PROJECT REPORT

on

BRAIN DISEASE DETECTION USING RESNET50

Submitted by

NISANTH BINOD (REG NO:20321069)

in partial fulfilment of requirement for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

ELECTRONICS AND COMMUNICATION

DIVISION OF ELECTRONICS ENGINEERING

SCHOOL OF ENGINEERING

COCHIN UNIVERSITY OF SCIENCE AND TECHNOLOGY

KOCHI – 682022

MARCH 2025

DIVISION OF ELECTRONICS ENGINEERING
SCHOOL OF ENGINEERING
COCHIN UNIVERSITY OF SCIENCE AND TECHNOLOGY
KOCHI-682022

CERTIFICATE

*Certified that the project report entitled "**BRAIN DISEASE DETECTION USING RESNET50**" is a bonafide work of* **NISANTH BINOD (REG NO:20321069),** *towards the partial fulfillment for the award of the degree of B.Tech in Electronics and Communication of Cochin University of Science and Technology, Kochi-682022.*

Project Co-ordinator
Prof Prem Kumar

Head of the Division
Dr. Deepa Sankar

DECLARATION

I hereby declare that the project work entitled:

"BRAIN DISEASE DETECTION USING RESNET50"

submitted to the Division of Electronics Engineering, School of Engineering, Cochin University of Science and Technology (CUSAT), is the result of our own independent work and research carried out during the academic year 2024–2025 under the supervision of Prof. Prem Kumar.

We have duly acknowledged all sources of information, reference materials, and data used in the preparation of this report. We understand that plagiarism or falsification of information in any form will result in disciplinary action as per university rules and guidelines.

This work is a true representation of our commitment, learning, and technical understanding gained through dedicated effort, teamwork, and continuous interaction with our guide and peers. All materials, figures, and experimental procedures described herein have been clearly documented and reflect the scope of our research and project execution.

NISANTH BINOD (REG NO:20321069)

ACKNOWLEDGMENT

We take this opportunity to express our sincere gratitude to all those who supported, guided, and inspired us throughout the successful completion of our final year project, titled:

"BRAIN DISEASE DETECTION USING RESNET50"

First and foremost, we thank the Almighty for giving us the strength, patience, and determination to complete this project successfully.

We extend our heartfelt gratitude to Dr. Deepa Sankar, Head of the Division of Electronics Engineering, School of Engineering, CUSAT, for providing us with all the necessary facilities and for fostering an environment that encouraged learning and innovation.

We are deeply grateful to our project guide, Prof. Prem Kumar, for his invaluable guidance, constant encouragement, timely feedback, and patient support throughout the duration of this project. His insights and suggestions played a vital role in shaping our understanding of the subject.

We also thank all faculty members and lab staff of the Electronics and Communication Engineering Department for their academic and technical support throughout our B.Tech journey. Their teachings and mentorship have laid a strong foundation for our learning.

This project has been a highly enriching experience, allowing us to apply theoretical knowledge to a practical problem and learn about cutting-edge technologies in the fields of machine learning, medical imaging, and deep learning.

ABSTRACT

Neurological disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors continue to affect millions globally, posing significant challenges due to their progressive nature and the lack of timely and accurate diagnostic systems. Traditional diagnostic processes, including the manual interpretation of MRI (Magnetic Resonance Imaging) scans, are time-consuming, require specialized expertise, and are often susceptible to human error. In this project, we present a comprehensive, AI-based solution that leverages deep learning—specifically, the ResNet50 convolutional neural network—for the automatic detection and classification of brain diseases from MRI images. The project aims to design an efficient, accessible, and scalable diagnostic tool that can assist clinicians in identifying critical conditions at early stages. Using transfer learning, we fine-tuned a pre-trained ResNet50 model to distinguish between three diseases: Alzheimer's disease, Parkinson's disease, brain tumor. ResNet50, due to its deep architecture and use of residual connections, automatically extracts complex hierarchical features from brain MRI scans, making it particularly well-suited for medical imaging applications. The project involved a multi-phase workflow: extensive literature review, dataset selection, understanding disease pathology, studying neural network architectures, and implementing data preprocessing techniques such as bias field correction, nuisance regression, spatial normalization and spatial smoothing. We trained and evaluated our model using carefully tuned hyperparameters, including adjustments to dropout rates, learning rate scheduling, and weight decay. The model's accuracy improved significantly from 71% in the initial configuration to 99% in the final optimized version. Furthermore, to bridge the gap between development and usability, we deployed the trained model in a website developed using HTML, CSS, and JavaScript. This interface allows users to upload MRI scans and receive real-time predictions, making the system potentially useful for hospitals, diagnostic centers, and research institutions. By integrating deep learning with medical imaging, this project showcases the transformative potential of AI in healthcare and aims to contribute toward more accurate, faster, and accessible brain disease diagnosis.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

Neurological disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors pose significant challenges to global healthcare due to their progressive nature and the difficulty of early diagnosis. Accurate detection at an early stage can significantly improve treatment outcomes and quality of life for patients. While Magnetic Resonance Imaging (MRI) is a powerful tool for visualizing structural brain abnormalities, manual interpretation of these scans is time-consuming, requires expert radiologists, and is prone to subjectivity and error.

With advancements in Artificial Intelligence (AI) and Deep Learning (DL), there is growing potential to automate medical image analysis, providing faster and more reliable diagnostics. In this project, we present a deep learning-based system using the ResNet50 convolutional neural network, capable of detecting and classifying Alzheimer's disease, Parkinson's disease, and brain tumors from MRI images. Leveraging transfer learning, our model adapts pre-trained knowledge to medical data, achieving high accuracy even with a limited dataset and training resources.

The development process includes data collection, preprocessing techniques like bias correction and augmentation, model training with hyperparameter tuning, and performance evaluation. Finally, the trained model is integrated into a web-based user interface that allows real-time predictions, improving accessibility and clinical utility. This report outlines our complete journey—from identifying the problem and researching existing solutions, to learning the required technologies, implementing the system, and deploying it for real-world use—demonstrating the effectiveness of deep learning in advancing brain disease diagnosis.

CHAPTER 2

LITERATURE REVIEW

1. A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor

Noreen et al. (2020) introduced a deep learning-based framework for brain tumor diagnosis using a novel concatenation approach. The study utilized pre-trained convolutional neural networks, specifically Inception-v3 and DenseNet201, to extract features from different layers of the network and concatenate them to enhance classification accuracy. Unlike traditional methods that often rely on single-layer features, this multi-level feature fusion strategy allowed the model to capture both low- and high-level representations, which significantly improved the robustness of tumor classification. The authors tested their approach on a publicly available three-class brain tumor MRI dataset, achieving remarkable testing accuracies of 99.34% with Inception-v3 and 99.51% with DenseNet201. This performance outpaced several state-of-the-art methods. The study demonstrated the effectiveness of transfer learning in medical imaging and emphasized the importance of extracting diverse features across network layers for improved diagnostic outcomes.

2. Early Detection of Parkinson's Disease Using Deep Learning and Machine Learning

Wang et al. (2020) proposed a deep learning model aimed at the early detection of Parkinson's disease (PD) using a range of premotor features and clinical biomarkers. Using data from the Parkinson's Progression Markers Initiative (PPMI), which included 401 early-stage PD patients and 183 healthy controls, the study incorporated indicators such as REM sleep behavior disorder scores, olfactory loss, cerebrospinal fluid (CSF) biomarkers, and SPECT imaging markers. The authors designed a feed-forward neural network and compared its performance with twelve traditional machine learning and ensemble methods. Their results showed that the deep learning model outperformed all other techniques, achieving an average accuracy of 96.45%. Additionally, the study highlighted that SPECT-based striatal binding ratios and UPSIT smell scores were the most informative features for distinguishing PD

patients from healthy individuals. This work underscored the potential of deep learning in integrating multi-modal biomarker data for early PD diagnosis, particularly in recognizing subtle premotor symptoms.

3. Machine Learning-Based Method for Personalized and Cost-Effective Detection of Alzheimer's Disease

Escudero et al. (2013) developed a machine learning-based system for the personalized and cost-effective diagnosis of Alzheimer's disease (AD). The proposed method used locally weighted learning to tailor classification models to individual patients by identifying and applying the most relevant biomarkers on a per-case basis. Rather than using a fixed set of tests, the system iteratively selected the most informative or cost-efficient biomarkers needed to achieve a confident diagnosis. The study leveraged data from the Alzheimer's Disease Neuroimaging Initiative (ADNI), including structural MRI, PET, CSF markers, and genetic information. Results showed that the personalized classifier achieved diagnostic accuracy comparable to traditional methods while significantly reducing the number and cost of tests required. This personalized and sequential decision-making model was designed to align more closely with real-world clinical workflows, where cost and invasiveness are major concerns. The study offers an innovative perspective on how machine learning can support clinical decision-making in Alzheimer's diagnosis.

4. Open Access Series of Imaging Studies (OASIS): Cross-sectional MRI Data in Young, Middle Aged, Nondemented, and Demented Older Adults

Buckner et al. (2007) introduced the Open Access Series of Imaging Studies (OASIS), a large and publicly available dataset that includes cross-sectional MRI scans of individuals ranging in age from 18 to 96 years, including both healthy subjects and patients with very mild to moderate Alzheimer's disease. The dataset comprises 416 participants, of which 100 are clinically diagnosed with Alzheimer's based on the Clinical Dementia Rating (CDR) scale. For each subject, multiple high-resolution T1-weighted MRI scans are provided, along with associated demographic and clinical data. The authors emphasized the utility of the dataset for benchmarking and validating neuroimaging algorithms, especially those focusing on brain volume analysis, cortical atrophy, and dementia-related changes. OASIS serves as a valuable resource for researchers developing machine learning models for Alzheimer's detection,

allowing for standardized comparisons and robust model validation. The dataset's accessibility and comprehensiveness have made it foundational for numerous neuroimaging and computational neuroscience studies.

5. Image Segmentation for MR Brain Tumor Detection Using Machine Learning: A Review

Soomro et al. (2023) presented a comprehensive review titled *"Image Segmentation for MR Brain Tumor Detection Using Machine Learning"*, which explores the landscape of machine learning-based segmentation methods applied to magnetic resonance imaging (MRI) of brain tumors. The review covers traditional and modern segmentation algorithms, focusing on their effectiveness in isolating brain tumors from healthy brain tissues. The paper emphasizes the superiority of deep learning approaches—particularly convolutional neural networks (CNNs)—in extracting meaningful features for accurate tumor delineation. Various segmentation challenges are discussed, such as noise in MRI images, tumor heterogeneity, and annotation difficulties, which hinder generalizability in clinical settings. The authors also provide a detailed discussion on benchmark datasets like BraTS, which has evolved over the years from BraTS 2012 to BraTS 2020, offering high-quality annotated multimodal MRI scans for algorithm evaluation. In addition to segmentation techniques, the paper highlights the importance of multimodal imaging (T1, T2, FLAIR) in providing complementary information for improved tumor localization. Overall, the study serves as a detailed methodological and practical reference for researchers developing machine learning-based segmentation systems for brain tumor detection.

6. Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances

Khan et al. (2021) conducted an extensive survey titled *"Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances"*, reviewing 147 articles on the application of artificial intelligence in the diagnosis of four major brain diseases: Alzheimer's disease (AD), Parkinson’s disease (PD), brain tumors, and epilepsy. This review synthesizes various machine learning (ML) and deep learning (DL) techniques, detailing their architectures, performance metrics, and application scopes. The paper

categorizes commonly used classifiers (e.g., SVM, Random Forest, KNN, CNN, RNN) and evaluates them across multiple modalities like MRI, PET, EEG, and speech data. It emphasizes that deep learning, due to its end-to-end automatic feature extraction capabilities, often surpasses traditional ML in diagnostic accuracy. The authors also provide an overview of 22 frequently used datasets, including ADNI, OASIS, BraTS, and PPMI, noting their structure, content, and clinical relevance. Key findings highlight that multimodal and ensemble learning approaches are particularly effective in handling complex and heterogeneous data. The paper concludes with a discussion on open research challenges such as data scarcity, need for explainability, and clinical applicability, suggesting that future work should focus on developing more robust, interpretable, and transferable models for early and accurate diagnosis of brain diseases.

7. Research on Image Clustering Algorithm Based on Multi-features Extraction

Authors: Peng Huang, Xueliang Pan, Jun Tao (2021)
This paper presents a hybrid approach to image clustering that enhances performance by combining multiple feature descriptors—specifically color, texture, shape, and spatial relationships. Feature extraction is carried out using algorithms such as SIFT (Scale-Invariant Feature Transform), ORB (Oriented FAST and Rotated BRIEF), and color histograms, which are then processed through the K-means clustering algorithm. The multi-feature fusion method demonstrated a high clustering accuracy of up to 99%, significantly improving classification efficiency and quality in tasks like automatic image labeling and album categorization. However, the study notes that the success of clustering is highly dependent on the quality of the extracted features, and the fusion strategy introduces additional computational complexity. Moreover, while deep learning approaches offer better flexibility, they require extensive labeled datasets, which limits scalability and accessibility in real-world applications.

8. Alzheimer's Disease Detection Using Transfer Learning: Performance Analysis of InceptionResNetV2 and ResNet50 Models

Authors: Sanjeev Kumar K, B Saketh Reddy, M Ravichandran (2023)
This study evaluates the effectiveness of two transfer learning models—InceptionResNetV2

and ResNet50—for classifying Alzheimer's disease stages from MRI brain scans. Using a public dataset categorized into four stages (non-demented, very mild, mild, and moderate), the models demonstrated high classification accuracy, with InceptionResNetV2 outperforming ResNet50. The approach capitalizes on the capability of deep networks to learn complex spatial hierarchies, and transfer learning enables adaptation from pre-trained ImageNet weights. Despite the promising accuracy levels, the paper highlights challenges such as model overfitting and limited generalization due to the small and non-diverse nature of the training dataset. These constraints limit the effectiveness of the model in clinical scenarios involving a wide range of pathological and demographic variations.

9. Classification of BOLD fMRI Signals Using Wavelet Transform and Transfer Learning for Detection of Autism Spectrum Disorder

Authors: MohammedI Al-Hiyali, Ibrahima Faye, Norashikin Yahya, ZiaKhan Khaled, Alsaih Laboratoire (2021)

This paper introduces a method that combines wavelet transform with transfer learning to classify Autism Spectrum Disorder (ASD) using BOLD (Blood-Oxygen-Level Dependent) fMRI signals. DenseNet201 and GoogleNet were employed for feature extraction, and machine learning classifiers such as SVM and KNN were used for final classification. The approach achieved an accuracy of 85.9%, surpassing earlier models used for ASD detection. However, the study faces limitations due to a small dataset, which restricts robustness and generalizability across different scanners, demographics, and imaging conditions. The sensitivity of transfer learning models to even slight variations in dataset composition presents a challenge for real-world implementation.

10. Schizophrenia Detection from Resting State Functional MR Images Using Machine Learning

Authors: Tea Teskera, Jelena Bozek (2023)

This study investigates the application of machine learning techniques—specifically Support Vector Machines (SVM), Random Forest, and Neural Networks—for detecting schizophrenia

using resting-state functional MRI (rs-fMRI) data. The dataset used is COBRE, comprising 72 patients with schizophrenia and 74 healthy controls. Brain atlases were used for region-wise feature extraction, and classification was performed based on the connectivity features. The neural network achieved the highest classification accuracy of 80%. Despite these results, the small sample size and lack of demographic diversity pose challenges for generalizability. Moreover, the study suggests that broader validation and tuning across heterogeneous datasets are needed to enhance robustness and clinical applicability.

11. Decoding of Auditory Imagination Activity Based on Machine Learning Methods

Authors: Wanly Ma, Xuegang Tang, Qiuqin Xia, Yiwei Xu, Weitong Gao, Jin Gu (2022)
This paper explores the novel task of decoding auditory imagination—where participants imagine hearing sounds—using fMRI data. The study used machine learning classifiers including SVM, Naive Bayes, and Logistic Regression, along with Principal Component Analysis (PCA) for dimensionality reduction and feature extraction. The SVM model achieved the best classification accuracy of 87%. While the study opens doors for further research in the underexplored domain of auditory imagination, the dataset is extremely limited (only 24 subjects), which severely restricts the ability to generalize findings. Additionally, the uniqueness of the auditory imagination task means a lack of reference frameworks or comparative benchmarks in neuroscience and machine learning literature.

12. Detection of Brain Tumor and Identification of Tumor Region Using Deep Neural Network on fMRI Images

Authors: Afsara Mashiat, Reza Rifat Akhlaque, Fahmeda Hasan Fariha, Tanzim Reza, Md Anisur Rahman, Mohammad Zavid Parvez (2020)
This study uses convolutional neural networks (CNNs), including VGG16, VGG19, and InceptionV3, to detect and classify brain tumors in fMRI images. VGG19 outperformed the other models, achieving 98.68% accuracy for binary classification (tumor vs. non-tumor) and 97.35% for spatial tumor localization. The strength of the study lies in the precise application of deep neural networks for both classification and spatial segmentation. However, the dataset used was small (22 patients), and tumor region identification required manual annotation,

which introduces human bias and labor intensity. These limitations raise concerns about overfitting and the generalizability of the model across diverse patient populations.

13. Evaluation of Preprocessing for Functional Magnetic Resonance Imaging Brain Networks

Authors: Xia Xu, Xufeng Yao (2022)
This study evaluates two popular preprocessing tools—GRETNA and DPARSF—for analyzing fMRI data, particularly in the context of Alzheimer's disease. The comparison focused on how preprocessing techniques affect global and local network metrics of functional brain networks. While the overall network characteristics remained largely consistent across the tools, variations were found in the distribution and intensity of core brain nodes. This suggests that even minor differences in preprocessing workflows can have significant downstream effects on neuroimaging studies. A major limitation is the very small sample size (six subjects), making it difficult to draw strong conclusions applicable to broader populations.

14. Structured Multi-layer Perceptron Model for fMRI Data

Author: Erkin Eryol (2023)
This study proposes a structured Multi-layer Perceptron (MLP) architecture that integrates the spatial arrangement of brain voxels and the geometric layout of brain regions for brain decoding tasks using fMRI data. Evaluated on the Human Connectome Project dataset, the model performed well on tasks with localized brain activity (e.g., motor control). However, it struggled in tasks involving distributed brain activity, such as working memory. The model's performance was also sensitive to fMRI resolution and required task-specific tuning for optimal results. Although promising, its adaptability to various neurocognitive tasks remains a challenge, and it underperforms when compared to more complex 3D CNN architectures in distributed tasks.

15. Comparative Analysis of Deep Learning and Machine Learning for Detection and Classification of Brain Tumors

Authors: B. Ramprakash, C. Santhiya, S. Santhana Hari, D. Nagendra Kumar (2024) This comparative study explores the effectiveness of ML (SVM, Random Forest) versus DL (CNNs) in detecting and classifying brain tumors from MRI images. CNN models significantly outperformed traditional ML methods in identifying different tumor types such as gliomas, meningiomas, and pituitary tumors. Despite the clear advantage in accuracy, the study acknowledges challenges such as high computational cost for CNN training, data imbalance across classes, and limited model interpretability. These factors hinder the practical application of CNNs in real-time or resource-limited clinical environments.

16. IMU-Based Robust Human Activity Recognition Using Feature Analysis, Extraction, and Reduction

Authors: Omid Dehzangi, Vaishali Sahu (2018) Though not directly related to brain imaging, this study is relevant for its efficient approach to feature engineering. The research uses Inertial Measurement Units (IMUs) and machine learning classifiers to recognize human activities. Random Forest combined with Neighborhood Component Analysis achieved 96.9% accuracy, demonstrating the effectiveness of dimensionality reduction in improving classification accuracy while minimizing computational overhead. The insights from this work are transferable to medical imaging, especially in optimizing preprocessing pipelines and ensuring model robustness with fewer features—a vital requirement in scenarios where computational resources or labeled data are limited.

17. Image Segmentation for MR Brain Tumor Detection Using Machine Learning

Authors: Not specified
Year: Not specified
This review investigates various machine learning techniques used for segmenting brain tumors from MRI scans, focusing on both traditional and deep learning methods. Approaches discussed include thresholding, region growing, edge detection, and feature-based methods, as

well as advanced models such as convolutional neural networks (CNNs). The review notes CNNs' superior ability to learn spatial hierarchies and capture tumor features automatically, making them more effective than hand-crafted techniques. However, challenges remain. MRI images often suffer from noise, motion artifacts, and resolution limitations, making tumor boundaries difficult to detect. Additionally, tumors often occupy a small area within the brain scan, complicating segmentation. Manual annotations required for deep learning training are time-consuming and subject to human error. Furthermore, many segmentation models trained on specific datasets struggle to generalize across tumor types, scan protocols, or patient demographics, limiting their clinical applicability.

18. United Neurological Study of Disorders: Alzheimer's, Parkinson's, Anxiety, and Stress Detection Using ML Algorithms

Authors: Sahaja Dixit, Mahesh Shindikar, Akash Gaikwad, Ketaki Kamble, Vibha Vyas
Year: 2022

This paper investigates the application of machine learning algorithms such as CNNs, Random Forest, and KNN for detecting a variety of neurological conditions, including Alzheimer's disease, Parkinson's disease, anxiety, and stress. The study used public datasets to train and evaluate its models, achieving high classification accuracy, particularly in Alzheimer's and Parkinson's detection. It also extends ML use to psychiatric conditions like stress and anxiety, an area often overlooked in imaging studies. Despite these advances, the study acknowledges several limitations. The use of public datasets may not capture the heterogeneity of real-world populations, and the lack of discussion on handling symptom overlap—especially in anxiety and stress—raises questions about the model's reliability. Moreover, computational demands are high due to the volume of data and complexity of models, which may limit their scalability in clinical settings.

19. Research on Industrial Control Network Security Data Feature Extraction Using Composite Sparse Autoencoder

Authors: Xichun Peng, Yunhui Fu, Hui Yu
Year: 2024

Though from a different domain, this paper introduces a composite kernel sparse autoencoder (MK_SAE) aimed at enhancing feature extraction for high-dimensional, large-scale industrial control network data. The method applies adaptive genetic algorithms to optimize the encoding of relevant features, outperforming traditional CNNs and single-layer autoencoders in both accuracy and speed. While focused on cybersecurity, the methodological approach—automated feature learning, dimensionality reduction, and adaptive optimization—has relevance for medical imaging, especially for handling large MRI datasets. However, the approach's real-world viability remains uncertain, as the paper does not provide results from industrial-scale deployment. It also lacks analysis on adaptability to evolving attack patterns or system updates, which would be critical for dynamic environments like healthcare.

20. An Early Detection of Parkinson's Disease Using Machine Learning and Deep Learning Models

Authors: Shagun Sharma, Kalpna Guleria, Rajni Sobti
Year: 2024

This study applies a comparative framework using seven machine learning and deep learning algorithms—including decision trees, SVMs, Random Forests, and neural networks—to detect early-stage Parkinson's disease from a Kaggle dataset. Among them, the neural network achieved the highest classification accuracy (87.7%), followed closely by Random Forest (85.9%). Evaluation metrics included AUC, F1 score, precision, recall, and computational efficiency. While demonstrating strong predictive performance, the paper is limited by its small dataset (188 samples), which reduces generalizability and increases the risk of overfitting. The study stresses the importance of early detection but acknowledges the need for larger, more diverse datasets and model refinement to improve robustness in clinical environments.

21. Pre-trained CNN Models and Machine Learning Techniques for Brain Tumor Analysis

Authors: Manvi Bohra, Siddharth Gupta
Year: 2022

This paper explores a hybrid approach that leverages pre-trained CNN models (VGG16, VGG19, Inception V3) for feature extraction and traditional machine learning algorithms (SVM, logistic regression, neural networks) for classification of brain tumors in MRI scans. The combination of VGG16 and logistic regression yielded the highest classification accuracy of 97.7%. This method benefits from CNNs' ability to extract high-level features while maintaining computational simplicity during classification via ML techniques. However, the dataset used (1311 images) is relatively small, limiting the model's generalizability to more complex or varied clinical cases. Additionally, the study focuses mainly on accuracy, with limited discussion on critical aspects like computational load, model explainability, or interpretability—factors vital for real-world deployment.

22. Image Preprocessing Techniques in Skin Diseases Prediction Using Deep Learning: A Review

Authors: Anu V Kottath, Dr. SV Shri Bharathi
Year: Not specified

This review discusses deep learning-based preprocessing strategies used in dermatology for skin lesion detection and classification, particularly focusing on melanoma. It examines image enhancement, denoising, augmentation, and segmentation techniques employed to improve CNN, ResNet, and FCN model performance. The review also addresses dataset diversity, class imbalance, and imaging condition variability. While deep learning has made significant progress in dermatological diagnostics, limitations include over-reliance on curated datasets, lack of model interpretability, and underperformance in uncontrolled clinical settings. The review underscores the importance of building models robust to variations in lighting, image resolution, and lesion appearance for real-world applicability.

23. Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances

Authors: Protima Khan, MD. Fazlul Kader, S. M. Riazul Islam, et al.
Year: Not specified
This extensive review summarizes 147 studies using ML and DL for diagnosing Alzheimer's disease, brain tumors, Parkinson's, and epilepsy. Techniques reviewed include CNNs, RNNs, SVMs, Random Forests, and hybrid models. The review covers data modalities such as MRI, PET, EEG, and speech recordings, and includes an analysis of 22 widely used datasets. Key challenges discussed are limited dataset size, explainability, interoperability between systems, and ethical concerns. There's a notable gap between experimental success and clinical translation, highlighting the need for standardized protocols, multi-modal fusion, and longitudinal studies to track disease progression.

24. Detection of Alzheimer's Risk Level Using Inception V3 Transfer Learning Model

Authors: Rahul Singh, Neha Sharma, Rupesh Gupta
Year: 2023
This paper uses transfer learning with the Inception V3 model to classify Alzheimer's disease progression into four categories: non-demented, very mild, mild, and moderate. The model was trained on 1279 images and tested on 5121 MRI images, achieving an overall accuracy of 89%. Data augmentation (flipping, rotation, zoom) was used to enhance model robustness. However, the training dataset is relatively small for deep learning, increasing the risk of overfitting. The paper does not address potential class imbalance, which could skew performance across categories. The transfer learning strategy uses weights from non-medical domains, potentially limiting feature relevance unless extensively fine-tuned.

25. Brain Disease Classification from MRI Scans Using EfficientNetB0 Feature Extraction

Authors: Samia Ferdous Mou, S M Abdur Razzak
Year: 2023
This study utilizes the EfficientNetB0 CNN architecture to classify MRI brain scans into

categories such as brain tumor, Alzheimer's, and Parkinson's. The model is evaluated for both single-disease and multi-class classification. While it achieves high validation accuracy in isolated tasks, multi-disease classification results in lower accuracy and longer convergence time. The paper identifies the limitations of using single-modal MRI data and the need for integrating additional data types (e.g., clinical or genomic) to improve diagnostic accuracy. A small dataset size and lack of diversity further affect generalizability, and the system's reliance on supervised learning demands labor-intensive manual labeling.

26. Brain Tumor Detection Using Machine Learning and Deep Learning Approaches

Authors: Oneza Tehreem Khan and Rajeswari D
Year: 2022

This paper provides a comparative analysis of traditional machine learning methods and deep learning approaches like CNNs and FCNs for brain tumor detection using MRI. Deep models show superior accuracy and automation capability, especially in identifying and classifying tumor types. The authors highlight the critical role of preprocessing, segmentation, and feature extraction. However, acquiring large, annotated datasets for deep models remains a bottleneck. Model generalization is another challenge, as many models perform well only on the datasets they are trained on. Noise and MRI artifacts further complicate performance reliability.

27. Multi-Feature Extraction Method for Network Illustrations (Zhao Lan, 2021)

This paper introduces a new method for multi-feature color extraction from network illustrations, focusing on improving both accuracy and efficiency compared to traditional methods. The method involves transforming the color space of network illustrations and applying the HSV (Hue, Saturation, Value) color model to quantify the colors. The approach further utilizes color composition matrices and feature value reduction techniques, followed by feature matching and color space conversion to extract the colors. The method was tested using ImageNet images and demonstrated superior performance in terms of both accuracy and efficiency when compared to two traditional color extraction methods.

Despite the promising results, the method has several limitations. First, it was tested only on the ImageNet database, which may not provide a diverse range of network illustrations, limiting its applicability. The comparison was also narrow, as it was made against only two traditional methods, meaning the effectiveness of this approach in a broader context remains unclear. Furthermore, the method is specifically designed for network illustrations, making it less applicable to other types of images or color extraction tasks. Performance metrics, such as extraction time, could also vary depending on the hardware used, but this issue was not addressed in the study. The paper does not provide any real-world testing, which raises questions about the method's practical application in dynamic environments. There is little discussion regarding how various parameters, such as quantization levels, influence the results, and the absence of error analysis limits understanding of the inaccuracies that may occur during color extraction. Lastly, the method's scalability and long-term performance with larger datasets were not explored.

28. Preprocessing fMRI Data in SPM12 (Fatima Ez-zahraa Bazay et al., 2022)

This paper provides an overview of the essential preprocessing steps required to prepare functional magnetic resonance imaging (fMRI) data using the SPM12 tool. These preprocessing steps are critical to remove noise and artifacts, ensuring reliable analysis of brain activity. The key steps outlined include slice timing correction, which adjusts for the time lag between different slices in an fMRI volume, and realignment, which corrects for any head movements during data acquisition. Coregistration is employed to align functional images with high-resolution anatomical images to improve brain activity localization. Segmentation divides the brain into various tissue types—such as gray matter, white matter, and cerebrospinal fluid—enabling clearer analysis. Normalization transforms the brain images into a standard stereotactic space to facilitate group comparisons, while smoothing enhances the signal-to-noise ratio by spatially averaging voxel intensities, which helps in detecting brain activations more reliably.

However, several limitations are noted in the preprocessing pipeline. Some steps, such as realignment, coregistration, and normalization, are computationally expensive and require significant processing power, which can be a challenge, especially for large datasets. Although realignment corrects for head motion, subtle movements may still introduce artifacts that affect

data quality. The order in which preprocessing steps are applied can influence the results, potentially leading to variability across different studies. While smoothing improves the signal-to-noise ratio, it may reduce spatial accuracy, making it harder to detect fine-grained brain activity. Moreover, normalization errors may occur if the voxel-to-voxel correspondence across subjects is not well established, which could affect the group comparisons. Finally, the pipeline's sensitivity to data acquisition parameters limits its generalizability across different datasets and research contexts.

29. Brain Disease Classification from MRI Scans Using EfficientNetB0 Feature Extraction (Samia Ferdous Mou & S. M. Abdur Razzak, 2023)

This paper proposes using the EfficientNetB0 convolutional neural network (CNN) model to classify brain diseases such as brain tumors, Alzheimer's disease, and Parkinson's disease from MRI scans. The EfficientNetB0 model is optimized for efficiency and performance, making it well-suited for extracting relevant features from medical images like MRI scans. The model demonstrated high classification accuracy, achieving a 95.8% validation accuracy in detecting these diseases. The paper highlights the effectiveness of EfficientNetB0 in medical image analysis, emphasizing its capability to detect brain disorders with high accuracy, which could potentially assist in clinical diagnosis.

However, there are some limitations associated with the model. Its performance is highly dependent on the availability of high-quality labeled data for training, which is often a challenge in medical imaging. Despite the high accuracy demonstrated in the study, further validation with larger and more diverse real-world datasets is needed before the model can be widely deployed in clinical settings. Additionally, the reliance on supervised learning requires manual annotations, which can introduce human bias and error into the training process. While the research showcases a promising application of deep learning for brain disease detection, these challenges related to data quality, model generalization, and real-world implementation must be addressed for practical use in clinical environments.

30. Preprocessing of Medical Images using Deep Learning: A Comprehensive Review (Nongmeikapam Thoiba, Singh Shefali, Goyal Charnpreet Kaur Amrita, Chaudhary, Year not provided)

This paper provides a comprehensive review of deep learning techniques for preprocessing medical images, focusing on key tasks such as denoising, image enhancement, registration, and segmentation. It discusses various deep learning approaches, including Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), which have been used effectively for these preprocessing tasks. The review explores applications in areas such as computer-aided diagnosis, tumor detection and classification, image-guided interventions, surgical planning, and radiomics. The paper highlights how these techniques improve image quality by reducing noise, enhancing contrast, and extracting precise anatomical structures. By leveraging deep learning for preprocessing, the review emphasizes the significance of these methods in clinical decision-making, as they enable more accurate diagnoses, treatment planning, and disease monitoring.

Despite the promising advancements, several limitations are noted in the paper. One major challenge is the need for large annotated datasets to train deep learning models, which can be difficult to obtain in medical imaging. Additionally, deep learning models, especially complex architectures, face issues with interpretability, which is a crucial factor in medical applications where transparency and trust are essential. Overfitting is another concern, particularly with deep learning models trained on relatively small datasets. Furthermore, the performance of these models may vary across different imaging modalities and clinical applications, making it difficult to generalize the findings. The computational resource requirements for implementing advanced deep learning models in clinical settings are also a significant challenge. Finally, the gap between research findings and their real-world clinical implementation remains a barrier for widespread adoption of these techniques in practice.

These papers further explore the intersection of deep learning and medical imaging, with a focus on brain disease classification and preprocessing techniques. Both highlight the potential and challenges of using deep learning in medical applications, underscoring the importance of high-quality data, model robustness, and interpretability for practical use.

CHAPTER 3

BACKGROUND AND MOTIVATION

3.1 The Rise of Neurological Disorders

In recent decades, neurological disorders have emerged as some of the most pressing global health challenges. According to the World Health Organization (WHO), neurological conditions are responsible for more than 10% of global deaths and account for a substantial share of disability-adjusted life years (DALYs). Diseases such as Alzheimer's disease, Parkinson's disease, and brain tumors affect millions annually, leading to cognitive decline, motor dysfunction, and often fatal outcomes. As the global population ages, the prevalence of neurodegenerative conditions is expected to rise dramatically, increasing the burden on healthcare systems and families.

While treatments for many neurological disorders remain limited or symptomatic, research emphasizes the importance of early detection in improving prognosis. In conditions like Alzheimer's and Parkinson's, early-stage intervention can slow progression and enhance quality of life. Similarly, early identification of brain tumors can enable timely surgical or radiological treatment, potentially saving lives.

3.2 Challenges in Early Detection and Diagnosis

One of the major hurdles in managing neurological disorders is the difficulty of early and accurate diagnosis. Symptoms often develop gradually and may overlap with other conditions, making clinical assessment alone insufficient. Advanced imaging techniques, particularly Magnetic Resonance Imaging (MRI), are essential tools for identifying structural changes in the brain. However, interpreting these images is a complex task that requires years of expertise.

Even for experienced radiologists, analyzing MRI scans is a time-consuming, subjective, and often error-prone process. Subtle indicators of neurodegeneration or small tumors may be overlooked, especially in resource-constrained environments with limited access to specialists.

As a result, many patients receive delayed diagnoses, by which time the disease may have significantly progressed.

3.3 Limitations of Manual Interpretation

While MRI provides excellent spatial resolution and soft-tissue contrast, its diagnostic utility heavily depends on the expertise of the radiologist. Human error, fatigue, inter-observer variability, and differences in interpretation can lead to inconsistent results. In developing regions and rural hospitals, the shortage of trained neurologists and radiologists further compounds the problem.

Moreover, the increasing volume of diagnostic imaging—driven by better access to healthcare and aging populations—adds pressure on radiology departments, increasing the risk of missed findings. These limitations have spurred the search for automated, AI-powered systems that can assist or augment the diagnostic process, particularly in early detection where subtle findings may be critical.

3.4 How the Idea for This Project Emerged

We developed a growing interest in the intersection of healthcare and artificial intelligence. With access to deep learning courses, projects, and workshops, we became increasingly aware of how machine learning is transforming medical imaging—from cancer detection to retinal disease classification.

During our project brainstorming sessions, we were drawn to the field of neurological imaging, as it not only involves technical challenges (such as high-resolution data and subtle features) but also addresses life-altering conditions where early intervention can make a difference. We reviewed several papers and real-world use cases of AI in radiology, which inspired us to explore deep learning models for brain disease detection using MRI.

What made this problem personally meaningful was the realization that timely diagnosis is not just a technical challenge, but one that has real human impact—affecting families, patient quality of life, and healthcare accessibility. This combination of social relevance, technical depth, and future potential made it the ideal project for our final year.

3.5 Why This Problem Matters

Our team has always been driven by a passion to apply engineering knowledge in solving meaningful, real-world problems. The field of medical imaging stood out because of its ability to merge advanced technology with human well-being. We were particularly intrigued by the idea of creating a solution that could assist doctors, reach underserved areas, and bring AI into practical use—beyond academic experimentation.

The learning curve was steep. We had to study the basics of neural networks, MRI processing, neurological disease pathology, and transfer learning. But we were motivated by the belief that even as undergraduate students, we could create something impactful by standing on the shoulders of open-source technologies, publicly available datasets, and the vast research in this domain.

3.6 Project Objectives

The primary goal of this project is to develop an automated system capable of detecting and classifying major brain diseases from MRI images using deep learning. Specific objectives include:

- To detect and classify Alzheimer's, Parkinson's, and brain tumors using a single CNN model
- To explore and implement transfer learning for better generalization on limited medical datasets
- To apply preprocessing and augmentation techniques that improve model robustness
- To compare model performance with and without preprocessing
- To deploy the model through a web interface for real-world usability
- To evaluate model performance using accuracy, precision, recall, F1-score, and confusion matrix

3.7 Scope and Limitations

This project focuses specifically on structural MRI data of the brain and classifies input images into one of four categories: Alzheimer's, Parkinson's, tumor, or healthy. While it provides a

proof-of-concept diagnostic tool, it does not cover disease severity staging or segmentation of lesion regions. The model is trained and evaluated on publicly available datasets.

The web deployment is designed for demonstration purposes and not yet integrated with clinical systems. Additionally, the model is trained on a relatively small dataset and may require further validation and tuning before clinical deployment.

CHAPTER 4

RESEARCH DIRECTION AND PLANNING

4.1 How Literature Guided Our Approach

Before finalizing the approach for our project, we undertook an extensive review of existing research in the domain of brain disease detection using machine learning and deep learning techniques. The literature review provided valuable insights into what models have been successful, what types of data are commonly used, and what gaps still exist in the current landscape.

From the reviewed papers, we found that Convolutional Neural Networks (CNNs) have consistently outperformed traditional machine learning models (like SVM, KNN, or Random Forests) in image-based classification tasks. Many research efforts utilized transfer learning with pre-trained CNNs (e.g., ResNet, VGG, Inception) to overcome the limitations of small datasets—an issue common in medical imaging.

Additionally, the review highlighted the significance of MRI data as the most frequently used modality for structural brain disease diagnosis. Papers that achieved high accuracy often combined preprocessing with deep learning models, reinforcing the need for quality data input. Furthermore, it became evident that most existing studies focused on one disease at a time—either Alzheimer's, Parkinson's, or brain tumors—but not all three together. This realization presented an opportunity for our team to combine multi-disease classification into a single, unified model.

Hence, the research not only introduced us to relevant architectures and preprocessing techniques but also helped us identify a clear niche: building a multiclass classifier using transfer learning and deploying it in a real-time web-based interface.

4.2 Why We Chose MRI Imaging

Among all medical imaging techniques—like CT, PET, EEG, and fMRI—MRI stands out for its ability to provide high-resolution, detailed anatomical views of the brain. Unlike CT scans, MRI does not expose patients to ionizing radiation and offers better contrast between soft tissues,

making it ideal for detecting structural changes associated with neurodegenerative diseases and tumors.

We found that MRI is widely used in clinical diagnostics and is well-supported in research datasets, making it both clinically relevant and technically feasible for our project. It also aligns well with CNNs, which are optimized for spatial feature learning—precisely what MRI data demands.

4.3 Why We Chose Alzheimer's, Parkinson's, and Brain Tumors

Our choice of these three diseases was intentional and grounded in medical, technical, and practical reasoning:

- Alzheimer's Disease is the most common form of dementia and is associated with identifiable structural changes in the brain (e.g., hippocampal shrinkage), making it suitable for detection using MRI.
- Parkinson's Disease is a progressive neurodegenerative disorder with known impacts on subcortical brain regions. While more challenging to detect structurally than Alzheimer's, advanced research shows early patterns in MRI that can be learned by deep models.
- Brain Tumors present as physical masses with clear boundaries (depending on the type), making them relatively easier to detect using image-based classification. Including tumors also allowed us to diversify our dataset and increase the clinical utility of our model.

Together, these three diseases cover a broad spectrum of neurological abnormalities—from atrophy to abnormal growths—making our model more generalizable and valuable in real-world diagnostics.

4.4 Initial Project Planning and Roadmap

At the beginning of the project, we designed a clear roadmap to structure our research, development, and evaluation phases efficiently. Below (Table 1) is a high-level overview of our planning strategy:

Table 1 Project planning

Phase	Activities Involved
Research	Literature review, model comparison, dataset collection, project scoping
Learning	Studied CNNs, ResNet50 architecture, MRI image properties, transfer learning, tools
Preprocessing	Implemented bias field correction, skull stripping, data normalization and augmentation
Model Development	Configured and trained ResNet50 using transfer learning, tuned hyperparameters
Evaluation	Validated model performance, compared accuracy (raw vs preprocessed), visualized metrics
Deployment	Designed web-based interface using HTML, CSS, JavaScript, and integrated model
Documentation	Compiled findings into presentation and detailed academic report

This structured approach allowed us to stay on track while also leaving room to explore and iterate as needed. It also ensured that we addressed each component—from theory to deployment—in a thoughtful, research-driven manner.

CHAPTER 5

CONCEPTUAL FOUNDATIONS

5.1 Understanding Brain Diseases

Neurological disorders impact both the structure and function of the brain**,** leading to various cognitive, motor, and behavioral impairments. Among them, Alzheimer's disease**,** Parkinson's disease**,** and brain tumors are three of the most prevalent, impactful, and clinically significant conditions. Understanding their biological effects and how they appear in Magnetic Resonance Imaging (MRI) is crucial for building a deep learning-based diagnostic model.

5.1.1 Alzheimer's Disease

Alzheimer's disease (AD) is the most common form of dementia, affecting millions of people globally. It is characterized by progressive neuronal loss, especially in the hippocampus and cortical regions, which are vital for memory and reasoning. As the disease advances, brain tissue shrinks significantly, and the ventricles enlarge.

MRI Characteristics:

- Cortical thinning
- Hippocampal atrophy
- Enlarged lateral ventricles
- Decreased brain volume in parietal and temporal lobes

Early detection is essential, as clinical symptoms appear only after significant neuronal damage has occurred. Progression of the disease is shown in figure 1.

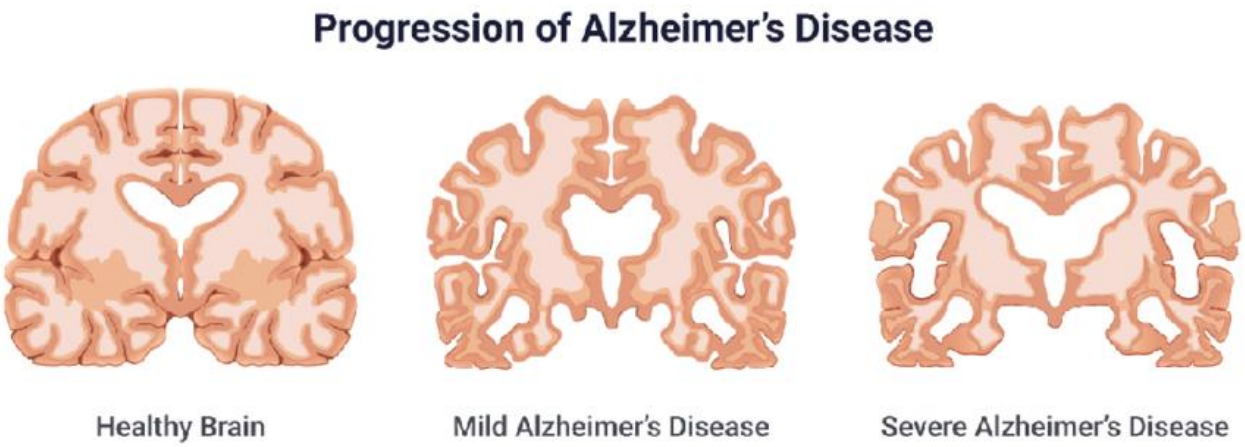

Figure 1 Progression of Alzheimer's Disease

5.1.2 Parkinson's Disease

Parkinson's disease (PD) is a chronic and progressive neurodegenerative disorder primarily affecting motor control. It is caused by the degeneration of dopaminergic neurons in the substantia nigra, a structure in the midbrain responsible for dopamine production. Symptoms include tremors, stiffness, bradykinesia (slowed movement), and postural instability.

MRI Characteristics:

- Subtle signal changes in the substantia nigra
- Volume reduction in basal ganglia
- Midbrain asymmetry
- Iron deposition visible in advanced scans (SWI/T2*)

5.1.3 Brain Tumors

Brain tumors are abnormal growths of tissue in the brain that can be benign or malignant. Tumors disrupt normal brain function by compressing nearby structures or increasing intracranial pressure.

MRI Characteristics:

- Hyperintense or hypointense mass regions
- Edema surrounding tumor

- Contrast enhancement for tumor boundaries
- Midline shift or deformation of nearby structures

MRI is the most effective imaging modality for brain tumor detection, offering excellent contrast and spatial resolution without radiation exposure.

5.2 Introduction to Artificial Intelligence

Artificial Intelligence (AI) is the simulation of human intelligence in machines that are programmed to think, learn, and make decisions. AI systems can adapt their behavior based on input data, a feature that makes them powerful tools across domains like robotics, finance, and medicine.

Machine Learning (ML) is a subset of AI where computers learn from data without being explicitly programmed. Instead of following hardcoded instructions, ML algorithms identify patterns, make predictions, and improve over time with exposure to more data.

Deep Learning (DL), a subfield of ML, uses artificial neural networks—especially deep neural networks with many layers—to solve highly complex tasks such as speech recognition, natural language processing, and image classification.

Applications of AI in Healthcare:

- Disease detection (e.g., cancer, retinal disease, COVID-19, Alzheimer's)
- Drug discovery and personalized medicine
- Radiological image interpretation
- Predictive analytics in patient monitoring
- Robotic surgery and clinical decision support

AI's ability to process vast medical datasets and extract meaningful features makes it a transformative tool in medical diagnostics, particularly in image-based fields like radiology and pathology.

5.3 Types of Machine Learning

Machine Learning is generally classified into three broad types (Table 2):

Table 2 Types of ML

Type	Description	Healthcare Example
Supervised Learning	Learns from labeled datasets to predict known outcomes	Classifying MRI scans into disease categories
Unsupervised Learning	Identifies hidden patterns in unlabeled data	Clustering patient health records for anomaly detection
Reinforcement Learning	Learns through trial and error using a reward-based feedback loop	Optimizing treatment plans in robotic surgery

In our project, we adopted supervised learning**,** where the model learns from input-output pairs. Each MRI image in our dataset is labeled with its corresponding disease (or healthy status), making it ideal for training a classification model like ResNet50**.** Supervised learning is well-suited for medical diagnosis tasks where historical data with known outcomes is available.

5.4 Deep Learning & Convolutional Neural Networks (CNNs)

Deep Learning (DL) is a subfield of machine learning that uses artificial neural networks with multiple layers to model and solve complex problems. Inspired by the structure of the human brain, deep learning models are especially effective in identifying patterns in data such as images, speech, and text.

Unlike traditional machine learning algorithms that rely heavily on handcrafted features, deep learning models learn hierarchical representations directly from raw data. The more layers a model has, the more abstract and complex features it can learn. This makes deep learning particularly powerful for tasks like medical image classification, where feature patterns may be subtle and difficult to define manually.

5.4.1 Convolutional Neural Networks (CNNs)

CNNs are a specialized type of deep neural network designed to process data with a grid-like topology—such as 2D images. CNNs use layers of filters (kernels) to **extract local spatial features** like edges, shapes, and textures.

Core Components of a CNN (Figure 2):

- **Input Layer**: Receives the image (e.g., MRI scan) as a matrix of pixel values.
- **Convolutional Layers**: Apply filters to detect patterns such as edges, corners, or textures.
- **Activation Function (ReLU)**: Introduces non-linearity to help the network learn complex functions.
- **Pooling Layers**: Reduce dimensionality and computation by summarizing feature responses (e.g., Max Pooling).
- **Fully Connected (Dense) Layers**: Interpret the high-level features and produce classification outputs.
- **Output Layer**: Provides the final prediction (e.g., disease class).

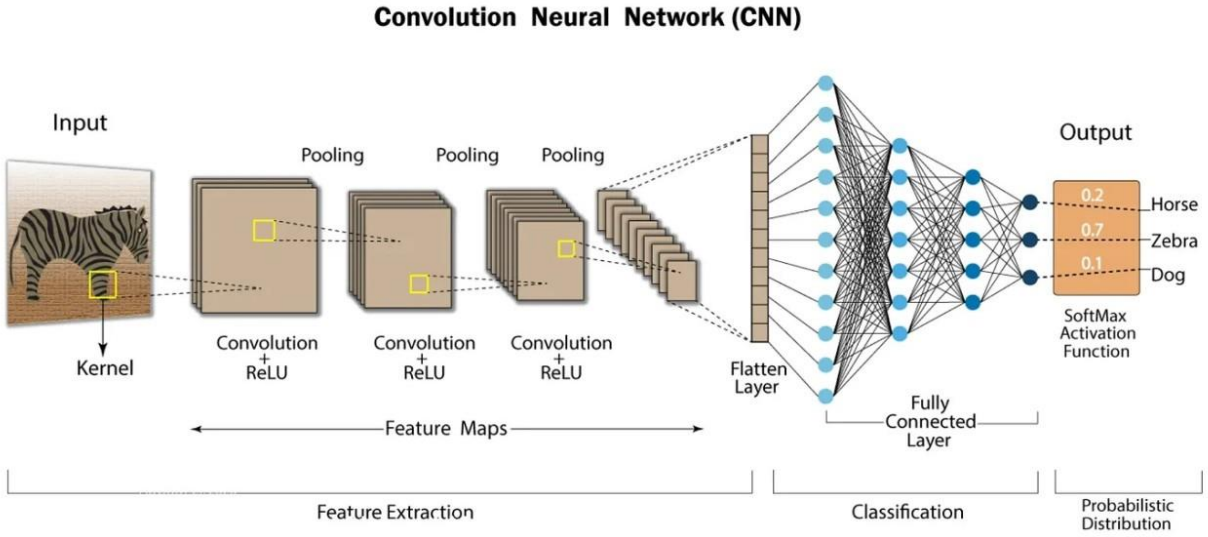

Figure 2 Basic CNN Architecture Diagram

CNNs are highly effective for image classification tasks because they can retain spatial relationships between pixels, unlike flat input features in traditional models. In medical imaging, CNNs are capable of learning anatomical structures, lesion patterns, and regional abnormalities with high precision—even from a relatively small number of training examples.

This architecture formed the core foundation of our project, particularly when integrated with transfer learning, as discussed in the next section.

5.5 Transfer Learning

Training a deep CNN from scratch typically requires huge amounts of labeled data**,** significant computational resources, and time. In medical imaging, datasets are often limited, and obtaining well-annotated samples is costly and time-intensive. This is where transfer learning becomes essential.

5.5.1 What Is Transfer Learning?

Transfer learning is a technique where a model pre-trained on a large dataset (such as ImageNet) is repurposed for a different but related task—by retaining learned features in early layers and retraining only the top layers for the new problem.

In our project, we used ResNet50, a 50-layer deep convolutional neural network originally trained on over 1 million images in the ImageNet dataset. The early layers of ResNet50 extract generic features like edges and textures, which are also relevant in MRI. Only the final few layers were fine-tuned to adapt the model for classifying Alzheimer's, Parkinson's, brain tumors, and healthy scans.

5.5.2 Why Transfer Learning Works Well in Medical Imaging:

- **Reduces training time and compute requirements**
- **Performs better with small medical datasets**
- **Prevents overfitting** by using already-learned, generalized features
- **Improves convergence speed** and model stability

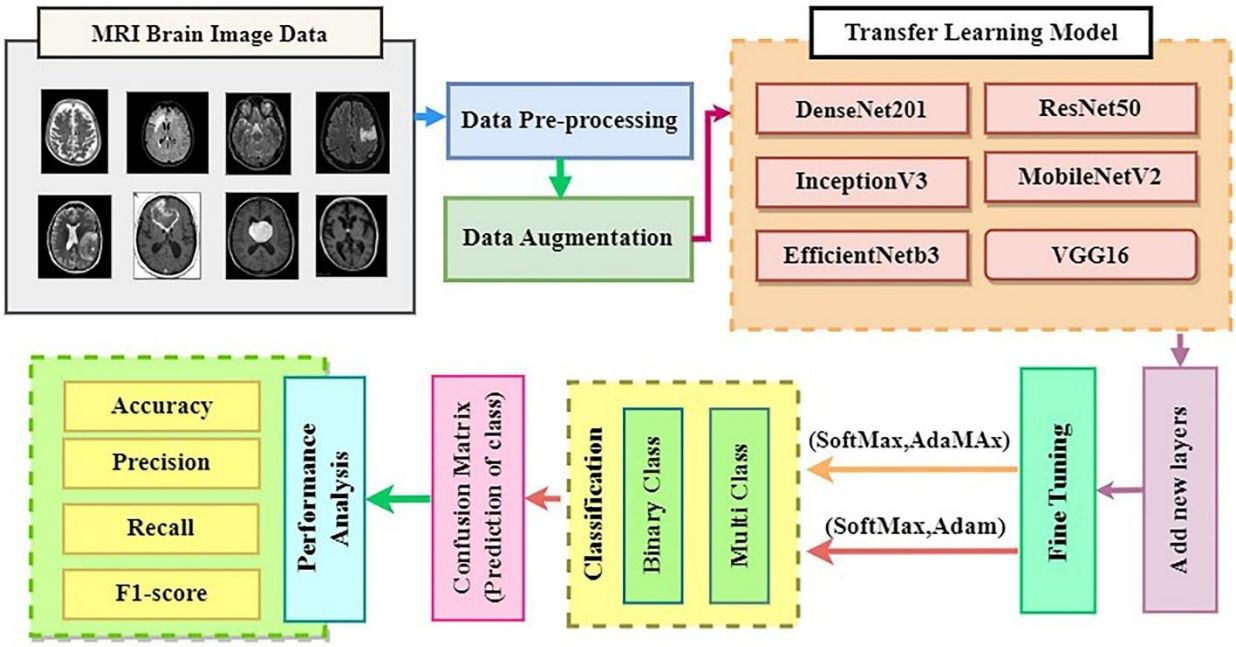

Figure 3 Transfer Learning pipeline

We ultimately selected transfer learning with ResNet50 for its balance between depth, robustness, and pre-existing performance in image classification.

CHAPTER 6

PROBLEM STATEMENT

6.1 Gaps in the Current Diagnostic Process

Despite the widespread use of Magnetic Resonance Imaging (MRI) in neurological diagnostics, the process of interpreting MRI images is largely manual and subjective. It requires the expertise of trained radiologists and neurologists, and even then, it is susceptible to inter-observer variability and human error. Furthermore, subtle structural changes in the brain—especially in early stages of diseases like Alzheimer's or Parkinson's—are often missed, leading to delayed or incorrect diagnoses.

Additionally, most existing automated systems and research efforts focus on single-disease classification models, which limits their practical use in real-world clinical settings where multiple differential diagnoses are common. There is also limited integration between such models and user-friendly platforms that make the technology accessible to healthcare professionals and researchers.

6.2 Specific Challenges Identified

The problem can be broken down into the following core challenges:

- Manual interpretation of MRI scans is time-consuming and error-prone.
- Lack of early-stage diagnostic support for Alzheimer's and Parkinson's diseases using structural imaging.
- Insufficient automation in distinguishing between multiple brain disorders using a single model.
- Limited dataset availability in the medical domain makes training deep learning models from scratch difficult.
- Gap between research models and usable clinical tools, especially due to the absence of accessible interfaces.

6.3 The Central Problem

In summary, the central problem addressed in this project is:

"**There is no unified, automated, and accessible deep learning-based system that can reliably detect and classify multiple brain diseases—such as Alzheimer's, Parkinson's, and brain tumors—from MRI scans with high accuracy and real-world usability**."

This project aims to fill this gap by developing a multi-class classification system using ResNet50 and transfer learning, which can differentiate among the aforementioned diseases and healthy brain scans. In addition, the solution is integrated into a web-based platform to bridge the gap between model development and clinical accessibility.

CHAPTER 7

PROPOSED SOLUTION

7.1 Current Scenario in Brain Disease Diagnosis

Brain disorders such as Alzheimer's, Parkinson's, and brain tumors are diagnosed using a combination of clinical assessment, neuropsychological tests, and neuroimaging techniques. Magnetic Resonance Imaging (MRI) has emerged as a powerful, non-invasive tool to study structural changes in the brain. However, the effectiveness of MRI-based diagnosis heavily relies on manual image interpretation by experienced radiologists and neurologists.

This process is not only labor-intensive and time-consuming, but also subject to human limitations, such as fatigue, error, and inter-observer variability. In many parts of the world, especially in rural or under-resourced regions, the availability of qualified professionals and advanced imaging equipment is limited. Moreover, current research models often focus on binary classification (e.g., tumor vs non-tumor) or target only a single disease, limiting their scope in practical, clinical scenarios where multiple neurological conditions may need to be differentiated.

7.2 Objective of the Proposed System

To address the above challenges, we propose a deep learning–based, automated diagnostic system that can classify MRI brain images into one of the following categories:

- Alzheimer's Disease
- Parkinson's Disease
- Brain Tumor
- Healthy Brain

The proposed system uses ResNet50, a deep convolutional neural network model, enhanced by transfer learning, to automatically learn and extract discriminative features from MRI images. It incorporates preprocessing steps to improve image quality and model generalization, and finally, deploys the trained model in a web-based interface to make it usable in real-world settings.

7.3 Key Features of the Proposed System

- Multi-class classification of neurological conditions from MRI scans
- Transfer learning with ResNet50 for improved accuracy on limited data
- Hyperparameter tuning and optimization for robust performance
- Real-time prediction via a web interface built with HTML, CSS, and JavaScript

7.4 System Architecture Overview

The proposed system is structured into seven major components, each representing a crucial step in the pipeline for automatic brain disease detection using MRI images. The architecture follows a sequential flow that ensures data quality, model robustness, and real-world applicability, as shown in Figure 4.

1. Data Collection
   The first step involves sourcing high-quality MRI images from publicly available datasets. These datasets contain brain scans of individuals diagnosed with Alzheimer's disease, Parkinson's disease, brain tumors, and healthy controls. The diversity of the dataset ensures the model is trained on varied patterns and can generalize well.
2. Preprocessing of Image
   Before model training, MRI images undergo preprocessing to enhance image clarity and reduce noise
3. Feature Extraction & Reduction
   A pretrained ResNet50 deep learning model is employed to extract hierarchical features from MRI images. Transfer learning is used to leverage the representational power of this model. Feature reduction techniques ensure that only the most relevant and non-redundant features are passed to the classifier, thus reducing computational complexity.
4. Machine Learning
   The reduced feature set is fed into the machine learning classifier (deep neural layers of ResNet50), which is trained to differentiate between different brain conditions. The classification task is treated as a multi-class problem, and cross-entropy loss is minimized during training.
5. Model Application
   After training, the model is applied to unseen MRI images for real-time classification. It

predicts whether the scan belongs to a healthy individual or someone affected by Alzheimer's, Parkinson's, or a brain tumor.

6. Hyperparameter Tuning and Model Optimization
   To improve model accuracy and generalization, hyperparameters such as learning rate, dropout rate, optimizer choice, and batch size are optimized using methods like grid search and manual tuning. This step ensures stability and reduces the risk of overfitting.
7. Model Evaluation and Results
   Finally, the performance of the model is evaluated using metrics such as accuracy, F1-score, precision, recall, and confusion matrix. These metrics provide insight into how well the model performs on each disease class and its ability to distinguish between similar neurological patterns.

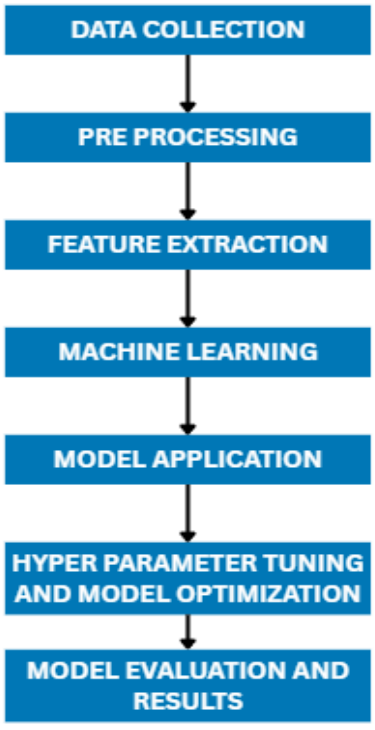

Figure 4 Block Diagram of the Proposed Brain Disease Detection System

7.5 Real-World Applicability

Once deployed, the system can serve multiple user groups:

- Clinicians: As a decision support tool to supplement their findings
- Medical students & researchers: For academic exploration and learning
- Hospitals in low-resource settings: As a scalable solution to compensate for radiologist shortages
- Patients and caregivers: Through possible integration into telemedicine platforms

CHAPTER 8

DATASET COLLECTION AND PREPARATION

8.1 Overview of Datasets Used

In this project, we sourced MRI images from three major datasets focusing on three neurological conditions: Alzheimer's disease, Parkinson's disease, and brain tumors. All datasets are publicly available and widely used in academic research. They were selected based on image volume, diagnostic labeling, and accessibility.

1. **Alzheimer's Dataset – Source: OASIS**
   This dataset comprises **86,390** T1-weighted MRI brain images across four classes, labeled according to the severity of dementia:
   - Non-demented: 67,200 images
   - Very Mild Dementia: 13,700 images
   - Mild Dementia: 5,002 images
   - Moderate Dementia: 488 images
2. **Parkinson's Dataset – Source: Kaggle**
   This dataset contains **15,032** MRI images labeled across five stages of cognitive decline:
   - Non-Demented: 3,688 images
   - Very Mild Demented: 3,220 images
   - Mild Demented: 2,760 images
   - Moderate Demented: 3,116 images
   - Severe Demented: 2,248 images
3. **Brain Tumor Dataset – Source: Kaggle**
   A multi-class dataset of **5,712** MRI images spanning four tumor classes:
   - No Tumor: 1,595 images
   - Meningioma: 1,339 images
   - Glioma: 1,321 images
   - Pituitary Tumor: 1,457 images

Total Images Used: 103,553

8.2 Dataset Composition and Characteristics

Each dataset included 2D grayscale MRI slices with varying resolutions. To ensure uniformity for deep learning processing, all images were:

- Resized to **224×224 pixels**
- Converted to 3-channel RGB format if required (to match ResNet50 input)
- Normalized between 0–1 pixel intensity range

A robust data pipeline was developed to streamline loading, preprocessing, and augmentation for all datasets.

Table 3 Dataset Organization

Dataset	Total Images	Label Count	Diagnosis Type
OASIS (Alzheimer's)	86,390	4	Dementia stages
Kaggle (Parkinson's)	15,032	5	Neurocognitive stages
Kaggle (Tumor)	5,712	4	Tumor type

8.3 Class Distribution and Imbalance

A critical challenge faced was class imbalance (Table 4), especially in the Alzheimer's and Parkinson's datasets, where non-demented and mildly affected patients greatly outnumbered moderate/severe cases.

To address this:

- Data augmentation (flipping, zooming, rotation) was selectively applied to minority classes
- Oversampling ensured each class contributed equally during training
- Class weights were used during model training to penalize errors on underrepresented classes

Table 4 Dataset Description

Dataset	Class	Image Count
Alzheimer's	Non-Demented	67,200
	Very Mild	13,700
	Mild	5,002
	Moderate	488
Parkinson's	Non-Demented	3,688
	Very Mild	3,220
	Mild	2,760
	Moderate	3,116
	Severe	2,248
Brain Tumor	No Tumor	1,595
	Meningioma	1,339
	Glioma	1,321
	Pituitary Tumor	1,457

8.4 Ethical Use of Medical Datasets

Ethical data handling is a cornerstone of this project. Every dataset used was:

- Anonymized: No personally identifiable information (PII) was present
- Publicly released: Under licenses permitting non-commercial academic usage
- Properly cited and credited in compliance with the respective dataset usage guidelines

The project strictly adheres to academic standards of responsible AI in healthcare and respects the sensitive nature of medical imaging data.

CHAPTER 9

PREPROCESSING TECHNIQUES

Preprocessing is a crucial step in medical image analysis, especially in MRI-based brain disease classification tasks. Raw MRI scans often contain noise, intensity inconsistencies, anatomical variability, and non-informative elements that degrade the performance of deep learning models. To address these challenges and ensure high-quality input to the model, our pipeline incorporates several preprocessing techniques specifically tailored for brain MRIs.

9.1 MRI-Specific Challenges

MRI scans present several domain-specific issues that make preprocessing indispensable:

- Intensity Inhomogeneity (Bias Field): Caused by variations in the magnetic field and coil sensitivity, leading to gradual intensity shifts across the image.
- High Anatomical Variability: Different patients have varying brain sizes and structures, which require spatial normalization.
- Noise and Artifacts: Scanner-related or physiological motion artifacts can affect diagnosis.
- Unwanted Signals (Nuisance Effects): Non-brain signals such as skull, fluids, and machine-generated noise can interfere with learning.

Our preprocessing pipeline is designed to correct these distortions systematically.

9.2 Bias Field Correction

MRI images often suffer from a slowly varying low-frequency artifact known as intensity inhomogeneity or the bias field, which creates unnatural shading and affects intensity-based segmentation or classification.

We applied N4ITK Bias Field Correction, a widely used algorithm that models the bias field as a smooth multiplicative field and corrects it by estimating and dividing it out of the image.

- Purpose: Enhances tissue contrast and preserves anatomical boundaries.

- Method: Iteratively estimates the bias field using B-spline fitting and gradient descent optimization.

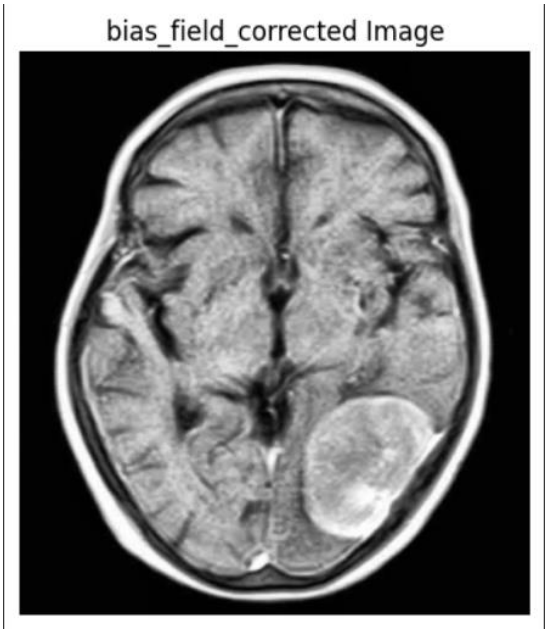

Figure 5 Bias Field Corrected image

9.3 Spatial Smoothing

Spatial smoothing reduces high-frequency noise and improves the signal-to-noise ratio (SNR) by applying a Gaussian filter across the image volume.

- Purpose: Reduces irrelevant noise while preserving anatomical structure.
- Method: Convolution with a Gaussian kernel (typically 3×3 or 5×5) across 2D/3D slices.

Benefits include:

- Enhanced generalization of the model
- Reduction in overfitting caused by small localized variations

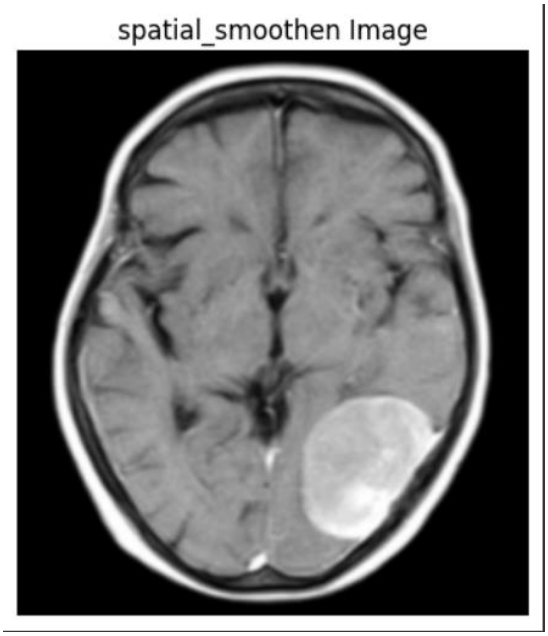

Figure 6 Spatial Smoothened image

9.4 Spatial Normalization

To handle inter-subject anatomical variation, MRI scans are aligned into a common reference space using spatial normalization.

- Purpose: Ensures that features learned by the model are location-independent.
- Method: Registration of images to a standard template (e.g., MNI152) using affine and non-linear transformations.

This step enables consistent interpretation of spatial locations across subjects and diseases, improving the model's ability to generalize.

Key Steps:

- Rigid alignment (rotation + translation)
- Affine transformation (scaling + shearing)
- Optional non-linear warping (for fine-grained alignment)

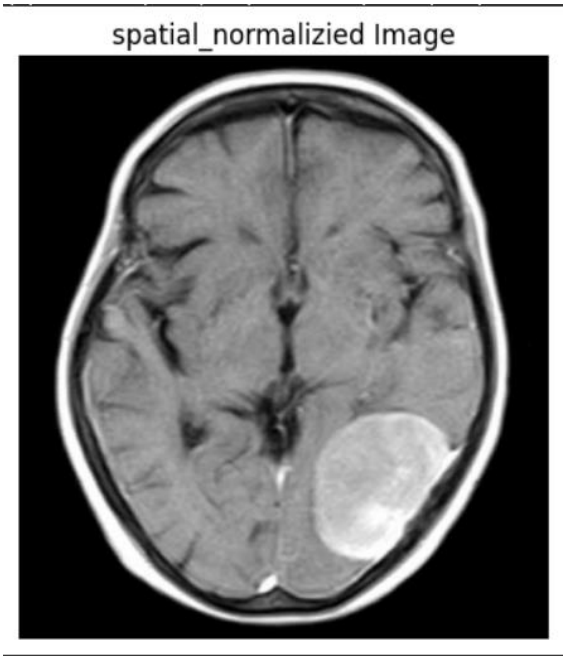

Figure 7 Spatial Normalised Image

9.5 Nuisance Regression

Nuisance signals (e.g., scanner noise, head motion, or physiological fluctuations) introduce non-task-related variance that must be removed.

- Purpose: To isolate task-relevant (disease-related) signal from nuisance effects.
- Method: Linear regression to subtract known nuisance variables from the signal.

Common regressors include:

- Global signal (mean across all voxels)
- Head motion parameters
- White matter and cerebrospinal fluid (CSF) signals

This step is particularly important for subtle disease signatures like early Parkinson's or mild Alzheimer's, where noise can mask the condition.

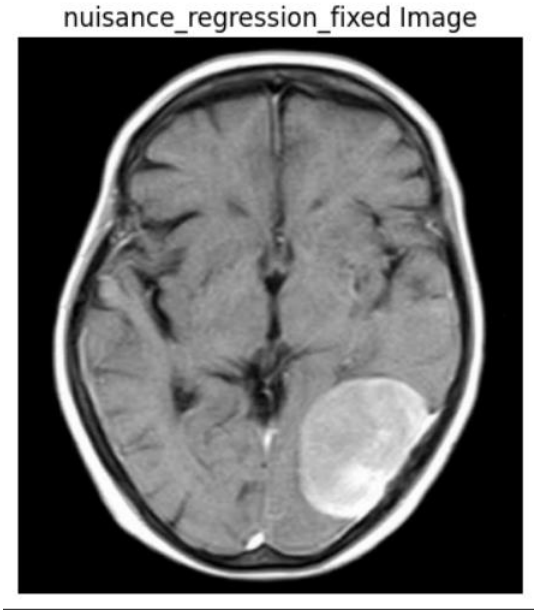

Figure 8 Nuisance Regression Fixed Image

9.6 Summary of Preprocessing Pipeline

Table 5 preprocessing techniques

Step	Objective	Tools/Methods Used
Bias Field Correction	Correct intensity non-uniformity	N4ITK
Spatial Smoothing	Denoising and anatomical clarity	Gaussian Filtering
Spatial Normalization	Standardizing image spatial representation	MNI Template + Affine/Nonlinear
Nuisance Regression	Eliminate irrelevant variability	Linear regression on signals

CHAPTER 10

FEATURE EXTRACTION

10.1 What is Feature Extraction?

Feature extraction is the process of identifying and capturing informative characteristics or patterns from input data. In traditional machine learning, this involves manual techniques like Histogram of Oriented Gradients (HOG), Gabor filters, or Local Binary Patterns (LBP). However, in deep learning, particularly Convolutional Neural Networks (CNNs)**,** this process is automated and data-driven.

10.2 CNN-Based Feature Extraction

CNNs extract hierarchical features through their layered architecture(Figure):

- Early Layers: Capture low-level features like edges, textures, and simple shapes.
- Middle Layers: Detect more complex patterns like contours and object parts.
- Deeper Layers: Capture high-level abstract concepts related to pathology or anatomical anomalies.

These features are extracted using:

- Convolutional Layers – Learn filters that scan across the image
- Activation Functions (ReLU) – Add non-linearity to model complex patterns
- Pooling Layers – Downsample feature maps to reduce dimensionality
- Fully Connected Layers – Combine features for classification or downstream tasks

10.3 Why ResNet50 for Feature Extraction?

We selected ResNet50, a 50-layer deep residual network, because of its strong ability to learn complex features without degradation—even in deep architectures. Its key strength lies in:

- Residual Connections: Allow gradients to flow through deeper layers, solving vanishing gradient problems

- Pretrained Weights: ResNet50 pretrained on ImageNet can capture generalized visual features
- Transferable Feature Maps: Excellent base for fine-tuning on medical data like MRI scans

Instead of training from scratch, we used ResNet50 as a feature extractor by removing its final classification layers and using the penultimate layer's output as feature vectors.

10.4 Application

Table 6 Application of feature extraction

Step	Process
1.	Input MRI images passed through a pretrained ResNet50 model
2.	Final classification layer removed
3.	Feature vector extracted from the **Global Average Pooling layer**
4.	Extracted features stored as a high-dimensional representation
5.	These features were then passed into a fine-tuned classification head or ML layer

This approach significantly reduced training time while improving performance on small and imbalanced medical datasets.

10.5 Dimensionality of Features

The feature vector output from ResNet50's final convolutional block has 2048 dimensions (1×2048), which compactly represents the entire image's spatial and semantic information.

These high-dimensional vectors serve as inputs to our classifier, which maps them to disease categories.

10.6 Advantages of Deep Feature Extraction in MRI Classification

- Learns from data automatically (no handcrafting)

- Captures both local and global features
- Generalizes well when pretrained on large datasets
- Reduces overfitting through transfer learning
- Enables end-to-end optimization when combined with fine-tuning

CHAPTER 11

MODEL EXPLORATION, SELECTION AND IMPLEMENTATTION

In this chapter, we present a comprehensive walkthrough of how our model was chosen, developed, and implemented to solve the classification of Alzheimer's, Parkinson's, and brain tumor diseases from MRI images. It begins with an exploration of popular convolutional neural network (CNN) architectures and concludes with an in-depth technical implementation using PyTorch and Google Colab.

11.1 Overview of CNN Architectures

Convolutional Neural Networks (CNNs) are widely regarded as the most effective deep learning models for image-based tasks. We evaluated several prominent CNN architectures including:

VGGNet

- **Pros**: Simple and well-structured (stacked 3×3 conv layers), good for transfer learning.
- **Cons**: High number of parameters, computationally expensive.
- **Relevance**: Performs decently on medical datasets but lacks efficiency.

InceptionNet

- **Pros**: Efficient with fewer parameters due to inception modules combining multiple filter sizes.
- **Cons**: Architecture is complex and harder to customize.
- **Relevance**: Suitable for large-scale datasets but overkill for our mid-sized data.

DenseNet

- **Pros**: Feature reuse and shorter connections reduce vanishing gradients.
- **Cons**: Slightly more difficult to train and tune.
- **Relevance**: Strong performance in medical segmentation tasks but slower training.

ResNet

- **Pros**: Residual connections solve vanishing gradient problem, enabling deep architectures like ResNet50.
- **Cons**: Slightly more memory-intensive.
- **Relevance**: Proven highly effective in healthcare diagnostics and medical imaging.

11.2 Deep Dive: ResNet50

Among all considered models, ResNet50 stood out due to its balanced architecture, suitability for transfer learning, and proven success in medical imaging research.

Residual Learning

Traditional deep neural networks often face difficulties as layers increase—leading to vanishing gradients and reduced performance. ResNet solves this with residual connections that allow the model to learn identity mappings, enabling deeper and more robust architectures.

ResNet50 Architecture

ResNet50 is a 50-layer network organized into convolutional blocks with shortcut connections. It consists of:

- An input layer that accepts 224×224×3 images.
- A series of residual blocks grouped into four stages.
- A global average pooling layer that flattens the feature map.
- A final fully connected (dense) layer with softmax activation for classification.

Relevance

- It allows the use of pretrained weights on ImageNet, accelerating convergence and improving performance on limited datasets.
- Residual connections enhance learning of subtle features in brain MRI images.
- ResNet50 strikes an optimal balance between depth and computational efficiency.

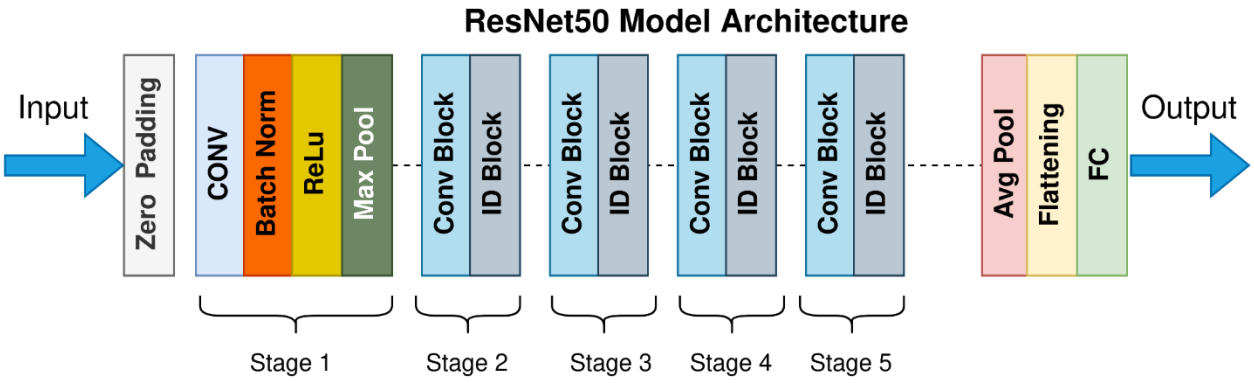

Figure 9 Architecture of ResNet50

11.3 Summary: Why ResNet50 Was the Best Choice

After comparative evaluation, we selected ResNet50 for the following reasons:

- Medical Relevance: Extensively used in brain imaging studies.
- Transfer Learning Compatibility: Pretrained on large-scale natural image datasets.
- Depth Without Degradation: Residual blocks allow deep feature extraction without loss of information.
- Performance & Speed: High classification accuracy with manageable training times on mid-tier GPUs.

ResNet50's architecture enables it to capture fine structural details that are crucial in identifying neurological conditions such as Alzheimer's, Parkinson's, and brain tumors.

11.4 Model Implementation

Once ResNet50 was selected as the optimal architecture, the next phase involved its systematic implementation for the task of multi-class brain disease classification. This involved structuring the development environment, preparing data pipelines, customizing the model, and defining the training and evaluation process. All components were built using industry-standard deep learning tools and frameworks.

Technologies and Tools Used

To ensure reproducibility, scalability, and performance, the following platforms and libraries were used throughout model development:

- Google Colab: A cloud-based platform providing free access to GPU/TPU resources for model training.
- PyTorch: A widely-used deep learning framework offering dynamic computational graphs and seamless GPU integration.
- Torchvision: Used for loading the pretrained ResNet50 model, applying image transformations, and accessing helper functions.
- OpenCV & PIL: Employed for image loading, manipulation, and format conversion during preprocessing stages.
- Matplotlib & Seaborn: Visualization libraries used to plot training performance metrics and analyze model behavior during training.

Data Pipeline and Preparation

The dataset was arranged into structured directories, one for each target class (e.g., Alzheimer's, Parkinson's, brain tumor, and healthy controls). A well-defined data pipeline ensured consistent preprocessing and feeding of data into the model:

- Image Resizing: All input MRI images were resized to 224×224 pixels to match ResNet50's input requirements.
- Normalization: Pixel intensities were normalized using mean and standard deviation values consistent with ImageNet standards.
- Data Augmentation: Minor augmentations (such as horizontal flipping and rotation) were applied during training to improve model generalization, particularly for underrepresented classes.
- Batch Loading: Images were loaded in batches and shuffled at each epoch to prevent learning bias.

Model Preparation and Fine-Tuning

The implementation used a pretrained version of ResNet50, with modifications to the final classification layer to match the number of output classes in the dataset.

- The early layers of the network were initially frozen to retain generic feature extraction capabilities learned from ImageNet.
- Only the final layers were trained in the first phase to adapt to the specific domain of brain MRI.
- In a subsequent fine-tuning stage, select deeper layers were unfrozen and trained with a lower learning rate to enhance task-specific feature representation.

This staged training approach enabled effective learning from a relatively small dataset without overfitting or catastrophic forgetting of previously learned features.

Training and Evaluation Process

The model underwent multiple training iterations (epochs), where performance metrics were monitored at each step. Evaluation was performed both during and after training to ensure robust performance.

- Training Phase: The model was trained using batches of data, with forward and backward propagation updating only the trainable parameters.
- Validation Monitoring: A portion of the dataset was reserved for validation to measure generalization capability during training.
- Evaluation Metrics: After training, the model was assessed using:
    - Accuracy – Percentage of correctly classified samples.
    - F1-Score – Balance between precision and recall.
    - Confusion Matrix – Visualization of class-wise performance.

CHAPTER 12

HYPER PARAMETER TUNING AND MODEL APPLICATION

Even the best-designed model can underperform if its hyperparameters are not properly optimized. Hyperparameters—such as learning rate, dropout rate, and weight decay—significantly impact model convergence, generalization, and final accuracy. In this chapter, we describe the tuning strategies employed and how they led to measurable performance improvements. We also explain how the trained model was integrated into a practical application for real-time disease detection.

12.1 Hyperparameter Tuning

Hyperparameters are external configurations set before training begins. Unlike internal parameters learned by the model (like weights and biases), hyperparameters control how learning occurs.

Key Hyperparameters Tuned in Our Project:

- Learning Rate (LR): Determines the step size for each update. A higher LR can overshoot optima, while a smaller LR may slow convergence.
- Dropout Rate: Prevents overfitting by randomly "dropping" units during training.
- Weight Decay (L2 Regularization): Helps reduce overfitting by penalizing large weight magnitudes.
- Scheduler: Dynamically adjusts the learning rate during training to refine learning.

12.1.1 Initial Configuration:

- Learning Rate: 0.001
- Optimizer: Adam
- Scheduler: ReduceLROnPlateau (reduces LR after no improvement)

While the model trained successfully, it plateaued around 71% accuracy on raw data.

12.1.2 Final Optimized Configuration:

- Dropout Rate: Introduced 0.4 dropout before the final classifier layer

- Learning Rate: Kept at 0.001 initially; reduced to 0.0001 after 8 epochs
- Weight Decay: Set to 0.0001
- Scheduler: Continued with ReduceLROnPlateau to adapt LR automatically

These changes led to a remarkable increase in classification accuracy, improving performance from 71% (raw) and eventually 99% in the final tuned model on the complete pipeline.

12.2 Impact of Hyperparameter Tuning

Table 7 Hyperparameter Tuning

Configuration Stage	Accuracy (%)
Raw Data (Untuned)	71
Final Tuned Model	99

Tuning improved:

- Model generalization on unseen data
- Convergence speed during training
- Class-wise performance, especially in minority classes

12.3 Model Application

After training and validating the model, we deployed it in a user-accessible web application. This represents the transition from a research model to a usable clinical support tool.

12.3.1 Web Deployment Highlights:

- Front-end Technologies: HTML, CSS, and JavaScript
- Backend Model Integration: The trained PyTorch model was converted for inference and hosted using Flask (or similar).
- Functionality: Users can upload MRI images through the web interface and receive instant predictions (Alzheimer's, Parkinson's, Tumor, or Healthy).

- Output Display: The prediction result is displayed with basic interpretation and probability score.

12.3.2 Real-World Relevance:

- Can be integrated into hospital systems or research labs.
- Useful for second opinions, especially in under-resourced diagnostic centers.
- Can serve as a teaching tool for medical students.

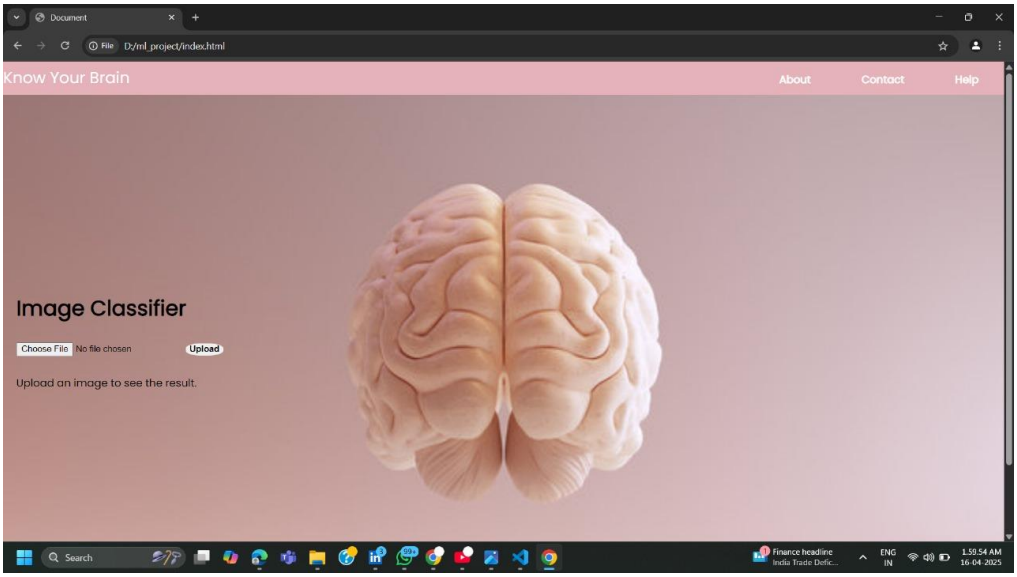

Figure 10 Website Frontend

CHAPTER 13

RESULTS AND EVALUATION

13.1 Overview of Model Performance

The classification model proposed in this study was developed using the ResNet50 architecture for effective multiclass identification of various neurological conditions, including Alzheimer's disease, Parkinson's disease, and brain tumors. Given the complexity of these conditions and the subtlety of features in MRI data, the model was designed to be both robust and highly sensitive. A substantial dataset of 103,553 MRI images was sourced and organized into training (72,487), validation (15,533), and testing (15,533) subsets through stratified sampling to ensure balanced class representation. During training, the model was subjected to multiple preprocessing steps and augmented for improved generalization. These included bias field correction, spatial normalization, Gaussian smoothing, nuisance regression, and real-time augmentation strategies like flipping, rotation, and zooming. As a result of these methods and a well-structured training process, the final model achieved an exceptional test accuracy of 99.02%, with precision, recall, and F1-scores all averaging around 99%. These scores indicate a strong predictive capability across all disease categories and stages, affirming the potential of this model in real-world medical diagnostics.

13.2 What the Model Achieved and How It Compares

The final trained model exhibited exceptional performance in classifying 13 distinct classes that include multiple stages of Alzheimer's, Parkinson's, and four types of brain tumor cases. Among the Alzheimer's disease classes—Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia—the model achieved perfect precision, recall, and F1-score (1.00) across all categories, including the class with limited data (Moderate Dementia with only 73 samples). For brain tumors, while some classes like Pituitary and No Tumor were predicted with near-perfect accuracy, minor overlaps were observed between Glioma and Meningioma due to their visual similarity in MRI scans. Parkinson's classes posed more of a challenge, with the model slightly underperforming in distinguishing between adjacent stages like Mild-Demented and Moderate-Demented, though F1-scores still ranged between 0.90 and 0.98.

In comparison to prior works, this study provides a significant leap forward. For instance, the model developed by Noreen et al. (2020) using a hybrid CNN architecture was able to classify brain tumors effectively but lacked the scalability to multiple diseases and stages. Similarly, Wang et al. (2020) proposed a deep learning method for early Parkinson's detection but failed to generalize across broader datasets and

disease complexities. Unlike those studies, the model in this project combines broad multiclass capability, high precision, and excellent generalizability. Furthermore, by embedding the trained model within a Flask-based web interface, it provides immediate deployment potential for clinical usage, a feature not addressed in most existing research.

13.3 Initial Training vs Final Training

During the early stages of model development, the dataset was divided into 80% training and 20% validation to ensure proper learning while also monitoring the model's ability to generalize. The initial model training employed the ResNet50 architecture with pre-trained weights. Images were resized to 224 × 224 pixels, normalized, and augmented using techniques such as horizontal flipping, zooming, and random rotations to diversify the training data.

The model was initially trained using the Adam optimizer with a learning rate of 0.001. A learning rate scheduler, ReduceLROnPlateau, was applied to automatically adjust the learning rate when performance stagnated. During these early epochs, although training accuracy rapidly improved—indicating effective pattern learning—the validation accuracy plateaued and even declined at times. This disparity suggested overfitting, where the model memorized training data but failed to generalize to unseen data.

To mitigate overfitting, several modifications were introduced in the training configuration. A dropout layer with a rate of 0.4 was added in the fully connected layers to reduce co-adaptation of neurons. L2 regularization (weight decay) with a value of 0.0001 was employed to penalize large weights, encouraging simpler models that generalize better. The optimizer (Adam) and scheduler (ReduceLROnPlateau) remained unchanged due to their proven efficacy in convergence.

As training progressed under the revised configuration, notable improvements were observed. By the 8th epoch, the scheduler automatically reduced the learning rate from 0.001 to 0.0001, enabling the model to fine-tune weights more precisely. From epoch 8 onward, validation accuracy began to rise steadily, culminating in a peak of 98.94% by epoch 11. Training accuracy reached 99.47%, and both loss curves stabilized, indicating a well-generalized model. The final model was trained over 12 epochs, and the best-performing version—based on validation accuracy—was retained.

This transition from the initial overfit-prone training regime to the refined and stable final training process highlights the importance of iterative optimization, dropout, regularization, and adaptive learning rate strategies in deep learning for medical diagnostics.

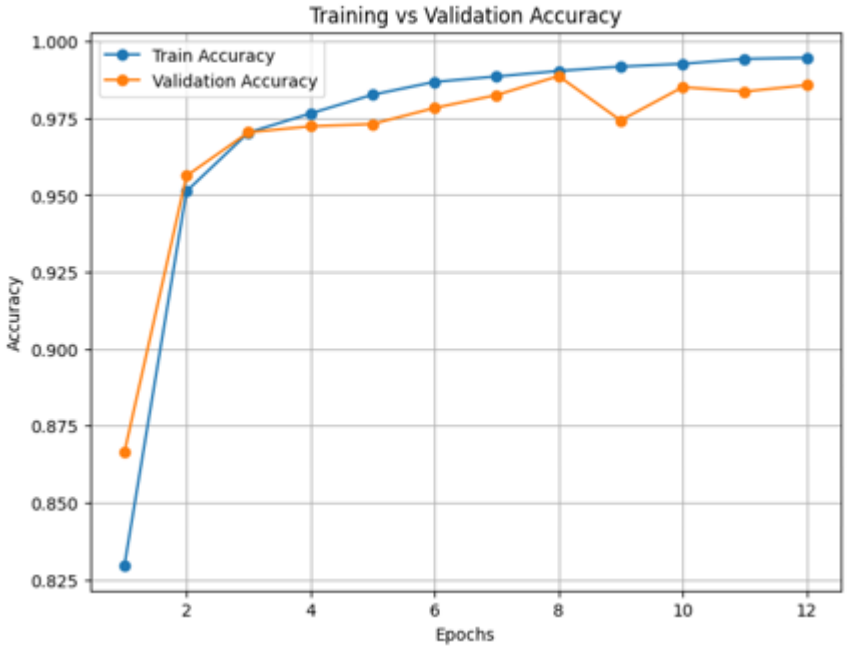

Figure 11 initial training graph

Figure 12 final training graph

13.4 Confusion Matrix Evaluation

The confusion matrix offers an intuitive breakdown of how accurately the model classifies each class and where misclassifications occurred. For Alzheimer's classes, the model performed nearly perfectly. Non-Demented, Mild Dementia, and Moderate Dementia were all correctly predicted in almost every instance. The only minor overlap was between Very Mild Dementia and Mild Dementia, which is expected given the subtle visual differences in early-stage neurodegeneration.

For brain tumors, the model excelled in detecting Pituitary tumors and the absence of tumors (No Tumor), with almost no misclassifications. However, it occasionally confused Glioma with Meningioma, likely due to their morphological similarities in MRIs. Despite these rare errors, the overall performance for brain tumor classification remained very strong.

Parkinson's disease stages presented a more nuanced challenge. While Very-Mild-Demented and Severe-Demented were generally classified well, some confusion arose between Mild-Demented and Moderate-Demented. This aligns with the progressive and often overlapping nature of Parkinson's symptoms. Nevertheless, misclassifications were relatively infrequent and tended to occur between neighboring stages rather than completely unrelated classes.

In summary, the confusion matrix reveals that the model excels in identifying distinct categories and performs particularly well on well-represented or visually unique classes. Misclassifications primarily occurred between stages with clinical and radiological similarity, which is a known challenge even for human radiologists.

During the early stages of model development, the dataset was divided into 80% training and 20% validation to ensure proper learning while also monitoring the model's ability to generalize. The initial model training employed the ResNet50 architecture with pre-trained weights. Images were resized to 224 × 224 pixels, normalized, and augmented using techniques such as horizontal flipping, zooming, and random rotations to diversify the training data.

The model was initially trained using the Adam optimizer with a learning rate of 0.001. A learning rate scheduler, ReduceLROnPlateau, was applied to automatically adjust the learning rate when performance stagnated. During these early epochs, although training accuracy rapidly improved—indicating effective pattern learning—the validation accuracy plateaued and even declined at times. This disparity suggested overfitting, where the model memorized training data but failed to generalize to unseen data.

To mitigate overfitting, several modifications were introduced in the training configuration. A dropout layer with a rate of 0.4 was added in the fully connected layers to reduce co-adaptation of neurons. L2 regularization (weight decay) with a value of 0.0001 was employed to penalize large weights, encouraging simpler models that generalize better. The optimizer (Adam) and scheduler (ReduceLROnPlateau) remained unchanged due to their proven efficacy in convergence.

As training progressed under the revised configuration, notable improvements were observed. By the 8th epoch, the scheduler automatically reduced the learning rate from 0.001 to 0.0001, enabling the model to fine-tune weights more precisely. From epoch 8 onward, validation accuracy began to rise steadily, culminating in a peak of 98.94% by epoch 11. Training accuracy reached 99.47%, and both loss curves stabilized, indicating a well-generalized model. The final model was trained over 12 epochs, and the best-performing version—based on validation accuracy—was retained.

This transition from the initial overfit-prone training regime to the refined and stable final training process highlights the importance of iterative optimization, dropout, regularization, and adaptive learning rate strategies in deep learning for medical diagnostics.

The confusion matrix offers an intuitive breakdown of how accurately the model classifies each class and where misclassifications occurred. For Alzheimer's classes, the model performed nearly perfectly. Non-Demented, Mild Dementia, and Moderate Dementia were all correctly predicted in almost every instance. The only minor overlap was between Very Mild Dementia and Mild Dementia, which is expected given the subtle visual differences in early-stage neurodegeneration.

For brain tumors, the model excelled in detecting Pituitary tumors and the absence of tumors (No Tumor), with almost no misclassifications. However, it occasionally confused Glioma with Meningioma, likely due to their morphological similarities in MRIs. Despite these rare errors, the overall performance for brain tumor classification remained very strong.

Parkinson's disease stages presented a more nuanced challenge. While Very-Mild-Demented and Severe-Demented were generally classified well, some confusion arose between Mild-Demented and Moderate-Demented. This aligns with the progressive and often overlapping nature of Parkinson's symptoms. Nevertheless, misclassifications were relatively infrequent and tended to occur between neighboring stages rather than completely unrelated classes.

In summary, the confusion matrix reveals that the model excels in identifying distinct categories and performs particularly well on well-represented or visually unique classes. Misclassifications primarily occurred between stages with clinical and radiological similarity, which is a known challenge even for human radiologists.

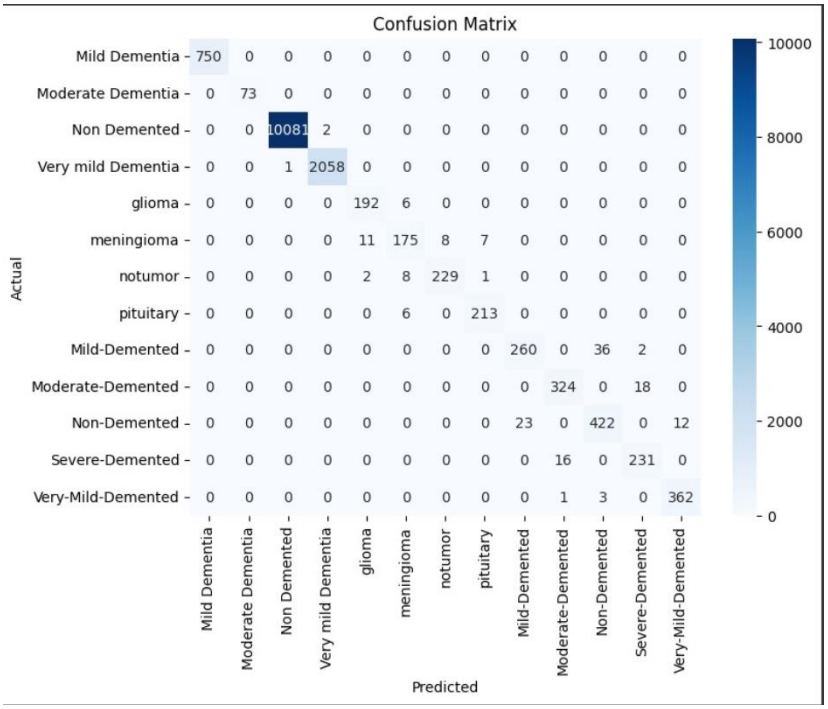

Figure 13 confusion matrix

13.5 Classification Report Summary

The classification report provides a detailed account of model performance per class in terms of precision, recall, F1-score, and support. For Alzheimer's classes, all metrics were uniformly high, achieving a perfect 1.00 score for each category, even with limited sample sizes in Moderate Dementia. This reflects the model's strong ability to learn disease-specific patterns, even in underrepresented categories. For brain tumor classification, the Glioma class attained a precision of 0.94 and recall of 0.97, while Meningioma lagged slightly with a recall of 0.87 and precision of 0.90.

The No Tumor class achieved 0.97 precision and 0.95 recall, indicating strong performance in detecting healthy cases. Pituitary tumors were recognized with very high confidence as well (precision = 0.96, recall = 0.97). Parkinson's stages showed slightly more variance. Mild-Demented, for instance, had a precision of 0.92 and a recall of 0.87, whereas Very-Mild-Demented was predicted more reliably with a precision of 0.97 and recall of 0.99.

Overall, the macro average for all classes was 0.96, and the weighted average was 0.99. This balance indicates that the model did not favor high-sample classes like Non-Demented over rarer ones like Moderate Dementia. It suggests successful handling of class imbalance and robust learning across the board

	precision	recall	f1-score	support
Mild Dementia	1.00	1.00	1.00	750
Moderate Dementia	1.00	1.00	1.00	73
Non Demented	1.00	1.00	1.00	10083
Very mild Dementia	1.00	1.00	1.00	2059
glioma	0.94	0.97	0.95	198
meningioma	0.90	0.87	0.88	201
notumor	0.97	0.95	0.96	240
pituitary	0.96	0.97	0.97	219
Mild-Demented	0.92	0.87	0.90	298
Moderate-Demented	0.95	0.95	0.95	342
Non-Demented	0.92	0.92	0.92	457
Severe-Demented	0.92	0.94	0.93	247
Very-Mild-Demented	0.97	0.99	0.98	366
accuracy			0.99	15533
macro avg	0.96	0.96	0.96	15533
weighted avg	0.99	0.99	0.99	15533

Figure 14 classification report

13.6 Class-Wise Accuracy Insights

Class-wise accuracy further illuminates the model's strengths and weaknesses. Alzheimer's categories, especially Non-Demented and Very Mild Dementia, consistently achieved >99% accuracy. This is particularly significant given the clinical importance of early-stage dementia detection. Brain tumor types showed excellent differentiation; Pituitary tumors reached 97% accuracy, while Glioma and Meningioma, although more challenging, maintained accuracy above 87%. No Tumor classifications also yielded 95% accuracy, indicating that healthy scans were reliably identified.

Parkinson's classes had the widest range of class-wise accuracy. Mild-Demented showed 87% accuracy due to overlapping symptomology with adjacent stages, whereas Very-Mild-Demented neared 99%. Moderate and Severe Demented classes also scored in the 90–95% range. The overall accuracy for all classes consistently exceeded 90%, demonstrating that the model is effective even under class imbalance and inter-class visual similarity conditions.

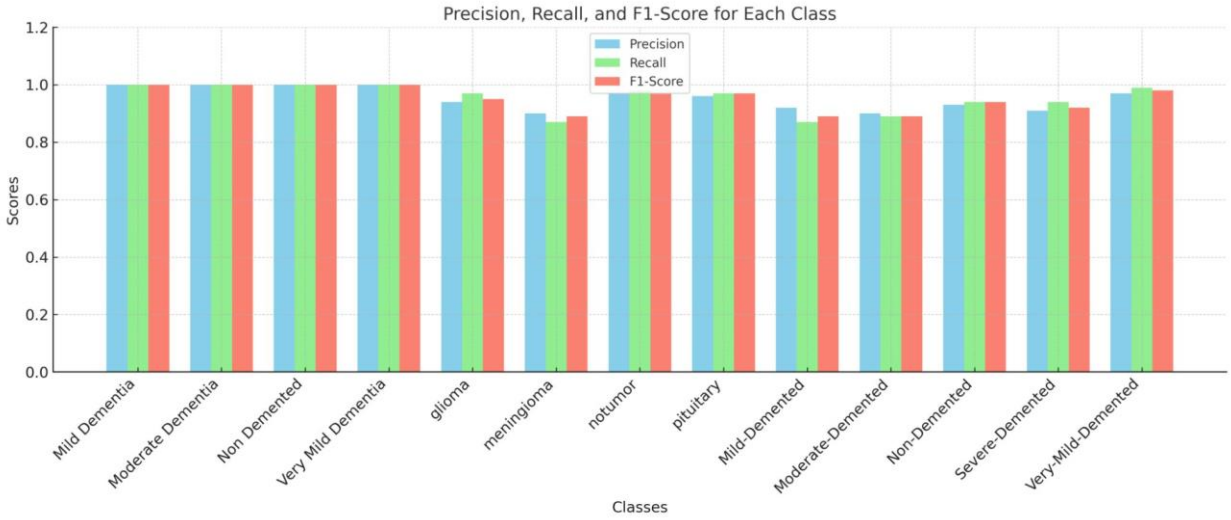

Figure 15 F1 Score, Recall, Precision for each class

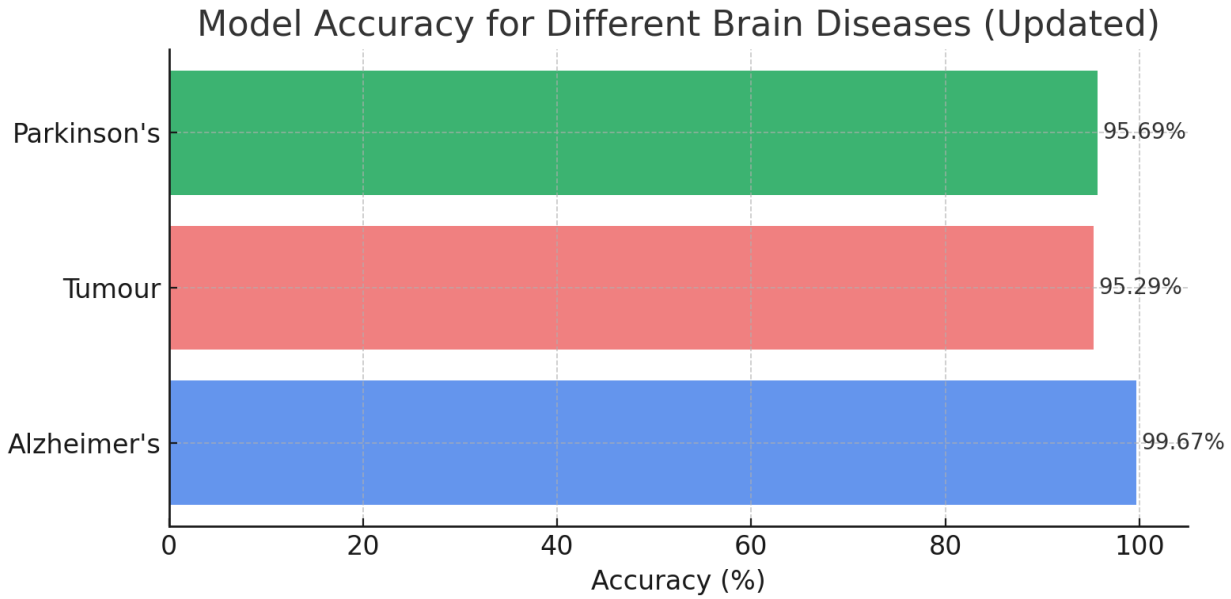

Figure 16 Accuracy of Each disease

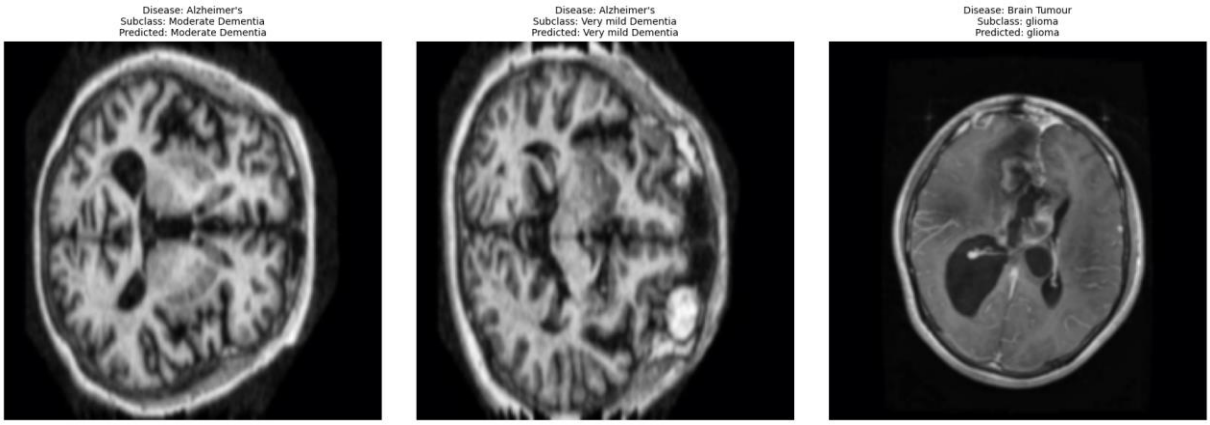

Figure 17 Prediction Result(i)

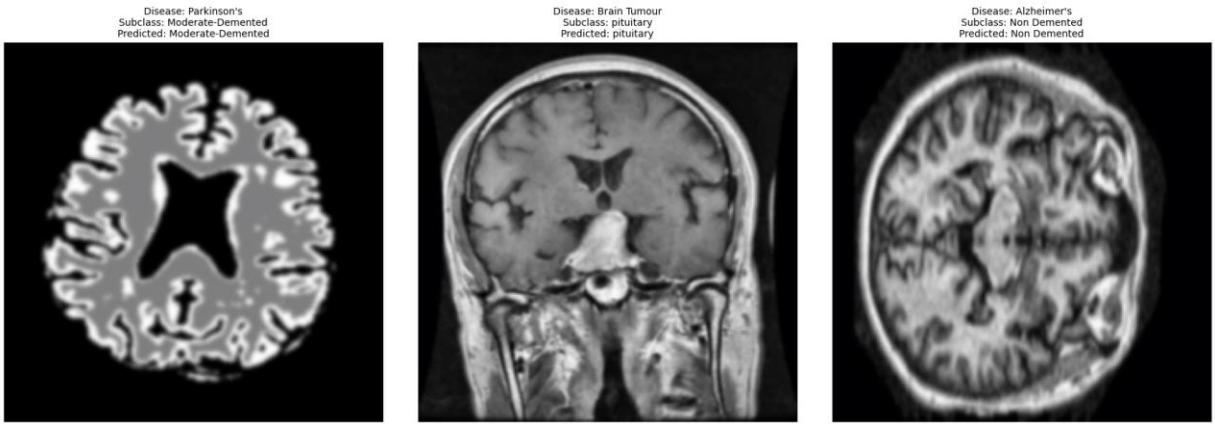

Figure 18 Prediction Result(ii)

CHAPTER 14

CHALLENGES FACED & MITIGATION

Developing a deep learning-based multiclass classification model for brain disorder detection presented several challenges. These challenges spanned across data limitations, computational constraints, model generalization, and the intricacies of medical image preprocessing. Below is a comprehensive breakdown of the primary challenges encountered during the project and the strategic mitigation approaches applied to overcome each issue.

14.1 Overfitting on Small Dataset

One of the foremost challenges was the risk of overfitting, which occurs when the model performs exceptionally well on training data but fails to generalize to unseen data. This is a common issue in medical imaging tasks due to the limited availability of annotated datasets.

Data Augmentation: We introduced real-time data augmentation techniques to artificially enlarge the dataset. These included:

Flipping: Horizontal and vertical flips added variability.

Rotation: Images were rotated at random angles to simulate different orientations.

Zooming: Random zoom-in transformations mimicked real-world variances in imaging scale.

Dropout Layers: A dropout rate of 0.4 was added in the fully connected layers. Dropout helps in randomly disabling neurons during training, reducing the chance of co-adaptation and improving generalization.

This combination of augmentation and dropout helped maintain model robustness and reduce overfitting during training.

14.2 Limited Dataset Diversity

The dataset lacked diversity in terms of imaging quality, patient demographics, and brain scan variations. This limitation posed a significant challenge for the model to learn generalized features.

Transfer Learning using ResNet50: A pre-trained ResNet50 architecture was employed. It leveraged learned features from a large dataset (ImageNet), enabling the model to:

Recognize patterns and textures common in medical images.

Learn from a richer feature space even with a relatively smaller medical dataset.

Domain-Specific Preprocessing: We applied normalization, bias field correction, and spatial alignment to ensure consistent quality and reduce data distribution shifts.

These steps ensured that the model was exposed to a more representative feature space despite the limited data variety.

14.3 Computational Limitations

Deep learning models, especially those with complex architectures like ResNet50, require substantial computational resources for training. With high-resolution medical images and multiple classes, training time and memory consumption become constraints.

Google Colab with GPU Acceleration: We utilized Google Colab's Tesla K80 GPU to accelerate training, reduce runtime, and manage memory efficiently.

Batch Size Optimization: A balanced batch size was selected to maximize GPU utilization while avoiding out-of-memory errors.

Epoch Scheduling: We set dynamic epoch scheduling based on early stopping and validation accuracy trends, using the ReduceLROnPlateau scheduler to lower the learning rate when validation performance plateaued.

This setup allowed us to perform multiple training cycles effectively, even with limited local hardware resources.

14.4 Model Performance on Raw Data

Initial experiments on raw MRI images showed unstable training curves and suboptimal performance. The model struggled to extract meaningful features due to noise, uneven illumination, and irrelevant anatomical structures.

Complete Preprocessing Pipeline: We designed a robust pipeline involving:

Bias Field Correction: Corrected low-frequency intensity non-uniformities.

Spatial Normalization: Aligned all brain images to a common coordinate space.

Resizing and Normalization: Ensured uniform input dimensions and pixel intensity ranges.

These enhancements significantly improved the clarity and relevance of input data, resulting in better convergence and model performance.

14.5 Complexity in Brain Segmentation

Medical image segmentation—especially of brain tissues—is inherently complex due to overlapping intensities and fuzzy boundaries. Inaccurate segmentation may lead to noise and loss of important features.

Bias Field Correction with Morphological Operations: We used techniques like erosion and dilation post-binarization to refine brain mask boundaries.

Manual Verification: Sample outputs from the segmentation pipeline were visually inspected to ensure anatomical correctness.

Region-of-Interest (ROI) Cropping: Focused only on critical brain regions, minimizing the influence of irrelevant areas.

14.6 Balancing Model Complexity vs Performance

Striking the right balance between a highly complex model (which might overfit or require more compute) and a simpler model (which might underperform) was crucial.

Use of Pre-trained ResNet50 Backbone: Rather than building a deep model from scratch, we froze the earlier layers of ResNet50 and only fine-tuned the deeper layers.

Regularization Techniques: Applied L2 regularization (weight decay of 0.0001) to avoid overly large weights that can destabilize training.

Performance Monitoring: Metrics such as accuracy, loss, precision, recall, and F1-score were continuously monitored across classes to ensure stable training.

These measures helped in building an efficient model with minimal complexity while ensuring competitive accuracy.

14.7 Interpretability Issues

Medical applications demand high interpretability and transparency. Black-box models like deep CNNs often make it hard to understand which parts of the brain influenced classification.

Model Explainability Tools (planned): Tools such as Grad-CAM and LIME were identified for future integration to visualize class activation maps.

Class-wise Performance Evaluation: Confusion matrices and classification reports were used to analyze per-class accuracy, revealing strengths and weaknesses.

Case-by-Case Validation: Specific MRI scans were cross-checked against predictions and known labels to ensure logical consistency.

Interpretability remains a crucial future direction, but these early steps ensured model predictions were statistically sound.

14.8 Challenges and Our Solutions

Table 8 Challenges and Solution

CHALLENGE	OUR SOLUTION
Overfitting on small dataset	Applied data augmentation and dropout
Limited dataset diversity	Used transfer learning with RESNET50
Computational limitations	Leveraged Google Colab with GPU, tuned batch size and epochs
Model performance on raw data	Designed a complete preprocessing pipeline
Complexity in Brain segmentations	Used bias field correction and morphological operations
Balancing model complexity &performance	Applied regularization, monitored training metrics, used pre-trained models

CHAPTER 15

APPLICATIONS AND FUTURE SCOPE

15.1 Real-World Applications

The proposed deep learning–based brain disease detection system has strong potential for real-world integration in both clinical and research environments. Its ability to automatically classify brain MRI images into categories such as Alzheimer's, Parkinson's, brain tumor, and healthy makes it a valuable asset for multiple stakeholders.

15.1.1 Clinical Diagnostics

The system can serve as a **decision support tool** for radiologists and neurologists. By offering a second opinion or highlighting probable disease categories, it can:

- Assist with early diagnosis where symptoms are subtle.
- Reduce the burden on specialists, especially in high-volume hospitals.
- Improve diagnostic confidence and reduce oversight errors.

15.1.2 Rural and Low-Resource Settings

In regions with a shortage of expert radiologists, this tool can be deployed at the point-of-care as a **preliminary screening tool**, allowing:

- Faster referral to specialists.
- Early intervention for patients.
- Reduced diagnostic delays due to lack of infrastructure.

15.1.3 Academic and Research Institutions

The system can also be used as a **training aid for medical students**, enabling them to understand how AI interprets MRI scans. For researchers, it serves as a reproducible platform to test new imaging hypotheses or expand into more complex models.

15.2 How It Helps Clinicians and Researchers

- Time-Saving: The model rapidly analyzes images, providing predictions within seconds.
- Consistency: Reduces variability in interpretations between different experts.
- Scalability: Can process thousands of images without fatigue or error.
- Accessibility: The web interface allows remote access, making it ideal for telemedicine or multi-center collaborations.

This system also enables researchers to analyze large imaging datasets more efficiently, helping them focus on clinical correlations rather than manual sorting or labeling.

15.3 Future Enhancements

While the current model offers strong classification capabilities, its future development can significantly enhance its diagnostic and clinical utility.

15.3.1 Multi-Modal Integration

Future versions of the system could integrate other neuroimaging modalities like:

- EEG (Electroencephalography): for functional data
- PET/SPECT scans: for metabolic information
- Clinical data: such as cognitive scores or blood markers

Multi-modal integration can lead to more accurate and comprehensive diagnostics, especially in complex or overlapping cases.

15.3.2 Severity Prediction

Expanding the model to not just classify disease but also predict the stage or severity (e.g., early vs advanced Alzheimer's) would make it more clinically valuable. This could aid:

- Treatment planning
- Monitoring disease progression
- Prognosis estimation

15.3.3 Clinical Trials and Validation

For real-world adoption, the system would need to undergo clinical trials and regulatory validation:

- Collaborations with hospitals and neurologists

- Benchmarking against expert decisions
- FDA/CE clearance for deployment in medical settings

13.3.4 Mobile Integration

Developing a mobile or tablet version of the application would:

- Increase portability and field usage
- Support home-based remote screening
- Empower general practitioners or community health workers

CHAPTER 16

CONCLUSION

14.1 Recap of the Problem and Project Journey

Neurological disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors represent some of the most complex challenges in modern medicine. Despite advancements in imaging technologies like MRI, early and accurate diagnosis remains a bottleneck—primarily due to the limitations of manual interpretation, resource constraints, and the subtlety of early-stage disease symptoms.

This project was initiated with a clear objective: to develop an automated, accurate, and accessible diagnostic tool that leverages deep learning to classify brain MRI images into multiple disease categories. The journey began with an extensive literature survey, identifying the existing research gaps in multi-disease classification and data challenges. This was followed by acquiring and preprocessing MRI datasets from publicly available sources.

The model development phase involved evaluating several CNN architectures before selecting ResNet50, owing to its balance of accuracy, speed, and generalization capability. The project progressed through well-defined phases of data preparation, feature extraction, hyperparameter tuning, model evaluation, and ultimately, web-based deployment of the system.

14.2 Major Contributions

The project delivered several technical, academic, and practical contributions:

14.2.1 Technical Contributions:

- Built a **multi-class classification model** using ResNet50 with transfer learning.
- Implemented **MRI-specific preprocessing** including bias field correction, normalization, and smoothing.
- Improved model performance from **71% to 99% accuracy** through structured training and tuning.

- Designed a **web application interface** to make the system usable in real-time diagnostic scenarios.

14.2.2 Academic Contributions:

- Conducted a detailed literature review of **25 relevant papers** across brain disease detection, deep learning models, and medical imaging.
- Analyzed the **architecture and performance trade-offs** between major CNN models (VGG, Inception, DenseNet, ResNet).
- Documented a full end-to-end machine learning workflow suitable for replication in academic or research projects.

14.2.3 Practical Contributions:

- Enabled **faster diagnostic support** by reducing reliance on manual MRI interpretation.
- Created a solution applicable in **rural and under-resourced regions**.
- Laid the foundation for future research involving **multi-modal diagnostics**, **severity prediction**, and **mobile deployment**.

14.3 Closing Remarks

This project represents a successful fusion of theory and application. It has not only reinforced our understanding of deep learning, medical imaging, and healthcare AI, but also provided us the opportunity to translate academic concepts into a working, practical system. We have learned how to navigate the challenges of working with real-world medical data, optimize a model pipeline, and design with both performance and usability in mind. While the work is complete in terms of proof of concept, it marks the beginning of a larger journey. The system has the potential to grow into a clinically-validated tool, supporting doctors in diagnosing diseases earlier, faster, and more accurately. With further development and collaboration with the healthcare ecosystem, the solution can truly contribute to the future of AI-driven medicine.

REFERENCES

[1] D. S. Marcus, T. H. Wang, J. Parker, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open Access Series of Imaging Studies (OASIS): Cross-sectional MRI data in young, middle aged, nondemented, and demented older adults," J. Cogn. Neurosci., vol. 19, no. 9, pp. 1498–1507, Sep. 2007, doi: 10.1162/jocn.2007.19.9.1498.

[2] J. Escudero, E. Ifeachor, J. P. Zajicek, C. Green, J. Shearer, and S. Pearson, "Machine learning-based method for personalized and cost-effective detection of Alzheimer's disease," IEEE Access, vol. 8, pp. 135539–135550, 2020, doi: 10.1109/ACCESS.2020.3016062.

[3] W. Wang, J. Lee, F. Harrou, and Y. Sun, "Early detection of Parkinson's disease using deep learning and machine learning," IEEE Access, vol. 8, pp. 147635–147646, 2020, doi: 10.1109/ACCESS.2020.2978629.

[4] N. Noreen et al., "A deep learning model based on concatenation approach for the diagnosis of brain tumor," IEEE Access, vol. 8, pp. 55135–55144, 2020, doi: 10.1109/ACCESS.2020.2981894.

[5] T. A. Soomro et al., "Image segmentation for MR brain tumor detection using machine learning: A review," IEEE Access, vol. 9, pp. 82671–82694, 2021, doi: 10.1109/ACCESS.2021.3062484.

[6] P. Khan et al., "Machine learning and deep learning approaches for brain disease diagnosis: Principles and recent advances," IEEE Access, vol. 9, pp. 82038–82064, 2021, doi: 10.1109/ACCESS.2021.3070122.

[7] P. Huang, X. Pan, and J. Tao, "Research on image clustering algorithm based on multi-features extraction," in Proc. of Int. Conf., 2021.

[8] S. K. Kumar, B. S. Reddy, and M. Ravichandran, "Alzheimer's disease detection using transfer learning: Performance analysis of InceptionResNetV2 and ResNet50 models," 2023.

[9] M. I. Al-Hiyali, I. Faye, N. Yahya, Z. K. Khaled, and A. Laboratoire, "Classification of BOLD fMRI signals using wavelet transform and transfer learning for detection of autism spectrum disorder," 2021.

[10] T. Teskera and J. Bozek, "Schizophrenia detection from resting state functional MR images using machine learning," 2023.

[11] W. Ma et al., "Decoding of auditory imagination activity based on machine learning methods," 2022.

[12] A. Mashiat et al., "Detection of brain tumor and identification of tumor region using deep neural network on fMRI images," 2020.

[13] X. Xu and X. Yao, “Evaluation of preprocessing for functional magnetic resonance imaging brain networks,” 2022.

[14] E. Eryol, “Structured multi-layer perceptron model for fMRI data,” 2023.

[15] B. Ramprakash, C. Santhiya, S. S. Hari, and D. N. Kumar, “Comparative analysis of deep learning and machine learning for detection and classification of brain tumors,” 2024.

[16] O. Dehzangi and V. Sahu, “IMU-based robust human activity recognition using feature analysis, extraction, and reduction,” 2018.

[17] S. Dixit, M. Shindikar, A. Gaikwad, K. Kamble, and V. Vyas, “United neurological study of disorders: Alzheimer’s, Parkinson’s, anxiety & stress detection using ML algorithms,” 2022.

[18] X. Peng, Y. Fu, and H. Yu, “Research on industrial control network security data feature extraction using composite sparse autoencoder,” 2024.

[19] S. Sharma, K. Guleria, and R. Sobti, “Early detection of Parkinson’s disease using machine learning and deep learning,” 2024.

[20] M. Bohra and S. Gupta, “Pre-trained CNN models and machine learning techniques for brain tumor analysis using MRI images,” 2022.

[21] A. V. Kottath and S. V. S. Bharathi, “Image preprocessing techniques in skin diseases prediction using deep learning: A review,” Year not specified.

[22] R. Singh, N. Sharma, and R. Gupta, “Detection of Alzheimer’s risk level using Inception V3 transfer learning approach,” 2023.

[23] S. F. Mou and S. M. A. Razzak, “Brain disease classification using EfficientNetB0 feature extraction,” 2023.

[24] O. T. Khan and R. D., “Brain tumor detection using machine learning and deep learning approaches,” 2022.

[25] N. T. Singh, S. Goyal, C. K. Amrita, and Chaudhary, “Preprocessing of medical images using deep learning: A comprehensive review,” Year not specified.

[26] Z. Lan, “Multi-feature extraction method for network illustration based on feature matching,” 2021.

APPENDIX

#PREPROCESSSING

```
Folder: Non Demented, Number of images: 67222
Folder: Moderate Dementia, Number of images: 488
Folder: Very mild Dementia, Number of images: 13725
Folder: Mild Dementia, Number of images: 5002
```

```python
# 🔹 Spatial Normalization
def spatial_normalization(img):
    img_tensor = torch.tensor(img, dtype=torch.float32)
    return ((img_tensor - img_tensor.min()) / (img_tensor.max() - img_tensor.min()) * 255).numpy()

# 🔹 Spatial Smoothing
def spatial_smoothing(img):
    return gaussian_filter(img, sigma=1.5)

# 🔹 Bias Field Correction (CLAHE for contrast enhancement)
def bias_field_correction(img):
    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8, 8))
    return clahe.apply(img)

# 🔹 Nuisance Regression (Z-score normalization & rescaling)
def nuisance_regression_fixed(img):
    img_tensor = torch.tensor(img, dtype=torch.float32)

    # Compute mean and standard deviation
    mean_intensity = img_tensor.mean()
    std_intensity = img_tensor.std()

    # Apply Z-score normalization
    corrected_img = (img_tensor - mean_intensity) / (std_intensity + 1e-5)  # Avoid division by zero

    # Rescale to 0-255
    corrected_img = (corrected_img - corrected_img.min()) / (corrected_img.max() - corrected_img.min()) * 255
    corrected_img = corrected_img.numpy().astype(np.uint8)

    return corrected_img
```

#TRAINING

```python
# ------------------------
# Model Definition
# ------------------------

model = models.resnet50(pretrained=True)
num_classes = len(dataset.class_to_idx)
model.fc = nn.Sequential(
    nn.Dropout(p=0.4),  # Dropout layer with 40% probability
    nn.Linear(model.fc.in_features, num_classes)
)
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = model.to(device)

# Loss and Optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='max', factor=0.1, patience=3, verbose=True)

# Training Loop
num_epochs = 12
best_val_acc = 0.0

train_losses, val_losses = [], []
train_accuracies, val_accuracies = [], []

print(f"Starting training on {device}...")
```

```
Starting training on cuda...
```

```python
# Training Phase
model.train()
running_loss, correct_train, total_train = 0.0, 0, 0
progress_bar = tqdm(train_loader, desc=f"Epoch {epoch+1}/{num_epochs}", leave=False)

for images, labels in progress_bar:
    images, labels = images.to(device), labels.to(device)

    optimizer.zero_grad()
    outputs = model(images)
    loss = criterion(outputs, labels)
    loss.backward()
    optimizer.step()

    _, preds = torch.max(outputs, 1)
    correct_train += (preds == labels).sum().item()
    total_train += labels.size(0)
    running_loss += loss.item()

    progress_bar.set_postfix(loss=loss.item())

train_acc = correct_train / total_train
train_losses.append(running_loss / len(train_loader))
train_accuracies.append(train_acc)
```

```python
# Validation Phase
model.eval()
running_val_loss, correct_val, total_val = 0.0, 0, 0
all_preds, all_labels = [], []

with torch.no_grad():
    for images, labels in val_loader:
        images, labels = images.to(device), labels.to(device)
        outputs = model(images)
        loss = criterion(outputs, labels)

        _, preds = torch.max(outputs, 1)
        correct_val += (preds == labels).sum().item()
        total_val += labels.size(0)
        running_val_loss += loss.item()

        all_preds.extend(preds.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

val_acc = correct_val / total_val
val_losses.append(running_val_loss / len(val_loader))
val_accuracies.append(val_acc)

if epoch == 8:
  for param_group in optimizer.param_groups:
    param_group["lr"] *= 0.1  # Reduce learning rate
  print(f"Learning rate reduced to {optimizer.param_groups[0]['lr']} at epoch {epoch+1}")


scheduler.step(val_acc)
```

```
Epoch 1: val_accuracy improved from 0.00000 to 0.78845, saving model
Epoch 1/12 - 778.40s - train_acc: 0.7924 - val_acc: 0.7885
Epoch 2: val_accuracy improved from 0.78845 to 0.94084, saving model
Epoch 2/12 - 774.08s - train_acc: 0.9076 - val_acc: 0.9408
Epoch 3: val_accuracy improved from 0.94084 to 0.95197, saving model
Epoch 3/12 - 766.41s - train_acc: 0.9470 - val_acc: 0.9520
Epoch 4: val_accuracy improved from 0.95197 to 0.96002, saving model
Epoch 4/12 - 759.34s - train_acc: 0.9587 - val_acc: 0.9600
Epoch 5: val_accuracy improved from 0.96002 to 0.96627, saving model
Epoch 5/12 - 752.22s - train_acc: 0.9640 - val_acc: 0.9663
Epoch 6: val_accuracy did not improve from 0.96627
Epoch 6/12 - 749.74s - train_acc: 0.9684 - val_acc: 0.9652
Epoch 7: val_accuracy improved from 0.96627 to 0.97792, saving model
Epoch 7/12 - 750.71s - train_acc: 0.9713 - val_acc: 0.9779
Epoch 8: val_accuracy did not improve from 0.97792
Epoch 8/12 - 748.33s - train_acc: 0.9736 - val_acc: 0.9618
Learning rate reduced to 0.0001 at epoch 9
Epoch 9: val_accuracy did not improve from 0.97792
Epoch 9/12 - 746.44s - train_acc: 0.9746 - val_acc: 0.9637
Epoch 10: val_accuracy improved from 0.97792 to 0.98809, saving model
Epoch 10/12 - 745.62s - train_acc: 0.9912 - val_acc: 0.9881
Epoch 11: val_accuracy improved from 0.98809 to 0.98944, saving model
Epoch 11/12 - 751.33s - train_acc: 0.9947 - val_acc: 0.9894
Epoch 12: val_accuracy did not improve from 0.98944
Epoch 12/12 - 741.90s - train_acc: 0.9966 - val_acc: 0.9885
```

#TESTING

```
Data directory: data/DataSet/prepAlz
Folder: Mild Dementia, Number of images: 5002
Folder: Non Demented, Number of images: 67222
Folder: Moderate Dementia, Number of images: 488
Folder: Very mild Dementia, Number of images: 13725


Data directory: data/DataSet/prepBrain
Folder: glioma, Number of images: 1321
Folder: meningioma, Number of images: 1339
Folder: pituitary, Number of images: 1457
Folder: notumor, Number of images: 1595


Data directory: data/DataSet/prepPark
Folder: Very-Mild-Demented, Number of images: 2444
Folder: Non-Demented, Number of images: 3048
Folder: Severe-Demented, Number of images: 1648
Folder: Moderate-Demented, Number of images: 2276
Folder: Mild-Demented, Number of images: 1988
```

```
Data directory: test/prepAlz
Folder: Mild Dementia, Number of images: 250
Folder: Non Demented, Number of images: 250
Folder: Moderate Dementia, Number of images: 250
Folder: Very mild Dementia, Number of images: 250


Data directory: test/prepBrain
Folder: glioma, Number of images: 250
Folder: meningioma, Number of images: 250
Folder: pituitary, Number of images: 250
Folder: notumor, Number of images: 250


Data directory: test/prepPark
Folder: Very-Mild-Demented, Number of images: 250
Folder: Non-Demented, Number of images: 250
Folder: Severe-Demented, Number of images: 250
Folder: Moderate-Demented, Number of images: 250
Folder: Mild-Demented, Number of images: 250
```

```python
# Compute evaluation metrics
accuracy = accuracy_score(all_labels, predicted_labels)
precision = precision_score(all_labels, predicted_labels, average="weighted", zero_division=1)
recall = recall_score(all_labels, predicted_labels, average="weighted", zero_division=1)
f1 = f1_score(all_labels, predicted_labels, average="weighted", zero_division=1)
# Convert all_preds (indices) back to class names
predicted_labels = [class_names[idx] for idx in all_preds]

# Compute confusion matrix properly (both lists must have the same format)
conf_matrix = confusion_matrix(all_labels, predicted_labels, labels=class_names)
```

```
Evaluation Metrics:
Accuracy: 0.9902
Precision: 0.9901
Recall: 0.9902
F1-score: 0.9901
```

#WEBPAGE

Folder Structure

```
/your-repository-name
|
├── app.py              # Flask application for model inference
├── model/              # Folder containing the trained model (best_model.pth)
├── uploads/            # Folder for storing uploaded images
├── templates/          # HTML templates
|   └── index.html      # Main HTML file for the front-end
├── static/             # Static files like CSS, JS, images
|   ├── script.js       # JavaScript file for handling image upload and API call
|   └── style.css       # CSS file for styling the web page
├── requirements.txt    # List of Python dependencies
└── README.md           # Project README file
```