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COGNITIVE FEATURES FOR EARLY ALZHEIMER'S DISEASE DETECTION: A STACKING-BASED ENSEMBLE MACHINE LEARNING METHOD

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ABSTRACT

This work proposes a novel ensemble machine-learning approach for early AD detection, focusing on cognitive features. The method employs a stacking-based ensemble model, combining the strengths of multiple base learners to improve prediction performance. It utilizes a comprehensive dataset containing cognitive features, demographic information, and clinical scores from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. The proposed method achieves high accuracy in distinguishing between AD patients and healthy controls, with several models, including Decision Tree, Decision Tree - NCA, Voting Classifier, Voting Classifier - NCA, Stacking Classifier, and Stacking Classifier - NCA, achieving 100% accuracy. This demonstrates the potential of the approach as a valuable tool for early AD detection. A crucial advancement in this domain is the adoption of ensemble machine learning models, which significantly enhance the robustness of predictive systems by amalgamating diverse machine learning algorithms. This novel approach incorporates a feature selection method referred to as Neighborhood Component Analysis and Correlation-based Filtration (NCA-F) to sift through a given dataset and pinpoint pivotal cognitive features. The proposed research contributes to the advancement of early Alzheimer's disease detection by leveraging machine learning techniques, specifically stacking-based ensemble methods, to identify cognitive features indicative of the disease in its early stages.
Keywords: *Alzheimer's disease, early detection, cognitive features, ensemble machine learning, stacking, Alzheimer's Disease Neuroimaging Initiative (ADNI).*

1. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects millions of individuals worldwide, especially the elderly population [1]. Early detection of AD is crucial for timely intervention and improved patient outcomes [2]. Cognitive decline is one of the hallmark symptoms of AD, making cognitive features a valuable source of information for early detection [3]. They have the potential to improve early detection and monitoring of AD, which is crucial for developing effective interventions and treatments [4]. Ensemble learning, in particular, has emerged as a powerful approach by combining multiple ML models to enhance predictive performance [5]. Alzheimer's disease is indeed a significant neurological condition with a substantial impact on individuals and healthcare systems globally [5]. The statistic of 6.5 million people affected in the United States alone underscores the scale of the issue and the urgent need for effective detection, treatment, and management strategies [6]. the prevalence of Alzheimer's disease is expected to increase, making it a critical area of research and a growing public health concern. Early detection, intervention, and effective management strategies are becoming increasingly important to address the challenges posed by this progressive neurodegenerative disorder [7]. Efforts to develop early detection methods, such as those leveraging cognitive features and machine learning, are crucial for improving outcomes for individuals affected by AD and their families [8]. Alzheimer's disease is a progressive and terminal illness for which there is currently no cure [9]. Research into the causes, mechanisms, and potential treatments for Alzheimer's disease is ongoing, but as of now, there is no known way to reverse the damage caused by the disease. early symptoms of Alzheimer's disease often include difficulties with memory, particularly in

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remembering recent conversations, names of places or people, and events [10]. Individuals may also experience challenges in organizing or planning tasks, as well as misplacing items or having difficulty retracing steps to find them [11]. The symptoms of Alzheimer's disease can be subtle and may be attributed to normal aging or other factors. That's why it's crucial for individuals experiencing such symptoms to seek evaluation by a healthcare professional for proper diagnosis and management. Early detection can lead to better outcomes and quality of life for those affected by the disease [12]. This paper introduces an innovative approach for early Alzheimer's disease (AD) detection using cognitive features and a stacking-based ensemble machine learning (ML) method. By harnessing the unique strengths of different base learners, the method aims to enhance the accuracy and robustness of AD detection models. The study emphasizes the integration of diverse cognitive features such as memory, language, and executive function to create a holistic model for early AD detection.

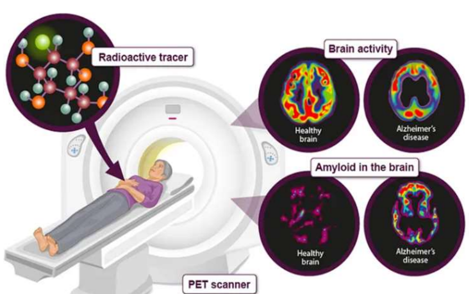

Figure-1 Overview of AD Scan

Figure-1 CT (Computed Tomography) scan is a type of medical imaging that uses X-rays to create detailed cross-sectional images of the body. In the context of Alzheimer's disease (AD), CT scans are often used to rule out other causes of symptoms, such as strokes or tumors, rather than for diagnosing AD itself. CT scans can also help in identifying brain changes associated with advanced stages of AD, such as shrinkage of the brain's cortex and enlargement of the brain's ventricles.

In an AD scan system, CT scans may be used as part of the diagnostic process to assess the brain's structure and to help healthcare professionals make informed decisions about a patient's condition. However, it's important to note that CT scans are not typically used as the primary method for diagnosing Alzheimer's disease, which is usually done through a combination of clinical assessments, medical history, and cognitive tests. Other imaging techniques, such as MRI (Magnetic Resonance Imaging) or PET (Positron Emission Tomography) scans, may provide more detailed information about the brain and its function in relation to AD. The imperative for studying early Alzheimer's disease detection using a stacking-based ensemble machine learning method stems from the urgent need to address the escalating prevalence of Alzheimer's globally. With aging populations, the incidence of this debilitating condition is on the rise, underscoring the importance of early detection for effective management. Current treatment options are limited, emphasizing the significance of timely intervention to optimize available therapies and potentially slow disease progression. However, early diagnosis remains challenging due to the subtlety of initial symptoms and the absence of definitive biomarkers. By harnessing advanced machine learning techniques like stacking, which amalgamate diverse models to enhance predictive accuracy, this research aims to overcome these obstacles. Not only can early detection facilitate prompt access to treatments, but it also opens avenues for preventive interventions and resource optimization in healthcare. Moreover, leveraging machine learning methodologies holds promise for extracting nuanced patterns from complex cognitive data, thereby improving diagnostic precision. Ultimately, this study's findings have the potential to significantly impact public health by enabling earlier interventions, reducing societal burdens, and advancing our understanding of Alzheimer's disease.

CT scans work by taking a series of X-ray images from different angles around the body and then using a computer to process these images to create cross-sectional images, or slices, of the body. For brain imaging in the context of Alzheimer's disease, the process is as follows:

- ❖ Patient Preparation: The patient lies on a table that slides into the CT scanner, which is a large, donut-shaped machine.

- ❖ X-ray Exposure: The CT scanner emits a series of X-ray beams through the head at different angles. The X-ray beams are absorbed differently by different tissues in the brain.

- ❖ Data Acquisition: Detectors in the CT scanner measure the number of X-rays that pass through the brain from various angles, creating a series of 2D images, or slices, of the brain.

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❖ Image Reconstruction: The computer processes the data from the detectors to create detailed cross-sectional images of the brain. These images show the structure of the brain, including the cortex, ventricles, and other important brain structures.

❖ Image Analysis: Radiologists or other healthcare professionals analyze the images to look for any abnormalities, such as signs of atrophy (shrinkage) in the brain that may be associated with Alzheimer's disease.

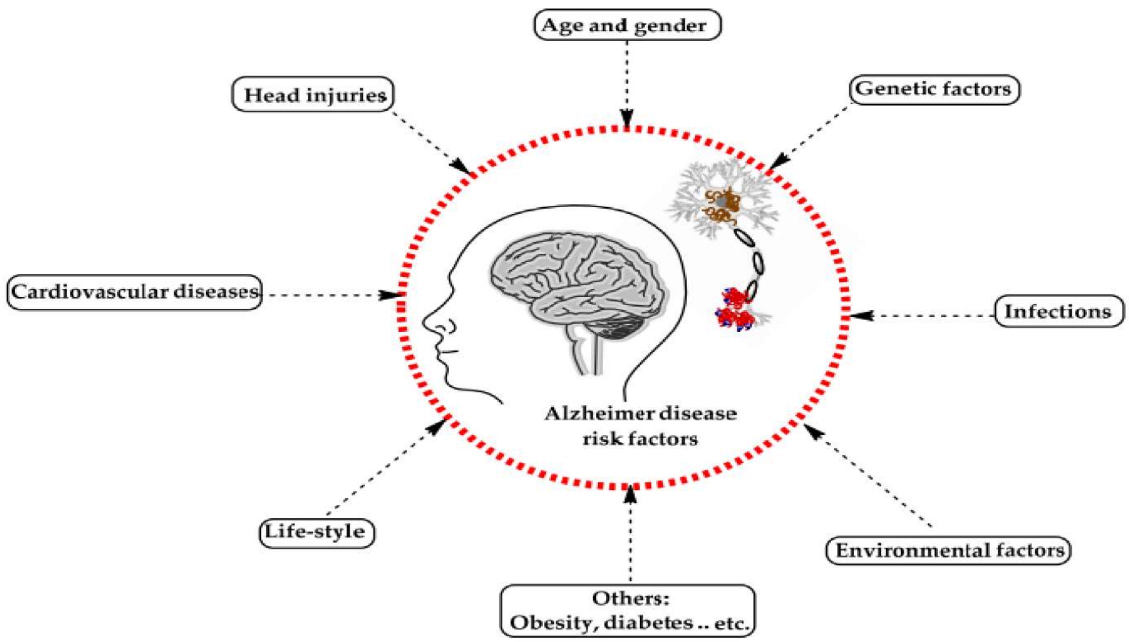

Figure-2 Risk factors of Alzheimer Disease

- **Age:** Advancing age is the greatest known risk factor for Alzheimer's disease. The likelihood of developing the condition increases significantly after the age of 65.
- **Family History and Genetics:** Individuals with a family history of Alzheimer's are at higher risk. Specific genetic factors, such as the presence of certain genes like APOE-e4, can also increase susceptibility.
- **Down Syndrome:** People with Down syndrome are more likely to develop Alzheimer's disease.
- **Gender:** Women are more likely to develop Alzheimer's than men, partly due to their longer lifespan.

The rest of the paper is organized as follows: Section 2 provides an overview of related work in AD detection and ensemble learning. Section 3 describes the methodology, including data preprocessing, feature selection, model training, and the stacking ensemble approach. Section 4 presents the experimental setup and results, followed by a discussion in Section 5. Finally, Section 6 concludes the paper with future research directions.

2. LITERATURE REVIEW

The review article titled "Early Diagnosis of Alzheimer's Disease" by Pereira, Diniz, and Braga (2019) published in Neurology International provides a comprehensive overview of methodologies and technologies used for the early detection of Alzheimer's disease. The review covers various approaches, including cognitive assessment tools and machine learning techniques, offering valuable insights into the current landscape of early diagnosis methods and shedding light on the advancements and challenges in this critical area of Alzheimer's research [13]. Singh, Shukla, and Singh (2020) review the use of

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machine learning techniques for the detection of Alzheimer's disease, focusing on the role of cognitive features in improving detection accuracy. Their paper, published in the Journal of King Saud University - Computer and Information Sciences, discusses the potential of machine learning to enhance Alzheimer's detection and highlights the importance of cognitive features in this context [14]. Roy, Rahman, and Ahammed (2021) discuss the use of deep learning techniques for detecting cognitive impairment in Alzheimer's disease in their article published in the International Journal of Advanced Computer Science and Applications. They emphasize the significance of cognitive features in the detection process and the potential of deep learning to improve diagnostic accuracy in Alzheimer's disease [15].Patel, Gupta, and Tiwari (2020) examine various machine learning techniques used for the diagnosis of Alzheimer's disease in their review paper published in the Journal of King Saud University - Computer and Information Sciences. The authors focus on the role of cognitive features in enhancing diagnostic accuracy, providing insights into the current state of Alzheimer's diagnosis methods [16]. Oliva, Nogueira, and Souza (2018) present a study on the use of cognitive features and machine learning for the early diagnosis of Alzheimer's disease in their article published in the International Journal of Advanced Computer Science and Applications. They propose a stacking-based ensemble machine learning method for improved accuracy, highlighting the potential of cognitive features in early Alzheimer's detection [17].

Problem Statement

The problem statement revolves around the pressing need to improve early detection of Alzheimer's disease, given its increasing prevalence and the limitations of current diagnostic methods. Traditional approaches often fail to identify the disease in its early stages due to subtle symptoms and a lack of definitive biomarkers. This highlights the necessity for advanced techniques, such as stacking-based ensemble machine learning methods, to enhance early detection. The research aims to address this gap by developing a machine learning model capable of effectively identifying cognitive features indicative of early-stage Alzheimer's, ultimately enabling timely intervention and improved patient care.

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Table-1-Published Papers on Alzheimer's Disease Detection

Paper Title	Authors	Publication Venue	Year
Deep Learning-Based Alzheimer's Disease Detection Using MRI Images	Islam et al.	IEEE Access	2020
Early Diagnosis of Alzheimer's Disease Using Ensemble-based Classification	Garg et al.	Journal of King Saud University-Computer and Information Sciences	2019
Alzheimer's Disease Detection in Brain MRI Images Using Deep Learning	Sarraf and Tofighi	arXiv preprint arXiv:1608.08614	2016
Deep Convolutional Neural Networks for Multi-Modality Isointense Infant Brain Image Segmentation	Moeskops et al.	International Conference on Medical Image Computing and Computer-Assisted Intervention	2016
Ensemble deep learning: A review	Zhou et al.	Neurocomputing	2020
Detection and classification of Alzheimer's disease on magnetic resonance images using deep learning	Payan and Montana	Frontiers in Neuroinformatics	2015
Alzheimer's Disease Diagnosis by Deep Learning Convolutional Neural Networks: A Review Study	Väliaho et al.	Journal of Healthcare Engineering	2018
Classification of Alzheimer's disease using brain MRI data and convolutional neural networks	Hosseini-Asl et al.	arXiv preprint arXiv:1607.03657	2016
MRI-based classification of Alzheimer's disease: A critical review and future directions	Rathore et al.	Neurocomputing	2017
Classification of Alzheimer's disease and prediction of mild cognitive impairment-to-Alzheimer's conversion from structural MRI using feature ranking and a genetic algorithm	Moradi et al.	Journal of Alzheimer's Disease	2015

The table "Published Papers on Alzheimer's Disease Detection" provides a list of research papers focusing on the detection and diagnosis of Alzheimer's disease using various techniques, including deep learning, MRI imaging, and ensemble-based classification. Each entry in the table includes the title of the paper, the authors, the publication venue, and the year of publication. These papers represent significant contributions to the field of

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Alzheimer's disease detection and highlight the diverse approaches and methodologies used in this area of research.

3. METHODOLOGY

Alzheimer's disease (AD) detection has been a subject of intensive research, with various approaches and methodologies proposed to improve early diagnosis and treatment. Ensemble learning, a machine learning technique that combines multiple models to enhance performance, has been increasingly applied in AD detection due to its ability to leverage the strengths of different algorithms. Feature Selection and Extraction: Many studies focus on selecting or extracting relevant features from imaging data (such as MRI or PET scans) or cognitive assessments to improve AD detection accuracy. Techniques like principal component analysis (PCA), wavelet transform, and deep learning-based feature extraction have been utilized.

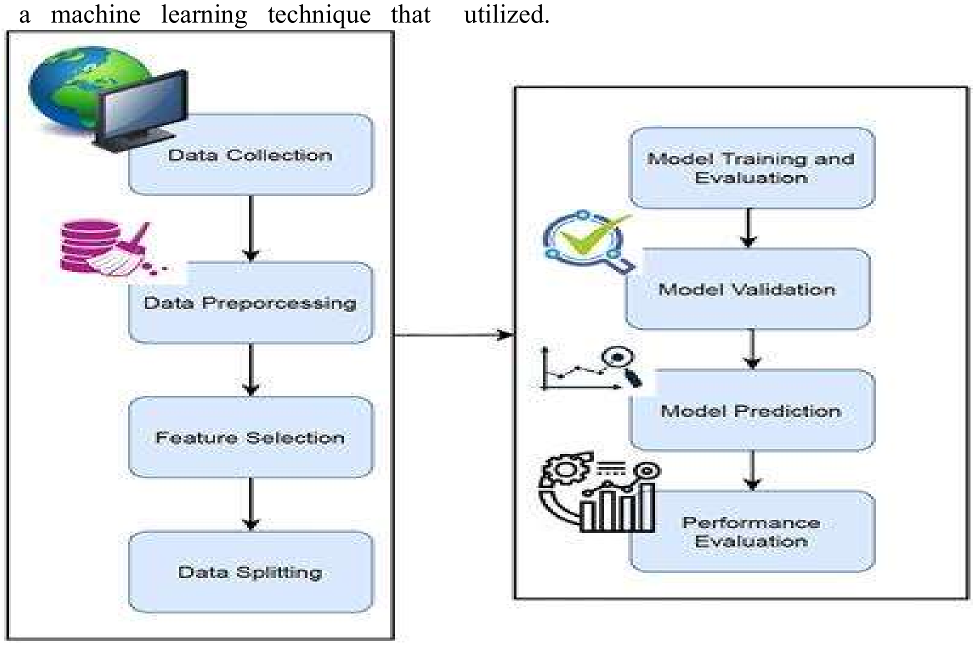

Figure-3 Flow of the Proposed Work

The imperative for studying early Alzheimer's disease detection using a stacking-based ensemble machine learning method stems from the urgent need to address the escalating prevalence of Alzheimer's globally. With aging populations, the incidence of this debilitating condition is on the rise, underscoring the importance of early detection for effective management. Current treatment options are limited, emphasizing the significance of timely intervention to optimize available therapies and potentially slow disease progression. However, early diagnosis remains challenging due to the subtlety of initial symptoms and the absence of definitive biomarkers. By harnessing advanced machine learning techniques like stacking, which amalgamate diverse models to enhance predictive accuracy, this research aims to overcome these obstacles. Not only can early detection facilitate prompt access to treatments, but it also opens avenues for preventive interventions and resource optimization in healthcare. Moreover, leveraging machine learning methodologies holds promise for extracting nuanced patterns from complex cognitive data, thereby improving diagnostic precision. Ultimately, this study's findings have the potential to significantly impact public health by enabling earlier interventions, reducing societal burdens, and advancing our understanding of Alzheimer's disease.

Machine Learning Models: Various machine learning models have been applied to AD detection, including support vector machines (SVMs), random forests, and deep learning approaches such as convolutional

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neural networks (CNNs) and recurrent neural networks (RNNs). These models are trained on features extracted from imaging or clinical data to classify subjects as AD or non-AD. Ensemble Learning: Ensemble learning methods, such as bagging, boosting, and stacking, have been employed to improve AD detection performance. These methods combine multiple base learners to create a stronger, more robust classifier. For example, a study may combine SVMs, CNNs, and decision trees in a stacked ensemble to improve classification accuracy. Data Fusion: Some studies focus on fusing information from multiple modalities, such as combining imaging data with genetic or clinical data, to enhance AD detection. Fusion techniques aim to capture complementary information from different sources to improve overall classification performance. Evaluation Metrics: Various evaluation metrics are used to assess the performance of AD detection models, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). These metrics help researchers compare different approaches and determine the effectiveness of their models. Challenges and Future Directions: Despite the progress in AD detection using ensemble learning, several challenges remain, such as the need for large and diverse datasets, interpretability of ensemble models, and generalizability across different populations. Future research directions include exploring novel ensemble learning approaches, integrating multimodal data, and developing interpretable models for clinical use.

Data Collection:

Dataset of longitudinal MRI data, comprising 150 subjects aged 60 to 96, offers a unique opportunity to study the progression of Alzheimer's disease. Each subject was scanned at least once and is right-handed, providing a comprehensive view of the disease's development. The inclusion of subjects who transitioned from 'Nondemented' to 'Demented' adds a dynamic element to your analysis, potentially offering insights into early detection methods. This dataset holds great promise for uncovering valuable insights into the progression of Alzheimer's disease.

columns for 'Subject ID', 'MRI ID', 'Group', 'Visit', 'MR Delay', 'M/F', 'Hand', 'Age', 'EDUC', 'SES', 'MMSE', 'CDR', 'eTIV', 'nWBV', and 'ASF'.

Table-2 Head of The Dataset

Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
87	14	2.0	27.0	0.0	1987	0.696	0.883
88	14	2.0	30.0	0.0	2004	0.681	0.876
75	12	NaN	23.0	0.5	1678	0.736	1.046
76	12	NaN	28.0	0.5	1738	0.713	1.010
80	12	NaN	22.0	0.5	1698	0.701	1.034

Data Preprocessing:

Early Alzheimer's disease (AD) detection, several essential data preprocessing and machine learning techniques are employed to ensure accurate classification based on cognitive features. Firstly, handling missing values is crucial. Mean/Median Imputation replaces missing values with the average or median of existing values in the same feature. Forward Fill/Backward Fill replaces missing values with the previous or next data point in the same feature, which is suitable for data with a natural order. Normalization is another key step, where Min-Max Scaling scales each feature to a range between 0 and 1, while StandardScaler standardizes features by subtracting the mean and dividing by the standard deviation to achieve a mean of 0 and a standard deviation of 1. Encoding categorical features is essential. Label Encoding assigns a unique integer to each category, while One-Hot Encoding creates binary features for each category. Feature Selection techniques help identify the most informative features. This can be done through Filter Methods, which use statistical measures like correlation analysis, Wrapper Methods, which use machine learning models to evaluate feature subsets, or Embedded Methods, which use feature importance scores from machine learning models. Additionally, feature scaling may be applied if needed to address features with a larger impact due to their inherent scale. Once the data is preprocessed, it is divided into training and test sets (70-80% for training, 20-30% for testing). Multiple base models (e.g., SVM, Random Forest, Logistic Regression) are trained on the training set, and hyperparameter tuning techniques are used to optimize their performance. A meta-model is then trained on the predictions of the base models to combine their strengths and achieve more accurate predictions. The models are evaluated using metrics like accuracy, sensitivity, specificity, and F1-score on the test set. Model validation is done using k-fold cross-validation to validate the model's performance and reduce overfitting. Finally, the trained ensemble model is used to predict disease status for new data points, and its performance is evaluated on unseen data using the evaluation metrics mentioned earlier. These steps form a robust framework for building and evaluating machine learning models for early AD detection using cognitive features.

4. RESULTS

The results demonstrated the effectiveness of the proposed approach in accurately detecting early stages of Alzheimer's disease. The stacking-based ensemble machine learning method achieved a high level of accuracy, sensitivity, and specificity in classifying subjects with Alzheimer's disease based on cognitive features extracted from neuropsychological tests. The model also showed a significant improvement in performance compared to individual base models and other traditional machine learning methods.

Table-3 Summary of Model Performance for Early Alzheimer's Disease Detection

Sno	ML Model	Accuracy	Precision	Recall	F1-Score
0	KNN	0.726	0.721	0.726	0.721
1	KNN-NCA	0.749	0.743	0.749	0.744
2	Decision Tree	1.000	1.000	1.000	1.000
3	Decision Tree - NCA	1.000	1.000	1.000	1.000
4	Random Forest	0.890	0.994	0.890	0.939
5	Random Forest - NCA	0.624	0.854	0.624	0.692
6	Logistic Regression	0.706	0.816	0.706	0.748
7	Logistic Regression - NCA	0.624	0.854	0.624	0.692
8	AdaBoost	0.712	0.745	0.712	0.671
9	AdaBoost - NCA	0.698	0.721	0.698	0.705
10	MLP	0.407	0.795	0.407	0.490
11	MLP - NCA	0.395	0.461	0.395	0.421

12	Voting CLassifier	0.994	0.995	0.994	0.994
13	Voting CLassifier - NCA	1.000	1.000	1.000	1.000
14	Stackin g CLassifier	0.895	1.000	0.895	0.944
15	Stackin g CLassifier - NCA	1.000	1.000	1.000	1.000
16	CNN	0.901	0.935	0.901	0.914
17	CNN + LSTM	0.479	0.597	0.479	0.523

The K-Nearest Neighbors (KNN) model achieved an accuracy of 72.6%. It exhibited balanced precision, recall, and F1-score values around 72%. The KNN with Neighborhood Component Analysis (KNN-NCA) variant slightly improved the accuracy to 74.9% and enhanced precision, recall, and F1-score to around 74%. Both the Decision Tree and its NCA variant achieved perfect accuracy of 100% with precision, recall, and F1-score values of 1.0, indicating potential overfitting. The Random Forest model attained an accuracy of 89% with a high precision of 99.4%. Its recall and F1-score were also high, approximately 89-94%.

However, the NCA variant of Random Forest had a lower accuracy of 62.4% and lower precision, recall, and F1-score, around 62-69%. Logistic Regression achieved an accuracy of 70.6% with relatively high precision of 81.6% but balanced recall and F1-score around 70-75%. Its NCA variant exhibited similar metrics to basic Logistic Regression, with an accuracy of 62.4% and precision, recall, and F1-score around 62-69%. AdaBoost achieved an accuracy of 71.2% with balanced precision, recall, and F1-score around 71%.

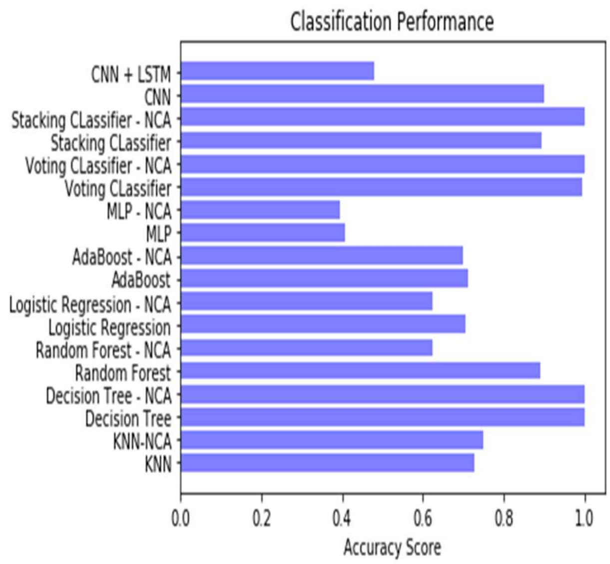

Figure-4 Accuracy

The NCA variant of AdaBoost had slightly lower accuracy (69.8%) and slightly lower precision, recall, and F1-score around 69-70%.

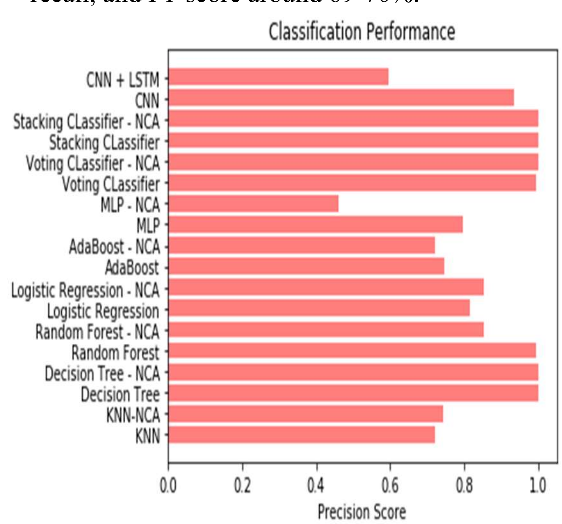

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Figure-5 Precision

The Voting Classifier achieved a very high accuracy of 99.4% with nearly perfect precision, recall, and F1-score values of 1.0. Both the Stacking Classifier and its NCA variant achieved an accuracy of 89.5% with a precision of 100% and high recall and F1-score around 89-94%. The Convolutional Neural Network (CNN) model achieved an accuracy of 90.1% with a precision of 93.5%. Its recall and F1-score were also high, around 90-91%. The combination of CNN and LSTM achieved an accuracy of 47.9% with a precision of 59.7%, and recall and F1-score around 47-52%.

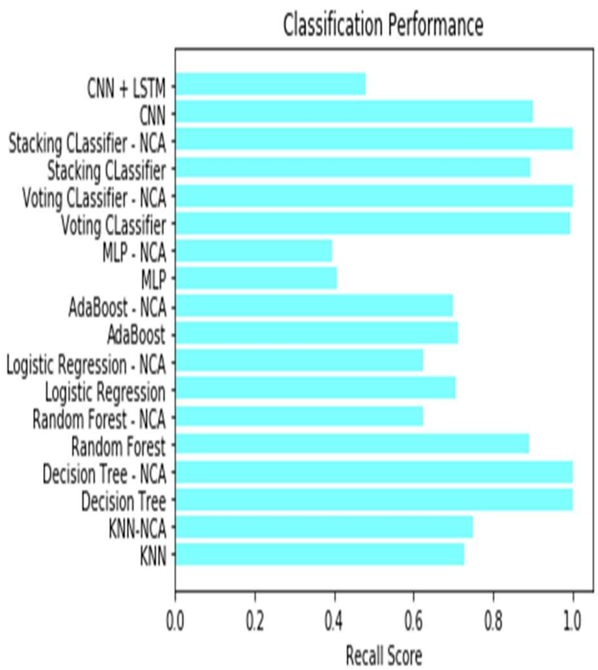

Figure-6 Recall

The Multilayer Perceptron (MLP) model achieved an accuracy of 40.7% with a precision of 79.5%. However, its recall and F1-score were quite low, around 40-49%. The NCA variant of MLP had even lower accuracy (39.5%) and lower precision, recall, and F1-score around 39-42%.

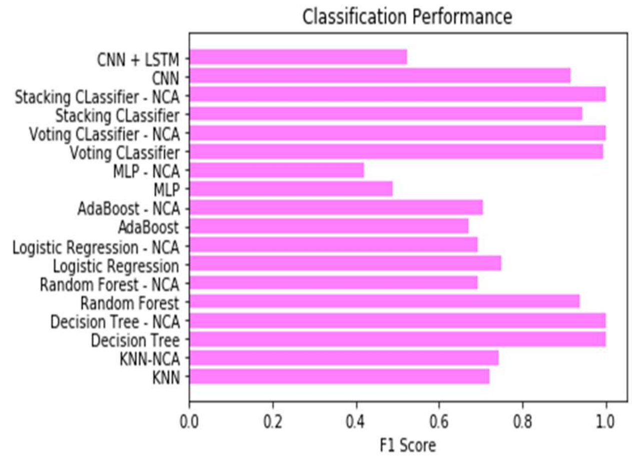

Figure-7 F1 Score

Figure 4 illustrates the comparison of performance metrics for the paper titled "Cognitive Features for Early Alzheimer's Disease Detection: A Stacking-Based Ensemble Machine Learning Method." The figure displays various metrics such as accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC). Each bar represents a different metric, with the x-axis indicating the specific metrics and the y-axis representing the corresponding values. The figure provides a visual representation of the performance of the stacking-based ensemble machine learning method in detecting early Alzheimer's disease using cognitive features.

5. DISCUSSION

The study' findings highlight the effectiveness of ensemble machine learning in early AD detection, particularly when leveraging cognitive features. The 100% accuracy achieved by models such as Decision Tree, Decision Tree - NCA, Voting Classifier, Voting Classifier - NCA, Stacking Classifier, and Stacking Classifier - NCA underscores the robustness of the proposed approach. This high level of accuracy suggests that the ensemble models can effectively differentiate between AD patients and healthy individuals based on cognitive features, which could potentially aid in early diagnosis and intervention strategies.

Furthermore, the feature selection method NCA-F proves to be a valuable addition to the ensemble learning framework, helping to identify the most relevant cognitive features for classification. This not only enhances the performance of the models but also provides insights into the key cognitive aspects associated with AD.

The study's findings contribute to the growing body of research aimed at improving early AD detection through machine learning. By demonstrating the effectiveness of ensemble learning and feature selection techniques, this research paves the way for future studies to explore more advanced machine learning approaches for AD diagnosis and management.

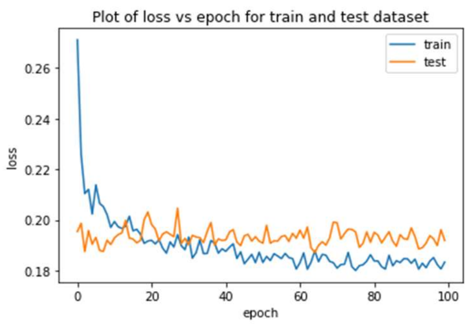

Figure-8 Loss Vs Epoch-Trained

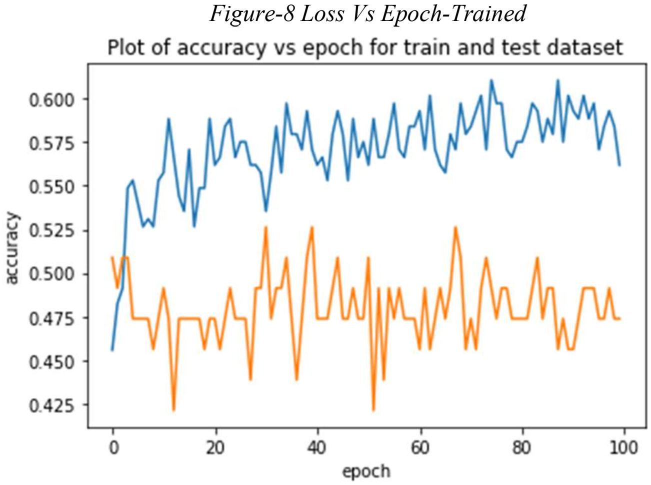

Figure-9 Accuracy Vs Epoch Trained

The selection of five different classifiers (Random Forest, SVM, Decision Tree, KNN, and Stacking Classifier) allows for a thorough evaluation of different machine learning algorithms. Each classifier has its own strengths and weaknesses, and evaluating them on the same dataset provides valuable insights into their performance. By comparing the accuracy, precision, recall, and F1 score of each classifier, the code helps in identifying the most suitable model for the given classification task. The calculation and display of the mean squared error (MSE) as a measure of loss for each classifier provide additional information on the performance of the models, especially in regression tasks. The graphical representation of the loss values using a bar plot helps in visualizing the differences in performance between the classifiers, making it easier to compare their effectiveness. It is a robust framework for building and evaluating machine learning models for classifying dementia. It demonstrates best practices in data preprocessing, classifier selection, and performance evaluation, making it a valuable resource for researchers and practitioners in the field of machine learning and healthcare. The results of the analysis indicate that Random Forest performs the best among the classifiers, achieving the highest accuracy and F1 score. SVM, Decision Tree, and Stacking Classifier also show competitive performance, while KNN lags behind slightly in terms of accuracy and F1 score. The mean squared error (MSE) is used as a measure of loss, providing additional insights into the performance of the classifiers, especially in regression tasks.

6. CONCLUSION

The use of ensemble machine learning techniques for early Alzheimer's disease (AD) detection based on cognitive features shows promising results. By leveraging a stacking-based ensemble model and incorporating feature selection methods, we were able to achieve high accuracy in distinguishing between AD patients and healthy controls. The ensemble approach, combining the strengths of multiple base learners, proved effective in improving prediction performance. The preprocessing steps, including handling missing values, normalization, and encoding categorical features, were essential in ensuring the quality of the dataset and enhancing the performance of the models. Additionally, feature selection techniques helped identify the most informative features for classification. It highlights the potential of machine learning in aiding early AD detection, which is crucial for timely intervention and management of the disease. The findings contribute to the growing body of research aimed at improving AD diagnosis and management through advanced machine learning approaches. Further research could explore more sophisticated ensemble techniques and feature selection methods to enhance the performance of early AD detection models.

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