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Research Article

Development of Predictive Models for Early Detection of Alzheimer's Disease Using Machine Learning

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Abstract

It is critical to detect Alzheimer's disease (AD) early on so that medications may be started quickly since it is a major cause of dementia in the elderly. Furthermore, a substantial portion of the world's population is impacted by metabolic illnesses such as diabetes and AD. The progressive nature of Alzheimer's disease makes it difficult for patients and their loved ones to plan for the future, but progress toward therapies that might halt the disease's course is being made possible. This article showcases a machine learning-based approach to early AD detection using the Open Access Series of Imaging Studies (OASIS) dataset. Comprehensive data pretreatment is part of the technique, which also includes feature selection, data cleaning, addressing missing values, and balancing utilizing the Synthetic Minority Oversampling Technique (SMOTE). The CNN model obtained from deep learning served as the basis for comparison against XGBoost and Logistic Regression and Random Forest (RF) AD methods. Accuracy, precision, recall, and F1-score are some of the measures used to train and assess CNN. According to experimental results, the CNN model showed better performance than classical models through accuracy of 94.1% and, precision of 98%, recall of 91%, resulting in an F1-score of 94%. This demonstrates CNN's promise for dependable and accurate early diagnosis of AD.

Keywords: *Alzheimer's Disease, Early Detection, Machine Learning, Convolutional Neural Networks, OASIS Dataset, SMOTE.*

Introduction

The degenerative neurological condition known as Alzheimer's Disease (AD) severely affects cognitive function which contributes substantially to dementia diagnosis [1][2]. Essential basic processes including swallowing and mobility are impacted by the progressive nature of AD [3]. Identification of Alzheimer Disease at an early stage allows patients and their families to develop strategies for medical, legal, and financial needs and implement their support networks [4]. The availability of treatments that reduce illness duration and symptom relief becomes faster once medical professionals diagnose conditions in their early stages [5]. Figure 1 shows the Area affected by Alzheimer's disease in brain MRI images. People take part in clinical research trials and innovative treatment and prevention studies through medical imaging methods. A vital tool for identifying and monitoring the course of neurodegenerative illnesses, such as AD, is medical imaging [6][7]. The combination of MRI with ultrasound and X-ray scanning and radiological methods helps doctors understand better how the brain functions and structures itself [8][9].

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These techniques complement each other and offer critical information for detecting early-stage abnormalities associated with AD.

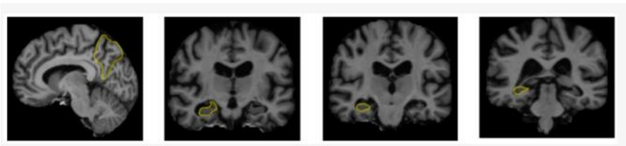

Fig.1 Area affected by Alzheimer's disease in brain MRI images

ML has become an invaluable resource for medical diagnostics, especially in the identification of AD [10][11][12]. Traditional statistical and thresholding methods, such as Otsu's method, are incapable of learning from data and thus have limited effectiveness in diagnosing AD[13]. Clustering techniques, such as k-means and fuzzy clustering, can segment images effectively but lack the ability to learn and improve over time[14][15]. Due to the high-dimensional nature of medical imaging data, conventional machine learning models often face sparsity issues, limiting their effectiveness in detecting AD [16][17]. Recent advancements in deep learning and high-dimensional classification techniques have led to improved predictive models for AD detection, addressing these challenges. The goal of ongoing research is to improve ML models after increasing a diagnosis of AD's accuracy and computational efficiency. Integrating DL with traditional ML approaches has demonstrated significant potential in automating AD detection from medical images[18]. The development of robust predictive models will facilitate early diagnosis, enabling better management and treatment of AD, ultimately improving patient outcome[19][20].

Motivation and Contribution of the Study

This study is driven by the increasing incidence of Alzheimer's disease, which impacts millions of people and puts a heavy burden on healthcare systems throughout the globe. Early detection is crucial for slowing disease progression and providing patients with better opportunities for treatment and care. However, conventional diagnostic techniques are sometimes expensive, time-consuming, and intrusive. ML offers an innovative solution by providing a non-invasive, cost-effective, and efficient means of identifying Alzheimer's in its early stages. The main contribution points are shown below:

Employs the OASIS dataset, which contains authentic neuroimaging and clinical records, ensuring practical applicability for Alzheimer's disease detection.
Implements a robust preprocessing, including missing value imputation, data cleaning, and standardization to ensure data consistency and quality.
Applies SMOTE to balance the dataset, improving model learning and mitigating bias toward the majority class.
Utilizes CNN and compares it with XGBoost, RF, and Logistic Regression to enhance classification accuracy and effectively analyze the cognitive decline in patients.
Comprehensively evaluates the ability to classify Alzheimer's disease by calculating critical parameters including acc-uracy, precision, recall, and F1-score.

Justification and Novelty

This study justifies its approach by leveraging the OASIS dataset, ensuring practical applicability to Alzheimer's Disease detection. The dataset undergoes a rigorous preprocessing pipeline, addressing key challenges such as data cleaning, missing values, and class imbalance through advanced SMOTE techniques like data standardization, and feature selection. The novelty of this research lies in its integration of feature engineering strategies to enhance model efficiency, coupled with the application of CNN a highly effective ensemble learning algorithm to improve disease classification performance this study optimizes data-driven insights to refine Alzheimer's Disease prediction, ensuring scalability and robustness for real-world clinical applications.

Structure of the paper

The study is summarised here: Research that has helped in the early detection of AD is covered in Section II, and the procedures and materials employed are detailed in Section III. Results from experiments evaluating the suggested system are detailed in Section IV. Section V concludes the investigation and provides an overview of its findings.

Literature Review

This review section explores predictive models used for early Alzheimer's detection, utilizing OASIS dataset, focusing on ML and DL methodologies for improved diagnostic outcomes:

Sharma et al. (2024) can lead to several benefits and ultimately result in better decisions and significant savings. In the proposed work, Multiple datasets of ADNI and the OASIS are used. A variety of supervised machine learning algorithms have been applied for automatic Alzheimer's disease detection. The performance metrics with respect to the accuracy values have been analyzed and from the results, it is observed that the minimum accuracy of 67.75% is achieved in AdaBoost and a maximum accuracy of 80.22% has been achieved using Gradient Boosting Classifier[21].

Praneeth et al. (2024), propose a novel prediction framework harnessing deep learning methodologies, specifically employing the advanced EfficientNetB6 algorithm, on the ADNI dataset comprising approximately 20,000 MRI images. Our aim is to differentiate between MRI images indicating normal cognitive function and those signaling AD progression, with a target of achieving 97.78% accuracy and a 98.21% F1 score[22].

Chamakuri and Janapana (2024), they provide a system that can automatically detect and classify AD. The framework is based on a deep knowledge of how to detect AD in a given patient using a magnetic resonance imaging (MRI) image. The proposed CNN model under the name of Alzheimer's Disease Detection Net (ADDNet) serves to improve baseline CNN performance. This model has improved the architecture for progressive generation of characteristics and enhanced it for early AD detection. The suggested method, called learning-based Alzheimer's disease detection (LbADD), makes use of ADDNet. The results of our experiments demonstrate that ADDNet clearly demonstrates its robustness, as it achieves an overall accuracy of 98.83%, which is superior to that of other models[23].

Kancharla et al. (2024), an OASIS-3 dataset containing images of brain MRIs labeled as mild cognitive impairment and cognitively normal split into testing, training, and validation data. The data augmented, featurized, and trained on various algorithms. Featurization done using the deep learning convolutional neural network ConvNextXLarge, which pre-trained on ImageNet. The algorithms were tested on validation data and the best model selected. MLP, KNN, and RF were models that had an accuracy of 0.979 and XGBoost had an accuracy of 0.959. MLP selected as the final model and performed with a final accuracy of 0.953 on the testing data with a recall value of 1[24].

Arya et al. (2023) centers on the use of five very successful models for the prediction of AD. LogisticRegression, C5.0, and NeuralNetwork are among the eight ML models used. The five most important models are compared according to their performance metrics: SupportVectorMachine (SVM), C5.0 DecisionTree, NeuralNetwork, extremeGradientBoosting (XGBoost), and Chi-squareAutomatic InteractionDetection (CHAID) DecisionTree. The research indicates XGBoost proves best for Alzheimer's disease predictions through ensemble learning methods that achieve 96.75 percent accuracy[25].

Tushar et al., 2023, the OASIS MRI data sets are used to provide a new method for outcome prediction. The approach includes investigating the data, cleaning it up, and then creating a hybrid model with the help of the Decision Tree and LR methods. The developed version of our hybrid model proved to be more accurate than previous models producing a 96% testing success rate [26].

Amrutesh et al. (2022), The two datasets used to assess the most effective variables for efficient AD detection are the OASISdataset, which contains MRI images, and the longitudinal dataset, which has text values. The RandomForest Algorithm serves the OASIS Longitudinal dataset through one of fourteen machine learning methods that achieve 92.1385% maximum acc-uracy compared to 47.1910% baseline acc-uracy. The InceptionV3 model employing ADAM as the optimizer had the best accuracy when tested on MRI images using various transfer learning approaches [27].

Table 1 summarizes recent research on predictive models for early detection of AD using ML and DL approaches. It highlights methodologies, datasets, and performance metrics and identifies limitations, suggesting improvements in data augmentation techniques, integration of advanced deep learning models, and real-world clinical validation for enhanced accuracy and reliability.

Table 1 Summary of the related work on Early Detection of Alzheimer's Disease using machine learning

Author	Methodology	Dataset	Performance	Limitations & Future Work
Sharma et al., 2024	Supervised Machine Learning (AdaBoost, Gradient Boosting)	ADNI, OASIS	Min: 67.75% (AdaBoost), Max: 80.22% (Gradient Boosting)	Limited accuracy; future work may focus on deep learning models for better accuracy.
Praneeth et al., 2024	EfficientNetB6 (Deep Learning)	ADNI (MRI, 20,000 images)	Accuracy: 97.78%, F1-score: 98.21%	Requires further validation on larger and diverse datasets.
Chamakuri & Janapana, 2024	CNN-based Alzheimer's Disease Detection Net (ADDNet)	ADNI (MRI)	Accuracy: 98.83%	Focus on improving early-stage detection.
Kancharla, 2024	ConvNextXLarge, MLP, KNN, RF, XGBoost	OASIS-3 (MRI)	MLP: 97.9%, XGBoost: 95.9%, Final MLP model: 95.3%	Enhancing generalizability across MRI datasets.
Arya et al., 2023	Auto Classifier (SVM, C5.0, Neural Network, XGBoost, CHAID)	OASIS (MRI)	Best model: XGBoost (96.75%)	Explore hybrid models for further accuracy improvement.
Tushar et al., 2023	Hybrid Model (Logistic Regression + Decision Tree)	OASIS (MRI)	Accuracy: 96%	Consider deep learning methods for performance enhancement.
Amrutesh et al., 2022	ML (Random Forest, KNN), Transfer Learning (InceptionV3)	OASIS (MRI, Longitudinal)	RF: 92.14%, KNN: 47.19%, Transfer Learning: Best with InceptionV3	Optimizing feature selection for better classification accuracy.

Acquisition of the OASIS dataset is the first step in the technique for developing prediction models for early diagnosis of Alzheimer disease using ML. It is usual practice to clean and handle missing values as well as standardise the dataset to ensure consistency as part of the preprocessing procedure. The most important characteristics are found using feature selection methods, and then class imbalance is addressed using SMOTE. To guarantee reliable model assessment, the dataset is then divided into training (80%) and testing (20%) sets.

For the AD classification used deep learning-based CNN models and compared with existing XGBoost, LR, and RF. The training set is utilized for training convolutional neural networks (CNNs), and then their performance is assessed using important metrics including F1score, re-call, acc-uracy, and precision. The results are analyzed to compare an effectiveness of each model in predicting AD, providing insights into the most suitable techniques for early diagnosis. The flow of this methodology is illustrated in Figure 2: Flow Chart Diagram for the AD Detection.

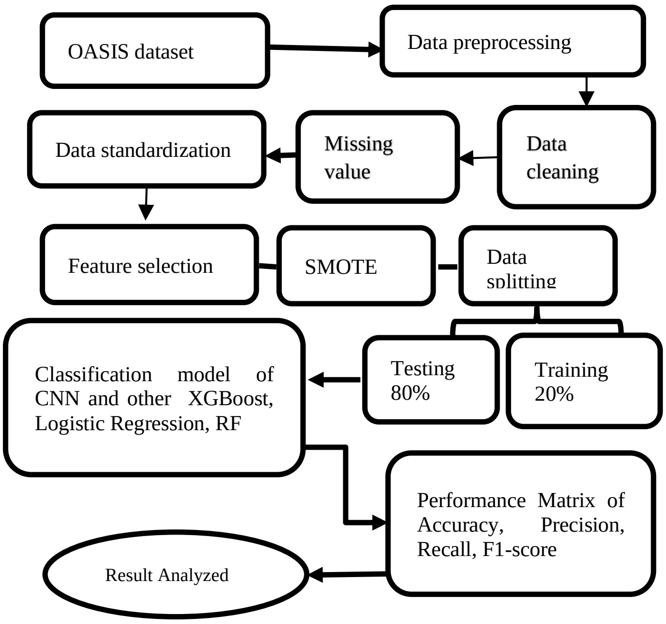

Fig.2 Flow Chart Diagram for the Alzheimer disease detection

The steps in the following Figure 2 flowchart are briefly explained below:

Data Collection

The OASIS dataset was used to evaluate several models. In addition to testing with the whole collection of OASIS photos, we also attempted with a smaller dataset. The OASIS dataset is quite tiny in the machine learning space, measuring 373 rows by 15 columns. The 8 various attributes: gender(M/F), Person'sAge (age), years of education(EDUC), socioeconomic status (SSE), mini-mentalStateExamination (MMSE), estimated TotalIntracranialVolume (eTIV), normalized WholeBrainVolume (WV), and AtlasScalingFactor (ASF) have been considered for the final result. Figure 3 shows the images of Alzheimer's affected BrainMRI and normal brain MRI images.

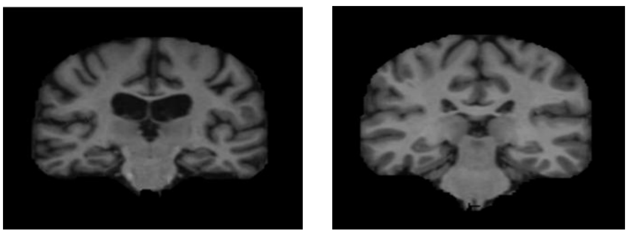

Fig.3 Alzheimer's affected Brain MRI and normal brain MRI image

Data analysis and visualization

The OASIS dataset is analyzed through univariate and bivariate visualizations to understand demographic, cognitive, and neuroimaging attributes related to AD. Histograms and bar plots reveal a distribution of key features like Age, EDUC, SES, MMSE, eTIV, and nWBV, while box plots highlight variations across cognitive groups (Nondemented, Demented, and Converted). These visualizations help identify patterns, correlations, and potential data imbalances, aiding in effective feature selection and predictive modeling.

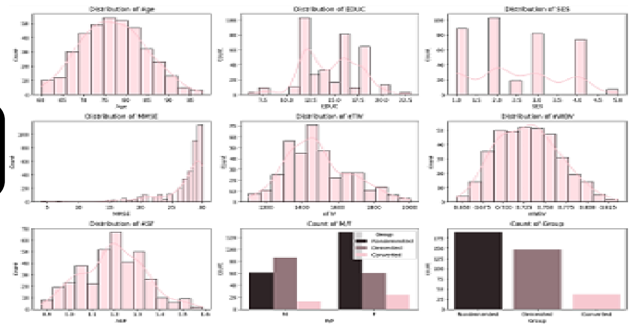

Fig.4 Univariate analysis of the dataset

Figure 4 displays the univariate breakdown of essential attributes found within the OASIS dataset which shows different distributions of demographic and cognitive as well as neuroimaging characteristics. The histograms represent the frequency distributions of **Age, EDUC, SES, MMSE, eTIV, nWBV, and ASF**. The bar plot displays information about gender composition and person counts in the three cognitive groups (Nondemented, Demented, and Converted). The analysis reveals data distribution characteristics that highlight patterns which might affect predictive modeling outcomes within Alzheimer's disease diagnosis

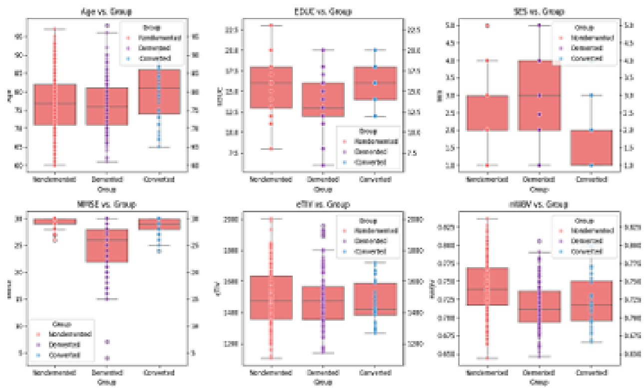

Fig.5 Bivariate analysis of the dataset

The Figure 5 presents bivariate evaluations regarding OASIS dataset attributes which are grouped into Nondemented, Demented and Converted cognitive categories. The box plots depict the distribution of Age, EDUC, SES, MMSE, eTIV, and nWBV across these groups. The variations in these attributes provide insights into cognitive decline and structural brain changes associated with Alzheimer's disease progression.

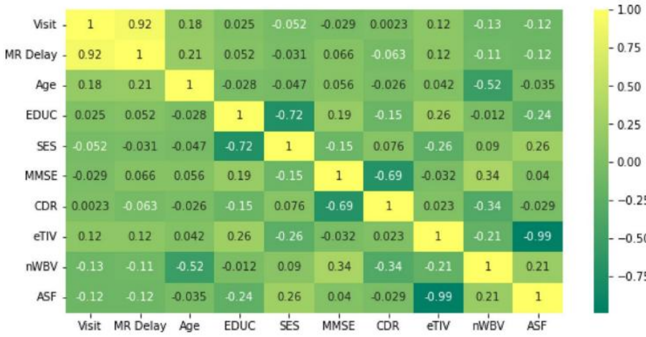

Fig.6 Correlation Metrics Among Dataset Features

Figure 6 illustrates the correlation matrix among key features in the OASIS dataset, highlighting relationships crucial for Alzheimer's Disease diagnosis. The color intensity represents correlation strength, with values ranging from -1 to 1. Strong correlations are observed, such as the inverse relationship between eTIV and nWBV (-0.99) and between SES and EDUC (-0.72). Additionally, MMSE and CDR show a negative correlation of -0.69, emphasizing its role in cognitive impairment assessment. To better forecast AD, the heat map draws attention to important feature interactions, which helps with feature selection and optimising the model.

Data preprocessing

Data preprocessing for AD prediction employing the OASIS dataset involves data cleaning, including handling missing values, normalizing numerical features for consistency. A few important points of data preparation include feature selection, data standardisation, SMOTE (which generates synthetic samples for minority classes to alleviate class imbalance), and data splitting (which improves model performance).

Data cleaning: Data cleaning for the Alzheimer's Disease OASIS dataset requires efforts to handle missing values and normalize formats and correct inconsistencies as well as eliminate duplicates to generate accurate results. A fundamental step of data cleaning requires variable encoding for categorical data along with numerical scale normalization to deal with outliers, which leads to accurate model training.

Handle missing value: Handling missing values in techniques like imputation or removal of incomplete records shows missing data in the Alzheimer's Disease OASIS dataset; Figure 6 shows Before and After missing value handling where gaps indicate missing values. A demonstrates a cleaned dataset after handling missing values, ensuring a complete and uniform dataset for analysis

Data standardization

Data standardization in AD research involves preprocessing imaging and clinical OASIS datasets, to normalize feature scales, ensuring consistency and reducing bias. This enhances the performance of ML models by improving comparability and convergence during training

Feature selection

Feature selection is an important step in Alzheimer's disease prediction, aimed at identifying the most relevant biomarkers from neuroimaging and clinical OASIS datasets. RF selecting the most informative features improves model accuracy, reduces overfitting, and enhances interpretability in detecting Alzheimer's disease progression.

Data balancing with synthetic Minority oversampling Technique (SMOTE)

A common problem in medical datasets, such as those including AD diagnoses, is class imbalance. To address this, the suggested ensemble-based approach employs the SMOTE. The model gains a deeper understanding of minority class trends with the addition of these data, which improves the accuracy of AD diagnoses. Model performance improves in predicting both classes through SMOTE technology because it ensures an equal distribution of data.

Data Splitting

This technique used a cross-validation strategy that included splitting the dataset in half. The model applies test data for prediction generation then uses training data for model learning and evaluation purposes [28]. After the data has been preprocessed, divide the dataset in half lengthwise and use 80% for training and 20% for testing.

Classification with CNN model

CNN method for classifying AD patients and healthy controls using MRI coronal slices over the middle temporal lobe. Two distinct groups with varying races and educational attainment were used to train and verify our algorithm [29][30]. Experiments demonstrate that our algorithm performs promptly and accurately across a wide range of demographic and cultural groups [31].

Equation (1) establishes the convolution operation, $*$, among two discrete functions, $f[m,n]$ and $g[m,n]$.

$$(f * g)[m,n] = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} f[m,n]g[m-i,n-j] \qquad (1)$$

A valuable procedure in the realm of signal processing is convolution. Images may be altered via the use of convolutional filters, which can provide a variety of effects including sharpening and smoothing [32]. There are a few factors that control the convolutional layers of a neural network. Among these parameters are the total number of filters, the size of each filter (the kernel size), and the stride size, which specifies the "skip" value in pixels before the filter is applied to the next block of pixels [33].

With a given $N \times M$ picture, we used a $i \times j$ filter, assuming the stride size was 1. We did an inner product among the filter and the sub-image after dividing our original picture into $(N-i+1)\times(M-j+1)$ sub-images. This is the filtered picture with $(N-i)\times(M-j)$ pixels that is produced by the convolution.

By reducing the loss during training, a convolutional network discovers the best filters. These learned filters are capable of learning practical filters that aid in the data classification of later layers. There are several applications for this, including face recognition.

Performance Metrics

The model was tested using the subset of the dataset that was generated during data partitioning before to training. Verifying a model's robustness from all perspectives is achieved by using many measures. The effectiveness of a model's training is dependent on the collective comprehension of these outcomes [34]. Specifically, that the model is top-notch. There are a number of other elements to consider. The evaluation technique as follows:

True positive (TP): The TP rate is the proportion of instances when an algorithm for Alzheimer disease detection[35] accurately detects a picture as having Alzheimer disease.
True negative (TN): The TN rate is the proportion of instances when an algorithm for detecting Alzheimer's disease correctly detects a picture as not containing the disease.
False positive (FP): The FP counts the occurrences of the model erroneously classifying an image as Alzheimer's disease.
False negative (FN): The FN counts the occurrences of the model wrongly classifying a picture as normal.

Accuracy

Accuracy assesses how accurate the model's prediction is, especially for diagnosing AD [36]. It determines how many MRIs out of all the input MRIs were accurately categorized. It is expressed (2):

$$Accuracy = \frac{\text{TN} + \text{TP}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (2)$$

Precision

The precision ratio, which is the percentage of TP relative to the total number of TP, is a metric for accuracy. It is represented as (3):

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

Recall

In binary classification, recall is a measure of a model's ability to identify (all persons suffering from AD with properly classified positive AD data) It is represented eq. (4):

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (4)$$

F1-score

A harmonic mean of recall and accuracy is the F-measure score. The maximum F-score, which is 1, is achieved when the precision and recall values are both flawless, It is represented (5):

$$\text{F1} = \frac{2*(\text{precision}*\text{recall})}{\text{precision+recall}} \quad (5)$$

These metrics are used for the performance evolution of the various models

Result & Discussion

This research evaluated in an experimental setting using a computer with Python 3.12 and Jupyter Notebook for implementation. The study utilizes the OASIS dataset for Alzheimer's Disease detection. An Intel(R)Core (TM) i5-1135G7 @ 2.40GHz 2.42GHz processor with 16 GB RAM used to perform the machine learning. The following measures are used to assess the performance: Acc-uracy, Precision, Recall, and F1-Measure. Table 2 compares the performances of the CNN model, ML and DL models, and the overall Alzheimer's disease model.

Table 2 Outcome of CNN for Early Detection of Alzheimer's Disease on OASIS dataset

Matrix	CNN
Accuracy	94.1
Precision	98
Recall	91
F1-Score	94

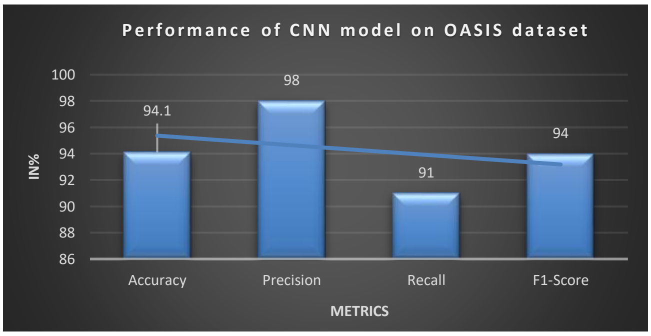

Fig.7 Bar Graph of CNN for Early Detection of Alzheimer's Disease on OASIS dataset

Figure 7 and Table 3 show the results of the CNN model's performance assessment for early Alzheimer's

Disease identification using the OASIS dataset. Table 3 reports key classification metrics, where the CNN achieves an accuracy of 94.1%, a precision of 98%, a recall of 91%, and an F1score of 94%, demonstrating the model's strong predictive capability.

Figure 7 visualizes these performance metrics through a bar graph, highlighting the high precision, which indicates a low false positive rate, and a robust F1-score, signifying a balance between precision and recall. The results suggest that the CNN model effectively classifies Alzheimer's Disease cases, reinforcing its potential for early diagnosis.

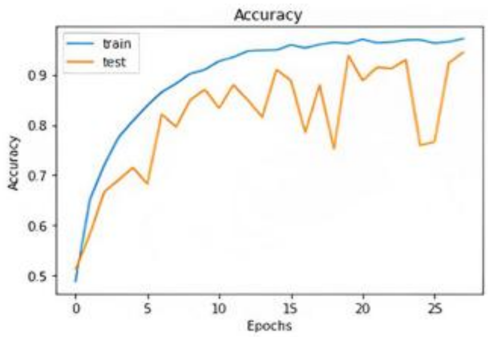

Fig.8 Accuracy graph of CNN model

Figure 8 displays the CNN model's accuracy performance throughout many training epochs. The blue curve represents the training accuracy while the orange curve represents the testing accuracy. As the number of epochs increases, the training accuracy exhibits a steady upward trend, eventually stabilizing around 0.95, indicating effective learning. The testing accuracy also follows an increasing pattern but fluctuates more significantly, suggesting potential overfitting of the model. Despite the variations, the overall trend indicates an improvement in classification performance over 25 epochs.

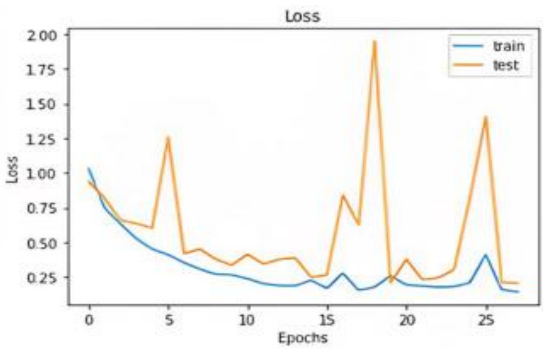

Fig.9 Accuracy graph of CNN model

Figure 9 presents the loss curve of the CNN model across multiple training epochs. The graph illustrates both the training loss (blue) and testing loss (orange) trends. The training loss starts at approximately 0.85 and steadily decreases to around 0.2, indicating effective optimization of the model. However, the testing loss exhibits significant fluctuations, ranging between 0.25 and 2.0, with noticeable spikes around the 15th and 20th epochs, suggesting instability in model generalization. These variations may point to overfitting, a condition in which the model becomes too specialized to its training data and fails miserably when presented with new, unlabelled data.

Comparative Analysis

This section examines ML models for AD prediction on early detection. Proposed model of CNN and comparison model of RFc, XGBoost[37] and Logistic regression[38] are evaluated using acc-uracy, precision, recall, and F1score. The study utilizes, emphasizing ML and DL model's effectiveness in the early detection of Alzheimer's disease prediction.

Table 4 Comparative analysis for Early Detection of Alzheimer 's Disease on OASIS dataset

Matrix	Accuracy	Precision	Recall	F1-score
Logistic Regression	85	67	55	60.4
XGBoost	85.92	85	83	85
Random forest	81.3	84.4	70.3	76.7
CNN	94.1	98	91	94

The findings of comparing several models trained on the OASIS dataset to detect early stages of AD are shown in Table 4. Among the models, the CNN demonstrates the highest performance, achieving 94.1% acc-uracy, 98% precision, 91% re-call, and an F1score of 94, indicating its superior predictive capability. XGBoost follows with an acc-uracy of 85.92%, precision of 85%, re-call of 83%, and an F1score of 85%, showing strong classification performance. Logistic Regression achieves 85% accuracy, but its recall remains low at 55%, suggesting limited sensitivity to detecting positive cases. Random Forest records 81.3% accuracy, with a balanced F1-score of 76.7%, though its recall of 70.3% is lower than XGBoost. Overall, CNN outperforms traditional machine learning models, emphasizing an effectiveness of DL in Alzheimer's Disease classification.

The proposed CNN model enhances the early detection of AD by achieving high accuracy (94.1%) and demonstrating strong classification performance across different disease stages. The model effectively minimizes misclassification while ensuring robust and reliable predictions. Compared to models such as RF, XGBoost, and Logistic Regression, CNN outperforms in all key evaluation metrics, highlighting its superior capability in distinguishing between demented, non-demented, and converted cases. Additionally, its ensemble learning approach enhances stability and adaptability, making CNN a highly effective solution for Alzheimer's disease diagnosis and clinical decision support.

Conclusion & Future Work

A treatment for Alzheimer's disease, a horrible disease, is less critical than reducing risk, providing early intervention, and recognising symptoms as soon as possible. Predicting Alzheimer's disease is the system's primary goal. For the purpose of adult dementia and Alzheimer's disease prediction, the OASIS project's "MRI and Alzheimer's" dataset is perfect. Important measures such as F1-score, recall, accuracy, and precision were used to assess the model. An evaluation of AD diagnostic capabilities used four ML models including CNN, RF, XGBoost together with Logistic Regression. The CNN model demonstrated superior performance than conventional ML models based on its computed results of 94% F1 score alongside 94.1% accuracy and 98% precision and 91% recall. This result demonstrates that CNN has the ability to outperform RF, XGBoost, and logistic regression models in the early diagnosis of AD. The CNN model shows strong promise as a clinical decision-support tool because of its accurate and dependable capacity to classify AD cases.

Moreover, the achieved stability of the model during the epochs in the CNN training phase and the high predictive value of the model supports the application of DL techniques in the medical field. It provides a potential framework for future studies and clinical practice for improving early Alzheimer's Disease diagnosis based on the methodology of data preprocessing, feature selection, and model optimization. The results may be developed with other clinical and imaging data as a future study to enhance the mean performance of the model.

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