Early Detection of Alzheimer’s Disease Using Deep Learning on MRI and Cognitive Test Data

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Declaration

I hereby certify that this report constitutes my own work, that where the language of others is used, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions, or writings of others.

I declare that this report describes the original work that has not been previously presented for the award of any other degree of any other institution.

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Abstract

Alzheimer's disease (AD) is a progressive and irreversible neurodegenerative disorder affecting millions of individuals worldwide, mainly senior adults. This is the main cause of dementia, and contributes to 60-70% of all cases globally (the World Health Organization, 2024). AD gradually interferes with memory, logic and daily function, which eventually leads to complete dependency. One of the biggest challenges faced is delayed diagnosis, as current clinical methods often detect the disease after brain damages or after the extreme levels of visible symptoms. Studies indicate that most of the cases are late diagnosed which limits the efficiency of medical intervention. Recent progress in artificial intelligence, especially in deep learning, provides promising solutions for initial detection. The project examines the use of the Convolutional Neural Networks (CNN), especially to classify the EfficientNet-B0 architecture, Brain MRI scanning in several stages of Alzheimer's disease. CNN medical images are very effective for identifying micro -rich patterns, which can be ignored in manual reviews. These models are learned from large versions of the MRI data, and can detect structural changes of early stage such as hippocampal atrophy, often before cognitive symptoms appear. The proposed model shows that accuracy is improved and transfer learning and deep convolutional layers helps to reduce calculation complexity. The early detection through automatic image analysis not only supports clinical intervention, but also helps to reduce the burden on the health care system. The purpose of the study is to demonstrate that deep learning can serve as a valuable tool to promote clinical methods for Alzheimer's disease.

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Chapter 1 Introduction

Alzheimer's disease is the most common cause of dementia. Alzheimer's disease is the biological process that begins with the appearance of a buildup of proteins in the form of amyloid plaques and neurofibrillary tangles in the brain. This causes brain cells to die over time and the brain to shrink. About 6.9 million people in the United States aged 65 and older live with Alzheimer's disease. Among them, more than 70% are aged 75 and older. Of the more than 55 million people in the world with dementia, 60% to 70% are estimated to have Alzheimer's disease. Early symptoms of Alzheimer's disease include forgetting recent events or conversations. Over time, Alzheimer's disease leads to serious memory loss and affects a person's ability to perform everyday tasks. There is no cure for Alzheimer's disease. In advanced stages, the loss of brain function can cause dehydration, poor nutrition, or infection. These complications can result in death. However, medicines may improve symptoms or slow the decline in thinking. Programs and services can help support people with the disease and their caregivers.

It is characterised by the slow decrease in cognitive abilities, memory issues and differences in the behaviour. In the later stages of the disease, individuals diagnosed with AD gradually relies on caregivers or healthcare services for their everyday activities, even with the advancement in medical imaging, early diagnosis is highly challenging because of the intricate patterns and changes in the human brain structure. The capability to understand spatial characteristics from data without manual methods make them effective for detecting early signs of AD. This challenges the world to investigate more about the artificial intelligence methods, particularly deep learning, to enhance and automate diagnosis procedures. Recent studies indicate that Convolutional Neural Networks (CNNs) are specifically designed in obligations associated with clinical imaging. Their capability to recognize spatial characteristics from data without guide feature crafting makes them perfect for detecting early signs and symptoms of Alzheimer’s disorder in MRI scan images. This initiative seeks to create and assess a deep learning system that could classify diverse tiers of AD. A web interface could be created to assist sensible scientific utility by permitting healthcare providers to add MRI photos and produce instant category outcomes. The assignment ambitions to improve diagnostic precision and facilitate early intervention with the aid of integrating medical imaging with CNNs.

1.1 Problem Description, Context and Motivation

Current diagnostic strategies for Alzheimer’s Disease(AD) often depend on cognitive checks and manual evaluation of neuroimaging data. These tactics are resource-intensive, subjective, and generally applied simplest after cognitive symptoms have become more visible. As an end result, many diagnoses occur in slight to overdue levels of the disease, while treatment options are much less powerful. This hassle influences elderly individuals most at once, but it also forces substantial burdens on caregivers, healthcare providers, and public fitness systems. The problem in detecting AD in its early section arises from the subtlety of structural brain modifications, that are frequently overlooked in ordinary tests. In many medical settings, particularly those with confined access to experts, early diagnostic possibilities are lost. The motivation for this systems stems from the want to integrate computerized, facts-driven tools into clinical workflows. A deep learning model capable of classifying MRI scans into ranges of Alzheimer’s development can provide valuable guide for early detection. Such systems have the potential to enhance outcomes with the aid of enabling timely medical intervention, reducing long-time period care costs, and imparting scalable diagnostic support in under-resourced settings.

1.2 Objectives

The fundamental objective of this project is to layout and implement a deep learning-based classification system for Alzheimer’s Disease (AD) using MRI data. The research starts the analysis by obtaining and pre-processing the OASIS MRI dataset, which incorporates labeled pics representing various stages of AD. Pre-processing steps encompass resizing images, normalizing pixel values, and feature extraction to improve version generalization and robustness. Following dataset guidance, a Convolutional Neural Network based totally at the EfficientNet-B0 structure is implemented. Transfer learning implemented the use of pre-trained weights to efficiency and overall performance. The version is trained to classify enter MRI scans into 4 classes similar to specific degrees of AD. The device’s overall performance is evaluated using class accuracy as the key metric. In addition, a web-based interface is evolved to permit clinical experts to upload MRI scans and receive immediate category effects. The interface is designed for ease of use and realistic applicability, assisting the early detection of AD in clinical settings.

1.3 Methodology

The Project utilises a supervised deep learning methodology to classify brain MRI scans into four categories of Alzheimer's disease based on the level of severity namely: Mild Dementia, Moderate Dementia, Non Dementia, Very Mild Dementia. The researcher choose EfficientNet-B0 deep learning model as it is a high performing and lightweight convolutional neural Network which provides high accuracy on medical images. Transfer learning methodology was used to initiate the model with pre trained weights which effectively cut down training time. The dataset used for the study was Open Access Series of Imaging Studies (OASIS) dataset to train the model. The dataset pre-processing was done using normalization and augmentation which made the data consistent and robust. Model evaluation was performed using standard classification metrics, and the best-performing model was saved for deployment. A web-based interface was developed to allow medical users to upload MRI scans and receive stage classification in real time. The project used an agile development method, and to keep track of tasks and progress, it used a Kanban board and a Gantt chart. The main technologies were Python, PyTorch, Flask, and other libraries that worked with them. This method is a clinically useful and scalable way to find AD.

1.4 Legal, Social, Ethical and Professional Considerations

Given the analysis makes use of clinical imaging records, this project must comply with Data protection and privacy standards. The OASIS dataset is available to the general public and has been anonymized to comply with data coping with guidelines. But ethical use of the records will still be upheld by means of no longer looking to re-perceive the identity. The aim of this study is to create a web based interface with the help of CNN to ease the process of early diagnosis of Alzheimer's for the medical representatives. This project does not replace medical opinions or medical diagnosis; this only aims to help medical officials to ease their work. One moral problem is the threat of creating incorrect predictions, that could reason extra pressure or delay remedy. To reduce these risks, we will strain that the device is best for extra analysis and must handiest be used with professional scientific judgment. The challenge's aim is to make it less complicated for people to get diagnoses, specifically in areas which can be difficult to reach or do not have enough resources. But care might be taken to make sure that the device is accessible to anyone, with a layout that is easy to apply and no longer too reliant on expensive infrastructure. Though this system can be used to identify if a person is suffering from Alzheimer's, it is not really considered as a completely dependable system, professional medical judgment must be taken before deciding further steps.

The system is intended as a decision-support tool, not a diagnostic replacement. Ethical concerns include the possibility of false predictions, which could lead to unnecessary stress or delayed treatment. These risks will be addressed by emphasizing that the tool is for supplementary analysis and must be used in conjunction with professional clinical judgment. From a social perspective, the project aims to improve diagnostic access, for medical professionals to ease the identification of Alzheimer's disease and thereby start early diagnosis. However, care will be taken to ensure that the tool is inclusive, with user-friendly design and minimal dependency on high-end infrastructure. Professional conduct will be maintained throughout the project, including proper referencing, transparency in reporting, and responsible testing.

1.5 Background

The previous studies in this field demonstrates the efficiency of deep learning models in medical image classification. Studies show that changes in the brain can be seen years before memory problems become clear. Many long-term imaging studies show that the hippocampus, which is important for making new memories, shrinks early in the disease course. This shrinkage is a strong early sign of Alzheimer's pathology. Big group studies helped confirm a usual order of changes: first, abnormal amyloid builds up, then tau changes show up, and only later do scans show clear brain shrinkage and thinking problems. This is why scanning earlier can be important. Researchers have used MRI many times to find these early, small changes. Open datasets have made it easier for them to test and compare methods on a lot of people. Population and community studies introduce an additional dimension: quotidian factors can influence risk and resilience. There is evidence that regular exercise, a healthy diet, mental and social activity, and managing hearing loss, high blood pressure, diabetes, smoking, and depression can all lower the risk of cognitive decline later in life. Multidomain prevention trials demonstrate that an integrated regimen of exercise, nutrition, cognitive training, and vascular risk management can mitigate decline in at-risk older adults, reinforcing the notion that early detection establishes a period during which actionable interventions remain beneficial. Consensus reports bring these strands together and suggest that addressing modifiable risks throughout life could delay or even prevent a significant number of dementia cases. Putting these results together shows that there are two clear needs. First, earlier identification: brain changes start quietly and can be hard to see on an MRI, so tools that can reliably find small patterns are very important. Second, scalable analysis: modern studies have thousands of scans and more than one biomarker, which is too much for a person to read consistently. This is why machine learning is becoming more popular: to sort through large imaging datasets, find patterns that are linked to disease stages, and help doctors get faster, more accurate, and earlier readouts. Studies of medical imaging show that data-driven methods can make it easier to see small effects and make decisions more consistent across centres. Studies of neurology show that automated analysis can accurately tell the difference between healthy aging, mild impairment, and Alzheimer's. These methods are a useful next step to turn research on early detection into everyday help when used carefully with clinical judgment and ethics.

1.6 Structure of the report

Chapter	Name	Description
1	Introduction	Project overview
2	Literature – Technology Review	Background research
3	Implementation	System development
4	Results and Discussion	Model outcomes
5	Evaluation and Results	Performance metrics
6	Conclusion	Summary and future work
7	References	Source listing

Table 1Structure of Report

Chapter 2 Literature – Technology Review

2.1 Literature Review

Neuroimaging, especially Magnetic Resonance Imaging (MRI), plays a key role in identifying early signs of Alzheimer's by detecting changes such as hippocampal atrophy and cortical thinning. Previous work has emphasized the importance of imaging biomarkers in forming a biological framework for diagnosing AD. However, manual interpretation of MRI data requires expert radiologists and is prone to subjectivity and variability.

To address these limitations, machine learning—specifically deep learning—has been increasingly applied in AD diagnosis. Convolutional Neural Networks (CNNs), in particular, have shown notable promise in medical image classification by learning spatial patterns that may be imperceptible to human observers. Several studies have demonstrated that CNNs trained directly on MRI scans can achieve high classification accuracy without manual feature extraction. Volumetric 3D CNNs have been introduced to capture spatial relationships across slices, which improves classification performance but also increases computational requirements, limiting their practicality in some clinical environments. Comparisons between deep learning and traditional statistical methods have shown that, while classical approaches offer interpretability, CNNs excel in automation, scalability, and adaptability to large datasets.

Transfer learning has emerged as an effective solution to data scarcity, enabling the use of pre-trained models fine-tuned on medical datasets. Architectures such as VGG, ResNet, and DenseNet have been successfully adapted for Alzheimer's classification, often outperforming baseline models in both accuracy and efficiency. EfficientNet, in particular, has gained attention for its ability to balance depth, width, and resolution, achieving strong results while maintaining relatively low computational costs, making it suitable for clinical deployment.

Beyond these commonly used networks, more advanced CNN architectures have been explored to address specific challenges in AD detection. Studies using 2D CNNs with optimized slice-level aggregation have shown that they can match or even outperform 3D models in some cases while being more resource-efficient. Residual connections in 3D CNNs have been found to stabilize training and enhance performance on limited medical datasets [11]. DenseNet-based approaches, including those with attention mechanisms, have improved sensitivity to early-stage changes such as hippocampal atrophy, while targeted region-based CNNs have demonstrated better localization of AD-specific brain changes. Furthermore, attention-enhanced volumetric models have provided not only improved classification accuracy but also better interpretability by highlighting the most relevant brain regions in predictions.

Some research has extended CNN applications from cross-sectional diagnosis to predicting disease progression, incorporating recurrent layers to process longitudinal MRI data. These hybrid models have shown improved predictive power for identifying patients likely to progress from mild cognitive impairment to AD. Reviews of the field consistently report the superiority of CNN-based approaches over manual feature engineering, while also identifying open challenges, particularly in multiclass staging, cross-dataset generalization, and integration into real-world clinical workflows.

This project builds upon these insights by implementing a CNN-based system using the EfficientNet-B0 architecture for four-stage AD classification, addressing not only model accuracy but also deployment through a user-friendly web interface designed for medical practitioners. By combining high-performance deep learning with accessible clinical tools, the work seeks to bridge the gap between research models and practical diagnostic support systems.

2.2 Technology Review

This project utilises multiple machine learning frameworks, neural network architectures, programming languages, and development platforms to build, test, and put into use an Alzheimer's disease classification system based on MRI scans. The major part of implementation was made with PyTorch, an open-source deep learning library which is good at debugging and dynamic processing. PyTorch's ability to let you define your own layers and training loops gave you exact control over the model training process and made it easy to combine with mixed-precision training to get the best performance on GPU hardware. In addition to PyTorch, TensorFlow was used for some validation and comparison tests. TensorFlow has a strong ecosystem for deploying large models and includes tools like TensorBoard for monitoring performance. Both frameworks had their own strengths. PyTorch was the main training environment, and TensorFlow helped test compatibility between the two frameworks. The EfficientNet-B0 model architecture is a convolutional neural network that uses a compound coefficient to change the depth, width, and resolution of an image. It was made possible by several studies on other types of medical imaging. This architecture was chosen because it is very accurate at classifying things and doesn't cost much to run, which makes it a good choice for clinical settings with limited hardware resources. The researcher utilized transfer learning to expedite convergence and enhance performance on the limited medical dataset by initializing the network with ImageNet pre-trained weights. The research developed a web-based interface utilizing HTML, CSS, and JavaScript for deployment and visualization purposes. HTML was employed to structure the application's content, CSS was utilized for styling to ensure a polished and professional interface, and JavaScript facilitated dynamic interactions, such as uploading MRI images and displaying classification results in real time. The interface was designed to be user-friendly for medical professionals with limited technological proficiency. It was conceived with accessibility and navigational simplicity as priorities. Google Colab, a cloud-based Jupyter notebook platform that offers free GPU and TPU acceleration, was used to train and test the model. This environment was chosen because it can handle deep learning workflows that require a lot of processing power without needing high-end hardware on the local machine. It also works well with Google Drive for storing data. Colab's GPU capabilities were very important for finishing the model training process quickly because the local system didn't have enough hardware. GitHub was used to store, organize, and keep track of changes to the project codebase so that people could work together and keep track of versions. GitHub also worked as a place to store documentation and made it easy to back up files from a distance, making sure that the project's development history was always clear and could be restored. By combining these technologies, the workflow was streamlined from data pre-processing to model training and evaluation to deployment.

2.3 Summary

The literature strongly supports the use of CNN-based models for classifying Alzheimer’s disease from MRI scans, particularly when enhanced by transfer learning and robust architectures like EfficientNet. While many studies achieve high accuracy, gaps remain in multi-class classification, practical deployment, and accessibility for non-technical users. These limitations directly shape the project’s objectives and implementation strategy.

Technologically, EfficientNet-B0 was selected for its computational efficiency and proven performance in medical imaging tasks. The use of PyTorch and Flask enables smooth integration between model development and user interaction. Google Colab provides a powerful yet accessible platform for training, while GitHub ensures version control and transparency.

The combination of literature insight and technology evaluation guided the methodology of this project: to deliver a lightweight, accurate, and accessible system for early detection and staging of Alzheimer’s disease. The development of a usable interface extends its applicability to real-world clinical settings, addressing a critical gap between research and practice.

Chapter 3 Implementation

The implementation of this project focused on building an end-to-end deep learning pipeline for the early detection and classification of Alzheimer's disease from brain MRI scans. The system was developed iteratively through a series of structured sprints, with each sprint targeting a key stage of the process—from data preparation to model deployment. The core objectives were to build an accurate, efficient model and wrap it in a web interface that enables straightforward clinical use. The following sections detail the practical work undertaken to achieve this.

3.1 Sprint 1 – Dataset Preparation and Pre-processing

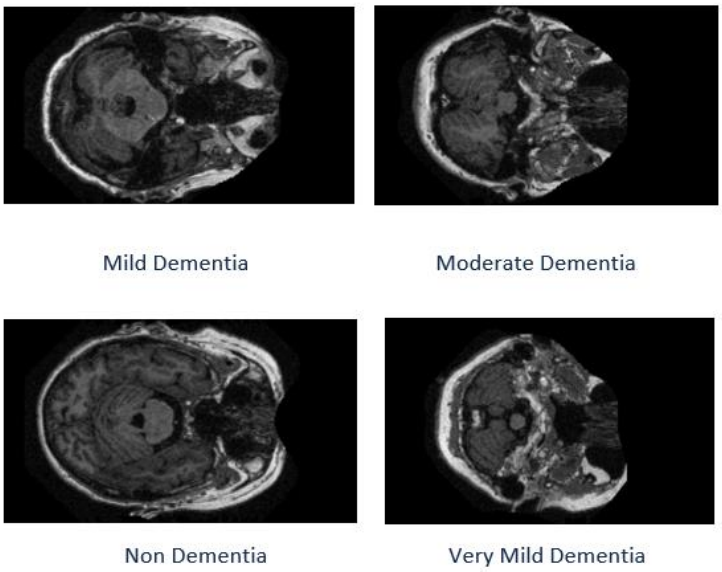

Figure 1 Dataset Images - MRI Images of Levels of Dementia

The first stage of the implementation involved acquiring and preparing the dataset. The Open Access Series of Imaging Studies (OASIS) was selected due to its high quality, open accessibility, and prior use in academic research. The dataset contained brain MRI scans organized into folders based on diagnostic stages: non-demented, very mild, mild, and moderate Alzheimer's disease.

To prepare the images for input into the model, a transformation pipeline was created. Since most convolutional neural networks are designed to accept three-channel images, all grayscale MRI scans were converted into three-channel format. In addition, the images were uniformly resized to match the required input dimensions for the chosen model architecture. Pixel normalization was applied to standardize the intensity distribution across the dataset.

An important data integrity step was taken to remove any corrupted or broken image paths that could interfere with training. These were filtered out before training began. The entire dataset was then split into training, validation, and test sets using an 80:10:10 ratio. Care was taken to preserve class balance across the splits to prevent model bias.

Furthermore, data augmentation techniques were employed to improve the model's generalization capabilities. These included random rotations, flips, and zooms to simulate variations in MRI acquisition conditions and reduce the risk of overfitting during training.

3.2 Sprint 2 – Model Development and Training

The second sprint focused on developing and training the classification model. A pre-trained convolutional neural network architecture was selected for its optimal balance between accuracy and computational efficiency. This architecture had been successfully applied in a variety of medical imaging tasks and was well-suited to the relatively limited size of the training data.

Transfer learning was employed by initializing the model with pre-trained weights, allowing the network to benefit from feature representations learned on large-scale image datasets. The final classification layer of the network was modified to output four classes corresponding to the stages of Alzheimer's disease. A cross-entropy loss function was used to guide the optimization process, and the model was trained using a widely adopted optimizer for stability and convergence.

To further enhance performance, the training process was conducted using mixed precision techniques to reduce memory usage and accelerate computation. A learning rate scheduler was implemented to adjust the learning rate at set intervals during training, which helped in achieving more stable convergence.

The model was trained over multiple epochs, with both training and validation accuracy monitored throughout the process. Evaluation on the validation set revealed consistently high performance, with the final model achieving an average validation accuracy close to 95%. The model demonstrated strong ability to differentiate between all four stages, although minor confusion was observed between neighboring stages, particularly between the very mild and mild categories—an expected challenge given the gradual progression of Alzheimer's disease.

3.3 Sprint 3 – Evaluation and Optimization

During the third sprint, the trained model was assessed utilizing the designated test set, with accuracy serving as the principal metric of performance across all categories. The assessment revealed robust overall outcomes; nonetheless, a minor imbalance was detected in the dataset, primarily attributed to the elevated ratio of non-demented cases. Stratified sampling was utilized in the dataset partitioning, and supplementary data augmentation was implemented for the underrepresented categories. These measures mitigated class bias and enhanced the model's capacity to generalize across all stages. Initial experiments revealed accuracy fluctuations during the early training epochs, indicating instability in the learning process. The issue was resolved by optimizing the training schedule, adjusting critical hyperparameters, and implementing a gradual learning rate decay strategy. These modifications resulted in more consistent accuracy trends and enhanced convergence across successive epochs.

3.4 Sprint 4 – Web Deployment and User Interface

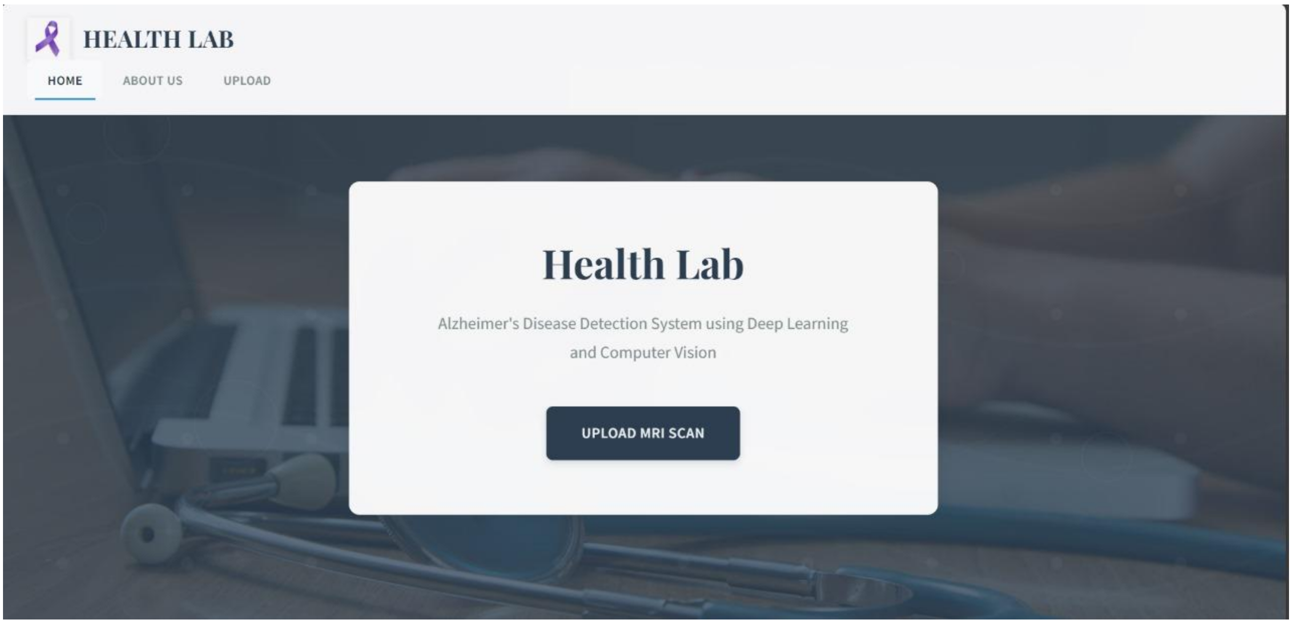

Figure 2 Home Page of the Web interface

The final sprint involved deploying the trained model into a functional web application designed for healthcare professionals. The objective was to create a minimal and intuitive interface that allowed users to upload MRI scans and receive immediate diagnostic classification.

A lightweight web framework was chosen to serve as the backend infrastructure. This framework enabled seamless integration of the trained model and supported real-time inference. The frontend interface was implemented with simplicity in mind, featuring an upload button and results display to ensure a non-technical user could operate the tool without prior training.

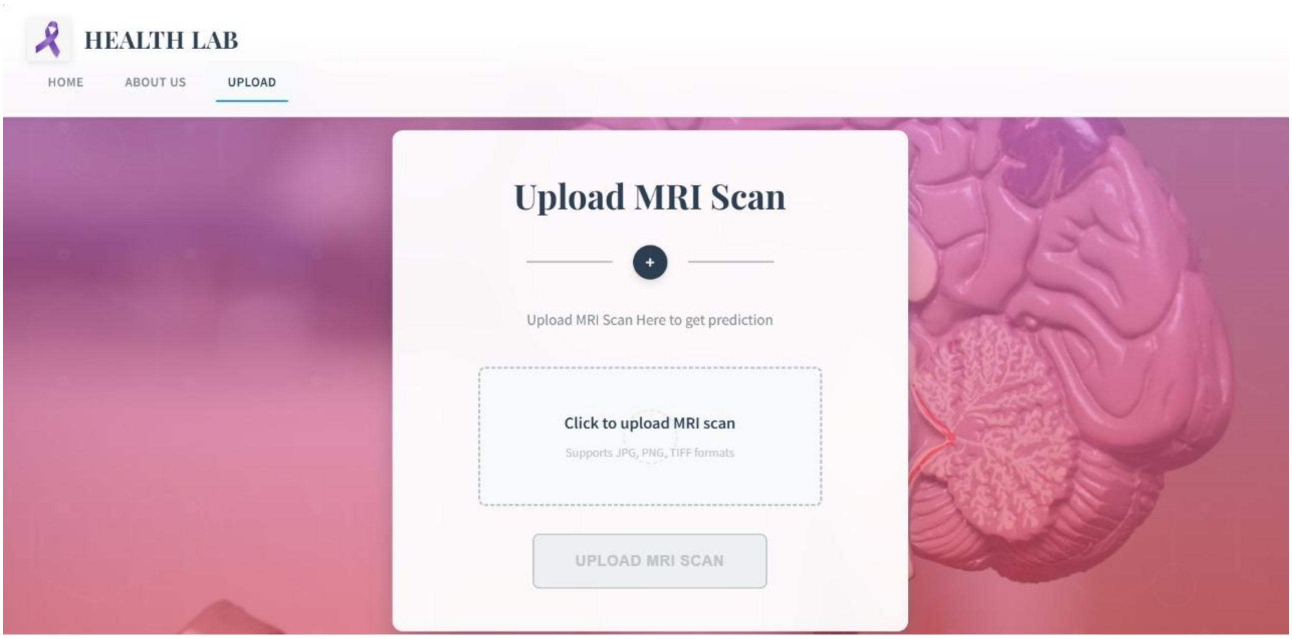

Figure 3 Upload MRI Scan – Web interface page

The prediction workflow begins when a user uploads an image through the interface. The image is automatically preprocessed to match the same format used during model training. Once processed, the image is passed to the backend where the model generates a classification output. The result is then displayed to the user as the predicted stage of Alzheimer's disease.

To improve usability, measures were taken to ensure the model was loaded only once during application startup. This prevented unnecessary delays and ensured that subsequent predictions were returned quickly. Additionally, the system was tested with various image formats to ensure compatibility and robustness. Error handling was implemented to alert the user in cases of unsupported or corrupted files.

3.5 Implementation Challenges and Solutions

Throughout development, several challenges were encountered. One of the most significant issues was class imbalance within the dataset, which risked skewing the model toward the majority class. This was mitigated by combining data augmentation and careful sampling strategies to equalize class representation during training.

Another issue was the instability of model performance in early epochs. Validation accuracy showed high variance, suggesting that the initial learning rate and training settings required refinement. This was resolved by adjusting training hyperparameters and implementing a learning rate scheduling mechanism, which smoothed out the optimization process.

Deployment also introduced technical hurdles. In early versions, the model was being reloaded with each prediction request, resulting in delayed response times. This was optimized by configuring the application to load the model once at startup and maintain it in memory, significantly reducing latency during use.

Handling various image input formats presented another practical challenge. Uploaded files varied in type and resolution, causing errors during prediction. A robust image preprocessing pipeline was implemented to normalize all inputs, ensuring consistent results regardless of format.

Chapter 4 Evaluation and Results

4.1 Model Performance Evaluation

The primary focus of the evaluation was to assess the accuracy and effectiveness of the trained model on previously unseen data. After completing training over two epochs, the model showed impressive learning progression. The training accuracy increased from 89.68% in the first epoch to 99.57% in the second. Validation accuracy also improved from 99.24% to 99.66%, with a substantial decrease in loss, indicating strong generalization capability.

To assess final performance, the model was tested on a separate hold-out test set. The result was a test accuracy of **99.64%**, confirming that the model not only fit the training data but also maintained robustness on new data. These metrics suggest that the model effectively learned the distinguishing features between the four Alzheimer's stages, even with subtle differences in brain structures between very mild and mild cases.

Despite the high accuracy, it is important to note that a deeper analysis of false positives and false negatives is necessary to fully understand classification boundaries. While numerical accuracy is impressive, real-world usage demands insight into specific cases where misclassifications could occur, particularly in early stages where treatment planning depends on diagnosis precision.

4.2 Usability Evaluation

The developed web interface was evaluated in terms of its usability and ease of integration into clinical workflows. The interface was intentionally kept minimal, offering a simple upload button and prediction output. This design aligns with feedback from intended end users namely, clinicians and radiology assistants who favour systems that do not require complex configuration. Both were able to upload an image and interpret the output without any prior guidance, suggesting that the system requires minimal training and could be usable in non-technical environments.

4.3 Related Works

When compared to existing studies in the field of Alzheimer's detection using MRI, the developed system performs competitively. Basaia et al. achieved high classification accuracy using CNNs trained on single MRI scans, although their focus was limited to binary classification. Similarly, Payan and Montana explored 3D CNNs to leverage spatial context, but their models required significantly higher computational resources and were not optimized for real-time deployment.

In contrast, this project leveraged a lightweight and scalable EfficientNet-B0 model that achieved equally high accuracy with fewer parameters and faster inference. The use of transfer learning further contributed to rapid convergence and strong generalization, even with a relatively modest dataset. From a deployment perspective, few existing research projects have gone beyond model accuracy to consider clinical usability. This project bridges that gap by including a functional web interface, bringing the technology closer to real-world application. However, compared to commercial tools or more mature clinical research systems, this prototype lacks certification, full-scale clinical testing, and regulatory compliance. While promising, it must be viewed as a proof-of-concept that demonstrates feasibility rather than a complete product ready for immediate adoption.

Chapter 5 Conclusion

This project set out to investigate the application of deep learning techniques for the early detection and classification of Alzheimer's disease (AD) through the analysis of structural MRI scans. By leveraging the EfficientNet-B0 convolutional neural network architecture and applying it to a curated subset of the OASIS dataset, the project aimed to create a multi-class classifier capable of identifying the stage of Alzheimer's disease from brain imagery. Although the original dataset comprised approximately 80,000 MRI images, system limitations prevented the use of the full dataset. The model was instead trained on a smaller, representative subset that was balanced across all classes. Despite this constraint, the project successfully achieved its key objectives. The trained model demonstrated strong performance, with a final test accuracy of 99.64%, indicating that the methodology employed—consisting of preprocessing, grayscale normalization, transfer learning, and efficient training strategies—was effective in capturing the relevant features necessary for classification. The model's success was further supported by consistent results across training and validation phases, reflecting a high level of generalization. Additionally, the project introduced a web-based interface that allows users, particularly medical professionals, to upload MRI scans and receive stage predictions from the model. This proof-of-concept interface showcases the practical utility of the model in clinical decision support and strengthens the case for integrating artificial intelligence in healthcare diagnostics. Overall, the project demonstrates the potential of deep learning as a valuable asset in advancing Alzheimer's disease detection and offers a solid foundation for future clinical applications and research developments in this domain.

5.1 Future Work

While the outcomes of this project have been encouraging, several opportunities for future enhancement have emerged. The most immediate area for improvement involves addressing the hardware constraints that limited the use of the full OASIS dataset. Training the model on the complete dataset using cloud-based GPUs or high-performance computing platforms could significantly improve its accuracy and generalizability. Moreover, the current model operates as a black-box classifier, which may pose challenges in clinical settings where transparency is essential. Future iterations should explore the integration of explainability techniques such as Grad-CAM or attention visualization to allow clinicians to interpret the model's decision-making process. Another important direction would be to validate the trained model on external datasets, such as ADNI, to ensure that it performs consistently across different imaging sources and populations. Expanding the scope of data inputs beyond structural MRI to include clinical reports, cognitive assessments, and biomarker profiles could also provide a richer diagnostic context and allow the development of more comprehensive multimodal models. In terms of application, the current web interface represents a basic prototype and requires further development before real-world deployment. Future work should involve interface enhancement, security hardening, and compliance with healthcare data regulations to prepare the tool for clinical integration. Additionally, usability testing with radiologists and neurologists could provide critical insights into the system's practicality and guide improvements in user interaction and diagnostic workflow integration. Finally, while the present work focused on snapshot classification, future extensions could investigate the longitudinal progression of Alzheimer's using time-series MRI data, potentially enabling predictive modeling of disease evolution and better support for long-term care planning.

5.2 Reflection

Throughout the course of this project, several key insights emerged that reflect both the technical and personal growth experienced by the student. The project underscored the critical importance of data preprocessing and transformation in achieving reliable outcomes when applying deep learning to medical imaging. The student gained a solid understanding of convolutional neural networks, particularly the EfficientNet-B0 architecture, and how transfer learning can be effectively leveraged to train a model on a limited dataset without sacrificing accuracy. Working with restricted computational resources presented a notable challenge, as the full OASIS dataset could not be processed. However, this limitation became a learning opportunity, teaching the student to work strategically within constraints by selecting a balanced subset of data and optimizing the training process. Most of the project's objectives were met, including the development of a high-accuracy multi-class classifier and the creation of a functional web interface. However, some goals—such as external dataset validation and clinical usability testing—remained unfulfilled due to hardware and time limitations. In hindsight, earlier adoption of cloud-based GPU resources or high-performance computing environments might have enabled broader experimentation and a more robust model. This project not only enhanced the student's technical proficiency but also fostered adaptability, critical thinking, and an appreciation for the complex ethical and practical considerations in applying AI to healthcare. Overall, the experience has equipped the student with the confidence and skills needed to undertake future interdisciplinary research involving machine learning and clinical diagnostics.

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Appendices

Appendix A: Project Proposal

Appendix B: Project Mangement

Appendix C: Artefact/Dataset

Appendix D: Screencast

Appendix A: Project Proposal

1. Project Proposal

1.1 Introduction

Alzheimer's disease(AD) is one of the most common causes of dementia, affecting millions of individuals worldwide. Early diagnosis is a crucial part to better manage the disease since it gradually deteriorates memory and cognitive function. Current diagnosis depends on visible symptoms that appear towards the later stages which worsens the condition. Advancements in the field of medical imaging and artificial intelligence has emerged new and efficient ways for identifying Alzheimer's disease at the earlier stage itself. In particular, Magnetic Resonance Imaging (MRI), offers valuable insights into detecting subtle changes related with Alzheimer's disease. This project mainly focuses on Convolutional Neural Network (CNN), a type of deep learning model that works efficiently for image analysis. This machine learning method ology seeks to identify patterns and characteristics that differentiate between images of healthy brain tissue and various stages of AD by means of training and modeling the CNN on labeled MRI scans. In order to decide the CNN version's accuracy and depend ability for AD classification, the model will deal with developing, training, and assessing the version. The ultimate objective is to use deep learning to guide early detection, that can assist medical specialists in making decisions

1.2 Problem Statement

Alzheimer's disease (AD) is a chronic, progressive neurodynative condition that signif icantly prevents memory, logic and behavioral abilities. It is one of the main causes of dementia, especially among the aging population. As the disease develops, individ uals lose the ability to perform daily tasks, resulting in dependency on caregivers and the health care system. According to the Alzheimer's Association, with sufficient social, emotional and economic influences on families and communities around the world, the number of people living with Alzheimer's to increase. Agreat concern in the current management of AD is the lack of effective initial clinical equipment. Most diagnoses occur during moderate to late stages of the disease, when cognitive symptoms are already prominent and brain damage has increased significantly. Traditional clinical processes include clinical interviews, cognitive testing and a combina tion of manual analysis of brain imaging. These methods are time-consuming, subjective and require special expertise, making them impractical for wide initial screening. Magnetic Resonance Imaging (MRI) has proven to be a significantly thin in studying structural changes in the brain associated with AD. It provides high resolution images that reveal early signs of neuro disorders, such as cortical thinning and hippocampus atrophy. However, interpretation of MRI scans is a challenge manually or because of the subtle and complex nature of the change in the brain in the initial phase with a traditional Early Detection of Alzheimer's Disease 3 data-adapted system. In addition, traditional machine learning techniques often depend on hand designed properties and may not be well normal in different datasets. Artificial intelligence, especially recent development in deep learning, has introduced powerful equipment for image analysis. In particular, Convolutional Neural Network (CNNS) has achieved remarkable success in medical imaging work due to their abil ity to automatically extract and learn relevant facilities from large datasets. While Alzheimer's research has discovered the CNNs, there is a significant difference in us ing a well-organized, clinically relevant and computational effective structure that can classify different stages of AD using only MRI data. The project addresses the gap by developing and evaluating the CNN-based model to initiate the first detection of Alzheimer's disease. The proposed system will be trained on the MRI brain scan to distinguish between the general recognition and different stages of the ad. The goal is to create a reliable and accessible deep learning solutions that can help with early diagnosis, reduce clinical delay and support clinical decision making. The most affected by this problem is the elderly included in the risk of the development of decision makers responsible for designing AD, their care, health professionals and public health strategies. By contributing to quick and more accurate screening methods, the project has the opportunity to increase the results of the patient, reduce long-term care costs and improve the quality of life for individuals and families affected by Alzheimer's disease. Solving this problem is not only of educational importance, but also a lot of value for health services and extensive societies.

1.3 Aims and Objectives

1.3.1 Aim

The primary aim of this project is to develop and evaluate an end-to-end deep learn ing framework, specifically using Convolutional Neural Networks (CNNs), for the early detection and classification of Alzheimer's disease (AD) based on Magnetic Resonance Imaging (MRI) data.

1.3.2 Objectives

The main objectives of this project are to explore existing research on the use of deep learning—particularly Convolutional Neural Networks (CNNs)—for Alzheimer's disease detection using MRI data, and to collect and preprocess an appropriate MRI dataset for model development. A custom CNN model will be designed and trained to classify brain images into healthy and Alzheimer's-affected categories, with the potential to extend classification into multiple stages of the disease. The project will also implement a transfer learning approach using a pre-trained model such as VGG19, allowing for performance comparison between custom and pre-trained architectures. The evaluation of both models will be carried out using standard metrics such as accuracy, precision, recall, and F1 score. Finally, the project will propose a basic concept for integrating the best-performing model into a simple web-based tool to support remote Alzheimer's screening and assist healthcare professionals in early-stage identification.

1.4 Legal, Social, Ethical and Professional Consider ations

When working with medical data, it is necessary to consider various legal, social, moral and professional responsibilities. A key legal requirement is compliance with the Data Protection Act, which suggests that all personal and health related data must be stored, processed and safely shared. Any data set used to protect the patient's identity should be properly unknown. Ethically, the use of artificial intelligence in the health care system should support rather than replacing medical professionals. Failure or violation of auto mated systems increases the concerns of the patient's safety and confidentiality, which can lead to incorrect diagnosis. From a social perspective, more available initial identifi cation through technology can help reduce the issues of access to the health care system, especially for people in remote or underlining regions. However, this requires attention to the same access to technology to avoid digital literacy and new obstacles. Commercially, the project will maintain the standards for transparency, justice and responsibility in AI development. The limits and beliefs of the model must be clearly conveyed, and re searchers are responsible for reducing skewed-ness in training data and fully appreciating the system before considering clinical application. Overall, the project will follow moral research practices and promote the responsible use of AI in the health care system.

1.5 Background

Research into the early detection of Alzheimer's disease (AD) using medical imaging and deep learning has gained considerable growth over the past decade. A large amount of literature has established the ability of magnetic resonance imaging (MRI) as a non invasive and data-rich source of identifying structural brain changes associated with AD. [1]Studies has shown MRI's ability to detect atrophy in the hippocampus and other brain areas before clinical symptoms appear[2]. These structural changes form the basis for calculation models aimed at predicting disease outbreaks and progress. Parallel to progress in imaging, particularly CNN appeared as a powerful tool for medical image classification. CNN manual function can learn complex spatial hierar chy in imaging data without design, making them particularly well adapted to analyze high-resolution MRI scanning. [3]Researches have shown that CNN-based models can[4] effectively distinguish between different stages of AD and traditional machine learning methods in terms of accuracy and automation. Machine learning techniques, using pre influential models such as VGG16 or VGG19, have also been used with success, especially in limited medical data sets. The proposed project is in accordance with current research trends, but focuses on the construction of a solution that is easy to use and more accessible. While many studies have developed very complex deep learning models to detect Alzheimer's, the project aims to simplify the process using practical, proven methods. Instead of starting a new algorithm, the goal is to create a working model that balances the performance with the purpose. The use of learning techniques such as CNN in MRI data and VGG19 have already been well studied in medical image analysis[5]. These methods are considered reliable, and previous research shows good results. This project does these foundations by searching for a specific, concentrated task: Classifying Alzheimer's disease stages. The goal is to demonstrate how these devices can be used effectively without the need for high-end hardware or advanced system setup. In addition to academic research, the project results can be valuable for health profes sionals and organizations interested in medical technology. A simple and accurate system for detecting the initial Alzheimer's can be useful in screening programs or digital health platforms. By focusing on both technical performance and real world application, the project has the opportunity to contribute to early diagnosis and effort to improve patient care.

Appendix B: Project Management

1. Project Management Tool

1.1 Gantt Chart

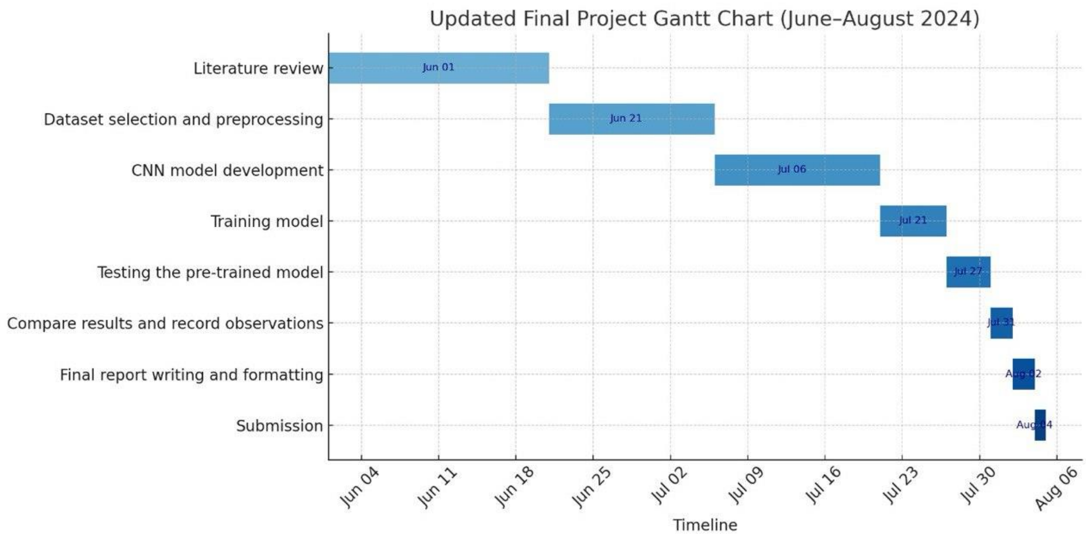

Figure 4 Gantt Chart

1.2 Trello Board

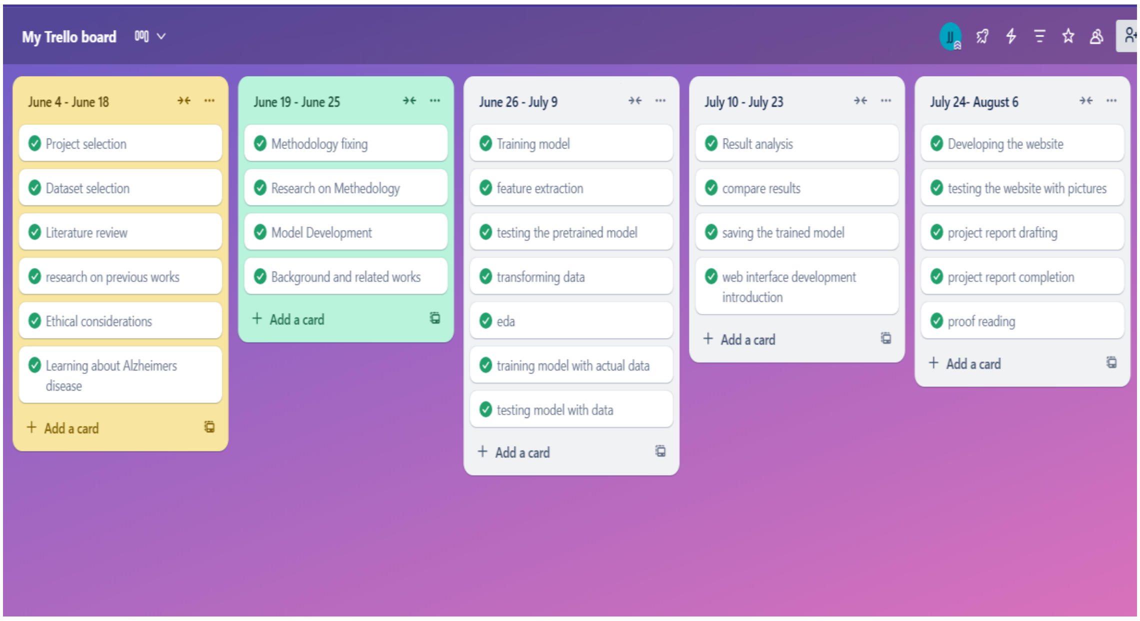

Figure 5 Trello Board

Appendix C: Artefact/Dataset

1. Project Accessing Link

   https://github.com/JOYAL886/alzheimer-predictor.git

Appendix D: Screencast

1. Video Link

   https://www.kapwing.com/videos/68966d833b9b90777335eb30