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# MCAD-DCMGC: Multi-class Classification of Alzheimer's Disease using DCGAN Combined with MobileNetV2 and Grad-CAM

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***Abstract*— Alzheimer is an advancing neurodegenerative disorder with different clinical stages, beginning with cognitively normal (CN) to mild cognitive impairment (MCI), further leading to Alzheimer's dementia (AD).By using neuroimaging datasets, early and accurate classification of all these stages are crucial for timely intervention and medical treatment planning. In this paper, we pro- pose MCAD- DCMGC, a novel deep learning-based framework which uses MobileNetV2 for multiclass classification of AD stages from structural MRI slices. To overcome the problem of class imbalance and to enhance model generalizability, we augmented the dataset by using Deep Convolutional Generative Adversarial Networks (DCGANs), generating synthetic MRI samples for underrepresented classes. Furthermore, to increase the clinical interpretability, we are using Gradient-weighted Class Activation Mapping (Grad-CAM) for clear vision of different regions contributing to the multiclass classification decision. The experimental results with proposed light weight model achieved a multiclass classification accuracy of 92.62%, accompanied by insightful visual explanations. This pro- posed framework has potential to support clinical decision-making by improving both the accuracy and transparency of automated Alzheimer's stage classification.**

***Index Terms*— Alzheimer's Disease, Neuroimaging, Magnetic Resonance Imaging (MRI), Deep Learning, Generative Adversarial Networks.**

## I. INTRODUCTION

Alzheimer affects millions of human beings globally and poses a significant public health challenge. The disease is signaled by developing cognitive diminish and structural changes in the brain, observable through MRI [1][2]. Precise classification of a person into CN, MCI, and AD stages is crucial for prompt diagnosis and intervention [3]. The classical machine learning era re- quired deep manual feature engineering, which may restrict generalizability across datasets [4]. In contrast, deep learning models, mainly CNNs, have shown superior performance by learning hierarchical representations directly from neuroimaging data [5][6]. However, high data requirements and class imbalance often hinder their effectiveness in clinical applications [7].

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To address all the above challenges, we propose a novel framework MCAD-DCMGC: Multiclass Classification of Alzheimer's Disease using Deep Convolutional generative adversial network combined with MobileNetV2 and Grad-CAM that combines a lightweight yet powerful CNN architecture—MobileNetV2[8]with DCGANs [9] based synthetic data augmentation, which improves classification accuracy across all Alzheimer stages. Additionally, we used the Grad- CAM [10] to show the brain regions that influence the network's predictions, ensuring the model remains interpretable for clinical usage.Novel contributions of this paper are illustrated below:

- To address the problem of class imbalance, Deep Convolutional based generative adversial networks were used to generate fake images of CN, MCI and AD.
- A lightweight CNN architecture MobileNetV2 is used here as feature extractor and clas- sifier for the classification of Alzheimer's stage.
- GRAD-CAM is used to indicate the highlighted regions which are strongly influenced by the model.

The experimental work depicts the potential of the hybrid approach in facilitating the auto- mated interpretation of Alzheimer staging from structural MRI data.Remaining paper is struc- tured as follows. Section 2 briefs about literature work used for performing multiclass classifica- tion of Alzheimer.Details of proposed framework MCAD-DCMGC: Multi-class Classification of Alzheimer's Disease using DCGAN combined with MobileNetV2 and Grad-CAM are de- scribed in section 3.Experimental results are depicted in section 4, performance evaluation and discussion are defined in section 5, and finally the paper concludes in section 6.

## II. Related Work

Alzheimer's disease is a progressive brain disorder that primarily affects older individuals with age over 65 years. Early screening of patients for CN, MCI, and AD stages of neurodegeneration is critical for medical diagnostic interventions[11]. Several research studies in past have utilized Machine Learning and Deep Learning frameworks for diagnosing MCI , as it is a early sign be- fore alzheimer[12]. Several features like age, gender, education, MMSE score, CDR, SES were extracted for performing classification by applying ML algorithms like Decision Trees, Random Forest, Xboost, and KNN. The highest accuracy of 99% was achieved using Random Forest[13]. PSO based algorithm was utilized to tune hyper parameters of CNN model while training but model suffered from class imbalance problem[14]. PSO was used to fine-tune hyper parameters of pre-trained VGG16 model used for obtaining classification accuracy. Only last two layers of pre-trained VGG16 model were unfreeze to avoid over fitting during training and to converge faster [15]. CNN architecture along with Grad-CAM was utilized to perform multi-class classi- fication for various stages of AD[16]. DL architecture ResNet50V2 along with transfer learning was used in classifying AD[17]. 3D CNN along with intelligent frame selection mechanism was employed to record small structural changes for Alzheimer multi-class classification[18]. Hy- brid model combining transformer with CNN was used to exploit local and global features for obtaining average accuracy of 96% on multi-modal input [19]. Connectome GAT was utilized on multimodal input to make graph where nodes depicts brain regions and edges represented connections between brain regions. Model achieved AUROC score of 94.00 [20]. TBAN along with EfficientNet was used to capture long-term dependencies along with localized information to solve class imbalance problem and achieve 95% accuracy[21].

The novelty of presented framework MCAD- DCMGC lies in the combination of DCGAN- based artificial data augmentation with a lightweight and powerful CNN (MobileNetV2) for improved classification of Alzheimer's stages. Unlike other research works , we address the crit- ical problem of class imbalance by generating realistic MRI images for imbalance classes (e.g., MCI,AD). Furthermore, the integration of Grad-CAM visualization enhances the interpretability of deep learning predictions, offering both performance and clinical transparency in Alzheimer diagnosis.

## III. Proposed Framework

Presented Framework MCAD- DCMGC works in four stages in Figure. 1:

Stage 1: Preprocessing of the dataset

Input: 2D central slices of MRI scans (T1-weighted or FLAIR), resized to (128×128). Class labels: CN, MCI, AD.

Addresses class imbalance problem for MCI and AD.

Stage 2. Synthetic Data Generation (Using DCGAN)

For each imbalance class (CN/MCI/AD), a DCGAN model is trained to generate synthetic MRI slices. The generator learns to synthesize realistic brain MR images conditioned on noise.
Stage 3.Classification using MobileNetV2
Augmented dataset = original + synthetic images.
Lightweight and efficient MobileNetV2 is fine-tuned (head layers) on this augmented data.
Classification is performed for CN, MCI, AD.
Stage 4: Visualization using Grad-CAM
Visual comparison shows improved region-specific activation after training with GAN-augmented data.
For handling class imbalance, we are using DCGN here, which helps to generate artificial images and improves the generalizability of the classifier. It enables data augmentation without manual annotations , which is require for boosting performance.It also helps to preserve spatial features and patterns of the brain.After augmenting the data, classifiers perform better.It also enhances interpretability with GRAD-CAM.
MobileNetV2 is a lightweight and systematic model that was developed mainly for scenarios where processing resources are limited, such as on mobile or embedded devices. It achieves high accuracy with considerably fewer parameters compared to larger models like VGG or ResNet. With fine-tuning, it can adapt to the patterns in MRI scans while utilizing pre-trained knowledge. It preserves spatial information, which is required for detecting structural changes in the brain.
GRAD-CAM generates heatmaps that highlight the regions of an MRI slice contributing most to the model's decision.It helps to show the clear view of "black-box" models to our medical professionals , in such a way it increases the trustworthiness of our model.It also helps us to verify whether the model is learning meaningful features or not.

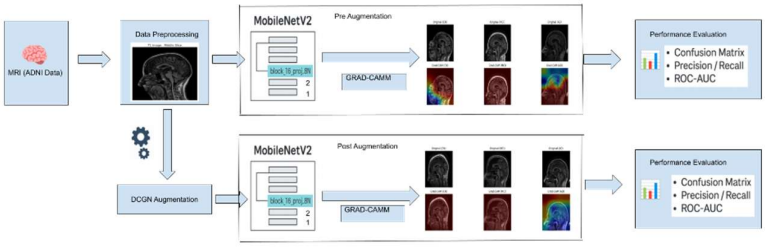



Figure 1: Proposed MCAD-DCMGC framework for performing multi-class classification on Alzheimer

## IV. Experimental Work

Dataset Description: We used the openly available ADNI1 Annual 2-Year 3T MRI dataset(ADNI; http://adni.loni.usc.edu/), which contains T1 MRI scans of individuals into three groups: CN(912), MCI(968), and AD(392). In parallel, we downloaded the clinical CSV files provided by ADNI, which consist of labels like subject IDs, scan dates, and other relevant details. Corresponding CSV entries were matched with MRI images for training. Each NIfTI image corresponds to a unique Image Data ID, which was used as the key to link the image path with its diagnosis in the CSV.Pre-processing on every individuals image was performed by taking central axial slices, changing their size to 128×128, and normalizing the images to a [0, 1] scale in Figure. 2 which represents brain MRI slices in axial, coronal and sagittal planes and for conducting experiments we have used axial plane. The dataset was then divided into training and test sets 80:20, ensuring balanced classes for evaluation.

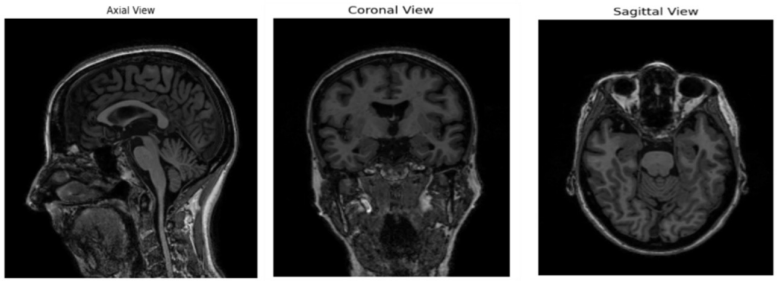
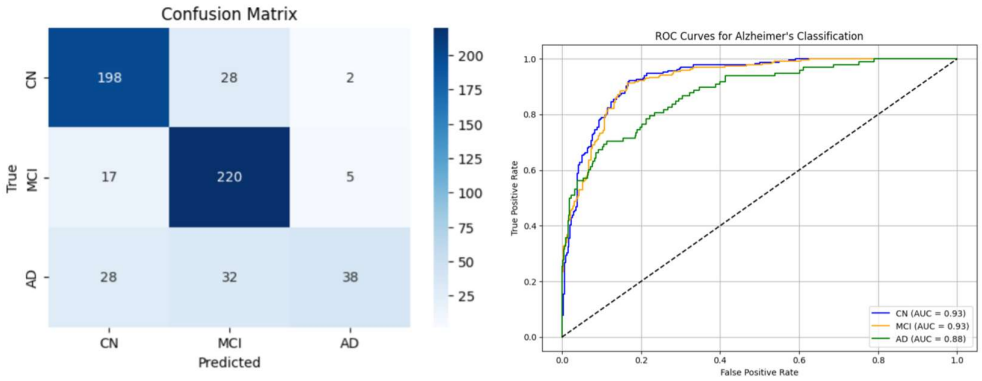



Figure 2: Representative brain MRI slices in axial, coronal, and sagittal planes.

Data Augmentation with DCGAN: To address the imbalance in classes, notably for MCI and AD, we used DCGANs to make fake MRI slices. Separate generators were trained per class (CN, MCI, AD), and artificial images were combined with the original dataset. This augmen- tation step significantly increased data diversity, thereby mitigating overfitting and improving generalizability.

Model Training: MobileNetV2: We utilize MobileNetV2, a lightweight CNN framework, for the feature extraction and classification. Then the model was initialized with ImageNet weights because these weights are loaded with rich, pre-learned features from natural images and with this we are excluding the original top layers specifically the global average pooling layer and the final fully connected dense layer which was earlier used for 1000 ImageNet classes, these layers are not useful for our task so we removed them and then modified the classification into 3 categories. After this, we froze the base layers during training and then added the custom head with global average pooling and dense layers. The model was trained on the augmented dataset using Adam optimizer, a learning rate of 1e-4, and sparse categorical cross-entropy as the loss function.In figure. 3 and figure. 4 defines the model performance visualization using Confusion Matrix and ROC curve before augmentation.

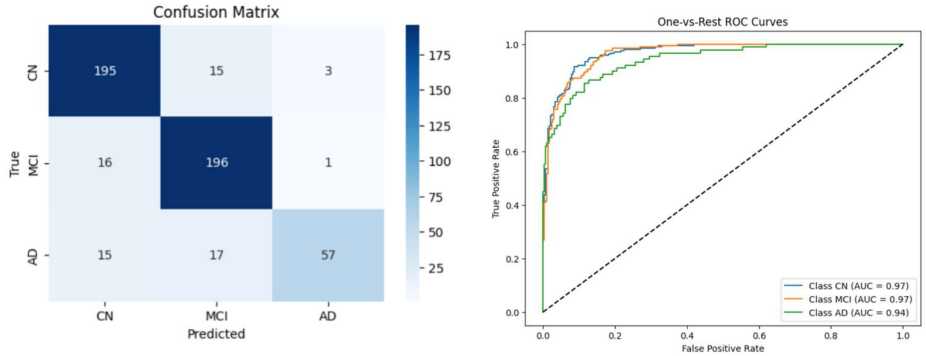



(a) Confusion Matrix of Mo- bileNetV2 (Pre-augmentation) (b) ROC Curve of Mo- bileNetV2 (Pre-augmentation)

Figure 3: Classification performance metrics of MobileNetV2 before augmentation.

TABLE I: CLASSIFICATION REPORT BEFORE AUGMENTATION (MOBILENETV2)

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| CN | 0.81 | 0.87 | 0.84 | 228 |
| MCI | 0.79 | 0.91 | 0.84 | 242 |
| AD | 0.84 | 0.39 | 0.53 | 98 |
| Accuracy | | | **0.80** | 568 |
| Macro Avg | 0.81 | 0.72 | 0.74 | 568 |
| Weighted Avg | 0.81 | 0.80 | 0.79 | 568 |



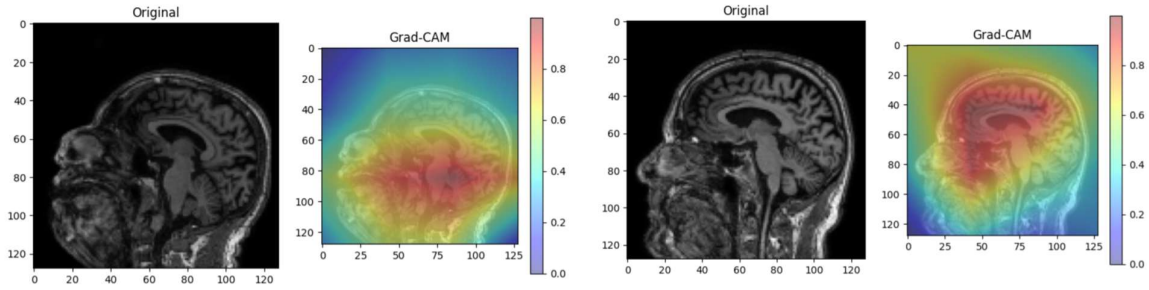

(a) Confusion Matrix of Mo- bileNetV2 (after augmentation) (b) ROC Curve of Mo- bileNetV2 (after augmentation)

Figure 4: Classification performance metrics of MobileNetV2 after augmentation.

TABLE II: CLASSIFICATION REPORT AFTER AUGMENTATION (MOBILENETV2 + DCGAN).

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| CN | 0.94 | 0.94 | 0.94 | 213 |
| MCI | 0.89 | 0.98 | 0.93 | 213 |
| AD | 0.99 | 0.78 | 0.87 | 89 |
| Accuracy | | | **0.93** | 515 |
| Macro Avg | 0.94 | 0.90 | 0.91 | 515 |
| Weighted Avg | 0.93 | 0.93 | 0.93 | 568 |

Grad-CAM Visualization: To increase clinical interpretability, we used Grad-CAM to visualize the brain regions that offered the most to each classification decision. These visual- izations confirmed the model's focus on AD-affected areas which is similar as the hippocampus and ventricular enlargement, provide credibility to the model's decisions.In figure. 5(a) and fig- ure 5(b) defines the class-discriminative heatmaps generated using GRAD-CAM before and after augmentation.




(a) GRAD-CAM visualization of Mo- bileNetV2 before augmentation.)

(b) GRAD-CAM visualization of Mo- bileNetV2 after augmentation

Figure 5: Grad-CAM visualizations highlighting model attention in MRI scans

## V. PERFORMANCE EVALUATION AND DISCUSSION

Our proposed MCAD-DCMGC model, integrates DCGAN-based aumentation with the Mo- bileNetV2 classifier, was evaluated on a held-out test set. It achieves a test accuarcy of 92.62% with a test loss of 0.2184. MCAD- DCMGC performs best in clinical and deep learning base- lines, specifically in the MCI and AD classes, which are previously difficult to categorize due to their intermediate nature. As before integration, only the MobileNetV2 model is able to achieve 80.28% and after combining DCGAN-based data augmentation with MobileNetV2, we achieve a test precision of 92.62% while keeping the model efficient and interpretable, ideal for deploy- ment in resource-constrained clinical settings.

The results of the proposed framework with and without DCGAN is in Table [ 1] and Table [ 2] respectively. In Table [1] the model achieved 80% test accuracy, but showed poor recall (0.39) and F1-score (0.53) for the AD class, which highlights class imbalance. And after using DCGAN, Table [ 2] summarizes the key points of classification report using precision, recall, and F1-score in the three classes: CN, MCI , and AD). The model illustrate a balanced perfor- mance, with F1-scores of 0.94 (CN), 0.93 (MCI), and 0.87 (AD), that defines high reliability in identifying both early and advanced stages of Alzheimer's progression.

## VI. CONCLUSION

This study introduces a lightweight framework MCAD-DCMGC, for the multistage classifica- tion of Alzheimer using a structural magnetic resonance data set. By integrating MobileNetV2 with DCGAN, the proposed method successfully handles the problem of class imbalance and limited sample size, which are common in medical neuroimaging data sets. The integration of Grad-CAM further enhances the clinical transparency of the model by representing the discrim- inative brain regions influencing its predictions.

Our experimental results demonstrate classification performance over different stages: CN, MCI, and AD, indicating the potential of this hybrid approach for early and automated diagno- sis. The method's effectiveness and ease of understanding also make it a good choice for use in real-world healthcare settings. Future work will

focus on extending this framework to include multimodal imaging and longitudinal data to further improve diagnostic accuracy and disease progression tracking.

## LIST OF ACRONYMS

TABLE III

| | |
|---|---|
| CN | Cognitive Normal |
| MCI | Mild Cognitive Impairment |
| AD | Alzheimer's Dementia |
| DCGAN | Deep Convolutional Generative Adversarial Networks |
| CNN | Convolutional Neural Networks |
| Grad-CAM | Gradient-weighted Class Activation Mapping |
| PSO | Particle Swarm Optimization |
| DL | Deep Learning |
| MMSE | Mini-mental state examination |
| CDR | Clinical Dementia Rating |
| SES | Socioeconomic Status |
| GAT | Graph Attention Network |
| TBAN | Tri Branch Attention Network |

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