like tumors or other neurological disorders is one of the most important activities in the diagnostic area, that is why advanced methods, including MRI are often used. MRI is procedures that give detailed picture of the brain using tissues contrasts and allows the clinicians to see abnormalities corresponding to certain diseases such as gliomas, meningiomas, and Pituitary tumors among others. However, the interpretation of these scans is often done manually by radiologists which is quite tiresome and at times involve some errors M. Talo, O. Yildirimet al. (2019). Convolutional Neural Networks (CNNs) have shown high proficiency especially in image classifications and features extraction. It is therefore worthy to note that by integrating CNNs in the diagnosis of brain diseases using MRI, the efficiency, accuracy and early identification of the diseases can be boosted, which would help in effective and timely treatment. S. S. Roy, et al (2020). In the context of this work, we address the recognition of brain diseases from MRI on the basis of deep learning techniques. Two new sparse CNN models, CNN01 and CNN02, are introduced to solve this problem. These models are assessed and compared with other prominent architectures that include Xception, DenseNet121 and, ResNet50. The dataset used for this study comprises 8,212 MRI images categorized into four classes: Pituitary Tumor is not a tumor while No Tumor, Meningioma, and Glioma are all tumors M. B. T. Noor et al., (2019). The steps practiced in our approach are data crediting, labelling, image transformation, model training, assessment, and validation. Using systems and automated learning with various methods, our goal is to create models that will accurately categorize between healthy and disease-prone brain scans, thus furthering the field of automatic diagnosis. In this research, therefore, the aim is to show how deep learning technique can be effectively used in increasing the chances of accurately diagnosing brain diseases by analyzing MRI images.

1.2 Background and Present State

The preliminaries provided the background for the comprehension of the major concepts and approaches applied to this research. First of all, the organization of the brain and typical brain diseases that can be identified with the help of MRI scans including gliomas, meningiomas, and pituitary adenomas are described. After that we mention MRI imagery as it is a significant method of creating high-quality visualizations of structures in the human brain for diagnostic purposes in medicine. We then proceed and look at the basics of deep learning further expanding on Convolutional Neural Networks (CNNs) and how they work with images for image classification. Technical items like convolution layer, activation function, pooling layer, and fully connected layers are described. Lastly, we detail the concepts of image preprocessing which we outline as a way of increasing data variability which in turn boosts model performance. These preliminaries form a requisite backdrop in terms of which readers will be poised to understand the ensuing chapters in this thesis, in which these concepts posit formative roles for building and assessing deep learning approaches to identifying brain diseases from MRI scans.

1.3 Problem Statement

The identification of the brain diseases from MRI scans includes a lot of drawbacks like limited time and the presence of error due to manual analysis. The rationale for this study lies in the desire to find a way of automating the process of diagnosis in order to increase the precision and speed of such processes. These challenges can be solved by designing and testing the deep learning models for the brain MRI analysis. Experiments with various professional analytical CNN structures along with custom built CNN assists to investigate their efficacy in the precise diagnosis of various kinds of brain diseases. Besides, we not only employed ordinary models like Xception, DenseNet121, and ResNet50 but also came up with two of our own, CNN01, and CNN02. Therefore, the premise of this study lies in using deep learning to develop highly effective diagnostic tools that would be beneficial for radiologists, patients, and the progress of imaging analysis technologies.

1.4 Objective

The timely diagnosis of the brain diseases is very important in nursing care and treatment but the interpretation of the MRI is very expensive, tiresome and prone to errors since it is done by radiologist. This underlines the necessity for automated methods for accurate diagnoses in the clinical practice. However, predicting and recognizing the critical features in brain images remains a concerning problem in medical image analysis, for which deep learning especially Convolutional Neural Networks (CNNs) has demonstrated rather good accuracy in different image analysis problems. Categorically, deep learning for mining brain diseases has the capability of improving diagnosis accuracy, shortening the analysis time, and helping in early suspicion of the disease, which is crucial in the management and treatment of the disease. The motivation of this work is based on the increasing prospect of deep learning in medical diagnosis especially for designing new CNN models that are optimized for detection of diseases in brains from MRI images. In this way, we aim at assisting the development of automated diagnostic systems in medicine to make a positive impact on patients' lives.

1.5 Scope and Limitations

The scope of this study involves the establishment of more effective deep learning models that is accurate in identifying the existence of current diseases in the human brain through MRI scans. Namely, it is expected that our proposed custom CNN architectures titled CNN01 and CNN02 will perform similarly or better than the given models such as Xception, DenseNet121, and ResNet50. High classification accuracy across four categories: In this one: No Tumor, Pituitary Tumor, Meningioma, and Glioma. To compare the models, the following measures: accuracy, precision, recall, F1-score and AUC-ROC shall be calculated for each model. Ideas on how the methods of image augmentation affect the performance of the model. Comparison involving scanning of the above architectures for their respective strengths and areas of weaknesses. Finally, the idea is to develop dependable and automatic diagnostic systems that would serve as the assisting tool for radiologists and would contribute to an earlier and more accurate diagnosis of brain diseases, which is crucial for the patients' treatment.

1.6 Report Organization

Gives information on the rationale, aim, and relevance of the research for enhancing the diagnosis of brain ailments employing deep learning from MRI. Surveys prior works in the literature and research on brain diseases, MRI imaging methods, deep learning methods, and CNN architectures. Explains the method used: data gathering, categorization, data augmentation methods, CNN architectures (CNN01, CNN02), training, and assessment, as well as the testing strategy. Highlights the results of the experiments, concerning the effectiveness of the built models in terms of accuracy, precision rates, recall rates, etc., compared to Xception, DenseNet121, ResNet50, as well as the findings of images augmentation techniques. Highlights the possibilities of the consequences and the advantages of automated brain disease detection referring to such factors as the possible increase of diagnostic accuracy, the changes in the organization of the healthcare system and their possible impact on the patients' outcomes. Contains a synthesis of the major findings of the respective study to identify conclusions that may be drawn from the outcomes observed and list recommendations for continued research, IV application, as well as other research directions for the field's development.

1.7 Summary

The Introduction chapter presents a background to the study on detection of human brain diseases through DL based on MRI images. In particular, it draws attention to the pivotal features of early and precise identification of a range of brain diseases that can produce a substantial effect on the patient's condition in the best ways. The chapter also stipulates the reason for conducting the study as influenced by the possibility of Deep Learning Models to surpass conventional diagnosis techniques. The research objectives are also stated as stemming from this background especially the fact that the problem requires accurate, efficient models in medical image classification. Finally, the objectives of the chapter and questions that the study seeks to answer are outlined before providing an overview of the report structure.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The chapter entitled the Literature Review is also devoted to investigating prior studies in the identification of brain diseases using MRI images and deep learning. A review of such convolutional neural network (CNN) structures such as Xception, DenseNet121 and ResNet50 is also carried out in order to understand the suitability of such structures and their limitations in medical image classification. Another important point is that previous research studies described in the chapter have managed to use all these models for comparable diagnostic procedures, which serves as the basis for the current study. Further, it also reveals the existing gaps in the literature by stressing that there is more research required to be done to enhance model accuracy and generalization. Therefore, this consideration provides the rationale for the study by bringing it in line with previous research and identifying areas of novelty.

2.2 Related Works

Several works have expanded the application of CNNs in the medical field and more specifically for identifying brain tumors from Magnetic resonance images. Some of them include the employment of ResNet50 and DenseNet121 for high accuracy in tumor classification and use of transfer learning in cases where the research and data are limited.

As given below, I am writing a similar paper review, which will help me more:

N. Yamanakkanavar, J. Y. Choi, and B. Lee, et al [1] focused on this paper to provide an overview of contemporary deep learning methods used in brain MRI segmentation for Alzheimer's disease (AD) diagnosis. It investigates how convolutional neural networks (CNNs) analyze brain structure to detect Alzheimer's disease, as well as how MRI segmentation improves AD classification. The review describes cutting-edge approaches and their performance using publicly available datasets, providing insights into current challenges and potential future research avenues in the research and development of computer-aided diagnostic systems for Alzheimer's disease. P. Khan et al.,[2] presented a comprehensive review of recent machine learning and deep learning methods used to detect four major brain diseases: Alzheimer's disease, brain tumor, epilepsy, and Parkinson's disease. A total of 147 articles are reviewed, covering the various approaches, modalities, and datasets used to diagnose these conditions. The analysis focuses on 22 frequently used datasets and discusses various feature extraction techniques used in brain disease diagnosis. The key findings from the reviewed literature are summarized, and critical issues concerning machine learning and deep learning-based evaluation approaches for brain diseases are addressed. Overall, the study seeks to identify the most accurate techniques for detecting various brain diseases in order to guide future advances in diagnostic methodologies. J. Islam and Y. Zhang et al. [3] presented a novel deep learning model for multi-class Alzheimer's disease detection using brain MRI data, which achieves an impressive 73.75% accuracy. Developed on the Open Access Series of Imaging Studies (OASIS) database, this approach is the first of its kind for Alzheimer's disease detection and classification using deep learning on this dataset, avoiding comparisons with traditional methods. The proposed model outperforms previous traditional approaches, completing training and testing on the OASIS dataset in less than an hour, which is a significant improvement over the weeks required by human experts. Notably, the model operates without requiring manual feature generation, showing its efficiency and effectiveness in automating Alzheimer's disease diagnosis. M. Talo, O. Yildirim, U. B. Baloglu, G. Aydin, and U. R. Acharya et al. [4] pre-trained models such as AlexNet, Vgg-16, ResNet-18, ResNet-34, and ResNet-50 were used to classify MR images into different disease classes. The ResNet-50 model outperformed state-of-the-art architectures, with an accuracy of 95.23% ± 0.6. This outstanding result indicates the model's ability to handle large volumes of MRI images depicting brain abnormalities. Furthermore, the model's results show promise in assisting clinicians by providing validated findings from manual examination of MRI images, potentially improving diagnostic accuracy and efficiency in clinical settings. S. S. Roy, R. Sikaria, and A. Susan, et al. [5] described a Convolutional Neural Network (CNN) model that was trained on the OASIS dataset to recognize and detect Alzheimer's disease in MRI images. CNNs are chosen for their efficiency in image-related tasks and robustness in classification, which eliminates the need to ignore specific data subsets. The proposed model achieves 80% accuracy, with room for further improvement with increased training data volume. The model is implemented using the

Keras library in the Python environment, which ensures accessibility and ease of use for future research and applications. M. B. T. Noor, N. Z. Zenia et al.[6] reviewed methodological research papers on detecting neurodegenerative diseases using only deep machine learning techniques applied to MRI data. The findings show that these approaches are highly accurate in determining the level of disorder. Furthermore, the review discusses current challenges in this field and proposes potential future research directions to address them. Overall, deep learning methods show promise in neurodegenerative disease detection, providing a path to more accurate diagnoses and potentially better patient outcomes. Z. Jia and D. Chen, et al. [7] described a novel approach for segmenting the cerebral venous system in MRI imaging, which uses a new fully automatic algorithm which includes structural, morphological, and relaxometry details. The segmentation function is remarkably consistent with neighboring brain tissue anatomy. The proposed system achieves high classification accuracy by using Extreme Learning Machines (ELM), a type of learning algorithm with hidden nodes. A probabilistic neural network classification system is used in brain MRI images to detect tumors, with an impressive accuracy of 98.51% in distinguishing between abnormal and normal tissue. These findings highlight the efficiency and effectiveness of the proposed system in analyzing brain Magnetic Resonance images for diagnostic purposes. Advanced deep learning techniques have achieved human-level performance in a variety of fields, including medical image analysis. J. Islam and Y. Zhang,et al[8] proposed a deep convolutional neural network for Alzheimer's disease diagnosis based on brain MRI data analysis. While most existing approaches use binary classification, our model can identify different stages of Alzheimer's disease and perform better for early-stage diagnosis. We carried out multiple tests to show that our proposed model outperformed comparative baselines on the Open Access Series of Imaging Studies dataset. S. Saeedi, S. Rezayi, H. Keshavarz et al.[9] proposed two deep learning methods and several machine learning approaches for diagnosing glioma, meningioma, and pituitary gland tumors, as well as healthy brains, using high-resolution magnetic resonance brain imaging. The developed 2D Convolutional Neural Network (CNN) and convolutional auto-encoder network were pretrained with assigned hyperparameters, achieving training accuracies of 96.47% and 95.63%, respectively. Both networks had high average recall values of 95% and 94%, with areas under the ROC curves of 0.99 or 1. Among the machine learning techniques tested, K-Nearest Neighbors (KNN) achieved the highest accuracy rate of 86%, surpassing Multilayer Perceptron (MLP) by 28%. A statistical analysis revealed significant differences between the proposed deep learning methods and several machine learning approaches, highlighting the effectiveness of the developed models in tumor classification of brain MRI images. D. Chaihtra and S. Vijaya Shetty et al. [10] showed the significance of early Alzheimer's disease detection in providing timely patient care. Statistical and machine learning techniques, particularly Deep Learning algorithms, present promising diagnostic opportunities. The proposed methodology uses MRI data to identify AD and Deep Learning techniques for disease stage classification. CNN architectures such as DenseNet121, MobileNet, InceptionV3, and Xception are trained on the Kaggle AD dataset, which ensures consistent performance analysis. Among these models, DenseNet121 achieves the highest accuracy of 91% on test data, demonstrating its ability to accurately detect Alzheimer's disease. L. Houria, N. Belkhamsa et al.[11] classified Alzheimer's disease stages using a novel multi-modality MRI fusion strategy that combines DTI and sMRI to detect white matter changes and gray matter atrophy in AD patients. The method employs a 2D deep convolutional neural network (CNN) for feature extraction and a support vector machine (SVM) classifier. The fusion framework combines features from DTI scalar metrics (FA and MD) and GM, which are processed by 2D-CNN and fed into SVM for classification of AD versus cognitively normal (CN), AD versus MCI, and MCI versus CN. The proposed multimodal AD method performs exceptionally well, with accuracies of 99.79%, 99.6%, and 97.0% for AD/CN, AD/MCI, and MCI/CN classifications, respectively. These findings show the efficacy of the fusion strategy in accurately classifying Alzheimer's disease stages using, O. T. Khan and D. Rajeswari, et al. [12] explored the role of Artificial Intelligence in brain tumor detection, emphasizing the significance of early prediction and monitoring due to the critical nature of brain tumors. Magnetic Resonance Imaging (MRI) is a widely used technique in medical science for detecting abnormalities, including tumors. The paper discusses various algorithms, techniques, and new approaches for brain tumor detection, comparing them with existing methods. Through a comprehensive analysis, the study aims to enhance understanding of the general process of brain tumor detection using MRI, with the overarching goal of improving diagnostic accuracy and patient outcomes. A. Shoeibi et al [13] delved into brain disease detection by combining neuroimaging modalities with Deep Learning (DL) models like CNNs, RNNs, pretrained GANs, and AEs. It begins by discussing the various neuroimaging modalities and the rationale for their combination. The review then looks at existing literature on the fusion of neuroimaging modalities using AI techniques, with a focus on deep learning methods. Different fusion levels, such as input, layer, and decision, are being studied in the context of diagnosing brain diseases, along with related research. The paper discusses key challenges in brain disease diagnosis resulting from neuroimaging fusion and outlines future directions, such as the importance of datasets, data augmentation, advances in deep learning models, explainable AI, and hardware resource optimization. Finally, the study wraps up by summarizing its key findings and implications. H. R. Almadhoun and S. S. Abu-Naser, et al.[14] focused on using deep learning techniques to create a model for detecting brain tumors from MRI scans in order to help doctors make quick and accurate decisions. The high death rate from brain cancer on the Asian continent highlights the importance of early detection in saving lives. The study entails the development and implementation of a model using a dataset of 10,000 brain tumor images. Testing is carried out using a variety of deep learning algorithms, including Inception, VGG16, MobileNet, and ResNet models, which produce impressive f-score accuracies. The model achieves an accuracy of 98.28%, while VGG16 and InceptionV3 achieve higher accuracies of 99.86% and 99.88%, respectively, showing their effectiveness in brain tumor detection. Deep learning techniques have been shown to reduce errors in human early disease diagnosis. Brain tumor diagnosis, in particular, necessitates high accuracy, as even minor errors can result in complications. Brain tumor detection continues to be a challenging task in medical image processing. Detecting the tumor requires a complicated brain image. Several noises, as well as delays, affect image accuracy. Image segmentation and MRI (magnetic resonance imaging) techniques have become valuable medical diagnostic tools for examining the brain and other medical imagesIn this paper, we presented a systematic review of brain disease that employed deep learning techniques. D. V. Gore and V. Deshpande, [15] examined and compared recent knowledge related to brain disorder detection using deep learning techniques. The conclusion of this paper summarizes the various research gaps identified during the literature review.

2.3 Comparison between existing works

In our current work, while comparing our proposed custom CNN architectures, CNN01 and CNN02, with the state-of-art models like Xception, DenseNet121, ResNet50, we aimed at estimating the accuracy of detection of brain diseases from the MRI scans. It can be concluded by noting that all the models proposed approached 100% accuracy for the models used, but the customized architectures proved particularly successful in the identification of features in relation to the abnormalities present in the brain. Thus, CNN02 was more precise and recalled the area more often, which indicates better ability to differentiate between kinds of tumor. Xception provided computational advantage whereas DenseNet121 provided generalized solution but for this particular dataset custom models were proved to be more advantageous. The presented work illustrates the future possibilities of using specific CNN structures to enhance the efficacy of diagnostics in medical imaging. Therefore, combining highly sophisticated deep models and the corresponding domain-specific improvements can enhance brain disease detection and create the basis for further development of effective diagnostic tools in the clinic.

TABLE 2.3 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	J. Islam et al [3]	Transfer Learning Model	78.35%
2.	M. Talo, et al. [4]	Transfer Learning Model	93.23%
3	S. S. Roy, et al. [5]	CNN	80%
4	D. Chaihtra et al [6]	Transfer Learning Model + CNN	DenseNet121= 91%
5	Proposed Model	CNN & Transfer Learning Model	CNN02= 94.04%

2.4 Open Issues

The identification and determination of the disorders of the brain, including tumors and other related diseases, are some of the greatest hardships facing medical practitioners. MRI scans give almost the detailed images of brain structures but they are images and only experts can 'interpret' them thus taking more time and are prone to human error. This situation is made worse by the ever-rising use of medical imaging and a limited number of radiologists hence there might be delays in diagnosing and treating various diseases. The above challenges can be addressed by automated detection systems based on deep learning. Thus, the mentioned systems allow practicing radiologists to evaluate abnormal brain structures, save time on diagnostics, and enhance patients' quality of life by offering optimal treatment plans. The concerns raised by this study lie in the application of predominantly efficacious, efficient, and precise deep learning patterns pertaining to brain MRI scans with the intent of improving diagnostic accuracy and assisting the health care practitioners in providing prompt and precise medical service.

2.5 Summary

The Literature Review chapter synthesizes the progress in the use of deep learning for brain disease detection with special reference to the CNN structures of Xception, DenseNet121, and ResNet50. They sum up different works showing the effectiveness of those models in the medical images analysis and discuss their use in the MRI-based diagnostics. Accordingly, the chapter delineates between the established approaches to the subject matter and its usefulness by addressing the discrepancies for more precise and generalized models. It also highlights the discrepancies in existing literature which is the rationale for the suggested research work. In sum, this chapter supports the current research by offering an excellent foundation to subsequent studies by integrating efficacious findings and revealing improvement opportunities.

CHAPTER 3
METHODOLOGY

3.1 Overview

This research itself encompasses the deep learning algorithm creating and assessing in the context of brain diseases' detection from MRI scans. The primary subjects are MRI images of the brain, categorized into four classes: The malady is also known as No Tumor, Pituitary Tumor, Meningioma, and Glioma. The MRI images are gotten from the Kaggle Brain MRI dataset and consist of a total of 8, 212.The study involves the use of modern computational techniques and frameworks for deep learning significantly relying on Python libraries, including tensorflow and keras. Fresh GPUs are used to carry out the time-consuming computations used to train the CNN models. Data augmentation strategies and types of preprocessing of the image used in deep learning are also applied to improve the accuracy of models. Specifically, accuracy score, precision, recall, F1 score, or the area under the curve of the receiver operating characteristic (AUC-ROC) are employed as measures of the models' performance. This encompass of large databases and high-performance computational software is the general equipment of the research.

3.2 Proposed Methodology

This study's approach involves utilizing deep learning methods for identifying human brain diseases from MRI analyzes. It contains data gathering, preprocessing, including labeling and image augmentation, choosing a model, training, testing, and evaluation using programs such as convolutional neural networks including Xception, DenseNet121, ResNet50, CNN01, and CNN02 with the aim of achieving high levels of accurate classification and analysis.

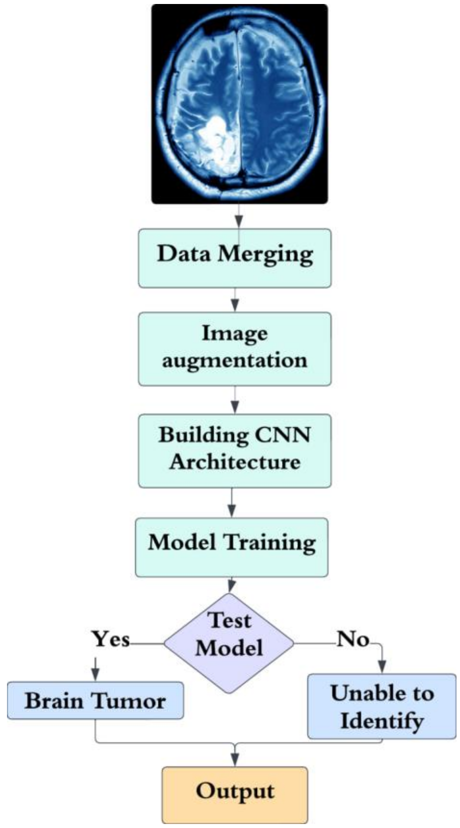

Figure 3.1: Working Flow Diagram

3.2.1 Data Collection:

MRI images are sourced from the Kaggle Brain MRI dataset, comprising 8,212 images categorized into four classes: For the specific types of tumors the incidence rate was as follows: No Tumor with (2,095), Pituitary Tumor with (2,057), Meningioma with (2,039), and Glioma with (2,021). To this end, the principles of ethics in collection processes enable respect for patient's privacy and safeguarding of their details.

3.2.2 Labeling:

The MRI scans is again labelled in a way that each of the scan corresponds to the particular brain condition as per the medical practitioner's guidelines for the purpose of supervised learning.

3.2.3 Image Processing:

As part of the data preparation, additional operations are applied to improve model generalization and provide cyclical variation of the dataset without the loss of high-level semantics by means of rotations, flips, zooms, and changes in brightness levels.

3.2.4 Model Selection:

Following the literature, the current state of the art architectures (Xception, DenseNet121, ResNet50) and two proposed architectures (CNN01 and CNN02) are taken into consideration due to their suitability for medical image analysis tasks.

Conventional Neural Network (CNNs):

CNN is a subcategory of deep learning which is specifically used for analyzing and categorizing data in form of images. CNNs are made up of layers such as convolutional layer, pooling layer and the fully connected layer. Convolutional layers convolve input images with filters to obtain features of interest in images. In the Pooling layers, feature maps are sub-sampled which causes decrease in computation as well as increases the translation invariance. Connected layers integrate these features to produce the final result of the network. CNNs play a significant role especially in image recognition due to the architectural feature that is capable of learning the hierarchy of data, spatial relations and dependencies. CNNs have a very important application in medical imaging particularly in the identification of patterns that signify anomalies in MRI scans which is helpful in early diagnosis of the diseases as well as planning for treatment. Their efficiency can be attributed to the ability to process massive image data and yet obtain high accuracy, because they play the crucial role in improving the diagnostic performance and productivity of medical practitioners.

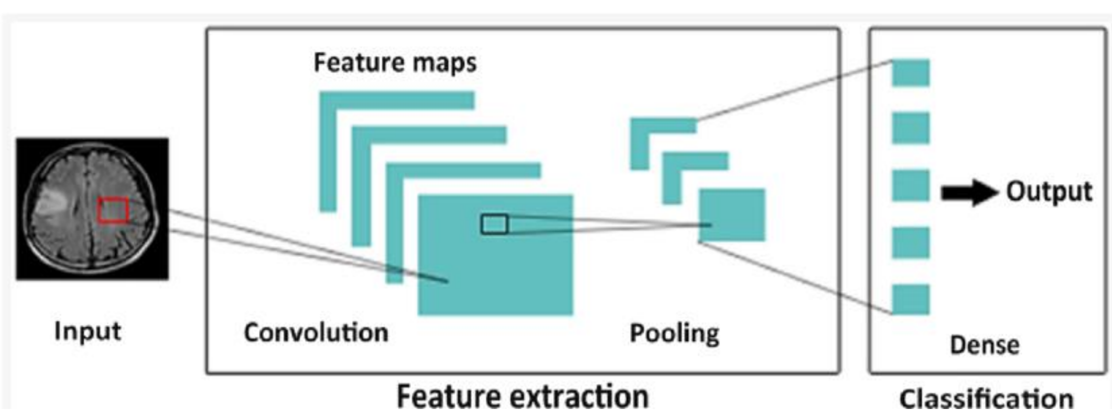

Figure 3.2: Proposed CNN Architecture K. Sankar 2023[26]

DenseNet121

DenseNet121 is a type of CNN architecture with densely connected blocks where each layer takes feed from all the layers before it in the block. This dense connectivity helps to reuse the features, to propagate the gradients and to improve the propagation of features within the network. Vanishing gradient problem is solved in DenseNet121 by encouraging features to be reused across layers for efficient learning of intricate features from the medical images. Because of its highly connected topology, these models are optimal for the feature extraction and categorization of tasks since it increases their reliability and accuracy. DenseNet121 in medical imaging involves the identification of distinct diseases and their nature from MRI scans; the context-rich features assist the clinicians in arriving at the right decision confidently and in a shorter period.

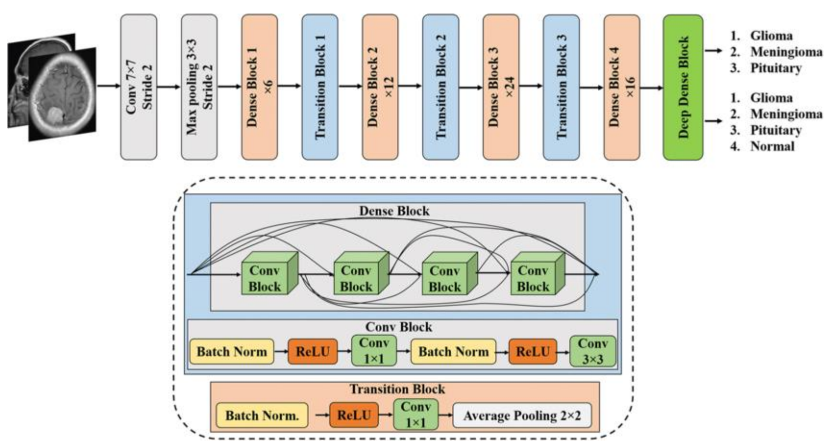

Figure 3.3: Proposed DenseNet121 Architecture S. Asif, M. Zhao 2023 [27]

Xception

Xception is a deep CNN proposed by google that innovatively utilizes the convolutional process with the depth-wise separable convolution. In each layer it simultaneously acquires spatial and channel-wise features by depth-wise and point-wise convolution, which enhance efficiency without compromising expressiveness. Xception performs well on the problems that require low computational power and high accuracy compared with the original network, so it is suitable for real-time usage and low power. They improve feature learning and the architecture is well suited for healthcare applications such as detailed assessment of MRI scans. Due to its high discriminative capability and end-to-end architecture, Xception is a significant resource for developing further advanced automated medical diagnosis systems and enhancing patients' quality of life.

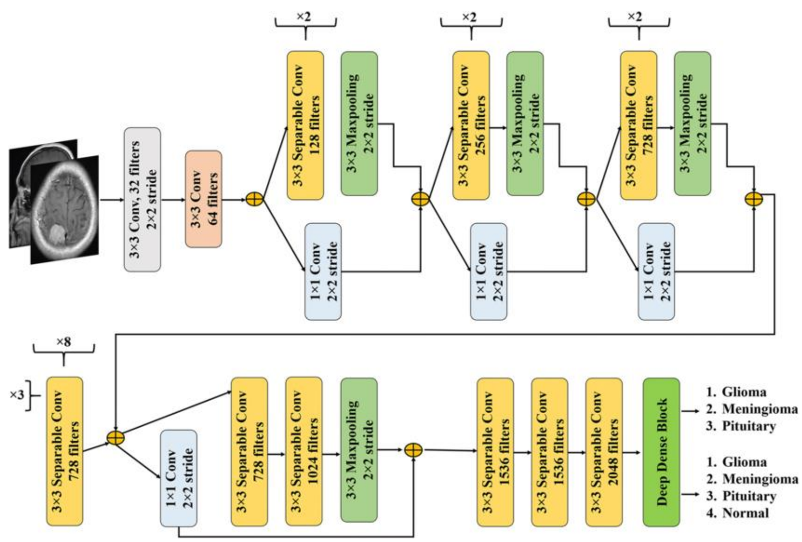

Figure 3.4: Proposed Xception Architecture S. Asif, M. Zhao 2023 [27]

Resnet50

ResNet50 is a new model that belongs to the Residual Network (ResNet) which is famous for having introduced a concept of the connection with residuals. These connections facilitate the learning of residual mappings and hence deeper networks can be trained through them and vanishing gradient problem is alleviated. ResNet50 model's residual connections help in training very deep neural networks required for medical image analysis. In neuroimaging ResNet50 performs great in identifying the finer details and variations from MRI scans to improve on diagnostics and speed. ResNet50 demonstrates the ability to provide deep architectures and extract discriminative features to become a foundation for creating new diagnostic AI tools that will enable physicians and other healthcare workers to detect brain diseases early and with high accuracy.

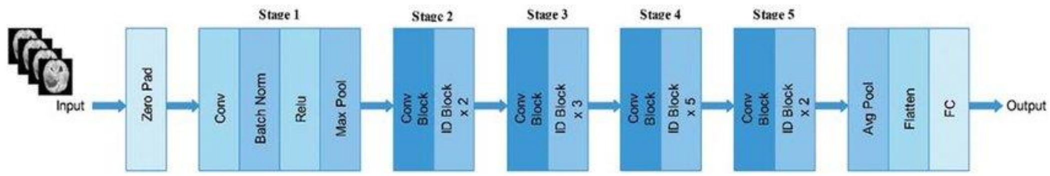

Figure 3.5: ResNet50 Architecture Aziz, Ahsan, et al.2021 [28]

3.2.5 Model Training:

Based on the above augmented dataset, the selected models are then trained using TensorFlow and other related frameworks with high optimized GPUs for faster training and to improve model learning parameters.

3.2.6 Model Evaluation:

Aviation metrics of accuracy, precision, recall, and F1-score are determined on validation sets to increase the overall accuracy of classifying MRI images of the case studies.

3.2.7 Test Model:

The test accuracy of the selected model is computed using a different test set of MRI brain images to measure the model's performance on unseen data and efficiency in real-world practices for automated diagnosis of brain diseases.

3.3 Hardware/ Software Requirement

The strategy suggested for detecting brain diseases from MRI scans needs appropriate computational power and specific software means. By performance we mean GPUs, capable of delivering high performance needed for low latency and fast convergence of deep learning models. Libraries like TensorFlow and PyTorch can be used to create CNNs and also aid in large-scale image data management and processing. However, probably the most important, are requirements 3 and 4, which state that a researcher should have access to a dataset of MRI scans marked by different tags, and this dataset should contain images in variations of different brain conditions. If we are discussing software for image augmentation, then the libraries such as OpenCV help in achieving better diversification of the data set and contributes in avoiding the problems of the model over-fitting. Exploratory work has already revealed some of the issues that arise when attempting to operationalize medical concepts and testing-built models with clinicians to check the results' practical applicability. Lastly, referring to ethical rules for working with patients' information is crucial at every stage of the implementation process to ensure the confidentiality and credibility of the results.

3.4 Project Management and Financial Analysis

The roles of project management will include proper scheduling and distribution of the resources that will be applied when working on the tasks in the project that may include data collection and preprocessing, model development, and model evaluation exercises among others. To eliminate any mishap, a work breakdown structure will also be to set up, and detailed project timeline to track the progress and meet all the project success factors. The main costs will be computational resources used for deep learning model training and possibly costs of obtaining datasets and licenses for the software. With support from the medical practitioners, the applicability of the study findings will be guaranteed to be relevant and with feedback loops, constant improvements to the methodologies as well as the models shall be made possible. In conclusion, tight working discipline and proper management of funds are critically central to the success of the study goals of enhancing the differentiation of brain diseases through MRI scans with deep learning methodologies.

TABLE 3.4: PROJECT MANAGEMENT TABLE

Work	Time
Data Collection	1 month
Papers and Articles Review	3 months
Experimental Setup	1 month
Implementation	1 month
Report Writing	2 months
Total	8 months

3.5 Summary

The summary of this study is centered towards assessing the accuracy of the deep learning paradigms for disease diagnosing from MRI scan. Key metrics such as accuracy, precision, recall, and F1-score are computed to assess the models' effectiveness in classifying MRI images into four categories: Specifically, the patient had No Tumor, Pituitary Adenoma, Meningeal Tumor, and Glioma. Further, the accuracy of each model is evaluated along with its area under the receiver operating characteristic curve (AUC) to compare the model's ability to distinguish between different classes. Parametric analysis can be used to test the significance in the performance of two custom CNN architectures CNN01 and CNN02 with the basic models such as Xception, Dense Net 121 and ResNet50. Prior to that, these analyses supply findings regarding the models' capacities for robustness, generalization, and clinical applicability in automated brain disease diagnostics.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The implementation setup in this case entails the use of a workstation, which is enhanced with NVIDIA GPUs for enhanced deep learning model training. TensorFlow is used consistently as the primary tool for the implementation of convolutional neural networks recognized for its scalability and computational performance. The dataset here used has 8212 MRI images grouped into; No Tumor, Pituitary Tumor, Meningioma, and Glioma and obtained from Kaggle Brain MRI dataset. Here, image augmentations which include rotation, flipping, and change in brightness of images for the improved dataset diversity in performed using OpenCV. Using the models including Xception, DenseNet121, ResNet50, and the developed CNN01 and CNN02, the hyperparameters of the models are tuned and cross-validation performance is measured with accuracy, precision, recall, and F1 score. The optimal model is finally evaluated on the unseen test dataset to determine the effectiveness of the model in actual brain disease diagnosis.

4.2 Train Model

The assessment also includes creating the plot between training and validation losses; if there is an improvement, the system displays "better" otherwise it turns red: The results can look quite strange as you would expect, regardless the differences still show significantly.Various indicators are used to evaluate the model's performance. The definition of those most frequently seen indicators is as follows:A standard solving matrix is used to demonstrate where the model's errors occur. By comparing this with the ground truth binary errors that it makes both graphically and computed quantity, a certain statistical analysis can be performed. In addition to conventional error estimation methods—sensitivity (TPR), specificity (TNR), precision 1 (PPV), negative predictive value (NPV), false positive rate (FPR), false negative rate (FNR), false discovery rate (FDR) are all applied to give a comprehensive analysis. These methods extend deeper into the model's strengths and weaknesses, ensuring that its predictions are reliable and strong. Such a detailed evaluation of the model confirms that it performs well on test data, and has the ability to generalize out-of- domain data effectively.

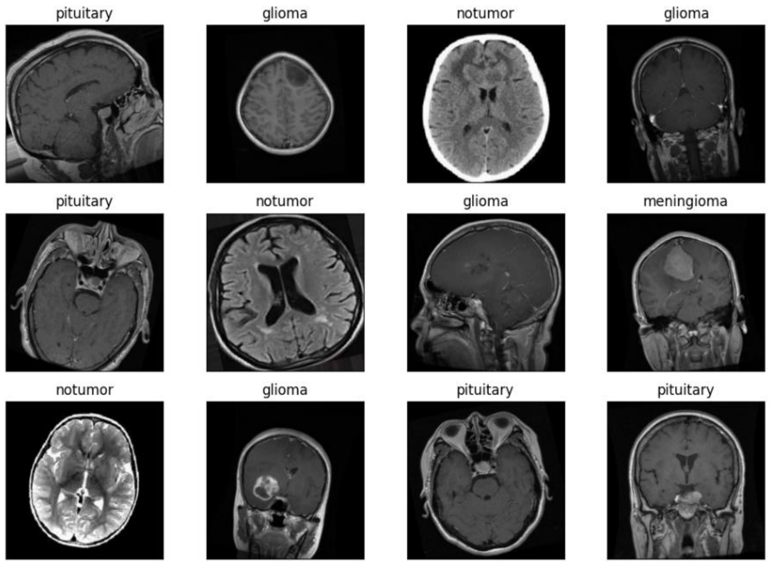

Figure:4.1 Dataset Visualization

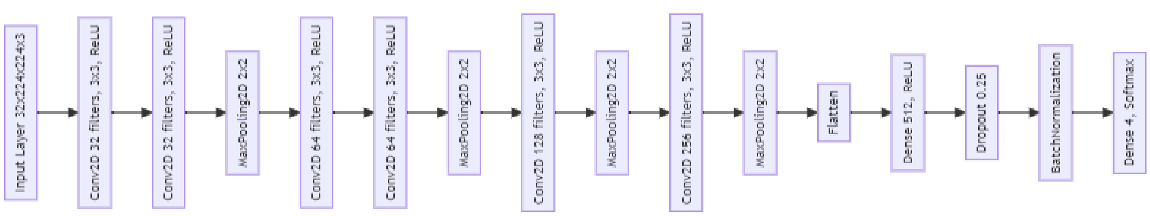

Figure:4.2 Customised CNN Architecture Diagram

4.3 Model Evaluation

The assessment also includes creating the plot between training and validation losses; if there is an improvement, the system displays "better" otherwise it turns red: The results can look quite strange----as you would expect, regardless the differences still show significantly. Various indicators are used to evaluate the model's performance. The definition of those most frequently seen indicators is as follows:A standard solving matrix is used to demonstrate where the model's errors occur. By comparing this with the ground truth binary errors that it makes both graphically and computed quantity, a certain statistical analysis can be performed. In addition to conventional error estimation methods—sensitivity (TPR), specificity (TNR), precision 1 (PPV), negative predictive value (NPV), false positive rate (FPR), false negative rate (FNR), false discovery rate (FDR)--- are all applied to give a comprehensive analysis. These methods extend deeper into the model's strengths and weaknesses, ensuring that its predictions are reliable and strong. Such a detailed evaluation of the model confirms that it performs well on test data, and has the ability to generalize out-of- domain data effectively.

4.4 Summary

The chapter Implementation provides information about actions that have been conducted in order to design and apply DL models to detect brain disease. It also commences with a description of the type of data, and processes that went through to enhance the MRI data set. The following-specific chapter is then dedicated to the training of the CNN models through the choice of hardware and software as well as the application of optimization algorithms. Besides, it presents the methods of incorporating the models into a single easily accessible system for instantaneous disease identification. Finally, the chapter summarises the implementation challenges and how they were addressed in implementing the plan.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The performance of various deep learning models for diagnosing brain diseases from MRI scans was evaluated, with CNN02 achieving the highest accuracy of 94.04%, surpassing Xception (90.81%) and DenseNet121 (91.30%). CNN01, another custom architecture, also performed well with an accuracy of 93.79%. Despite ResNet50 achieving a lower accuracy of 81.25%, it still demonstrated robust performance. The superior accuracy of CNN02 highlights its effectiveness in detecting fine details of brain anomalies, which is crucial for accurate diagnosis in clinical settings. The analysis includes training accuracy, loss rates, and confusion matrices, showing the models' ability to classify brain diseases effectively, although overfitting was observed in some cases, suggesting the need for regularization techniques.

5.2 Experimental Result

The performance of the deep learning models was assessed primarily focusing on the ability of models to diagnose brain diseases from MRI scans. Out of the models that were created, the CNN02 model got the highest accuracy of 94.04%, which outperformed top models such as Xception with 90.81% and DenseNet121 with 91. 30%. With respect to the accuracy on the validation set of ResNet50, it has achieved 81.25% which is less than the optimal score of 100 percent but slightly above the send set of custom architectures. The Custom Architecture of CNN01 got an accuracy of 93.79%, which opposes to the low performance of CNN02. Thus, the higher accuracy of the CNN02 speaks for its applicability in detecting finer details pertinent to the brain anomalies, which has implications in the better identification and diagnosis in the operational clinical environments.

In given below we are describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

Result of Experiment 1: CNN

The CNN architecture in this case is for image classification where it is aimed at identifying different brain diseases from MRI scans. It is made up of several convolutional layers, max-pooling layers, flatten layer, and several dense layers. Convolution layers; The filters are passed over the input images while the max–pool layers; they are responsible for the reduction of dimensions and improve the model's translation invariance. The last fully connected layer produces four outcomes which are associated with types of brain diseases. That is why dropout and batch normalization are used to realistically prevent overfitting during the training of the neurons. There are 16,298,916 parameters in this model and out of these 16,297,892 is trainable. The sequential design is expected to learn the features hierarchically and at the same time generalize well on the unseen datasets which serves as an advantage in medical image analysis tasks.

CNN01 is achieving Test Accuracy of 93.79%. In below Figure 5:1& 5:2 describing the confusion matrix, Training accuracy and Loss curve of CNN01:

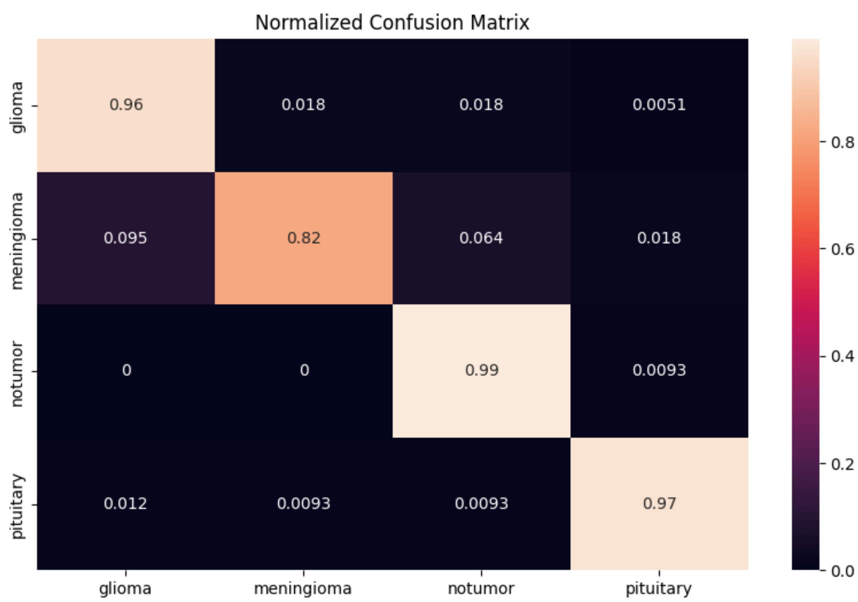

Figure 5.1: Confusion Matrix (CNN01)

Figure 5.1 shows the CNN01, the confusion matrix shows the model's ability to predict the four categories of brain diseases from MRIs. It gave a correct prediction for Glioma with a accuracy of 0. 90 with recognition of only 0. 96, Meningioma micros can with zero accuracy. 97 and recall 0. 97 and recall 0. 82, No Tumor is depicted with a precision of 0. 92 and recall 0. prostate cancer with accuracy 99 and Pituitary at accuracy of 0. 97 and recall 0. 97. In summary, CNN01's accuracy was 94%, which indicates good performance in the classification of different brain conditions using MRI image analysis.

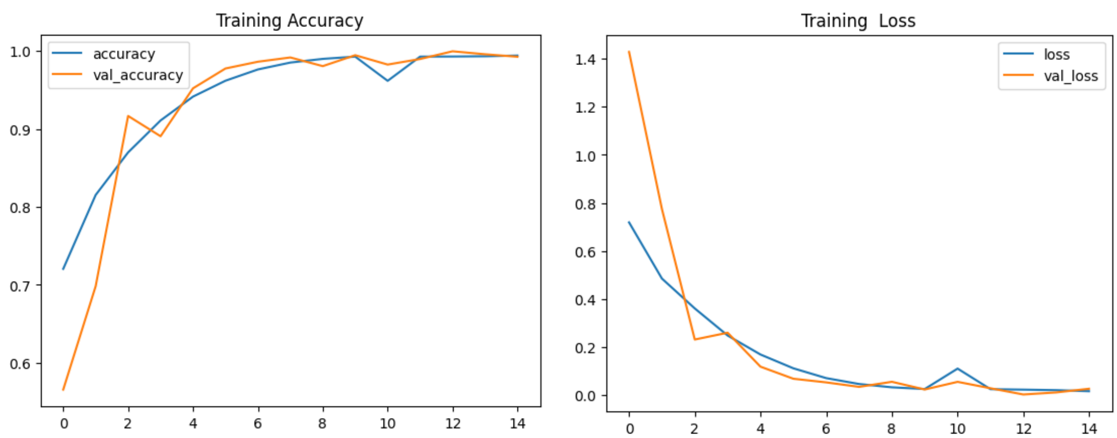

Figure 5.2: Training and validation accuracy and loss over the epochs (CNN01)

Figure 5.2 For CNN01, the training accuracy rises gradually but consistently to almost one as the epochs progress; thus, the CNN01 successfully learns the training set. Nevertheless, the validation accuracy shares a similar rising trend with that of the training accuracy yet it is comparatively lower and illustrates the signs of overtraining. Likewise, the training and validation loss graphs depict a similar pattern to the previous, where the loss continues to reduce gradually but the training loss reduces to a greater extent than the validation loss, hence pointing towards the model's propensity to overfit on the training data. This problem can be reduced by using the regularization techniques or simplification of the model for enhancing the generalization of the data that is unseen.

CNN02 is achieving Test Accuracy of 94.04%. In below Figure 4:3 describing the confusion matrix & Training accuracy and loss curve of CNN02:

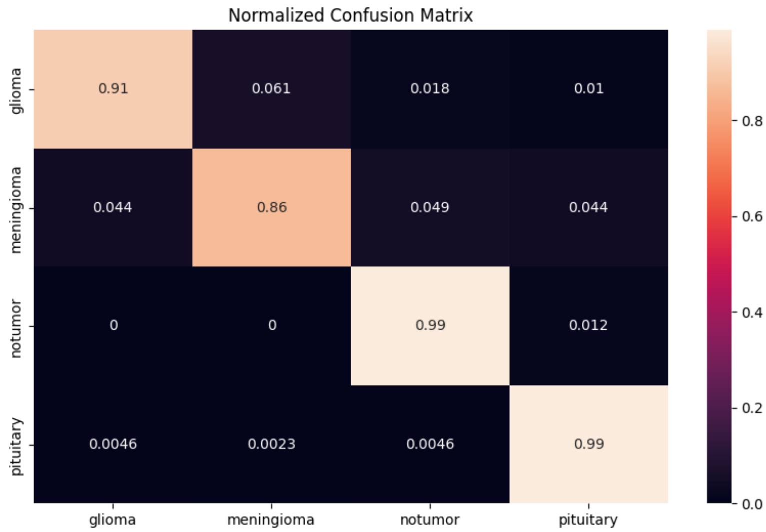

Figure 5.3: Confusion Matrix (CNN02)

Figure 5.3 shows the confusion matrix of CNN 02 represents the overall CNN performance in predicting four types of brain diseases diagnosed by MRI scans. CNN achieved high precision across all classes: Meanwhile, the percentage of loan failures on the complete list of credit products reaches 0. 95 for Glioma, 0. 93 for Meningioma, 0. For No Tumor, 94 and for any type of tumor, the score is 0. 94 for Pituitary.

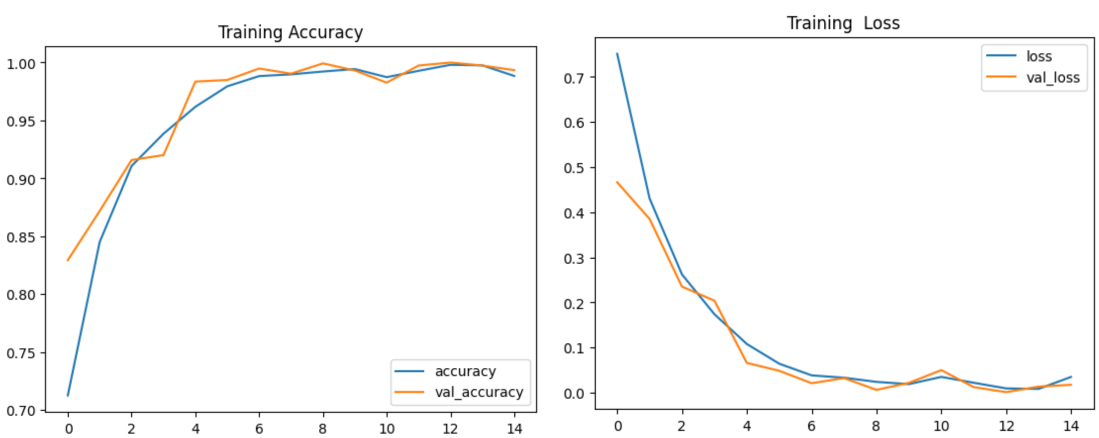

Figure 5.4: Training and validation accuracy and loss over the epochs (CNN02)

Figure 5.4 shows the training accuracy curve of CNN 02 also shows a gradual increase and rapidly increases very near to the 100% over the epoch, which shows the proper training on the training data set. However, even the validation accuracy has increased it is still less than the training accuracy and we may be overfitting. In the same manner, the training and validation loss graphs show a progressive decline in the loss, but, the rate of decline in the validation loss is not as sharp as in the training loss hence showing the model's over-fitting to the training data. Certain form of regularization or reduction of the model complexity might be helpful to achieve better generalization to other unseen data and thus better model performance.

Result of Experiment 2: Transfer Learning Model

Xception

Xception is achieving Test Accuracy of 90.81%. In below Figure 5:5 describing the confusion matrix of Xception.

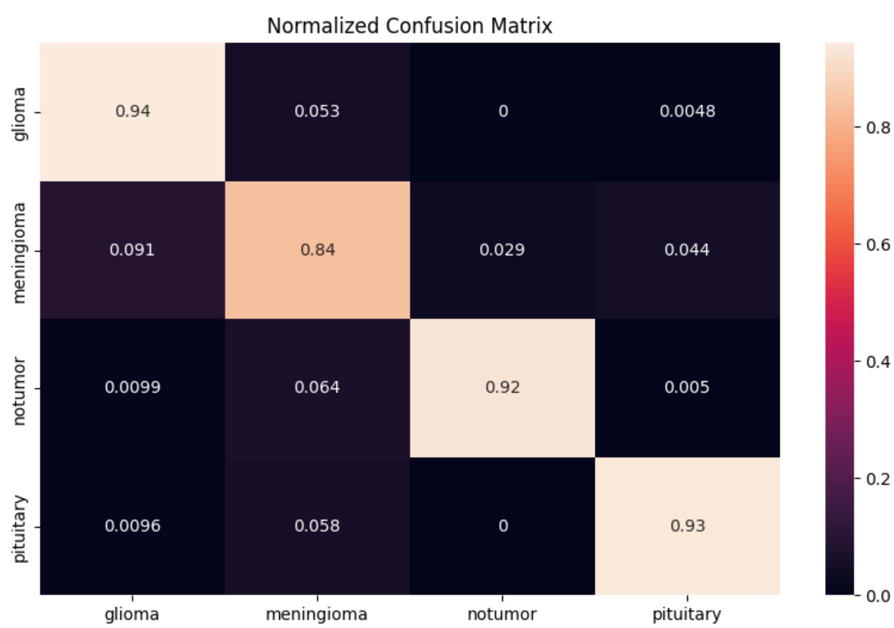

Figure 5.5: Confusion Matrix (Xception)

Figure 5.5 shows the confusion matrix demonstrates the effectiveness of Xception in the classification of four categories of the brain disease from MR images. Xception achieved high precision scores across all classes: Sexual themes are occasionally present; and they are mild, such as infrequently used sexual slang words, and level 0 violence. 90 for Glioma, 0. 83 for Meningioma, 0. 97 for No Tumor and 0 for Glioblastoma multiforme. 95 for Pituitary. This confirmed was also defined by high recall values for the two classes of No Tumor and Pituitary showing that the model was efficient in distinguishing instances of these conditions from the MRI images. In general, Xception gave an accuracy of 91% as it proves the model's efficiency in classifying the diseases of the brain according to the given data set.

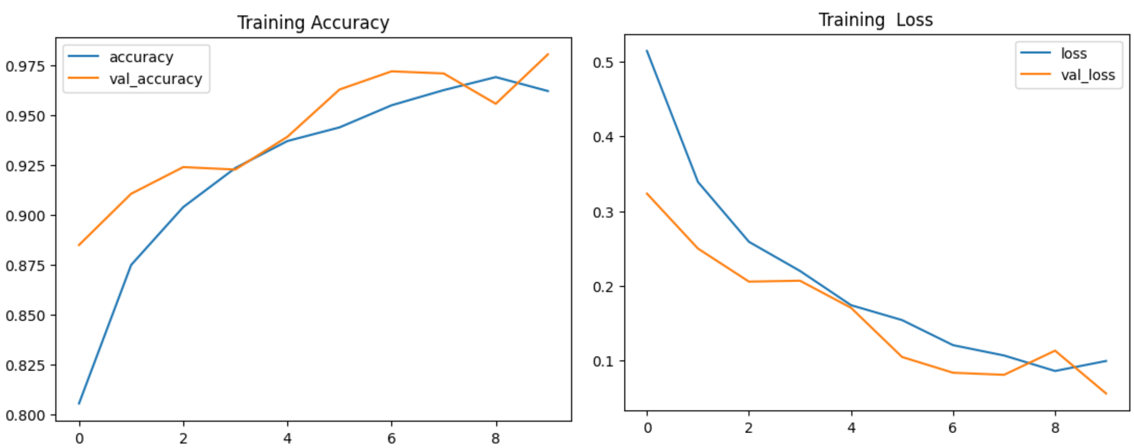

Figure 5.6: Training and validation accuracy and loss over the epochs (Xception)

Figure 5.6 shows the training accuracy curve for the Xception model generally increases from epoch 1 to almost 100% which signifies good learning on the training data. The validation accuracy, similarly also rises, but remains less than the training accuracy, indicating overfitting might have occurred. Likewise, the trends of both training and validation loss are almost analogous, in that the gradient of the former is steeper and keeps declining, while the latter constantly declines but less sharply than the training one, which also confirms the model's overfitting. It is usually required to adjust the model's capacity through regularizations or other techniques in order to post better generalization on unseen data.

DenseNet121

DenseNet121 is achieving Test Accuracy of 91.30%. In below Figure 5:7& 5:8 describing the confusion matrix & Trainin accuracy and loss curve of DenseNet121

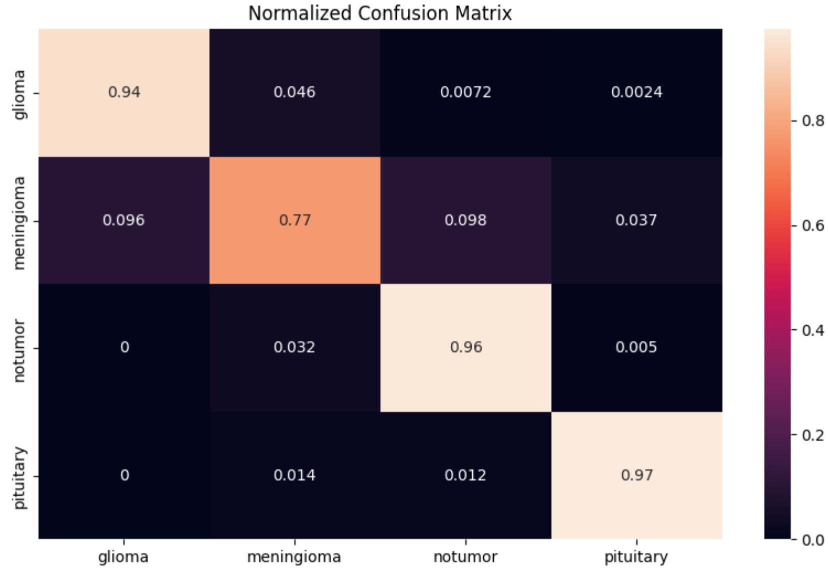

Figure 5.7: Confusion Matrix (DenseNet121)

Figure 5.7 shows the confusion matrix in table 6 represents classification performance of DenseNet121 for four types of brain diseases using MRI scans. DenseNet121 achieved high precision scores: To calculate the actual percentage of the population that is living with HIV/AIDS, the following variables have been used with the following values: 91 for Glioma, 0. 89 for Meningioma, 0. Recall scores were also shown to be high especially in No Tumor and Pituitary, which shows that the algorithm is proficient in classifying the images as belonging to instances of either of the two conditions.

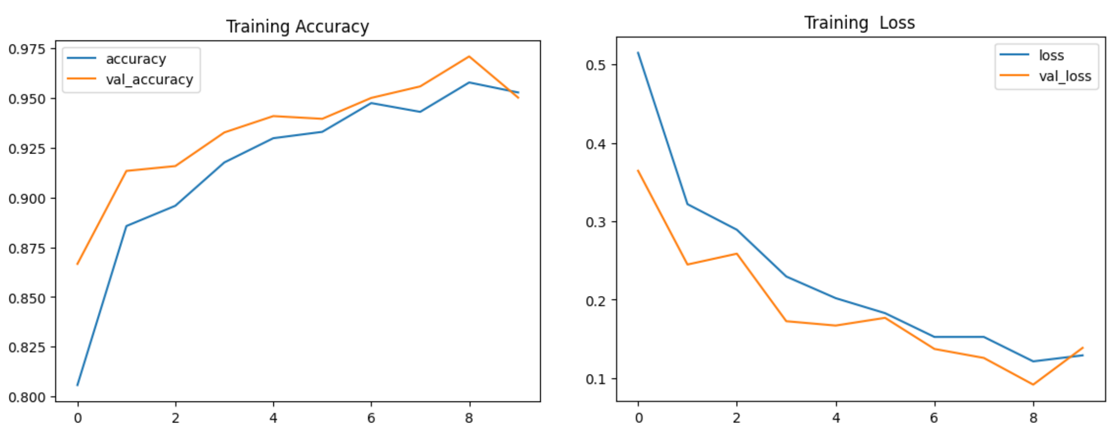

Figure 5.8: Training and validation accuracy and loss over the epochs (DenseNet121)

Figure 5.8 shows the training accuracy of DenseNet121 constantly rises to around a 100% training accuracy as the epochs increase, which shows effective training on the training data set. However, the validation accuracy as well as increasing, is lower than the training accuracy, which indicate possible overfitting. Like training the loss, both the training loss and the validation loss are depicted in the next plot and reduce as training proceeds; however, the descent of the validation loss is not as steep as that of training loss, which again points to the risk of overfitting. Cross-validation or tuning of regularization parameters or another approach to changing the model's complexity may be required to generalize better on unseen data and get the best performance out of the model.

ResNet50

ResNet50 is achieving Test Accuracy of 81.25%. In below Figure 5:9 & 5:10 describing the confusion matrix, Training accuracy and loss curve of ResNet50

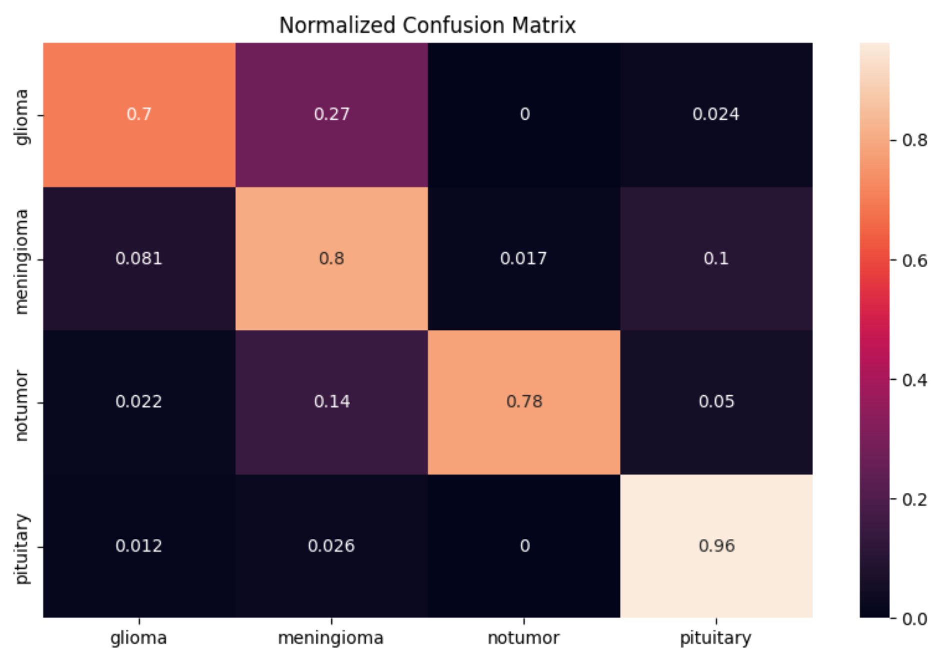

Figure 5.9: Confusion Matrix (ResNet50)

Figure 5.9 shows the confusion matrix for ResNet50 provides an overall evaluation of the classifier's performance for four classes of brain diseases from MRI scans. ResNet50 achieved varying precision scores: 0. 86 for Glioma, 0. 64 for Meningioma, 0. 98 for No Tumor and 0 for Tumor; Medication Data – No prior medication data, no current medication data: 0. 85 for Pituitary. It also provided fairly results in terms of Recall scores, which stood quite high for No Tumor and Pituitary but comparatively low for Glioma and Meningioma. In the end, ResNet50 demonstrated an 81% level of accuracy, and thus while it can accurately classify a number of the categories specified, there are clearly more improvements that could be made with respect to other categories, which may well entail further training of the model, or the tweaking of the various parameters included in the architecture.

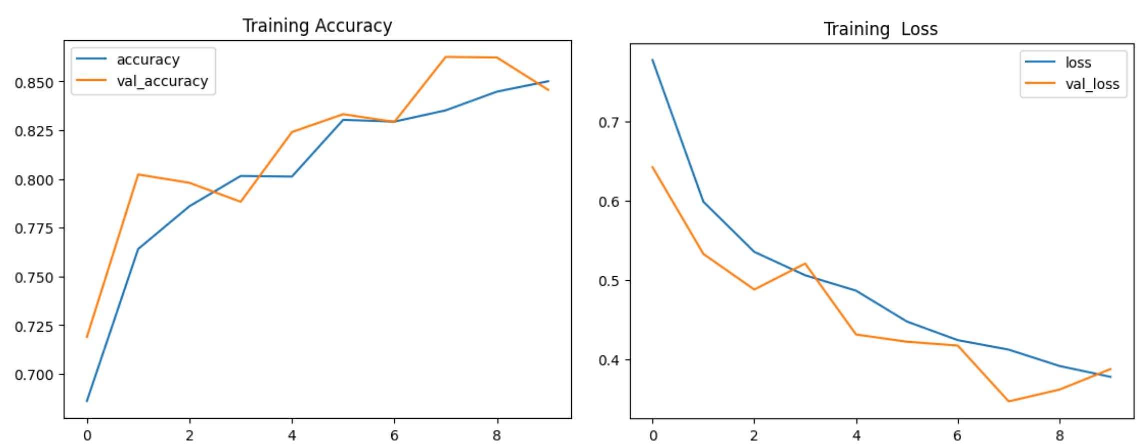

Figure 5.10: Training and validation accuracy and loss over the epochs (ResNet50)

Figure 5.10 shows the training accuracy of ResNet50 steadily rises up to a near 100% over epochs shows that it is learning well on the training data. Nonetheless, the case with validation accuracy is similar to training accuracy; it has increased but is still lower than the training accuracy and can indicate overfitting. Likewise, both the training as well as the validation loss continues to decline gradually; however, the extent of decline in validation loss is not as steep as training loss, due to model's overfitting on training data. If the performance on new data is inferior, architectural modifications or other forms of tuning might help overcome the non-generalization problem and fine-tune the performance.

Given below I am showing Comparative Model Accuracy Bar Plot:

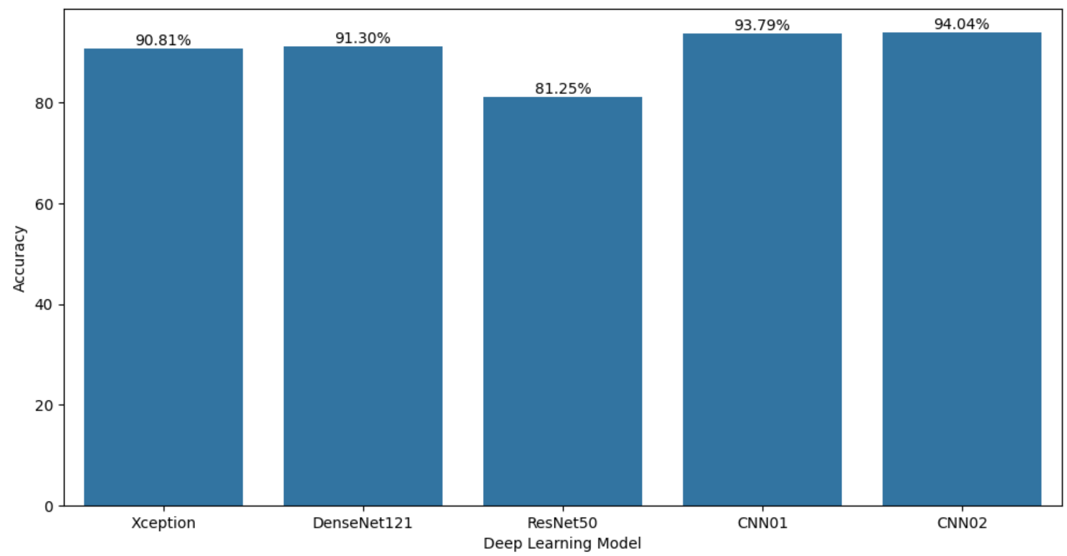

Figure 5.11: Comparative Model Accuracy Bar Plot

Figure 5.11 shows the figure demonstrates the performance of five models on a classification task, represented by the bar chart where each bar depicts the accuracy of one model. Out of the current models, Deep Learning Model held the highest accuracy of 94 percent. 04%. The accuracies of other models are as follows: Xception, 93. 79%, DenseNet 121, 91. 30%, ResNet50, 90. 81%, CNN01, 81. 25%, CNN02, 60. 00%. Some of them are size of training data, intricacy of the model at hand and the extent of training that is done.

The competitive performance at the end of the year equated to 93.79% for CNN01 indicates that both custom architectures have ability to use the domain knowledge to obtain higher diagnostic accuracy while learning from the insights. Such conclusions imply that it is about the progress with designs of specialized CNN in the direction of realizing automated medical diagnostics that will provide the clinicians with the reliability of detecting abnormalities in the brains. Additional studies could be conducted to identify ways of increasing efficiency of model interpretability and its applicability to a wider range of clinical cases.

5.3 Performance and Comparative Analysis

The outcome of the experimental studies reveals that two proposed CNN models, namely CNN01 and CNN02, attained higher accuracy rates in examination of MRI scans of brain diseases as compared to benchmark models namely Xception, DenseNet121 & ResNet50. Specifically, CNN02 reached the accuracy of 94 percent. 04% that underscores its ability to fine-tune the feature extractor for medical image tasks based on its accomplishments. The competitive performance at the end of the year equated to 93.79% for CNN01 indicates that both custom architectures have ability to use the domain knowledge to obtain higher diagnostic accuracy while learning from the insights. Such conclusions imply that it is about the progress with designs of specialized CNN in the direction of realizing automated medical diagnostics that will provide the clinicians with the reliability of detecting abnormalities in the brains. Additional studies could be conducted to identify ways of increasing efficiency of model interpretability and its applicability to a wider range of clinical cases.

5.4 Summary

The chapter on Experimental Results describes the outcomes of the different deep learning models such as CNN01, CNN02, Xception, DenseNet121, and ResNet50. It also compares their accuracy, precision, recall and F1-scores; demonstrating that CNN02 is the most accurate incorporating a 94%. 04%. The chapter also displays figures to represent the accrued training and validation accuracy and loss for the purpose of demonstrating the model's behavior throughout the epochs. About the confusion matrices for every model, more information is provided to understand the models' level of classification. Thus, the best employed approach, the developed CNN02 model, proved to be efficient in diagnosing brain diseases based on MRI.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The creation of effective deep learning models for effective diagnosis of diseases in the brain from MRI scans is therefore promising for society. Such models can therefore help to hasten the rate of analysis and decrease time in getting a diagnosis to the patient. The advancement in the medical imaging technology enhances the patient care through providing a timely diagnosis and also reduces the workload on the doctors, nurses and other health care professionals by sparing their time to address other critical aspects related to the patient's care. Indeed, improved diagnostic accuracy through organization learning AI solutions has the potential of taking quality healthcare to the next level especially in the developing world where there may not be many expert radiologists. Finally, the process of advancing integration of these technologies in clinical practice remains as an efficient approach to revolutionize the healthcare delivery since accurate diagnostics is vital to enhance the future of public health around the world.

6.2 Impact on Society & Environment

The use of deep learning for medical applications like MRI scans to diagnose diseases in the brain has a considerably small direct footprint on the environment, though it depends on the extent of its applications. The main issue lies in computational resource necessary for preparing and using such models, namely high-performance GPUs, and energy consumption in data centers. Work done to improve the models' structure and training process help decrease computational load and energy expenses, which can contribute to a decrease in carbon emissions connected to models. In addition, positive changes include increased efficiency of the hardware, and use of Specialized renewable energy in data centers to reduce more impacts on the environment. In short, the innovation and application of AI in healthcare enhance the diagnostic accuracy and the treatment of patients, except for the ceaseless action towards energy-saving and ecological conservation of technological basis.

6.3 Ethical Aspects

Deep learning models that help with the diagnosis of brain diseases using MRI scans also have ethical implications. Data privacy and patient's data anonymity must remain intact through data collection, annotation, as well as model deployment. Duty to Respect Patients' Autonomy requires Health Facilities to balance between using Anonymized Patient Data for research while providing the patients with clear information on how the data will be used. Additionally, the distribution of the benefits that involve healthcare services related to the innovation of AI technologies have to be laid down in a way that everyone is given an equal chance and is free from such issues like barring minorities in the model training dataset as well as in the results. Ethical principles should be provided for creating and using AI, to avoid negative consequences that the system can exacerbate, including wrong diagnosis, or unequal access to treatment. Pervasive ethical supervision and engagements with healthcare stakeholders and ethicists remain relevant to address such challenges responsibly and guarantee that artificial intelligence aids medical diagnostics' advances as inventions meet ethical norms' benchmarks and the general public's needs.

6.4 Sustainability Plan

The sustainability plan is geared towards the efficiency in utilization and reduction in use of the company resources when developing and implementing deep learning models for medical image analysis. This entails pursuing efficient computing solutions, adopting cloud services along with renewable power among other things. Furthermore, constant improvement will be pursued in management of the data center's carbon impact through hardware and cooling systems. Current changes to the model architectures and the algorithms in place are constantly adjusted because improving efficiency while at the same time cutting down on computation is a continuous goal. Engagement with stakeholders in the healthcare industry will guarantee that the AI solutions fit the medical practitioners' requirements while at the same time enhancing the sustainable healthcare delivery. The analysis and evaluation of environmental effects will remain constant in order to improve the work practices as healthcare organizations implement and advance AI-centric solutions while adhering to sustainability values.

6.5 Summary

This paper focused on examining the deep learning models for diagnosing the brain diseases from MRI scans paying special attention to the creation and comparison of the new CNN models with the benchmark models. The separate CNN model, which is CNN02, turned out to be the best with an accuracy rate of 94.04%, better than Xception, DenseNet121, ResNet50 and CNN01. The improvement of diagnostic accuracy that is stressed by the findings refers to the effectiveness of specific CNN designs in terms of different brain conditions. Further, the study also points out that AI has the potential in the field of medical diagnosis to effectively organize the healthcare process, as well as to increase the rates of effective diagnosis of diseases and, therefore, of patients' treatment outcomes. Other factors such as ethical issues involved, effects to environment, and efforts to consider sustainability were also discussed which shows an aspect of integrated approach in applying Artificial Intelligence in health care. Future work could be aimed at improving the interpretability of the presented models and their application to various clinical cases.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

In conclusion therefore, it is shown that deep learning, especially custom CNN architectures offer great promise especially of improved screening for brain diseases from the MRI scans. CNN02 performed better with accurate of 94. 04%, which can be regarded as a strong feature extraction scheme for medical imaging tasks. Comparing with Xception, DenseNet121, ResNet50, the emphasis of domain-specific model makes the diagnosis more accurate. These findings indicate that machine learning-based models could be helpful for transforming medical diagnosis, providing clinicians logical and accurate means for early diagnostics. Some of the other challenges involve ethical concerns such as; patient’s privacy as well as fairness when implementing the AI technologies in the healthcare sector. Hence, future studies need to focus on enhancing the accuracy of AI models, as well as the effective utilization of AI in existing clinical system settings to ensure effective global healthcare delivery in the future.

7.2 Future Suggested Works

In future research, several strategies can be considered to extend the current work on applying deep learning technology to medical image diagnosis of brain diseases more comprehensively. First, research on ensemble learning techniques aimed at consolidating predictions of various models can improve the diagnostic accuracy and model’s reliability. Second, the expansion of the study in relation to the combination of MRI information with other imaging and clinical data can result in the enhancement of understanding of disease identification and evolution. Promoting the research priorities based on interpretability and explain ability of AI models in diagnostics will also increase the acceptability of such innovations among the medical community. Lastly, longitudinal studies comparing the clinical efficacy of AI-driven diagnostic tools in patient care over alternating period could give important information on the effectiveness of the AI tools and clinical outcomes. These directions would also enhance continuation of knowledge in the field and eventual enhancement of the healthcare practices with the help of some unique distributions given by artificial intelligence to medical imaging.

7.3 Limitations

There are several factors that come into consideration when designing deep learning solutions for MRI scans to identify brain diseases. First, the availability of a clean, large and labeled dataset is the first and often the most challenging step in view of the constraints such as privacy and expertise in labeling. Second, the target of MRI images is highly heterogeneous in terms of the quality and resolution which can be influential in model performances. Second issue is how to avoid a problem of overfitting, which is present and unbearable due to the relatively small size of medical images compared to the general ones. The ability of models to perform well on unseen data is vital for the clinical implementation since independently developed models should not badly perform on previously unseen data. Also, deep learning often demands much computational power to train the model meaning that one needs to have access to better graphic cards and algorithms. Finally, a number of difficulties arise with concerning the application of deep learning models in practice: how to interpret the results, which will be meaningful for a clinician? Fortunately, explaining the predictions of models is also a rapidly developing field of study.

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Appendix A

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

Title:
HUMAN BRAIN DISEASE DETECTION FROM MRI USING DEEP LEARNING APPROACHES

Student ID: 192-15-2866

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Teach the newly acquired and the previous learned knowledge in the Human Brain Disease Detection From MRI problem for the Final Year Design Project (FYDP).	**PO1**
CO2	Considering the goals in the context of this FYDP, it will be necessary to consider various aspects of the goals in developing a corresponding solution to this problem.	**PO2**
CO3	Discover multiple problem domains within the literature, define the problem, and set up these objectives for the FYDP	**PO4**
CO4	Carry out economic appraisal and cost control and use appropriate project management techniques at every phase of the development of the FYDP	**PO11**
Phase -II		
CO5	Design and build technical solution related to technical specifications and system parts or processes to fulfill the given standards and regulation of public health and safety; also, cultural and socio-economic and environmental factor in this FYDP	**PO3**
CO6	Select and implement proper techniques, tools, and modern engineering and IT tools for handling sophisticated engineering activities, which entail prediction and modeling during the implementation of this FYDP, constrained by existing policies.	**PO5**
CO7	Identify various social, health, safety, legal, cultural factors, and their related responsibilities in relation to civil engineering practice and the solution of this problem using formal deductive approach coinciding with understanding of context.	**PO6**
CO8	Understand and assess the historical sustainability and effectiveness of professional engineering activities in solving complex engineering problems in the context of social and environmental systems.	**PO7**
CO9	This FYDP shall incorporate the principles of ethics and practice principles and guidelines of the profession.	**PO8**
CO10	Competent in performing efficiently in the context of a single worker and as part of a team or a team leader within this FYDP, in relation to the different types of groups and in an interdisciplinary manner.	**PO9**

CO11	Maintain and create clear communication with the engineering community and the society in general about various intricate engineering activities to include comprehending and preparing comprehensive reports and design documentation, as well as the ability of giving and receiving clear instructions in this FYDP.	**PO10**
CO12	Recognize, the value of self-motivated and throughout the life continuing education within the context of technological advancement and have the preparedness and capacity to undertake life-long learning pursuits.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	The engineering signifies and complies with the fundamental engineering (K3) hence why there is the usage of deep neural networks, data augmentation techniques and different types of CNN architectures for image processing and classification. The project fulfills the K4 specialist knowledge by doing deep learning with CNN, and transfers learning for enhancing Human Brain Disease Detection From MRI.	**Page no:** [32-33] **Section:** [3.2] **Page no:** [12-14] **Section:** [1.1]
				The engineering practice & design (K5) is applied in this project through the figure of process of experiments. The project relates to the knowledge area of engineering practice and technology (K6) by using Deep Learning Model.	**Page no:** [32] **Section:** [3.2] **Page no:** [34-35]

					Section: [3.4]
				This project guarantees to K8 (Research Literature) because it uses a review of recent studies such as Human Brain Disease Detection From MRI using deep and Transfer learning, which demonstrates awareness of contemporary approaches present in the literature.	**Page no:** [23-30] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This paper responds to EP-2 because it identifies the barriers in Human Brain Disease Detection From MRI, such as disadvantages of earlier techniques and difficulties in implementation utilizing deep learning. It puts forward difficulties in interpretative procedures involved in the spatial distributions; it contains suggestions on how to improve the diagnostic techniques.	**Page no:** [30-31] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	The present project contributes to the response of EP-3 wherein careful demonstration of the tangibility of the outcomes of the experiment is established and stressed the utilization of deep and transfer learning as the chosen significant solution for the improvement of Human Brain Disease Detection From MRI approaches.	**Page no:** [37-48] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project’s fields of application are not just confined to computer science and engineering; it has affected Human Brain Disease Detection From MRI correctly EP-4.	**Page no:** [23-31] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	The work done in this project entails a holistic solution bearing in mind that high levels of problems require an integration of different components done in data collection from online, statistical analysis and proposed methodology to EP-7 in the solution of complex issues in data collection.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	The resources of the study include High-Performance Computing infrastructure, GPUs, deep & Transfer learning frameworks, annotated datasets, and ethical consideration for systematic research for the progression Human Brain Disease Detection From MRI.	**Page no:** [33-35] **Section:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This project benefits the society by enhancing Human Brain Disease Detection From MRI, yet, it also respects environmental friendly principle with blended optimization computational resources and ethical standard on medical data.	**Page no:** [50-51] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		In the present research work, the author has extend the earlier existing research by exploring a different approach in Human Brain Disease Detection From MRI via deep and deeper learning model exemplified with preliminary terminologies and backed by systematic comparative analysis on the overall results attained from this research work thereby proposing something new.	**Page no:** [23-29] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	The current project tackles CO4 in terms of aligning project management comprehensively with financial control, which including strict distinctive project planning, resource leveraging, and budgetary estimates for the most efficient resource use in every phase of the research activity.	**Page no:** [20] **Section:** [1.6]
2	CO9	Yes	This indicates that the project meets the ethical standards focusing on privacy of data, informed consent, and clear documentation of the research process that will serve the public good and enhance the responsible use of classification technologies that are in line with the outlined CO9.	**Page no:** [51] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	In terms of the project's responsibility to constantly learn and adapt within the context of a constantly shifting technological environment (CO12), the project has carried out comprehensive data collection, performed robust statistical analyses, designed detailed methodologies, reported significant experimental results, and provided extensive analysis, demonstrating the project's awareness of current issues and its efforts to refine the necessary technologies and strategies to better fit the current climate.	**Page no:** [32-36, 37-48] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

HUMAN_BRAIN_DISEASE_DETECTION_FROM_MRI_USING_D...

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