



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 5, May 2025

Alzheimer's Disease Detection from MRI Scans with Deep Learning

Abhilash T P, Harshitha P, Thejaswini M, Keerthana K S, Himavanth K

Associate Professor, Department of Information Science and Engineering, SIET, Tumkur, Karnataka, India

U.G. Student, Department of Information Science and Engineering, SIET, Tumkur, Karnataka, India

U.G. Student, Department of Information Science and Engineering, SIET, Tumkur, Karnataka, India

U.G. Student, Department of Information Science and Engineering, SIET, Tumkur, Karnataka, India

U.G. Student, Department of Information Science and Engineering, SIET, Tumkur, Karnataka, India

ABSTRACT: Alzheimer's Disease (AD) is a chronic neurodegenerative disease that impacts millions of people worldwide, mostly the elderly. Early and precise diagnosis is essential to decelerate its progression. This study introduces a deep learning-based method employing Convolutional Neural Networks (CNN) to identify Alzheimer's stages from MRI brain scans. The model categorizes input images into four groups: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Utilizing the OASIS (Open Access Series of Imaging Studies) dataset, the new model achieved a training accuracy of 86.34% and validation accuracy of 86.45%. A Flask application was created to perform real-time classification of images, with potential to aid in clinical diagnostics.

KEYWORDS: Alzheimer's Disease, Convolutional Neural Network, Magnetic Resonance Imaging (MRI), OASIS (Open Access Series of Imaging Studies) Dataset, Flask, Deep Learning

I. INTRODUCTION

Alzheimer's Disease is the most common form of progressive dementia, affecting mostly elderly persons and leading to progressive impairments of memory, reasoning, language functions, and behavioral consistency. With the progression of worldwide population aging, the number of Alzheimer's cases will increase substantially, making early and precise diagnosis more important than ever. Early diagnosis not only enables proper medical treatment in time, but it also facilitates effective planning for long-term care and care, which can enhance patients' and caregivers' quality of life.

Traditional methods for Alzheimer's diagnosis tend to depend on visual interpretation of neuroimaging results and hand-crafted feature extraction with machine learning models like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), or Decision Trees. These are highly domain-dependent and need complicated preprocessing pipelines. In addition, they usually fail to generalize across various Magnetic Resonance Imaging (MRI) datasets due to the complex and heterogeneous nature of brain morphology and disease progression patterns.

Conversely, Deep Learning—Convolutional Neural Networks (CNNs)—has transformed medical image analysis with the capability to learn features automatically from raw imaging data. Convolutional Neural Networks (CNNs) are particularly well-suited to identify subtle structural variations in brain Magnetic Resonance Imaging (MRI) scans corresponding to various phases of Alzheimer's Disease due to their ability to learn to detect fine-grained spatial hierarchies within images. These models render manual feature engineering unnecessary, drastically shortening development time with enhanced classification accuracy.

In this paper, a classification model based on Convolutional Neural Networks (CNN) is proposed to identify and distinguish several stages of Alzheimer's Disease, i.e., Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, from T1-weighted Magnetic Resonance Imaging (MRI) scans of the OASIS (Open Access Series of Imaging Studies) database. The model is trained and validated employing supervised learning methods to guarantee efficient performance across classes. For facilitating usability in clinical settings, a Flask-based web interface has also been implemented, through which medical experts can upload Magnetic Resonance Imaging (MRI) scans and obtain

stage-wise predictions in real time. This incorporation of deep learning with a real-world web-based application proves the viability of using AI for cost-effective, fast, and accurate Alzheimer's diagnosis in real-world healthcare setups.

II. LITERATURE SURVEY

From the increasing evidence on Alzheimer's detection through Artificial Intelligence (AI), there has been a recent emphasis on new feature extraction and classification methods for early diagnosis. These works investigate both traditional as well as quantum-enhanced Artificial Intelligence (AI) methods, particularly within handwriting dynamics and Magnetic Resonance Imaging (MRI) scan analysis. One such research study [1] explored the handwriting behavior of Alzheimer's patients, focusing on cognitive decline characteristics such as pressure, velocity, and spatial arrangement. The study suggested a Variational Quantum Classifier (VQC) and compared its performance with traditional Artificial Intelligence (AI) models. It showed that handwriting-based features can contribute to early-stage Alzheimer's detection and quantum approaches can be as efficient as or even superior to traditional classifiers.

Another study [2] employed the DARWIN handwriting dataset, which comprises handwriting samples of healthy subjects and Alzheimer's patients. The authors applied classical and quantum kernel-based classification methods, such as Quantum Support Vector Machines (QSVC). Their findings emphasized the potential of quantum methods in enhancing classification accuracy and interpretability, rendering them applicable to clinical decision support in early-stage detection. In a third work [3], the authors reported a hybrid Classical-Quantum Convolutional Neural Network (CQ-CNN) model that was trained on 3D Magnetic Resonance Imaging (MRI) brain images. The method blended U-Net-based segmentation and synthetic data generated by diffusion to mitigate class imbalance problems. The model reported an impressive 97.5% accuracy while significantly lowering parameter numbers and computational expense, demonstrating that the combination of diffusion modeling and Convolution Neural Network (CNN) can lead to dramatically improved performance in resource-limited environments.

Combined, these researches show a transition from traditional models towards data-efficient next-generation AI methods—such as handwriting analysis and 3D imaging of the brain—highlighting that traditional deep learning remains pivotal, particularly in real-world applications where access to quantum resources is not available.

III. METHODOLOGY

The proposed system for detecting Alzheimer's Disease from Magnetic Resonance Imaging (MRI) scans is based on a Convolutional Neural Network (CNN) model. The methodology comprises several key steps: dataset acquisition, image preprocessing, model building, training, validation, and deployment. An overview of the methodology is as follows:

A. Dataset Collection

The model is trained on the OASIS (Open Access Series of Imaging Studies) dataset, which has T1-weighted Magnetic Resonance Imaging (MRI) scans of patients labeled into four stages of dementia:

- Non-Demented
- Very Mild Demented
- Mild Demented
- Moderate Demented

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

The publicly accessible dataset provides patient metadata and imaging labels that are crucial for supervised learning.

A. Data Preprocessing

- Raw text data is frequently unstructured and noisy. As a result, a number of preprocessing procedures were used to clean and standardize the data. These actions consist of: The preprocessing pipeline aims to improve model

performance and filter out noise. It consists of:

- Normalization: Pixel values are normalized to the range 0 to 1 to enhance convergence during training.
- Image Resizing: All Magnetic Resonance Imaging (MRI) images are resized to a constant size of 128×128 pixels.
- Augmentation: Rotation, flipping, and zooming are used to avoid overfitting and enhance dataset diversity.

B. CNN Model Development

The A custom CNN model is developed using Keras with TensorFlow backend. The architecture consists of:

- Convolutional layers for feature extraction
- Max-pooling layers for down sampling
- A dense decision-making fully connected layer
- A softmax output layer for multi-class classification

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

Where z_i is the output score for class i and n is the number of output classes. The activation function used in hidden layer is ReLU: $f(x) = \max(0, x)$

The model learns to recognize patterns in Magnetic Resonance Imaging (MRI) scans that are associated with various stages of Alzheimer's.

C. Training and Validation

The data is split into 80% training and 20% validation. The Categorical Cross-Entropy Loss function is employed to measure the prediction error of the model:

$$L = - \sum_{i=1}^n y_i \cdot \log(\hat{y}_i)$$

Where:

- y_i is the true class label (one-hot encoded),
- $\hat{y}_i$ is the predicted probability for class i ,
- n is the number of classes.

The model is trained using the Adam optimizer over multiple epochs. Accuracy is tracked using the following metric:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100$$

D. Web Deployment

For purposes of demonstration of practical application, the model is deployed with Flask, a light Python web framework. The web user interface is such that users can upload a Magnetic Resonance Imaging (MRI) image and obtain a classification response in real time.

IV. EXPERIMENTAL RESULTS

The Convolution Neural Network (CNN) model was trained and tested on the OASIS (Open Access Series of Imaging Studies) Magnetic Resonance Imaging (MRI) dataset. The dataset was divided into 80:20 for training and validation.

A. Training Setup

- Input Image Size: 128×128×3
- Batch Size: 32
- Epochs: 25

- Optimizer: Adam
- Loss Function: Categorical Cross-Entropy
- Activation Functions: ReLU (hidden layers), Softmax (output layer)

B. Performance Metrics

The following metrics were measured:

- Accuracy
- Loss
- Precision
- Recall
- Prediction Time per Image

C. Observations

Metric	Training Set	Validation Set
Accuracy	86.34%	86.45%
Loss	0.41	0.39
Average Prediction Time	—	< 2 seconds

Accuracy and loss plots across training epochs assured the stability and generalization of the model. No overfitting was noticed significantly. The Flask-based Graphical User Interface (GUI) effectively rendered stage classification upon uploading images, demonstrating system usability for real-world use.

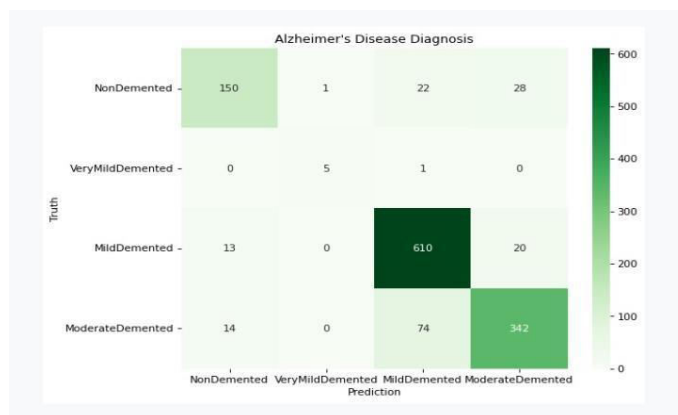


Fig 1: Confusion Matrix

Model Classification

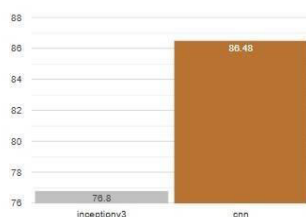


Fig 2: Model-wise comparison of classification accuracy for Alzheimer's Disease detection.

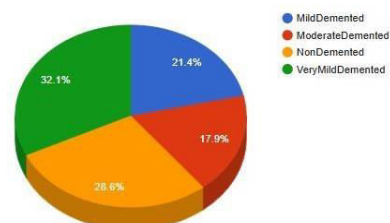


Fig 3: Percentage representation of each Alzheimer's class used for CNN model training.

V. CONCLUSION

This study illustrates the effective application of a Convolutional Neural Network (CNN) model for Alzheimer's stage classification based on Magnetic Resonance Imaging (MRI) scans. The system attained more than 86% accuracy and gives real-time classification through a web interface. The model has the potential to be integrated into clinical processes through effective preprocessing and light architecture. Future directions might involve integrating transfer learning, multimodal information (e.g., text, genomics data), and applying Explainable AI techniques for visual region localization.

REFERENCES

- [1] J. Cheng, H. Wang, S. Wei, F. Liu, and Y. Chen, "Alzheimer's Disease Prediction Algorithm Based on Group Convolution and a Joint Loss Function," *Computational and Mathematical Methods in Medicine*, vol. 2022, Article ID 1854718, 2022.
- [2] S. El-Sappagh, H. Saleh, F. Ali, E. Amer, and T. Abuhmed, "Two-stage deep learning model for Alzheimer's disease detection and prediction of the mild cognitive impairment time," *Neural Computing and Applications*, vol. 34, pp. 14487–14509, 2022.
- [3] J. V. Shanmugam, B. Duraisamy, B. C. Simon, and P. Bhaskaran, "Alzheimer's disease classification using pre-trained deep networks," *Biomedical Signal Processing and Control*, vol. 71, p. 103217, 2021.
- [4] N. Mahendran and D. R. V. PM, "A deep learning framework with an embedded-based feature selection approach for the early detection of Alzheimer's disease," *Computers in Biology and Medicine*, vol. 141, p. 105056, 2022.
- [5] Y. Eroglu, M. Yildirim, and A. Cinar, "mRMR-based hybrid convolutional neural network model for classification of Alzheimer's disease on brain magnetic resonance images," *International Journal of Imaging Systems and Technology*, vol. 32, pp. 517–527, 2021.
- [6] M. G. Lanjewar, J. S. Parab, and A. Y. Shaikh, "Development of framework by combining CNN with KNN to detect Alzheimer's disease using MRI images," *Multimedia Tools and Applications*, vol. 82, pp. 12699–12717, 2022.
- [7] Y. Al-Khuzai, O. Bayat, and A. D. Duru, "Diagnosis of Alzheimer's disease using 2D MRI slices by the convolutional neural network," *Applied Bionics and Biomechanics*, vol. 2021, Article ID 6690539, 2021.
- [8] R. Jain, N. Jain, A. Aggarwal, and D. J. Hemanth, "Convolutional neural network-based Alzheimer's disease classification from magnetic resonance brain images," *Cognitive Systems Research*, vol. 57, pp. 147–159, 2019.
- [9] K. Zhou, Z. Liu, W. He, J. Cai, and L. Hu, "Application of 3D Whole-Brain Texture Analysis and the Feature Selection Method Based on within-Class Scatter in the Classification and Diagnosis of Alzheimer's Disease," *Therapeutic Innovation & Regulatory Science*, vol. 56, no. 4, pp. 561–571, 2022.
- [10] S. Guan et al., "multi-instance distillation for Alzheimer's prediction," *IEEE J. Biomed. Health Inform.*, vol. 25, no. 8, pp. 2959–2969, 2021.
- [11] Z. Breijyeh and R. Karaman, "Comprehensive Review on Alzheimer's Disease: Causes and Treatment," *Molecules*, vol. 25, no. 24, p. 5789, 2020.
- [12] X. Cui et al., "Adaptive LASSO logistic regression with particle swarm optimization for Alzheimer's diagnosis," *Chemom. Intell. Lab. Syst.*, vol. 215, 2021, Art. no. 104316.
- [13] J. Johnson et al., "Brain Imaging in Alzheimer's Disease," *Cold Spring Harb. Perspect. Med.*, vol. 2, no. 4, 2012.
- [14] L. Alessandrini et al., "EEG-Based Alzheimer's Recognition Using LSTM," *Sensors*, vol. 22, no. 9, p. 3696, 2022.
- [15] Ghazal, T.M., Abbas, S., Munir, S., Ahmad, M., Issa, G.F., Zahra, S.B., Khan, M.A., & Hasan, M.K. (2022). Alzheimer Disease Detection Empowered with Transfer Learning. *Comput. Mater. Contin.*, 70, 5005–5019.
- [16] Liu, J., Li, M., Luo, Y., Yang, S., Li, W., & Bi, Y. (2021). Alzheimer's disease detection using depthwise separable convolutional neural networks. *Comput. Methods Programs Biomed.*, 203, 106032.
- [17] Folego, G., Weiler, M., Casseb, R.F., Pires, R., & Rocha, A. (2020). Alzheimer's Disease Detection Through Whole-Brain 3D-CNN MRI. *Front. Bioeng. Biotechnol.*, 8, 534592.
- [18] Wen, J., Thibeu-Sutre, E., Diaz-Melo, M., Samper-González, J., Routier, A., Bottani, S., et al. (2020). Convolutional neural networks for classification of Alzheimer's disease: Overview and reproducible evaluation. *Med. Image Anal.*, 63, 101694.
- [19] Beheshti, I., Demirel, H. (2016). Feature-ranking-based Alzheimer's disease classification from structural MRI. *Magn. Reson. Imaging*, 34, 252–263.
- [20] Suk, H.-I., Lee, S.-W., & Shen, D. (2014). Hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis. *Neuroimage*, 101, 569–582.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details