Performance Comparison of CNN, Random Forest, and Logistic Regression Algorithms for Alzheimer's disease Detection on Structured Clinical Data

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Abstract
Early and accurate prediction of Alzheimer's disease (AD) is very important for improving patient care and proper management. This work presents a comparative performance evaluation of three different Machine Learning (ML) algorithms; Convolutional Neural Network (CNN), Random Forest (RF), and Logistic Regression (LR) for AD detection using structured clinical data. The dataset obtained from Kaggle comprises numerical features including age. Mini-Mental State Examination (MMSE) scores, Activity Daily Living (ADL), and other cognitive indicators. Python programming language was used as the tool and libraries like; pandas, numpy, sklearn, keras, tensorflow, statsmodel and others were used on jupyter notebook to implement the models. After preprocessing, and feature selection, the models were trained and evaluated using standard classification metrics. Results showed that the CNN model significantly outperformed the RF and LR models, achieving an overall accuracy of 93%, with precision, recall and F1-score consistently above 0.90. The RF model exhibited moderate performance, while the LR model underperformed with an accuracy of around 46%. This study demonstrates that CNNs can reliably detect AD with structured health data, offering a scalable, non-invasive diagnostic alternative, particularly in resource limited healthcare settings. Future work should explore integrating genetic, imaging and longitudinal data to further enhance predictive accuracy.

Keywords: Alzheimer's disease Prediction, Machine Learning, Convolutional Neural Networks, Random Forest, Logistic Regression

I. Introduction

Alzheimer's disease (AD) is a progressive neurological disorder that affects the memory, language and cognitive ability, as well as the quality of life of the affected persons. AD is the leading cause of dementia, accounting for approximately 60-80% of all dementia cases around the world [1]. While growing old remains the most important risk factor, AD is not a natural part of aging.

[2] and [3] opined that AD presents a substantial public health burden, particularly in low and middle income countries (LMICs) where healthcare systems are often outdated and not well equipped to handle the growing prevalence of age related diseases. Nigeria for example with of 260 million people and an increasing elderly population, is witnessing a sharp increase in AD cases, with the current prevalence rate estimated at 4.9% [4] [2].

AD diagnosis is often delayed as conventional diagnostic approaches rely heavily on observable clinical symptoms, which emerge in the later stages of the disease. This costly delay hinders timely intervention, exacerbates patient deterioration and poses severe

DOI: https://doi.org/10.5281/zenodo.16412898

emotional and financial strain on caregivers [5] [6]. Also, Nigeria's healthcare system faces unique challenges including fragmented geriatric services, limited awareness, cultural stigma, and the persistent loss of skilled professionals to brain drain [7][8][9].

Machine Learning (ML) has become a powerful tool in the early prediction and classification of Neurological diseases. It offers promising alternatives to traditional diagnostic techniques by uncovering complex patterns in structured health data [10][11]. Unlike image-based diagnostics, this study focuses on using numerical health indicators to predict the likelihood of AD. By comparing the performance of Convolutional Neural Network (CNN), Random Forest (RF) and Logistic Regression (LR) models, this study aims to identify the most effective algorithms for AD prediction using numerical clinical datasets. The goal is to provide clinicians, public health policy makers with more accessible, scalable and interpretable decision support tools that can improve early diagnosis and resource allocation.

The use of Machine Learning (ML) techniques in Alzheimer's Disease (AD) has significantly advanced early diagnostic capabilities of processing large clinical datasets and uncovering subtle disease indicators and biomarkers often missed bytraditional diagnostic approaches [12]. Among the commonly used algorithms, Convolutional Neural Networks (CNN), Random Forest (RF) and Logistic Regression (LR) offer varying levels of complexity, accuracy and interpretability in predicting disease prediction.

CNNs, originally designed for image processing, have proven to be highly adaptable for structured clinical datasets. They automatically extract intricate feature patterns, making them particularly effective for classification tasks involving complex, non-logistic relationships [13]. While much of CNN-based AD research focuses on MRI imaging and biomarker data [14][15], recent studies indicate emerging relevance of CNNs for structured health data, including cognitive scores and clinical assessments [16].

Random Forest (RF) is and ensemble ML algorithm that builds multiple decision trees and merges them to obtain more accurate and stable predictions [17]. RF models are well suited for clinical datasets because of their resilience to overfitting, capacity to handle missing data and ability to rank features by importance [18]. Their interpretability and robustness have made RF a popular tool in medical classification tasks.

Logistic Regression (LR), and more commonly LR in classification tasks remain widely used for its simplicity and low computational cost [19]. However, limitation in capturing non-logistic dependencies can hinder its effectiveness in complex clinical scenarios where disease progression is influenced by multiple interacting variables.

Most of the existing studies on AD prediction have heavily relied on MRI based datasets or hybrid data models [20][21]. Limited work has been done to comprehensively compare multiple ML algorithms on structured numerical datasets, which better reflects the typical format of patient health records in many healthcare settings.

[22] made significant contribution by conducting an in depth analysis of the structured AD dataset to identify most predictive variables for model training. Their study applied data mining and feature selection techniques to isolate key variables such as Mini-Mental state examination (MMSE) scores, Clinical Dementia Rating (CDR), demographic attributes like age and gender, and specific cognitive tests results that directly influence the predictive accuracy of Alzheimer's classification models. They emphasized the critical importance of selecting clinically meaningful variables to improve the precision and reliability of ML models, particularly when using non image datasets.

This work builds on the work of [22] by adopting their feature selection approach and applying it to compare the performance of CNN, RF and LR models on a structured

DOI: https://doi.org/10.5281/zenodo.16412898

clinical dataset. Unlike image based studies, this investigation focuses on accessible, cost effective health data, positioning it as a practical tool for early Alzheimer's detection, especially in resource-limited healthcare environments.

II. Methodology

This study comparatively evaluates the performance of CNN, RF, and LR models for Alzheimer's disease prediction using structured clinical dataset. The work follows a systematic approach involving dataset selection, data preprocessing, model development and performance evaluation. Python programming language was the implementation tool used with libraries like pandas, numpy, sklearn, tensorflow, keras and others.

Dataset description

The dataset used for this research work was sourced from Kaggle [23], titled Alzheimer's Disease Dataset, which consists of preprocessed structured numerical health records. Unlike previous studies that predominantly employed MRI or image based datasets, this dataset focused on clinical and demographic variables. The dataset is publicly available at https://www.kaggle.com/datasets/rabieelkharoua/alzheimers-disease-dataset/data. The features include; age, gender, educational level, MMSE scores, Activity Daily Living (ADL), and other cognitive and behavioural indicators. The target variable is "Diagnosis" which is binary. 0 indicating no Alzhiemer's diasease and 1 indicates the presence of AD. One of the columns, "Doctor in Charge," was identified as confidential and excluded from the analysis to maintain data privacy and integrity. See the summarized frame of the dataset on table 1. The dataset had 35 columns and 2149 rows.

Table 1

Summarized frame of Alzheimer's Disease Dataset

Patient ID	Age	Gender	Ethnicity	BMI	…	ADL	…	Personality Changes	Diff. Completing Task	Forgetfulness	D
4751	73	0	0	22.92	…	0	…	0	1	0	0
4752	89	0	0	26.82	…	0	…	0	0	1	0
4753	73	0	3	17.79	…	0	…	0	1	0	0
…	…	…	…	…	…	…	…	…	…	…	…
6879	77	0	0	15.47	…	0	…	0	0	0	1
6898	78	1	3	15.29	…	0	…	0	0	1	1
6899	**72**	**0**	**0**	**33.28**	**…**	**1**	**…**	**1**	**0**	**1**	**0**

Essential features were selected based on their clinical relevance and contribution to AD prediction accuracy. Variables with predictive significance were prioritized to train the models.

Prior to model training, the dataset underwent preprocessing steps to enhance data quality and ensure model reliability. They include; encoding categorical features (Gender and class labels were encoded using one-hot encoding to ensure model compatibility), confidential data handling (The "Doctor in charge" column was removed from the dataset to protect sensitive information), train-test split (The dataset was partitioned into training and testing sets using an 80:20 split to allow unbiased evaluation), and cross validation (To ensure the stability of the results, 5-fold cross-validation was applied during model training). The correlation matrix heatmap and comprehensive statistical report of the dataset are shown in figures 1 and 2 respectively.

DOI: https://doi.org/10.5281/zenodo.16412898

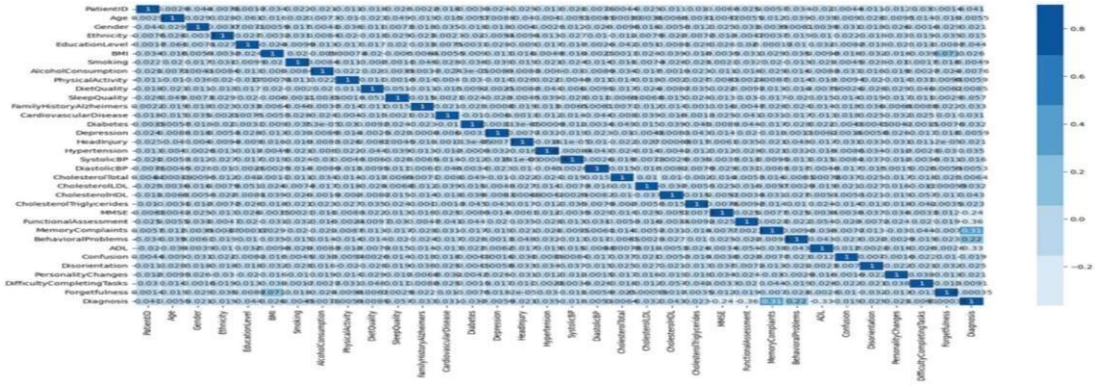

Fig 1. Correlation heat map of dataset

OLS Regression Results

Dep. Variable:	Diagnosis	R-squared:	0.439
Model:	OLS	Adj. R-squared:	0.430
Method:	Least Squares	F-statistic:	50.06
Date:	Sun, 06 Apr 2025	Prob (F-statistic):	3.68e-237
Time:	17:34:16	Log-Likelihood:	-843.25
No. Observations:	2149	AIC:	1754.
Df Residuals:	2115	BIC:	1947.
Df Model:	33		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.9354	0.141	6.627	0.000	0.659	1.212
PatientID	3.579e-05	1.26e-05	2.834	0.005	1.1e-05	6.06e-05
Age	-0.0015	0.001	-1.767	0.077	-0.003	0.000
Gender	-0.0011	0.016	-0.070	0.944	-0.032	0.030
Ethnicity	-0.0038	0.008	-0.489	0.625	-0.019	0.012
EducationLevel	-0.0120	0.009	-1.384	0.166	-0.029	0.005
BMI	-0.0003	0.001	-0.281	0.779	-0.002	0.002
Smoking	-0.0286	0.017	-1.652	0.099	-0.063	0.005
AlcoholConsumption	-0.0011	0.001	-0.794	0.427	-0.004	0.002
PhysicalActivity	-7.826e-05	0.003	-0.029	0.977	-0.005	0.005
DietQuality	0.0014	0.003	0.530	0.596	-0.004	0.007
SleepQuality	-0.0075	0.004	-1.682	0.093	-0.016	0.001
FamilyHistoryAlzheimers	-0.0145	0.018	-0.802	0.422	-0.050	0.021
CardiovascularDisease	0.0230	0.022	1.030	0.303	-0.021	0.067
Diabetes	-0.0003	0.022	-0.013	0.990	-0.043	0.043
Depression	0.0085	0.020	0.436	0.663	-0.030	0.047
HeadInjury	-0.0311	0.027	-1.150	0.250	-0.084	0.022
Hypertension	0.0319	0.022	1.445	0.149	-0.011	0.075
SystolicBP	-3.027e-05	0.000	-0.100	0.920	-0.001	0.001
DiastolicBP	0.0002	0.000	0.412	0.680	-0.001	0.001
CholesterolTotal	-1.157e-05	0.000	-0.063	0.950	-0.000	0.000
CholesterolLDL	-0.0003	0.000	-1.907	0.057	-0.001	9.84e-06
CholesterolHDL	0.0005	0.000	1.554	0.120	-0.000	0.001
CholesterolTriglycerides	0.0001	7.7e-05	1.534	0.125	-3.29e-05	0.000
MMSE	-0.0130	0.001	-14.291	0.000	-0.015	-0.011
FunctionalAssessment	-0.0558	0.003	-20.521	0.000	-0.061	-0.050
MemoryComplaints	0.3518	0.019	18.217	0.000	0.314	0.390
BehavioralProblems	0.3154	0.022	14.597	0.000	0.273	0.358
ADL	-0.0507	0.003	-19.072	0.000	-0.056	-0.046
Confusion	-0.0161	0.019	-0.829	0.407	-0.054	0.022
Disorientation	-0.0207	0.022	-0.960	0.337	-0.063	0.022
PersonalityChanges	0.0003	0.022	0.013	0.990	-0.043	0.043
DifficultyCompletingTasks	0.0012	0.022	0.057	0.955	-0.041	0.043
Forgetfulness	0.0033	0.017	0.194	0.846	-0.030	0.037

Omnibus:	43.283	Durbin-Watson:	1.877
Prob(Omnibus):	0.000	Jarque-Bera (JB):	39.377
Skew:	0.282	Prob(JB):	2.81e-09
Kurtosis:	2.651	Cond. No.	1.06e+05

DOI: https://doi.org/10.5281/zenodo.16412898

Fig 2. Comprehensive statistics report of dataset

From the statistical report, variables with p-value higher than 0.05 were dropped using the ".drop()" function, and not used as independent variables as seen in figure 3. Our dependent variable became the Diagnosis and independent variables became; MMSE, Functional impairments, memory complaints, Behavioural Problems and Activity Daily Lining (ADL).

```
columns_to_drop = ['PatientID','Age', 'Gender', 'Ethnicity', 'EducationLevel', 'BMI', 'Smoking', 'AlcoholCons
alzheimers_disease1 = alzheimers_disease.drop(columns=columns_to_drop)
```

```
X1 = alzheimers_disease1.drop('Diagnosis', axis = 1)
```

```
y1 = alzheimers_disease1['Diagnosis']
```

Fig 3. Code showing dropping of unwanted columns

III. Model Implementation

Three Machine learning models were implemented and trained on the preprocessed dataset.

Convolutional Neural Network (CNN) Model

Although CNNs are traditionally employed in image classification tasks, they can be effectively adapted to handle structured numerical data using a one-dimensional convolutional neural architecture. In this study, a 1D-CNN model was implemented to classify whether a patient has Alzheimer's disease based on structured clinical inputs.

The model architecture began with an explicit Input layer that matched the shape of the reshaped training data. The input was passed through a Conv1D layer with 64 filters, a kernel size of 3, and ReLU activation, using same padding to preserve feature dimensions. This was followed by a MaxPooling1D layer to downsample the feature map and reduce dimensionality.

A second Conv1D layer with 128 filters and the same kernel configuration was added, followed by another MaxPooling1D layer. The output from the final convolutional block was flattened to create a 1D vector, which was fed into a Dense layer with 128 neurons and ReLU activation. To mitigate overfitting, a Dropout layer with a dropout rate of 0.5 was incorporated.

The final layer was a Dense output layer with a single neuron and a sigmoid activation function, suitable for binary classification (0 = No Alzheimer's, 1 = Alzheimer's). The model was compiled using the Adam optimizer, and binary cross-entropy was set as the loss function. Training was conducted over 10 epochs with a batch size of 32, and performance was validated using a held-out test set as shown in figure 4.

DOI: https://doi.org/10.5281/zenodo.16412898

```
Epoch 1/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - accuracy: 0.6680 - loss: 0.5939 - val_accuracy: 0.8302 - val_loss: 0.3800
Epoch 2/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8435 - loss: 0.3618 - val_accuracy: 0.8744 - val_loss: 0.3297
Epoch 3/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8799 - loss: 0.3334 - val_accuracy: 0.8767 - val_loss: 0.3141
Epoch 4/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8898 - loss: 0.2883 - val_accuracy: 0.8814 - val_loss: 0.3101
Epoch 5/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8849 - loss: 0.3083 - val_accuracy: 0.8884 - val_loss: 0.2856
Epoch 6/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8922 - loss: 0.3061 - val_accuracy: 0.9047 - val_loss: 0.2730
Epoch 7/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8832 - loss: 0.3220 - val_accuracy: 0.9116 - val_loss: 0.2651
Epoch 8/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8796 - loss: 0.3283 - val_accuracy: 0.9023 - val_loss: 0.2724
Epoch 9/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.9162 - loss: 0.2734 - val_accuracy: 0.9256 - val_loss: 0.2542
Epoch 10/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.9103 - loss: 0.2737 - val_accuracy: 0.9326 - val_loss: 0.2496
```

Fig 4. CNN training

This architecture enabled the model to learn spatial relationships among the features, thus improving predictive performance on structured tabular data.

Random Forest (RF) Model

The Random Forest model was implemented using an ensemble of 10 decision trees. The model's hyperparameters, such as maximum depth, minimum samples per split, and the number of estimators, were fine-tuned using grid search to optimize performance. Random Forest's feature importance functionality was used to assess the contribution of each variable to the model's predictions. See Figure 5 for RF model prediction.

DOI: https://doi.org/10.5281/zenodo.16412898

```
# To predict Diagnosis in our test dataset, using the model we just built
rand_pred = rand_reg.predict(X_test1)
rand_pred
```

```
array([0.96, 0.05, 0.99, 0.  , 0.  , 0.82, 0.05, 0.  , 0.03, 0.05, 0.97,
       0.01, 0.02, 0.98, 0.28, 0.99, 0.28, 1.  , 0.01, 0.97, 0.01, 0.02,
       0.06, 0.02, 1.  , 0.11, 0.14, 0.01, 0.02, 0.09, 0.75, 0.86, 0.95,
       0.88, 0.03, 0.99, 0.03, 0.94, 0.  , 0.  , 0.  , 0.91, 0.01, 0.76,
       0.  , 0.97, 0.05, 0.92, 0.  , 0.  , 0.4 , 0.05, 0.93, 0.  , 0.81,
       0.1 , 0.07, 0.08, 0.  , 0.99, 1.  , 0.  , 1.  , 0.02, 0.85, 0.07,
       1.  , 0.92, 0.08, 0.02, 0.  , 0.07, 0.16, 0.59, 0.  , 0.02, 0.35,
       0.  , 0.03, 0.94, 0.73, 0.  , 0.93, 1.  , 0.  , 0.02, 0.03, 0.14,
       0.04, 0.83, 0.98, 0.01, 0.43, 0.09, 1.  , 0.01, 0.99, 0.21, 0.  ,
       0.83, 0.01, 0.  , 0.13, 0.  , 0.07, 1.  , 0.01, 0.  , 0.06, 1.  ,
       0.24, 0.99, 1.  , 0.86, 1.  , 0.  , 0.01, 0.91, 0.07, 0.  , 0.39,
       0.  , 0.01, 0.09, 0.  , 0.03, 0.49, 0.  , 0.  , 0.99, 0.7 , 0.02,
       0.  , 1.  , 1.  , 0.06, 0.34, 1.  , 1.  , 0.12, 0.03, 0.  , 0.17,
       1.  , 0.91, 0.  , 0.04, 0.  , 0.  , 1.  , 0.02, 0.  , 0.85, 0.99,
       0.06, 0.92, 0.02, 0.84, 0.06, 1.  , 1.  , 0.94, 0.  , 0.  , 0.78,
       0.  , 1.  , 0.  , 0.9 , 0.  , 1.  , 0.33, 1.  , 0.02, 0.  , 0.1 ,
       0.11, 0.  , 0.  , 0.33, 0.  , 0.95, 0.98, 0.99, 0.  , 0.03, 1.  ,
       0.13, 0.  , 0.  , 0.98, 0.02, 0.92, 0.64, 0.07, 0.03, 0.08, 0.  ,
       0.01, 0.01, 0.02, 0.86, 0.02, 0.96, 0.07, 0.12, 0.  , 0.05, 0.99,
       0.92, 0.03, 1.  , 0.7 , 0.  , 0.  , 0.09, 0.91, 0.39, 0.03, 0.11,
       1.  , 0.  , 0.  , 0.  , 0.02, 0.87, 0.06, 0.99, 0.  , 0.26, 0.41,
       0.07, 0.  , 0.08, 0.18, 0.  , 0.99, 0.03, 0.12, 0.  , 0.92, 0.01,
       0.88, 0.  , 0.01, 1.  , 0.91, 0.  , 0.99, 0.  , 0.  , 1.  , 0.17,
       0.17, 0.02, 0.  , 0.99, 0.99, 0.98, 1.  , 0.01, 0.96, 0.4 , 0.  ,
       0.  , 1.  , 0.  , 1.  , 0.02, 0.01, 0.97, 0.78, 0.26, 0.98, 1.  ,
       0.16, 0.01, 0.  , 0.04, 0.97, 0.07, 0.  , 0.99, 0.01, 0.01, 0.15,
       0.  , 0.  , 0.8 , 0.95, 0.  , 1.  , 0.01, 1.  , 0.01, 0.94, 0.  ,
       0.8 , 0.01, 1.  , 0.7 , 0.  , 0.  , 0.  , 0.11, 0.97, 0.  , 0.02,
       0.  , 0.  , 0.02, 0.03, 0.05, 0.  , 0.07, 0.06, 0.  , 0.7 , 0.59,
       1.  , 0.06, 0.02, 0.  , 0.  , 0.72, 0.  , 0.95, 0.74, 0.92, 0.  ,
       0.96, 0.11, 0.88, 0.02, 1.  , 0.94, 0.12, 0.1 , 0.04, 0.82, 1.  ,
       0.  , 0.02, 0.04, 0.  , 0.01, 0.95, 0.  , 0.  , 0.  , 0.95, 0.07,
       0.14, 0.  , 1.  , 0.99, 0.43, 0.9 , 0.23, 0.02, 0.78, 1.  , 0.09,
       0.18, 1.  , 0.02, 0.99, 0.03, 0.06, 0.95, 0.  , 0.  , 0.99, 0.  ,
       0.01, 0.04, 0.  , 0.91, 0.  , 0.02, 0.  , 0.02, 0.98, 0.06, 0.  ,
       0.13, 0.46, 0.01, 0.  , 0.01, 0.03, 0.  , 0.09, 0.97, 0.98, 0.01,
       0.07, 1.  , 0.01, 0.  , 0.04, 0.  , 1.  , 1.  , 0.24, 0.  , 0.93,
       0.99, 0.23, 1.  , 0.01, 1.  , 0.59, 0.  , 0.  , 0.02, 0.77, 0.01,
       0.87, 0.94, 1.  , 0.  , 0.  , 0.  , 0.99, 0.  , 0.96, 0.  , 1.  ,
       0.01])
```

Fig 5. RF Model prediction

Logistic Regression (LR) Model

Given the binary nature of the target variable, Logistic Regression was applied. The model was configured with L2 regularization to prevent overfitting. Logistic Regression was included as a baseline model due to its computational simplicity and widespread use in clinical predictive analytics. Figure 6 shows the LR model prediction array.

```
array([[-0.41542562, -1.43454811, -1.14522572,  1.94635578, -0.42405371,
        -0.03230156],
       [ 2.40716979, -1.28733774,  0.80140875, -0.51378068, -0.42405371,
         1.40328034],
       [-0.41542562, -0.10609068, -0.75622076,  1.94635578, -0.42405371,
         1.00944007],
       ...,
       [-0.41542562,  1.18953741,  1.45764945, -0.51378068, -0.42405371,
         1.33106908],
       [-0.41542562,  0.25858092, -1.71663507, -0.51378068, -0.42405371,
         1.45907644],
       [-0.41542562,  1.26362387,  1.25797417,  1.94635578, -0.42405371,
        -0.95961895]])
```

Fig 6. LR prediction

Evaluation Metrics

The performance of each model was evaluated using the following metrics;

1. Accuracy: The proportion of correctly classified instances, out of total predictions.
2. Precision: The ratio of correctly predicted positive observations to the total predicted positive observations.
3. Recalls: The ratio of correctly predicted positive observations to all actual positive cases.
4. F1- Score: The harmonic mean of precision and recall, providing a balanced evaluation.

IV. Results and Discussion

The performance of the Convolutional Neural Network (CNN), Random Forest (RF), and Logistic Regression (LR) models on test data was compared based on key classification metrics.

DOI: https://doi.org/10.5281/zenodo.16412898

CNN Results

The CNN model achieved superior performance across all evaluation metrics. The confusion matrix for the CNN is depicted in table 2 and figure 7.

Table 2

Confusion matrix of CNN model

	Predicted: No AD	**Predicted AD**
Actual: No AD	261	14
Actual: AD	15	140

The classification report for the CNN is summarized in table 3.

Table 3

Classification report of CNN model

Metric	**Class 0 (No AD)**	**Class 1 (AD)**
Precision	0.95	0.91
Recall	0.95	0.90
F1-Score	0.95	0.91

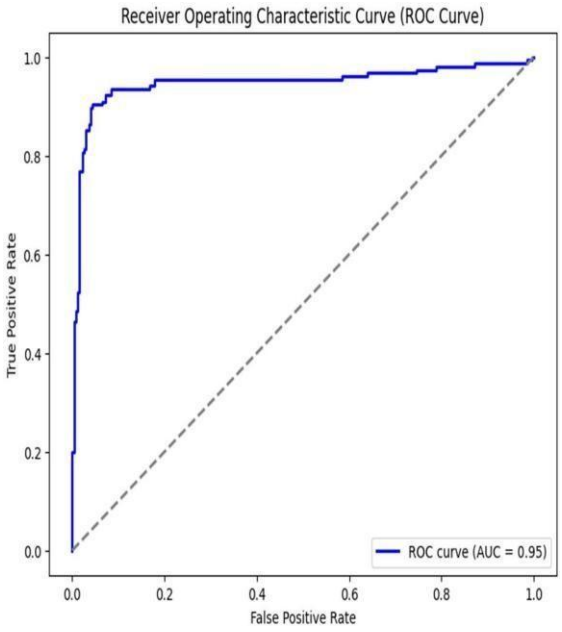

Fig 7. ROC Curve of CNN Model

The overall accuracy of the CNN model is 93%. The CNN model achieved a precision of 0.91, a recall of 0.90, and an F1-score of 0.91 for Alzheimer's disease prediction, indicating excellent model performance in classifying both positive and negative cases.

LR Results

The Logistic Regression model achieved an accuracy of approximately 46.14%. Given its limited ability to capture complex patterns in the dataset, the model underperformed significantly compared to CNN and RF. Based on the accuracy, the precision, recall, and F1-score were estimated to be approximately 0.45 each, reflecting the low classification ability of the model. The low accuracy and poor precision and recall highlight the inadequacy of logistic models in handling this type of clinical data.

RF Results

The Random Forest model demonstrated moderate predictive performance with an R-squared value of approximately 77.67%. Based on the model's overall performance, precision, recall, and F1-score were estimated to be approximately 0.75 each. This suggests that while the Random Forest model was able to capture important patterns in the data, its predictive accuracy was inferior to the CNN model.

V. Comparative Summary

Based on the comparative analysis, both the Random Forest (RF) and Logistic Regression (LR) models performed worse than the Convolutional Neural Network (CNN) when it came to predicting Alzheimer's disease using structured numerical data. CNN's robustness in correctly categorizing both positive and negative cases was demonstrated by its maximum precision, recall, and F1-score. Even while it demonstrated a respectable capacity for prediction, the Random Forest model struggled to capture the intricate feature relationships found in the dataset. The Logistic Regression model had the worst performance, finding it difficult to accurately categorize the cases because of its limited ability to represent nonlogistic interactions. In general, the CNN model was the most dependable and successful method for predicting Alzheimer's disease in this investigation.

VI. Limitations of the Study

DOI: https://doi.org/10.5281/zenodo.16412898

This study is subject to limitations. The dataset used is relatively small, and may not fully capture the diversity of the global alzheimers patient population. Also, the study relied solely on numerical clinical features without integrating genetic or longitudinal data, which could further enhance model accuracy. Finally, the exclusion of imaging data, which is often pivotal in Alzheimer's diagnosis, may limit the generalizability of the findings to broader clinical applications.

VII. Conclusion

This work demonstrated the comparative evaluation of Convolutional Neural Network (CNN), Random Forest (RF), and Logistic Regression (LR) models in predicting Alzheimer's disease using structured clinical data. The CNN model consistently outperformed the other models across all evaluated metrics, establishing its superiority in handling complex, nonlogistic data relationships. Random Forest showed moderate performance, while Logistic Regression was the least effective in this context.

Based on these findings, it is recommended that future research should employ larger, more diverse datasets and explore the integration of genetic, imaging, and longitudinal patient data to improve prediction accuracy.

Also, optimization of Random Forest and Logistic Regression models may also provide more balanced comparisons. Healthcare practitioners and researchers are encouraged to adopt deep learning models like CNN for early and accurate Alzheimer's disease detection, especially when using structured numerical datasets.

References

[1] Alzheimer's Association. (2024). What is Alzheimer's disease? https://www.alz.org/alzheimers-dementia/what-is-alzheimers

[2] Akinyemi, R. O., Yaria, J., & Ojagbemi, O. (2022). Dementia in Africa: Current evidence, knowledge gaps, and future directions. Alzheimer's & Dementia, **18** (4), 790–809. https://doi.org/10.1002/alz.12432

[3]Adeloye, D., Auta, A., & Ezejimofor, M. (2019). Prevalence of dementia in Nigeria: A systematic review of the evidence. Journal of Global Health Reports, **3**, e2019014.

[4] Nigeria Population Commission. (2023). National population census. https://worldpopulationreview.com/countries/nigeria-population

[5] Adebusoye, L. A., Olowookere, O. O., Ajayi, S. A., Cadmus, E. O., & Labaeka, E. O. (2021). Integrative care of the older persons in Nigeria: An appraisal of the Geriatric Centre, University College Hospital, Ibadan. West African Journal of Medicine, **38** (9), 839–844.

[6] Oyinlola, O., & Olusa, O. (2020). Social work with older persons living with dementia in Nigeria: COVID-19. Journal of Gerontological Social Work, **63** (6–7), 638–641. https://doi.org/10.1080/01634372.2020.1774832

[7] Lawal, L., Lawal, A. O., & Amosu, O. P. (2022). The COVID-19 pandemic and health workforce brain drain in Nigeria. International Journal for Equity in Health, **21** (1), 174. https://doi.org/10.1186/s12939-022-01764-8

[8] Oyinlola, O. (2024). Addressing the challenges of dementia care in Nigeria: A call for a comprehensive national strategy. Public Health Challenges, **3**, e186. https://doi.org/10.1002/puh2.186

[9]Adene, G., Igwe, J. S., Gift-Adene, A. Oliver, I. C., W. W., Agu E. U. (2025). Evaluating Awareness And Adoption Of Machine Learning For Neurological Disease Prediction In Nigeria. 2025 Hybrid International Conference, Department of Philosophy,University of Nigeria.

[10] Ekpe, N. M., Chukwuemeka, A. O., Adene, G., & Ogbaga, L. A. (2025). Applications of artificial intelligence and machine learning in clinical practice. EKETE-International Journal of Advanced Research, **3** (1), 1–15.

[11] Dike, M. O., Okeiyi, E. K., Azemobor, D., Ituma, C., & Adene, G. (2025). Efficient heart disease prediction model through Rete algorithm-based rule matching. EKETE-International Journal of Advanced Research, **3** (2), 59–74.

[12] Don, S. M., Jayatilake, A. C., & Ganegoda, G. U. (2021). Involvement of machine learning tools in healthcare decision making. Journal of Healthcare Engineering, 6679512. https://doi.org/10.1155/2021/6679512

[13] Mahmud, M., Kaiser, M. S., McGinnity, T. M., & Hussain, A. (2021). Deep learning in mining biological data. Cognitive Computation, **13** (1), 1–33. https://doi.org/10.1007/s12559-020-09773-7

[14] Mehmood, A., Yang, S., Feng, Z., Wang, M., Ahmad, A. S., & Khan, R. (2021). A transfer learning approach for early diagnosis of Alzheimer's disease on MRI images. Neuroscience, **460**, 43–52. https://doi.org/10.1016/j.neuroscience.2021.01.002

[15] Odusami, M., Maskeliūnas, R., & Damaševičius, R. (2021). Detection of early stage from functional brain changes in magnetic resonance images using a finetuned ResNet18 network. Diagnostics, **11** (6), 1071. https://doi.org/10.3390/diagnostics11061071

[16] Asokan, S., & Seshadri, A. (2024). Application of deep learning in the diagnosis of Alzheimer's and Parkinson's disease: A review. Current Medical Imaging, **20**, e280323215043. https://doi.org/10.2174/1573405620666230328113721

[17] Mishra, V., Singh, Y., & Rath, S. K. (2019). Breast cancer detection from thermograms using feature extraction and machine learning techniques. Proceedings of the IEEE 5th International Conference for Convergence in Technology (pp. 1–6). IEEE.

[18] Sharma, S., Guleria, K., Tiwari, S., & Kumar, S. (2022). A deep learning based convolutional neural network model with VGG16 feature extractor for the detection of Alzheimer Disease using MRI scans. Measurement: Sensors, **24**, 100506. https://doi.org/10.1016/j.measen.2022.100506

[19] Radhika, P., Nair, R., & Veena, G. (2019). A comparative study of lung cancer detection using machine learning algorithms. Proceedings of the IEEE International Conference on Electrical, Computer and Communication Technologies (pp. 1–6). IEEE.

[20] Pradhan, A., Gige, J., & Eliazer, M. (2021). Detection of Alzheimer's disease (AD) in MRI images using deep learning. International Journal of Engineering Research, **10** (3), 580–585. https://doi.org/10.17577/IJERTV10IS030310

[21] Shah, A., Lalakiya, D., Desai, S., Shreya, & Patel. (2020). Early detection of Alzheimer's disease using various machine learning techniques: A comparative study. Proceedings of the 4th International Conference on Trends in Electronics and Informatics (pp. 522–526). IEEE. https://doi.org/10.1109/ICOEI48184.2020.9142975

[22] Adene, G., Igwe, J. S., Gift-Adene, A. U., Alozie, O. C., & Iweama, W. C. (2025). Unveiling novel predictors of Alzheimer's disease: A functional and behavioral-based clustering approach. International Journal of Scientific Research in Modern Science and Technology, **4** (2), 1–15. https://doi.org/10.59828/ijsrmst.v4i2.301

[23]Rabie, E. K. (2024, June 11). Alzheimer's disease dataset. Kaggle. https://www.kaggle.com/datasets/rabieelkharoua/alzheimers-disease-dataset