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Alzheimer's Disease Detection Using Lightweight Convolutional Neural Network on MRI Scans

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ABSTRACT

This research suggests a lightweight Convolutional Neural Network (CNN) model for Alzheimer's Disease (AD) detection and classification from Magnetic Resonance Imaging (MRI) scans. Two models were trained: a binary model distinguishing AD from non-AD cases and a multi-class model distinguishing four stages of dementia (Non-Demented, Very Mild-Demented, Mild Demented, and Moderate Demented). The models were trained on a Kaggle dataset with high accuracy (97.5% binary, 89.3% multi-class). The research demonstrates the viability of lightweight CNNs for low-cost and precise AD diagnosis, with class imbalance managed through data augmentation.

INTRODUCTION

Alzheimer's Disease is a progressive neurodegenerative disorder and one of the main causes of dementia worldwide (Murguiondo-Pérez *et al.*, 2025; Cummings *et al.*, 2025; Li *et al.*, 2022). Early detection is crucial to facilitate early intervention, yet current diagnostic methods are largely based on expensive or invasive methods (Cummings *et al.*, 2025; Vrahatis *et al.*, 2023; Zhang *et al.*, 2023). MRI scanning provides a non-invasive technique for detecting alterations in the brain as observed in AD (Murguiondo-Pérez *et al.*, 2025; Kaštelan *et al.*, 2025; van Oostveen *et al.*, 2021). This study employs deep learning, specifically convolutional neural networks, to generate an automated, accurate, and inexpensive means of AD identification and classification from MRI scans.

Problem Statement

Early and correct diagnosis of AD remains challenging due to subtle changes in the brain early in the disease course, limited access to advanced imaging in low-resource settings, and the need for specialized radiologists. In addition, AD classification sets typically exhibit class imbalance with fewer instances of more severe conditions like Moderate Demented. A cost- efficient, computerized system able to reliably detect AD and differentiate its stages with widely available MRI scans.

Main Objective and Specific Objectives

Main Objective

To implement a light-weight CNN-based system for automatic detection and classification of Alzheimer's Disease from MRI scans.

Specific Objectives

1. To implement and train a binary CNN model to classify AD and non-AD cases.
2. To use a multi-class CNN model to predict four stages of dementia.
3. To manage class imbalance through data augmentation techniques.
4. To evaluate model performance in terms of accuracy, precision, recall, and F1-score.
5. To validate the models on test images of another dataset.

Impact of the Research / Significance

This research presents an effective and scalable method for AD detection, capable of potentially increasing early diagnosis availability in low-resource settings. The lean CNN models require less computational capacity than typical deep learning models, positioning them as candidates for deployment on simple hardware. Accurate staging classification of dementia may ultimately result in personalized treatment planning, improved patient outcomes, and reduced healthcare costs. The models also contribute to the growing level of AI-aided medical diagnosis, which opens up the use of deep learning in medicine to wider applications.

Deep learning has been a hit in recent years in the field of medical image processing, particularly in Alzheimer's Disease (AD) diagnosis. Automatic learning of hierarchical features from unprocessed data is a capability

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which makes it a stronger contender to read MRI images, which are of high dimension and complexity. Beyond medicine, deep learning has been applied with great success to carry out other functions like vehicle detection and monitoring. For instance, Meng *et al.* (2025) suggested a deep ensemble transfer learning-based approach along with swarm intelligence for detecting multiple vehicles from UAV images, exhibiting broader applications of the same (Meng *et al.*, 2025)

For the purpose of AD diagnosis, Menagadevi *et al.* (2023) suggested computer-aided diagnosis based on multiscale pooling residual autoencoder to feature extraction from MRI scans and followed by K-Nearest Neighbor (KNN) and Extreme Learning Machine (ELM) classifiers-based classification. Their model performed very well at 96.88% through KNN and 98.97% through ELM but because it is based on traditional classifiers and has a higher training time, it is not suitable for real-time or mass deployment (Menagadevi *et al.*, 2023).

Similarly, Alsadhan *et al.* (2025) proposed DEMNET model, for which preprocessing, oversampling, and deep feature learning were employed. Though they achieved 95.23% accuracy for multi-class classification, high computational cost and overfitting limited its stability (Alsadhan, 2025).

Loddo *et al.* (2021) created ensemble model with pre-trained architectures AlexNet, ResNet101, and InceptionResNetV2 to achieve accuracy of 97.7% for multi-class classification. But the model did not utilize preprocessing operations and interpretability, and its ensemble architecture was computationally complex. Khemariya *et al.* (2025) presented a hybrid system named HTLML, which processed MRI images by parallel processing with the assistance of DenseNet201 and DenseNet121 and combined their results on the basis of voting.

While achieving 91.75% accuracy, the absence of data augmentation and utilization of minimal data restricted it from generalizing (Khemariya & Sonker, 2025).

Zhang *et al.* (2023) used 2D and 3D CNNs to efficiently extract features from segmented brain areas and obtained 95.34% accuracy with appropriate sensitivity and specificity [9]. But the performance of the technique on heterogenous and larger sets is yet to be understood. Techa *et al.* (2022) used both CNN and also SVM in multi-class classifications. They achieved 94.80% accuracy but the use of external classifier such as SVM could restrain model's scalability and flexibility.

Yaqoob *et al.* (2024) employed ResNet50 pre-trained model with less preprocessing step of thresholding and resizing.

The accuracy of the model was 94.1%, but not data augmented and overfitting-sensitive. Mmadumbu *et al.* (2025) also demonstrated that deep learning-based models outperform default classifiers overwhelmingly by a tremendous margin of 94.63%, but without employing methods of class imbalance minimization and overfitting.

Ahmed *et al.* (2022) proposed DAD-Net, a CNN architecture with preprocessing and feature optimization with 90% accuracy. However, the relatively low architecture and dataset size were somehow drawbacks. Tuvshinjargal and Hwang (2022) attempted to mix VGG-C transform and CNN, with Z-score scaling and intensity quantization, and only reached 77.46% with almost zero robustness.

Sorour *et al.* (2024) suggested a hybrid CNN-LSTM model to leverage spatial and temporal data in MRI scans with 98.50% accuracy. Training the model, however, required an enormous dataset and vast computation power and was therefore impossible for low-resource environments. Hu *et al.* (2023) also introduced the VGG-TSwinformer model by integrating CNN and Transformer models for longitudinal MRI analysis. While the model provided a novel use of temporal attention mechanisms and achieved accuracy of 77.20%, it was plagued with inadequate feature fusion across MRI planes and was unable to make use of multimodal biomarkers to their full potential (Hu *et al.*, 2023).

Despite the papers considered here emphasizing the potential of deep learning for AD diagnosis, they also reveal current limitations such as excessive computational needs, limited dataset sizes, overfitting, and non-availability of data augmentation. The current study bridged these limitations by introducing a light, scalable CNN model for binary and multi-class AD classification with improved performance at reduced resource consumption.

MATERIALS AND METHODS

Dataset

The training dataset was downloaded from Kaggle, containing 5120 training and 1280 test .parquet format MRI scans categorized as Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Test images for prediction were taken from a different Kaggle dataset.

Preprocessing

Images were normalized to 150x150 pixels and then normalized (divided pixel values by 255). Data augmentation included brightness, zoom, and horizontal flip to enhance model resilience. Class imbalance was addressed by resizing minority classes (e.g., Moderate Demented) to match majority class sample size (2566 samples per class after augmentation).

Model Architecture

1. Two CNN models were implemented in TensorFlow: Binary Model: Separates AD from non-AD using three convolutional layers (32, 64, 128 filters), max-pooling, and two dense layers (151 units each), ending with a sigmoid output.

2. Multi-Class Model: Separates four stages of dementia with the same structure but using 154-unit dense layers and softmax output for four classes.

Training

Models were trained up to 100 epochs with batch size 50, using Adam optimizer (learning rate=0.001), early stopping (patience=10), and learning rate reduction (factor=0.2, patience=5). Binary models used binary cross-entropy loss, and multi-class models used sparse categorical cross-entropy.

Evaluation

The performance was evaluated on accuracy, loss, confusion matrices, and classification reports (precision, recall, F1-score). Models were stored as .h5 files so they can be reused in the future.

Table 1: The detailed architecture of the Binary model

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 150, 150, 32)	896
max_pooling2d_3 (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_4 (Conv2D)	(None, 75, 75, 64)	18,496
max_pooling2d_4 (MaxPooling2D)	(None, 37, 37, 64)	0
conv2d_5 (Conv2D)	(None, 37, 37, 128)	73,856
max_pooling2d_5 (MaxPooling2D)	(None, 18, 18, 128)	0
flatten_1 (Flatten)	(None, 41472)	0
dense_3 (Dense)	(None, 154)	6,386,842
dense_4 (Dense)	(None, 154)	23,870
dense_5 (Dense)	(None, 4)	620

Table 2: The detailed architecture of the multi-class model

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 150, 150, 32)	896
max_pooling2d (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_1 (Conv2D)	(None, 75, 75, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 37, 37, 64)	0
conv2d_2 (Conv2D)	(None, 37, 37, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 18, 18, 128)	0
flatten (Flatten)	(None, 41472)	0
dense (Dense)	(None, 151)	6,262,423
dense_1 (Dense)	(None, 151)	22,952
dense_2 (Dense)	(None, 1)	152

Code and Data Availability

The whole codebase, from Jupyter notebook (Alzheimer.ipynb) to model weights (alzheimer_binary_model.h5, alzheimer_multi_class_model.h5) and sample test images, are available in a public GitHub repository:
https://github.com/zindazed/computer_vision_finals.git.
The repository has all the scripts required to preprocess data, train models, and make predictions.
Following are step-by-step setup and run instructions for the project:

Setup Instructions

Clone the Repository

Open terminal and run: git clone
https://github.com/zindazed/computer_vision_finals.gitcd computer_vision_finals

Install Dependencies

1. Make sure Python 3.8 or later is installed.
2. Installed listed packages from notebook:
   1. pip install tensorflow keras matplotlib scikit-learn pandas numpy seaborn pyarrow pillow
   2. Checked TensorFlow version (should be ~2.19.0)

Datasets

Downloaded training dataset from Kaggle:

1. https://www.kaggle.com/datasets/borhanitrash/alzheimer-mri-disease-classification- dataset
2. Placed the .parquet files (train-00000-of-00001-c08a401c53fe5312.paquetandtest-00000-of-00001-44110b9df98c555parquet) in a Data/ folder within the repository.

Downloaded test images from

1. https://www.kaggle.com/datasets/lukechugh/best-alzheimer-mri-dataset-99-accuracy.
2. Placed sample test images (e.g., none.jpg, mild.jpg, moderate.jpg, very.jpg) into the repository root.

Run the Notebook

Start Jupyter Notebook:

Open Alzheimer.ipynb and execute all cells to:

1. Preload and preprocess the .parquet datasets.
2. Train binary and multi-class models (or load pre-trained weights from .h5 files).
3. Compare model performance and visualize (e.g., confusion matrices, accuracy/loss plots).
4. Make predictions for test images.

Use Pre-trained Models:

1. The repository includes alzheimer_binary_model.h5 and alzheimer_multi_class_model.h5.
2. To make predictions for new images, modify the predict_single_image function call in the notebook to accept the path to your test image (e.g., predict_single_image("test_images/none.jpg", binary_model, multi_class_model)).
3. Such a setup enables users to re-run the study, train models anew, or utilize pre-trained models to forecast on new MRI scans.

RESULTS AND DISCUSSION

Data Exploration

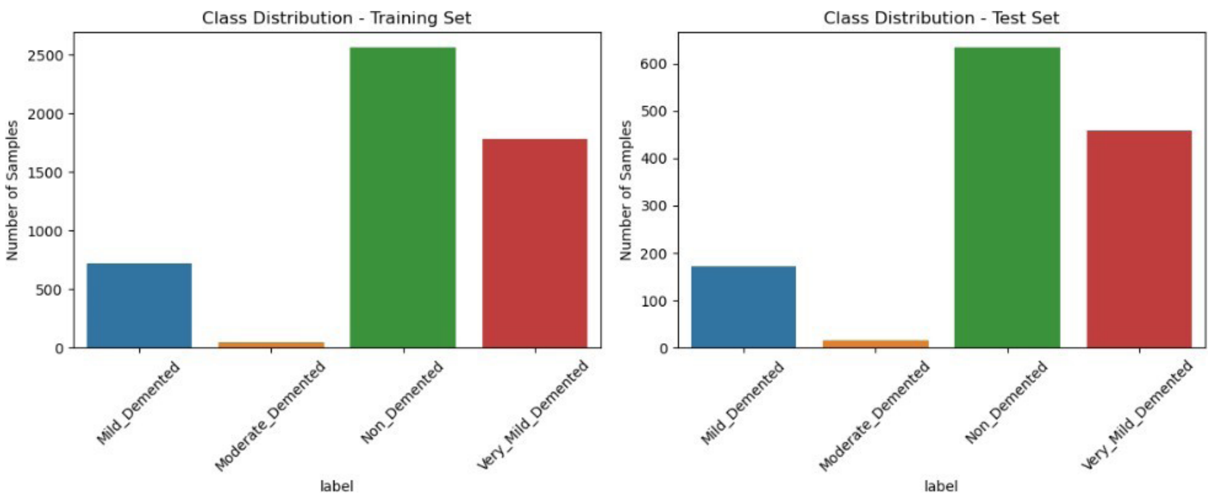

Figure 1: Class distribution in training and test datasets reveals an imbalance, with more 'Non_Demented' and 'Very_Mild_Demented' samples.

The training dataset had imbalanced classes: Non-Demented (2566 samples), Very Mild Demented (1781), Mild Demented (724), and Moderate Demented (49). Augmentation balanced classes to 2566 samples each.

Binary Model Performance

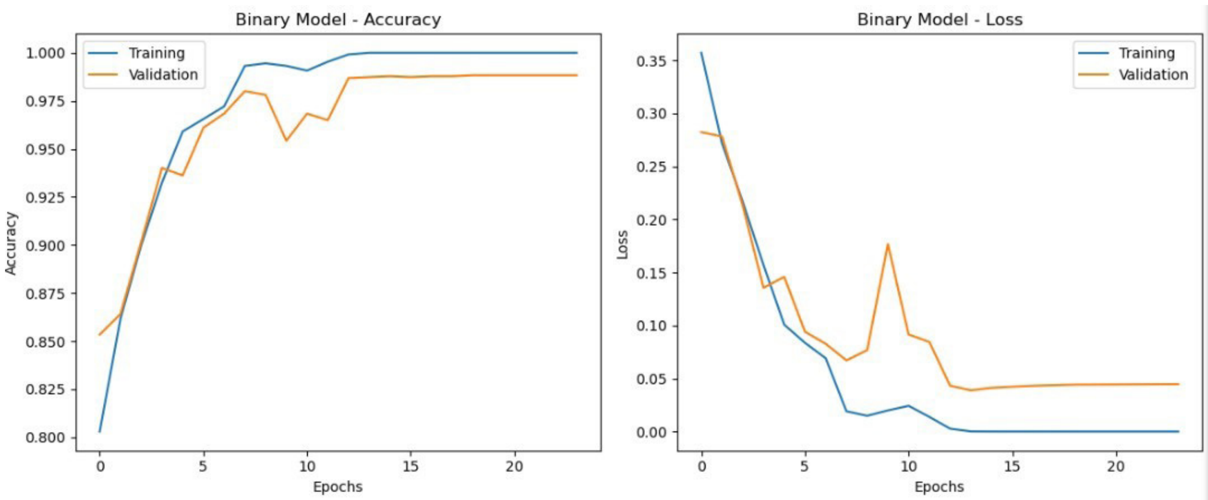

Figure 2: Accuracy/loss plots for binary model.

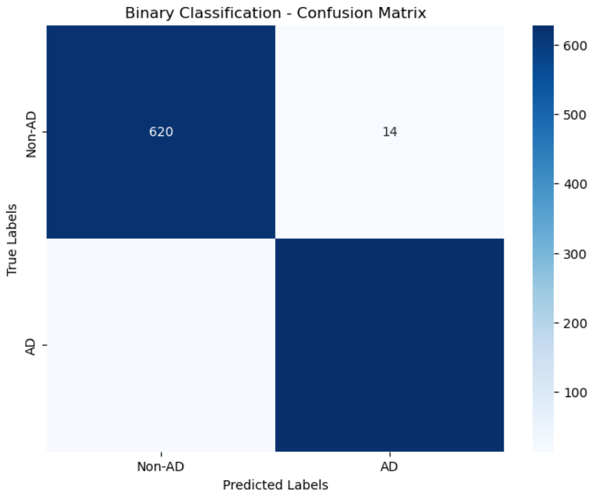

Figure 3: Confusion matrix for binary model

The test accuracy of the binary model was 97.5% and the test loss was 0.0803. The confusion matrix was marked by high true positives (620 Non-AD, 629 AD) with minimal misclassifications (14 Non-AD, 17 AD). The classification report featured precision, recall, and F1-scores of 0.97–0.98 for both classes.

Multi-Class Model Performance

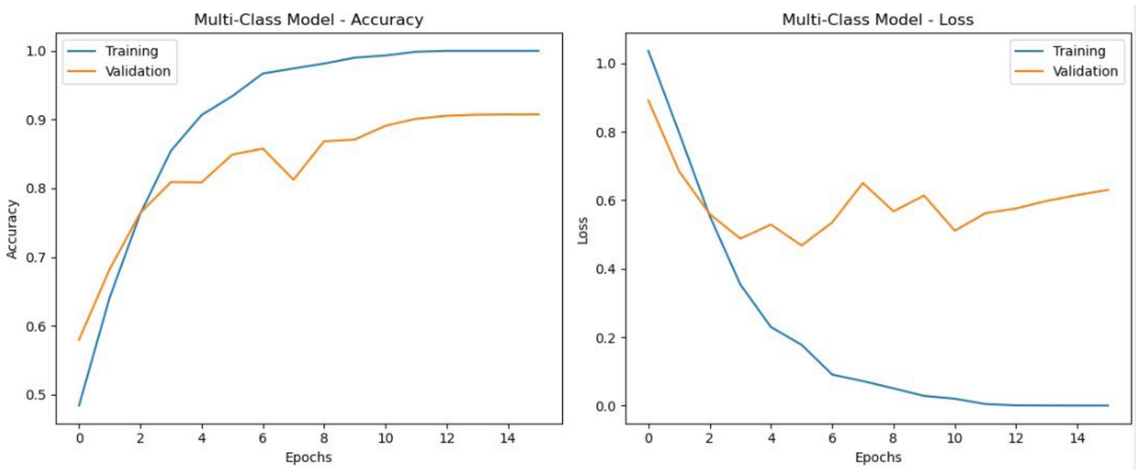

Figure 4: Accuracy/loss plots for multi-class model

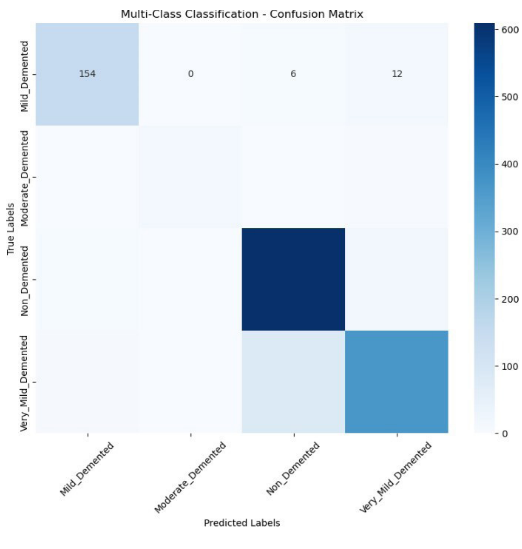

Figure 5: Confusion matrix for multi-class model

Multi-class classification model carried out with a test accuracy of 89.3% and a resulting test loss of 0.3541, illustrating a very high overall predictive power. Insight into the confusion matrix revealed excellent performance in the Non-Demented class with recall as high as 96%, indicating that the model was similarly well capable of identifying most healthy subjects. High reliability classification was also achieved in the Mild Demented class with recall at 90%. On the other hand, the Recall for the Moderate Demented class was lower at 80%, suggesting greater struggle to distinguish this class due to the comparatively fewer training samples for this level that were likely the cause of the model's inability to generalize so well.

The classification report also echoed these results, with the F1-scores of 0.85 for the Very Mild Demented, and 0.91 for the Mild Demented and Non-Demented classes. These results both call out the model's strengths and weaknesses: it will consistently detect most cases, particularly for the adequately represented classes, but its accuracy falls off for underrepresented stages of dementia.

Clinically, the high recall for the Non-Demented group is beneficial for screening as it reduces mislabelling healthy individuals with dementia, thereby decreasing unnecessary anxiety and medical intervention. Good performance at the Mild Demented stage is also crucial., as it facilitates early and accurate detection at this stage, and hence timely intervention, treatment planning, and appropriate lifestyle modifications that can retard the progression. However, the similarly low recall for the Moderate Demented group represents a limitation, as misclassification in this case would postpone detection of disease worsening, and thus attendant opportunity for increased care, support, and resource allocation. These findings suggest that although the model offers promise as an ancillary diagnostic tool, further refinements particularly for handling underrepresented stages are required to maximize its clinical validity and utility.

Test Image Predictions

Four test images (Non-Demented, Mild Demented, Moderate Demented, Very Mild Demented) from an independent dataset were predicted with high confidence. For example, a Non-Demented image was classified as Non-AD (confidence 0.9999) and Non-Demented (confidence 0.9999), while a Mild Demented image was classified as AD (confidence 1.0000) and Mild Demented (confidence 0.9931).

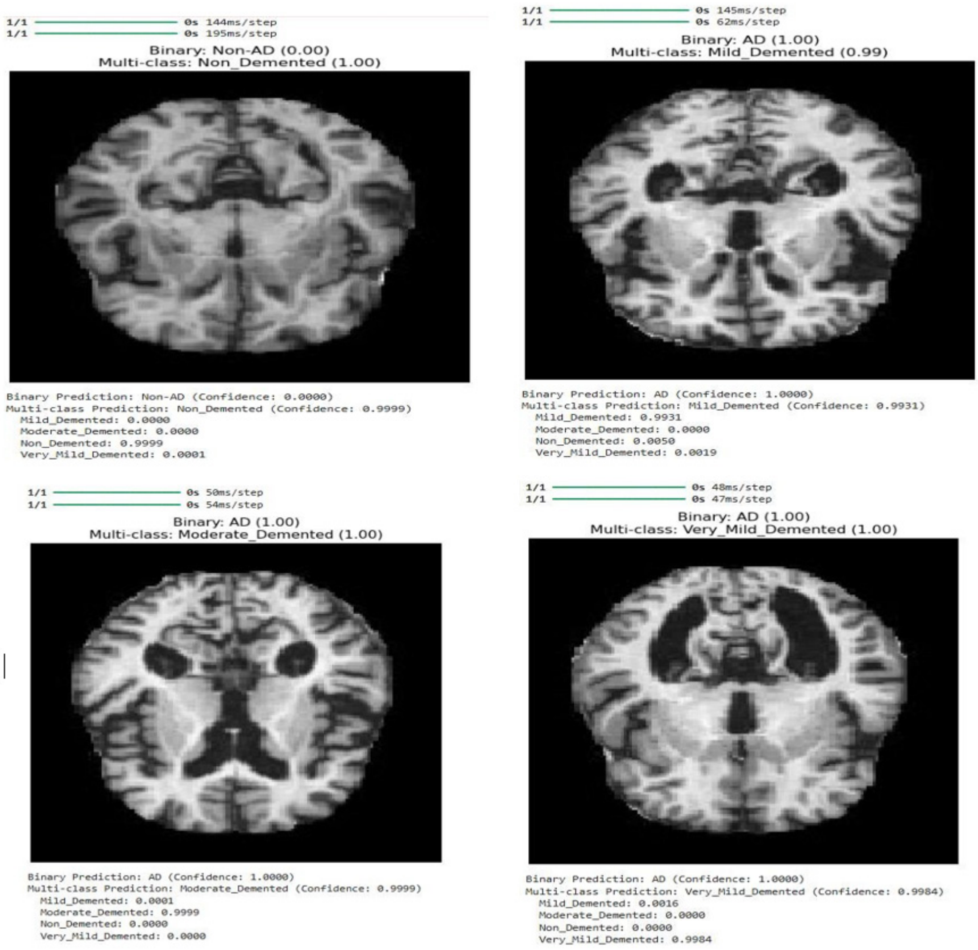

Figure 6: MRI Brain Scans Classification Results Using The Proposed Deep Learning Model. Each Image Shows The Ground Truth Category (Non-Demented, Mild Demented, Moderate Demented, Very Mild Demented) Along With The Model's Predicted Class And Associated Confidence Score. The Model Demonstrates High Accuracy across all Dementia Stages.

Discussion

The multi-class model was less accurate than the binary model, merely because it is easier to distinguish between two classes than between many classes. The multi-class model would require the algorithm to detect subtle differences between various levels of dementia, which is in itself a harder task. This difficulty is highlighted by the decreased accuracy of the multi-class model, especially in correctly classifying the Moderate Demented class, where cognitive states have less distinct boundaries and are more prone to misclassification.

Data augmentation played an important role in reducing the class imbalance by artificially increasing the ratio of minority classes. However, the process could not fully address the insufficiency of adequate original samples, particularly for the minority classes, and thus the model failed to generalize properly. As a result, some classes continued to suffer from reduced predictive power despite the augmentation.

Plateauing of validation loss in observation suggests that the model is perhaps overfitting training data, learning patterns that generalize less well to novel samples. This might be addressed by applying more forceful regularization techniques, such as higher dropout rates, weight decay, or employing early stopping methods. Further, exploring deeper architectures or transfer learning with pre-trained networks may still improve the model's ability to distinguish between the more nuanced phases of dementia and reduce overfitting.

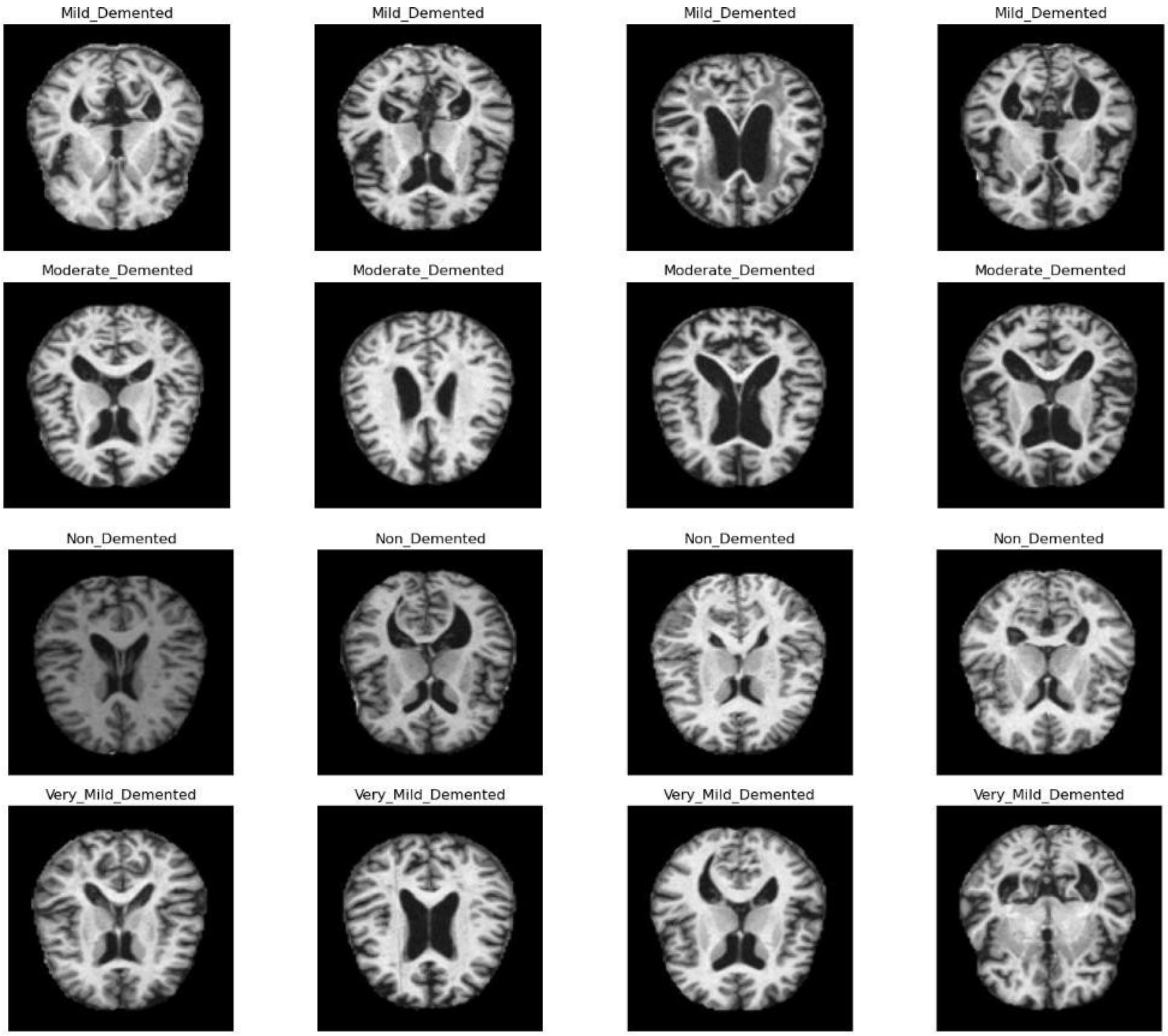

Figure 7: Visual exploration of the training dataset, with four representative images shown for each of the Mild, Moderate, Non, and Very Mild Demented classes.

CONCLUSION

This work successfully designed and tested light-weight Convolutional Neural Network (CNN) models for detecting and classifying Alzheimer's Disease (AD), with high accuracy but light computation. The models were designed to be light-weight, making them highly suitable for deployment in light-resource settings such as rural clinics, mobile health platforms, or communities with minimal access to heavy computation facilities. This is significant for real-world application, as it renders diagnostic hardware more accessible and enables intervention early on in disadvantaged groups.

The results also showed that the binary classifier model distinguishing Alzheimer's Disease cases from cognitively normal cases performed extremely well. This makes it applicable for screening at the front end, where one is only interested in ruling in potential cases as quickly and as accurately as possible. On the other hand, the multi-class classification model, while more challenging to train, worked well in distinguishing several stages of dementia, (Mild, Moderate, and Severe Demented classes). Such a model is clinically relevant because it would enable medical practitioners to track disease progression, customize treatment procedures, and improve patient management.

Performance, however, was restricted in minority classes, particularly minority classes with few samples. This highlights the need for data balancing for achieving fair and reliable classification in every stage. The future research could involve more robust performance by combining transfer learning with pre-trained networks, which can enrich feature representations and facilitate generalization. Accordingly, use of more extensive and diverse datasets would enhance the robustness and clinical reliability of the models. In addition, employing advanced augmentation strategies generative adversarial networks (GANs) to generate synthetic samples, mixup, or domain-specific manipulation can also facilitate class distribution balancing and improved accuracy for minority phases of AD.

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