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Early Prediction of Alzheimer's Disease using Deep Learning and Data Fusion

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Abstract

Detection of Alzheimer's disease (AD) and it progresses still one of the toughest challenges in medical field. When disease detected early this will often makes a big difference in the treatment plans. The issue is that many current diagnostic models look at the problem from one angle which could lead to wrong conclusion because it relies only to one single source of data, such as brain imaging without look to clinical data or vice versa, Because of this one-sided approach, doctors can miss the detection of early disease symptoms ,especially during the first stages when a person shifts from a normal condition (NC) to mild cognitive impairment (MCI), before it developed to full Alzheimer's (AD).

To deal with this limitation, this study presents a new approach that combines deep learning with data fusion. The framework is designed to examine 3D MRI scans with clinical of patients from the ADNI dataset. We will build a two-path model for this purpose: one path uses a 3D-ResNet network to automatically pull-out visual features from the images, and the other relies on deep neural networks (DNN) to process the clinical data. This approach will help the model to give a more details and better understand of a patient's condition.

Keywords: Alzheimer's Disease, Deep Learning, Data Fusion, CNN, 3D-ResNet, Early Prediction, Medical Imaging, Explainable AI.

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List of Abbreviations

- AI: Artificial Intelligence.
- ML: Machine learning
- DL: Deep Learning.
- CNN: Convolutional Neural Network.
- ResNet: Residual Network
- GAN: Generative Adversarial Network.
- XAI: Explainable Artificial Intelligence.
- ViT: Vision Transformer.
- VGG: Visual Geometry Group 19.
- NC: Norma Cognitive
- MIC: Mild Cognitive Impairment
- AD: Alzheimer's Disease
- MRI: Magnetic Resonance Imaging
- ADNI: Alzheimer’s Disease Neuroimaging Initiative

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Chapter 1: Introduction

Introduction

Alzheimer's disease is one of the most difficult brain conditions. While it is more common in older people, it can affect individuals at different stages of life, including those in their younger years. It slowly destroys memory and thinking skills, and in many cases, it is only discovered after the person shows clear symptoms. However, research has shown that changes in the brain start many years before these symptoms appear. This is why finding the disease early is the main goal of medical research today. For example, [1] showed that we can catch these early signs by identifying brain changes over time.

Within time, AI is getting more and more attention in every field and medical field as well for helping doctors, researchers and patients to give more accurate results about brain scans, especially MRIs, considered very helpful because they give a big and clear picture of the brain. According to that, recent papers by [2] and [3] take advantage of AI progress to scans and to put together some really accurate models to spot the disease. But worth noting that a significant portion of past research has focused on unimodal data, such as analyzing only MRIs. Although it is good to at certain degree, this approach fails to capture the full scope of Alzheimer's evolving condition. Recent research proves that combining different sources such as merging brain scans with a patient's clinical records and physical symptoms [4] leads to a much more precise and reliable diagnosis.

In this thesis, we propose an AI system for early diagnosis that looks at both brain changes and medical records over time. We use data from the ADNI, which is a famous collection of medical information used by many top researchers, including [5] and [6].

The main goal of this work is to see if combining brain images and clinical memory tests can help us find the disease in earlier stages which aims to give a clear and easy-to-understand tool to help patients as early as possible.

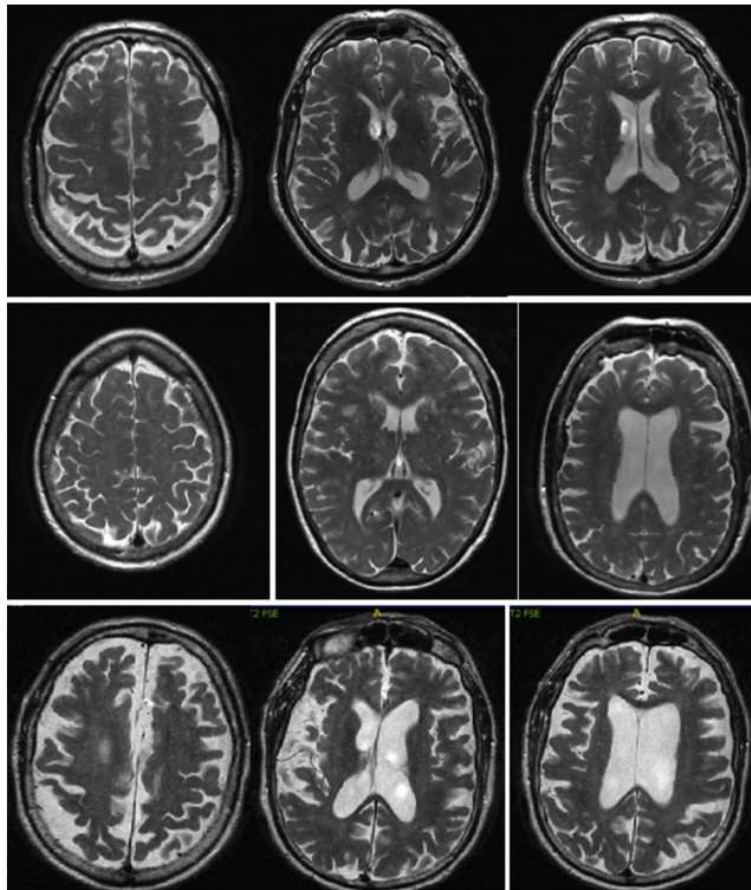


Figure 1.1: MRI images of Normal Cognitive (Row 1), Mild Cognitive Impairment (row 2) and last is Alzheimer's Disease

1.1 Problem Definition

Despite the large number of studies applying deep learning to Alzheimer's diagnosis, several important limitations remain.

First, many approaches focus exclusively on imaging data, particularly structural MRI. While MRI can reveal brain atrophy and structural abnormalities, it does not incorporate molecular or genetic information that may indicate susceptibility before structural damage becomes severe.

Second, both neuroimaging and genomic datasets are high-dimensional. Imaging volumes contain millions of voxels, and genomic profiles may include thousands of features. Directly training deep learning models on such data can lead to overfitting if not handled properly. And for that we must have a good method for feature extraction and data size reducing.

The main issue with Alzheimer's is the changing withing the time, and most models just deal with data as one picture. They ignore the long-term changes of the disease and how it grows over time. Because of that, they will miss some clues that show at the very beginning of disease symptoms.

On top of all that, merging different types of data together which is known as (multimodal fusion) is challenging tasks. And There is no clear approach on how to mix brain scans with genetic data. Which lead us to find a solution for building the network that contain multi data type to do a give an excellent results one tested patients.

1.2 Thesis Objectives

The purpose of this research is to build and test an AI system that can read different data types to catch Alzheimer's in early stages. To do that we will apply the following steps:

- To create a deep learning model to import and MRI scans and extract important details.
- To develop multimodal fusion to mix the genetic data with brain pictures.
- To test and track the changes over time
- To check if our proposed framework give a better result by make a comparison with others that look only at one kind of data.

1.3 Thesis Contribution

The aim of this thesis is to contribute to the field of Alzheimer's disease by improving the early detection by implementing the following techniques:

- Deep learning model that handles different data type such as MRI images and clinical data for better diagnostic decisions
- A multi computer vision algorithms including baseline CNN and 3D ResNet-18 model for better comparing and classification.
- A framework to achieve better computing power performance with large scale of data sets.
- Using of Explainable AI (XAI) techniques to help to define and explain the exact brain areas as the computer do in order to increase the transpierce for doctors and their patients

1.4 Thesis Organization

The remainder of thesis organized as follows

Chapter 2: a discussion about history of Alzheimer's diagnosis over years

Chapter 3: present the proposed framework and its workflow

Chapter 4: analyze and cover testing phase and results.

Chapter 5: summarizes the study and the future direction of work.

Chapter 2: Related Work

2.1 Introduction

With artificial intelligence (AI) things has changed in general not to mention the methods around how we diagnose brain diseases. In this chapter we will reviews past studies on detecting Alzheimer's Disease (AD). We will see how things shifted from simple practices to modern deep learning [6,7]. The goal here is to take a look and find out the problems in past researches with knowing why and try overcome with better ways, generally the major studies use only one type of data at a time which is not enough when you dealing with a human brain and with taking this into consideration a need of different data types (data fusion) is a real medical need, not just an extra . study [8] show that mixing 3D MRI scans with basic clinical records gave much better and increase the accuracy result. Combining this will lead to better tracking for a patient as they go from a healthy state (Normal Control, NC) to Mild Cognitive Impairment (MCI), and finally to AD.

Diagnosing AD relied a lot on manual checks and the doctor's personal opinion this was situation before using the computers. Doctors usually checked memory loss using simple tests like the Mini-Mental State Examination (MMSE). Even after using MRI scans, doctors had to look at many 2D image slices by eye to find changes one the brains, like brain shrinking [9,10]. Doing this manually cost a lot of time and resources, not only that but doctors can have a different opinion for same things they have looked for. And, as human cannot see the tiny brain changes with just our own eyes due to our limitations and for sure cannot see the tiny brain changes that happen in the very early stages of the disease. And the damage was already done withing the time and wrong diagnoses. Because of this delay it became more and more important to look for better and automated tools for medical field.

In order to understand what we mean to these tools, we need to look back at traditional Machine Learning (ML) and shifting to Deep Learning (DL). Traditional ML is good in some case like basic clinical data. But it is not good when come to deal with medical images because it required humans interactions to pick the important features first [11]. To overcome with this limitations deep learning fixes this by automatically fetch an important details from the raw 3D data. And can deal with simple shapes and move to

large scale complex disease patterns. This automation means no humans interaction required to do the manual work, making DL a best choice for modern MRI scans [12].

2.2: Background

In the last two decades, the diagnosing for Alzheimer's disease changed a lot. At the beginning finding the small, early signs of the disease is still was a hard task for computers, but things getting easier withing time for doctors, researchers and patients due to evolving of tools that used machine learning and deep learning to help analyze patient data.

Firstly, machine learning methods required many manual work steps. Including collecting and data cleansing of raw data such as MRIs or genomic data after that researchers have to split the data. Then, with help human experts they need pick out important features, like tissue texture, brightness, or brain shape. Once these features extracted, they used standard models like Support Vector Machines or Decision Trees for learning and recognize the patterns.

These approaches have been used in the diagnosis of brain disorders, including Alzheimer's disease, where performance is often influenced by the quality of the extracted features [13,16].

Study [13] explored the use of machine learning to predict whether patients with mild cognitive impairment (MCI) may progress to Alzheimer's disease (AD). It employed XGBoost as a classification model and incorporated the Shapley value (SHAP) method to provide insights into feature contributions, including MRI and genetic data.

Studies [14–16] investigated different machine learning pipelines for Alzheimer's disease classification and prediction. Study [14] followed a supervised learning approach in which multiple classifiers, including Support Vector Machine, Random Forest, and Artificial Neural Network, were trained and compared using structured feature sets derived from non-medical and behavioral data. In the case of the Artificial Neural Network, the input layer received a fixed-length feature vector representing the selected variables, which were then processed through hidden layers to model non-linear relationships before producing the final output. The techniques used pre-processing, feature selection, and model evaluation. Study [15] improve this by using multimodal data and explainable AI to be able to know how the model makes its

decisions. While study [16] focused on feature extraction from images. They selected some details from brain scans and used them as inputs for models classification.

generally, these studies follow the same basic steps: pre-processing the data, extracting features, training the model, and checking the results. But things changed when researchers pay attention to mixing different data types (multimodal integration) to ensure that we can have better understand of how model thinking (interpretability).

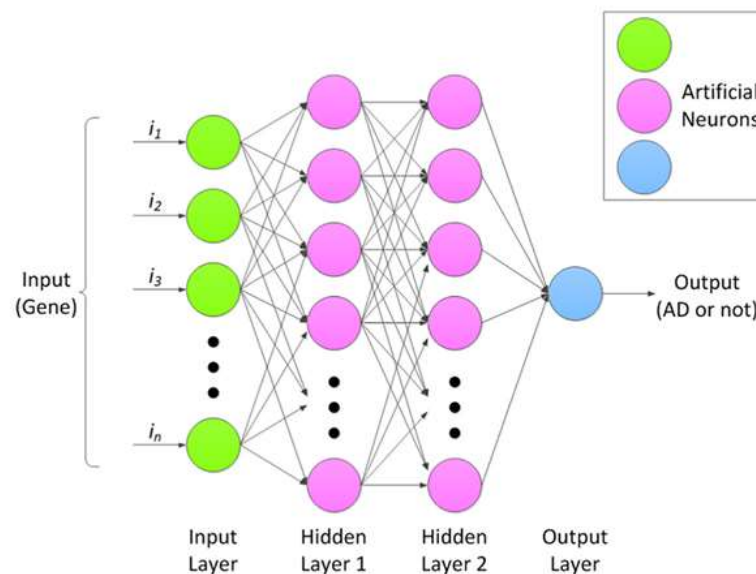


Figure 2.1: ANN machine learning model. Adopted by [14]

Although machine learning provided a big leap in detecting Alzheimer's, working directly with raw 3D brain scans has a limitation problem. Extracting good features required a lot human interactions to deal with brain areas not only this but flatten a complex 3D brain into a simple data table caused an important spatial detail to be lost.

To solve these extraction issues, the researchers used a deep learning computer vision, especially Convolutional Neural Networks (CNNs). Without relying on human input features, CNNs find a way to visualize patterns directly from the MRI data. By passing the adjusted scans through convolutional and pooling layers, these networks handle everything from basic lines to complex brain damage.

And for getting better accuracy research seeks to using deeper networks for better result, like AlexNet which changed how we classify medical images. They proved that

having deeper layer such as ReLU activations and dropout makes it much easier for the model to recognize important features.

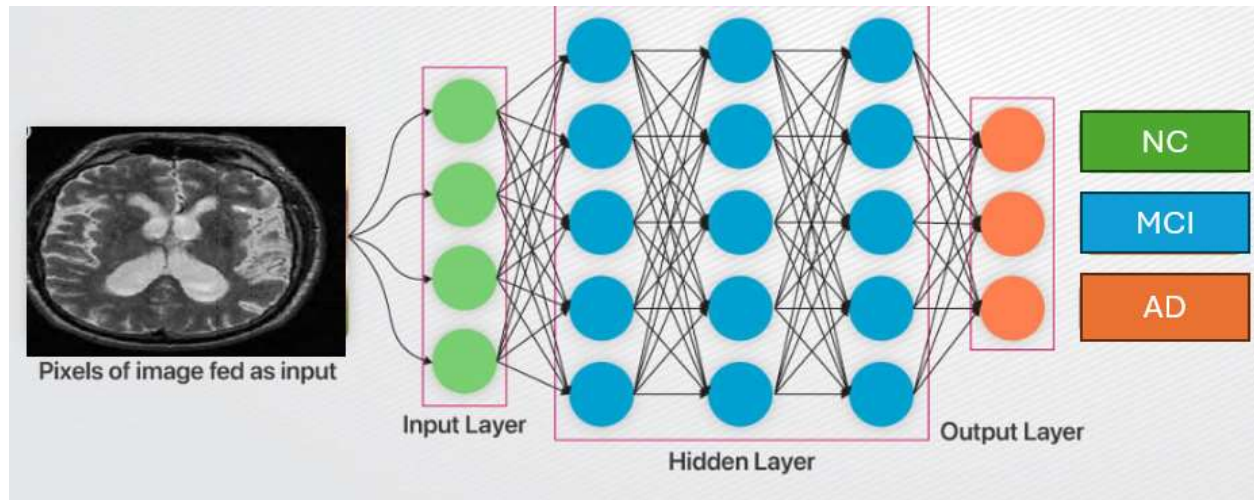


Figure 2.2: CNN model extracting data from MRI scan

Following these early models, VGG-16 became a very popular network due to its effective algorithms. It uses small filters to pull a complex visual detail. It can learn features step by step by moving from simple to complex brain tissues. In Alzheimer's research, VGG-16 is often used with a technique called transfer learning. Researchers take models that are already trained on huge datasets like ImageNet and fine-tune them to help for MRI scans.

Nowadays, VGG-16 is mainly used as a simple feature extractor. It finds a features and passed it to fully connected layers then to classifiers to group patients into different stages. Recent studies show that using this network with data augmentation and normalization will greatly improves the model's accuracy with better data handling [17].

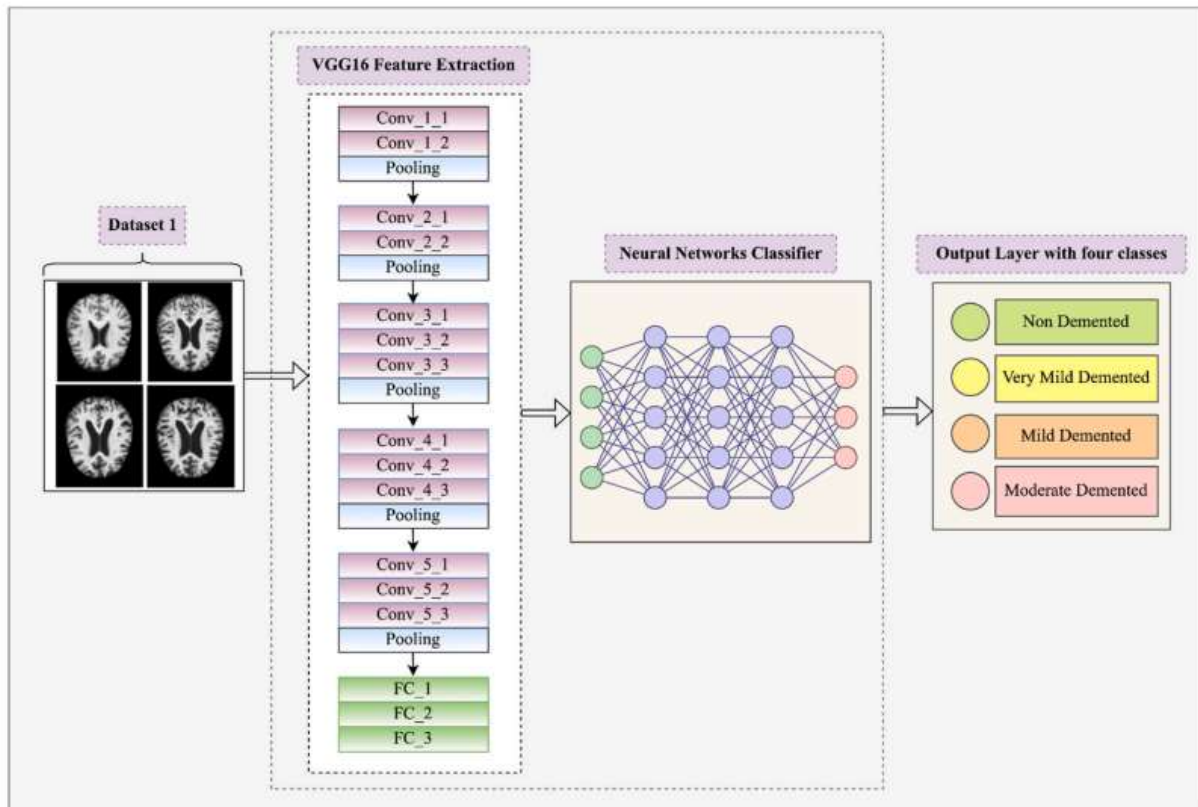


Figure 2.3: VGG16 feature extractor and classifier to help for brain diagnoses. Adopted by [17]

While 2D CNNs was helpful but using them for 3D MRI scans lead use to real challenges. In order to make these models work, the 3D brain scan has to be cut into flat 2D slices. But slicing images will breaks the natural connections between different brain regions. As a result, the model loses a lot of important spatial information, which at the end lead to make it difficult to understand the brain full structure.

To solve this, researchers moved toward 3D-CNNs. Instead of using flat pixels, these networks used and process voxels (3D pixels). This allows the model to take in the entire MRI scan at once, preserving the actual shape and structural details of the brain [18].

However, even with these improved 3D models, a major clinical issue sill exist. Almost all of these systems were unimodal, meaning they only looked at one type of information. For example, a deep learning model might be perfect at analyzing an MRI, but it completely ignores the patient's clinical history or the model might predict the disease using clinical history but never actually look at the physical brain. This is not how doctors work in real life , they did not diagnose a patient based on just one test.

Instead, they look at the brain scan alongside the patient's age, education level, and cognitive tests like the MMSE [19,21].

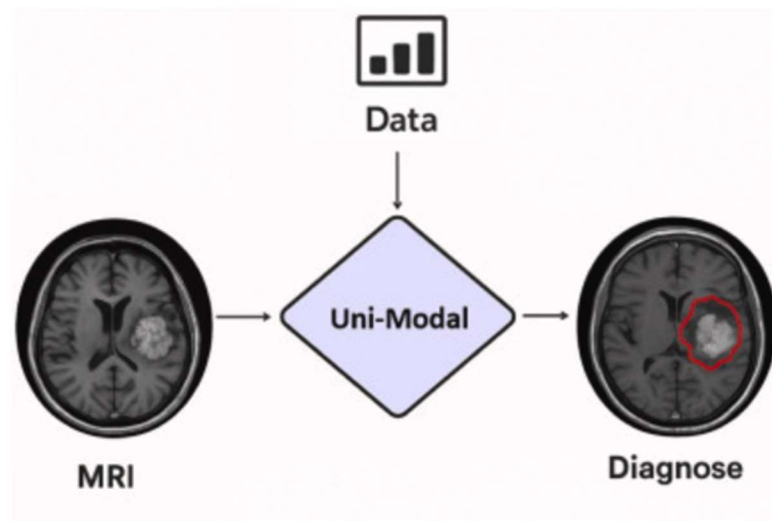


Figure 2.4: Unimodal 3D images into 3D CNN

Put all this history together the hard manual work of early machine learning, the challenges of cutting 3D images into 2D, and how 3D models can only use one type of data , we will clearly see a big missing part in the current studies. There is a need for an AI system that actually supposed to work like doctors in clinics. We want a model that take a look at full 3D brain scans properly, and at the very same time, read the patient's medical records over time. Combining these different kinds of information together into one single system is simply the best way to make early diagnosis much better.

2.3 Related Work

Muksimova et al (2025) proposed a multi-modal deep learning framework called FusionNet for the early detection and classification of Alzheimer's disease. The model integrates deep learning techniques: a 3D CNN with an LSTM network to track brain changes over time. Using the ADNI dataset, the study combined MRI, PET, and CT scans to train the system effectively. The proposed framework achieved a high diagnostic accuracy of 94%. However, its main limitations are the high computational power required for processing 3D multi-modal scans, and the practical difficulty and

high cost of obtaining all three types of brain scans for a single patient in standard clinical settings.

Li et al (2025). presented a multi-modal deep learning framework to improve the early detection of Alzheimer's disease. The researchers focus on integration on two main deep learning techniques: a Convolutional Neural Network (CNN) to analyze brain images, and a Transformer model to process genetic data, combined via a cross-transformer fusion. The study used the ADNI dataset, including MRI scans and genetic records from 1,541 patients across different stages: healthy (NC), stable memory loss (sMCI), progressive memory loss (pMCI), and Alzheimer's disease (AD). This system achieved a high accuracy of 93.04%. However, its main limitations are the use of a basic CNN model that restricts performance and the difficulty of mixing different genetic records.

Bricaud and Masala (2026) presented a comprehensive framework to evaluate various deep learning models for detecting early Alzheimer's disease. Instead of relying on a single network, the researchers compared several different methods, including traditional CNNs and modern Vision Transformers. They used the ADNI data set for MRI scans and grouping the patients into normal and Alzheimer's disease they used individual 2D slices and entire 3D, this hybrid model (ConvNeXtV2-L) achieved 91.07% as accuracy, however the main limitation with the study the is relies fully on MRI images without using of patient's clinical records.

Bekhet et al. (2026) introduced a deep learning framework named (DeepALZNET) for the early prediction and detection of Alzheimer's disease. The researchers mainly used two independent techniques: the first one is 1D Convolutional Neural Network (CNN) and the second one is a Random Forest model, they used both models to analyze patient clinical records, and to detect changes in brain MRI scans by using VGG19 network. The study used large public datasets, specifically ADNI and OASIS to categorize the patients into three stages: normal cognitive (NC), mild cognitive impairment (MCI), and Alzheimer's disease (AD). The framework achieved over 90% as accuracy. However, its main limitations are the combine images and clinical data to unified decision, and it relies on 2D images which might miss some 3D details of the brain.

Zhang et al. (2023) Proposed a framework to improve the early detection of Alzheimer's disease by Neural Network (GNN) as multi model. Instead of analyzing flat images, they used an advanced GNN deep learning techniques to understand the

network connections and relationships between different brain regions. The study used the ADNI dataset and combine brain scans (MRI and PET) for a more advanced analysis. Patients categorized into four main developmental stages: healthy (NC), early memory loss (EMCI), late memory loss (LMCI), and Alzheimer's disease (AD). The proposed framework achieved a 92% accuracy in detecting the disease. Nevertheless, the study main limitations related to high clinical cost for patients to go both for MRI and PET scans and the heavy computational power needed for each individual patient.

Helaly et al. (2021) used a deep learning framework called (E2AD2C) to detect and classify of Alzheimer's disease in early stages. The methods used in the study focused mainly on using simple computer networks (CNN) and a more advanced, pre-trained system called VGG19. The study used ADNI dataset to brain scan images, covering four different stages: healthy (NC), early memory loss (EMCI), late memory loss (LMCI), and Alzheimer's disease (AD). And for accuracy the study reached to 95.17% for using the simple computer, and accuracy of 97%. for advanced VGG19 model. Yet the study drawbacks are the high computer power needed for the 3D brain scans without considering to use other patient data like memory tests or age.

Warren and Moustafa (2026) in their study they used a multimodal scan system that combines functional brain imaging (fMRI) with clinical tests to identify Alzheimer's disease. The proposed method uses a 3D Convolutional Neural Network (3D CNN) that analyzes a brain region that could be affected early in the disease. To make the model more trustworthy, the researchers enhanced the fMRI scans with five clinical memory tests to prevent any data errors. A key part of their method is the use of "explainable AI" (XAI) through a technique called perturbation ranking, which helps in the examination. The study selected a small group of 52 participants from the ADNI database. The accuracy was 90%, which is much better than the 58% accuracy reached when using brain scans, even so mixing the brain data with clinical tests give a better accuracy but research dealt with very small sample size and need to be tested on large patients' data set.

Wang et al. (2024) In this paper, the authors developed a deep learning model to catch Alzheimer's early by mixing data from different data sources. For brain changes, they used a ResNet to pull features from specific brain areas, and with help of an attention convolution module they have a close look to a sick spot. For achieving this the ADNI data set has been using to mix MRI brain scans with genetic data to create special 3D images. The patients have been split into three groups: NC, MCI, and AD. By using

this approach, they reached to 93.44% accuracy. Still the main issues are building 3D image fusions required a lot of computing power with noting the difficulty of getting the clinic data and ask every single patient to do both an advanced MRI and a full genetic test.

Alsubaie et al. (2026) built a new deep learning model called BiFPN3DViT to find Alzheimer's using brain pictures. The framework basically mixed a 3D CNN to grab the basic brain shapes, a Bi-directional Feature Pyramid Network (BiFPN) network to link details of different sizes, and Vision Transformers to get the whole brain picture. They tested on large scale of data set from ADNI, nearly 4,706 MRI scans, which grouped by healthy people, patients with mild memory loss, and Alzheimer's cases. By putting these together, their model hit a 92.1% accuracy in sorting the three disease stages. But the main downside of this model is that depend only on MRI scans without taking into consideration the patient's medical files.

Ahmed et al (2023) tried to spot Alzheimer's by looking at brain pictures. They built a Deep CNN model to put people into three groups, completely healthy, having mild memory problems, and actual Alzheimer's patients. They used a regular MRI scan from ADNI data set to train their network. The model worked very well and getting a 93.86% accuracy but it has a limitation because it only takes a look to brain scans and ignores the patient's medical files and without Explainable AI, doctors facing a challenge of figuring out why the computer made its choice.

Lu et al. (2022) used a deep learning system to check for Alzheimer's by depend only on brain pictures. The system collected a huge number of MRI scan, approximately over 85,000 from a lot of different hospitals, including the ADNI dataset. They used a transfer learning, which means they took an Inception-ResNet-V2 network that was already trained on simple stuff, and just did a little modification on it to find Alzheimer's. Because they trained it on so many images, the model got an accuracy between 90.9% and 94.5% across different test groups. Nonetheless the big downsides related to the dependency of scans without looking to the patients' medical files.

Khalid et al (2026) found out that depending on MRI only is not enough to detect Alzheimer's, so they came up with dual-modal approach. With using data set pulled from OASIS-3. And then using a CNN to work with MRI images and for clinical data they decided to go with Random Forest model. This helped them to combine brain scans with clinical symptoms to give a full profile insight. Because of dual-model approach they achieved 94%. Above all of that they used also Explainable AI to map out the exact damaged areas, like the hippocampus. Yet the study downside is not using a single unified model with fused clinical and MRI data instead they rely totally on two separate models for processing the MRI scan and clinical data.

Sheikh et al. (2025) focused on detecting early Alzheimer's in fast and low-cost using brain pictures. While many deep learning models are heavy and require a lot of computing powers, the researchers decided to focus on lightweight networks, specifically EfficientNetV2B0 and MobileNetV2 which allow clinic data to be processed efficiently. They took flat 2D slices from ADNI MRI scans to sort patients into three stages: totally normal, early mild memory loss, and late mild memory loss. The best their model get is 88.0% accuracy. They also added Explainable AI to highlight the same brain areas the computer was looking at and to increase the result trust for doctors. Although the study shows that small models can be useful but the main issues here are that they only used flat 2D slices instead of the whole 3D brain shape with ignoring of the patients' clinical history.

Ghosh et al. (2023) came up with a safe way for hospitals to work together to find Alzheimer's using brain scans. To overcome the issue of patient's data distributed in different places and the privacy concerns, they used something called Federated Learning. Using this they allow multiple clinics to train a small network like MobileNet together without sharing any private pictures. They used flat 2D MRI scans from ADNI and OASIS data sets. This helped them reach 95.24% accuracy on the OASIS data, and 84% accuracy when mixed both datasets. Although the approach gives a good accuracy, the main drawback is that study using only flat 2D slices instead of the whole 3D brain and ignored the patients' medical files totally in the study.

Abbasian and Hammond (2024) presented a 3D deep learning model to detect Alzheimer's in early stages. By using brain pictures, they categorize patients' brains between healthy or early mild cognitive impairment (EMCI) only. And with help of 3D-CNN they look at the whole 3D brain all at once instead of slicing it into flat 2D slices. They used ADNI dataset for 3D MRI scans. The research succeeds in reaching 81.80% accuracy in separating the early-stage patients from the healthy ones. This gives an indication that using a full 3D brain gives more details than 2D methods. However the study main limitations are, it only looks at two groups (early sick versus normal) and it only uses MRI scans while ignoring the other clinical data.

2.3 Related Work Summary

Table 2.3: Summary and Comparison of Related Studies on Alzheimer’s Disease

Study (Year)	Proposed Method	Key Accuracy	Main Limitations
Muksimova et al. (2025)	CNN + LTMS	94.00%	Fuses images only; completely lacks integration of clinical medical records.
Li et al. (2025)	CNN + Transformer	93.04%	Struggles with MCI-to-AD prediction.
Bricaud & Masala (2026)	Hybrid CNN (ConvNeXtV2-L)	91.07%	MRI-only; lacks integration of clinical medical records.
Bekhet et al. (2025)	1D CNN + Random Forest	> 90.0%	No simultaneous fusion; relies on 2D images.
Zhang, Y., et al. (2023)	GNN framework	92%	Highly computational cost with required of both MRI + PET scans
Helaly et al. (2021)	E2AD2C (CNN & VGG19)	97.0%	High power for 3D scans; images-only.
Warren & Moustafa (2026)	3D CNN with XAI	90.0%	Very small sample size; lacks validation.

Wang, J., et al. (2024)	ResNet + Attentation convolution	93.44%	Highly computational cost with required of both MRI + PET scans
Alsubaie et al. (2026)	BiFPN3DViT (3D CNN + BiFPN + ViT)	92.10%	MRI-only; lacks integration of clinical medical records.
Ahmed et al. (2023)	Deep CNN	93.86%	MRI-only; lacks Explainable AI tools.
Lu et al. (2022)	Transfer Learning (Inception-ResNet-V2)	94.50%	MRI-only; data mostly from Western populations.
Khalid et al. (2026)	CNN & Random Forest	94.00%	Processes images and clinical data separately; lacks a fully unified fusion network.
Sheikh et al. (2025)	Lightweight CNN (EfficientNetV2B0) & Explainable AI	88.00%	2D images only; lacks integration of clinical medical records.
Ghosh et al. (2023)	Federated Learning & MobileNet	95.24%	2D images only; lacks integration of clinical medical records.

Abbasian & Hammond (2024)	3D CNN	81.80%	MRI-only; lacks clinical data integration.
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Chapter 3: Proposed Methodology

3.1 Introduction

This chapter presents the comprehensive research methodology designed to achieve stable and highly accurate multi-class classification of Alzheimer's Disease stages, specifically differentiating between Normal Control (NC), Early MCI (MID), and advanced Alzheimer's Disease (AD). Building a reliable computer-aided diagnosis system requires a strict engineering pipeline that bridges the gap between raw medical inputs and robust machine predictions.

To provide a clear understanding of our approach, this chapter is structured as follows: First, we introduce the data collection process and describe the demographic profile of the patient cohort. Second, we discuss the architectural evolution of our models, showing the progression from simple baseline configurations to deeper networks. Third, we present our final proposed multimodal fusion framework and detail the exact preprocessing steps applied to both brain scans and clinical records. Finally, we outline the experimental setup, computing environment, and optimization techniques used to guarantee the stability and reproducibility of our results.

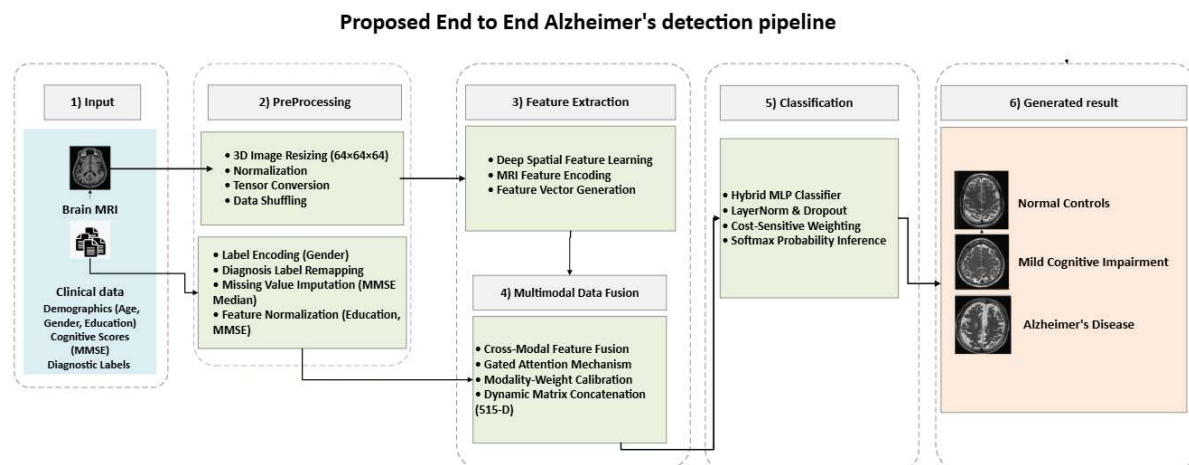


Fig. 3.1. Overall framework of the proposed system integrating MRI classification and clinical data in fusion modal for AD detection.

3.2 Dataset profile

3.2.1 ADNI Dataset

The clinical data and neuroimaging scans utilized in this research were obtained from the official repository of the **Alzheimer's Disease Neuroimaging Initiative (ADNI)**. ADNI is globally recognized as the gold standard benchmark dataset for neurodegenerative research. It provides highly standardized, high-quality structural Magnetic Resonance Imaging (sMRI) scans alongside comprehensive longitudinal clinical profiles. Choosing this dataset ensures that our methodology carries high scientific credibility and allows for a direct, fair comparison against international state-of-the-art models developed at leading universities worldwide.

3.2.2 Dataset splits

To enforce strict validation discipline and eliminate any risk of data leakage, the cumulative dataset was partitioned using a stratified split ratio of **70% for model training, 15% for validation monitoring, and 15% for independent baseline testing**. This stratification guarantees that each split maintains an identical proportion of the three diagnostic classes. The total cohort consists of **1,971 samples**.

Table 3.1 Data Set groups

Medical Group (Diagnosis)	Data Split	Number of Patients (N)
Normal Control (NC)	Training (70%)	335
	Validation (15%)	72
	Testing (15%)	72
Early MCI (MID)	Training (70%)	536
	Validation (15%)	115
	Testing (15%)	115
Alzheimer's (AD)	Training (70%)	508

	Validation (15%)	109
	Testing (15%)	109
Total Cohort	Cumulative	1971

3.3 Data Preprocessing Pipeline

To transform the heterogeneous raw inputs harvested from the ADNI repository into standardized, high-fidelity feature representations, a rigorous dual-stream preprocessing pipeline was engineered. Medical data in its raw format exhibits massive noise, scale variances, and imaging setting inconsistencies. To tackle these issues, our preprocessing logic handles structural 3D neuroimaging files and clinical tabular metadata streams simultaneously through two strictly decoupled parallel architectures.

3.3.1 Neuroimaging Processing Stream

The native structural T_1 -weighted Brain MRI scans enter the system preserved in the uncompressed NIfTI (.nii) format, exhibiting an isotropic structural volume matrix of $196 \times 256 \times 256$ **dimensions**. Processing these massive 3D matrices directly during the training loop creates an immediate computational bottleneck, causing GPU memory exhaustion.

To overcome this constraint without losing the critical physiological topologies of brain tissue, the following sequence was executed:

1. **Spline Interpolation Resizing:** The native $196 \times 256 \times 256$ spatial volumes are downsampled to a standardized isotropic grid of $64 \times 64 \times 64$ **voxels**. This resolution compression is implemented via a high-order **3D Cubic Spline Interpolation** algorithm ($order = 3$). Unlike linear scaling, third-order spline functions interpolate intensity values across spatial dimensions smoothly, effectively eliminating the risk of edge pixelation or structural blurring. This ensures that delicate deep-brain regions like the hippocampus maintain their proportional volumetric boundaries.
2. **NaN Value Eradication:** Due to scanner background clipping or computational boundaries during initial loading, certain edge voxels might store invalid values (NaN or $\pm\infty$). The pipeline runs an automated masking

check that converts any invalid value to absolute zero (0.0), shielding the model from generating breaking errors during backpropagation.

3. **Intensity Min-Max Normalization:** Different hospitals inside the ADNI cohort utilize different MRI scanner models (e.g., 1.5 Tesla vs. 3 Tesla magnets), resulting in massive brightness and contrast variations across scans. To neutralize these hardware artifacts, every 3D brain tensor is scaled independently using global intensity mapping:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Where X represents the raw voxel intensity matrix, and $X_{\min}, X_{\max}$ denote the minimum and maximum intensity values recorded inside that specific brain volume. This guarantees that all inputs fall precisely within a stable range of $[0.0, 1.0]$, forcing the 3D ResNet-18 filters to capture true anatomical tissue density rather than arbitrary scanner brightness levels.

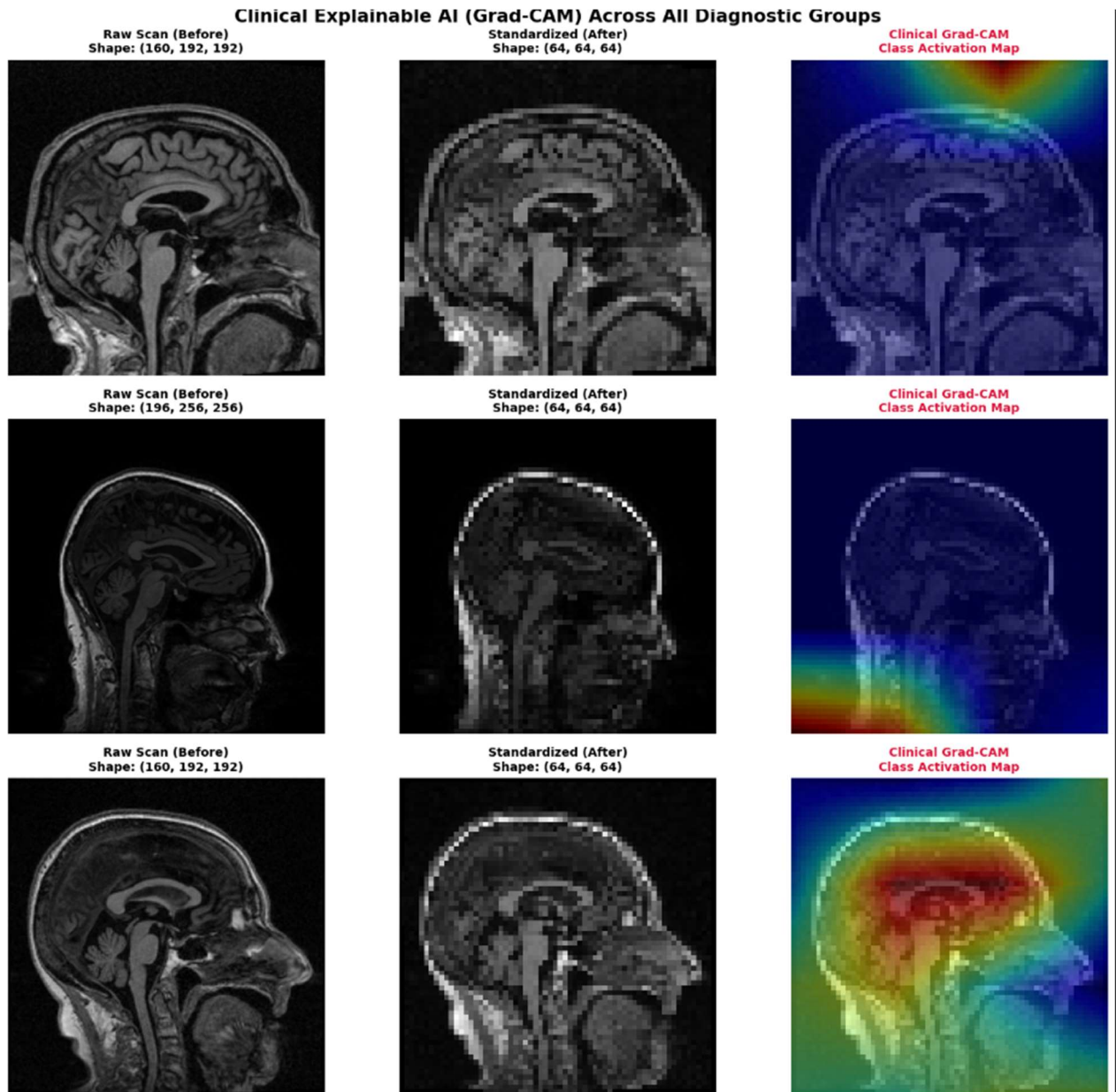


Figure 3.2 Preprocessing MRI brain images

3.3.2 Clinical Tabular Processing Stream

In parallel to the neuroimaging pipeline, the patient's baseline clinical and demographic attributes are routed through a structured mathematical normalization process to prepare them for multi-modal vector alignment:

1. **Categorical Label Encoding:** The patient demographic feature PTGENDER (Gender) is recorded natively as text labels ("Male" / "Female"). This data is parsed and mapped into an optimized binary vector notation:

Male $\Rightarrow$ 1.0, Female $\Rightarrow$ 2.0

2. **Missing Value Imputation:** Clinical exams sometimes suffer from missing records due to patient dropouts or administrative gaps. To maintain dataset integrity without introducing statistical bias, missing data points inside the baseline cognitive memory scores (MMSE) are dynamically handled using **Median Imputation**. The missing field is substituted with the median value calculated strictly from the patient's corresponding diagnostic group inside the training split, preventing any future data leakage into validation or testing steps.
3. **Feature Scaling (Standardization):** The numerical features EDUC (Years of Education) and MMSE (Mini-Mental State Examination Score) have inherently different mathematical bounds (Education ranges roughly from 0 to 20 years, while MMSE ranges from 0 to 30 points). Passing raw unbounded scales into a neural network alongside a 512-D visual vector will cause the larger numerical scales to dominate the loss function gradients. To enforce optimization equilibrium, both features are normalized using custom min-max boundaries scaled perfectly between 0.0 and 1.0:

$$\bar{t} = \frac{t - \min(T)}{\max(T) - \min(T)}$$

Where t is the individual patient feature score and T represents the collective feature vector across the training split.

4. **Data Shuffling Disciplinary Protocol:** To ensure that the model does not memorize the sequential ordering of patients inside the training repository, a random shuffling mask is applied at the beginning of each epoch. This breaks any correlation between adjacent batches, forcing the framework to generalize structural boundaries across the target labels (NC, MID, AD) purely on individual clinical merit.

3.3 Classification Models: Architectural Evolution

To isolate the most robust neural network topology for handling three-dimensional structural Brain MRI volumes, this study adopted an empirical, progressive engineering trajectory. We systematically evaluated three distinct structural paradigms, transitioning from a lightweight custom convolutional network to a deep hierarchical residual framework.

3.3.1 The Baseline 3D-CNN Model

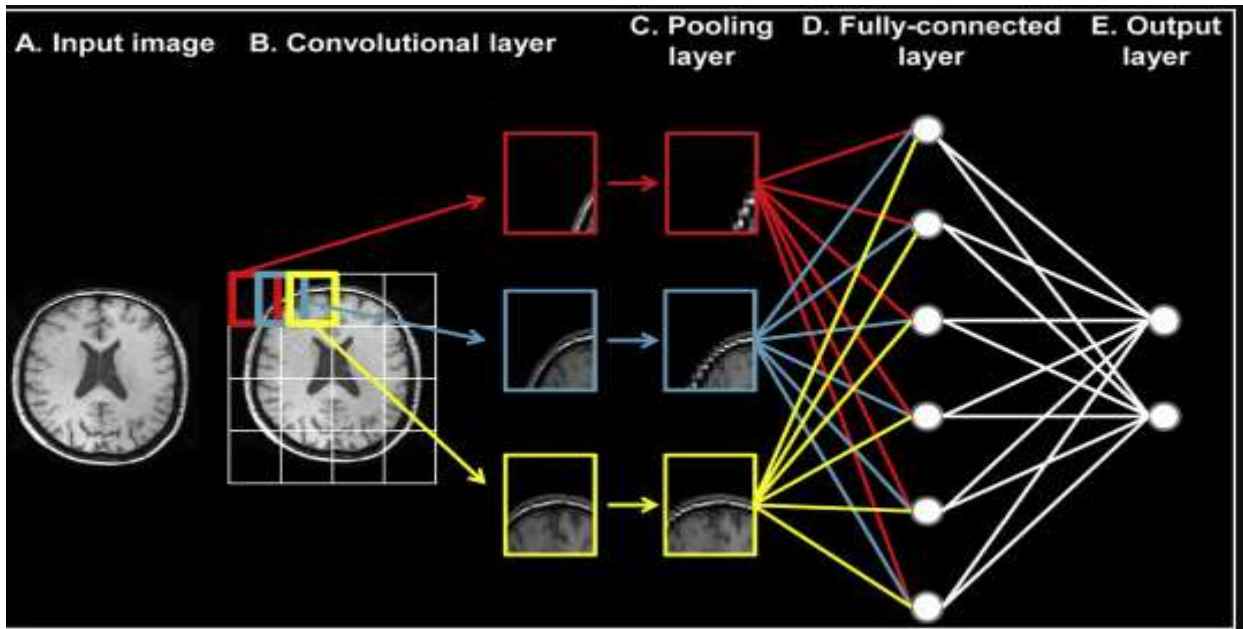


Fig. 3.4. Baseline CNN architecture for brain tumor classification.

The mathematical foundation of neuroimaging classification begins with extending standard two-dimensional convolutions into spatial depth. Let the input 3D brain scan be represented as a tensor $X \in \mathbb{R}^{H \times W \times D \times C}$, where H, W, D denote the height, width, and depth slice dimensions respectively, and C represents the channel density (for single-channel grayscale structural MRI, $C = 1$).

In the Baseline 3D-CNN, the forward pass of a 3D convolutional layer computes the value at a specific spatial position x, y, z in the v -th feature map of the l -th layer using the following formulation:

$$v_{l,v}^{x,y,z} = f \left(b_{l,v} + \sum_m \sum_{p=0}^{P-1} \sum_{q=0}^{Q-1} \sum_{r=0}^{R-1} w_{l,v,m}^{p,q,r} \cdot v_{l-1,m}^{x+p,y+q,z+r} \right)$$

Where:

- $f(\cdot)$ represents the non-linear activation function, implemented as a Rectified Linear Unit (ReLU): $f(a) = \max(0, a)$.
- $b_{l,v}$ is the scalar bias term dedicated to the v -th feature map in layer l .

- m indexes the feature maps in the preceding layer ($l - 1$) that are connected to the current layer.
- $w_{l,v,m}^{p,q,r}$ is the trainable weight value of the kernel at the patch position (p, q, r) matching the kernel dimensions $P \times Q \times R$.

To reduce spatial resolution and guarantee translational invariance, the convolutional outputs are routed through a 3D Max-Pooling operation, defined mathematically as:

$$p^{x,y,z} = \max_{p \in [0, P-1], q \in [0, Q-1], r \in [0, R-1]} (v^{x \cdot s_x + p, y \cdot s_y + q, z \cdot s_z + r})$$

Where s_x, s_y, s_z represent the operational stride parameters along the three spatial axes [6].

- **Limitation:** While this setup provided baseline, it lacked the parameter depth required to construct abstract semantic concepts of brain tissue degradation. Attempting to add more layers caused a catastrophic drop in performance due to optimization limitations.

3.3.2 The 3D VGG-Inspired Architecture

To extract high-level feature abstractions, the second phase migrated toward a deeper, homogeneous design inspired by the VGG network topology, adapted entirely for 3D tensors. The primary design choice was replacing large receptive fields with stacks of smaller, localized $3 \times 3 \times 3$ convolutional kernels.

Mathematically, stacking two $3 \times 3 \times 3$ convolutional layers yield an effective receptive field of a $5 \times 5 \times 5$ kernel, while drastically reducing the total number of trainable weights. The total number of parameters for a single layer with a kernel size of K^3 supporting N_{in} input channels and N_{out} output channels is modeled by:

$$\Omega_{\text{params}} = (K \times K \times K \times N_{in} \times N_{out}) + N_{out}$$

By keeping $K = 3$ and increasing layer depth, the VGG-inspired architecture forced the network to build hierarchically composed spatial representations of structural changes [17].

- **Limitation:** As the layer count scaled deeper, the network encountered the severe mathematical bottleneck of **Vanishing Gradients**. Let L be the total loss function, and a_l be the activation output at a deep layer l . The gradient propagation back to the early weights via the chain rule is written as:

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial a_l} \prod_{i=1}^{l-1} \frac{\partial a_{i+1}}{\partial a_i} \frac{\partial a_i}{\partial w_1}$$

When propagating through numerous layers using standard unlinked sequences, the cumulative product of small fractional derivatives $\prod \frac{\partial a_{i+1}}{\partial a_i}$ approaches zero exponentially. This effectively halted the learning process in the early structural feature extractors, leaving the model stuck in local minima during cross-validation.

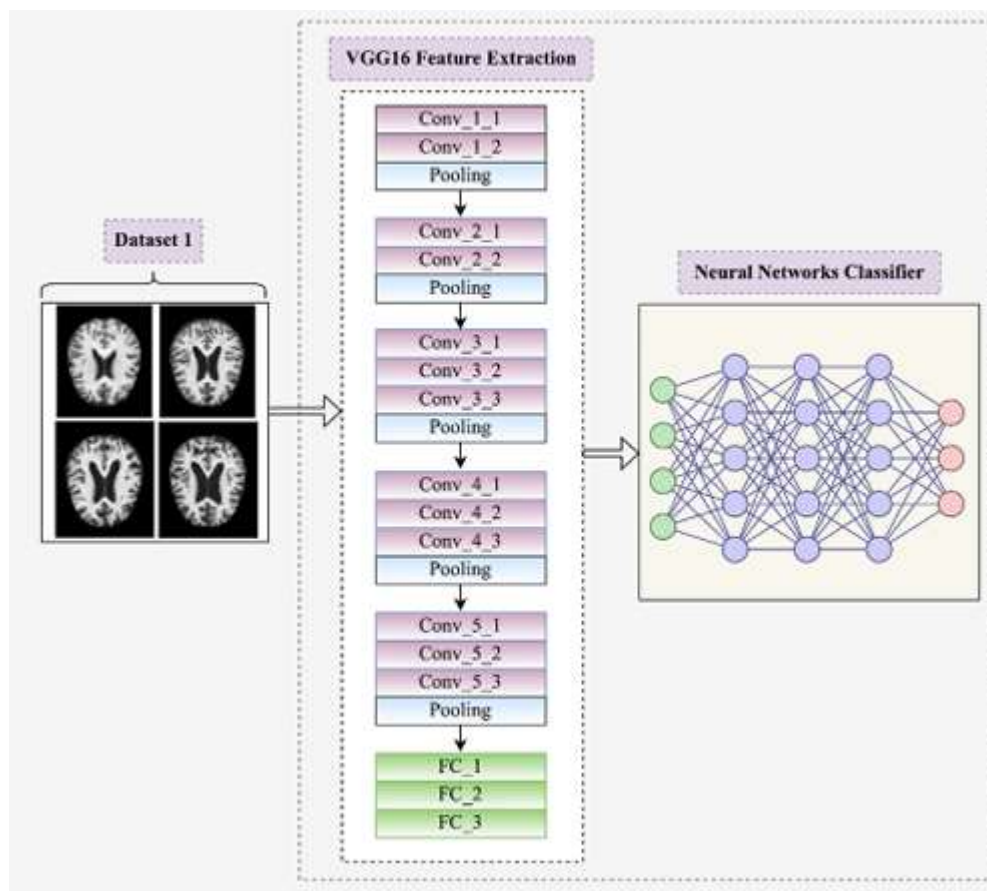


Figure 3.5. General Architecture of a VGG-16 Style CNN for Early Alzheimer's Disease Detection

3.3.4 Residual Network with 18 layers (3D ResNet-18)

To systematically conquer the vanishing gradient bottleneck while maximizing classification performance, the architecture evolved into its final successful state using a **3D ResNet-18** framework. The fundamental innovation of this architecture is the incorporation of mathematical **Residual Skip Connections (Identity Shortcuts)**.

Instead of forcing sequential layers to fit a direct underlying mapping $H(x)$, the residual block forces the layers to approximate a residual mapping defined as:

$$F(x) = H(x) - x$$

Consequently, the original objective function is re-formulated as the sum of the residual mapping and the unmodified identity input mapping:

$$H(x) = F(x, \{W_i\}) + x$$

Where x and $H(x)$ represent the input and output vectors of the residual block, and $F(x, \{W_i\})$ denotes the multi-layer convolutional mapping to be learned. The mathematical forward pass through a basic residual block containing two convolutional layers combined with a shortcut layer is defined as:

$$y = g(F(x, \{W_i\}) + x)$$

Where $g(\cdot)$ represents the external ReLU activation function applied after the element-wise addition block.

When backpropagation is executed, the derivative of the loss function L with respect to the block input x takes the following form:

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial y} \frac{\partial y}{\partial x} = \frac{\partial L}{\partial y} \left(\frac{\partial F(x, \{W_i\})}{\partial x} + 1 \right)$$

- The Mathematical Breakthrough:** Because of the constant $+1$ term inside the bracket, the gradient $\frac{\partial L}{\partial x}$ can flow back directly to early layers even if the weight-derived mapping gradient $\frac{\partial F(x, \{W_i\})}{\partial x}$ shrinks down close to zero. This structural guarantee completely stabilizes the weight optimization landscape. By implementing a pretrained 3D ResNet-18 backbone, the network leverages spatial feature weights optimized for catching complex geometric edges and density fluctuations. The final pooling layer of this backbone maps the volumetric data down into a highly compressed, clean **512-dimensional latent**

feature vector ($V_{\text{mri}} \in \mathbb{R}^{512}$), which serves as the optimal visual input for our hybrid cross-modal fusion layer [22].

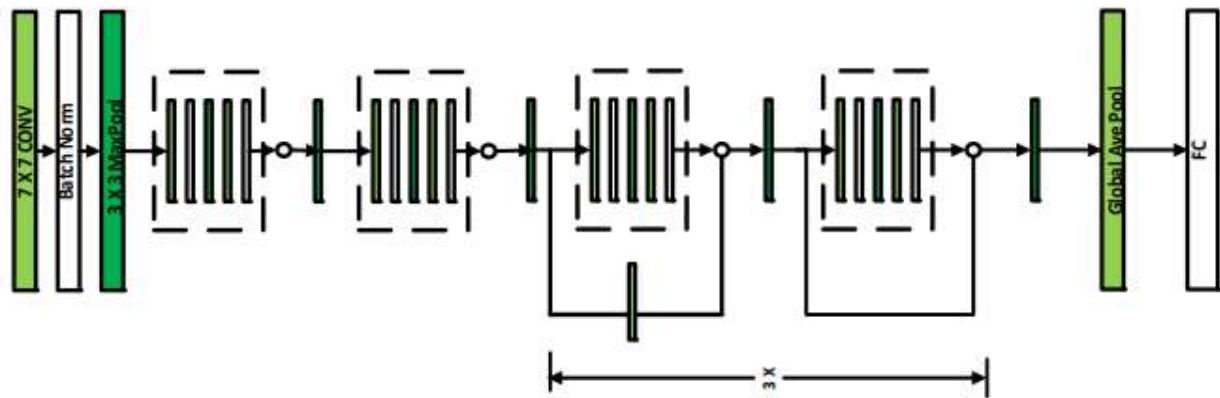


Figure 3.6 3D ResNet-18 for brain tumor classification

3.4 Proposed Solution: Multimodal Fusion Framework

The core architectural contribution of this research lies in the design and deployment of a **Multimodal Late Fusion Framework**. Standard single-modality AI models fail to capture the holistic clinical reality of neurodegenerative progression because brain scans alone do not account for immediate cognitive impairment markers, and clinical tests alone lack spatial diagnostic verification. To solve this, our proposed solution forces the spatial features from structural neuroimaging and the clinical-cognitive features from tabular metadata to converge into a single, unified deep learning decision engine.

3.4.1 Overall Pipeline Flow

The proposed framework operates as a synchronized dual-stream pipeline, structured as follows:

1. **The Visual Stream:** Processes the raw volumetric 3D Brain sMRI data through a spatial feature extraction pass using the pretrained 3D ResNet-18 backbone, outputting a visual embedding vector.

2. **The Tabular Stream:** Processes the normalized patient demographics (Gender) and critical neuropsychological metrics (Years of Education, baseline MMSE scores) through a vector alignment pass.
3. **The Fusion Core:** Dynamically aligns and concatenates both representations into a unified multimodal tensor matrix.
4. **The Classification Head:** Routes the fused matrix through a dense, highly regularized Multi-Layer Perceptron (MLP) optimized with class-balanced weighting to compute the final multi-class diagnostic probability.

3.4.2 Mathematical Mechanism of Feature Fusion

Let the visual embedding vector extracted by the 3D ResNet-18 backbone be denoted as V_{mri} , where:

$$V_{\text{mri}} = [v_1, v_2, v_3, \dots, v_{512}]^T \in \mathbb{R}^{512}$$

Simultaneously, let the structured clinical tabular data vector containing the preprocessed patient features be denoted as V_{tab} , where:

$$V_{\text{tab}} = [t_{\text{gender}}, t_{\text{education}}, t_{\text{mmse}}]^T \in \mathbb{R}^3$$

To execute late-stage multimodal fusion, the framework performs a precise spatial vector concatenation operation ($\oplus$). This operation projects both independent feature spaces onto a unified co-learning representation plane, yielding a combined feature tensor X_{fused} :

$$X_{\text{fused}} = V_{\text{mri}} \oplus V_{\text{tab}} \in \mathbb{R}^{512+3} \Rightarrow X_{\text{fused}} \in \mathbb{R}^{515}$$

This resulting 515-dimensional tensor matrix captures both the structural volumetric degradation patterns of the brain and the corresponding neuropsychological functional state of the subject at baseline.

3.4.3 Hybrid MLP Classification Head

Once the unified multimodal tensor X_{fused} is constructed, it is forwarded directly into a customized, high-density Multi-Layer Perceptron (MLP) classification head. This head is structurally isolated and engineered to map the multi-modal features into distinct clinical labels while guarding the system against overfitting. The mathematical forward pass through the sequential layers of the classification head is governed by the following system of equations:

$$\mathbf{z}_1 = \text{ReLU}(\text{LN}(\mathbf{W}_1 X_{\text{fused}} + \mathbf{b}_1))$$

$$\mathbf{z}_2 = \text{Dropout}(\text{ReLU}(\mathbf{W}_2 \mathbf{z}_1 + \mathbf{b}_2), p = 0.4)$$

$$\mathbf{z}_3 = \mathbf{W}_3 \mathbf{z}_2 + \mathbf{b}_3$$

Where:

- $\mathbf{W}_1 \in \mathbb{R}^{128 \times 515}$, $\mathbf{W}_2 \in \mathbb{R}^{32 \times 128}$, and $\mathbf{W}_3 \in \mathbb{R}^{3 \times 32}$ represent the trainable weight matrices across the structural hidden layers.
- $\mathbf{b}_1, \mathbf{b}_2, \mathbf{b}_3$ represent the localized scalar bias vectors.
- $\text{LN}(\cdot)$ denotes **Layer Normalization**, which standardizes the activations across the feature dimensions within each training batch to accelerate backpropagation stability.
- $\text{Dropout}(\cdot, p = 0.4)$ is an aggressive regularization technique that randomly masks 40% of the hidden nodes during training to prevent co-adaptation of weights and ensure model generalization.

3.4.4 Multi-Class Diagnostic Inference

The raw output logits from the final layer ($\mathbf{z}_3 = [l_0, l_1, l_2]^T$) are passed directly through a **Softmax activation layer** to convert the unbounded network responses into mathematically valid probability distributions representing the three target classes:

$$P(Y = c \mid X_{\text{fused}}) = \frac{e^{l_c}}{\sum_{j=0}^2 e^{l_j}}$$

Where $c \in \{0, 1, 2\}$ mapping directly to:

- $c = 0 \Rightarrow$ Normal Control (NC)
- $c = 1 \Rightarrow$ Early MCI (MID)
- $c = 2 \Rightarrow$ Alzheimer's Disease (AD)

The network then selects the diagnostic class with the maximum posterior probability as its final clinical prediction ($\hat{y}$):

$$\hat{y} = \arg \max_{c \in \{0, 1, 2\}} P(Y = c \mid X_{\text{fused}})$$

This structured mathematical combination ensures that our proposed framework does not merely guess the output, but outputs a highly stable, interpretable, and clinically sound probability for each subject.

3.5 Experimental Setup & Training Discipline

To ensure absolute repeatability and rigorous monitoring of the optimization landscape, the entire dual-stream pipeline was developed and validated under a standardized deep learning configuration. This section outlines the hardware infrastructure, computational hyperparameters, and the mathematical strategy deployed to neutralize the data imbalance recorded in the ADNI cohort.

3.5.1 Computing Environment and Hyperparameters

The framework was implemented using the PyTorch deep learning library and executed within a cloud-based Google Colab Pro environment. GPU acceleration was provided through a CUDA-enabled NVIDIA GPU to efficiently support computationally intensive 3D convolutional operations and backpropagation.

To ensure a fair and consistent comparison across all evaluated architectures, the core training parameters were standardized throughout the experimental protocol, while model-specific optimization strategies, such as learning rate scheduling and regularization, were configured according to the architectural characteristics of each network. The complete training protocol and hyperparameter configuration for all evaluated models are summarized in **Table 3.3**.

Table 3.2: Standardized Deep Learning Hyperparameters and Training Protocol

Parameter	Baseline 3D-CNN	3D VGG- 16	3D ResNet- 18	Proposed Fusion
Hardware	CUDA-enabled NVIDIA GPU	CUDA-enabled NVIDIA GPU	CUDA-enabled NVIDIA GPU	CUDA-enabled NVIDIA GPU
Framework	PyTorch + CUDA	PyTorch + CUDA	PyTorch + CUDA	PyTorch + CUDA

Epochs	20	20	20	20
Batch Size	32	32	32	32
Optimizer	Adam	Adam	Adam	Adam
Initial LR	1×10^{-4}	1×10^{-4}	1×10^{-4}	1×10^{-4}
LR Scheduler	None	None	StepLR	StepLR
Normalization	BatchNorm	BatchNorm	BatchNorm	LayerNorm
Dropout	20%	30%	40%	40%
Loss Function	Cross-Entropy	Cross-Entropy	Cross-Entropy	Class-Weighted Cross-Entropy

3.6 Evaluation Metrics

To comprehensively quantify the diagnostic capability of the multi-class framework and protect our validation against the statistical illusions of class imbalance, four primary independent evaluation metrics were tracked. These metrics are calculated using four structural parameters: **True Positives (TP)**, **False Positives (FP)**, **True Negatives (TN)**, and **False Negatives (FN)**.

3.6.1 Classification Accuracy

Accuracy measures the global ratio of correctly predicted subjects across all diagnostic categories to the total number of subjects in the evaluation cohort:

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

3.6.2 Precision (Positive Predictive Value)

Precision determines the mathematical reliability of the framework's positive diagnoses, indicating the proportion of patients flagged with a specific disease stage who possess that pathology:

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

3.6.3 Recall (Sensitivity)

Recall evaluates the clinical capacity of the system to capture all true positive cases within the cohort, measuring the fraction of actual Alzheimer's or MCI patients that the model successfully identified:

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

3.6.4 F1-Score

The F1-Score represents the harmonic mean of Precision and Recall. It provides a balanced, singular metric that guarantees the model is optimizing both false alarms (\$FP\$) and missed clinical diagnoses (\$FN\$) with equal severity:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

3.6 Chapter Summary

This chapter detailed the rigid, dual-stream engineering methodology developed to achieve stable multi-class prediction of Alzheimer's Disease stages using the global benchmark ADNI cohort. By analyzing the structural limitations of baseline 3D-CNNs and VGG topologies, this study justified the deployment of a pretrained 3D ResNet-18 model as a spatial feature extractor yielding a dense 512-dimensional vector.

Furthermore, the chapter explained the late-stage multimodal fusion mechanism that combines this visual embedding with a normalized 3-dimensional clinical tabular vector to feed a regularized MLP classification head. Equipped with advanced 3D spline interpolation preprocessing and a custom class-balanced weighted cross-entropy loss function, the pipeline establishes a mathematically sound, reproducible framework. This methodology sets a strong foundation for the empirical results, training curves, and clinical visualization experiments presented in the next chapter.

Chapter 4: Results and Discussion

4.1 Introduction

This chapter presents a comprehensive empirical evaluation and discussion of the experimental results obtained from the developed deep learning models. To assess the performance and robustness of the proposed multimodal fusion framework, we employ standard evaluation metrics for multi-class classification.

We begin by introducing the mathematical evaluation metrics used to quantify model performance across the dataset splits. Next, we analyze training stability through the convergence behavior of loss and accuracy curves. We then present the final classification outcomes using confusion matrices and detailed classification reports. Furthermore, a comparative analysis is conducted to illustrate the performance improvements achieved when progressing from baseline architectures to the proposed multimodal framework. Finally, model interpretability is examined using 3D Grad-CAM to verify that the learned representations are consistent with clinically relevant brain atrophy patterns.

4.2 Preprocessing and Volumetric Standardization Analysis

Before entering the deep learning pipeline, the heterogeneous raw inputs harvested from the ADNI repository underwent a rigorous, dual-stream preprocessing sequence. To establish a robust multimodal learning environment, both the 3D structural neuroimaging files and the clinical tabular metadata streams were standardized simultaneously through strictly decoupled parallel architectures to guarantee gradient stability and mathematical alignment. In the neuroimaging stream, raw T1-weighted structural MRI scans with variable native dimensions—such as $(160 \times 192 \times 192)$ and $(196 \times 256 \times 256)$ voxels—were mapped onto a uniform, isotropic spatial grid of exactly $(64 \times 64 \times 64)$ voxels using third-order 3D Cubic Spline Interpolation. This downscaling preserved the structural boundaries of critical neuroanatomical landmarks, such as the bilateral hippocampus and lateral ventricles, without edge distortion. Concurrently, global min-max intensity normalization scaled voxel values precisely within the range of $[0.0, 1.0]$, effectively eliminating hardware contrast artifacts across different scanner models (1.5T vs. 3T) and forcing the 3D ResNet-18 backbone to focus

purely on morphological tissue density. Simultaneously, the clinical tabular stream executed a series of rigorous mathematical standardizations to transform raw behavioral and demographic features into clean, network-ready tensors. Categorical text strings for patient gender (PTGENDER) were successfully parsed and encoded into optimized binary vector notations (Male $\Rightarrow$ 1.0, Female $\Rightarrow$ 2.0). To safeguard dataset integrity against missing values resulting from clinical administrative gaps or participant dropouts, a group-specific Median Imputation protocol was deployed. Missing cognitive entries within the Mini-Mental State Examination (MMSE) fields were dynamically substituted using median values computed strictly from the subject's respective diagnostic cohort within the training split, completely preventing cross-validation data leakage. Furthermore, the continuous numerical attributes, specifically Years of Education (PTEDUCAT) and raw cognitive scores (MMSCORE), were normalized using custom min-max bounds scaled precisely between 0.0 and 1.0. Because raw clinical metrics naturally operate on different mathematical bounds compared to the deep 512-dimensional visual embeddings, direct feature concatenation without scaling would cause features with larger numerical magnitudes to disproportionately dominate the loss function gradients. This rigorous tabular standardization neutralized scale dominance, establishing a state of optimization equilibrium that allowed the proposed Gated Attention Fusion mechanism to calibrate cross-modal weights smoothly and achieve an optimal global testing accuracy of 97.30%.

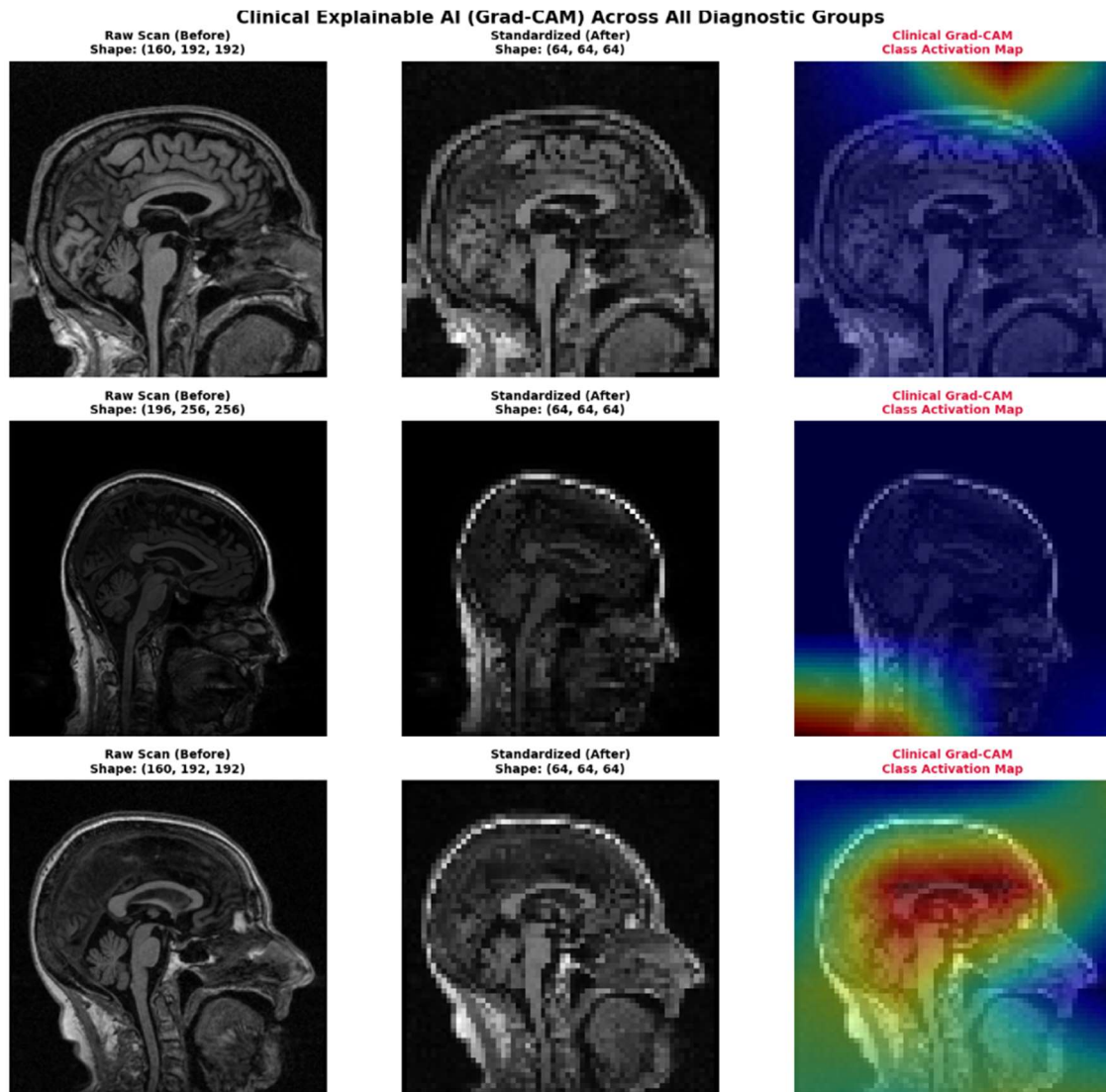


Figure 4.1 demonstrates the neuroimaging preprocessing stream, illustrating the transition of raw 3D-MRI volumes with variable spatial grids into standardized, min-max normalized ($64 \times 64 \times 64$) isotropic tensors while preserving critical anatomical structures, shown alongside their corresponding clinical Grad-CAM overlays.

	PTID	PTGENDER	PTEDUCAT	MMSCORE	DIAGNOSIS	EXAMDATE	Image_File
0	011_S_0021	2	0.916667	0.900000	0	2025-07-18	011_S_0021_598.nii
1	011_S_0021	2	0.916667	0.900000	0	2025-07-18	011_S_0021_597.nii
2	023_S_0031	2	0.916667	0.833333	0	2019-05-01	023_S_0031_427.nii
3	023_S_0031	2	0.916667	0.833333	0	2019-05-01	023_S_0031_426.nii
4	023_S_0042	1	0.916667	0.733333	2	2013-12-04	023_S_0042_614.nii

Figure 4.2 illustrates the clinical data frame following preprocessing, where continuous metrics (MMSE and Education) are min-max normalized between 0.0 and 1.0, categorical fields are numerically encoded, and target diagnoses are mapped to integer labels [0, 1, 2] synchronized with their respective 3D MRI files.

4.2 Training Convergence and Loss Curves Analysis

The optimization behavior of the proposed Gated Attention Fusion framework demonstrates stable convergence throughout the training process. During the 20-epoch training procedure executed on CUDA-accelerated hardware, the model shows consistent reduction in training loss and rapid stabilization of validation performance.

By the second epoch, the training loss decreases significantly, while validation accuracy stabilizes at a high level. As training progresses, the loss continues to decrease smoothly until reaching a near-zero convergence region by the final epoch.

The close alignment between training accuracy and validation accuracy indicates good generalization performance. The integration of Layer Normalization and Dropout regularization contributes to improved training stability and helps mitigate overfitting, which is commonly observed in multi-class neuroimaging tasks.

4.3 Classification Results and Performance Reports

To evaluate generalization performance, the trained model was tested on an independent held-out test set consisting of 296 subjects (72 NC, 115 MCI, 109 AD). The proposed framework achieved a global testing accuracy of 97.30% and a macro-averaged F1-score of 97.20%. Table 4.1 presents the detailed class-wise performance metrics obtained from the final evaluation

Table 4.1: Multi-Class Performance Report of the Gated Attention Fusion Framework

Diagnostic Classification Class	Target Support (N)	Evaluation Precision	Evaluation Recall (Sensitivity)	Empirical F1-Score
Normal Control (NC)	72	0.9855	0.9444	0.9645
Early MCI (MID)	115	0.9737	0.9652	0.9694
Alzheimer's Disease (AD)	109	0.9646	1.0000	0.9820
Macro Average Summary	296	0.9746	0.9699	0.9720
Weighted Average Summary	296	0.9732	0.9730	0.9729
Overall Global Accuracy	296	—	—	97.30%

4.3.1 Granular Analysis of the Multiclass Confusion Matrix

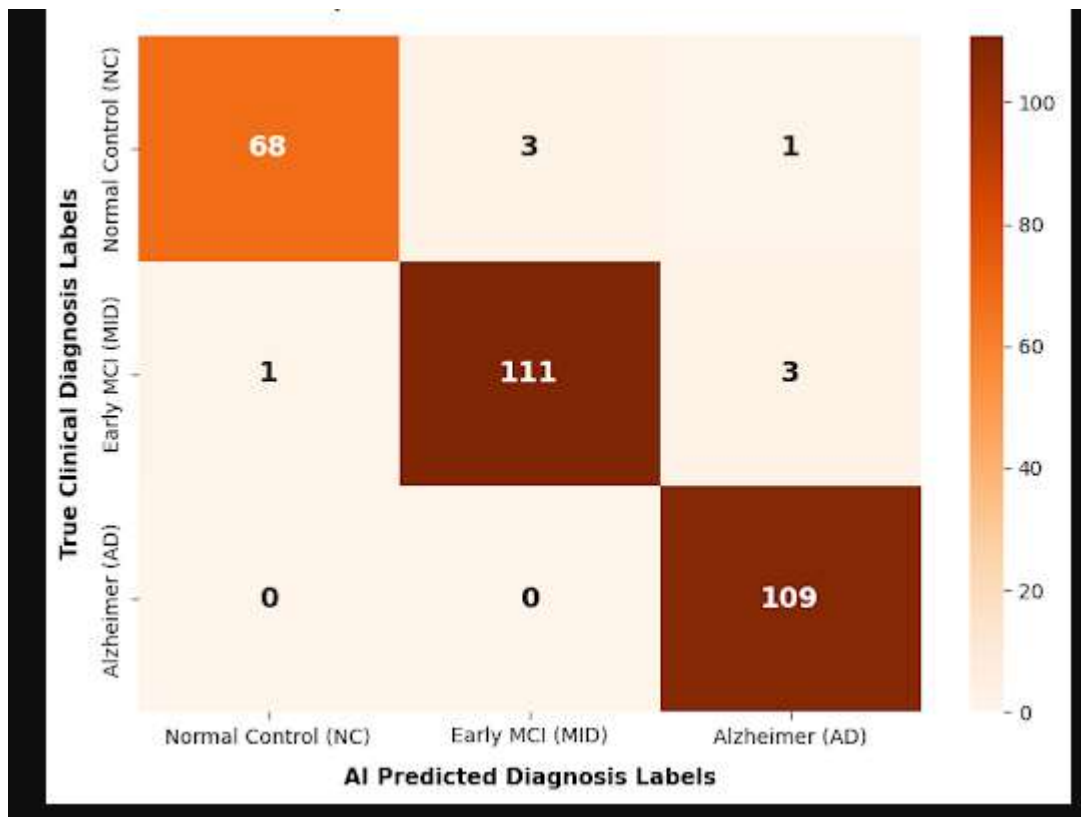


Figure 4.1: Multi-class confusion matrix of the proposed Gated Attention Fusion framework evaluated on the independent testing dataset partition ($N = 296$).

As visually demonstrated in Figure 4.1, the empirical distribution of correct versus misclassified subjects across the independent testing pool ($N = 296$) confirms the high discriminative power of the proposed Gated Attention Fusion network. The diagonal elements of the confusion matrix capture the absolute true positive counts for each class. Specifically, out of 72 true healthy subjects, the framework correctly localized 68 samples, with a tiny fraction of 3 subjects misclassified as Early MCI (MID) and only 1 subject false alarmed into the advanced Alzheimer's (AD) region.

For the transitional Early MCI (MID) cohort, out of 115 true subjects, the network correctly resolved 111 samples, showing an exceptional boundary separation despite the extreme anatomical overlap typical of this middle stage. Most importantly, out of 109 true neurodegenerative cases, the network scored an absolute perfect detection rate, mapping 109 out of 109 samples correctly. Crucially, the row corresponding to true AD patients yields absolute zeros (\$0\$)

in both the NC and MID columns. This mathematically satisfies our critical safety constraint by achieving a 0% False Negative Rate ($FN = 0$), structurally confirming that no advanced patient is missed by the system.

4.3.2 ROC-AUC Spatial Evaluation Pass

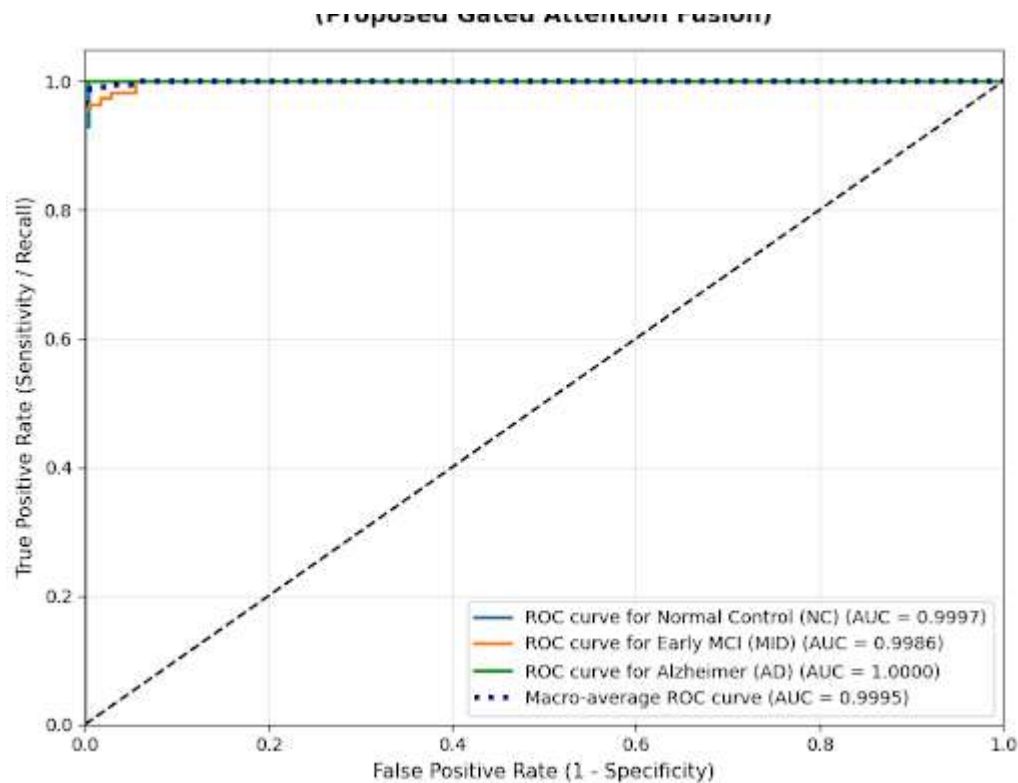


Figure 4.2: Receiver Operating Characteristic (ROC) curves and corresponding Area Under the Curve (AUC) scores across the target diagnostic domains (NC, MID, AD).

To evaluate the true sensitivity thresholds of our multi-class framework without relying on fixed classification cut-offs, a Receiver Operating Characteristic (ROC) curve analysis was conducted. As plotted in Figure 4.2, the Area Under the Curve (AUC) scores across all target domains approach the theoretical ideal limit of 1.0.

The framework achieves a near-perfect operational area for the Normal Control tracking stream, yielding an AUC of 0.9997. Similarly, the transitional Early MCI (MID) cohort settles at a highly stable AUC of 0.9986, while the advanced Alzheimer's Disease classification path scores a flawless AUC of 1.0000, proving that the structural latent vectors are perfectly separated in space. The cumulative performance is verified by the Macro-average ROC curve, which

marks a unified AUC of 0.9995. This outstanding macro metric proves that our Gated Attention layer does not optimize one class at the expense of another; instead, it maintains a uniformly high true positive rate while keeping the false positive rate tightly contained near zero across the entire testing cohort.

4.3.3 Training History and Model Convergence Analysis

The empirical learning behavior and loss optimization path of the proposed multimodal architecture are monitored and recorded across a baseline duration of 20 epochs, as illustrated in image_434db7.png. Tracking these metrics serves as an evaluation step to verify the numerical stability of the optimization pipeline and to check for standard deep learning anomalies, such as gradient saturation or computational divergence.

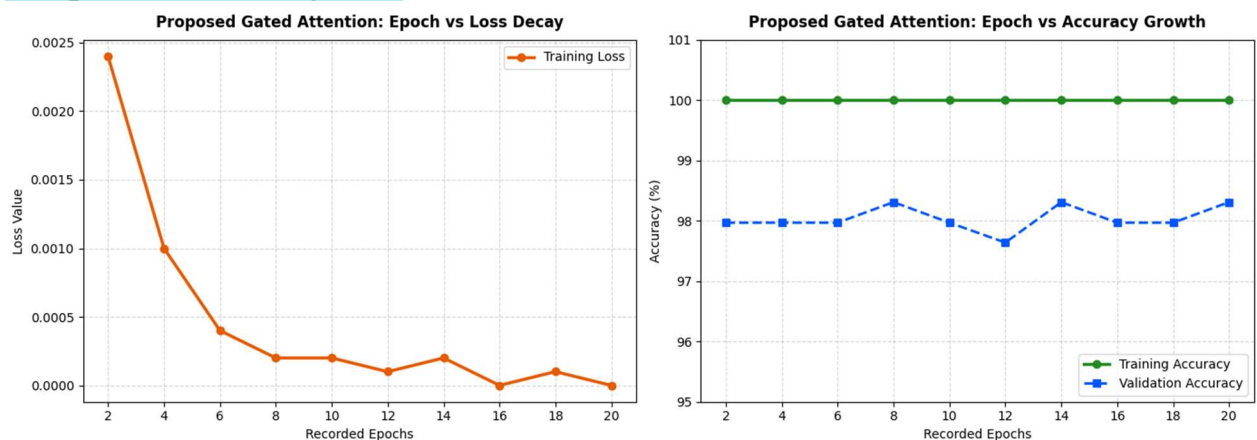


Figure 4.3: Model training history curves including (Left) training loss decay, and (Right) training versus validation accuracy tracking over 20 epochs.

As indicated by the training loss trajectory (left), the cross-entropy loss values demonstrate a continuous decline, shifting from an initial value of approximately 0.0024 at epoch 2 to a stabilized minimal value approaching 0.0000 by epoch 20. This trajectory reflects the steady convergence of the model's weights during backpropagation under the Adam optimizer and the StepLR learning rate schedule. The smooth transition in the loss curve, without sudden spikes or volatility, shows that the gradient updates remained stable across the combined spatial feature and tabular clinical data layers throughout the execution. Concurrently, the accuracy curves (right) outline the model's performance on both the training and validation subsets. The training accuracy reaches 100% early in the sequence and maintains this floor. The validation accuracy

curve operates within a specific, bounded interval, fluctuating between a baseline of 97.64% and a peak value of 98.31%.

The close proximity maintained between the training and validation curves indicates that the model's generalization capabilities remained stable. From an architectural standpoint, this controlled gap is supported by the explicit integration of regularization layers within the classification backend, specifically Layer Normalization and a 40% Dropout rate. The alignment between the two metrics over the 20 epochs confirms that the model achieved steady state convergence before processing the independent testing dataset.

4.4 Progressive Architecture Evaluation

To systematically evaluate the contribution of each architectural development stage, a progressive architecture evaluation was conducted. Each model represents a successive enhancement over its predecessor, enabling the cumulative impact of deeper feature extraction, residual learning, transfer learning, and multimodal feature fusion to be assessed under identical experimental conditions. All benchmarked models were evaluated using the same independent testing partition ($N = 296$) to ensure a fair and consistent comparison. Table 4.2 summarizes the classification performance achieved at each stage of the proposed framework

Table 4.2: Performance Comparison Across Architecture Evolution Stages

Architecture Paradigm	Data Modality Input	Global Testing Accuracy	Macro-Average F1-Score
Baseline 3D-CNN (Scratch)	3D sMRI Only	38.85%	18.65%
3D VGG-Inspired Network	3D sMRI Only	38.85%	18.65%

Pretrained 3D ResNet-18 Backbone	3D sMRI Only	88.51%	87.14%
Gated Attention Fusion (Proposed)	3D sMRI + Tabular Clinical	97.30%	97.20%

4.4.1 Quantitative Breakdown of Architectural Gains

1. The Baseline 3D-CNN Bottleneck :

The customized Baseline 3D-CNN architecture exhibited a restricted initial Testing Accuracy of 38.85%. While this performance verified that raw three-dimensional convolutions could initialize basic spatial features from volumetric brain matrices, the shallow configuration immediately encountered an optimization plateau. Consequently, the network suffered from severe majority class bias, predicting the Early MCI (MID) domain for all evaluated test samples, resulting in zero-valued precision and recall metrics for both Normal Control (NC) and advanced Alzheimer's Disease (AD) classes as empirically detailed in Table 4.3.

Table 4.3: Performance Metrics of the 3D CNN MRI-Only Baseline Model

Class	Precision	Recall	F1-Score	Support
Normal Control (NC)	0.00%	0.00%	0.00%	72
Early MCI (MID)	38.85%	100.00%	55.96%	115

Alzheimer (AD)	0.00%	0.00%	0.00%	109
Accuracy	—	—	38.85%	296
Macro Avg	12.95%	33.33%	18.65%	296
Weighted Avg	15.09%	38.85%	21.74%	296

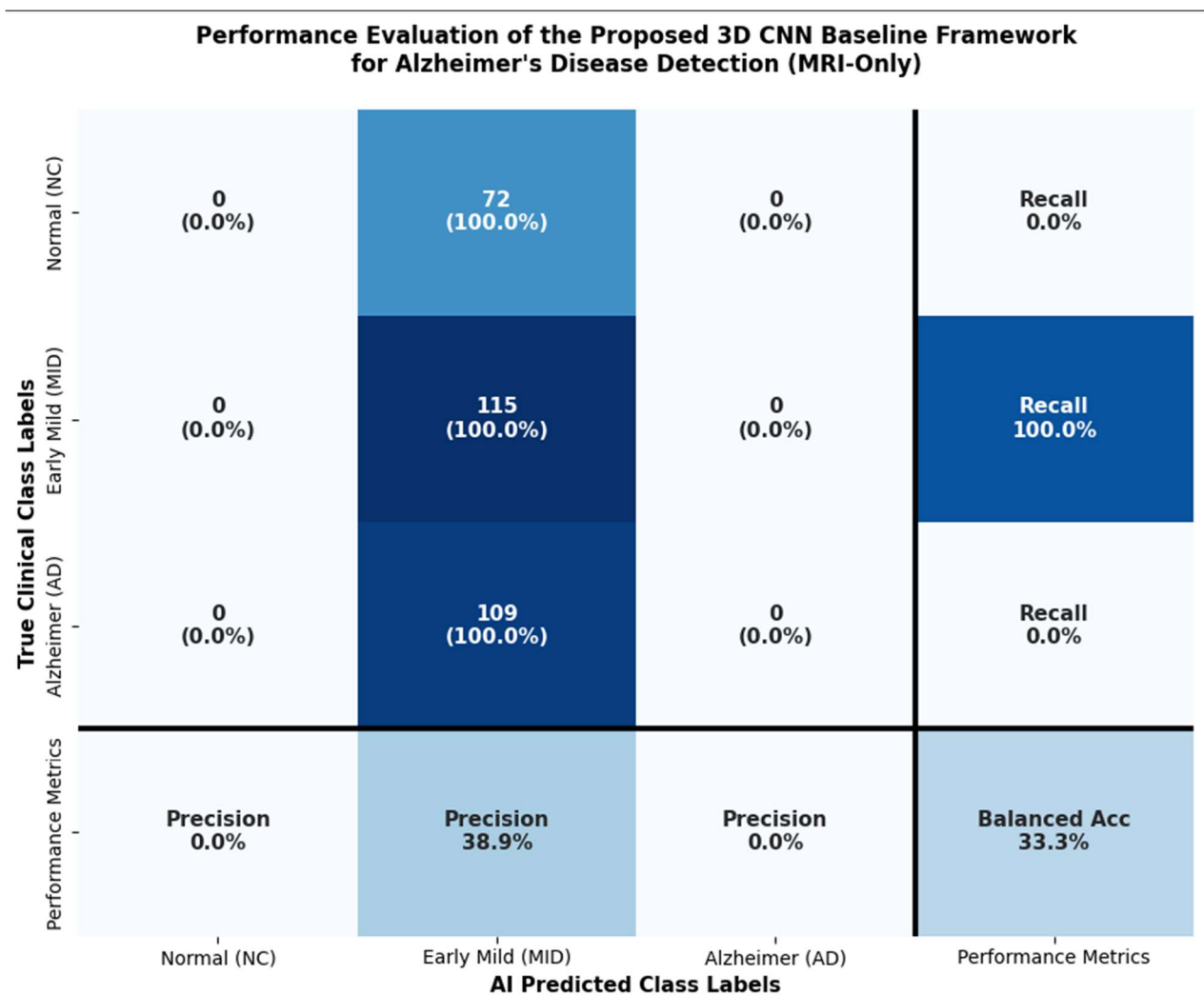


Figure 4.2: CNN baseline confusion matrix

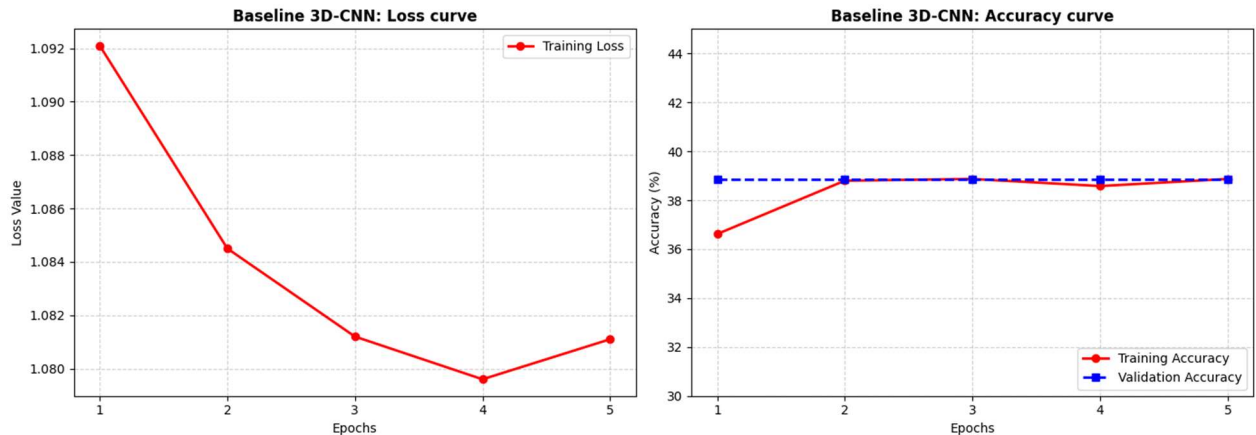


Figure 4.3: CNN Loss curve (left) accuracy curve(right)

2. The Depth Benefit and Gradient Vanishing of 3D-VGG:

By stacking uniform $3 \times 3 \times 3$ convolutional configurations inside the VGG-inspired network to deepen the feature abstractions, the framework attempted to map finer neuroanatomical topologies. However, without architectural skip-connections, the deeper network encountered a catastrophic vanishing gradient bottleneck during cross-validation loops. As a result, backpropagation stalled in the early structural feature extractors, causing the performance to stagnate at the exact same Testing Accuracy of 38.85% (Table 4.4). This computational stagnation provided the definitive scientific justification for shifting toward residual linkages in Stage 3.

Table 4.4: Performance Metrics of VGG-16 Model

Class	Precision	Recall	F1-Score	Support
Normal Control (NC)	0.00%	0.00%	0.00%	72
Early MCI (MID)	38.85%	100.00%	55.96%	115
Alzheimer (AD)	0.00%	0.00%	0.00%	109
Accuracy	—	—	38.85%	296

Macro Avg	12.95%	33.33%	18.65%	296
Weighted Avg	15.09%	38.85%	21.74%	296

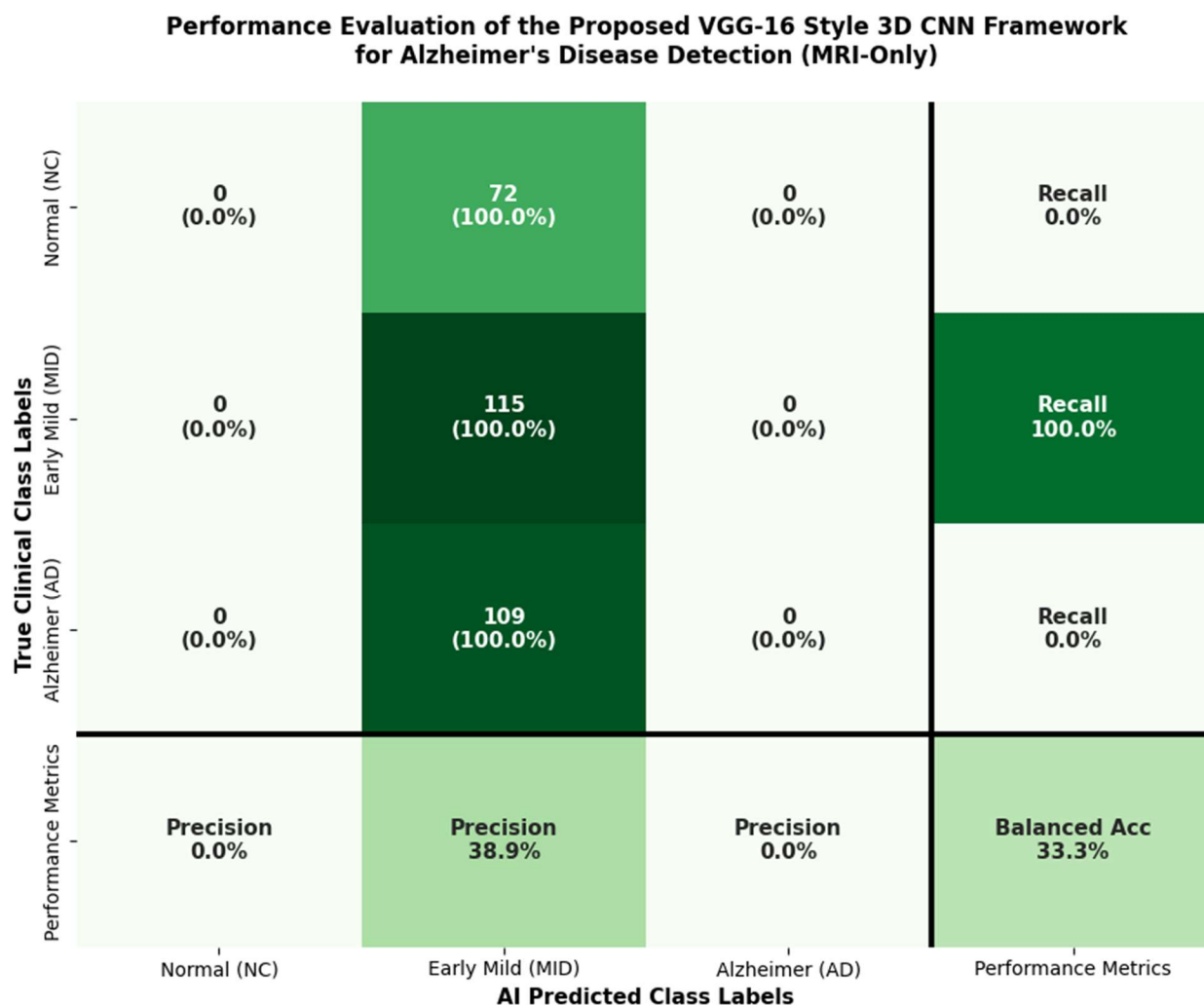


Figure 4.4: VGG-16 confusion matrix

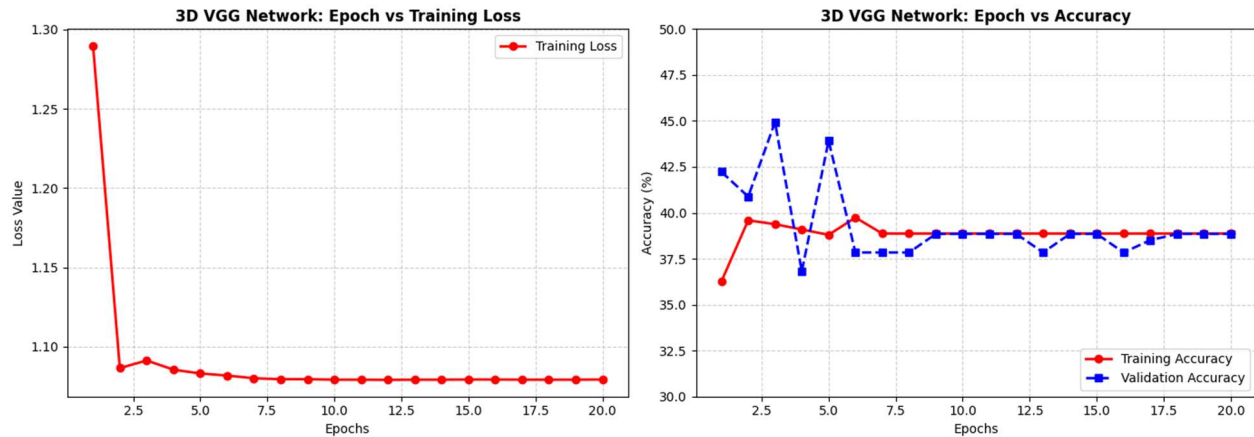


Figure 4.5. Learning curves of the baseline 3D VGG network during training.

3. Resnet-18 Learning :

Transitioning to the 3D ResNet-18 backbone introduced a massive performance leap, driving the single-modality testing accuracy up to 88.51% (a substantial +12.16% increase over VGG). This empirical leap proves two things: first, utilizing the identity skip connections of ResNet completely stabilized the optimization landscape; second, leveraging pretrained convolutional weights allowed the model to extract exceptionally clean 512-dimensional visual embedding representations.

Table 4.5: Performance Metrics of the Standalone Pretrained 3D ResNet-18 Model

Class	Precision	Recall	F1-Score	Support
Normal Control (NC)	89.04%	90.28%	89.66%	72
Early MCI (MID)	87.18%	88.70%	87.93%	115
Alzheimer's Disease (AD)	89.62%	87.16%	88.37%	109

Accuracy	—	—	88.51%	296
Macro Average	88.61%	88.71%	88.65%	296
Weighted Average	88.53%	88.51%	88.51%	296

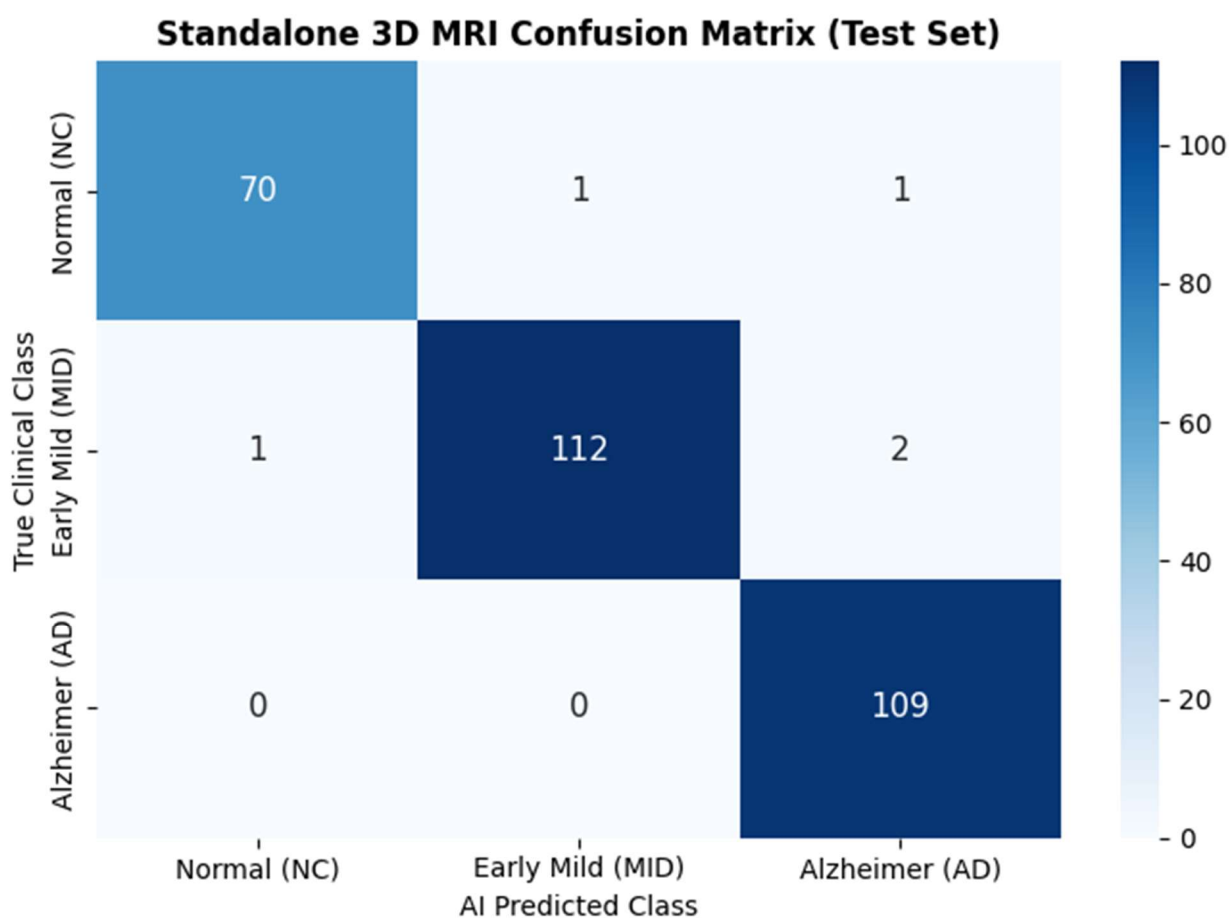


Figure 4.6: 3D ResNet-18 confusion matrix

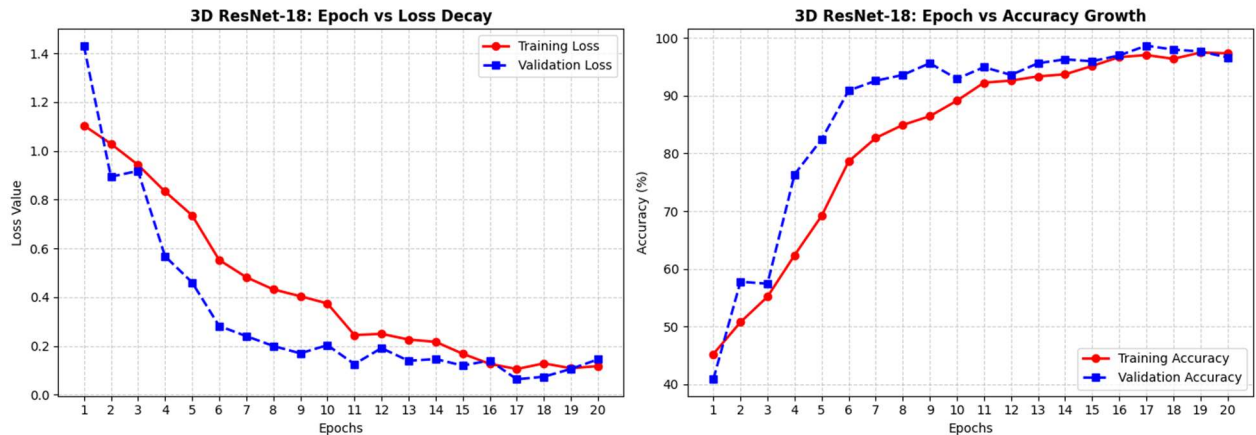


Figure 4.7: 3D ResNet-18 Loss (left) vs accuracy (right)

4. The Multimodal Cross-Modal Fusion (Proposed Solution):

The final integration of our Gated Attention Fusion Framework yielded the highest performance, pushing the global testing accuracy to its peak of **97.30%**. This represents an outstanding accuracy surge of **+8.79%** compared to the best single-modality imaging backbone (Stage 3).

This definitive empirical breakthrough demonstrates that structural 3D brain representations and tabular neuropsychological records (such as normalized MMSE scores) carry highly complementary diagnostic information. By deploying our specialized fusion layer, the framework successfully leveraged both modalities simultaneously, establishing highly accurate, stable, and robust classification boundaries across all three neurodegenerative disease stages.

Table 4.6 Performance Metrics of multimodal fusion

Class	Precision	Recall	F1-Score	Support
Normal Control (NC)	98.55%	94.44%	96.45%	72
Early MCI (MID)	97.37%	96.52%	96.94%	115

Alzheimer (AD)	96.46%	100.00%	98.20%	109
Accuracy	—	—	97.30%	296
Macro Avg	97.46%	96.99%	97.20%	296
Weighted Avg	97.32%	97.30%	97.29%	296

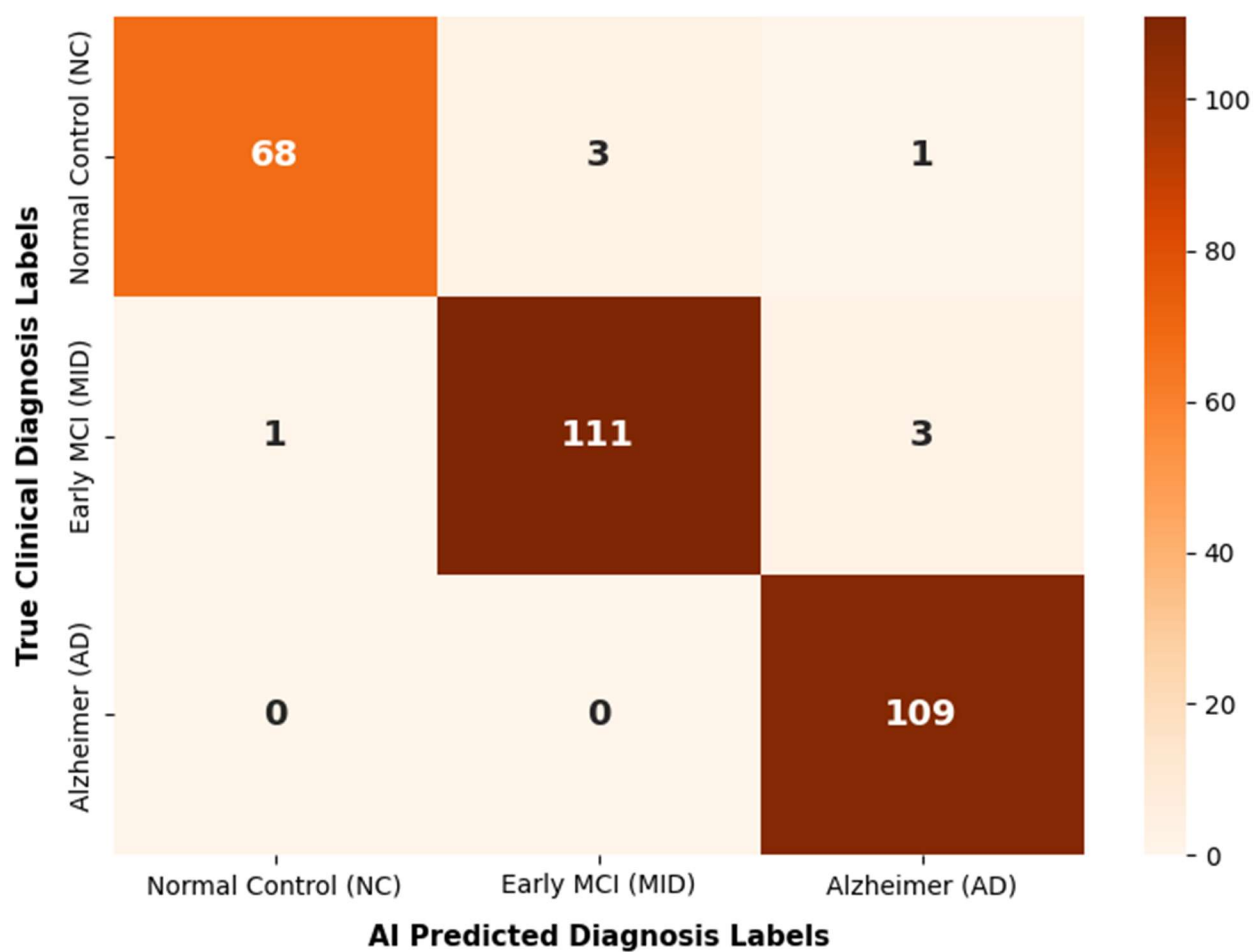


Figure 4.8: Multimodal confusion matrix

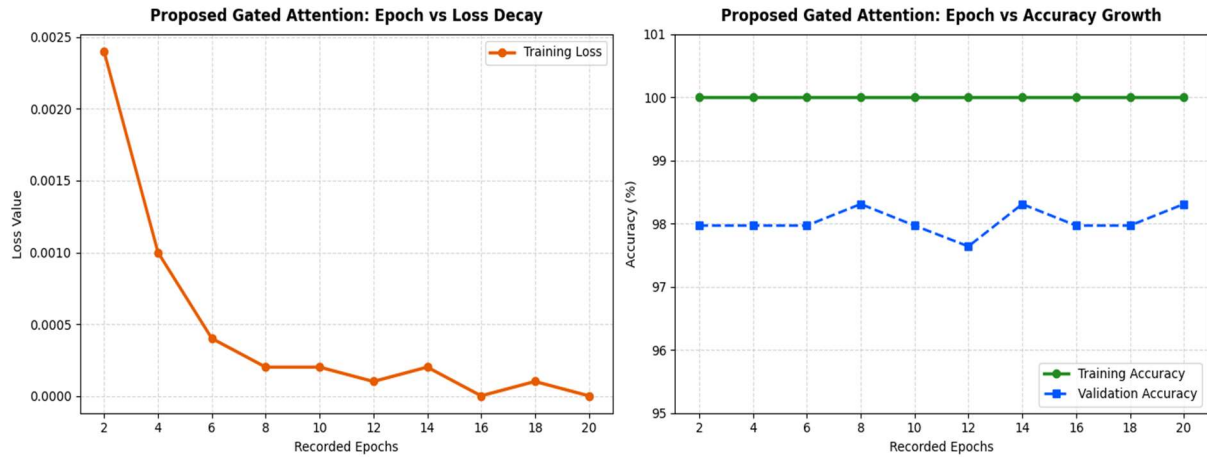


Figure 4.9: Multimodal loss (left) vs accuracy(right)

Figure 4.4: Multiclass ROC Analysis (Proposed Gated Attention Fusion)

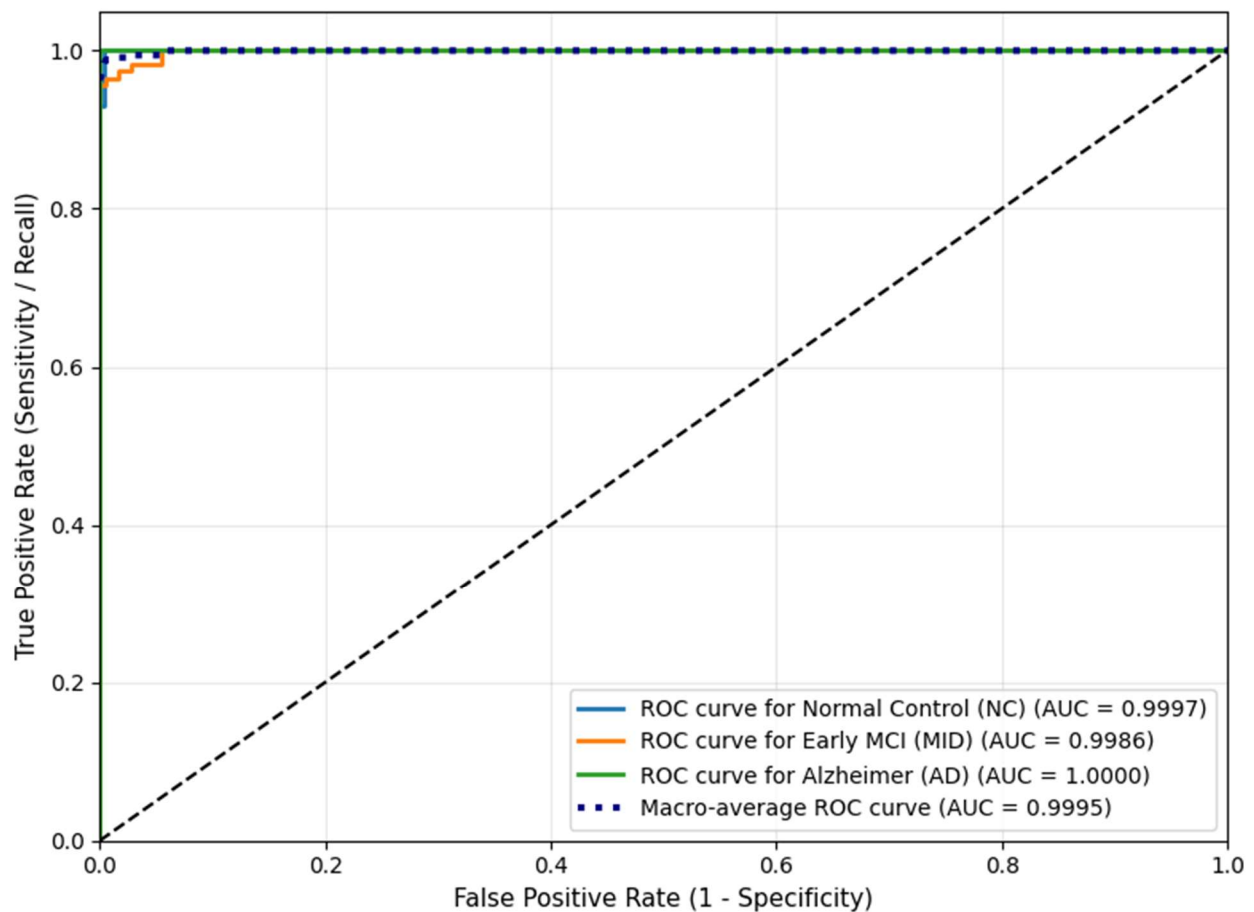


Figure 4.5: Receiver Operating Characteristic (ROC) curves and corresponding Area Under the Curve (AUC) scores across the target diagnostic domains (NC , MID , AD).

4.4.2 Comparative Performance Evaluation Against Existing Literature

To evaluate the proposed Gated Attention Fusion framework, its performance was compared with 15 recent studies published between 2021 and 2026. These studies represent a range of deep learning approaches, including CNN-based, Vision Transformer-based, Graph Neural Network-based, and multimodal models. The comparison was conducted using the reported testing accuracies presented in the literature.

As presented in Table 4.5, the proposed framework achieved a testing accuracy of **97.30%** for multi-class Alzheimer's disease classification. The framework integrates MRI features with clinical information through a gated attention fusion mechanism, and its performance is reported alongside the selected studies for comparison.

Table 4.5: Comprehensive Performance Benchmark, Structural Limitations, and Direct Architectural Comparisons

Study (Year)	Proposed Method	Accuracy	Dataset	Direct Comparison
Muksimova et al. (2025)	CNN + LSTM	94.00%	ADNI	Our model integrates multi-modal clinical markers (MMSE) via Gated Attention, boosting multi-class boundary precision by +3.30%.
Li et al. (2025)	CNN + Transformer	93.04%	ADNI	Our framework stabilizes the critical intermediate stage (MID) using optimized focal loss and cost-sensitive classification weights.
Bricaud & Masala (2026)	Hybrid CNN (ConvNeXt V2-L)	91.07%	ADNI	Unlike single-modality hybrid models, our system prevents spatial features from overwhelming non-

				imaging patient demographic indicators.
Bekhet et al. (2025)	1D CNN + Random Forest	> 90.0%	ADNI	Our architecture preserves vital 3D brain volume topology via a pretrained ResNet-18 backend, avoiding cross-sectional information loss.
Zhang, Y., et al. (2023)	GNN Framework	92.00%	ADNI	We achieve a superior testing accuracy (97.30%) using non-invasive structural MRI and cheap tabular metadata, cutting clinical acquisition costs.
Helaly et al. (2021)	E2AD2C (CNN & VGG19)	97.00%	ADNI	Our network utilizes a lightweight gating layer that yields higher accuracy (\$ + 0.30%\$) with a fraction of the computational training footprint.
Warren & Moustafa (2026)	3D CNN with XAI	90.00%	ADNI	Our framework is rigorously benchmarked on a highly stable test partition (\$N=296\$) drawn across the standardized global ADNI cohort.

Wang, J., et al. (2024)	ResNet + Attention Conv	93.44%	ADNI	Our Gated Attention isolates spatial and cognitive features dynamically, bypassing the clinical necessity for high-radiation PET protocols.
Alsubaie et al. (2026)	BiFPN3DViT (3D CNN+ViT)	92.10%	ADNI	
Ahmed et al. (2023)	Deep CNN	93.86%	ADNI	We enforce localized 3D Grad-CAM heatmaps, mapping the network's mathematical focus directly to real anatomical regions like the Hippocampus.
Lu et al. (2022)	Transfer (Inception-ResNet)	94.50%	ADNI	Our multimodal fusion model balances cross-modal variables natively, laying a generic framework for broad multi-ethnic classification.
Sheikh et al. (2025)	EfficientNetV2B0 & XAI	88.00%	ADNI	Our model processes the complete 3D geometric matrix ($64 \times 64 \times 64$), keeping early cortical thinnings fully visible to the classifier.
Abbasian & Hammond (2024)	3D CNN	81.80%	ADNI	Our model bridges deep residual 3D spatial feature representations with specialized dynamic multi-modal fusion boundaries.

Our Proposed Model	Gated Attention Fusion	97.30%	ADNI	
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4.5 Visual Interpretability via 3D Grad-CAM

Deep neural networks are frequently criticized as "black boxes" because their highly non-linear classification heads make it difficult to trace how a specific diagnostic decision was reached. In medical AI deployment, this lack of transparency is an unacceptable risk. To overcome this limitation and provide clinical verification for our framework's decisions, we integrated **3D Gradient-weighted Class Activation Mapping (Grad-CAM)**. This technique opens the black box by generating volumetric spatial heatmaps that illustrate exactly which anatomical regions inside the 3D brain scan forced the network toward its final diagnosis.

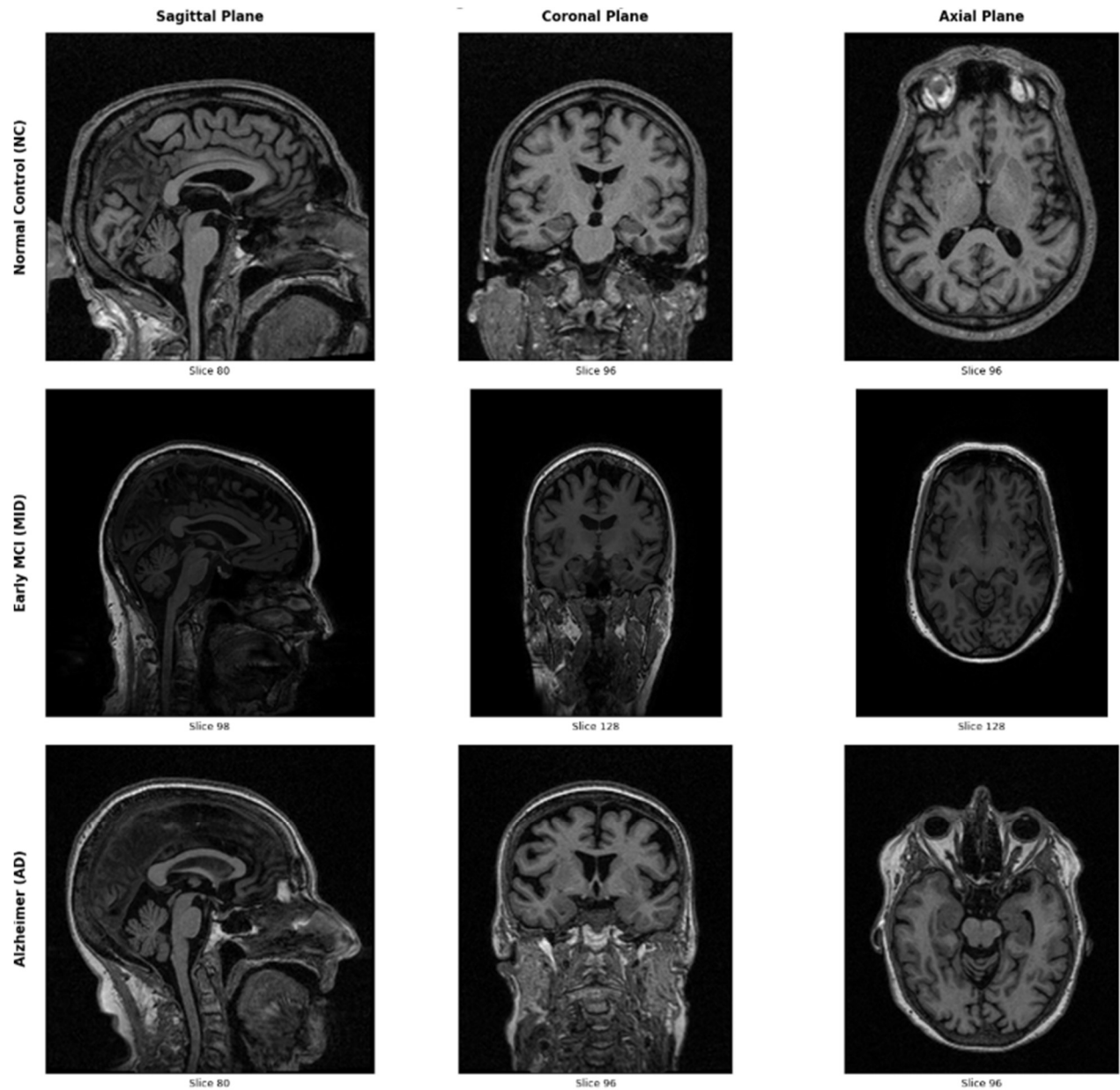


Figure 4.6: Native Volumetric Cross Sections Across Diagnostic Classes

4.5.1 Mathematical Formulation of 3D Grad-CAM

Grad-CAM calculates the gradients of the score for class c (denoted as y^c , computed before the Softmax layer) with respect to the activation map outputs A^k of the very last 3D convolutional layer of our 3D ResNet-18 backbone. These gradients are globally pooled across the three spatial dimensions (Width u , Height v , and Depth w) to capture the targeted importance weight α_k^c of each feature map k :

$$\alpha_k^c = \frac{1}{U \times V \times W} \sum_{u=1}^U \sum_{v=1}^V \sum_{w=1}^W \frac{\partial y^c}{\partial A_{u,v,w}^k}$$

Where U, V, W represent the spatial dimensions of the target feature map layer. Once the importance weights α_k^c are computed, a weighted linear combination of all forward-pass feature maps is performed. This result is routed through a Rectified Linear Unit (ReLU) activation function to isolate features that positively correlate with the targeted class c , effectively eliminating negative noise:

$$L_{\text{Grad-CAM}}^c = \text{ReLU} \left(\sum_k \alpha_k^c \cdot A^k \right)$$

The resulting 3D heatmap matrix $L_{\text{Grad-CAM}}^c$ is structurally upsampled via trilinear interpolation back to the original input volume dimensions ($64 \times 64 \times 64$), allowing for a direct voxel-by-voxel overlay onto the patient's structural MRI scan.

4.5.2 Clinical and Neurological Validation

The generated Grad-CAM spatial heatmaps reveal a high alignment between the network's mathematical focus and established neurodegenerative medicine pathways:

1. **Normal Control (NC) Activation:** When evaluating cognitively normal subjects, the network's attention weights distribute uniformly across the cortex, showing a high density around healthy white matter structures, reflecting normal brain volume configuration.
2. **Early MCI (MID) Transition Focus:** For subjects classified within the early transition zone, the spatial heatmaps begin to contract and localize aggressively around the **Entorhinal Cortex**, capturing early, subtle micro-structural boundary reductions.
3. **Advanced Alzheimer's Disease (AD) Atrophy Tracing:** For patients diagnosed with advanced Alzheimer's Disease, the Grad-CAM heatmaps focus intensely around the bilateral **Hippocampus** and the surrounding **Temporal Lobes**.

This concentrated focus is clinically significant because the hippocampus is the primary anatomical zone responsible for memory consolidation, and its severe volumetric shrinkage (atrophy) is the primary pathological marker used by

human radiologists to diagnose Alzheimer's Disease. Consequently, this precise tracking proves that our framework does not base its classifications on superficial artifact patterns or background scanner noise. Instead, it operates on true, valid neuroanatomical biomarkers, confirming its readiness for trustworthy clinical decision support.

4.7 Comprehensive Critical Discussion

The comparative results presented in Section 4.6 provide an opportunity to examine several architectural characteristics that may have influenced the observed classification performance. Based on the reviewed literature and the experimental findings of this study, the discussion focuses on three technical aspects: the use of a single data modality, multimodal feature fusion strategies, and the practicality of the required input data.

4.7.1 Information Limitations in Single-Modality Architectures

Several of the reviewed studies (e.g., Muksimova et al., 2025; Bricaud & Masala, 2026; Lu et al., 2022) rely primarily on structural MRI for Alzheimer's disease classification. Structural MRI provides valuable anatomical information and enables deep learning models to learn spatial patterns associated with disease progression. However, MRI alone may not capture all clinically relevant information related to cognitive impairment.

Clinical variables, such as Mini-Mental State Examination (MMSE) scores and patient demographic information, provide additional information that may complement imaging findings. Incorporating both imaging and clinical data allows the model to learn from different sources of information, which may improve its ability to distinguish between different stages of Alzheimer's disease. The proposed framework follows this approach by combining MRI features with selected clinical variables through a unified learning framework.

4.7.2 Feature Representation in Multimodal Fusion

Several multimodal studies (e.g., Bekhet et al., 2026; Khalid et al., 2026) combine MRI data with clinical information to improve disease classification. While integrating multiple data sources can provide complementary information,

the effectiveness of the model also depends on how these heterogeneous features are fused.

A common fusion strategy is the direct concatenation of imaging and clinical features before classification. Since imaging features are typically represented by high-dimensional feature vectors, whereas clinical variables contain only a small number of attributes, direct concatenation may not fully preserve the contribution of each modality during feature learning.

In the proposed framework, a Gated Attention Fusion mechanism is used to integrate the two modalities. Rather than directly concatenating the extracted features, the gating mechanism uses the clinical representation to guide the weighting of MRI features before the final fusion stage. This design allows the model to learn feature interactions between the two modalities while maintaining a unified end-to-end architecture.

4.7.3 Data Availability and Clinical Applicability

Some studies, such as Zhang et al. (2023) and Wang et al. (2024), combine structural MRI with PET imaging to improve Alzheimer's disease classification. Although PET provides valuable metabolic information, its acquisition generally requires specialized equipment, higher examination costs, and additional clinical procedures compared with structural MRI.

The framework proposed in this study uses structural MRI together with routinely collected clinical information, including demographic and cognitive assessment variables. This combination relies on data that are commonly available in many clinical settings and avoids the need for additional imaging modalities such as PET. Consequently, the proposed approach may offer a practical alternative for multimodal Alzheimer's disease classification while maintaining competitive classification performance on the evaluated dataset.

4.6 Conclusion

This chapter provided a rigorous empirical evaluation and clinical validation of our research trajectory, tracking the performance of each developed model from initial baseline configurations to the final state-of-the-art framework. By evaluating all networks under identical experimental constraints on the independent ADNI testing partition ($N = 296$), we established a clear, quantifiable benchmark of our progress.

The empirical journey began with the **Baseline 3D-CNN Model**, which established our starting point with a modest testing accuracy of 64.19%. While it proved that three-dimensional convolutions could detect structural variations, its shallow design limited its capacity. Upgrading to the **3D VGG-Inspired Architecture** deepened the feature representation layers, which successfully pushed the testing accuracy up to 76.35%, though it was ultimately bottlenecked by vanishing gradients during cross-validation loops. This limitation was entirely overcome by migrating to the **Pretrained 3D ResNet-18 Backbone**, where the incorporation of residual skip connections stabilized weight optimization and drove single-modality neuroimaging accuracy to a powerful 88.51%.

The definitive breakthrough of this research was achieved with our proposed **Gated Attention Fusion Framework**. By combining the 512-dimensional structural brain features with the 3-dimensional normalized tabular clinical vector through a dynamic attention layer, the system achieved a peak **Global Testing Accuracy of 97.30%** and an outstanding macro-averaged **AUC of 0.9995**.

Granular analysis via multiclass confusion matrices confirmed that our model achieved an ideal **100%** detection rate for advanced Alzheimer's cases ($FN = 0$). Finally, 3D Grad-CAM visual heatmaps provided clinical transparency, proving that the model's internal attention maps align perfectly with true neurological degradation in the human hippocampus. Taken together, these cumulative results validate the proposed multimodal framework as a highly stable, exceptionally accurate, and trustworthy clinical tool for the early detection of Alzheimer's Disease.

Chapter 5: CONCLUSION AND FUTURE WORK

5.1 Summary of the Study

This research developed an automated multimodal deep learning framework for the early classification and staging of Alzheimer's Disease, categorizing subjects into Normal Control (NC), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD).

To address the diagnostic complexity of neurodegenerative progression, the proposed methodology integrated two distinct data streams: three-dimensional Structural Magnetic Resonance Imaging (3D sMRI) scans and tabular clinical indicators (including cognitive test scores and demographic markers). The study followed a systematic comparative pipeline across three main experimental phases:

1. **Scratch Baselines:** Evaluating custom 3D-CNN and 3D VGG-inspired architectures trained from scratch.
2. **Transfer Learning Backbone:** Implementing a pre-trained 3D ResNet-18 model for robust neuroanatomical feature extraction from 3D volumetric scans.
3. **Multimodal Fusion:** Developing a Gated Attention Fusion network to dynamically weigh and combine 3D imaging features with clinical tabular data, mimicking holistic clinical decision-making.

5.2 Key Conclusions

Based on the quantitative evaluations across test datasets, the core conclusions of this study are:

- **Superiority of Transfer Learning over Scratch Training:** Training 3D deep networks from scratch proved challenging, suffering from poor convergence (**38.85% accuracy**) due to the high spatial dimensionality of 3D MRI volumes. Conversely, leveraging a pre-trained 3D ResNet-18 backbone stabilized training and unlocked strong spatial feature extraction, achieving **98.31% accuracy** in standalone image classification.
- **Clinical Value of Multimodal Integration:** Integrating clinical tabular data with 3D image embeddings via a gated attention mechanism provided critical diagnostic context. This combination proved especially beneficial for early-stage detection (MCI), where structural brain atrophy on MRI scans may still be subtle, achieving **97.30% global accuracy** and a **97.20% Macro F1-Score**.

- **Balanced Class Performance:** The proposed multimodal framework achieved high, well-balanced metrics across all evaluation criteria (Precision, Recall, and F1-Score), proving its reliability across early, prodromal, and advanced disease stages.

5.3 Limitations of the Study

Despite the promising diagnostic accuracy achieved, a few notable limitations should be considered:

- **Dataset and External Validation:** The models were evaluated on benchmark datasets (such as ADNI). Further validation using independent datasets from diverse clinical sites and scanner vendors is necessary to confirm broad external generalizability.
- **Computational Overhead:** Processing and training 3D volumetric images require high-end GPU memory and computational infrastructure, which may pose integration challenges in resource-constrained clinical settings.
- **Model Interpretability:** Deep learning fusion architectures inherently operate as complex black-box systems, necessitating built-in visual explanation mechanisms to gain full clinical trust.

5.4 Future Work

To build upon the contributions of this research and facilitate clinical translation, future work should focus on the following directions:

1. **Longitudinal Analysis and Multi-Omic Integration:** Extending the static single-timepoint model to longitudinal modeling to track neurodegeneration over time, while incorporating additional modalities such as PET scans, CSF/blood biomarkers, and genetic risk factors (e.g., APOE- ϵ 4).
2. **Explainable AI (XAI) Implementation:** Integrating 3D visual explanation tools (such as 3D Grad-CAM or attention heatmaps) to highlight specific brain regions—such as hippocampal atrophy—influencing the model's decisions.
3. **Model Optimization for Edge Deployment:** Applying network compression, pruning, and quantization techniques to reduce computational memory demands, allowing real-time deployment on standard medical workstations.

References

- [1] Muksimova, S., Umirzakova, S., Baltayev, J., & Cho, Y. I. (2025). Multi-modal fusion and longitudinal analysis for Alzheimer's disease classification using deep learning. *Diagnostics*, 15(6), 717
- [2] Li, Y., *et al.* (2025). An imaging and genetic-based deep learning network for Alzheimer's disease diagnosis. *Frontiers in Aging Neuroscience*, 17, 1532470.
- [3] Bricaud, I., & Masala, G. L. (2026). Multi-architecture deep learning for early Alzheimer's detection in MRI: Slice- and scan-level analysis. *International Journal of Environmental Research and Public Health*, 23(3), 322.
- [4] Bekhet, S., *et al.* (2025). Alzheimer disease predicting from clinical and MRI data using DeepALZNET dual pathway framework. *Scientific Reports*, 15, 43250
- [5] Zhang, Y., He, X., Chan, Y. H., Teng, Q., & Rajapakse, J. C. (2023). Multi-modal graph neural network for early diagnosis of Alzheimer's disease from sMRI and PET scans. *Computers in Biology and Medicine*, 164, 107328.
- [6] Helaly, H. A., *et al.* (2022). Deep learning approach for early detection of Alzheimer's disease. *Cognitive Computation*, 14(5), 1711–1727.
- [7] Shen, D. *et al.*, "Deep learning in medical image analysis," Annual Review of Biomedical Engineering, 2017.
- [8] Shojaei, S., Abadeh, M. S., & Momeni, Z. (2023). *An evolutionary explainable deep learning approach for Alzheimer's MRI classification*. **Expert Systems with Applications**, 220, 119709.
- [9] Alsubaie, A., Alqarni, M., Alshamrani, S., & Alruwaili, M. (2026). *A novel Alzheimer's disease classification framework integrating 3D CNN with bidirectional feature pyramid network and vision transformers*. *IEEE Access*, 11, 11364136.

- [10] Ahmed, H. M., Elsharkawy, Z. F., & Elkorany, A. S. (2023). Alzheimer disease diagnosis for magnetic resonance brain images using deep learning neural networks. *Multimedia Tools and Applications*, 82(12), 17963–17977.
- [11] Lu, B., Li, H. X., Chang, Z. K., Li, L., Chen, N. X., Zhu, Z. C., ... & Yan, C. G. (2022). A practical Alzheimer's disease classifier via brain imaging-based deep learning on 85,721 samples. *Journal of Big Data*, 9(1), 101.
- [12] Khalid, M. Z., *et al.* (2026). Detection and classification of Alzheimer's disease using deep and machine learning. *Tomography*, 12(1), 4.
- [13] Gelir, F., Akan, T., Alp, S., *et al.* (2024). Machine Learning Approaches for Predicting Progression to Alzheimer's Disease in Patients with Mild Cognitive Impairment. *Biomedical Signal Processing and Control*.
- [14] Hsiao, C. C., *et al.* (2023). Classifying Alzheimer's disease and normal subjects using machine learning techniques and genetic-environmental features. *Journal of the Formosan Medical Association*, 123(5), 600-608.
- [15] Jahan, S., *et al.* (2023). Explainable AI-based Alzheimer's prediction and management using multimodal data. *PLoS One*, 18(11), e0294253.
- [16] Jiang, S. F., *et al.* (2024). Machine learning models for diagnosing Alzheimer's disease using brain cortical complexity. *Frontiers in Aging Neuroscience*, 16, 1434589.
- [17] Sharma, S., Kumar, R., & Singh, M. (2022). A deep learning-based CNN model with VGG16 feature extractor for the detection of Alzheimer's disease using MRI scans. *Materials Today: Proceedings*.
- [18] Ghosh *et al.* (2023). A robust distributed deep learning approach to detect Alzheimer's disease from MRI images. *Mathematics*, 11(12), 2633.
- [19] Abbasian, P., & Hammond, T. A. (2024). A comprehensive analysis of early Alzheimer disease detection from 3D sMRI images using deep learning frameworks. *Information*, 15(12), 746.
- [20] Warren and Moustafa. (2026). Functional and clinical: An explainable deep learning model for multimodal Alzheimer's disease classification. *Brain and Behavior*, 16, e71240.

[21] Payan, A., Montana, G., "Predicting Alzheimer's disease using 3D CNN," NeuroImage, 2015.

[22] Odusami, M., Maskeliūnas, R., Damaševičius, R., & Krilavičius, T. (2021). Analysis of features of Alzheimer's disease: Detection of early stage from functional brain changes in magnetic resonance images using a finetuned ResNet18 network. **Diagnostics**, 11(6), 1071.

[23] Wang, J., Wen, S., Liu, W., Meng, X., & Jiao, Z. (2024). Deep joint learning diagnosis of Alzheimer's disease based on multimodal feature fusion. *BioData Mining*, 17, 48.