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EARLY PREDICTION OF ALZHEIMER'S DISEASE USING CONVOLUTIONAL NEURAL NETWORK

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Abstract

Alzheimer's disease (AD) is a progressive neurological disorder that shows considerable difficulties in both diagnosis and treatment. Achieving an early and precise diagnosis is crucial for alleviating symptoms and enhancing patient outcomes. Although technological advancements have been made, there is still a pressing need for automated decision-support tools to aid clinicians. Deep learning approaches have shown amazing gains and impressive results in medical image processing this recent years, offering encouraging answers to these problems. In this study, we propose a convolutional neural networks (CNNs) framework trained and tested on a publicly available magnetic resonance imaging (MRI) dataset. We employ extensive data augmentation, dropout regularization, and early stopping to mitigate overfitting. The proposed approach seeks to distinguish between different stages of AD, tackling one of the most intricate aspects of managing the disease. Experimental findings reveal that the proposed model achieved an overall accuracy of 99.3%, with precision, recall, and F1-score exceeding 98% for all classes, and AUC values over 0.99. This result demonstrates the potential of the framework to delivers superior predictive accuracy and robustness compared to current leading methods, highlighting its potential as a dependable tool for clinical applications in AD detection and prognosis.

1.0 INTRODUCTION

Alzheimer's disease (AD) is a debilitating neurodegenerative disease that causes delusions, psychosis, and short-term memory loss, which were previously mistakenly assumed to be caused by stress or aging. AD requires ongoing medication for management. It is a complex and costly process for the early detection of this disease because usually we collect a huge number of data and apply some advanced tools for predictions [1]. The most common medical imaging tool used to study the disease process and assess the morphometric alterations of important regions affected during AD is Magnetic Resonance Imaging (MRI). MRI is a crucial tool for both medical diagnosis and research into Alzheimer's disease. [2-3].

Advancements in machine learning (ML) and deep learning (DL) have greatly improved data analysis capabilities. These technologies enable large-scale data processing through diverse algorithms, allowing for the rapid detection of patterns within datasets [4].

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This progress has led to substantial improvements in diagnostic techniques, leveraging sophisticated methodologies that often surpass human perception and reasoning. Furthermore, the field of machine learning has reached unprecedented levels of advancement, largely due to the development of novel deep neural network architectures. These networks possess the capability to model highly complex relationships, effectively representing any finite deterministic mapping between input and output sets [5].

One critical area benefiting from these advancements is the early prediction of Alzheimer's disease, that continues to impact millions worldwide. Timely and accurate prediction of Alzheimer’s is essential for improving patient management and treatment outcomes. The disease is characterized by structural brain changes, including cortical, hippocampal atrophy, and alterations in regional glucose metabolism. These pathological can be quantitatively assessed, particularly through Medical imaging methods, like Magnetic Resonance Imaging (MRI), offer crucial insights into illness development and facilitating early intervention.

Recent developments in artificial intelligence, namely in the areas of convolutional neural networks (CNNs) and deep learning, present remarkable potential in analyzing medical images for this purpose. Deep learning methods, especially CNNs, are revolutionizing how we approach image classification tasks. For instance, Shaibu et al. [6] conducted a comprehensive evaluation of machine learning algorithms and highlighted the conditions under which predictive models achieve optimal performance, thereby emphasizing the need for rigorous model selection and validation strategies. Their findings are particularly relevant to Alzheimer’s disease prediction, where the reliability of classifiers is critical for clinical adoption. In a related study, Omonayin et al [7] evaluated deep learning architectures for real-time waste classification in IoT environments, providing evidence of CNNs’ effectiveness in real-world image analysis. Similarly, Karthikeyan et al. [8] investigated the use of deep learning techniques to identify false data, underscoring the importance of AI-driven reliability in intelligent systems. Furthermore, Vemulapalli, et al. [9] applied machine learning algorithms to Modern farming strategies, demonstrating the relevance of ML-based models in precision farming applications.

Sarraf and Tofighi in 2016 [10] were among the first to leverage a pre-trained AlexNet model to classify AD using functional MRI (fMRI) data. Their work achieved a notable accuracy of over 90%, demonstrating the power of transfer learning in medical applications. However, these models rely on relatively small or homogeneous datasets, which restrict their ability to generalize across diverse clinical settings. Following this, Basaia et al. [11] developed a CNN specifically designed for identifying different stages of AD using structural MRI scans, further validating the robustness of deep learning in this domain. The ability to identify relevant features is critical to the success of these models. CNNs often incorporate techniques like data augmentation and feature selection to enhance their accuracy. For instance, Liu et al. [12] in 2018 used 3D-CNNs combined with transfer learning to extract spatiotemporal features from MRI scans. This approach produced state-of-the-art results in predicting early stages of AD [13].

A growing trend in this field involves using multiple imaging modalities to improve prediction accuracy. Suk et al. in [14] combined MRI and PET data in their CNN model, showing that integrating information from different imaging sources significantly boosts performance. This multimodal approach emphasizes how combining complementary data can lead to more reliable predictions. While CNNs deliver impressive results, their "black-box" nature has been a challenge for clinical adoption. Recent studies have begun addressing this issue with explainable AI techniques. For example, Oh et al. in [15] used Grad-CAM to visualize key regions in brain images that influenced the classification decision. Such efforts make the models more transparent and easier for healthcare professionals to trust and use.

2.0 MATERIALS AND METHODS

2.1 Alzheimer's Disease Dataset

For this research, we utilized a publicly available dataset sourced from Kaggle [16]. The dataset comprises a total of 6,400 MRI images, with a resolution of 176×208 pixels. The dataset representing different alzheimer disease stages, figure 1 provides visual examples of these stages.

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The dataset categorizes Alzheimer's progression into four distinct classes:

- **Very mild dementia:** This represents the earliest dementia stage, where cognitive decline is low and often goes unnoticed. Individuals at this stage typically maintain their independence.
- **Mild dementia:** Cognitive deterioration is more evident at this stage, although individuals can still perform daily activities with some assistance.
- **Moderate dementia:** This stage present more pronounced cognitive decline, necessitating greater levels of support in daily activities.
- **Non-dementia:** This category includes individuals who exhibit no signs of cognitive impairment, maintaining normal cognitive function.

By leveraging this dataset, we aim to analyze MRI images corresponding to different stages of Alzheimer's disease, facilitating the development of more effective diagnostic and classification models.

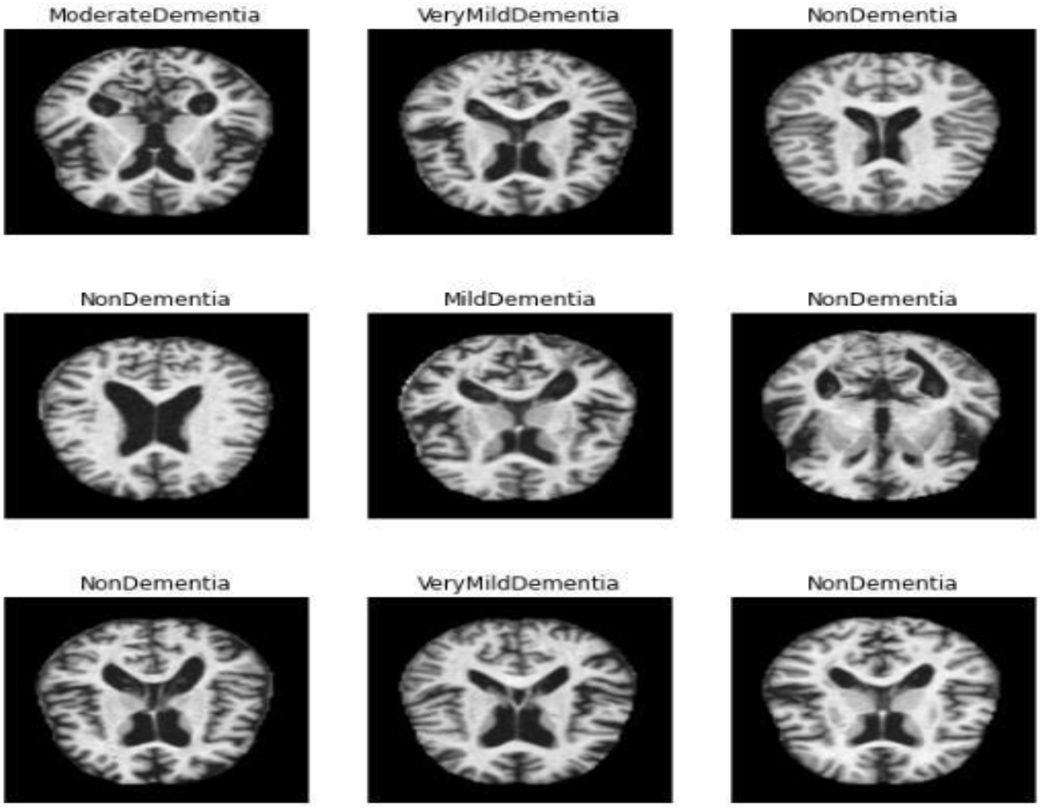

Figure 1: Classes of the alzheimer’s stages dataset.

2.2 Preprocessing and Data Augmentation

The preprocessing is a critical component of deep learning before applying any algorithm to conduct studies. This step is essential for enhancing the performance of the proposed approach. After completing the pre-processing steps, data augmentation was carried out. This step generated a more diverse set of images, enabling the model to train more effectively on varied scenarios. Data augmentation was performed using the Image data generator function, which produces batches of tensor image data. Changes were applied to various image parameters, including rotation, rescaling, horizontal flipping, and vertical flipping, to enhance the dataset's diversity for improved model training.

2.3 Proposed Model

A CNN is a deep learning architecture allowing the network to locate important features like edges, corners, and textures and pick up on local patterns. A standard convolutional block has several layers that improve feature extraction at different levels of abstraction. Pooling layers downsample the feature maps, which means they keep the most important information while lowering the spatial dimensions.

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This process makes the computer work faster and helps prevent overfitting. After there are fully connected layers, they combine the features that were taken out to learn global patterns and make predictions.

Figure 2 gives a general idea of how the CNN architecture works by showing the order of the layers in the network. It also goes into detail about the parameters for each layer, giving a full picture of how the model is put together.

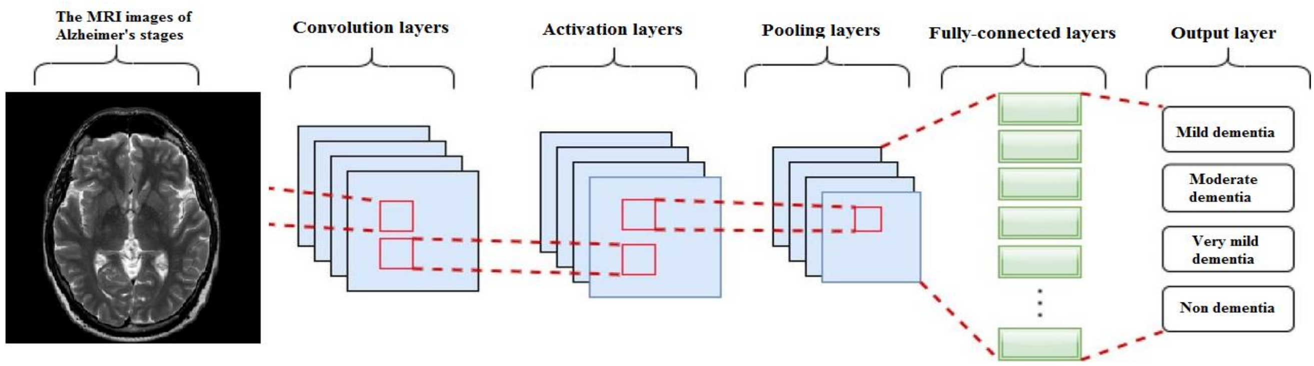

Figure 2: CNN architecture for MRI image classification.

The experiment employs a CNN model, which is ideally suited for image classification tasks because it effectively captures spatial hierarchies and local patterns in images. In our CNN design, the input shape corresponds to the dimensions of the training data, specifically (64, 64, 1), indicating the image's dimension and number of channels.

- **Convolutional Layers:** These Conv2D layers use trainable filters to extract key characteristics from the input images. Following each convolutional stage, a ReLU activation function is used to create non-linearity, increasing the model's ability to learn complex patterns. Furthermore, Batch Normalization is used to normalize activations, which stabilizes the training process.
- **Pooling Layers:** After each Conv2D, MaxPooling2D layer is used with a pooling of (2,2) window. This approach reduces the spatial size of the feature maps while keeping critical information, which helps to reduce computing demands and minimize overfitting.
- **Flattening Layers:** The Flatten layer reduces 2D feature maps to 1D feature vectors, making them appropriate for fully linked layers. The network consists of two dense layers with 512 and 256 units, respectively, that use ReLU activation to learn advanced representations from the retrieved information.
- **Output Layer:** The output layer utilizes a softmax function to provide the probability distribution for potential classes, representing the model's confidence in each classification.

The choice of architectural components in the proposed CNN is motivated by both theoretical and empirical considerations. Successive convolutional layers were adopted to capture increasingly abstract spatial hierarchies within MRI scans, while max-pooling operations ensure efficient dimensionality reduction and computational feasibility. Dropout layers and batch normalization were introduced to improve generalization and reduce overfitting risks, which are prevalent in medical image analysis with limited datasets. Unlike earlier models, our configuration is explicitly optimized for Alzheimer's prediction tasks by balancing architectural depth with regularization. This methodological justification substantiates the novelty of our approach as an adaptation of CNN design principles to the specific challenges of Alzheimer's disease classification.

Table 1: Summary of the proposed CNN model.

Layer	Output	Parameters
Conv 2D	(176, 208, 16)	448
Conv 2D-1	(176, 208, 16)	2320
max pooling 2D	(88, 104, 16)	-
Sequential	(44, 52, 32)	2160
Sequential-1	(22, 26 ,64)	7392
Sequential-2	(11, 13 ,128)	27072
Dropout	(11, 13 ,128)	-
Sequential-4	(5, 6 ,256)	103296
Dropout	(5, 6 ,256)	-
Flatten	7680	-

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Sequential-5	512	3934720
Sequential-5	128	68176
Sequential-5	64	8512
Dense	4	260

This architecture enables the CNN to effectively learn and classify MRI images with different of Alzheimer's stages.

3.0 RESULT AND DISCUSSION

The experiment was conducted on CPU Intel(i7) with 4 cores and 8 GB RAM to implement the proposed approach and construct our model. We utilized the jupyter editor IDE with Python 3.9 programming language using Tensorflow 2.15, keras 2.12.0 Scikit-Learn 1.3.2 and pandas 2.1.3.

3.1 Evaluation Metrics

Measuring performance is crucial for designing and evaluating machine learning models. To evaluate the performance of the suggested model, multiple indicators were taken into account. By focusing on these metrics, the ability of CNN classifiers to correctly identify and classify MRI images can be assessed while minimizing the false positives and false negatives. Equations listed below provide the mathematical expressions for performance indicators.

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (4)$$

3.2 Experiment Parameters

In this section, we detail the hyperparameters, evaluation metrics, and performance analysis of the CNN model when tested on MRI datasets. Additionally, we compare its performance with other models to assess its effectiveness.

The Adam optimizer was selected for training the CNN model, with a learning rate of 0.001 and cross-entropy loss function to ensure stable and efficient convergence. However, due to the sensitivity of cross-entropy to scaling and continuous gradient updates, overfitting can become a challenge in CNN-based models. To mitigate overfitting, early stopping was implemented. This technique continuously monitored validation accuracy and halted training once no further improvement was observed, preventing unnecessary computations and reducing the risk of overfitting. The specific hyperparameters and configuration settings used to implement the proposed sequential CNN model are summarized in Table 2, providing the experimental setup

Table 2: Experiment parameter of CNN model.

Layer	**Parameter**
Learning rate	0.001
Activation function	ReLU
Dropout	50%
Optimizer function	Adam Optimizer
Activation function	softmax
Loss function	Categorical cross-entropy

3.3 Evaluation of The Model

Evaluating the performance of the proposed model's is essential to determine its suitability. Accuracy is one of the most commonly used metrics for assessing the classification models. It is calculated by comparing the stages labels with the current labels across the evaluation dataset, providing insight into the classification capability.

The proposed CNN model was subjected to a structured training, validation, and testing process over 100 epochs. Figures 3, 4, 5, and 6 show the model's learning and generalization over time by showing the training accuracy, validation accuracy, and testing accuracy.

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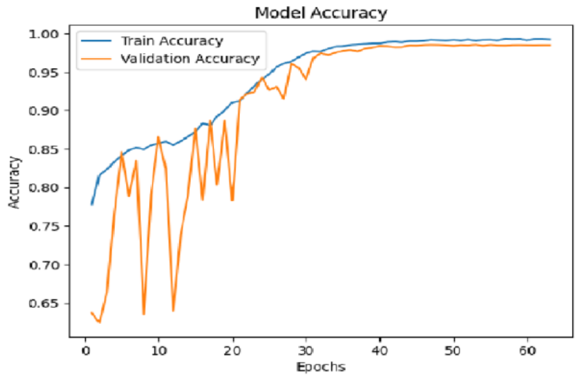

Figure 3: Accuracy performance in the validation and training dataset.

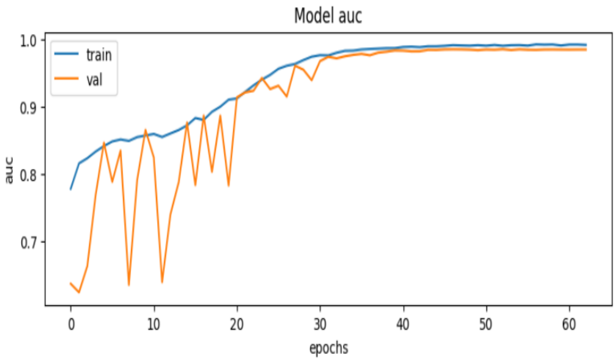

Figure 4: AUC in the validation and training dataset.

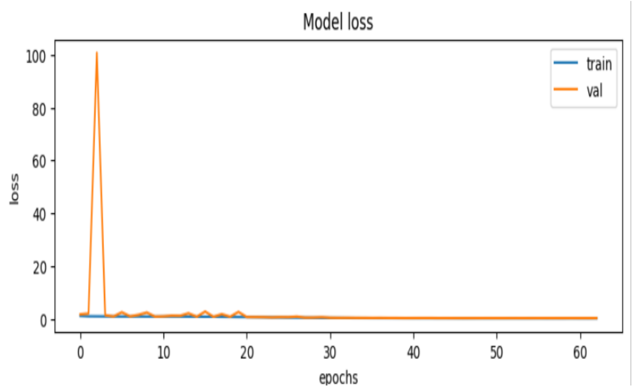

Figure 5: Loss training in dataset.

The ROC curves and corresponding AUC values provide crucial insights into the discriminative power of the proposed CNN. AUC values consistently exceeding 0.99 indicate that the model achieves near-perfect separation between Alzheimer's stages, particularly in distinguishing very mild from non-dementia cases, which is clinically the most challenging scenario. This strong ROC/AUC performance confirms not only the accuracy of the model but also its reliability in clinical decision-support contexts, underscoring its value as a robust predictive tool beyond simple accuracy scores.

To mitigate overfitting, several strategies can be employed, including reducing the number of hidden layer, applying regularization techniques, and incorporating dropout to enhance generalization. To further evaluate the CNN model performance, a classification report is generated. This report provides a comprehensive summary of key evaluation offering valuable insights and ability to differentiate between different categories within classification task.

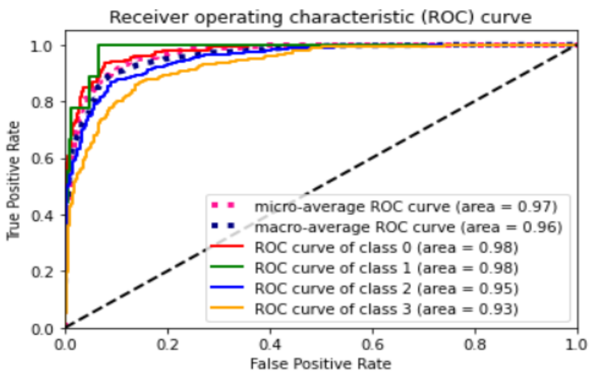

Figure 6: The ROC curve in different stages of alzheimer's disease.

Table 3: Performance of our proposed techniques in different stages of AD.

Stages of Alzheimer's	Accuracy	Precision	Recall	F1-score
Mild dementia (class 0)	98.92%	98.97%	98.92%	98.93%
Moderate dementia (class 1)	98.81%	98.82%	98.81%	98.81%
Very Mild dementia (classl 2)	99.47%	99.49%	99.47%	90.61%
Non dementia (class 3)	99.13%	99.14%	99.13%	99.14%

The analysis MRI images for the early and accurate prediction of AD has gained significant attention due to the increasing prevalence of this neurodegenerative disorder. In this study, we leveraged the CNN to develop a system capable of

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facilitating early diagnosis, which could potentially aid in prevention and disease management.

To construct the CNN model, we employed a combination of essential parameters and functions, including the softmax activation function, categorical cross-entropy loss, early stopping, and accuracy metrics, with the Adam optimizer. The network architecture consisted of multiple layers, including Conv2D, MaxPooling, and Dropout layers, followed by a Flatten layer, which transitions the model from convolutional feature extraction to fully connected layers. The architecture was further refined with dense layers, ensuring effective learning and classification.

Ultimately, we achieved an optimal result at epoch 63, where the model attained a training loss of 0.20 and an accuracy of 99%. Following training, the model's generalization ability was assessed using various evaluation metrics on a separate dataset and the result demonstrate high classification performance, with 1,267 correct predictions out of 1,279 test samples, indicating a near-perfect classification ability.

In summary, the results highlight the strong predictive capabilities of our CNN-based model in detecting Alzheimer's disease at an early stage with an accuracy of 99%. However, further improvements are needed due to MRI dataset variability and potential model instability. Despite these challenges, the proposed CNN model demonstrates significant potential for assisting in the classification and early detection of Alzheimer's disease by effectively processing and analyzing MRI scans.

3.4 Comparison With State of Arts Works.

To validate the efficacy of our technique, we conducted a comparative analysis with two alternative models using the same dataset. Table 4 presents a comparison of the accuracy achieved by our proposed method in relation to these models. The experimental results demonstrate that our model achieves superior performance, outperforming all other approaches with a validation accuracy of 99.60%. This outstanding performance is related to the feature extraction capabilities and the structural advantages of the CNN utilized in our model.

Overall, the suggested model accurately detects Alzheimer's disease (AD) early on due to its great predictive capabilities. These findings support the promise of our therapeutic strategy, applications in which early detection is essential for efficient illness management and treatment.

Table 4: Performance comparison of our proposed model with state of arts works.

Reference	Dataset	Image	Model	Classifier	Accuracy
[18]ML.Martin et al. 2020.	Center of Biomedical Technology	MEG	Deep Learning	CNN	92%
[19]NJ.Dhinager et al., 2020	OASIS	MRI	Deep Learning	Random Forest	57%
[20].SA.Soliman et al., 2020	ADNI	MRI	Deep Learning	CNN	80%
[21] D.Jalindre et al.,2022	KAGGLE	MRI	Deep Learning	CNN	93%
Proposed work	KAGGLE	MRI	Deep Learning	CNN	99%

3.5 Limitations and Future Work

While the proposed CNN model achieved high classification accuracy (≈99%) on the Kaggle MRI dataset, certain limitations must be acknowledged. First, the dataset is relatively small and may not fully represent the diversity of clinical populations, raising concerns about generalizability. Second, the model's performance on multi-center datasets with different acquisition protocols remains untested. Third, despite applying dropout and early stopping, overfitting risks remain given the high reported accuracy.

Future research should focus on expanding the dataset through collaborations with hospitals, integrating multimodal data (MRI, PET, and clinical records), and applying federated learning to ensure privacy-preserving training across institutions. Furthermore, exploring transfer learning or hybrid models (e.g., CNN + transformer or CNN + LSTM)

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to improve performance and interpretability.Theexplainable AI (XAI) methods such as Grad-CAM should be incorporated to enhance interpretability and clinician trust in the model's predictions.

4.0 CONCLUSION

Alzheimer's disease (AD) has arisen as a major worldwide health concern in recent years, needing early identification and treatment to enhance patient outcomes. Given the critical role of early diagnosis in facilitating effective treatment, deep learning has gained considerable attention as a promising approach for leveraging large-scale datasets to assist in Alzheimer's disease classification.

In this study, we employed Convolutional Neural Networks (CNNs) for the classification and prediction of MRI images to facilitate the early detection of Alzheimer's disease, focused on accurately identifying different stages of AD through deep learning-based feature extraction and classification. Looking ahead, our future work will focus on expanding the study by evaluating the proposed technique on more diverse datasets, ensuring scalability and generalizability across real-world application. Furthermore, presenting this research in clinical settings will be an essential step in demonstrating its practical applicability within healthcare institutions.

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