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LEVERAGING AN ADAPTIVE RANDOM FOREST ALGORITHM AND ENHANCED FEATURE EXTRACTION BATTERY (FEB) TECHNIQUE TO INCREASE THE STATISTICAL PRECISION OF SCHIZOPHRENIA PREDICTIVE ANALYSIS

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Abstract

The word "dementia" is applied to refer usually to a decrease in mental abilities, that may encompass diminished memory, challenges regarding speaking and listening, poor judgment, as well as shifts in character and conduct. This is an ongoing, incurable illness which primarily impacts elderly individuals. Disorders like cognitive impairment and memory loss condition have its potential to injure and exacerbate the brain. Dementia has no known cure, and there is no means to stop it. The signs of dementia have been found to show up to ten years prior to the illness actually reveals themselves. In order to take advantage of signs of dementia in the initial phases of dementia estimation, ML (machine learning) experts developed a variety of techniques. The research of algorithms as well as statistical models that enable systems to carry out particular tasks with no specific instructions is known as machine learning. The issue of risk assessment as well as early identification of AD has been determined, and our system's solution makes use of supervised learning algorithms for foreseeing dementia sooner. Additionally, it produces a summary that details the precision of the method that we utilized. In contrast to earlier studies that depended on warning signs for AD and utilized statistical tests for comparison or progressive screening using regression techniques, prompt identification of dementia is essential to provide avoidance or just delaying the progression of the disorder.

Keywords— *Parkinson detection, Dementia detection, Signal processing, machine learning, Neural network.*

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I. INTRODUCTION

Dementia is a significant worldwide health issue.Dementia is a set of symptoms which may show up when specific clusters of brain cells cease to function regularly. Memory, recalling, and interaction-related brain regions are the usual locations where dementia forms. Dementia is usually caused by Alzheimer's disease. For dementia to be considered early-onset, it must start prior to the age of 65, and for dementia to be late-onset, it must start after the age of 65 According to the 2015 Global Alzheimer Report, there are currently 46.8 Over one million individuals globally suffer from mental illness. By 2030, that metrics are expected to rise to seventy-four million and is expected to grow to 131.5 mile by 2050. Parkinson's disease, frontotemporal dementia, and cognitive decline with Lewy body lesions are only a few of the several kinds of insanity body lesions, and Hypertension syndrome. Nearly 75% of instances are caused by cognitive impairment condition. Mixed dementia is a condition that develops when both Alzheimer's and vascular dementia arise at the same time. Dementia is not one of the medical disciplines to which Machine Learning (ML) methods are being utilized, despite there being many others. The patient's societal shame on experiencing a recollection situation contributes to the average four-year delay between the start of signs and clinician communication, which worsens the condition. At this point, physicians suffer from no control over the progression of the illness or the incapacitating behavioural changes associated with dementia. If there was a simple method to detect dementia earlier on in the course of the disease, patients would be a lot more inclined to look for promptly diagnosis and therapy.

By using methods for supervised learning, the system we've suggested makes it possible to figure out dementia early. Additionally, it produces a summary that details the precision of the algorithm we employed. Large amounts of information can be rapidly examined using machine learning algorithms, which can then be used to spot patterns and hazards that doctors might not have noticed right away. Clinicians can act early to possibly slow or prevent the development of dementia by using machine learning to identify potential risk factors for dementia. Based on the findings of the articles that were evaluated, a number of significant problems pertaining to machine learning-based brain disorder diagnosis are discussed in this project. This study discovered the most reliable way of diagnosing dementia, which can be used to advance other methods in the future.

- The proposed system is implemented by considering the standard dataset collected from OASIS-MRI images with Dementia and Non-Dementia data.
- The input images are pre-processed by removing the noisy data from the database, resizing the images.
- By applying filters, the images are further enhanced. The presented system extract the unique intensity pixels from the database.
- Training data and testing data are separated from the data.
- Using Deep analysis through random forest regression algorithm, the extracted features are mapped in terms of correlation.
- The accuracy of the system is enhanced by a stronger correlation between processing of the experimental information as well as data used for training.
- The productivity of a framework varies analysed using amount of correlated pixel points from the training data with respect to the test data.
- Further the system is improved by testing the similar problem with multiple database on Dementia.

The remainder of the essay is structured as a thorough literature review in the second section. In the third section, the choice of system tools and issue identifications are covered. In the fourth section, the system architecture and specific system design stages are covered. Potential development is discussed as the end of the article.

II. BACKGROUND STUDY

Jang et al. (2017) planned to use deep learning approaches to increase the precision of functional magnetic resonance imaging (fMRI) analyses. For the purpose of extracting task-specific features from fMRI volumes and classifying them, the authors presented a deep neural network (DNN) that was initially initialised with a deep belief network (DBN). The study showed that the suggested strategy performed better than traditional methods in precisely identifying brain areas linked to particular tasks. In order to increase the precision of fMRI analysis and make it easier to comprehend how the brain works, the research emphasises the promise of deep learning approaches.

Aghdam et al. (2018) planned to employ neural networks and feature selection methods to increase the accuracy of diagnosing cognitive decline condition. For the purpose of early Alzheimer's disease diagnosis, the authors developed a unique method combining a feature selection method and a multi-layer perceptron (MLP) neural network. The research revealed that when compared to conventional diagnostic techniques, the suggested method had a greater diagnostic accuracy to treat Alzheimer's. The fact checking emphasises the potential for improving early therapy and detection of cognitive impairment by merging cutting-edge machine learning algorithms with medical diagnosis.

Hachinski et al. (2019) aimed to raise awareness about the connection between stroke and dementia and to propose a global action plan for reducing the burden of dementia through stroke prevention. The authors reviewed the evidence linking stroke and dementia and proposed a set of recommendations for promoting brain health and preventing stroke and dementia. The recommendations included improving public education and awareness, optimizing risk factor management, promoting healthy lifestyle choices, and enhancing research collaboration and funding. The paper highlights the importance of a multifactorial approach to reducing the risk of dementia and the need for coordinated global action.

Li et al. (2019) aimed to investigate the use of machine learning techniques for predicting the development of utilizing data from many neuroimaging modalities to study the disorder. The Initiative for the Study of Alzheimer's Disease Neuroimaging provided the authors with the data. and created a machine learning model to forecast when AD will start to manifest in individuals using a combination of structural Magnetic resonance imaging, functional Magnetic resonance imaging, and PET imaging data. The study demonstrates promising results in predicting AD using machine learning algorithms and highlights the potential of multi-modal neuroimaging data for early detection and intervention of AD.

Liu et al. (2020) aimed to assess how dementia affected the clinical results of COVID-19 participants. The link between dementia and the outcomes of COVID-19 patients was reported in 11 papers, which were subjected to the research team's methodical examination and meta-analysis. According regarding the findings, people with dementia had a noticeably higher risk than those without dementia of developing a severe COVID-19 illness, requiring ICU admission, and dying. The study emphasises the necessity of providing this vulnerable demographic with specialised care as well as the significance of taking dementia into account as a potential risk factor for poor COVID-19 outcomes.

A.Javeed et al. (2020) the grid-based search procedure is used to maximize the suggested diagnosis method. To assess the accuracy of the suggested technique, two distinct kinds of tests are conducted. The recommended RSA-based random forest framework is created in the second test, whereas the first trial just produces a model based on random forests. The Cleveland information set, a web-based repository of heart disease statistics, is used in studies. As it generates 3.3% better accuracy compared to the traditional using only 7 features and a random forest model, the suggested technique is successful yet more complicated than a typical random forest framework. Additionally, compared to five other innovative machine learning theories, the suggested approach performs better.

Z. Cheng et al. (2022) In order to detect dementia, this paper suggests taking advantage of phrases that stop since they provide context-free material. A model handling just context phrases, a model working stop words and Part-of-Speech (PoS) tag sequences, as well as a model reading both are created as a consequence in this study. The studies described above demonstrate that both language and grammar play a comparable part in categorization.

S.S.Khan et al.(2022) With the help of video evidence obtained from a designated dementia section and marked for agitation incidents, the author showed a demonstration of the idea. Through roughly 24 hours of everyday behaviour for training and 11 hours of videos with regular actions and anxiety incidents for testing, we were able to achieve a zone according to the operating characteristic curve of the receiver of 0.754 for the unsupervised neural network that was used. In addition to a chance to enhance safety and wellness, this research project provides up opportunities for utilising the monitoring systems already in place in LTC along with various areas of mental health to identify anxiety or violence.

Vain et al. (2021) The suggested approach has a 74% success rate in identifying MCI and may categorize dementia into four distinct groups based on the degree to which it is in the MRI scan. To illustrate the internal functioning of the model graphically, the authors also used Grad CAM and Visual Explainable A.I. (XAI). The distinguishing characteristics of the MRI images that the CNN algorithm was able to recognise when testing are validated by this innovative method. The study of performance has been conducted using three distinct datasets: the raw data set, graphically converted pictures and a GAN-augmented information.

L. Ilia's et al. (2022) The Siamese networks used in this paper to identify people with AD have an accuracy of up to 83.75%. Then, we present two approaches for learning that involve multiple tasks, in which the most important work is binary classification of dementia and the additional job is prediction of dementia severity. (Multiclass classification). In a multi-task learning environment, our algorithm identifies patients with AD having a success rate of 86.25%. At last, we introduce a few innovative approaches for distinguishing between the grammatical structures adopted by those with AD and those used by non-AD individuals. The results show that patients with AD and those without AD have substantial variations in language.

III. SYSTEM DESIGN

The inability to perform daily activities is a symptom of dementia, an incurable brain disorder. Reduced memory is one of the primary reasons of mild cognitive impairment (MCI). Creating a ML model that reliably predicts the likelihood of getting dementia based on past demographics, medical information, and the results of cognitive tests. This evaluates the effectiveness of various machine learning algorithms and then decides the one that is most accurate and trustworthy algorithm for the forecast model. It determines the predictive algorithm's universality and dependability using separate information.

Large datasets may contain patterns that are hidden to the naked eye, but machine learning algorithms can be trained to find them. These algorithms can precisely predict a person's likelihood of acquiring dementia by looking at past demographics, medical records, and the results of cognitive testing. The most accurate and reliable machine learning algorithm for the forecast model can be chosen by evaluating and evaluating the effectiveness of various machine learning techniques. With the use of specific data, the prediction algorithm's reliability and universality may also be evaluated.

Recent setbacks in dementia studies may imply that early detection and examination are essential for a successful course of therapy. Machine learning-based neuroimaging improves dementia diagnosis precision for a variety of categories. The machine learning-based method for categorization consists of several stages, including feature extraction and selection, feature reduction of dimension, and classifier method. These methods require a high level of expertise and numerous, time-consuming refining processes.

Although dementia diagnosis and treatment may be revolutionised by machine learning, there are also ethical and privacy issues to take into account. For instance, there is a chance that algorithms based on machine learning could be used to discriminate against those who are thought to be at a high risk of dementia. This might lead to discrimination in the workplace or the rejection of healthcare or insurance coverage. It is crucial to create strong ethical standards and legal frameworks for the application of machine learning in healthcare in order to allay these worries. Machine learning has the potential help enhance dementia early detection and diagnosis, as well as the creation of individualised treatment programmes

METHODOLOGY

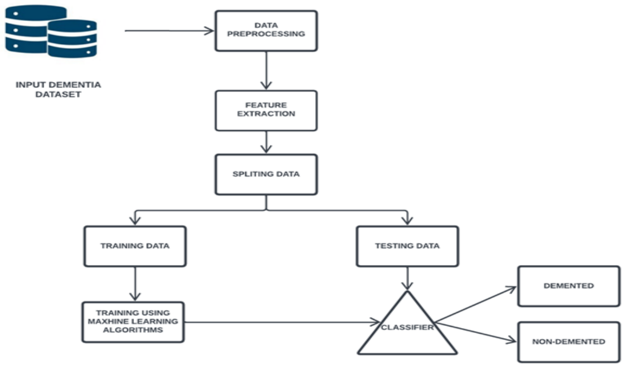

Fig. 1. System architecture of Proposed Detection system

• Early detection of dementia symptoms before they worsen is possible with the aid of machine learning techniques. By doing so, the disease may be better managed and changes may be made early.

• The suggested algorithms may evaluate big and intricate data sets, finding patterns and danger signs that clinicians might not instantly recognise. As a consequence, dementia risk calculations may become more precise.

• When dementia is detected early, more focused therapy strategies can be employed to halt progress of the condition and enhance the effects on patients.

Implementation plan

The goal of the project to use machine learning to predict dementia early on aims to tackle the rising fear over elderly people and the rise in cases of dementia that goes along with it. Chronic dementia affects remembering, thinking, and behaviour as well as other cognitive functions. The creation of machine learning algorithms for dementia early diagnosis can have a number of advantages. First of all, early identification and treatment can enhance the efficacy of therapies and possibly halt the worsening of the illness.

As a result, health care policies and initiatives that seek to avoid or reduce the incidence of dementia can be guided by the recognition of dementia risk variables.

Lastly, it can help advance our knowledge of the fundamental causes of dementia, which will help us create fresh medications and remedies.

Data collection

The study looks at a continuous OASIS - MRI data set of right-handed (R) type aged 60 to 96 demented and nondemented people. Men and women who participated in the survey of 150 responders for 373MR Meetings both attended scanning events at least twice. The data collection used for training included the following: Sex, age, social economic status (SES), level of education (EDUC), group, visit, and mini-mental state Subject ID, MRI ID, The MMSE (Mini-Mental State Examination) and the Clinical Cognitive Rating (CCR) are specifically included for cognitive evaluation, cognitive severity staging, estimated total intracranial volume (e-TIV) for brain volume measurement, and normalized whole cerebral volume (n-WBV). For instance, some people who had dementia at first turned out to be the non-dementia managed form.

Preprocessing

Following the gathering of numerous documents, dementia data is pre-processed. A total of patient records, some of which have missing numbers, are included in the dataset. The leftover patient records are used for pre-processing after those records were eliminated from the collection of data. The characteristics of the provided information are presented, along with binary classification and the multiclass variable. The multi-class variable is used to investigate whether dementia exists or not.

Feature extraction

In order to emphasise important relationships and trends that machine learning algorithms can use to generate estimates, feature extraction transforms the raw data. Two variables involving gender and age are selected from the attributes of the record set to determine the patient's private data. Due to the fact that they include crucial medical information, the other characteristics are essential. The diagnosis of dementia and determining its extent depend heavily on medical evidence.

Training dataset

A range of methodologies for Artificial intelligence techniques such as decision trees, random forests, K nearest neighbours, and logistic regression, and XG boost, can be implemented in the data we have and given to the vector features in order to figure out the possibility of dementia or to assess the course of the illness. The predictive abilities of the models developed by machine learning can be evaluated using a variety of metrics, including area under the receiver operating characteristic (ROC) curve, accuracy, precision, recall, and others.

Classification

The amount of data characteristics considered has a significant impact on how well any ML model functions. It's crucial to choose the appropriate qualities rather than picking several in order to keep superior performance. SUB ID, MRI ID, Visit, and Hand features were eliminated because they had no bearing on the categories. Since the information set only includes MRI scans of right-handed individuals, the hand feature was eliminated. Demented, non-demented, and converted are the three categories of dementia that are recognised.

The random forest method is created by first combining N decision trees, after which predictions are made for each one that was generated in the initial stage.

You can use the following stages and diagram to show how the process works:
Step 1: A maximum of K points from the training group should be chosen at random.
Step 2: Create the decision trees connected to the selected data points. (Subsets).
Step 3Choose N for the decision tree size you wish to create.

Step 4: Re-do Steps 1 and 2.
Step 5: Look up the forecasts of each decision tree for the new data points and assign the new information to the group that receives the most votes.

Random Forest algorithm pseudocode

1. Separate the dataset for dementia into training and test groups.
2. Create a blank list to hold the decision trees.
3. for i between 1 and n_estimators (the number of trees):
   a. Randomly select a portion of the training data. (With replacement)
   b. Create a decision tree using the sampled data
   C. add the decision tree to the collection of decision trees
4. for every test case:
   a. Make an estimate by combining the forecasts of all the forest's decision trees.
5. Use a performance measure, such as accuracy, AUC, etc., to assess the model's performance on the testing set.

The Random Forest algorithm, in general, mixes different decision trees to enhance reliability of predictions and minimise excessive fitting. . Random Forest generates a varied collection of decision trees that accurately represent various elements of the data by randomly selecting the training data and characteristics. Random Forest generates a strong and reliable forecast by combining all decision tree predictions.

V. Validation and Evaluation

Our results are evaluated using Accuracy, Precision, Recall, F1-score, and Specificity. The dementia class was used as the positive input for all of these indicators. The literature has made considerable use of the holdout validation technique provides an indicator for assessing the effectiveness of systems for diagnosis based on ML. A dataset is split into two halves in a holdout validation approach; one segment is used for training and the other section is used to test the suggested ML framework. 30% of the dataset is used for testing, while 70% is used to train the ML model. As a consequence, we trained and tested the proposed RF-FEB model using the aforementioned data and partitioning criteria. Following data partitioning, we compare the proposed model's performance to that of other modern machine learning algorithms for predicting dementia using evaluation measures. Accuracy, precision, recall, F1-score, Matthew's correlation coefficient (MCC), and area under the curve (AUC) are the evaluation criteria. utilizing plot for the RF-FEB model. The suggested RF-FEB model's evaluation metrics are stated

$$\text{Accuracy} = (TN+TP) / (TN+FP+TP+FN) \text{ --- (1)}$$

In binary classification Actual Positives (TP), Actual Negatives (TN), counterfeit positives (FP), and erroneous negatives (FN) are each of the four outcomes that might occur.True positives (TP) are situations where a positive value was actually recorded despite the model's prediction of a negative value. False positives (FP) are situations where a positive value was predicted by the model but turned out to be a negative value. True negatives (TN) are situations where a negative value was really recorded notwithstanding the model's negative prediction. False negatives (FN) are situations in which Even though the model foresaw a bad result, the actual result was good.
.

$$\text{Precision} = TP / (TP+FP) \text{ --- (2)}$$

The percentage of precise optimistic forecasts throughout the board the model's positive predictions is measured by a binary classification statistic called precision. It is calculated using the ratio of genuine positives to the sum of true positives and false positives. A greater precision score indicates that the model is making predictions that are more accurate.

Recall = TP / (TP+FN) --- (3)

Retention was a percentage of accurately anticipated positive cases among all actual positive cases in the dataset and is used in binary classification. It is calculated using true positives to the total of incorrect negatives and true affirmative is the ratio. Increased recall scores show that the model is accurately finding more positive cases in the dataset.

Specificity = TN / (TN+FP) --- (3).

The degree to which a binary classification model can accurately identify negative cases is known as specificity. It is computed by by the quantity when divided by the total number of true negative (TN) cases (TN) and false positive (FP) cases. A high specificity score means that the classification of negative cases is reliable and that the rate of false positives is minimal.

f1_score = 2*((p*r) / (p+ r)) --- (4)

It's precise and recall of a binary classification model are assessed using the F1 score. It is established by harmonically averaging precision and recall. A high F1 score indicates good memory, accuracy, and the ability to distinguish between positive and negative events. To determine the model's accuracy, the formula adds together the number The overall number of forecasts (true positives, true negatives, false positives, and false negatives) by the total amount of true beneficial and true negative projections. This approach is widely employed. to assess how well binary classification models perform.

VI. RESULT AND DISCUSSIONS

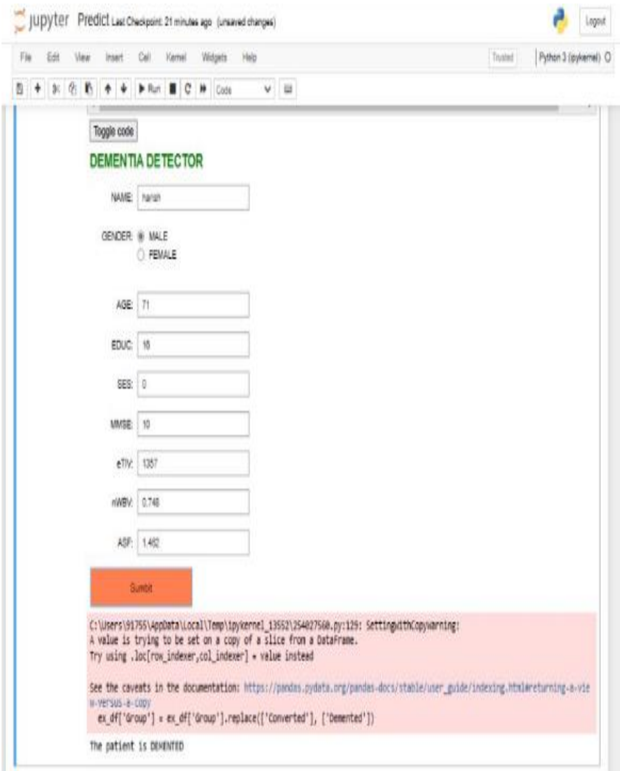

Fig 2. Dementia detector using Google Collab

Fig. 2. Shows the system Dementia detector simulation using Google Collab.

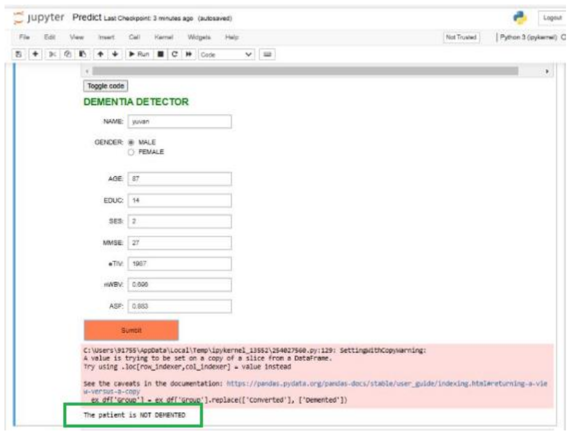

Fig 3. Dementia detector result

Fig. 3. Shows the system outcome showing the dementia detector detecting the result as normal or Not a Dementia patient.

Comparative Performance

	Model_Name	Accuracy	AUC Score	Precision	Recall	F1-Score
0	Logistic Regression	0.964286	0.961451	0.984127	0.953846	0.968750
1	Naive Bayes	0.964286	0.961451	0.984127	0.953846	0.968750
2	KNN	0.607143	0.609977	0.587302	0.672727	0.627119
3	Decision Tree	0.955357	0.958333	1.000000	0.912281	0.954128
4	Random Forest	0.955357	0.957051	0.980769	0.927273	0.953271
5	ADA Boost	0.937500	0.937821	0.942308	0.924528	0.933333
6	Gradient Boosting	0.955357	0.954487	0.942308	0.960784	0.951456
7	XG Boost	0.973214	0.975000	1.000000	0.945455	0.971963
8	XG Boost-imp features	0.973214	0.975000	1.000000	0.945455	0.971963
9	Stacking classifier	0.973214	0.975000	1.000000	0.945455	0.971963

Fig 4. Comparison of performance

Fig 4. Shows the comparison of performance with different machine learning algorithms. Naive Bayes, decision trees, logistic regression, decision trees with k-nearest neighbours, and support vector machines (SVM) with various kernels (RBF, linear, polynomial, and sigmoid) are some examples of these techniques. These fashions are created and tested with ADASYN dataset. The performance measure of Mathew's correlation constant (MCC), Recall and accuracy is considered for analysis. The best accuracy is obtained using Random forest (RF) with polynomial kernel of 88%. The machine learning reduce the over fitting problem. To reduce the challenges in over fitting problem feature extraction battery (FEB) model is created.

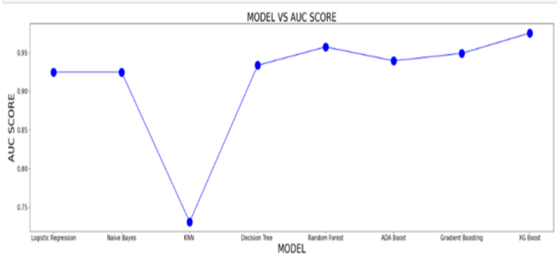

Fig 5. AUC plot

Fig 5. Shows the accuracy plot of proposed machine learning models. On the whole the area under curve (AUC) plot is optimum in all machine learning models, where the XGBOOST model and Random forest algorithm ahead in AUC score.

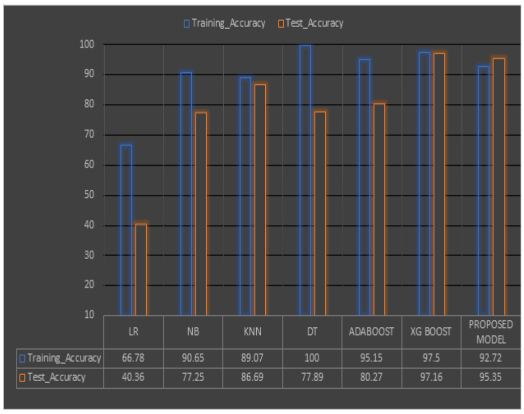

Fig 6. Training Accuracy vs. Testing Accuracy

Fig 6. Shows the training accuracy vs. testing accuracy on different machine learning algorithms. The above figure shows the algorithm such as Linear regression (LR) 40.36% testing accuracy, Naïve Bayes (NB) with 77.25% accuracy, K-Nearest Neighbor (KNN) with 77.89% accuracy, AdaBoost 80.27% accuracy is achieved. XGBoost The mathematical framework attained the maximum degree precision 97.16% and the the suggested technique's precision was 95.35%. Perhaps different dataset with comparison of hybrid algorithms are utilized in future for further enhancement.

Techniques for Predicting Alzheimer Disease are compared:

We assessed the effectiveness of many ML-based autonomous diagnostic methods that were put out by researchers for Alzheimer prediction in the existing literature. Compares the effectiveness of earlier ML-based dementia prediction strategies together with our suggested model. we as a species recently constructed benchmark (FEB-RF) accomplished noticeably convenient than Particularly updated presented scenarios, including those Aghdam , F. G. Gutierrez , G. Mirzaei and H. Adeli, and S.S.Khan

Comparative analysis of classification accuracy with earlier suggested Alzheimer detection systems.

Study(year)	Method	Accuracy (%)
H. Chen (2012)	PNN	83.00
Stuke.H, Hildebrand t.H (2017)	SVM	89.00
W.Alghamdi et al (2018)	GB	88.00
Lovestone.S (2019)	XG Boost+ Random forest	88.00
L.Minku (2020)	Decision tree	74.00
K.Gourlia (2020)	Random forest	84.00
Ralbovsky. N (2021)	ANN + SVM	84.00
Adeli et al (2022)	MLP	70.00
Dallora.A (2023)	Auto encoder + Ad boost	90.00
Proposedmodel	FEB+RF	95.00

Fig 7. Comparative analysis

VII.CONCLUSION

Huge data sets can be successfully examined by algorithms for machine learning, and such evaluations can reveal similarities and warning variables that clinicians might not have noticed right away. Clinicians can take early action to possibly slow or prevent the start of dementia by using machine learning to estimate the likelihood of dementia. To improve the efficiency of machine learning methods for estimating the chance of dementia, more study is required. When using machine learning for healthcare apps, it's crucial to take ethical issues like confidentiality of information, prejudice and well-informed permission into account. Machine learning can greatly aid in the identification and avoidance of dementia with careful planning and ongoing research, and eventually enhance patient results and their standard of life.

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