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Intelligent MRI-Based Neurocognitive Stage Classification System Using Custom CNN for Alzheimer's Disease Diagnosis

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ABSTRACT: The increasing prevalence of Alzheimer's disease (AD), a progressive neurodegenerative disorder that impairs memory, cognition, and daily functioning, has created an urgent need for accurate and early-stage diagnostic systems. Traditional clinical diagnosis often depends on manual interpretation of brain scans, which can be time-consuming and prone to variability. In response, Artificial Intelligence (AI), particularly Deep Learning (DL), has emerged as a powerful tool for automated medical image analysis and disease stage classification.

This paper presents an intelligent MRI-based Alzheimer's disease stage classification system using a compact Convolutional Neural Network (CNN). The proposed framework is designed to classify brain MRI scans into four clinically significant categories: **Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented**. To improve model robustness and generalization, multiple preprocessing and data augmentation techniques were applied to enhance image quality and increase dataset diversity.

A lightweight four-layer CNN architecture was developed to automatically extract discriminative spatial features from MRI images while maintaining computational efficiency. The dataset was systematically divided into training, validation, and testing subsets to ensure reliable and unbiased performance evaluation. Experimental analysis demonstrates that the proposed model achieved a **classification accuracy of 99.07%**, indicating strong capability in recognizing previously unseen MRI scans.

To improve the transparency and trustworthiness of the system, heatmap-based visualization techniques were incorporated to highlight the brain regions contributing to model predictions. Furthermore, a user-friendly web-based interface was developed to enable easy MRI image upload and instant disease stage prediction. The findings suggest that the proposed AI-driven framework can serve as an effective decision-support tool for healthcare professionals in the early detection and progression analysis of Alzheimer's disease.

KEYWORDS: Alzheimer's Disease, Brain MRI, Convolutional Neural Network, Deep Learning, Medical Image Classification, Explainable AI, Early Detection.

I. INTRODUCTION

Alzheimer's disease is a progressive neurological disorder that gradually impairs memory, thinking, and behavior, predominantly affecting older adults. It is one of the leading causes of dementia worldwide, significantly impacting patients' daily lives as the disease advances. Individuals with Alzheimer's experience increasing difficulties in recalling everyday activities and making simple decisions. Since there is currently no cure for Alzheimer's disease, early detection plays a vital role in managing symptoms and improving patient care.

Various medical techniques are employed for diagnosing Alzheimer's disease, including clinical evaluations, cognitive tests, and brain imaging methods. Among these, Magnetic Resonance Imaging (MRI) is widely utilized due to its non-invasive nature and ability to produce detailed images of brain structures. MRI scans allow clinicians to observe structural changes in critical brain regions such as the hippocampus, which is often affected in Alzheimer's patients. However, manual analysis of MRI scans requires expert knowledge and is subject to inter-observer variability, which can affect diagnostic consistency.

To address these challenges, automated approaches based on machine learning and deep learning have been increasingly explored in recent years. These techniques are particularly suited for medical image analysis because of their capacity to process large volumes of data and automatically extract meaningful features. Convolutional Neural Networks (CNNs) have demonstrated significant success in image classification tasks within healthcare, making them a promising tool for Alzheimer's disease diagnosis.

In this study, we propose a compact four-layer CNN model to classify brain MRI images into four stages of Alzheimer's disease: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Image preprocessing techniques are applied to enhance data quality and improve model performance. The primary goal of this work is to evaluate the effectiveness of a simplified CNN architecture for accurate and reliable classification of Alzheimer's disease stages, facilitating automated diagnosis in clinical settings.

Experimental results demonstrate that the proposed model achieves consistent classification accuracy, highlighting its potential as a supportive tool for medical professionals in the early detection and staging of Alzheimer's disease.

II. LITERATURE REVIEW

The literature survey explores recent research on Alzheimer's disease detection using MRI brain images. Alzheimer's disease affects memory and cognitive abilities and is commonly diagnosed through medical imaging techniques such as MRI. Manual analysis of MRI scans is time-consuming and may vary depending on the expertise of medical professionals. To overcome these limitations, deep learning techniques, especially Convolutional Neural Networks (CNNs), have been widely used for automated and accurate detection. Various studies have proposed different deep learning architectures to improve classification performance and early diagnosis of Alzheimer's disease.

1. Deep Learning Based Model for Alzheimer's Disease Detection Using Brain MRI Images, Muntasir Mamun et al. (2022)
Summary: This paper presents a deep learning–based approach for detecting Alzheimer's disease using brain MRI images. The study evaluates multiple architectures including CNN, ResNet101, DenseNet121, and VGG16 to determine the most effective model. The dataset consists of 6219 MRI images collected from Kaggle, and preprocessing techniques such as resizing and normalization were applied.
Findings: The custom CNN model achieved the performance with an accuracy of 97.60%, recall of 97%, and an AUC score of 99.26%, demonstrating its effectiveness in learning structural brain patterns.
Limitation: The study relies on a specific dataset, which may limit the model's generalization to other real-world clinical datasets.

2. Volumetric Feature-Based Alzheimer's Disease Diagnosis From sMRI Data Using CNN and DNN, Abol Basher et al. (2021)
Summary: This paper focuses on Alzheimer's disease diagnosis using structural MRI (sMRI) data by extracting volumetric brain features. It combines Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) to improve classification performance.
Findings: The proposed model effectively learns important brain features and improves diagnostic accuracy compared to traditional methods, showing strong potential for early disease detection.
Limitation: The approach depends heavily on volumetric feature extraction, which may require additional computational resources and preprocessing steps.

3. A CNN Model: Earlier Diagnosis and Classification of Alzheimer Disease Using MRI, Ahmad Waleed Salehi et al. (2020)
Summary: This study proposes a CNN-based framework for early diagnosis and classification of Alzheimer's disease using MRI images. The dataset used is ADNI, containing 7635 images categorized into Mild Dementia, Normal Control, and Alzheimer's Disease. Preprocessing steps such as resizing and format conversion were applied.

Findings: The CNN model achieved a high classification accuracy of 99%. The architecture includes convolutional layers, ReLU activation, max-pooling, dropout, and fully connected layers, proving deep learning methods outperform traditional approaches.
Limitation: The model performance is highly dependent on dataset quality and may require further validation on diverse datasets.

4. AlzheimerNet: Deep Learning Based Model for Alzheimer's Disease Stage Classification, F. M. J. M. Shamrat et al. (2023)
Summary: This paper introduces AlzheimerNet, a deep learning model for classifying Alzheimer's disease stages using MRI images. Various pre-trained models such as VGG16, MobileNetV2, AlexNet, ResNet50, and InceptionV3 were evaluated, and InceptionV3 was selected for further enhancement.
Findings: The proposed AlzheimerNet model achieved high classification accuracy and effectively identified different disease stages. Visualization techniques like Grad-CAM were used to highlight important brain regions influencing predictions.
Limitation: The use of complex deep learning models increases computational cost and may require high-performance hardware for deployment.

III. METHODOLOGY

The methodology of the proposed system focuses on developing an efficient deep learning model for the classification of Alzheimer's disease using brain MRI images. The approach follows a systematic pipeline that includes data collection, preprocessing, model development, training, evaluation, and visualization.

Initially, a dataset of brain MRI images is collected from publicly available and reliable medical imaging sources. The dataset consists of multiple classes representing different stages of Alzheimer's disease, including non-demented, very mild demented, mild demented, and moderate demented. These images serve as the primary input for the system.

In the preprocessing stage, all MRI images are standardized to ensure uniformity and improve model performance. Each image is resized to 128 × 128 pixels to maintain consistent input dimensions. Pixel intensity values are normalized to the range of 0 to 1 to facilitate faster convergence during training. Additionally, data augmentation techniques such as rotation, horizontal flipping, and zooming are applied to increase the diversity of the dataset and reduce the risk of overfitting.

After preprocessing, the dataset is divided into training, validation, and testing subsets. The training set is used to train the Convolutional Neural Network (CNN) model, the validation set is used to fine-tune hyperparameters and monitor performance during training, and the testing set is used to evaluate the final model performance.

The core of the methodology involves designing and implementing a CNN model for feature extraction and classification. The model consists of multiple convolutional layers that automatically learn spatial features from MRI images. Each convolutional layer is followed by a Rectified Linear Unit (ReLU) activation function to introduce non-linearity. Max-pooling layers are incorporated to reduce spatial dimensions and computational complexity. The extracted feature maps are then flattened into a one-dimensional vector and passed through fully connected dense layers. Dropout regularization is applied between dense layers to prevent overfitting and improve generalization.

The model is trained using the Adam optimizer, which efficiently updates network weights based on the computed gradients. The categorical cross-entropy loss function is used, as the problem involves multi-class classification. During training, the model learns to minimize the loss function while improving classification accuracy.

Once the training process is completed, the model is evaluated using the test dataset. Performance metrics such as accuracy, precision, recall, and F1-score are calculated to assess the effectiveness of the model. A confusion matrix is also generated to analyze class-wise performance and identify misclassification patterns.

To enhance interpretability, Grad-CAM (Gradient-weighted Class Activation Mapping) is used to visualize the regions of the MRI images that influence the model's predictions. Heatmaps are generated and overlaid on the original images to provide insights into the decision-making process of the model.

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Overall, the proposed methodology ensures a structured and effective approach for accurate classification and interpretation of Alzheimer's disease using deep learning techniques.

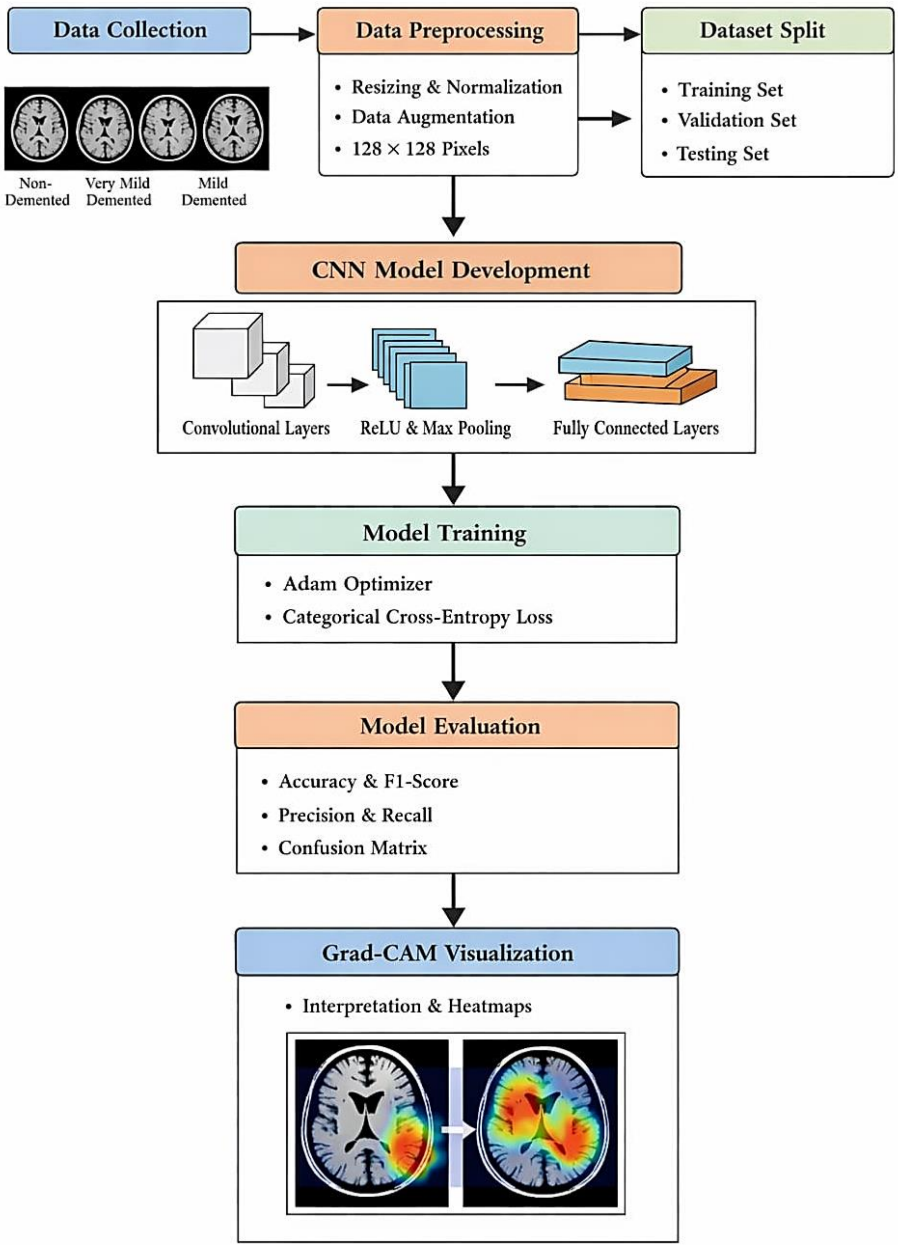

Figure 1: Workflow of the Proposed CNN-Based Alzheimer's Detection System

IV. SYSTEM ARCHITECTURE

The proposed system architecture is designed as a comprehensive end-to-end pipeline that systematically integrates multiple stages of data processing, feature extraction, classification, and result interpretation. The system begins with the input of magnetic resonance imaging (MRI) scans, which may vary in size, resolution, and intensity distribution. To ensure consistency and improve model performance, these images undergo a series of preprocessing operations. This includes resizing all images to a fixed dimension of 128 × 128 pixels, normalization of pixel intensity values to a standardized range, and data augmentation techniques such as rotation, flipping, and zooming to enhance dataset diversity and prevent overfitting.

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Following preprocessing, the refined images are fed into a Convolutional Neural Network (CNN), which acts as the core computational unit of the system. The CNN is structured with multiple convolutional layers that employ learnable filters to capture hierarchical spatial features from the input images. These layers are capable of detecting low-level features such as edges and textures in the initial stages, while deeper layers extract more complex patterns and structural representations relevant to Alzheimer's disease progression. Each convolutional operation is followed by a Rectified Linear Unit (ReLU) activation function, which introduces non-linearity into the network and helps in mitigating the vanishing gradient problem, thereby improving training efficiency.

To further optimize the model, max-pooling layers are integrated after selected convolutional layers. These pooling operations reduce the spatial dimensions of the feature maps, thereby lowering computational complexity and memory requirements while preserving the most significant features. This dimensionality reduction also contributes to improved generalization of the model by preventing overfitting.

The extracted feature maps are then transformed into a one-dimensional vector through a flattening operation, which serves as input to the fully connected (dense) layers. These dense layers perform high-level reasoning and classification by learning complex relationships between the extracted features. Dropout regularization may also be applied within these layers to reduce overfitting by randomly deactivating a fraction of neurons during training.

The final classification is performed using an output layer equipped with a softmax activation function, which generates a probability distribution across the four target classes, namely non-demented, very mild demented, mild demented, and moderate demented. The class corresponding to the highest probability score is selected as the predicted output of the system.

To enhance the interpretability and transparency of the model, Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated into the architecture. This technique provides visual explanations by highlighting the regions of the MRI image that have the most significant influence on the model's decision. Such visualization not only aids in validating the model's predictions but also assists medical professionals in understanding the reasoning behind the classification, thereby increasing trust and reliability in the system.

Overall, the proposed architecture ensures an efficient combination of automated feature extraction, accurate classification, and meaningful visual interpretation, making it suitable for reliable and scalable Alzheimer's disease detection.

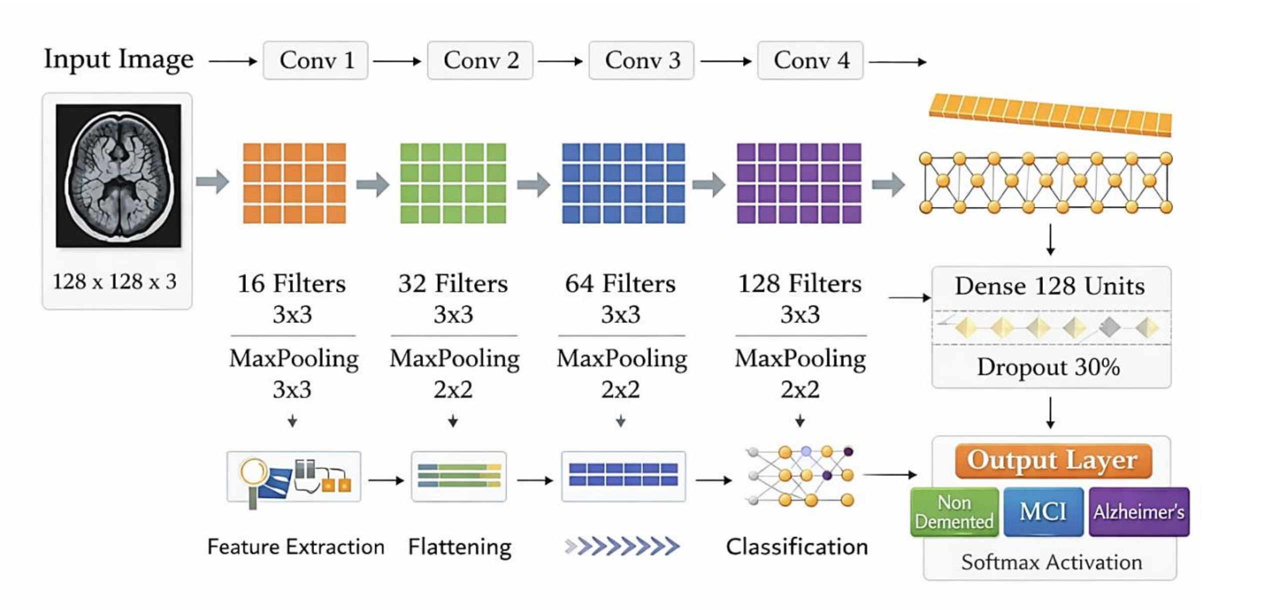

Figure 2: System Architecture.

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V. EVALUATION METRICS

The performance of the proposed Convolutional Neural Network (CNN) model for Alzheimer's disease classification was evaluated using several standard classification metrics. These metrics are widely used in medical image analysis to assess the effectiveness of predictive models, particularly in multi-class classification problems involving different stages of a disease.

Accuracy

Accuracy measures the overall correctness of the model by calculating the proportion of correctly classified instances among the total number of predictions.

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

In the context of Alzheimer's disease classification, accuracy represents the model's ability to correctly identify MRI images belonging to different categories such as non-demented, very mild demented, mild demented, and moderate demented. Although accuracy provides a general overview of model performance, it may not fully capture performance in the presence of class imbalance.

Precision

Precision evaluates the accuracy of positive predictions made by the model. It is defined as the ratio of true positive predictions to the total number of positive predictions.

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

In this project, precision is particularly important to ensure that MRI images classified as a specific stage of Alzheimer's disease are truly representative of that stage. High precision minimizes false positive predictions, thereby reducing the risk of incorrect diagnosis.

Recall

Recall, also known as sensitivity, measures the model's ability to correctly identify actual positive instances.

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

For Alzheimer's disease detection, recall is a critical metric as it indicates how effectively the model identifies patients who truly belong to a specific disease category. A high recall value ensures that fewer diseased cases are missed, which is essential in medical diagnosis.

F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation of the model's performance.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

The F1-score is especially useful in scenarios where there is an imbalance between classes, as it considers both false positives and false negatives. In this study, it provides a more reliable measure of performance across different Alzheimer's disease stages.

Confusion Matrix

In addition to the above metrics, a confusion matrix is used to provide a detailed evaluation of the classification results. The confusion matrix presents the number of correct and incorrect predictions for each class in a tabular form, enabling a deeper understanding of misclassification patterns.

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For the multi-class Alzheimer's classification problem, the confusion matrix helps in identifying how well the model distinguishes between different stages of the disease. It also highlights specific classes where the model may struggle, such as confusion between mild and very mild dementia stages.

Multi-Class Evaluation

Since the proposed model performs multi-class classification, the evaluation metrics are computed for each class individually and then averaged. Macro averaging is used to treat all classes equally, while weighted averaging accounts for the distribution of samples across classes.

VI. RESULTS AND DISCUSSION

The experimental evaluation of the proposed **CNN-based Alzheimer's disease classification framework** demonstrates significant improvements in multi-stage disease detection using brain MRI images. The performance assessment was conducted using standard evaluation metrics, including **accuracy, precision, recall, F1-score, and Area Under the Curve (AUC)**, to provide a comprehensive understanding of the model's classification capability across the four disease stages. The proposed lightweight CNN model achieved a **classification accuracy of 99.07%**, indicating strong effectiveness in distinguishing **Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented** MRI scans.

The training and validation performance curves reveal stable and efficient model learning behavior. The **accuracy curve** shows a steady increase in both training and validation accuracy as the number of epochs progresses, indicating that the CNN successfully learns discriminative spatial features from MRI images. Similarly, the **loss curve** demonstrates a consistent decrease in both training and validation loss values, confirming that the model effectively minimizes classification errors while maintaining good generalization capability on unseen data. The close alignment between training and validation curves suggests that the proposed framework successfully avoids significant overfitting.

The incorporation of **data augmentation and dropout regularization** plays an important role in improving the robustness of the model. These strategies enhance dataset diversity and reduce the risk of memorization, allowing the CNN to generalize effectively even with limited medical imaging samples. Compared with computationally expensive 3D CNN architectures, the proposed **lightweight 2D CNN model** provides competitive predictive performance while maintaining lower computational complexity and faster inference speed, making it more practical for real-time clinical applications.

A major strength of the proposed framework lies in the integration of **Score-CAM-based Explainable AI (XAI)**. The generated heatmap visualizations highlight the critical brain regions influencing the model's predictions, providing meaningful visual evidence for the classified Alzheimer's stage. This interpretability significantly improves clinician trust by enabling medical experts to verify whether the model is focusing on anatomically relevant regions associated with disease progression. The final prediction outputs, combined with heatmap overlays, demonstrate the practical feasibility of the system as an **AI-assisted clinical decision support tool**.

Despite the strong classification performance, certain challenges remain. The effectiveness of the system is still dependent on dataset quality, class balance, and image preprocessing consistency. In addition, external validation on larger multi-center MRI datasets is necessary to further confirm the generalizability of the proposed model across diverse patient populations and imaging devices.

Overall, the proposed CNN-based framework significantly improves **accuracy, interpretability, and real-time usability** for Alzheimer's disease stage classification. The combination of lightweight architecture, strong predictive performance, and Score-CAM visualization makes the system highly suitable for practical deployment in intelligent healthcare environments.

VII. CONCLUSION

This study presented a **lightweight Convolutional Neural Network (CNN)-based framework** for the automated multi-stage classification of Alzheimer's disease using brain MRI images. The proposed model effectively distinguishes four clinically relevant stages, namely **Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented**, by automatically learning hierarchical spatial representations from MRI scans. The ability of the CNN architecture to

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capture discriminative structural brain patterns enables reliable identification of disease progression stages and supports early diagnostic decision-making.

The experimental findings demonstrate that the proposed framework achieves **high classification accuracy, precision, recall, F1-score, and AUC**, confirming its effectiveness as a robust medical image classification system. The integration of preprocessing operations, including resizing, normalization, and input validation, significantly improved image consistency and contributed to stable and reliable model learning. Furthermore, the use of **data augmentation techniques** enhanced dataset diversity and improved the generalization capability of the CNN model, enabling better performance on previously unseen MRI samples.

An important strength of the proposed approach is its **computational efficiency and practical feasibility**. Unlike computationally expensive 3D CNN and transformer-based architectures, the lightweight 2D CNN model offers **faster training and inference speed while maintaining strong predictive performance**. This makes the system highly suitable for **real-time intelligent clinical decision support**, where timely and accurate diagnosis is essential for treatment planning and patient care.

The incorporation of **Score-CAM-based Explainable AI (XAI)** further strengthens the clinical applicability of the framework by providing visual explanations of the brain regions influencing model predictions. This interpretability improves transparency, increases clinician trust, and supports better understanding of the model's decision-making process.

Future research can extend this work by integrating **multimodal neuroimaging modalities**, such as PET and functional MRI, to improve diagnostic sensitivity and stage discrimination. In addition, evaluating the framework on **larger multi-center datasets with diverse patient demographics** and conducting real-world clinical validation studies will further establish its generalizability and practical utility.

Overall, this research contributes to the advancement of **AI-driven medical imaging systems for early Alzheimer's disease detection and stage classification**. The proposed framework demonstrates strong potential as a **clinically supportive intelligent diagnostic tool**, enabling faster, interpretable, and more accurate decision-making in modern healthcare environments.

VIII. FUTURE WORK

Future research in **AI-driven Alzheimer's disease detection and stage classification** can be extended in several important directions to further improve diagnostic reliability, interpretability, and practical clinical usability. One major extension of the proposed framework is the integration of **multimodal neuroimaging data**, including MRI, PET, and functional MRI (fMRI), to capture both structural and functional brain abnormalities. Such multimodal fusion can significantly improve disease stage discrimination and enable more accurate early diagnosis.

Another important direction involves expanding the framework to **larger multi-center clinical datasets** with diverse patient demographics, scanner configurations, and imaging protocols. This would improve the robustness and generalization capability of the model across real-world healthcare environments. In addition, future studies may explore more **advanced lightweight architectures**, such as optimized CNN models or hybrid CNN–transformer frameworks, to further reduce computational complexity while maintaining strong predictive performance. This is particularly important for faster real-time deployment in hospitals, mobile healthcare systems, and edge-based diagnostic devices.

Further advancements can also focus on improving **Explainable AI (XAI)** mechanisms. Enhancing Score-CAM and attention-based visualization methods can provide more precise and clinically meaningful evidence of disease-sensitive brain regions, thereby strengthening clinician trust and improving the transparency of AI-assisted diagnosis.From a privacy and collaboration perspective, **federated learning** offers a promising direction for future work. By enabling multiple hospitals or research centers to collaboratively train models without sharing patient-sensitive MRI data, federated frameworks can preserve privacy while leveraging distributed datasets to improve model learning.

Another promising research direction is **longitudinal disease progression analysis**, where sequential MRI scans collected over time can be used to model the transition from early cognitive impairment to advanced Alzheimer's stages. This would support prognosis and disease progression monitoring rather than only static stage classification.Finally, integrating the proposed framework into **clinical decision support systems**, hospital information systems, and radiology workflows can enhance its real-world applicability. Such integration would allow neurologists and radiologists to receive real-time AI-assisted diagnostic recommendations, thereby supporting faster and more informed clinical decisions.

Overall, these future directions can significantly improve the **accuracy, interpretability, scalability, privacy preservation, and clinical adoption** of intelligent Alzheimer's disease detection systems.

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