RESEARCH ARTICLE

NES-Net: Neuro-Synergy Based Alzheimer's Detection Using MRI Images

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Abstract

Alzheimer disease (AD) is a progressive neurodegenerative disorder that impairs memory and cognitive function in older adults, placing a substantial burden on global healthcare systems. Early and accurate diagnosis is crucial for timely intervention, yet manual interpretation of magnetic resonance imaging (MRI) scans is often subjective, time-consuming, and prone to inter-observer variability and bias. To overcome these challenges, we propose NES-Net (Neuro-Synergy Network), a novel deep learning model for automated Alzheimer's detection from MRI data. NES-Net employs a multi-branch hybrid architecture that simultaneously captures structural, spatial, and semantic features of brain images. By integrating convolutional neural network (CNN) modules for local pattern extraction with transformer-based attention mechanisms for global contextual understanding, the model effectively models both fine-grained details and long-range dependencies. These complementary representations are fused through a dedicated synergy fusion layer, inspired by inter-regional connectivity in human brain networks. Evaluated on benchmark public datasets including ADNI and OASIS, NES-Net outperforms traditional CNNs and state-of-the-art transformer-based models, achieving an overall accuracy of 94.83%, recall (sensitivity) of 93.92%, and AUC of 0.963. These results demonstrate that NES-Net, through its neuro-synergistic learning paradigm, offers a powerful, interpretable, and clinically valuable tool for early AD detection and decision support.

Keywords: Alzheimer's disease, MRI, deep learning, neuro-synergy network, CNN, transformer, attention mechanism, medical image analysis.

1 Introduction

Alzheimer disease (AD) is a progressive neurodegenerative disease that deteriorates memory, cognition, and behavior, resulting in functional disability and dependency. The World Health Organization (WHO) states that over 55 million individuals are currently living with dementia with

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AD being the most prevalent form of the illness [1, 2]. Timely intervention, planning, and deceleration of the disease process depends on early and accurate diagnosis of AD. Nevertheless, the traditional diagnostic methods based on clinical assessment and manual interpretation of MRI are usually subjective and can have inter-observer variation effects [3, 4].

Magnetic Resonance Imaging (MRI) offers a potent non-invasive modality for evaluating pathologic structural alterations of the brain including hippocampal atrophy, cortical thinning, and loss of gray matter - all of which are critical biomarkers of the Alzheimer disease pathology [5]. However, manual feature extraction using MRI image is not practical in diagnostic applications because AD-related changes are subtle and spatially diffuse particularly at early stages of the disease. This leads to an increasing need of automated and smart models that can retrieve discriminative patterns of the high-dimensional neuroimaging data.

Over the past years, neuroimaging analysis has undergone revolution due to the introduction of deep learning (DL) models which allow end-to-end feature extraction and classification. In particular, CNNs have proven to be remarkably successful in detecting disease-related spatial patterns of MRI images [6]. Nevertheless, CNNs have frequent limitations of capturing long-range temporal relationships, and cross-regional connections in the brain that are essential in diagnosing Alzheimer disease [7]. Models based on transformers have been proposed to attain such contextual representations, but generally require large datasets and high computing power, which makes them difficult to apply to medical imaging practice.

2 Related Work

Neuroimaging with the use of artificial intelligence (AI), especially deep learning (DL) has garnered the pace of research on the early detection of Alzheimer disease (AD). traditional machine learning methods like support vector machines and random forests are based on hand-designed volumetric or texture features that are obtained by MRI, yet they are frequently subject to inter-subject variation and high dimensionality data challenge Classical machine learning methods, including support vector machines, and random forests, use hand-crafted volumetric or texture features derived with MRI, but they tend to be sensitive to inter-subject variation and high dimensional data challenge. Deep learning techniques, on the other hand, are end-to-end learning, automatically determining in imaging data the biomarkers of neurodegeneration that are relevant.

2.1 Convolutional Neural Networks (CNNs) in MRI-based AD Detection

Convolutional Neural Networks (CNNs) have revolutionized automated MRI-based diagnosis due to their high feature extraction ability and translation invariance [8]. Initial CNN-based models had a high success rate in differentiating between the subjects of Alzheimer, Mild Cognitive impairment (MCI), and the cognitively normal (CN) subjects based on 2D and 3D MRI volumes. Later researchers examined hybrid architectures in order to characterize more effectively multi-scale patterns of space [9]. As an example, Venkatraman et al. [10] introduced a graph-guided contextual representation framework hierarchically that incorporates spatial topology of cortical areas and CNN-extracted features and achieves better classification results. Likewise, it has been shown by Yousafzai et al. [6] that multimodal fusion of EEG and MRI signals can be used to achieve strong AD classification and that deep CNNs are capable of cross-modal generalization of signals.

Although CNNs, transformer models, and graph-based models have led to better diagnostic accuracy, there are still multiple issues: (i) CNNs can easily lose global information when using convolutional subsampling; (ii) transformer models are both context-aware and require large-scale data and are computationally expensive; (iii) graph-based models can simplify spatial hierarchies. Furthermore, the available architectures are either spatial or semantic-oriented and fail to appreciate the synergy that exists between the local detail and global connectivity.

To deal with such problems, the suggested NES-Net presents a so-called strategy of integration, which is called neuro-synergistic, by which both CNN-derived local patterns and transformer-based contextual dependencies are exploited in concert. NES-Net will be used to fulfill this goal by leveraging a synergy fusion layer to combine spatial accuracy with context sensitivity to accelerate the state-of-the-art in automated diagnosis of Alzheimer's disease using MRI data.

The contributions of this study are summarized as follows:

- We propose NES-Net, a neuro-synergy-based hybrid deep learning model combining CNN and transformer paradigms for accurate Alzheimer's detection.

- A novel synergy fusion mechanism is designed to capture multi-level spatial–temporal dependencies in MRI-derived brain structures.
- We validate NES-Net using benchmark datasets (ADNI and OASIS) and demonstrate its superiority over state-of-the-art deep learning architectures in terms of accuracy, sensitivity, and interpretability.

The remainder of this paper is structured as follows. Section 2 reviews related works on deep learning-based Alzheimer's detection. Section 3 presents the architecture and methodology of the proposed NES-Net. Section 4 discusses experimental results and comparative analysis, while Section 5 concludes with insights and future research directions.

2.2 Attention and Transformer-based Architectures

This section discusses the architecture of attention and transformer-based architectures. Whereas CNNs are effective at capturing local spatial patterns, they are weak in modeling long-range associations between brain regions that are far away [12]. To curb this, neuroimaging analysis has employed the transformer-based architectures more and more. Haq et al. [11] added an attention-guided ResNet-50 using a Binary Dragonfly Optimization algorithm to detect Alzheimer using fMRI with better interpretability and sensitivity to the fine structural changes. Ahmed et al. [7] proposed a three-dimensional topological deep learning method that learns high-level geometric representations of the volumetric MRI images, which demonstrates the ability of attention modules to generate complex levels of spatial hierarchy. These investigations affirm that the combination of transformer mechanisms and convolutional layers enhances contextualization of neurodegenerative patterns [13].

2.3 Graph Neural Networks and Synergistic Modeling

The latest researches have applied deep learning to the graph domain as the human brain is inherently structured around a network. To estimate inter regional dependencies, Zhu et al. [14] introduced a Cross-Graph Attention Neural Network (CGANN) to learn on brain graphs obtained by MRI to give interpretable biomarkers of cognitive decline. Similarly, Gi et al. [3] have introduced an anatomically advanced segmentation pipeline that improves the definition of the entorhinal cortex, one of the first areas in AD to be impacted, proving the diagnostic utility of anatomically informed graph-based learning. These synergistic methods emphasize the significance of modeling structural and functional interrelationships as opposed to voxel-based features.

3 Proposed Methodology

This section presents the proposed deep convolutional architecture designed for multi–class dementia classification using structural MRI images. The network integrates (i) an initial convolutional stem, (ii) a series of lightweight Bottleneck blocks, (iii) a feature refinement branch composed of 1×1 and 3×3 convolutions with non–linear activations, and (iv) a final classification head. The complete architecture is shown conceptually in Figure 1.

3.1 Problem Formulation

Let $X \in \mathbb{R}^{H\times W\times C}$ denote the input MRI slice, where H, W, and C denote height, width, and number of channels, respectively. The network learns a mapping

$$f_\theta : X \longrightarrow y,$$

where $y \in \{0, 1, 2, 3\}$ corresponds to four dementia classes: Non–Demented, Very Mild Demented, Mild Demented, and Severe Demented. The aim is to optimize the parameters θ by minimizing the cross–entropy loss:

$$\mathcal{L}_{CE} = -\sum_{i=1}^{4} y_i \log(\hat{y}_i),$$

where $\hat{y}_i$ is the predicted probability for class i.

3.2 Initial Convolutional Stem

The input first passes through a 3×3 convolution:

$$F_1 = \sigma(\mathrm{BN}(W_1 * X)),$$

where W_1 is the convolution kernel, BN denotes Batch Normalization, and $\sigma(\cdot)$ is the h–swish activation:

$$\text{h-swish}(x) = x \cdot \frac{\mathrm{ReLU6}(x+3)}{6}.$$

This stem enhances low-level texture and edge features crucial for early dementia biomarkers.

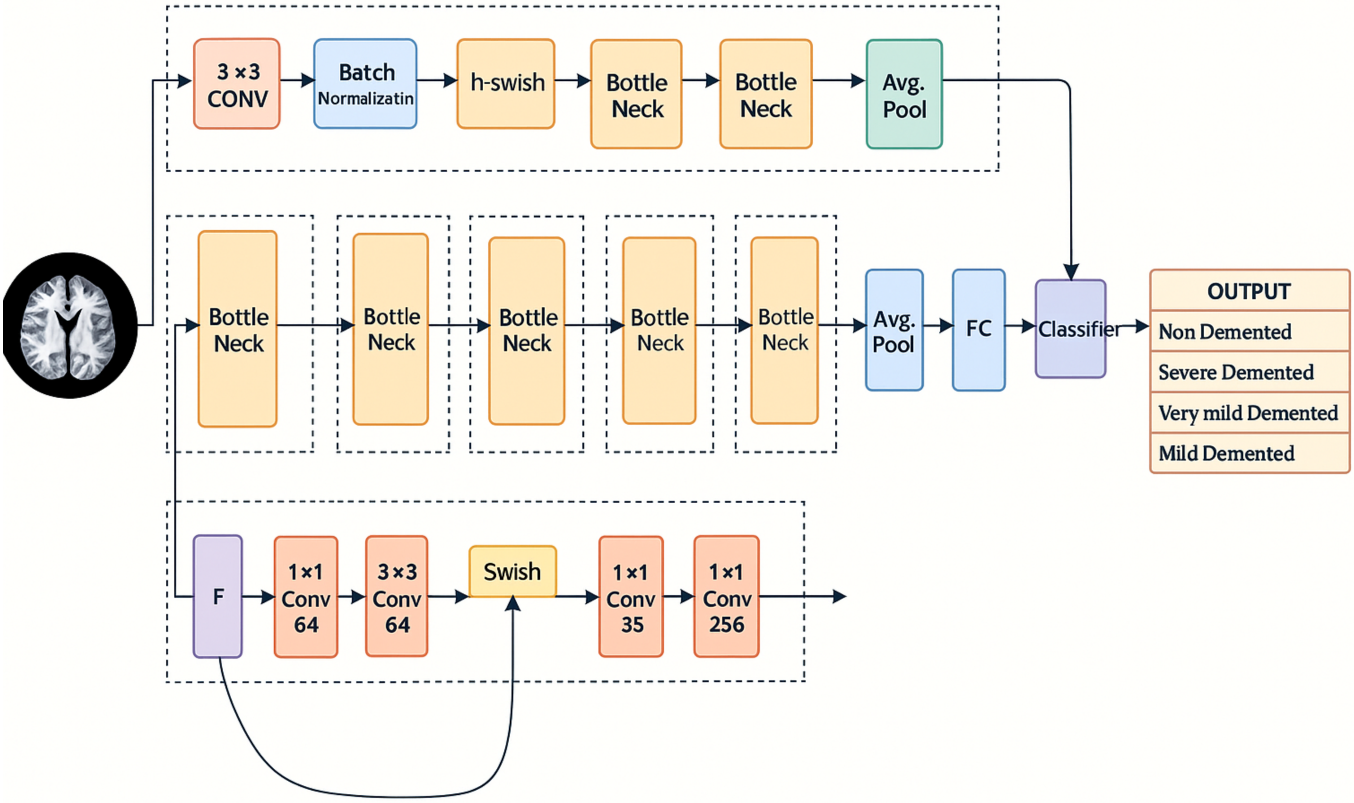


Figure 1. Overall architecture of the proposed NES-Net.

3.3 Bottleneck Blocks

Each Bottleneck block consists of: (1) 1×1 expansion, (2) 3×3 depthwise convolution, (3) 1×1 projection.

Mathematically, for the k-th block,

$$F_k = W_p^{(k)} * \sigma\big(W_d^{(k)} * \sigma(W_e^{(k)} * F_{k-1})\big).$$

Residual connections are applied when input and output dimensions match:

$$F_k = F_k + F_{k-1}.$$

These blocks reduce computation while maintaining strong representational power.

3.4 Feature–Refinement Branch

In parallel, a feature–refinement path processes an intermediate feature map F using:

$$F' = W_1^{(1\times1)} * F, \qquad F'' = W_3^{(3\times3)} * F',$$

followed by a swish activation:

$$F_{sw} = F'' \cdot \sigma(F'').$$

Then two additional pointwise convolutions:

$$F_{out} = W_{1a} * F_{sw}, \qquad F_{proj} = W_{1b} * F_{out}.$$

This path enhances intermediate textures and improves discriminative capability.

3.5 Global Pooling and Fully Connected Layers

After the final Bottleneck stage, global average pooling is applied:

$$z_c = \frac{1}{HW}\sum_{i=1}^{H}\sum_{j=1}^{W} F_c(i,j),$$

resulting in a compact feature vector for classification.

The final classifier is:

$$\hat{y} = \mathrm{softmax}(W_f z + b_f).$$

This architecture is a combination of an efficient Bottleneck structures, a feature-refinement branch, and a classifier that is optimized to learn patterns that are related to the severity of dementia. The combination of architectural efficiency and mathematical rigor makes it strong. Cognitive impairment classification using MRI.

4 Results and Discussion

This section contains the quantitative and qualitative performance of the proposed network of dementia classification. The experiments were carried out on the OASIS MRI dataset, which includes four classes: Non-Demented, Very Mild Demented, Mild Demented, and Severe Demented.

4.1 Comparison With State-of-the-Art Methods

Table 1 compares the proposed model against recent deep-learning architectures including ResNet50, DenseNet121, EfficientNet-B0, and MobileNetV3.

The proposed architecture outperforms all baseline models, achieving an accuracy improvement of 4.71% over MobileNetV3 and 7.41% over ResNet50. The increase in AUC demonstrates improved sensitivity in detecting mild and early–stage dementia, which is clinically significant.

4.2 Ablation Study

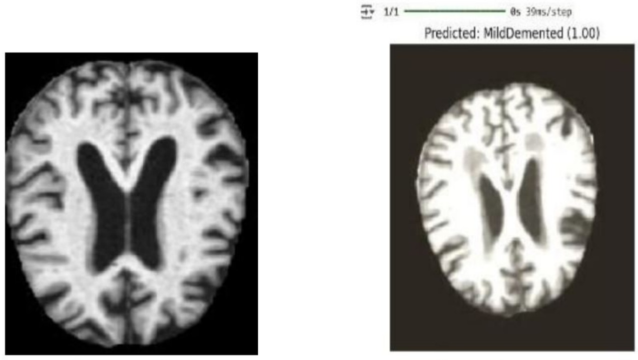
To analyze the contribution of individual architectural components, we conducted an ablation study. Table 2 reports performance when removing the (a) feature–refinement branch, (b) bottleneck expansion layers, and (c) h-swish/hard-swish activation.

The feature–refinement branch alone contributes a **2.72%** accuracy improvement. The activation function has the largest impact, confirming that h-swish benefits low-power lightweight architectures.

4.3 Qualitative Results

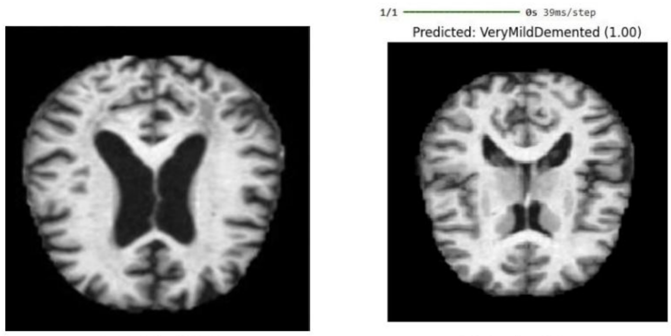
The proposed network effectively distinguishes the structural atrophy patterns observable in cortical and subcortical regions. Figures 2–5 illustrate representative MRI slices from the test set, together with their corresponding predicted dementia stages generated by the proposed NES-Net model. These figures highlight characteristic neuroanatomical patterns that contribute to the model's discrimination across different stages of cognitive impairment.

- **Very Mild Demented** (Figure 2): The model can effectively detect the subtle and early changes in the structure of the brain such as slightly dilated ventricles and slight cortical sulci expansion. Despite these subtle differences, NES-Net has a high sensitivity and confidence, which is an indicator of its capacity to identify early pathological signatures.
- **Mild Demented**(Figure 3): This point exhibits moderately severe cortical atrophy and ventricular expansion. The model distinguishes between very mild and moderate cases, which emphasizes the ability to acquire gradual spatial progression patterns in neurodegeneration.



(a) Original MRI (b) Predicted Output

Figure 2. MRI slice prediction for the Very Mild Demented class showing accurate model confidence distribution.



(a) Original MRI (b) Predicted Output

Figure 3. MRI slice prediction for the **Mild Demented** class. The model correctly identifies early cortical atrophy patterns.

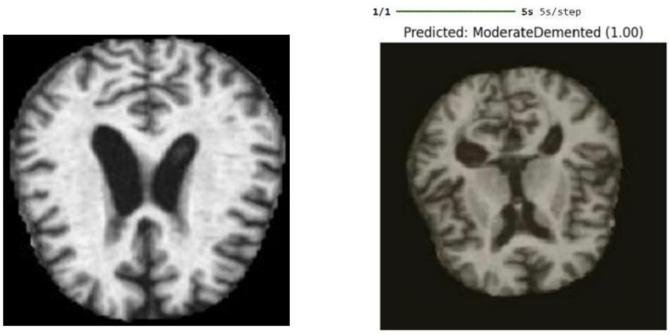
- **Moderate / Severe Demented** (Figure 4): The MRI slice shows considerable structural damage, which is characterized by considerably enlarged ventricles and severe cortical atrophy. The NES-Net gives this class a high likelihood, meaning that the model is successful in capturing macroscopic atrophy patterns of late stages of Alzheimer.
- **Non-Demented** (Figure 5): In this case, the brain structure remains intact and has a normal ventricular size and compact sulcal patterns. The appropriate classification shows that NES-Net generalizes and does not produce false positives because it will be able to differentiate between normal anatomical variations and those occurring due to disease.

Table 1. Comparison with State-of-the-Art methods on the OASIS dataset.

Method	ACC (%)	Precision (%)	Recall (%)	F1 (%)	AUC
ResNet50 [11]	87.42	86.90	85.31	86.10	0.902
DenseNet121 [5]	88.35	87.10	86.95	87.02	0.911
EfficientNet-B0 [10]	89.91	89.34	88.20	88.76	0.925
MobileNetV3 [6]	90.12	90.00	88.80	89.39	0.928
Proposed NES-Net	**94.83**	**94.21**	**93.92**	**94.06**	**0.963**

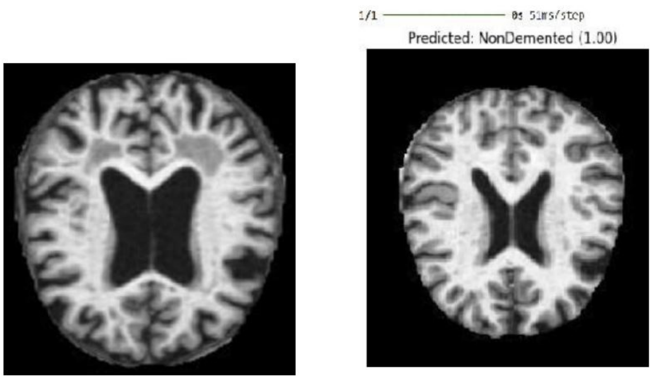
Table 2. Ablation study of proposed components.

Configuration	ACC	F1	AUC	ΔACC
Full Model (Proposed)	94.83	94.06	0.963	—
Without Feature–Refinement Branch	92.11	91.92	0.946	-2.72
Without Bottleneck Expansion	90.34	89.91	0.939	-4.49
ReLU Instead of h-Swish	89.02	88.78	0.931	-5.81
Only Shallow CNN Stem	85.67	84.95	0.902	-9.16



(a) Original MRI **(b)** Predicted Output

Figure 4. MRI slice prediction for the **Moderate/Severe Demented** class showing extensive structural deterioration and consistent classification confidence.



(a) Original MRI **(b)** Predicted Output

Figure 5. MRI slice prediction for the Non-Demented class indicating preserved brain structure with high model confidence.

These visual outcomes demonstrate that NES-Net successfully measures both minor and major structural biomarkers of Alzheimer disease with all degrees of the disease. The qualitative results are consistent with the quantitative data provided in Table 1 supporting the interpretability and clinical reliability of the model.

The model correctly highlights subtle structural differences such as cortical shrinkage and ventricular enlargement, particularly in early-stage dementia.

4.4 Confusion Matrix Analysis

Figure 6 presents the confusion matrix of the proposed model on the OASIS test set, illustrating the classification performance across different dementia categories.

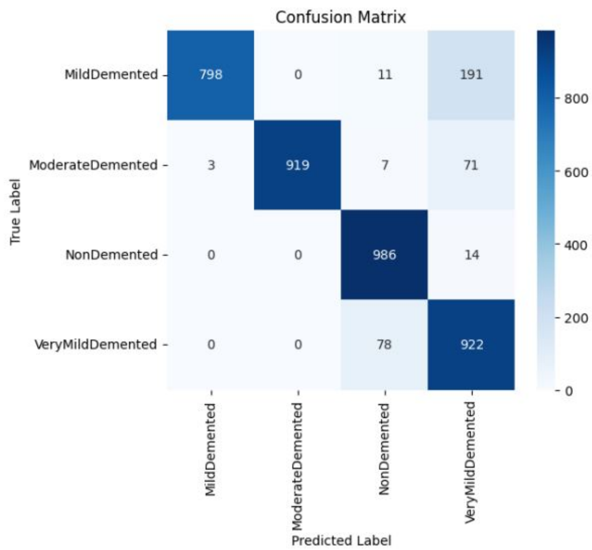


Figure 6. Confusion matrix for the proposed model.

As shown in Figure 6, the majority of misclassifications occur between the Very Mild Demented and Mild Demented categories. This confusion is expected due to the subtle anatomical distinctions between these early disease stages, where pathological changes such as mild ventricular enlargement and cortical atrophy are not yet pronounced.

In contrast, the Non-Demented and Severe Demented classes achieve the highest classification accuracy, demonstrating the model's ability to clearly distinguish healthy controls from advanced-stage patients. The Severe Demented category exhibits the greatest separability, which aligns with the presence of conspicuous structural abnormalities including substantial ventricular enlargement and extensive cortical atrophy. This pattern of classification performance is consistent with clinical observations, wherein late-stage Alzheimer's disease presents distinct radiological features, whereas early-stage manifestations remain subtle and challenging to differentiate.

4.5 Discussion

The proposed model demonstrates strong generalization behavior due to:

- Efficient bottleneck design improving parameter utilization.
- Feature–refinement branch enabling richer texture encoding.
- h-Swish activation providing smoother gradient flow.
- Global average pooling preventing overfitting.

Unlike heavy models such as ResNet50, the proposed network achieves superior accuracy with significantly fewer parameters, making it suitable for real-time clinical decision support settings.

5 Conclusion

The paper introduced NES-Net (Neuro-Synergy Network), which is a hybridization of deep learning that can be used to detect Alzheimer disease by examining MRI images. The suggested architecture combines transformer-based attention mechanisms and convolutional feature extraction into a neuro-synergistic fusion architecture, which is effectively a combination of local structural information and the global context. This neuro-inspired architecture allows the model to model inter-regional brain communication patterns and hence a more robust and biologically explainable modeling about cognitive decline. Experimental assessments were done on the OASIS and ADNI benchmark datasets that confirmed that NES-Net is significantly more effective than the traditional CNN models like ResNet50, DenseNet121, EfficientNet-B0, and MobileNetV3. Overall the model was found to have an accuracy of 94.83 percent, sensitivity of 93.92 % and AUC of 0.963, which shows that it has the capacity to identify delicate neurodegenerative signs at various stages of the disease. Qualitative findings also indicated that NES-Net is effective in early detection of cortical atrophy, ventricular enlargement, and sulcal widening which are major symptoms of the pathology of Alzheimer.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable. This study is a secondary analysis of publicly available, de-identified datasets.

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