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Attention-Driven Hybrid Deep Learning for Automated Alzheimer's Disease Severity Assessment via MRI Neuroimaging

Mahimul Islam Nadim [1], Zahura Zaman [2], Md Mizanur Rahman [1*], Abdullah Al Taky [1], Meherunnesa Tania [2], Ikteder A. Udoy [2], Khadiza Khanom [3], Md. Obaidul Islam [1], Suman Ahmmed [4], Ohidujjaman [4]

[1] *Department of Computer Science & Engineering, Daffodil International University, Dhaka 1216, Bangladesh.*

[2] *Department of Computing, Boise State University, Boise, ID 83725, United States.*

[3] *Department of Computer and System Science, Stockholm University, Stockholm 16407, Sweden.*

[4] *Department of Computer Science and Engineering, United International University, Dhaka 1212, Bangladesh.*

Abstract

Early, accurate diagnosis of Alzheimer's Disease (AD) is vital for effective intervention. Properly classifying its progression from cognitively normal to moderate dementia is essential for tailoring treatment and management plans. The proposed research is a hybrid deep learning framework that integrates the EfficientNet-B3 and the ResNet50 with sophisticated attention units in order to classify the MRI scans of Alzheimer's disease in multi-classes. The model proposed combines both a Convolutional Block Attention Module (CBAM) based on the refinement of channels and space features and Multi-Head Self-Attention based on cross-branch feature interaction. The dual-branch architecture yields complementary features, with EfficientNet-B3 being able to pick fine-grained patterns and ResNet50 being able to pick strong hierarchical representations. The characteristics in both branches are mapped to 512 dimensions, operated by multi-head attention classification. The model and extensive preprocessing were implanted on a series of 33,984 augmented Alzheimer's MRI images in four categories (MildDemented, ModerateDemented, NonDemented and VeryMildDemented. This hybrid model had outstanding performance of 98.21% test accuracy, 98.23% precision, 98.21% recall, and 98.21% F1-score, which was far much better than the accuracies of other baseline architectures such as VGG16 (74.11%), ResNet50 (93.68%), EfficientNetB0 (63.52%), DenseNet121 (64.12%), and CustomCNN (68.87%). These findings support the usefulness of hybrid systems consisting of attention mechanisms to diagnose Alzheimer's disease automatically by using neuroimaging information.

Keywords:

Alzheimer's Disease;
Structural MRI; Deep Learning,
Multi-Class Classification;
EfficientNet-B3;
ResNet50, CBAM;
Multi‐ Head Self-Attention (MHSA);
Hybrid Architecture;
Computer‐ Aided Diagnosis.

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1- Introduction

Alzheimer's disease (AD) is a neurodegenerative disorder that is progressive and the most prevalent cause of dementia disrupting over 55 million individuals globally and estimated to increase to 139 million by 2050 [1]. AD sufferers are faced with multifaceted problems such as progressive memory impairments, language and communication difficulties, poor judgment and decision-making, disorientation of time and place, inability to perform activities of daily living (ADLs) such as bathing and dressing, change of behavior, and ultimate loss of independence to the level of full-time care. This expansion poses massive social and economic pressures. The intervention and management require early and

* **CONTACT**: mizanurrahman.cse@diu.edu.bd

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correct diagnosis. Structural MRI (sMRI) is an essential non-invasive technique in identifying the changes related to AD in the brain. Manual interpretation, however, is subjective, time-consuming, and inconsistent, particularly in early stages, which underscores the necessity of scalable, automated diagnostic solutions.

This paper constructs an overall deep learning framework for the multi-classification of the stages of Alzheimer's disease (AD) by Structural Magnetic Resonance Imaging (sMRI). The main aim is to clearly differentiate four stages of cognitive impairment that are clinically critical, including NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. To do this, we apply and make a strict comparative analysis of some of the state-of-the-art.

Convolutional Neural Network (CNN) networks, such as EfficientNet, ResNet, and DenseNet. Also, the Hybrid-Ensemble model is created and tested to examine the possibility of using varying architectural advantages. The overall aim is to methodically benchmark these models using standardized Alzheimer's MRI data to determine which works best and most robustly architecture towards a more accurate and automated stage-wise classification, thus offering a useful tool to aid in clinical diagnosis.

The importance of this work is two-fold, as it meets the most important requirements in both clinical practice and the study of Alzheimer disease (AD). To begin with, the standardization of diagnoses through automation of the diagnostic process by deep learning, inter-observer variability of hand interpretation of MRI (removing manual interpretation), and throughput are increased. This is first of all to facilitate large-scale screening programs, which are increasingly becoming necessitated by the increasing prevalence of AD in the world. Secondly, using a four-class system of classification, that is, distinguishing between NonDemented, VeryMildDemented, MildDemented, and ModerateDemented, this study offers a more analytical and, importantly, clinically appropriate measure of disease progression than traditional binary classifications [1]. This fine-tuning of staging is essential to the creation of individualized treatment plans and a more thorough monitoring of patient progression over time. Thirdly, the paper lays a lot of emphasis on preventing overfitting by using extensive data augmentation and effective regularization techniques. This attention is paramount in improving the level of generalization within the model, which will make it reliable and have a possibility of being implemented in reality within the clinical context. This work has a deep motivation in its possible clinical impact. Early diagnosis of Alzheimer's is crucial since early intervention can greatly reduce the rate of disease progression and enhance the life quality of the patients.

This study will enable clinicians to be able to make quicker and more dependable diagnoses by creating an effective and automated decision-support system. This, in its turn, may result in the earlier initiation of treatment and an improved patient management outcome. Consequently, the present research is not a purely technical effort but a move towards closing the gap between the most current research on AI and the application in the field of clinical neurology and the completion of the process of better healthcare delivery to the victims of Alzheimer's disease. Much work has been devoted to the use of deep learning to classify Alzheimer's disease (AD) based on MRI. A large number of studies in the early and influential periods had tended to binary classification (e.g., AD vs. Cognitive Normal) and posted high accuracy [1]. Multi-class classification has been an important tendency, and papers have verified that it is viable through different approaches, including Siamese networks and alternative approaches that combine segmentation and classification networks. Other methods have used more sophisticated backbones, such as Vision Transformers that report high accuracy on certain datasets.

Nevertheless, a review of the available literature discloses the usual shortcomings of other studies that the present study will solve. To begin with, there is the problem of inconsistent benchmarking because the studies mention results on a variety of different datasets (e.g., ADNI, OASIS, Kaggle) with different pre-processing steps, and it is challenging to directly compare the performance. Secondly, although various papers implement one new architecture or a hybrid of several models, there is a significant gap in providing an organized comparative study of several current, state-of-the-art architectures such as EfficientNet, ResNet, and DenseNet on a similar dataset and task. Moreover, other forms of research give almost flawless outcomes (e.g., 100%), which is hard to reproduce, and these results should be emphasized with strong and open evaluation systems. Our study is a systematic and repeatable comparison evaluation compared to these works. We apply and extensively benchmark five of the top CNN models: VGG16, ResNet50, EfficientNetB0, DenseNet121, and a hybrid dual-branch model and an Alzheimer's MRI dataset of 33,984 images augmented using various methods in 4 classes on a uniform standardized dataset.

Our approach dwells on solid data preprocessing, thorough augmentation measures, and systematic architectural comparisons to make the results reproducible. The proposed hybrid architecture amounts to EfficientNet-B3 and ResNet50 with the attention mechanisms (CBAM and multi-head self-attention), which yield a high test accuracy of 98.21% and significantly outperform all the baseline architectures. The main contribution of ours is to prove that the hybrid architectures with complementary feature extraction pathways and attention-based fusion mechanisms are better for developing multi-class AD stage classification. The article provides empirical evidence that is proven to be valid in terms of architectural selection in automated neuroimaging-based AD diagnosis, which is vital in clinical applications as well as in future research in medical image analysis.

1-1- Literature Review

Mora-Rubio et al. [2] examined the process of early AD detection with the help of deep learning on MRI data. Since AD leads to progressive memory and cognitive impairment from mild cognitive impairment (MCI) to severe dementia, it is therefore necessary to detect it at an early stage to implement effective intervention. Their experiment used state-of-the-art 3D CNNs (EfficientNet, DenseNet, Siamese networks, and Vision Transformers) to process structural MRI images, namely, assessing frontotemporal atrophy as an essential biomarker in AD and reaching 89% accuracy in the process of AD and healthy controls. In this paper, deep learning with advanced 3D CNNs (EfficientNet, DenseNet, and Siamese network) and Vision Transformer is applied to both MRI data of ADNI [3] and OASIS [4] datasets. Image preprocessing and data augmentation are more accurate. 89% accuracy of AD vs. control; the model has no cure, and it is difficult to differentiate early MCI.

Ali et al. [5] proposed MRI data and a multi-stage convolutional neural network-based model to detect and sub-classify AD. The first step is to have a 26-layer CNN model identify healthy people and AD patients. Subsequently, using the concept of transfer learning, it detects the progressions of dementia, mild, moderate, and severe, using frozen weighted layers of the previous layers. Essential findings of experiments on an online AD dataset showed a 98.24% and 99.70% accuracy in classifying and subclassifying dementia, respectively. The model was tested on a different dataset, bringing out an accuracy of 100 percent, which proved its strength. The comparative analysis with the already known pre-trained models also proved the excellence of the suggested framework in the process of diagnosis and classification of the stages of Alzheimer's.

According to the study by Özaltın [6] on the detection of Alzheimer disease based on the brain MRI images through the combined sources of deep learning and feature selection, this research gained interest in this study. The experiment used a sample of 6,400 MRI scans obtained from Kaggle, classified into four different groups. The researchers attempted some of the pretrained CNN models; the best results were with DenseNet201, achieving a high accuracy of 82.11%. In order to enhance efficiency, they obtained deep features of CNNs and compression via a custom algorithm (FTNCA). These improved features were classified with the assistance of machine learning models such as KNN and SVM. The combination of ResNet-50 and FTNCA and KNN resulted in the highest accuracy with reduced features, which demonstrates the effectiveness of deep learning and feature selection optimization. In the study by Vinukonda & Jagadesh [7], the authors suggested that Alzheimer's disease (AD) is a progressive disease that affects memory and cognitive functions over time. Diagnosis should be done early, but this is hard. This paper suggests a hybrid deep learning system with MRI, which is a better DeepLabV3+ lesion segmentation, LeNet-5 feature extraction, and Enhanced ResNext classification of four stages of AD is non-dementia, very mild, mild, and moderate dementia. Their other innovative technique was the selection of features in order to enhance accuracy. The model attained an accuracy of 98.12 and a high AUC of 0.97 with promising results in early AD detection and staging.

Lokesh et al. [8] gave a critical insight into early diagnosis of Alzheimer disease (AD), which is important to reduce the rate at which the cognitive decline progresses. The deep learning (DL) methods have demonstrated a better capacity than the conventional diagnosis because they can analyze brain MRI and identify small changes in brain connectivity. The problem still persists because of the untrustworthy biomarkers and limitations of datasets. Due to this reason, the Kaggle MRI dataset was selected due to its heterogeneity and being relevant. In this work, deep learning models such as AZ Net, DenseNet, ResNet, EfficientNet, and InceptionNet were created with the help of transfer learning and other techniques that were used to classify AD stages. Among them, the model was found to be highly accurate with an amazing multi-class classification accuracy of 99.96%, indicating a very successful early detection system.

Hussain et al. [9] proposed AD is one of the main causes of dementia, which is impairing memory, cognition, and daily functioning over time. To be treated effectively, early diagnosis is necessary, although conventional machine learning models usually require large labeled datasets and are not well adaptable to new data, which means they require long periods of retraining. Deep learning models enhance efficiency at the expense of high computational resources and data. To mitigate these issues, this paper uses transfer learning with the pretrained CNN models "AlexNet, Google, and MobileNetV2" on different optimization techniques. The models were found to be highly accurate, with 99.4 and 98.2 percent accuracy on Kaggle MRI and OASIS datasets, respectively, as a seen indication of transfer learning potential in enhancing the diagnosis of AD with limited datasets. This development will foster the previous, more precise diagnosis, which is advantageous to patient treatment and disease management.

This paper demonstrated a Siamese Convolutional Neural Network (SCNN) [10], which applies triplet loss to project MRI images into a feature space, which was then used to classify Alzheimer's disease into four stages. The pretrained and non-pretrained CNNs have been tested in order to produce embeddings. The model was tested on ADNI and OASIS datasets, with an accuracy of 91.83 and 93.85, respectively. This is because this model is able to capture minor differences in the structure of the brain, which is an indication of a high possibility in the diagnosis of early and multiclass AD. The present study that was submitted by Mujahid et al. [11] has an emphasis on the significance of the early detection of Alzheimer disease (AD) based on MRI images and deep learning methods. Machine learning involves hand-extracted features and human intervention traditionally, which is inaccurate and time-consuming. The authors employed an ensemble model of EfficientNet-B2 and VGG16 to extract automated features and classify them to address these problems. The dataset was also an imbalanced dataset, so they used the Adaptive Synthetic Oversampling Technique (ADASYN) to balance the dataset. Their model was very accurate, 97.35%, when used to classify in multi-class and was better than other ways previously used and therefore showed efficiency and strength in the detection of AD at early stages. A hybrid deep learning model of multi-class AD classification has been proposed by Sorour et al. [12], which overcomes the limitations on computation of the existing methods. They use IDeepLabV3 as a lesion segmentation model, LeNet-5 as a feature extraction model, and EResNext as a classification model with a result of 98.12% accuracy and an AUC of 0.97 in four AD stages. Contrarily, this paper presents a combined deep learning architecture that is composed of IDeepLabV3+ to fragment lesions, LeNet5 to extract the features, and EResNeXt to categorize four stages of AD. The selection of features is a new approach that optimizes the classification. The proposed model has an accuracy of 98.12 and AUC of 0.97, which is more efficient, multi-class, and clinically viable as compared to former binary or single-model models. It is reported that Alzheimer disease (AD) diagnosis is urgent in the context of increased healthcare expenditures and AI development.

In this paper, we provide a new deep learning architecture that uses a combination of multi-residual blocks, spatial grouped queries, and multi-head attention on MRI-based AD classification. It was tested on four publicly available datasets (Kaggle, OASIS, and ADNI) with very high accuracies—almost 100 percent in binary problems and over 99.6 percent in multiclass problems. Methods of explainability such as GradCAM variants contribute to the comprehension of the disease development. The model is very good in feature extraction and accurate AD stage detection in the various MRI views. This study was supported by Baili et al. [13], who believe that the diagnoses of Alzheimer's disease (AD) and Parkinson's disease (PD) are more correctly diagnosed in the early stage of the diseases to manage them better. This paper introduces two deep learning frameworks, Residual-based Attention CNN (RbACNN) and Inverted Residual-based Attention CNN (IRbACNN) models, which apply self-attention to enhance feature extraction and interpretability. Transparency and clinical trust are augmented by explainable AI (XAI) techniques. Preprocessing of images such as histogram equalization and batch balancing maximizes the quality of data. The models were also able to perform at a high level of 99.92 percent accuracy, which is encouraging in regard to the ability to diagnose neurodegenerative disease at a very early stage and with a lot of detail. A 2024 study of brain shrinkage and cognitive decline in AD by Eqtidar M. Mohammed et al. had the most prevalent cause of late-stage dementia therein [14]. This paper includes a five-part analysis: (1) reviewing the imaging techniques (MRI) to diagnose AD; (2) analyzing popular deep learning (DL) models in the detection of AD; (3) several frequently used datasets; (4) a systematic evaluation of 45 high-quality articles by leading publishers (IEEE, Springer, MDPI, etc.); and (5) the role of preprocessing and the challenges that remain unresolved in the field of AD diagnosis. The paper presents a general overview and bridges various gaps in research.

This research was presented by Slimi et al. [15], who proposed a hybrid deep learning algorithm, which additionally incorporated two already trained CNN models to achieve more precise detection of the disease of interest, namely Alzheimer's, using MRI images. The model has 99.85% accuracy in classification and is very resistant to noise through combining properties of both networks. This hybrid architecture demonstrates high performance and stability in comparison with single models and thus becomes an attractive method of making early AD diagnosis and clinical decisions. Grødem et al. [16] compared the performance of modern deep learning models in detecting Alzheimer's using T1-weighted MRI. SFCN is a simple 3D CNN model that achieved an ROC AUC of 96.0% compared to EfficientNet's 94.9%. SFCN was also very accurate (91.4) even using relatively few parameters (as few as 720). Such findings indicate that simpler architectures such as SFCN can outperform more complicated models such as EfficientNet to classify AD vs. healthy controls with the least number of preprocessing.

This work provided an automatic system of detection of Alzheimer's disease based on 6400 MRI images of four categories [17]. At first, a number of pretrained CNN models (e.g., DenseNet-201, ResNet-50) were employed, the highest accuracy of which was 82.11 percent with DenseNet-201. Deep features were generated and decreased with a new FTNCA approach to enhance the efficiency and then categorized with machine learning algorithms. The highest accuracy of 100 percent with only 344 features by ResNet-50 + FTNCA + KNN pipeline demonstrated a significant improvement and high possibilities of early AD diagnosis. This study was about early detection of Alzheimer's utilizing transfer learning with MRI data [18]. It grouped the patients into four categories, including non-demented, very mild, mild, and moderate dementia. On 12800 augmented images, four pre-trained CNNs were used, including AlexNet, ResNet-50, GoogleNet (InceptionV3), and SqueezeNet. The highest accuracy was obtained with AlexNet (98.05%); the next accuracy was with GoogleNet (97.80%), and the last accuracy was with ResNet-50 (91.11). Transfer learning was useful in overcoming the problem of scarcity of medical data. Early diagnosis of Alzheimer's disease (AD) is crucial to effective treatment and slowing the progression, which Şener et al. [19] demonstrated. Deep learning models such as EfficientNetB0, AlexNet, and EfficientNet121 were implemented using MRI data of the ADNI dataset, where three classes were used: AD, Cognitive Normal (CN), and Mild Cognitive Impairment (MCI). High accuracy levels of the study were achieved: 98.94% (CN vs AD), 99.58% (AD vs CN+MCI), and 98.42% (MCI vs CN). The model proved to be reliable as results were statistically proven using the McNemar test. There is great potential for deep learning in the early detection and grading of AD.

In this paper, Omar Altwijri et al. [20] suggested a new deep learning approach to automatic detection of AD based on MRI scans. It is difficult to detect the disease early due to the visual similarity that exists between normal aging brains and early-stage AD. The methodology uses existing CNNs and an optimized preprocessing system to enhance the accuracy in diagnosis, especially in a limited number of data instances. The proposed model reached a high of 99.3% accuracy with six performance metrics compared to the VGG16 and ResNet50 with four Kaggle-based AD stages (normal, very mild, mild, moderate). The application of the deep learning technique in this study to classify Alzheimer's disease based on MRI data was through multiple benchmark CNN models, which included deep learning techniques [21]. It will also increase the accuracy and recall by using ensemble methods such as stacking and majority voting, with majority voting demonstrating the highest accuracy and recall. This method has a decent test accuracy of 90% as well as balanced precision (0.90) and recall (0.89), which illustrates the advantage of ensembling in detecting AD. The research identifies potential in the future by proposing the combination of various types of medical data and researching other forms of AI to enhance the diagnosis again. Table 1 is the clear summary representation of existing works.

Table 1. Summary of Existing most Relevant Works.

Author & Year	Core Aim	Method	Main Result	Contribution
Mora-Rubio et al. (2023) [2]	Early stage AD detection	EfficientNet, DenseNet, Siamese, ViT on ADNI / OASIS	~89 % accuracy (AD vs control)	Demonstrates model variety and challenges in early detection
Ali et al. (2024) [5]	Stage classification of AD	26-layer CNN + transfer learning to identify dementia stages	98.24 % dementia vs normal, 99.70 % sub-class accuracy	Strong robustness across multiple datasets
Özaltın (2024) [6]	Detecting AD from MRI	Pretrained CNNs + FTNCA feature reduction + ML classifiers	ResNet-50 + FTNCA + KNN → 100 % accuracy on reduced features	Shows deep feature selection + CNN hybrid can be extremely effective
Vinukonda and Jagadesh (2025) [7]	Multi-class staging of AD	DeepLabV3+ (segmentation) + LeNet-5 + Enhanced ResNeXt + novel feature selection	98.12 % accuracy, AUC ~0.97	Combines segmentation + classification for fine AD stages
Lokesh et al. (2023) [8]	Multi-model comparison on AD	AZ Net, DenseNet, ResNet, EfficientNet, InceptionNet via transfer learning	99.96 % multi-class accuracy	Benchmarking many DL architectures on MRI AD dataset
Hussain et al. (2025) [9]	Transfer learning for AD diagnosis	Pretrained CNNs (AlexNet, GoogleNet, MobileNetV2) + optimizers	99.4 % (Kaggle), 98.2 % (OASIS)	Validates transfer learning's strength on limited MRI data
Hajamohideen et al. (2023) [10]	Multi-class AD classification	Siamese CNN with triplet-loss embeddings	91.83 % (ADNI), 93.85 % (OASIS)	Embedding-based representation helps separability
Mujahid et al. (2023) [11]	Ensemble DL for AD	EfficientNet-B2 + VGG16, oversampling (ADASYN)	97.35 % accuracy	Shows ensemble + balancing improves performance
Sorour et al. (2024) [12]	Multi-class AD classification	Hybrid (DeepLabV3++ LeNet-5 + EResNext) + feature selection	98.12 % accuracy, AUC 0.97	More efficient and clinically applicable multi-class model
Lincoln & Maswood (2025) [22]	Deep attention + explainable AD classification	Multi-residual + grouped query + multi-head attention + GradCAM explainability	100 % binary, > 99.6 % multiclass accuracy	Adds interpretability to highly accurate models
Baili et al. (2025) [13]	Explainable AD / PD classification	RbACNN&IRbACNN (residual attention CNNs) + XAI	99.92 % accuracy	High-accuracy model with built-in interpretability
Mohammed et al. (2024) [14]	Survey & gap analysis in AD imaging	Systematic review of DL, datasets, preprocessing	Identified 45 key papers, challenges, gaps	Gives big-picture of current research and open issues
Slimi et al. (2024) [15]	Hybrid CNN ensemble for AD	Merge two pretrained CNNs + noise robustness	99.85 % accuracy	Ensemble method with robustness to noise
Grødem et al. (2024) [16]	Lightweight model benchmarking	3D CNN (SFCN) vs EfficientNet on T1 MRI	SFCN: ROC AUC 96.0 %, EfficientNet 94.9 %	Shows lightweight models can outperform complex ones
Eroltu (2024) [17]	CNN + feature selection for AD	Pretrained CNNs + FTNCA feature reduction + ML classification	ResNet-50 + FTNCA + KNN → 100 % with 344 features	Efficient pipeline reducing feature count dramatically
Alqahtani et al. (2023) [18]	Early AD detection via TL	AlexNet, ResNet-50, InceptionV3, SqueezeNet on augmented MRI data	AlexNet: 98.05 %, GoogleNet: 97.80 %, ResNet-50: 91.11 %	Transfer learning used to overcome small medical datasets
Şener et al. (2024) [19]	Early AD / MCI classification	EfficientNetB0, AlexNet, EfficientNet121 on ADNI	98.94 %, 99.58 %, 98.42 % (various class splits)	Strong classification across AD, CN, MCI classes
Altwijri et al. (2023) [20]	Automated AD diagnosis	Pretrained CNNs + refined preprocessing on MRI	99.3 % accuracy over four classes	Improves diagnosis especially with limited data
Nasir et al. (2024) [21]	Ensemble CNN for AD	Stacking + majority voting among CNNs	90 % test accuracy (precision 0.90, recall 0.89)	Shows ensemble methods can stabilize results

2- Research Methodology

The research methodology will be structured so as to tackle obstacles of automated diagnosis of the Alzheimer disease by way of using brain MRI data. Through the combination of strict data preprocessing, augmentation, and a collection of high-performance deep learning architectures, the following section outlines the overall experimental steps followed. It gives a solid argument behind every methodological decision so that the reproducibility, reliability and validity of the results may be established. The following scheme includes dataset acquisition, data curation, augmentation plans, the architectural basis of the two benchmarking as well as the suggested hybrid model, which preconditions the solid and interpretable findings. A diagram of the entire research procedure and plan of action is shown in Figure 1.

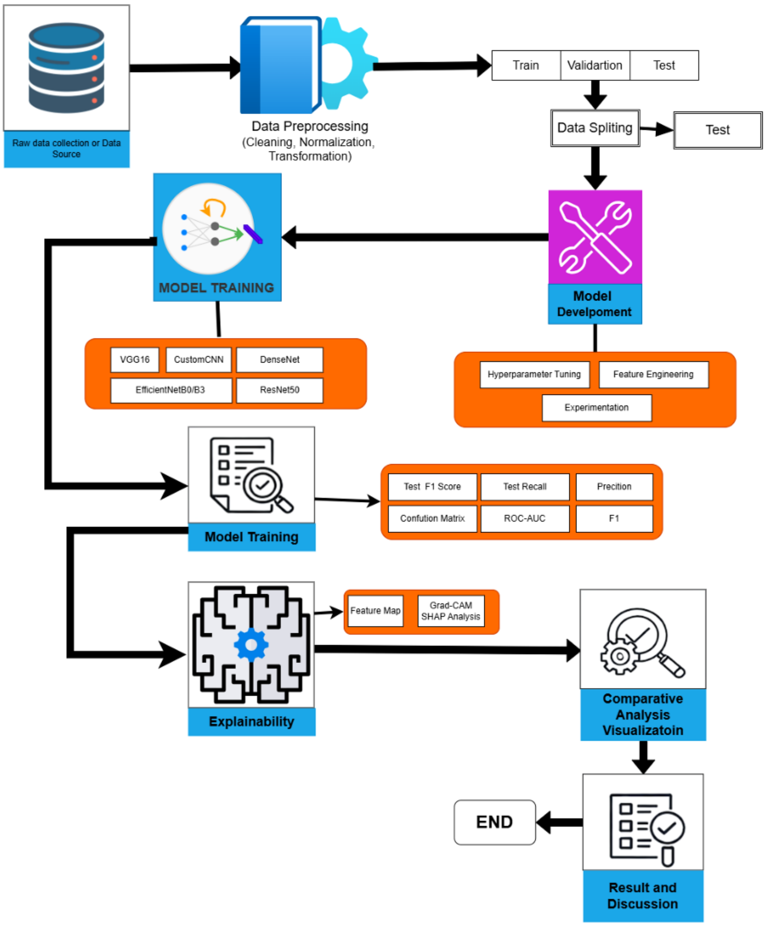

Figure 1. Working Flow (Methodological) Diagram

2-1- Dataset Description

In this research, an augmented dataset of Alzheimer disease MRIs, which consisted of 33,984 brain MRI images in four different categories representing different levels of disease severity, was used. This dataset consisted of 4000+ unique patients' MRI images. The data set consisted of NonDemented (9,600 images), MildDemented (8,960 images), VeryMildDemented (8,960 images), and ModerateDemented (6,464 images), with a moderate balance of classes, which needed thorough consideration when creating the model. An 80:10:10 split ratio was used to divide the dataset, which resulted in 27,187 training samples, 3,398 validation samples, and 3,399 test samples. This stratified partitioning made the representative distribution of all levels of dementia severity across training, validation, and testing subsets, which allows strong model assessment. Figure 2 shows representative MRI images of each category of the disease.

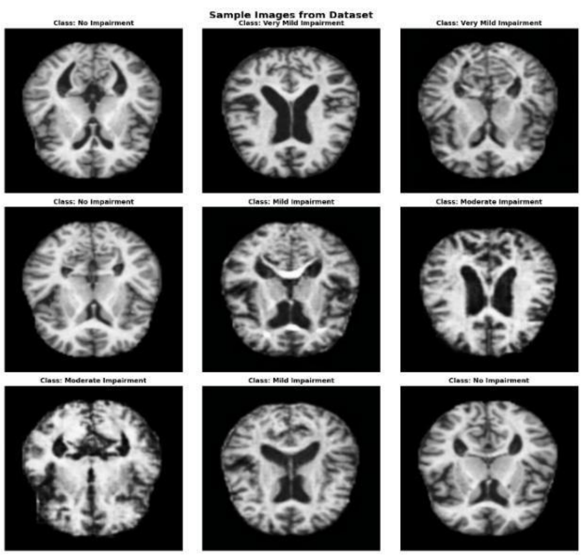

Figure 2. Representative MRI samples from each disease category

2-2- Data Preprocessing

To improve the quality of the images and to equalize the attributes of the input, a complete pre-processing pipeline was introduced. First, lengths of all MRI images were reduced to 224×224 pixels with Lanczos interpolation so as to retain finer structural details that are important in neuroanatomical examination. LAB color space contrast limited adaptive histogram equalization (CLAHE) with 8×8 tile grid size and clip limit of 2.0 was used to increase the local contrast and reduce the effect of noise amplification. This was followed by fast non-local means denoising with h=10, templateWindowSize=7, and searchWindowSize=21 to minimize the artifacts of Gaussian noise inherent in the MRI acquisition. The pre-processed images were intensity normalized into the range to ensure that they were optimized with gradients when training. The efficiency of pre-processing was verified by image quality assessment based on Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) with an average score of 68.77 percent of verification by all classes, denoting the high retention of derivable diagnostic information. Figure 3 presents the visual overview of the overall MRI preprocessing workflow and major steps in it.

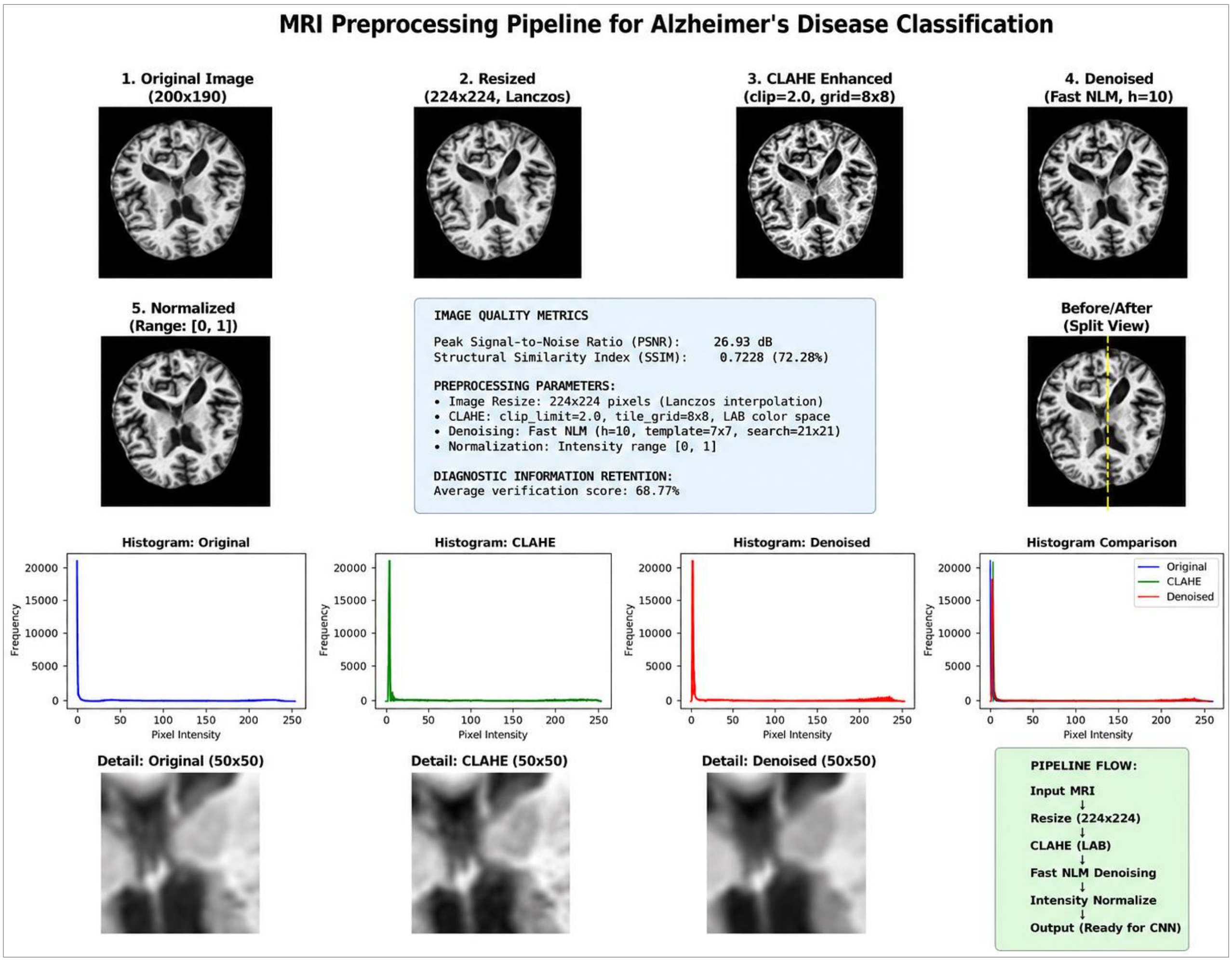

Figure 3. preprocessing pipeline Alzheimer dataset

2-3- Data Augmentation

To mitigate overfitting and enhance model generalization, an extensive data augmentation strategy was applied exclusively to the training set. Geometric transformations included random horizontal flipping with probability 0.5 and random rotation within ±15 degrees to simulate natural anatomical variations. Photometric augmentations comprised random brightness and contrast adjustments (±20%), color jittering with saturation variation (±20%), and random affine transformations with translation limits of 10% along both axes. Quality-preserving augmentations such as Gaussian blur (kernel size 3-5) achieved high SSIM scores (0.986) while maintaining anatomical integrity. All augmented images underwent standardization using ImageNet pretrained model statistics (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]) to leverage transfer learning benefits. Validation and test sets received only resize and normalization transformations to ensure unbiased performance evaluation. Brightness augmentation achieved the highest fidelity in terms of PSNR and SSIM, while Blur produced the lowest RMSE, indicating it preserved pixel accuracy most effectively. The effects of the applied augmentation techniques across different disease categories are illustrated in Figure 4.

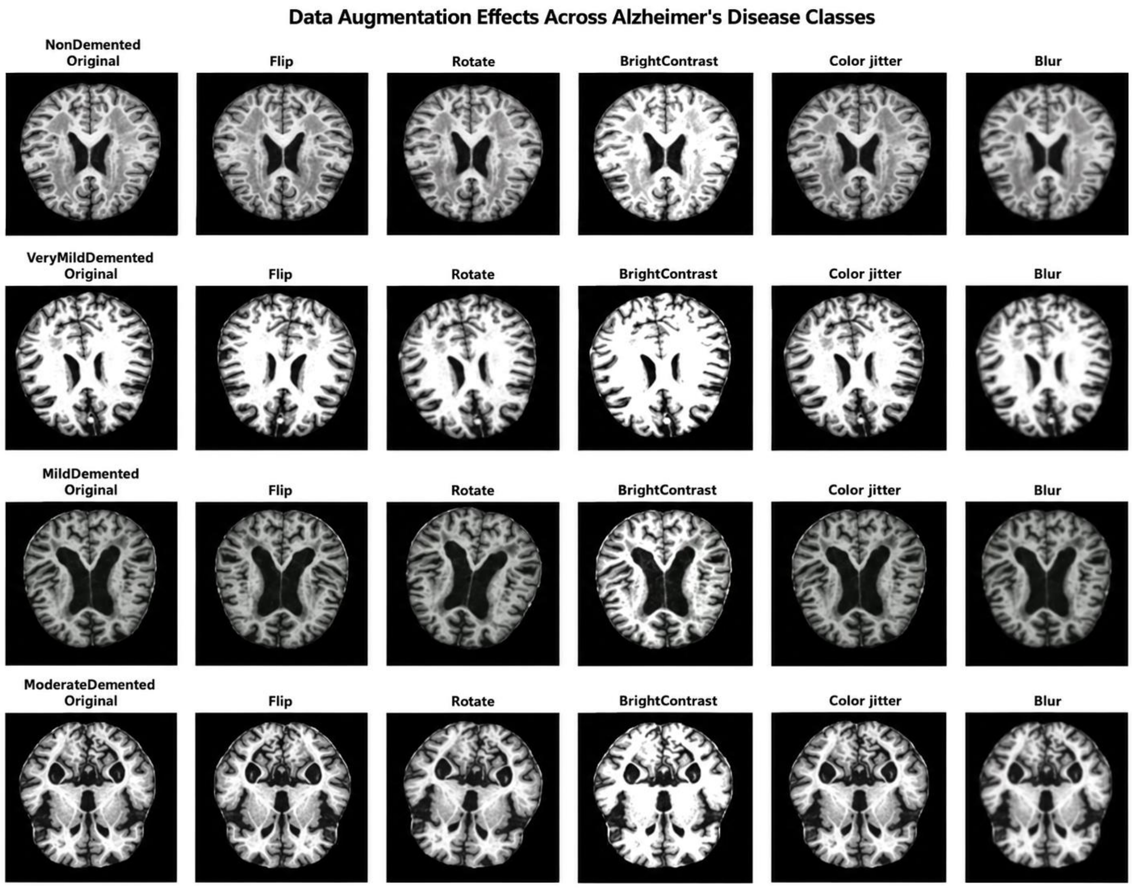

Figure 4. **Multi-Class Augmentation (Flip, Rotate, Jitter, Blur)**

2-3-1- Peak Signal-to-Noise Ratio (PSNR)

- A full-reference metric comparing the maximal signal power to the noise power between an original and a processed image.
- Expressed in decibels (dB), PSNR quantifies similarity: higher values indicate that the processed image closely matches the original with minimal distortion.
- A high PSNR generally signifies **better** reconstruction quality in image enhancement or compression tasks.
- Among the augmentations tested, Brightness yielded the highest average PSNR (~22.1 dB), indicating the least overall noise introduction.

2-3-2- Root Mean Squared Error (RMSE)

- Defined as the square root of the mean of squared pixel-wise differences between two images.
- RMSE ranges from zero upwards, with zero indicating a perfect match and larger values signifying greater deviation from the reference image.
- Lower RMSE values correspond to more accurate pixel reconstruction, though this metric may not fully reflect perceived visual quality.
- Blur augmentation achieved the lowest average RMSE (~23.0), showing it best preserved individual pixel intensities compared to other transforms.

2-3-3- Structural Similarity Index Measure (SSIM)

- A perception-based full-reference metric evaluating luminance, contrast, and structural information similarity between images.
- SSIM values typically range from 0 to 1, where 1 denotes identical structure and appearance to the reference image.
- Because SSIM models human visual perception, higher scores reflect better preservation of image structures and textures.

- Brightness augmentation achieved the highest average SSIM (~0.98), indicating superior maintenance of structural and perceptual image quality.

Figure 5 visualizes the output of all metrics that clearly represents the quality of the augmented images.

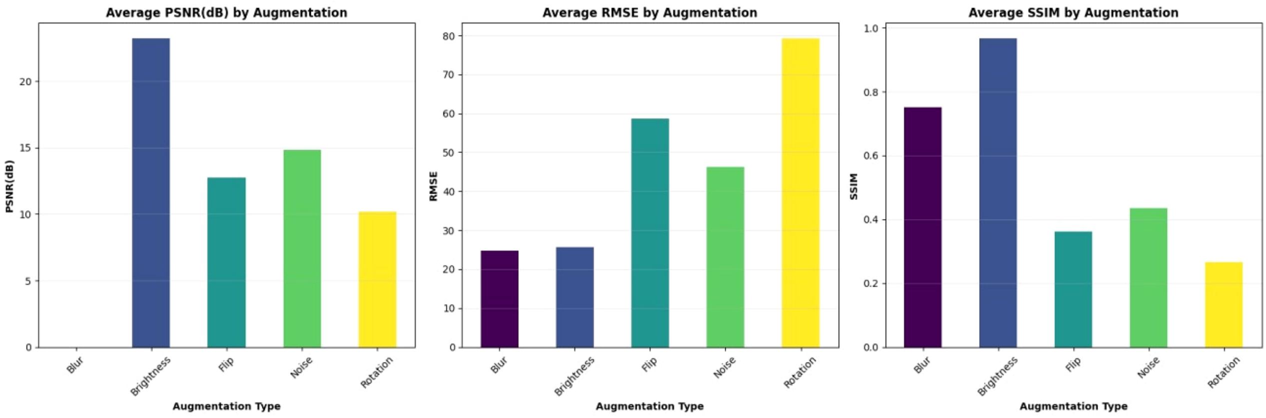

Figure 5. Data augmentation quality metrics visualization displaying PSNR, RMSE, and SSIM values

2-4- Model Description

Five distinct architectures were implemented and evaluated to establish comprehensive performance baselines before proposing the hybrid model.

2-4-1- VGG16

VGG16 employed a deep sequential architecture with 25.95M parameters, utilizing 3×3 convolutional filters organized in five convolutional blocks followed by three fully connected layers for classification. The architecture is mathematically represented as:

$$y = f_{FC}(f_{pool}(f_{conv5}(f_{pool}(f_{conv4}(\ldots f_{conv1}(x)))))) \tag{1}$$

where, f_{convi} denotes the i-th convolutional block and f_{pool} represents max-pooling operations.

2-4-2- ResNet50

ResNet50 introduced residual learning with skip connections to address vanishing gradient problems in deep networks. The residual block is formulated as:

$$y = F(x, \{W_i\}) + x \tag{2}$$

where, $F(x, \{W_i\})$ represents the residual mapping and the identity shortcut x enables gradient flow. The model contained 16.02M parameters organized in bottleneck blocks with 1×1, 3×3, and 1×1 convolutions.

2-4-3- EfficientNetB0

EfficientNetB0 leveraged compound scaling to balance network depth, width, and resolution through a single scaling coefficient. The compound scaling is expressed as:

$$\text{depth: } d = \alpha^{\phi}, \text{ width: } w = \beta^{\phi}, \text{ resolution: } r = \gamma^{\phi} \tag{3}$$

subject to $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$ and $\alpha \geq 1, \beta \geq 1, \gamma \geq 1$. The architecture utilized depthwise separable convolutions and squeeze-and-excitation blocks with only 0.33M parameters.

2-4-4- DenseNet121

DenseNet121 implemented dense connectivity patterns where each layer received feature maps from all preceding layers, formulated as:

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}]) \tag{4}$$

where, $[x_0, x_1, \ldots, x_{l-1}]$ represents concatenation of feature maps and H_l denotes the composite function. The model contained 0.66M parameters with efficient feature reuse.

2-4-5- Customized Convolutional Neural Networks

Custom CNN served as a lightweight baseline with 0.42M parameters, consisting of four convolutional blocks with progressive channel expansion (32→64→128→256) followed by global average pooling and dense classification layers.

2-4-5- Proposed Hybrid Model Architecture

The proposed architecture integrates complementary strengths of EfficientNet-B3 and ResNet50 through a sophisticated dual-branch framework enhanced with attention mechanisms (Figure 6). The model comprises 39.62M trainable parameters organized into five interconnected modules.

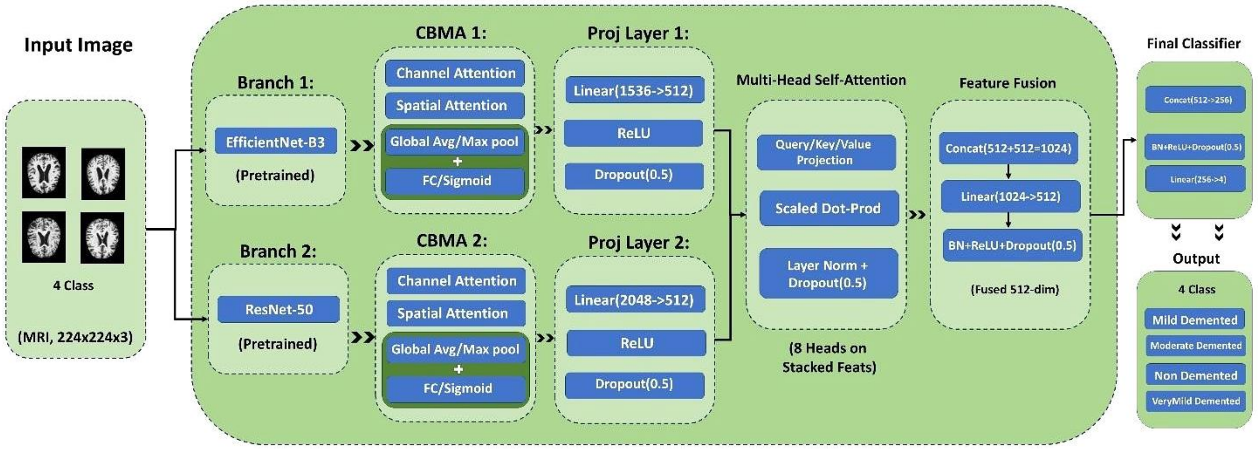

Figure 6. Proposed dual-branch attention-enhanced hybrid architecture

Branch 1 (EfficientNet-B3 Pathway) extracts fine-grained features through compound-scaled MBConv blocks, producing a 1536-dimensional feature vector $\mathbf{f}_{\text{eff}} \in \mathbb{R}^{1536}$. Branch 2 (ResNet50 Pathway**)** captures robust hierarchical representations through residual blocks, generating a 2048-dimensional feature vector $\mathbf{f}_{\text{res}} \in \mathbb{R}2048$.

Convolutional Block Attention Module (CBAM) was integrated after feature extraction in both branches to refine representations through sequential channel and spatial attention. The channel attention mechanism aggregates spatial information using both average and max pooling:

$$M_c(\mathbf{F}) = \sigma(MLP(AvgPool(\mathbf{F})) + MLP(MaxPool(\mathbf{F}))) \tag{5}$$

where σ denotes the sigmoid activation and MLP contains a bottleneck with reduction ratio $r = 16$. The channel-refined features $\mathbf{F}' = M_c(\mathbf{F}) \otimes \mathbf{F}$ are subsequently processed by spatial attention:

$$M_s(\mathbf{F}') = \sigma(Conv_{7\times 7}([AvgPool(\mathbf{F}'); MaxPool(\mathbf{F}')])) \tag{6}$$

where, $[\cdot;\cdot]$ denotes concatenation along the channel dimension and $\otimes$ represents element-wise multiplication. The final CBAM output is computed as:

$$\mathbf{F}'' = M_s(\mathbf{F}') \otimes \mathbf{F}' \tag{7}$$

Feature Dimension Alignment projects both branch outputs to a common 512-dimensional space through learned transformations:

$$\mathbf{h}_{\text{eff}} = \text{ReLU}(W_{\text{eff}}\mathbf{f}_{\text{eff}} + b_{\text{eff}}) \in \mathbb{R}^{512} \tag{8}$$

$$\mathbf{h}_{\text{res}} = \text{ReLU}(W_{\text{res}}\mathbf{f}_{\text{res}} + b_{\text{res}}) \in \mathbb{R}^{512} \tag{9}$$

where, dropout with rate 0.5 provides regularization.

Multi-Head Self-Attention enables cross-branch feature interaction through 8 parallel attention heads. The projected features are stacked as $\mathbf{H} = [\mathbf{h}_{\text{eff}}; \mathbf{h}_{\text{res}}] \in \mathbb{R}^{2\times 512}$. For each attention head i, query, key, and value matrices are computed as:

$$\mathbf{Q}_i = \mathbf{H}W_i^Q,\ \mathbf{K}_i = \mathbf{H}W_i^K,\ \mathbf{V}_i = \mathbf{H}W_i^V \tag{10}$$

where, $W_i^Q, W_i^K, W_i^V \in \mathbb{R}^{512\times 64}$ project to head dimension $d_k = 64$. Scaled dot-product attention is computed as:

$$\text{head}_i = \text{SoftMax}\left(\frac{Q_i K_{Ti}}{\sqrt{dk}}\right) \mathbf{V}_i \tag{11}$$

The multi-head attention output concatenates all heads and applies output projection:

$$\text{MultiHead}(\mathbf{H}) = \text{Concat}(\text{head}_1, \ldots, \text{head}_8)W^O + \mathbf{H} \tag{12}$$

where the residual connection preserves original feature information and $W^O \in \mathbb{R}^{512\times512}$.

Feature Fusion and Classification processes the attended features through progressive dimensionality reduction. The EfficientNet and ResNet attended outputs are concatenated:

$$\mathbf{z} = [\mathbf{h}^{att}{}_{eff}; \mathbf{h}^{att}{}_{res}] \in \mathbb{R}^{1024} \tag{13}$$

A three-layer fusion network with batch normalization transforms the concatenated features:

$$\mathbf{z}_1 = \text{ReLU}(\text{BN}(W_1\mathbf{z} + b_1)),\ \mathbf{z}_1 \in \mathbb{R}^{1024} \tag{14}$$

$$\mathbf{z}_2 = \text{ReLU}(\text{BN}(W_2\mathbf{z}_1 + b_2)),\ \mathbf{z}_2 \in \mathbb{R}^{512} \tag{15}$$

The final classification layer outputs probability distribution over four classes:

$$\mathbf{y} = \text{SoftMax}(W_{out}\mathbf{z}_3 + b_{out}),\ \mathbf{z}_3 \in \mathbb{R}^{256} \tag{16}$$

where, $\mathbf{y} \in \mathbb{R}^4$ represents class probabilities for MildDemented, ModerateDemented, NonDemented, and VeryMildDemented categories.

In summary, the methodology outlined above was developed to ensure rigorous data quality, robust augmentation practices, and fair architectural comparison across models. Each step was carefully selected to strengthen the reliability and generalizability of the results. By integrating both established baselines and a novel hybrid approach, this study provides a replicable and transparent foundation for advancing automated Alzheimer's disease diagnosis using MRI data.

3- Result and Discussion

This part indicates and evaluates the experimental results of the suggested hybrid model, the fixed-point models, and a collection of ablation experiments. The standard metrics that are used to evaluate performance are accuracy, precision, recall and F1-score based on various disease severity classes. Visualizations and tabular summaries allow gaining explicit comparative knowledge, and limitations and future research directions are also presented.

3-1- Performance Matrices

This part provides a comparative analysis of five well-known CNN architectures, such as VGG16, ResNet50, EfficientNetB0, DenseNet121, and a hybrid CNN with CBAM and multi-head self-attention, which is proposed in the paper. The accuracy, precision, recall, and F1-score metrics are used to measure performance to determine their benchmark on the augmented four-class Alzheimer MRI dataset with reference to both classification efficacy and the efficiency of the parameter [23, 24].

Accuracy measures the proportion of correctly classified instances out of all instances in the dataset:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}$$

Recall (also called true positive rate or sensitivity) quantifies the fraction of actual positive instances that are correctly identified by the model:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{18}$$

Precision denotes the fraction of predicted positive instances that are actually positive, reflecting the model's exactness in positive predictions [25]:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{19}$$

F1-score is the harmonic mean of precision and recall, providing a single measure that balances both metrics and is particularly useful for imbalanced datasets:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{20}$$

3-2- Result Summary

An analysis was made on the five existing architectures of VGG16, ResNet50, EfficientNetB0, DenseNet121 and Custom CNN as baselines and a robust hybrid architecture. An indicator of the vast difference in the efficacy and parameter efficiency is the result of their performance, which is summarized in the Table 2 below and graphically presented in Figure 7. Among Pretrained models ResNet50 was highly accurate (93.68) among the baselines, But our Proposed Hybrid Model Achieved the highest accuracy 98.21% with similar precision, recall and F1-Score Value, other lightweight models showed moderate to lower accuracy indicating a performance-parameter trade off. A metric-wise summary is given in the following Table 2.

Table 2. Result Summary of Implemented Deep Learning Models

Model	Parameters (M)	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG16	25.95	74.11	74.68	74.11	74.06
ResNet50	16.02	93.68	93.80	93.68	93.69
EfficientNetB0	0.33	63.52	63.50	63.52	62.95
DenseNet121	0.66	64.12	66.17	64.12	64.08
Custom CNN	0.42	68.87	70.64	68.87	66.80
Proposed Model	**39.62**	**98.21**	**98.23**	**98.21**	**98.21**

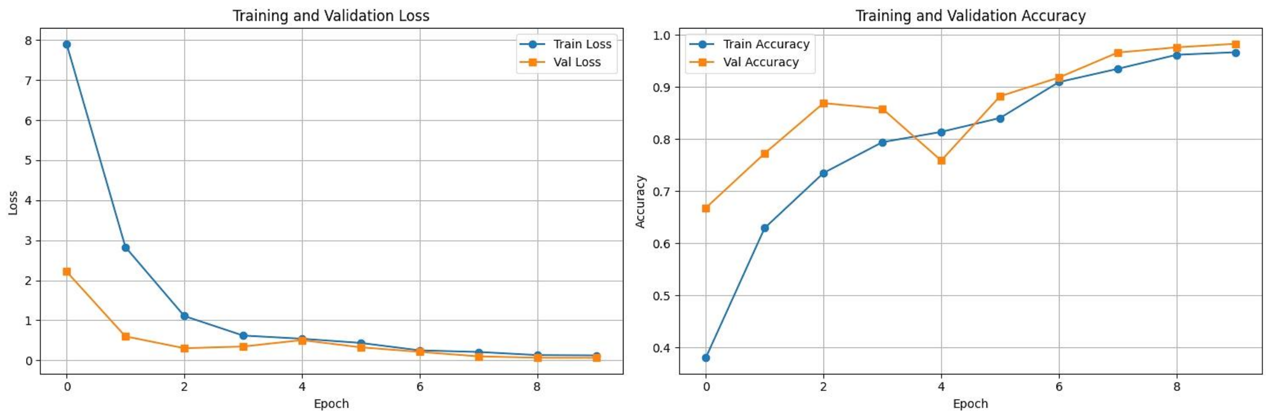

Figure 7. Training and Validation Metrics for the Proposed Model

The visual performance metrics of models are compared with each other in all of the architectures. The hybrid approach has a great improvement in all evaluation metrics compared to the proposed model and the base architectures. Although ResNet50 was found to perform well when comparing it to other traditional models, its accuracy and F1 score are lower than the hybrid one by around 5%. Models that were more parameter-efficient like EfficientNetB0 and DenseNet121 traded accuracy and model size. Multi-head self-attention combined with channel and spatial attention modules was crucial in the improvement of feature extraction, resulting in improved overall and class-based performance. The significance of this comparative superiority is to design architectures that are able to multiscale image patterns of MRI and draw attention to clinical areas of interest.

3-3- Result Details of Proposed Hybrid Model Architecture

The hybrid architecture proposed, which combines EfficientNet-B3 and ResNet50 branches discriminated by CBAM and multi-head self-attention, proved to be exceptionally effective. On the held-out test set model accuracy was 98.21; precision, recall, and F1-score were all above 98. These measures indicate the strong generalization and ability of the model to differentiate minute neuroanatomical variations across all classes of severity of dementia.

3-3-1- Loss and Accuracy Graph Analysis of Proposed Hybrid Model Architecture

Figure 7 displays the training and validation performance curves, which depict convergence behavior and other model learning dynamics. Interestingly, the evaluation based on classes showed that the results of the moderately demented were classified perfectly and all other classes had high results all the time, which showed great sensitivity and specificity. The combination of multi-branch feature fusion and attention systems was important in the capture of the intricate patterns typical of Alzheimer disease development.

3-3-2- Confusion Matrix of Proposed Hybrid Model Architecture

The confusion matrix (Figure 8) shows the individual prediction of the hybrid model on the test set. Correctly classified samples are represented as diagonal elements, with MildDemented (891), ModerateDemented (646), NonDemented (921), and VeryMildDemented (880) having high counts of true positives. The range of minimal off-diagonal values is a sign of minimal misclassifications, which is evidence that the model has a good discriminative ability in all levels of Alzheimer's disease severity.

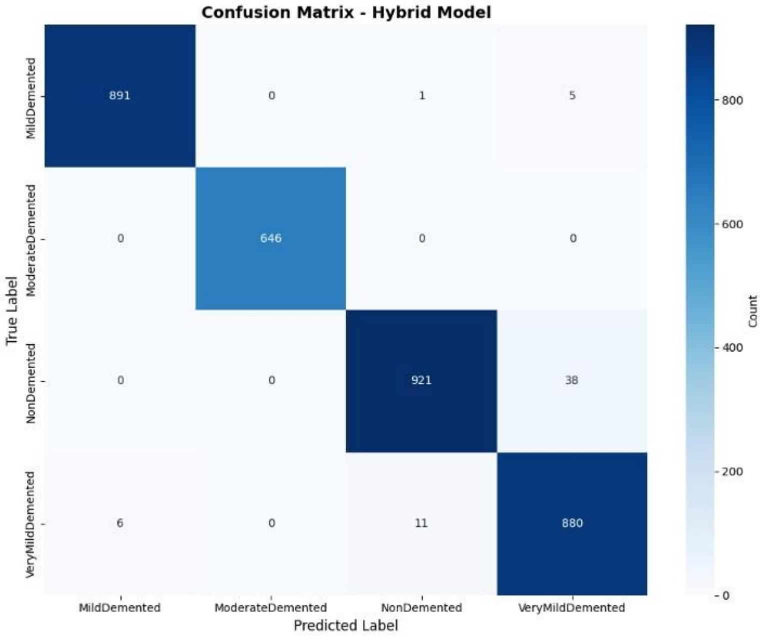

Figure 8. **Confusion Matrix of the Proposed Hybrid Model**

3-3-3- Curve (ROC, Precision-Recall) Analysis of Proposed Hybrid Model Architecture

Figure 9 shows multi-class ROC curves of the 4 levels of Alzheimer severity: MildDemented, ModerateDemented, NonDemented, and VeryMildDemented; each curve has an area under the curve (AUC) of 1.0, which is a perfect situation for separating classes. The dotted diagonal line would signify the chance performance, which would show the best discrimination of the model.

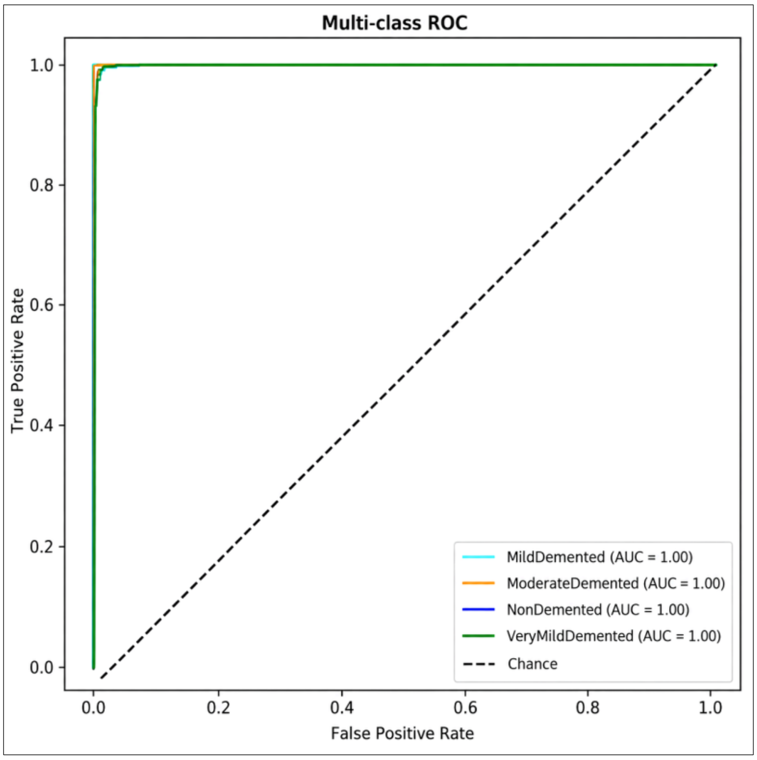

Figure 9. **Multi-class ROC curves comparison**

4- Web Application Integration and Deployment

The hybrid model presented is implemented as a web-based facility that allows patients, clinicians, and researchers to submit brain MRI scans in one of the following formats: DICOM or standard image and obtain results of four-class Alzheimer's classification within minutes using a responsive web interface. Figure 10 illustrates the entire system workflow, i.e., during user authentication and visualization of results. The system workflow starts with user authentication and user login to the platform to provide secure access. After the authentication, the users are allowed to post brain MRI images that are further processed by CLAHE enhancement and denoising algorithms to enhance the quality of the images. The images are preprocessed, and then they are stored in the system registry and then processed through the classification model, which processes the MRI results and gives an output concerning the severity stage of Alzheimer's disease. Attention maps are generated to understand the areas of interest that affected the choice made by the model, which can be interpreted by clinics. The results of the classification (prediction scores and attention visualization) are presented in a friendly dashboard that is easily accessible to clinicians. A researcher and batch processing mode are also supported by the system, where multiple MRI scans can be analyzed in bulk by accessing an API interface, which makes it more efficient in large-scale studies and clinical research.

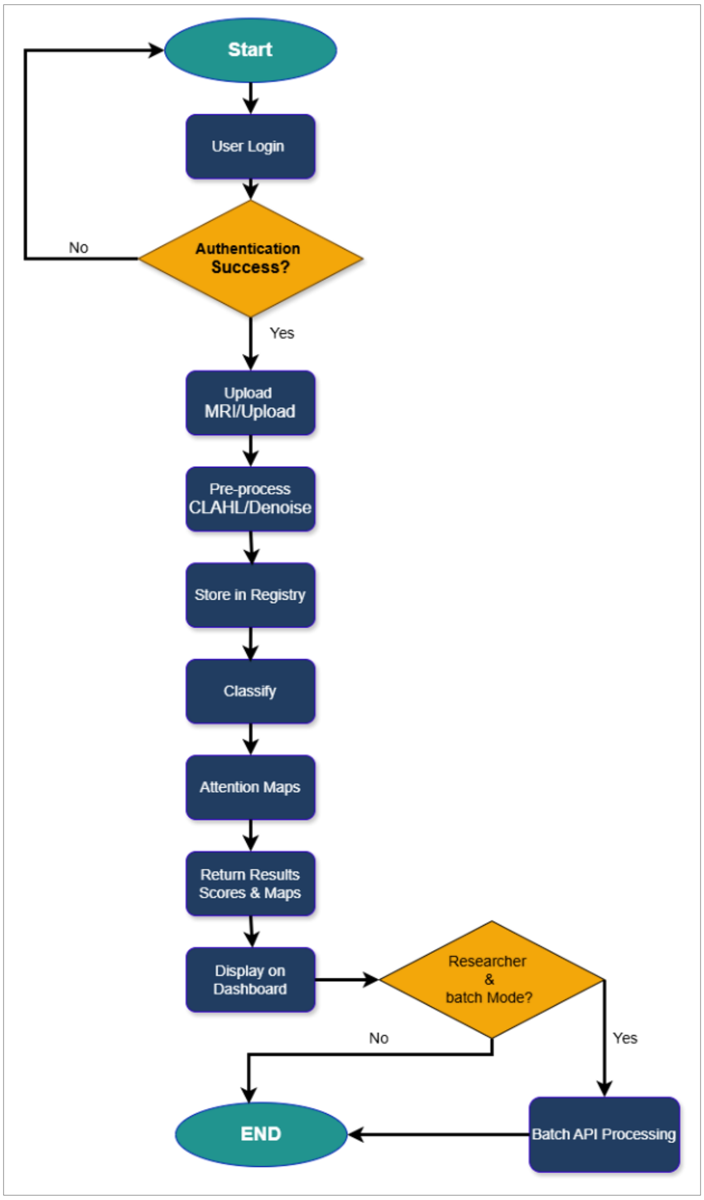

Figure 10. Web app Integration Flow

Uploaded images are ingested into this central registry, which provides secure storage, metadata extraction, and automated preprocessing pipelines (including CLAHE enhancement, denoising, and intensity normalization) to harmonize the data from various sources. Role-based dashboards tailor the experience: clinicians will see confidence scores, CBAM attention map visualizations, and stock disease progression time series charts while providing researchers with batch processing tools and API keys for programmatic ingestion (see Figure 11).

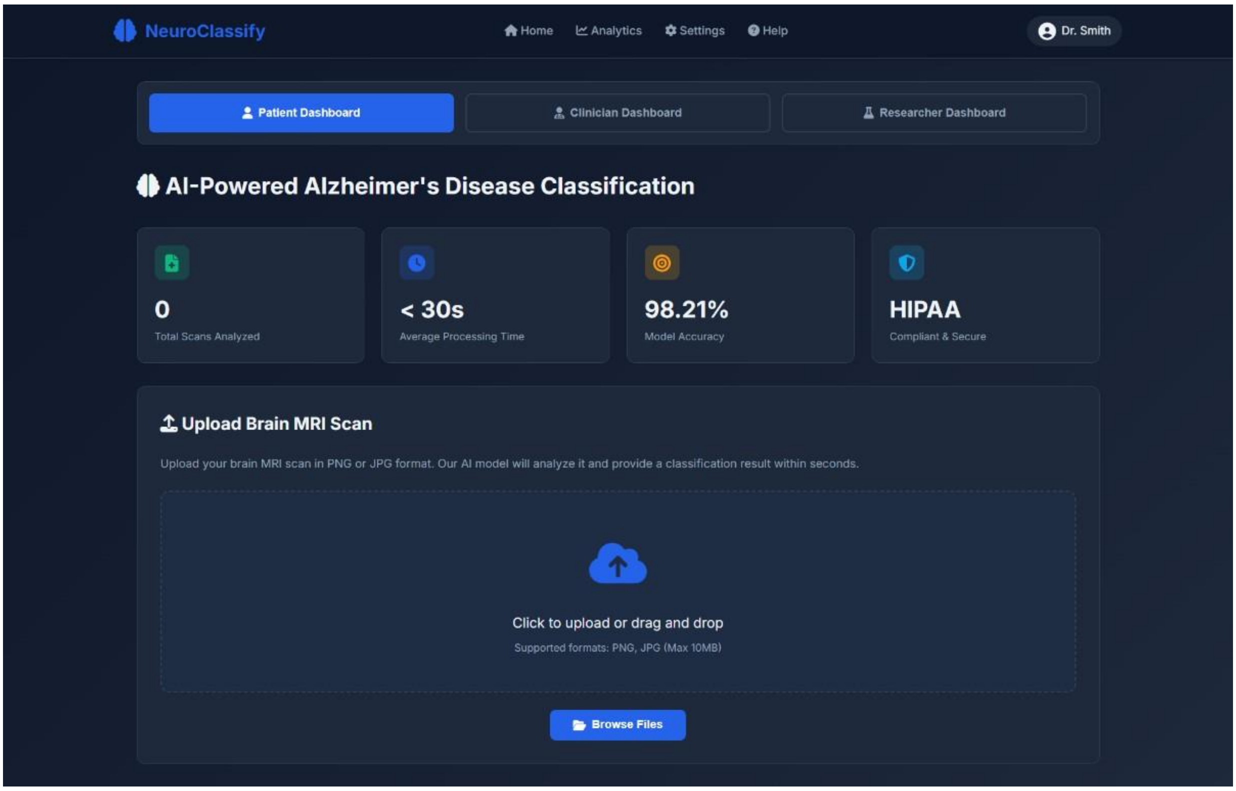

Figure 11. **Dashboard of the Web app**

The backend relies on a Flask-based REST API (/upload, /classify, and /attentionmaps endpoints) coupled with containerized deployment over a cloud/on-premises cluster, which provides horizontal scalability along with quantized model inference using TensorRT for delivering less than 30-second latent scan times under concurrent load. The system produces detailed diagnostic results along with the class probabilities and confidence measures as shown in Figure 12.

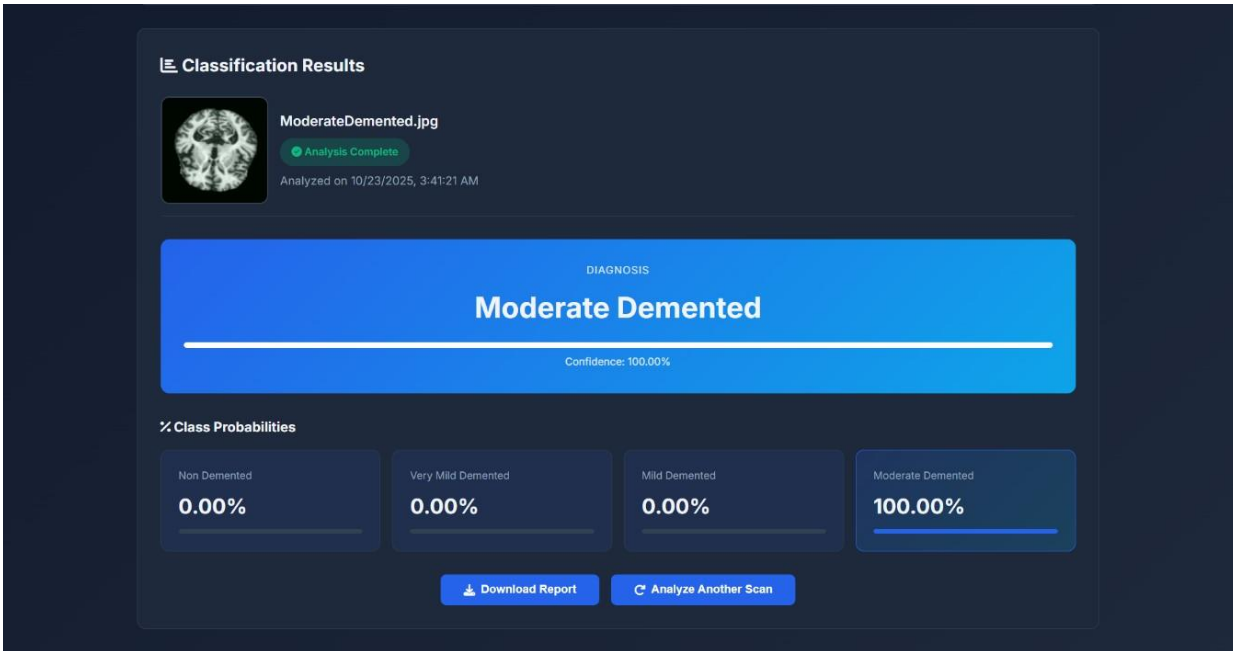

Figure 12. **Diagnosis Result**

5- Explainable AI

In a bid to overcome the black-box character of deep learning models and improve clinical intelligibility, we applied various methods of explainability to visualize the decision-making process of the hybrid architecture. Two complementary techniques were used: Gradient-weighted Class Activation Mapping (Grad-CAM) and Integrated Gradients, which give pixel-wise attribution maps of diagnostically relevant regions of the brain.

I. Grad-CAM Visualization: Individual Grad-CAM heatmaps were obtained on both EfficientNet-B3 and ResNet50 branches by calculating gradient-weighted activations of the last convolutional layers of each network. The EfficientNet branch showed selective coverage of cortical areas and hippocampal formation, whereas ResNet50 showed a large activation of ventricles and white matter tracts. Representations of both branches were combined as Grad-CAM maps averaged, showing the hybrid outputs in agreement on salient diagnostic properties, and this time around, the main activation areas that stood out and were observed to be relevant to the progression of Alzheimer disease were regions of neurodegeneration such as the temporal lobe, hippocampus, and ventricular enlargement as shown in Figure 13.

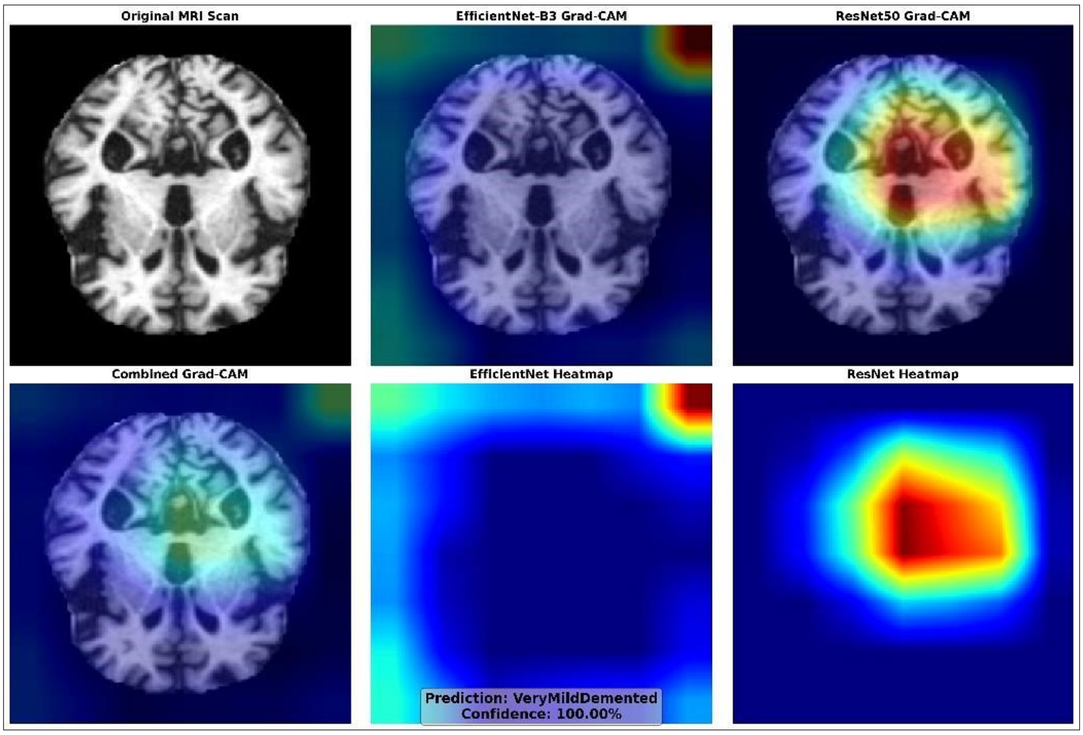

Figure 13. **Explainability Visualizations Using Grad-CAM and Heatmap Techniques**

II. Integrated Gradients Analysis: This attribution algorithm estimated the importance of pixels by interpolating between a functionally equivalent baseline (black image) and the input MRI using 50 integration steps and adding gradients along the way. The attribution heatmaps were used to determine fine-grained anatomical features that were used to make classification decisions, with more attribution scores being found in disease-relevant structures (see Figure 14).

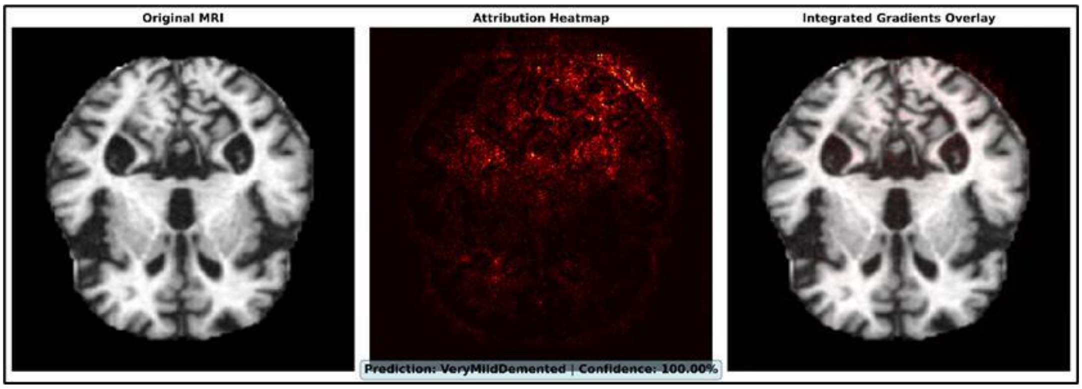

Figure 14. **Integrated Gradients Explainability Analysis for VeryMildDemented Classification**

III. Clinical Validation: These explainable visualizations may allow clinicians to ensure that model predictions are consistent with known neuropathological markers, which breeds trust in AI-aided diagnosis and enables regulatory acceptance of clinical use. The attention maps were always in line with familiar Alzheimer biomarkers that confirmed that the model was learning clinically meaningful features as opposed to random associations.

6- Conclusion

This study introduced an advanced hybrid deep learning framework for the automated classification of Alzheimer's disease using brain MRI images. The proposed architecture combines the strengths of EfficientNet-B3 and ResNet50, integrated with attention mechanisms, to improve feature representation and classification performance. Experimental evaluation on a large dataset of 33,984 augmented MRI images demonstrated the effectiveness of the proposed approach, achieving an overall test accuracy of 98.21%, precision of 98.23%, recall of 98.21%, and an F1-score of 98.21%. These results significantly outperform several widely used baseline architectures, including VGG16, ResNet50, EfficientNetB0, and DenseNet121.

In addition, class-wise evaluation revealed highly consistent and reliable performance across all disease stages, with perfect classification results for the ModerateDemented class and very high F1-scores for the VeryMildDemented, MildDemented, and NonDemented categories. Such strong predictive capability is particularly valuable for early-stage diagnosis, where identifying subtle structural abnormalities in brain MRI scans remains a major clinical challenge.

Beyond predictive performance, the study also emphasizes model interpretability through explainable artificial intelligence (XAI) techniques. Visualization methods such as Grad-CAM and Integrated Gradients highlighted clinically relevant brain regions, including the hippocampus, temporal lobe, and ventricular structures. These results confirm that the model focuses on meaningful anatomical patterns associated with Alzheimer's pathology, thereby enhancing transparency and clinical reliability.

Furthermore, the development of a browser-based web application with dedicated dashboards for clinicians, patients, and researchers demonstrates the practical feasibility of integrating the proposed system into real-world healthcare settings. Despite these promising outcomes, several limitations remain. The dataset was obtained from a single source, and external validation across multiple institutions was not performed. Moreover, the current approach relies solely on structural MRI data and does not incorporate multimodal imaging or longitudinal analysis.

Future research should therefore focus on multicenter validation, multimodal data integration, longitudinal disease progression modeling, and advanced explainability techniques to further improve reliability and clinical applicability. Overall, the findings demonstrate that hybrid attention-based deep learning architectures hold significant potential as decision-support tools for improving the early detection and management of Alzheimer's disease.

6-1- Limitations

The research has several limitations that should be acknowledged. First, the study relies on a single data source, which may limit the generalizability of the model to different populations and MRI acquisition protocols. Although the model achieves high accuracy, it largely operates as a black box, and more advanced explainability techniques are required to enhance clinical trust and facilitate regulatory acceptance. In particular, the AUC value of 1.0 raises concerns regarding potential model overfitting.

Furthermore, the analysis is based exclusively on structural MRI data. Incorporating additional imaging modalities or biomarkers may improve diagnostic accuracy and provide deeper insights into disease progression. The current model is also designed for cross-sectional classification and does not account for temporal dynamics that could be used to predict disease progression or support personalized treatment strategies, thereby limiting its prognostic capability.

Finally, the complexity and high computational requirements of the model may hinder its implementation in resource-constrained clinical settings. Additional optimization is therefore necessary to improve its accessibility and practical applicability. Addressing these challenges in future studies will be essential for translating this promising AI-based approach into an effective clinical tool.

7- Declarations

7-1- Author Contributions

Conceptualization, M.I.N., Z.Z., and M.M.R; methodology, M.I.N. and M.M.R.; software, M.M.R., A.A.T., and M.T.; validation, M.M.R., M.T., and O.; formal analysis, I.A.U., K.K., and M.O.I; investigation, K.K. and O.; resources, M.O.I., M.M.R., and M.T.; data curation, S.T.D., M.M.J., and M.M.R.; writing—original draft preparation, M.I.N., Z.Z., and M.M.R; writing—review and editing, K.K., M.O.I., S.A., and O.; visualization, M.M.R. and O.; supervision, S.A. and O; project administration, M.M.R. and I.A.U; funding acquisition, S.A. and O. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

Publicly available datasets were analyzed in this study. This data can be found here: [https://www.kaggle.com/datasets/uraninjo/augmented-alzheimer-mri-dataset] (accessed on May 2026).

7-3- Funding

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7-5- Institutional Review Board Statement

This research was ethically approved by the Department of Computer Science & Engineering, Daffodil International University (DIU). Additionally, this study is closely observed by the United International University (UIU),Bangladesh.

7-6- Informed Consent Statement

Not applicable.

7-7- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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