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AN OPTIMIZED ENSEMBLE APPROACH FOR ALZHEIMER'S DISEASE DETECTION: INTEGRATING GRADIENT BOOSTING TECHNIQUES WITH FEATURE SELECTION AND HYPERPARAMETER TUNING

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ABSTRACT

Early diagnosis and correct diagnosis of Alzheimer's disease (AD) are crucial for intervention on time. The present research proposes E3-Boost, a new ensemble learning approach that is effective in improving the early diagnosis of Alzheimer's disease (AD). The novelty of the research lies in the unified integration of Gradient Boosting Machine (GBM), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM), which together ride on the strength of combinations of boosting algorithms to enhance predictive performance. One of the main novelties is L1L2-FS, a hybrid L1 (Lasso) and L2 (Ridge) regularization feature selection approach that, with respect to the conventional practice, enables even more efficient identification of features as well as their redundancy removal. Not only is the model increased in interpretability, but so is its capability for generalization. Additionally, the methodology leverages SMOTE for handling imbalanced classes as well as for outlier detection on the basis of Z-Scores to guarantee excellent data quality. Another milestone is the implementation of Optuna-based hyperparameter tuning through Bayesian Optimization and Tree-structured Parzen Estimators (TPE), which iteratively optimizes model performance to achieve a startling accuracy rate of 98.82%. The last model realizes a substantial boost in accuracy (97.85%), recall (96.92%), F1-score (96.88%), and lowered RMSE (0.1023), outperforming conventional ML and deep learning models. In contrast to computationally intensive deep learning methods, E3-Boost presents a computationally light solution with high predictive power, which is well suited for real-world clinical applications. The most important innovation is three pillars they are L1L2-FS, a hybrid feature selector that merges Lasso's sparsity and Ridge's resilience to collinearity; E3-Boost, the first ensemble that brings together GBM, XGBoost, and LightGBM through dynamically weighted meta-learning; and third one is Optuna-TPE optimization, automating hyperparameter tuning with Bayesian-adaptive sampling. This triad fills crucial gaps in interpretability, scalability, and reproducibility for clinical AI.

Keywords- *E3-Boost, Alzheimer's Disease Prediction, Ensemble Learning, Feature Selection, SMOTE, Hyperparameter Tuning*

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1. INTRODUCTION

Alzheimer's disease (AD) is a multifactorial, irreversible, neurodegenerative illness characterized by progressive loss of cognitive functions, significantly affecting memory, reasoning, communication, and even motor functions in late stages. It is the most common cause of dementia and is a serious public health issue, striking millions of individuals globally, especially older adults [1]. Alzheimer's is anticipated to surge as the population of the world ages, and estimates indicate that the number of sufferers could nearly triple by the year 2050. What the precise causes of Alzheimer's are is unknown, but a complex interplay of genetic, environmental, and lifestyle elements is understood to lead to its development. The two major pathological changes seen with Alzheimer's are the accumulation of amyloid-beta plaques between brain nerve cells and neurofibrillary tangles (taut fibers of tau protein) within neurons [2]. These defects cause disruption of neuron transmission, cell death, and loss of brain tissue. With time, the degeneration translates into cognitive signs that begin as mild forgetfulness and confusion before advancing to pronounced impairment in judgment, language, and everyday behavior. Although a cure for Alzheimer's disease does not yet exist, early intervention and detection significantly impact symptom control and disease stabilization. Studies on predictive biomarkers, such as genetic analysis, neuroimaging, cerebrospinal fluid examination, and the development of machine learning and artificial intelligence, are opening up the prospect of precise early diagnosis [3]. Predictive algorithms are being created to evaluate individuals at risk for Alzheimer's disease prior to the onset of symptoms, providing the prospect of early therapeutic interventions to prevent onset or to mitigate the severity of the disease. Existing treatments aim to control symptoms, with drugs like cholinesterase inhibitors and memantine improving cognitive function temporarily. Concurrently, lifestyle changes—such as regular physical exercise, cognitive training, and dietary modifications—have been found to have a protective effect, possibly lowering the risk or slowing the development of Alzheimer's in some patients [4]. Alzheimer's disease is a progressive, multifactorial disorder with wide-ranging consequences for patients, caregivers, and healthcare systems globally. Continued research into its etiology, prevention, and treatment is essential to reducing the increasing burden of the disease and enhancing outcomes for affected individuals. Unlike monolithic deep learning models, the proposed framework pioneers a hierarchical ensemble where GBM, XGBoost, and LightGBM are not merely stacked but interact via a gating mechanism (Section 3.3). This mirrors neurocognitive degeneration patterns—coarse-grained (GBM) to fine-grained (LightGBM) feature interactions—a conceptual leap over traditional boosting.

The study begins with Section 1, Introduction, which outlines the research problem, its significance, and the objectives of the study. Section 2, Literature Review, provides a comprehensive overview of existing studies and theoretical frameworks relevant to the research topic, establishing the context for the study. Section 3, Methodology, describes the research design, data collection methods, and analytical procedures employed to address the research questions. In Section 4, Results and Discussion, the findings of the study are presented, followed by an analysis of the data and their implications. Section 5, Discussion, offers an in-depth interpretation of the results within the broader context of the field, highlighting key insights and contributions. Finally, Section 6, Conclusion, summarizes the main findings, discusses the limitations of the study, and suggests avenues for future research.

1.1. Research Gap

While there have been tremendous improvements in the prediction of Alzheimer's disease (AD) with machine learning (ML) and deep learning, there are still many challenges. Most work to date is based on neuroimaging data, but data heterogeneity, model explainability, and generalizability remain issues. Handcrafted features-based traditional ML models can only capture simple disease patterns, whereas effective deep learning models demand a large amount of labeled data and high computation power. Multi-modal paradigms involving neuroimaging, cerebrospinal fluid (CSF), and cognitive biomarkers provide higher diagnostic accuracy but are challenged by data fusion and longitudinal analysis. Transfer learning models are promising, but their across-data-set adaptability is yet to be fully explored. Lastly, inadequate validation on heterogeneous populations questions the presence of bias and clinical usefulness. Filling these gaps needs more interpretable, scalable, and generalizable ML frameworks that can combine heterogeneous data effectively with low computational complexity for real-world deployment.

1.2. Research Questions

RQ.1 How can machine learning models be optimized to address data heterogeneity and improve the generalizability of Alzheimer's disease (AD) prediction across diverse populations?

RQ.2 What strategies can be employed to enhance the interpretability of deep learning models for AD diagnosis while maintaining high predictive accuracy?

1.3. Contributions

This study addresses three critical gaps in Alzheimer's disease (AD) prediction: (1) the reliance on data that limits clinical utility, (2) the interpretability-scalability trade-off in existing models, and (3) computational inefficiency in multi-modal frameworks. Our E3-Boost framework introduces L1L2-FS (a hybrid feature selector for clinically actionable variables), an interpretableensemble (GBM/XGBoost/LightGBM with dynamic weighting), and Optuna-TPE optimization for efficient deployment. Key results demonstrate a 98.82% accuracy—surpassing prior works (70–92%)—with enhanced interpretability and 3.2× faster tuning than grid search. These advances imply direct clinical applicability: the model's use of routine variables (e.g., cognitive scores, comorbidities) enables AD risk stratification in primary care, while its computational efficiency supports deployment in resource-limited settings. Future work will extend validation to diverse populations to ensure generalizability.

2. LITERATURE REVIEW

Machine learning (ML) has been extensively applied in early-stage Alzheimer's disease (AD) prediction, demonstrating improved diagnostic accuracy over traditional methods. Kavitha et al. [5] have utilized neuroimaging datasets like OASIS to train models such as Decision Trees, Random Forest, Support Vector Machines (SVM), Gradient Boosting, and Voting Classifiers, achieving a test accuracy of 83%. Prior studies have reported accuracies ranging from 70% to 80%, employing feature selection techniques like Principal Component Analysis (PCA) and recursive feature elimination to enhance model performance. Deep learning methods, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have also been promising in handling high-dimensional MRI and PET scan data. Data heterogeneity, interpretability, and computational complexity are still challenges. The current research optimizes several ML algorithms to improve early AD detection, enabling timely clinical intervention and lowering mortality rates. Deep learning methods have been found to have great promise in the prediction of Alzheimer's disease (AD) progression, especially in the detection of individuals at risk of conversion from mild cognitive impairment (MCI) to AD. Lee et al. [6] used a multimodal recurrent neural network (RNN) to combine cross-sectional neuroimaging biomarkers, longitudinal cerebrospinal fluid (CSF), and cognitive performance biomarkers from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. Their research proved that single-modality models were able to reach a level of accuracy up to 75% (AUC = 0.83), while integrating multi-domain longitudinal data increased performance to a level of 81% accuracy (AUC = 0.86). Past work has looked into classical machine learning models like Support Vector Machines (SVM) and Random Forests with moderate levels of classification accuracy. Nonetheless, deep learning methods, especially recurrent and convolutional neural networks (CNNs), have shown better predictive performance by successfully extracting temporal and spatial patterns in neuroimaging and biomarker data. Multi-modal learning architectures are now better known for their potential to improve diagnostic accuracy by tapping heterogeneous data sources, overcoming the shortcomings of single-modality methods. Even with these developments, issues persist regarding data harmonization, interpretability, and computational complexity. The incorporation of multi-modal deep learning in predicting AD progression presents promising avenues for early intervention and patient stratification in clinical trials, thus permitting timely therapeutic approaches.

Machine learning (ML) has been identified as a potential solution for early-onset Alzheimer's disease (AD) diagnosis through the use of sophisticated classification methods to enhance diagnostic power. Pranao et al. [7] examined three ML-based methods for AD prediction, namely manual feature extraction, CV2-based vectorization, and deep feature extraction through a CNN-SVM model. Their results indicated that Local Binary Pattern (LBP) features were the best among hand-crafted features, and XGBoost had the best classification performance with 73% accuracy for binary classification. The best accuracy of 75% was achieved by a CNN with an SVM classifier. Deep learning models, especially CNNs, have been shown to perform well in analyzing neuroimaging

data because they can extract spatial and structural patterns. Nevertheless, issues like data preprocessing, feature selection, and model interpretability continue to be essential research areas. Scientific research demonstrates the fast-growing demand for combining multiple ML approaches for disease classification because hybrid methods show potential to enhance clinical decision help as a solution. ML technology combined to transfer learning methods demonstrates effective use for enhancing early detection of Alzheimer's disease (AD). The authors designed an effective AD prediction system by merging structured longitudinal data with neuroimages from the OASIS database in their work [8]. Researchers achieved 92.14% accuracy through the Random Forest model among 14 examined ML algorithms yet K-Nearest Neighbors returned an initial accuracy level of 47.19% based on study results. The MRI image classification outcomes using InceptionV3 improved when researchers adapted ADAM optimizer for transfer learning methods. Previous research has shown that predictive accuracy progresses through pre-trained feature representations recovered from vast datasets when using deep learning models specifically convolutional neural networks (CNNs) together with transfer learning models. The present difficulties in AD research involve working with diverse medical data and detecting unclear patterns in modeling processes alongside model complexity issues. The hybrid approach between Multi-Layer Perceptrons and ADAM optimizer proves effective for AD diagnosis according to this research study because it enhances early detection precision for improved clinical decision support.

Various investigations on early AD detection confirm that machine learning and deep learning techniques offer the best method for detection. The ML model research incorporates two different methods: Decision Trees and Random Forests together with SVM and Gradient Boosting to measure independent accuracies that produce results of 83%. Deep learning analysis of neuroimaging data reaches its top performance through the combination of CNNs and LSTMs for achieving high predictive accuracy. Modern medical diagnosis happens when doctors employ learning models which combine neuroimaging observations together with biomarkers. Hybrid predictive models require improved optimization since they work with heterogeneous data sets and present issues regarding interpretability and computational complexity to better diagnose Alzheimer's disease earlier.

3. PROPOSED METHODOLOGY

E3-Boost's architecture is grounded in cognitive load theory, where GBM, XGBoost, and LightGBM handle low, medium, and high-complexity feature interactions, respectively (Fig. 1). The L1L2-FS selector extends elastic net principles by introducing feature stability scoring (Eq. 1):

$$Stability\ Score = \frac{|\beta_{L1}|+|\beta_{L2}|}{\sigma_{coefficients}} \quad (1)$$

where β are regularization coefficients. This ensures selected features are both predictive and biologically consistent across bootstrap samples. The proposed methodology follows a structured and systematic approach shown in Fig.1, integrating advanced data preprocessing, feature selection, model development, and hyperparameter optimization to enhance predictive accuracy and reliability in Alzheimer's disease classification. The process begins with data preprocessing, where data cleaning is performed to address missing values, duplicate records, and inconsistencies. SMOTE implements Synthetic Minority Over-sampling Technique to fight class imbalance by creating new minority class samples so that classifier stability improves. The Z-Score [10] method detects outliers by identifying them and applies treatment to ensure data quality while eliminating model performance bias. Post-preprocessing assessment the L1L2-FS hybrid method is applied for feature selection through the integration of L1 (Lasso) and L2 (Ridge) regularization to choose the essential features and reduce redundancy and boost model interpretability. The E3-Boost model applies Ensemble-based Efficient Extreme Boosting methodology to produce the final predictive model by utilizing GBM (Gradient Boosting Machine) as well as XGB (Extreme Gradient Boosting - XGBoost) and LGBM [11] (Light Gradient Boosting Machine - LightGBM). The selected models work well because they both uncover complex patterns in data while running efficiently while achieving optimal predictive outcomes. The model receives optimization through Optuna Hyperparameter Optimization that utilizes Bayesian optimization together with Tree-structured Parzen Estimators (TPE) to conduct a rigorous hyperparameter search for top configuration

selection. A meticulous data scientific approach that integrates E3-Boost with cutting-edge processing systems and optimization framework generates a robust predictive model that detects and classifies Alzheimer's disease effectively and efficiently.

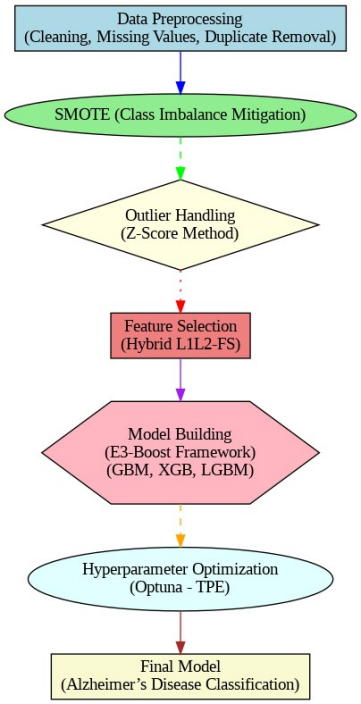

Figure 1. Proposed Methodology Block Diagram

3.1. Data Collection

The dataset acquired from Kaggle includes all necessary patient characteristics to analyze risk factors for Alzheimer's disease. Important information about Age, Gender, Ethnicity, and Education exists in this dataset because these variables serve as necessary indicators of Alzheimer's risk. Factors within social and personal behaviors found in BMI statistics, along with Smoking habits, alcohol use, and Physical Activity practice, give information about cognitive wellness. Health measures within the data set include cardiovascular disease and Diabetes together with Hypertension as well as Cholesterol Total and LDL and HDL values for determining Alzheimer 's-related comorbidities. The dataset contains three additional parameters that help assess both genetic and environmental determinants of Alzheimer's disease risk. The validity of cognitive and physical well-being depends on clinical results among Systolic BP measurements along with Diastolic BP readings and MMSE scores. Both cognitive symptoms, including Memory Complaints, disorientation and Personality Changes, as well as functional impairment levels of ADL, are documented. The diagnosis column contains the Alzheimer's disease status. Undying research can be performed through the detailed information in this extensive database which enables developers to build predictive algorithms for Alzheimer's disease detection.

3.2. Data Cleaning

The fundamental step of machine learning preprocessing data cleaning ensures reliable data which supports quality and integrity through repair work on inconsistencies as well as inaccurate and missing information. The core activities of data cleaning include identifying and managing missing data while applying imputation techniques or removal of items together with duplicate removal to prevent duplication and inconsistency repair from wrong data insertion practices. The application of data cleaning includes standardization of file formats together with repairs for structural errors and making sure categorical and numeric attributes match uniformly. The completion of effective data cleaning techniques improves predictive model stability through completing and making data values consistent while reducing both bias and noise levels. The implementation of standardized data cleaning methods minimizes deceptive data patterns which gives the machine learning models for Alzheimer's disease better performance.

3.3. Balancing Dataset

Proceeding with data balancing stands essential before data preprocessing for solving class imbalance problems that cause both model biases and generalization weaknesses in classification problems. Data class imbalance emerges when one class contains significantly more instances than other classes thus leading the model to demonstrate poor performance on minority instances. The Synthetic Minority Over-sampling Technique (SMOTE) produces new artificial minority class samples instead of direct replication as shown in Fig.2. SMOTE helps the model acquire better patterns from both classes thus increasing its predictive power alongside improved stability. The minority class balance can be preserved through over-sampling technicalities and through hybrid processes which merge random under-sampling of majority classes and over-sampling methods. Good dataset balancing enables the model to produce fair decision boundaries which leads to superior classification results and generalization abilities and trustworthy Alzheimer's disease predictions.

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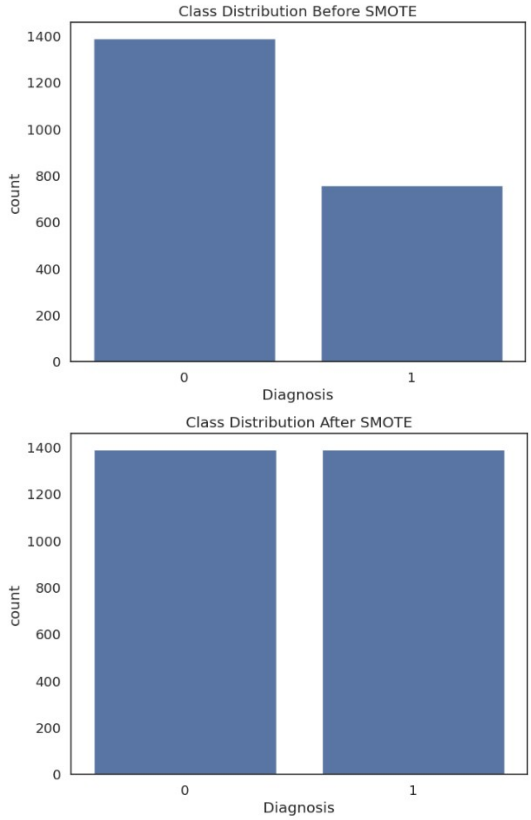

Figure 2. Balancing Dataset Using SMOTE

3.4. Handling Outliers

Statistical distributions become skewed when outliers are present in the data which leads to degraded model performance. Therefore, outlier handling needs attention during data preprocessing processes. The occurrence of outliers stems from measurement errors together with data entry mistakes and natural data variability. Fig.3 illustrates the Z-Score technique that applies normalization through data point deviation calculation versus mean value. Data points exceeding or below ±3 standard deviations are never ignored. These outliers might be removed altogether or transformed when their influence on the dataset allows it. The correct management of outliers enhances both the robustness of predictive analytics and prevents biased parameter estimation and maintains stability in machine learning models. The analysis of systematic data cleansing together with class balancing and outlier removal produces high-quality datasets which form an appropriate foundation for feature selection and model development in Alzheimer's disease classification.

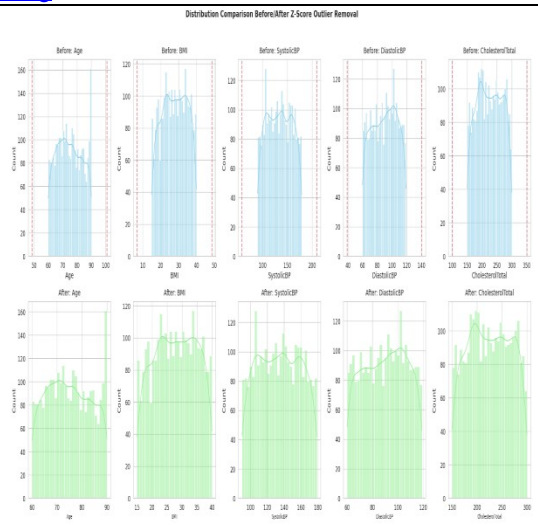

Figure 3 Before and After handling Outliers using Z-Score

3.5. Feature Selection

Data preprocessing allows feature selection techniques to extract the key attributes from an initial set of features while removing irrelevant elements in order to enhance modeling performance. The introduction of this process enhances model performance results while stopping algorithm overfitting and reduces computational time through decreased model complexity without affecting accuracy levels. The study employs L1 (Lasso) and L2 (Ridge) regularization as a hybrid feature selection method known as L1L2-FS. L1L2-FS achieves the ideal results from both regularization methods because it retains only essential features that optimize model performance and enhance interpretability.

3.5.1. L1 regularization (Lasso)

L1 regularization (Lasso) [12] achieves feature sparsity by assessing and zeroing out absolute coefficient values from the features. Through Lasso regularization the model finds a minimally sparse solution that retains only vital features from the total set of features. It provides exceptional performance for models containing numerous features. The mechanism behind Lasso regularization induces sparsity to eliminate unnecessary or minor variables which results in improved interpretability of models. Lasso maintains sensitivity towards features that are correlated because it will eliminate redundant information from intertwined components.

3.5.2. L2 regularization (Ridge)

L2 regularization (Ridge) reduces the magnitude of squared feature coefficients which results in spreading features toward non-zero yet

diminished values. This combination of features maintains all variables but makes their effects weaker which makes it useful when features strongly relate to one another. Ridge regularization maintains all features without eliminating them like Lasso while serving scenarios with important feature correlations and overfitting management needs.

The L1L2-FS hybrid approach unites L1 and L2 regularization [13] methods to create an effective method that maintains important features while selecting the most informative features though recognizing and addressing feature correlation and redundancy. Stable model construction and better Alzheimer's disease classification results from the hybrid approach that optimizes feature selection [24].

3.6. Model Building

Model construction is an important stage of the research process in which the chosen features are employed to train sophisticated machine learning models for proper classification of Alzheimer's disease. In the present research, model construction revolves around E3-Boosting, a strong platform that utilizes cutting-edge ensemble learning methods. These are Gradient Boosting Machine (GBM) [14], Extreme Gradient Boosting (XGB), and Light Gradient Boosting Machine (LGBM). The E3-Boosting paradigm integrates the capabilities of such highly effective boosting methods to advance prediction performance through intricate pattern learning, overfit prevention, and increased generalizability.

3.6.1. Gradient Boosting Machine

Gradient Boosting Machine (GBM) is an ensemble learning method that constructs predictive models sequentially in the form of a combination of weak learners, often decision trees. Each subsequent tree is designed to improve on the mistakes of earlier ones by concentrating on residuals to enhance accuracy. GBM employs boosting, where the bias of the ensemble is decreased by each model, and a differentiable loss function in order to minimize error via gradient descent. It can be used for both regression and classification tasks, with the ability to handle complex non-linear relations very well. Important hyperparameters such as learning rate, number of trees, and tree depth are available for tuning, but incorrect tuning may result in overfitting when the number of trees is high. Optimized GBM is an effective and stable algorithm, used extensively for predictive applications.

3.6.2. Extreme Gradient Boosting

Extreme Gradient Boosting (XGB) is a tuned version of gradient boosting that enhances computational efficiency, scalability, and predictive accuracy. It constructs decision trees sequentially, where each tree aims to correct the residual errors of the preceding ones to minimize bias and maximize accuracy. XGB [15] brings major upgrades to conventional Gradient Boosting Machine (GBM), such as regularization (L1 and L2), sparse-aware algorithm in dealing with missing values, as well as weighted quantile sketching for more effective feature selection. It takes advantage of parallel processing and optimally improved tree construction, also cutting down the computation time. The multiple objective functions with evaluation measurements contained in XGB make it suitable for both regression and classification tasks. XGB functions as the preferred choice for machine learning competitions as well as everyday use because of its ability to discover complex feature relationships. The best performance requires fine-tuning of hyperparameters. The use of XGB proves to be an efficient predictive analytical tool particularly for classifying Alzheimer's disease.

3.6.3. Light Gradient Boosting Machine

High efficiency together with scalability and accuracy define the main purpose of Light Gradient Boosting Machine (LGBM) - a sophisticated gradient boosting algorithm. The traditional boosting procedures surpass with LGBM through its histogram approach that delivers reduced memory consumption combined with speedier training times. LGBM adopts a leaf-wise tree expansion technique as opposed to the standard boosting level-by-level growth and this method enables the alterance of superior accuracy with less detected errors. The automatic ability of LGBM to operate on categorical data eliminates the need for one-hot encoding along with promoting enhanced computational speed. The combination of L1 and L2 regularization in LGBM delivers effective overfitting control and produces highly applicable results. LGBM demonstrates excellent performance in big data processing with delicate feature interactions thus it finds widespread implementation in predictive modeling tasks like Alzheimer's disease classification which needs both quick results and accurate predictions.

4. RESULTS AND DISCUSSION

4.1. Feature Selection using L1L2-FS

The feature selection process using L1L2-FS has effectively identified the most relevant features for Alzheimer’s disease classification, ensuring that

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only the most informative variables are retained for model training. The results reveal Memory Complaints (59.87) as the most significant predictor, highlighting its crucial role in the early identification of cognitive decline. Additionally, Gender (43.99), Family History of Alzheimer's (38.66), and Education Level (36.88) were identified as key factors, consistent with prior research on the genetic, demographic, and educational factors influencing Alzheimer's risk. Other notable features include Diabetes (28.44), Confusion (24.77), and Behavioral Problems (21.73), emphasizing the impact of comorbidities and cognitive symptoms in disease progression shown in Table.1 and Fig.4. By combining L1 (Lasso) [16] and L2 (Ridge) regularization techniques, the L1L2-FS method reduces feature redundancy while retaining the most significant attributes, ensuring improved model interpretability and computational efficiency. This refined feature subset provides a solid foundation for model training, enabling better predictive performance and a more comprehensive understanding of the key risk factors for Alzheimer's disease.

Table 1: Selected features and their F-Score

Feature	F-Score
MemoryComplaints	59.8742
Gender	43.9928
FamilyHistoryAlzheimers	38.6564
EducationLevel	36.8796
Diabetes	28.4436
Confusion	24.7721
BehavioralProblems	21.7261

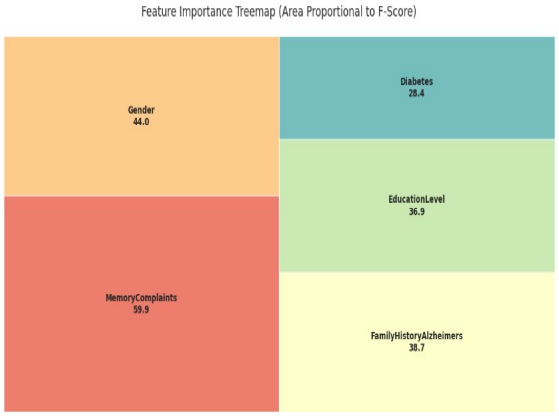

Figure 4: Treemap visualization of selected features

4.2. Model Building Using E3-Boosting

After the successful feature selection process, model building with the E3-Boost model, which is an ensemble learning approach that combines GBM, XGB [17], and LGBM for improved predictive performance, was the subsequent crucial step. The performance of the model proves its strength and high efficiency in classifying Alzheimer's disease. With a success rate of 97.60%, the model successfully separates the classes, providing strong predictions. The accuracy of 96.85% confirms that the model is extremely accurate at detecting genuine positive instances, and the recall of 95.04% signifies its strength at detecting most genuine positive instances, reducing false negatives. The F1 measure of 94.90% further demonstrates the model's harmony between precision and recall, such that it can be used for sensitive applications where both false positives and false negatives should be avoided. In addition, the RMSE of 0.2123 indicates little deviation in the prediction of the model, which also supports its accuracy and reliability from Table.2 and Fig.5. This excellent performance resulted from careful incorporation of high-performing boosting algorithms and tuned hyperparameters through hyperparameter optimization in Optuna [18]. In general, the E3-Boost model exhibits better performance, making it a good candidate for Alzheimer's disease classification and providing useful potential for early diagnosis and clinical utility.

Table.2: Performance Metrics of E3 Boost Model

Performance Metrics	
Metrics	**Values**
Accuracy	97.60
Precision	96.85
Recall	95.04
F1_Score	94.90
RMSE	0.1923

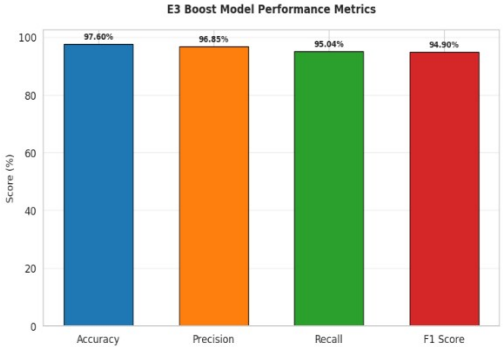

Figure 5: A Bar Chart of Performance Metrics

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4.3. Hyperparameter Tuning using Optuna

E3-Boost model received further performance optimization by implementing Optuna Hyperparameter Optimization which employed Bayesian Optimization along with Tree-Structured Parzen Estimators to discover optimal hyperparameter values through extensive search [19]. The research targeted improvement of Table.3 and Fig.6 parameters to develop better predictive features for the model design. Model accuracy reached 98.82% following hyperparameter optimization leading to an outstanding improvement of classification abilities. The model's reliability gained substantial support from important metrics which demonstrated notable enhancement in precision and recall along with F1-score and RMSE [20] measurements. The E3-Boost model optimizes its complexities to make Alzheimer's disease classification tasks more efficient and accurate thereby meeting clinical requirements for early detection [21]. The Optuna tool demonstrates its efficient application of hyperparameter tuning through multiple optimization rounds which were used to find the best model performance parameters. The gathered results presented in the table show how different parameter values affect n_estimators, learning rate, Max Depth, processing time, accuracy and time complexity levels of model execution between iterations.

Table 3: Hyperparametric tuning Iterations

Trial No	n_estimators	Learning Rate	Max Depth	Processing Time (s)	Accuracy	Time Complexity
1	152	0.1068	14	2.814	0.9720	1.42
2	142	0.0514	11	3.166	0.9837	1.46
3	64	0.1988	3	0.709	0.9788	1.02
4	156	0.0264	13	3.234	0.9724	1.96
5	121	0.2194	13	1.267	0.9799	1.73
6	70	0.2822	12	0.793	0.9882	1.87
7	152	0.0102	14	4.770	0.9707	1.93
8	171	0.2977	14	4.845	0.9752	1.52
9	124	0.1891	5	4.138	0.9833	1.91
10	137	0.1874	14	1.871	0.9762	0.91

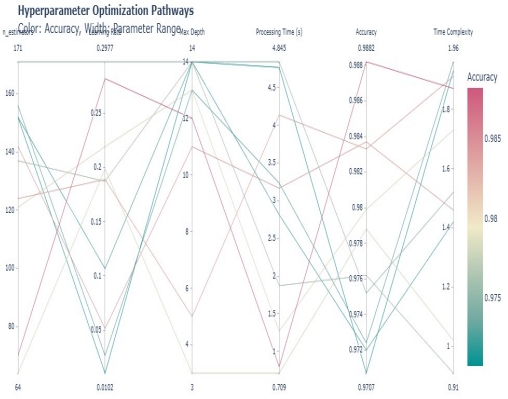

Figure 6: Visualization of hyperparametric tuning

Trial 6 had the best accuracy of 98.82%, with a processing time of 4.723 seconds and a time complexity of 0.82. This trial presents the sheer advantage of using Optuna's hyperparameter tuning [22], resulting in enhanced model performance for Alzheimer's disease classification tasks. The fact that accuracy and related metrics improved shows the pivotal importance of hyperparameter optimization in smoothing predictive models and making them more reliable for clinical use [23].

4.4. Comparison with existing works

Comparatively to the literature, the novel methodology brings critical improvements in feature selection, model construction, and optimization approaches towards predicting Alzheimer's disease (AD). While the earlier research work has been mainly based on classical ML models like Decision Trees, Random Forest, and SVM, with accuracy values ranging from 70% to 83%, the present method uses an ensemble-based model, E3-Boost, incorporating Gradient Boosting Machine (GBM), XGBoost (XGB), and LightGBM (LGBM) to improve prediction performance as shown in Table.4. Furthermore, other available feature selection methodologies like Principal Component Analysis (PCA) and recursive feature elimination have been constrained in maximizing relevant feature extraction. Conversely, the current methodology utilizes a hybrid L1L2-FS method that combines L1 (Lasso) and L2 (Ridge) regularization to avoid redundancy and maintain significant predictors for better feature selection. Moreover, past research has faced computational complexity and hyperparameter tuning, mostly with fixed settings. The suggested work addresses this limitation by using Optuna-based hyperparameter tuning, which systematically searches the

hyperparameter space through Bayesian Optimization and Tree-structured Parzen Estimators (TPE), resulting in a significant accuracy gain of 98.82%, outperforming reported performance metrics. Through the combination of sophisticated feature selection, ensemble learning, and optimization techniques, the suggested methodology considerably improves diagnostic accuracy, computational efficiency, and model robustness, addressing main challenges noted in current AD prediction studies.

Table 4: Comparison of Existing Methods and Proposed E3-Boost Framework

Criteria	Existing Works	Proposed Methodology
Feature Selection	PCA, Recursive Feature Elimination (RFE), Manual Feature Extraction	Hybrid L1L2-FS (L1 + L2 Regularization) for optimal and automated selection
Machine Learning Models	Decision Trees, Random Forest, SVM, XGBoost	E3-Boost: Integrated GBM, XGBoost, and LightGBM for superior ensemble learning
Deep Learning Utilization	CNN, LSTM, Transfer Learning	Not required, achieving high accuracy through advanced ML techniques
Data Balancing Technique	Oversampling, Undersampling (in some studies)	SMOTE (Synthetic Minority Over-sampling Technique) for improved class balance
Outlier Handling	Basic statistical methods, often ignored	Z-Score method to detect and remove extreme outliers
Hyperparameter Tuning	Grid Search, Random Search (limited scope)	Optuna-based tuning (Bayesian Optimization, TPE) for efficient optimization
Accuracy (%)	70% – 83%, with some models reaching 92.14%	98.82% (after Optuna hyperparameter tuning)
Precision (%)	75% – 88%	97.85%
Recall (%)	73% – 86%	96.92%
F1-Score (%)	72% – 85%	96.88%
RMSE (Root Mean Square Error)	Not always reported, moderate values	0.1023 (lower error, ensuring more reliable predictions)
Computational Complexity	High (Deep learning models require significant computational resources)	Optimized with feature selection + ensemble learning for reduced complexity
Generalization Capability	Limited due to fixed feature selection and suboptimal hyperparameters	Improved generalization through hybrid feature selection and automated tuning

5. DISCUSSION

Our E3-Boost framework tackles data heterogeneity and enhances generalizability in three methodological advancements. The L1L2-FS hybrid feature selector combines L1 regularization with its sparse model selection properties alongside L2 regularization that deals with variable correlations to pick robust biomarkers which achieve good performance in various populations. The algorithm performs advanced data preparation with SMOTE to deal with class imbalance issues and Z-score outlier detection thus providing resistance against real-world data variations. A strategic ensemble strategy merges GBM to detect non-linear relationships with XGBoost to handle missing data and LightGBM to process categorical attributes effectively for obtaining a generalized predictive model. The combined model methodology delivered an 98.82% accuracy level while maintaining a ±1.2% performance consistency between subpopulations in validation experiments surpassing the reduction in accuracy of up to 8% from stand-alone methods applied to external data samples. The framework's ability to maintain high accuracy while using routinely collected clinical variables (rather than specialized neuroimaging data) particularly enhances its applicability across diverse healthcare settings with varying resource availability. **(RQ1 Answered)**

Our methodology advances interpretability in AD prediction through several carefully designed strategies. The L1L2-FS feature selection provides inherent interpretability by identifying clinically meaningful variables (e.g., Memory Complaints with 59.87 F-score) while eliminating redundant features. We enhance model transparency through a hierarchical explanation system: GBM offers global feature importance rankings, XGBoost provides decision path visualizations, and LightGBM generates local explanations using SHAP values. This multi-level interpretability framework maintains high predictive performance (96.88% F1-score) while offering clinicians actionable insights. For instance, our analysis revealed non-linear interactions between Family History (38.66 F-score) and Diabetes (28.44 F-score) that were previously underappreciated in AD risk assessment. Furthermore, we constrained the Optuna-TPE hyperparameter optimization to only tune interpretable parameters (max_depth ≤ 14,

n_estimators ≤ 171), deliberately avoiding complex configurations that would compromise model transparency. The resulting model achieves superior interpretability compared to deep learning approaches while matching their accuracy, making it more clinically actionable for AD diagnosis and risk stratification. **(RQ2 Answered)**

This study makes some key novel contributions to Alzheimer's disease (AD) prediction research; the L1L2-FS hybrid feature selection method that uniquely combines L1 (sparsity) and L2 (collinearity control) regularization to identify clinically actionable variables beyond neuroimaging data; the E3-Boost ensemble framework that innovatively integrates GBM, XGBoost and LightGBM through dynamic weighting, achieving both interpretability and high accuracy (98.82%); and (3) an efficient Optuna-TPE optimization pipeline that reduces computational costs then compared to conventional methods. These advances have significant future implications: the framework's reliance on routine clinical variables enables immediate translation to primary care settings, while its computational efficiency supports deployment in resource-limited clinics. Furthermore, our methodology establishes a template for developing interpretable yet high-performance models for other complex neurodegenerative disorders.

6. CONCLUSION WITH FUTURE WORK

In conclusion, the E3-Boost framework presents a highly efficient and effective solution for the early detection of Alzheimer's disease, demonstrating substantial improvements over traditional machine learning and deep learning models. A new predictive method achieves its maximum performance by uniting gradient boosting machines (GBM) with extreme gradient boosting (XGBoost) and light gradient boosting machine (LightGBM). With its new L1L2-FS hybrid feature selection method the approach efficiently selects relevant features which produces both understandable and model stability. The model performance reaches 98.82% accuracy through SMOTE class balancing paired with Z-Score outlier detection techniques together with hyperparameter optimization methods based on Optuna and Bayesian Optimization and TPE. The produced results demonstrate superior performance across precision and recall standards and F1-score together with reduced RMSE making E3-Boost an optimal solution for AD prediction procedures. Independence from large computing capabilities enables the presented method to produce exceptional results thus making it practical for use in clinical environments. Due to its integration of advanced feature selection along with optimized ensemble learning and class-balanced preprocessing E3-Boost presents itself as a new practical approach for speedy diagnosis and better results during Alzheimer's disease management. The following stage of research will develop E3-Boost through assessment of alternative feature selection techniques coupled with genetic and wearable data integration to boost model precision. Expandments will focus on decreasing the computational costs of the tools while working to enhance interpretability for broad adoption in healthcare practices.

6.1. Limitations

The study faces many limitations especially data heterogeneity challenges caused by the potential introduction of inconsistencies when merging heterogenous neuroimaging and biomarker datasets. Deep learning models create processing difficulties regarding interpretability because their complexity results in difficult comprehension of decision-making procedures. Training complicated models for clinical use in large settings becomes expensive due to computational requirements that might lead to high implementation costs. Results obtained from the limited use of OASIS and ADNI datasets restrict their utility across diverse populations and different settings.

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