RESEARCH ARTICLE

The study of language cognition and syntactic processing in Alzheimer's disease patients

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Alzheimer's disease, a crippling neurodegenerative condition, necessitates accurate staging for efficient management and treatment. Previous techniques for predicting Alzheimer's stages are often inaccurate and fail to capture complicated cognitive patterns. These conventional approaches may not fully tackle the nuances of cognitive decline, leading to suboptimal outcomes. To tackle these drawbacks, this study developed and verified a stacked ensemble model, AlzStack, to enhance the accuracy of predicting Alzheimer's stages. AlzStack combined three base classifiers including random forest (RF), support vector machine (SVM), and gradient boosting machine (GBM) with a logistic regression (LR) meta-classifier in a stacking framework. The model was advantaged from thorough hyperparameter tuning and extensive data preprocessing such as mean imputation and min-max scaling. The results demonstrated that AlzStack surpassed previous models in terms of accuracy, precision, recall, F1-score, and Matthew's correlation coefficient (MCC). The results also showed that AlzStack provided a more dependable and efficient technique for Alzheimer's stage prediction, underscoring its possibility for enhanced diagnostic and therapeutic tactics. This research improved detection accuracy and informed more efficient Alzheimer's disease treatment tactics by utilizing the AlzStack model.

Keywords: Alzheimer's disease; stacked model; prediction accuracy; base classifiers; meta classifier; hyperparameter tuning.

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Introduction

Alzheimer's disease (AD) is a neurodegenerative disorder that causes progressive deterioration of cognitive skills such as memory, reasoning, and language capabilities [1]. It primarily impacts the elderly and creates major obstacles in research and clinical environments. The precise staging of Alzheimer's disease is essential for developing efficient treatment tactics, tracking the progression of the disease, and executing suitable interventions [2]. Early and accurate classification of disease stages allows personalized care and customized therapeutic techniques that are vital to improving patient results [3]. Despite advances in neuroimaging methods and cognitive evaluation tools, predicting and staging Alzheimer's disease remains difficult [4]. Conventional techniques for Alzheimer's stage prediction have used fundamental statistical models and machine learning approaches [5], which frequently use linear classifiers, decision trees, or other basic algorithms, and may not fully capture the complex trends of cognitive decline seen in Alzheimer's patients. The constraints of these traditional models comprise insufficient management of high-dimensional and noisy data, decreased accuracy, and inadequate generalizability across various patient cohorts.

Current advances in machine learning (ML) have substantially improved the early detection and classification of Alzheimer's disease, indicating a shift toward more advanced techniques for diagnosis. Researchers investigated the utilization of machine learning and principal component analysis (PCA) for Alzheimer's disease (AD) prediction and developed a novel technique by combining PCA for dimensionality reduction, improving the efficiency of classification algorithms, while using import vector machine (IVM), regularized extreme learning machine (RELM), and support vector machine (SVM) on structural magnetic resonance (sMR) imaging data to enhance early AD diagnostic accuracy. The results showed that RELM, when paired with feature selection, substantially improved classification accuracy, efficiently differentiating between AD, mild cognitive impairment (MCI), and normal controls [6]. Saied *et al*. used various techniques and random forest (RF) signals captured through antennas positioned around the head to track variations related to AD and checked the possibility of combining machine learning with RF signal processing by implementing machine learning algorithms to S-parameter data. This non-invasive method was a new technique that provided a patient-friendly substitute for conventional imaging-based diagnosis. The high accuracy in this study emphasized the possibility of RF signal processing to present effective and less intrusive diagnosis solutions for AD [7]. Further, Battineni *et al*. sophisticated the area by utilizing multimodal machine learning algorithms to improve AD detection from MRI data through the framework combined with numerous supervised classifiers and demonstrated that gradient-boosting algorithms outperformed others, which highlighted the significance of integrating numerous data sources, like various MRI modalities and applying different machine learning methods to enhance diagnosis accuracy [8]. The utilization of multimodal data and various classifiers represents an important step ahead in improving AD detection techniques. Franzmeier *et al*. developed a model to forecast cognitive decline in AD based on inherited AD biomarkers, which used support vector regression and included data from multiple biomarkers such as cerebrospinal fluid, MRI, amyloid-PET, and FDG-PET. This extensive model sought to forecast cognitive decline rates, demonstrating its ability to improve clinical study by decreasing sample size needs. The study emphasized the importance of incorporating different biomarkers and sophisticated ML methods to improve forecasts about cognitive decline and enhance research and treatment tactics [9]. IN addition, Li *et al*. conducted an extensive survey of ML uses in different AD research domains such as disease categorization, repurposing drugs, subtyping, and biomarker identification to focus on both the difficulties and chances provided by high-dimensional omics and imaging data. The results highlighted how machine learning methods could efficiently incorporate diverse data sources to improve comprehension and management of AD and the transformative possibilities of ML in tackling various aspects of AD research and treatment [10]. Diogo *et al*. created a multi-diagnostic ML classifier that performed well across diverse datasets and MRI protocols with a highly balanced accuracy and Matthew's correlation coefficient when differentiating between normal controls and AD patients. The results emphasized the possibility of developing versatile diagnosis tools that could be implemented in various medical environments, rendering them more flexible and helpful in everyday situations [11]. Khan *et al*. also presented an improved multi-modal ML technique that incorporated a variety of data sources including MRI images and clinical outcomes, which performed well with the RF model and reflected an increasing focus on integrating numerous modalities to enhance diagnosis and early identification of AD. The results showed the efficiency of incorporating various kinds of data and models to attain more precise and early identification of AD, resulting in advances in diagnosis methodologies [12]. Bogdanovic *et al*. investigated the use of explainable ML models to present deeper insights into AD using XGBoost and Shapley values and attained high efficiency and provided valuable interpretability of feature significance in AD diagnostic. This method tackled the requirement for transparency in machine learning models, allowing clinicians to effectively comprehend the factors impacting predictions and aiding informed choices during the process of diagnosis [13]. Park *et al*. explored the possibility of utilizing comprehensive health records for AD risk prediction and early diagnosis with the machine learning models including random forest and support vector machines. The results showed the possibility of incorporating enormous quantities of actual-world information into predictive models for more efficient AD handling [14]. Chang *et al*. performed a meta-analysis on the utilization of machine learning and new biomarkers for AD diagnosis emphasizing the growing role of ML in improving accuracy in diagnosis by analyzing cognitive tests, imaging, and cerebrospinal fluid biomarkers. The results highlighted the importance of ongoing creativity in this area to enhance diagnostic precision and comprehension of AD and emphasized current developments and the significance of incorporating novel biomarkers and machine-learning methods to improve the area of AD diagnosis [15].

The previous AD staging techniques frequently show the low precision and struggle to capture intricate cognitive decline trends, which usually depend on a single classifier and do not take full advantage of the various features required for precise forecasting. To tackle these drawbacks, this research proposed a stacked ensemble approach, AlzStack model, to improve the accuracy and dependability of AD stage prediction and surpass the limitations of current techniques in capturing intricate cognitive trends using combined numerous classifiers with a meta-classifier to present a powerful predictive tool. This research proposed a new ensemble model designed especially for AD stage prediction, which would outperform previous techniques in terms of prediction accuracy, precision, recall, F1-score, and Matthew's correlation coefficient (MCC) and offer insights into the model's practical uses, especially in clinical environments where precise disease staging was crucial for personalized treatment and management.

Materials and methods

Dataset and data processing

Cognitive linguistic Alzheimer's dataset was used in this study, which was specially curated to aid in the prediction of Alzheimer's disease stages with a concentration on different linguistic and cognitive features associated with disease progression. A total of 13 features were covered by the dataset including patient ID, sentence length, grammar errors, word finding difficulty, complex sentence use (%), speech pause frequency, repetition count, vocal fluency, pronoun utilization (%), comprehension score, semantic errors, memory recall score, and Alzheimer’s stage. These features aided in capturing the linguistic and cognitive shifts associated with Alzheimer's disease progression. The dataset was compiled from clinical observations of patients with Alzheimer's disease at various stages. Each patient's speech pattern and cognitive skills were evaluated, and the resultant data contained important indicators that might indicate the seriousness of Alzheimer's. By evaluating these features, the proposed AlzStack model could accurately forecast the Alzheimer's stage, leading to superior diagnostic and patient care. The dataset was first cleaned and prepared for modeling by using mean imputation, where missing values were replaced by the mean of the relevant feature. Mathematically, for a feature F with missing values, each missing value was replaced with the mean $\bar{F}$ of the non-missing values of that feature shown as follows.

$$\bar{F} = \frac{1}{n}\sum_{i=1}^{n} F_i \quad (1)$$

where $\bar{F}$ was the mean of non-missing values of the feature. $\sum_{i=1}^{n} F_i$ was the sum of all the non-missing values of that feature. *n* was the count of those non-missing values. This technique guaranteed that the data was balanced and that the lack of specific values did not skew the model's findings. After addressing missing values, the next stage was to scale numerical attributes, which was accomplished through min-max scaling that normalized the attributes by scaling them within the range [0, 1] with the equation as follows.

$$F' = \frac{F - F_{min}}{F_{max} - F} \quad (2)$$

where F was the original feature value. F_{min} and F_{max} were the minimum and maximum values of the feature. F′ was the scaled value. This normalization procedure was required for algorithms such as SVM, which were sensitive to feature magnitudes. Bringing all attributes to a common scale allowed the model to better comprehend and analyze the data, resulting in enhanced efficiency and more precise predictions. The dataset was divided into training and testing sets with 80% of the data as training set and 20% as testing set. The training set was utilized to develop and fine-tune the model, while the testing set assessed the model's generalization efficiency on previously unseen data.

Base classifiers

The proposed AlzStack Model consisted of three base classifiers including RF, SVM, and gradient boosting machine (GBM), each with their own set of strengths to tackle the dataset's intricacy. These classifiers were chosen based on their capacity to deal with different elements of the data and enhance overall model efficiency. RF was a powerful ensemble learning algorithm that generated numerous decision trees while training. Each tree in the forest was trained on a randomly selected subset of the data and features, which assisted decrease overfitting, a common problem with intricate models. The ultimate classification decision was made by combining the results of all individual trees, usually through majority voting. This approach was especially useful for managing datasets with a large number of features and guaranteed that the model was robust to noise and variability in the data. The SVM was an effective classifier that sought the optimum hyperplane that divided various classes in the feature space. SVM excelled in circumstances where classes were separated, and it was especially good at operating in high-dimensional spaces, which rendered it ideal for capturing complex relationships within the dataset like those relating to linguistic features. SVM improved the model's accuracy in classifying complicated data points by concentrating on the most important boundaries between classes. GBM was another efficient ensemble learning technique that created a series of weak learners, usually decision trees, with each new learner attempting to fix the mistakes made by the prior ones. This sequential technique enabled GBM to incrementally enhance the model's accuracy by tackling the drawbacks of previous iterations. GBM was especially effective for datasets with complicated feature interactions as it might optimize the model's efficiency by concentrating on difficult-to-predict instances and thus improving the overall predictive accuracy. These base classifiers worked together to present an extensive modeling technique, utilizing their capabilities to enhance the AlzStack model's capability to manage various and complicated datasets.

Metaclassifier

In the proposed AlzStack model, the logistic regression (LR) served as the meta-classifier, making the ultimate decision within the ensemble framework. LR had the responsibility for combining the predictions produced by the base classifiers and generating the final classification decision. LR was chosen because it was simple and effective in both binary and multi-class classification tasks. Despite its simplicity, LR was an effective tool for modeling the likelihood of a specific outcome using input features, which operated by estimating the relationship between the predictors and the target feature utilizing a logistic function and yielded probabilities that could be utilized to calculate class memberships. The main objective of meta-classifier was to combine and weight the predictions of the base classifier. Each base classifier provided its view of the data, and LR was tasked with determining the best way to integrate these diverse predictions to improve overall model accuracy and assisted in mitigating the individual shortcomings of each base classifier and enhanced the ensemble model's effectiveness. This technique took advantage of LR's capability to efficiently manage both linear and non-linear relationships, rendering it ideal for integrating the base classifiers' diverse results to produce a more resilient and precise final forecast that took advantage of each component classifier's advantages while tackling their shortcomings.

Stacking classifier

The stacking classifier was an important component of the AlzStack model, which aimed to enhance prediction efficiency by integrating the advantages of numerous machine learning algorithms. Unlike other ensemble methods such as bagging or boosting that mainly concentrated on averaging predictions or reweighting misclassified samples, stacking employed a hierarchical approach, which incorporated numerous base classifiers of RF, SVM, and GBM, all of which specialized in learning various trends from data. These base classifiers created predictions independently, capturing numerous viewpoints and nuances of the dataset. Once the base classifiers had made their predictions, the results were fed into the metaclassifier, a higher-level model that played an important role in integrating the predictions from the base classifiers, finding relationships between their results that might not be apparent from the raw data alone. The final prediction was generated by the LR metaclassifier by combining predictions from RF, SVM, and GBM. This multi-layered technique enabled the stacking classifier to capitalize on the individual advantages of each algorithm. RF with its capacity to manage high-dimensional datasets and intricate interactions between features made reliable predictions on structured data. SVM with its efficacy in high-dimensional spaces and versatility with various kernels provided a distinctive viewpoint on data separation. GBM with its iterative boosting procedure improved predictions by concentrating on hard-to-classify instances. By merging these various models, the stacking classifier guaranteed that the shortcomings of one model were balanced by the advantages of another, leading to improved overall predictive accuracy and resilience. In addition, stacking reduced overfitting compared to a single classifier. The metaclassifier frequently generalized well on unseen data because it learned from the base models' predictions rather than directly from raw data, which minimized the risk of overfitting due to noise or irregularities in the training data, guaranteeing that the model remained dependable in real-world applications. Overall, the stacking method in the proposed AlzStack model was able to ensemble learning and integrate the predictive capabilities of various models into a cohesive, highly precise system for enhancing Alzheimer's disease diagnostic or other predictive tasks.

Hyperparameter tuning

Hyperparameter tuning was an essential step in optimizing the efficiency of each classifier in the AlzStack model. Correct hyperparameter selection ensured that the model generalized well, enhanced accuracy, and reduced overfitting. Utilizing cross-validation, the most efficient hyperparameters for each base classifier and metaclassifier were determined automatically. GridSearchCV was used to conduct an exhaustive search across several predefined hyperparameter values, scoring each combination using a performance metric like accuracy or F1-score. This procedure guaranteed that the selected hyperparameters improved model effectiveness while preventing overfitting, laying the groundwork for dependable forecasts in Alzheimer's disease progression. The hyperparameters for each classifier were selected to best suit the dataset's characteristics, resulting in a fine-tuned model that captured intricate relationships while keeping generalizability.

Model training

After GridSearchCV determined the optimum hyperparameters, the model training stage began with the stacking classifier, which combined RF, SVM, GBM, and LR. Each base classifier learned different patterns from the data including that RF detected intricate feature interactions, SVM found optimum decision boundaries, and GBM refined forecasts through iterative learning. The meta-classifier, LR, integrated these insights and utilized the results from the base models to generate the ultimate forecast of Alzheimer's stages. To handle various and high-dimensional data, RF used an ensemble of decision trees, which efficiently reduced overfitting and improved generalization. SVM concentrated on determining the best margin between classes, while kernel functions such as radial basis function (RBF) handled nonlinear relationships and difficult decision boundaries. GBM created a series of decision trees that corrected mistakes generated by prior trees, improving the model's capacity to identify complex patterns and nuances in data. The mixture of models guaranteed that the stacking classifier used a wide spectrum of analytical viewpoints, improving its predictive accuracy. During the training stage, the stacking classifier learned to correlate linguistic features such as speech rate, pause duration, and vocabulary usage with Alzheimer's disease stages. The model captured how these attributes changed as the disease progressed, allowing it to more precisely predict stages. Cross-validation and regularization methods assisted to avoid overfitting, whereas diverse base models contributed to a stronger and more generalized model. Therefore, the stacking classifier was well-equipped to deal with unknown data and generate accurate predictions regarding Alzheimer's stages.

Prediction

After training, the AlzStack Model was used to predict Alzheimer's stages using the stacking classifier and the metaclassifier to produce the ultimate forecast for each test sample. This procedure efficiently tested how well the model learned from the training data, generalized to novel unknown data, and correctly forecasted Alzheimer's stages.

Evaluation of model’s effectiveness

Overall, the AlzStack model was a powerful ensemble learning framework designed to forecast the stages of Alzheimer's disease utilizing a diverse set of cognitive and linguistic features, which employed a stacking methodology that combined RF, SVM, and GBM as base classifiers and LR as the metaclassifier (Figure 1). The AlzStack model utilized Java and the Weka tool and was compared to other individual classifiers such as RF, SVM, GBM, and LR for effectiveness assessment. Numerous key assessment metrics were utilized including accuracy, precision, recall, F1-score, and MCC. The accuracy computed the percentage of correct results across all cases evaluated, which was a fundamental indicator of a classifier's overall effectiveness, encompassing both true positives and true negatives with the formula below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

where *TP* was the true positives. *TN* was the true negatives. *FP* was false positives. *FN* was false negatives. Higher accuracy indicated that the classifier was more accurate overall. The precision was the percentage of true positives among those predicted to be positive, which was particularly crucial in cases where the cost of false positives was large. The precision was determined as follows.

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

High precision implied that, when the classifier predicted a positive class, it was probably to be correct. Recall, also known as sensitivity or true positive rate, measured how numerous actual

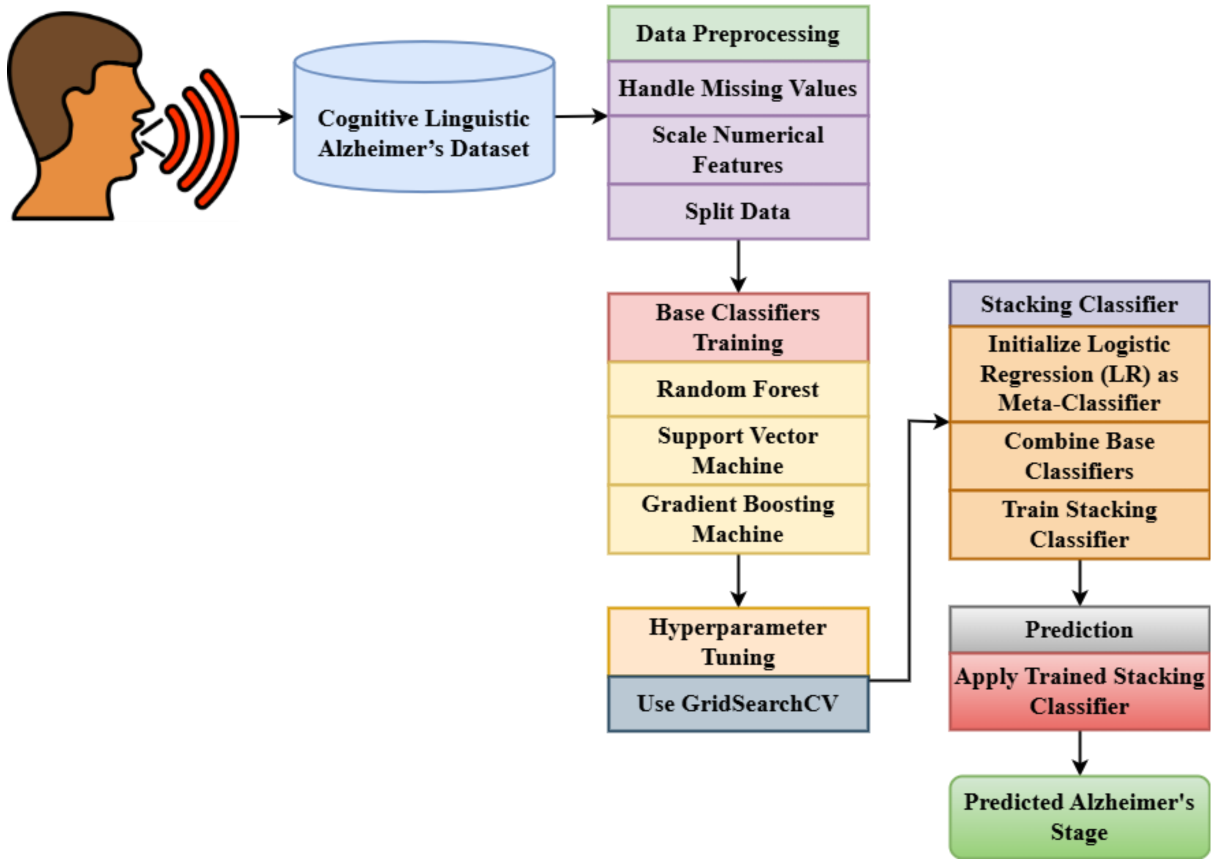

Figure 1. Flow diagram of proposed AlzStack model.

positives the classifier correctly detected, which was important in situations where losing a positive case was costly. The recall was calculated as below.

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

A high recall indicated that the classifier correctly recognized most actual positive cases. The F1-score balanced precision and recall, which was particularly useful when the dataset was imbalanced. The harmonic mean of precision and recall was calculated as follows.

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (6)$$

A higher F1 score indicated that the classifier was performing well in terms of precision and recall. MCC was a more comprehensive metric that considered all four categories of TP, TN, FP, and FN. It was especially useful when dealing with imbalanced datasets and was calculated using the following formula.

$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (7)$$

An MCC value nearing 1 indicated a high positive correlation between predicted and actual classifications.

Results and discussion

The comparison results of the effectiveness of each classifier across multiple metrics showed that the proposed AlzStack model consistently outperformed the others, recording the highest values across all metrics (Table 1). The accuracies across classifiers demonstrated that the AlzStack

Table 1. Comparison of performance metrics across different models.

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
Random forest (RF)	88.4	86.6	85.2	85.9	82.0
Support vector machine (SVM)	86.2	85.0	83.5	84.2	81.3
Gradient boosting machine (GBM)	89.1	87.5	86.1	86.8	83.1
Logistic regression (LR)	84.6	83.0	81.7	82.3	80.0
AlzStack model	93.5	91.3	90.7	91.0	89.5

model showed better efficiency with the highest accuracy than the other models, which was due to the stacking technique that integrated the individual advantages of RF, SVM, and GBM. The model advantaged from multiple viewpoints on the dataset, which led to more precise generalizations. In contrast, single classifiers such as LR and SVM tended to miss out on the more nuanced trends that the ensemble technique captured, resulting in underperformance in comparison. Furthermore, the AlzStack model surpassed others in terms of precision, which was because of how the stacking ensemble decreased the likelihood of false positives by cross validating the results of numerous classifiers before making a prediction. The proposed model guaranteed that positive predictions were more dependable, especially in Alzheimer's stages that could otherwise be confused with adjacent stages. In contrast, single classifiers were more susceptible to over-identification of specific stages, resulting in lower precision. The recall comparison results showed that the AlzStack model could accurately detect true positives and achieve the highest recall, which was attributed to the combined knowledge of the base classifiers that worked together to ensure fewer cases of Alzheimer's disease stages being undetected. SVM and RF tended to underperform in recall because they might miss subtle indicators of early-stage Alzheimer's, whereas the ensemble approach captured these cases more efficiently. The AlzStack model also performed well in terms of the F1-score. By balancing precision and recall, the model could consistently make accurate predictions, which was a direct result of the ensemble technique that the complementary powers of RF, SVM, and GBM prevented the model from sacrificing recall for precision or vice versa. Individual models tended to either miss positive cases with low recalls or incorrectly identify them with low precisions, resulting in lower F1 scores than the proposed AlzStack model. Eventually, the AlzStack model demonstrated the highest MCC score and resilience, particularly in dealing with imbalanced data. MCC considered all aspects of classification performance including true positives, false positives, true negatives, and false negatives and provided a more comprehensive measure than accuracy alone. The ensemble technique managed class imbalance more efficiently than individual classifiers of LR or SVM, rendering the AlzStack model more dependable in real-world situations where class distributions were frequently skewed.

Overall, the proposed AlzStack model showed substantial advancements in forecasting Alzheimer's stages based on cognitive and linguistic attributes and better efficiency across all key assessment metrics including accuracy, precision, recall, F1-score, and MCC. The stacking ensemble technique was extremely efficient, combining the advantages of several machine learning algorithms to improve predictive efficiency, dependability, and precision. By combining viewpoints from RF, SVM, GBM, and LR, the model attained a more nuanced comprehension of Alzheimer's stages, surpassing single classifiers in all metrics. These findings highlighted the importance of ensemble techniques in medical diagnosis, where precise disease stage classification had an important effect on patient care and results. The resulted AlzStack model improved the accuracy of Alzheimer's stage prediction, allowing for more dependable diagnoses and tailored treatment tactics. By tackling the drawbacks of prior models for comprehending cognitive decline, this study helped to improve patient outcomes, inform superior Alzheimer's disease management, provide a flexible and accurate technique for Alzheimer's disease staging, and demonstrate the possible uses in other neurodegenerative disorders as well. The model's capability to manage complicated cognitive data and precise predictions showed the potential for enhancing patient care and advancing medical research. Future research may look into expanding the usage of this framework beyond medicine, possibly adapting it for usage in financing, cybersecurity, or e-commerce, where precise categorization is critical for making decisions. Extending the model's application to these domains could emphasize its adaptability and influence on different machine-learning difficulties.

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