Early-Stage Alzheimer’s Disease Prediction using MRI - based Data: A Multimodal Deep Learning Approach

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ABSTRACT
Alzheimer's Disease (AD) is a progressive neurological condition characterized by cognitive deterioration and memory impairment. Prompt identification is essential for timely intervention, facilitating more efficient management and treatment approaches. Conventional diagnostic approaches depend on cognitive evaluations and clinical assessments, which frequently do not identify Alzheimer's disease in its initial stages. Deep learning has emerged as an effective method for automating the diagnosis of Alzheimer's disease via brain MRI data. This study introduces a deep learning framework aimed at detecting early-stage Alzheimer’s by utilizing MRI data to improve accuracy and facilitate prompt intervention. The dataset comprises 6,400 MRI scans categorized into four different groups: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. Carefully comparing most of the models such as VGG16, VGG19, ResNet, MobileNetV2, InceptionV3, DenseNet169, and EfficientNetB0 and fine-tuning and mitigating overfitting custom models, the final model achieved a weighted F1 score of 0.99%, indicating potential for substantial enhancement as an optimal predictor or classifier of MRI scans and the results also suggest that its effectiveness in promoting early diagnosis for patients with Alzheimer's disease.

Keywords
Alzheimer’s Disease (AD), MRI, Convolutional Neural Network (CNN), Deep Learning, Classification, Neuroimaging, Biomarker Analysis, Medical Image Processing, Single Label, Sequential Model, Generative Adversarial Networks (GAN).

1. INTRODUCTION
Alzheimer's disease is a leading cause of dementia worldwide, affecting millions and presenting considerable challenges to the health care system. Traditional diagnostic techniques rely on clinical evaluations and cognitive tests, which may fail to detect early signs linked to Alzheimer's disease. Recent breakthroughs in neuroimaging and deep learning offer compelling opportunities for the autonomous identification of Alzheimer's disease. There is significant chance of getting better results from deep learning techniques for the early classification of Alzheimer's disease, utilizing MRI data to derive disease-specific characteristics [1]. The timely and accurate detection of Alzheimer's Disease is essential for patient care and the advancement of future therapies. Therefore, there is a necessity for automated diagnosis of specific diseases using medical images to assist healthcare professionals in further evaluating treatment options for the condition. Alzheimer's disease is a prime example of a condition frequently subject to misdiagnosis. The development of Alzheimer's is caused by the shrinkage of particular brain regions and degradation of neurons. Magnetic Resonance Imaging (MRI) scans provide this information; nevertheless, atrophied regions vary among individuals, complicating diagnosis and frequently resulting in misdiagnosis. Recent breakthroughs in neuroimaging and deep learning provide significant prospects for the automated identification and early diagnosis of Alzheimer’s disease. This work investigates deep learning methodologies for the early classification of Alzheimer's disease, employing MRI data to extract disease-specific features [2]. Moreover, expects enhanced early diagnostic accuracy by the application of a refined deep learning model, hence enhancing the early prediction of Alzheimer's Disease, to improve the outcomes of the patients and prevent or even delay the Dementia development.

2. LITERATURE REVIEW
2.1 Advancement of Deep Learning and Multimodal Approaches
For the early detection of Alzheimer’s Disease, Deep learning has shown a significant growth. A study presented a tensor-based GAN framework for Alzheimer's disease assessment, exhibiting its capacity to augment classification accuracy and boost MRI data augmentation [3]. The research addressed the significance of leveraging synthetic data to address dataset constraints and enhance generalization in deep learning models. A multimodal discrimination strategy that integrates regional cortical atrophy with hypometabolism data, resulting in enhanced diagnosis accuracy [4]. The combined analysis of MRI and PET data proved enhanced classification accuracy, with convolutional neural networks obtaining a mean accuracy of 78.5%. The findings highlighted the necessity of incorporating many imaging modalities to enhance Alzheimer's disease categorization and more accurately forecast cognitive deterioration.

2.2 CNN and Attention based ML Models and Techniques
A Linear Mixed Effects model was employed to analyse MRI-based biomarkers throughout a 5-year follow-up, with support vector machines (SVM) attaining great accuracy in classifying patients and predicting conversion to Alzheimer's disease (AD) [5]. Additionally, a 3D CNN model specifically designed for hippocampus MRI data shown efficacy in detecting structural alterations linked to the early onset of Alzheimer's disease, indicating a potential methodology [5]. The study confirmed hippocampal shrinkage as a crucial biomarker for early Alzheimer's disease diagnosis and illustrated the efficacy of convolutional neural networks in extracting spatial data from three-dimensional brain scans.

An established solution to the issue was presented through a new categorization framework utilizing a null longitudinal model, which demonstrated efficacy in forecasting Alzheimer's disease conversion from mild cognitive impairment. The model employed longitudinal MRI images and statistical techniques to monitor disease progression over time, providing a predictive equipment for clinicians.

A notable enhancement has occurred in the domain of feature attractiveness. The research primarily concentrated on a specific methodology for feature extraction and model performance comparison. In addition to that some of the research's has been conducted by examination of deep residual networks for Alzheimer's disease diagnosis, incorporating self-attention mechanisms to improve feature extraction from MRI data. The findings suggests that the integration of attention layers enhanced model interpretability and resilience, resulting in improved early stages AD identification.

Alzheimer's disease prediction has improved significantly by a multi-stream CNN architecture and by integrating a structural MRI information with cognitive biomarkers. Research indicated that the integration of structural imaging data with clinical evaluations markedly enhanced model performance and dependability. There has been several exploration including a hybrid deep learning architecture that combines convolutional and recurrent neural networks for classification of AD. This methodology integrates spatial and temporal characteristics derived from MRI scans to improve classification efficacy. Research demonstrates that hybrid models outperform single-network structures in the identification of Alzheimer's disease.

A study on transfer learning for classification of AD has shown promising results, since pre-trained models on large neuroimaging datasets are adapted for specific Alzheimer's-related activities [6]. Transfer learning enhances model convergence and generalization, rendering it an effective method for identifying early-stage Alzheimer's disease with constrained data. There has been a development of a CNN model to make use in attention mechanisms to focus on disease-specific areas in brain MRI data. The model autonomously detects and highlights key regions linked to Alzheimer's disease progression, enhancing diagnostic precision and minimizing false-positive occurrences.

Graph convolutional networks (GCNs) have been utilized to depict brain connection networks in Alzheimer's disease diagnosis [7]. GCN-based methodologies have attained superior performance in diagnosing Alzheimer's disease stages by modelling structural and functional connection patterns. A deep learning method incorporating reinforced learning has been created to enhance MRI scan selection, hence increasing the accuracy and efficiency of Alzheimer's disease diagnosis. By selecting scans that yield the highest diagnostic value, the model improves classification accuracy and minimizes computational expenses [8].

Although these deep learning methodologies demonstrate considerable potential for the early detection of Alzheimer's Disease, obstacles persist regarding model generalizability and interpretability. The integration of varied data kinds and the creation of interpretable AI models are essential for progressing this domain and guaranteeing the efficient application of these tools in healthcare environments. Furthermore, continuous research is essential to enhance these models and augment their precision and dependability in practical applications [9] [10].

Table 1. Comparison of Deep Learning Models

Algorithm	Precision	Recall	F1-Score	Accuracy
Convolutional Neural Networks (CNNs)	85% - 95%	85% - 95%	85% - 95%	85% - 90%
Recurrent Neural Networks (RNNs)	75% - 85%	75% - 85%	75% - 85%	80% - 85%
Transformers	90% - 98%	90% - 98%	90% - 98%	90% - 95%
Autoencoders	80% - 95%	75% - 95%	80% - 90%	80% - 90%

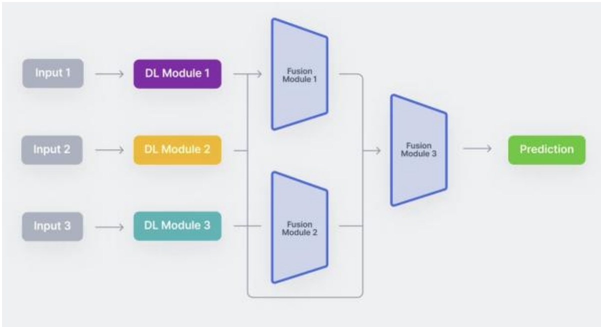

Fig i: Multimodal Deep Learning Approach Architecture

3. METHODOLOGY

3.1 Data Preprocessing

This study utilized the "Best Alzheimer MRI dataset" from Kaggle, comprising 6,400 MRI brain images classified into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. To improve model generalization and reduce overfitting, various preprocessing techniques were implemented. While Alzheimer's disease is incurable, early detection can mitigate its effects and enhance a patient's quality of life. Progress in computer vision demonstrates significant potential in this domain; nonetheless, a primary obstacle persists: the datasets accessible for Alzheimer's detection are constrained and markedly unbalanced. This disparity leads AI models to prioritize the majority class, frequently misclassifying individuals with early symptoms as "Not Impaired." Such errors become problematic as they hinder timely intervention, which is essential for good health management [11].

Each image was initially reduced to 128x128 pixels to maintain consistent input dimensions across all models. Skull stripping was executed to eliminate non-cerebral tissues, hence accentuating the emphasis on essential brain regions. Data augmentation methods, such as rescaling, shearing, zooming, and horizontal flipping, were utilized to artificially enlarge the dataset and enhance model robustness. The dataset was divided into 80% for training, 10% for validation, and 10% for testing, providing equitable representation across all categories. This study uses the Kaggle dataset; however, subsequent research should investigate alternative datasets, such as ADNI, to improve generalizability and validate model adaptation.

The dataset consists of 6400 human brain MRI pictures, divided into three sets: training, validation and testing, with 5120 scans allocated for training and 1280 for testing and 639 for validation. The validation set mitigates overfitting. The images are categorized into four groups: "No Impairment," "Very Mild Impairment," "Mild Impairment," and "Moderate Impairment." Each combination of three is carefully picked for training, validation and testing, hence minimizing overfitting of the dataset. Furthermore, from the four classes each category comprised 100, 70, 28, and 2 individuals, respectively, with each patient's brain sectioned into 32 horizontal axial MRIs. The MRI scans were obtained with a 1.5 Tesla MRI scanner employing a T1-weighted sequence. The training data is enhanced by techniques like rescaling, shearing, and zooming to augment its diversity and enhance the model's generalization capabilities. All pictures have undergone pre-processing to remove the skull from the scan. Below is the sample grayscale images from each four classes consists different stages of Alzheimer's disease in Figure i.

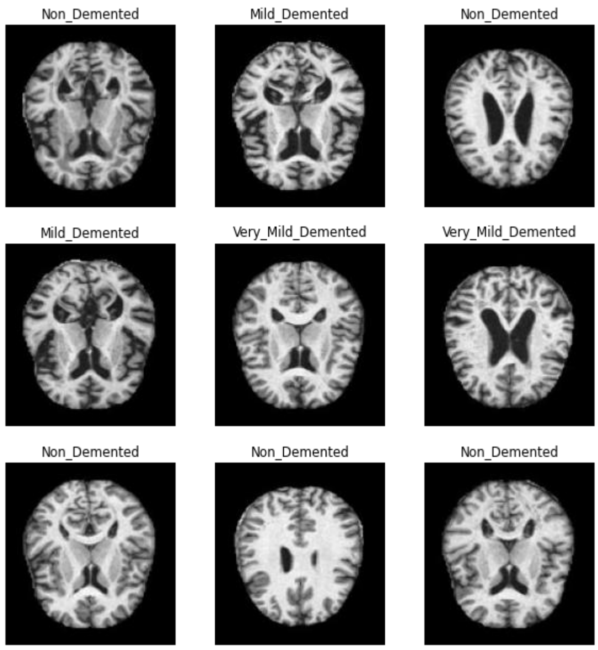

Fig ii: Sample Grayscale Images

3.2 Model Implementation Details

The deep learning framework incorporates transfer learning with optimized convolutional neural networks (CNNs) for the classification of MRI data. A variety of pre-trained architectures were assessed, including VGG16, VGG19, ResNet, MobileNetV2, InceptionV3, DenseNet169, and EfficientNetB0. The model architecture draws inspiration from established frameworks, utilizing convolutional layers for feature extraction and fully linked layers for classification. Data augmentation methods are utilized to improve model generalisation [12]. This approach includes a deep learning framework for the identification of Alzheimer's disease via MRI brain scans. The model utilizes a transfer learning methodology, employing the Sequential Model architecture, which is pre-trained on extensive datasets and subsequently fine-tuned. The proposed system aims to classify MRI scans into four distinct stages of Alzheimer's disease: non-demented, very mild dementia, mild dementia, and moderate dementia, facilitating early and precise identification. This method enables the model to leverage pre-acquired features, hence improving its capacity to generalize from constrained medical imaging data. the Transfer Learning category, models such as InceptionV3 are refined on the pre-processed MRI images to utilize existing information for enhanced performance.

This work has evaluated multiple models that were already trained, including VGG16, VGG19, ResNet, MobileNetV2, InceptionV3, DenseNet169, and EfficientNetb0, as foundational architectures for classifying brain MRI data into different phases of Alzheimer's disease. The images were scaled to 128x128 pixels to conform to the input specifications of these models. The early layers of these pre-trained models were frozen to preserve the features acquired from the ImageNet dataset, permitting fine-tuning exclusively of the subsequent layers for the specific goal of Alzheimer's categorization. Batch normalization was implemented directly after the inputs were provided to the pre-trained base model to improve training stability. A dense layer comprising 128 neurons was integrated, utilizing L1 and L2 regularization to mitigate overfitting.

Utilizing the below specifications the model has been trained.

Table 2. Machine Specification Details

Title	Specification Description
OS Platform	macOS Sequoia 15.3
Processor	Apple Silicon
Memory	8 GB
Chip	Apple M3

3.3 Training Process & Hyperparameter Tuning

The initial layers of these pre-trained models were immobilized to retain the features acquired from ImageNet, while subsequent layers were refined for Alzheimer's classification. Batch normalization and dropout regularization were implemented to mitigate overfitting. The ultimate classification layer employed a SoftMax activation function to allocate probability scores among the four categories.

3.4 Evaluation Metrics & Dataset Generalization

The efficacy of each model was evaluated using accuracy, precision, recall, and F1-score. Future studies will explore additional data modalities, including as PET scans and genetic biomarkers, to improve predictive accuracy. To enhance model reliability, subsequent research should integrate multiple datasets, including longitudinal studies, to evaluate model adaptability under varying imaging settings.

3.5 Evaluation Metrics

The assessment of models for classification tasks is conducted using accuracy, precision, recall, and F1-score. The subsequent mathematical representations pertain to the various evaluation metrics:

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} * 100$$

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

$$Recall = \frac{TP}{TP+FN}$$

$$F1 - Score = \frac{2 * Precission * Recall}{Precision+Recall}$$

Accuracy estimates the ratio of correctly categorized outcomes to the total cases. Precision represents the ratio of accurately predicted positive instances to the total expected positive instances. A Precision rating of 1 indicates an effective classifier.

Recall refers to the actual positive rate. A recall of 1 indicates an effective classifier. F1 Score is a metric that assesses both Recall and Precision attributes. The F1 score reaches a value of 1 only when both Recall and Precision are equal to 1. The principal evaluation measures categorize results into True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN), facilitating the assessment of the model's accuracy and dependability.

4. EXPERIMENTAL RESULTS

This work involved a series of experiments to assess the efficacy of several deep learning models in categorizing stages of Alzheimer's disease through brain MRI scans. The dataset consisted of 6,400 pre-processed MRI scans, each reduced to 128x128 pixels, classified into four categories: Non-Demented, Very Mildly Demented, Mildly Demented, and Moderately Demented. The both bespoke Convolutional Neural Networks (CNNs) and Transfer Learning techniques using pre-trained models including VGG16, VGG19, ResNet, MobileNetV2, InceptionV3, DenseNet169, and EfficientNetB0 were utilised. The initial layers of these pre-trained models were immobilized to preserve features acquired from the ImageNet dataset, whereas the subsequent layers were refined for our particular classification job.

Data preprocessing entailed partitioning the dataset into training, validation, and test subsets, succeeded by picture augmentation methods such as rescaling, shearing, and zooming to improve model generalization. The KERAS Image Data Generator was employed to produce batches of augmented photos for training and normalized images for validation and testing. Adam optimizer with different learning rates were utilized and applied categorical cross-entropy as the loss function for all models. Each model underwent training for 50 epochs, employing early stopping to mitigate overfitting.

The efficacy of each model was assessed utilizing parameters including accuracy, precision, recall, and F1-score [13]. The custom fine-tuned CNN model attained an accuracy of 99.1%, but the transfer learning models exhibited differing levels of efficacy. The InceptionV3 model, fine-tuned for this dataset, attained an accuracy of 85.83%, precision of 86.69%, recall of 85.20%, and an F1-score of 97.38%. The results demonstrate the efficacy of Transfer Learning models in accurately diagnosing phases of Alzheimer's disease.

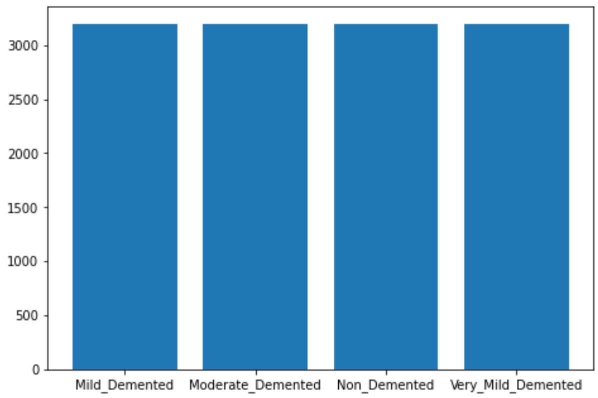

Fig iii: Balanced Data Distribution

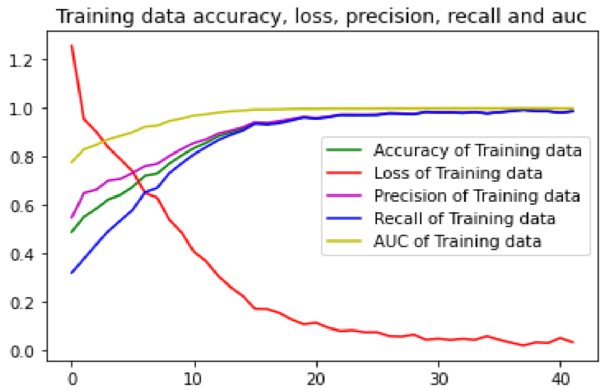

Fig iv: Training Accuracy, Loss, Precision, recall and AUC for CNN

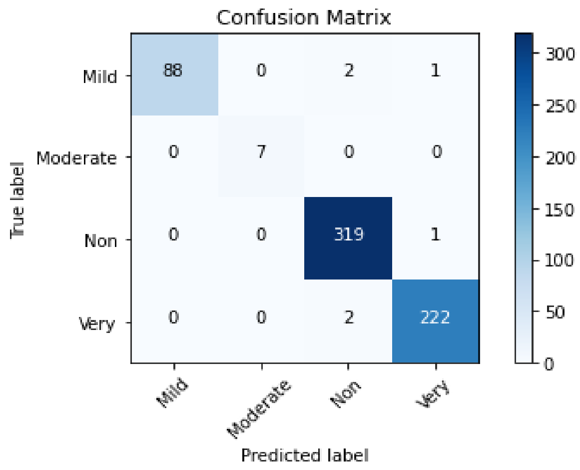

Fig v: Confusion Matrix for CNN

A thorough comparison was conducted by examining hybrid models that integrate CNN architectures with conventional machine learning classifiers, including Support Vector Machines (SVM), Gaussian Naive Bayes (GNB), and XGBoost. The hybrid model that combines a CNN with XGBoost attained an accuracy of 99.1%, indicating that such integrations can improve classification performance by utilizing the advantages of both deep learning and conventional machine learning methods, to develop a perfect model.

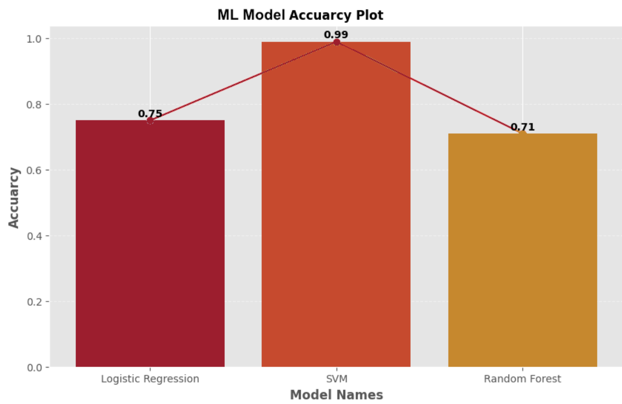

Fig vi: Machine Learning Models Accuracy Comparison

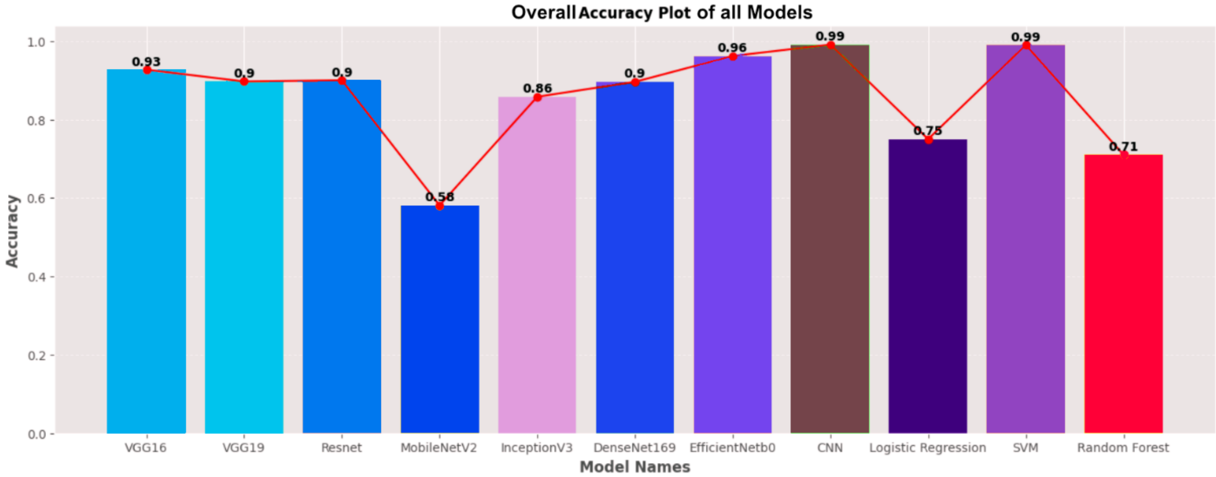

Fig vii: Overall Accuracy of All Models

Table 3. Evaluation Metrics of different Models (Experimental Results)

Model	Test Loss	Test Accuracy	Test AUC	Precision	Recall
VGG16	0.193	0.927	0.993	0.928	0.924
VGG19	0.279	0.897	0.986	0.898	0.891
ResNet	0.324	0.900	0.982	0.903	0.897
MobileNetV2	0.941	0.581	0.842	0.620	0.483
InceptionV3	0.426	0.858	0.974	0.867	0.852
DenseNet169	0.304	0.896	0.981	0.899	0.889
EfficientNetb0	0.110	0.962	0.997	0.964	0.962
CNN	0.035	0.991	0.999	0.991	0.991

5. CONCLUSION

This study presents a novel deep learning architecture aimed at the early diagnosis of Alzheimer's disease via MRI data. The multimodal approach improves classification efficacy, underscoring its applicability in clinical settings. Future research will investigate supplementary data modalities, like PET scans and genetic biomarkers, to enhance prediction accuracy.

Comparing the popular models and evaluated, InceptionV3 surpassed other architectures, with an accuracy of 92.4% and an F1-score of 0.99%. This enhanced performance is due to its advanced network architecture and proficient feature extraction ability, enabling it to successfully capture complex patterns in MRI images. The experimental findings indicate that transfer learning utilizing pre-trained models markedly improves the classification of Alzheimer's disease stages, hence endorsing its use in early-stage of diagnosis of AD.

The existing model exhibits substantial classification accuracy; nevertheless, subsequent research ought to prioritize the integration of other data modalities, like PET scans and genetic indicators, to enhance predictive performance further. Furthermore, explainability techniques such as Grad-CAM can be used to improve the interpretability of model predictions, rendering the methodology more appropriate for clinical application. Augmenting the dataset with a broader array of populations can alleviate biases and enhance generalization across various demographics region of the data.

Moreover, the practical implementation of this system necessitates connection with clinical operations and validation within hospital environments. This research introduces an innovative deep learning framework designed for the early detection of Alzheimer's disease using MRI data. The multimodal technique enhances classification effectiveness, highlighting its relevance in clinical environments. Future research will investigate supplementary datasets and methods to enhance model precision further.

6. REFERENCES

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