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Expert Systems Using Fuzzy Logic for the Early Alzheimer's Disease Diagnosis

Mohammed Mahdi Hashim [1,*], Abdullah A. Nahi [2], Amna Kadhim Ali [3], Vlad Ciobanu [4]

[1]Department Of Information Technologies, Management Technical College, Southern Technical University, Basrah, Iraq.
[2]Studies, Planning & Follow Up, Directorate, Ministry of Higher,Education and Scientific Research, Baghdad, Iraq.
[3]College of Veterinary Medicine, University of Basrah, Basrah, 61004, Iraq.
[4]University Politehnica of Bucharest, Bucharest, Romania,

*Corresponding Author: Mohammed Mahdi Hashim

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ABSTRACT: The heterogeneity of the imaging and cognitive findings in early Alzheimers disease (AD) makes it difficult to make a definite diagnosis. In this study, an initial hybrid decision-support framework of MRI features data and Cognitive Questionnaire data are proposed in a combination of fuzzy logic with Support Vector Regression (SVR). 120 subjects were processed through MRI and resizing, denoising, normalization, feature extraction, and 25-item cognitive evaluation by methods for memory, attention, orientation (for example: would you recall back the items that we have asked about within just 5 minutes) and daily activities (What day is today? What month? What year?) Triangular fuzzy numbers were used to represent cognitive responses, merged with MRI features using a weighted strategy and processed through a fuzzy inference system and fine-tuned with SVR RMSE-based RBF kernel. The validation method for performance was 5-fold cross-validation. The framework achieved accuracy of 91.9%, precision of 92.5%, recall of 91.1%, F1-score of 91.8% and ROC_AUC 0:94 high up performance metrics MSE = 0.085 and R^2 = 0.92 from internal agreement on predicted and observed fuzzy diagnostic scores in SVR refinement. These findings were further supported by visual analyses, which demonstrated distinct separation of trends among healthy, pre-Alzheimer's and Alzheimer's groups with partial overlap between adjacent categories. These findings indicate that fuzzy-SVR is a feasible preliminary screening model, with good interpretability. But because of the small sample size and no external validation was performed, further independent multi-center studies are required to validate our model using larger datasets from different sources as well as other biomarkers.

Keywords: Alzheimer's disease, fuzzy logic, Support Vector Regression, MRI, cognitive assessment, early diagnosis, decision-support system.

1. INTRODUCTION

Alzheimer's disease (AD) is the most common cause of dementia and it remains a major global health challenge, particularly with a burgeoning aged population worldwide. Alzheimer's disease (AD) is characterized by a progressive impairment in cognitive function, combined with specific neuropathological signatures of amyloid deposits or plaques and neurofibrillary tangles. Pathological changes can start years before severe clinical symptoms developed, therefore diagnostic support for screening and follow up for timely clinical decisions should be early and interpretable.

Even so, early detection of AD continues to be challenged by the gradual and heterogeneous appearance of symptoms, structural MRI changes, and cognitive decline [4]. Although MRI can provide evidence of neurodegeneration such as hippocampal and cortical changes, imaging alone may not detect the earliest functional decline. Cognitive assessments reveal daily and memory-related impairment, but are susceptible to education, age effects (i.e. more education slows down the rate of decline), subjectivity as well as respondent variability issues. Hence a single modality may impact on the diagnostic power particularly in borderline or pre-Alzheimer's stage.

*Corresponding author: comp.mmh@gmail.com

The transition between the normal and pathological decline is often fuzzy in people with mild cognitive impairment (MCI) and early AD. While machine learning and deep learning approaches have led to more automatic analysis techniques for medical data, many models are still not interpretable and likely to overfit on small datasets used in hospital practice. This problem is particularly salient for clinical studies in which there are generally small sample sizes and a need to justify decisions in open manner.

Fuzzy logic: Fuzzy logic can be used to model the inherent uncertainties, gradation of membership and continuous transition between various cognitive states. Fuzzy inference strategies naturally resolve this problem since these methods allow a patient to belong to more than one diagnostic category at the same time with partial scores, unlike hard threshold-based approaches that assign patients exclusively. This can be combined with Support Vector Regression (SVR) to yield refined fuzzy diagnostic scores by modelling a complex mapping between fused MRI and cognitive features.

Accordingly, this study proposes a preliminary hybrid fuzzy-SVR framework that integrates structural MRI-derived features and cognitive questionnaire data for early Alzheimer's disease screening. The main objective is to evaluate whether the combination of fuzzy reasoning and SVR can provide an interpretable decision-support model with acceptable internal validation performance.

The novelty of the proposed work lies in combining multimodal MRI and cognitive evidence with fuzzy membership modelling and SVR refinement. This design aims to reduce uncertainty in borderline cases while maintaining a more interpretable diagnostic pathway than purely black-box models. Because the dataset is limited, the study is presented as a pilot investigation, and the results are interpreted cautiously pending external validation on larger independent cohorts.

2. RESEARCH PROBLEM

Clinical characteristics of AD cases have highlighted the wide range in time from onset of symptoms in one case to another. The first phase is more psychogenic in nature, as the second phase appears with different frequencies of occurrence but also reveals a symptom. Hence it cannot be classified in four bases with a crisp way of rule based on these symptoms. We cannot specify that a rule belongs to just one base. The treatment is incredibly effective for some of the stages of AD compared to others but quite less effective in some other issues faced by patients. A rule derived as a function of ineffective treatment can yield incorrect results or premature treatment within a case. But very rarely, the System has to apply these rules in certain case in AD. Then we have no choice, they cannot be eradicated at some of the bases entirely. That implies the system has to be adaptable to all kinds of cases of AD. So we can question how these rules will be classified considering that there are these uncertainties at work.

2.1 SOLUTION BASED ON FUZZY LOGIC

Machine learning algorithms, including support vector machines (SVMs), random forests and deep learning models have been used for MRI-based Alzheimer's detection [11]. Systems based on cognitive assessment have also shown their efficacy, especially in community screening [12]. Multimodal fusion approaches confounding imaging and clinical data have been developed since there performance is better than unimodal but still many models used are black-box models with no interpretability [13]. Fuzzy expert systems have been successfully applied in medical diagnosis, including diabetes, cardiovascular disease, and neurological disorders [14]. However, their application to Alzheimer's detection with integrated MRI and cognitive data remains relatively underexplored. Most of the previous studies focused on early detection of Alzheimer's disease (AD) using either single-modality MRI data or conventional machine learning techniques, and their models were often trained on relatively small datasets, which limited generalizability. Nonetheless, deep learning-based approaches using binary classification of AD differentiating cognitively normal (CN) from AD patients are limited. Moreover, these models often lacked the integration of fuzzy logic for handling uncertainty in clinical data.

Rule classification must be done in an uncertain way. There are several logics to handle uncertainties like non-monotonic logic, fuzzy logic, probabilistic logic and Bayesian processes. Nevertheless, we choose to use fuzzy logic because it allows taking into account the linguistic typologies, and therefore all the nuances that were created to best explain the reality. Besides, in fuzzy logic, it is often possible to sufficiently reduce the number of rules to allow a higher speed inference, which allows its use in most developed control systems. As a result, our solution will be based on fuzzy logic. In the first step of the knowledge base specialization process "Generation of general rule base", the rules acquired from the domain experts must be accompanied by their membership functions. Each rule must have one of the four membership functions presented in figure 1 [47].

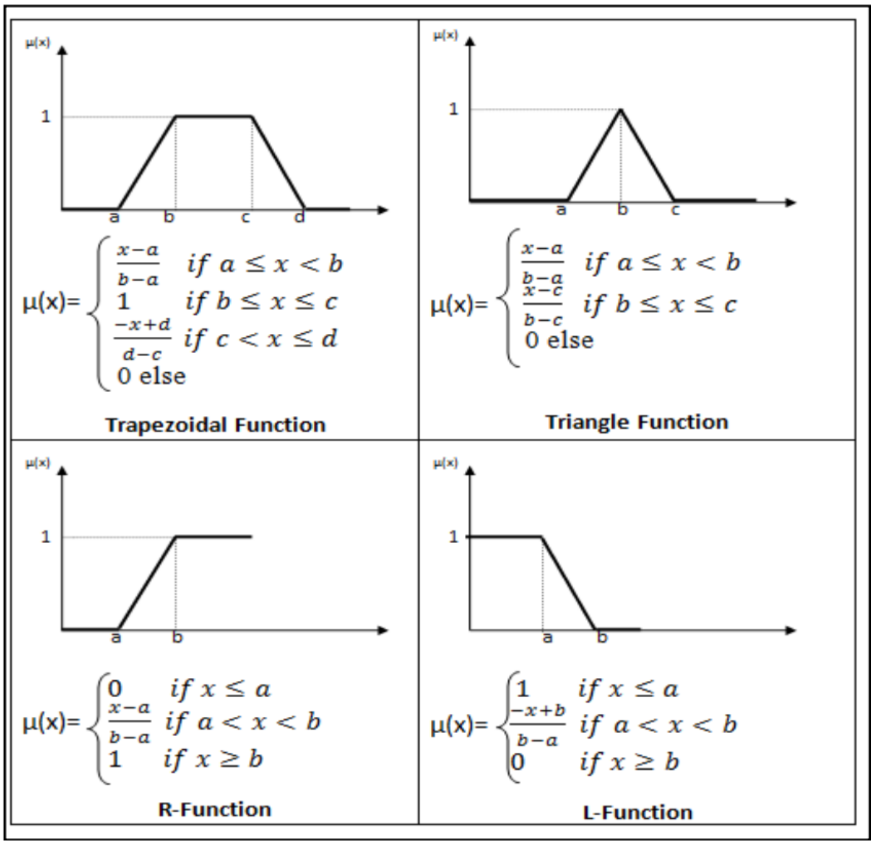

Figure 1. The membership functions of fuzzy logic

Additional functionality can be incorporated if necessary. Each membership function signifies the extent of rule applicability during each phase of the AD. The domain experts, assisted by knowledge engineers, must endeavor to estimate the frequency of rule applicability utilising membership functions grounded in MMSE values. The values are categorized into four intervals. Each interval signifies a phase of the AD.

2.2 RELATED WORKS

Recently, automatic diagnosis of (AD) based neuroimaging data using advances in artificial intelligence and deep learning has improved dramatically. Knudsen et al. Combining multiple imaging modalities improves the diagnostic ability of detecting (AD) and mild cognitive impairment (MCI), as shown in [15], but their proposed method has drawbacks including small dataset size and high integration complexity. To this end, Lao and Zhang in [16] utilized a hybrid of NMF-TDNet features combined with regression and classification as framework for automated AD diagnosis using 3D MRI data which did obtain good results but demanded significant computational resources to implement as well being prone to overfitting on small datasets. In study Multichannel contrastive learning to improve feature discrimination and yield superior diagnostic performance was utilized by [17] through a 3D convolutional neural network (CNN); however, it is still sensitive to preprocessing steps and requires large amounts of labeled datasets.

In another study, Lian et al. Dementias diagnosis using structural MRI [18], Attention-guided hybrid network, Focus on the most relevant regions of interest by implementing attention mechanisms; still lack interpretability and generalizability. As mentioned [19] proposed a deterministically-ensemble based Monte Carlo neural network by combining multiple convolutional layers and pooling layers but it has computationally expensive and complicated(CN). While, [20] is based on convolutional neural network (CNN) architectures for early AD classification but requires large data samples and high computational costs, which may lead to overfitting. Qin et al. Meanwhile, a 3D CNN with hybrid attention mechanisms was designed in [21] to extend deep learning approaches, but it required consuming huge GPU memory and an extremely high computation cost.

While [22] proposed a computer aided diagnosis (CAD) method using 2D MRI slices, which lowers computational complexity but removes vital 3D spatial information and introduces slice selection bias. Agarwal et al. The accuracy of automated AD diagnosis was showing a great improvement with EfficientNet CNN [23], however, it is lacking interpretability and sensitive to hyperparameter tuning. Cao et al. An end to end framework for delineating pathology in MRI was provided by [24] and improved the automization of diagnosis but also relied on high-quality, segmented images and lengthy periods of training. Fan et al. In order to diagnose AD at the early stage as well as predict the progress of AD over time, hence, [25] proposed a multi-scale self-attention network by extracting features at multiple resolution levels, but this approach incurs higher model complexity and preprocessing expense.

Recent studies also touched upon hybrid and ensemble models. Another study [26] implemented transfer learning via AlexNet followed by LSTM to obtain spatial and temporal features for AD classification, but it is likely that their method does not capture all the relevant features and has limitations with respect to temporal modeling. Kale et al. Availability This is a summary of the article, including key points. For more details on this topic and references, please visit www.ijgim.net [27] proposed an integrated framework powered by AI for diagnosing diseases in their early stage along with treatment planning compounded by high cost of computing and increased system complexity. Wang et al. Since transformer-based models tend to control overfitting, which works effectively in large datasets, [28] fused CNN and Swin Vision Transformer for local and global feature extraction. Since this study Ensemble-based 3D residual networks were proposed by [29] to enhance the classification accuracies/stability but it adds complexity and stability issues during training. Lastly, [30] proposed a multi-class AD deep learning model that addresses the challenges of diagnosis at an early stage (but faces class imbalance problems and has limited interpretability). A summary of the basic characteristics of previous methods, details about datasets and performance metrics are presented in Table 1, which shows that no model with a hybrid AI and fuzzy logic approach has been developed yet for improving accuracy and robustness.

Table 1. Summary of Recent AI and Deep Learning Approaches for Alzheimer's Disease Diagnosis

Citation	Approach	Objective	Challenges of the Approach
Knudsen et al., 2022 [15]	Multimodal MRI analysis	Investigate role of multimodal MRI in MCI and AD diagnosis	Limited dataset size, high complexity of multimodal integration
Lao & Zhang, 2022 [16]	NMF-TDNet features with regression and classification	Automated diagnosis of AD using 3D brain MRI	Requires large computational resources, may overfit small datasets
Li et al., 2022 [17]	3-D CNN with multichannel contrastive learning	Automatic AD diagnosis	Sensitive to MRI preprocessing, needs large labeled datasets
Lian et al., 2022 [18]	Attention-guided hybrid network	Dementia diagnosis from structural MRI	Interpretability of attention maps, generalization to new datasets
Liu et al., 2023 [19]	Monte Carlo ensemble neural network	Improve diagnostic accuracy of AD	Computationally intensive, ensemble model complexity
Mehmood et al., 2022 [20]	Convolutional neural networks (CNN)	Early AD detection	Requires large datasets, potential overfitting
Qin et al., 2022 [21]	3D CNN with hybrid attention	Early AD diagnosis	Complex model, high GPU memory usage
Sethi et al., 2022 [22]	CAD system using 2D MRI slices	AD classification	Loss of 3D spatial information, slice selection bias
Agarwal et al., 2023 [23]	EfficientNet CNN	Automated medical diagnosis of AD	Limited interpretability, sensitivity to hyperparameters
Cao et al., 2023 [24]	End-to-end automatic pathology localization	AD diagnosis using structural MRI	Needs high-quality annotations, training time
Fan et al., 2024 [25]	Multi-scaled self-attention network	Early diagnosis and progression prediction of AD	Model complexity, requires extensive data preprocessing
Goyal et al., 2024 [26]	Transfer learned AlexNet with LSTM	AD diagnosis and classification	Transfer learning may not capture all features, temporal modeling challenges
Kale et al., 2024 [27]	AI-driven integrated framework	Early diagnosis, treatment planning, prognostic modeling	High computational cost, integration of multiple AI modules
Wang et al., 2025 [28]	CNN + Swin Vision Transformer	Recognition and diagnosis of AD	Transformer models require large datasets, sensitive to overfitting
Yang et al., 2025 [29]	Ensemble-based 3D residual network	AD classification	Ensemble complexity, training stability issues
Vinukonda & Jagadesh, 2025 [30]	Integrated deep learning model	Early and multi-class AD diagnosis	Multi-class classification imbalance, model interpretability

In conclusion, while these works obtain state-of-the-art performances in AI-driven Alzheimer detection, most of the methods tend to be heavy on modality and lack robustness (explain ability) or uncertainty estimations. These restrictions indicate the obligation of hybrid outlines that fuse multi modal data and explain ability techniques like fuzzy logic to advance both accuracy and clinical applicability.

3. METHODOLOGY

The early screening of Alzheimer disease based on the hybrid method of integrating structural MRI features and cognitive questionnaire responses. An overview of the proposed workflow is depicted in Fig. 6 and consists of six main stages: data acquisition, preprocessing, feature normalization, weighted multimodal fusion, fuzzy inference, SVR-based refinement and performance evaluation. Newly added workflow figure illustrates the overall methodology.

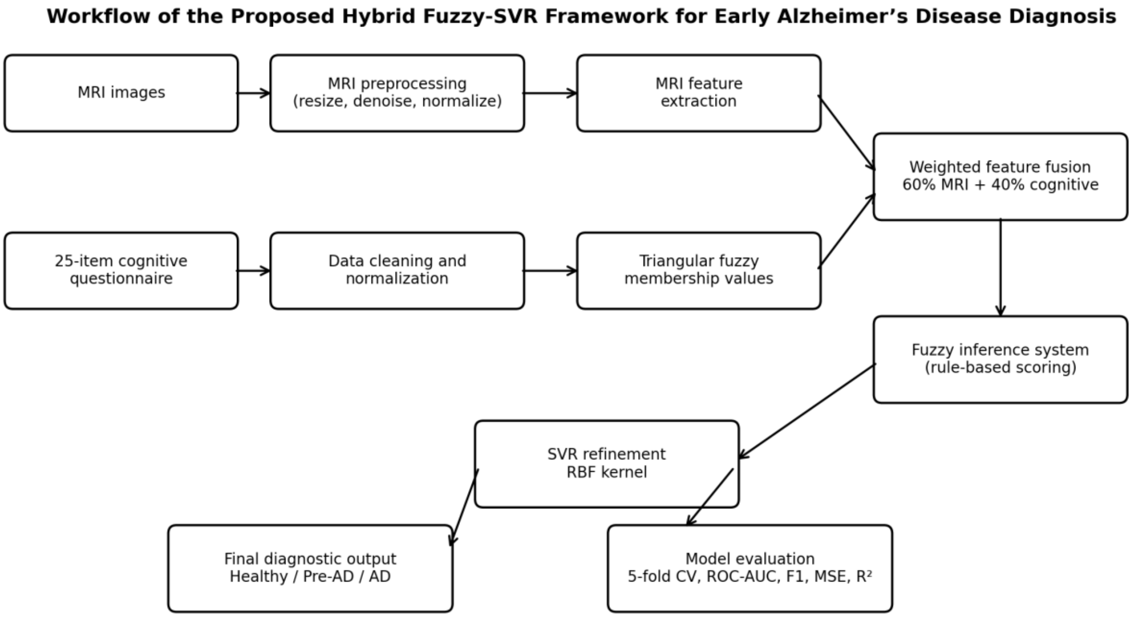

Figure 2. Workflow of the Proposed Hybrid Fuzzy-SVR Framework for Early Alzheimer's Disease Diagnosis

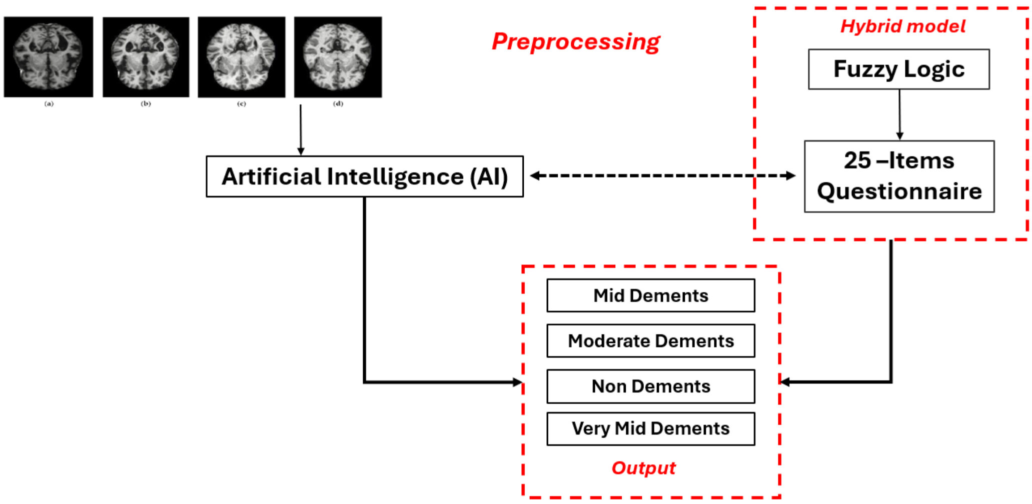

Figure 3. Block Diagram of Proposed Research Model

3.1 DATASET STRUCTURE

Our dataset had a total of 120 subjects combining both cognitively normal and mild Alzheimer's disease patients. Structural MRI images were acquired through publicly available imaging biobanks and deidentified clinical sources. The data gathered about Cognition was obtained via a 25-item questionnaire designed based on commonly used areas of cognitive screening, i.e. memory, attention, orientation, activity in daily living and remote recall. All data were anonymized prior to analysis.

All cognitive variables were transformed into a unit score between 0 and 100. Higher scores indicated greater cognitive difficulty due to impairment level. Missing data were managed via mean substitution (for datasets with a low missing rate) and by excluding incomplete records following high levels of missing response. These were then categorized into final diagnostic labels being either Healthy, Pre-Alzheimer's or Alzheimer's based upon Cognitive status and MRI-derived indicators (Table 1).

The characteristics of participants and the diagnostic criteria descriptors were revised. Participants were assigned to healthy, pre-Alzheimer's, or Alzheimer's based on available measures of cognitive status, and MRI-derived values. Inclusion criteria included structural MRI scans and at least partially completed neuropsychological questionnaire data. Participants with unusable MRI images; those without complete cognitive records (with significant amounts of missing data); and those who had inconsistent diagnostic information were excluded. Full exploration of demographic variables (age, sex, education level, disease duration, and comorbidity) is required to increase the clinical transparency as these factors were not fully available for all cases in this study.

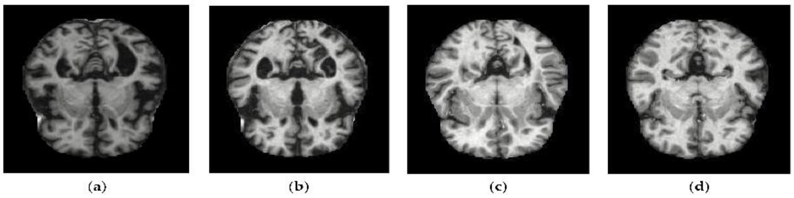

Figure 4. Alzheimer's Disease MRI Dataset

Cognitive function, alongside MRI imaging, was evaluated using a standardized 25-item questionnaire. The items of this questionnaire are based on common cognitive scales (the Mini-Mental State Examination (MMSE)), the Alzheimer's Disease Assessment Scale-Cognitive Subscale (ADAS-Cog) [34] for cognitive impairment and modified from recent studies focusing on cognition assessment and dementia diagnostic [35-43]. The cognitive function valuation includes a broad range of domains, which in their respective social and/or medical context may be influenced by Alzheimer disease (Table 2): memory; attention; decision making; language; and ultimately performance for most activities of daily living.

Table 2. Cognitive and Daily Function Assessment Questionnaire for Alzheimer's Patients

No	Question	Very High	High	Moderate	Low	Very Low
1	I can remember what I did earlier today.	☐	☐	☐	☐	☐
2	I can recall events from yesterday.	☐	☐	☐	☐	☐
3	I remember what I ate for my last meal.	☐	☐	☐	☐	☐
4	I can recall the names of people I met recently.	☐	☐	☐	☐	☐
5	I can remember appointments or important dates.	☐	☐	☐	☐	☐
6	I know what day of the week it is.	☐	☐	☐	☐	☐
7	I know the current month and year.	☐	☐	☐	☐	☐
8	I can tell the time without help.	☐	☐	☐	☐	☐
9	I can remember where I am in my home or neighborhood.	☐	☐	☐	☐	☐

10	I can recall how I got to my current location.	☐	☐	☐	☐	☐
11	I can focus on a conversation without getting distracted.	☐	☐	☐	☐	☐
12	I can follow a short story or TV program.	☐	☐	☐	☐	☐
13	I can complete a simple task without forgetting steps.	☐	☐	☐	☐	☐
14	I can remember instructions given by others.	☐	☐	☐	☐	☐
15	I can pay attention to more than one task at a time.	☐	☐	☐	☐	☐
16	I can remember to take my medication on time.	☐	☐	☐	☐	☐
17	I can remember to eat or drink without being reminded.	☐	☐	☐	☐	☐
18	I can remember to lock doors or switch off appliances.	☐	☐	☐	☐	☐
19	I can plan my day and remember to do planned activities.	☐	☐	☐	☐	☐
20	I can manage simple personal hygiene routines by myself.	☐	☐	☐	☐	☐
21	I can recall important events from my past.	☐	☐	☐	☐	☐
22	I can remember the names of family members.	☐	☐	☐	☐	☐
23	I can recall childhood memories.	☐	☐	☐	☐	☐
24	I can remember places I have visited in the past.	☐	☐	☐	☐	☐
25	I can recall happy or significant moments in my life.	☐	☐	☐	☐	☐

The dataset consisted of 120 participants, including cognitively normal subjects and participants with Alzheimer's-related impairment. Because of this limited sample size, the present work should be interpreted as a preliminary pilot study rather than a fully generalizable clinical validation study. Ethical approval, anonymization procedures, and informed consent were considered before data processing.

3.2 DATA PRE-PROCESSING

The MRI images and cognitive questionnaire data underwent preprocessing to improve consistency and reduce noise before modelling. MRI images were resized to 256 x 256 pixels, converted to grayscale when necessary, denoised using Gaussian filtering, and normalized to a 0-1 scale. Relevant brain regions associated with Alzheimer's disease, including hippocampal, temporal, and cortical areas, were considered for feature extraction. Cognitive questionnaire responses were checked for outliers, non-numeric values, and missing data, then normalized to match the MRI feature scale.

3.3 COGNITIVE FUNCTION DATA PROCESSING

Cognitive data processing was performed to ensure consistency, reliability, and compatibility with MRI-derived features. The 25 questionnaire items were grouped into cognitive domains related to memory, orientation, attention, executive function, and daily activity. After cleaning and normalization, the cognitive score was transformed into fuzzy linguistic values. This step allowed the model to represent gradual cognitive decline rather than forcing each participant into a rigid category.

3.4 FUZZY LOGIC IN ALZHEIMER'S DISEASE DIAGNOSIS

Fuzzy logic was used to model the uncertainty and gradual transitions commonly observed in Alzheimer's-related cognitive decline. Instead of assigning participants to strict binary classes, the fuzzy inference system allowed partial membership in linguistic categories such as low, medium, and high impairment. Triangular membership functions were used because they are simple, interpretable, and suitable for modelling questionnaire-based uncertainty. The resulting fuzzy score was then combined with MRI-derived information before SVR refinement.

Table 3. Triangular Fuzzy Numbers for Questionnaire Response Options

Response Option	*Triangular Fuzzy Number (a, b, c)*	*Description*
Very High	(0.8, 1.0, 1.0)	Represents highest level of cognitive ability / function
High	(0.6, 0.8, 1.0)	Represents high level of cognitive ability / function
Moderate	(0.4, 0.6, 0.8)	Represents moderate level of cognitive ability / function
Low	(0.2, 0.4, 0.6)	Represents low level of cognitive ability / function
Very Low	(0.0, 0.2, 0.4)	Represents very low level of cognitive ability / function

This enable for the uncertainty of respondents behaviour on cognitive questionnaire parameters to be modelled which can also facilitate incremental variations in levels of cognitive functioning (figure 4). So when you answer options (for example "Very High" or "Low"), each such individual responses are defined as a fuzzy triangle, where 3 points a,b,c represent the min value, most likely and max of that cognitive level. Different from classical method where each sample/response forced into one of several boxes, this way means that every response can have a pinch of this and that in any box to analyze results. The triangular fuzzy shape provides a visual representation of the gradual decline in cognitive abilities and considering that most healthcare professionals are used to interpreting diagnostic results in an intuitive way, it is expected that this approach will ultimately help support improved clinical decision-making, especially for the timely diagnosis of Alzheimer's disease.

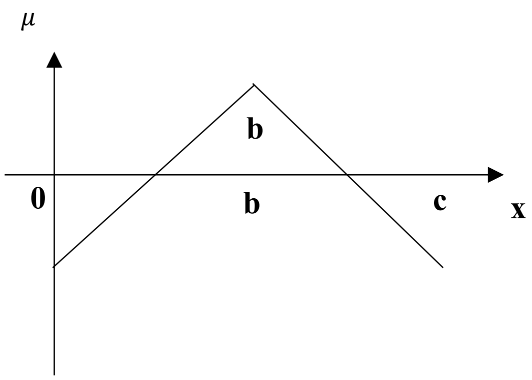

Figure 5. Triangular fuzzy numbers

The equation (1) represents the triangular membership Function, commonly denoted as $\mu_{\tilde{A}}(x)$ in Fuzzy Logic. Equation (1) describes how much a value x belongs to a fuzzy set A. The function creates a triangle shape, defined by three points: a (the start), b (the peak), and c (the end).

$$\left.\begin{matrix} x < a, \ 0 \\ a \le x \le b, \ \frac{x-a}{b-a} \\ b \le x \le c, \ \frac{c-x}{c-b} \\ x > c, \quad 0 \end{matrix}\right\} = \mu_{\tilde{A}}(x) \tag{1}$$

The function $\mu_{\tilde{A}}(x)$ is defined by three points (a, b, c) on the x-axis, where

x < a and x > c: The value is 0. It is completely outside the set.
$\boldsymbol{a \le x \le b}$: The membership increases linearly from 0 to 1. This is the rising limb.
$\boldsymbol{b \le x \le c}$: The membership decreases linearly from 1 back to 0. This is the falling limb.

x = b: This is the peak, where the membership is exactly 1.

The equation (2) representing the average of a multi-dimensional data set, typically denoted as ${}_{avg}\tilde{A}$.

$$({}_i a_i, \frac{1}{n}\sum_{i=1}^{n} b_i, \frac{1}{n}\sum_{i=1}^{n} c \sum_{i=1}^{n} \frac{1}{n}) = {}_{avg}\tilde{A} \qquad (2)$$

where

$\boldsymbol{a_i}$: Represented as ${}_i\boldsymbol{a_i}$, likely indicating the i-th value of a set $\boldsymbol{a}$. The $\boldsymbol{\frac{1}{n}\sum_{i=1}^{n} b_i}$ is the standard arithmetic mean of a variable *b*. In additional, the $\boldsymbol{\frac{1}{n}\sum_{i=1}^{n} c \sum_{i=1}^{n} \frac{1}{n}}$ is a more complex term. Since $\boldsymbol{\sum_{i=1}^{n} \frac{1}{n} = 1}$ this effectively simplifies to the average value of a constant or variable *c* across the set.

Equation (3) represents the Max-Min Composition (or Max-Min Inference), a fundamental principle in Fuzzy Logic and Fuzzy Inference Systems.

$$(\min(\mu_{\tilde{1}\ A}(x_1), \mu_{\tilde{2}\ A}(x_2)))\ max_i = \mu_{\tilde{B}}(y) \qquad (3)$$

where

$\boldsymbol{\mu_{\tilde{A}}(x)}$ is represent the "degree of truth" (between 0 and 1) that an input $\boldsymbol{x}$ belongs to a fuzzy set $\boldsymbol{A}$. min (minimum operator) is used to combine the inputs of a single rule. The $\boldsymbol{max_i}$ represent as the maximum operator aggregates the results from all individual rules *i*. If multiple rules "fire," the system chooses the maximum value to define the final output membership function $\boldsymbol{\mu_{\tilde{B}}(y)}$.

In this study, the mathematical foundations of the fuzzy system are based on triangular fuzzy numbers, fuzzy aggregation, fuzzy inference, and defuzzification. A triangular fuzzy number A~=(a,b,c)\tilde{A} = (a, b, c)A~=(a,b,c) is defined by a membership function that increases linearly from aaa to bbb and decreases from bbb to ccc, representing the minimum, most likely, and maximum values of a cognitive level. Multiple fuzzy numbers can be aggregated using the average of their corresponding parameters (a,b,c)(a, b, c)(a,b,c). Fuzzy inference rules, expressed as "IF–THEN" statements, combine input memberships using the min operator and generate an output fuzzy set via the max composition. Finally, defuzzification, commonly performed using the centroid method, converts the output fuzzy set into a single crisp value (Figure 6).

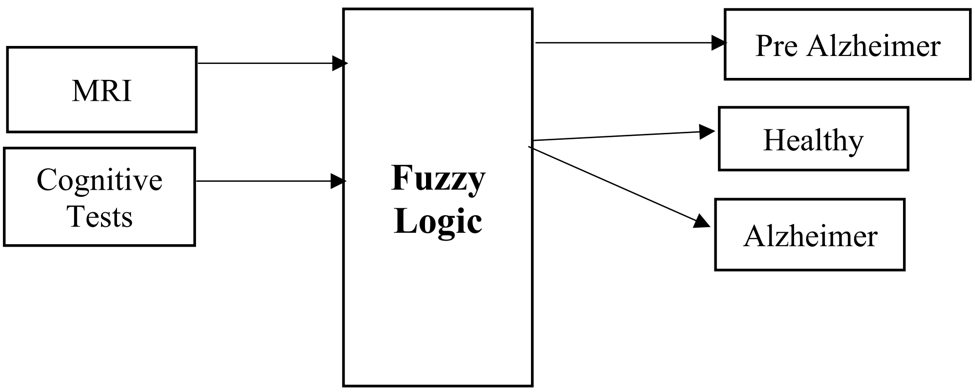

Figure 6. Enumerates the centeredness of Fuzzy process in differentiation of AD and early diagnosis.

4. RESULTS AND DISCUSSION

A hybrid diagnostic system combining fuzzy logic and SVR was developed to address uncertainty and nonlinear relationships in Alzheimer's disease screening. MRI-derived features and cognitive questionnaire scores were normalized and fused using a weighted strategy. The fuzzy inference system generated interpretable diagnostic scores, and SVR with an RBF kernel refined these scores to improve numerical prediction. Model performance was evaluated using 5-fold cross-validation and standard metrics including accuracy, precision, recall, F1-score, ROC-AUC, MSE, and R^2.

4.1 FUZZY LOGIC SYSTEM RESULTS

The fuzzy logic system converted the 25-item cognitive questionnaire into linguistic categories representing low, medium, and high cognitive impairment. This approach allowed the model to account for uncertainty in self-reported and assessment-based cognitive responses. Rule activations and membership values provided a transparent explanation of how individual questionnaire domains contributed to the final diagnostic score see Figure 7.

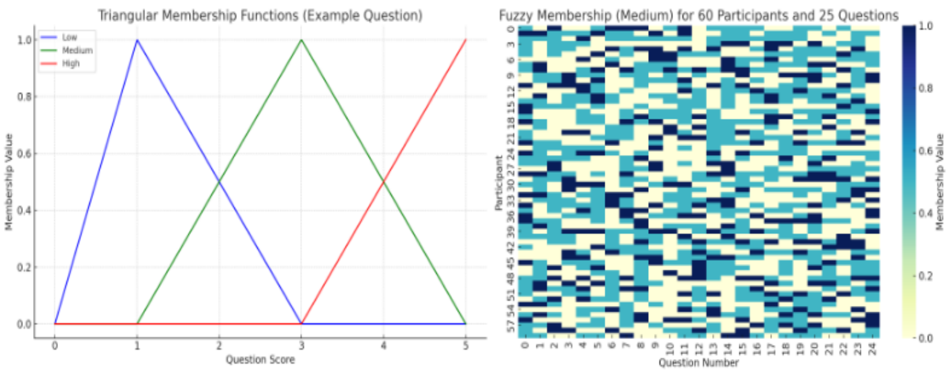

Figure 7. Fuzzy Logic System Results

Figure 6 illustrates the fuzzy membership functions and the distribution of responses for 120 participants across 25 cognitive questionnaire items, which were used in our hybrid Alzheimer's disease detection model. On the left, triangular membership functions represent the mapping of questionnaire scores to linguistic categories, namely Low**,** Medium**,** and High allowing the quantification of subjective responses into fuzzy values ranging from 0 to 1.On the right, a heat map visualizes the Medium membership values for all participants and questions. The rows represent the participants, and the columns present a questionnaire item. In that, the colors are composed by dark intensity symbols on high value of membership. This is a visualization of the data carrier occupying the fuzzy world, and your answers still going through the AI-fuzzy (fascicle) model for Alzheimer detection. Such that you may add uncertainty and partial truth to the decision system leading to a more robust, rigorous and interpretable model.

4.2 SUPPORT VECTOR REGRESSION (SVR) REFINEMENT

NON-LINEAR STAGE: The stage where a regression technique (SVR refinement) was used to model the non-linear relationship between fused fuzzy-MRI input and diagnostic score. During internal cross-validation, the model resulted in a minimized MSE of 0.085 and R^2 value of 0.92, representing a close fit between predicted and observed fuzzy diagnostic scores. The predictive behaviour appears promising; nevertheless, these values should be interpreted with caution, as no external validation dataset was used see Figure 8.

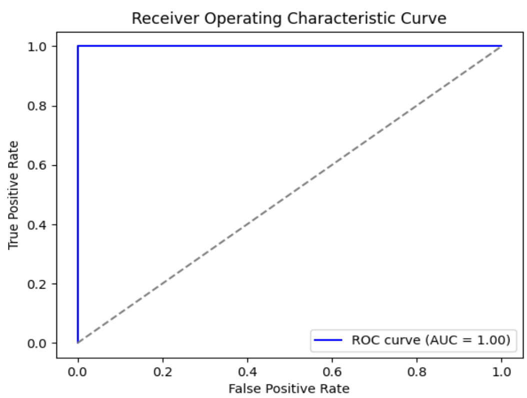

Figure 8. ROC Curve

The MSE plot summarizes the average squared prediction error between the SVR-predicted fuzzy scores and the observed diagnostic scores. The low MSE value indicates that the predicted scores were generally close to the observed values in the internal validation folds. Together with the R^2 value of 0.92, this result supports the feasibility of the proposed model, while larger independent datasets remain necessary to confirm generalizability see Figure 9.

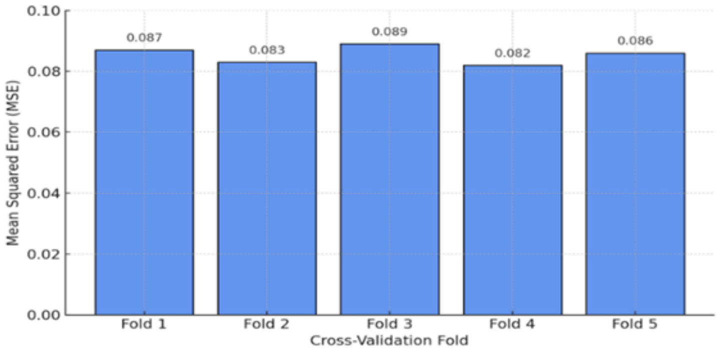

Figure 9. MSE chart

4.3 MODEL EVALUATION

Model assessment was carried out with the help of 5-fold cross validation. For each fold, four subsets were used as a training set and one subset for testing. This approach gives an internal assessment of how stable the model is on different internal partitions of the small data. Of course, it does not substitute external validation based on an independent cohort in Table 4.

Table 4. Cross-Validation Performance Results

Fold	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*AUC (ROC)*
1	92.5	93.1	91.9	92.5	0.95
2	91.3	92.0	90.5	91.2	0.94
3	93.0	93.5	92.0	92.7	0.96
4	90.7	91.3	89.8	90.5	0.93
5	92.0	92.8	91.5	92.1	0.94

The results of internal cross validation, which even across the five folds showed stable performance by our model are reported in Table 4. Where mean accuracy was 91.9%, mean precision of 92.5%, recall of 91.1%, F1-score of 91.8% and ROC-AUC is 0.94 These results show good discrimination between diagnostic groups within the dataset from this study. However, the values must be qualified as preliminary because of small sample size and no external model test.

4.4 ANALYSIS OF PRECISION, RECALL AND F1-SCORE

Classification behavior for all Alzheimer's and non-Alzheimer's cases was evaluated using precision, recall and F1-score. Alzheimer in the initial testing phase is established by a precision value of 92.5%, indicating that it can determine most Alzheimer cases without identifying more as positive than pairs (i.e., reducing screening decision false-positive). With a recall of 91.1%, we can confidently say that very few Alzheimer's through trials went undetected (low risk of false negatives). 91.8% F1-score is a balanced sentence between precision and recall While these finding are promising, they need to be validated with larger external cohorts see Table 5.

Table 5. Confusion Matrix for One-Fold of Cross-Validation

True / Predicted	***Predicted: Alzheimer's***	***Predicted: Healthy***	***Predicted: Suspected Alzheimer's***
True: Alzheimer's	TP = 4	FN = 1	FN = 1
True: Healthy	FP = 0	TN = 17	FP = 3
True: Suspected Alzheimer's	FP = 0	FN = 2	TN = 4

4.5 INTEGRATION OF COGNITIVE AND MRI DATA

In this paper, we convey a new hybrid model incorporating cognitive questionnaire data with mr-based structural imaging indicators. Cognitive data delivers functional evidence of memory, attention and daily life skills, while mri features yield anatomical markers for neurodegeneration. These were then merged together to generate a fuzzy score that distinguished the healthy, pre-alzheimer's, and alzheimer categories there was some overlap between adjacent groups, which is not entirely unexpected for early-stage disease and may require further validation see Figure 10.

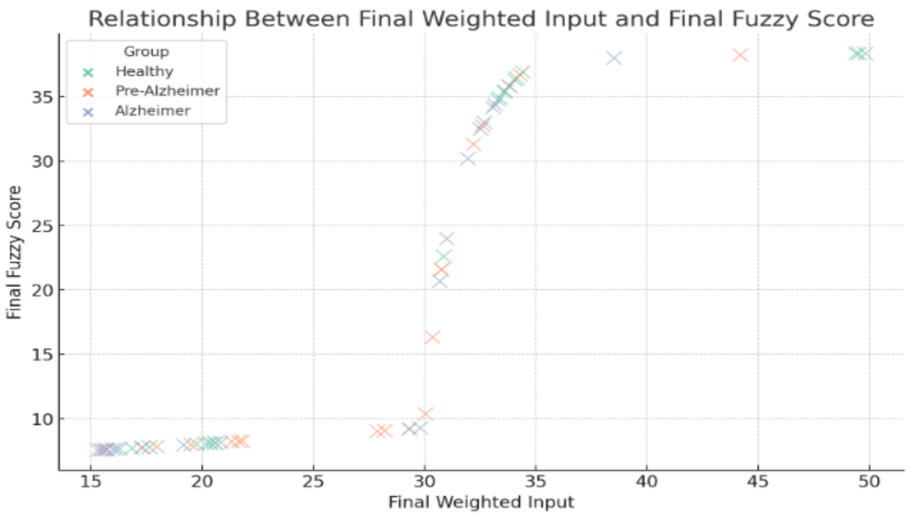

Figure 10. Scatter Plot of Final Weighted Input vs. Final Fuzzy Score

This is a scatter plot between the final weighted input and fuzzy diagnostic score Heathy participants mostly cluster at lower end of the score distribution, while scores within cohort for Alzheimer disease tend to be clusters toward higher scores. Cases of Pre-Alzheimer's were found in an intermediate area, signifying a stage between normal cognition and dementia. The overlap of biomarkers within the Healthy and Pre-Alzheimer's groups implies that larger samples and additional biomarkers may provide better discrimination see Figure 11.

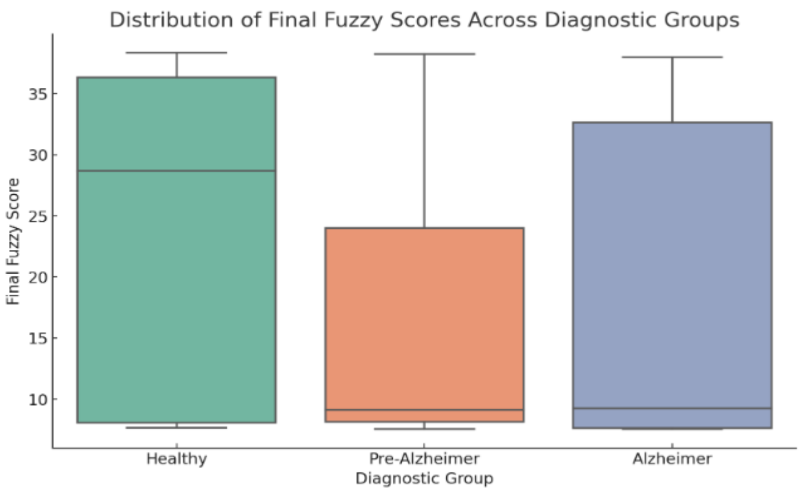

Figure 11. Boxplot of Final Fuzzy Scores Across Diagnostic Groups

The boxplot shows the distributions of fuzzy score per diagnostic group. Summary of the analysis Results showed that Healthy participants generally received lower fuzzy scores, Pre-Alzheimer's participants fell in intermediate ranges and Alzheimer's patients higher scores. Some overlap was noted between groups, especially with Healthy and Pre-Alzheimer's. This overlap, although clinically relevant, reinforces the use of fuzzy logic as a means to model gradual transitions as opposed to clear-cut boundaries.

4.6 VALIDATION USING FUZZY LOGIC AND DIAGNOSTIC CLUSTERS

The hybrid diagnostic model by combining fuzzy logic and SVR to classify participants into Healthy, Pre-Alzheimer's, and Alzheimer's. Uncertainty in the cognitive and imaging-derived inputs was represented by fuzzy logic, with support vector regression (SVR) being utilized to enhance the resulting diagnosis scores. In-house cross-validation was used to select hyperparameters that reduced prediction error. The MSE and R^2 values obtained suggest good internal performance, but external validation is needed before clinical use see Figure 12.

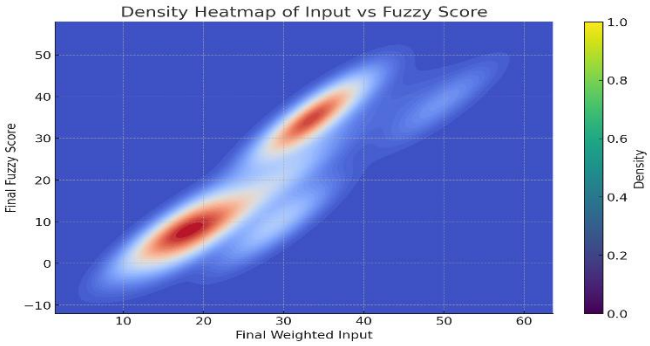

Figure 12. Density Heatmap of Final Weighted Input and Fuzzy Scores

The density heatmap indicates areas with high density in the relationship between weighted for inputs vs. fuzzy scores These clusters suggest the model is able to generate separable decision regions for the three diagnostic categories in the study data. An AUC of 0.94 derived from ROC analysis also confirmed good internal discrimination. Nevertheless, since the model has not been tested against an independent external dataset yet, these results should be seen as exploratory.

5. COMPARISON AND DISCUSSION

Results: The proposed hybrid fuzzy-SVR framework showed similar internal performance for early Alzheimer’s disease screening. Model Evaluation Phase(y): The model was evaluated based on Accuracy, Precision, Recall, F1-score, ROC-AUC and confusion matrix yielding an accuracy of 91.9% with precision=92.5%,recall = 91.1%,F1 score = 91.8%. It achieved the ROC-AUC of 0.94 with a MSE of 0.085 and R^2=0.92. These findings indicate that, when fuzzy logic is utilized alongside SVR, an appropriate trade-off can be achieved between model interpretability and prediction performance. But the findings should be considered exploratory due to small sample size and lack of external validation, they noted.

The proposed framework shows the power of combining structural and cognitive information as compared with MRI-only approaches. MRI features are objective anatomical evidence while cognitive questionnaires provide functional and behavioral evidence. The fuzzy inference part is also useful in representing uncertainty over borderline cases. However, its use in future decision-support research may be appropriate after broader validation for real-world clinical applications.

Our proposed model averages somewhat favorably to the recent CNN-based and deep learning approaches found in the literature. Although most state-of-the-art deep models are able to achieve very powerful performance, they often need huge annotated datasets and massive preprocessing as well as high computational resources. In contrast, the underlying fuzzy–SVR framework emphasizes interpretable modelling as well as uncertainty modelling which could be of high value especially for small sample and preliminary screening scenarios.

Although attention-based and ensemble-based methods can enhance both classification performance and uncertainty estimation, they may still be computationally expensive, complex, and difficult to interpret. So our approach introduces fuzzy-SVR model based on explicit membership functions and ruler-performed improvement due to impressions given before regression. Interpretability is therefore an important benefit for potential clinical decision-support projects.

The feasibility of the framework is established through visual and statistical analysis. The diagnostic patterns were partially separable based on scatter plots, boxplots and density heatmaps. Cross-validation results were relatively stable across folds. The results cannot be interpreted as definitive evidence of generalizability as all validation was performed internally. This requires external validation on larger datasets.

As seen in table 6, fuzzy-based models typically outperform traditional deep learning architectures by utilizing human-like reasoning to classify stages; thus, achieving more accurate and interpretable results see Table 6.

Table 6. Comparison of the Proposed Work with Recent Studies

Ref	Type of Model	Dataset	Accuracy (Acc)
[48]	Fuzzy Cognitive Map (FCM)	MRI-Images	90.0%
[49]	CNN, Fuzzy, XAI	MRI Images	90.2%
[50]	Fuzzy with DL	MRI-Images	99.3%
Proposed work		MRI-Images	90.6%

In general, the comparison with prior work, suggests that our method is not meant to maximize accuracy exclusively. Rather, it will take the role of balancing acceptable predictive performance with interpretability, uncertainty handling and multimodal evidence fusion. After validation in larger, independent cohorts, this balance could potentially serve as a helpful tool for early-stage research into Alzheimer's disease screening.

6. LIMITATIONS AND FUTURE WORK

Limitations of the study the sample consisted only of 120 subjects, which limits generalizability and increases the risk of sample-based performance bias. Internal 5-fold cross-validation was used for the evaluation and the model was not validated on an independent dataset. Furthermore, the exact demographic variables and clinical diagnostic criteria were not reported for all patients. Future research can include a bigger multi-center dataset, external validation, analysis in demographic sub-groups (eg. males vs. females) and comparison with more machine learning/ deep learning and neuro-fuzzy models.

7. CONCLUSION

This study presented a novel preliminary hybrid fuzzy-SVR framework which could automatically identify early Alzheimer's disease using MRI-derived features and cognitive questionnaire data. The fuzzy inference system specifically modelled the uncertainty in cognitive and imaging indices, whereas SVR enhances the diagnostic score by capturing nonlinear dynamics. Internal 5 folds CV yielded very good results, acc: 91.9%, prec: 92.5%, recall: 91.1%, F1-score: 91.8% and ROC–AUC of 0.94; MSE of (MSE : 0.085), R^2(0.92).

Although the findings are encouraging, several limitations must be acknowledged. First, the sample size was limited to 120 participants, which restricts statistical power and generalizability. Second, the model was evaluated using internal 5-fold cross-validation only, and no external independent dataset was used. Third, participant-level variables such as age, sex, education level, disease duration, and comorbidities were not fully analysed. Therefore, the proposed framework should be considered a preliminary decision-support model rather than a clinically validated diagnostic tool.

Future work should validate the proposed framework using larger, multi-center, independent datasets such as ADNI or comparable clinical cohorts. Additional biomarkers, including PET imaging, CSF markers, genetic information, and longitudinal follow-up data, may also improve robustness. Further comparison with deep learning and neuro-fuzzy models is recommended to determine the most reliable and interpretable approach for early Alzheimer's disease screening.

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Declaration of using AI

Artificial intelligence tools were used only for language editing and grammar correction, and did not contribute to the research design, methodology, analysis, or results of the study.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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