Academic Research Journal of Science and Technology (ARJST)
Volume 5, Issue 05, Aug 2026
Peer-Reviewed | Open Access | Crossref DOI & Global Indexing |
Google Scholar | Multidisciplinary

eISSN:3048-9644

Alzheimer’s Disease classification Using Bilateral Residual Adaptive Intelligent Multiclass Network

Dr G.P.SUJA*,
*Assistant Professor, Department of Computer Science & Research Centre,
Muslim Arts College (Autonomous), Thiruvithancode, Kanniyakuamri-629 174.
E-Mail : sujamaran89@gmail.com
ORCID: https://orcid.org/0000-0002-9303-4589
DOI: https://doi.org/10.63300/arjst0505082026.01

Date of Submission: 21-07-2026 Date of Acceptance: 01-08-2026

Abstract

Early Alzheimer's disease (EAD) diagnosis enables individuals to take preventative actions before irreversible brain damage occurs. Cross-sectional imaging studies of AD demonstrate that the characteristics of the abrasion sites in AD patients, as revealed by magnetic resonance imaging (MRI), are highly diverse and distributed across the image space. In AD memory and cognitive abilities deteriorate, affecting the capacity to do basic activities. In and around brain cells, aberrant amyloid and tau protein accumulation is believed to cause it. Amyloid deposits create plaques surrounding brain cells, whereas tau deposits form tangles inside brain cells. The plagues and tangles harm healthy brain cells, causing shrinkage. This damage seems to be occurring in the hippocampus, a brain region involved in memory formation. There are presently no methods that provide the most accurate outcomes and suggestions. The current techniques do not identify AD early. So, we proposed Bilateral Residual Adaptive Intelligent Multiclass Network (BRAIM-Net) method for identifying the earlier prediction of AD. In BRAIM-Net, two datasets are used, namely an MRI image dataset and a text dataset. The MRI image dataset has been trained with CNN-deep residual network (ResNet) layers. Deep ResNet enables this ResNet model to extract more information from network levels. The Modified Adam Optimization has selected the best feature information from MRI scans of Alzheimer's patients and transferred it to another area while keeping the most important data. Using the BRAIM-Net approach, a multiclass classification has been carried out. Finally, users can enter their queries and the system will retrieve medical advice. The experimental results indicate that the classification accuracy of the approach proposed in this research can reach 97.86%..

Keywords: *Alzheimer’s Disease, Cognitive Impairment, Early Diagnosis, Magnetic Resonance Imaging, Medical Recommendation, Multiclass Prediction.*

I. INTRODUCTION

Alzheimer’s disease (AD) classification is helpful for the early identification of cognitive decline and different stages of neurodegeneration using MRI and patient-related information. Due to variations in brain structure and disease progression, effective feature extraction and classification are essential for reliable AD prediction. Hybrid deep-learning approaches with adaptive weight selection have been employed for early AD detection [1], while CNN-based architectures have been applied for accurate MRI-based multiclass classification [2]. Deep-learning models combining convolutional, sequential, and transfer-learning strategies have also improved AD classification [3]. Structure-focused convolutional networks have been introduced to capture neurodegenerative patterns from MRI images [4]. Moreover, ensemble learning using VGG16, MobileNet, and InceptionResNetV2 has been investigated for multiclass AD diagnosis [5], whereas deep ensemble and quantum machine-learning approaches have been employed to enhance disease detection [6]. Deep CNN-based approaches have further supported early-stage dementia classification [7], and integrated deep representations have been applied for multiclass AD stage identification using MRI datasets [8].

Different machine-learning and deep-learning techniques have also been investigated to improve AD prediction and diagnosis. CNN-based deep learning has been utilized for MRI-based AD diagnosis [9], while multi-locus analysis with machine learning has been explored for genetic variant analysis [10]. Multifractal feature analysis with K-Nearest Neighbor has been used for early AD stage detection [11], and Decision Tree classification has been employed for AD prediction [12]. Furthermore, deep Siamese CNN has supported multiclass AD classification [13], Random Forest has been applied for diagnostic classification and biomarker identification [14], and Gradient Boosting with ResNet-50 has been investigated for classification using clinical and image information [15]. However, challenges related to generalization, computational complexity, feature representation, MRI noise, and efficient multiclass prediction remain, motivating the development of a more robust and optimized AD classification framework.

The primary contributions of this research are summarized as follows:

- A BRAIM-Net (Bilateral Residual Adaptive Intelligent Multiclass Network) framework is presented for early multiclass prediction of Alzheimer’s disease.
- Bilateral filtering is employed to reduce noise in MRI images while preserving important brain structural information.
- CNN with ResNet is integrated for deep feature learning and extraction of Alzheimer’s-related patterns from MRI images.
- Modified Adam Optimization (MAO) is incorporated for effective feature selection and optimization.
- MRI images and text/numerical patient records are utilized to support comprehensive AD analysis.
- A medical recommendation module is incorporated to provide recommendations based on user inputs and predicted disease conditions.

The remainder of this paper is organized as follows. Section 2 reviews related studies, Section 3 presents the proposed BRAIM-Net, Section 4 discusses the experimental results, and Section 5 concludes the study with future research directions.

II. BACKGROUND STUDY

Gasmi et al. (2024) [1] developed a hybrid deep-learning framework for early AD detection using EfficientNetV2B3, Inception-ResNetV2, and adaptive weight selection. However, high computational complexity and limited generalization create a need for a more efficient AD classification framework.

El-Assy et al. (2024) [2] proposed a CNN-based framework for early multiclass AD classification using complementary MRI features. However, dataset dependency and training requirements limit generalization, indicating the need for robust cross-dataset classification.

Sorour et al. (2024) [3] developed a deep-learning framework combining convolutional, sequential, and transfer-learning strategies for AD classification. However, increased computational complexity highlights the need for a simpler and optimized multiclass prediction framework.

Academic Research Journal of Science and Technology (ARJST)
Volume 5, Issue 05, Aug 2026
Peer-Reviewed | Open Access | Crossref DOI & Global Indexing |
Google Scholar | Multidisciplinary
eISSN:3048-9644

Odimayo et al. (2024) [4] developed a structure-focused deep-learning framework to identify neurodegenerative patterns from brain MRI images. However, computational cost and limited fine-grained feature representation indicate the need for efficient structural feature learning.

Alruily et al. (2025) [5] proposed an ensemble deep-learning framework using complementary pretrained features for multiclass AD diagnosis. However, increased processing requirements highlight the need for efficient feature optimization with lower computational complexity.

Jenber Belay et al. (2024) [6] developed an ensemble framework combining deep MRI features with quantum machine learning for multiclass AD detection. However, hardware and computational requirements indicate the need for lightweight and efficient feature learning.

Dardouri (2025) [7] presented a deep-learning approach for identifying different dementia stages from discriminative MRI characteristics. However, limited MCI samples and testing conditions highlight the need for improved clinical generalization using representative datasets.

Shahid et al. (2025) [8] developed a multiclass AD framework using complementary deep MRI representations for disease-stage classification. However, limited dataset diversity and MRI noise indicate the need for robust preprocessing and optimized feature learning.

Table 1: Comparative Analysis of Recent Alzheimer's Disease Classification Methods

Author + Year	Concept	Methods Used	Limitations	Research Gap
Mousavi et al. (2025) [9]	MRI-based AD diagnosis	Deep learning, CNN	Dataset-specific dependency	Diverse dataset validation needed
Segmen & Yildiz (2026) [10]	Genetic variant analysis for AD	Multi-locus analysis, ML	Genetic-data dependency	Multimodal clinical validation needed
Elgammal et al. (2022) [11]	Early AD stage detection	Multifractal analysis, KNN	Feature-dependent classification	Robust deep feature learning needed
Dana & Alashqur (2014) [12]	AD prediction	Decision Tree	Limited predictive capability	Advanced multiclass prediction needed
Mehmood et al. (2020) [13]	Multiclass AD classification	Siamese CNN	High computational requirements	Efficient multiclass learning needed
Song et al. (2021) [14]	AD diagnosis and biomarker identification	Random Forest	Limited feature representation	Improved feature optimization needed
Fulton et al. (2019) [15]	AD classification using clinical and image data	Gradient Boosting, ResNet-50	Computational and data complexity	Efficient multimodal classification needed

Table 1 studies use machine learning, deep learning, genetic analysis and MRI-based techniques for AD prediction and classification. However, limitations in generalization, computational complexity, feature learning and multimodal integration indicate the need for a robust and optimized multiclass AD framework.

III. MATERIALS AND METHODS

Academic Research Journal of Science and Technology (ARJST)
Volume 5, Issue 05, Aug 2026
Peer-Reviewed | Open Access | Crossref DOI & Global Indexing |
Google Scholar | Multidisciplinary
eISSN:3048-9644

The proposed BRAIM-Net aims to support early and multiclass prediction of Alzheimer's disease using MRI images. It integrates bilateral filtering, CNN–ResNet, and Modified Adam Optimization (MAO) for noise removal, feature learning, and optimization, achieving 97.86% classification accuracy. Finally, the predicted AD stage is used to provide appropriate medical recommendations.

3.1 Data set collection

The proposed work aims at the early detection of AD. The data set play an important role. The training data is needed to train the model for performing needed actions. Most of the data in the data set used for training the model and data set is also separated into test data. The proposed system executes the algorithm on AD-related datasets obtained from https://www.kaggle.com/tourist55/alzheimers-dataset-4-class-of-images with 1253 MRI images and https://www.kaggle.com/code/hyunseokc/detecting-early-alzheimer-s/data 374 records; Figure 1 shows the sample Multiclass MRI image data's

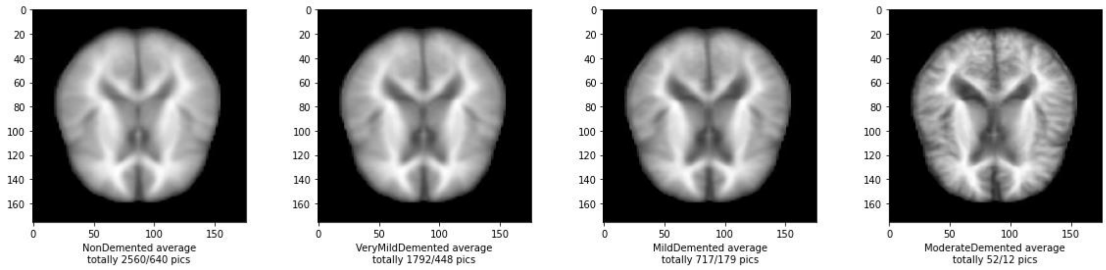

Figure 2(a): sample MRI image Demented Categories

3.2 BRAIM-Net (Bilateral Residual Adaptive Intelligent Multiclass Network) for classification

The proposed BRAIM-Net (Bilateral Residual Adaptive Intelligent Multiclass Network) integrates bilateral filtering, CNN, ResNet, Modified Adam Optimization (MAO), and multiclass classification for early Alzheimer's disease prediction from MRI images. Initially, MRI images are normalized and standardized, while bilateral filtering removes noise and preserves important brain structures; subsequently, CNN–ResNet learns deep structural features related to brain atrophy, and MAO selects and optimizes the informative features to generate an effective feature vector for multiclass classification into different AD stages. In real-time operation, a new MRI image undergoes the same preprocessing and is passed through the trained BRAIM-Net to obtain the predicted disease class, which can then support the medical recommendation module; reproducibility can be maintained by using the same dataset split, preprocessing settings, CNN–ResNet configuration, MAO parameters, number of training epochs, and random seed across repeated experiments.

eISSN:3048-9644

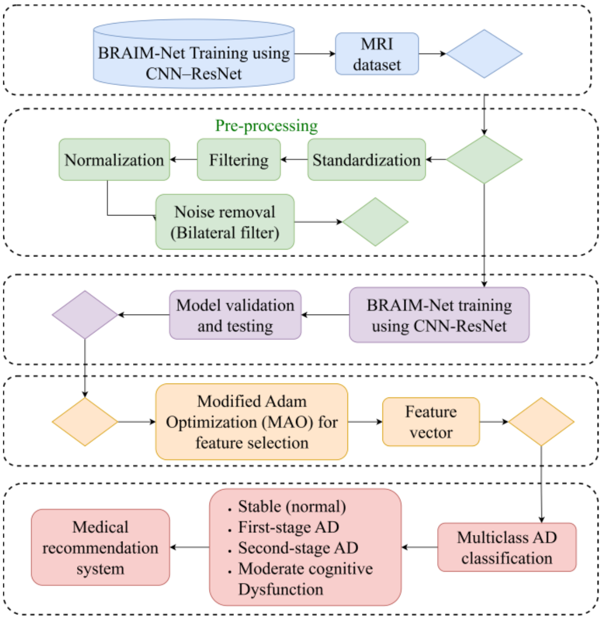

Figure 2: Flow chart for BRAIM-Net model

The figure 1 illustrates the overall workflow of the proposed BRAIM-Net for early Alzheimer's disease prediction using MRI images. The MRI images undergo preprocessing and bilateral noise removal, followed by CNN–ResNet training, model validation, Modified Adam Optimization (MAO) and feature-vector generation. Finally, multiclass classification identifies the corresponding AD stage, and the predicted result is used by the medical recommendation system to provide appropriate recommendations.

$$I_f(p) = \frac{\sum q\in\Omega w(p,q)I(q)}{\sum q\in\Omega w(p,q)} \tag{1}$$

Equation (1) $I_f(p)$ is the filtered pixel, $I(q)$ is the neighboring pixel, $w(p,q)$ is the similarity weight, and Ω is the neighborhood. It removes MRI noise while preserving important brain structures.

$$F = ReLU\left(W * I_f + b\right) \tag{2}$$

Equation (2) I_f is the filtered MRI image, W and b are the weight and bias, and F is the extracted feature. CNN extracts important structural features from the MRI image.

$$R = F + \mathscr{F}(F) \tag{3}$$

Equation (3) F represents CNN features, $\mathscr{F}(F)$ represents learned residual features, and R is the enhanced representation. This helps BRAIM-Net learn deeper AD-related features.

$$\theta_{t+1} = \theta_t - \eta \frac{\widehat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \tag{4}$$

Equation (4) θ_t represents model parameters, η is the learning rate, and $\widehat{m}_t, \hat{v}_t$ are gradient estimates. The optimization updates model parameters for improved feature learning.

$$P_k = \frac{e^{z_k}}{\sum j=1Ce^{z_j}}, \qquad \hat{y} = \mathrm{argmax}_k P_k \tag{5}$$

Equation (5) z_k is the class score, C is the number of AD classes, and P_k is the class probability. The highest probability determines the final predicted AD class $\hat{y}$.

Algorithm: Bilateral Residual Adaptive Intelligent Multiclass Network

```
Input:
  X ← MRI images
  Y ← Corresponding class labels
  E ← Number of training epochs
Output:
  Ŷ ← Predicted AD classes
  M ← Trained BRAIM-Net model
Begin
  Load MRI images X and class labels Y
  Preprocess X
    Normalize MRI images
    Standardize MRI images
    Apply bilateral filtering for noise removal
  Divide X and Y into training, validation, and testing sets
  Initialize BRAIM-Net model M
  For epoch = 1 to E do
    Extract image features using CNN
    Learn deep residual features using ResNet
    Optimize features using Modified Adam Optimization (MAO)
    Train BRAIM-Net using optimized features
    Validate model performance
  End For
  Generate optimized feature vectors
  Perform multiclass AD classification
  Predict AD classes Ŷ using test MRI images
  Evaluate BRAIM-Net using testing data
  Pass predicted AD classes to the medical recommendation system
  Return Ŷ, M
End
```

The pseudocode describes the BRAIM-Net process from MRI preprocessing to multiclass AD prediction. It uses bilateral filtering, CNN–ResNet feature learning, and Modified Adam Optimization, followed by classification and medical recommendation.

4. Experimental Results and Discussion

This section presents the performance evaluation of the proposed BRAIM-Net for Alzheimer's disease classification. The model is compared with existing classification algorithms using accuracy, precision, recall and F1-score. The results demonstrate the effectiveness of BRAIM-Net in achieving improved multiclass classification performance

Academic Research Journal of Science and Technology (ARJST)
Volume 5, Issue 05, Aug 2026
Peer-Reviewed | Open Access | Crossref DOI & Global Indexing |
Google Scholar | Multidisciplinary
eISSN:3048-9644

Table 2: Performance comparison for BRAIM-Net algorithm for classification

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression [11]	91.42	91.18	90.96	91.07
KNN [12]	92.36	92.14	91.87	92.00
Decision Tree Classifier [13]	93.21	92.98	92.76	92.87
Neural Network [14]	94.48	94.23	94.05	94.14
Random Forest Classifier [15]	95.32	95.08	94.91	94.99
Gradient Boosting Classifier [16]	96.41	96.17	95.94	96.05
Proposed BRAIM-Net	97.86	97.62	97.48	97.55

Table 2 compares the classification performance of BRAIM-Net with six existing algorithms using accuracy, precision, recall, and F1-score. The proposed BRAIM-Net achieves the highest values of 97.86%, 97.62%, 97.48%, and 97.55%, respectively. The results show that BRAIM-Net provides better overall classification performance than the compared methods.

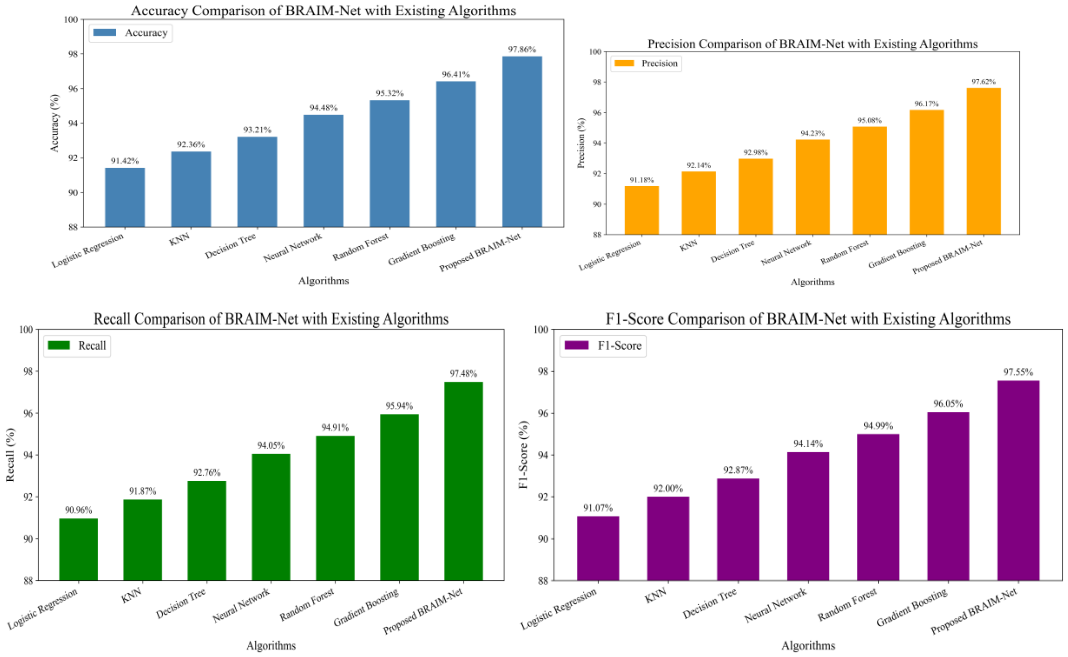

Figure 3: Performance Comparison of BRAIM-Net with Existing Classification Algorithms

The figure 3 compares the Accuracy, Precision, Recall, and F1-Score of BRAIM-Net with existing classification algorithms. The proposed BRAIM-Net achieves the highest performance with 97.86% accuracy, 97.62% precision, 97.48% recall and 97.55% F1-score. These results indicate that BRAIM-Net provides better overall classification performance than the compared algorithms.

5. CONCLUSION

This research presents BRAIM-Net (Bilateral Residual Adaptive Intelligent Multiclass Network) for early detection and multiclass classification of Alzheimer's disease using MRI images and patient-related data. BRAIM-Net integrates bilateral filtering for noise reduction, CNN–ResNet for deep structural feature learning, Modified Adam Optimization (MAO) for effective feature optimization, and multiclass classification for identifying different stages of AD. A medical recommendation module is also incorporated to provide recommendations according to user inputs and predicted conditions. Experimental results demonstrate that

eISSN:3048-9644

BRAIM-Net achieves 97.86% accuracy, 97.62% precision, 97.48% recall, and 97.55% F1-score, outperforming the considered comparative classification algorithms. These results indicate the effectiveness of BRAIM-Net for reliable early AD prediction and medical image analysis. Future work can extend BRAIM-Net using larger and more diverse clinical datasets to improve generalization. The framework can also incorporate multimodal information, explainable prediction techniques, and lightweight architectures. Further investigation can focus on real-time clinical validation, automated hyperparameter optimization, and deployment on resource-constrained healthcare systems to enhance practical applicability and support clinical decision-making.

References:

[1] K. Gasmi, A. Alyami, O. Hamid, M. O. Altaieb, O. R. Shahin, L. Ben Ammar, H. Chouaib, and A. Shehab, “Optimized hybrid deep learning framework for early detection of Alzheimer’s disease using adaptive weight selection,” Diagnostics, vol. 14, no. 24, Art. no. 2779, 2024, doi: 10.3390/diagnostics14242779.

[2] M. El-Assy, H. M. Amer, H. M. Ibrahim, et al., “A novel CNN architecture for accurate early detection and classification of Alzheimer’s disease using MRI data,” Scientific Reports, vol. 14, Art. no. 3463, 2024, doi: 10.1038/s41598-024-53733-6.

[3] S. E. Sorour, A. A. Abd El-Mageed, K. M. Albarrak, A. K. Alnaim, A. A. Wafa, and E. El-Shafeiy, “Classification of Alzheimer’s disease using MRI data based on deep learning techniques,” Journal of King Saud University - Computer and Information Sciences, vol. 36, no. 2, Art. no. 101940, 2024, doi: 10.1016/j.jksuci.2024.101940.

[4] S. Odimayo, C. C. Olisah, and K. Mohammed, “Structure focused neurodegeneration convolutional neural network for modelling and classification of Alzheimer’s disease,” Scientific Reports, vol. 14, Art. no. 15270, 2024, doi: 10.1038/s41598-024-60611-8.

[5] M. Alruily, A. A. Abd El-Aziz, A. M. Mostafa, M. Ezz, E. Mostafa, et al., “Ensemble deep learning for Alzheimer’s disease diagnosis using MRI: Integrating features from VGG16, MobileNet, and InceptionResNetV2 models,” PLOS ONE, vol. 20, no. 4, Art. no. e0318620, 2025, doi: 10.1371/journal.pone.0318620.

[6] Jenber Belay, Y. M. Walle, and M. B. Haile, “Deep ensemble learning and quantum machine learning approach for Alzheimer’s disease detection,” Scientific Reports, vol. 14, Art. no. 14196, 2024, doi: 10.1038/s41598-024-61452-1.

[7] S. Dardouri, “An efficient method for early Alzheimer’s disease detection based on MRI images using deep convolutional neural networks,” Frontiers in Artificial Intelligence, vol. 8, Art. no. 1563016, 2025, doi: 10.3389/frai.2025.1563016.

[8] S. B. Shahid, M. Kaikaus, M. H. Kabir, M. A. Yousuf, A. K. M. Azad, A. S. Al-Moisheer, N. Alotaibi, S. A. Alyami, T. Bhuiyan, and M. A. Moni, “Novel deep learning for multi-class classification of Alzheimer’s in disability using MRI datasets,” Frontiers in Bioinformatics, vol. 5, Art. no. 1567219, 2025, doi: 10.3389/fbinf.2025.1567219.

[9] S. M. Mousavi, K. Moulaei, and L. Ahmadian, “Classifying and diagnosing Alzheimer’s disease with deep learning using 6735 brain MRI images,” Scientific Reports, vol. 15, Art. no. 22721, 2025, doi: 10.1038/s41598-025-08092-1.

eISSN:**3048-9644**

[10] H. Segmen and M. Yildiz, "A multi-locus and machine learning-based assessment of SNCA variants in Alzheimer's disease," International Journal of Molecular Sciences, vol. 27, no. 11, Art. no. 5143, 2026, doi: 10.3390/ijms27115143.

[11] Y. M. Elgammal, M. A. Zahran, and M. M. Abdelsalam, "A new strategy for the early detection of Alzheimer disease stages using multifractal geometry analysis based on K-nearest neighbor algorithm," Scientific Reports, vol. 12, no. 1, Art. no. 22381, 2022.

[12] D. Dana and A. Alashqur, "Using decision tree classification to assist in the prediction of Alzheimer's disease," in Proc. 6th Int. Conf. Computer Science and Information Technology (CSIT), 2014, pp. 122–126.

[13] Mehmood, M. Maqsood, M. Bashir, and Y. Shuyuan, "A deep Siamese convolution neural network for multi-class classification of Alzheimer disease," Brain Sciences, vol. 10, no. 2, Art. no. 84, 2020.

[14] M. Song, H. Jung, S. Lee, D. Kim, and M. Ahn, "Diagnostic classification and biomarker identification of Alzheimer's disease with random forest algorithm," Brain Sciences, vol. 11, no. 4, Art. no. 453, 2021.

[15] L. V. Fulton, D. Dolezel, J. Harrop, Y. Yan, and C. P. Fulton, "Classification of Alzheimer's disease with and without imagery using gradient boosted machines and ResNet-50," Brain Sciences, vol. 9, no. 9, Art. no. 212, 2019.