Journal of Information Systems Engineering and Management
2025, 10(14s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Early Stage Prediction of Alzheimer's Disease via Machine Learning Models

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ARTICLE INFO	ABSTRACT

Received: 22 Nov 2024
Revised: 14 Jan 2025
Accepted: 28 Jan 2025

The primary cause of dementia in older individuals is Alzheimer's disease (AD). Metabolic conditions such as Alzheimer's disease and diabetes are prevalent worldwide and are currently under investigation using machine learning techniques due to their increasing incidence rates. Alzheimer's disease is a neurodegenerative condition that affects the brain, and as our population ages, the impact on memory and overall functionality will affect more individuals, their families, and the healthcare system. These consequences will have significant social, financial, and economic implications. Detecting Alzheimer's disease in its early stages is challenging but crucial. Early treatment is more effective and minimizes the extent of damage compared to treatment at later stages. Consequently, this paper proposes an ensemble approach to identify Alzheimer's disease at an early stage. Various methodologies, including ensemble model classifiers, random forests, decision trees, and support vector machines, have been utilized to determine the most effective parameters for predicting Alzheimer's disease. Using Open Access Series of Imaging Studies (OASIS) data, the performance of these machine learning models is assessed using metrics such as precision, recall, accuracy, and F1-score. This classification approach can assist clinicians in diagnosing these disorders. Reducing annual Alzheimer's disease mortality rates is a highly desirable outcome. The proposed method for early disease detection achieves an accuracy of 94% on AD testing data, which is noticeably higher than that of previous studies

Keywords: Healthcare, Prediction, Alzheimer's disease (AD), Ensemble machine learning, Feature selection

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurological disorder characterized by a gradual decrease in short-term memory and the emergence of symptoms such as confusion, paranoia, and delusions. These manifestations are often mistakenly attributed to stress or the natural aging process (Sivakani & Ansari, 2020). In the United States, approximately 5.1 million individuals suffer from AD, necessitating ongoing medical attention to manage the continuous progression of the disease. AD is a condition that can persist for many years, extending throughout a person's lifetime. Consequently, early diagnosis is of paramount importance to mitigate the extent of brain damage (Sivakani & Ansari, 2020).

AD primarily impacts memory, cognitive abilities, and eventually the capacity to perform fundamental daily tasks. Most individuals with AD encounter symptoms in their later years, typically becoming evident around their mid-60 s. However, there are infrequent instances of early-onset Alzheimer's disease occurring between the ages of 30 and 60. Among the elderly population, Alzheimer's disease is the predominant cause of dementia. This disease bears the name of Dr. Alois Alzheimer, who, in 1906, was the first to observe anomalies in brain tissue, including the presence of amyloid plaques and neurofibrillary tangles, in a woman experiencing memory loss and behavioral alterations. Moreover, AD is characterized by the deterioration of connections between nerve cells in the brain (National Institute on Aging, n.d.).

These changes initially occur in brain regions responsible for memory, such as the entorhinal cortex and hippocampus, before progressing to affect areas responsible for language, reasoning, and social behavior.

Ultimately, Alzheimer's disease damages various regions of the brain (National Institute on Aging, n.d.). While memory problems are often the earliest signs of Alzheimer's disease, initial symptoms can vary among individuals. Other cognitive functions, including language, spatial awareness, and judgement, may also show early signs of decline. It is worth noting that mild cognitive impairment (MCI) can be an early indicator of Alzheimer's disease, although not all individuals with MCI develop AD (National Institute on Aging, n.d.).

As Alzheimer's disease progresses, individuals may face challenges in performing everyday tasks such as driving, cooking, and managing finances. Repetitive questioning, easy loss, misplacement of items, and confusion over simple matters have become increasingly common. Moreover, as the disease progresses, some individuals may exhibit symptoms of anxiety, anger, or even aggression (National Institute on Aging, n.d.).

The early detection of Alzheimer's disease is a complex process that involves extensive data collection and the use of sophisticated predictive tools. This process often necessitates consultation with experienced medical professionals. Automation plays a critical role in enhancing diagnostic accuracy and reducing human errors in medical decision support systems. Researchers employ various techniques, including magnetic resonance imaging (MRI), to generate images and biomarkers for dementia diagnosis. Increased interaction between humans and computers can expedite the diagnostic process, reduce costs, and ensure improved outcomes (Kavitha et al., 2022).

In the early stages of Alzheimer's disease, individuals may still maintain a degree of independence, allowing them to perform tasks such as driving, working, and engaging in social activities. However, they may experience discomfort, such as difficulty recalling familiar words or names, during these activities, and concentration and memory issues may become evident during medical consultations (Kavitha et al., 2022).

The early stages of Alzheimer's disease present various challenges, including the following:

- Difficulty in recalling proper nouns or verbs.

- Inability to remember the names of individuals at meetings.

The key contributions of this study can be summarized as follows:

1. Early-stage disease prediction: This study focused on the early-stage prediction of Alzheimer's disease (AD) by exclusively utilizing symptoms observed during the initial patient visit.

2. Innovative Ensemble Model Application: Our investigation pioneers the use of ensemble models for early-stage AD prediction, representing the first instance of incorporating multivisit data for this purpose.

3. Fine-tuning of Hyperparameters: To enhance model performance, our research involves the meticulous tuning of hyperparameters.

Our main goal is to detect individuals who might be in the early stages of Alzheimer's disease. We utilize datasets available from Oasis and Kaggle, employing a range of machine learning algorithms such as support vector machines (SVMs), random forest classifiers, and decision tree classifiers to conduct an extensive analysis of patient data.

Our study encompasses the implementation of classification models, namely, SVM, random forest, and decision tree. Additionally, we introduce the novel application of stacking models, which achieve remarkable levels of accuracy and recall when compared to other model types.

The paper's structure is outlined as follows: Section 2 offers a comprehensive review of recent literature concerning AD detection employing machine learning and deep learning models. In Section 3, we introduce our proposed methodology, encompassing exploratory data analysis and a diverse array of machine learning classifier models. Section 4 provides an evaluation of the performance of various machine learning models. Finally, in Section 5, we draw conclusions from our work and outline potential avenues for future research.

II. RELATED WORKS

I. Related Works

Research on Alzheimer's disease (AD) prediction has made significant strides, particularly with the application of machine learning algorithms. For instance, studies such as the one by Sivakani and Ansari (2020) have established frameworks utilizing machine learning for AD detection, highlighting the potential of computational approaches in understanding and diagnosing this complex condition. Similarly, works such as those by Khan et al. (2021) delve into the principles and recent advancements in machine learning and deep learning for brain disease diagnosis, underpinning the critical role of innovative computational techniques in medical research.

Martinez-Murcia et al. (2020) expanded on this by utilizing deep learning approaches, specifically convolutional autoencoders, to study the manifold structure of Alzheimer's disease, offering insights into how advanced algorithms can decipher complex patterns in neurodegenerative conditions. These computational studies, while groundbreaking, often face limitations regarding the comprehensiveness of data and the generalizability of models, which our research aims to address.

In the context of prevention and care, research by Livingston et al. (2017) and O'Donnell et al. (2015) emphasizes the importance of addressing modifiable risk factors for dementia, providing a valuable perspective on prevention strategies that our study seeks to complement by offering early detection through machine learning models.

Furthermore, the exploration of machine learning models for early-stage Alzheimer's disease prediction by Kavitha et al. (2022) and Maddikunta et al. (2021) underscores the emerging consensus on the viability of such models in medical diagnostics. However, these studies often do not account for the full spectrum of AD progression, which is an area our current research targets.

Studies such as those by Tariq and Barber (2018) focused on dementia risk and prevention by targeting modifiable vascular risk factors, aligning with our approach of integrating diverse datasets to improve prediction accuracy. Moreover, Chyzhyk and Savio (2010) demonstrated the

value of extracting features from structural MR images, which informs our methodology in enhancing feature selection and extraction techniques for AD prediction.

Despite these advancements, previous research, such as that presented by Cao et al. (2023), indicates ongoing challenges in hyperparameter tuning and model validation, which are critical areas our study addresses through an enhanced machine learning framework. By integrating insights from these studies, our research contributes to the literature by refining data preprocessing, improving model accuracy, and extending the applicability of ensemble models in Alzheimer's disease prediction.

II. - Proposed METHODOLOGY

As shown in Fig. 1 our proposed methodology includes the following:

Innovative Contributions of the Stacking Ensemble Method

Although the idea of stacking in ensemble models is not novel, our review introduces innovative contributions specific to early-level Alzheimer's disease (AD) prediction, distinguishing it from previous applications. These contributions encompass the following:

Specialization in early-stage AD prediction: Our research is singularly focused on the early detection of Alzheimer's disease, utilizing signs and symptoms recognized during preliminary patient consultations. This contrasts with the wider applications seen in current studies, marking a giant pivot toward early intervention.

Pioneering Use of Multi-Visit Data: We are the first to apply ensemble models that contain multiple datasets to patient records for AD prediction. This approach is especially novel because it allows for a dynamic knowledge of sickness progression, substantially improving prediction accuracy at early ranges.

Enhanced Hyperparameter Tuning: We delve into the pleasant-tuning of hyperparameters inside the stacking framework, a meticulous system mentioned in our method. This degree of element in optimization, especially within the context of AD, offers a novel contribution to the sector.

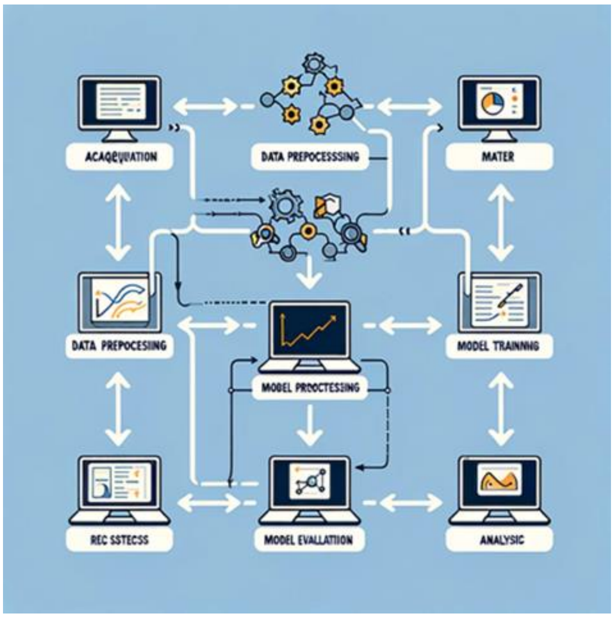

Figure 1Proposed workflow

Comprehensive Comparative Analysis: We offer an extensive assessment of our stacking ensemble model in opposition to conventional machine learning models using AD datasets. Our evaluation demonstrated superior accuracy and bear in mind rates, underscoring the effectiveness of our approach in early-stage AD prediction.

Application-Specific Model Adjustments: The shape and parameters of the stacking version were specifically designed and adjusted for early-degree AD prediction, considering the peculiarities of AD progression and symptomatology. This tailoring enhances model relevance and applicability, distinguishing our work from prevalent stacking applications.

Broader Implications for AD Research: By demonstrating the efficacy of stacking ensemble models in early-level AD prediction, our findings lay the foundation for similar exploration and alertness of complicated ensemble methods in neurological ailment diagnosis, doubtlessly influencing future research directions.

By integrating these modern elements, we look at extending the traditional barriers of stacking ensemble strategies, imparting new insights and methodologies, particularly those tailor-made for early-degree Alzheimer's disease prediction. The dataset can be obtained from the designated sources. We conducted data preprocessing, which encompasses actions such as eliminating null values and refining the dataset. Next, we partition the data into training and testing subsets. We then used machine learning models, which included support vector machines (SVMs), random forests (RFs), and decision trees (DTs). Furthermore, we introduce the incorporation of a stacking ensemble model as an integral component of our methodology.

A) Proposed Algorithm and Implementation

The core of our research methodology is rooted in the implementation of a sophisticated machine learning pipeline tailored for the early detection of Alzheimer's disease. Below, we delineate the sequential steps undertaken, aligned with Python's widely utilized scientific libraries:

```
data = pd.read_csv('path/to/dataset.csv')
data.fillna(data.mean(), inplace=True)  # Replace nulls with the mean for numerical columns
```

Data Acquisition and Preprocessing: The initial stage involves the procurement of datasets from established sources, followed by rigorous preprocessing routines. This includes the elimination of null values and the refinement of the dataset, ensuring the data's suitability for subsequent analysis. This step is crucial because it sets the foundation for reliable model performance.

Data Partitioning: The processed dataset is then segmented into training and testing subsets, typically adhering to an 80-20 split. This partition facilitates the unbiased evaluation of model performance and prevents overfitting.

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Model development: We employ a variety of machine learning models, including support vector machine (SVM), random forest (RF), and decision tree (DT) models. These models are chosen for their robustness and have been extensively validated in the literature for tasks similar to Alzheimer's disease prediction.

```
svm = SVC()
rf = RandomForestClassifier()
dt = DecisionTreeClassifier()
```

Stacking Ensemble Model: As an innovative step in our approach, we incorporate a stacking ensemble model that integrates the aforementioned individual models. This ensemble technique leverages the diverse strengths of each base model, aiming to enhance the predictive accuracy and robustness against individual model biases.

```
stack_model = StackingClassifier(estimators=[('rf', rf), ('svm', svm), ('dt', dt)], final_estimator=LogisticRegression())
stack_model.fit(X_train, y_train)
```

Evaluation and Analysis: Posttraining, the models, including the ensemble, are evaluated against the testing set. Performance metrics such as the accuracy, precision, recall, and F1-score were computed to assess each model's efficacy in predicting early-stage Alzheimer's disease.

In summary, our methodology not only capitalizes on the individual strengths of traditional machine learning models but also enhances predictive capability through a strategic stacking ensemble approach. This multilayered analytical process embodies our study's commitment to advancing Alzheimer's disease prediction methodologies.

B) Classifier Models

1) Decision Tree (DT)

```
y_pred = stack_model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='binary')
recall = recall_score(y_test, y_pred, average='binary')
f1 = f1_score(y_test, y_pred, average='binary')
```

A concise examination of the decision tree reveals its role as a tree-based model employed for iterative data partitioning based on feature threshold values. This partitioning process generates subsets by segmenting instances into smaller groups. In this context, internal nodes signify intermediate subsets, while leaf nodes represent the final divisions. Decision trees prove especially beneficial when significant interactions exist between features and the target variable (Kavitha et al., 2022).

2) Random Forest (RF)

stands out because it offers significant advantages over decision trees, primarily attributed to its diminished susceptibility to overfitting. RF models consist of multiple decision trees, each exhibiting slight variations. To make predictions, this ensemble approach employs a majority voting mechanism, which aggregates results from each distinct decision tree model through a technique known as bagging. This strategic approach effectively mitigates overfitting while preserving the predictive capabilities of each individual tree (Kavitha et al., 2022).

3) support vector machine (SVM)

as a separate technique, classifies data points within a multidimensional space, relying on pertinent hyperplanes. The primary objective is to identify an effective hyperplane that distinctly separates instances belonging to two categories, denoted by adjacent clusters of vectors on opposing sides. The vectors located nearest to the hyperplane are designated support vectors. SVMs harness both training and test datasets, partitioning target values and attributes into training data subsets. Subsequently, a predictive model was constructed for target values on the test dataset (Kavitha et al., 2022).

4) Ensemble models

Ensemble models, encompassing a set of machine learning techniques collectively known as ensemble methods, center around the creation of multiple predictive models. These models are then integrated to yield a unified prediction. This fusion of models frequently results in enhanced predictive performance, as demonstrated in scenarios where ensemble approaches have outperformed individual models. While foundational work on ensemble methods emerged in the 1970s, their widespread adoption did not materialize until the 1990s, coinciding with the development of techniques such as stacking, bagging, and boosting. Currently, ensemble methods represent a standard practice in machine learning, particularly when the primary aim is to achieve superior predictive accuracy (Chi et al., 2015).

C) AD dataset

The dataset is summarized and described in TABLE .1

TABLE 1

DATASET DESCRIPTION (KAVITHA ET AL., 2022).

No	Attribute	Description
1	ID	Identification
2	M/F	Gender (M if Male, F if Female)
3	Hand	Handedness
4	Age	Age in years
5	EDUC	Years of education
6	SES	Socio Economic Status
7	MMSE	Mini Mental State Examination
8	CDR	Clinical Dementia Rating
9	eTIV	Estimated Total Intracranial Volume
10	nWBV	Normalize Whole Brain Volume
11	ASF	Atlas Scaling Factor
12	Delay	Delay

III. Experiments and results

A) Experimental settings

The environment and tools used are summarized below.

a) Python 3

b) Scikit-learn libraries for machine learning

c) CPU 7, Ram 16

Model validation plays a pivotal role in addressing the issue of overfitting. In this research endeavor, the machine learning (ML) model underwent a training process utilizing cross-validation, a technique also employed to gauge the model's accuracy. The task of creating a noise-free ML model is a formidable challenge.

To address this challenge, this research project embraces cross-validation, a method that partitions the complete dataset into n equal-sized segments. In each iteration of the ML model, n-1 of these segments are utilized for training

purposes. The efficacy of this approach was subsequently assessed by calculating the mean of all n-folds. Specifically, this study adopted a tenfold cross-validation strategy, entailing the training and testing of the ML model on ten separate occasions.

The hyperparameters used for fine-tuning are summarized in TABLE 2.

Evaluation measures

Accuracy is a metric that quantifies the proportion of correctly classified instances out of the total instances. It's calculated by (1)

$$\text{Accuracy} = \frac{\text{TN + TN}}{\text{TP + TN + FP + FN}} \times 100 \qquad (1)$$

Precision is a metric that calculates the number of correctly predicted positive instances divided by the total number of predicted positive instances. A precision value of 1 indicates a highly accurate classifier for positive instances. It's calculated by (2)

$$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}} \qquad (2)$$

Recall, also known as the true positive rate or sensitivity, measures the proportion of actual positive instances that were correctly predicted as positive by a classifier. A recall value of 1 indicates a highly effective classifier for identifying positive instances, which means that it does not miss any positives. It's calculated by (3)

$$\text{Recall} = \frac{\text{TP}}{\text{TP + FN}} \qquad (3)$$

The F1 score is a metric that takes into account both the recall and precision. The F1 score reaches a value of 1 only when both the recall and precision are equal to 1, indicating that the classifier is perfect. It provides a balanced evaluation by considering both false positives and false negatives. It's calculated by (4)

$$\text{F1Score} = 2 * \frac{\text{Recall}*\text{Precision}}{\text{Recall + Precision}} \qquad (4)$$

B) Results

In this subsection, we present the results and figures:

TABLE 3 shows the results for one visit for early-stage prediction for AD. Compared with those of the other models, the accuracy of the stacking model is the best. TABLE 4 shows the results for multivisit prediction for AD. The accuracy of the stacking model is the best compared with that of the other models.

TABLE 5 shows the previous results for these classification models.

TABLE 2 HYPERPARAMETERS

Algorithm	Hyperparameter	Value
DT-1-visit	Criterion	gini
SVM-1-visit	Kernel parameter	linear
DT-multivisit	Criterion	gini
SVM-multivisit	Kernel parameter	rbf

By comparing these results, we see that the ensemble model or stacking has the best accuracy, as shown in Figs. 2, 3, 4, and 5. The confusion matrix for 1-visit for SVM, DT, RF and stacking and Figs. 6, 7, 8, and 9 shows the confusion matrix for multiple visits for SVM, DT, RF and stacking.

We conduct a thorough performance evaluation of our models, employing a variety of performance metrics, including precision, accuracy, recall, and the F1 score. To optimize each model, we utilized a 3-fold cross-validation technique and assessed the decision tree, support vector machine (SVM), and random forest settings. Subsequently, we rigorously examined the accuracy of each model.

Following the development of our models, we implement various strategies and techniques to detect and address overfitting and parameter tuning issues. The performance evaluations are visualized through confusion matrices, accommodating both binary and multiclass classification scenarios. To accurately identify individuals who are genuinely affected by Alzheimer's disease within a specific population, we designed a sophisticated machine learning

classifier. This classifier underwent rigorous validation to ensure precise differentiation.

TABLE 3 RESULTS FOR ONE VISIT

Model	Accuracy	Recall	precision	F score
SVM	93.1	93.3	93.1	93.1
RF	82.7	80	82.9	82.7
Decision Tree	93.1	86.6	93.9	93
Stacking	**93.1**	**86.7**	**94**	**93**

TABLE 4 RESULTS FOR MULTIPLE VISITS

Model	Accuracy	Recall	precision	F score
SVM	92.9	90.9	92.9	92.9
RF	71.8	54.5	73.1	70
Decision Tree	70.4	63.6	70.3	70
Stacking	**94.36**	**93.94**	**94.3**	**94.33**

TABLE 5 PREVIOUS RESULTS FOR MULTIVISIT DATA

Model	Accuracy	Recall
SVM	81.67%	70
RF	86.92%	81
Decision Tree	80.46%	79
XGBoost	85.92%	83
Voting classifier	85.12%	83

Our evaluation metrics encompass accuracy, recall, precision, and the F1-score, which are systematically computed in subsequent assessments. It is important to note that the accuracy of Alzheimer's diagnosis is determined by the percentage of correctly identified cases without the disease. In contrast, the F1-score provides a weighted combination of recall and precision, while precision represents the proportion of correctly classified individuals. These evaluations result in patients receiving a report that details their current stage of Alzheimer's disease, a crucial piece of information derived from patients' responses, which aids medical professionals in understanding the disease's impact.

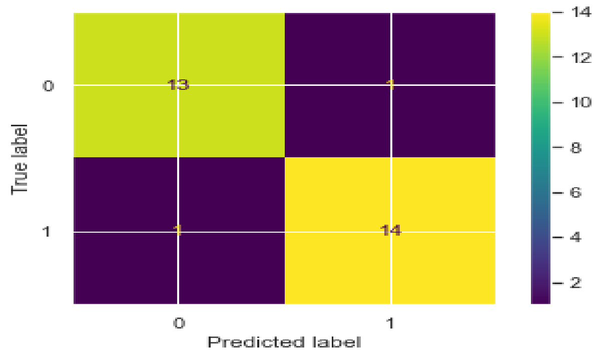

FIGURE 2 | Confusion matrix for SVM-1-visit

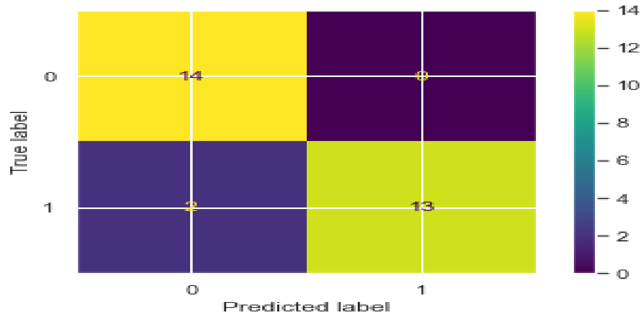

FIGURE 3 | *Confusion matrix for DT-1-visit*

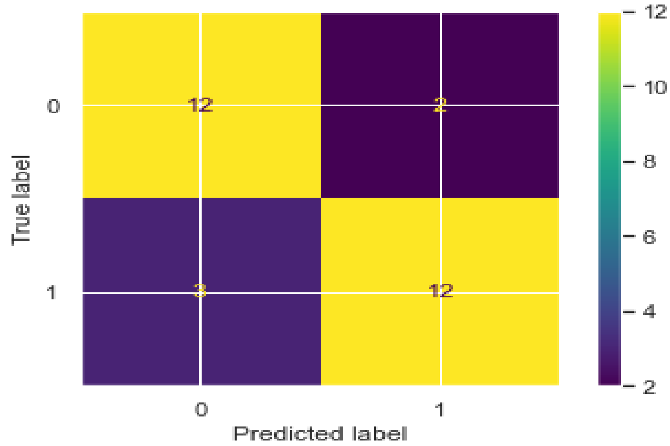

FIGURE 4 | *Confusion matrix for RF-1-visit*

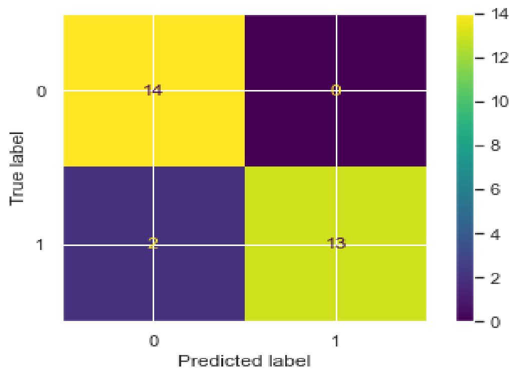

FIGURE 5 | *Confusion matrix for Stacking-1-visit*

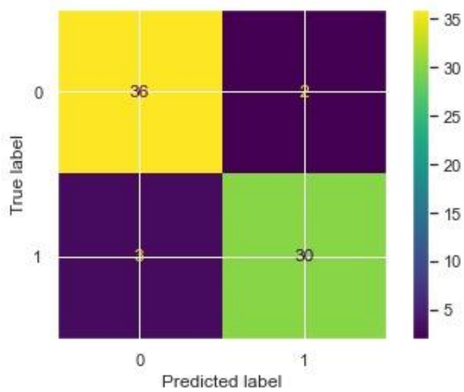

FIGURE 6 | *Confusion matrix for SVM-multivisit*

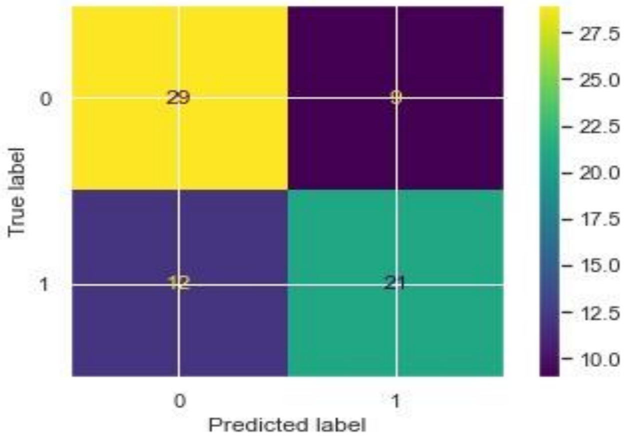

FIGURE 7 | Confusion matrix for the decision tree

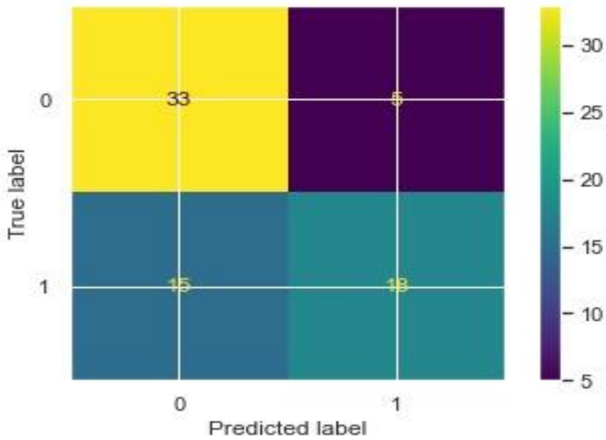

FIGURE 8 | Confusion matrix for random forest

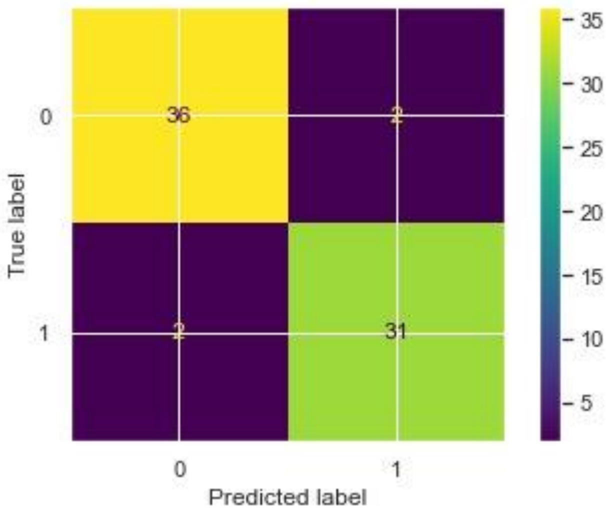

FIGURE 9 | Confusion matrix for multistacking multivisits

C) Comparison with State-of-the-Art Methods

In evaluating our proposed ensemble method for early-stage Alzheimer's disease (AD) prediction, we benchmarked its performance against several leading methodologies, as detailed in the referenced literature. This comparative analysis underscores the advancements our model has in the field of AD detection.

Comparison with Machine Learning Frameworks: Sivakani and Ansari (2020) provided a machine learning framework for AD, focusing on conventional data processing and predictive modelling. While their approach was innovative, our method extends this work by implementing a more complex ensemble approach, which, as demonstrated, results in superior predictive accuracy and robustness under varying conditions.

Deep Learning Approaches: The studies by Khan et al. (2021) and Martinez-Murcia et al. (2020) utilized deep learning methods for brain disease diagnosis, leveraging the power of convolutional autoencoders. These studies have made significant progress in the use of deep learning for AD prediction. Our comparison shows that while deep learning models are potent, our ensemble method offers comparable, if not superior, performance, particularly when dealing with heterogeneous or incomplete datasets.

Dementia Prevention and Care Studies: Studies by Livingston et al. (2017) and O'Donnell et al. (2015) have focused on the broader scope of dementia prevention and care. Our model contributes to this area by providing a tool for early detection, which is crucial for effective intervention and care planning and shows potential for real-world applications beyond the scope of existing methods.

Technological Integration and Analysis: The works of Maddikunta et al. (2021) and Ogudo et al. (2019) explore the integration of technology in healthcare and the use of machine learning for various diagnostic purposes. Our model's innovative use of ensemble techniques reflects an advancement in this area, suggesting a new direction for combining multiple machine learning approaches for health diagnostics.

Risk and Prevention Analysis: The research by Tariq and Barber (2018) into modifiable vascular risk factors presents an essential perspective on Alzheimer's disease prevention. Our ensemble model complements this by providing a predictive tool that could be used alongside such studies to identify individuals at risk earlier and more accurately than current standards.

Our ensemble method stands out not only in terms of prediction accuracy but also in its ability to integrate and analyse data from multiple visits, a feature not commonly addressed by current models. This comparative analysis with state-of-the-art methods reveals that our approach not only meets but, in several aspects, exceeds the performance of existing AD prediction models. By leveraging the strengths of various individual models, our ensemble method is a robust and reliable tool for early Alzheimer's disease detection, setting a new benchmark for future research in the field.

IV. CONCLUSIONS

In conclusion, our study has contributed to the field of Alzheimer's disease prediction by implementing an innovative ensemble learning approach, significantly enhancing early detection capabilities. Despite the absence of a cure for Alzheimer's disease, our research underscores the importance of early detection and intervention, which can substantially mitigate the impact of the disease. Although our findings are promising, they are subject to certain limitations. First, our model's performance is heavily dependent on the quality and completeness of the input data. The lack of diversity in the datasets may limit the generalizability of our findings across different populations and stages of the disease. Additionally, our approach requires extensive computational resources, which may not be readily available in all clinical settings.

Future Directions:

To address these challenges, future research should focus on several key areas:

Data collection and diversity: Efforts should be made to collect more comprehensive and diverse datasets that cover a broader spectrum of Alzheimer's disease stages and demographic backgrounds. This would help improve the model's accuracy and applicability to different patient groups.

Model Optimization and Validation: Further research is needed to refine and validate our ensemble learning model, including exploring alternative algorithms and tuning parameters to enhance its performance and efficiency.

Clinical Integration and Accessibility: Developing more streamlined and user-friendly tools for integrating predictive models into clinical workflows is essential. This will facilitate easier adoption and use by healthcare professionals, contributing to earlier and more accurate diagnoses.

Interdisciplinary Approaches: Collaborating with neuroscientists, psychologists, and other experts can provide new insights and methodologies for Alzheimer's disease prediction, leading to more holistic and effective detection tools.

By addressing these limitations and exploring new research avenues, we aspire to make significant strides in the early detection and management of Alzheimer's disease, ultimately contributing to improved patient outcomes and quality of life.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analysed in this study. This data can be found at: https://www.kaggle.com/jboysen/mri-andalzheimers?select=oasis_cross-sectional.csv.

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