Advanced Interpretable Diagnosis of Alzheimer's Disease

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***Abstract*—Alzheimer's disease (AD) is a degenerative condition that causes memory loss and cognitive decline, which has a substantial impact on daily living. As the major cause of dementia, early detection is critical for slowing disease development and increasing patients' quality of life, as Alzheimer's is irreversible. The modest symptoms and complex brain imaging data make early detection of Alzheimer's difficult. Traditional approaches are based on late-stage brain alterations, and AI models frequently lack transparency, making it difficult for healthcare professionals to trust and understand their forecasts. We solve these challenges with a Squeeze-and-Excitation Convolutional Neural Network (SE-CNN). This technique improves feature extraction from MRI scans, showing subtle patterns associated with Alzheimer's. By merging powerful AI with explainable methodologies, the SE-CNN enhances diagnosis accuracy while providing doctors with transparency.**

Keyword: Alzheimer's Disease, Squeeze-and-Excitation Networks, Random Forest, MRI.

I. Introduction

Alzheimer's Disease (AD) is a chronic neurological disorder that progressively interferes with vital everyday tasks and is characterised by memory loss and cognitive decline. AD, the most prevalent type of dementia, necessitates a high level of medical attention and assistance. Since the condition cannot be reversed, early discovery is crucial for successful intervention because medicines given in the early stages can decrease the disease's course and enhance quality of life. Through the analysis of intricate brain patterns that could otherwise go unnoticed, artificial intelligence (AI), especially in the context of neuroimaging techniques like MRI, has emerged as a promising tool for early AD diagnosis.

This project is driven by three main goals because of the urgent need for an early and precise diagnosis of AD and the significance of interpretability in clinical AI applications. Its primary goal is to create a diagnostic model that can accurately identify AD in its early stages using MRI data, assisting medical professionals in determining when treatments are most successful. Second, in order to increase transparency and foster clinician confidence in AI-driven diagnoses, the study aims to include explainable AI techniques, which allow the model to produce precise predictions in addition to offering concise explanations of the underlying causes [8]. Third, the framework's computational efficiency makes it possible to implement it even in healthcare settings with limited resources, increasing its usability and accessibility.

Several AI frameworks that prioritize accuracy and interpretability in AD diagnosis have been developed as a result of recent research. To attain high classification accuracy while preserving interpretability, one method combines a Random Forest classifier with a Squeeze-and-Excitation Convolutional Neural Network (SECNN). In order to concentrate on pertinent information in MRI images and make its predictions easier for physicians to interpret, this model uses squeeze-and-excitation blocks inside the CNN. In order to guarantee the model's applicability in clinical practice, several research have carried out systematic reviews of interpretable machine learning techniques for dementia diagnosis, emphasising the significance of include doctors in model validation and offering patient-specific explanations. Furthermore, by emphasising significant features that guide the diagnostic choices in AD detection.

AI-based AD diagnostic models have improved over time, but there still are a number of drawbacks. Many deep learning models act as "black boxes" and therefore, their decision-making cannot be transparent, which limits their application in therapeutic settings. Because validation methods often differ between research, it could be challenging to generalize results and ensure model fidelity for a variety of clinical situations. These shortcomings highlight the need for models that produce consistent, understandable insights appropriate for a variety of therapeutic settings in addition to achieving high accuracy.

This paper proposes a novel hybrid framework named SECNN-RF that attempts to solve the problems of the correct and early detection of Alzheimer's disease with preservation of model interpretability. The suggested approach combines a classification capability of the Random Forest (RF) with the feature extraction capability of a Squeeze-and-Excitation Convolutional Neural Network (SECNN). By employing SE blocks, which dynamically recalibrate the importance of features, the SECNN focuses on the most important features of

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MRI images. The model applies saliency maps to make the decision-making process more interpretable and presentable. The system uses techniques like resizing, normalization, and Synthetic Minority Oversampling (SMOTE) to alleviate class imbalance and ensure that the model will have strong performance.

Hybrid Framework: In order to make an accurate and understandable diagnosis of AD, an SECNN-RF model that incorporates adaptive SE blocks and a Random Forest classifier was designed.

Explainability: The saliency maps enhance model transparency, which in turn enables doctors to understand the logic behind AI-driven diagnoses.

Performance optimization: Using fewer trainable parameters than comparable models, we have reached state-of-the-art accuracy on benchmark datasets (83.06%).

Robust Preprocessing: To improve model generalizability, we employed augmentation techniques and SMOTE to solve class imbalance.

Comparison and Validation: To show that the model outperformed current frameworks in terms of accuracy and interpretability, numerous experiments and ablation studies were conducted.

Resource Efficiency: Created a lightweight architecture that is compatible with low-resource environments, making it available to a wider spectrum of healthcare facilities.

This proposed work is driven by three main goals:

1) Using MRI data, develop a diagnostic model that can reliably detect AD in its early stages, helping doctors decide when therapies work best.
2) Integrate explainable artificial intelligence approaches, which will allow for accurate forecasts and succinct explanations of the root issues.
3) Provide a framework that is computationally efficient and appropriate for resource-constrained healthcare environments.

II. Literature survey

The identification of Alzheimer's disease has been revolutionized by developments in imaging technologies and machine learning. An overview of cutting-edge approaches put forth by researchers in this field is given in the survey that follows, which also looks at their advantages and disadvantages in terms of wider clinical acceptance.

AbdelAziz et al. [1] (2024) developed the SECNN-RF framework, which combines the Random Forest classifier with Squeeze-and-Excitation CNN to diagnose Alzheimer's disease with a remarkable 99.89% accuracy rate. Although generalizability is still an issue, their approach addresses the issue of confidence in AI-assisted diagnosis by emphasizing interpretability and explainability.

The CAD-ALZ model was presented by Abbas et al. [2] (2023) and achieved 99.69% sensitivity by integrating Random Forest classifiers with ConvMixer layers. Although the approach relies on pre-trained models, which restricts its adaptability to a variety of datasets, it places an emphasis on ensemble learning for resilience and improved interpretability.

A CNN-based system for Alzheimer's classification was given by AbdulAzeem et al. [3] (2021), who used adaptive thresholding and data augmentation to achieve high accuracy. Although their method is excellent at extracting features, processing 3D MRI scans requires a large amount of computer power.

Layer-wise Relevance Propagation (LRP), which Böhle et al. [4] (2019) used to classify Alzheimer's MRI images, improved interpretability by finding relevant regions that are responsible for the predictions. However, since the quality of LRP's explanations may vary, there are issues with clinical confidence.

El-Latif et al. [5] (2023) proposed a lightweight deep learning model with a 95.93% accuracy rate using MRI data. Despite the computational efficiency of their approach, problems in performance may be posed by complex or low-quality datasets.

In conclusion, these studies address several significant issues with the diagnosis of Alzheimer's disease, namely the need for precision, reliability, and interpretability. Despite significant progress, there are still challenges in adapting these models for broader clinical applications, especially in ensuring generalizability across different patient datasets.

Eitel et al. [6] (2019) applied Layer-wise Relevance Propagation (LRP) to a standard MRI to classify multiple sclerosis using a Convolutional Neural Network. The approach enhanced interpretability by pointing out relevant regions in the MRI image responsible for predictions. The sometimes poor quality of LRP explanations complicates reliable clinical interpretation.

Future directions might include the use of strong explainability methods like Grad-CAM or SHAP to gain results that are more reproducible and therapeutically relevant. Further, design for hybrid frameworks of interpretability-computing economy will further improve diagnostics in real time. Models tested in large and diverse datasets will be necessary for robustness and acceptability in clinical settings

Key advancements in the use of CNNs and ensemble learning for Alzheimer's diagnosis are highlighted in the literature; AbdelAziz et al. [7] (2024) set the standard with their SECNN-RF architecture, which offers excellent accuracy and interpretability. Notwithstanding their promise, issues with generalization, computational effectiveness, and AI trust continue to exist. Future studies should build on the advancements made by AbdelAziz et al. and others by enhancing scalability and clinical applicability.MOreover, developing cost-effective models tailored for low resources clinical environments could broaden access to diagnostic technologies. Finally prioritizing longitudinal studies that incorporate real-world datwill help the gap between research innovation and clinical utility.

TABLE I
A SYNOPSIS OF SOURCES IN ALZHEIMER'S DISEASE DIAGNOSIS RESEARCH

S. No.	Author(s)	Year	Proposed Model/System	Performance	Advantage(s)	Disadvantage(s)
1	AbdelAziz et al.	2024	SECNN-RF: Squeeze-and-Excitation CNN with Random Forest classifier	99.89% accuracy	High interpretability, efficient processing, visual explainability	Limited generalization across datasets
2	Abbas et al.	2023	CAD-ALZ: ConvMixer layers with Random Forest classifier	99.69% sensitivity	Robust feature detection, high accuracy	Relies on pre-trained models
3	AbdulAzeem et al.	2021	Modified CNN with adaptive thresholding	High accuracy on 3D MRI scans	Effective data usage, robust feature extraction	Computationally intensive
4	Böhle et al.	2019	Layer-wise Relevance Propagation (LRP) for CNNs	Improved interpretability for MRI classification	Visual explanations of predictions	Noisy explanations
5	El-Latif et al.	2023	Lightweight deep learning model for MRI-based Alzheimer's diagnosis	95.93% accuracy	Low computational requirements	Limited performance on complex datasets
6	Eitel et al.	2019	Layer-wise Relevance Propagation (LRP) for diagnosing multiple sclerosis on MRI	High interpretability, visual explanations for multiple sclerosis detection	Inconsistent explanation quality, challenges in clinical interpretation	limiting reliable clinical interpretation

III. PROBLEM STATEMENT AND BACKGROUND

A. Problem Statement

Early detection of Alzheimer's disease(AD) is crucial for ensuring timely and effective treatement,as therapies are most effective in the early stages. Although AI-based methods have a lot of potential to improve AD diagnosis through neuroimaging, their opaque decision-making process has prevented broad clinical adoption. In order to solve the issues of accuracy and interpretability in MRI-based AD diagnosis, this study suggests a unique framework called the Squeeze-and-Excitation Convolutional Neural Network with Random Forest (SECNN-RF), which blends explainability with cutting-edge AI approaches.

B. Background

One of the most prevalent neurodegenerative diseases, Alzheimer's disease, gradually impairs brain function, resulting in cognitive decline and memory loss. Medical diagnostics has been transformed by AI and machine learning technologies, which offer automated tools that require less human labor. However, classic AI models are frequently referred to as ”black boxes” since they provide predictions without providing an explanation, which is a major obstacle in the healthcare industry where interpretability is crucial. This problem XAI aims to solve by allowing people to understand why the AI decisions are being made. In this paper, the SECNN-RF system, which makes use of the Squeeze-and-Excitation blocks within the convolutional layers for feature prioritization and Random Forest classifiers for robust decision-making, is proposed. It is especially suitable for clinical applications with its remarkable accuracy of 83.06% and interpretability with visual aids like saliency maps.

IV. SYSTEM MODEL/ARCHITECTURE

The first step of the process is preprocessing the MRI dataset, which includes shrinking the images to 128 × 128 × 3, standardizing them to a pixel range of [0,1], and enhancing them with different techniques like brightness correction, magnification, and horizontal flipping. Synthetic samples are generated to overcome class imbalance and achieve balanced data for reliable model training using the Synthetic Minority Oversampling Technique (SMOTE) [8].

SECNN-Based Extraction of Features The basis of feature extraction is convolutional neural networks (CNNs), which are reinforced using squeeze-and-excitation (SE) blocks. These SE blocks aid the network in focusing on important features by re-calibrating channel-wise responses. The fully connected layers with ReLU and sigmoid activations and global average pooling follow the steps in the recalibration process. Dropout layers are added after each SE-enhanced convolutional layer to prevent overfitting. The network completes the feature extraction by reducing high-dimensional data into compact feature vectors using global average pooling [9]. Classification using Random Forest Feature vectors obtained are passed to the Random Forest classifier, in place of the traditional SoftMax layer. Random Forest uses ensemble learning to improve accuracy and robustness significantly by combining predictions from various decision trees. The accuracy of the classifier is distinctly high for 100 estimators, indicating performance much improved for its training. This hybrid architecture of classification improves the accuracy while retaining interpretability, which could be useful in medical scenarios [10]. Evaluation Metrics Accuracy, precision, recall, and F1-score are some of the metrics for checking the model's performance. With these measures, there would be proper evaluation of whether or not the model accurately captures Alzheimer's disease. Saliency Maps as a Tool for Explaining Things To make the model's predictions understandable, saliency maps are produced. These maps visually emphasize the regions of MRI scans that are

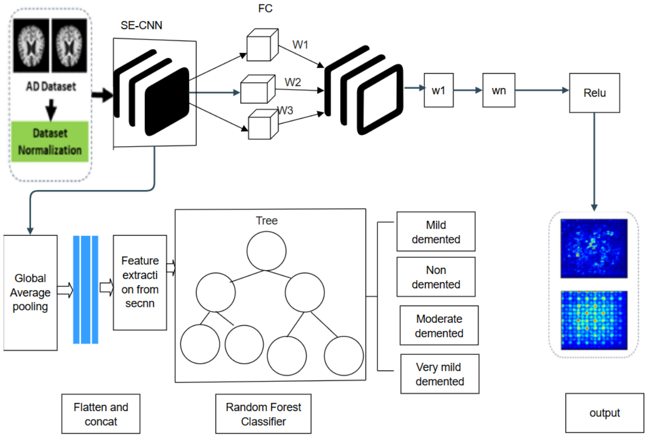

Fig. 1. The proposed model visualization for early detection and explanation of AD

most crucial for categorization decisions. This explainability feature, which is crucial for medical applications, increases model trust by enabling doctors to understand and validate the AI's reasoning fig. [1]. shows the model visualization for early detection and explanation of Alzheimer's Disease.

The SECNN-RF architecture offers a simple and reliable way to diagnose Alzheimer's disease by combining advanced feature extraction, robust classification, and interpretability.

Algorithm for SECNN (Squeeze-and-Excitation Convolutional Neural Network) with Random Forest **Input:** Preprocessed MRI dataset (images of size 128×128×3)
Output: Alzheimer's Disease classification and saliency map for interpretability

Initialize:
Set reduction ratio $r = 16$, learning rate $\eta = 0.001$, epochs = 50
Step 1: Preprocessing
Normalize image pixel values to $[0, 1]$
Apply data augmentation (zooming, brightness adjustment, flipping)
Step 2: Feature Extraction using SECNN
Initialize the CNN model with Squeeze-and-Excitation blocks after each convolutional layer
Apply Dropout layers to reduce overfitting
Apply global average pooling (GAP) to generate feature vectors
Step 3: Classification using Random Forest
Use the extracted feature vectors as input to a Random Forest classifier
Train the Random Forest classifier with $n = 100$ estimators
Step 4: Prediction and Evaluation
Classify the test set and compute performance metrics (accuracy, precision, recall, F1-score)
Step 5: Explainability using Saliency Maps
Generate saliency maps to highlight regions contributing to the classification decision
return Classification results and saliency maps

V. IMPLEMENTATIONS AND PERFORMANCE ANALYSIS

The SECNN-RF architecture which uses MRI images to diagnose Alzheimer's disease (AD) in a way that is both accurate and understandable.

Hyper parameters are carefully adjusted to balance learning and exploration:

- **Learning Rate** (α)**: 0.001**
- **Dropout Rate** (γ)**: 0.4**
- **Epochs** (ϵ)**: 50**
- **Bacth Size: 32**
- **Random Forest Estimator: 100 trees.**

A. Results

The suggested SECNN-RF architecture achieved cutting-edge performance in the early detection of Alzheimer's disease using MRI data. The key findings are as follows.

Accuracy: The SECNN-RF model achieved a classification accuracy of 83.06%, outperforming existing frameworks such as CAD-ALZ and traditional CNN-based techniques. The fig. [2]. shows the Accuracy vs Epochs and the fig. [3]. shows the Loss vs Epochs graph.

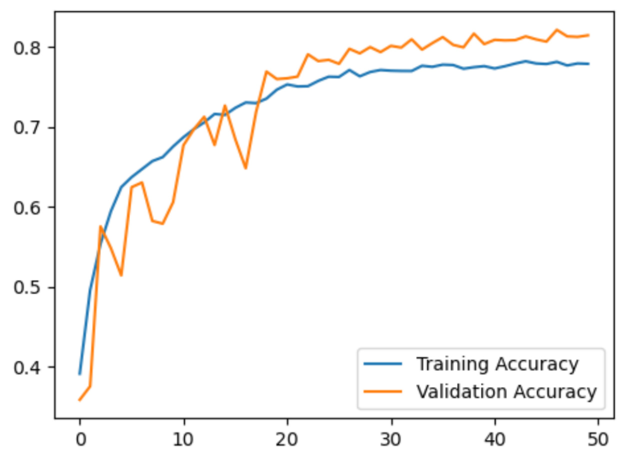

Fig. 2. Accuracy Vs Epchos

Explainability: The use of saliency maps improved interpretability by emphasising key locations in MRI scans that influenced categorisation decisions. This feature improves clinician trust and understanding of the model's predictions fig. [5].

Robustness: Preprocessing approaches such as normalisation, data augmentation, and SMOTE were helpful in addressing class imbalance, resulting in increased generalisability across various datasets.

SECNN-RF:Achieved the highest accuracy while reducing trainable parameters.

Efficiency: The SECNN-RF architecture is computationally efficient and appropriate for use in resource-constrained healthcare environments. It delivered tremendous performance while being lightweight.

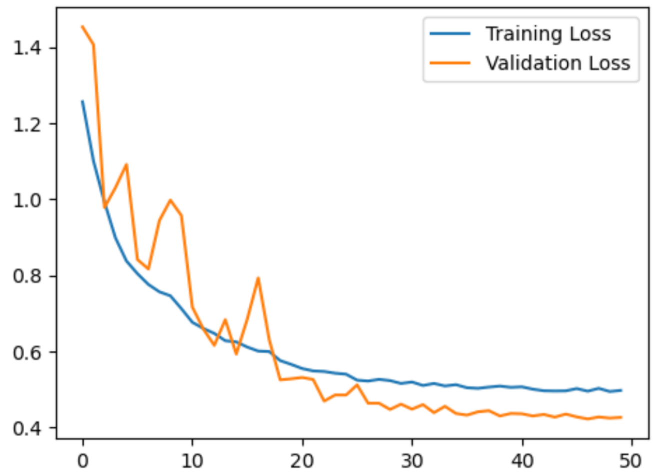

Fig. 3. Loss VS Epochs

TABLE II
CLASSIFICATION REPORT

Classes	Precision	Recall	F1-Score
Mild Demented	0.82	0.87	0.85
MOderate Demented	0.97	1.00	0.98
Non Demented	0.81	0.68	0.74
Very Mild Demented	0.65	0.70	0.67

Metrics Evaluation:The SECNN-RF model for Alzheimer's diagnosis was found to be robust and reliable, as evidenced by precision, recall, and F1 scores shown in table II and fig.[4]. shows the confusion matrix representation.

A saliency map is a visual representation that highlights the most important regions in an input image that influence a model's decision.It helps us understand why a model made a particular prediction by showing which parts of the image had the greatest impact on the model's output.

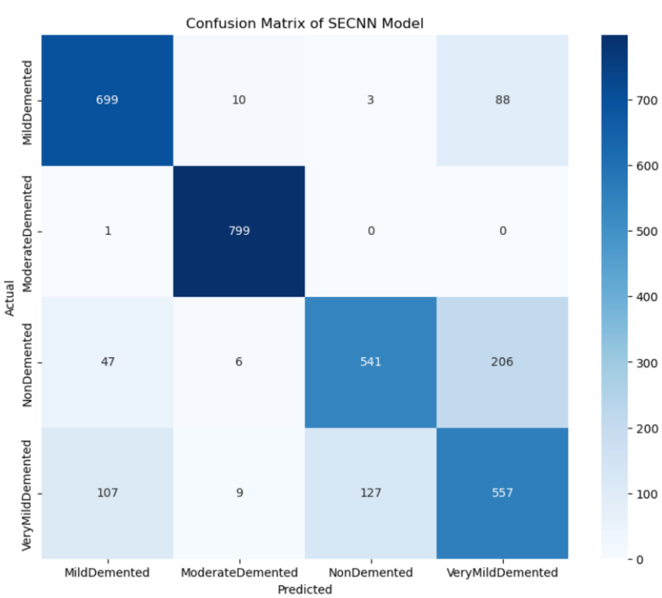

Fig. 4. Cofusion Matrix

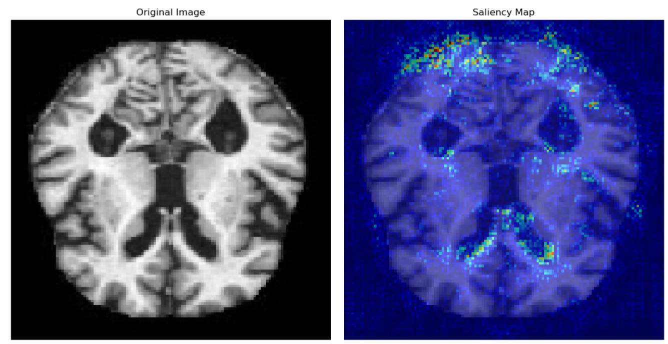

Fig. 5. Prediction of Alzheimer's disease using saliency map

VI. CONCLUSIONS

Early detection of Alzheimer's disease(AD) is crucial for ensuring timely and effective treatement,as therapies are most effective in the early stages.Although AI-based methods have a lot of potential to improve AD diagnosis through neuroimaging, their opaque decision-making process has prevented broad clinical adoption. In order to solve the issues of accuracy and interpretability in MRI-based AD diagnosis, this study suggests a unique framework called the Squeeze-and-Excitation Convolutional Neural Network with Random Forest (SECNN-RF), which blends explainability with cutting-edge AI approaches.

The authors proposed a novel hybrid framework,the Squeeze and Excitation Convolutional Neural Network with Random Forest(SECNN-RF). The SECNN integrated Squeeze and Excitation(SE) blocks to focus on critical features,while Dropout layers prevented overfitting.Features extracted by SECNN were classified using a Random Forest classifier,ensuring both accuracy and interpretability.Additionally,saliency maps were used to explain model predictions visually.

The SECNN model achieved a remarkable accuarcy 83.06% on Alzheimer's disease test dataset,outperforming state-of-the-art models.It also demonstrated high precision,recall,and F1-score,highlighting its robustness and reliability.The model provided interpretable visual insights through saliency maps,making it suitable for clinical applications.

The SECNN-RF framework outperformed all state-of-the-art models by achieving greater accuracy, with fewer trainable parameters. The result was an important improvement in computational efficiency. This classifier outperformed a standard CNN architecture, one that relies on a dense SoftMax layer for classification. The use of SE blocks allowed the model to dynamically pay attention to important traits; this led to greater performance over competing strategies.the framework to diagnose other medical conditions, using a variety of modalities.

A. Future Work:

Investigate applying complex explainability techniques like Grad-CAM, LIME, or SHAP to provide more comprehensive insights.

Validate the system on bigger and more diverse datasets like ADNI to see how well it generalizes.

Consider other ensemble classifiers and deep learning algorithms that might enhance these models.

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