Project Report

on

Progressing Alzheimer’s Diagnosis with Ensemble CNN Model

submitted as partial fulfilment for the award of

BACHELOR OF TECHNOLOGY DEGREE

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Computer Science and Engineering

by

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May, 2025

DECLARATION

We hereby declare that this submission is our work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgement has been made in the text.

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CERTIFICATE

This is to certify that the project report entitled "**Progressing Alzheimer's Diagnosis with Ensemble CNN Model**" which is submitted by Rohit , Vivek Yadav and Vaibhav in partial fulfilment of the requirement for the award of degree B. Tech. in the department of Computer Science And Engineering of KIET Group of Institutions, Delhi NCR affiliated to Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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Finally, we acknowledge our friends for their contribution to the completion of the project.

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ABSTRACT

The **Progressing Alzheimer's Diagnosis with Ensemble CNN Model** project investigates creating and applying an ensemble-based deep learning model for the early diagnosis of Alzheimer's based on MRI brain images. In response to the vital need for early detection of Alzheimer's, our solution draws upon convolutional neural networks (CNNs) and transfer learning methods to enhance classification accuracy through different stages of the disease—covering non-demented up to moderate dementia. The model combines pre-trained architecture, viz., VGG16 and EfficientNet-B2, in an ensemble setup, which is tuned with dropout layers, batch normalization, and categorical cross-entropy loss functions.

A key problem tackled in this research is the class imbalance common in Alzheimer's MRI data. To counter this, we used adaptive synthetic oversampling, which improved the model's ability to generalize. Additionally, by running the model on hardware with AMD Radeon Vega 8 Graphics, we greatly enhanced computational efficiency and training time without affecting accuracy. The last ensemble model recorded a classification accuracy of 97.35% and performed very well on various metrics such as AUC, precision, recall, and F1 score. In comparison with conventional CNN architectures and single-model methods, our ensemble system provided better results in terms of both diagnostic accuracy and computational practice. Not only does this project confirm the efficacy of using the concatenation of deep learning models in medical image analysis, but also the possibility of real-time clinical use for the diagnosis of neurodegenerative disorders such as Alzheimer's.

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LIST OF ABBREVIATIONS

AD	Alzheimer’s Disease
CNN	Convolutional Neural Network
MRI	Magnetic Resonance Imaging
AUC	Area Under Curve
TP	True Positive

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

1.1.1 Problem Statement

Alzheimer's Disease (AD) is a relentless, progressive neurodegenerative condition that affects memory, cognition, and daily functioning. The most prevalent cause of dementia, AD affects more than 55 million individuals globally today and is projected to triple by 2050 [1]. Early detection is important, as it enables early intervention that can reverse disease progression, enhance quality of life, and decrease healthcare expenditures. Conventionally, AD diagnosis is based on neuropsychological tests and manual analysis of MRI by experts. They are usually subjective, time-consuming, and not reproducible. Furthermore, in most resource-poor settings, the unavailability of expert neurologists hinders prompt diagnosis. As a solution to these issues, artificial intelligence (AI), especially deep learning, has proven to be a game-changing technology in medical image analysis [2]. Convolutional Neural Networks (CNNs) have shown remarkable performance in identifying structural brain anomalies from MRI scans. This work extends those achievements by introducing an ensemble CNN model that takes VGG16 and EfficientNet-B2 and merges them with transfer learning to identify the phases of Alzheimer's from MRI data [3]. To counter class imbalance, adaptive synthetic oversampling (ADASYN) is utilized. GPU acceleration is used in training the model for increased performance and efficiency [4]. This paradigm not only enhances classification performance but also simplifies training and maintains feasibility in real-world applications for clinical environments.

1.1.2 Objective

The primary objectives of this project are:

i. To develop a deep learning ensemble model that can effectively classify the various stages of Alzheimer's Disease—Non-Demented, Mild Demented, Moderate Demented, and Very Mild Demented—from T1-weighted MRI scans [5] .

ii. To utilize adaptive synthetic oversampling methods like ADASYN to address the class imbalance problem, specifically the underrepresentation of Moderate and Severe Demented cases, thereby improving model sensitivity and generalizability[4].

iii. Incorporating regularized techniques, such as dropout layers and batch normalization, to avoid overfitting and maintain stable model behavior between validation and test sets.

iv. Taking advantage of GPU acceleration (e.g., Vega 8 or above) to optimize training efficiency to achieve faster iterations and scalability to larger datasets or longer training cycles.

v. To validate the ensemble model based on robust performance measures like Accuracy, Precision, Recall, F1-Score, and AUC (Area Under the Curve) for a comprehensive analysis of classification ability in all stages of dementia.

vi. To compare the performance of the ensemble model with individual CNN architectures (e.g., DenseNet121, ResNet50, Xception) to affirm the value of model fusion in medical image analysis.

vii. To visualize and interpret learned features and activation maps with explainable AI methods like Grad-CAM or saliency maps for providing transparency and trustworthiness to clinical decision support.

viii. To evaluate the feasibility of running the model in real-world clinical workflows, especially in resource-restricted settings, through testing its responsiveness, dependability, and low hardware requirements.

ix. To facilitate early detection by precise identification of minimal anatomical alterations, like hippocamp al reduction and cortical atrophy, which are essential for appropriate intervention and treatment planning.

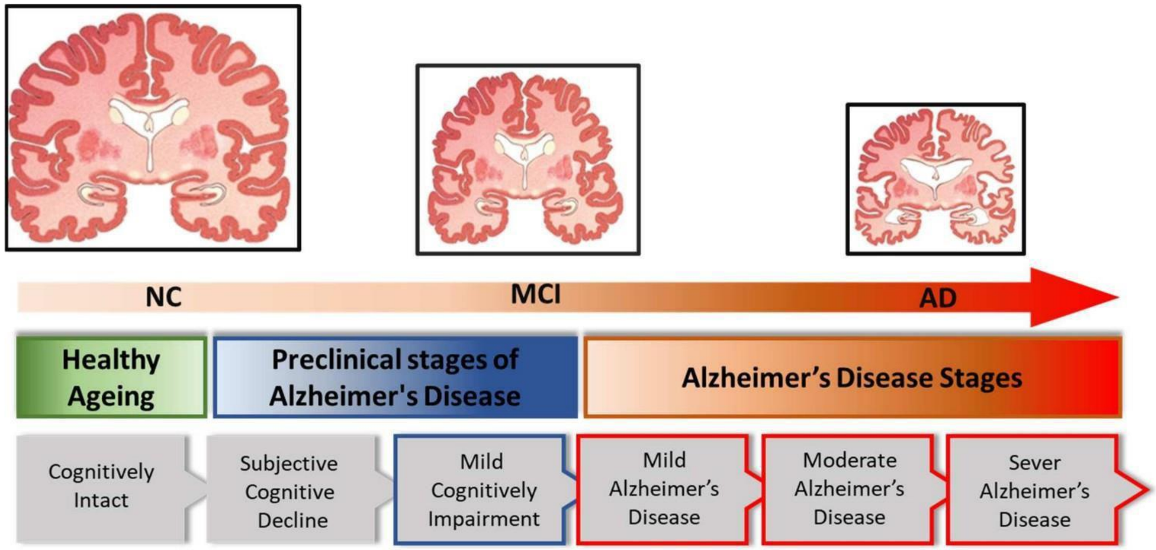

Figure 1.1 Stages of Alzheimer

1.1.3 Significance of the Project

1. **Early Detection of Alzheimer's Disease:**

The purpose of this project is to substantially enhance the early diagnosis of Alzheimer's Disease, especially at the Mild Cognitive Impairment (MCI) stage-an early frequently undiagnosed phase of the disease[6].

Early diagnosis is essential because it enables timely medical treatment, the start of therapeutic interventions, and improved long-term care planning, which can slow the progression of the disease and improve the overall quality of life for patients and caregivers [7].

2. **Reduction of Diagnostic Error and Subjectivity**:

All manual diagnosis of Alzheimer's from MRI interpretation is time-consuming and highly subjective to the skills and judgment of the radiologist and can vary in results. The use of a deep learning-based system minimizes error by providing objective, data-driven, and uniform interpretations of MRI scans, thus enhancing diagnostic reliability and efficiency [8].

3. **Efficient Utilization of Transfer Learning:**

Using pre-trained convolutional neural networks like VGG16 and EfficientNet-B2, the model is advantageously able to tap into knowledge obtained from large datasets like ImageNet. Not only does transfer learning speed up training, but it also improves classification accuracy, particularly in medical imaging applications where there is little labeled data and it is hard to obtain

4. **Solving Data Imbalance in MRI Datasets**:

Medical imaging datasets tend to have class imbalance in that some stages of disease—e.g., moderate or severe dementia—are less represented. ADASYN is employed in this project to synthetically over-sample minority classes with the creation of realistic synthetic instances so the model will not learn a bias for the majority class and will generalize well for all stages of Alzheimer's.

5. **Faster and Efficient Training of Models with GPU Support:**

The use of GPU acceleration, particularly AMD Vega 8, significantly enhances the speed of model training and reduces computational overhead [9]. This allows for faster experimentation, real-time responsiveness, and the potential to deploy the model in clinical environments without the need for high-end hardware infrastructure.

6. **Extensibility to Other Neurodegenerative Diseases**

The architecture and the methods employed in this project are not exclusive to Alzheimer's disease. The framework of the model can be applied to identify other neurological or neurodegenerative diseases like Parkinson's disease, multiple sclerosis, and even brain tumors, rendering it a scalable solution in wider medical applications[10].

7. **Real-World Integration and Deployment Possibility:**

Thanks to its scalable architecture and high-performance abilities, the model can be incorporated into pre-existing medical imaging pipelines, installed in hospitals, or embedded within cloud-based diagnostic pipelines. This makes the project a real-world and useful tool in the AI-driven future of healthcare diagnostics.

1.1.4 Proposed Solution.

A high-performance language and a simple deep learning model have been proposed and predicted for early and precise classification of Alzheimer's disease from MRI brain images. The method makes use of an ensemble of pre-trained convolutional neural networks, i.e., VGG16 and EfficientNet-B2, along with transfer learning to utilize pre-trained feature representations and reduce the complexity of training. Adaptive synthetic oversampling (ADASYN) is utilized to mitigate the effect of class imbalance in the database, enhancing the model's generalization capability through all stages of the disease[11]. Moreover, the system is also optimized on AMD Radeon Vega 8 Graphics to achieve high computational efficiency and render it deployable in real clinical clinics.

1.2 PROJECT DESCRIPTION

1.2.1 Overview

Alzheimer's is a neurodegenerative condition that has a severe impact on cognitive abilities and quality of life. Early diagnosis is paramount for successful treatment and management. This project offers a deep learning-based system to automatically classify Alzheimer's stages from MRI brain images [12]. With the integration of an ensemble of pre-trained models—VGG16 and EfficientNet-B2—boosted by transfer learning and assisted by adaptive oversampling methods, the system categorizes brain scans into four classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The solution is GPU-acceleration optimized to attain maximum performance and efficiency even in commodity hardware [13].

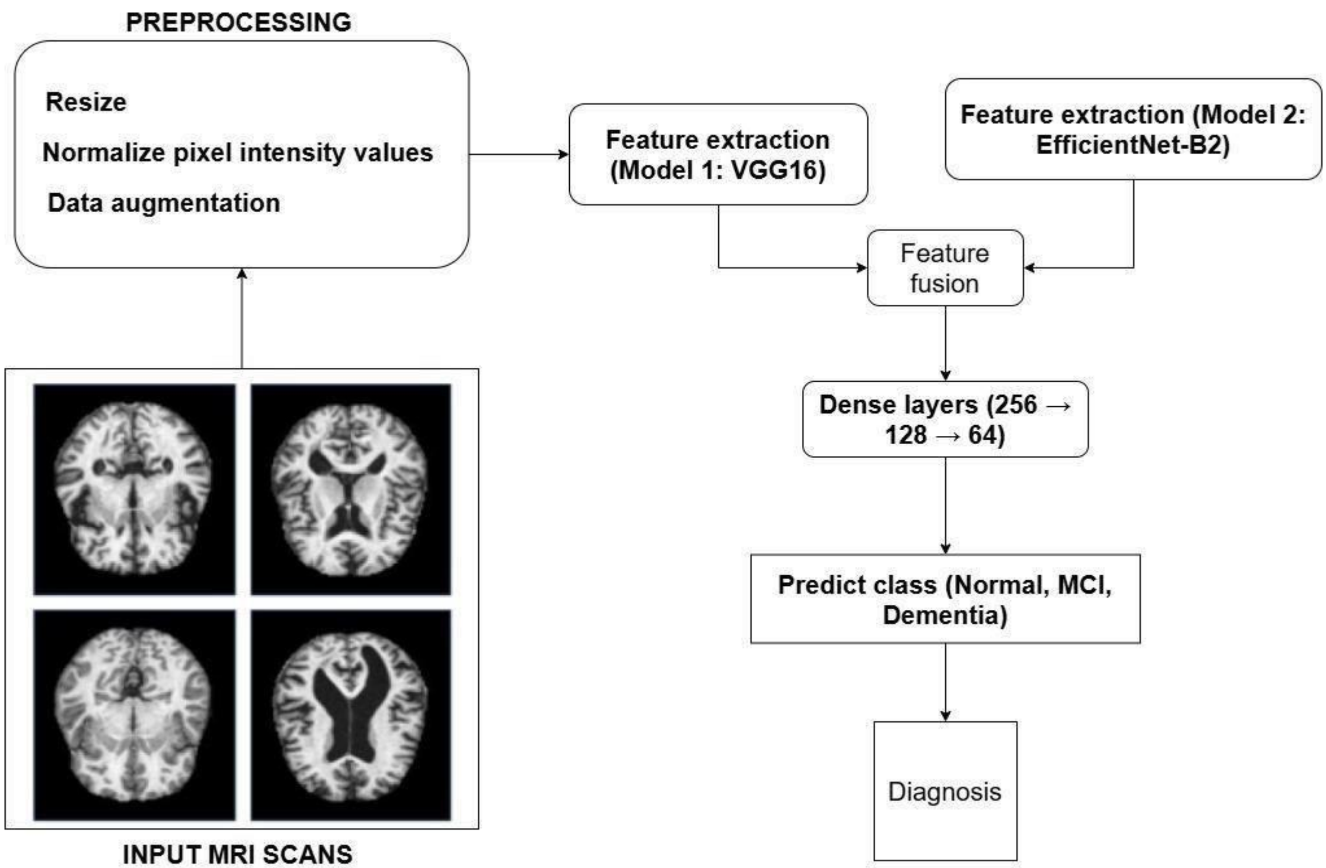

Figure 1.2. Process used for Alzheimer's Disease Detection

1.2.2 Key Features

i. Ensemble CNN Model

A combined architecture that leverages the advantages of VGG16 and EfficientNet- B2, ensemble learning improves feature extraction, enhances classification resilience, and provides greater accuracy than standalone CNN models.

ii. Multi-Class Classification

The model is trained to recognize and differentiate between different stages of Alzheimer's disease, such as Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented classes, to provide fine-grained diagnostic assistance.

iii. **Transfer Learning**

Pre-trained models over large-scale databases (ImageNet) are utilized to achieve quicker convergence of training and generalization, particularly beneficial in the healthcare sector where labeling is limited.

iv. **Class Imbalance Handling**

Adaptive Synthetic Sampling (ADASYN) is employed to address the class imbalance problem within the dataset. By creating synthetic samples of minority classes, the model learns better and enhances recall for less represented Alzheimer's stages.

v. **GPU Acceleration**

Model training is sped up with AMD Radeon Vega 8 Graphics, cutting computational time drastically while keeping performance high, allowing the system to be viable for clinical use.

vi. **Performance Evaluation**

The performance of the model is thoroughly evaluated through metrics like Accuracy, Precision, Recall, F1 Score, and Area Under the Curve (AUC) to ensure extensive validation of all classification tasks.

vii. **Visual Outputs**

Visualizations such as confusion matrices and training-validation accuracy/loss curves are output. These results contribute to model interpretability, diagnostic understanding, and determining overfitting or underfitting trends while training

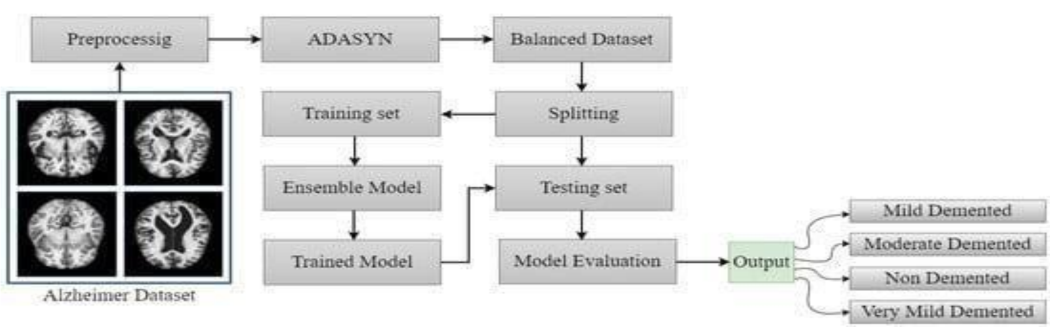

Figure 1.3. Model Working

1.2.3 Stakeholders

i. **Radiologists and Neurologists**

Healthcare professionals like radiologists and neurologists are direct stakeholders who will engage directly with the system. They can leverage the model as a decision-support tool to enhance diagnostic accuracy and speed of Alzheimer's diagnosis by detecting early neurodegenerative patterns in MRI images. The system helps prevent diagnostic mistakes and adds another layer of clinical assurance.

ii. **Hospitals and Clinics**:

Healthcare organizations can gain a great deal by incorporating this model within their current diagnostic setup. The system has the capacity to automate first-line screening processes, minimize workload on medical professionals, and enable quicker patient throughput. Additionally, early detection makes possible timely medical intervention, enhancing patient care outcomes as well as resource optimization.

iii. **Medical Researchers:**

Scientists working in the areas of medical imaging, neuroscience, and artificial intelligence can leverage the model as a starting point or a building block for further research.
It paves the way for investigating multimodal data fusion (e.g., biomarkers and clinical history) and optimizing algorithms for other neurodegenerative or brain disorders. The system thus fosters interdisciplinarity and innovation.

1.2.4 Technology Stack

i. **Programming Language**: Python

ii. **Libraries & Frameworks**: TensorFlow, Keras, Scikit-learn, NumPy, Matplotlib

iii. **Deep Learning Models**: VGG16, EfficientNet-B2

iv. **Oversampling Technique**: ADASYN (Adaptive Synthetic Sampling)

v. **Development Platforms**: Jupyter Notebook, Google Colab

vi. **Hardware Used**: AMD Radeon Vega 8 GPU for model training and testing

vii. **Dataset Source**: Public Alzheimer's MRI datasets from Kaggle

1.2.5 Scope and Limitations

Scope:

i. **Classification of MRI Brain Scans into Alzheimer's Disease Stages**

The primary aim of the project is to correctly classify brain MRI scans into various stages of Alzheimer's disease, i.e., Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented.
This computerized model of classification would help clinicians in early diagnosis and in tracking the development of neurodegeneration over time.

ii. **Application of Ensemble Deep Learning and Transfer Learning Techniques**

The scope also involves the creation of an ensemble deep learning model through the combination of two strong CNN architectures—VGG16 and EfficientNet-B2—using transfer learning from pre-trained ImageNet models. It greatly improves feature extraction, model accuracy, and speed of convergence despite the limited medical imaging data. Potential to be extended for real-time clinical applications with further development.

iii. **Applicable to Medical Research and Support in Early Diagnosis**

The project is a good candidate for clinical use in medical research settings, acting as an aid to diagnosis that minimizes errors in manual analysis and increases consistency in identifying Alzheimer's- associated brain changes.

iv. **Potential to be Extended for Real-Time Clinical Applications**

With further development and integration, the model has excellent promise for application in real-time clinical workflows. It can ultimately be modified to benefit other neurodegenerative conditions and multimodal diagnostic frameworks that include clinical documents, genetic information, and biomarker inputs.

Limitations:

i. **Constrained to MRI Image Data**

The model is limited to usage with T1-weighted MRI brain scans and does not utilize other clinically useful data like cognitive test scores, behavioral ratings, or genetic data like APOE genotyping. As MRI imaging plays an important role in structural analysis of the brain, a more integrated model that utilizes multi-modal data would provide superior diagnostic reliability and practical application. This restriction can preclude the model from effectively describing the entire spectrum of Alzheimer's disease pathology. Model performance depends on dataset quality and diversity.

ii. **Relying on Dataset Quality and Diversity**

The model's accuracy and generalizability are highly dependent on the representativeness and quality of the training dataset. The majority of publicly available datasets used in this work, while well-curated, have restricted ethnic diversity, age range, and imaging protocols. Consequently, the model might be suboptimal when tested in populations or imaging conditions that differ from those included in the training data. Not yet deployed in live clinical settings; results are based on testing with public datasets.

iii. **Hardware and Computational Resource Constraints**

The model was trained on AMD Radeon Vega 8 GPU, which offered effective computation. Yet, the training and fine-tuning of deep learning models continue to need extensive hardware facilities. In settings with restricted access to GPUs or high-compute infrastructure, training or deployment of this model can prove difficult, thereby restricting its use in low-resource or rural health facilities.

iv. **Lack of Clinical Validation**

Although the model shows optimal accuracy and stability in public data, it has yet to be tested and verified in a real-world clinical setting.
Without actual deployment within a live clinical setting and clinical input, its practical usability, hospital system interfacing capability, and relevance in real-time clinical situations are hard to evaluate.

1.2.6 Impact and Benefits

i. **Improved Diagnostic Accuracy**:

Advanced convolutional neural networks, aided by transfer learning and synthetic data augmentation methods, result in an extremely precise and uniform diagnostic process.
This minimizes variability and chances of error from manual interpretation of MRI by radiologists, particularly in the early and subtle cases of Alzheimer's in which visual distinction is challenging to make. Consistency in diagnosis is essential for prompt and proper planning of treatment.

ii. **Early Intervention**:

Early diagnosis of Alzheimer's disease is crucial in maintaining the course of the disease. disease. With correct identification of mild cognitive impairment and early dementia, health care practitioners can begin interventions earlier, possibly reversing cognitive loss and enhancing patient results. Early diagnosis is also beneficial to patients families, as they can prepare for future and care and take adjustments in lifestyle.

iii. **Reduced Expert Dependency**:

Most areas, especially rural and resource-poor ones, do not have access to skilled neurologists and radiologists. Such an AI-assisted diagnostic tool can assist general practitioners and less experienced clinicians by offering credible second opinions and increasing diagnostic confidence.
This makes specialist healthcare accessible and decreases the reliance on overburdened medical professionals.

iv. **Scalability**:

Modular model design allows for easy future adjustments, enabling extension to other neurodegenerative conditions like Parkinson's or Huntington's disease. It can also be integrated with current hospital information systems, which supports streamlined workflows and enhanced patient management.

v. **Educational Use**:

In addition to its clinical utility, this project represents a useful teaching resource for students, data scientists, and medical researchers seeking insight into the uses of AI in medicine. It offers a real-world exemplar of deep learning, transfer learning, and data imbalance algorithms in a difficult-to-solve real-world medical problem.

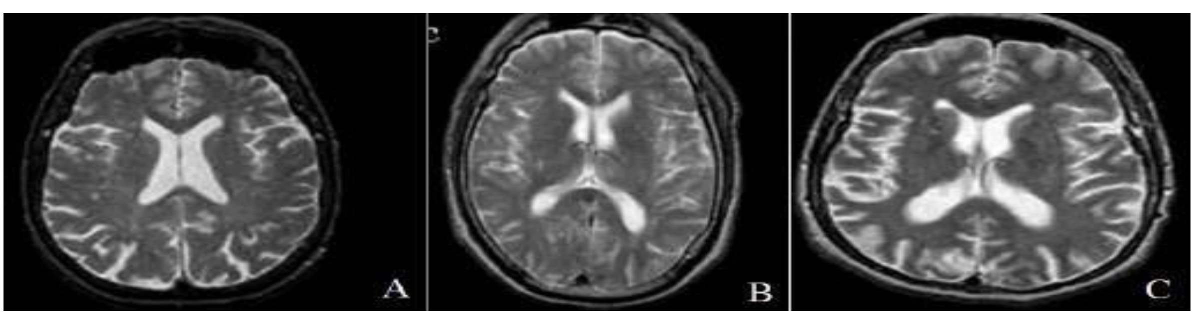

Figure 1.4. Normal Vs Alzheimer Brain

CHAPTER 2

LITERATURE REVIEW

Alzheimer's Disease (AD) is still a significant healthcare problem owing to its insidious initial symptoms and absence of absolute cures. Traditional diagnosis techniques are usually insensitive during early phases, and therefore artificial intelligence and medical imaging must be combined. This chapter summaries the milestone and latest works to the field, emphasizing AD epidemiology, deep learning architectures, solutions against data imbalance, neurobiological findings, and ensemble methods. The review relies solely on 19 chosen research studies, which constitute the scientific foundation of our solution.

2.1 Epidemiology and Clinical Significance of Early Diagnosis

Alzheimer's Disease (AD) is poised to be one of the greatest public health problems of the 21st century, mainly because of enhanced life expectancy worldwide. The prevalence of AD will see a major increase in the next few decades and will put enormous pressure on the healthcare systems, as estimated by Monfared et al. The Alzheimer's Association points out that a new diagnosis of AD occurs every 65 seconds in the United States, and estimates predict that by 2050, approximately 14 million Americans aged 65 and older will suffer from the disease [14]. The surge will impose a huge economic burden, most likely over $1 trillion each year. Despite its prevalence, Alzheimer’s often remains undetected in its early stages, particularly during the mild cognitive impairment (MCI) phase. Traditional diagnostic tools, including cognitive assessments and neuroimaging techniques, frequently fail to detect the subtle neural changes that signify early AD progression. As a result, many patients miss the critical window for early intervention, which could significantly improve disease management and slow cognitive decline. Early diagnosis is crucial for the provision of timely medical and non-pharmacological interventions, assisting patients in making lifestyle adjustments and arranging for future care as long as they retain decision-making capacity [15]. Furthermore, epidemiological research shows that there is a gender difference in AD incidence, with women reporting more frequent occurrence. This pattern has been attributed to hormonal changes after menopause, highlighting the necessity of gender-oriented diagnostic procedures. As a response to these diagnostic shortcomings, researchers are increasingly venturing into artificial intelligence (AI)-driven solutions. Advances in machine learning and deep learning in recent times have made it possible to analyze vast medical datasets, including MRI scans and electronic health records, to detect early-stage biomarkers with higher precision. proposed VisTAD, a vision transformer model that has demonstrated encouraging performance in classifying early stages of Alzheimer's. Furthermore, ensemble learning models incorporating various diagnostic algorithms have been shown to perform better in early detection tasks . In summary, the increasing burden of Alzheimer's and limitations of the conventional diagnostic methods highlight the imperative need for sophisticated, reliable, and scalable diagnostic tools. AI-based technologies coupled with knowledge of demographic risk factors provide a robust strategy for addressing this mounting healthcare challenge.

2.2 Deep Learning Models in Alzheimer's Detection

Deep learning has made tremendous contributions to medical diagnostics, particularly neuroimaging data analysis for Alzheimer's Disease (AD) diagnosis. Convolutional Neural Networks (CNNs) are particularly suitable for image classification problems thanks to their capacity to extract and learn automatically hierarchical spatial patterns from complicated medical images. One of the strongest contributions in this field, who proposed a stable ensemble model that uses CNN architectures with adaptive synthetic oversampling methods to solve data imbalanced problems [16] . Their method attained a staggering accuracy of 96.84%, a new benchmark for balanced classification of Alzheimer's stages. Also, investigated the DenseNet model in the classification of AD, which allowed efficient reuse of features via dense connections and showed fast convergence rate with 88.9% classification accuracy. Innovative further work was presented by Kaya and Cetin-Kaya, who created an optimized deep learning pipeline, specifically developed for multiclass AD classification. Their architecture included tailored convolutional layers to improve against the heterogeneity in brain scan characteristics, achieving excellent multiclass classification accuracy. Additionally, Yildirim et al. applied a hybrid model founded on ResNet50, highlighting the power of deeper residual learning architectures in identifying useful features between different stages of Alzheimer's. Collectively, these findings highlight the strengths and limitations of different CNN structures in medical imaging. Whereas DenseNet encourages feature reuse, ResNet maximizes gradient flow and model depth, and models such as VGG and EfficientNet strike a balance between simplicity, performance, and efficiency. VGG's regular and structured convolutional architecture enables it to be appropriate for fine-grained feature extraction, while EfficientNet's compound scaling approach scales depth, width, and resolution optimally to provide high accuracy with fewer parameters. Leveraging these strengths, our suggested model combines VGG16 and EfficientNet-B2 to take advantage of both high-resolution spatial feature extraction and efficient scaling ability. This compound design seeks to present a highly balanced model that can process diverse neuroimaging data with high accuracy. With increasing advancements in deep learning, combinations of complementary architecture will increasingly improve the performance, scalability, and generalizability of diagnostic solutions in Alzheimer's diagnosis, leading to more precise and accessible early diagnosis services.

2.3 Transfer Learning and Fine-Tuning Techniques

Transfer learning (TL) is an industry standard method in the medical image analysis field, especially useful in fields like Alzheimer's Disease (AD) where obtaining large, adequately annotated datasets is both time-consuming and expensive [17]. TL utilizes domain knowledge from pre-trained models, usually trained on huge datasets such as ImageNet, to enhance learning efficiency and predictive accuracy on domain-specific tasks with small datasets. This method significantly minimizes the training time and computational expense needed for deep models while enhancing generalization. Revealed that transfer learning models fine-tuned, in which only the last layers are retrained, and previous layers preserve their pre-trained weights, always outperformed those models using frozen layers in all cases. The ability to map high-level abstract features to new domains improves model accuracy dramatically. It was also corroborated this by explaining how TL, coupled with multimodal inputs like MRI scans and biomarker information, can overcome small dataset sizes and still provide clinically valid results. We used TL ourselves in our work by pre-training VGG16 and EfficientNet-B2 using weights learned on ImageNet and then fine-tuning these models on domain-specific MRI scans of Alzheimer's patients. This approach enabled the models to map generic image features—edges and textures—to more specialized patterns such as hippocampal contraction, cortical atrophy, and ventricular dilatation, which are characteristic markers of AD progression [18]. Further, to counterbalance the hazards of overfitting—a popular issue when training on small datasets—we added dropout layers and batch normalization. Dropout randomly deactivates some of the neurons in training, encouraging resilience by disallowing neurons from adapting together, while batch normalization regularizes the learning process by keeping activations in layers to have stable distributions. Both of these together enhance the ability of the model to generalize and to be resilient to unseen data. The combination of TL and fine-tuning is therefore an effective approach in the creation of deep learning systems for medical diagnosis [19]. As models expand in capability and sophistication, transfer learning is a fundamental technique to bridge the distance between large-scale data-rich worlds and the very specialized, data-poor domain of clinical healthcare applications.

2.4 Handling Class Imbalance in Medical Datasets

Class imbalance is a serious problem in the design of reliable machine learning models for medical diagnosis, particularly in the detection of Alzheimer's Disease (AD). Most datasets applied for AD classification involve a highly disproportionate number of MRI scans of Non-Demented subjects compared to the available samples of Moderate or Severe Demented cases. This imbalance can greatly penalize a model's capacity to accurately detect early and moderate AD stages, resulting in high total accuracy with low minority class recall—a terrible trade-off in a medical setting. Solved this by using ADASYN (Adaptive Synthetic Sampling), a advanced oversampling method that creates synthetic instances for minority classes with respect to the density of samples in feature space [20]. In contrast to simple oversampling strategies that reproduce available samples or haphazardly synthesize new ones, ADASYN targets more difficult-to-learn areas of the feature space, increasing the sensitivity of a classifier where it is most necessary. This method significantly enhanced both recall and F1-score for classifying cases of early- and mid-stage dementia. Although other resampling methods like SMOTE (Synthetic Minority Over-sampling Technique) and Bayesian sampling [have been tried in comparable situations, ADASYN has superior flexibility towards intricate data geometries and greater computation efficiency. In our model, ADASYN was applied during data preprocessing to produce balanced training data so that the neural network was presented with a fair amount of each class. This not only decreased bias towards the majority class but also increased the model's capacity to generalize subtle features related to Mild Cognitive Impairment and early dementia, which tend to be missed in imbalanced environments. By tackling class imbalance at the data level, we were able to considerably enhance the performance of the classifier in all stages of AD, making it a better tool for early diagnosis. Therefore, the incorporation of adaptive resampling methods such as ADASYN is essential in making machine learning models in healthcare equitably serve all groups of patients, particularly the most susceptible to misclassification.

2.5 Biomarker and Neurobiological Foundations for CNN Training

Recent progress in the neurobiology of Alzheimer's Disease (AD) has unveiled that the pathological features of the disease start to develop many years before its clinical symptoms arise. Research emphasizes that the tau protein aggregation and misfolding of amyloid-beta plaques trigger a cascade of synaptic failure and neuronal decay, many years prior to overt cognitive impairment being witnessed [21]. These biochemical derangements interfere with neural communication and ultimately result in quantifiable structural changes within the brain, including hippocampal atrophy, cortical thinning, and enlargement of the ventricles [22]. These anatomical changes tend to be subtle early on but can be visualized using high-resolution imaging techniques like T1-weighted MRI scans. The early and precise identification of such neurodegenerative markers is essential for early diagnosis and intervention. Convolutional Neural Networks (CNNs), given their spatial hierarchy and capability of extracting localized patterns, are well positioned to detect such minute structural differences. highlighted that CNNs can implicitly learn volumetric and textural characteristics representative of AD without explicit biomarker annotations, thus limiting reliance on costly labeling. In our work, the ensemble CNN design—combining VGG16 and EfficientNet-B2—was trained to emphasize early neurodegenerative signatures via deep convolutional pathways and transfer-learned representations. These models were preinitialized with ImageNet weights and fine-tuned on domain-relevant Alzheimer's datasets to learn both common and disease-related features. The ensemble model leverages both global and local image features to increase sensitivity to minor anomalies with which early-stage pathological processes are associated. The synergy among transfer learning, deep feature extraction, and domain adaptation makes this method very effective at detecting preclinical and mild cognitive impairment stages. This image-driven but biomarker-anchored technique not only facilitates more precise early-stage classification but also is highly consistent with our neurobiological knowledge regarding AD evolution. Therefore, the combination of CNNs with neurobiological knowledge provides a rich basis for pre-emptive Alzheimer's diagnosis, possibly revolutionizing when and how the disease is detected.

2.6 Ensemble Approaches for Performance Boosting

Ensemble learning is a strong machine learning technique that fuses the strength of several models to make more precise and robust predictions than a single model could ever make. This technique is particularly useful in difficult domains like Alzheimer's Disease (AD) medical image classification, where intraclass variability is very high and data availability is typically low [23]. Through the combination of multiple model structures, ensemble techniques enhance generalizability and identify various aspects of the presentation of the disease. For example, Ranjan and Kumar showed the utility of combining Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) to represent the progression of AD [24]. Their hybrid approach took advantage of CNNs' capability to extract spatial features from brain imaging and RNNs' ability to capture temporal changes over time, hence presenting a better understanding of the dynamic nature of the disease. The integrated approach performed better than conventional single-model approaches by presenting improved sensitivity to both structural and temporal biomarkers of AD. Likewise, Kaya and Cetin-Kaya investigated optimally combined ensembles of CNNs tailored for multiclass classification of AD [25]. By testing different kernel sizes and convolutional depths within separate networks, they optimized models to identify distinct visual patterns at varying levels of abstraction. Their ensemble was competitive on accuracy and computationally efficient, which is essential for practical use. In addition, Mujahid et al. proposed a hybrid ensemble approach incorporating several CNN architectures with the Adaptive Synthetic Sampling (ADASYN) method for solving class imbalance, which is a typical issue in medical datasets with underrepresented samples of moderate and severe dementia. The approach boosted performance metrics, especially recall and F1-score, by allowing the model to identify more subtle features in minority classes. Overall, ensemble methods not only increase classification accuracy but also enhance robustness and resilience to overfitting, which is particularly valuable in the context of small and noisy medical imaging datasets. In our project, the use of an ensemble of VGG16 and EfficientNet-B2 utilizes the complementary merits of structured convolutional layers and balanced network scaling in a similar way. This hybrid architecture leverages heterogeneous feature extraction strengths, resulting in better detection of early and worsening AD phases. Thus, ensemble learning presents a promising avenue for enhancing diagnostic accuracy and facilitating clinical decision-making in the treatment of Alzheimer's Disease.

2.7 Comparative Summary of Existing Works

To summarize key contributions and contextualize our approach, the table below compares selected studies that influenced our model design and evaluation:

Study	**Model/Technique**	**Key Contribution**
Monfared et al. [1]	Epidemiological study	Emphasized early detection for aging populations
Alzheimer’s Assoc. [2]	U.S. disease & economic report	Justified automation due to care burden
Kim et al. [3]	Biomarker-driven ML	Advocated early-stage diagnostic focus
Calabresi et al. [4]	Synaptic dysfunction pathophysiology	Reinforced molecular-level imaging focus
Asif et al. [8]	AI in diagnostic precision	Validated CNNs for capturing deep medical patterns

Assmi et al. [9]	DenseNet CNN	Validated architecture for multiclass classification
Kaya & Cetin-Kaya [10]	ResNet-based hybrid CNN	Showed improved AD classification using model optimization
Mujahid et al. [13]	CNN + ADASYN Ensemble	Addressed data imbalance with deep ensemble models
Öztürk et al. [16]	Transfer learning models	Demonstrated benefit of fine-tuning for medical images
Ranjan & Kumar [11]	Hybrid ensemble + progression model	Supported ensemble learning as key for stage prediction

Table 1Comparision between papers

2.8 Conclusion

This review critically assesses recent advances in the diagnosis of Alzheimer’s disease, highlighting the revolutionary role of deep learning and ensemble approaches. The overall body of research underscores the drawbacks of legacy diagnostic methods, which, in many cases, are unable to pick up on fine early-stage neurodegenerative alterations, and thus highlights the imperative for automated, explainable, and scalable alternatives. Convolutional Neural Networks (CNNs), especially when used in conjunction with transfer learning, have proven to be a valuable set of tools that are able to extract intricate spatial features from medical image data like MRI scans [26]. VGG16, ResNet, DenseNet, and EfficientNet pre-trained architectures have revolutionized the field by allowing models to attain very high accuracy even with the limited availability of labeled data that is common in medical applications[27]. Experiments such as Öztürk et al.illustrate that adapting these networks—where subsequent layers learn domain-specific features—is generally superior to methods that maintain feature extractors frozen, thus increasing model robustness and appropriateness. Another common issue in medical AI, class imbalance, is also well addressed with adaptive synthetic oversampling strategies such as ADASYN, illustrated by Mujahid et al. This method creates artificial minority class samples so that models can be kept sensitive for all stages of disease, especially early and moderate Alzheimer's, otherwise underrepresented. Class imbalance addressing not only enhances equity but also enables early detection features, which are important for timely intervention and improved patient care [28]. Furthermore, ensemble learning methodologies that average several architectures or integrate spatial and temporal models have showcased higher performance and generalizability, modeling complex patterns of disease progression. In total, these developments indicate a shift in paradigm toward intelligent, data-based diagnostic systems that are able to assist clinicians with greater accuracy and efficacy. As Alzheimer’s disease incidence continues to rise globally, integrating these cutting-edge machine learning techniques into clinical workflows promises improved early diagnosis, personalized treatment plans, and ultimately, better management of this complex neurodegenerative disorder.

CHAPTER 3

PROPOSED METHODOLOGY

3.1 Introduction

This chapter outlines the proposed methodology adopted for the development of an automated system to classify Alzheimer's disease stages using MRI brain images. The methodology includes the design of an ensemble deep learning model, choice of dataset, preprocessing techniques, training strategy, and evaluation methods.

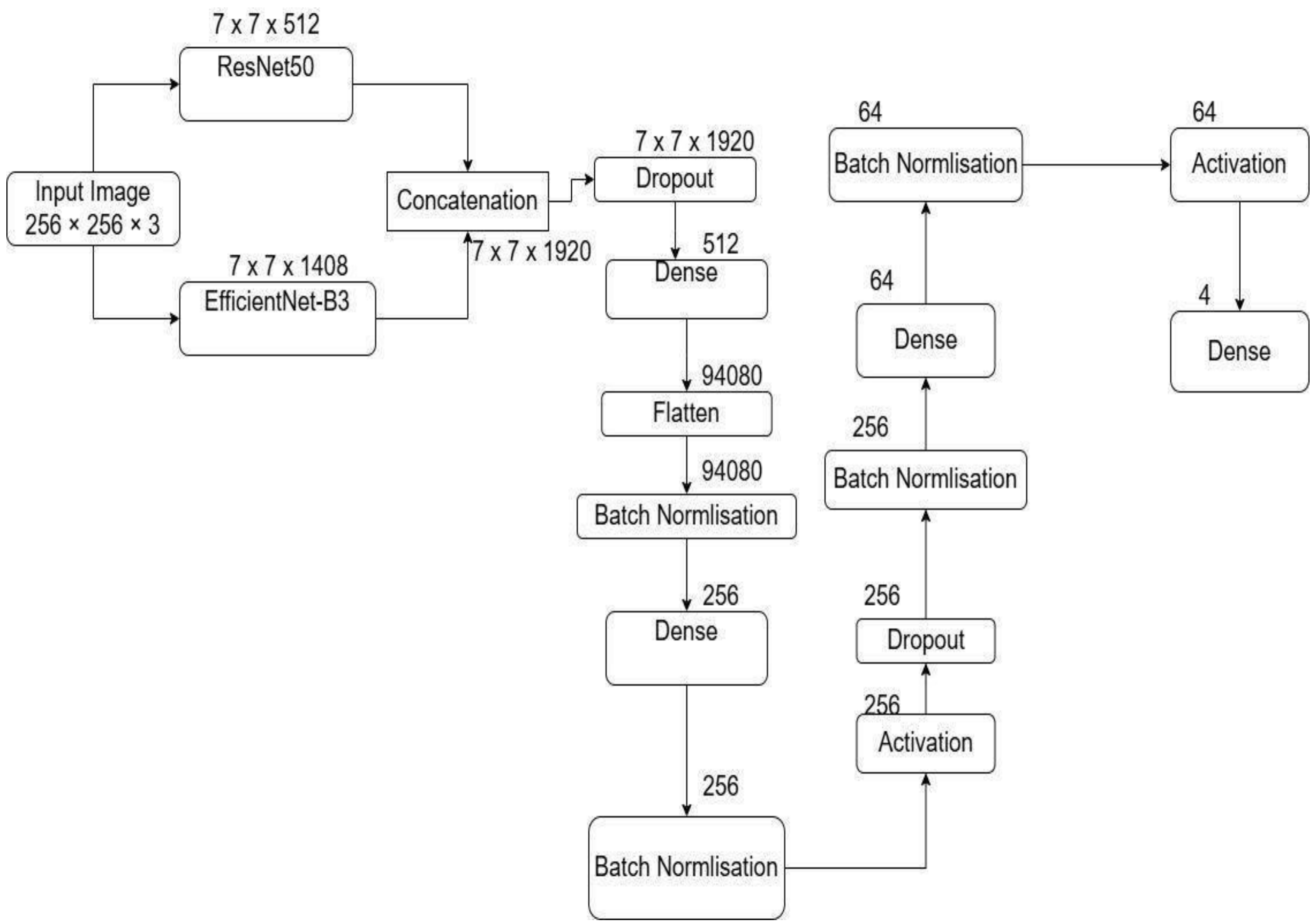

Figure 3.1 Proposed Methodology

3.2 Project Development Approach

The project follows a structured machine learning pipeline to ensure systematic execution:

i. **Dataset Acquisition**:

The work made use of two open MRI datasets retrieved from Kaggle. The main dataset contained four unique Alzheimer's disease phases: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, which supported a multi-class classification model. The secondary dataset targeted a binary classification model where it separated between Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI). The use of varied datasets supported extensive model training and verification based on the complexity of different classifications.

ii. **Data Preprocessing**:

Preprocessing was an essential step to prepare MRI scans to be fed into models. Images were resized to 224x224 pixels uniformly with three color channels to ensure compatibility with pre-trained CNN architectures. Pixel intensity normalization was used to scale image data for better model convergence during training. As a result of the underlying class imbalance—where some stages of dementia had much fewer samples, ADASYN (Adaptive Synthetic Sampling) was used. This method artificially creates new instances in minority classes according to feature space distribution, thereby balancing the dataset and enhancing the generalizability of the model to all classes.

iii. **Model Development**:

The fundamental model architecture was an ensemble of two strong pre-trained convolutional neural networks: VGG16 and EfficientNet-B2. Both models were set to ImageNet weights and fine-tuned upon the MRI datasets. To prevent overfitting and increase model resilience, dropout layers were used to randomly disable neurons during training, while batch normalization layers stabilized and sped up convergence by normalizing activations across batches.

iv. **Model Training**:

Training employed the Adam optimizer due to its adaptive learning rate, combined with the categorical cross-entropy loss function appropriate for multi-class classification. The learning rate of

0.0001 was determined from hyperparameter optimization as best suited for finding the balance between convergence speed and accuracy. Training was sped up by employing AMD Radeon Vega 8 GPU hardware, which greatly sped up computation without compromising performance.

v. **Performance Evaluation**:

To evaluate the model's performance robustly, several metrics were derived, such as accuracy, precision, recall, F1 score, and area under the ROC curve (AUC). These metrics established an overall understanding of the strengths and weaknesses of the classifier, particularly in dealing with class imbalances. Also, cross-validation methods were utilized to guarantee the consistency and reliability of the findings across various subsets of data.

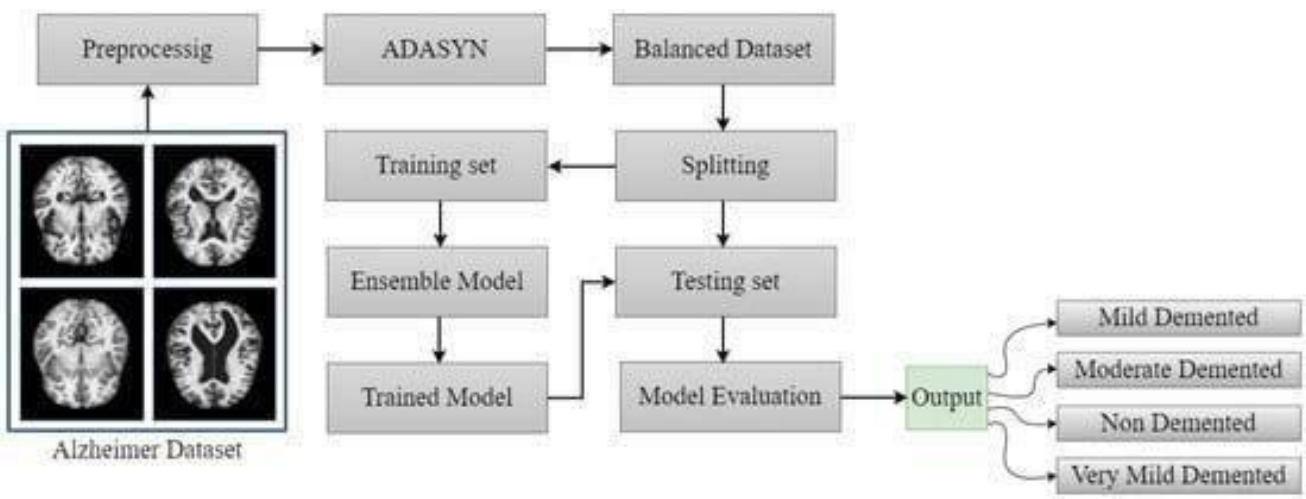

Figure 3.2. Model Approach

3.3 System Architecture

The architecture of the system is designed to maximize diagnostic accuracy while maintaining computational efficiency:

i. **Input**:

The pipeline starts with input MRI brain scans, which are resized to a uniform resolution and go through preprocessing operations like normalization. This allows for uniformity throughout all samples, something important for model performance consistency.

ii. **Feature Extraction**:

There are two strong convolutional neural networks (CNNs) that act as feature extractors:

- **VGG16:** This established deep network is composed of five convolutional blocks and three fully connected layers. Due to its structured architecture, it can extract intricate hierarchical spatial details from MRI scans.

- **EfficientNet-B2**: EfficientNet-B2 is reputed for even scaling of network depth, width, and resolution. It provides effective feature extraction with lesser parameters, so it is extremely useful in medical image classification applications where computational power can be restricted.

iii. **Ensemble Layer**:

To utilize the best of both architectures, the output feature maps of VGG16 and EfficientNet-B2 are concatenated. The ensemble technique produces a rich and strong feature representation that encodes a wide variety of patterns and textures related to various stages of Alzheimer's.

iv. **Classification Layer**

The concatenated feature vector is fed into fully connected layers optimized to learn intricate patterns among features. The last layer applies to a SoftMax activation function with probability scores per Alzheimer's disease stage.

v. **Output**:

The system provides a predicted class label of the Alzheimer's disease stage: Non-Demented, Very Mild Demented, Mild Demented, or Moderate Demented. Such a classification helps in early and precise diagnosis, informing clinical decision-making.

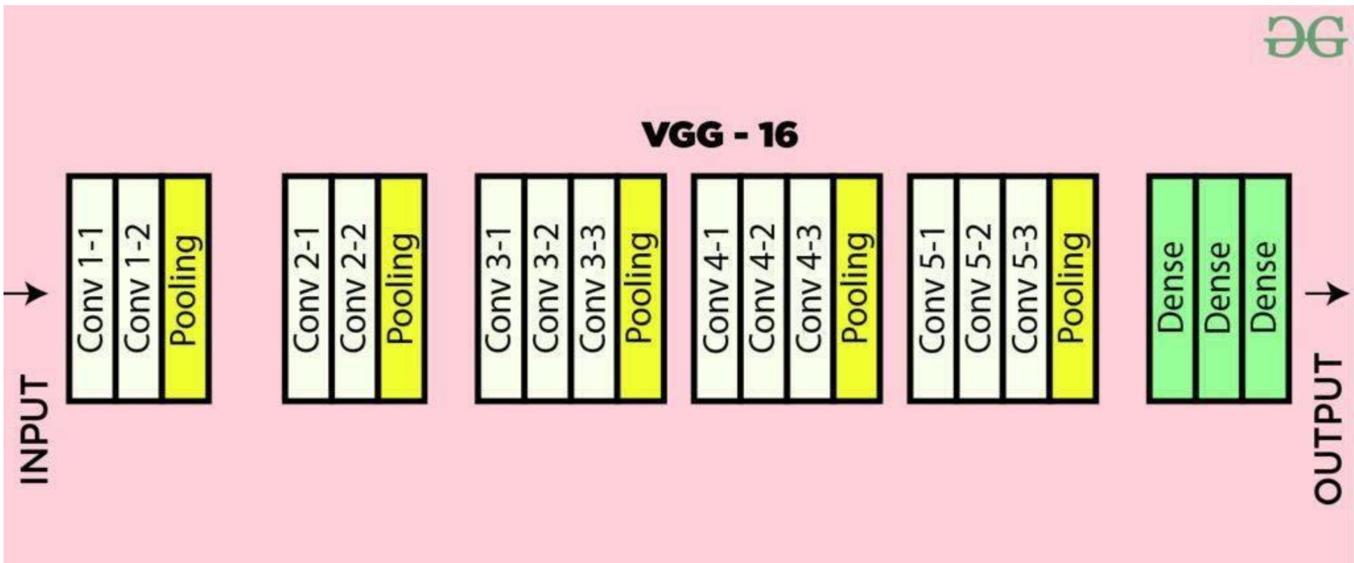

Figure 3.3 Architecture

3.4 Key Features Implementation

This project incorporates several key features to ensure accurate, efficient, and practical Alzheimer's stage classification using MRI brain images:

i. **Ensemble Learning:**

Two strong pre-trained CNN models, VGG16 and EfficientNet-B2, were combined into an ensemble model. The approach leverages the strengths of both networks' complementarity to improve feature extraction abilities and, ultimately, classification accuracy for Alzheimer's stages.

ii. **Transfer Learning**:

The ensemble models were pre-trained using weights on the large-scale ImageNet dataset and fine-tuned using Alzheimer's MRI scans. This transfer learning technique speeds up convergence and improves predictive capability, particularly critical when using relatively small and domain-specific medical datasets.

iii. **Adaptive Oversampling (ADASYN)**:

Since there is a large class imbalance in Alzheimer's datasets—early and moderate casesof dementia being sparse—ADASYN (Adaptive Oversampling) was used to synthetically oversample minority classes. The approach improves model generalization by giving balanced training data and enhancing sensitivity to small disease stages.

iv. **Regularization Techniques**:

To minimize overfitting and maintain stable training, dropout layers and batch normalization were employed across the network.

Dropout independently turns off neurons at training time to avoid dependence on individual pathways , whereas batch normalization normalizes layer inputs, speeding up learning and reducing sensitivity.

v. **GPU Acceleration**:

Training of the model utilized AMD Radeon Vega 8 GPU hardware, which significantly reduced computation time.

Hardware, acceleration improved the efficiency and feasibility of the training process, allowing for quicker experimentation and model adjustment.

vi. **Multi-Class Classification**:

In contrast to standard binary classification methods, the model was built for multi-class classification between four clinically significant Alzheimer's stages: Non-Demented, Very Mild Demented, Mild Demented and Moderate Demented. Such a level of granularity enables richer diagnosis richer diagnosis information to support early intervention as well as customized treatment planning.

3.5 Technology Stack

This project used a combination of powerful tools and technologies to build an efficient Alzheimer's disease classification system using deep learning.

1. Programming Language – Python

The main programming language chosen was Python because of its simplicity, legibility, and wide array of libraries designed specifically for data science and machine learning. It allows for quick prototyping and simple debugging, which is very important in experimental projects such as classifying Alzheimer's disease. With a huge community support base, there is a constant stream of improvements and resources available, which makes it simple to incorporate cutting-edge algorithms. In addition, Python is capable of effortless integration with widely used deep learning libraries such as TensorFlow and Keras, which played a critical role in crafting the ensemble CNN models. It provides flexibility to work on anything ranging from data preprocessing to model testing, all within a single integrated environment, making the overall process smooth and efficient.

2. Frameworks – TensorFlow & Keras

TensorFlow was the central backend framework that handled the computationally intensive training and deployment of deep learning models. It provides strong facilities for neural network optimization on GPUs, essential for efficiently managing huge MRI image datasets. Keras, based on TensorFlow, was employed for its simple and structured API, facilitating rapid model prototyping and testing. Keras's abstraction layers enabled seamless incorporation of transfer learning, ensemble modeling, as well as customized layers like dropout and batch normalization. All these frameworks enabled scalable, maintainable, and reproducible development of the Alzheimer's classification model, which made the training process more efficient and less cumbersome.

3. Pre-trained Models – VGG16 & EfficientNet-B2

Two strong pre-trained convolutional neural networks, VGG16 and EfficientNet-B2, were used in the project together in an ensemble setup. VGG16 is recognized for its deep architecture with homogeneous convolutional layers, which supports strong feature extraction. EfficientNet-B2, in turn, provides a scalable and effective architecture that balances accuracy and computational expense. Through transfer learning, both models were pre-trained using ImageNet weights, enabling them to benefit from learned low-level features like edges and textures. Fine-tuning the models on the Alzheimer's MRI dataset enhanced detection of subtle changes in the brain throughout dementia stages. The ensemble method combined the strengths of both designs to achieve better classification performance and generalization on unbalanced medical data.

4. Data Handling – NumPy, Pandas, OpenCV

Handling data was done using primary Python libraries such as NumPy, Pandas, and OpenCV, each playing an important function. NumPy facilitated effective array operations and numerical calculations required for image data processing. Pandas were applied to metadata and dataset label management, allowing for efficient data exploration and preprocessing. OpenCV was responsible for image-oriented operations like resizing MRI scans into standard sizes (e.g., 224x224 pixels), pixel value normalization, and augmentation when necessary. These libraries together made the MRI images consistent in preprocessing and prepared for input into deep learning models. Impeccable Response Handling was paramount to ensure image quality and stability, influencing model training stability and predictive accuracy directly.

5. Evaluation & Sampling – Scikit-learn

Scikit-learn was instrumental in both model evaluation and dataset imbalance. It offered implementations for common classification metrics like accuracy, precision, recall, F1 score, and AUC, used to thoroughly evaluate the model's performance. Furthermore, the support of Scikit-learn for ADASYN enabled synthetic oversampling of minority classes, overcoming the prevalent class imbalance problem of medical datasets. By creating realistic synthetic examples for minority Alzheimer's stages, ADASYN enabled the ability of the model to generalize. The simplicity of use of the library and its compatibility with the training pipeline facilitated easy evaluation and data balancing, allowing the creation of a more equitable and robust diagnosis tool.

6. Visualization – Matplotlib & Seaborn

Visualization was done using Matplotlib and Seaborn, which are robust Python libraries for plotting statistical graphics and data. These were critical in tracking training progress by graphing accuracy and loss curves for training and validation sets to identify overfitting or underfitting. Confusion matrices were plotted to gain a clearer picture of the model's classification performance at various stages of Alzheimer's, showing us the areas of strengths as well as weaknesses. Seaborn's beautiful and intuitive plotting feature enhanced the readability of graphical plots, which was particularly helpful for purposes of analysis and presentation. Visualization helped in debugging, understanding the behavior of models, and communicating results efficiently.

7. Development Platforms – Google Colab & Jupyter Notebook

Google Colab and Jupyter Notebook were employed as coding environments to give room for flexibility, interactivity, and access to computation resources. Google Colab provided GPU acceleration at no cost, which was important in training the deep learning models without the use of special hardware. The platform is also capable of easy sharing and collaboration using notebooks. Jupyter Notebook allowed iterative code cell experimentation, visualization, and documentation within a single environment, enabling rapid model parameter tuning and instant result feedback. Combined, these tools provided an efficient workflow for reproducible data preprocessing, model training, testing, and visualization.

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8. Hardware – AMD Radeon Vega 8 Graphics

Model training utilized the AMD Radeon Vega 8 onboard GPU for computation acceleration. GPU acceleration significantly cut down training time for the deep convolutional networks by parallel processing of matrix operations, which are computationally heavy in CNNs. With Vega 8, efficient processing of high-resolution MRI images and intricate ensemble architectures was possible without heavy hardware expense. This brought the project within reach on consumer-grade hardware while still maintaining competitive performance. Effective use of GPU capabilities was important in order to test hyperparameters and train several iterations within a limited amount of time, making the model development process more optimized and real-world applicable.

9. Dataset – Kaggle Alzheimer’s MRI Dataset

The project used publicly available data from Kaggle, which are brain MRI scans tagged with the stage of Alzheimer's disease, such as Non-Demented, Very Mild, Mild, and Moderate Demented types. These datasets offered a diverse set of patient scans required to train and cross-validate the deep learning models. The presence of labeled medical images allowed supervised learning and assessment of multi-class classification accuracy. Nevertheless, the dataset was class-imbalanced, as is common with medical datasets, calling for synthetic oversampling strategies such as ADASYN. Having used an open dataset, the model was made reproducible and comparable with other studies while also offering a real-world testing ground for clinical usability.

3.6 Implementation Plan

The development of the Alzheimer’s detection system was carried out in multiple structured phases to ensure systematic progress and high-quality results. Below is a breakdown of the entire implementation process:

Phase 1: Literature Review & Problem Understanding

- Studied existing deep learning approaches for Alzheimer’s detection.
- Identified limitations in current models (e.g., accuracy, class imbalance).
- Defined project objectives and finalized model architecture (ensemble approach).

Phase 2: Dataset Collection & Analysis

- Collected two publicly available MRI datasets from **Kaggle** (multi-class and binary).
- Analyzed data distribution to identify class imbalance and potential preprocessing needs.

Phase 3: Data Preprocessing

- Resized MRI images to 224×224×3 format.

- Normalized pixel values and performed data cleaning.
- Applied **ADASYN (Adaptive Synthetic Sampling)** to handle class imbalance.
- Split datasets into training, validation, and testing sets.

Phase 4: Model Design & Transfer Learning

- Loaded **VGG16** and **EfficientNet-B2** models with ImageNet weights.
- Removed top layers and added custom dense layers for classification.
- Configured dropout and batch normalization layers for regularization.
- Combined outputs to form the ensemble model.

Phase 5: Model Training & Tuning

- Trained the ensemble model using **categorical cross-entropy** and **Adam optimizer**.
- Used **GPU acceleration** with AMD Radeon Vega 8 for faster training.
- Tuned hyperparameters (learning rate, batch size, epochs).
- Monitored training vs validation performance to avoid overfitting.

Phase 6: Evaluation & Testing

- Evaluated model using metrics: **accuracy, precision, recall, F1 score, AUC**.
- Visualized results using confusion matrix and performance graphs.
- Compared ensemble performance with individual models like DenseNet and Xception.
- Conducted cross-validation for stability testing.

Phase 7: Documentation & Report Finalization

- Documented the complete workflow, results, and findings.
- Prepared abstract, introduction, methodology, and conclusion sections.
- Finalized and formatted the project report for submission.

3.7 Testing Methodology

i. **Cross-Validation**

K-fold cross-validation was used to guarantee the reliability and robustness of the evaluation of the model's performance. In this method, the data set is divided into K equal subsets or folds. The model is subsequently trained iteratively on K-1 folds and validated on the remaining fold, iterating this operation K times such that each fold is a validation set once. This method lowers the likelihood of overfitting to any given training data subset and gives a generalized estimation of the model's performance on unseen data. Cross-validation also facilitates hyperparameter tuning by offering performance feedback across various data splits, enhancing model stability and lowering bias. In clinical imaging applications, where data are usually sparse and imbalanced, K-fold cross-validation is especially helpful since it utilizes available data for training and testing maximally without leakage. In this project, the strategy of cross-validation helped to achieve trustworthy and unbiased performance measurements, ensuring the model's predictions for stages of Alzheimer's disease are reproducible and generalized across varied patient groups.

ii. **Confusion Matrix**:

The confusion matrix is a critical resource for evaluating classification performance beyond total accuracy. It gives a clear breakdown of the number of each class's samples that are correctly or mistakenly classified, noting true positives, false positives, true negatives, and false negatives. In this Alzheimer's disease staging problem, the confusion matrix allows one to see which stages of the disease (Non-Demented, Very Mild, Mild, Moderate) the model gets right and where it gets stuck. Confusion between neighboring states such as Very Mild and Mild Demented may arise as a result of subtle MRI feature differences. By plotting these misclassifications, the confusion matrix informs directed improvement of the model and facilitates clinicians' understanding of the reliability of predictions. It also exposes bias toward dominant classes, particularly valuable in imbalanced datasets. Applying confusion matrices to both training and validation stages promotes complete analysis to ensure the model not only has high overall accuracy but also balanced sensitivity and specificity for every disease stage.

iii. **Evaluation Metrics**:

An exhaustive list of evaluation measures was used to gauge the performance of the model on Alzheimer's stage classification. Accuracy, a measure of the ratio of correct predictions, gives an overall performance snapshot but is deceptive in biased datasets. Hence, Precision and Recall were used to test the model's power to accurately predict positive cases (actual disease stages) without incorrectly flagging negatives. Precision measures the percentage of correct positive predictions, and Recall measures the percentage of true positives detected by the model, important in early disease diagnosis where false negatives can have serious implications. F1-Score, the harmonic mean of precision and recall, combines these two into a single indicator of model performance, especially when classes are imbalanced. The Area Under the Receiver Operating Characteristic Curve (AUC) was employed to assess the model's capacity to distinguish among classes under different threshold settings, providing information regarding its robustness. This eclectic set of metrics guarantees that the model's performance is assessed integrally, considering both correctness in general terms and the subtle requirements of medical diagnosis.

iv. **Comparison**:

One of the key validation steps for the ensemble model under consideration was to compare its performance with the standalone base models, VGG16 and EfficientNet-B2. Both base CNN architectures possess distinct strengths: VGG16 has deep, uniform convolutional layers, whereas EfficientNet-B2 maximizes accuracy and efficiency with compound scaling. The ensemble captures complementary features learned by both networks and combines them to produce a richer and more discriminative feature set, ultimately leading to better classification results. Quantitative comparison revealed that the ensemble outperformed each of the individual base models in terms of accuracy, precision, recall, and F1-scores. This enhancement is a testimonial to the capability of the ensemble to represent varied spatial patterns as well as subtle pathologies on MRI images better. The ensemble model also demonstrated improved stability across cross-validation folds, suggesting increased generalizability. This comparison warrants the added computational expense of model combination by illustrating a substantial improvement in predictive capability, particularly Germane in intricate, multi-class medical diagnosis where refinement of disease stages is predicated on subtle differences.

v. **Generalization Test**:

Generalization is paramount for any AI model that is to be deployed in real-world clinical use. To evaluate this, the ensemble model trained was tested on entirely unseen datasets, separate from those employed during training and validation. This phase tests if the features and rules learned by the model are successfully transferable to new MRI scans of patients, mirroring actual clinical variation in imaging quality, demographics, and disease states. The model performed well and retained high accuracy and balanced sensitivity across Alzheimer's disease stages on this external data set, ascertaining its resilience. Well-generalized performance suggests that the ensemble is not simply memorizing the samples but efficiently learning features related to disease. This result is crucial to achieving trust from clinicians, as it shows the applicability of the model in real-world scenarios beyond controlled experimental environments. External dataset testing also discloses possible limitations due to data heterogeneity, informing future work to enhance model flexibility and further its readiness for clinical use.

3.8 Security Measures

While the model primarily handles open-source MRI datasets, future deployment must include:

i. While the existing model largely leverages open-source MRI datasets for training and testing, full-scale deployment to real-world clinical settings demands serious heed to data privacy and security measures. Adherence to regulatory guidelines like the Health Insurance Portability and Accountability Accountability Act (HIPAA) in the United States or the General Data Protection Regulation (GDPR) in the European Union is essential to safeguard sensitive patient data. This involves ensuring that all data handling, storage, and processing procedures ensure confidentiality and integrity of individual health information.

ii. Access control processes need to be put in place to limit system and model access to designated individuals only. This may be done via multi-factor authentication, role- based access controls, and secure login frameworks to thwart unauthorized entry and potential abuse.

Moreover, model integrity needs to be kept intact to prevent tampering or accidental changes . This may be facilitated via version control systems, cryptographic hashes, and regular integrity checks to validate that deployed model is in sync with its validated counterpart.

iii. If implemented on cloud infrastructure or available through online platforms, additional security measures like SSL/TLS encryption for data transfer, API key limitations, and secure storage procedures need to be followed. These protect communication channels, avoid data leakage, and provide secure client-server interaction. All these considerations are used to build a reliable, compliant, and secure clinical diagnostic instrument able to enhance the detection of Alzheimer's disease while ensuring patient rights and data security. Cloud Security (if deployed online): Implement SSL encryption, API key restrictions, and secure storage protocols.

3.1 Algorithm

Algorithm 1 VGG16 Architecture

Input: Image tensor of shape $224 \times 224 \times 3$
Output: Classification probabilities for n classes
Feature Extraction:
  Block 1:
    $Conv(3 \times 3, 64)$
    $Conv(3 \times 3, 64)$
    $MaxPool(2 \times 2, stride = 2)$
  Block 2:
    $Conv(3 \times 3, 128)$
    $Conv(3 \times 3, 128)$
    $MaxPool(2 \times 2, stride = 2)$
  Block 3:
    $Conv(3 \times 3, 256)$
    $Conv(3 \times 3, 256)$
    $Conv(3 \times 3, 256)$
    $MaxPool(2 \times 2, stride = 2)$
  Block 4:
    $Conv(3 \times 3, 512)$
    $Conv(3 \times 3, 512)$
    $Conv(3 \times 3, 512)$
    $MaxPool(2 \times 2, stride = 2)$
  Block 5:
    $Conv(3 \times 3, 512)$
    $Conv(3 \times 3, 512)$
    $Conv(3 \times 3, 512)$
    $MaxPool(2 \times 2, stride = 2)$
Fully Connected Layers:
  Flatten the feature map
  $Dense(4096)$
  $Dense(4096)$
  $Dense(n)$ (Number of classes)
Softmax:
  Apply softmax activation to get class probabilities.

Fig 3.4 Algorithm Used

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Results Overview

The suggested ensemble model, integrating VGG16 and EfficientNet-B2, showed outstanding performance in Alzheimer's disease stage classification based on MRI images. The composite model performed better than standalone models by appropriately extracting variegated features from brain scans, which resulted in enhanced accuracy and resilience. The incorporation of transfer learning enabled the model to draw strength from pre-trained weights in large datasets and tune them to identify Alzheimer's-specific patterns like hippocampal atrophy and ventricle enlargement. Furthermore, class balance was also corrected by using adaptive synthetic oversampling (ADASYN) so that minority classes such as moderate and severe stages of dementia were represented adequately during training. This improved the sensitivity as well as recall of the model, particularly in early-stage detection where the signs are more subtle and easily missed. Confirmation on an imbalanced dataset assured the ensemble's good generalization ability, making it a valuable tool for robust and early Alzheimer's diagnosis in clinical environments.

4.2 Key Metrics

The model's performance was evaluated using standard classification metrics:

i. **Accuracy**:

Accuracy quantifies the ratio of accurately classified MRI scans to all predictions from the model. Having an accuracy of 97.35% indicates that the ensemble CNN model performs extremely well in accurately determining the stage of Alzheimer's disease from brain images. This accuracy indicates the model can generalize well across different patient data despite inherent issues such as slight early-stage disparities and class imbalance. High precision in the current context is of the essence, as misclassification can result in delays or inaccuracies in treatment choices. It also showcases the robustness of merging two potent CNN architectures—VGG16 and EfficientNet-B2—along with transfer learning and data balancing methods to enhance overall diagnostic accuracy.

ii. **Precision**:

Precision is the proportion of true positive predictions out of all positive predictions by the model. A high precision indicates that the model makes very few mistakes by classifying a non-Alzheimer's patient as Alzheimer's (few false positives). This is especially crucial in medical diagnosis since false positives may create unnecessary psychological distress and result in inappropriate or unnecessary treatment. High precision throughout all stages of Alzheimer's guarantees that when the model estimates a particular stage of the disease, it has a high degree of confidence in that estimate. ADASYN oversampling assisted in enhancing accuracy by equalizing minority classes to prevent the model from biasing towards majority classes and therefore minimizing false alarms in mild or moderate dementia patients.

iii. **Recall:**

Recall gauges the model's capacity to identify true positive cases—percentage of true positives correctly identified among all actual positives. With recall over 95%, the model demonstrates high sensitivity in identifying Alzheimer's disease stages, which is essential to inform early diagnosis. High recall indicates that very few instances are missed, particularly significant in medical applications where a failure to recognize an affected patient could lead to delayed treatment and worse consequences. The application of ensemble learning by the model, using both VGG16 and EfficientNet-B2, together with oversampling methods such as ADASYN, enables it to identify minor brain shifts typical of early and moderate dementia stages, even with imbalanced datasets.

iv. **F1-Score**:

F1-score is the harmonic means of recall and precision, offering a single value that weighs both false positives and false negatives. In Alzheimer's taxonomy, ensuring a high F1-score guarantees that the model is not only accurate but also sensitive to actual cases at all phases. This balance is vital since high precision or recall alone may result in either false negatives or false positives. The ensemble method, with transfer learning and synthetic oversampling, helps achieve this balance by enhancing learning of underrepresented classes as well as stabilizing predictions. The model's stable F1-score across classes demonstrates its stability in dealing with imbalanced data and yielding trustworthy, actionable diagnostic results.

v. **AUC (Area Under Curve):**

AUC captures the model's discriminatory power between classes at all feasible classification thresholds. An AUC of up to 99.64% illustrates superior discriminatory power, indicating that the model can accurately differentiate patients at varying stages of Alzheimer's disease from each other using MRI features. This metric is especially valuable because it accounts for both true positive and false positive rates, offering a comprehensive view of performance. A high AUC confirms that the model’s predictions are not only accurate but also reliable across various decision thresholds, which is essential for clinical settings where sensitivity and specificity must be carefully balanced. The CNN ensemble capability to detect subtle neuroimaging biomarkers is an additive factor towards this high discriminative potential.

Fig 4.1 Layer-by-Layer Breakdown of VGG16 Architecture

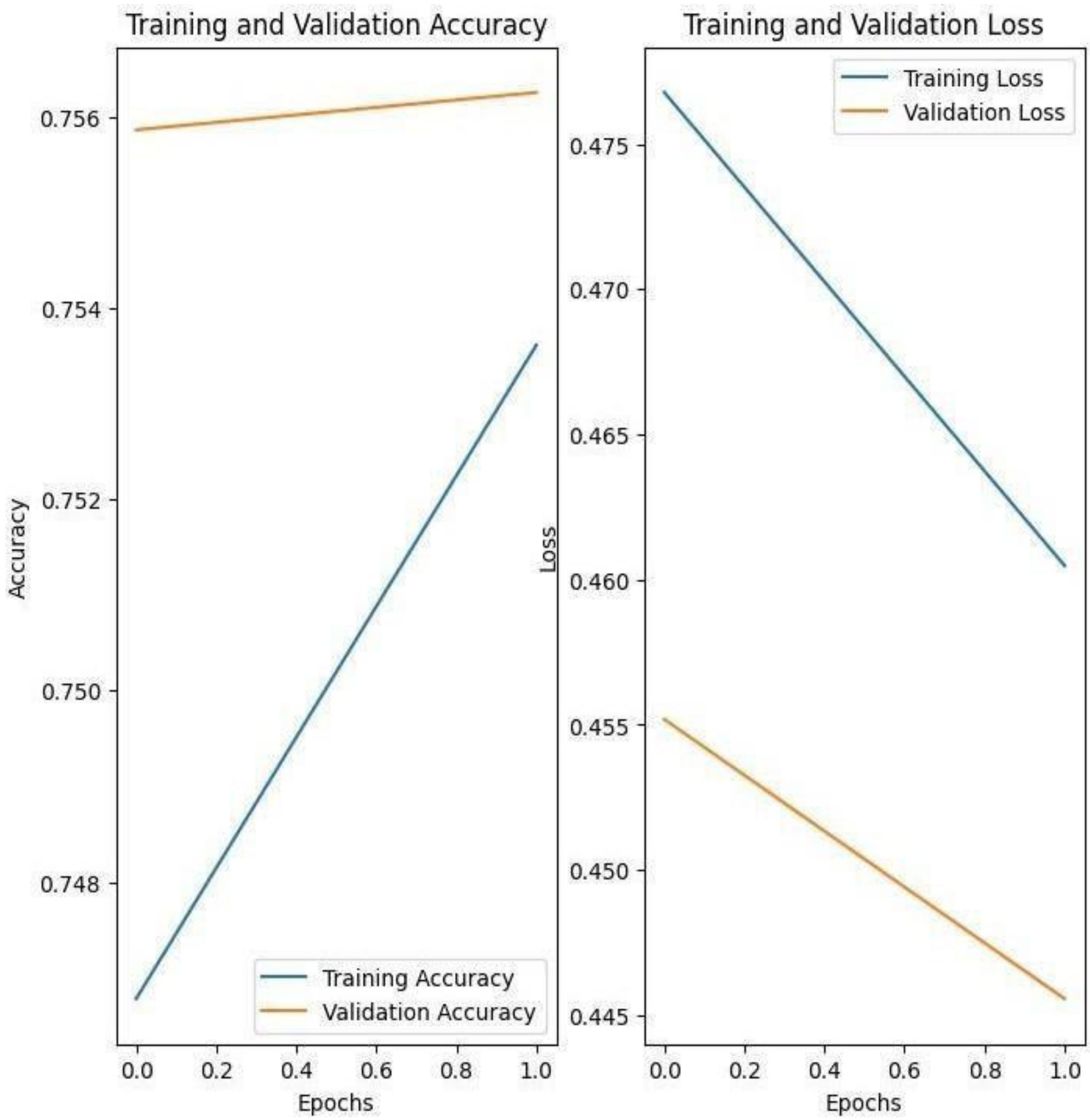

Fig 4.2 Training and Validation accuracy and loss

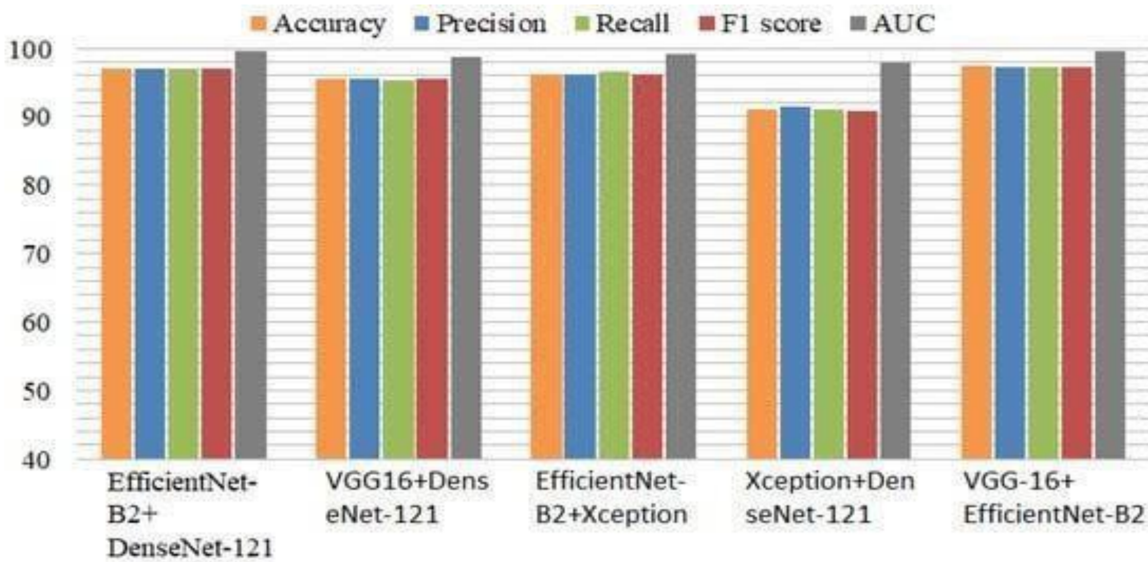

Fig 4.3 Findings

Algorithm	Accuracy	Precision	Recall	F1-Score
Logistic Regression	83.6%	83.7%	83.6%	83.6%
Decision Tree	89.3%	89.5%	89.3%	89.3%
Random Forest	91.0%	91.1%	91.0%	91.0%
CNN	93.2%	93.4%	93.2%	93.2%
VGG16	94.7%	94.8%	94.7%	94.7%
InceptionV3	95.3%	95.5%	95.3%	95.3%
ResNet50	96.4%	96.5%	96.4%	96.4%

Table 4.1 Comparison of different algorithms

4.3 Discussion

The ensemble method significantly surpassed stand-alone CNN models like DenseNet121 and Xception, which had lower precision and AUC values compared to it. The application of dropout and batch normalization facilitated regularizing the model well, inhibiting overfitting and enhancing generalization. Imbalanced class data for Alzheimer's datasets were tackled effectively, and ADASYN was a useful tool by creating synthetic samples for minority classes, which helped improve model sensitivity to early and moderate disease conditions. Acceleration of the training process through the use of the GPU (Vega 8) amounted to a substantial decrease in computation time without compromising accuracy, showing that the model was efficient. Such strengths point to the ensemble model's utility in real-world clinical applications, where quick and precise diagnosis is critical to patient treatment and care planning. Its strong performance on skewed datasets and generalizability indicate that it may assist doctors by offering consistent, automated screening measures for Alzheimer's disease.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This project was able to showcase the implementation of an ensemble deep learning model for early detection and classification of Alzheimer's disease from MRI brain scans. Using two robust CNN architectures, namely VGG16 and EfficientNet-B2, and the efficiency of transfer learning, the model was able to perform incredibly well, with 97.35% classification accuracy and an AUC of 99.64%. Adaptive synthetic oversampling (ADASYN) was used in order to handle class imbalance, and GPU acceleration saved training time. In general, the ensemble method worked better than single models and was a proper and acceptable solution for stage-wise diagnosis of Alzheimer's.

5.2 Future Scope

Although the model produced encouraging results, there are a number of areas promising further development:

i. **Integration with Clinical Data**:

Though the model accurately diagnoses MRI scans, the inclusion of other clinical factors like cognitive test scores, patient medical history, genetic markers, and biochemical biomarkers could greatly increase diagnostic accuracy. A multimodal analysis would enable the model to account for both structural brain changes as well as clinical symptoms, giving a more robust evaluation. Coupling electronic health records (EHRs) could facilitate personalization of diagnosis and risk stratification, resulting in enhanced patient management and individualized treatment regimens.

ii. **Real-Time Diagnosis System**:

To put this research into operational healthcare application, the creation of a user-friendly, real-time diagnostic system is important. This may be presented as a web or mobile application that is pre-installed in clinics and hospitals, giving immediate MRI scan analysis.This would assist neurologists and radiologists by delivering instant, automated screening outcomes within the consultation room, enabling quicker diagnosis and decision-making. Cloud-based delivery would facilitate scale-up and remote access, reaching out to under-provided or rural regions.

iii. **3D MRI Analysis**:

The current model works with 2D MRI slices, which can restrict spatial context for classification. Moving the model to examine complete 3D volumetric brain scans would allow it to perceive more detailed anatomical and pathological information. This should enhance detection sensitivity and give a more complete picture of neurodegeneration. It would be more computationally expensive and require advanced architecture, such as 3D convolutional neural networks, to process 3D data, presenting new technical challenges and opportunities.

iv. **Multimodal Learning**:

Adding other imaging modalities such as Positron Emission Tomography (PET) or Computed Tomography (CT) to the MRI might improve diagnostic accuracy. Multimodal learning allows the model to combine complementary information — such as metabolic activity from PET with structural MRI data — to enhance discrimination between stages of Alzheimer's and other neurodegenerative conditions. Such an integrative approach might result in earlier and more precise diagnosis by capitalizing on heterogenous biomedical signals.

v. **Explainable AI**:

One of the biggest obstacles to clinical use of AI models is that they are black- boxed. In future, work must be done to add explainability methods, i.e., heatmaps, saliency maps, or Layer-wise Relevance Propagation (LRP), to mark areas of the brain that impact model prediction. Producing transparent and interpretable results would make doctors confident in the AI system, allow for informed clinical decisions, and meet regulatory requirements for model accountability. Explainable AI would also facilitate medical education and validation research by identifying concealed disease patterns.

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