Interpretable Alzheimer's Disease Diagnosis via CNNs and MRI: An Explainable AI Approach

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***Abstract*—Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that impairs memory, cognition, and daily functioning, often accompanied by significant behavioral and personality changes in older adults. While there is currently no cure, treatment interventions are most effective during the early and middle stages, emphasizing the critical need for early diagnosis—especially as global aging trends contribute to a rising prevalence of AD. This study aims to enhance early detection of Alzheimer's Disease by leveraging machine learning and deep learning techniques on MRI scans from the Open Access Series of Imaging Studies (OASIS) dataset. We employed a diverse set of models, including Random Forest and Logistic Regression from classical machine learning, Extra Trees from ensemble learning, and Convolutional Neural Networks (CNNs) from deep learning. Performance was assessed using accuracy, precision, recall, and area under the curve (AUC). Results indicate that CNNs achieved the highest accuracy and AUC scores, while Extra Trees excelled in precision and recall—highlighting the potential of both deep learning and ensemble-based methods in supporting early AD diagnosis through neuroimaging.**

***Index Terms*—Alzheimer's Disease, Early Detection, Machine Learning, Deep Learning, MRI, CNN, Brain Disorder, Extra Trees**

I. Introduction

It is estimated that nearly 7 million Americans are currently living with Alzheimer's disease, a number that exceeds the population of many large American cities [1] [2]. The majority of individuals affected by Alzheimer's are aged 65 and older, with approximately 1 in 9 people (10.9%) in this age group being affected. As the population of Americans aged 65 and above continues to grow, the prevalence of Alzheimer's disease and other forms of dementia is expected to increase [3]. Without significant advancements in medical prevention or treatment, the number of Americans aged 65 and older with Alzheimer's is projected to reach 12.7 million by 2050.

Alzheimer's disease is a progressive neurological disorder that causes a gradual decline in memory, cognitive abilities, and the capacity to perform basic daily tasks. In addition to cognitive impairment, individuals with Alzheimer's often experience changes in behavior and personality. Unlike normal aging, Alzheimer's results from complex pathological changes in the brain that begin years before clinical symptoms become evident, ultimately leading to the loss of neurons and their connections. The clinical manifestations of Alzheimer's disease include deficits in thinking, memory, reasoning, and behavior, which may also be observed in other forms of dementia. This overlap in symptoms is why Alzheimer's disease is often referred to as a type of dementia [4].

Alzheimer's disease is not just a condition characterized by memory loss; it is also a leading cause of mortality among older adults. Approximately one in three seniors dies with Alzheimer's disease or another form of dementia, with Alzheimer's claiming more lives than both breast cancer and prostate cancer combined. Between 2000 and 2021, deaths attributed to Alzheimer's more than doubled. Furthermore, individuals diagnosed with Alzheimer's at age 70 are twice as likely to die before reaching age 80 compared to their peers without the disease.

Currently, there is no cure for Alzheimer's disease; however, the U.S. Food and Drug Administration (FDA) has approved several medications to help manage certain symptoms, particularly in individuals in the early to middle stages of the disease. Despite these advancements, no method currently exists to completely cure or reverse the progression of dementia. Nevertheless, early, accurate, and comprehensive diagnosis of Alzheimer's disease is crucial as it allows for timely intervention, which can slow the disease's progression. Experts increasingly emphasize the importance of early diagnosis in managing Alzheimer's disease [5].

This study focuses on detecting the early signs of Alzheimer's disease (AD) to enable timely and effective interventions. To achieve this goal, we analyzed brain MRI images to identify early indicators of the disease. The Open Access Series of Imaging Studies (OASIS) dataset was used to train and validate our models. We initially performed exploratory data analysis to understand the distribution of the dataset and applied necessary preprocessing steps to prepare the data for modeling. Our approach involved five models: the Random Forest (RF) Classifier and Logistic Regression (LR) for shallow learning, Extra Trees (ET) for ensemble learning, and a Convolutional Neural Network (CNN) for deep learning [6]. These models were evaluated using metrics such as accuracy, precision, recall, and the area under the curve (AUC). For the deep learning model, we additionally assessed training and validation accuracy and loss. By comparing these models based on the evaluation metrics, we aimed to identify the most suitable model for this dataset.

II. Related Work

Alzheimer's Disease (AD) is a neurodegenerative disorder that places a significant burden on healthcare systems worldwide. It is characterized by a progressive decline in cognitive function, memory loss, and behavioral changes, which can severely impact patients' quality of life and lead to high financial costs. As the leading cause of dementia globally, early detection of AD is crucial, as early intervention can help slow disease progression and improve outcomes.

Machine learning (ML) and deep learning (DL) models have proven effective in analyzing MRI scans to detect subtle brain changes that could indicate early-stage AD [7], potentially allowing for more accurate and timely diagnoses. Various ML algorithms, including Random Forest (RF), Logistic Regression (LR), and ensemble learning methods like Extra Trees (ET), have been explored for AD diagnosis with promising results in classification accuracy [8], [9]. Recently, Convolutional Neural Networks (CNNs) have emerged as powerful tools for automated feature extraction from MRI scans [9]. CNNs are capable of learning complex patterns, offering more robust feature extraction than traditional ML methods, and research has demonstrated their effectiveness in classifying AD patients [10]. However, there is still debate on whether DL models consistently outperform traditional ML approaches in AD detection. Traditional diagnostic methods for Alzheimer's disease, such as cognitive assessments and MRI scans, have limitations. While MRI scans provide valuable structural information about the brain, they often lack the sensitivity required to detect AD in its early stages [11]. As a result, there is growing interest in using ML and DL techniques to develop more reliable and objective tools for early AD detection. Diagnosing AD can be challenging, but recent research has focused on improving diagnostic accuracy. One approach involves integrating multiple types of medical data, including MRI scans, PET scans (which provide insights into brain activity), and genetic information. Combining these diverse data sources can lead to a more comprehensive understanding of the disease and more accurate diagnoses. This multimodal deep learning approach leverages recent advancements in DL to provide a more holistic view of Alzheimer's and its impact on patients [12].

The evaluation of ML and DL models for AD detection typically involves performance metrics such as accuracy, precision, recall, and area under the curve (AUC). For DL models, additional metrics like training and validation accuracy and loss are also used to assess performance and stability. These metrics provide valuable insights into a model's effectiveness and generalizability for real-world applications. While ML and DL methods are widely researched for AD detection using MRI scans, similar techniques are also being applied to brain tumor detection. For example, Hammad et al. (2021) proposed a DL model for brain tumor detection from MRI images, demonstrating the broader potential of DL in medical image analysis beyond AD [13].

Some studies suggest that CNNs may outperform other methods, particularly in terms of accuracy and AUC, which evaluates a model's ability to distinguish between AD and non-AD cases. However, other research indicates that ensemble learning models, such as Extra Trees, can achieve similar results, particularly in precision (accurately identifying AD cases) and recall (detecting true AD cases without omission).

III. Methodology

This paper presents the development of a tool for the early-stage detection of Alzheimer's disease (AD) using machine learning (ML) and deep learning (DL) algorithms applied to MRI data. The overall approach is summarized in the high-level diagram shown in Figure 1, while Figure 2 outlines the architecture of the process steps. A detailed explanation of each step is provided in the following sections.

Fig. 1. Steps of the Methodology

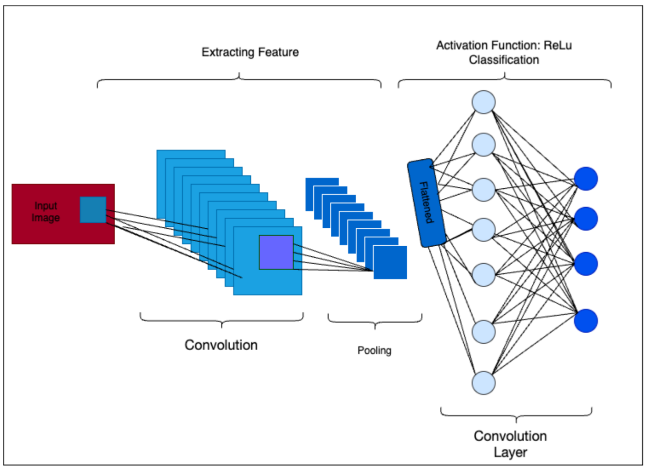

Fig. 2. Illustration of the CNN Architecture

A. Data Collection For this study, we used the Open Access Series of Imaging Studies (OASIS) dataset, sourced from Kaggle [14]. This publicly available dataset is updated annually with new versions. It contains 1.32 gigabytes of data, including 86,437 brain MRI images.

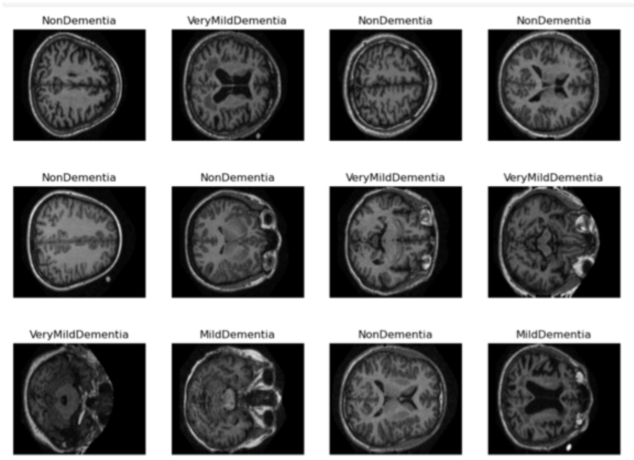

Fig. 3. Part of Collected Data

The images are classified into four categories based on the stages of Alzheimer's disease: Mild Dementia, Moderate Dementia, Non-Dementia, and Very Mild Dementia. This dataset is an important resource for detecting and analyzing early signs of Alzheimer's disease. A sample of the collected data is shown in Figure 3.

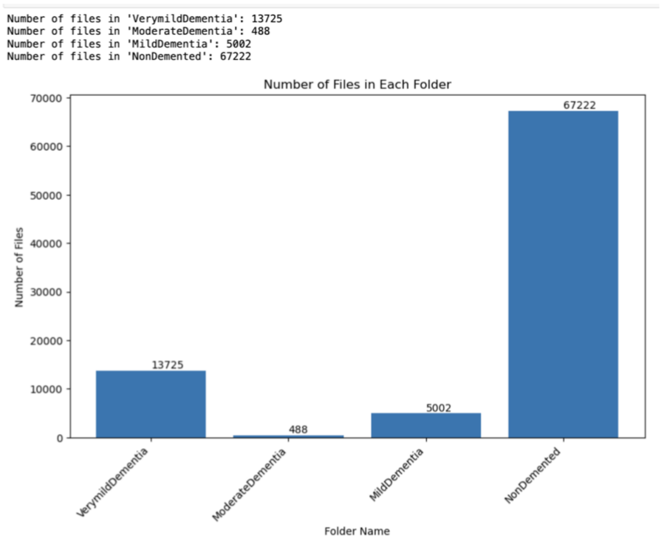

Fig. 4. Representation of Each class

B. Exploratory Data Analysis In the Exploratory Data Analysis (EDA) phase of our study on dementia severity classification, we used a Python script to count the number of images in each category to assess the data's balance. The dataset was organized into four folders representing the categories: Very Mild Dementia, Moderate Dementia, Mild Dementia, and Non-Demented. The analysis, shown in Figure 4, revealed a significant class imbalance. Specifically, the Non-Demented class had a disproportionately large number of images—86,437—while the Moderate Dementia class contained only 488 images. This imbalance could lead to machine learning models favoring the majority class, which may result in biased predictions.

C. Pre-Processing:

1. Balancing the Dataset: To tackle the issue of class imbalance, we balanced the dataset to ensure fair model training and prevent skewed performance. Class imbalance can lead to models that perform well on the majority class but poorly on the minority class. To achieve balance, we reduced the number of images in each category—Non-Demented, Mild Dementia, Moderate Dementia, and Very Mild Dementia—so that each category contained 450 images, based on the category with the fewest samples. This approach ensures fairness and improves model accuracy across all classes [15]. The balanced dataset for each category is shown in Figure 5.

2. Image Resizing and Normalization: To maintain consistency and facilitate model processing, we resized all MRI images to a standard dimension of 128x128 pixels. This resizing ensures that the models receive consistent input sizes, which aids in more efficient learning. Additionally, we applied normalization to scale pixel values to a standard range, helping speed up model convergence during training. These preprocessing steps enhance the efficiency of model learning and contribute to better performance.

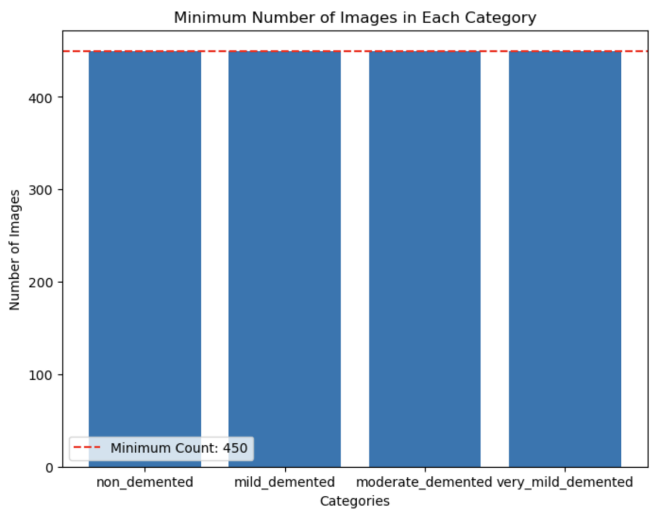

Fig. 5. Preview of Balanced Dataset

3. One-Hot Encoding of Labels: We used one-hot encoding to represent dementia status. This technique converted categorical integer labels into a binary matrix, which is well-suited for classification tasks. By using one-hot encoding, we avoided assuming an ordinal relationship between categories, improving the interpretability of the labels. We utilized the OneHotEncoder from the machine learning library to transform categorical labels into a format suitable for model training [15].

4. Data Splitting: We split the dataset into training and testing sets, allocating 80% of the data for model training and the remaining 20% for model testing. This split ensures that the model is trained on a substantial portion of the data while reserving a separate subset for evaluating its performance [16]. The distribution of the dataset into training and testing sets is illustrated in Figure 6.

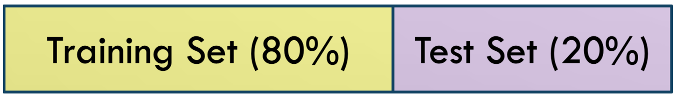

Fig. 6. Preview of Balanced Dataset

D. Model Implementation

1. Random Forest (RF): The RandomForestClassifier is a powerful ensemble technique that builds multiple decision trees to reduce overfitting and improve prediction accuracy. This model is particularly effective for Alzheimer's MRI image detection due to its ability to handle high-dimensional data and identify important features within complex datasets. Its strength lies in aggregating predictions from multiple decision trees, providing a well-rounded approach to capturing subtle variations in brain imaging. This makes it highly valuable for accurately classifying the different stages of Alzheimer's disease.

2. Logistic Regression (LR): Logistic Regression is known for its simplicity and fast training times, making it an ideal baseline model for comparing more complex techniques. In Alzheimer's detection using MRI images, the interpretability of LR is a key advantage, as it offers clear insights into how image features relate to the stages of the disease. Although this model is simple, it effectively demonstrates the linear separability of the data and provides a foundation for more sophisticated analyses.

3. Extra Trees (ET): The ExtraTreesClassifier is an ensemble model similar to Random Forest but uses a more randomized approach for node splitting. We chose this model for its computational efficiency and robustness, making it well-suited for detecting Alzheimer's disease in MRI images. It excels at identifying early, subtle signs of Alzheimer's by handling multiple classes, which represent varying levels of dementia severity. Its random approach to tree construction enhances feature selection, helping to reduce overfitting and improve model performance [17].

4. Convolutional Neural Network (CNN): Convolutional Neural Networks (CNNs) are powerful tools for image analysis, particularly due to their deep structure that enables them to learn hierarchical feature representations. They are highly effective in analyzing the complex patterns present in MRI images, which is critical for early Alzheimer's detection. The CNN's ability to identify and enhance patterns that differentiate stages of Alzheimer's disease from brain images makes it an essential part of our methodology, providing a robust approach to detecting the progressive markers of this neurodegenerative disorder [18].

E. Evaluation: In the evaluation phase, we assessed the performance of our model using key metrics such as accuracy, precision, recall, and ROC-AUC. These metrics offered valuable insights into the model's ability to predict dementia severity across all stages. A thorough analysis of these performance indicators ensures that our classification system is both reliable and effective [1].

IV. RESULT ANALYSIS

Our investigation into machine learning (ML) and deep learning (DL) models for the early detection of Alzheimer's Disease (AD) using MRI scans yielded valuable insights. The Open Access Series of Imaging Studies (OASIS) dataset was used for training and validating the models.

TABLE I
PERFORMANCE METRICS OF SELECTED ML MODELS (IN %)

ML Model	**Accuracy**	**Precision**	**Recall**	**ROC-AUC**
Random Forest	85.84	85.68	85.84	96.44
Logistic Regression	83.07	82.96	83.02	95.05
Extra Trees	89.18	89.22	89.18	97.66
CNN	93.76	73.28	73.30	98.36

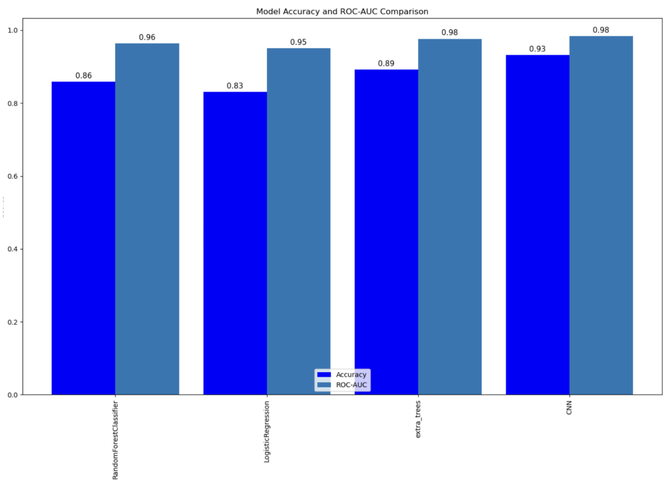

Fig. 7. Comparison of Model Accuracy and ROC-AUC

We implemented five models: Random Forest (RF) and Logistic Regression (LR) for shallow learning, Extra Trees (ET) for ensemble learning, and Convolutional Neural Networks (CNN) for deep learning. The models were evaluated based on metrics including Accuracy, Precision, Recall, and Area Under the Curve (AUC). Additionally, for the CNN model, we calculated training and validation accuracy and loss to assess its performance [19]. As shown in Table 1, all models achieved promising results, with accuracy greater than 0.80 in distinguishing Alzheimer's Disease (AD) from non-AD cases. The Convolutional Neural Network (CNN) model, in particular, demonstrated significant potential, reaching the highest overall accuracy (0.9375) and AUC (0.9950), as depicted in Figure 7. These results highlight the CNN model's strong ability to detect early AD, though trade-offs may exist with other evaluation metrics. Although the CNN model achieved the highest accuracy, its Precision and Recall scores were lower (0.7329) compared to the Extra Trees (ET) model, which achieved Precision and Recall scores of 0.8921 and 0.8917, respectively (Figure 8). This indicates that the CNN model may have a higher rate of false positives, potentially misclassifying non-AD cases as AD [16]. In contrast, the ET model demonstrated a better balance between Precision and Recall, highlighting its ability to more accurately differentiate between AD and non-AD cases. The Random Forest (RF) and Logistic Regression (LR) models, representing shallow learning techniques, also performed well with accuracy scores above 0.83. However, their Area Under the Curve (AUC) values were lower than those of the other models, suggesting that further hyperparameter tuning or feature engineering could enhance their performance.

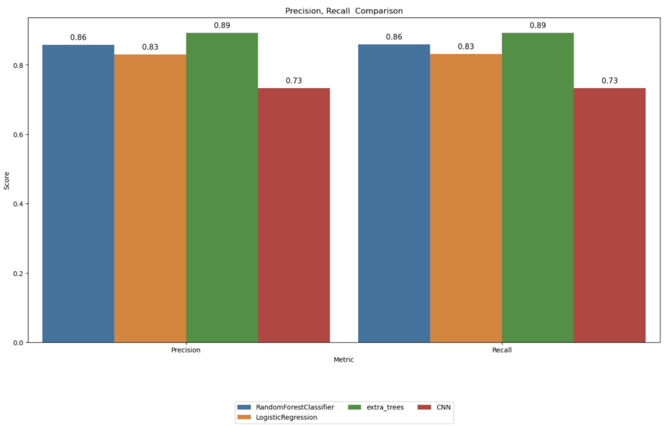

Fig. 8. Comparison of Precision and Recall

The Extra Trees (ET) model, as an ensemble learning approach, emerged as a strong alternative with the second-highest accuracy (0.8917) and a well-balanced performance in terms of Precision and Recall. This suggests its effectiveness in accurately classifying both AD and non-AD cases. In contrast, the CNN model's lower Precision and Recall scores highlight the need for further exploration. Techniques like data augmentation or experimenting with different CNN architectures could help address these challenges.This study explored the potential of various machine learning (ML) and deep learning (DL) models for early AD detection using MRI scans. While the CNN achieved the highest overall accuracy, the ET model provided a compelling alternative, offering balanced performance in terms of accuracy and the ability to correctly identify both AD and non-AD cases.

V. Discussion

This study highlights the effectiveness of deep learning and ensemble models in diagnosing Alzheimer's Disease (AD) from MRI scans. The CNN model achieved the highest accuracy and AUC, indicating strong capability in detecting early brain changes. However, its lower precision and recall suggest some misclassification of non-AD cases, pointing to the need for refinement using techniques like regularization or explainability tools such as Grad-CAM. On the other hand, the Extra Trees (ET) model showed more balanced performance with high precision and recall, making it more suitable in clinical scenarios where minimizing false positives and false negatives is critical. The superior performance of ensemble methods like ET can be attributed to their robustness in handling noisy data and preventing overfitting through randomized tree construction. The clear class imbalance in the original dataset was effectively addressed through downsampling, but this approach may limit generalizability. Future studies should consider data augmentation or synthetic sample generation (e.g., SMOTE) to enhance diversity without sacrificing volume. Additionally, our current models rely solely on structural MRI data. Integrating multimodal data—such as PET scans, genetic markers, and clinical records—could provide a more comprehensive diagnostic tool. Overall, this study demonstrates the practical utility of interpretable AI models in enhancing AD diagnosis and supports their integration into clinical workflows. The trade-offs observed between model types highlight the importance of context-specific model selection, where precision, recall, or interpretability might take precedence depending on clinical goals.

VI. Clinical Relevance

The early and accurate detection of Alzheimer's Disease (AD) is vital for initiating timely medical interventions, patient counseling, and care planning. Traditional diagnostic methods, such as clinical evaluations and cognitive testing, are often limited by subjectivity and may fail to detect early neurodegenerative changes. In contrast, our proposed AI-driven framework utilizes structural MRI data and interpretable machine learning models—including CNNs and Extra Trees classifiers—to support objective, data-driven diagnosis of Alzheimer's across varying stages.

Clinically, the integration of explainable AI models addresses a critical barrier in medical AI adoption for trust and transparency. By employing models with strong interpretability and robust classification performance, our system offers the potential to complement radiologists' expertise and reduce diagnostic uncertainty. The high accuracy of the CNN model in detecting subtle brain abnormalities, combined with the balanced precision and recall of the Extra Trees model, ensures reliable identification of both AD and non-AD cases. Moreover, the model's interpretability enables clinicians to understand key image regions contributing to the diagnosis, thereby enhancing clinical decision-making and aligning with the ethical standards of explainable healthcare AI. This framework has the potential to be integrated into clinical decision support systems (CDSS) to enhance early AD diagnosis, reduce misdiagnosis rates, and ultimately improve patient outcomes through earlier intervention and treatment planning.

VII. CONCLUSION

Our study used the Open Access Series of Imaging Studies (OASIS) dataset, which consists of MRI scans, to develop computational models for the early detection of Alzheimer's Disease (AD). We demonstrated that advanced techniques such as Random Forest, Logistic Regression, Extra Trees, and Convolutional Neural Networks (CNNs) are effective in identifying early signs of AD, showing potential improvements in diagnostic accuracy.

Our findings suggest that CNNs outperform other models in accurately identifying Alzheimer's Disease cases, as evidenced by their higher accuracy and AUC scores. However, the Extra Trees model also shows strong performance, particularly in precision and recall, indicating its potential value in clinical settings where minimizing false positives and false negatives is crucial for accurate AD diagnosis. Additionally, our comparative analysis highlights the importance of selecting the right machine learning models based on specific diagnostic needs. While CNNs may be preferred for their high sensitivity in detecting subtle pathological changes, ensemble methods like Extra Trees provide a more balanced approach, making them more reliable when both precision and recall are essential.This research contributes to the ongoing fight against Alzheimer's Disease through technological advancements [20]. It emphasizes the importance of continuously refining these models and suggests that future research should focus on integrating multimodal data sources, improving model robustness with advanced training techniques, and validating findings on larger, more diverse datasets. These steps are essential to ensure the models' generalizability and applicability to different populations. By leveraging machine learning techniques, this study marks a significant step forward in combating Alzheimer's Disease. It holds promise for improving the quality of life for affected individuals by enabling earlier and more accurate interventions.

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