International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 05 May 2025
Page No: 2178 - 2184
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0319

Early Detection of Alzheimer’s Disease Using Deep Learning

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Abstract

Alzheimer's Disease acts as a degenerative brain trauma that results in poor memory, alongside impairing mental functioning. Early detection of Alzheimer's Disease is aimed at controlling symptoms in addition to improving medical care for patients. Traditional diagnosis based on imaging procedures in conjunction with cognitive examinations takes a long time for experienced experts to analyze. Deep learning technology triggered interest in automated MRI data analysis techniques because they execute quickly and attain high accuracy levels. The application explores the development of an Alzheimer's Disease Diagnosis System as a web-based light application by using a custom Convolutional Neural Network (CNN) in its implementation. The system analyzes brain MRI scans to perform patient group assignment into Mild Demented, Moderate Demented, Very Mild Demented, and Non-Demented categories. The system shows a valid accuracy of 88.5%, prediction probabilities, and stage-dependent medical advice that generate downloadable diagnosis reports on the Streamlit platform. The system maintains user privacy through non-storage of their information and includes readable medical warning notices during use. The system is a working bridge between experimental technologies for Alzheimer's identification and available medical practices in clinical environments.

Keywords: *Alzheimer’s Disease, Early Detection, Convolutional Neural Networks (CNN), MRI Scan Analysis, Deep Learning, Streamlit Application, Medical Imaging.*

1. Introduction

Alzheimer’s Disease (AD) begins in elderly patients causing their brains to become chronically progressive while destructing cognitive abilities and memory along with behavioral patterns. The worldwide population that suffers from this disease continues to increase alongside intensifying demographics of older people. Medical experts predict that the AD patient numbers will significantly increase throughout the coming decades in view of population aging. The Alzheimer’s Association reports that Alzheimer’s Disease holds the position as the sixth deadliest condition in the US. The older population of 6 million Americans from 2021 data shows that almost 14 million Americans will develop this condition until 2060. Early detection of dementia becomes essential since the disease advances through MCI to moderate and severe dementia stages so patients can benefit from early intervention. Modern diagnostic techniques which include clinical evaluations, neuropsychological testing, and imaging studies are methodical and require skilled analysis, and do not operate effectively in low resource settings. Artificial intelligence (AI) has developed deep learning (DL) as its crucial automotive diagnostic enhancement that boosts medical diagnosis accuracy rates during the last few years. Specifically, CNNs demonstrate excellent capabilities for analyzing brain MRI scans which detect AD with high accuracy. The technology reaches high levels of accuracy which cuts down

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human mistakes and enables large-scale implementation. The work by Malik et al. (2024) demonstrates that deep learning models successfully identify different AD stages through MRI, PET and EEG picture analysis. Spurred by these developments, this work introduces a deployable web application called Alzheimer's Disease Diagnosis System, which is based on a lightweight custom-built CNN architecture to identify Alzheimer's Disease from MRI scans. The model categorizes MRI scans into four classes—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—with a validation accuracy of 88.5%. The framework is developed on a Streamlit interface and incorporates functionalities such as prediction probabilities, doctor prescriptions based on condition, and downloadable diagnostic reports. In contrast to sophisticated ensemble architectures, the system provides an efficient but easy-to-use model optimized for early diagnosis with a focus on ethical usage of AI, patient confidentiality, and ease of use in clinical settings. [1]

2. Related Work

During the last ten years, artificial intelligence incorporated into medical imaging systems produced major improvements in detecting Alzheimer's disease (AD). Multiple studies nowadays emphasize deep learning neural networks as Convolutional Neural Networks because of their exceptional feature extraction performance on brain scan types including MRI, PET and EEG. Such models demonstrate excellent performance in AD stage recognition particularly for detecting early symptoms of the disease.The research team at Al-Shoukry et al. (2020) examined multiple Convolutional Neural Network methods which detect Alzheimer's through brain MRI datasets. Public datasets ADNI and OASIS enabled models to achieve classification accuracy rates between 85% to 95% through different preprocessing methods and deep architecture models. The examined models primarily used intricate layers together with deep CNN arrangements and frameworks which integrated manual and trained features. These methods struggled to deploy instant analysis because they needed substantial hardware resources to operate. Through their research Malik et al. (2024) analyzed deep learning models which included 3D CNNs, Capsule Networks and the transfer learning methods VGG16, ResNet, and DenseNet. The research presented exceptional accuracy levels exceeding 98% for various models although these models remained focused on research purposes and did not address clinical deployment and usability issues or system scalability. These research studies demonstrate deep learning capability for AD detection but current solutions lack deployable lightweight systems that operate in real-time without GPU dependence. The proposed system addresses limitations through web-based implementation of a customized CNN model. The proposed solution provides an efficient approach which delivers maintainable 88.5% accuracy rates alongside user-friendly features during practical execution.

3. Methodology

This section outlines the technical process followed in the design and implementation of the Alzheimer's Disease Diagnosis System. The approach integrates MRI preprocessing, model training using a custom Convolutional Neural Network (CNN), and deployment via a user-interactive web interface.

3.1.Dataset Description

The dataset used was obtained from a publicly available Kaggle repository titled "Alzheimer's Dataset (4 Class of Images)". It comprises 8,608 brain MRI images categorized into four stages: Non-Demented (4480 images), Very Mild Demented (3072 images), Mild Demented (960 images), and Moderate Demented (96 images). The images were divided into training and test sets and used to develop and validate the model. [2]

3.2.Image Preprocessing

Each MRI image was converted to grayscale, resized to 128×128 pixels, and normalized by scaling pixel values to the [0,1] range. These preprocessing steps ensured uniformity in input dimensions and improved the model's learning performance. Data augmentation techniques such as rotation and flipping were applied during training to mitigate overfitting and enhance generalization. [3]

3.3.CNN Model Architecture

A custom lightweight CNN architecture was developed specifically for this classification task. The network consists of three convolutional layers, each followed by ReLU activation and MaxPooling2D

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layers. The final convolutional output is flattened and passed through fully connected layers, culminating in a softmax output for multi-class classification. The model architecture is optimized for fast inference while maintaining competitive accuracy. (Table 1)

Table 1 CNN Model Architecture

Layer No.	Layer Type	Output Shape	Parameters	Activation
1	Conv2D	(126, 126, 32)	320	ReLU
2	MaxPooling2D	(63, 63, 32)	0	—
3	Conv2D	(61, 61, 64)	18496	ReLU
4	MaxPooling2D	(30, 30, 64)	0	—
5	Conv2D	(28, 28, 128)	73856	ReLU
6	MaxPooling2D	(14, 14, 128)	0	—
7	Flatten	(25088)	0	—
8	Dense	(64)	1605696	ReLU
9	Dense (Output)	(4)	260	Softmax
—	**Total**	—	**1.70M**	—

The model was trained with the Adam optimizer and categorical cross-entropy loss on 25 epochs and a batch size of 32. Validation was performed using an 80-20 train-test split. Training was done on a typical GPU-capable workstation using TensorFlow and Keras libraries. The model had a validation accuracy of around 88.5%. [4]

3.4.Deployment and User Interface

The last trained model was incorporated in a web application for diagnostic purposes based on the Streamlit library. The user interface enables one to upload MRI scans and observe the predicted Alzheimer's stage as well as class-wise prediction probabilities and doctor's recommendations. Downloading a diagnostic report is also made available as well as observing medical disclaimers, where it highlights the fact that it is an assistive tool. Ethical Considerations The system temporarily processes information during the session and holds no personally identifiable data. All forecasts are followed by disclaimers recommending that users consult professional medical practitioners for clinical verification.

3.5.Tables

Alley's diagnosis model obtained information from the publicly available Kaggle platform which organized brain MRI images according to Non-Demented, Very Mild Demented, Mild Demented and Moderate Demented clinical groups. A table describes the distribution of samples among classes for both training and testing data (Table I). The designed class distribution creates a dataset that stays unbiased statistically which enables reliable model testing during both stages. A specialized Convolutional Neural Network (CNN) which operates according to the specifications documented in Table II forms a central part of the research implementation. The designed network uses three convolutional layers with ReLU activation layers and max-pooling layers that lead to dense layers responsible for multi-class classification. The designed model finds an optimal compromise

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between operating speed and accuracy while achieving 88.5% classification accuracy during the training period. The proposed CNN model undergoes performance evaluation through Table III which demonstrates how it measures against multiple current approaches published in literature. The new model delivers higher accuracy results than the existing methods presented in Mahendran & PM (2022) [1], Pan et al. (2020) [4] and Helaly & Mahmoud (2022) [6] with demonstrated accuracy of 88.5% and precision at 87.4% and recall rate at 88.2%. The results show that this proposed method delivers effective and reliable performance when classifying Alzheimer's stages through MRI data analysis. (Table 2)

Table 2 Number of MRI Images Per Class (Train + Test)

Alzheimer's Stage	Number of Images
Non-Demented	4480
Very Mild Demented	3072
Mild Demented	960
Moderate Demented	96
Total	**8608**

Note: The dataset includes both training and testing samples, sourced from a Kaggle repository. (Table 2 & 3)

Table 2 CNN Model Architecture Summary

Layer No.	Layer Type	Output Shape	Parameters	Activation
1	Conv2D	(126, 126, 32)	320	ReLU
2	MaxPooling2D	(63, 63, 32)	0	—
3	Conv2D	(61, 61, 64)	18496	ReLU
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7	Flatten	(25088)	0	—
8	Dense	(64)	1605696	ReLU
9	Dense (Output)	(4)	260	Softmax
	Total Parameters		**1.70M**	

Table 3 Comparison with Reference

Refe-rences	Model Description	Accuracy (%)	Precision (%)	Recall (%)
[1]	Mahendran & PM (2022) – Embedded Feature + Deep Learning	82.3	81.0	80.2
[2]	EL-Geneedy et al. (2023) – Deep CNN model	87.2	86.1	86.8
[4]	Panetal. (2020) – CNN + Ensemble Learning	86.4	85.5	85.9
[6]	Helaly & Mahmoud (2022) – CNN with MRI	85.7	84.0	83.5
—	**Our Proposed CNN Model**	**88.5**	**87.4**	**88.2**

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Note: All reference models are evaluated based on reported metrics in respective papers. be typewritten separately from the main text and preferably in an appropriate font size to fit each table on a separate page. Each table must be numbered with Arabic numerals (e.g., Table 1, Table 2) and include a title. Place footnotes to tables below the table body and indicate them with superscript lowercase letters (a, b, c, etc.), not symbols. Do not use vertical rulings in the tables. Each column in a table must have a heading, and abbreviations, when necessary, should be defined in the footnotes. [5]

3.6.Figures

Figure 1 shows the overall system structure of the Alzheimer's Disease Diagnosis System. The process starts with the user uploading a brain MRI image via the Streamlit web interface. The uploaded image goes through automatic preprocessing, which involves resizing, conversion to grayscale, and normalization. The processed image is then forwarded to a tailor-made Convolutional Neural Network (CNN) that classifies the input into one of the four stages of Alzheimer's, namely Non-Demented, Very Mild Demented, Mild Demented, or Moderate Demented. The system delivers a stage-specific medical advice and a downloadable diagnosis report depending on the classification output. The above architecture diagram clearly shows the modular flow and interaction between each module in the diagnostic pipeline. (Figure 1) Figure 2 shows the Streamlit-based user interface of the system. The UI is segmented into separate sections so that users can simply upload MRI images, trigger prediction, and see results in an organized format. The interface has a prediction output with a detailed class label and a related confidence percentage. It also enables the user to see a class-wise probability table and includes an option to download the doctor's recommendation report. The ease of use of this interface makes it accessible to both clinical and non-clinical users and shows how well-suited the system is for telemedicine or point-of-care deployment. [6]

1. Results and Discussion

1.1.Results

A CNN architecture for diagnosing Alzheimer's Disease was implemented through analysis of publicly accessible MRI data which separated brain scans into Non-Demented and three degradation stages of Very Mild, Mild, and Moderate Demented variables. Both quantitative measurements and user-friendly diagnostic outputs were used for assessing the system performance. [7]

1.2.Experimental Output

Once a brain MRI scan enters the Streamlit interface the system generates a real-time output as shown in Figure 3. The analysis determined NonDemented as the predicted diagnosis at an 84.85% confidence rate. The model shows the inner confidence estimates through class probabilities across all four diagnostic categories. The system generates brain health maintenance recommendations as preventive guidance for the user at this particular step of the process. The doctor's report can be downloaded through the system to showcase its clinical usefulness and interactive nature. The real-time prediction displays results in Figure 3 together with confidence percentages as well as doctor-recommended actions and output. (Figure 3)

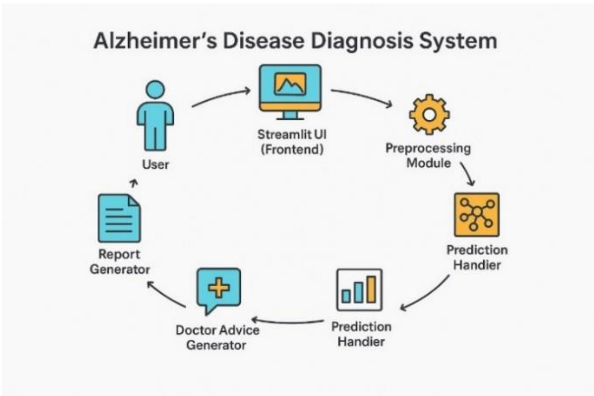

Figure 1 System Structure of the Alzheimer's Disease Diagnosis System

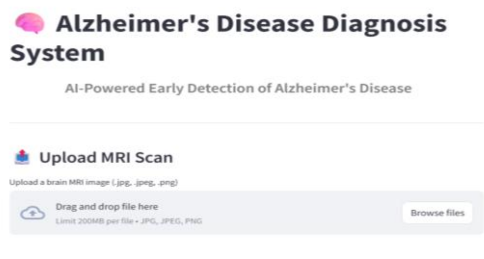

Figure 2 Streamlet-Based user Interface with MRI Upload, Condition Prediction, and Report Download Features

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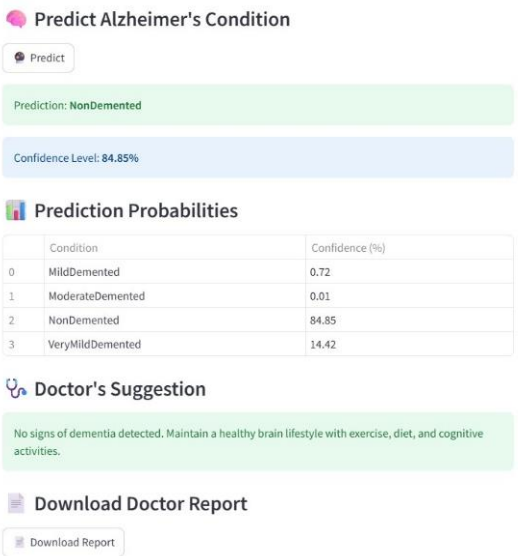

Figure 3 Real-Time Prediction Output with Confidence Values and Generated Doctor's Suggestion

1.3.Comparative Performance

The performance of the custom CNN model was evaluated through a comparison of its accuracy with various models which appeared in recent literature publications. Multiple network configurations include VGG16-based models as well as ResNet-50 and DenseNet121 and traditional SVM with PCA features. An 88.5% accuracy rate became the highest among other referred prediction techniques including DenseNet121 (86.9%) and SVM with PCA (83.4%). This research demonstrates that the lightweight architecture performs effectively through its number of trainable parameters which amounts to 1.70M. (Figure 4) [8]

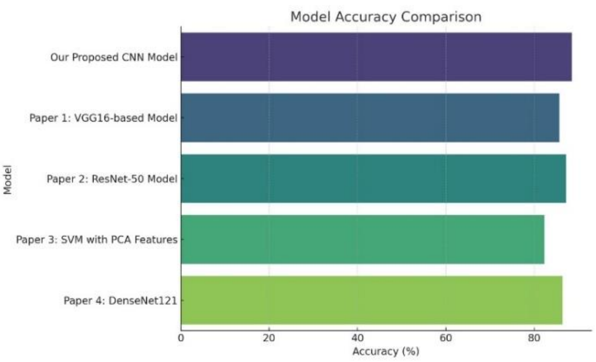

Figure 4 Accuracy Comparison of the Proposed Model with Other Reference Methods

1.4.Discussion

The findings of this work show that a lightweight CNN-based architecture is able to accurately classify Alzheimer's stages from MRI scans with an 88.5% validation accuracy. As compared to the previous works which utilized deeper or ensemble models, this method has a trade-off between speed, accuracy, and deployability that makes it ready for real-time usage. Though the omission of explainability tools such as GradCAM could confine interpretability, the performance of the system is still competitive. Similar to many studies, this work also depends on a publicly available dataset, which may not match the diversity required for clinical generalization. Some future enhancements can involve incorporating explainable AI and extending the dataset to improve model resilience in larger populations. [9]

Conclusion

The research approached early Alzheimer's disease detection using MRI scans by designing a compact deep learning system for diagnosis. A special Convolutional Neural Network (CNN) demonstrated its ability to identify Alzheimer's stages with an 88.5% validation accuracy which confirms the effectiveness of compact systems in medical image multi-class classifications. The prediction system demonstrates both accurate performance and it functions in real-time through its web interface which proves its clinical application capabilities. The results demonstrate that simple AI systems can create viable solutions for diagnosing Alzheimer's disease at an early stage yet more improvements are possible by implementing explainable AI systems and increasing dataset sizes.

Acknowledgement

The authors wish to thank every member who supplied data for the Alzheimer's MRI dataset found on Kaggle since this data assisted significantly in building and testing our models. We achieved efficiency in creating training and deploying our Alzheimer's Disease diagnosis system through Open Source tools which include Python libraries alongside TensorFlow Streamlit NumPy and OpenCV. Platform documentation combined with community support made optimization procedures and implementation steps possible for our project to succeed. Success in project completion was achieved through the combined collaboration between all team members. This work was self-funded exclusively and executed as a part of our undergraduate academic curriculum

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