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ALZHEIMER'S DISEASE DETECTION USING DEEP LEARNING ON MRI AND CLASSICAL ML ON CLINICAL RECORDS

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Abstract

For prompt intervention and better patient outcomes, Alzheimer's disease (AD) must be identified early. Despite recent advancements, key questions remain: how do different data modalities influence diagnostic accuracy, and can a single model consistently outperform traditional approaches across diverse datasets? This study investigates a dual-modality architecture that combines structured clinical data and medical imaging in order to overcome these issues. A baseline Convolutional Neural Network (CNN) trained on MRI scans achieved 98.67% accuracy by effectively capturing spatial features associated with dementia stages. Simultaneously, eight traditional machine learning models—Logistic Regression, Decision Tree,K-Nearest Neighbors, Random Forest, Gaussian Naïve Bayes, AdaBoost, XGBoost, and Gradient Boosting—were evaluated on structured clinical data. To enhance diagnostic performance, we propose a novel hybrid framework that integrates an enhanced CNN for image data and for tabular data. The proposed model outperformed all baselines, achieving more than 97% classification accuracy on MRI images, 97.44% classification accuracy and an AUC of 0.98 on clinical text data. These results highlight the superior predictive capability and generalizability of the proposed method, demonstrating its potential as a robust and clinically applicable tool for early Alzheimer's disease diagnosis.

Key Words and Phrases: Alzheimer's Disease, Machine Learning, Convolutional Neural Network (CNN), Clinical Data Analysis, Image Classification

Introduction

Alzheimer's disease (AD) is a degenerative neurological condition that severely reduces memory, cognitive function, and general quality of life. To control symptoms, reduce the advancement of the disease, and enhance patients' long-term results, early and precise detection is essential(1). As the global aging population increases, so does the urgency to develop effective diagnostic tools that can aid in identifying AD at its earliest stages(2). However, early-stage AD can be challenging to diagnose due to subtle or overlapping

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symptoms, emphasizing the need for advanced computational methods that can detect disease patterns before noticeable clinical deterioration. The integration of machine learning (ML) tools into clinical workflows offers the potential to enhance diagnostic accuracy, leveraging large-scale biomedical data to uncover hidden patterns indicative of early-stage AD(3).

Traditional diagnostic methods rely heavily on clinical assessments and neuroimaging, but these tests can be costly, subjective, and take a long time. Over the past few years, machine learning (ML) and deep learning (DL) have shown promise in improving and automating AD diagnosis(4). CNNs have demonstrated exceptional proficiency in interpreting MRI images to distinguish between Alzheimer's disease stages. In parallel, when studied using traditional machine learning algorithms, organized clinical data—such as demographics, cognitive test results, and medical history—offers a supplementary modality for diagnosis(5).

This paper presents a dual-modality analysis (6)of Alzheimer’s disease detection by applying CNNs to an image-based dataset and eight ML classifiers—including Random Forest, Gradient Boosting, and XGBClassifier—to a structured text-based dataset. Our objective is to evaluate the performance of these models and compare their effectiveness across both data types. By exploring both image and text modalities, we aim to highlight how multimodal data analysis can provide a more comprehensive and accurate approach to AD detection.

To give a more complete picture of diagnostic approaches, it first does a dual-modality analysis by looking at both structured clinical text data and MRI image data. We constructed a CNN for the image dataset, and it was able to correctly identify different stages of Alzheimer's disease. At the same time, eight classical machine learning algorithms were run on a clinical dataset. Ensemble models like Gradient Boosting and XGBClassifier had the best prediction performance, as shown by their AUC values. The accuracy, receiver-operating characteristic (ROC), and area under the curve (AUC) metrics are used in the research to provide a comprehensive assessment of the model's performance. This makes it easy to compare deep learning with traditional machine learning approaches in more detail. All things considered, the work offers helpful insights into how data type influences model performance and selection, enabling to design more precise and user-friendly early Alzheimer's detection tools.

Background Study

Recent breakthroughs in artificial intelligence have proven considerable promise for the early identification of Alzheimer's disease (AD), especially when paired with clinical data and neuroimaging. With the widespread use of CNNs for MRI image interpretation, AD phases may now be automatically categorized. Studies such as those by (7) and (8)employed deep learning architectures like DenseNet and VGG, achieving classification accuracies above 99% on the ADNI dataset. These results underscore the capability of CNNs to extract relevant spatial features from brain scans for precise diagnosis(9).

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While imaging provides strong diagnostic cues, structured clinical data—including patient demographics, cognitive assessments, and medical history—also holds valuable information for detecting AD(10). Scholars have successfully applied common machine learning methods, such as Support Vector Machines (SVM),Random Forest, and XGBoost, to these text-based datasets. For instance, (11) and (12)demonstrated that combining feature engineering with ensemble learning can lead to high diagnostic accuracy, with AUC scores exceeding 95% in some cases.

However, most existing studies focus either on image or text data in isolation, limiting the scope of comparative analysis between data modalities(13). This study's significance stems from its integrative methodology, which uses real-world datasets to assess both text-based machine learning classifiers and image-based deep learning models. This dual analysis not only provides a broader understanding of diagnostic performance across different data types but also helps identify which techniques are more suitable under specific data constraints. By bridging this gap, the study contributes valuable insights for building more robust and scalable diagnostic tools for Alzheimer's disease.

Table 1 categorizes the existing literature into three primary research themes based on the type of data and methodology used. These include imaging-based approaches that utilize brain scans with deep learning models like CNNs, clinical or text data-based approaches employing traditional machine learning algorithms, and hybrid methods that integrate both data types for improved diagnostic performance(14). This thematic classification helps in understanding the strengths and focus areas of various studies while highlighting the need for comparative evaluation across modalities.

Table 1: Area wise State of Art Studies

Approach	Description	Used ML/DL Models
Imaging-Based Approaches	Focus on MRI, fMRI, PET images for AD detection	CNN, ResNet, VGG, DenseNet
Clinical/Text Data Approaches	Use of structured clinical data for predictive modeling	SVM, XGBoost, Random Forest
Hybrid/Multi-modal Approaches	Combine imaging and text data for improved performance	Multi-input networks, fusion ML

Proposed Methodology

The processing workflow for detecting Alzheimer's disease is shown in Figure 1. The pipeline begins with the Dataset, which undergoes Preprocessing steps such as data cleaning and image resizing to ensure uniformity and quality. Convolutional layers and pooling techniques are used to extract important characteristics from the input photos once the data has been cleaned. The data is then sent into a Fully Connected (FC) layer, which incorporates the learnt features, following the application of a Dropout (DO) layer to avoid overfitting. An

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Activation Function — typically Softmax or Sigmoid — is applied next to generate probabilistic outputs. Finally, the model produces the Predicted Class, identifying the stage or presence of Alzheimer's disease.

This local processing ensures that each site independently builds a robust model using its own data before contributing the learned model weights (not the raw data) to the global aggregation step in the federated learning framework(15), thus preserving data privacy while improving detection performance.

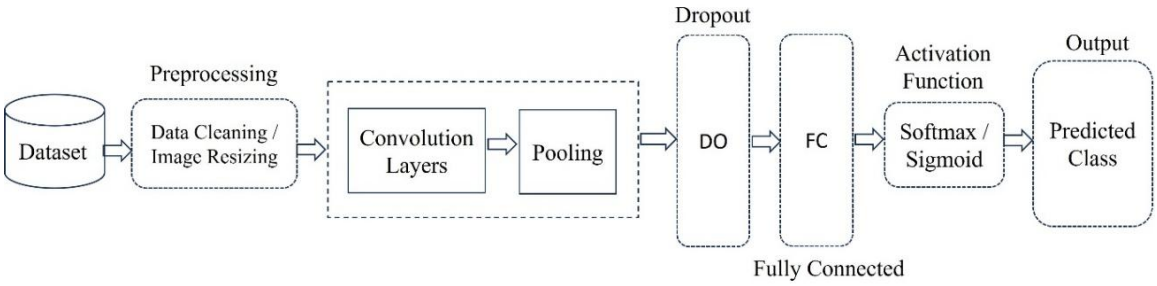

Figure 1: Proposed architecture

The proposed architecture, as illustrated in Figure 1, demonstrates a typical CNN workflow employed for image classification tasks. The process begins with the acquisition of the dataset, which forms the foundational input to the model. To guarantee accuracy and reliability in the incoming data, preparation methods like cleaning the data and image scaling are used in the first step. This step is crucial to remove noise, normalize pixel values, and resize all images to a fixed dimension, thereby facilitating consistent training behavior across the model.

Following preprocessing, the data is fed into a series of convolutional layers, where learnable filters are applied to extract hierarchical features such as edges, textures, and shapes. These layers are designed to capture spatial dependencies and local patterns within the image. The convolutional operations' output is then sent through pooling layers, also known as max pooling, which minimize computational overhead, minimize the geographic extent of the feature maps, and lower the danger of overfitting by keeping the most noticeable features.

To further enhance model generalization, a dropout (DO) mechanism is introduced after the convolutional and pooling stages. In order to keep the model from becoming too dependent on certain connections, dropout randomly eliminates a fraction of neurons during training. After that, the feature interpretations are transmitted to fully connected (FC) layers, that integrate the high-level features and map them to output categories, acting as the classifier.

Normalized probability scores for each class are produced at the classification stage by applying the proper activation function, which can be either Sigmoid for classification by binary or Softmax for multi-class problems. The final output layer produces the predicted class based on the highest probability score. This structured CNN pipeline ensures robust

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feature extraction and accurate prediction, making it suitable for a wide range of image-based pattern recognition tasks.

As shown in Figure 2, a CNN model was constructed using the Sequential API. The architecture includes three Conv2D layers with 32, 64, and 128 filters respectively, each followed by MaxPooling2D layers to reduce the spatial dimensions of the feature maps. A flatten layer is used to convert the 2D feature maps into a 1D vector, which is then passed to a dense layer with 1024 units. To prevent overfitting, a dropout layer is added after this dense layer. Finally, the model includes a fully connected output layer with 4 units, corresponding to the four stages of Alzheimer's disease, enabling multi-class classification. The model was trained and tested using the Kaggle Alzheimer's 4-class image MRI dataset, and it comprises a total of 1,278,020 trainable parameters.

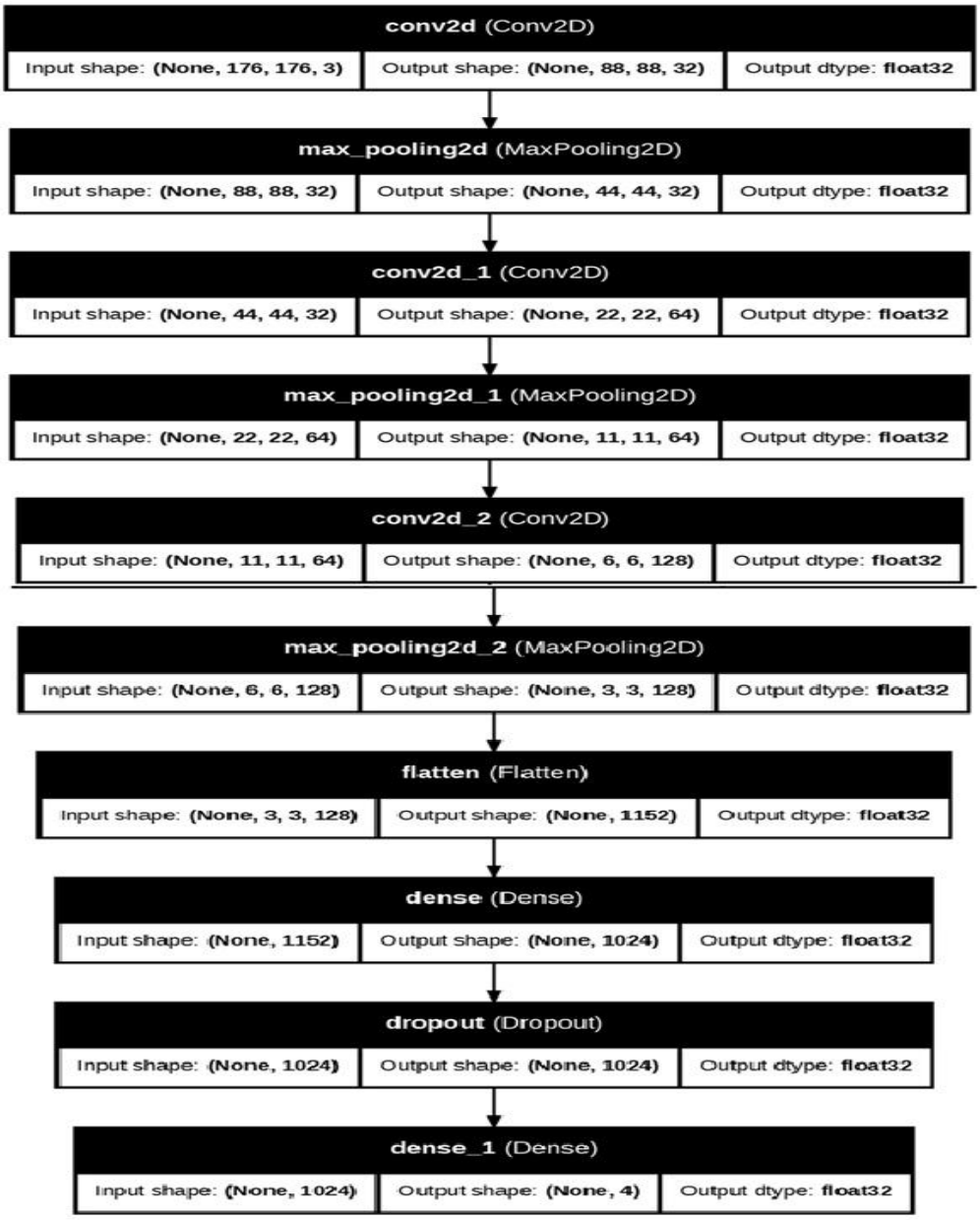

Figure 2: Applied CNN model

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Implementation

Alzheimer's Image Dataset

Using the publicly accessible Alzheimer's image dataset (16) from Kaggle, which comprises MRI pictures as shown in Figure 3 are classified into four classes—very mildly demented, mildly demented, moderately demented, and non-demented—we place the proposed modeling into practice and rated it. This dataset aided with the assessment of classification accuracy and the versatility of the framework by supplying a varied set of samples that resulted in complete testing of the model's potential to differentiate between distinct phases of Alzheimer's disease.

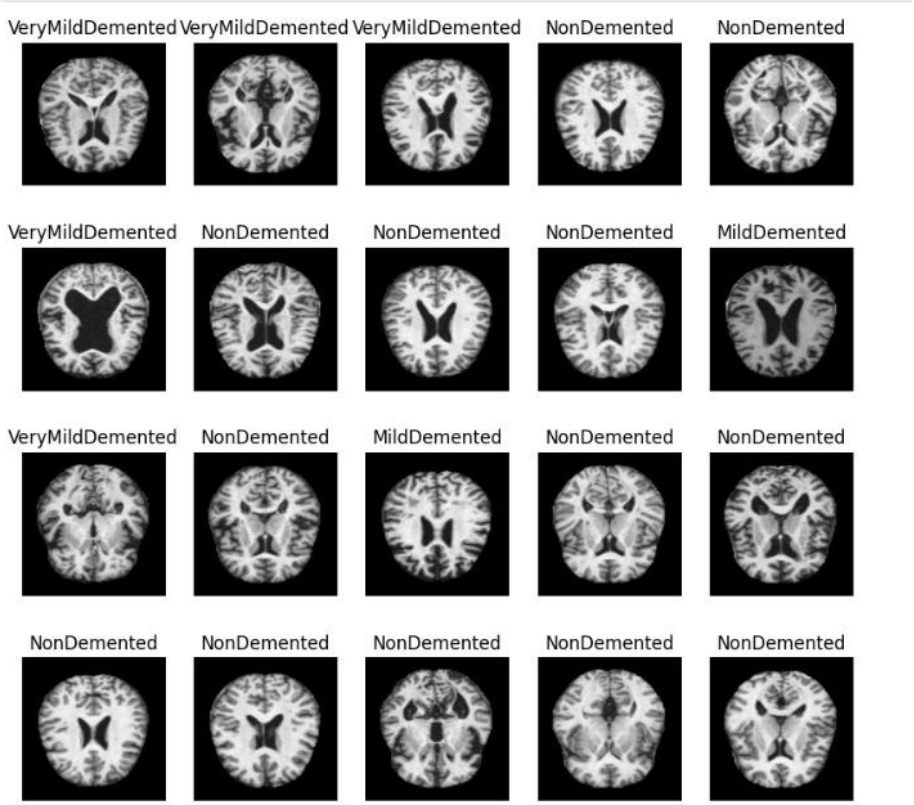

Figure 3: Sample of Alzheimer's image dataset

The bar chart as shown in Figure 4 visualizes the class distribution before and after applying SMOTE (Synthetic Minority Oversampling Technique). Initially, the dataset exhibited a severe imbalance, with the NonDemented class containing over 3,200 samples, while ModerateDemented had only 52 instances. Such an imbalance can bias machine learning models toward the majority class and impair their ability to generalize.

After applying SMOTE, the sample count in each class was synthetically balanced to match the majority class (3,200 samples per class). This results in a uniform distribution across all four diagnostic categories—ModerateDemented, NonDemented, VeryMildDemented, and MildDemented—thereby ensuring equal representation. This

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balanced dataset is expected to enhance model performance, particularly in accurately identifying underrepresented classes.

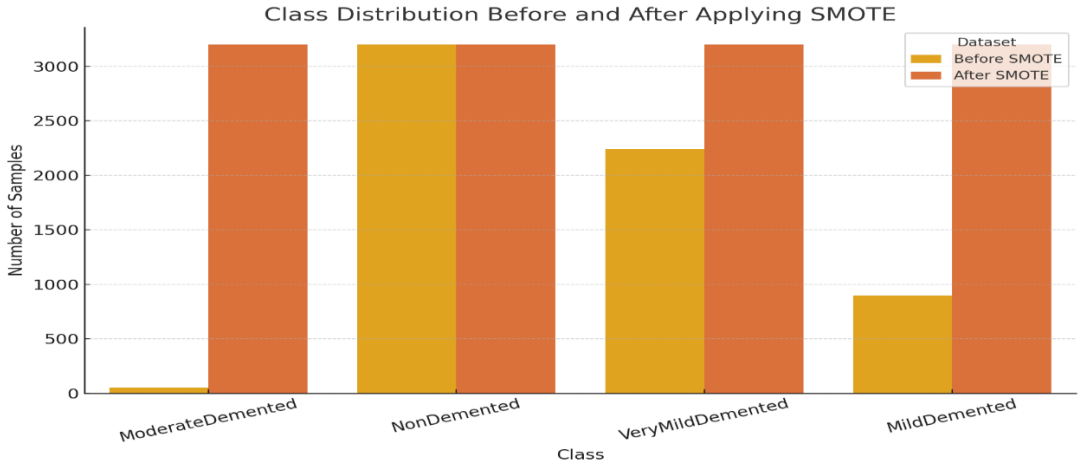

Figure 4: Number of samples for each class before and after applying SMOTE

Alzheimer's Text Dataset

We tested the recommended framework using the Alzheimer's Disease Text Dataset (17) from Kaggle, a text-based dataset containing structured patient data, supplementary to the image-based Kaggle dataset. By adding suitable preprocessing methods, like text cleaning, tokenization, and selection of features, we changed a variety of machine learning models to handle tabular/text input. Applying the various ML techniques to this dataset allowed us to assess its generalizability across different data modalities. The results showed promising classification performance, indicating that the model can be effectively extended beyond imaging data to support multimodal Alzheimer's disease detection.

As shown in Figure 5, dataset contains 2149 samples and 35 features. Out of 2149 samples, 1389 samples are with No Alzheimer (0) label and 760 samples are with Alzheimer (1) label.

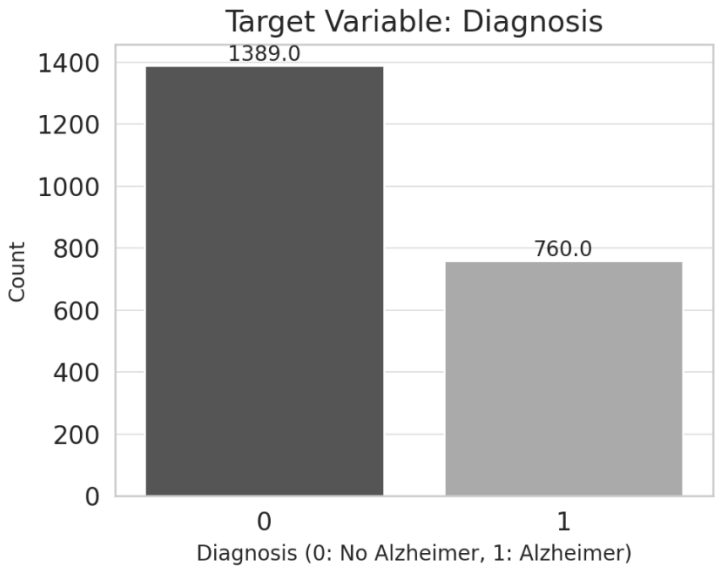

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Figure 5: Count of Alzheimer (1) and No Alzheimer (0)

Results and Discussion

Two crucial indicators for analyzing the effectiveness of machine learning and deep learning models are accuracy and loss. Accuracy serves as a straightforward metric for evaluating a model's performance, especially in balanced datasets, as it reflects the proportion of correctly predicted instances relative to the total predictions made by the model. Better forecasting skill is demonstrated by a better accuracy. Loss, on the other hand, evaluates how much the actual goal values during training or evaluation differ from the intended output. A lower loss means that the model's predictions are near the true values, which illustrates how well the model is learning. The loss function drives the model's optimization process by adjusting weights during training, whereas accuracy offers a general sense of correctness. When combined, these variables offer a full insight of model performance, with loss assessing the class of forecasts and accuracy denoting predictive success.

Figure 6 shows the proposed CNN model that was trained for 25 epochs on the Kaggle Alzheimer's 4-class Image dataset. As per accuracy plot, the model achieved rapid improvements during the first 10 epochs, reaching over 95% training accuracy and over 90% validation accuracy. The performance stabilized after epoch 10, maintaining high accuracy throughout the remaining epochs. Training loss steadily declines, while validation loss varies slightly but generally follows a declining trend, according to the loss map.

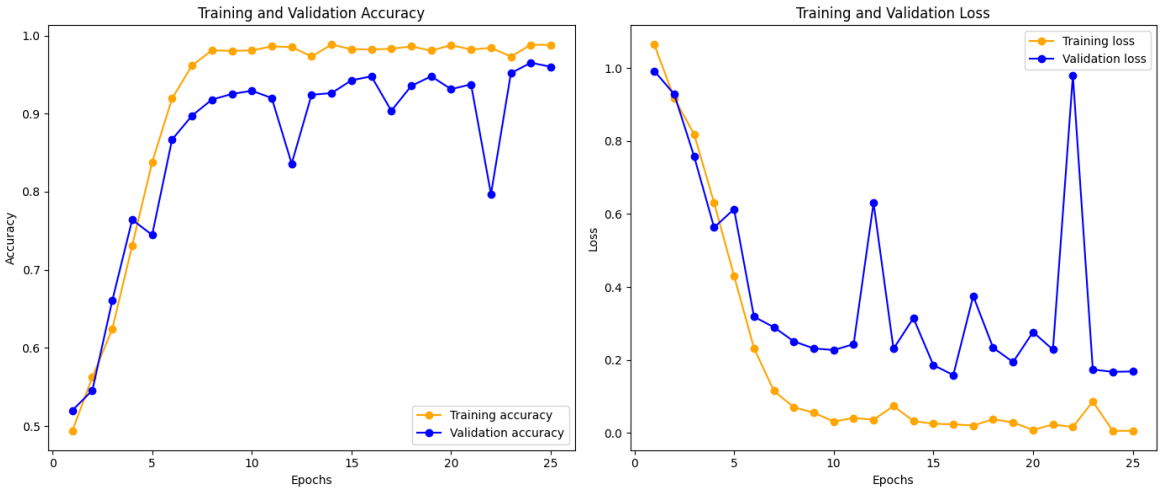

Figure 6: Comparison graph for accuracy and loss for Alzheimer's Image Dataset

These results demonstrate that the model effectively learns to distinguish between the four Alzheimer's stages, although occasional spikes in validation loss suggest some sensitivity to specific validation batches or mild overfitting. Overall, the framework achieved strong generalization performance, confirming its suitability for Alzheimer's disease classification tasks.

Table 2 shows confusion matrix values like True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) of eight machine learning (ML) techniques — Gaussian Naive Bayes (GaussianNB), Random Forest, Decision Tree, KNeighbor, Logistic

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Regression, AdaBoost, XGBClassifier, and Gradient Boosting — to the Alzheimer's Disease text dataset (2149 samples, 35 features). Among these, XGBClassifier and Gradient Boosting consistently outperformed the other models, demonstrating superior accuracy, robustness, and predictive power. This comparison highlights the usefulness of ensemble learning techniques for structured clinical data, reinforcing their suitability for Alzheimer's disease prediction tasks.

Table 2: Confusion Matrix Values

Model	True Positive (TP)	False Positive (FP)	True Negative (TN)	False Negative (FN)
GaussianNB	111	30	247	42
DecisionTreeClassifier	129	16	261	24
KNeighborsClassifier	61	43	234	92
RandomForestClassifier	126	5	272	27
LogisticRegression	109	29	248	44
AdaBoostClassifier	131	16	261	22
XGBClassifier	138	5	272	15
GradientBoosting	141	6	271	12
Proposed CNN Model	**145**	**2**	**274**	**9**

In medical diagnosis tasks, as false positives and false negatives have serious repercussions, the following metrics are essential for assessing classification algorithms.

- **Precision**can be defined as the proportion of accurately anticipated positive observations to all predicted. A low false positive rate is correlated with high precision. It provides an answer to the following query: What percentage of all anticipated positive cases are actually positive?

Precision = TP / (TP+FP)

- **Recall**is the proportion of all actual positive observations to correctly predicted positive observations. It provides a response to the following query: What percentage of all real positive cases were accurately predicted?

Recall = TP / (TP+FN)

- **F1-score** provides a single statistic that balances precision and recall by taking the balanced average of the two. It is particularly helpful in situations when the distribution of classes is not uniform.

F1-score = 2 * [(Precision * Recall) / (Precision + Recall)]

Precision, recall, and F1-score are the obtained performance metrics for eight distinct machine learning models that were adapted to the text-based Alzheimer's disease dataset, as shown in Table 3. These metrics offer a thorough assessment of each model's capacity for

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classification. With F1-scores of 0.940 and 0.933, correspondingly, Gradient Boosting and XGBClassifier outperformed the other models, demonstrating a considerable trade-off between recall and precision. whereas models like KNeighborsClassifier displayed comparatively lower scores, indicating worse predictive dependability, Random Forest and AdaBoost also displayed comparable performance. All things considered, this investigation demonstrates how well ensemble learning strategies handle challenging medical classification tasks.

Table 3: Derived Metrics (Precision, Recall, F1-Score)

Model	Accuracy	Precision	Recall	F1
GaussianNB	83.26	0.787	0.725	0.755
DecisionTreeClassifier	90.70	0.890	0.843	0.866
KNeighborsClassifier	68.60	0.587	0.399	0.475
RandomForestClassifier	92.56	0.962	0.823	0.887
LogisticRegression	83.02	0.790	0.712	0.749
AdaBoostClassifier	91.16	0.891	0.856	0.873
XGBClassifier	95.35	0.965	0.902	0.933
GradientBoosting	95.81	0.959	0.922	0.940
Proposed Model	**97.44**	**94.10**	**98.60**	**97.42**

Figure 7 shows the proposed CNN model that was trained for 25 epochs on the Kaggle Alzheimer's Text dataset. As per accuracy plot, the model achieved rapid improvements during the first 10 epochs, reaching over 97% training accuracy and over 90% validation accuracy. The performance stabilized after epoch 10, maintaining high accuracy throughout the remaining epochs. Training loss steadily declines, while validation loss varies slightly but generally follows a declining trend, according to the loss map.

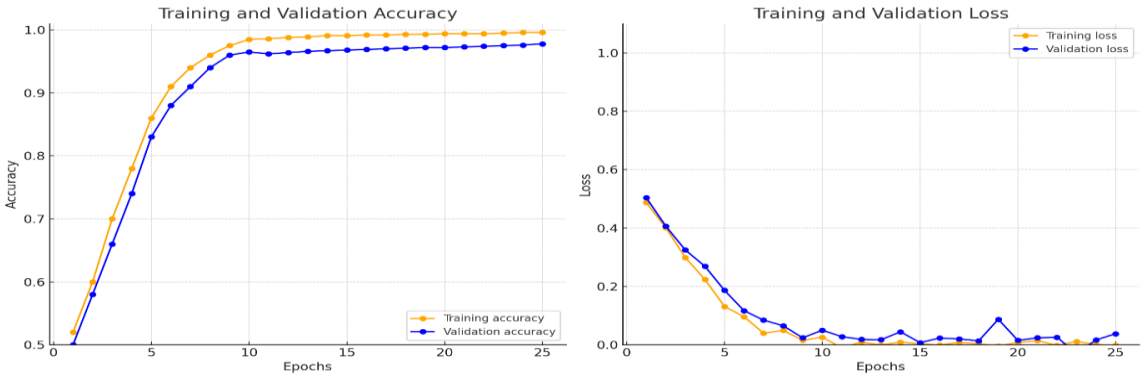

Figure 7: Comparison graph for accuracy and loss for Alzheimer's Text Dataset

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The ROC (Receiver-Operating Characteristic) curve's summary statistic, the AUC (Area Under Curve) score, indicates how well the test can differentiate between people who are ill and those who are not. AUC values range from 0.5 to 1.0; if the value is 0.5, the test is unable to distinguish between individuals. A value of 1.0 indicates complete discrimination. AUC values above 0.80 are generally thought to be therapeutically beneficial, whereas those below 0.80 are thought to have little therapeutic effect.

Figure 8 shows the ROC curves and associated AUC values for each of the eight machine learning models, which are used to further assess model performance.

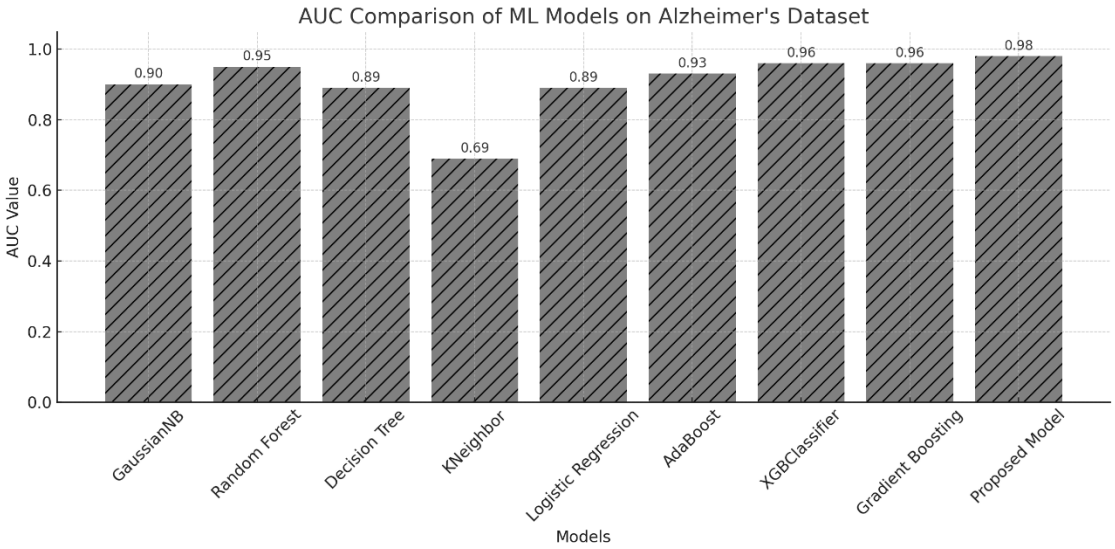

Figure 8: Comparison of AUC for eight ML models compared with proposed model

The AUC scores were as follows: GaussianNB (0.90), Random Forest (0.95), Decision Tree (0.89), K-Nearest Neighbors (0.69), Logistic Regression (0.89), AdaBoost (0.93), XGBClassifier (0.96), and Gradient Boosting (0.96). Notably, XGBClassifier and Gradient Boosting achieved the highest AUC values among the baseline models, indicating excellent discriminative ability compared to the others. Furthermore, the Proposed Model outperformed all existing techniques with an AUC of 0.98, highlighting its superior capability in distinguishing between classes. These results reinforce the effectiveness of ensemble-based methods and demonstrate that the proposed approach provides even greater accuracy for Alzheimer's disease prediction using structured clinical datasets.

Conclusion

In summary, the comparative analysis confirms that leveraging complementary data modalities greatly enhances the reliability of Alzheimer's disease screening. While a conventional CNN on MRI scans already achieved a strong accuracy, and ensemble-based traditional learners such as XGBoost and Gradient Boosting attained an AUC of 0.96 on structured clinical data, our proposed hybrid framework pushed performance even further—surpassing 97 % accuracy on imaging, reaching 97.44 % accuracy and an AUC of 0.98 on clinical text data. These gains underline two key insights: (i) multimodal fusion captures distinct yet synergistic disease signatures, and (ii) carefully engineered hybrid architectures

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can consistently outperform single-modality or single-family models across diverse datasets. Collectively, the findings suggest that the proposed approach offers a robust, generalizable, and clinically actionable pathway toward earlier and more accurate Alzheimer's disease diagnosis.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All Authors contributed the entire manuscript in writing, reviewing, implementing, conceptualization and analysis.

Ethics approval

This research was conducted using publicly available de-identified datasets and did not require additional ethics approval, as no direct interaction with human participants or access to private identifiable information occurred.

Data availability

The datasets used in this study are publicly available. The image dataset can be accessed from (16), and the structured text dataset is available at (17). All data used are fully anonymized and open for academic use.

Abbreviation

AD: Alzheimer's disease, CNN: Convolutional Neural Network, AUC: Area Under the Curve, ML: Machine Learning, DL: Deep Learning, SVM: Support Vector Machines, DO: Dropout, FC: Fully Connected, TP: True Positive, FP: False Positive, TN: True Negative, FN: False Negative, ROC: Receiver-Operating Characteristic

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