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# Alzheimer Disease Prediction Using Deep Learning

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**Abstract:** Alzheimer's disease (AD) poses a substantial healthcare concern, particularly given its incidence among those aged 60 and up. Early detection of Alzheimer's disease remains difficult, with few good diagnostic techniques available. Furthermore, clinical trials for AD drugs have a high failure rate, and a definite solution remains elusive. AD evolves through various stages, ranging from extremely mild to severe, making it difficult to discern between them and resulting in increasing health issues, memory loss, and increased reliance on others for everyday activities. Early detection, particularly in mild instances, shows promise for guiding interventions to reduce disease progression and limit brain damage. Deep learning (DL) has emerged as a promising approach for early AD detection, although existing algorithms struggle to detect subtle changes in brain networks among individuals with mild dementia. Nonetheless, researchers are actively developing methods for early identification using MRI images. This study utilizes a dataset of 6400 MRI images and employs a DL algorithm with a neural network classifier for early AD diagnosis, achieving promising results in terms of accuracy, precision, recall, AUC, and F1-score. Comparative analysis with previous studies confirms the superior performance of the proposed model. Overall, this research contributes to the exploration of various machine learning (ML) and DL approaches applicable to AD stage identification.
**Keywords:** Alzheimer's Disease, Deep Learning, Convolutional Neural Network (CNN), MRI Images.

## 1. Introduction

Alzheimer's is a progressive degenerative brain disease clinically known as dementia, marked by irreversible changes affecting memory cells. Memory loss occurs due to the degeneration of visual cortical tissues and alterations in nerve cell activity. Cognitive functions affected by Alzheimer's disease include preeminently speech, reading, and writing. Advanced stages of the disease may pose complications, such as respiratory distress and death owing to heart failure. Forecasts by investigators suggest that by 2050, one out of every 85 persons will be diagnosed with AD. This ranks Alzheimer's second in terms of severity among all brain disorders in the entire world; it typically affects the hippocampus, and then spreads outward, resulting in neuronal destruction. As the disease progresses, loss of neuronal cell leads to shrinkage of brain tissues. Alzheimer's disease is an untreatable and irreversible brain disorder. Early diagnosis may restrict the deleterious consequent effects on Alzheimer's disease.The study has concluded that 10-15% diagnosed with Mild Cognitive Impairment (MCI) develop Alzheimer's disease within a year's time. Early diagnosis in MCI patients often makes the difference between preventing the progression of the disease into AD. During the middle phase of MCI, the patients show clinical symptoms analogous to Alzheimer's disease. The most important step that needs to be taken is the early diagnosis and treatment of Alzheimer's disease. MRI scans can uncover changes in brain function and structure, aiding in the diagnosis of MCI condition.
Pretrained CNNs provide the necessary classes for image processing tasks and various detection stages for Alzheimer's disease (AD) in MRI scans, utilizing pre-trained models such as MobileNet, CNN, Dense Net, and ResNet with successful MRI analysis. This helps in identifying the stage of AD, rather than using MRI scans alone, by adopting many architectures which are combined to improve the performance of the model.

The proposed CNN model will be trained and tested on a large dataset of MRI images from Alzheimer's patients and healthy controls. The dataset is going to be preprocessed for enhancing image quality and correcting for differences in imaging protocols. Next, the architecture of the CNN will be fine-tuned, and all the characteristics that matter will be captured from

MRI scans and classified into AD-positive or AD-negative with superior accuracy. The newly developed CNN model performance will be evaluated on common measures such as accuracy, precision, recovery, and F1 score. The proposed model will be evaluated against other existing diagnostic methods and deep learning methodologies that have been described in the existing literature.

## 2. Related Work

Many studies initiated via deep learning models are concerned with Alzheimer's Disease (AD) detection, whereas Sharma et al. in "Detection of Alzheimer's Disease using Deep Learning Models with VGG16 Feature Extractor," discuss in detail some of the current researches in the flavor of early detection of AD. Among them, the work of Revathi et al. tallies largely in context with an early detection of AD. For example, blood pressure and diabetes were studied using SVM and random forest models, in their effects on cognitive disabilities. They further fine-clustered the risk for AD with multinomial logistic regression to show the multi-fputedness involved in AD detection, with the import of diverse factors.

On the other side, Jain et al. brought a unique concept of extraction by combining ImageNet, CNNs, and the architecture of VGG16. Their findings exhibited a fantastic noise prediction accuracy of 95.73%. This suggests a viable possibility of deep learning methods toward a more effective detection of AD due to imaging data. Further advancements were presented by Odusami et al. after developing a random concatenated model. For their study on MRIdatasets, over the support of the models ResNet18 and DenseNet121, high values of precision, recall, and accuracy metrics were achieved, proving further the prospectiveness of deep learning in Alzheimer's Disease diagnosis.

Khan et al. investigated a hybrid machine learning model that allows th detection of both Alzheimer's disease and mild cognitive impairment. This hybrid model was able to effectively distinguish AD and MCI at appreciable accuracies while using classifiers such as XGBoost, random forest, andSVM. Furthermore, Lei et al. explored the usage for an AD detection of a layered independently recurrent neural network model. The research highlighted the much more flexible arrangementsin a neural network fitted into medical imaging processing, which became an invitation for imminent development of several AD detection strategies.

Using 3D convolutional neural networks, Sarraf and Tofighi (2016) advocated for the automated classification of Alzheimer's disease (AD), mild cognitive impairment (MCI), and the cognitively normal population (CN) on MRI data. Great success was achieved by their deep learning model in terms of differentiating such cognitive states, possibly boding well for AD diagnosis using 3D CNNs.

Liu et al. (2018) offered a transformative approach in DeepAD, an innovative framework for detecting Alzheimer's disease. DeepAD integrates multimodal MRI data with graph convolutional networks (GCNs). DeepAD achieves significant advances beyond other classic regression schemes in differentiating between Alzheimer's patients and healthy controls by using at least both structural and functional MRI features.

Another significant study was conducted by Suk et al. (2014), wherein they presented a deep learning framework known as convolutional deep belief networks (CDBN) for the diagnosis of diseases using MRI data for AD. Their algorithm has yielded higher classification accuracy than other feature-based classifiers by analyses of spatio-hierarchical patterns captured in MRI images.

Along similar lines of research, Liu et al. (2019) introduced a novel GCN architecture for AD classification on multisubject functional connectivity networks derived from rs-fMRI. Their GCN models incorporate complex brain network properties toward good performance in such classification tasks. Further, recent advances in transfer learning have been employed toward diagnosing AD. For instance, Li et al. (2020) administered MRI images to classify Alzheimer's disease with a pre-trained deep learning model called Inception-ResNet-V2. Their transfer learning approach considerably abated the need for massive annotated datasets while achieving competitive performance in AD diagnosis tests.

These papers taken together illustrate the broad other of 3D CNNs, graph convolutional networks, and transfer learning techniques that are utilized to perform AD detection. The improvements constitute valuable avenues that greatly promise more accurate and effective diagnosis of AD and better patient care and management regimes.

**These drawbacks in the existing system are:**

1. Existing AD detection systems may provide a low accuracy for stages in discrimination from one to the other, leading to misdiagnosis or delayed commencement of treatment.

2. Traditional means of feature extraction in AD detection can be done only in very complex and time-consuming modes, indicating the need for manual intervention and specialist knowledge, which might impede the scalability and efficiency of diagnosis.

3. As per the fact that, having already manifested their diagnosis like AD detection based on MRI scans, the cost is usually high in itself such that the advanced medical facilities are not that easy for the whole population.

4.The inefficacy of any systematic techniques and benchmarks for detection systems may result in inconsistent findings, making it hard to compare one approach against another.

5.Some of the current techniques may lack general application across varied patient groups or imaging datasets, thus limiting their applicability in real-world clinical settings with differing demographics and imaging characteristics.

6. Recently developed deep learning models used for AD detection may also have some interpretability issues, making it difficult for medical professionals to understand the actual cause of a particular diagnosis and thus directly or indirectly affecting the trust and acceptance of AD systems.

| AUTHOR | TITLE | TECHNIQUE USED | DATASET | PERFORMANCE ANALYSICS | LIMITATIONS |
|---|---|---|---|---|---|
| Jie Zhao et al | Alzheimer's Disease Prediction through Deep Learning Models on MRI Data | Convolutional Neural Networks (CNN) | ADNI | Accuracy: 92.4% | Limited dataset size and generalizability |
| Yueming Jin et al | Deep Learning for Alzheimer's Disease Classification and Prediction: A Review | CNN, RNN | ADNI, OASIS | Accuracy ranges between 85-94% | Interpretability of deep models |
| Liu et al. (2020) | Multi-modal fusion for Alzheimer's Disease diagnosis | Autoencoders and CNN | ADNI, MRI, PET | Achieved AUC of 0.91 for Alzheimer's diagnosis | Complex model structure, overfitting risk |
| Tanveer et al. (2021) | Deep Generative Models for Alzheimer's Disease Progression Prediction | Generative Adversarial Networks (GANs) | Longitudinal MRI data, ADNI | Precision: 89%, able to predict disease progression | Data sparsity, computationally expensive |
| Wang et al. (2019) | Graph Convolutional Networks for Alzheimer's | Graph Convolutional Networks (GCNs) | ADNI, resting-state fMRI | Classification accuracy: 88% | Incomplete graph structure and small dataset |

| | | | | | |
|---|---|---|---|---|---|
| | Disease Classification | | | | |

## 3. Proposed Work

### *A. Process flow*

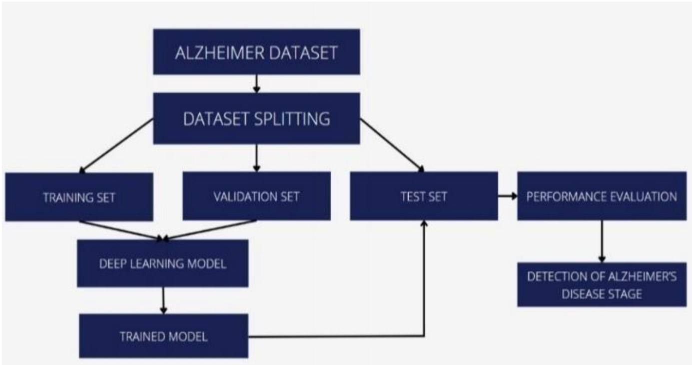



***Fig 1 Process Flow***

Splitting the Dataset is a process of dividing the dataset into smaller subsets for training, validation, and testing. This allows the learning model to learn from one data set, validate its learning from another set, and finally test on one more distinct set to know its performance.

Training Dataset: A subordinate part of training the deep learning algorithm in forming predictive models. The training dataset is said to comprise labeled items or examples (data points) for allowing the model to train in establishing relevant patterns in terms of Alzheimer's disease.

Validation Set: A set that is used for hyperparameter tuning and preventing overfitting of the model. This also assesses a model's performance on unseen samples from training.

Test Set: A set kept apart from training and validation, on which the model finally gets tested. The model is evaluated on this set of samples that it has never before captured from other sources.

Deep Learning Model: A deep learning model is one that has many layers of interconnected nodes (neurons). Deep learning models excel at understanding nuanced patterns from complex data, making them ideal for tasks such as disease diagnosis.

Trained Model: A deep learning model that is trained on the training set and validated using the validation set. This is the final model to be used for testing and implementing in real-world settings.

Performance Evaluation: In simple terms, performance evaluation refers to assessing how a trained model's evaluation functions on the test set. Accuracy, precision, recall, and F1 score are the metrics usually adopted in this procedure.

Detection of Alzheimers Disease: Refers to the deep learning model's aim to identify and categorize different stages or signs of Alzheimer's disease using the respective input.

### *B.DATASET*

1. Alzheimer's MRI Preprocessed Dataset This dataset comprises some MRI images wisely selected from reliable sources including public archives and medical facilities. All the images in the dataset were standardized to have a resolution of 128 by 128 pixels for uniformity and analysis.
2. This dataset comprises of 6400 MRI images classified into four groups depending on the phases of dementia progression.
3. 1. Mild Demented (Class 1): This class contains 896 images which shows people in a very early stage of the disease.
4. 2. Mildly Demented (Class 2): This category has 64 images of patients suffering from the disease at a relatively advanced level than Class 1.
5. 3.Non-Demented (Class 3): This class has the largest number of 3200 images in the sample and people without dementia. The course offers a good point of comparison and analysis.
6. 4.Minimally Impaired Demented Class 4: There are 2240 photographs in this category, but they are more impaired than those in Class 1.Model

## 7. Architecture

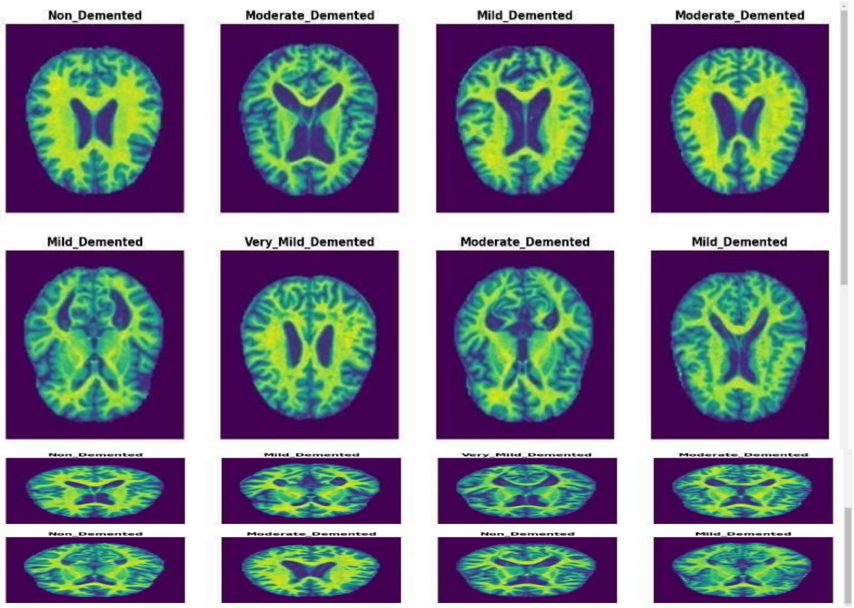
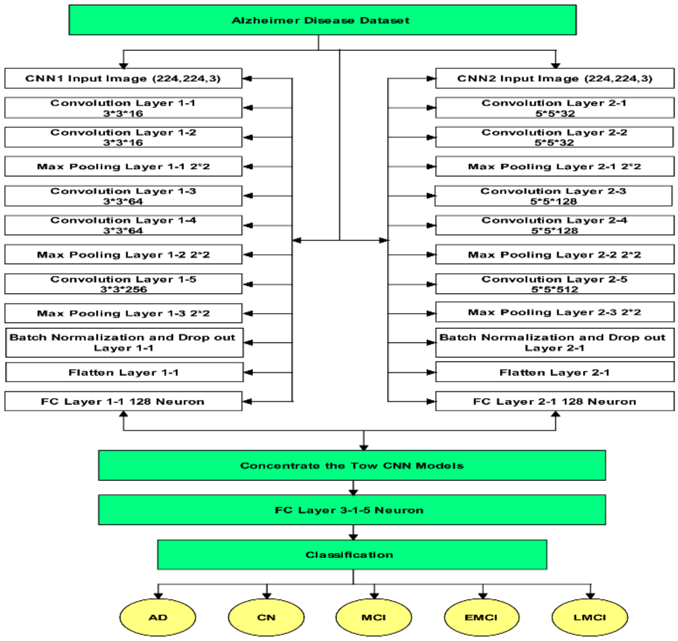



*Fig 2 Sample Dataset images*




These filters extract local features from the images provided. Feature maps are down- sampled using a 2x2 max-pooling layer at a stride of 2 for the capture of key information. The following two convolutional layers comprise 64 filters each, which improves the representation of higher-level information. A second round of max-pooling is performed to reduce spatial dimensions. This is followed by a 3x3 convolutional layer with a number of filters of 256 to capture more complicated patterns. Dropout of 20% is used as well to prevent overfitting, and batchnormalization is implemented to normalize activations in order to increase the stability of training. Finally, a fully connected layer with 128 neurons is added to gain global insights from flattenedfeature maps.

The second CNN model has nearly similar structure but the filter sizes are different. The algorithm starts off with two convolutional layers, each 32 filters measuring 5×5 in size. The next of these layers are 2×2 max-pooling layers with a stride of 2. The next two convolutional layers each have 128 5 × 5 filters. The following layer consists of a convolutional layer that includes 512 5x5 filters. Dropout with a dropout of 20% is used in place to avoid the overfitting and to stabilize further by the use of batch normalization. The last layer used is a fully connected layer with neurons of size 128, which is used for getting the global view from feature maps.

Prediction, which is the possibility of the input belonging to one of five classes, is generated by aggregating features that are extracted from each CNN network and then processing its output by passing it through a Fully Connected network. Then, this highest value is used to calculate the predicted class. Table 2 gives a step-by-step explanation of the network architecture, operations it involves, its size, filter count, and the output for each convolutional layer. Also, the parameters for each layer are defined. All these parameters can be trained as well as fused into the backpropagation algorithm, and so in Table 3, the hyperparameters generated by the CNN model are listed.

8. **D .Evaluation Metrics**

9. In order to check the model, we used the split of the original dataset before it's trained. To ensure robustness, more than one metric is used. How good a candidate the model's training effectiveness depends on how well these metrics are understood. In order to measure the performance of our model, we used a number of indicators.

10.

11. 1.Accuracy: Accuracy is the number of correct actual forecasts. Values over 80% are considered good, while those over 90% are considered excellent. The following expressions calculate this metric.

12. Accuracy =TP+TN

13. TP+TN+FP+FN

14. TP, TN, FN, and FP represent the abbreviations for True Positive, True Negative,False Negative, and False Positive values respectively.

15.

16. 2.Accuracy: The formula used to calculate accuracy is a fraction of correct optimistic predictions divided by the total number of optimistic predictions46. Accuracy ratings in the range of 80% are often considered acceptable.

17. Accuracy = TP TP+FP

18. 3.Recall: Recall that it is also known as the sensitivity score or the true positive rate. Recall involves relating correct optimistic predictions to all correct positives43. Good recall valuesrange between 70 and 90%. The following is the formula for calculating the recall.

19.

20. Recall = TP

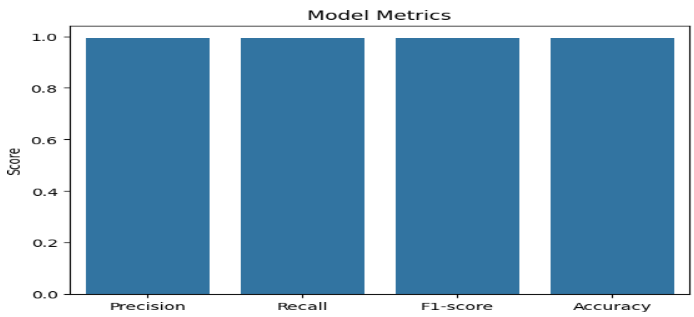
21. TP+FP

22. 4. F1-score: The F1 score can be distinguished by unique values for each category the classifier identifies. The score of F1 can be computed by using the following formula.

23.

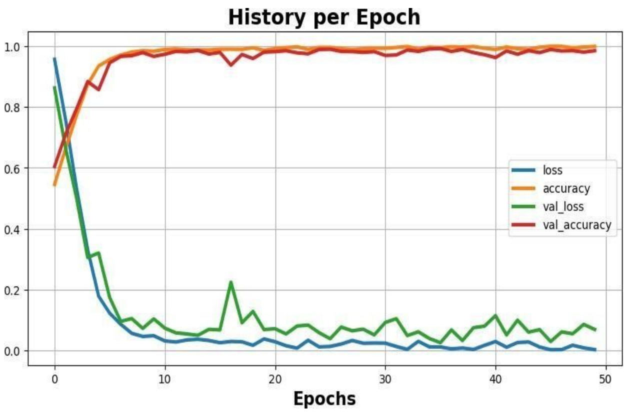
$$\textbf{F1-score} = \frac{\textbf{2 x Precision x Recall}}{\textbf{Precision + Recall}}$$

24.




25. 4.**Results and discussions**

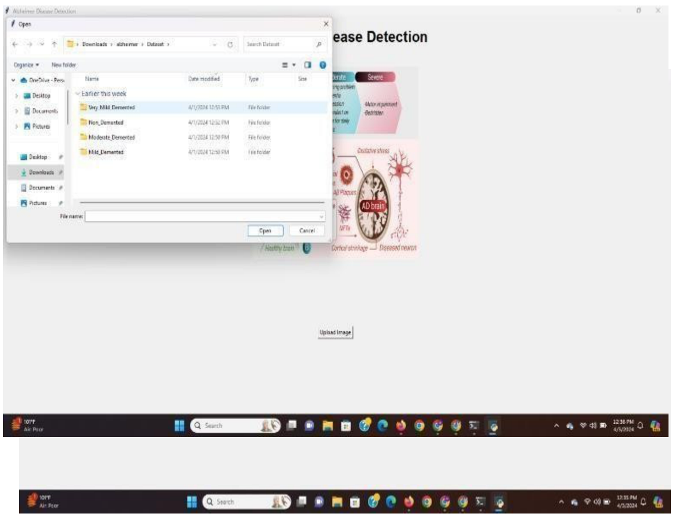
26. The Results and Discussion section analyzes andexplains the study's findings, highlighting their significance and potential applications. This section summarizes research findings and highlights their significance in the are.




27.
28.

*Fig 3 history vs history per epoch curve*

29.




30. ***Fig 4 User Interface window***

***Fig 5 Upload an image to predict the stage of Alzheimer'sdisease***

**31.**

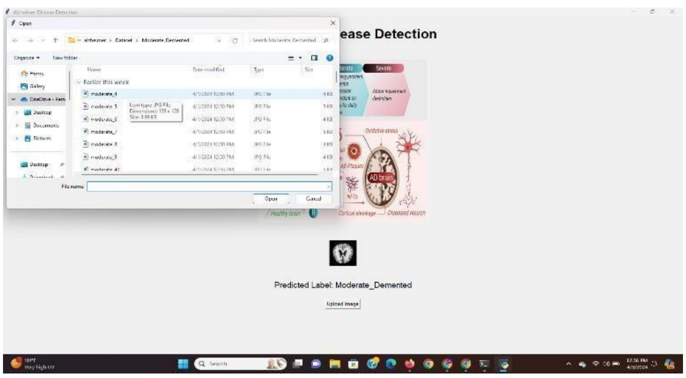



***Fig 6 Predicting the stage of disease byuploading Moderate-Demented image***

**32.**

## 33. 5.Conclusion

34. This research showed how we can predict Alzheimer's disease (AD) using the incorporation of brain imaging data in the construction of a Convolutional Neural Network (CNN) model. We obtained excellent accuracy at 98.52% and little loss of 6.93% as achieved with training for 60 epochs. Our results thereby lay the foundation for deep learning techniques, including CNNs, for early detection and diagnosis of Alzheimer's disease, which is critical for prompt intervention and

treatment. Its impressive accuracy in identifying patterns and features related to Alzheimer's disease from brain imaging data makes our model an efficient tool. This study promotes the whole field of AD detection by introducing a new technique with its promising accuracy results. The proposed technology will help doctors and researchers in earlier detection of Alzheimer's diseases, and, therefore, will be followed by more active therapies and better output for the patients. The future work will involve testing the approach in a database of a larger size by checking its usefulness in clinical environments and more data modalities for better accuracy.

35.

## 36. 6. Future Scope

37. Future work for our CNN-based Alzheimer's prediction algorithm involves several potential improvements and advancements. First, kinds of different data modalities-such as genetic information, biomarkers, and so on-can be included to increase the accuracy of predictions. Transfer learning approaches may benefit, as they use well-pretrained pieces on huge datasets obtained from related domains. Further elaboration on neural network topologies, such as attention mechanisms or recurrent neural networks, may further enable a better and more appropriate capture of temporal dependencies in longitudinal data. Future deployments in clinical environments and validation in prospective studies will take significant strides toward applicability in the real world. Responsible healthcare implementation will rely not only on the accuracy of the model but also on privacy and, importantly, interpretability of models. In conclusion, these directions are likely to improve performance of our model and may be helpful to treat patients correctly and improve Alzheimer's diagnosis better.

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