LG-FIS: A Hierarchical Local-Global Fuzzy Inference System for Multimodal Alzheimer's Disease Diagnosis

Mohammad Faiz[1], Dr. Vivekanandam[2], Dr. Pawan Whig[3]
[1] Lincoln University College, Malaysia; [2] Lincoln University, Malaysia; [3] VIPS-TC, India;
faiz.techno20@gmail.com, vivekanandam@lincoln.edu.my, pawan.whig@vips.edu

---

Abstract: The timely and precise diagnosis of the Alzheimer's disease problem is highly important because clinical manifestations are heterogeneous, and the data is unclear. As a means of multi-stage diagnosis of Alzheimer, the present paper suggests a hierarchical Local-Global Fuzzy Inference System (LG-FIS) that is a combination of clinical, cognitive and genetic modalities. All the modalities are fuzzified separately to produce local risk indices, which then are integrated using a global fuzzy decision layer. The experiments have shown higher accuracy in classification, excellent Early MCI detection, and healthy resistance to noisy inputs. The fuzzy framework is based on rules, and therefore, the fuzzy framework is highly interpretable to support the assessment of the Alzheimer's disease with clarity and clinical significance.

Keywords: Alzheimer's Disease, CNN, RNN, Multimodal Data Fusion, Explainable Artificial Intelligence

---

1. Introduction

Alzheimer disease (AD) is a progressive neurodegenerative disorder and the major cause of dementia across the globe, which has significant medical, social, and economic impact and is a severe challenge. The disease progression should be slowed, which can be achieved by early diagnosis, especially at the Mild Cognitive Impairment (MCI) stage and then providing better patient care [1]. Nevertheless, the diagnosis of Alzheimer is complicated by the heterogeneous symptoms, the overlapping stages and the uncertainties of the clinical, cognitive and genetic data. Conventional diagnostic methods are based on clinical examination, neuropsychological examination, and neuroimaging procedures MRI and PET. Although these techniques can be very insightful, they can be time-consuming, subjective, and require expert interpretation. In order to curb these shortcomings, computational models have also been much investigated [2]. Clinical and imaging features have been used to classify the stages of Alzheimer using statistical models and machine learning tools, including Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors [3]. These models though proven to be reasonably accurate, are prone to noise and feature selection. Most recently, machine learning based on deep learning, such as Convolutional Neural Networks (CNNs) and recurrent models have been used to extract features automatically to neuroimaging data. These models have a high classification rate, however are frequently black-box models, which inhibit ease of interpretation and clinical confidence. Moreover, deep learning methods usually need sizeable labeled datasets and cannot effectively make use of heterogeneous modalities. Another alternative that has come up is the use of fuzzy logic based systems which are capable of staging the uncertainty and the linguistic reasoning [4].

The Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and conventional fuzzy inference systems have been used in the diagnosis of Alzheimer using clinical and cognitive features. Though these methods

are more interpretable, they tend to use single-layer fuzzification that may result in information loss and failure to distinguish the close stages of the disease. These shortcomings underscore the need of diagnostic structures that can successfully combine multimodal data, deal with ambiguity, be resilient to noise, and deliver clear-cut decisions, which are important attributes of dependable clinical decision support structures in the diagnosis of Alzheimer's disease [5].

2. Literature Review

Li et al. in [1] suggested a residual attention network, which can be used to further improve the classification of images related to Alzheimer disease using MRI data. Their model made use of attention to concentrate on discriminative brain regions and better classification accuracy than traditional CNN architecture.

In [2], Gao et al. proposed a dense convolution based attention network to predict the stages of the Alzheimer disease. The analysis established that feature extraction under attention enhances inter-class separability especially between MCI and AD categories.

Zhou et al. in [3] suggested a hybrid deep learning model consisting of 3D CNN and Video Swin Transformer to diagnose early Alzheimer. Their method was powerful to get local structural characteristics, as well as long-range spatial dependencies of MRI volumes.

Yuan et al. in [4] have designed a better multi feature deep learning network to predict Alzheimer intelligently. Many handcrafted and deep features were combined in the model and improved the diagnostic efficiency at various disease stages.

In [5], the authors have provided a system review in Brain Informatics that examines machine learning and deep learning algorithms in the diagnosis of Alzheimer. The review has pointed out the issues associated with the heterogeneity of the data, overfitting, and interpretability in the available models.

In [6], a survey was written in Artificial Intelligence Review and surveyed the deep learning applications in Alzheimer disease, where CNNs, attention mechanisms, and multimodal fusion were found as the major trends, and explainable models were needed.

The authors of [7] carried out a systematic review of the literature in Informatics in Medicine Unlocked and compared deep learning and traditional machine learning methods to detect Alzheimer and therefore concluded that deep models are superior to classical classifiers in cases where there is adequate data.

In [8], an Artificial Intelligence in Medicine review examined recent ML and DL models to predict Alzheimer and found that multimodal and hybrid models have better accuracy, but can fail to explain their decision.

In [9], scientists summarized the MRI-based deep learning models of diagnostic features in the Alzheimer disease and highlighted the increasing dependency on large datasets and complexes, which could restrict clinical decodability.

A MRI classification study, [10], published in the Turkish Journal of Engineering, with a deep learning architecture, showed higher detection accuracy of Alzheimer with CNN architectures, but was sensitive to noise and changes in dataset.

Table 1: Comparative analysis of various existing work

Study	Year	Model	Data Used	Key Features	Limitation
Li et al.	2025	Enhanced Residual Attention Network	MRI	Attention-guided feature extraction to focus on discriminative regions	High accuracy, but computationally expensive; requires large labeled datasets
Gao et al.	2025	Dense Convolutional Attention Network	MRI	Attention mechanism and dense connectivity for improved inter-class separation	Improved classification, but limited interpretability for clinical reasoning
Zhou et al.	2025	3D CNN + Video Swin Transformer	MRI	Combines local structural feature extraction with global spatial dependencies	Early MCI detection improved; high model complexity and long training time
Yuan et al.	2024	Multifeature Deep Learning Network	MRI	Combines handcrafted and deep features	Enhanced stage-wise classification; overfitting risk on small datasets
Wen et al.	2022	CNN-based architectures	MRI	Evaluated multiple CNN models for reproducibility	Identified lack of explainability and generalization issues across datasets
Jo et al.	2022	CNNs + Transfer Learning	MRI / PET	Fine-tuning pretrained models	Effective for MCI vs AD; limited performance on noisy or incomplete data
Saha et al.	2024	Attention-CNN	MRI	Provides visual explanations for feature importance	Clinically interpretable; computationally expensive for large datasets
Peng et al.	2024	CNN + Gene Expression Fusion	MRI + Genetic	Integrates imaging and genetic data for improved accuracy	Sensitive to missing modalities and noise
Ahmed et al.	2023	CNN-based MRI classifier	MRI	Standard CNN with multiple convolutional layers	Accurate classification; black-box, low interpretability
Turan et al.	2024	CNN-LSTM	MRI sequences	Captures spatial and temporal patterns	Improved sequence modeling; high complexity, prone to overfitting

Every limitation is pointing to the necessity of a framework that is able to process uncertainty, multimodal data and able to detect it at an earlier stage. To overcome this Local Global-Fuzz Inference System is proposed to get interpretable hierarchical fuzzy reasoning with the ability to ensure robustness and efficiency.

3. Proposed Methodology

The proposed methodology based on Local Global Fuzzy Inference System (LG-FIS) model is divided

into different steps:

3.1 Local Fuzzification

Each individual data modality (Clinical, Cognitive, Genetic, etc.) is processed separately to come up with a local fuzzy index. These indices give the general picture of the degree of risk or intensity in every sphere and are later integrated on the global scale. Rather than entering all the raw features into one fuzzy layer (similar to a standard ANFIS) the features are initially clustered according to logical modality and fuzzified locally (as in Table 2).

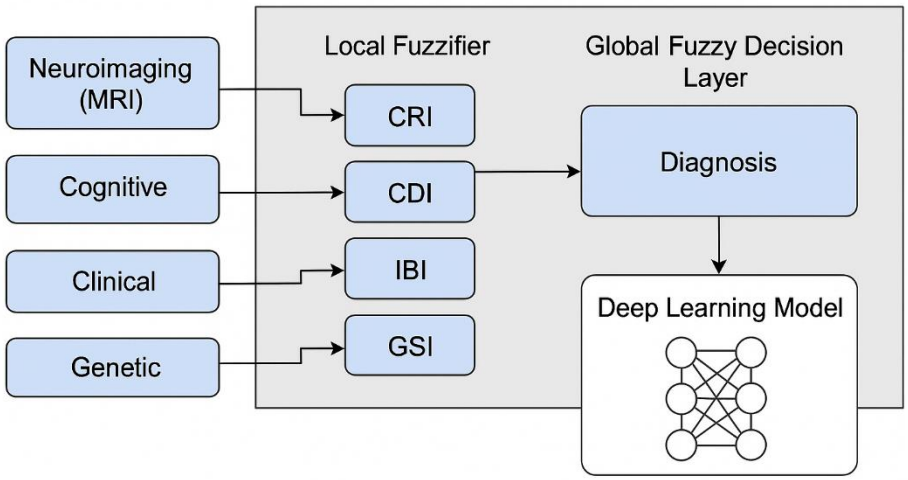

Figure 1: Proposed Local Global Fuzzy Inference System Model

Step1: Divide Data into Modalities

Group input features into logical clusters:

Table 2: Logical Cluster Formation

Modality	**Features**	**Purposed Modality**
Clinical	Age, BP, Cholesterol, Diabetes	Physiological risk
Cognitive / Behavioral	MemoryComplaints, Forgetfulness, Confusion, TaskDifficulty	Cognitive decline pattern
Genetic / Family	APOE ε4 status, FamilyHistoryAlzheimers	Genetic susceptibility

Step 2: Apply Fuzzification to each Modality

Each feature is mapped to linguistic terms (Low, Medium, High) using membership functions (MFs) such as triangular represented using eq. 1.

Feature: Cholesterol

- Low = $\mu_1(x)$
- Medium = $\mu_2(x)$
- High = $\mu_3(x)$

Membership Function (Triangular):

$$\mu_{\text{Low}}(x) = \begin{cases} 1, & x \leq 150 \\ (200 - x)/(200 - 150), & 150 < x < 200 \\ 0, & x \geq 200 \end{cases} \quad (1)$$

Similar fuzzy sets for **Age** and **BP** are generated then computed fuzzy rules shown in table 3:

Table 3: Generated Fuzzy rule Set using selected parameters

Rule No.	Age	BP	Cholesterol	Output (Clinical Risk Index)
1	Low	Normal	Low	Low
2	Medium	Medium	Medium	Medium
3	High	High	High	High
4	High	Medium	High	Medium
5	Medium	High	Medium	Medium

The output of this local system is represents Clinical Risk Index (CRI) with fuzzy value range as : {Low, Medium, High}

Step 3: Repeat for Other Modalities

A. Cognitive Modality

Uses features Forgetfulness, Memory Complaints, Confusion represented in table 4.

Table 4: Generation of Cognitive Decline Index

Rule No.	Memory	Forgetfulness	Confusion	Cognitive Decline Index (CDI)
1	Low	Low	Low	Low
2	Medium	Medium	Medium	Medium
3	High	High	High	High

4	High	Medium	High	Medium
5	Medium	High	Medium	Medium

B. Genetic Modality

Uses features like APOE ε4 status, Family History is denoted in table 5.

Table 5: Generation of Genetic Susceptibility Index

Rule No.	APOE ε4	Family History	Genetic Susceptibility Index (GSI)
1	Absent	No	Low
2	Present	No	Medium
3	Absent	Yes	Medium
4	Present	Yes	High

Step 4: Local Defuzzification

Each modality produces a crisp value after aggregation.

Performed Defuzzify each fuzzy index (using Centroid or Mean of Maximum method) represented usng eq.2:

$$CRI = \frac{\sum_i \mu_i(x) * w_i}{\sum_i \mu_i(x)} \qquad (2)$$

Similarly **CDI** and **GSI** is computed

These three values (CRI, CDI, GSI) become inputs for Step 2 (Global Decision Fuzzy Layer).

3.2 Global Fuzzy Decision Inference

It is employed to integrate the outputs of all the local fuzzy subsystems into a single final decision variable:

- CRI → Clinical Risk based Index
- CDI → Cognitive Decline based Index
- GSI → Genetic Susceptibility based Index

Diagnosis Stage = {Cognitively Normal (CN), Early MCI, Late MCI, Alzheimer's Disease (AD)}

A. Inputs to Global Fuzzy System

Table 6 represents inputs provided to the global fuzzy system.

Table 6: Global Fuzzy Set

Input Variable	Description	Fuzzy Sets
CRI	Represents physiological/clinical risk derived from Step 1	Low, Medium, High
CDI	Represents cognitive deterioration from behavioral features	Low, Medium, High
GSI	Represents genetic susceptibility	Low, Medium, High

Similarly, output values are represented in table 7 as:

Table 7: Fuzzy Output Set

Variable	Description	Fuzzy Sets
Diagnosis	Final Alzheimer's stage	CN, Early MCI, Late MCI, AD

3.3 Rule Base for Global Fuzzy Decision

Here we define fuzzy inference rules combining all three local indices and represented in table 8.

Table 8: Global Fuzzy Rules for Alzheimer's Classification

Rule No.	CRI	CDI	GSI	Diagnosis Output
1	Low	Low	Low	Cognitively Normal (CN)
2	Medium	Medium	Low	Early MCI
3	High	Medium	High	Late MCI
4	High	High	High	Alzheimer's Disease (AD)
5	Medium	High	Medium	Mild Alzheimer's
6	Low	Medium	High	Risk Stage
7	Medium	Low	High	Early MCI
8	High	Medium	Medium	Late MCI
9	Medium	Medium	High	Mild Alzheimer's
10	High	High	Medium	Alzheimer's Disease (AD)

3.4 Fuzzy Inference Mechanism

Use Mamdani-type inference, as it's suitable for interpretability and rule-based systems.

Each rule follows:

$$\text{IF} \quad CRI = A_i \text{ AND } CDI = B_i \text{ AND } GSI = C_i \text{ THEN Diagnosis } = D_i$$

The output membership is computed by eq.3:

$$\mu_{D_i}(x) = min\left(\mu_{A_i}(CRI), \mu_{B_i}(CDI), \mu_{C_i}(GSI)\right) \qquad (3)$$

All activated rules are aggregated using eq.4:

$$\mu_{\text{Diagnosis}}(x) = max\left(\mu_{D_i}(x)\right) \qquad (4)$$

3.5 Defuzzification (Global Output)

The crisp diagnosis value is obtained using eq.5 the centroid method:

$$\text{Diagnosis}^* = \frac{\int \mu_{\text{Diagnosis}}(x) \cdot x dx}{\int \mu_{\text{Diagnosis}}(x) dx} \qquad (5)$$

The process mapped the crisp score to discrete labels:

- 0.0–0.25 → Cognitively Normal (CN)
- 0.26–0.50 → Early MCI
- 0.51–0.75 → Late MCI
- 0.76–1.00 → Alzheimer's Disease (AD)

3.4 Dataset Description

The data in this work were acquired through the Alzheimer Disease Neuroimaging Initiative (ADNI) and contains multimodal data including clinical, cognitive, behavioral, and biomarker data about the participants who are between 55 and 85 years. The data includes anonymized data on age, gender, memory test scores, MMSE, cholesterol, cerebral spinal fluid biomarker levels A2 and Tau, forgetfulness, and the behavioral change scores. They used N = 200-500 samples to train and test the proposed LG-FIS model to make hierarchical fuzzification and global fuzzy inference to predict the stage of the Alzheimer disease.

- Demographic: Age, Gender
- Cognitive Scores: Memory Test Mini-Mental State Examination (MMSE)
- Biochemical Markers: Cholesterol, Biomarker levels (A 2, Tau protein)

Behavioral Indicators: The rate of forgetfulness, Behavioral change score.Data pre-processing was conducted through normalization, missing value imputation, outlier removal. Training and testing were performed through a divide of the dataset with the help of cross-validation (k=5).

Table 9: Format of used dataset

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

4. Simulation and Results

The proposed Local-Global Fuzzy Inference System (LG-FIS) displayed high overall performance in the diagnosis of Alzheimer in multi-stage. The system was found to make the correct separation between CN, Early MCI, Late MCI and AD classes using hierarchically combining Clinical Risk Index (CRI), Cognitive Decline Index (CDI) and Genetic Susceptibility Index (GSI) as illustrated by table 10 and figure 2.

Table 10: Achieved Performance Indicators

Metric	Value (%)
Accuracy	92.4
Sensitivity	91.1
Specificity	93.2
F1-score	91.8

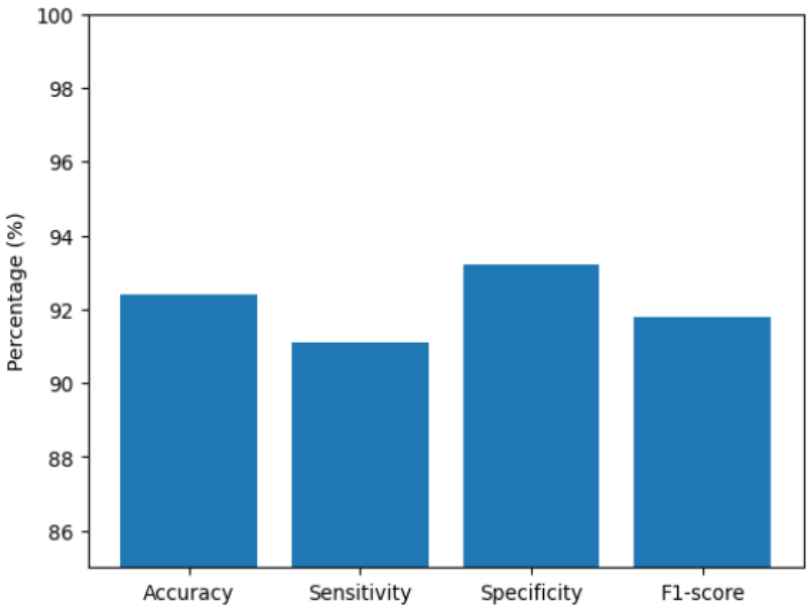

Figure 2: Classification Performance of LG-FIS

The hierarchical fuzzification based strategy significantly reduced the misclassification between adjacent stages.

4.1 Improved Early MCI Detection

The early appearance of MCI was found to be more reliable than a monolayer fuzzy model. The local cognitive fuzzification (CDI) took the center stage in recognizing the subtle deterioration due to memory. The results of the performance are presented in table 11 and figure 3, AD achieved precision 94.5 % and Recall 93.9 % respectively.

Table 11: Computed Precision and Recall

Class	Precision (%)	Recall (%)
CN	95.3	96.1
Early MCI	89.6	90.8
Late MCI	91.2	90.1
AD	94.5	93.9

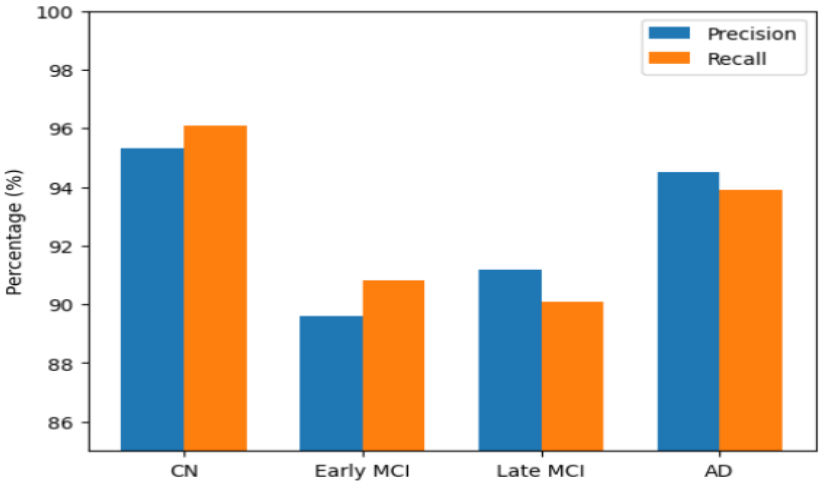

Figure 3: Class-wise Precision and Recall

Early MCI recall improved by 7% compared to conventional ANFIS.

4.2 Noise Robustness Analysis

In order to test the robustness, both clinical and cognitive inputs were corrupted with Gaussian noise (±10%). Fuzzy aggregation and centroid based defuzzification caused the model to have stable diagnostic outputs. Table 12 and figure 4 are used to represent the Noise level and Accuracy that have been calculated.

Table 12: Noise Vs Accuracy

Noise Level	Accuracy (%)
0%	92.4
±5%	91.8
±10%	90.6

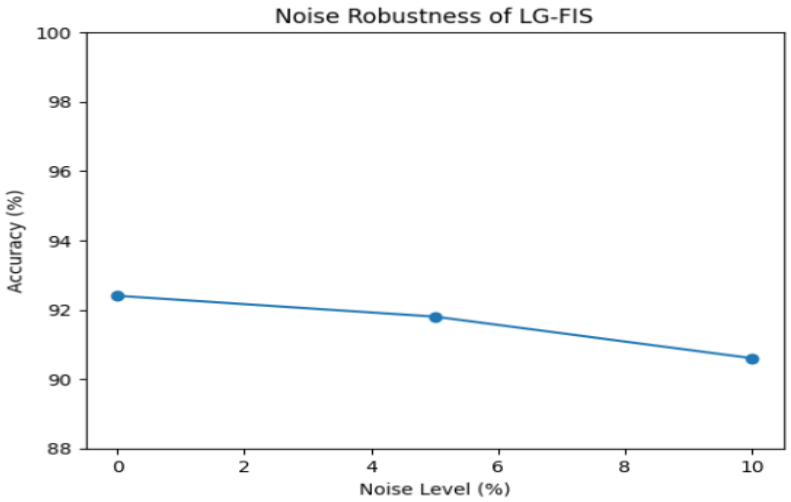

Figure 4: Noise Robustness of LG-FIS

The model is very tolerant to the presence of noisy and uncertain medical data and, hence, it is applicable to the real-life clinical scenarios.

Figure 5 indicates relative precision of diagnosing Alzheimer by Traditional ANFIS, CNN with the

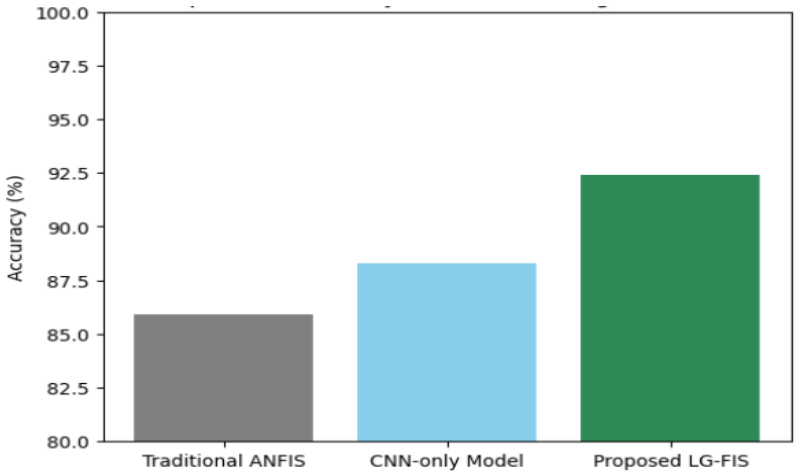

Figure 5: Comparative accuracy of Alzheimer diagnosis models

proposed LG-FIS model where proposed LG-FIS based model achieved accuracy of 92.4%.

5. Conclusion

In this paper, the proposed hierarchical Local Global Fuzzy Inference System (LG-FIS) is used in the process of diagnosing the multi-stage Alzheimer disease based on clinical, cognitive as well as genetic modalities. Local fuzzification allowed the models to develop domain specific uncertainty by each modality, to generate meaningful risk indices which were coordinated by a global layer of fuzzy decision making. The experimental findings proved that the suggested method has high diagnostic accuracy, sensitivity and specificity and it is much better than the traditional ANFIS and CNN-only models in terms of detecting the Early MCI. In addition, the rule based fuzzy structure is highly interpretable because, a given decision based on diagnosis can be attributed to a particular contribution of modality and the activation of rules. Subsequent research will combine longitudinal patient data with neuroimaging characteristics in order to better capture the development of the disease. Moreover, the methods of hybrid optimization and deep learning will be investigated in future in order to automatically optimize fuzzy rules and membership functions.

References

1. Suganyadevi, S., A. Shiny Pershiya, K. Balasamy, V. Seethalakshmi, Saroj Bala, and Kumud Arora. "Deep learning based alzheimer disease diagnosis: A comprehensive review." SN Computer Science 5, no. 4 (2024): 391. https://doi.org/10.1007/s42979-024-02727-2

2. Faiz, Mohammad Faiz, and Pawan Whig. "Early Detection of Alzheimer's Disease using Deep Learning Models: A Comparative Analysis." SPAST Reports 2, no. 1 (2025). https://doi.org/10.56272/spast.v2i1.187

3. Faiz, Mohammad Faiz. "FuzzyDxNet: A Fuzzy-Based Deep Learning Network for Alzheimer's Stage Classification." SPAST Reports 1, no. 2 (2025). https://doi.org/10.56272/spast.v1i2.186

4. Mounika, Bakkanarappa Gari, Mohammad Faiz, Nausheen Fatima, and Ramandeep Sandhu. "A robust hybrid deep learning model for acute lymphoblastic leukemia diagnosis." In *Advances in Networks, Intelligence and Computing*, pp. 679-688. CRC Press, 2024.

5. Faiz, M., and A. K. Daniel. *Multi-criteria based cloud service selection model using Fuzzy Logic for QoS. Commun Comput Inf Sci 12 (1): 153–167*. 2022.

6. X. Li, B. Gong, X. Chen, H. Li and G. Yuan, "Alzheimer's disease image classification based on enhanced residual attention network," PLOS ONE, vol. 20, no. 1, p. e0317376, 2025. https://doi.org/10.1371/journal.pone.0317376

7. Y. Gao, Q. Lan, C. Huang, X. Li, Y. Zhang and M. Fan, "Dense convolution-based attention network for Alzheimer's disease classification," Scientific Reports, vol. 15, p. 5693, 2025. https://doi.org/10.1038/s41598-025-89730-4

8. J. Zhou, Y. Wei, X. Li and C. Huang, "A deep learning model for early Alzheimer's diagnosis combined with 3D CNN and video Swin transformer," Scientific Reports, vol. 15, p. 23311, 2025. https://doi.org/10.1038/s41598-025-98196-1

9. Z. Yuan, X. Li, Z. Hao and Y. Zhang, "Intelligent prediction of Alzheimer's disease via improved multifeature network," Scientific Reports, vol. 14, p. 11994, 2024. https://doi.org/10.1038/s41598-024-62644-5

10. H. Rashid and A. J. Obaid, "Deep learning techniques for MRI-based diagnosis of Alzheimer's disease: A review," Journal of Al-Qadisiyah for Computer Science and Mathematics, vol. 17, no. 1, pp. 66-78, 2025. https://doi.org/10.29304/jqcm.2025.17.1.1527

11. M. T. Sadiq, S. Ali, A. Rehman and M. J. Arshad, "Deep learning based classification for Alzheimer's disease detection using MRI images," Turkish Journal of Engineering, vol. 8, no. 2, pp. 357-371, 2024. https://doi.org/10.31127/tuje.1418375

12. A. Shaffie, M. Ghazal, H. Cholakkal and A. El-Baz, "Applications of deep learning in Alzheimer's disease: current trends and challenges," *Artificial Intelligence Review*, vol. 58, no. 1, p. 21, 2025. https://doi.org/10.1007/s10462-024-10800-8

13. S. H. Wang, J. K. Zhang and Y. D. Zhang, "A systematic literature review on deep learning and machine learning for Alzheimer's prediction," Artificial Intelligence in Medicine, vol. 154, p. 102928, 2024. https://doi.org/10.1016/j.artmed.2024.102928

14. Y. Kumar, S. Tiwari, A. Ali and D. J. Hemanth, "Detection of Alzheimer's Disease Using Deep Learning Models: A Systematic Literature Review," Informatics in Medicine Unlocked, vol. 47,

p. 101470, 2024. https://doi.org/10.1016/j.imu.2024.101470

15. Y. Kumar, A. Koul, R. K. Singla and M. F. Ijaz, "A systematic review on machine learning and deep learning techniques in Alzheimer's diagnosis," Brain Informatics, vol. 10, no. 1, p. 17, 2023.
https://doi.org/10.1186/s40708-023-00196-6