Hybrid Predictive Model on Detection of Neurodegenerative Disorder using Machine Learning Classification Algorithms

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Abstract- ***The aim of this paper is to design a Hybrid Predictive Model on Detection of Neurodegenerative Disorder using Machine Learning Classification Algorithms, with major focus on detection of Alzheimer's disease (AD), while the objectives is to ensure that the developed model can predict if a patients has Alzheimer disease or not through their hand writing on paper. The variables used for the predictions are collected amongst healthy people and Alzheimer patients which includes (Total_time, displacement, (gait movement rate time (gmrt_air reading), gmrt_paper reading, speed_air, speed_paper, num_of_pendown, pressure_mean) and a target class with (Patients = P and Healthy = H). The study employed three machine learning classification algorithm methods which include: Support Vector Machine, Neural Network and Decision Tree algorithms. The data was analyzed with R and JASP platform while the experiments are done using DARWIN dataset containing 25 handwriting tasks with a total of 174 participants (89 Alzheimer patients and 85 healthy people) sourced from UCI and Kaggle machine learning repository. From the result, the experiment shows that the use of a hybrid approach involving three classification algorithms in health related data prediction to develop a model called (Ikem-Alzheimer-Model) is one of the best and more accurate method suitable for data prediction and hence has more percentage acceptance level when it comes to health issues, therefore it could be adopted for future use by medical practitioners to make decision on the subject matter. Finally, the results prediction accuracy was concluded by comparing the three developed models involving their different F1 scores, confusion matrix, Evaluation Metrics, Roc Curves, and Precision (positive predictive value) shown in Table13 of this paper.***

Indexed Terms- ***Artificial Intelligence, Machine Learning, Health Science, Classification Model, Alzheimer disease prediction, health diagnosis and prediction of neurodegenerative disorder, Hybrid Predictive Model on neurodegenerative disorder.***

I. INTRODUCTION

Neurodegenerative diseases are a class of neurological disorders where neurons from the central nervous system die or are damaged causing severe disabilities, and eventually death. It can also be a type of disease in which cells of the central nervous system stop working or die (NCI, 2023). Neurodegenerative disorders usually get worse over time and have no cure. They may be genetic or be caused by a tumor or stroke. Neurodegenerative disorders also occur in people who drink large amounts of alcohol or are exposed to certain viruses or toxins. Examples of neurodegenerative disorders include amyotrophic lateral sclerosis, multiple sclerosis, Parkinson's disease (PD), Alzheimer's disease (AD), Huntington's disease (HD), multiple system atrophy, tauopathies, and prion diseases. They are typically encountered in old age which might appear earlier. In the past years, their incidence increased significantly and it is expected that the increase will continue, as the world's population ages (Laske et al., 2015). Neurodegenerative diseases are problematic and can become a burden since their cause is unknown and no cure has been discovered. Treatments are currently targeting the alleviation of symptoms and due to recent advances in artificial intelligence, a significant help can come from the computational approaches targeting diagnosis and monitoring, e.g., detection of disease onset, characterization of the disease, improvement of the differential diagnosis,

quantification of the disease progression, tracking of the medication effects. These tasks can be automated or at least improved with the help of machine learning algorithms and intelligent modeling tools. It has been estimated that nearly 6.8 million people expired every year due to neurological disorders (Zhang et al., 2017). The population keeps on mounting because of state-of-the-art medical advancements and hygiene which affects; the ageing populations by increasing number of people suffer from neurodegenerative maladies. Therefore, it is crucial to diagnose the neuro related diseases at an early age to curtail the damages that the diseases impart on the human brain. Early detection of the diseases at a prior stage would warrant accurate diagnoses which will enable imparting correct treatment at an early stage. However, detecting neuro diseases at an early stage is challenging, not only for the affected individuals or their caregiver who may not recognize the initial symptoms but also for the clinicians who may not be able to diagnose the condition confidently. The symptoms of neurodegenerative diseases are generally voice impairment, loss of memory, difficulty in gait movement etc.

II. RELATED LITERATURE REVIEW

Machine learning algorithms can detect subtle changes in brain structure and function, helping to distinguish individuals with AD from healthy controls and providing a means to monitor disease progression over time. Additionally, machine learning models can analyze clinical data, including motor movement, cognitive, and psychiatric assessments, to identify relevant features and patterns that contribute to accurate diagnosis and prognosis (Lois et al., 2018). It also plays a crucial role in predictive modeling for AD risk assessment. By incorporating genetic data and other relevant factors, machine learning algorithms can predict an individual's likelihood of developing AD, aiding in early intervention and counseling.

Felix et al., (2019) also use Decision Tree which stands out as a highly effective tool in the diagnosis of Huntington's disease as one of the neurodegenerative diseases. Decision Tree achieved an impressive average accuracy of 100% in accurately classifying gait signals from subjects with AD. This remarkable accuracy underscores the robustness of the Decision Tree algorithm in distinguishing individuals with AD based on their gait dynamics. Additionally, the Decision Tree emerges as a pivotal machine learning algorithm employed for the prediction and identification of potential contributing genes in Alzheimer's disease (Cheng et al., 2020). According to (Mannini et al., 2016) Support Vector Machine (SVM) emerges as a crucial classifier for gait classification, playing a significant role in the context of Huntington's disease diagnosis, alongside other pathological conditions. The utilization of SVM to differentiate gait patterns among diverse clinical groups, including individuals with Huntington's disease, post-stroke patients, and healthy elderly individuals, employing data collected from inertial sensors.

III. METHODOLOGY

Three different classification algorithms was applied in this paper, Decision tree, neural network algorithms and support vector machine because of their ability to uncover or translate hidden pattern from a model and also accuracy in data prediction for effective decision making.

IV. DECISION TREE ALGORITHMS

Decision tree (Han and Kamber; 2001) could be seen as a type of tree structure typically in a form of flowchart design. These tree structures are used to carry out classification and prediction modeling of objects in a class in a form of nodes and internodes. Both root and the internal nodes are taken as the test cases in the modeling process which in terms used as a separator with different features(Han and Kamber; 2001). According to (Yan et al; 2020), these decision trees uses a classification or regression models to form a tree structure. The structure breaks down a particular data set into various smaller and smaller subsets as the associated decision tree development id in progress. The researcher further noted that the decision tree is build up with the nodes and leaf nodes, where the decision nodes has two or more different branches while leaf nodes shows the classification or decision results(Yan et al; 2020) stated. Figure 1: Illustrate the structure of a decision tree

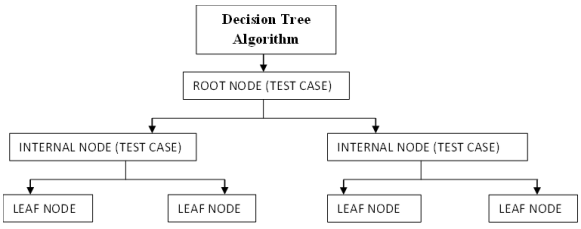

Figure 1: Illustrate the structure of a decision tree

Adoption of decision tree for this study did not just come but it was adopted because of its powerful technique for classification and prediction ability on a particular data set. Hence the identification and prediction of diabetes disease in a patient will have a very significant outcome after the analysis of the data

set has been concluded and presented for future use. The proposed system diagram is shown in figure 2 below:

V. SUPPORT VECTOR MACHINE (SVM) ALGORITHM

This algorithm is a popular machine learning technique used for classification and regression analysis by classifying the data into various hyper plan for easier prediction on the dataset. Here are some common application areas of SVM algorithms: Image classification, Text classification, Bioinformatics, Financial forecasting and Medical diagnosis. These algorithms offer robust performance, especially in high-dimensional spaces, and are often used as a baseline for comparison with other machine learning techniques.

VI. NEURAL NETWORK ALGORITHM

This is a computational models inspired by the structure and function of the brain. A neural network consist of layers of interconnected nodes (neurons) that process and transmit information. Neural network algorithms can be divided into Backpropagation, Stochastic Gradient Descent (SGD), Gradient Descent and Levenberg-Marquardt Algorithm. The neural network training can be done as supervised learning, unsupervised learning and reinforcement learning.

ANALYSIS OF THE EXISTING SYSTEM

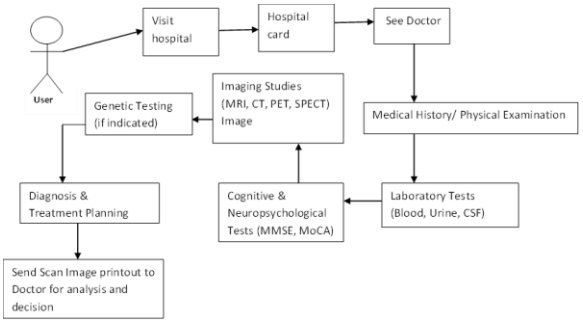

Figure 2: Analysis of the existing System

In this system analysis phase, a patient visits the hospital which a patient hospital card is requires before the patient can see the medical doctor for diagnosis and other necessary examination. The medical doctor first checks the patients' medical history before partaking into the physical examination which will enable the doctor to recommend for further medical examination either by Imaging Studies (MRI, CT, PET, SPECT) or Genetic Testing. Once the results of the genetic test or virtual scans are out, it will be forwarded to the medical Doctor for diagnosis and treatment plan can be initiated on the patient. The diagrammatical analysis of the existing system is shown figure 2 above.

THE PROPOSED SYSTEM DIAGRAM

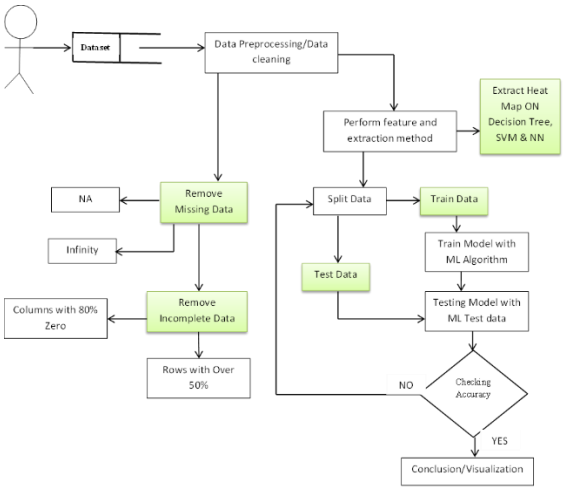

Figure 2: Diagram of the proposed model

The above diagram illustrates how the proposed system loads the Alzheimer's (DARWIN.csv) dataset into the JASP machine learning platform. The dataset was first of all undergo data preprocessing/data cleaning stage, it is here that the researcher understood and discovered some missing values which was removed. Then extraction and feature process are performed. The dataset was now Split into two parts (TEST and TRAIN) with a percentage rate of 34% and 140% respectively making up to the total of 174 before checking on the extract heat Map on the three algorithms (Decision Tree, SVM and NN) before applying the various machine learning algorithms to produce the proposed predictive model called (Ikem-Alzheimer-Model).

In summary, the researcher adopted the R and JASP analytical platform for the analysis while dataset was gotten from Kaggle repository and UCI machine learning repository.

Table 1: SYSTEM ALGORITHM

INPUT	DARWIN dataset from Kaggle repository and UCI machine learning repository
OUTPUT	Hybrid Predictive Model on Detection of Neurodegenerative Disorder using Machine Learning Classification Algorithms Model Name: (Ikem-Alzheimer-Model).

VII. RESULTS

EXPERIMENTS ON THE DATASET USING R

The first process was launching of the RStudio IDE after a successive launching, the following steps were done to design the model.

Step1: Loading packages to be used (that is libraries)
Step 2: Loading My Dataset to R Dataframe
Step 3: Exploring the data, at this stage, skimr::skim Alzheimer's dataset (DARWIN.csv)
Step 4: Converting outcome from numeric to factor and renaming them for easy understanding
Step 5: Changing some response by patients from alphabet to Numeric (YES = 1 and NO = 0)
Step 6: Plot Observations to view all the dataset
Step 7: Checking For Missing Values in Each Variable
Step 8: Replacing or removal of the missing values for each variable
Step 9: Normalizing the dataset

MODEL BUILDING

Step 10: The dataset was Split into two with the percentage of (140% = training and 34%=testing) respectively
Step 11: applying decision tree algorithm
Step 12: Using GINI MODEL to build (Ikem-Alzheimer-Model).
Step 13: Analyzing the Prediction of the Model built With Gini Model
Step 14: Confusion Matrix
Hence the confusion matrix is used for more accuracy on the rate at which the model predicts user data.
Step 15: Validating the Model On the test Dataset
Step 11 was carried out again using Neural Network and SVM algorithms on the same dataset in other to complete the hybrid use of the three algorithms and it is done following other steps below for a more accurate prediction of the model produced.

EXPERIMENTS ON THE DATASET USING JASP PLATFORM

The first process was launching of the JASP PLATFORM after a successive launching, the following steps were done to build the model.

Step 1: Loading the dataset from the location Alzheimer's dataset (DARWIN.csv)
Step 2: Select machine learning packages
Step 3: Select first classification algorithm (Decision Tree)
Step 4: Set the target and features (Class: P or H)
Step 5: Click to start the analysis on the dataset
Step 6: Click on Data split
Step 7: Click Confusion Matrix
Step 8: Class Proportions
Step 9: Click Evaluation Metrics
Step 10: Click ROC Curve Plot
Step 11: click Andrews Plot
Step 12: click decision tree plot
Download visualizations results
Step 13: Start prediction accuracy by checking (F1 score, confusion matric, and Roc Curve and precision (positive predictive value) and network weight results).
Step 3: was carried out again to use Neural Network and SVM algorithms on the same dataset in other to complete the hybrid use of the three classification algorithms and it is done following other steps below for a more accurate prediction of the model produced which are predicted by looking at the output F1 score, ROC curve, confusion matric and decision tree models built.

EXPERIMENT OUTPUT

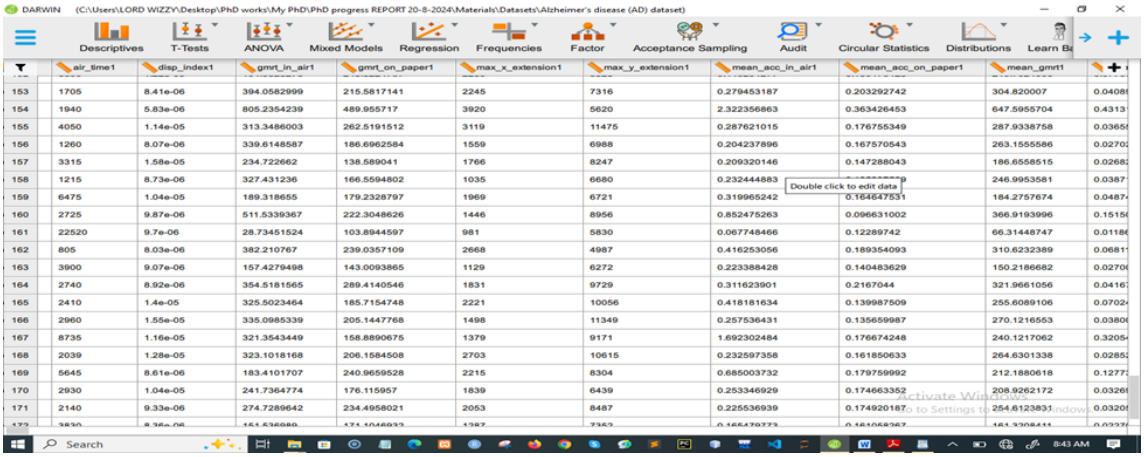

Figure 3a: JASP View on the dataset (Fieldwork 2025)

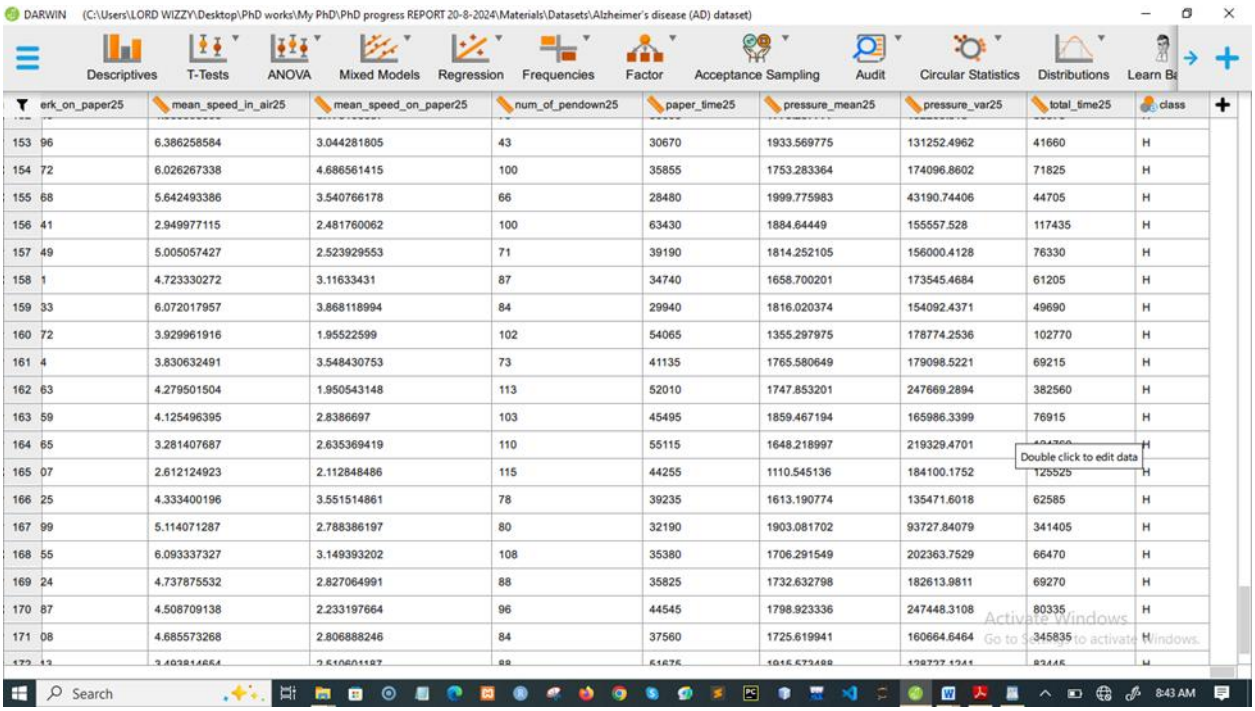

Figure 3b: JASP View on the dataset (Fieldwork 2025)

Experiment on dataset using Decision Tree Classification

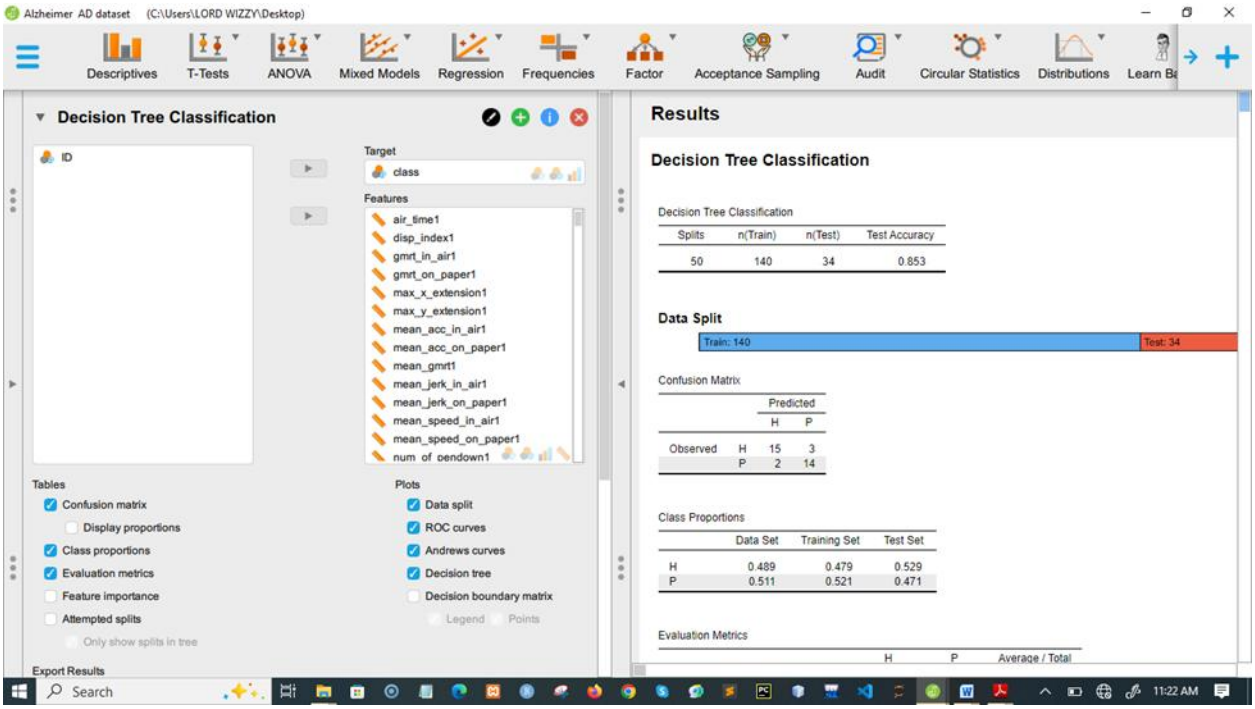

Figure 4: JASP Platform View on the prediction of dataset using Decision Tree Classification (Fieldwork 2025)

Confusion Matrix (Table 1)

		Predicted	
		H	P
Observed	H	15	3
	P	2	14

Class Proportions (Table 2)

	Data Set	Training Set	Test Set
H	0.489	0.479	0.529
P	0.511	0.521	0.471

Evaluation Metrics (Table 3)

	H	P	Average / Total
Support	18	16	34
Accuracy	0.853	0.853	0.853
Precision (Positive Predictive Value)	0.882	0.824	0.855
Recall (True Positive Rate)	0.833	0.875	0.853
False Positive Rate	0.125	0.167	0.146
False Discovery Rate	0.118	0.176	0.147
F1 Score	0.857	0.848	0.853
Matthews Correlation Coefficient	0.707	0.707	0.707
Area Under Curve (AUC)	0.854	0.854	0.854
Negative Predictive Value	0.824	0.882	0.853
True Negative Rate	0.875	0.833	0.854
False Negative Rate	0.167	0.125	0.146
False Omission Rate	0.176	0.118	0.147
Threat Score	2.143	1.750	1.946
Statistical Parity	0.500	0.500	1.000

Note. All metrics are calculated for every class against all other classes.

ROC Curves Plot

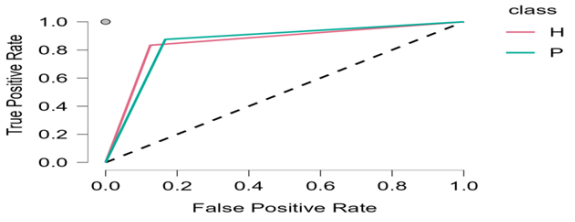

Figure 5: ROC Curves Plot (Fieldwork 2025)

Andrews Curves Plot

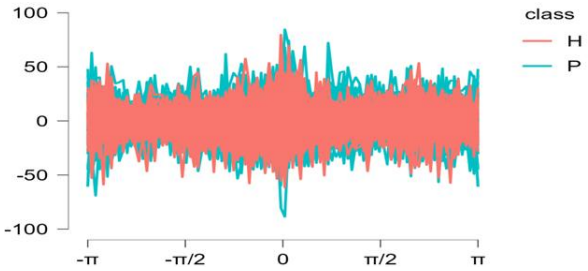

Figure 6: Andrews Curves Plot (Fieldwork 2025)

Decision Tree Plot

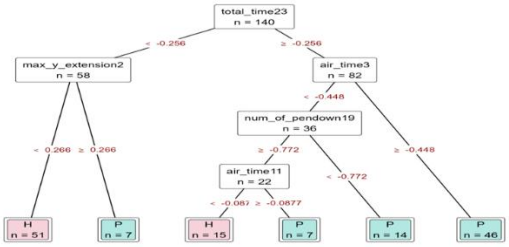

Figure 7: Decision Tree Plot (Fieldwork 2025)

Experiment on dataset using Neural Network Classification

Neural Network Classification

Neural Network Classification (Table 4)

Hidden Layers	Nodes	n(Train)	n(Test)	Test Accuracy
1	1	140	34	0.853

Note. The model is optimized with respect to the *sum of squares* .

Data Split

Figure 8: Neural Network Data split (Fieldwork 2025)

Confusion Matrix (Table 5)

		Predicted	
		H	P
Observed	H	13	1
	P	4	16

Class Proportions (Table 6)

	Data Set	Training Set	Test Set
H	0.489	0.507	0.412

Class Proportions (Table 6)

	Data Set	Training Set	Test Set
P	0.511	0.493	0.588

Evaluation Metrics (Table 7)

	H	P	Average / Total
Support	14	20	34
Accuracy	0.853	0.853	0.853
Precision (Positive Predictive Value)	0.765	0.941	0.869
Recall (True Positive Rate)	0.929	0.800	0.853
False Positive Rate	0.200	0.071	0.136
False Discovery Rate	0.235	0.059	0.147
F1 Score	0.839	0.865	0.854
Matthews Correlation Coefficient	0.717	0.717	0.717
Area Under Curve (AUC)	0.850	0.889	0.870
Negative Predictive Value	0.941	0.765	0.853
True Negative Rate	0.800	0.929	0.864
False Negative Rate	0.071	0.200	0.136
False Omission Rate	0.059	0.235	0.147
Threat Score	1.444	2.667	2.056
Statistical Parity	0.500	0.500	1.000

Note. All metrics are calculated for every class against all other classes.

Network Weights (Table 8)

Node	Layer		Node	Layer	Weight
Intercept		→	Hidden 1	1	-0.333
air_time1	input	→	Hidden 1	1	0.582
disp_index1	input	→	Hidden 1	1	1.977
gmrt_in_air1	input	→	Hidden 1	1	-1.358
gmrt_on_paper1	input	→	Hidden 1	1	-1.985
max_x_extension1	input	→	Hidden 1	1	1.153

Network Weights (Table 8)

Node	Layer		Node	Layer	Weight
max_y_extension1	input	→	Hidden 1	1	-1.721
mean_acc_in_air1	input	→	Hidden 1	1	0.830
mean_acc_on_paper1	input	→	Hidden 1	1	0.422
mean_gmrt1	input	→	Hidden 1	1	0.261
mean_jerk_in_air1	input	→	Hidden 1	1	0.671
mean_jerk_on_paper1	input	→	Hidden 1	1	0.369
mean_speed_in_air1	input	→	Hidden 1	1	1.685
mean_speed_on_paper1	input	→	Hidden 1	1	-1.174
num_of_pendown1	input	→	Hidden 1	1	-0.226
paper_time1	input	→	Hidden 1	1	0.829
pressure_mean1	input	→	Hidden 1	1	-1.189
pressure_var1	input	→	Hidden 1	1	-0.432
total_time1	input	→	Hidden 1	1	0.317
air_time2	input	→	Hidden 1	1	1.370
disp_index2	input	→	Hidden 1	1	-0.176
gmrt_in_air2	input	→	Hidden 1	1	-1.103
gmrt_on_paper2	input	→	Hidden 1	1	-1.045
max_x_extension2	input	→	Hidden 1	1	0.383
max_y_extension2	input	→	Hidden 1	1	-0.653

Note. The weights are input for the logistic sigmoid activation

ROC Curves Plot

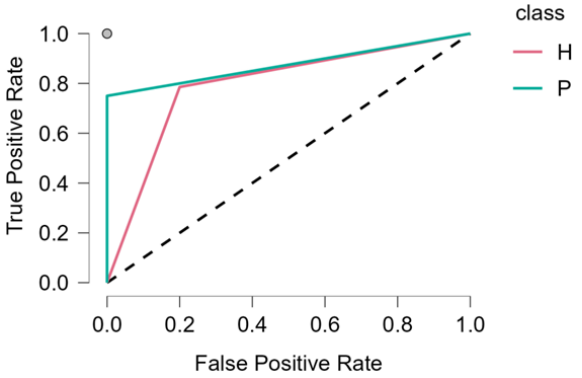

Figure 9: NN ROC curve Plot (Fieldwork 2025)

Andrews Curves Plot

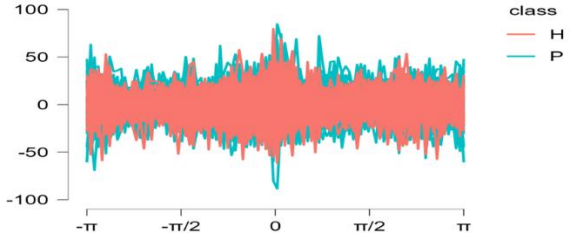

Figure 10: Andrews curve Plot (Fieldwork 2025)

Logistic Sigmoid Activation Function

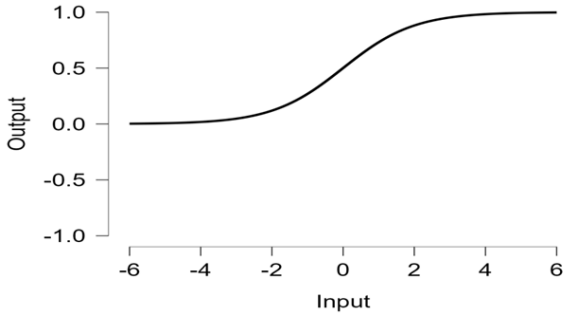

Figure 11: Neural Network Logistic Sigmoid Activation Function Plot (Fieldwork 2025)

Network Structure Plot

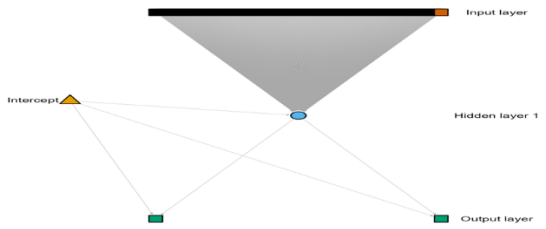

Figure 12: Neural Network, Network Structure Plot (Fieldwork 2025)

Experiment on Dataset using Support Vector Machine Classification (Table 9)

Support Vectors	n(Train)	n(Test)	Test Accuracy
72	140	34	0.882

Data Split

Figure 13: Dataset Split (Fieldwork 2025)

Confusion Matrix (Table 10)

		Predicted	
		H	P
Observed	H	12	0
	P	4	18

Class Proportions (Table 11)

	Data Set	Training Set	Test Set
H	0.489	0.521	0.353
P	0.511	0.479	0.647

Evaluation Metrics (Table 12)

	H	P	Average / Total
Support	12	22	34
Accuracy	0.882	0.882	0.882
Precision (Positive Predictive Value)	0.750	1.000	0.912
Recall (True Positive Rate)	1.000	0.818	0.882
False Positive Rate	0.182	0.000	0.091
False Discovery Rate	0.250	0.000	0.125
F1 Score	0.857	0.900	0.885
Matthews Correlation Coefficient	0.783	0.783	0.783
Area Under Curve (AUC)	0.909	0.909	0.909
Negative Predictive Value	1.000	0.750	0.875
True Negative Rate	0.818	1.000	0.909
False Negative Rate	0.000	0.182	0.091
False Omission Rate	0.000	0.250	0.125
Threat Score	1.500	4.500	3.000
Statistical Parity	0.471	0.529	1.000

Evaluation Metrics (Table 12)

	H	P	Average / Total

Note. All metrics are calculated for every class against all other classes.

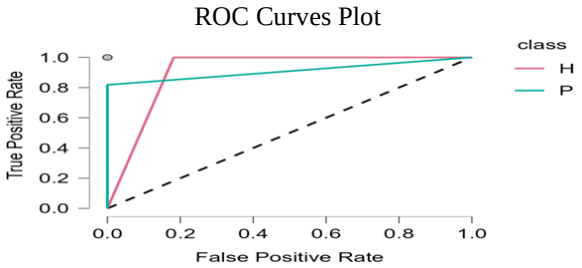

Figure 14: SVM ROC Curve Plot (Fieldwork 2025)

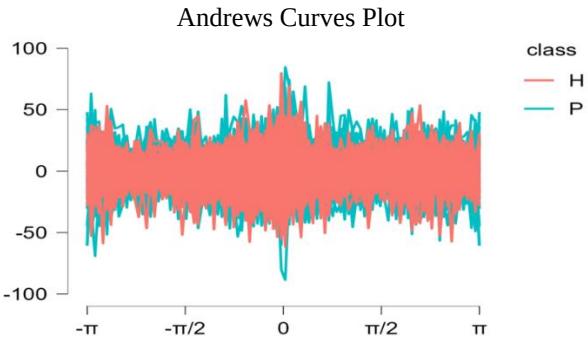

Figure 15: Andrews Curves Plot (Fieldwork 2025)

Support Vectors

Row	air_time1	disp_index1	gmrt_in_air1	gmrt_on_paper1	max_x_extension1	max_y_extension1	mean_acc_in_air1	mean_acc_on_paper1	mean_gmrt1	mean_jerk_in_air1
6	−0.393	−0.923	0.313	−0.757	−0.705	−1.423	−0.519	−0.619	−0.102	−0.504
7	−0.132	0.103	−0.043	−0.183	−0.382	0.025	−0.597	−0.496	−0.107	−0.574
10	−0.130	0.400	−0.642	−0.251	0.115	−0.066	−0.612	−0.456	−0.551	−0.562
11	0.059	0.549	−0.115	0.710	−0.086	2.783	0.686	0.207	0.219	0.727
12	−0.287	−0.084	0.002	−0.144	−0.326	0.635	−0.490	−0.339	−0.059	−0.464
13	7.193	−1.185	0.329	−0.452	−0.327	−1.359	2.978	−0.621	0.038	3.081
18	0.078	−1.185	−0.870	−0.379	−0.616	−0.941	−0.501	−0.537	−0.763	−0.444
21	−0.384	−0.513	0.460	0.345	0.419	−1.068	-3.159×10^{-4}	0.147	0.464	0.007
23	−0.244	−0.132	−0.411	−0.230	−0.144	−0.381	−0.436	0.293	−0.381	−0.403
25	−0.405	−0.757	1.415	0.187	−0.170	−0.448	−0.485	−0.341	1.060	−0.401
26	−0.311	−0.602	−0.367	−0.410	−0.213	−0.317	−0.516	−0.697	−0.427	−0.491
27	−0.383	−1.015	0.466	0.045	−0.320	−0.372	−0.488	−0.152	0.342	−0.510
29	−0.382	−0.049	0.753	−0.431	−0.390	−0.748	−0.413	−0.400	0.341	−0.377
34	−0.231	−0.248	0.309	0.796	−0.089	1.099	−0.274	0.570	0.549	−0.346
37	−0.283	−1.292	−0.723	−0.274	−0.456	−1.073	−0.475	−0.268	−0.617	−0.571
38	0.166	−0.938	−0.243	0.383	0.059	−0.750	0.214	0.214	−0.016	0.230
40	0.047	0.847	0.458	1.376	2.178	2.280	2.260	0.205	0.896	2.230
44	−0.240	0.936	−0.114	−0.172	−0.206	2.013	−0.519	−0.230	−0.151	−0.500
47	−0.381	−0.135	0.117	−0.462	−0.394	−0.839	−0.435	−0.606	−0.113	−0.313
48	−0.260	−0.837	−0.799	−0.273	−0.064	−1.111	−0.021	−0.268	−0.668	0.048
50	−0.281	1.798	0.754	0.486	−0.133	2.819	0.162	−0.065	0.727	0.205
51	1.332	−0.016	−1.462	−0.865	−0.605	−0.683	−0.913	−0.880	−1.377	−0.745
52	−0.241	1.174	1.849	0.255	0.077	2.936	−0.388	−0.372	1.388	−0.467
53	−0.348	−0.501	0.228	−0.124	−0.254	−0.153	−0.556	−0.189	0.106	−0.542
56	3.810	1.174	−0.787	0.019	10.086	−0.363	0.343	−0.280	−0.537	0.454
57	−0.377	−0.067	0.622	0.573	−0.061	−0.239	−0.200	0.118	0.672	−0.115
60	−0.102	−2.357	−1.125	0.385	−0.260	−2.627	−0.271	−0.040	−0.618	−0.302
63	−0.064	0.995	−0.330	0.968	0.724	0.011	−0.365	0.531	0.178	−0.357
65	−0.139	−0.203	−0.762	−0.515	−0.515	−0.481	−0.505	−0.608	−0.745	−0.542
67	−0.265	−0.861	−0.216	−0.799	−0.601	−1.184	−0.394	−0.537	−0.486	−0.402
68	−0.411	−1.179	3.469	2.664	0.009	−0.573	1.164	2.105	3.525	0.958
69	−0.339	−0.798	0.433	1.093	−0.158	0.468	−0.517	1.309	0.760	−0.491
71	−0.002	−0.340	−0.621	0.362	0.144	0.448	0.704	-9.759×10^{-4}	−0.278	0.805
72	0.243	0.549	0.129	−0.373	−0.363	0.844	3.342	−0.049	−0.068	3.383
74	−0.370	−0.635	−0.256	−0.141	−0.078	−1.237	−0.524	0.008	−0.237	−0.460
75	0.081	0.728	−0.563	0.401	0.189	0.914	0.078	0.010	−0.221	0.127
76	−0.294	−1.167	2.759	2.593	1.178	−0.779	4.992	2.838	3.003	4.865
77	−0.373	−0.287	0.006	−0.663	−0.599	−0.948	−0.546	−0.955	−0.275	−0.577
79	−0.189	1.085	0.378	0.500	0.305	2.456	−0.304	0.356	0.473	−0.259

Figure 16: SVM classification model (Fieldwork 2025)

Table 13: RESULT COMPARISON ON THE THREE DEVELOPED MODELS

ALGORITHMS	F1 SCORE	PRECISION/SUPPORT	ROC CURVE	CONFUSION MATRIX
DECISION TREE	H(Healthy) = 0.857 : 85% Accuracy P(Patients) = 0.848 : 85% Accuracy	PRECISION (positive predictive value) H = 0.882 : 88% P = 0.824 : 82%	True Positive Rate H= 0.833 P= 0.875	H = 15 P = 3 AND P = 2 H = 14 With a Difference of 1 for both
		SUPPORT H(Healthy) = 18 persons P(Patients) = 16 persons	False Positive Rate	

			H= 0.125 P= 0.167	Healthy and Patients
NEURAL NETWORK	H(Healthy) = 0.839 : 84% Accuracy P(Patients) = 0.865: 87% Accuracy	PRECISION (positive predictive value) H = 0.765 : 77% P = 0.941 : 94%	True Positive Rate H= 0.929 P= 0.800	H = 13 P = 4 AND P = 1 H = 16 With a Difference of 3 for both Healthy and Patients
	NETWORK WEIGHT Intercept: P= 1.469 Hidden 1: P = -3.886 Intercept: H= -1.067 Hidden 1: H = 2.657	SUPPORT H(Healthy) = 14 persons P(Patients) = 20 persons	False Positive Rate H= 0.200 P= 0.071	
SUPPORT VECTOR MACHINE	H(Healthy) = 0.857: 86% Accuracy P(Patients) = 0.900: 90% Accuracy	PRECISION (positive predictive value) H = 0.750 : 75% P = 1.000 : 100%	True Positive Rate H= 1.000 P= 0.818	H = 12 P = 18 AND P = 4 H = 0 The Difference of 12 for H(Healthy) and 14 for Patients
		SUPPORT H(Healthy) = 12 persons P(Patients) = 22 persons	False Positive Rate H= 0.182 P= 0.000	

THE MODEL RESULT SUMMARY

The experiment conducted on the dataset with 140 trains and 34 tests produced a significant result within the three applied machine learning algorithms producing a new model called “Ikem-Alzheimer-Model”.

DECISION TREE MODEL: This algorithm predicted an accuracy score for H (Healthy) = 0.857: 85% Accuracy and P(Patients) = 0.848 : 85% Accuracy, while PRECISION accuracy score on (positive predictive value) showed H (Healthy) 0.882 : 88% while Alzheimer's patients P = 0.824 : 82%. This means that between H (Healthy) and P (Alzheimer's patients) has a percentage difference of 6%. More so, the confusion matric on Decision tree shows a very close predictive difference of 1 amongst Healthy people and Alzheimer's patients from their handwriting task. Therefore, Decision tree predictive model has a significant accuracy in predicting the early warning signs of Alzheimer's disease amongst Healthy people.

NEURAL NETWORK MODEL: This algorithm when applied on the dataset predicted an F1 Score accuracy of H (Healthy) = 0.839 : 84% Accuracy and P(Alzheimer's Patients) = 0.865:

87% Accuracy, while PRECISION accuracy score on (positive predictive value) predicted H (Healthy) = 0.765 : 77% while P (Alzheimer's patients) = 0.941 : 94%. This means that between H (Healthy) and P (Alzheimer's patients) has a percentage difference of

17% and the confusion matric on NEURAL NETWORK shows a very close predictive difference of 3 amongst Healthy people and Alzheimer's patients from their handwriting task. The NETWORK WEIGHT which helps in predicting both hidden input value predicted a model with H (Healthy) on network intercept of -1.067 and hidden of 2.657 against P(Alzheimer's Patients) with intercept of 1.469 and hidden of -3.886. From the NEURAL NETWORK predicted model, we can conclude by say that H (Healthy people) has a difference of 1.59 while P(Alzheimer's Patients) has a difference of -2.417.

SUPPORT VECTOR MACHINE MODEL: This algorithm when applied on the dataset predicted an F1 Score accuracy of H (Healthy) = 0.857: 86% Accuracy and P(Alzheimer's Patients) = 0.900: 90% Accuracy, while PRECISION accuracy on (positive predictive value) predicted H (Healthy) = 0.750 : 75% while P (Alzheimer's patients) = 1.000 : 100%. This means that between H (Healthy) and P (Alzheimer's patients) has a percentage difference of 25%. The confusion matric on SUPPORT VECTOR MACHINE shows P (Alzheimer's patients) 14 accuracy difference against H (Healthy People) 12 accuracy. From the experiment, SVM as one of the machine learning algorithms has shown much strength in grouping a strong hyper plan class on the experiment with a highest percentage rate of 25% between H (Healthy people handwriting) and P (Alzheimer's patients handwriting) against the other two algorithms having 1% and 6% respectively.

CONCLUSION

As earlier stated, that the aim of this work is to design a Hybrid Predictive Model on Detection of Neurodegenerative Disorder using Machine Learning Classification Algorithms, with major Alzheimer's disease (AD). This paper was able to build a model called Ikem-Alzheimer-Model with a hybrid approach involving decision tree classification algorithm, Neural Network classification algorithm and Support Vector Machine classification algorithm. The Ikem-Alzheimer-Model can now be applied in easier prediction and decision making towards identification of early warning sign of neurological disorders with focus to Alzheimer's disease (AD).

RECOMMENDATION

The researcher therefore recommends the following:

1. Other scholars could improve on the study by getting more variables
2. The Ikem-Alzheimer-Model accuracy could be compared with other machine learning techniques for enhance accuracy in solving neurological disorders
3. Analysis of the model can be developed using three data analytical programming languages such as Python, R and JASP platform involving the integration of three neurological diseases for effective diagnosis and dictation.
4. Full adoption of machine learning tools should be used in solving real life challenging problems more especially in health related problems more especially in Nigeria.
5. Other organizations should be encouraged to apply machine learning tools for easy decision making.

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