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# Hybrid Model based on ANFIS with Gray Level Co-occurrence Matrix for Dementia Prediction

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**Abstract**

Dementia is a brain condition in which cognitive abilities decline more quickly than expected from the usual consequences of biological aging. It impacts memory and a person's physical and mental health. Early stages of dementia are challenging to anticipate, and there is presently no treatment for this condition. Therefore, a precise and prompt diagnosis of dementia is strongly advised in order to give the patient the best possible treatment. This study provides a hybrid model for the automatic diagnosis of dementia from T1-weighted magnetic resonance imaging (MRIs). The proposed model consists of two stages: the first step implements gray level co-occurrence matrix (GLCM) to extract texture features from imaging data, and the second step applies an adaptive neuro-fuzzy inference system (ANFIS) for the prediction of dementia from these extracted texture features. The proposed framework has been evaluated on the benchmark Dementia dataset comprising 5154 2D T1w MRI scans. In order to assess the model's performance, the proposed model is also compared with a neural network, fuzzy logic, and other machine learning (ML) techniques using the same dataset. The accuracy of the proposed model is recorded as 82.5%, which is greater than that attained by existing ML methods.

*Keywords*: Dementia; GLCM; Machine learning; Medical diagnosis; ANFIS; Texture features.


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## 1. Introduction

Dementia is a brain condition in which cognitive abilities decline more quickly than may be anticipated from the usual effects of biological aging. Language difficulties, amnesia, confusion, and other behavioral problems are some of its symptoms. It frequently starts out slowly but increases over time. In addition to these symptoms, the body's functions steadily worsened, and the typical survival time following diagnosis is three to nine years. Alzheimer's, Lewy bodies, and vascular dementia make up the majority of cases of this condition [1]. Data from the World Health Organization shows that more than 55 million

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people worldwide currently have dementia, and this figure is projected to increase to 78 million by 2030. Developing nations will account for the majority of the increase. 60 % of dementia patients currently reside in underdeveloped and developing nations, and it will be 71 % by the end of 2050. The fastest increases in elderly populations are mostly occurring in China, India, and the south Asian and western Pacific regions. This raises a red flag for these countries to combat this illness [2] successfully.

Early stages of dementia are difficult to forecast since doing so requires gathering a lot of data using advanced techniques, and there is no cure for this disorder at this time. Thus the accurate and timely diagnosis of this disorder is highly recommended in order to promote its optimal management. A treatment administered at the initial stage is more beneficial and less harmful than one provided later. Early diagnosis may help improve physical and mental health and take the necessary steps to start the right therapy as soon as possible, which will also increase the likelihood of a longer life expectancy. Currently, dementia is diagnosed through cognitive exams, laboratory tests, and psychosocial assessments.

Additionally, since no single test can diagnose dementia, doctors will probably do a combination of tests that can assist them in identifying the issue. These methods are time-consuming, and a qualified neurologist and/or psychiatrist must be involved. Also, these methods can diagnose dementia in later stages, not in the early stages [3].

Magnetic resonance imaging (MRI) is a preferred neuro-imaging examination for dementia diagnosis because it does not expose patients to radiation. It helps physicians to diagnose brain diseases by identifying the structural changes in various parts of the brain, such as the hippocampus, temporal lobe, and frontal lobe, and it ultimately leads to the prediction of the severity and type of dementia. These MRI scans highlight the atrophy in the brain volume and changes in the pattern of tissue characteristics in individuals with dementia. However, MRI scan analysis is difficult since it relies on manual guiding and visual interpretation for estimation. Since a large number of brain slices must be scanned, diagnosing dementia takes a long time. In these situations, automated techniques are found to be more accurate and reliable than human evaluation; thus, they can be applied to medical decision-making [4].

Machine learning (ML) techniques are widely employed for forecasting and visualizing medical disorders to recommend personalized prescriptions. Apart from enhancing patient's life, ML benefits medical professionals in making treatment decisions. In recent years, ML approaches, including logistic regression (LR), k-nearest neighbor (KNN), decision tree (DT), and others, have shown promising outcomes in detecting demented patients throughout the years [5]. But these techniques suffer from the issues of handling uncertainty, non-linearity, and higher dimensionality present in the medical data as MRI data is widely acknowledged for its large volumes and high complexities, which make learning-based tasks challenging to obtain promising performance. Thus, scientists are increasingly feeling the need to move towards hybrid artificial intelligence (AI) to diagnose dementia. Hybrid AI is touted to solve fundamental problems that machine learning faces today [6]. Shi *et al.* [7] suggested that hybrid models can be useful for medical image analysis. A hybrid model is a system that incorporates two or more different ML/soft computing approaches. Due to the integration of several methodologies into a single computational model, these systems have a wider range of capabilities, including the ability to reason and learn in a complex environment.

This paper presents a hybrid model for the automatic diagnosis of Dementia from two-dimensional (2D) T1weighted magnetic resonance imaging (MRI) data. The proposed approach classifies dementia into AD (Alzheimer's disease), MCI (Mild cognitive impairment), and CN (healthy subjects). It works in two steps: the first implements a gray-level co-occurrence matrix (GLCM) for texture feature extraction from imaging data, and the second applies an adaptive neuro-fuzzy inference system (ANFIS) for the identification of dementia from these extracted texture features. GLCM is used as a feature extractor in the proposed model since it can extract texture features from images. The texture features of images are important in the diagnosis of dementia as it depicts certain repeated local patterns and arrangement regularity in specified regions of images [8]. For the proposed approach, ANFIS is introduced as a classifier since it concatenates the human cognitive abilities of fuzzy systems with the learning capacity of neural networks for parameter evaluation and automatic optimization of fuzzy inference systems through learning algorithms [9]. The proposed framework has been evaluated on the benchmark dataset of Dementia. This benchmark dataset consists of 5154 2D images of Dementia with 3 classes. In order to validate the efficiency of the proposed approach, it is compared with the neural network (NN) [10] approach, fuzzy logic (FL) approach [11], and other ML techniques based on accuracy parameters.

The structure of this research article is as follows: After the introduction, section 2 reviews the prior literature that is relevant to the current work. The methodology used to develop the proposed hybrid framework is described in section 3. The outcomes of the experiment are analyzed and discussed in section 4. Finally, the summary of the paper is described in section 5.

## 2. Related Work

In recent years, researchers have proposed various techniques, including ML-based models for predicting and classifying dementia disease. These techniques seemed to hold potential for diagnosis of dementia, particularly over the past ten years [12]. In order to diagnose dementia and forecast its progression, research is continuously being carried out in this domain.

For automatic dementia diagnosis, ROI (region of interest) based methods have been employed. These approaches focused on volumetric measurement of a specific part of the brain, i.e., the *entorhinal cortex* [13] or *cerebral parenchyma* [14] or *medial temporal lobe* [15]. But these ROI-based methods rely mostly on manual or semi-automatic segmentations, which are time-consuming and prone to errors and inter/intra-rater variability.

To overcome the limitations of ROI-based approaches, Moller *et al*. [16] proposed a whole-brain morphometry method for dementia diagnosis. This approach warps the MRI scan of the given patient to the standard template by high dimensional deformation, where shape differences between these two scans are encoded in the deformations. But this approach always requires non-linear alignments to a template in order to achieve voxel-wise inter-subject correspondence. Due to the high anatomical variability of brain structures, it is difficult to evaluate the accuracy of this inter-subject matching.

ML-based approaches have been used to diagnose dementia in order to get around the constraints of the whole brain morphometry methods. Khedher *et al.* [17] implemented a support vector machine (SVM) for the diagnosis of dementia from T1w MRI images. The presented approach was implemented using the dataset of 630 MRI scans with 02 classes, i.e., 401 cases of MCI and 229 cases of CN. The experiments predicted an accuracy of 77.62 % for the proposed model. Naïve Bayes (NB) classifier was employed by Bhagyashree and Sheshadri [18] for the classification of dementia disorder. The cognitive screening instrument for dementia (CSID) tool was used to gather the data from 466 subjects to compute CSID COG SCORE. The experiments have been performed on the WEKA platform by applying the wrapper method for feature selection and SMOTE for imbalanced data reduction. The proposed approach gave an overall sensitivity of 70.4 %.

Zhu *et al*. [19] used different ML models, i.e., SVM, NB, random forest, AdaBoost, and NN, for the diagnosis and classification of dementia by employing a clinical dataset of 5272 records. Among undertaken ML techniques, the NB classifier gave the best performance with an accuracy of 81 %. SVM and convolutional neural network (CNN) based diagnostic models were introduced by Grueso and Viejo-Sobera [20] to predict whether patients with MCI might develop AD or remain stable. The presented approaches were applied to the neuro-imaging dataset of 116 instances. The accuracies of 75.4 % and 78.5 % were observed in the case of SVM and CNN, respectively. Kavitha *et al*. [21] applied various ML techniques for AD prediction using a decision tree, SVM, gradient boosting, and voting classifiers on Open Access Series of Imaging Studies (OASIS) data. The experimental results predicted maximum accuracy of 81.67 % on SVM.

These ML-based diagnostic models have been found to be better than ROI based approach and whole-brain morphometry method for dementia diagnosis. But these techniques predicted low accuracy due to issues of non-linearity and higher dimensionality present in the imaging data. Thus, researchers nowadays focus on the development of hybrid models. Compared to earlier pieces of work, the current study aims to present an efficient hybrid model for the diagnosis of Dementia from two-dimensional (2D) T1w MRI scans in order to assist neurologists and psychiatrists in accurately detecting dementia. The proposed model has been validated by carrying out experimentation on a benchmark dataset of Dementia consisting of T1w MRI scans with three classes: AD (Alzheimer), MCI (mild cognitive impairment), and CN (healthy control). The presented hybrid model has been validated based on four evaluation metrics: accuracy, recall, precision, and f-score.

The contributions of this paper can be summarized as follows.

- A hybrid system has been presented for efficient diagnosis of dementia from MRI scans in order to reduce manual directing and visual reading.
- The proposed model works on the assessment of texture features since dementia occurs due to the formation of amyloid-β plaques and tau-related neurofibrillary tangles between and within the brain neurons that ultimately leads to changes in the texture pattern of various parts of the brain. These changes can be effectively captured by the texture analysis of MRI scans before neuronal death.
- The proposed model considers the whole brain as ROI (region of interest) instead of a specific part of the brain since dementia leads to atrophy over all brain regions.

The experimental studies revealed that the proposed approach can achieve better performance when compared to conventional ML techniques.

## 3. Materials and Methods

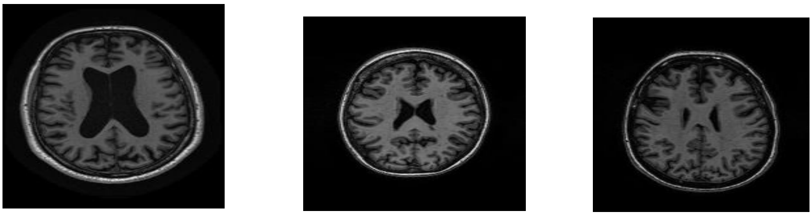
The current research study presents an ML-based hybrid model for the diagnosis of dementia from 2D T1w MRI images. To implement the proposed model, the experiments have been performed on the computer with configuration Intel Core i31.70 GHz CPU, 4GB RAM, and 64-bit operating system. MATLAB 2018a platform has been used, and Neuro-Fuzzy Designer 2.3.1 toolbox and Image Browser 10.2 toolbox were employed for the development of the hybrid model.

### 3.1. *Data collection*

For the experimental study, the proposed hybrid model has been applied to the benchmark dataset of dementia. This dataset has been collected from <https://www.kaggle.com/datasets/katalniraj/adni-extracted-axial>. This dataset consists of 2D MRI axial images extracted from the ADNI baseline dataset, which consisted of Nifti images. The subjects included in the dataset have ages 55-89 years. The images have been extracted from the ADNI Baseline dataset (NIFTI format), which consisted of 199 instances. The original images can be downloaded from <https://ida.loni.usc.edu/login.jsp?project=ADNI>. This dataset contains 2D T1w MRI images in *.png* format. It consists of 5154 images of Dementia with 3 classes, i.e., AD (Alzheimer's), MCI (mild cognitive impairment), and CN (healthy control). The details of collected MRI images in the benchmark dataset are presented in Table 1. Fig. 1 represents the sample of collected 2D MRI scans in the dataset.

Table 1. Details of MRI images in the benchmark dataset.

| Class | No. of MRI Images |
|---|---|
| AD | 1124 |
| MCI | 2590 |
| CN | 1440 |
| Total Instances | 5154 |

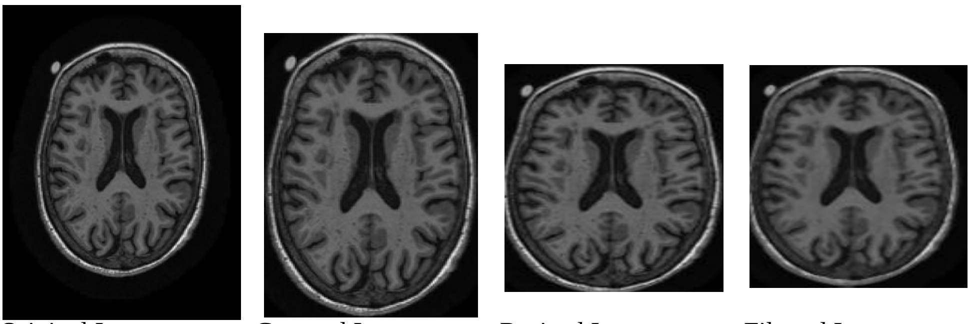


AD MCI CN

Fig. 1. Sample of collected 2D MRI images.

### 3.2. *Data preprocessing*

After data collection, various preprocessing operations, including cropping, resizing, and filtering, were performed on the collected images of the dataset. The collected images were cropped to remove unwanted regions, and these cropped images were then resized to [175,125] px. After resizing the operation, the images are filtered using *median filtering* to smooth the edges and remove the noise. Fig. 2 displays an MRI image in the dataset undergoing various preprocessing operations.



Original Image (256*160) Cropped Image (193*119) Resized Image (175*125) Filtered Image (175*125)

Fig. 2. Preprocessing operations carried out on collected images.

### 3.3. *Implementation of the proposed hybrid model*

After preprocessing, the proposed hybrid model has been implemented for dementia disorder prediction. The collected neuro-imaging data $D$ has been preprocessed using cropping, resizing, and filtering operations. The processed dataset $D_{preprocessed}$ was applied to GLCM to obtain texture feature vector $V$. This extracted feature vector was converted to .csv file $X$, which was randomly split in the ratio of 75:25 into two sets referred to as trainset $X_{train}$ and testset $X_{test}$. A train set was used to train the proposed model, and the test set was employed to assess the model's performance afterward. The details of both these sets are presented in Table 2. After the train-test split, the ANFIS classifier is applied to the $X_{train}$ to train the hybrid model. The presented hybrid model has been validated using

$X_{test}$ for its performance evaluation. The performance of the trained hybrid model has been measured by four important parameters: *accuracy*, *recall*, *precision*, and *F-score*. The pseudo-code for training and testing the proposed hybrid model is presented in algorithms 1 and 2, respectively. The overall framework for the proposed hybrid model is presented in Fig. 3.

Table 2. Details of instances in the train set and test set for benchmark dataset.

| Output Class | Train Set | Test Set |
|---|---|---|
| AD | 870 | 254 |
| MCI | 1929 | 661 |
| CN | 1066 | 374 |
| Total Instances | 3865 | 1289 |

Algorithm 1. Training process of the proposed hybrid model (GLCM-ANFIS)
Input: Dementia neuro-imaging dataset (D) with N images, Feature vector (V) of size N*23
Output: Hybrid Model (GLCM-ANFIS)
Steps:

1. For I=1:N Do
   $D_{preprocessed}$[I] = Preprocess(D[I]), i.e., preprocess each MRI image through cropping, resizing, and median filtering
   End For
2. For I=1:N Do
   V[I] = GLCM($D_{preprocessed}$[I]) i.e. extract 23 texture features from each preprocessed MRI scan by applying GLCM
   End For
3. X = CSV(V) i.e. convert Feature vector to .csv file
4. [$X_{train}$, $X_{test}$]= Split(X), i.e., split the dataset into two sets in a 75:25 ratio: train set and test set
5. GLCM-ANFIS= ANFIS($X_{train}$), i.e., apply ANFIS classifier on the train set
6. Return GLCM-ANFIS

Algorithm 2. Testing the proposed hybrid model (GLCM-ANFIS)
Input: Hybrid Model (GLCM-ANFIS), Test set ($X_{test}$) with M instances and target output T, Output label (L) vector
Output: Classification Results (R)
Steps:

1. For J=1:M Do
   L[J] = Predict(GLCM-ANFIS, $X_{test}$[J]), i.e., returns the predicted class labels for the predictor data in the test set based on the trained hybrid model
   End For
2. Compute confusion matrix H from T and L
3. Calculate performance metrics from H

4. Classification results R = Performance metrics results
5. Return R

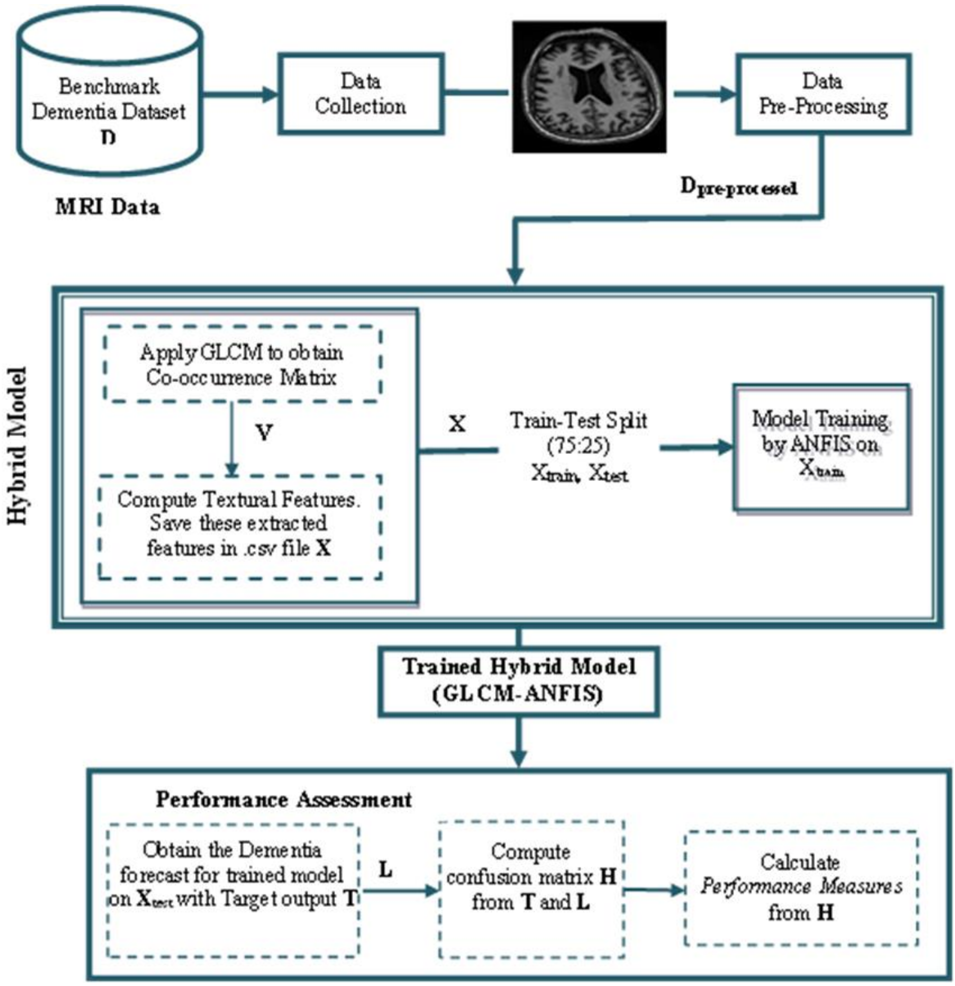



Fig. 3. Framework for the proposed hybrid technique.

Magnetic resonance imaging plays a significant role in the diagnosis of dementia as they contain crucial information for medical practitioners. However, the analysis of MRI images is extremely laborious and time-consuming due to their large volumes. This study presents a hybrid methodology to distinguish disease-specific atrophy from that of normal aging by incorporating T1w MRI as the imaging modality. The proposed hybrid model (GLCM-ANFIS) works in two steps: the first step implements gray level co-occurrence matrix (GLCM) for texture feature extraction from MRI data, and the second step applies adaptive neuro-fuzzy inference system (ANFIS) for the identification of dementia from these extracted texture features.

Neuro-imaging assists medical professionals in the timely identification of dementia since these images comprise crucial data required to distinguish demented patients from healthy ones. But the analysis of such images takes a lot of time due to their large sizes, and the whole information in these images is not required for performing the disease classification. Thus, feature extraction is therefore carried out to compute the features [22]. GLCM is a second-order statistical texture analysis approach where texture information is extracted from images by analyzing the statistical distribution of pixel intensities at specific points relative to one another in the image. These second-order features represent the degree of association among these pixels on average. It inspects the spatial connection among pixels to define the frequency of a particular combination of pixels appearing in an image in a given direction $\boldsymbol{\theta}$ and offset $\boldsymbol{d}$ [8].
Let $I$ be the image with size $a*b$ and $N$ gray levels.
A GLCM is a matrix of size $N*N$ for image $I$.

The matrix element $P_{ij}(i, j \mid d, \theta)$ is the relative frequency with which pixel $i$ and pixel $j$ occur in the given neighborhood at a particular displacement distance $d$ and at a particular angle $\theta$. The mean and standard deviation for the GLCM matrix in the horizontal and vertical direction is given from Eq. (1) to Eq. (4) represented as under:
GLCM mean:

$$\mu_i = \sum_{i,j}^{N-1} i(P_{ij}) \tag{1}$$

$$\mu_j = \sum_{i,j}^{N-1} j\left(P_{ij}\right) \tag{2}$$

GLCM standard deviation

$$\sigma_i = \sqrt{\sum_{i,j}^{N-1} P_{ij}}\,(i-\mu_i)^2 \tag{3}$$

$$\sigma_j = \sqrt{\sum_{i,j}^{N-1} P_{ij}}\,(j-\mu_j)^2 \tag{4}$$

The details of extracted texture features are presented from Eq. (5) to Eq. (15).
Contrast: It quantifies regional variations present in the image.

$$F_1 = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \tag{5}$$

Correlation: It measures the grey-level linear dependence between pixels (relative to each other) at the specified positions.

$$F_2 = \sum_{i,j=0}^{N-1} P_{ij}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \tag{6}$$

Energy: It provides information on image homogeneity.

$$F_3 = \sqrt{\sum_{i,j=0}^{N-1} P_{ij}^2} \tag{7}$$

Homogeneity: It reflects the familiarity of the distribution of elements in the GLCM to the GLCM diagonal.

$$F_4 = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (8)$$

Mean: It evaluates the average value of all the pixels present in the image.

$$F_5 = \frac{\sum_a \sum_b I(a,b)}{a*b} \quad (9)$$

Standard Deviation: It measures the deviation of pixel value from its mean.

$$F_6 = \sqrt{\frac{\sum_a \sum_b \ (I(a,b)-\mu_I)^2}{(a*b)}} \quad (10)$$

Entropy: It describes how much uncertainty or randomness is present in an image.

$$F_7 = -\sum_0^{N-1} Prob(I) * \log(Prob(I)) \quad (11)$$

where $Prob(I) = \frac{n_k}{a*b}$, k = {0, N-1} i.e., the probability of each intensity level of a pixel

RMS: It measures the amount of change per pixel due to the processing.

$$F_8 = \sqrt{\frac{1}{a*b} \sum_0^{a-1} \sum_0^{b-1} [O(a,b) - P(a,b)]^2} \quad (12)$$

where O refers to the original image and P refers to the processed image
Variance: It gives an idea of how the pixel values are spread.

$$F_9 = \frac{\sum_a \sum_b \ (I(a,b)-\mu_I)^2}{(a*b)} \quad (13)$$

Kurtosis: It measures the peak for the frequency distribution of pixels

$$F_{10} = \frac{1}{(a*b)} \sum_a \sum_b \left[\frac{I(a,b)-\mu_I}{\sigma_I}\right]^4 - 3 \quad (14)$$

Skewness: It measures the degree of asymmetry of the histogram of the image

$$F_{11} = \frac{1}{(a*b)} \sum_a \sum_b \left[\frac{I(a,b)-\mu_I}{\sigma_I}\right]^3 \quad (15)$$

For the proposed model, the GLCM approach has been applied for extracting texture features from processed 2D MRI images. This approach has been implemented by computing a co-occurrence matrix in four directions, i.e., $0^o$, $45^o$, $90^{o,}$ and $135^{o,}$ with an offset value of '1' from each MRI image, thus generating four co-occurrence matrices. From each co-occurrence matrix; four 'second order' statistical features, i.e., '*Contrast*, *Correlation*, *Energy*, and *Homogeneity'* were computed for each direction; hence extracting total 16 textural features. Apart from these extracted features, first-order texture features, i.e., Mean, Standard Deviation, Entropy, RMS, Variance, Kurtosis, and *Skewness*, were also calculated from the image. Thus total 23 features are extracted for each image which would be taken as input parameters for the classifier. The class of dementia is considered as an output label for the dataset. In the benchmark dataset, there are three classes which are labeled as 0 for Alzheimer's disorder, 1 for mild cognitive impairment, and 2 for healthy control. The extracted features are saved in a .csv file. Fig. 4 shows the screenshots for .csv files extracted from GLCM for the demented dataset. In Fig. 4, columns A to W present the extracted texture feature value for each MRI scan, and the last column, X represents the output label (i.e., 0-AD, 1-MCI, and 2-CN) for the respective MRI scan. The total size of the .csv file becomes 5154*24 with 23 input attributes (i.e., A to W) and 01 output attribute (i.e., X).

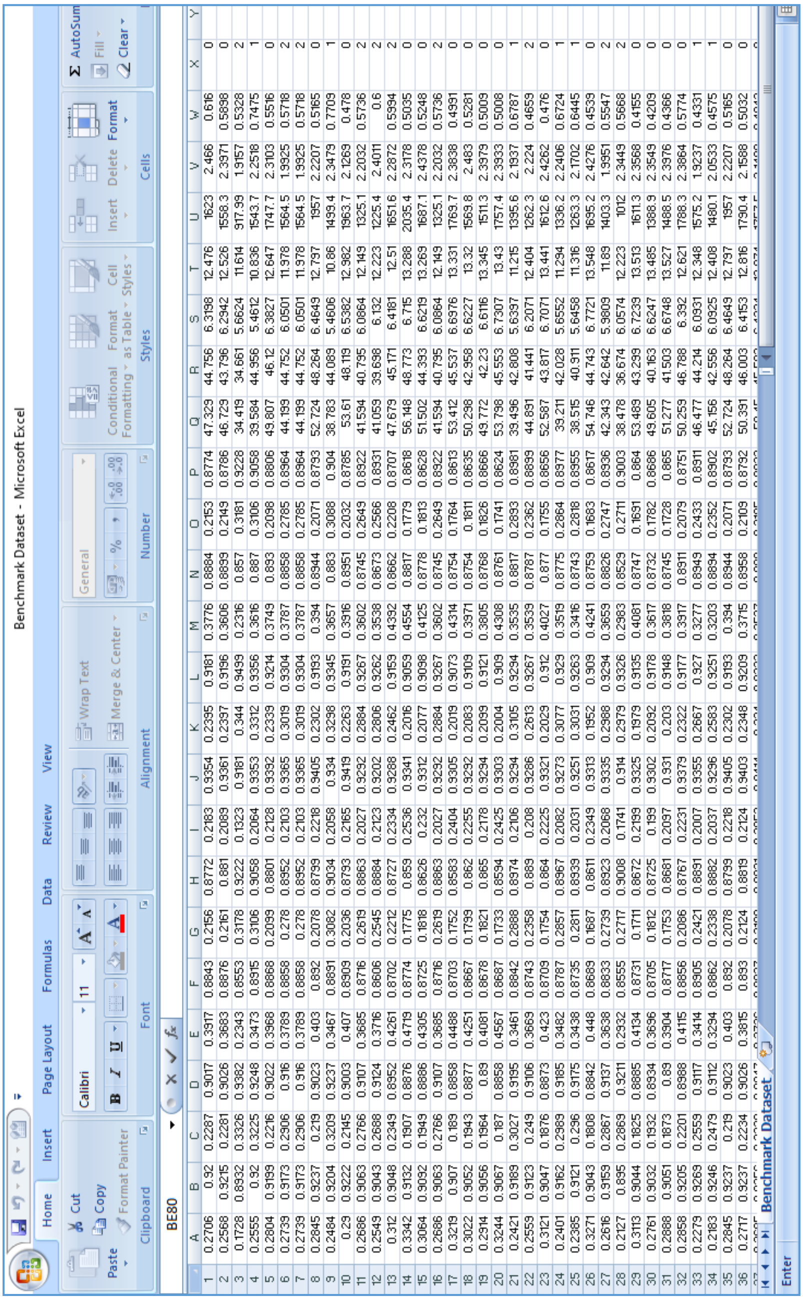



Fig. 4. CSV file extracted for Demented Dataset.

3.3.2. *Adaptive neuro-fuzzy inference system (ANFIS) implementation for classification*

Neuro-Fuzzy System (NFS) refers to a hybrid system that integrates the concurrent processing and learning capacity of neural networks (NN) with human cognitive abilities of fuzzy logic (FL). NN is a simplified mathematical model of a brain-like system that works like a parallel distributed computation network. NN is a basic computational paradigm working well with unprocessed data. But it does not have interpretation functionality. FL works with reasoning on a higher level using linguistic data acquired from the domain expert, thereby depicting the intrinsic inadequacies of human knowledge with linguistic variables. But it is not robust in relation to the topological changes of the system, thereby lacking the learning and generalization ability. By fusing FL with NN to design a hybrid system known as NFS, the individual merits of these two ML approaches are enhanced, and the de-merit is conquered [9].

In the proposed hybrid model, an adaptive network-based fuzzy inference system (ANFIS) has been applied as it is found to be the preferable NFS architecture and the most widely used by researchers. ANFIS applies a neural network to learn the parameters of the fuzzy system, including fuzzy rules and their weights, in an iterative way. It uses either standard back-propagation or the hybrid learning approach for fuzzy rule base optimization. Fig. 5 displays the intact framework of ANFIS, and it has five layers. *The first layer* fuzzifies the input variables, *the second layer* performs the fuzzy AND task of the fuzzy rules in the antecedent part, *the third laye*r normalizes the membership function parameters, *the fourth layer* executes the conclusion part of fuzzy rules, and *the final layer* computes the output of the fuzzy system by adding the outputs from the previous layer. NFS is optimized by tuning the antecedent parameters (i.e., membership function parameters) and consequent parameters (i.e. the polynomial coefficients of the consequent part).

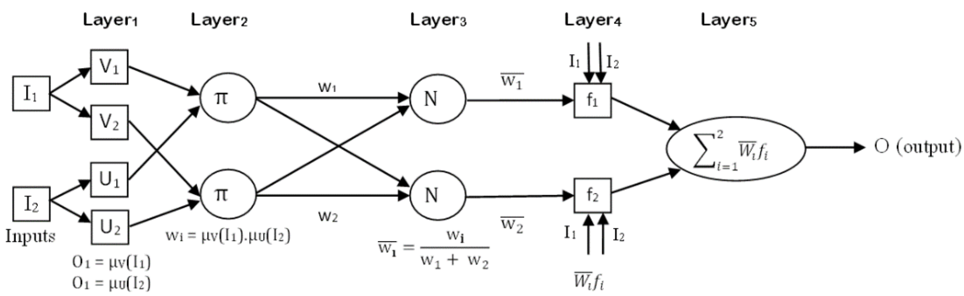



Fig. 5. ANFIS architecture.

In the current research, the ANFIS classifier has been applied for model training using extracted texture features to diagnose dementia disorder. Table 3 depicts the parameters which are used to incorporate ANFIS in the proposed hybrid model. The standard values (defined for ANFIS) have been taken for these parameters. The proposed hybrid technique has been implemented with *subtractive clustering* and *hybrid learning*.

Subtractive clustering has been applied on the *trainset* with *input parameters* and output labels as output data, along with a cluster radius of 0.6 to train the model. Subtractive clustering transforms cluster centers into fuzzy rules for the evaluation of a particular demented class. The generated fuzzy rules are optimized using the back-propagation algorithm, and the output constants are optimized usingthe *leastsquare* method. Training of the proposed model was completed in 200 epochs.

Table 3. Parameters for ANFIS approach to training the proposed hybrid model.

| Parameter | ANFIS model |
|---|---|
| Clustering Type | Subtractive Clustering |
| Input Membership Function | Gaussmf |
| Output Membership Function | Linear |
| AND Rule | Prod |
| OR Rule | Probor |
| Implication Rule | Prod |
| Aggregation Rule | Sum |
| De-fuzzification Rule | Wtaver |
| Learning Rule | Hybrid Learning |

Table 4 depicts the detail of generated ANFIS model after the training process. The implementation of ANFIS resulted in a generation of 18 fuzzy rules. The trained ANFIS has 456 linear parameters and 1330 non-linear parameters with 3865 training data pairs. Fig. 6 displays the architecture of the trained ANFIS, which is generated as five-layered architecture where the first layer has 23 nodes since the train set has 23 input parameters. Each node takes the input variable and fuzzifies it in the next layer using the *gauss* function as a membership function. The third layer has 18 nodes due to the generation of 18 fuzzy rules. This layer performs the AND operation of the fuzzy rules in the antecedent part, normalizes the membership function parameters, and executes the conclusion part of fuzzy rules. The fourth layer defuzzifies the output from the previous layer. The final layer computes the output of the fuzzy system by adding the outputs from the fourth layer. Fig. 7 depicts the rule base of the trained ANFIS classifier. It has 18 rows and 24 columns. These 18 rows refer to 18 fuzzy rules. For each fuzzy rule, there are 23 input parameters and 01 output parameter represented using the *gauss* membership function and *linear* function, respectively.

Table 4. Details of generated ANFIS classifier.

| Parameter | Value |
|---|---|
| Number of nodes | 938 |
| Number of linear parameters | 456 |
| Number of non-linear parameters | 874 |
| Number of training data pairs | 3865 |
| Number of fuzzy rules | 18 |

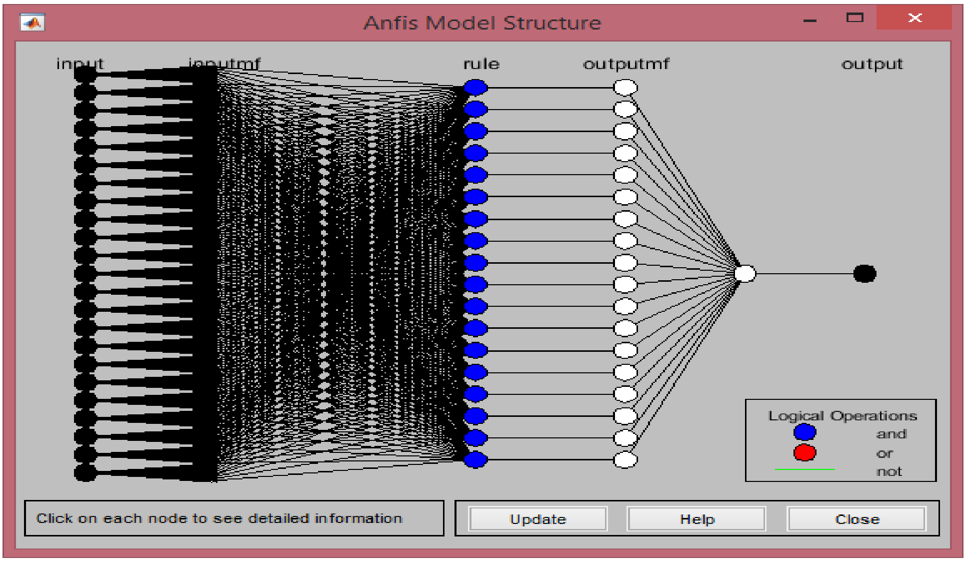



Fig. 6. Architecture of generated ANFIS.

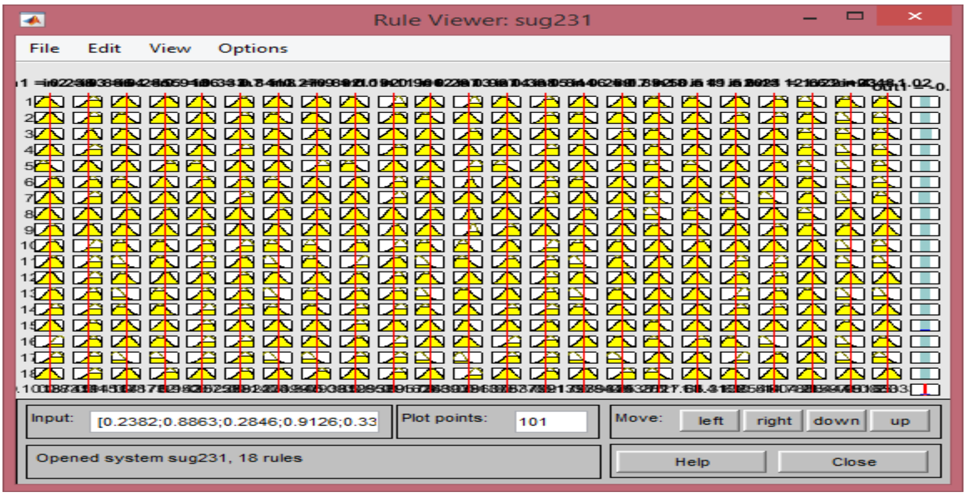



Fig. 7. Rule base of trained ANFIS.

## 4. Results and Discussion

This research study provides a hybrid model for dementia prediction based on GLCM and ANFIS from T1w 2D MRI images. The experiments have been carried out on the Matlab platform using the benchmark dementia dataset. Medical specialists expect the prediction method to accurately foretell the ailment under consideration for medical diagnosis. The performance of the proposed hybrid model has been evaluated on four metrics such as *accuracy*, *recall*, *precision*, and *f-score*. The reason behind this is that accuracy indicates the model's performance, whereas precision and recall provide information on *False Positives* and *False Negatives*, respectively. In the case of the imbalanced dataset, accuracy for the majority class is predicted to be high, while it is discovered to be low for the minority class. However, because there are far more instances of the majority class than there are of the minority class, the trained model's overall accuracy remains high. In this case, accuracy cannot be used to make a reliable prediction for the minority group. As a result, more realistic evaluation metrics are required. In order to avoid misclassification of the disease, this prediction method is expected to have minimal *false positives* and *false negatives*. F-score helps resolve the issue of "low variance and high bias" vs. "high variance and low bias" along with the issue of overfitting in an imbalanced dataset. Since the current research study deals with an automatic diagnosis of dementia and the collected dataset for dementia disorder is imbalanced, hence the performance of the provided hybrid framework was evaluated on these four metrics. These metrics are computed from the confusion matrices obtained for the trained model presented below:

Classification Accuracy =

$$\frac{\sum_{i=1}^{\text{Total no.of Classes}} \frac{\text{True Positive}_i + \text{True Negative}_i}{\text{True Positive}_i + \text{True Negative} + \text{False Positive}_i + \text{False Negative}_i}}{\text{Total no.of Classes}} \tag{16}$$

$$\text{Average Precision} = \frac{\sum_{i=1}^{\text{Total no.of Classes}} \frac{\text{True Positive}_i}{\text{True Positive}_i + \text{False Positive}_i}}{\text{Total no.of Classes}} \tag{17}$$

$$\text{Average Recall} = \frac{\sum_{i=1}^{\text{Total no.of Classes}} \frac{\text{True Negative}_i}{\text{True Negative}_i + \text{False Positive}_i}}{\text{Total no.of Classes}} \tag{18}$$

$$\text{F-score} = 2 * \frac{Precison * Recall}{Precision + Recall} \tag{19}$$

The experiments have shown that the proposed hybrid system (GLCM-ANFIS) can be applied efficiently for dementia diagnosis. This model diagnoses dementia from an MRI scan and classifies it to AD, MCI, or CN. Fig. 8 presents the confusion matrix for the proposed approach on the *testset*. The test set consists of 254 cases of AD, 661 cases of MCI, and 374 cases of CN. Out of 254 AD instances, 194 have been correctly classified, whereas 60 have been misclassified as MCI cases. In the case of MCI, 590 have been correctly classified, whereas 19 and 52 records have been misclassified as AD and CN cases, respectively. For CN records, 279 have been correctly predicted, whereas 03 and 92 records have been misclassified as AD and MCI instances, respectively. This model has generated 60 FN and 22 FP for AD, 71 FN and 152 FP for MCI, and 95 FN and 52 FP for CN.

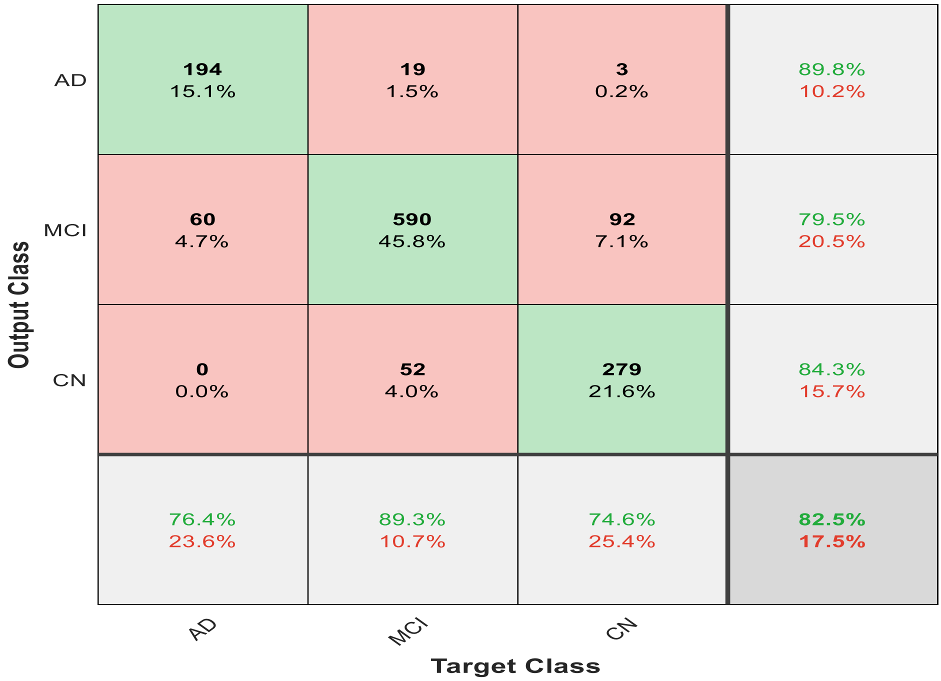



Fig. 8. Confusion matrix of GLCM-ANFIS Model for dementia disorder.

The proposed model predicted the highest precision of 89.8 % with the lowest false positive rate of 10.2 % for AD and the lowest precision of 79.5 % with the highest false positive rate of 20.5 % for MCI. It achieved the highest recall of 89.3 % with the lowest false negative rate of 10.7 % for MCI, whereas the lowest recall of 74.6 % with the highest false negative rate of 25.4 % for CN. Since the dataset is class imbalanced, it also has been found to have an impact on the performance of the model.

The main purpose of the current study is to offer a hybrid ML framework for timely diagnosis of dementia. This study explored the possibility of a hybrid model to distinguish demented patients from healthy ones. The validity of this hybrid model has been done on *Test Set* using four evaluation metrics. This model was evaluated with a neural network and fuzzy logic using the same dataset for validating its performance. Table 5 presents the overall experimental results of the GLCM-ANFIS, FL, and NN approach for dementia prediction on *testset*. The proposed model yielded a classification accuracy of 82.47 %, recall of 80.01 %, and precision of 84.54 %. It predicted an f-score of 0.8225. NN and FL achieved an accuracy of 75.95 % and 71.99 %, respectively. Recalls of 71.01 % and precision of 78.48 % were observed in the case of FL, whereas NN predicted recall and precision of 69.88 % and 70.43 %, respectively. The *former* predicted an f-score of 0.7015, whereas the *latter* obtained an f-score of 0.7456.

Table 5. Experimental results for GLCM-ANFIS model on the test set.

| Performance Metric | GLCM-ANFIS | Fuzzy Logic (FL) | Neural Network (NN) |
|---|---|---|---|
| Accuracy | 82.4670 % | 75.9503 % | 71.994 % |
| Recall | 80.0785 % | 71.0102 % | 69.88 % |
| Precision | 84.5399 % | 78.4788 % | 70.43 % |
| F-Score | 0.8225 | 0.7456 | 0.7015 |

The proposed hybrid model was also compared with conventional ML approaches using the same dementia dataset based on accuracy parametersto evaluate the proposed approach's effectiveness for dementia diagnosis. Table 6 presents these comparison results. The naïve bayes approach predicted less than 50 % accuracy, whereas support vector machine and linear discriminant analysis achieved accuracies in the 50-60 % range. Neural network, fuzzy logic, and decision tree obtained accuracies of 70-80 %. K-nearest neighbor predicted accuracy greater than 80 % but still less than the proposed model that achieved the highest accuracy of 82.47 %. The experimental outcomes revealed that the proposed hybrid framework outperformed existing machine learning approaches, and it has been found to be an efficient model for dementia diagnosis that may assist the medical practitioner in diagnosing undertaken disease. The proposed approach provides higher classification accuracy and better recall and precision values when compared to conventional approaches like fuzzy logic and neural network. Thus, the experimental evaluation proved the effectiveness of the proposed algorithms.

Table 6. Evaluation of the proposed hybrid model with different machine learning approaches for dementia diagnosis on the same dataset.

| ML Technique | Classification Accuracy (%) |
|---|---|
| Naïve Bayes | 44 |
| Support Vector Machine | 51.2 |
| Linear Discriminant Analysis | 56.1 |
| Neural Network | 71.994 |
| Fuzzy Logic | 75.95 |
| Decision Tree | 77 |
| K-Nearest Neighbor | 81.8 |
| *Proposed hybrid model* (GLCM-ANFIS) | **82.47** |

To further evaluate the efficiency of the proposed dementia diagnostic model, a comparative analysis of the presented hybrid model has been performed with the latest ML-based dementia diagnostic approaches provided in the literature [23-28]. Table 7 shows the comparison of the outcome of this study with the previous work done by other researchers for the period 2020-2022 on the same ADNI dataset for dementia diagnosis. Although the size of the dataset and methodology may differ, these datasets have been collected in MRI format from the ADNI platform, consisting of three classes, i.e., AD, MCI, and CN. The diagnosis task involves three-way classification (AD vs. MCI vs. CN) in each research study. So, it is worth comparing the classification performance.

Table 7. Comparison of the proposed hybrid model with existing work provided in the literature on the same ADNI dataset for dementia diagnosis.

| Author/Year | Methodology | Dataset Details | Classes Details | Classification Type | Accuracy |
|---|---|---|---|---|---|
| Gill *et al.* [23] | Information gain feature ranking and logistic model tree classifier | Instances = 340 Classes = 3 | AD=145 MCI=112 CN=83 | AD vs. MCI vs. CN | 58.8% |
| Abrol *et al*. [24] | ResNet | Instances = 828 Classes = 3 | AD=237 MCI=434 CN=157 | AD vs. MCI vs. CN | 75.1% |
| Lin *et al.* [25] | Linear discriminant analysis scoring method for multimodal data fusion with binary extreme learning machine | Instances = 746 Classes = 3 | AD=105 MCI=441 CN=200 | AD vs. MCI vs. CN | 66.7% |
| Niyas & Thiyagarajan [26] | Ensemble Classifier (Dynamic Ensemble Selection Performance) | Instances=1737 Classes = 3 | AD=342 MCI=872 CN=523 | AD vs. MCI vs. CN | 82% |
| Zhang *et al.* [27] | Generative Adversarial Network | Instances=1732 Classes = 3 | AD=345 MCI=856 CN=531 | AD vs. MCI vs. CN | 80.34% |
| Beheshti *et al.* (2022) [28] | Support vector machine | Instances=144 Classes = 3 | AD=39 MCI=51 CN=54 | AD vs. MCI vs. CN | 70% |
| H. Kour *et al.(current study)* | GLCM-ANFIS | Instances=5154 Classes = 3 | AD=1124 MCI=2590 CN=1440 | AD vs. MCI vs. CN | 82.47% |

This comparison is made on the basis of accuracy parameters since the doctors want the diagnostic model to predict the undertaken disease accurately. Some researchers worked on several ML-based models, such as logistic regression [23], LDA [25], and SVM [28], for dementia diagnosis. Other researchers implemented deep learning-based classifiers, i.e., resNet [24] and generative adversarial network [27], to predict dementia. Apart from this, ensemble classifiers [26] were also introduced for the diagnosis of dementia. SVM based diagnostic model described in [28] observed a classification accuracy of 70 %, in contrast to the approaches used in [23] and [25] which observed classification accuracy of 58.8 % and 66.7 %, respectively. But a small dataset was used for this study. The resNet model developed by [24] yielded a prediction rate of 75.1 % for dementia diagnosis. An accuracy of 80.27 % was noted in case of generative adversarial network [27]. Ensemble classifier [26] achieved a classification accuracy of 82 %; thus, this model produced a good performance. But the proposed hybrid method (GLCM-ANFIS) achieved a classification accuracy of 82.47 %, which is better as compared to other dementia diagnostic models described in the literature. This comparison further proves the effectiveness of our proposed dementia diagnostic method. Hence, the proposed hybrid model is found to be efficient for dementia diagnosis.

## 5. Conclusion

This paper introduces a hybrid method for image-based multiclass diagnosis of dementia disorder. The proposed model deals with the vital challenge of identifying dementia from MRI scans. The experimental results have led to the conclusion that the proposed framework can successfully diagnose the disease under investigation. The proposed model provides better classification accuracy compared to other traditional ML techniques. This model can be beneficial for radiologists and neurologists for the early diagnosis of dementia. The current study is limited to 2D images. In the future, this study will be extended to 3D images. The proposed approach will be further improved by incorporating other soft computing approaches and class-imbalanced data reduction techniques.

## Appendix

***Abbreviations*****: AD** Alzheimer's disease, **ANFIS** Adaptive neuro-fuzzy inference system, **CN** Healthy control, **DT** Decision tree, **FIS** Fuzzy inference system, **FL** Fuzzy logic, **FN** False negative, **FP** False positive, **GLCM** Gray level co-occurrence matrix, **KNN** K-nearest neighbor, **LR** Logistic regression, **MCI** Mild cognitive impairment, **ML** Machine learning, **MRI** Magnetic resonance imaging, **NN** Neural network, **SVM** Support vector machine, **TN** True negative, **TP** True positive

**Data Availability Statement:** Publicly available dataset from ADNI was employed and analyzed in this study. This data can be found at: https://www.kaggle.com/datasets/katalniraj/adni-extracted-axial

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