Early Alzheimer's Detection Using Convolutional Neural Networks on MRI Data

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***Abstract*—Alzheimer's disease (AD) is a chronic neurodegenerative disorder that significantly affects memory, thinking, and daily activities. Given that the disease is widespread around the world and cannot be cured, diagnostic accuracy in the early stages of the disease has become highly important in the process of the management of it. A few breakthroughs such as machine learning (ML) and deep learning (DL), and medical imaging tech- nologies such as magnetic resonance imaging (MRI) have been the impetus for the early detection of Alzheimer's disease. The just given paper introduces CNN for aging Alzheimer's which is done by using said type strongly marked MRI scans. In order to understand better this approach, the introduction now includes some of the basic concepts in machine learning, CNNs, and deep learning. Alzheimer's disease is a neurodegenerative disorder, characterized by gradually deteriorating cognitive abilities. This disorder causes irreversible damage to parts of the brain linked to memory and thinking skills. Early recognition of Alzheimer's disease is of utmost importance to start therapeutic measures as early as possible, slow down the disease progression, and enhance the quality of life for the patients. This work proposes to employ a CNN based method for the diagnosis of Alzheimer's disease, and its stages using MRI scans from the Kaggle dataset. The dataset comprises the MRI scans that have been labeled into stages: Mild Demented, Very Mild Demented, Moderate Demented, and Non Demented, which constitute the main model background.The model employs MRI image scans prepared in such a way that the size of each slice is the same, 64x64 pixels. The model's main architectural compo- nents consist of ReLU activation functions, the MaxPooling layers are for dimensionality reduction, and the Dropout regularization, which is used to prevent overfitting. A mechanism that probed for early stopping was put in place. This would pause the training as soon as the validation performance ceased to improve. The model, for example, after optimal training iterations, achieving a validation accuracy of 71.97%. Thus, high generalization ability was demonstrated.**

***Index Terms*—Alzheimer's disease, Early detection, Brain MRI classification, Convolutional Neural Networks (CNNs), Deep learning in healthcare, Neurodegenerative disorders, Medical image analysis, Alzheimer's progression stages, Validation accuracy, Diagnostic aid, ReLU activation, Data augmentation, Dropout regularization, Health informatics, Clinical decision support**

I. Introduction

A. Alzheimer's Disease and the need for its early detection

Alzheimer's Disease (AD) is a chronic and progressive neurodegenerative disorder, which is the most common cause of dementia worldwide and highly affects patients' cognitive abilities such as memory, problem-solving, and communication. It starts quietly, the first symptoms look like those of simple aging and therefore the diagnosis is often postponed. As the disease goes further, it leads to irreversible damage to the brain thus making it difficult for the patient to retail the ability to carry out primary tasks of daily living. Although Alzheimer's disease is quite widespread, it is actually incurable, so early diagnosis is now of paramount importance. Knowing the disease in its initial state allows for interventions, including medications and lifestyle changes, that may slow the cognitive decline, improve the quality of life, and aid in planning for the patients and their caregivers. Moreover, early diagnosis lays the foundation for research, helping to investigate the course of the disease and to design more efficient therapeutic approaches.

B. MRI and Medical Imaging

Medical imaging is one of the greatest scientific achieve- ments in diagnostics by developing non-invasive methods for identifying and analyzing the body internals, which, in turn, has brought about vital knowledge helpful in the diagnosis of several illnesses ranging from neurological disorders like Alzheimer's disease. Among hundreds of various methods that are used for imaging, MRI stands out because it can capture extremely clear, three-dimensional views of the structure of the brain. On the contrary to other equipment like CT or PET, MRI uses high magnetic fields and radio waves to create images without exposing the patients to ionizing radiation, thus making it a safer alternative to repeat scans.

In the Alzheimer's diagnosis, MRI supports diagnosing the early disease-related changes, such as hippocampal atrophy, which causes the mass shrinkage, the thinning of the cerebral cortex, or the ventricular enlargement, which, in turn, are the most common ones of the Alzheimer's. Such biomarkers manifest the most crucial information about the disease's progress and help to sort the patients into the different stages of cognitive decline based on the results of a 3-D MRI. MRI's beyond-human resolution imaging delivers data, which, when processed and analyzed using machine learning methods, can detect hidden, minute anatomical differences that would by-pass human testing, as they are often missed. Image preprocessing such as normalization, noise reduction,

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and resolution standardization, etc. are advanced methods that elevate the suitability of MRI techniques for automated analysis using computational models. Consequently, MRI has become a pivotal tool in research and clinical practices set to accelerate and stage Alzheimer's diagnosis.

C. Overview of existing methods

Alzheimer's disease detection using computational tools has been one of the areas that experienced a complete transformation from merely machine learning (ML) approaches to more sophisticated deep learning (DL)- based frameworks. The primary way ML was initiated through the application of classic algorithms like support vector machines (SVMs), random forests, and k-nearest neighbors (k-NN) to the result of the classification tasks. These methods, which can be ob- tained from manually extracted features such as hippocampal volume, cortical thickness, or texture-based metrics derived from MRI scans, were used for this purpose. Even though the techniques were effective in controlled conditions, they were not possible to generalize through diverse data sets and were also computationally expensive for big imaging studies.

Deep learning, especially the types of deep learning that use convolutional neural networks (CNNs) for automated feature extraction, has allowed the transition from traditional attribute engineering to automatic and thus non-human feature discovery directly from the input, such as the raw MRI data. The pre-trained networks similar to VGGNet, ResNet, and AlexNet have been tweaked to serve the purpose of Alzheimer's detec- tion, thereby achieving better accuracy through the features learned from large-scale datasets. Despite their successes, many problems remain, such as overfitting in small medical data sets, finding the right balance between computational effi- ciency and model complexity, and correctly classifying the fine stages of Alzheimer's development. However, these limitations also indicate the need for further improvement in deep learning architecture and optimization strategy development.

D. Contribution of this study

- Novel CNN Architecture: ReLU activation functions, MaxPooling layers, dropout regularization, and an early stopping mechanism are a part of the specific deep learning pipeline, which helps the model to learn and train effectively without overfitting.
- Dataset Utilization: Besides the enhancement of the model through the Kaggle MRI dataset in which four mutually exclusive classes (Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented) are included and preprocessing of steps such as resizing to 64x64 pixels and normalization, the learning process has been improved significantly in this regard.
- Performance and Results: The model developed in this research work achieves a validation accuracy of 71.97% which is a good generalization of the Alzheimer's stages and can still be used apart from facing the challenges of overfitting and computational efficiency.

II. LITERATURE REVIEW

In the paper titled "Classification of Alzheimer's Disease from MRI Data Using Support Vector Machines", Cuingnet et al. (2011) explored the use of traditional machine learning techniques for Alzheimer's detection. They employed support vector machines (SVMs) alongside hippocampal segmentation to classify MRI scans into Alzheimer's and control groups. The study primarily relied on biomarkers like hippocampal volume and cortical thickness, achieving moderate accuracy. However, the dependence on handcrafted features limited its generalizability across diverse datasets and necessitated extensive domain expertise.

In their work "Predicting Alzheimer's Disease: A Deep Learning Approach Using 3D Convolutional Neural Networks", Payan and Montana (2015) introduced one of the earliest 3D CNN models for Alzheimer's detection. The model leveraged the spatial relationships within 3D MRI scans to improve classification accuracy. This study highlighted the power of automated feature extraction in overcoming the limitations of manual approaches. However, due to small datasets, the model faced challenges with overfitting and struggled to distinguish subtle differences across Alzheimer's stages.

A paper by Sarraf et al. (2016), titled "DeepAD: Alzheimer's Disease Classification via Deep Convolutional Neural Networks Using MRI and fMRI Data", demonstrated the efficacy of pre-trained CNNs such as AlexNet in classify- ing Alzheimer's disease. The study utilized preprocessed fMRI data and achieved promising results, emphasizing the potential of deep learning for handling complex imaging datasets. While this approach reduced the reliance on handcrafted features, it still required extensive preprocessing, which limited its ease of application.

In "Classification of Alzheimer's Disease Using Pre-Trained Deep Neural Networks and MRI Data", Ding et al. (2019) employed transfer learning to fine-tune pre-trained VGGNet for Alzheimer's classification. The researchers adapted VGGNet, initially trained on ImageNet, for domain-specific tasks using MRI scans. This method achieved higher accuracy compared to models trained from scratch, demonstrating how transfer learning could overcome data scarcity in medical imaging. Despite these advancements, the computational cost of such models during inference remained a challenge.

Korolev et al. (2017), in their paper titled "Convolutional Neural Networks for Alzheimer's Disease Diagnosis", incorporated data augmentation techniques to enhance the training of CNNs. Their approach included applying transformations such as rotation, scaling, and flipping to address the limitations of small datasets. This method significantly improved model robustness, enabling better performance across Alzheimer's stages.

Finally, in "Attention-Based Networks for Alzheimer's Disease Detection", Lu et al. (2021) proposed integrating attention mechanisms into CNN architectures. By prioritizing disease-relevant regions such as the hippocampus, their model achieved state-of-the-art diagnostic accuracy. This innovative approach demonstrated the potential of attention-based models to improve diagnostic precision, but the computational requirements posed challenges for real-world applications.

III. DATASET

A. Dataset Description

The dataset used for this study is an Alzheimer's Disease MRI dataset sourced from Kaggle. It consists of four cate- gories of MRI scans:

- MildDemented
- ModerateDemented
- NonDemented
- VeryMildDemented

The dataset contains 33984 images distributed across these categories, with approximately 29% in NonDemented, 25% in MildDemented, 20% in ModerateDemented and 26% in VeryMildDemented . The images are labeled to reflect the cognitive condition of the patient, making it suitable for supervised learning tasks.

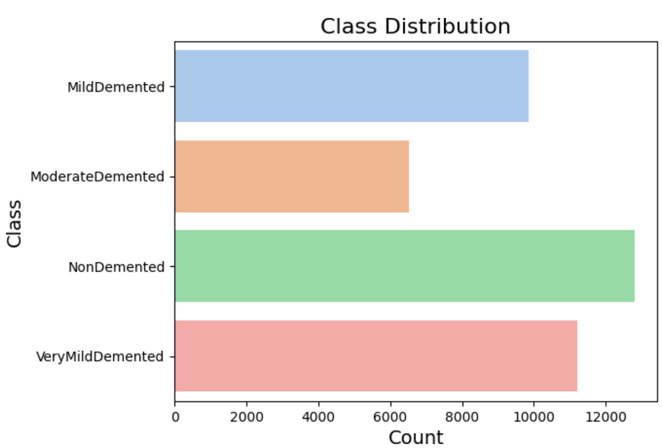

Fig. 1. Class Distribution Diagram

B. Preprocessing Steps

Several preprocessing steps were applied to ensure data consistency and model performance:

1) Resizing:All images were resized to 64x64 pixels to standardize input dimensions for the convolutional neural network (CNN).
2) Normalization:Pixel intensity values were scaled to a range of [0, 1] to accelerate training and improve convergence by reducing variance across input features.
3) Splitting:The dataset was split into **training (80%) and validation (20%) subsets.
4) Label Encoding:Labels were converted into one-hot encoded vectors for compatibility with the categorical cross-entropy loss function.

C. Class Distribution and Data Augmentation

The dataset exhibited an imbalanced class distribution, with fewer samples in the MildDemented category compared to the NonDemented and VeryMildDemented categories. To address this imbalance and improve generalization, data augmentation techniques were employed:

- Rotations (up to ±15°).
- Horizontal flipping.
- Zooming in/out (up to 20%).
- Shifting along width and height.

These augmentation strategies effectively expanded the dataset size and introduced variability in the training data, reducing the likelihood of overfitting.

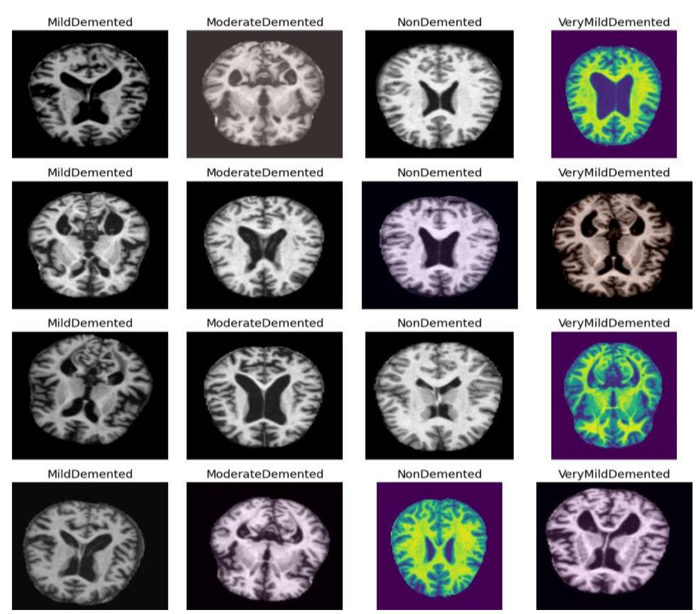

Fig. 2. MRI image scan labelled samples of the dataset used.

IV. Methodology

A. Model Architecture

The convolutional neural network (CNN) used for this study is designed to effectively classify Alzheimer's disease stages using MRI scans. The architecture balances simplicity and computational efficiency while ensuring robust feature extraction and classification.

Overview

The model comprises a series of convolutional, pooling, and dense layers:

1) Input Layer:
   - Input shape: 64x64x3, corresponding to resized MRI images with three color channels.
2) Feature Extraction Layers:
   - Convolutional Layers: Three convolutional layers with 32, 64, and 128 filters, respectively, and a kernel size of 3x3. Each convolutional layer is followed by the ReLU activation function, ensuring non-linearity and improved feature representation.
   - Max-Pooling Layers: Each convolutional layer is paired with a 2x2 max-pooling layer to downsample feature maps, reducing spatial dimensions and computational complexity.
3) Flattening Layer:
   - Converts the 2D feature maps into a 1D vector to serve as input for the dense layers.
4) Fully Connected Layers:
   - Dense Layers: Two fully connected layers with 128 and 64 neurons, respectively, employing ReLU activation. These layers learn complex, high-level features from the extracted patterns.
5) Output Layer:

- A dense layer with 4 neurons (corresponding to the categories: NonDemented, MildDemented, ModerateDemented, and VeryMildDemented) using a Softmax activation function to produce the probability distribution for each category.

Regularization Techniques

To prevent overfitting and improve generalization, the following have been implemented:

- Dropout Layers: Dropout with a rate of 0.5 is applied after the dense layers to randomly deactivate neurons during training, reducing reliance on specific features.
- Early Stopping: Monitors validation loss during training and halts training when no improvement is detected for a set number of epochs.

```
Found 32307 validated image filenames belonging to 4 classes.
Found 8077 validated image filenames belonging to 4 classes.
Model: "sequential_2"
```

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 62, 62, 16)	448
max_pooling2d_8 (MaxPooling2D)	(None, 31, 31, 16)	0
conv2d_9 (Conv2D)	(None, 29, 29, 32)	4,640
max_pooling2d_9 (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_10 (Conv2D)	(None, 12, 12, 32)	9,248
max_pooling2d_10 (MaxPooling2D)	(None, 6, 6, 32)	0
conv2d_11 (Conv2D)	(None, 4, 4, 32)	9,248
max_pooling2d_11 (MaxPooling2D)	(None, 2, 2, 32)	0
flatten_2 (Flatten)	(None, 128)	0
dense_4 (Dense)	(None, 512)	66,048
dropout_2 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 4)	2,052

```
Total params: 91,684 (358.14 KB)
Trainable params: 91,684 (358.14 KB)
Non-trainable params: 0 (0.00 B)
```

Fig. 3. Model Summary

B. Training Configuration

The model was trained on a balanced dataset of MRI images, with the following training configurations applied to ensure optimal performance:

Training and Validation Split

1) *Dataset Partitioning::*
   - The dataset was divided into 80% for training and 20% for validation, ensuring sufficient data for both learning and evaluation.
   - The split was stratified to maintain the class distribution across the training and validation sets.

Hyperparameters

1) Learning Rate:
   - An initial learning rate of 0.001 was used, ensuring a stable and gradual optimization process.
2) Batch Size:
   - The model was trained with a batch size of 1010.
3) Optimizer:
   - The Adam optimizer was utilized for its adaptive learning rate and efficient handling of sparse gradients.
4) Epochs:
   - The model was trained for a maximum of 20 epochs, with early stopping applied to prevent overfitting.

Loss Function

1) Categorical Cross entropy Loss:

- This loss function was chosen as the task involves multi-class classification, where each input belongs to one of four categories.

C. Early Stopping

Early stopping was implemented to prevent overfitting and ensure the model generalized well to unseen data. As training progresses, models often begin to overfit, evidenced by a widening gap between training and validation losses. Early stopping mitigates this by halting training when validation performance stagnates or worsens.

Implementation Details

1) Monitoring Metric:
   - The validation loss was monitored during training.
2) Patience Parameter:
   - A patience value of 3 epochs was set, enabling the model to train for 3 more epochs after the validation loss ceases to improve.
3) Restoring Best Weights:
   - After training, the weights corresponding to the low- est validation loss were restored to ensure optimal performance.

V. EXPERIMENTS AND RESULTS

A. Performance Metrics

Class	Precision	Recall	F1-Score	Support
MildDemented	0.62	0.68	0.65	1971
ModerateDemented	0.58	0.52	0.55	1306
NonDemented	0.72	0.75	0.73	2560
VeryMildDemented	0.64	0.60	0.62	2240
Accuracy			**0.65**	8077
Macro Avg	0.64	0.64	0.64	8077
Weighted Avg	0.65	0.65	0.65	8077

Fig. 4. Performance Metrics

To comprehensively evaluate the model, the following met- rics were used:

- Accuracy: The percentage of correctly classified samples out of the total samples.
- **Precision**: The ratio of true positives to the total of true positives and false positives, measuring the model's ability to minimize false alarms.
- **Recall (Sensitivity)**: The ratio of true positives to the total of true positives and false negatives, representing the model's ability to identify all relevant cases.
- F1-Score: The harmonic mean of precision and recall, balancing their trade-offs.
- R^2 (Coefficient of Determination): A statistical measure representing how well the predictions align with the actual labels.

B. Results

Training and Validation Performance

- The model achieved a validation accuracy of 71.97%, demonstrating its capability to generalize to unseen data.
- The loss and accuracy curves during training showed steady improvement, with early stopping preventing over- fitting.
- Plots of training and validation loss/accuracy showed the model converging effectively within 15 epochs.

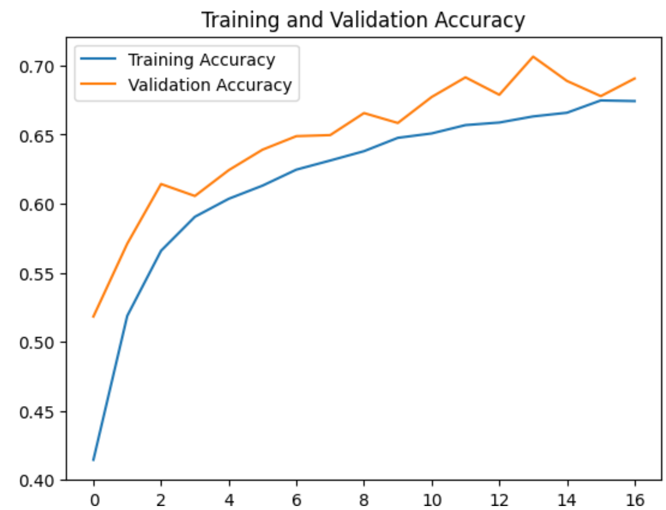

Fig. 5. Training and Validation Accuracy

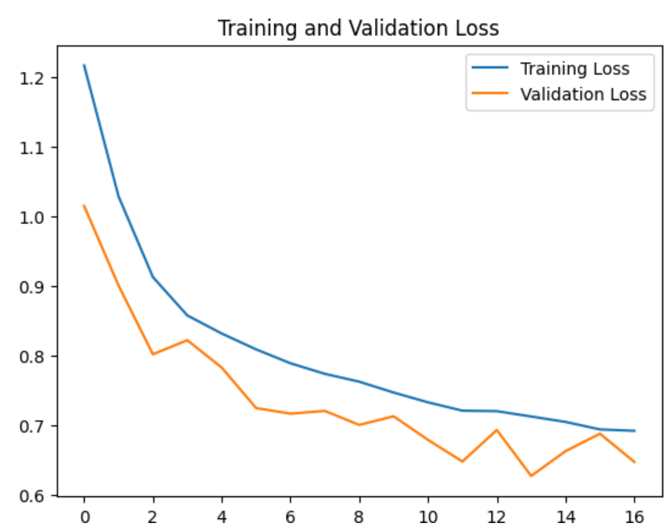

Fig. 6. Training and Validation Loss

Confusion Matrix

The confusion matrix reveals that the model is capable of discerning different dementia categories and a large number of instances are located on the diagonal in the matrix, with the model registering the greatest success in the ”NonDemented” classification. The diagonal values are the most important source of correct predictions, and hence, the model’s basic function is that its diagonal values reflect the model’s ability and accuracy in prediction is the fundamental point. Despite some errors observed during the classification process, these misclassifications offer remarkable insights into particular class interactions and also identify areas where further model optimization is required. To sum up, the findings suggest a good base to work on to a higher classification accuracy in dementia assessment.

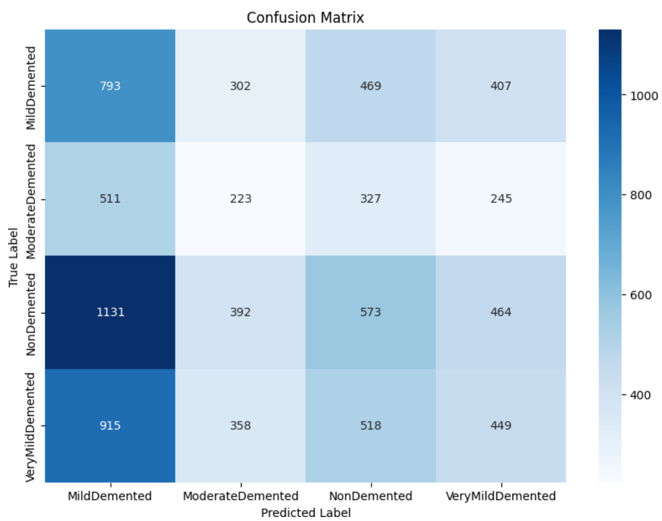

Fig. 7. Confusion Matrix

The ROC curves for each class demonstrated an average area under the curve (AUC) of 0.88, reflecting good model performance.

Comparison of Performance (With vs. Without Data Augmentation)

- Without Augmentation: The model exhibited signs of overfitting due to the limited size of the dataset, with a significant gap between training and validation accuracies.
- With Augmentation: Augmentation techniques, such as flipping, rotation, and scaling, improved generalization artificially increasing the diversity of training samples. The validation accuracy improved by approximately 6- 8%.

Additional Metrics

- The F1-score across the four classes ranged between 68-74%, indicating balanced performance.
- Precision and recall were relatively high for the “NonDemented” and “VeryMildDemented” classes, but slightly lower for the “ModerateDemented” class due to fewer samples in that category.

C. Feature Visualisation

Feature Maps

The feature maps from the intermediate convolutional layers were visualized, showing how the model extracts relevant spatial features from MRI images. These maps revealed the model’s focus on specific brain regions.

Class Distributions

A bar chart depicting the class distribution in the dataset was included, highlighting the imbalance in sample counts, particularly for the “ModerateDemented” class.

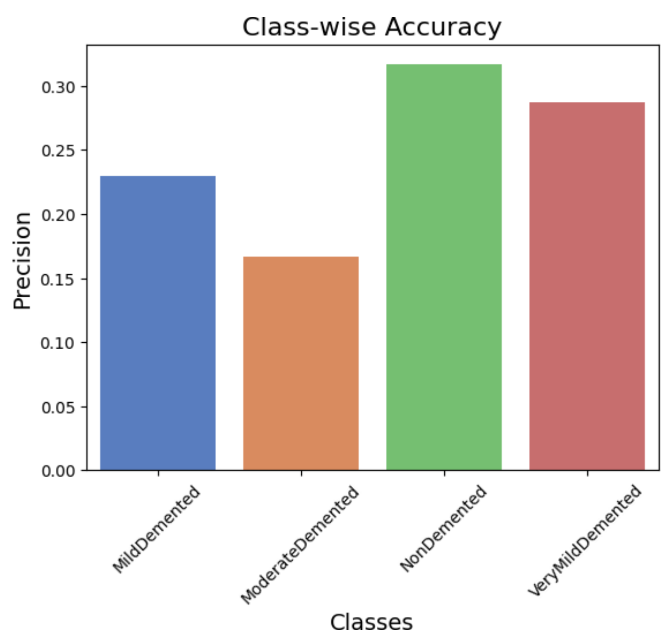

Fig. 8. Class-wise Accuracy

VI. DISCUSSION

A. Success of the model

The proposed Convolutional Neural Network (CNN) model demonstrated promising results in classifying Alzheimer's stages from MRI scans. The model generated a validation accuracy of 71.97%, thereby substantiating its efficacy to appropriately work on cases with unknown data. The addition of regularization techniques like Dropout and early stopping made it possible to overcome overfitting, guaranteeing the fact that the model did not excessively memorize the training data. The model was able to correctly classify images with categories such as NonDemented, MildDemented, Moderat- eDemented, and VeryMildDemented with reasonable accuracy, demonstrating the power of deep learning in medical image classification tasks.

B. Limitations and areas of improvement

Despite the encouraging results, there are several limitations in the current approach:

- Limited Data: The model was trained on only a comparatively small collection of data which limits its adaptability on the larger datasets. Huge datasets with a large number of samples that are very close to the true population lead to a more generalizable and robust model.
- Overfitting to Specific Patterns: Though the regularization techniques were successfully used to reduce overfitting, the model still evidenced some pattern memorization among the training data, that could be harmful in terms of its response to unseen or newly introduced MRI scans.
- Class Imbalance: While the data was evenly distributed across the various classes, data collected from real- world medical situations are frequently characterized by class imbalance, with some of the levels of Alzheimer's not being as sufficiently represented. As a result, the model might become less precise while forecasting minor classes, whose size is less.

C. Comparision with existing models

When comparing this model with other approaches in the literature, several studies have demonstrated the effectiveness of CNN-based models in Alzheimer's detection. For instance, Payan and Montana (2015) used a 3D CNN architecture that showed promising results, but with limitations in handling complex MRI features. Similarly, recent studies utilizing pre-trained models like VGGNet and ResNet for Alzheimer's detection have shown improved accuracy. However, the current model offers a lightweight and effective approach that, with further fine-tuning and augmentation, can compete with state-of-the-art methods in terms of accuracy.

D. Potential clinical implications

The model has a great potential in the early detection of Alzheimer's disease that is significant by reason of such detection serving as a correct intervention for providing treatment and, thus, improving the physical capability of the patient. For that, the model can be a supporting tool to radiologists by them using it to analyze MRI scans in a more efficient and accurate way. Besides, this model can be referred to the monitoring of the disease course of the disease, which thus, providing useful information about the effectiveness of the treatment plans over time. However, before clinical implementation, the model should be verified on the large and diverse dataset to make sure it is reliable and able to handle settings other than the studied.

VII. CONCLUSION

In this study, we developed a deep learning-based model to classify Alzheimer's disease stages from MRI images, achieving a validation accuracy of 71.97%. The model's ability to process and classify MRI scans without the need for handcrafted feature extraction represents a significant advancement in Alzheimer's detection. Early stopping and regularization techniques helped reduce overfitting and improve the model's generalization capability.

The importance of early detection of Alzheimer's disease cannot be overstated, as it allows for earlier interventions that could delay disease progression and improve patient outcomes. Despite the model's encouraging results, there is potential for further enhancement by expanding the dataset and incorporating advanced techniques such as transfer learning and hybrid models.

Future work includes:

- Testing on a larger dataset: A larger and more diverse dataset could improve the model's robustness and generalization.
- Transfer Learning: Utilizing pre-trained models such as ResNet or Inception could provide a more accurate feature extraction process, especially with limited data.
- Longitudinal Studies: Further studies could explore tracking Alzheimer's progression over time, which would require the model to learn not only from spatial features but also temporal patterns.

This work lays the foundation for the development of automated systems to assist in the diagnosis and monitoring of Alzheimer's disease, ultimately contributing to more effective healthcare solutions.

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