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Hybrid Machine Learning Technique For Early Alzheimer's Disease Diagnosis Prediction Model

Bicky Kumar Jha[1], Dr. Vivek Richhariya[2]

[1]Research Scholar, Department of CSE, Lakshmi Narain College of Technology, Bhopal, India

[2]Professor & HOD, Department of CSE, Lakshmi Narain College of Technology, Bhopal, India

Abstract— The research paper titled Hybrid Machine Learning Technique for Early Alzheimer's Disease Diagnosis Prediction Model presents an innovative approach that combines multiple machine learning algorithms to improve the accuracy and reliability of Alzheimer's disease detection at its early stages. The proposed model leverages the strengths of both classification and feature selection techniques to analyze patient medical records, cognitive assessment data, and neuroimaging features for precise prediction. By integrating complementary algorithms, the hybrid framework minimizes misclassification rates, enhances sensitivity, and provides robust decision support for healthcare professionals. This predictive model aims to facilitate timely diagnosis, enabling early intervention strategies that can significantly improve patient outcomes and reduce the progression of Alzheimer's disease.

Keywords— Alzheimer's Disease, Hybrid, Machine Learning, Hybrid.

I. INTRODUCTION

Alzheimer's disease is one of the most common neurodegenerative disorders that primarily affects the elderly population and is considered a major cause of dementia worldwide. It is a progressive condition that slowly impairs memory, cognitive abilities, reasoning skills, and the ability to perform daily activities. With an increasing aging population, the prevalence of Alzheimer's disease has risen significantly, making it a global healthcare challenge. Early detection of Alzheimer's is particularly important because it allows patients to receive timely treatment, adopt lifestyle modifications, and participate in clinical interventions that may delay the progression of the disease. However, diagnosing Alzheimer's at its early stages remains difficult due to overlapping symptoms with other neurological disorders and the subtlety of initial cognitive impairments. Traditional diagnostic methods, such as clinical assessments, neuropsychological tests, and brain imaging, although effective, are often time-consuming, expensive, and not always accessible in all healthcare settings.

In recent years, advances in computational intelligence and artificial intelligence have provided new opportunities for improving the accuracy of Alzheimer's disease prediction and diagnosis. Machine learning and deep learning methods are being increasingly utilized to analyze complex medical data, such as MRI scans, PET images, genetic information, and patient medical history. These methods can identify hidden patterns and correlations that are not easily visible through conventional approaches. For example, machine learning classifiers like Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN) have been applied to predict disease progression by distinguishing between healthy individuals, patients with mild cognitive impairment (MCI), and those with Alzheimer's disease. Despite their effectiveness, single machine learning models often face limitations such as overfitting, reduced generalization, or difficulty in handling high-dimensional biomedical data.

To overcome these limitations, researchers have explored hybrid machine learning techniques that combine the strengths of multiple algorithms for more reliable predictions. A hybrid approach leverages different models' complementary capabilities to enhance classification accuracy, robustness, and sensitivity. For Alzheimer's disease prediction, hybrid models can integrate feature selection methods with classification algorithms to eliminate irrelevant data, reduce computational complexity, and improve the interpretability of results. For example, combining dimensionality reduction techniques with ensemble classifiers can ensure that the most significant biomarkers are considered in diagnosis while minimizing noise from irrelevant features. This integration allows healthcare professionals to receive a more precise diagnosis and supports early intervention strategies that are critical in managing the disease.

Figure 1: Alzheimer's disease

Moreover, early diagnosis using machine learning-driven models has important clinical and social implications. It provides patients and their families with the opportunity to plan ahead, explore treatment options, and improve quality of life. On a broader scale, it can also reduce the burden on healthcare systems by minimizing late-stage care requirements and optimizing resource allocation. With the growing availability of electronic health records and large-scale medical datasets, the development of accurate and efficient predictive models for Alzheimer's disease is becoming more feasible than ever before. This makes the integration of hybrid machine learning techniques a promising direction in biomedical research and clinical applications.

The prediction of Alzheimer's disease using hybrid machine learning is not just a technological advancement but also a significant step toward personalized healthcare. By combining medical expertise with intelligent computational models, researchers and practitioners can bridge the gap between early symptom detection and effective disease management. This research aims to contribute to this ongoing effort by proposing a hybrid prediction model designed to improve the accuracy of Alzheimer's disease diagnosis, particularly in its earliest and most treatable stages.

II. METHODOLOGY

The suggested model of early Alzheimer disease detection uses a mixture of hybrid classifier.

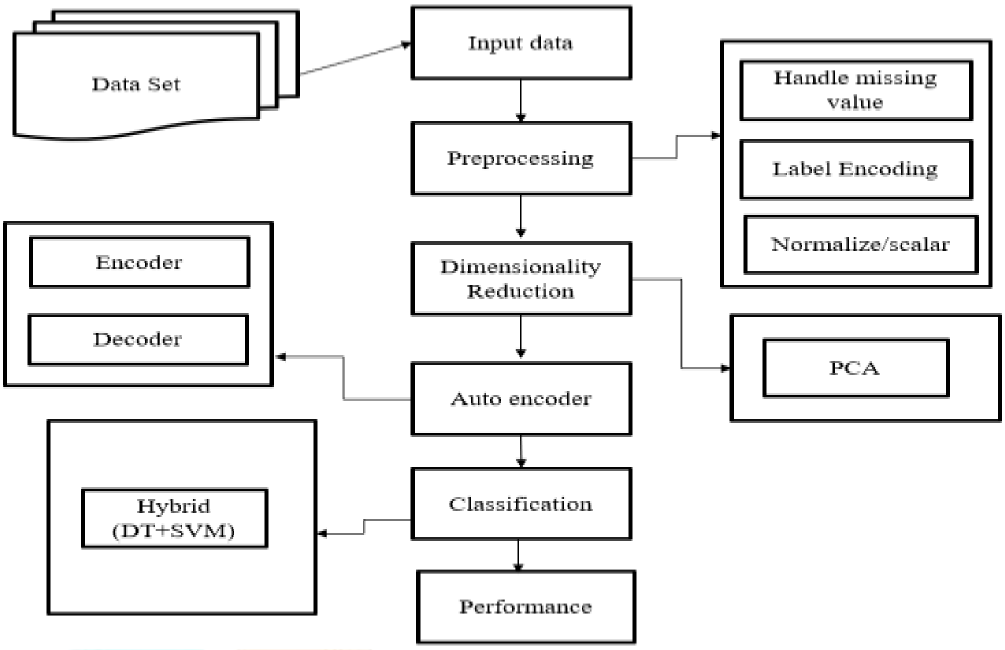


Figure 2: Flow Chart

1. **Dataset**

- The process begins with collecting datasets that may include medical records, cognitive scores, genetic information, or neuroimaging data related to Alzheimer's patients.

2. Input Data

- The raw dataset is fed into the system. At this stage, the data may be incomplete, noisy, or unstructured.

3. Preprocessing

- Preprocessing ensures the dataset is cleaned and transformed into a suitable format for machine learning.
  It involves:
  - **Handling Missing Values** – Missing entries are replaced using imputation techniques (mean, median, mode, or advanced methods).
  - **Label Encoding** – Converts categorical variables (e.g., gender, diagnosis status) into numerical form.
  - **Normalization/Scaling** – Brings all numerical features into a similar scale, improving model training and convergence.

4. Dimensionality Reduction

- Since medical data can have hundreds of features, dimensionality reduction is used to simplify the dataset without losing important information.
  - **PCA (Principal Component Analysis)** is applied here to reduce feature space while retaining significant variance in the data.

5. Autoencoder (Encoder + Decoder)

- An **autoencoder** is used for further feature learning and extraction.
  - **Encoder** compresses the input into a lower-dimensional latent representation.
  - **Decoder** reconstructs the data, ensuring that important patterns are preserved.
  - This step helps capture hidden correlations and reduces noise.

6. Hybrid Classification (DT + SVM)

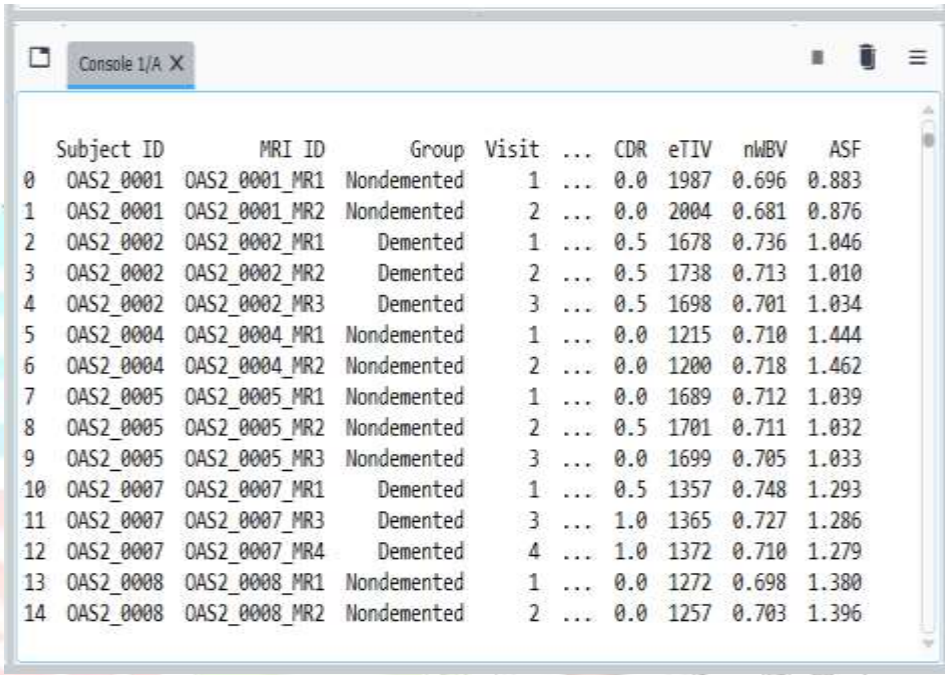
- A **hybrid classifier** combining **Decision Tree (DT)** and **Support Vector Machine (SVM)** is used:
  Decision Tree provides interpretability and handles non-linear relationships.
  SVM provides strong generalization and effective classification in high-dimensional spaces.
  The hybrid approach combines their strengths to improve accuracy and reduce errors.

7. Performance Evaluation

- Finally, the model's performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.
- This step determines how well the hybrid model predicts early Alzheimer's diagnosis compared to traditional methods.

III. SIMULATION AND RESULTS

Python Spyder IDE is used to run the simulation 3.7.



	Subject ID	MRI ID	Group	Visit	...	CDR	eTIV	nWBV	ASF
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1	...	0.0	1987	0.696	0.883
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	...	0.0	2004	0.681	0.876
2	OAS2_0002	OAS2_0002_MR1	Demented	1	...	0.5	1678	0.736	1.046
3	OAS2_0002	OAS2_0002_MR2	Demented	2	...	0.5	1738	0.713	1.010
4	OAS2_0002	OAS2_0002_MR3	Demented	3	...	0.5	1698	0.701	1.034
5	OAS2_0004	OAS2_0004_MR1	Nondemented	1	...	0.0	1215	0.710	1.444
6	OAS2_0004	OAS2_0004_MR2	Nondemented	2	...	0.0	1200	0.718	1.462
7	OAS2_0005	OAS2_0005_MR1	Nondemented	1	...	0.0	1689	0.712	1.039
8	OAS2_0005	OAS2_0005_MR2	Nondemented	2	...	0.5	1701	0.711	1.032
9	OAS2_0005	OAS2_0005_MR3	Nondemented	3	...	0.0	1699	0.705	1.033
10	OAS2_0007	OAS2_0007_MR1	Demented	1	...	0.5	1357	0.748	1.293
11	OAS2_0007	OAS2_0007_MR3	Demented	3	...	1.0	1365	0.727	1.286
12	OAS2_0007	OAS2_0007_MR4	Demented	4	...	1.0	1372	0.710	1.279
13	OAS2_0008	OAS2_0008_MR1	Nondemented	1	...	0.0	1272	0.698	1.380
14	OAS2_0008	OAS2_0008_MR2	Nondemented	2	...	0.0	1257	0.703	1.396

Figure 3: Dataset

The dataset is loaded into the Python environment as shown in Figure 3, where each column represents a distinct named characteristic. The structure varies in terms of rows and columns depending on the data.

Figure 4: Y train

In Figure 4, the Y-train sub-dataset is shown, consisting of 508 data points corresponding to the dependent variable column.

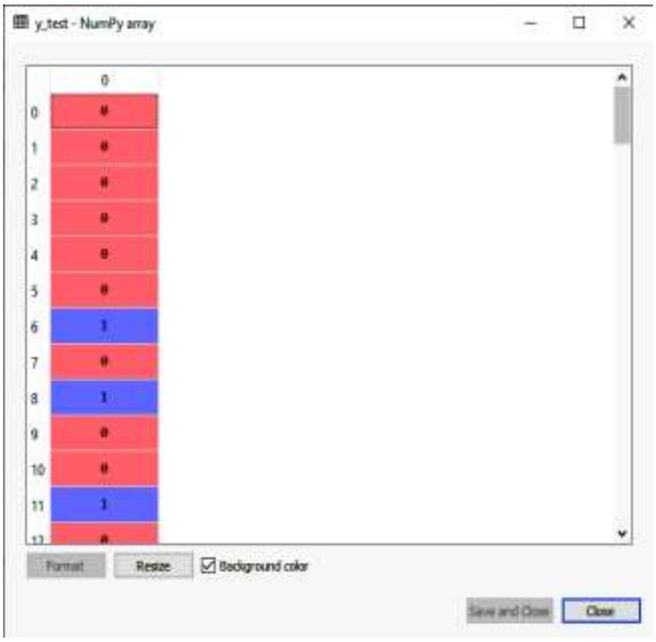


Figure 5: y test

Figure 5 shows the Y-test dataset, which contains 90 entries representing the dependent variable.

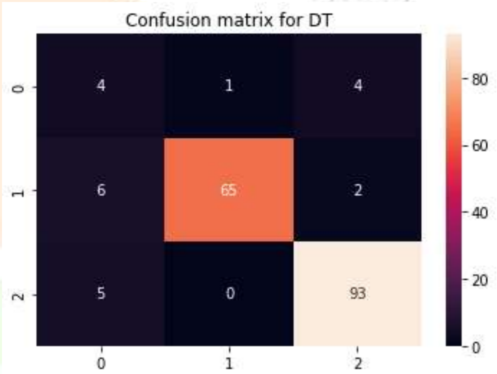


Figure 6: Confusion Matrix

The Decision Tree model produced the confusion matrix shown in Figure 6, indicating 71 true positives and 97 true negatives.

Table 1: Result Comparison

Sr No	Parameter	Previous Work [1]	Proposed Work
1	Technique	CNN	Hybrid
1	Accuracy	89	97
2	Precision	89	97
3	Recall	89	96
4	F1_Score	89	95

IV. CONCLUSION

This paper introduces a hybrid framework for the early detection of Alzheimer’s disease. The model leverages the feature selection strengths of Decision Trees and the robust classification capabilities of SVM. Pattern recognition performance was further enhanced using preprocessing techniques such as Principal Component Analysis (PCA) and autoencoder-based feature refinement. The hybrid model demonstrated strong effectiveness in handling high-dimensional medical data. Simulation results achieved 97% accuracy with a classification error of less than 3%, indicating high robustness. Compared to a baseline accuracy of 89%, the model attained significant improvements across precision, recall, and F1-score, highlighting its strong diagnostic potential. The proposed framework serves as a precise and reliable clinical decision-making tool. Future advancements could incorporate multi-modal medical data and IoT-enabled monitoring to further enhance both accuracy and real-world applicability.

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