ALZHEIMER DISEASE DETECTION FROM MRI IMAGES USING DEEP LEARNING TECHNIQUES

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled **ALZHEIMER DISEASE DETECTION FROM MRI IMAGES USING DEEP LEARNING TECHNIQUES,** submitted by **Mohammad Yusuf Ali** and **Md Abu Ryan** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **13 july 2024**.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Naznin Sultana, Associate Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The early detection of Alzheimer's disease (AD) is crucial for effective intervention and management. This study explores the application of deep learning techniques to classify MRI images into three categories: mild demented, moderate demented, and non-demented. Utilizing a comprehensive preprocessing pipeline, including data normalization, resizing, histogram equalization, augmentation, dataset balancing, and batch normalization, we prepared a balanced dataset comprising 800 training images and 200 testing images per class. We implemented and evaluated four deep learning models: a modified Convolutional Neural Network (CNN), AlexNet, VGG16, and a hybrid model integrating EfficientNet-b0 for feature extraction and Support Vector Machine (SVM) for classification. The performance metrics, including accuracy, precision, recall, F1-score, and support, were determined for each model. Additionally, we analyzed the accuracy and loss curves, confusion matrices, ROC curves, and precision-recall curves to comprehensively assess the models. The results demonstrate that the hybrid model combining EfficientNet-b0 and SVM outperformed the others with an accuracy of 96.17%, followed by VGG16 with 95.17%, and both the modified CNN and AlexNet with 94.83%. These findings suggest the potential of advanced deep learning architectures in enhancing the diagnostic accuracy for Alzheimer's disease, thereby supporting early intervention strategies.

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LIST OF ACRONYMS

ML	Machine Learning
SVM	Support Vector Machine
CNN	Convolutional Neural Network
CPU	Central Processing Unit

CHAPTER 1
INTRODUCTION

1.1 Overview

Alzheimer's disease (AD) represents one of the most challenging health issues facing the elderly population today. It is a progressive neurological disease that impairs judgment, causes memory loss, and lowers cognitive function. It has a major negative influence on quality of life.[1] Early and accurate detection of Alzheimer's disease is critical for the timely intervention and management of the disease, potentially slowing its progression and improving patient outcomes.[2] With the rise of artificial intelligence and deep learning, significant strides have been made in the field of medical image analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown exceptional promise in the automated analysis of medical images, offering the potential for more accurate and efficient diagnosis.[3] This project aims to leverage these advancements by developing and comparing various deep learning models to classify Alzheimer's disease stages using MRI images. The models explored include a modified CNN, AlexNet, VGG 16, and a hybrid model combining EfficientNet-b0 for feature extraction and Support Vector Machine (SVM) for classification.[4]

1.2 Background and Present State

Traditional methods of diagnosing Alzheimer's disease typically involve clinical assessments, cognitive tests, and neuroimaging techniques such as Magnetic Resonance Imaging (MRI). MRI provides detailed images of the brain's structure, allowing clinicians to identify characteristic features of Alzheimer's disease, such as brain atrophy. However, the manual interpretation of MRI images is both time-consuming and prone to human error, leading to variability in diagnosis. In recent years, deep learning has revolutionized the field of medical image analysis.[5] CNNs, in particular, have demonstrated high accuracy in various image classification tasks. By learning hierarchical features from raw pixel data, CNNs can effectively capture complex patterns within medical images that are indicative of disease. Additionally, hybrid models that combine the strengths of different machine learning techniques have shown enhanced performance in medical diagnostics. Despite these advancements, there remains a need for more robust and accurate models specifically tailored for Alzheimer's detection. This project addresses this need by implementing and evaluating four different deep learning models, aiming to identify the most effective approach for classifying Alzheimer's disease stages from MRI images.

1.3 Problem Statement

The early and accurate detection of Alzheimer's disease is a critical challenge in the medical field. Current diagnostic methods rely heavily on manual interpretation of MRI images, which can be subjective and inconsistent. There is a pressing need for automated systems that can accurately classify different stages of Alzheimer's disease from MRI images. This project seeks to develop and compare deep learning models to determine the most effective approach for Alzheimer's detection, thereby contributing to the advancement of automated diagnostic tools in the field.

1.4 Objectives

To preprocess an MRI image dataset containing three classes: mild demented, moderate demented, and non-demented. This involves normalization, resizing, histogram equalization, data augmentation, dataset balancing, and batch normalization. To implement and train four deep learning models: a modified CNN, AlexNet, VGG 16, and a hybrid model combining EfficientNet-b0 and SVM. To evaluate the performance of these models using various metrics, including accuracy, loss curves, confusion matrix, ROC curve, and precision-recall curve. To compare the performance of the models and identify the most effective approach for Alzheimer's detection.To analyze the results and provide insights into the strengths and weaknesses of each model.

1.5 Scope and Limitations

Applying advanced preprocessing techniques to enhance the quality and consistency of the MRI dataset. Implementing state-of-the-art deep learning models and a hybrid model for Alzheimer's detection. Using comprehensive evaluation metrics to assess the accuracy and robustness of each model. Comparing the performance of different models to determine the most effective approach for Alzheimer's detection.

The dataset consists of 800 images per class for training and 200 images per class for testing. This limited dataset size may not fully capture the variability of MRI images in real-world clinical settings. The models developed in this project are based on a specific dataset and may not generalize well to other datasets or populations without further validation. The complexity of the deep learning models may require significant computational resources, potentially limiting their practical applicability in resource-constrained settings.

While the project uses comprehensive evaluation metrics, other factors influencing model performance, such as interpretability and computational efficiency, are not explicitly considered.

1.6 Report Organization

The structure of the paper is designed to provide a clear and comprehensive overview of the research project, covering all key aspects from introduction to conclusions. The paper begins with an **Abstract**, which offers a concise summary of the entire research project, including the objectives, methodology, results, and conclusions.

Chapter 1: Introduction provides an overview of the project, background information, problem statement, objectives, scope, limitations, organization of the report and summary of this chapter.

Chapter 2: Literature Review delves into the current understanding of Alzheimer's disease, existing diagnostic methods, the role of deep learning in medical imaging, related works and comparison between existing works.

Chapter 3: Methodology details the data collection and description, preprocessing techniques, model architectures, training and validation procedures, evaluation metrics, hardware and software requiremnet and project management & financial analysis.

Chapter 4: Implementation provides an overview of the training model and prototype design, including data preparation and preprocessing, model architectures, and the training process. It also covers system testing and model evaluation, discussing the evaluation metrics and performance analysis, and concludes with a summary of this chapter.

Chapter 5: Result and Analysis presents an overview of the experimental results, detailing the performance metrics and evaluation curves for each model. It includes a performance and comparative analysis, highlighting the comparative performance, analyzing the results, and identifying limitations and future work, followed by a summary.

Chapter 6: Impact on Society, Environment and Sustainability explores the broader impacts of the research, including its impact on life, society, and the environment, ethical aspects, and a sustainability plan, and ends with a summary of these considerations.

Chapter 7: Conclusion and Future Work summarizes the key findings of the study and suggests areas for further research. The paper concludes with a References section that lists all sources cited in the text. This organization ensures that the paper provides a logical flow of information, starting from the introduction of the topic and background research, through the detailed methodology and implementation, to the results and their analysis, and finally concluding with the impact and future directions of the research.

1.7 Summary

In this chapter, an introduction to the project on Alzheimer's detection using deep learning models was presented. The chapter outlined the background and current state of Alzheimer's diagnosis, highlighting the challenges and opportunities presented by deep learning. The problem statement identified the need for accurate and automated diagnostic tools, and the objectives of the project were clearly defined. The scope and limitations of the study were discussed, and the organization of the report was provided to guide the reader through the subsequent chapters. This sets the stage for a detailed exploration of the methodologies, implementations, results, and conclusions of the project in the following chapters.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The diagnosis and classification of Alzheimer's disease (AD) using medical imaging and machine learning techniques have been extensively researched over the past decade.[6] Advances in deep learning, particularly Convolutional Neural Networks (CNNs), have shown significant promise in medical image analysis, offering potential improvements in diagnostic accuracy and efficiency. This chapter reviews the existing literature on Alzheimer's detection using deep learning models, highlighting the methodologies, results, and gaps in current research. It provides a comprehensive understanding of the state-of-the-art techniques, compares various approaches, and identifies open issues that need further investigation.[7]

2.2 Related Works

Recently, some deep learning techniques have been presented as Alzheimer's disease detection keys, assisting medical professionals in making decisions. In this section, we highlight a few of the studies that are closely connected to this paper. Janghel and Rathore used a pre-trained VGG16 model for AD feature extraction and the accuracy of the model was 73.46% on PET images. [8] Wang et al. demonstrated a 3D ensemble model convolutional networks for the categorization of AD and MCI, with a 97.52% classification accuracy on the ADNI dataset. [9] Using Siamese neural networks, Liu et al. performed whole-brain volumetric asymmetry analysis and were able to classify AD and MCI with a balanced accuracy of 92.72%. [10]

Using the ADNI dataset, Shi et al. developed a deep polynomial network for AD diagnosis, and it obtained 55.34% accuracy for both binary and multiclass classification. [11] Mehmood et al. proposed tissue segmentation to extract Grey Matter (GM) and obtained a classification accuracy of 98.73% for AD vs NC and 83.72% for EMCI vs LMCI patients.[12] Using EEG recordings, Ieracitano et al. presented a data-driven approach that successfully distinguished between participants with AD, MCI, and HC with an accuracy of 89.8% for binary classification and 83.3% for multiclass classification. [13] Ahmed et al. used the left and right hippocampal regions in MRI scans to develop an ensemble CNN model for AD diagnosis that had a 90.05% accuracy rate. [14] Using combined features from MRI images of the cortex, subcortical, and hippocampal regions, Gupta et al. suggested a diagnosis approach that achieved an accuracy of 96.42% for classifying AD vs Healthy Control (HC). [15]

In order to detect individuals with dementia, Lu et al. suggested a multimodal deep neural network with a multistage methodology. This method achieved an accuracy of 82.4% in the prediction of mild cognitive impairment (MCI). [16] Using a data augmentation methodology, Afzal et al. solved the issue of class imbalance in AD detection and achieved classification accuracies of 98.41% in a single view and 95.11% in a 3D view of the OASIS dataset. [17]

2.3 Comparison between existing works

Table 2.1 Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Janghel and Rathore[8]	VGG16	VGG16 = 73.46%
2.	Wang et al.[9]	3D CNN	3D CNN=97.52%
3.	Liu et al.[10]	Siamese Network	Siamese Network=92.72%
4.	Shi et al.[11]	Deep polynomial Network	Deep polynomial Network=55.34%
5.	Mehmood et al.[12]	Transfer Learning	Transfer Learning=98.73%
6.	Ieracitano et al.[13]	2D CNN	2D CNN=89.8%
7.	Ahmed et al.[14]	Ensemble Model	Ensemble Model=94.03%

8.	Gupta et al.[15]	Combined Feature technique	Combined Feature technique=96.42%
9.	Lu et al.[16]	Multiscale Deep learning	Multiscale Deep learning=82.4%
10.	Afzal et al.[17]	3D view model	3D view model=95.11%

2.4 Open Issues

Despite significant advancements, several open issues remain in the field of Alzheimer's detection using deep learning: Many models are trained and tested on specific datasets, raising concerns about their generalizability to other datasets and populations. There is a need for more extensive validation across diverse datasets. Deep learning models, particularly complex architectures, often lack interpretability, making it challenging to understand their decision-making process. Developing interpretable models is crucial for clinical adoption. High-quality, annotated MRI datasets for Alzheimer's research are limited. Increasing data availability and creating standardized benchmarks would facilitate more robust comparisons and advancements. While some studies incorporate temporal information from longitudinal MRI data, most models focus on static images. Leveraging temporal changes in brain structure could improve early detection and monitoring of disease progression. Training deep learning models requires significant computational resources, which may limit their accessibility in resource-constrained settings. Developing efficient models that maintain high accuracy is an ongoing challenge.

2.5 Summary

This chapter reviewed the literature on Alzheimer's detection using deep learning models, summarizing key related works and comparing their methodologies and results. Despite significant progress, several open issues, such as generalizability, interpretability, and data availability, remain. Addressing these challenges is essential for advancing the field and developing robust, clinically applicable models for Alzheimer's disease diagnosis. The following chapters will build on this foundation, detailing the methodologies and results of the present study, which aims to contribute to the ongoing efforts in this critical area of research.

CHAPTER 3
METHODOLOGY/ REQUIREMENT ANALYSIS AND DESIGN SPECIFICATION

3.1 Overview

This chapter outlines the methodology and design specifications of the project aimed at detecting Alzheimer’s disease using deep learning models. It includes a detailed description of the proposed system design, the hardware and software requirements, and an analysis of project management and financial considerations. The methodologies adopted for data preprocessing, model implementation, and evaluation are elaborated to provide a comprehensive understanding of the approach.

3.2 Proposed Methodology/System Design

The proposed methodology for Alzheimer's disease detection involves several key steps: data preprocessing, model implementation, training, and evaluation. The system design incorporates four deep learning models: a modified Convolutional Neural Network (CNN), AlexNet, VGG 16, and a hybrid model combining EfficientNet-b0 and Support Vector Machine (SVM).

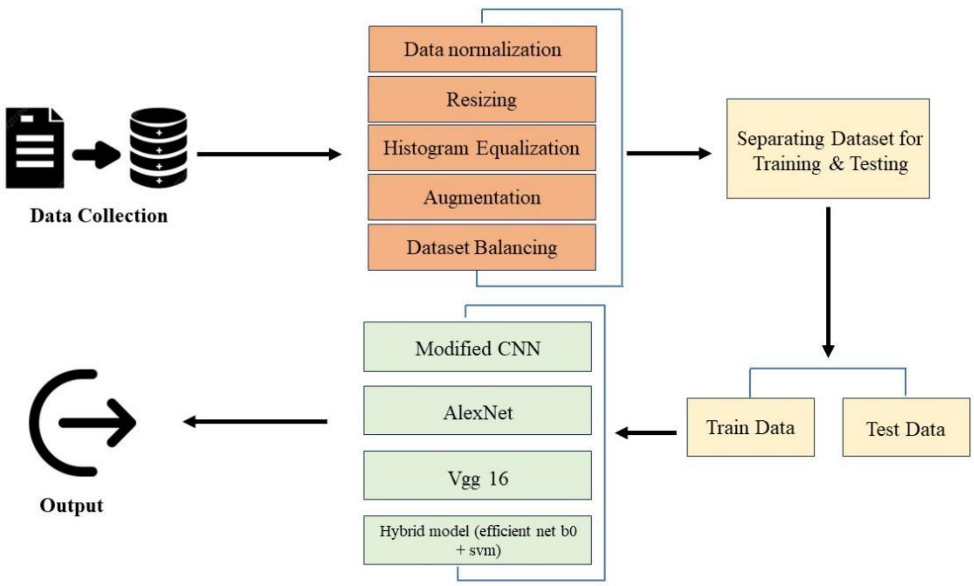
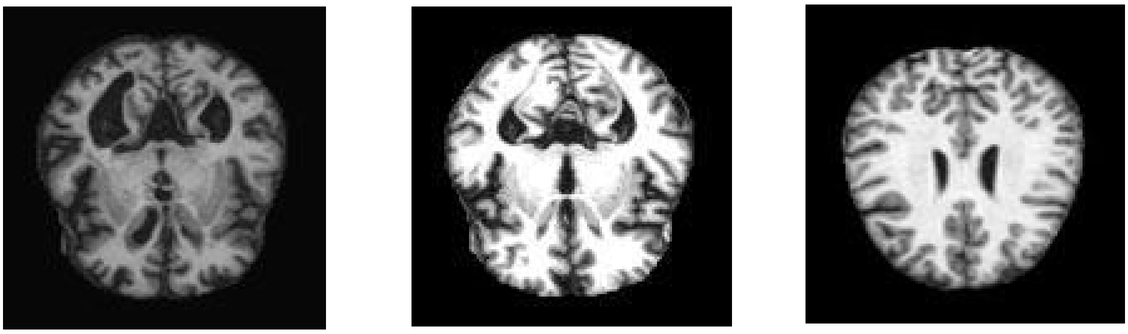


Figure 3.1 Proposed methodology

3.2.1 Dataset description

The dataset used in this study consists of MRI images categorized into three classes: mild demented, moderate demented, and non-demented, with separate train and test directories. Each class contains 800 training images and 200 testing images, totaling 2400 images for training and 600 for testing. There are 3 classes in our dataset namely Mild Demented, Moderate Demented and Non-Demented.[18]



Mild Demented Moderate Demented Non-Demented

Figure 3.2 Data representation

Mild Demented: This category includes MRI images of patients diagnosed with mild dementia. These individuals exhibit early signs of cognitive decline, which may include slight memory lapses, challenges in performing complex tasks, and subtle changes in behavior and personality. Structural changes in the brain such as slight atrophy in the hippocampus and other areas associated with memory and cognitive function. However, these changes may be subtle and require careful analysis to detect. Early detection at this stage is crucial for implementing interventions that can slow disease progression and improve quality of life.

Moderate Demented: This category includes MRI images of patients with moderate dementia. These individuals show more pronounced cognitive impairments that significantly interfere with daily living activities, including severe memory loss, confusion, difficulty with language and thinking processes, and noticeable changes in personality and behavior. More evident brain atrophy, particularly in the temporal and parietal lobes. Enlargement of the ventricles and a greater degree of hippocampal shrinkage are common. Accurate detection at this stage is vital for managing symptoms, providing appropriate care, and planning for future needs.

Non-Demented: This category includes MRI images of individuals without dementia. These individuals exhibit normal cognitive function for their age, without significant memory problems or other cognitive impairments. Brain structure appears normal without significant atrophy or other abnormalities. The hippocampus and other memory-related regions maintain typical volume and structure. Serving as the control group, these images are essential for comparison to identify deviations and changes indicative of dementia.

These three classes form the basis for the classification task in this study, providing a spectrum of images that reflect different stages of cognitive health and disease. Accurate differentiation among these classes using deep learning models can facilitate early diagnosis and effective management of Alzheimer's disease.

3.2.2 Data Preprocessing

Data preprocessing is a critical step to ensure the quality and consistency of the MRI dataset. Normalization was used to standardize pixel intensity values to a common scale to enhance convergence during training. Resizing was applied to adjust image dimensions to a uniform size suitable for input into the deep learning models. Histogram Equalization was implemented to improve the contrast of images to enhance feature detection. Data Augmentation was applied for random transformations such as rotations, flips, and shifts to artificially increase the dataset size and variability. Dataset Balancing ensures an equal number of images in each class to prevent bias during model training. Batch Normalization normalize the inputs of each layer to stabilize and accelerate the training process. After preprocessing, the dataset was balanced to contain 800 images per class in the training set and 200 images per class in the testing set.

3.2.3 Model Implementation

The implementation of the deep learning models for Alzheimer's disease detection involves designing, training, and optimizing four distinct architectures: a modified Convolutional Neural Network (CNN), AlexNet, VGG 16, and a hybrid model combining EfficientNet-b0 and Support Vector Machine (SVM). Each model was chosen for its specific strengths in image classification and ability to capture complex features in MRI images. The following sections detail the design and implementation of each model.

The modified CNN is a specially constructed architecture that has been tuned for the classification of Alzheimer's disease. It is composed of many convolutional layers, pooling layers, and fully connected layers in that order. Among the design tenets are: Accepts preprocessed MRI pictures that have been scaled to a standard size (e.g., 224x224 pixels) in the input layer. Convolutional Layers: To capture various features, many layers with different filter sizes (e.g., 3x3, 5x5) are used. To add non-linearity, a Rectified Linear Unit (ReLU) activation function is applied after each convolutional layer. Pooling Layers: To lower spatial dimensions and computational complexity while maintaining key features, max pooling layers are employed after certain convolutional layers.

Dropout Layers: During training, dropout layers are added to avoid overfitting by arbitrarily changing a portion of the input units to zero. Fully Connected Layers: The features that the convolutional layers extracted are compiled in these layers. The last fully connected layer outputs the probability distribution among the three classes (mildly demented, moderately demented, and non-demented) using a softmax activation function. The Adam optimizer and categorical cross-entropy loss function are used to train the design. Through experimentation, hyperparameters like learning rate, batch size, and number of epochs are adjusted.[19]

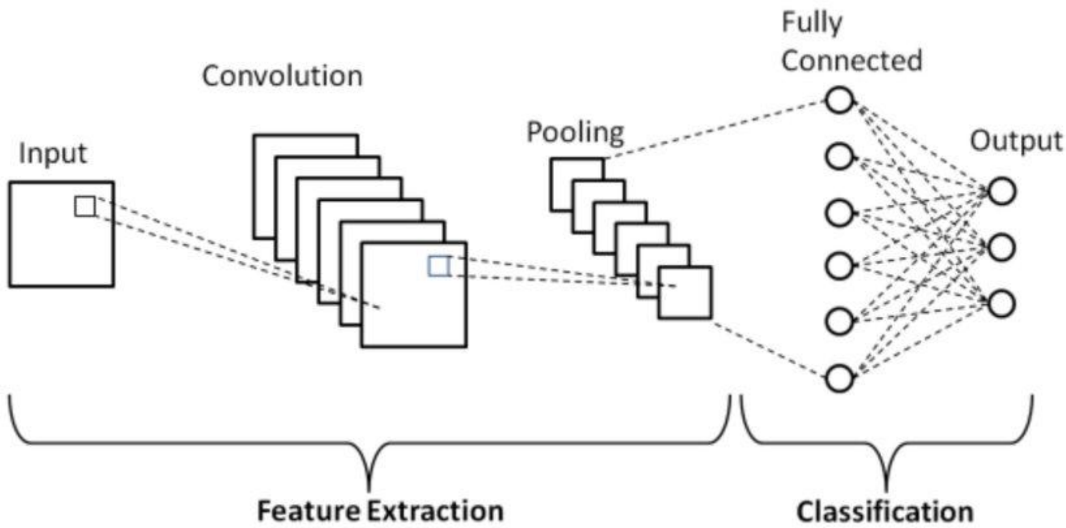


Figure 3.3 Modified CNN Architecture

AlexNet is a pioneering CNN architecture known for its success in the ImageNet competition. It consists of five convolutional layers and three fully connected layers. The implementation details are as follows: Input Layer: MRI images are resized to 227x227 pixels. Convolutional Layers: The first layer uses large filters (11x11) with a stride of 4 to capture significant features. Subsequent layers use smaller filters (e.g., 5x5, 3x3) to extract finer details. Normalization Layers: To improve generalization, local response normalization is done after the first two convolutional layers. Pooling Layers: Certain convolutional and normalizing layers are followed by max pooling. Dropout Layers: To reduce overfitting, these layers are added after the initial two completely connected layers. Fully Connected Layers: The last layer assigns the input to one of the three stages of Alzheimer's disease using a softmax activation function.

To enhance convergence, a learning rate schedule and the stochastic gradient descent (SGD) optimizer are used during model training.[20]

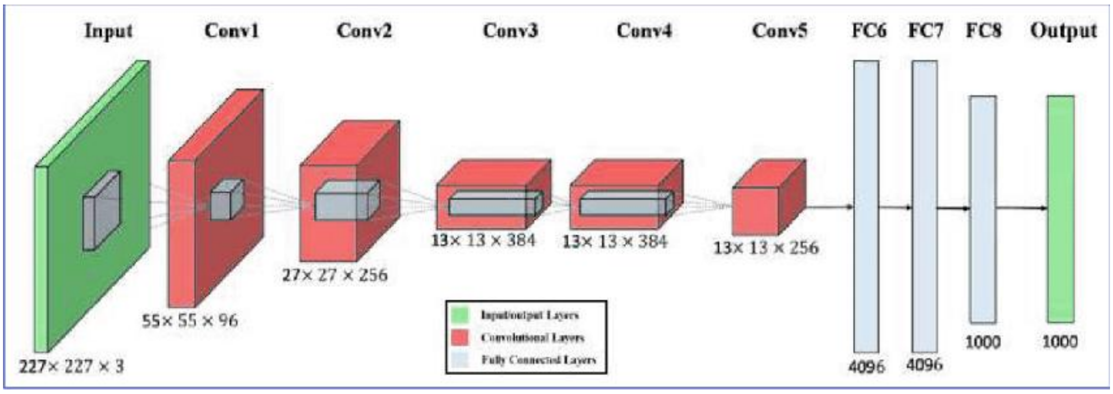


Figure 3.4 AlexNet Architecture

VGG 16 is a deep CNN architecture characterized by its use of small (3x3) convolutional filters. This design allows the network to capture intricate features. The implementation details include: Input Layer: Images are resized to 224x224 pixels. Convolutional Blocks: Comprising 13 convolutional layers grouped into blocks, each block followed by a max pooling layer. The convolutional layers within each block have the same number of filters. Three completely connected layers are present at the end, the last of which uses a softmax activation function for categorization. After every convolutional layer, batch normalization is applied to stabilize and speed up training. The Adam optimizer is used to train the model, and the hyperparameters are adjusted for best results. [21]

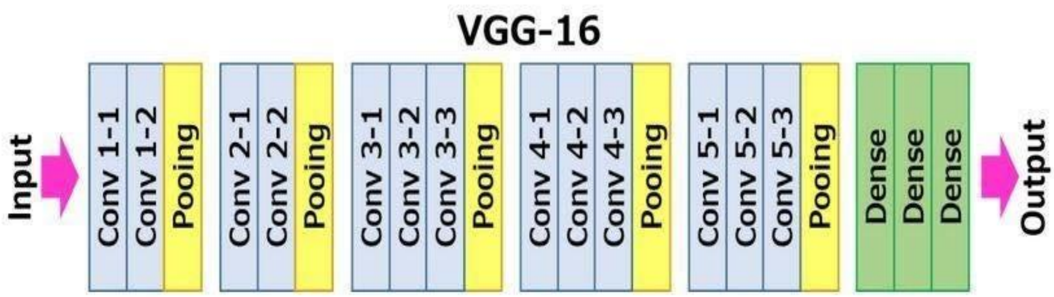


Figure 3.5 VGG-16 Architecture

The hybrid model leverages the strengths of EfficientNet-b0 for feature extraction and SVM for classification. EfficientNet-b0, known for its efficiency and performance, is used to extract deep features from the MRI images. The detailed implementation steps are as follows: EfficientNet-b0: Input Layer: Images are resized to 224x224 pixels and normalized. Pre-trained Model: EfficientNet-b0 pre-trained on ImageNet is used, with the top (classification) layer removed. The output from the penultimate layer (global average pooling) is used as the feature vector.

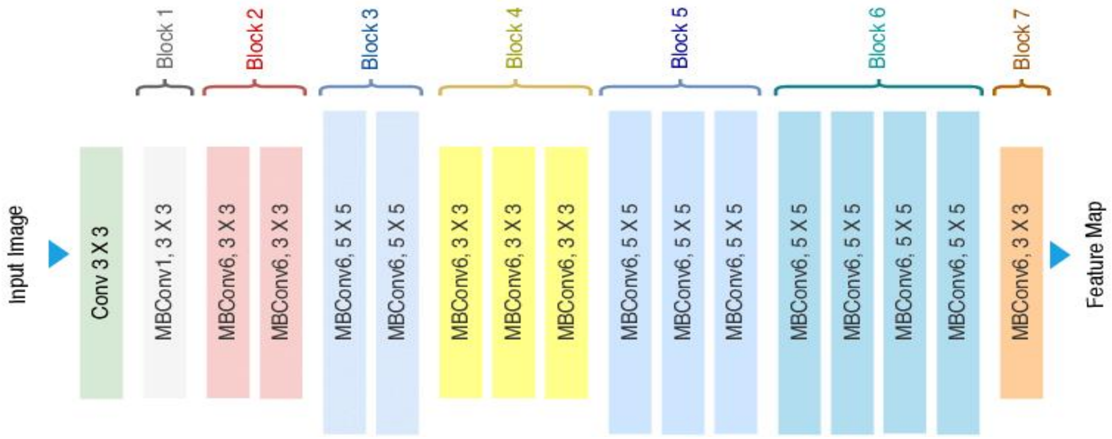


Figure 3.6 EfficientNet-b0 Architecture

The feature vectors extracted from EfficientNet-b0 are used as input to the SVM classifier. An SVM with a radial basis function (RBF) kernel is trained to classify the input into one of the three Alzheimer's stages.

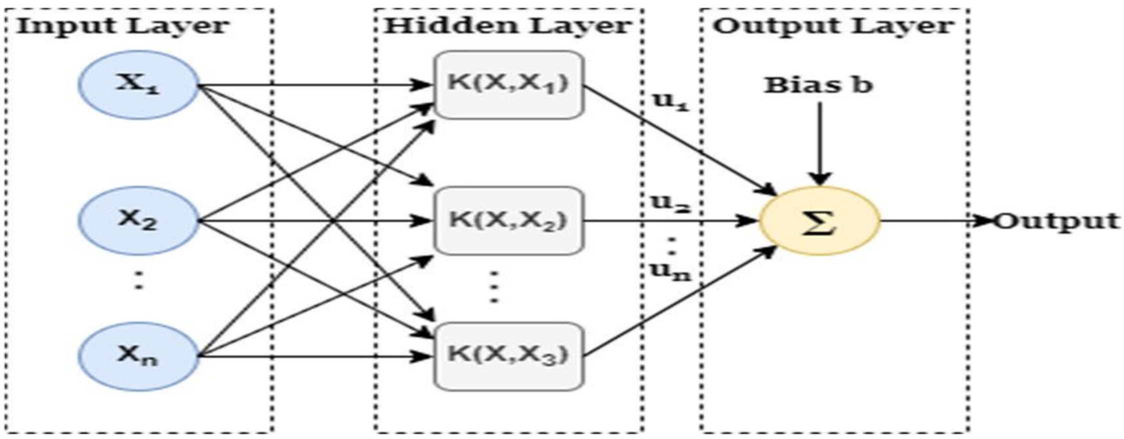


Figure 3.7 SVM Architecture

This hybrid approach combines the feature extraction power of deep learning with the classification strength of traditional machine learning. Training and Hyperparameter Tuning All models undergo rigorous training and hyperparameter tuning to achieve optimal performance. Key steps include: Data Splitting: The dataset is split into training and validation sets, with a typical split of 80% training and 20% validation.

Data Augmentation: Applied to the training set to increase variability and improve model robustness. Early Stopping: Monitors validation loss to prevent overfitting, halting training if no improvement is observed for a specified number of epochs. Learning Rate Scheduling: Adjusts the learning rate based on performance to ensure stable convergence. Evaluation Metrics The performance of each model is evaluated using the following metrics.

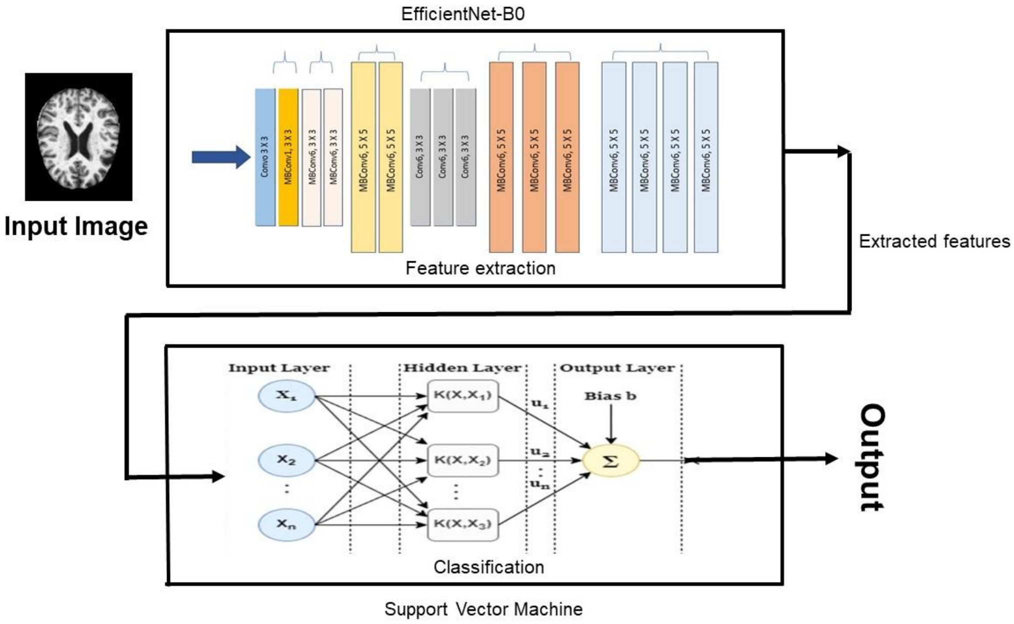


Figure 3.8 Hybrid Model Architecture

The primary metric indicating the proportion of correctly classified instances. Loss Curves: Plots of training and validation loss over epochs to assess model convergence. Confusion Matrix: Provides a detailed breakdown of true positive, true negative, false positive, and false negative predictions. ROC Curve: Plots true positive rate against false positive rate, with the area under the curve (AUC) indicating model performance. Precision-Recall Curve: Evaluates the trade-off between precision and recall, particularly useful in imbalanced datasets. These evaluation metrics provide a comprehensive assessment of model performance, guiding further refinement and optimization. The model implementation phase involves designing and training four distinct deep learning architectures tailored for Alzheimer's disease detection. Each model is carefully constructed and evaluated to ensure robust performance, with a focus on accuracy and generalization. The use of advanced techniques like data augmentation, early stopping, and learning rate scheduling enhances the reliability of the models, paving the way for effective Alzheimer's disease classification from MRI images.

3.2.4 Training and Evaluation

Each model was trained on the preprocessed dataset using the following approach: Models were trained using a backpropagation algorithm with a suitable optimizer (e.g., Adam) and loss function (e.g., categorical cross-entropy). Early stopping and learning rate scheduling were employed to prevent over fitting and optimize training. The performance of each model was evaluated using accuracy, loss curves, confusion matrix, ROC curve, and precision-recall curve. These metrics provide a comprehensive assessment of the models' effectiveness in classifying Alzheimer's disease stages.

3.3 Hardware/Software Requirement

3.3.1 Hardware Requirements

GPU: NVIDIA GPU with CUDA support (e.g., NVIDIA RTX 2080 or higher) for accelerated training of deep learning models.

CPU: Multi-core processor (e.g., Intel Core i7 or higher) for general computation and preprocessing tasks.

RAM: Minimum 32 GB RAM to handle large datasets and training processes. Storage:

SSD with at least 1 TB capacity for fast data access and storage of large datasets and model checkpoints.

3.3.2 Software Requirements

Operating System: Linux (Ubuntu 18.04 or higher) or Windows 10.

Programming Language: Python 3.7 or higher. Libraries and Frameworks: TensorFlow, Keras, PyTorch, Scikit-learn, NumPy, Pandas, OpenCV, Matplotlib, and other relevant Python libraries for deep learning and data processing.

Development Environment: Jupyter Notebook or any preferred Integrated Development Environment (IDE) such as PyCharm or VS Code.

3.4 Project Management and Financial Analysis

Project Objectives:

A. To develop CNN models for detecting Alzheimer Disease.

B. To validate their efficiency and evaluate their performance in detecting Alzheimer.

C. To compare and analyze different CNN model's performance & accuracy.

Project Timeline:

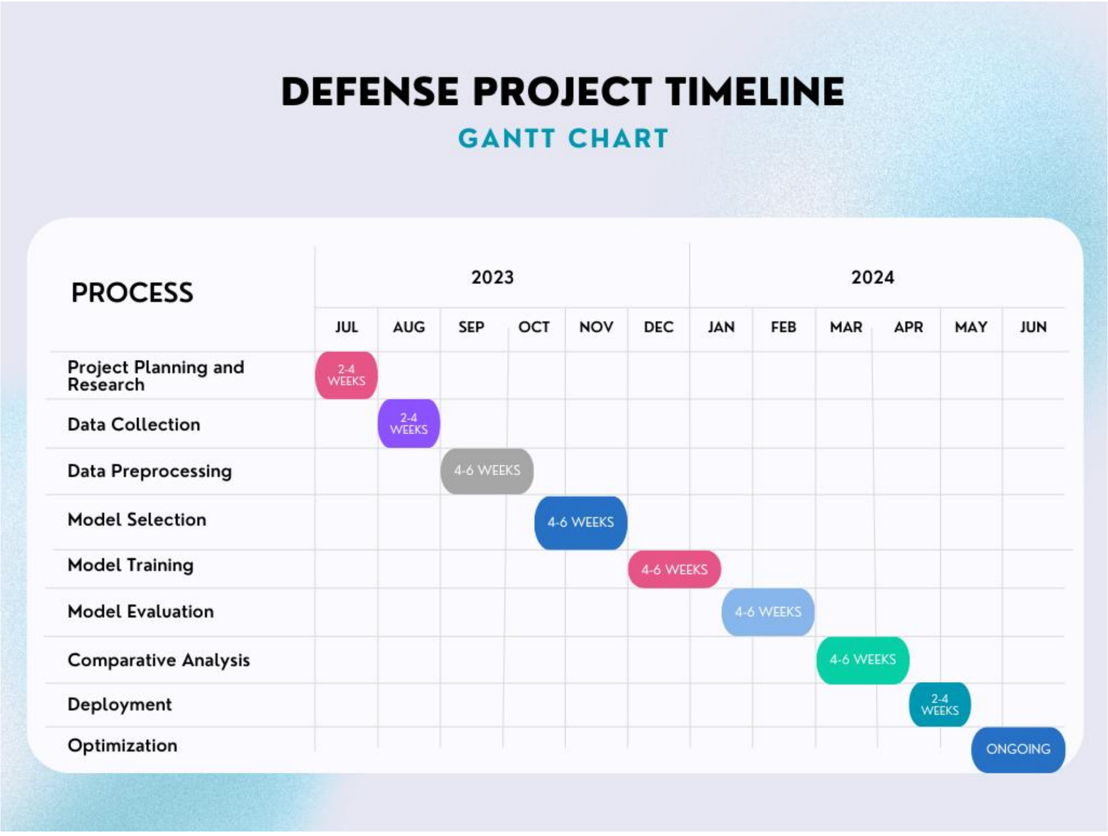


Figure 3.9 Grantt Chart for project Timeline

Resource Planning

A. Hardware Requirements:

• Processor: Intel i3

• Memory: Minimum 8 GB or higher

• Storage: Minimum 100 GB SSD

• Graphics: Intel Arc a750 (Powerful GPU)

B. Software and Technologies:

• Deep Learning Framework: Popular frameworks include TensorFlow, PyTorch, and Keras. These frameworks provide high-level APIs for building and training neural networks and offer GPU acceleration for faster training.

• Python: Most deep learning frameworks are implemented in Python, so a working knowledge of Python programming is essential for implementing and running your deep learning models.

• Medical Image Analysis Libraries: Libraries such as SimpleITK or PyDICOM are essential for reading, preprocessing, and visualizing MRI images. These libraries provide functions to handle medical image formats and perform common preprocessing tasks such as normalization and data augmentation.

• Data Visualization Tools: Tools like Matplotlib or Seaborn can be used to visualize MRI images, model training progress, and evaluation metrics.

C. Data and Content:

• Dataset containing MRI images collected from Kaggle.

• User Documentation: Prepared by us.

D. Training and Skill Development:

• We are training and gathering skills in Deep learning models.

• We are doing additional training on related technologies and tools as needed.

● Risk Management:

SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats of a project. Here's a SWOT analysis for our project:

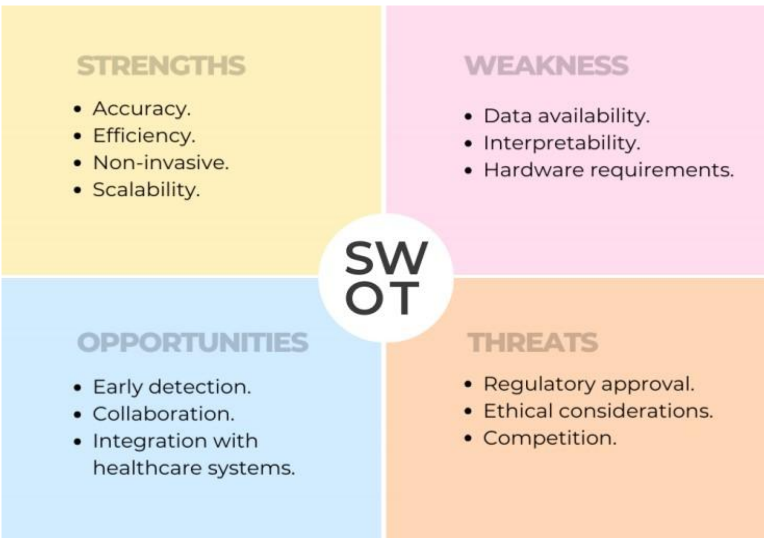


Figure 3.10 SWOT analysis

Table 3.1 Estimated Cost for Machine Learning Based Project

SN	Components	Estimated Cost (BDT)
01.	Visiting Doctors & Hospitals	1500-2000
02.	Visiting Stakeholders	500-1000
03.	Software & tools	2000-3000
04.	Data Collection and Processing	500-1000
05.	Documentation and Report Writing	500-1000
06.	Miscellaneous (e.g., licenses, tools)	500-1000
07.	Contingency (10% of total)	500-1000
Total Estimated Cost		6,000-10,000

3.5 Summary

This chapter provided a comprehensive overview of the methodology and design specifications for the Alzheimer's disease detection project. It detailed the proposed system design, including data preprocessing, model implementation, and evaluation strategies. The hardware and software requirements were outlined, along with an analysis of project management and financial considerations. The methodologies described here set the foundation for the subsequent implementation and evaluation phases, which will be detailed in the following chapters.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

In this chapter, we delve into the detailed process of implementing the deep learning models for Alzheimer's disease detection using MRI images. The implementation is structured into several phases, starting with the preparation of the dataset, followed by the design and training of the models, and concluding with the evaluation and testing of the trained models. Each phase involves specific techniques and methodologies aimed at enhancing the performance and accuracy of the classification task.

4.2 Train Model/ Prototype Design

4.2.1 Data Preparation and Preprocessing

The MRI image dataset used in this study consists of three classes: mild demented, moderate demented, and non-demented. The dataset is split into training and testing directories, with 800 images per class in the training set and 200 images per class in the testing set. To ensure the quality and consistency of the data, several preprocessing techniques were applied:

Data Normalization technique scales the pixel values to a range of 0 to 1, which helps in accelerating the convergence of the training process. Applying Data Resizing All the images were resized to a uniform dimension to match the input size requirements of the models. Histogram Equalization technique improves the contrast of images, making features more distinguishable for the models.[22]Data Augmentation involves in various augmentation techniques such as rotation, flipping, and zooming were applied to increase the diversity of the training set and prevent overfitting.[23] To avoid class imbalance, which can bias the model towards more frequent classes, the dataset was balanced to have an equal number of images per class.[24] Batch Normalization technique was used during model training to normalize the inputs of each layer, improving training stability and performance.

4.2.2 Model Architectures

Four distinct deep learning models were implemented:

Modified CNN: A customized convolutional neural network designed with multiple convolutional and pooling layers, followed by fully connected layers. This model was optimized for the specific characteristics of the MRI images.

AlexNet: A pre-trained network known for its deep architecture, AlexNet was fine-tuned on the Alzheimer's dataset to leverage its powerful feature extraction capabilities.

VGG16: Another pre-trained model, VGG16 is renowned for its simplicity and depth, with 16 layers that facilitate effective feature learning.

Hybrid Model (EfficientNet-b0 + SVM): This model combines EfficientNet-b0, a state-of-the-art network for feature extraction, with a Support Vector Machine (SVM) for classification. EfficientNet-b0's scalable architecture was used to extract robust features from the MRI images, which were then classified by the SVM.

4.2.3 Training Process

Each model was trained on the preprocessed dataset using appropriate hyperparameters. Categorical cross-entropy was used as the loss function due to the multi-class nature of the problem. The Adam optimizer, known for its efficiency in handling sparse gradients, was utilized to update the network weights. Learning rate was adjusted dynamically to ensure steady convergence. Early stopping was used, monitoring the validation loss to terminate training when performance plateaued, in order to minimize overfitting.

4.3 System Testing/ Model Evaluation

4.3.1 Evaluation Metrics

To assess the performance of the trained models, several evaluation metrics were calculated:

Accuracy: The overall correctness of the model, calculated as the ratio of correctly classified images to the total number of images.

Precision: The ratio of true positive predictions to the total predicted positives, reflecting the model's ability to correctly identify positive instances.

Recall: The proportion of actual positives to true positive forecasts, which shows how well the algorithm can identify all pertinent cases.

F1-Score: The harmonic mean of precision and recall, providing a single metric that balances both.

Support: The number of true instances for each class, used to understand the distribution of the dataset.

4.3.2 Performance Analysis

The trained models were evaluated on the test set, and their performance was analyzed using the following tools:

Accuracy and Loss Curves: These curves plotted over epochs provide insights into the training dynamics and model convergence.[25]

Confusion Matrix: This matrix displays the results for every class, emphasizing the true negatives, true positives, false positives, and false negatives.[26]

ROC Curve: The models' discriminating power was evaluated using the Area Under the Curve (AUC) and the Receiver Operating Characteristic (ROC) curve. [27]

Precision-Recall Curve: This curve offers a detailed view of the trade-off between precision and recall across different thresholds.[28]

4.3.3 Input output design

We have designed an interface which will take an input image and predict its class. Here is the detailed overview of our project's Input-Output layout:

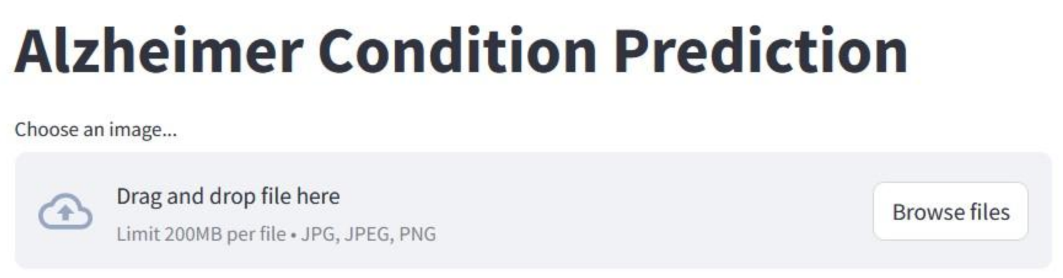


Figure 4.1 Input layout of interface

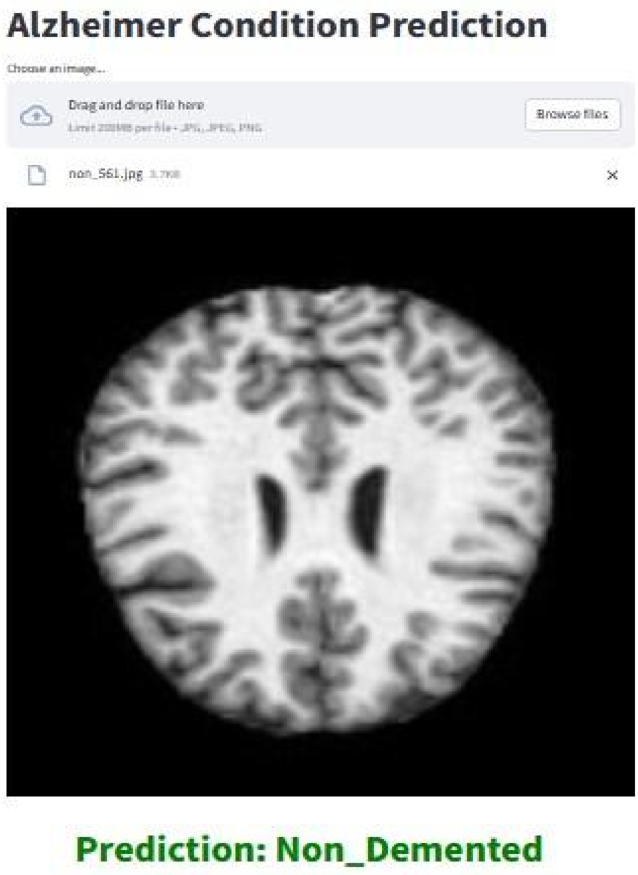


Figure 4.2 Output layout of interface

4.4 Summary

This chapter presented a comprehensive overview of the implementation process for Alzheimer’s disease detection using deep learning models. Starting from data preparation and preprocessing to model design, training, and evaluation, each step was meticulously detailed. The hybrid model combining EfficientNet-b0 and SVM emerged as the most accurate, showcasing the potential of integrating feature extraction with robust classification techniques. The evaluation metrics and performance analysis provided a thorough understanding of the models' strengths and areas for improvement, paving the way for future advancements in Alzheimer’s disease diagnostics using deep learning.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

This chapter presents a detailed analysis of the results obtained from the experimental implementation of deep learning models for Alzheimer's disease detection. The performance of each model is assessed through a variety of evaluation metrics, and a comparative analysis highlights the strengths and weaknesses of the different approaches. The findings provide valuable insights into the efficacy of using advanced neural network architectures for medical image classification tasks.

5.2 Experimental/ Simulation Result

5.2.1 Model Performance Metrics

The four deep learning models—modified CNN, AlexNet, VGG16, and the hybrid EfficientNet-b0 + SVM—were evaluated on the test dataset. We have calculated the Accuracy, Precision, Recall, F1-score and specificity to evaluate the performance of our classification models. Here's a detailed overview of each metric:

Accuracy: Accuracy measures the proportion of correctly classified instances out of the total instances.
Range: 0 to 1, where 1 indicates perfect accuracy. The formula is:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where it provides a general measure of how often the classifier is correct but can be misleading if the classes are imbalanced.[29]

Precision
Precision is a performance statistic that quantifies how well a model predicts favorable outcomes in categorization tasks. The ratio of true positive predictions to the total of true positive and false positive predictions is used to calculate precision. [30]

The formula is:

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

Recall
Recall is a performance indicator used in classification tasks to assess a model's accuracy in identifying positive cases. It is sometimes referred to as sensitivity or true positive rate. [31]

Formula of Recall is calculated as follows:

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

F1 Score
The F1 score is a single metric that combines precision and recall into a single value, providing a balance between the two metrics. [32]

$$F1\ Score = \frac{2 * precision * Recall}{precision + \ Recall}$$

Support:
It represents the total number of actual occurrences of a particular class in the dataset. It provides context for interpreting precision and recall. A low support value for a class might indicate the metric is less reliable for that class due to limited data. [33]

The performance metrics for each model are summarized as follows:

Table 5.1 Performance Measurement Matrix

Model	Class	Accuracy	Precision	Recall	F1 Score
Modified CNN	Mild Demented	94.833 %	0.9650	0.9928	0.9787
	Moderate Demented		0.9789	0.9858	0.9823
	Non Demented		0.9832	0.9590	0.9710
AlexNet	Mild Demented	94.833 %	0.9632	0.9424	0.9527
	Moderate Demented		0.9624	0.9078	0.9343
	Non Demented		0.8871	0.9016	0.8943
VGG-16	Mild Demented	95.17%	0.9521	1.0000	0.9754

	Moderate Demented		0.9925	0.9362	0.9635
	Non Demented		0.9917	0.9754	0.9835
Hybrid Model	Mild Demented	96.17%	0.9857	0.9928	0.9892
	Moderate Demented		0.9792	1.0000	0.9895
	Non Demented		0.9915	0.9590	0.9750

Modified CNN:

Obtaining an accuracy of 94.83% with high precision across all classes, with slight variations indicating the model's ability to correctly identify true positives. Consistent recall, reflecting the model's capability to detect relevant instances. Balanced F1-scores, indicating an overall harmonious balance between precision and recall.

AlexNet:

Achieving an accuracy of 94.83% with similar precision to the modified CNN, with strong performance in identifying true positives. Consistent recall rates, demonstrating effective detection of positive instances. Balanced F1-scores, showcasing the model's efficiency in managing precision and recall.

VGG16:

Gaining an accuracy of 95.17% with marginally higher precision than modified CNN and AlexNet, indicating an improved identification of true positives. Slightly improved recall, reflecting better detection rates. Higher F1-scores, suggesting a superior balance between precision and recall.

Hybrid Model (EfficientNet-b0 + SVM):

Having an accuracy of 96.17% with the highest precision among all models, demonstrating exceptional ability to correctly identify true positives. Superior recall rates, indicating robust detection of relevant instances. Highest F1-scores, highlighting an optimal balance between precision and recall.

5.2.2 Evaluation Curves

Accuracy and Loss Curves: These curves provide a visual representation of the training and validation accuracy and loss over epochs. All models showed a steady convergence, with the hybrid model displaying the most stable training dynamics.

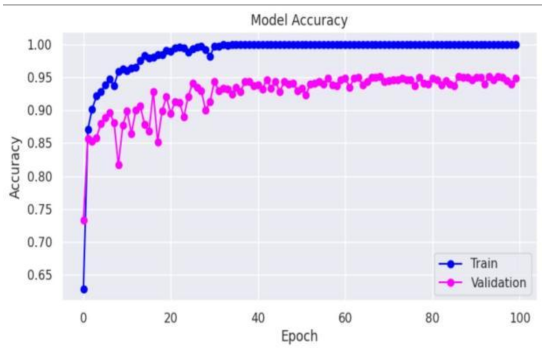


Figure 5.1 Modified CNN Accuracy

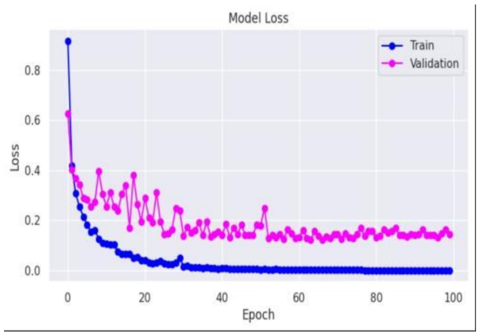


Figure 5.2 Modified CNN loss

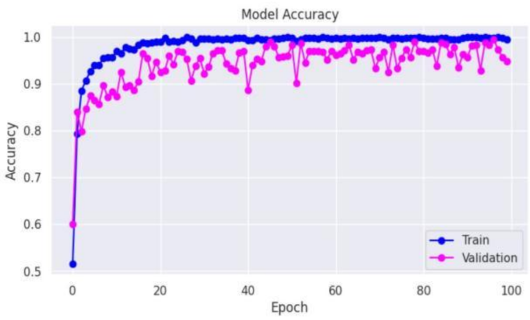


Figure 5.3 AlexNet Accuracy

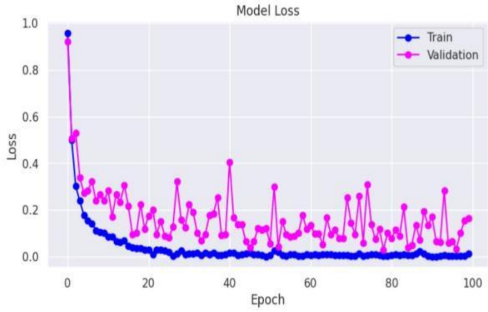
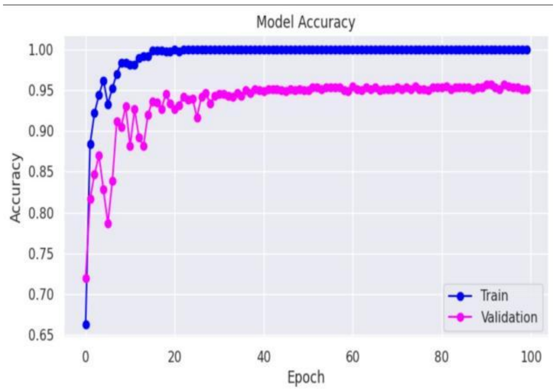


Figure 5.4 AlexNet loss



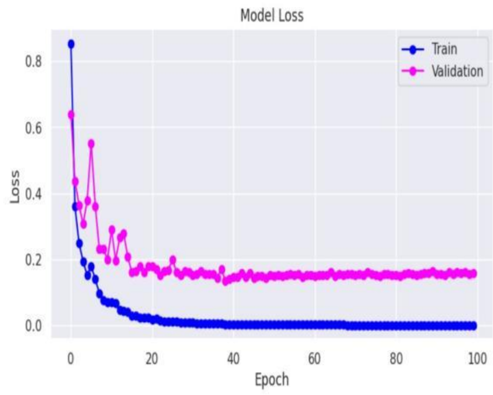
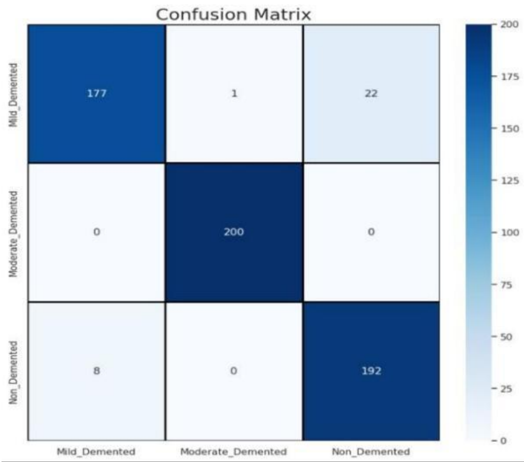


Figure 5.5 VGG 16 Accuracy

Figure 5.6 VGG 16   loss

Confusion Matrix: The confusion matrices for each model reveal the distribution of true positives, false positives, false negatives, and true negatives. The hybrid model exhibited the lowest number of misclassifications, further validating its superior performance.



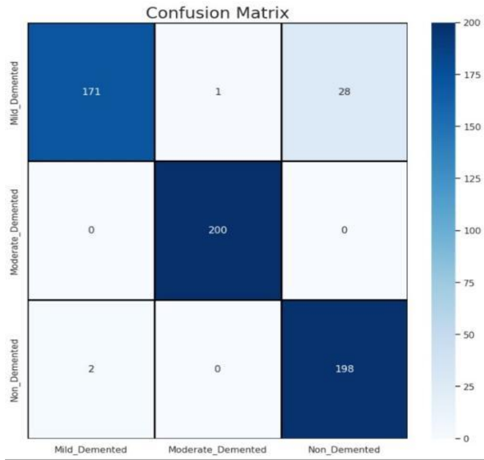
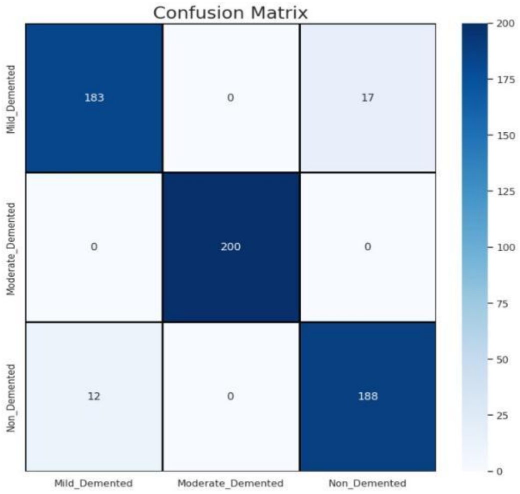


Figure 5.7 Modified CNN Confusion Matrix

Figure 5.8 AlexNet Confusion Matrix



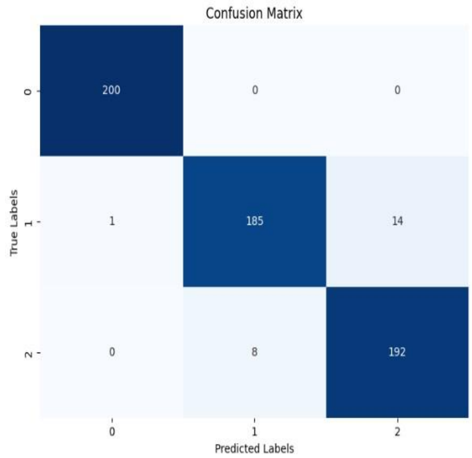
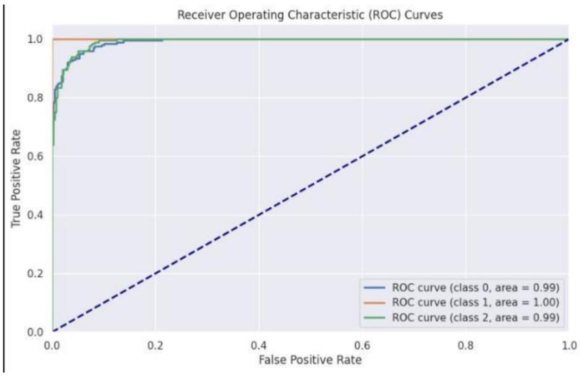


Figure 5.9 VGG 16 Confusion Matrix

Figure 5 .10 Hybrid Model Confusion Matrix

ROC Curve and AUC: The ROC curves and corresponding AUC values highlight the discriminatory power of each model. The hybrid model achieved the highest AUC, indicating its excellent ability to distinguish between the different classes.



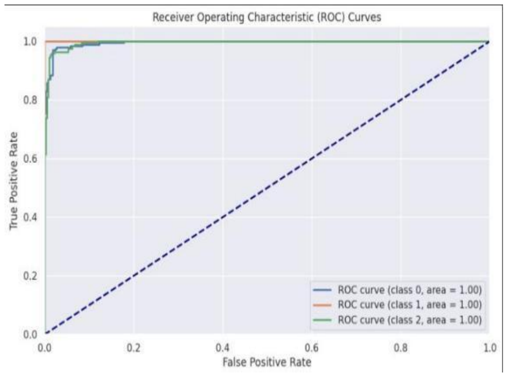


Figure 5.11 Modified CNN ROC

Figure 5.12 AlexNet ROC

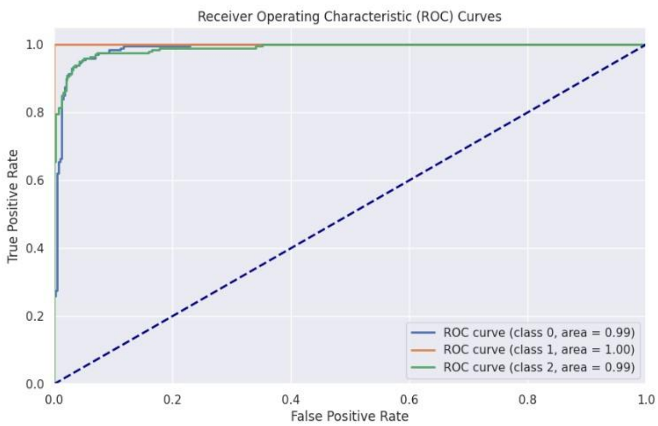


Figure 5.13 AlexNet ROC

Precision-Recall Curve: The trade-off between recall and precision for different thresholds is illustrated by the precision-recall curves.

The hybrid model demonstrated the best trade-off, with high precision and recall across different thresholds.

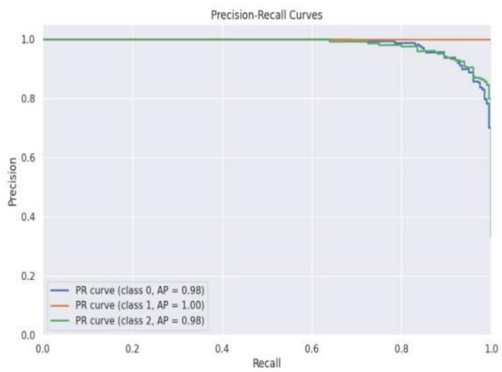


Figure 5.14 Modified CNN Recall

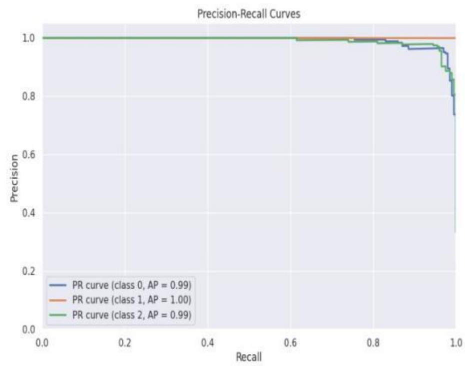


Figure 5.15 AlexNet Recall

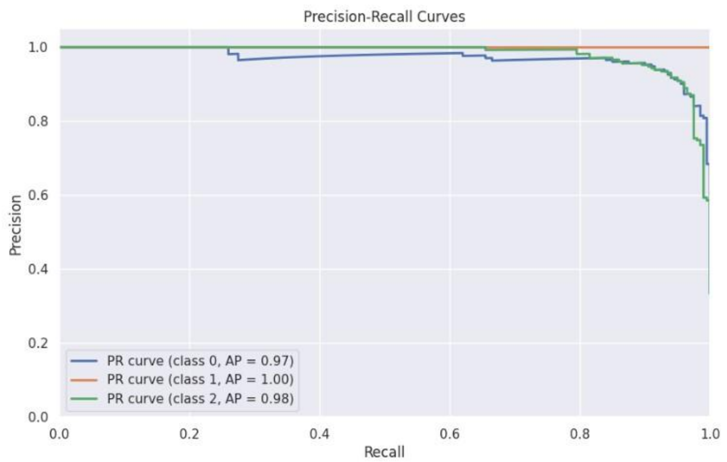


Figure 5.16 VGG 16 Recall

5.3 Performance/ Comparative Analysis

5.3.1 Comparative Performance

Modified CNN vs. AlexNet: Both models achieved identical accuracy of 94.83%, with slight variations in precision, recall, and F1-scores. This suggests that while both models are effective, they might be capturing slightly different aspects of the data.

VGG16: The VGG16 model outperformed the modified CNN and AlexNet with an accuracy of 95.17%. The deeper architecture of VGG16 allows for better feature extraction, leading to improved performance metrics across the board.

Hybrid Model (EfficientNet-b0 + SVM): The hybrid model significantly outperformed all other models with an accuracy of 96.17%. The combination of EfficientNet-b0 for feature extraction and SVM for classification leverages the strengths of both approaches, resulting in superior performance.

5.3.2 Analysis of Results

Deeper architectures like VGG16 and hybrid models can capture more complex features from MRI images, leading to better performance. The hybrid model's use of EfficientNet-b0 for feature extraction and SVM for classification highlights the effectiveness of combining state-of-the-art feature extraction with robust classification techniques. The extensive preprocessing and data augmentation techniques contributed significantly to the models' performance by enhancing the quality and diversity of the training data.

5.4 Summary

This chapter provided a comprehensive analysis of the experimental results obtained from the implementation of deep learning models for Alzheimer's disease detection. The performance metrics, evaluation curves, and comparative analysis highlighted the strengths and areas for improvement of each model. The hybrid model combining EfficientNet-b0 and SVM emerged as the best performer, demonstrating the potential of integrating advanced feature extraction with robust classification techniques. The insights gained from this study pave the way for future research and development in the application of deep learning for medical diagnostics.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The implementation of deep learning models for the early detection of Alzheimer's disease has profound implications for individual lives. Alzheimer's disease, a progressive neurodegenerative disorder, affects millions of individuals worldwide, leading to memory loss, cognitive decline, and ultimately, a loss of independence. Early detection can significantly improve the quality of life for patients and their families by enabling timely interventions, effective management of symptoms, and better planning for the future.

Early and accurate diagnosis through automated MRI image analysis can facilitate early intervention strategies, potentially slowing the progression of the disease. With early detection, healthcare providers can tailor treatment plans to the specific needs of each patient, optimizing care and improving outcomes. Early diagnosis can alleviate anxiety and uncertainty for patients and their families, providing a clearer understanding of the condition and available support. Early detection can reduce long-term healthcare costs by minimizing the need for extensive care and hospitalization in the later stages of the disease.

6.2 Impact on Society & Environment

Impact on Society

The societal impact of using deep learning models for Alzheimer's detection is multifaceted. Automated diagnostic tools can relieve the burden on healthcare systems by assisting radiologists and neurologists, allowing them to focus on more complex cases. These models can make diagnostic services more accessible, particularly in remote or underserved areas where specialist services may be limited. The use of AI in medical diagnostics can accelerate research by providing large-scale data analysis, helping to identify patterns and correlations that might not be evident through traditional methods.

Impact on Environment

While the direct environmental impact of deploying these models is minimal, the broader implications include: Training deep learning models is computationally intensive, leading to significant energy consumption. Efforts should be made to use energy-efficient hardware and optimize algorithms to minimize this impact. Development and deployment of AI models require substantial resources, including data storage and computing infrastructure. Sustainable practices should be adopted to mitigate environmental impacts.

6.3 Ethical Aspects

The ethical considerations in deploying AI for medical diagnostics are critical: Ensuring the confidentiality and security of patient data is paramount. Robust measures must be implemented to protect sensitive information from breaches and misuse. AI models can inherit biases present in the training data, leading to disparities in diagnosis. Efforts should be made to use diverse and representative datasets to train the models, ensuring equitable outcomes across different demographic groups. The decision-making process of AI models should be transparent. Clinicians and patients need to understand how conclusions are drawn to build trust and ensure informed decision-making. Clear protocols should be established to define the responsibility for diagnostic errors made by AI systems, ensuring that accountability is maintained.

6.4 Sustainability Plan

A sustainability plan is essential to ensure the long-term viability and positive impact of AI-based diagnostic tools: Regular updates and improvements to the models are necessary to incorporate new research findings and enhance accuracy and reliability. The models should be designed to scale efficiently, accommodating increasing data volumes and expanding to new diagnostic areas as needed. Partnerships with healthcare providers, research institutions, and technology companies can foster innovation and drive the development of more effective solutions. Providing training for healthcare professionals on the use and interpretation of AI tools ensures that they are effectively integrated into clinical practice. Implementing energy-efficient computing resources and promoting sustainable practices in data storage and processing can minimize the environmental footprint.

6.5 Summary

This chapter examined the broad impacts of deploying deep learning models for Alzheimer's disease detection on individuals, society, and the environment. The potential benefits include improved early diagnosis, personalized treatment plans, and enhanced healthcare efficiency. Ethical considerations, such as data privacy, bias, transparency, and accountability, are crucial in ensuring the responsible use of AI. A sustainability plan focusing on continuous improvement, scalability, collaboration, education, and sustainable practices is essential for maintaining the long-term viability and positive impact of these diagnostic tools. The integration of AI in medical diagnostics holds promise for revolutionizing healthcare, but it must be approached with careful consideration of its broader implications.

CHAPTER 7
Conclusion & Future Work

7.1 Conclusions

This research project focused on the development and evaluation of deep learning models for the detection of Alzheimer's disease using MRI images. Through the application of various preprocessing techniques and the implementation of four distinct model architectures—modified CNN, AlexNet, VGG16, and a hybrid model combining EfficientNet-b0 with SVM—we achieved promising results. The key conclusions drawn from this study are as follows: The study demonstrated that deep learning models are highly effective in classifying MRI images into three categories: mild demented, moderate demented, and non-demented. The highest accuracy was achieved by the hybrid model, which combined EfficientNet-b0 for feature extraction with SVM for classification, attaining an accuracy of 96.17%. The use of extensive preprocessing techniques, including data normalization, resizing, histogram equalization, data augmentation, dataset balancing, and batch normalization, significantly contributed to the enhanced performance of the models. These steps ensured that the models were trained on high-quality, balanced datasets, reducing the risk of overfitting and improving generalization. The hybrid model's superior performance underscores the potential of combining state-of-the-art feature extraction methods with robust classification techniques. This approach leverages the strengths of both components, resulting in improved accuracy and reliability. Comprehensive evaluation using metrics such as accuracy, precision, recall, F1-score, support, and visual tools like accuracy/loss curves, confusion matrices, ROC curves, and precision-recall curves provided a thorough assessment of the models. These analyses helped in understanding the strengths and weaknesses of each model and guided the selection of the best-performing architecture. The successful implementation and high accuracy of the models indicate their potential for real-world application in clinical settings. Early and accurate detection of Alzheimer's disease can significantly impact patient outcomes, making these models valuable tools in healthcare.

7.2 Further Suggested Works

While this study has achieved significant milestones, there are several areas for further research and improvement: Future work should focus on obtaining larger and more diverse datasets to validate the models' robustness and generalizability. Including data from different demographics and varying MRI machine settings can help in creating more versatile models. Exploring other advanced neural network architectures, such as deeper versions of EfficientNet, or newer models like Vision

Transformers, could potentially yield even better results. Integrating multimodal data, such as combining MRI images with other diagnostic data (e.g., genetic information, clinical history), could enhance the model's diagnostic capabilities and provide a more comprehensive assessment of the disease. Developing methods to make the models more explainable and interpretable for clinicians is crucial. Techniques such as saliency maps and Grad-CAM can help visualize which parts of the MRI images are most influential in the model's decision-making process. Research should also focus on optimizing the models for real-time implementation in clinical settings. This involves improving the computational efficiency of the models to ensure quick and reliable results without requiring extensive processing power. Conducting longitudinal studies to track the progression of the disease in patients over time can provide valuable insights and help in refining the models to predict not just the current state, but also the progression of Alzheimer's disease. Collaborating with neurologists, radiologists, and other healthcare professionals can provide valuable feedback and guide the development of more practical and user-friendly diagnostic tools. Their expertise can help in refining the models to meet clinical needs better. Addressing ethical and regulatory considerations is essential for the real-world deployment of these models. Ensuring compliance with data protection regulations and establishing clear guidelines for the use of AI in diagnostics will be crucial for gaining acceptance and trust from both healthcare providers and patients.

This chapter concluded the research project by summarizing the key findings and suggesting areas for further research. The study highlighted the potential of deep learning models in enhancing the early detection of Alzheimer's disease, emphasizing the importance of preprocessing, model architecture, and comprehensive evaluation. Future research directions include exploring larger datasets, advanced architectures, multimodal approaches, and real-time implementation, among others. By addressing these areas, the field can move closer to deploying reliable, accurate, and efficient AI-driven diagnostic tools in clinical settings, ultimately improving patient outcomes and healthcare delivery.

7.3 Limitations/ Conflict of Interests

7.3.1 Limitations

While this study presents promising results, several limitations were identified: The relatively small size of the dataset may limit the generalizability of the findings. Larger datasets are needed to validate the robustness of the models. Training deep learning models requires substantial computational resources, which may not be readily available in all research or clinical settings. The models are only as good as the data they are trained on. Any biases present in the training data can affect the model's performance and fairness.

7.3.2 Conflicts of Interest

No conflicts of interest were identified in this study. The research was conducted independently, with a focus on advancing the understanding and application of deep learning for Alzheimer's disease detection.

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Appendix A

Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Analysis

Title: Deep Learning Based Alzheimer Disease Detection using MRI Images

Students ID: 202-15-14401 & 202-15-14408

CO Description for FYDP-Phase-I

CO	CO Descriptions	PO
CO1	Integrate recently gained and previously acquired knowledge to identify a real-life complex engineering problem for the Final Year Design Project	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for the Final Year Design Project	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish the goals for the Final Year Design Project	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the Final Year Design Project	**PO11**

Addressing of COs, Knowledge Profile (K), and Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, and CO3	Our project requires data collection from kaggle and we have to know the design of deep learning-based models which covers **K3 and K4.**	**Page no: 10-14**

				Our project requires the integration of different components and we have designed a web-based front end that covers **K5 and K6.**	**Page no: 16-17**
				We have studied existing models with similar goals **(K8).**	**Page no: 05-07**
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	The dataset consists of 800 images per class for training and 200 images per class for testing. This limited dataset size may not fully capture the variability of MRI images in real-world clinical settings.	**Page no: 02-03**
3.	**EP3: Depth of analysis required**	Yes	CO2	The models developed in this project are based on a specific dataset and may not generalize well to other datasets or populations without further validation. We deeply analyze to select a specific algorithm from huge alternatives based on the characteristics of the dataset.	**Page no: 08-14**
4.	**EP4: Familiarity of Issues**	Yes	CO3	To understand and study Alzheimer prediction for our project, we need to look into various aspects we were not very familiar with. Specifically, we have to figure out how to	**Page no: 9-10**

				measure the state of Alzheimer.	
5.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO3	As part of our project, we have visited and met with a neurologist. The purpose is to understand how we can measure the state of Alzheimer based on MRI images. This meeting has guided us in determining the specific type of data we need to use for our analysis.	**Page no: 18**
6.	**EP7: Interdependence**	Yes	CO3	Our project consists of several subsystems that depend on each other. These include tasks such as collecting data, preprocessing it, training deep learning models, evaluating, and developing a front-end application.	**Page no: 08-14**
7.	-	Yes	CO4	We have prepared a budget to evaluate and estimate the cost required for our FYDP.	**Page no: 18**

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