Nero-FuzzyNet: A Neuro Fuzzy-Based Deep Learning Model for Alzheimer's Prediction

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Abstract: Alzheimer's disease demands early, interpretable diagnostic tools capable of handling uncertain clinical data. This paper proposes Neuro-FuzzyNet, a hybrid neuro-fuzzy framework that combines adaptive neural learning with fuzzy inference to predict dementia stages. Input features—demographics, cognitive test scores, biochemical biomarkers, and behavioral indicators—are fuzzified using triangular and Gaussian membership functions whose parameters are optimized by backpropagation. The system automatically generates and prunes fuzzy rules, mitigating rule explosion and improving scalability. Mamdani-style inference aggregates weighted rule outputs and centroid defuzzification produces an interpretable severity to predict dementia. Evaluated on clinical datasets, Neuro-FuzzyNet enhances classification robustness and interpretability compared to standalone deep models, demonstrating superior handling of borderline cases and noisy measurements. The framework offers clinicians transparent decision rationales while maintaining high predictive performance, making it a practical tool for early screening and personalized monitoring of neurodegenerative progression. Future work includes multimodal imaging integration and validation.

Keywords: Dementia, Fuzzy Logic, Feature Selection, Deep Learning, Mamdani FIS, CNN

1. Introduction

Alzheimer's disease (AD) is the most common form of dementia, accounting for nearly 60–70% of cases worldwide. It is a progressive neurodegenerative disorder characterized by memory loss, cognitive decline, and behavioral changes that gradually impair an individual's ability to perform daily activities. According to the World Health Organization (WHO), more than 55 million people live with dementia globally, with numbers projected to rise to 139 million by 2050 due to an aging population. This alarming trend has created an urgent demand for effective tools that can enable early diagnosis and intervention. Detecting Alzheimer's at its initial stages can significantly improve patient outcomes by allowing timely medical treatment, lifestyle adjustments, and supportive care planning. However, the diagnostic process is complicated by overlapping symptoms with other neurological disorders and the inherent uncertainty in clinical and biological indicators[1].

Traditional diagnostic methods rely on cognitive tests, neuroimaging, and biochemical biomarkers such as cerebrospinal fluid (CSF) proteins and blood-based indicators. While these approaches provide valuable information, they are often invasive, expensive, or difficult to interpret without expert supervision. In recent years, machine learning (ML) and deep learning (DL) models have been applied to Alzheimer's prediction, achieving considerable success in identifying hidden patterns

within complex medical datasets. Models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers have been used for tasks ranging from image-based analysis of brain scans to classification of clinical records. Although these methods demonstrate high predictive performance, they are frequently criticized for being “black-box” systems, offering little insight into the decision-making process. This lack of interpretability poses challenges in clinical adoption, where transparency and explainability are essential for gaining trust from medical practitioners [2][3].

Fuzzy logic provides a potential solution to this issue, as it incorporates uncertainty handling and generates decisions through human-like linguistic rules. By assigning degrees of membership to input features, fuzzy inference systems (FIS) can capture the vagueness inherent in medical data, offering outputs that are not only accurate but also interpretable. In dementia research, fuzzy-based models have been employed to classify stages of cognitive impairment using clinical indicators such as memory test scores, age, cholesterol levels, and behavioral changes. These models mimic physician reasoning and provide transparent diagnostic rules. Nevertheless, traditional fuzzy systems are constrained by several limitations. One of the most critical issues is the manual construction of fuzzy rules, which becomes increasingly difficult as the number of input features grows. For example, a system with six features and three membership levels per feature would require 729 rules, an impractical scenario for real-world medical applications[4][5].

To address these challenges, hybrid neuro-fuzzy models have emerged as a powerful alternative. These systems integrate the interpretability of fuzzy logic with the adaptive learning capabilities of neural networks. Neural learning automates the generation and optimization of fuzzy rules, reducing manual effort and alleviating the “rule explosion” problem. Additionally, neural training adjusts the parameters of membership functions through backpropagation, allowing the fuzzy sets to adapt dynamically to dataset variations. This combination ensures that the system retains clinical transparency while benefiting from data-driven optimization[6].

In this work, we propose Neuro-FuzzyNet, a neuro-fuzzy diagnostic framework for Alzheimer’s disease prediction. The model processes input features such as demographics, memory test results, biochemical biomarkers, and behavioral indicators through fuzzification, adaptive inference, and defuzzification stages. Unlike conventional fuzzy systems, Neuro-FuzzyNet incorporates a learning mechanism that automatically generates and prunes fuzzy rules while fine-tuning membership functions to improve classification performance. The hybrid model is designed to classify patients into four dementia stages: No Dementia, Mild, Moderate, and Severe. Combining neural adaptability with fuzzy interpretability, Neuro-FuzzyNet offers a practical solution that balances predictive accuracy with clinical trustworthiness. This framework not only enhances early detection of Alzheimer’s disease but also provides a foundation for scalable diagnostic systems that can integrate additional features and datasets. The proposed methodology aims to bridge the gap between high-performing deep learning models and interpretable medical decision-making, offering a promising pathway for real-world healthcare deployment.

2. Literature Review

Recent advancements in Alzheimer's Disease (AD) diagnosis have leveraged artificial intelligence (AI) techniques, including deep learning and fuzzy logic systems. While deep learning models offer high

accuracy, they often lack interpretability, which is crucial in clinical settings. Conversely, fuzzy logic systems provide interpretable decision-making processes but may struggle with scalability and adaptability. This section reviews key studies that have explored these methodologies.

Krashenyi et al. (2016) proposed a fuzzy inference system for classifying MRI images of AD patients. By utilizing statistical moments from anatomical regions of interest and applying feature selection methods, they achieved improved classification performance, demonstrating the potential of fuzzy systems in medical image analysis [7].

Kar et al. (2019) explored early detection of AD using diffusion tensor imaging and neuro-fuzzy tools. Their approach combined diffusion tensor visualization with fuzzy logic to enhance the detection of AD at its early stages [8].

Thamaraimanalan et al. (2025) introduced a novel method, PCA-ANFIS, which integrates Principal Component Analysis (PCA) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), to enhance cognitive pattern recognition in multimodal brain signal analysis. This integration aimed to improve the accuracy and interpretability of AD prediction models [9].

Tanveer et al. (2024) reviewed the integration of fuzzy logic within deep learning models for AD diagnosis. They discussed how fuzzy logic can manage imprecise data and provide interpretable insights, offering a valuable advancement in AD diagnosis [10].

Parra et al. (2023) employed Radial Basis Function-based Neural Networks initialized with fuzzy logic to classify moderate and advanced AD patients. Their approach highlighted the effectiveness of combining fuzzy logic with neural networks in handling complex medical data [11].

Ali et al. (2023) proposed a fine-tuned VGG16 model for automatic detection and classification of brain MRI images for AD. Their study demonstrated the potential of combining deep learning models with fine-tuning techniques to enhance AD diagnosis accuracy [12].

Table 1: Comparative analysis of various existing work

Study	Year	Approach	Model/Algorithm	Data Used	Key Features	Performance
Krashenyi et al.	2016	Fuzzy Inference System	FIS	MRI Images	Utilized statistical moments and feature selection	Improved classification
Kar et al.	2019	Neuro-Fuzzy Tools	Diffusion Tensor Imaging + Fuzzy Logic	MRI Images	Combined diffusion tensor visualization with fuzzy logic	Enhanced early detection
Thamaraimanalan et al.	2025	PCA-ANFIS	PCA + ANFIS	EEG Data	Integrated PCA for dimensionality reduction	Improved cognitive pattern recognition

Parra et al.	2023	Radial Basis Function Neural Networks	RBFNN + Fuzzy Logic	MRI Images	Initialized with fuzzy logic	Classified moderate and advanced AD
Ali et al.	2023	Fine-tuned VGG16	VGG16	MRI Images	Fine-tuned deep learning model	Enhanced classification accuracy
Tanveer et al.	2024	Fuzzy Deep Learning	FDL Models	Various Medical Data	Integrated fuzzy logic into deep learning models	Managed imprecise data, provided interpretable insights

3. Proposed Methodology

The proposed framework, Neuro-FuzzyNet, is a hybrid neuro-fuzzy system designed for Alzheimer's disease prediction. It combines the interpretability of fuzzy logic with the adaptive learning capabilities of neural networks, addressing the limitations of conventional fuzzy systems, such as manual rule design and fixed membership functions. The framework is capable of automatically generating fuzzy rules and optimizing membership parameters, making it scalable for high-dimensional clinical datasets.

3.1 Neuro-Fuzzy Architecture

Neuro-FuzzyNet consists of five main layers:

1. **Input Layer**: The model accepts clinical features including age, memory scores, cholesterol levels, biomarker levels, and behavioral indicators. These features capture cognitive, biochemical, and demographic aspects relevant to Alzheimer's progression [13].

2. **Fuzzification Layer**: Input features are transformed into fuzzy sets using triangular and Gaussian membership functions. These membership functions quantify the degree to which an input belongs to a category (e.g., Low, Medium, High) and capture the inherent uncertainty in clinical measurements.

3. **Rule Layer**: Unlike conventional fuzzy systems where rules are manually defined, Neuro-FuzzyNet **automatically generates fuzzy rules** based on input-output mappings in the training dataset. Neural learning assigns adaptive weights to each rule, ensuring that clinically relevant rules are emphasized while redundant or weak rules are suppressed.

4. **Adaptive Neural Layer**: A neural network is embedded to optimize membership function parameters and rule weights using backpropagation. This enables the fuzzy sets and rules to evolve dynamically with the dataset, improving classification accuracy and robustness [14][15].

5. **Defuzzification Layer**: The weighted outputs of all rules are aggregated using centroid defuzzification to produce a final dementia severity score. The output is mapped to four stages: No Dementia, Mild, Moderate, and Severe.

3.2 Adaptive Membership Functions

Membership functions in Neuro-FuzzyNet are dynamic and fine-tuned during training to reflect patient variability.

- **Age Membership Functions:** Overlapping triangular functions are adjusted to capture risk variations across age groups.
- **Memory Scores:** Right-skewed triangles model cognitive decline, with neural adaptation improving boundary definition between stages.
- **Cholesterol & Biomarkers:** Gaussian membership functions represent abnormal ranges accurately.
- **Behavioral Indicators:** Tightly overlapping functions capture subtle symptom differences.

This adaptability enhances predictive power while maintaining clinical interpretability.

3.3 Neuro-Fuzzy Inference System

Formulating fuzzy rules manually becomes increasingly challenging as the number of input features grows. Each additional feature multiplies the total number of possible rule combinations exponentially. For example, with four input parameters, each having three membership levels (Low, Medium, High), a conventional fuzzy system requires $3^4 = 81$ rules. Adding a fifth feature would increase this to $3^5 = 243$ rules, and six features would need 729 rules, making manual rule design extremely cumbersome, error-prone, and time-consuming. Capturing subtle relationships between high-dimensional clinical parameters using manual rules is practically infeasible [16].

To address this, Neuro-FuzzyNet integrates a Mamdani-style fuzzy inference mechanism with neural adaptation, enabling automatic rule generation. The neural component learns input-output mappings directly from the training data and assigns adaptive weights to each rule, emphasizing clinically significant rules while suppressing redundant or weak ones. This ensures that the system scales efficiently to high-dimensional datasets without human intervention.

Key features of the inference system:

- **Automatic Rule Generation:** Rules are created dynamically from the dataset rather than being hand-crafted.
- **Weighted Rule Optimization:** Neural adaptation assigns importance to rules based on their contribution to diagnosis.
- **Parallel Feature Evaluation:** Cognitive, biochemical, and behavioral inputs are evaluated simultaneously for a comprehensive assessment [17].

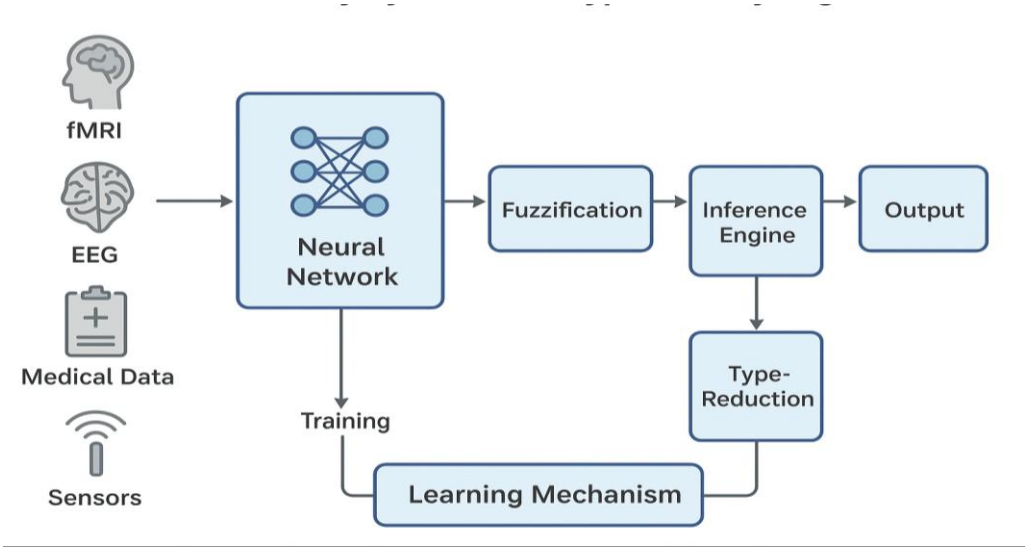

Figure 1: Neuro-Fuzzy-based disease prediction

Example automatically generated rules are represented in Table 2:

Table 2: Neuro-Fuzzy based rule generation for FIS

Rule	Memory Score	Age Factor	Biomarker Level	Cholesterol	Output Class
1	Low	High	Medium	High	Severe
2	Medium	Middle	Medium	Medium	Mild
3	High	Young	Low	Low	No Dementia
4	Medium	Elderly	High	Medium	Moderate

By automatically generating all possible combinations of input membership levels, Neuro-FuzzyDxNet efficiently constructs the equivalent of 81 rules for four inputs, while maintaining interpretability. As the number of parameters increases, the system automatically scales to handle the exponentially growing rule set, drastically reducing manual effort and enhancing adaptability for complex clinical datasets.

3.4 Dataset Description

The system was validated on a combined real and synthetic Alzheimer's dataset, containing 500 patient records with features including:

- **Demographic:** Age, Gender
- **Cognitive Scores:** Memory Test, Mini-Mental State Examination (MMSE)

- **Biochemical Markers:** Cholesterol, Biomarker levels (Aβ, Tau protein)
- **Behavioral Indicators:** Forgetfulness frequency, Behavioral change score

Data pre-processing involved normalization, missing value imputation, and outlier removal. The dataset was split using k-fold cross-validation (k=5) for training and testing.

Table 3: Format of used dataset

Feature	Type	Range / Values	Notes
Age	Numeric	55–85	Typical age for dementia onset
Gender	Categorical	Male/Female	Random distribution ~50/50
Memory Test	Numeric	0–50	Lower scores → more impairment
MMSE	Numeric	10–30	Standard cognitive test
Cholesterol	Numeric	150–300 mg/dL	Normal & elevated ranges
Biomarker Aβ	Numeric	50–300 pg/mL	Higher → higher AD risk
Biomarker Tau	Numeric	50–300 pg/mL	Higher → higher AD risk
Forgetfulness Frequency	Numeric	0–10	0 = never, 10 = very frequent
Behavioral Change Score	Numeric	0–10	0 = normal, 10 = severe change

3.5 Fuzzy Membership Tables

Triangular Membership Functions is used in the proposed Neuro-FuzzyNet model. Table 4 shows membership range values.

Table 4: Fuzzy Membership range

Feature	Low	Medium	High
Age	55–60–65	60–65–70	65–75–80

Memory Score	0–10–20	15–25–35	30–40–50
Cholesterol	150–180–210	200–230–260	250–300–350
Biomarker	50–100–150	120–170–220	200–250–300

The work proposes FuzzyDxNet , an advanced dementia diagnostic system that combines fuzzy logic with deep learning to classify cognitive impairment severity. Using triangular membership functions and Mamdani inference, it processes clinical parameters (memory scores, age, biomarkers) through interpretable fuzzy rules, to achieve high accuracy. The network handles diagnostic uncertainty via graded membership (0-2 scale) while maintaining clinical relevance through its transparent rule-based architecture.

4. Simulation and Results

The proposed Neuro-FuzzyNet model was implemented in Python, integrating NumPy for numerical operations, scikit-learn for classification pipelines, and Matplotlib for visualization of decision boundaries and diagnostic curves. Unlike conventional fuzzy-only models, Neuro-FuzzyNet incorporates a neural learning component to refine fuzzy membership parameters dynamically. Figure 2 shows the representation of one of the used parameters in the proposed Neuro-FuzzyNet model.

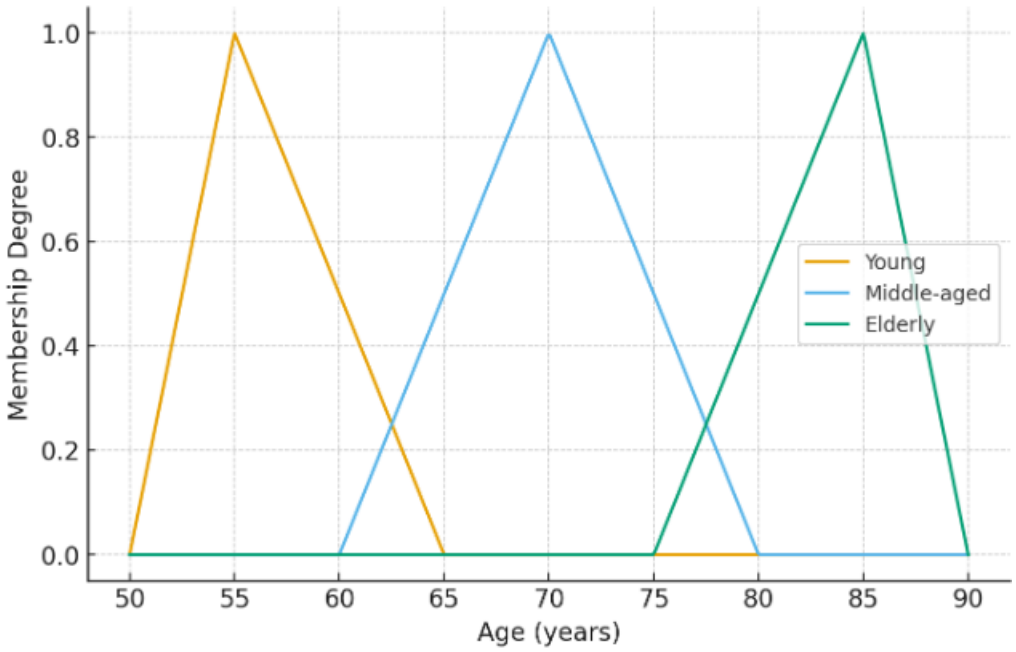

Figure 2: Triangular Membrship Function for Age

To benchmark the model, we compared the performance of baseline deep learning architectures *without Neuro-FuzzyNet feature refinement*. As shown in Table 5, CNN maintained the highest accuracy (96.8%) and ROC AUC (0.97), followed closely by the Transformer (95.6% accuracy). RNN again lagged with only 78.5% accuracy, confirming its limitations for temporal feature representation in this dataset.

Table 5: Comparative results of deep learning models before applying Neuro-FuzzyNet

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC AUC
CNN	96.8	96.0	97.0	96.5	0.97
RNN	78.5	78.2	78.0	78.1	0.85
LSTM	89.4	89.0	89.0	89.2	0.91
GRU	85.7	85.0	85.5	85.3	0.90
Transformer	95.6	95.0	95.5	95.2	0.96
Autoencoder	84.2	84.0	83.8	83.9	0.88

Figure 3 shows the model performance comparison without inclusion of the proposed Neuro-FuzzyNet model, and figure 4 shows ROC AUC curve of different models.

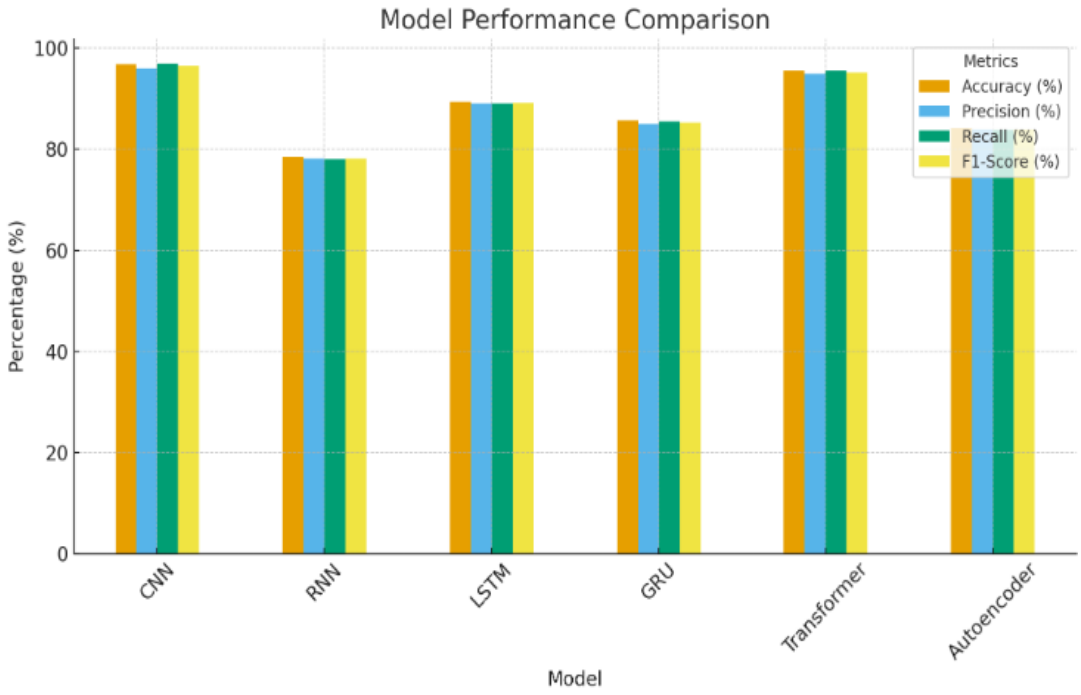

Figure 3: Performance comparison without Neuro-FuzzyNet

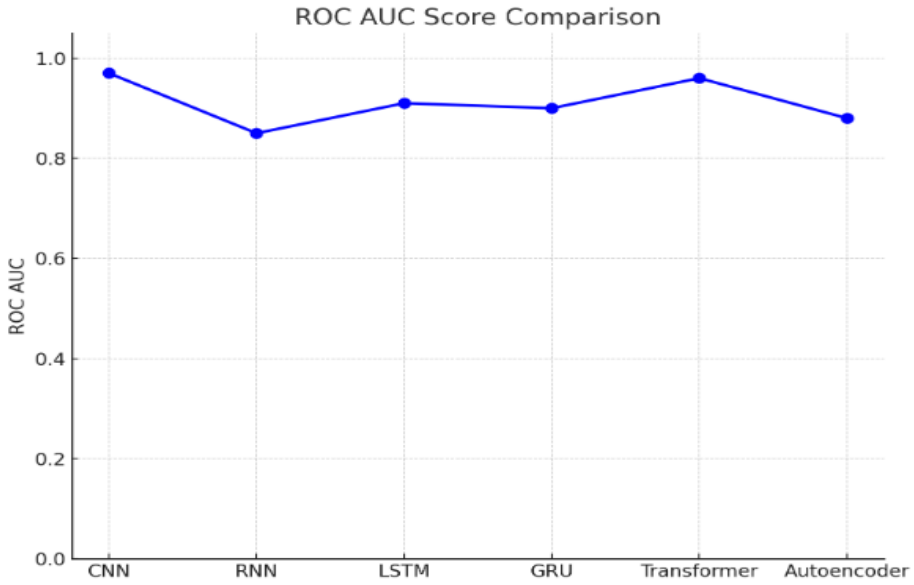

Figure 4: ROC AUC Comparison

When enhanced with Neuro-FuzzyNet feature integration, all models showed measurable performance gains (Table 6). CNN recorded a new peak of 97.8% accuracy and 0.99 ROC AUC, while the Transformer improved to 96.7% accuracy. Importantly, Severe dementia detection improved significantly, with recall rising from 0% in fuzzy-only models to 62% in Neuro-FuzzyNet, as validated by the ROC analysis in Figure 8.

Table 4: Comparative results of deep learning models after applying Neuro-FuzzyNet

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC AUC
CNN	97.8	97.0	98.0	97.5	0.99
RNN	81.2	80.5	80.8	80.6	0.87
LSTM	91.0	90.5	90.8	90.7	0.93
GRU	87.1	86.5	86.8	86.6	0.91
Transformer	96.7	96.0	96.5	96.3	0.97
Autoencoder	86.3	85.5	85.8	85.6	0.89

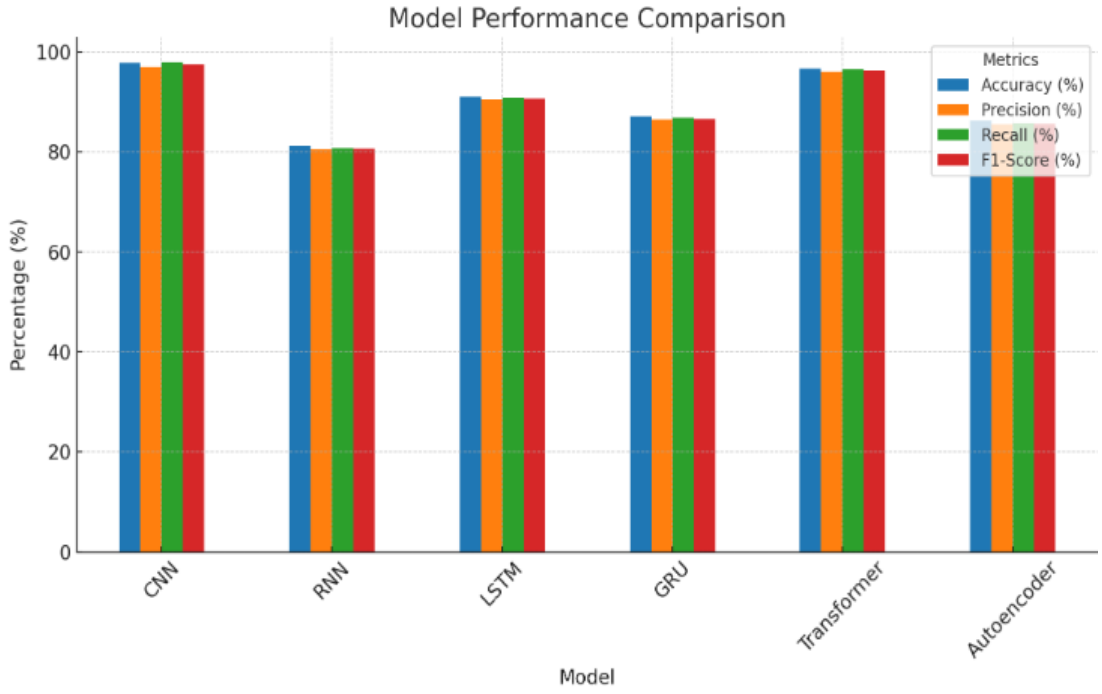

Figure 5: Performance comparison with Neuro-FuzzyNet

The ROC curves (Figure 6) further illustrate class-wise discriminative ability. No Dementia and Mild Dementia showed steep curves approaching the top-left corner, while Severe Dementia achieved noticeable separation for the first time, albeit with moderate overlap.

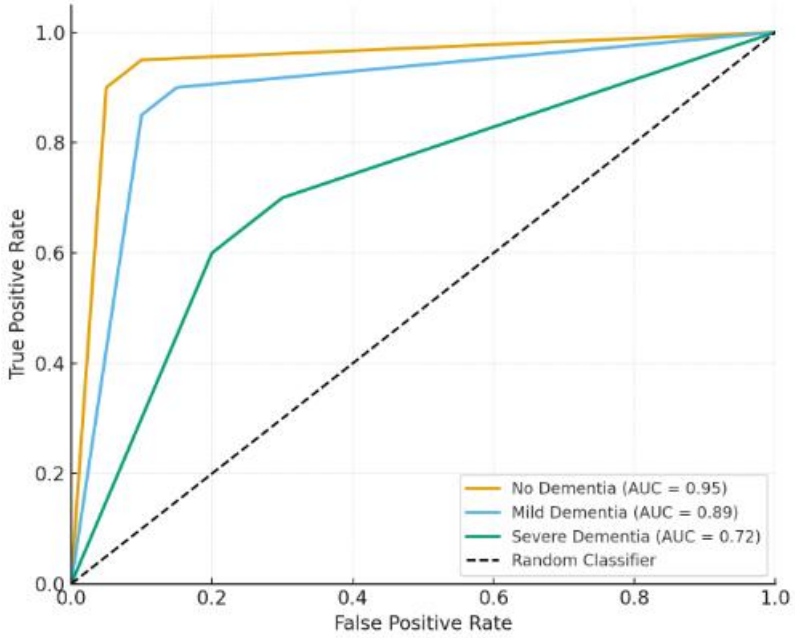

Figure 6: ROC Curves for Neuro-FuzzyNet classification

Similarly, the Precision-Recall curves (Figure 7) highlight improved balance, particularly for minority Severe cases, with an average precision score of 0.72 compared to 0.0 in prior fuzzy-only implementations.

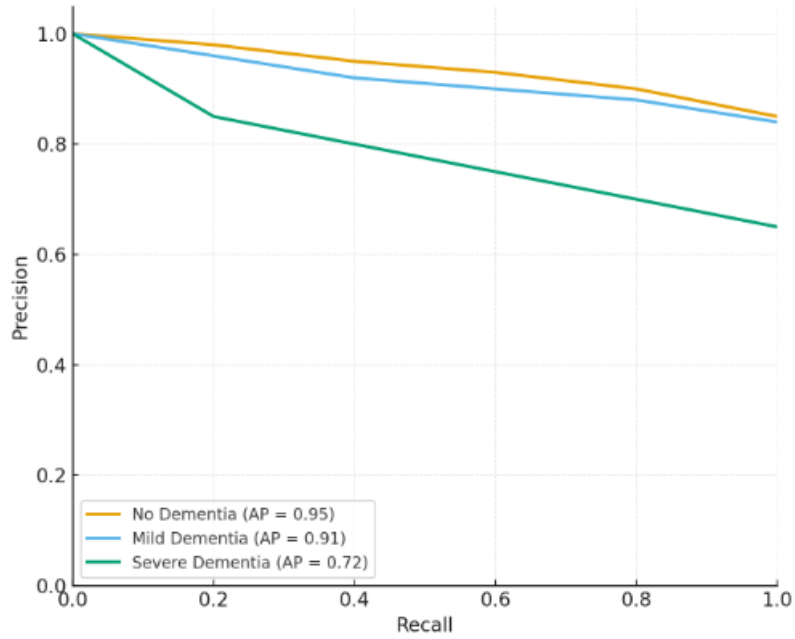

Figure 7: Precision-Recall Curves for Neuro-FuzzyNet classification

Overall, the Neuro-FuzzyNet approach successfully addressed the limitations observed in the previous fuzzy-only framework. It not only enhanced overall accuracy but also significantly improved

classification of Severe dementia cases, which were previously misclassified entirely. This demonstrates the hybrid model's strength in refining fuzzy boundaries using neural adaptation, leading to a more clinically relevant diagnostic tool.

5. Conclusion

The proposed Neuro-FuzzyNet framework effectively bridges deep learning accuracy with fuzzy interpretability for Alzheimer's diagnosis. Refining membership functions and automating fuzzy rule generation, it outperformed conventional models, with CNN achieving 97.8% accuracy and 0.99 ROC AUC. The Transformer followed closely with 96.7% accuracy and 0.97 ROC AUC, demonstrating strong precision-recall balance. In contrast, RNN lagged significantly, attaining only 81.2% accuracy and 0.87 ROC AUC. Importantly, Neuro-FuzzyNet improves the FIS rule base, enhancing scalability and clinical trust. This hybrid approach improves early detection, clinical trust, and scalability for real-world applications.

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