ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN1915

Rapid Alzheimer's Disease Diagnosis Using Advanced Artificial Intelligence Algorithms

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Abstract:- Alzheimer's disease (AD) is a leading cause of dementia, predominantly impacting the elderly and characterized by progressive cognitive decline. Early and precise detection is critical for effective management and improved patient outcomes. Traditional diagnostic methods such as neuroimaging and cerebrospinal fluid analysis are often invasive, expensive, and time-consuming. Advances in artificial intelligence (AI) and machine learning (ML) provide promising alternatives that are non-invasive, efficient, and cost-effective. This study explores the application of various ML algorithms to predict Alzheimer's disease. The methodology involved data preprocessing and feature selection using the Spearman algorithm to enhance computational efficiency and model performance. We evaluated k-Nearest Neighbors (k-NN), Naive Bayes (NB), Decision Trees (DT), and Ensemble methods. Results indicate that the Ensemble method achieved a predictive accuracy of 94.07% using only 13 features. These results demonstrate the potential of ML algorithms in revolutionizing AD diagnostics, offering scalable and accurate solutions for early detection.

Keywords:- *Alzheimer's Disease; Early Prediction; Machine Learning; Artificial Intelligence; Feature Selection; Predictive Accuracy.*

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that primarily affects the elderly population, leading to cognitive decline, memory loss, and behavioral changes. It is the most common cause of dementia, accounting for 60-80% of cases, and poses a significant burden on patients, caregivers, and healthcare systems worldwide [1]. Despite extensive research, the exact etiology of Alzheimer's remains unclear, and there is currently no cure [2]. Early and accurate detection of Alzheimer's disease is crucial for managing symptoms, slowing progression, and improving the quality of life for affected individuals [3].

Traditional diagnostic methods for Alzheimer's disease, such as neuroimaging and cerebrospinal fluid analysis, are often invasive, time-consuming, and expensive [4]. In recent years, the integration of artificial intelligence (AI) and machine learning (ML) in medical diagnostics has shown promising potential in addressing these challenges. Machine learning algorithms can analyze large datasets, identify patterns, and make predictions with high accuracy, offering a non-invasive, efficient, and cost-effective approach to early detection of Alzheimer's disease [5].

These advancements underscore ML's transformative role in advancing early detection Alzheimer’s disease.

II. LITERATURE REVIEW

Alzheimer's disease (AD) is a significant neurodegenerative disorder causing dementia. Early diagnosis is crucial for effective intervention. Recent research has focused on leveraging machine learning (ML) and deep learning (DL) techniques for early prediction and diagnosis of AD.

Supervised learning approaches have been extensively used in the detection of Alzheimer's Disease (AD). Support Vector Machines (SVMs) are among the earliest and most widely applied techniques. For instance, [6] demonstrated that SVMs could classify MRI scans of AD patients with an accuracy of around 89% by analyzing brain atrophy patterns. Similarly, Random Forests (RFs) have shown high effectiveness in AD detection.

In research [7], various machine learning classifiers, including Decision Tree, Random Forest, SVM, Gradient Boosting, and Voting classifiers, were utilized on the OASIS dataset, achieving an accuracy of 83%. In another study, [8] employed machine learning algorithms such as Gradient Boosting Trees (GBT), Logistic Regression (LR), and Random Forests (RF) on EHR data, which significantly improved the early prediction accuracy of Alzheimer's Disease (AD).

Deep learning techniques have also been highly successful in the field. Furthermore, [9] applied deep convolutional autoencoders on MRI images, achieving over 80% accuracy in predicting AD. Studies by [10] and [11] demonstrated significant performance improvements in AD classification using deep neural networks.

Additionally, Convolutional Neural Networks (CNNs) have been effective in analyzing medical imaging data. According to [12], CNNs could automatically extract relevant features from MRI images, achieving a diagnostic

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN1915

accuracy of 92%, significantly surpassing traditional methods.

This study aims to provide an AI-based solution for Alzheimer's disease detection. To reduce computational costs and enhance model performance, the Spearman feature selection algorithm was employed [13]. Using these features, classification was performed with various machine learning algorithms in MATLAB. The results demonstrate that Alzheimer's disease can be effectively detected using this machine learning technique, indicating a promising direction for future research and clinical application in the early diagnosis of Alzheimer's disease.

III. MATERIAL AND METHOD

This research aims to accurately predict Alzheimer's disease using machine learning algorithms. The study was done according to the flow diagram as shown in Fig 1 Flow Diagram. Initially, data preprocessing was conducted to ensure data quality and consistency. Following this, Spearman feature selection algorithm was employed to identify the most highly correlated features [13], optimizing computational efficiency and improving model performance. Subsequently, multiple machine learning algorithms, including k-Nearest Neighbors, Naive Bayes, Decision Trees, and an Ensemble method, were utilized. These models were evaluated based on classification performance evaluation criteria resulting in a robust and precise diagnostic tool for Alzheimer's disease prediction.

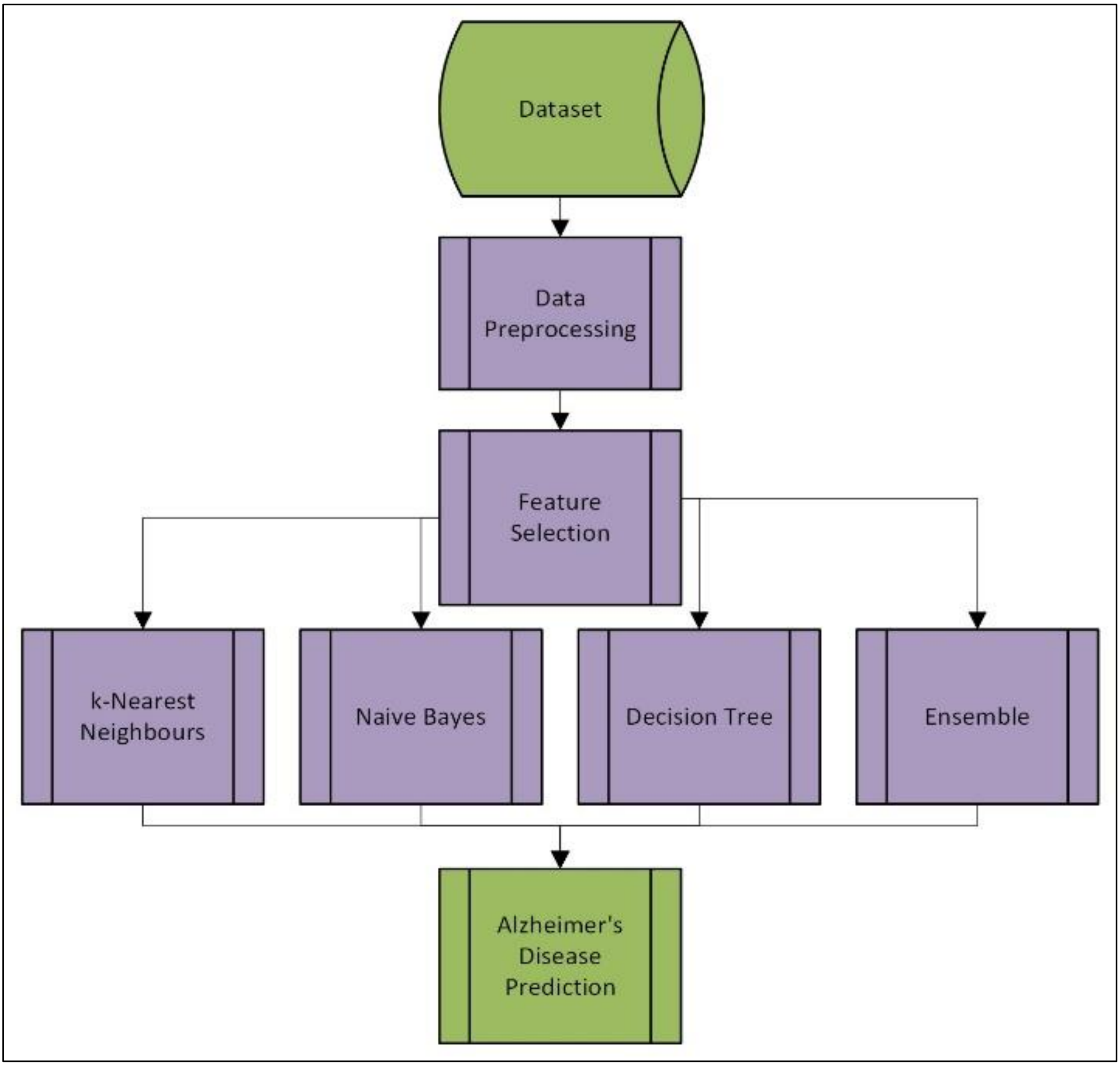

Fig 1 Flow Diagram

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN1915

A. Dataset

The dataset utilized for this research was obtained from the open-source platform Kaggle [14]. This dataset comprises 35 distinct features that provide various information related to Alzheimer's disease.

Table 1 Features and Descriptions provides a detailed description of these features. The dataset is categorized as multi-type, containing both categorical and numerical data. During data preprocessing, features such as "PatientID" and "DoctorInCharge" were excluded as they are not necessary for the machine learning algorithms employed in this study.

Table 1 Features and Descriptions

S.No	Feature	Description
1	PatientID	Identifier for each patient
2	Age	Age of the patient
3	Gender	Gender of the patient (1 for male, 0 for female)
4	Ethnicity	Ethnic background of the patient
5	EducationLevel	Education level of the patient
6	BMI	Body Mass Index
7	Smoking	Smoking status (1 for smoker, 0 for non-smoker)
8	AlcoholConsumption	Amount of alcohol consumption
9	PhysicalActivity	Level of physical activity
10	DietQuality	Quality of diet
11	SleepQuality	Quality of sleep
12	FamilyHistoryAlzheimers	Family history of Alzheimer's disease (1 for yes, 0 for no)
13	CardiovascularDisease	Presence of cardiovascular disease (1 for yes, 0 for no)
14	Diabetes	Presence of diabetes (1 for yes, 0 for no)
15	Depression	Presence of depression (1 for yes, 0 for no)
16	HeadInjury	History of head injury (1 for yes, 0 for no)
17	Hypertension	Presence of hypertension (1 for yes, 0 for no)
18	SystolicBP	Systolic blood pressure
19	DiastolicBP	Diastolic blood pressure
20	CholesterolTotal	Total cholesterol level
21	CholesterolLDL	LDL cholesterol level
22	CholesterolHDL	HDL cholesterol level
23	CholesterolTriglycerides	Triglycerides level
24	MMSE	Mini-Mental State Examination score
25	FunctionalAssessment	Functional assessment score
26	MemoryComplaints	Complaints about memory (1 for yes, 0 for no)
27	BehavioralProblems	Presence of behavioral problems (1 for yes, 0 for no)
28	ADL	Activities of Daily Living score
29	Confusion	Presence of confusion (1 for yes, 0 for no)
30	Disorientation	Presence of disorientation (1 for yes, 0 for no)
31	PersonalityChanges	Presence of personality changes (1 for yes, 0 for no)
32	DifficultyCompletingTasks	Difficulty completing tasks (1 for yes, 0 for no)
33	Forgetfulness	Presence of forgetfulness (1 for yes, 0 for no)
34	Diagnosis	Diagnosis of Alzheimer's disease (1 for yes, 0 for no)
35	DoctorInCharge	Confidential information, value set to "XXXConfid" for all patients.

B. Performance Evaluation Criteria:

To evaluate the performance of the proposed model in this research paper, we utilized a variety of performance metrics. These metrics included Accuracy rate (AR), Sensitivity (Se), Specificity (Sp), F_O score (F_O), Kappa, and the Area under the ROC curve (AUC).

C. Classification Models

This study is based on four distinct classification models: 1. k-Nearest Neighbors (k-NN) 2. Naive Bayes, 3. Decision Tree (DT), and 4. Ensemble Methods.

➢ *k-Nearest Neighbors (k-NN):*

k-NN is a non-parametric method extensively utilized for its simplicity and effectiveness in classifying data points by examining their proximity to the nearest neighbors. This algorithm assumes that similar data points are often in proximity within the feature space. Its ability to adapt to various data distributions and its ease of implementation make k-NN an invaluable tool in our classification approach [15].

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN1915

➢ *Naive Bayes:*

Naive Bayes is a probabilistic classification algorithm rooted in Bayes' theorem, leveraging the assumption of feature independence for computational efficiency and methodological simplicity. During training, it computes prior probabilities for each class and conditional probabilities of features given each class. When predicting the class of a new instance, it computes the updated likelihood using Bayes' theorem and selects the class with the highest computed probability. This approach is esteemed for its computational efficiency, scalability with extensive datasets, straightforward implementation, and robust performance in many domains [16]

➢ *Decision Tree (DT):*

Decision Trees are hierarchical machine learning models that recursively partition data based on feature values. They excel in capturing non-linear relationships and provide interpretable insights into feature importance. DTs can handle both categorical and numerical data, making them versatile for various tasks. Their tree-like structure offers transparent decision-making processes, valuable for many applications. While prone to overfitting, techniques like pruning and ensemble methods can mitigate this limitation. DTs' ability to uncover complex patterns and their interpretability make them a crucial tool in data analysis and predictive modeling [17].

➢ *Ensemble Methods:*

Ensemble methods, such as Random Forests and Gradient Boosting, enhance prediction accuracy by amalgamating several base models. This strategy leverages the strengths and mitigates the weaknesses of individual models, leading to superior overall performance. Our research employs these methods to forge a robust, high-performance classification system [18].

These models were critically assessed to gauge and contrast their effectiveness in solving the problems. Our aim was to utilize a range of classification techniques to identify the most efficient model for the dataset, thereby ensuring precise and dependable prediction outcomes.

IV. RESULT

In this study, we aimed to detect Alzheimer's disease using a comprehensive dataset and employed several machines learning algorithms, including Decision Trees (DT), k-Nearest Neighbors (k-NN), Ensemble methods, and Naive Bayes (NB). After preprocessing the dataset, the correlation value was determined using the Spearman algorithm. This algorithm optimizes the size of the dataset and prediction accuracy by selecting the highly correlated features.

As discussed, four machine learning algorithms have been employed. In Table 2 Performance Evaluation Criteria, it is indicated that the optimal performance for each machine learning algorithm was achieved at varying feature levels. This research highlights very significant findings. The Ensemble model demonstrated a high predictive accuracy for Alzheimer's Disease, achieving 94.07% accuracy using only 13 features. This result indicates that a reduced number of features can effectively predict Alzheimer's Disease, offering the advantage of lower computational cost while maintaining high accuracy.

V. DISCUSSION

The integration of machine learning (ML) algorithms in Alzheimer's disease (AD) detection marks a significant improvement over traditional diagnostic methods, which are often invasive, costly, and time-consuming. This study builds on previous research by demonstrating the efficiency of ML models in predicting AD with high accuracy and reduced computational requirements.

Our findings corroborate earlier studies that highlighted the effectiveness of supervised learning techniques for AD detection. Support Vector Machines (SVMs) and Random Forests (RFs) have shown promising results in classifying MRI scans and clinical data [6]. For instance, SVMs have achieved around 89% accuracy, while RFs have also proven highly effective. In comparison, our study demonstrates superior performance using the Ensemble method, achieving predictive accuracy of 94.07% using only 13 features. This underscores the importance of feature selection and algorithm optimization in enhancing predictive accuracy.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have also been successful in AD prediction, achieving diagnostic accuracy of up to 92% by automatically extracting relevant features from MRI images [12]. However, these models typically require significant computational resources. In contrast, our approach using the Spearman feature selection algorithm optimizes the dataset, reducing computational costs while maintaining high accuracy. This efficiency is crucial for clinical applications where resources may be limited.

The methodology employed in this study involved rigorous data preprocessing and the use of various ML algorithms, including k-Nearest Neighbors (k-NN), Naive Bayes (NB), Decision Tree (DT) and Ensemble method. The Ensemble method achieved 94.07% accuracy with 13 features. This result highlights the potential for developing simplified, yet highly accurate diagnostic tools that are both scalable and practical for clinical use.

VI. CONCLUSION

This study highlights the efficiency of machine learning algorithms in the early detection of Alzheimer's disease. Utilizing the Spearman feature selection algorithm, we optimized the dataset, achieving high predictive accuracy with reduced computational costs. Notably, the Ensemble method reached 94.07% accuracy with only 13 features. This result underscores the potential of ML techniques to provide non-invasive, cost-effective, and accurate diagnostic solutions. Future research should aim to refine these models

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN1915

further and explore their integration into clinical settings to improve early detection and patient outcomes.

Table 2 Performance Evaluation Criteria

Level	Model	Acc	Sen	Spe	F_O	Kapp	AUC
1	**Naive**	73,0263	0,6842	0,7763	0,7274	0,4605	0,7303
	K-NN	72,6974	0,6776	0,7763	0,7236	0,4539	0,727
	Ensemble	72,6974	0,6776	0,7763	0,7236	0,4539	0,727
	DT	72,6974	0,6776	0,7763	0,7236	0,4539	0,727
2	**Naive**	71,3816	0,7105	0,7171	0,7138	0,4276	0,7138
	K-NN	76,6447	0,9145	0,6184	0,7379	0,5329	0,7664
	Ensemble	75,3289	0,9474	0,5592	0,7033	0,5066	0,7533
	DT	75,3289	0,9474	0,5592	0,7033	0,5066	0,7533
3	**Naive**	79,9342	0,9211	0,6776	0,7808	0,5987	0,7993
	K-NN	83,2237	0,8947	0,7697	0,8275	0,6645	0,8322
	Ensemble	82,2368	0,9211	0,7237	0,8105	0,6447	0,8224
	DT	82,8947	0,9145	0,7434	0,8201	0,6579	0,8289
4	**Naive**	82,2368	0,8684	0,7763	0,8198	0,6447	0,8224
	K-NN	84,2105	0,9211	0,7632	0,8347	0,6842	0,8421
	Ensemble	83,8816	0,9474	0,7303	0,8248	0,6776	0,8388
	DT	83,2237	0,9342	0,7303	0,8197	0,6645	0,8322
5	**Naive**	90,1316	0,8816	0,9211	0,9009	0,8026	0,9013
	K-NN	91,7763	0,9145	0,9211	0,9178	0,8355	0,9178
	Ensemble	93,75	0,9408	0,9342	0,9375	0,875	0,9375
	DT	93,75	0,9474	0,9276	0,9374	0,875	0,9375
6	**Naive**	90,7895	0,8947	0,9211	0,9077	0,8158	0,9079
	K-NN	90,1316	0,9079	0,8947	0,9013	0,8026	0,9013
	Ensemble	93,0921	0,9276	0,9342	0,9309	0,8618	0,9309
	DT	93,4211	0,9474	0,9211	0,934	0,8684	0,9342
7	**Naive**	90,1316	0,8816	0,9211	0,9009	0,8026	0,9013
	K-NN	90,1316	0,8553	0,9474	0,899	0,8026	0,9013
	Ensemble	92,7632	0,9276	0,9276	0,9276	0,8553	0,9276
	DT	93,0921	0,9342	0,9276	0,9309	0,8618	0,9309
8	**Naive**	89,8026	0,875	0,9211	0,8974	0,7961	0,898
	K-NN	85,1974	0,8092	0,8947	0,8498	0,7039	0,852
	Ensemble	93,4211	0,9408	0,9276	0,9342	0,8684	0,9342
	DT	93,0921	0,9342	0,9276	0,9309	0,8618	0,9309
9	**Naive**	85,1974	0,9474	0,7566	0,8413	0,7039	0,852
	K-NN	89,1447	0,8553	0,9276	0,89	0,7829	0,8914
	Ensemble	93,0921	0,9276	0,9342	0,9309	0,8618	0,9309
	DT	93,75	0,9474	0,9276	0,9374	0,875	0,9375
10	**Naive**	89,1447	0,875	0,9079	0,8911	0,7829	0,8914
	K-NN	87,1711	0,8618	0,8816	0,8716	0,7434	0,8717
	Ensemble	93,75	0,9408	0,9342	0,9375	0,875	0,9375

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN1915

	DT	93,4211	0,9474	0,9211	0,934	0,8684	0,9342
11	**Naive**	85,1974	0,9211	0,7829	0,8464	0,7039	0,852
	K-NN	89,1447	0,875	0,9079	0,8911	0,7829	0,8914
	Ensemble	93,4211	0,9408	0,9276	0,9342	0,8684	0,9342
	DT	93,0921	0,9342	0,9276	0,9309	0,8618	0,9309
12	**Naive**	84,5395	0,9211	0,7697	0,8386	0,6908	0,8454
	K-NN	87,1711	0,8684	0,875	0,8717	0,7434	0,8717
	Ensemble	93,4211	0,9408	0,9276	0,9342	0,8684	0,9342
	DT	93,4211	0,9474	0,9211	0,934	0,8684	0,9342
13	**Naive**	89,4737	0,8882	0,9013	0,8947	0,7895	0,8947
	K-NN	86,8421	0,875	0,8618	0,8684	0,7368	0,8684
	Ensemble	**94,0789**	**0,9474**	**0,9342**	**0,9407**	**0,8816**	**0,9408**
	DT	93,0921	0,9342	0,9276	0,9309	0,8618	0,9309
14	**Naive**	84,8684	0,9211	0,7763	0,8425	0,6974	0,8487
	K-NN	83,2237	0,8092	0,8553	0,8316	0,6645	0,8322
	Ensemble	93,4211	0,9342	0,9342	0,9342	0,8684	0,9342
	DT	93,0921	0,9342	0,9276	0,9309	0,8618	0,9309
15	**Naive**	84,8684	0,9211	0,7763	0,8425	0,6974	0,8487
	K-NN	85,5263	0,8553	0,8553	0,8553	0,7105	0,8553
	Ensemble	93,75	0,9474	0,9276	0,9374	0,875	0,9375
	DT	91,4474	0,8947	0,9342	0,914	0,8289	0,9145
16	**Naive**	89,1447	0,875	0,9079	0,8911	0,7829	0,8914
	K-NN	85,5263	0,8487	0,8618	0,8552	0,7105	0,8553
	Ensemble	92,7632	0,9276	0,9276	0,9276	0,8553	0,9276
	DT	92,1053	0,9211	0,9211	0,9211	0,8421	0,9211
17	**Naive**	82,2368	0,9342	0,7105	0,8072	0,6447	0,8224
	K-NN	84,8684	0,8684	0,8289	0,8482	0,6974	0,8487
	Ensemble	92,7632	0,9342	0,9211	0,9276	0,8553	0,9276
	DT	93,75	0,9474	0,9276	0,9374	0,875	0,9375
18	**Naive**	88,8158	0,8553	0,9211	0,8869	0,7763	0,8882
	K-NN	83,2237	0,8224	0,8421	0,8321	0,6645	0,8322
	Ensemble	92,7632	0,9342	0,9211	0,9276	0,8553	0,9276
	DT	92,1053	0,9145	0,9276	0,921	0,8421	0,9211
19	**Naive**	82,5658	0,9276	0,7237	0,8131	0,6513	0,8257
	K-NN	84,2105	0,8355	0,8487	0,8421	0,6842	0,8421
	Ensemble	93,75	0,9474	0,9276	0,9374	0,875	0,9375
	DT	93,75	0,9474	0,9276	0,9374	0,875	0,9375
20	**Naive**	87,8289	0,8421	0,9145	0,8768	0,7566	0,8783
	K-NN	83,2237	0,8355	0,8289	0,8322	0,6645	0,8322
	Ensemble	92,4342	0,9211	0,9276	0,9243	0,8487	0,9243

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN1915

	DT	93,0921	0,9342	0,9276	0,9309	0,8618	0,9309
21	**Naive**	87,1711	0,8289	0,9145	0,8696	0,7434	0,8717
	K-NN	82,5658	0,8092	0,8421	0,8253	0,6513	0,8257
	Ensemble	93,75	0,9474	0,9276	0,9374	0,875	0,9375
	DT	93,0921	0,9342	0,9276	0,9309	0,8618	0,9309
22	**Naive**	88,1579	0,875	0,8882	0,8815	0,7632	0,8816
	K-NN	84,8684	0,9079	0,7895	0,8446	0,6974	0,8487
	Ensemble	93,75	0,9474	0,9276	0,9374	0,875	0,9375
	DT	91,1184	0,8947	0,9276	0,9109	0,8224	0,9112
23	**Naive**	89,4737	0,875	0,9145	0,8943	0,7895	0,8947
	K-NN	85,5263	0,9276	0,7829	0,8491	0,7105	0,8553
	Ensemble	93,4211	0,9408	0,9276	0,9342	0,8684	0,9342
	DT	93,75	0,9474	0,9276	0,9374	0,875	0,9375
24	**Naive**	88,8158	0,8684	0,9079	0,8877	0,7763	0,8882
	K-NN	85,1974	0,9145	0,7895	0,8474	0,7039	0,852
	Ensemble	93,4211	0,9474	0,9211	0,934	0,8684	0,9342
	DT	91,1184	0,8947	0,9276	0,9109	0,8224	0,9112
25	**Naive**	82,8947	0,9276	0,7303	0,8172	0,6579	0,8289
	K-NN	81,9079	0,8158	0,8224	0,8191	0,6382	0,8191
	Ensemble	92,7632	0,9276	0,9276	0,9276	0,8553	0,9276
	DT	91,1184	0,8947	0,9276	0,9109	0,8224	0,9112
26	**Naive**	83,5526	0,9211	0,75	0,8268	0,6711	0,8355
	K-NN	83,8816	0,9145	0,7632	0,832	0,6776	0,8388
	Ensemble	94,0789	0,9474	0,9342	0,9407	0,8816	0,9408
	DT	91,4474	0,9013	0,9276	0,9143	0,8289	0,9145
27	**Naive**	82,8947	0,9276	0,7303	0,8172	0,6579	0,8289
	K-NN	82,8947	0,8947	0,7632	0,8237	0,6579	0,8289
	Ensemble	92,1053	0,9145	0,9276	0,921	0,8421	0,9211
	DT	93,75	0,9474	0,9276	0,9374	0,875	0,9375
28	**Naive**	83,5526	0,9211	0,75	0,8268	0,6711	0,8355
	K-NN	81,9079	0,8158	0,8224	0,8191	0,6382	0,8191
	Ensemble	93,0921	0,9145	0,9474	0,9306	0,8618	0,9309
	DT	93,75	0,9474	0,9276	0,9374	0,875	0,9375
29	**Naive**	82,2368	0,9276	0,7171	0,8089	0,6447	0,8224
	K-NN	83,5526	0,8289	0,8421	0,8355	0,6711	0,8355
	Ensemble	93,0921	0,9276	0,9342	0,9309	0,8618	0,9309
	DT	93,75	0,9474	0,9276	0,9374	0,875	0,9375
30	**Naive**	82,2368	0,9276	0,7171	0,8089	0,6447	0,8224
	K-NN	82,5658	0,9211	0,7303	0,8146	0,6513	0,8257
	Ensemble	93,4211	0,9408	0,9276	0,9342	0,8684	0,9342

	DT	92,4342	0,9211	0,9276	0,9243	0,8487	0,9243
31	**Naive**	88,4868	0,875	0,8947	0,8848	0,7697	0,8849
	K-NN	82,8947	0,8289	0,8289	0,8289	0,6579	0,8289
	Ensemble	92,4342	0,9211	0,9276	0,9243	0,8487	0,9243
	DT	90,7895	0,8882	0,9276	0,9075	0,8158	0,9079
32	**Naive**	90,4605	0,8947	0,9145	0,9045	0,8092	0,9046
	K-NN	80,2632	0,9013	0,7039	0,7905	0,6053	0,8026
	Ensemble	93,4211	0,9408	0,9276	0,9342	0,8684	0,9342
	DT	92,4342	0,9211	0,9276	0,9243	0,8487	0,9243
	Acc: Accuracy, Sen: Sensitivity, Spe: Specificity, F_O: F_O Score, Kapp: Kappa, AUC: Area Under the Curve						

ACKNOWLEDGMENT

In this research, the dataset was obtained from a publicly accessible open-source repository intended for research purposes. There are no conflicts of interest among the authors.

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