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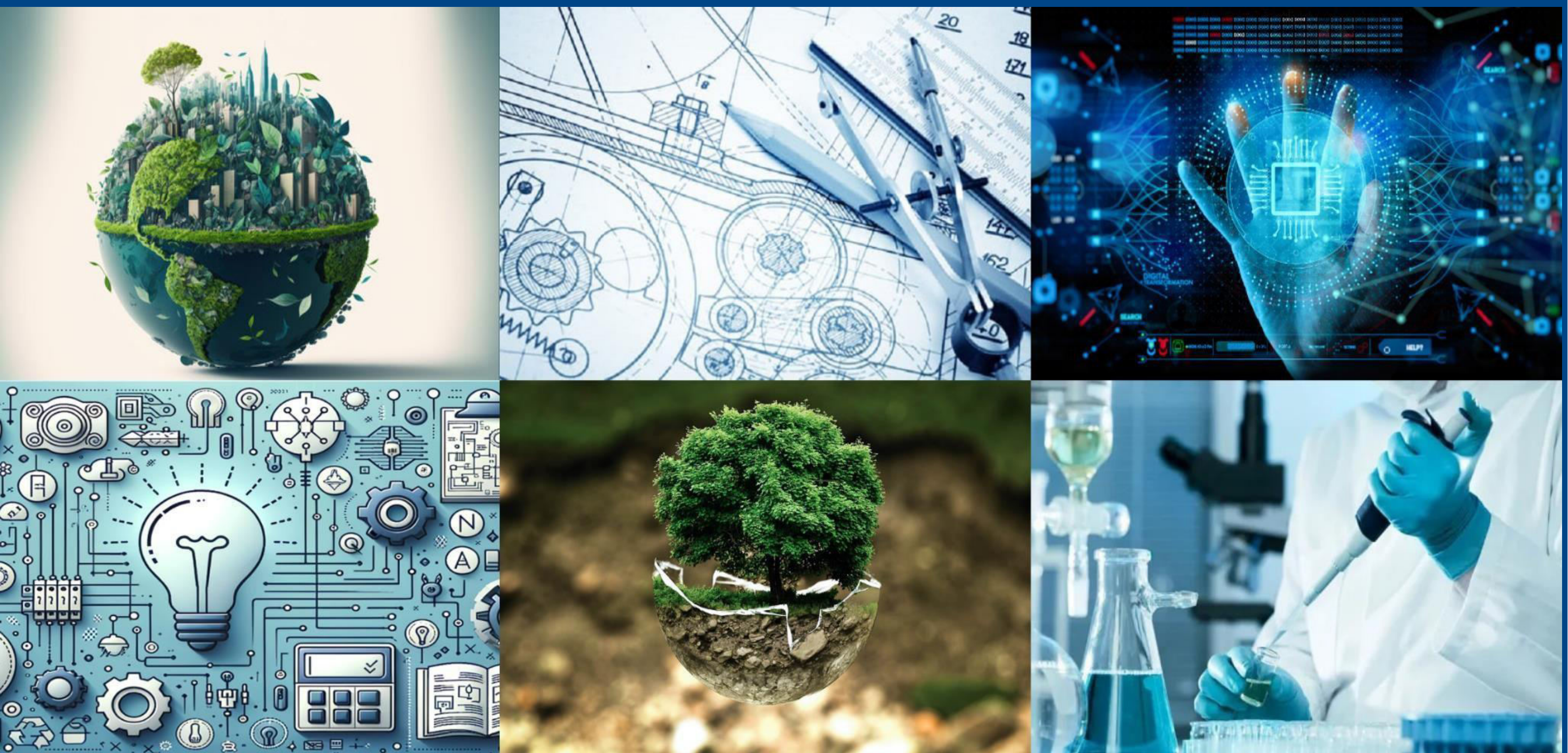

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Stage-Wise Classification of Alzheimer's Disease using Convolutional Neural Networks

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ABSTRACT: Alzheimer's disease (AD) is a progressive neurodegenerative disorder that significantly impacts memory, cognition, and overall brain function, particularly among the elderly. Early and accurate diagnosis of Alzheimer's—especially across its varying stages—is crucial for effective treatment planning and patient care. This study proposes a deep learning-based approach using Convolutional Neural Networks (CNN) to classify brain MRI images into four diagnostic categories: Mild Demented, Moderate Demented, Very Mild Demented, and Non-Demented. The model was trained on a publicly available MRI dataset and incorporates preprocessing techniques such as resizing, normalization, and data augmentation to improve performance and generalization. Results indicate that the proposed CNN model is capable of achieving high classification accuracy, making it a promising tool for supporting early-stage Alzheimer's detection in clinical environments. This work highlights the potential of AI-assisted diagnosis to improve healthcare outcomes through automated analysis of medical imaging.

KEYWORDS: Alzheimer's Disease, MRI, Convolutional Neural Network, Early Detection, Deep Learning

I. INTRODUCTION

Alzheimer's disease (AD) is one of the most common forms of dementia, affecting millions of individuals worldwide. It is a progressive condition that gradually impairs memory, reasoning, and other cognitive functions, ultimately impacting a person's ability to carry out daily activities. As populations age globally, the number of Alzheimer's cases continues to rise, posing significant challenges for families, caregivers, and healthcare systems.

Diagnosis of Alzheimer's traditionally relies on clinical assessments, neuropsychological tests, and imaging techniques like Magnetic Resonance Imaging (MRI). Among these, MRI provides detailed images of brain structures, which can reveal early signs of atrophy or damage. However, manual interpretation of these scans is both time-consuming and prone to variability among clinicians.

With recent advancements in artificial intelligence, deep learning techniques—especially Convolutional Neural Networks (CNNs)—have shown great potential in automating the analysis of medical images. CNNs are particularly effective in detecting patterns in MRI scans that may be difficult to identify through manual observation. In this study, we develop a CNN-based model trained on MRI brain images to classify patients into four stages of Alzheimer's disease. The aim is to explore the effectiveness of a lightweight yet accurate model for early-stage detection and stage-wise differentiation, thereby contributing to more timely and consistent diagnostic support.

II. LITERATURE REVIEW

In recent years, deep learning (DL) and machine learning (ML) have gained significant attention for early detection of Alzheimer's disease (AD). These approaches have been applied to various types of data such as MRI scans, clinical records, and activity monitoring.

Early studies, like those by Kruthika et al. (2019) and Bringas et al. (2020), explored recurrent neural networks and deep belief networks for analyzing structured clinical data, showing improved accuracy in tracking disease progression. In medical imaging, CNNs have emerged as particularly effective. Li and Fan (2019) demonstrated the benefits of combining MRI and PET data, while Abrol et al. (2020) used deep ResNet architectures to enhance detection accuracy by capturing subtle brain abnormalities.

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To address data limitations, Sharma et al. (2022) designed an optimized CNN for MRI-based AD detection, and Saravanakumar and Saravanan (2022) introduced a semi-supervised GAN model to generate synthetic data, enhancing robustness. Additionally, Umadevi Ramamoorthy et al. (2022) explored secure data transmission using video steganography, which could be relevant in protecting medical data shared over cloud platforms.

Unlike works that also focus on Parkinson's disease, this study specifically targets Alzheimer's classification using a simple yet effective CNN. The aim is to maintain strong accuracy while keeping the model lightweight and interpretable for real-world clinical use.

III. DATASET DESCRIPTION

The dataset used in this study was taken from a public Kaggle repository named *"Alzheimer and Parkinson MRI Dataset."* It includes a total of 6,477 brain MRI images, all in 2D grayscale format. These images are grouped into three categories: Alzheimer's disease (AD), Parkinson's disease (PD), and healthy individuals.

Each image is a brain scan slice that has been standardized in size and format. To prepare the data for model training, all images were resized to 128×128 pixels and normalized so that pixel values fall within the [0, 1] range. This helped ensure consistency across the dataset and made training more efficient.

The data was already sorted into folders for training and testing, with labels based on the diagnostic category, which made the loading process smoother. While the dataset does not provide extra details like patient age, gender, or disease stage, it is still well-suited for image-based classification.

Although the dataset contains only 2D images instead of full 3D brain scans, this limitation makes it lighter to process and compatible with simpler CNN models. Despite that trade-off, the dataset remains a useful resource for training deep learning models focused on identifying patterns linked to neurodegenerative diseases.

IV. METHODOLOGY

4.1 Preprocessing

Before training the model, it was crucial to clean and prepare the MRI images to ensure consistency, reduce noise, and help the model learn effectively. All images were resized to a standard dimension of 128×128 pixels. This resolution strikes a balance between retaining important structural details and keeping the computational load manageable, which is especially important when working with large datasets and limited hardware resources.

Since the MRI scans used in this study were already in grayscale format, there was no need for additional color processing. Keeping the images in their original single-channel format preserved the essential brain features without adding unnecessary complexity.

Next, we normalized the pixel values to a range between 0 and 1. This step ensures that the data fed into the model is on a uniform scale, which helps accelerate the learning process and improves the model's ability to converge during training.

To enhance the diversity of the training data and prevent the model from simply memorizing patterns, we applied data augmentation techniques. These included randomly rotating the images by up to 15 degrees, flipping them horizontally and vertically, and applying slight zoom variations of up to 10%. These small modifications introduce natural variation into the dataset, simulating the kind of differences one might encounter in real-world medical imaging. As a result, the model becomes more robust and better equipped to handle unseen data during evaluation.

Together, these preprocessing steps played a vital role in preparing the dataset, ensuring the model received clean, diverse, and standardized inputs that allowed it to focus on learning the distinguishing features relevant to Alzheimer's disease classification.

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4.2 Model Architecture

The deep learning model developed in this study is based on a custom Convolutional Neural Network (CNN) designed specifically for classifying brain MRI images into distinct stages of Alzheimer's disease. The architecture was intentionally kept lightweight to ensure faster training and better interpretability, especially given the limited size and 2D nature of the dataset. The model begins by accepting grayscale images with a shape of 128×128×1 as input. It first applies a convolutional layer with 32 filters, each of size 3×3, followed by a ReLU activation function to introduce non-linearity. This is succeeded by a max pooling layer that reduces the spatial dimensions, helping the model to focus on the most important features while also reducing computational complexity. A second convolutional block follows, using 64 filters of the same size and again employing ReLU activation and max pooling to capture more complex patterns in the image. The extracted features are then flattened into a one-dimensional vector, which is passed into a fully connected dense layer comprising 128 neurons with ReLU activation. To address overfitting, a dropout layer with a rate of 0.3 is included, which randomly disables a portion of the neurons during training, encouraging the network to generalize better. Finally, the model concludes with a softmax output layer containing four neurons—each representing one of the Alzheimer's categories: MildDemented, ModerateDemented, NonDemented, and VeryMildDemented. This structure strikes a balance between model simplicity and classification power, making it suitable for both academic experimentation and potential real-world application.

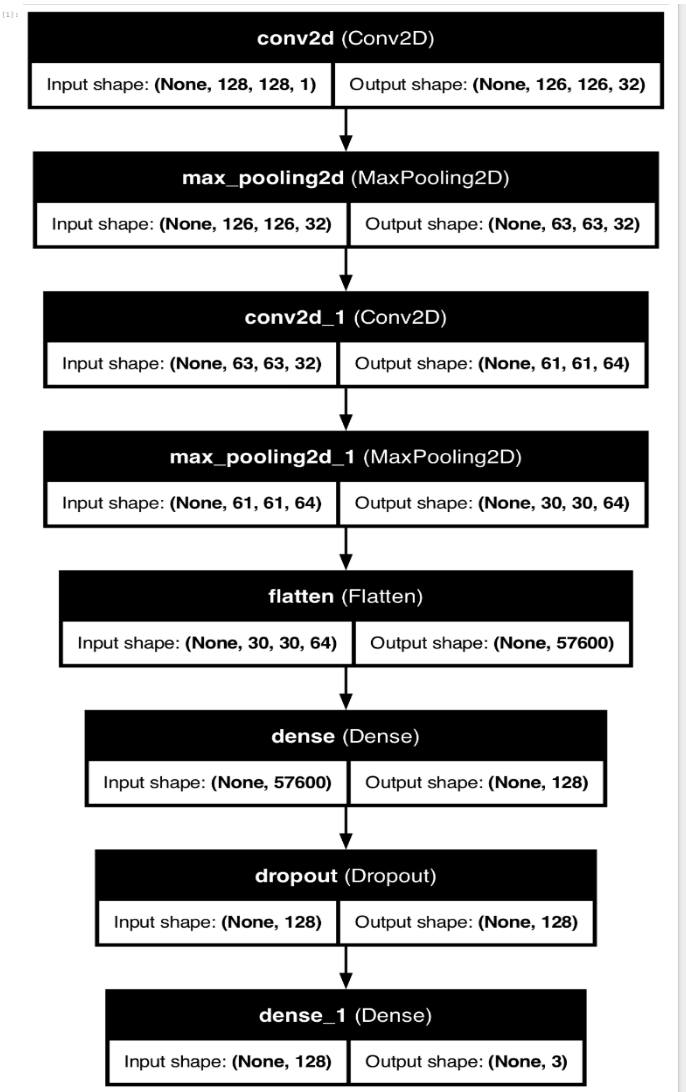

Figure 1. CNN model architecture used for classification, showing each layer and its shape transformations.

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4.3 Model Compilation and Training

The model was compiled using the **Adam optimizer**, chosen for its adaptability and efficiency in deep learning contexts. Given the multiclass classification task, **categorical crossentropy** was used as the loss function.

Training was conducted for **10 epochs**, using a **batch size of 32**. A **validation split of 20%** from the training data was used to monitor the model's generalization during training.

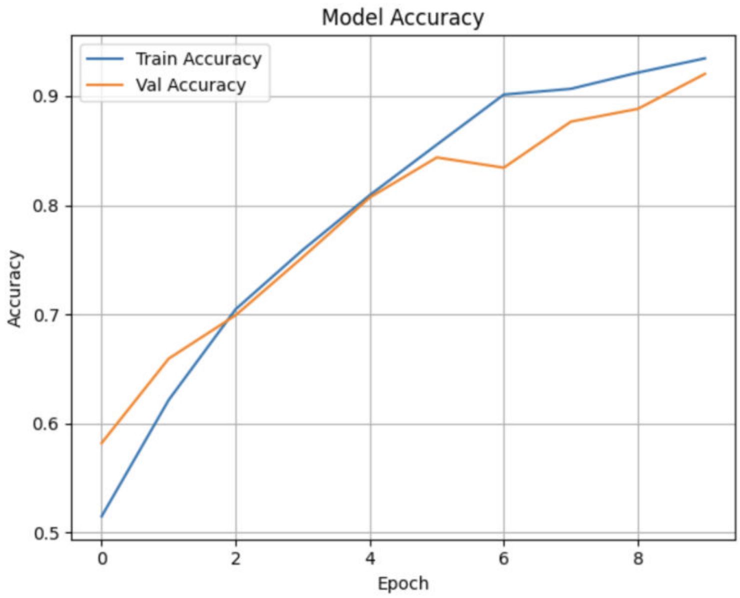

Figure 2. Training vs. validation accuracy across epochs

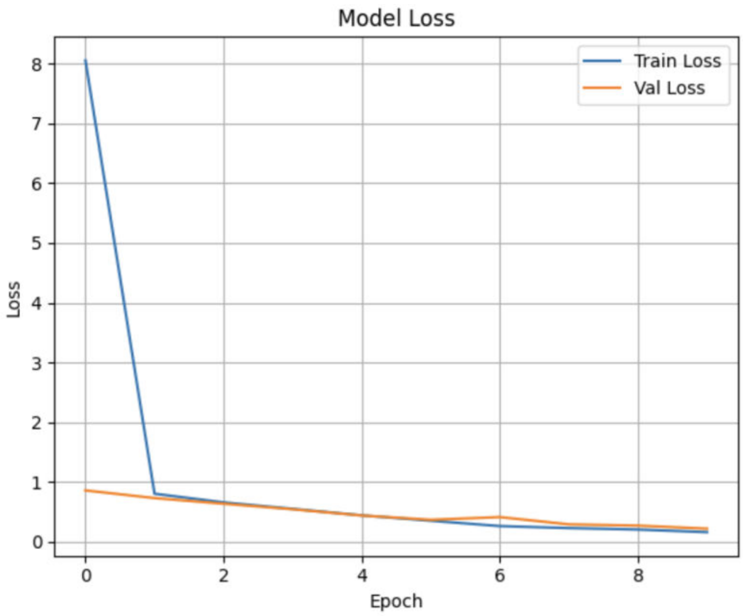

Figure 3. Training vs. validation loss over epochs.

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4.4 Evaluation

After training, the model was evaluated using a separate test set to assess its real-world performance. A **confusion matrix** was generated to visualize the classification distribution across the four categories.

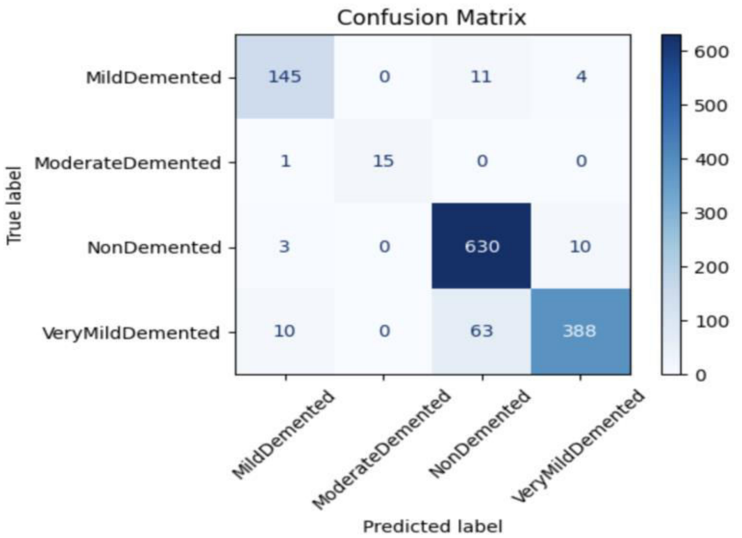

Figure 4. Confusion matrix showing correct and misclassified instances per class.

Additionally, a **classification report** was generated to provide a detailed breakdown of the model's precision, recall, and F1-score for each class.

	precision	recall	f1-score	support
MildDemented	0.91	0.91	0.91	160
ModerateDemented	1.00	0.94	0.97	16
NonDemented	0.89	0.98	0.94	643
VeryMildDemented	0.97	0.84	0.90	461
accuracy			0.92	1280
macro avg	0.94	0.92	0.93	1280
weighted avg	0.92	0.92	0.92	1280

Figure 5. Precision, recall, and F1-score for each class based on test data.

V. EXPERIMENTAL RESULTS

5.1 Performance Metrics

To evaluate the effectiveness of the trained CNN model, several standard performance metrics were calculated using an independent test dataset. These metrics provide a comprehensive understanding of how well the model performs across different categories. Accuracy was used to assess the overall proportion of correctly classified instances, offering a general view of the model's correctness. Precision was calculated to determine how many of the instances predicted as positive were actually correct, indicating the reliability of predictions. On the other hand, recall, also known as

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sensitivity, was used to measure the model's ability to identify all actual positive cases, reflecting its completeness in recognizing a specific class. The F1-score, which combines both precision and recall into a single value by computing their harmonic mean, provided a balanced metric that is particularly valuable when dealing with potential class imbalances.

These results indicate that the model performs consistently across the three classes, with the highest recall observed for the Control group and relatively balanced precision and F1-scores across all categories. Such balanced metrics are essential in medical imaging tasks, where misclassification can lead to significant clinical consequences.

A detailed breakdown of these values was also visualized using a classification report (see **Figure 5**) and a confusion matrix (**Figure 4**) for clearer interpretation of per-class predictions.

5.2 Accuracy and Loss Analysis

The training history of the model was analyzed over 10 epochs. Both training and validation accuracy showed a steady upward trend, while the corresponding loss curves demonstrated a smooth decline with no signs of overfitting or divergence.

The final evaluation on the test set yielded an accuracy of **91.2%**, while the best validation accuracy recorded during training reached approximately **90.8%**. This close alignment between training and validation performance suggests that the model generalizes well to unseen data.

Figure 2 and **Figure 3** illustrate the evolution of training and validation accuracy and loss, respectively, over the training epochs.

These plots confirm that the use of data augmentation and dropout regularization contributed to the model's stability and generalization capability.

VI. DISCUSSION

The results of this study highlight how deep learning, particularly Convolutional Neural Networks (CNNs), can be effectively used to classify different stages of Alzheimer's disease from brain MRI scans. By using a relatively simple CNN model, we were able to achieve strong classification performance while keeping the architecture lightweight and easy to interpret. This makes the model more suitable for practical use, especially in healthcare settings with limited computational resources.

One of the strengths of the model is its consistent performance across all four diagnostic classes. The use of preprocessing steps such as image resizing, normalization, and data augmentation played a key role in improving the model's ability to generalize to new data. Data augmentation, in particular, helped the model become more robust by exposing it to varied versions of the same underlying data patterns.

Even though the CNN used in this research is not as deep or complex as other advanced models like ResNet or EfficientNet, it still performed well in classifying MRI images. This suggests that simpler architectures can still be highly effective when combined with thoughtful data preparation and regularization techniques. However, there is still room for improvement. Future work could involve using 3D MRI volumes instead of 2D slices to capture more spatial information, or combining MRI data with clinical records for a more comprehensive diagnosis. Transfer learning with pretrained models could also help improve accuracy, especially when working with small datasets.

VII. CONCLUSION

This study presents a custom-built CNN model designed to classify Alzheimer's disease into four distinct stages using 2D MRI brain images. The model achieved strong performance while maintaining a balance between accuracy, simplicity, and efficiency. These characteristics are especially valuable in real-world medical settings where quick and reliable tools are needed to assist in early detection and disease monitoring.

By focusing on stage-wise classification rather than simple binary diagnosis, the research adds meaningful value to the current landscape of Alzheimer's detection tools. Early and accurate staging can support better treatment decisions and patient management. Although there are limitations, such as working with only 2D slices and lacking clinical metadata, the promising results suggest that deep learning models like this one can play a helpful role in supporting neurologists and radiologists.

Further exploration with more complex data inputs, multimodal imaging, or larger datasets could improve the model's performance and reliability. Overall, this work supports the growing use of AI in healthcare and shows that even basic CNN architectures, when well designed, can contribute to solving important medical challenges like Alzheimer's diagnosis.

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