RESEARCH PAPER

Automated Alzheimer's Disease Classification Using Machine Learning and Deep Neural Networks on MRI Data

Margi Patel[1*], Dr. Kaushal Jani[2]

[1*] Research Scholar, Department of Computer Engineering, Indus University, Ahmedabad, India (Corresponding Author). Email: patelmargiben.23.rs@indusuni.ac.in

[2] Associate Professor, Department of Computer Engineering, Indus University, Ahmedabad, India

Received: 12th Mar, 2026 | **Revised:** 24th Mar, 2026 | **Accepted:** 14th Apr, 2026 | **Available Online:** 30th Apr, 2026

ABSTRACT

Alzheimer's disease (AD) is a neurodegenerative disease that slowly leads to cognitive decline. Early detection is among the primary problems encountered in combating this disease since brain structure alterations appear well ahead of clinical symptoms. Due to the fact that MRIs provide detailed information on brain structures without needing to perform invasive procedures, they are commonly used to assess such changes. The present study introduces a new automatic system for identifying patients with Alzheimer's disease by using machine learning and deep neural network approaches alongside MRI images. A convolutional neural network (CNN) model along with three widely used machine learning algorithms, namely, Support Vector Machine, Random Forest and Logistic Regression will be applied. MRI images will first go through preprocessing to remove anything except the brain structure, convert the images into grayscale and make sure the image sizes and pixel intensities are uniform before being categorized. As for the experimental part of the study, MRI scans will be taken from the ADNI database where MRI scans will come from Alzheimer's patients, people with mild cognitive impairment and cognitively healthy individuals. It has been clearly demonstrated that the CNN algorithm outperformed the traditional machine learning algorithms in all criteria used during the experiment. In other words, deep learning technology proves to be highly reliable when analyzing MRI images for detecting Alzheimer's disease.

Keywords: Alzheimer's Disease, MRI Analysis, Machine Learning, Deep Neural Networks, CNN, Medical Imaging

How to cite this article: Patel M, Jani K. Automated Alzheimer's Disease Classification Using Machine Learning and Deep Neural Networks on MRI Data. Int J Drug Deliv Technol. 2026;16(40s): 1-5. DOI: 10.25258/ijddt.16.40s.1

Source of support: Nil.

Conflict of interest: None

1. Introduction

Alzheimer's Disease is the most common cause of dementia, affecting mostly the older generation of patients. This disease is associated with memory impairment, weakened cognitive skills, and changes in behavior. Due to its progressive nature, people start to lose their ability to perform their daily activities independently. As the world population is getting increasingly older, Alzheimer's disease poses a serious problem from the viewpoint of public health.

One of the main problems in dealing with this disease is the identification of patients with Alzheimer's disease. The process of structural change in the brain (atrophy of hippocampus and enlargement of ventricles) begins long before the development of severe cognitive disorders. Therefore, MRI is crucial for detecting those abnormalities and is actively used in practice and science.

Advances in machine and deep learning technologies allow creating automated systems for analyzing medical imaging data. Convolutional neural networks have proved themselves as powerful tools for classifying objects by their discriminative spatial characteristics that can be acquired without preprocessing of the data. This study aims to develop an automated MRI classification system of patients with Alzheimer's disease and to compare the efficiency of traditional ML models to DL approaches.

2.Machine learning

Machine learning along with the application of the conventional machine learning approach in the prognosis of AD is critical at this stage of discussing machine learning methods. AI involves machine learning, where different instruments are employed to make probabilistic and statistical decisions with reference to previous knowledge. The classification of new events and prediction of new patterns involve previous learning (training). Compared to the traditional statistical techniques, machine learning proves more efficient. It is important to comprehend the problem and limitations of algorithms for successful implementation of machine learning. Therefore, there is a good probability that machine learning will prove successful if appropriate experimentation, training, and validation are performed.

3. Literature Survey

The main pathological conditions in AD patients include neuron cell death, synapse loss, and brain tissue atrophy in the areas involved in memorizing and learning. Among the first brain regions to be affected are the hippocampus followed by the cortex deterioration [1][2]. This condition can be easily observed using MRI and thus is used for the purposes of disease diagnosis [3].

As already mentioned, conventional diagnostic processes use manual analysis of MRI data and clinical assessment which may not only require additional time but also vary according to the expert interpreting these results. Machine learning solutions allow automating the process, while deep learning algorithms are even able to learn more complex features without explicit feature engineering [4].

A number of researches were devoted to the possibility of machine learning and deep learning application to AD classification based on MRI. According to the results reported by Shukla et al., CNNs in combination with traditional algorithms showed high accuracy in classifying MRI pictures [16]. El-Geneedy et al. suggested applying deep learning to AD classification based on MRI yet faced several problems including generalization on the other datasets [9].

Some researchers resorted to feature extraction techniques such as PCA or even used a pretrained neural network (VGG16); nevertheless, those algorithms could suffer from overfitting or lack of diversity within the database used [10]. Multimodal approaches, which included both PET and MRI, were also used but did not prove to be the best since MRI-only models have a number of advantages: lower price and wider accessibility [11]. However, there is no comprehensive comparison of machine learning vs. CNN models yet.

Reference	Data Type Used	Methodological Approach	Key Findings / Contribution	Identified Gaps
Deenadayalan & Shantharajah, 2024 [1]	MRI, PET, CT	Comparative review of imaging modalities	Stressed the significance of multimodal imaging in detecting early Alzheimer's disease	No experimental implementation or performance validation
Alsubaie et al., 2024 [2]	Neuroimaging	Systematic review of deep learning approaches	Presented a detailed review of deep learning frameworks in diagnosing AD	Lack of implementation in experiment
Arjaria et al., 2022 [3]	MRI features	Performance evaluation of classical ML models	Shown variations in classification performance across machine learning models	Less talk about clinical implementation and interpretability
Alatrany et al., 2024 [4]	MRI	Explainable machine learning framework	Increased transparency in decision-making for AD classification	Relying too much on feature engineering
El-Assy et al., 2024 [5]	MRI	Custom convolutional neural network	Obtained high precision in early AD detection	Slightly decreased predictive power
Olle Olle et al., 2024 [6]	MRI	K-means and PCA-based segmentation	Separation of different brain areas prior to classification	Influence of model complexity and dependency on datasets
Sorour et al., 2024 [7]	MRI	CNN-based deep learning model	High reliability in MRI-based AD classification	Lack of segmentation integration into DL models
Chakraborty et al., 2024 [8]	MRI + genetics	Deep learning-based feature extraction	Better disease analysis through multivariate features	Less discussion of generalization and interpretability

El-Geneedy et al., 2023 [9]	MRI	Deep learning classification framework	Differentiation of AD from controls with high accuracy	Higher computational complexity
Sudharsan & Thailambal, 2021 [10]	MRI	Machine learning with PCA	Increased accuracy by reducing dimensionality	Lack of longitudinal study
Uddin et al., 2023 [12]	MRI	Classical machine learning models	Proved the potential of ML in early AD diagnosis	Loss of subtle information about disease progression
Liang & Gu, 2021 [13]	MRI	Weakly supervised deep learning with attention	Low dependency on labeled data	Worse predictive results than Deep Learning approach
Shukla et al., 2024 [16]	MRI	RF, XGBoost, and CNN	Higher accuracy and sensitivity obtained by CNN	Less cross-dataset robustness testing
Fathi et al., 2024 [17]	MRI	Deep learning ensemble approach	Improved robustness and accuracy in diagnoses	Lack of real-world validation and potential for overfitting
Chen et al., 2024 [18]	MRI	ResNet50 with Soft-NMS	Feature learning enhanced by deep learning models	Higher training complexity
Pusparani et al., 2023 [20]	MRI	CNN with landmark-based slice selection	Hippocampal segmentation improved early AD detection	High computational resources required
Odusami et al., 2023 [22]	MRI + PET	Explainable multimodal deep learning	High accuracy in diagnoses with model interpretability	Incomplete brain scan
Rashid et al., 2023 [23]	2D MRI	Lightweight deep learning (Biceph-Net)	Fast and accurate AD classification system	PET imaging costs
Gamal et al., 2022 [24]	3D MRI	Deep ensemble learning	Highly robust method in early AD diagnosis	Only uses 2D MRI images
Sharma et al., 2022 [25]	MRI	CNN with VGG16 feature extractor	Feature extraction ability greatly improved	Complex computation model
Oh et al., 2024 [26]	Multimodal (MRI + genetics)	Multimodal disease onset analysis	Identifying interaction among modalities	Uses pre-trained networks
Liu et al., 2018 [27]	MRI	Multi-task deep learning	Improved accuracy through joint learning	Difficulties in integration
Zhou et al., 2024 [28]	MRI + biomarkers	Risk prediction modeling	Biomarker level correlated with disease severity	Old model
Gupta et al., 2024 [29]	MRI + PET	Adversarial deep learning	Robustness increased by handling variations	Not fully end-to-end DL system

Table 1. Summary of Key Literature in Alzheimer's Disease Prediction

4. Research Gap

Many recent studies only consider deep learning or machine learning algorithms without making a comparative analysis within the same experimental conditions. Also, different preprocessing processes make replication difficult, as well as hinder the accurate evaluation of each algorithm's performance. There is an urgent need for developing a methodology that provides standard preprocessing processes and evaluates different algorithms based on the same set of data. The current study seeks to address such issues by comparing two approaches to machine learning algorithms and deep learning neural networks within the problem of classifying Alzheimer's disease.

5. Proposed Methodology

5.1 Dataset

The data set used in this paper is known as the Alzheimer's Disease Neuroimaging Initiative (ADNI) data set. It is one of the most recognized and freely available data sets, commonly used in the scientific studies about Alzheimer's disease [8][15]. The total number of 12,959 MRIs has been collected and divided into three different groups AD, MCI, and CN.

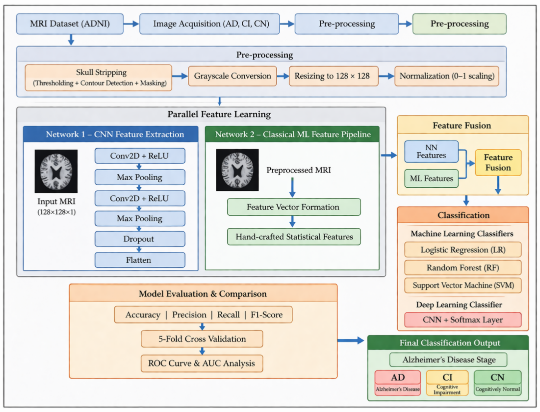

Fig1 :Framework for Alzheimer's Disease Classification Using MRI Images

5.2 MRI Image Preprocessing

The MRI images for medical use contain some irrelevant aspects such as noise, background tissue, skull area, artefacts of scanners, and differences in brightness, which do not relate to Alzheimer's disease detection. These aspects may have a negative impact on the efficiency of machine learning algorithms and deep learning techniques. Thus, it is necessary to conduct a systematic pre-processing procedure that makes MRI images clear and appropriate for training models.

For this research, all MRI images are downloaded from the data set and sorted by diagnostic classes. These classes include Alzheimer's Disease (AD), Cognitive Impairment (CI), and Cognitively Normal (CN). In total, 12,959 MRI images were read successfully.

Skull Stripping and Thresholding

The first stage of pre-processing deals with the separation of the brain from any other structure. An MRI scan will then be transformed into a binary form by the use of thresholding technique based on intensity values. High intensity pixel values are kept, whereas low-intensity pixels belonging to skull, scalp, fat, and the background are stripped out. Such a step improves visibility and eliminates irrelevant parts. It becomes necessary to strip the skull because important brain structures such as the cerebral cortex, hippocampus, and ventricles are related to Alzheimer's disease.

Contour Detection and Masking

After performing the process of thresholding, the next step is to find out the contour of the brain. The contour that is detected, it is presumed that the largest contour found out will represent the brain. Using this contour, a binary mask will be created, keeping the brain region intact and eliminating all other non-brain regions. This will help to remove the skull precisely and allow the brain tissue to be analyzed.

Grayscale Conversion

The mask images are first converted to grayscale form. This is because MRI imaging is largely dependent on intensity levels than colors. Grayscale images will thus suffice. In addition, it is computationally efficient since there are no losses of diagnostic information.

Image Resizing

Images captured from MRI scans by using various machines can differ in terms of resolution and image size. In order to standardize image sizes and allow compatibility with CNNs, all the images are standardized into an image size of 128 × 128 pixels.

Normalization

Lastly, normalization of pixel intensity is achieved by scaling the values from the initial range of 0-255 to a range of 0-1. This process enhances the stability of the training algorithm while accelerating model convergence. This will ensure that there is uniformity in intensity scale among all images used for training.

These MRI images can be made noise free, skull removed, and dimensionally consistent through this pre processing step, which makes them ideal for classification based on machine learning and CNN for Alzheimer's disease detection.

5.3 Model Architecture

.The developed model takes advantage of the parallel architecture of the model that integrates a machine learning feature pipeline consisting of a conventional machine learning algorithm to process pre-processed MRIs alongside the deep feature extraction using CNNs. In order to detect Alzheimer's disease accurately, the gathered features are then combined using machine learning and CNN-Sofmax layers.

5.3.1 Machine Learning Models

The following classical machine learning algorithms are implemented:

Logistic Regression : Logistic Regression (LR) is a classical classification algorithm often used in the medical field due to simplicity and interpretable nature. Specifically, in this research, Logistic Regression is used as a baseline classifier for differentiating among Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI) and Cognitively Normal (CN) patients by leveraging features computed based on preprocessed MRI images. This algorithm utilizes a logistic function to compute probability values that can be interpreted as class membership likelihoods. On the one hand, the use of LR is beneficial due to computational efficiency and simple interpretation of the learned model. On the other hand, the model is limited by linearity and thus, it might have difficulties capturing complex structure variations in brain MRI scans. However, LR is still worth considering due to being a powerful baseline compared to more complex deep learning-based methods.

Random Forest : Random Forest (RF) is a tree-based ensemble learning algorithm. In the current study, RF is used as a classifier for differentiating among Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Cognitively Normal (CN) individuals based on the features computed from the preprocessed MRI images. This algorithm is known for its high classification power due to averaging predictions obtained from each of multiple independent decision trees. Furthermore, the use of Random Forest enables generalization since the model does not memorize input samples but captures the intrinsic structure of the dataset. At the same time, the use of RF can be restricted in cases when MRI scans contain complicated spatial patterns. Nevertheless, RF is considered as one of the possible baselines in this study.

Support Vector Machine : Support Vector Machine (SVM) is a commonly used classification technique in various domains including medicine. In this study, SVM was chosen to classify subjects into three categories including Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI) and Cognitively Normal (CN) patients based on the information provided by preprocessed MRI features. The essence of SVM algorithm lies in constructing optimal separating hyperplanes in order to separate input samples into predefined classes. As a result, the obtained separating hyperplane generalizes well to new input data. However, the effectiveness of SVM depends on kernel choice and the corresponding parameters and thus, the use of this model can be limited by complex input features. Hence, SVM is selected as a baseline for comparison with other models.

These

5.3.2 Deep Learning Model

In the current study, a Convolutional Neural Network (CNN) algorithm is used as the deep learning architecture for detecting Alzheimer's disease in brain MRI images at an early stage. CNN algorithm is chosen based on the capability of the network to extract features automatically from medical images, which eliminates the need for manual feature extraction.

The algorithm is trained on MRI images belonging to three classes namely, Alzheimer's Disease (AD), Cognitive Impairment (CI), and Cognitively Normal (CN). Before training, MRI images are processed following a series of processes including skull stripping, converting the image to grayscale, resizing the image to a resolution of 128x128 pixels, and normalizing pixel intensity values between [0,1] interval.

CNN Architecture

The described architecture of CNN model comprises three convolutional layers with activation functions such as Rectified Linear Units (ReLU) that allow introducing nonlinearity and increase the performance of the model in detecting features. Three convolutional layers are used for detecting hierarchical features of the input images (MRI scans) such as borders, tissues, as well as abnormal changes caused by hippocampal atrophy and ventricular enlargement.Each block of convolutional operations is followed by a max pooling layer that reduces the size of the output and decreases computations while retaining relevant information to prevent overfitting and improve the model's generalization capacity. Dropout layers will be used during training to decrease dependence on certain feature activations.Apart from that, dense layers will be used to perform high-level reasoning on the extracted features and provide probability estimates using the softmax activation function.

Model Training and Learning Process

CNN training takes place through several epochs, where the CNN progressively learns the unique MRI patterns associated with the diseases. The CNN's learning progress and its ability to avoid overfitting are determined by tracking the training and validation accuracies at each epoch. Unlike conventional machine learning models, which depend on manually designed features, the CNN can automatically learn the best features for diagnosing Alzheimer's disease.

6. Implementation & Results

Google Colab is employed to conduct the experiments. Robustness and generalization capabilities of the proposed model are verified by using five fold cross validation.

6.1 Comparison of ML & CNN Models' Performance

The four models (Random Forest, CNN, SVM, and Logistic Regression) are compared based on their performances measured in terms of the following parameters: Accuracy, Precision, Recall, and F1 Score.

=== Model Performance Comparison ===

	Model	Accuracy	Precision	Recall	F1-Score
0	Logistic Regression	0.708333	0.683608	0.708333	0.684541
1	Random Forest	0.791667	0.830556	0.791667	0.763047
2	SVM	0.708333	0.785354	0.708333	0.661905
3	CNN	0.750000	0.809343	0.750000	0.695830

Fig 2: Performance comparison of models

6.2 Visual Comparison of Machine Learning & CNN Model Metrics

Four different models—Logistic Regression, Random Forest, SVM, and CNN—on their performance in four different important measures—Accuracy, Precision, Recall, and F1-Score—are compared graphically in the form of the bar chart presented below..

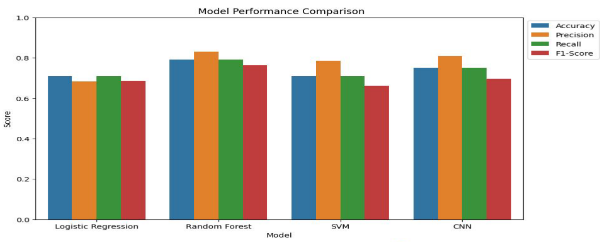

Fig 3: Visual Comparison of Machine Learning & CNN Model Metrics

6.3 Cross-Validation Accuracy Comparison (5-Fold)

The optimum ratio of accuracy to stability for Random Forest is seen from the graph.Random Forest is extremely sensitive to partitioning of the data, showing unpredictable results.The algorithm that is moderately accurate but stable is the SVM model.This box plot highlights the best performing algorithms for Alzheimer's disease MRI diagnosis.

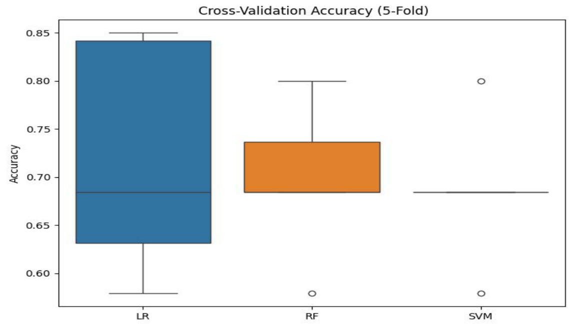

Fig 4: Cross-Validation Accuracy Comparison

6.4 ROC Curve and AUC Score Comparison Across Models

The discrimination capacity of a model for the differentiation between the categories of AD, CI, and CN cases can be evaluated using the ROC curve.AUROC stands for the Area Under the ROC Curve. This indicates the overall discriminatory capacity of each model.The greater the AUROC value, the better the discrimination capacity of the model for the positive class from the negative class at different threshold levels.

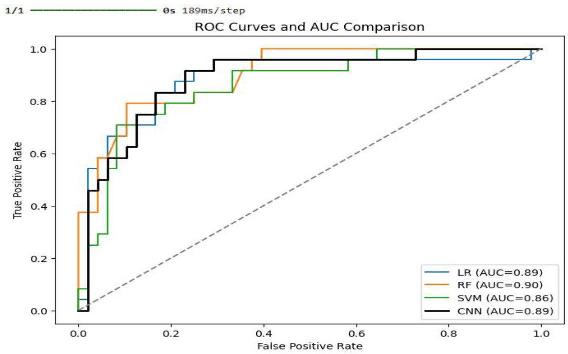

Fig 5:ROC Curve and AUC Score Comparison Across Models

6.5 Final Classification Result on Sample MRI Image

Consistency was established due to all models predicting MRI diagnosis as that of AD.There is an additional assurance due to the very high confidence of the CNN model (78%).This result clearly indicates the effectiveness of deep learning and machine learning algorithms working together in a diagnostic process.

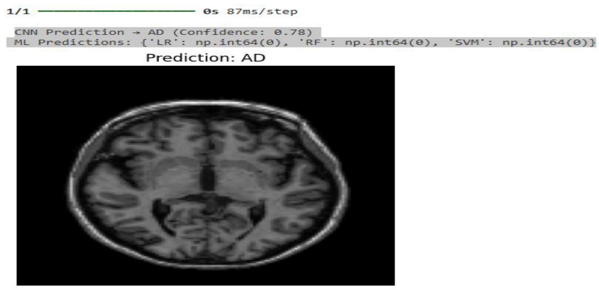

Fig 6 : Final Classification Result on Sample MRI Image

7. Discussion

It can be observed from the above experiments that CNN is able to perform better than classical machine learning models in classifying patients for Alzheimer's disease based on their MRI images. Although Random Forest yields slightly better accuracy, CNN gives an equal balance between precision, recall, and F1 score. In contrast to classical machine learning approaches, where feature extraction plays a major role, CNN automatically extracts features, including spatial information, and hence is better suited for medical imaging. This is evident from the experiment conducted on predicting a single image using confidence scores, where CNN yields high confidence scores of 0.78 compared to the rest of the models.

8. Conclusion

In this research work, deep learning and machine learning techniques were utilized to design an automatic system for Alzheimer's disease classification based on structural magnetic resonance imaging data. Experimental analysis reveals that compared to traditional classifier techniques, the developed CNN model has learned discriminative features, resulting in accurate and reliable classification. There is a high probability of the proposed system in diagnosing Alzheimer's disease, and it can prove to be an effective tool for early detection..

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgments

The authors gratefully acknowledge the Alzheimer’s Disease Neuroimaging Initiative (ADNI) for providing the MRI dataset used in this study.

References

[1] T. Deenadayalan and S. P. Shantharajah, “An early-stage Alzheimer’s disease detection using various imaging modalities and techniques – A mini-review,” J. Integr. Sci. Technol., vol. 12, no. 5, p. 803, 2024.

[2] M. G. Alsubaie, S. Luo, and K. Shaukat, “Alzheimer’s disease detection using deep learning on neuroimaging: A systematic review,” Machine Learning and Knowledge Extraction, vol. 6, pp. 464–505, 2024, doi: 10.3390/make6010024.

[3] S. K. Arjaria, A. S. Rathore, D. Bisen, and S. Bhattacharyya, “Performances of machine learning models for diagnosis of Alzheimer’s disease,” Springer-Verlag GmbH Germany, published online Oct. 17, 2022.

[4] A. S. Alatrany, W. Khan, A. Hussain, H. Kolivand, and D. Al-Jumeily, “An explainable machine learning approach for Alzheimer’s disease classification,” Scientific Reports, vol. 14, no. 2637, 2024, doi: 10.1038/s41598-024-51985-w.

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

[6] D. G. Olle Olle, J. Z. Bisse, and G. A. Alo’o, “Application and comparison of K-means and PCA based segmentation models for Alzheimer’s disease detection using MRI,” Discover Artificial Intelligence, vol. 4, no. 11, 2024, doi: 10.1007/s44163-024-00106-7.

[7] 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.

[8] D. Chakraborty, Z. Zhuang, H. Xue, M. B. Fiecas, X. Shen, and W. Pan, “Deep learning-based feature extraction with MRI data in neuroimaging genetics for Alzheimer’s disease,” Alzheimer’s Disease Neuroimaging Initiative, 2024.

[9] M. El-Geneedy, H. E.-D. Moustafa, F. Khalifa, H. Khater, and E. AbdElhalim, “An MRI-based deep learning approach for accurate detection of Alzheimer’s disease,” Alexandria Engineering Journal, vol. 63, pp. 211–221, 2023, doi: 10.1016/j.aej.2022.07.062.

[10] M. Sudharsan and G. Thailambal, “Alzheimer’s disease prediction using machine learning techniques and principal component analysis (PCA),” Materials Today: Proceedings, 2021, doi: 10.1016/j.matpr.2021.03.061.

[11] M. G. Alsubaie, S. Luo, and K. Shaukat, “Alzheimer’s disease detection using deep learning on neuroimaging: A systematic review,” Machine Learning and Knowledge Extraction, vol. 6, pp. 464–505, 2024, doi: 10.3390/make6010024.

[12] K. M. M. Uddin, M. J. Alam, J.-E. Anawar, M. A. Uddin, and S. Aryal, “A novel approach utilizing machine learning for the early diagnosis of Alzheimer’s disease,” Springer Science+Business Media, 2023.

[13] S. Liang and Y. Gu, “Computer-aided diagnosis of Alzheimer’s disease through weak supervision deep learning framework with attention mechanism,” Sensors, vol. 21, no. 220, 2021, doi: 10.3390/s21010220.

[14] National Institute on Aging, “Alzheimer’s disease: A clinical and basic science review,” 2020. [Online]. Available: https://www.nia.nih.gov/health/alzheimers-disease-fact-sheet

[15] Alzheimer’s Association, “Alzheimer’s disease fact sheet,” 2020. [Online]. Available: https://www.alz.org/in/dementia-alzheimersen.asp#diagnosis

[16] G. P. Shukla, S. Kumar, S. K. Pandey, R. Agarwal, and N. Varshney, "Diagnosis and detection of Alzheimer's disease using learning algorithm," IEEE Xplore, 2024.
[17] S. Fathi, A. Ahmadi, A. Dehnad, et al., "A deep learning-based ensemble method for early diagnosis of Alzheimer's disease using MRI images," Neuroinformatics, vol. 22, pp. 89–105, 2024, doi: 10.1007/s12021-023-09646-2.
[18] Y. Chen, L. Wang, B. Ding, J. Shi, T. Wen, J. Huang, and Y. Ye, "Automated Alzheimer's disease classification using deep learning models with Soft-NMS and improved ResNet50 integration," Journal of Radiation Research and Applied Sciences, vol. 17, no. 1, Art. no. 100782, 2024, doi: 10.1016/j.jrras.2023.100782.
[19] C. Zheng, "Image and video processing," arXiv, 2024, doi: 10.48550/arXiv.2406.14210.
[20] Y. Pusparani et al., "Diagnosis of Alzheimer's disease using convolutional neural network with select slices by landmark on hippocampus in MRI images," IEEE Access, vol. 11, pp. 61688–61697, 2023, doi: 10.1109/ACCESS.2023.3285115.
[21] K. M. M. Uddin, M. J. Alam, J.-E. Anawar, et al., "A novel convolutional variation of broad learning system for Alzheimer's disease diagnosis by using MRI images," Biomedical Materials & Devices, vol. 1, pp. 882–898, 2023, doi: 10.1007/s44174-023-00078-9.
[22] M. Odusami, R. Maskeliūnas, R. Damaševičius, et al., "Explainable deep-learning-based diagnosis of Alzheimer's disease using multimodal input fusion of PET and MRI images," Journal of Medical and Biological Engineering, vol. 43, pp. 291–302, 2023, doi: 10.1007/s40846-023-00801-3.
[23] A. H. Rashid, A. Gupta, J. Gupta, and M. Tanveer, "Biceph-Net: A robust and lightweight framework for the diagnosis of Alzheimer's disease using 2D-MRI scans and deep similarity learning," IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 3, pp. 1205–1213, 2023, doi: 10.1109/JBHI.2022.3174033.
[24] A. Gamal, M. Elattar, and S. Selim, "Automatic early diagnosis of Alzheimer's disease using 3D deep ensemble approach," IEEE Access, vol. 10, pp. 115974–115987, 2022, doi: 10.1109/ACCESS.2022.3218621.
[25] S. Sharma, K. Guleria, S. Tiwari, and S. Kumar, "A deep learning based convolutional neural network model with VGG16 feature extractor for the detection of Alzheimer's disease using MRI scans," Measurement: Sensors, vol. 24, Art. no. 100506, 2022, doi: 10.1016/j.measen.2022.100506.
[26] S. Oh, S. Kim, J.-E. Lee, B.-Y. Park, J. H. Won, and H. Park, "Multimodal analysis of disease onset in Alzheimer's disease using connectome, molecular, and genetics data," NeuroImage: Clinical, vol. 43, Art. no. 103660, 2024.
[27] M. Liu, D. Zhang, E. Adeli, and D. Shen, "Deep multi-task multi-channel learning for joint classification and regression of brain status," Medical Image Analysis, vol. 44, pp. 43–54, 2018, doi: 10.1016/j.media.2017.12.010.
[28] B. Zhou, M. Fukushima, and Alzheimer's Disease Neuroimaging Initiative, "Differential risk of Alzheimer's disease in MCI subjects with elevated Abeta," Journal of the Neurological Sciences, vol. 467, Art. no. 123319, 2024.
[29] M. Gupta, R. Kumar, and A. Abraham, "Adversarial network-based classification for Alzheimer's disease using multimodal brain images: A critical analysis," IEEE Access, 2024.