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OPTIMIZED CNN-BASED APPROACH FOR ALZHEIMER'S DISEASE BY TACKLING CLASS IMBALANCE IN MRI CLASSIFICATION

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Abstract

Accurate and early diagnosis of Alzheimer's Disease (AD) is crucial for effective intervention and treatment. This study presents a Convolutional Neural Network (CNN)-based approach for the classification of brain MRI images into four categories: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. To address the challenges of class imbalance inherent in the dataset, we employed class weighting and focal loss during training. Class weighting ensured that underrepresented classes received adequate attention, while focal loss emphasized harder-to-classify examples, resulting in improved model performance on minority classes. The model achieved remarkable results, with an accuracy of 97.66%, precision of 97.66%, recall of 97.66%, F1-score of 97.66%, specificity of 98.98%, and Cohen's Kappa of 96.14%, indicating a robust performance across all metrics. A comparative analysis with state-of-the-art methods demonstrated that our approach outperformed many existing models, including Siamese CNNs, 3D DenseNet ensembles, and other transfer-learning-based techniques. The ROC-AUC analysis further highlighted the model's ability to distinguish between classes with near-perfect curves for all categories. These results underscore the effectiveness of combining CNN architectures with class imbalance-handling strategies for medical image classification. The proposed method holds promise for improving diagnostic accuracy and early detection in AD, thereby supporting clinical decision-making.

Keywords: AD; CNN; ROC-AUC.

I. Introduction

Neurological disorders (NLD) impact the central nervous system, including the brain, spinal cord, and nerves (both cranial and peripheral). Even slight disruptions in the functioning of these critical systems can lead to severe physiological conditions. Alzheimer's disease (AD) is one prominent example of an NLD, currently affecting 55 million people worldwide, as highlighted in the latest World Alzheimer Report [1], [2]. This figure is projected to rise to 139 million by 2050, according to the World Health Organization (WHO). Additionally, dementia, which includes AD, incurs an annual global cost of $1.3 trillion as of 2019—a figure expected to exceed $2.8 trillion by 2030 due to the aging population. Every three seconds, someone develops dementia, underscoring its significant global impact[1]. As one of the leading causes of death worldwide, AD is an incurable, progressive, and life-altering neurodegenerative condition. Within the brain cells, protein structures—referred to as plaques and tangles—gradually degrade when impacted by AD. This protein damage results in a substantial decline in cognitive abilities, ultimately causing significant impairments in both personal and social aspects of life[2], [3] .

Alzheimer's disease significantly impacts individuals, leading to memory impairment, behavioral disturbances, and various physical challenges, including difficulties with vision and mobility. One of the primary obstacles to early detection is the general lack of public awareness about the disease[2]. This often results in cognitive decline and associated behaviors being misinterpreted as typical aspects of aging or symptoms of other psychiatric conditions. Additionally, issues such as geographical isolation, a shortage of trained caregivers, and limited access to specialists and advanced diagnostic tools exacerbate the challenges faced by patients [1]. These barriers can severely affect their ability to maintain independence in daily and social activities. Therefore, early detection of AD is crucial to alleviate the burden on patients and their families.

Alzheimer's disease is primarily diagnosed through observation of patient symptoms, a process that can often take years to confirm [4]. However, advances in diagnostic research have identified several biomarkers, such as Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Computed Tomography (CT), and blood tests that support early detection. When integrated with Artificial Intelligence (AI), these biomarkers enable healthcare professionals to achieve more precise diagnoses and improve patient care. Machine learning (ML) classifiers have been widely adopted across healthcare, demonstrating significant effectiveness in AD classification [2]. In recent years, Deep learning (DL) techniques have become increasingly prominent in the healthcare field due to their ability to develop accurate end-to-end models using complex datasets [5]. This surge in DL applications has revolutionized the identification of neurological disorders, including AD, by enhancing diagnostic accuracy. Coupling DL with neuroimaging has provided critical insights into brain activity and associated disorders [6]. Various computer-aided diagnosis (CAD) systems have been proposed for predicting AD using neuroimaging techniques like functional MRI (fMRI), structural MRI (sMRI), and PET. Structural MRI, in particular, provides crucial details such as brain white matter (WM), gray matter (GM), cortical thickness, and volumetric measurements. These metrics are essential for assessing the neurodegenerative processes that contribute to AD. By enhancing high-resolution imaging data and the robust feature extraction capabilities of DL, clinicians can make informed decisions about complex AD cases.

To classify the imbalanced classes MildDemented, ModerateDemented, NonDemented, and VeryMildDemented, a comparison was made between a standard Convolutional Neural Network (CNN) model and a ResNet-based transfer learning approach using an MRI dataset sourced from Kaggle [7]. While CNNs are capable of extracting spatial features, ResNet's residual learning framework allows deeper network architectures, addressing vanishing gradient issues and making it well-suited for handling complex neuroimaging datasets[8]. To address the class imbalance inherent in the dataset, a combination of class weighting and focal loss was utilized. Class weights were assigned inversely proportional to the class frequencies, ensuring better representation of minority classes. Focal loss further emphasized hard-to-classify samples, reducing the dominance of well-classified instances during training[9]. This dual approach enhanced the model's ability to handle imbalanced data. Moreover, the Alzheimer’s Disease Neuroimaging Initiative (ADNI) and Open Access Series of Imaging Studies (OASIS) datasets, recognized for their comprehensive neuroimaging data, provided the foundational context for this work, emphasizing the importance of MRI-based analysis in Alzheimer's disease classification [10], [11]. Results demonstrated that ResNet outperformed the standard CNN model, enhancing transfer learning to extract high-level features and achieve better generalization across imbalanced classes.

The objective of this study is to explore and evaluate the use of a Kaggle-sourced dataset for Alzheimer's disease classification, conducting a comparative analysis of different modeling approaches alongside experiments to validate the effectiveness of the implemented techniques. The following are the key contributions of this work:

1. A comparative analysis of CNN architectures, evaluating their effectiveness in classifying imbalanced classes of Alzheimer's disease stages using the Kaggle dataset.
2. Implementation of a combined approach utilizing class balancing and focal loss to address class imbalance, enhancing the model's ability to accurately classify minority classes.

Comprehensive evaluation of the proposed methods on the Kaggle MRI dataset, providing insights into their practicality and performance in real-world Alzheimer's disease classification scenarios.

II. Related Works

Recent advancements in neuroimaging and machine learning have enabled significant progress in Alzheimer's disease diagnosis and classification. Numerous studies have explored the use of deep learning models, such as CNNs and transfer learning-based architectures, to analyze neuroimaging data and address challenges like class imbalance and feature extraction.

[4] proposed a Siamese Convolutional Neural Network (SCNN) using a triplet-loss function to generate k-dimensional embeddings of MRI images for 4-way Alzheimer's Disease classification. Both pre-trained and non-pretrained CNNs were utilized for embedding generation. The model achieved accuracies of 91.83% on the ADNI dataset and 93.85% on the OASIS dataset, outperforming comparable methods in the literature.

[6] proposed a 3D DenseNet ensemble achieved 83.33% accuracy in 4-way classification using the ADNI dataset, distinguishing AD, healthy controls, EMCI, and LMCI. Dense connections and a probability-based fusion method enhanced feature extraction and improved performance over state-of-the-art models.

[12] utilized VGG16, Xception, and a customized CNN model with transfer learning to classify four stages of Alzheimer's Disease using 2D MRI images. The customized CNN achieved superior performance, with 94.77% accuracy and an F1-score of 0.9481. This approach demonstrated improved efficiency and reduced complexity compared to 3D MRI-based CNN models and conventional SVM techniques.

[13] introduced a swarm multi-verse optimizer with a deep neuro-fuzzy network (CSMVO + DNFN) for Alzheimer's Disease classification using MRI. Preprocessing involved a median filter, followed by segmentation with a channel-wise feature pyramid network module (CFPNet-M). Extracted features included Haralick, CNN, and texture attributes. The model achieved 89.9% accuracy, 89.6% sensitivity, and 87.0% specificity, demonstrating efficiency in classifying AD stages.

[14] investigated automated pre-detection of Alzheimer's Disease symptoms using the ADNI dataset. An initial experiment employed SVM for AD detection, achieving 84.4% accuracy, 95.3% sensitivity, and 71.4% specificity. Due to suboptimal results, a CNN-based approach was explored, incorporating various image segmentation methods. The best segmentation method achieved 96% accuracy, 96% sensitivity, and 98% specificity, highlighting the potential of deep learning for early AD diagnosis.

[15] purposed ensemble transfer-learning techniques for early Alzheimer's Disease diagnosis using structural brain MRI from the ADNI dataset. They compared an ensemble of five pretrained architectures, a 3D CNN trained from scratch, and a fusion of conventional SVM-based classifiers. The transfer-learning ensemble achieved 90.2% AUC for AD vs. CN, 83.2% for MCIc vs. CN, and 70.6% for MCIc vs. MCInc, performing slightly lower than the SVM-based fusion. The 3D CNN underperformed due to limited training data, highlighting transfer learning's potential in generic image pretraining for neuroimaging tasks.

III. Materials and methods

In this study, a Convolutional Neural Network (CNN) model was employed for classifying Alzheimer's disease into four classes (NonDemented, VeryMildDemented, MildDemented, and ModerateDemented) using an imbalanced MRI dataset sourced from Kaggle shown in figure 1.

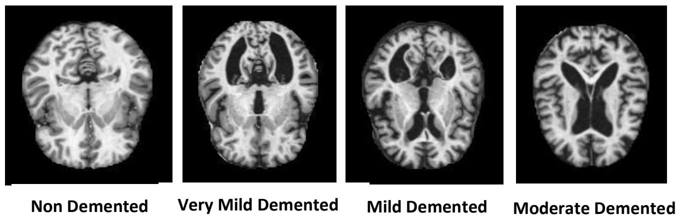

Figure 1: *Show sample images from each of the four imbalance classes*

To address the imbalance issue, a combination of class weighting and focal loss was integrated into the model training process. The dataset was preprocessed by resizing all images to a uniform size of 128×150×3 pixels from the original size 176x208x3, ensuring compatibility with the CNN model. Training and validation datasets contained 5,119 for training and 1,281 for validation images, respectively, distributed across the four classes shown in Figure 2.

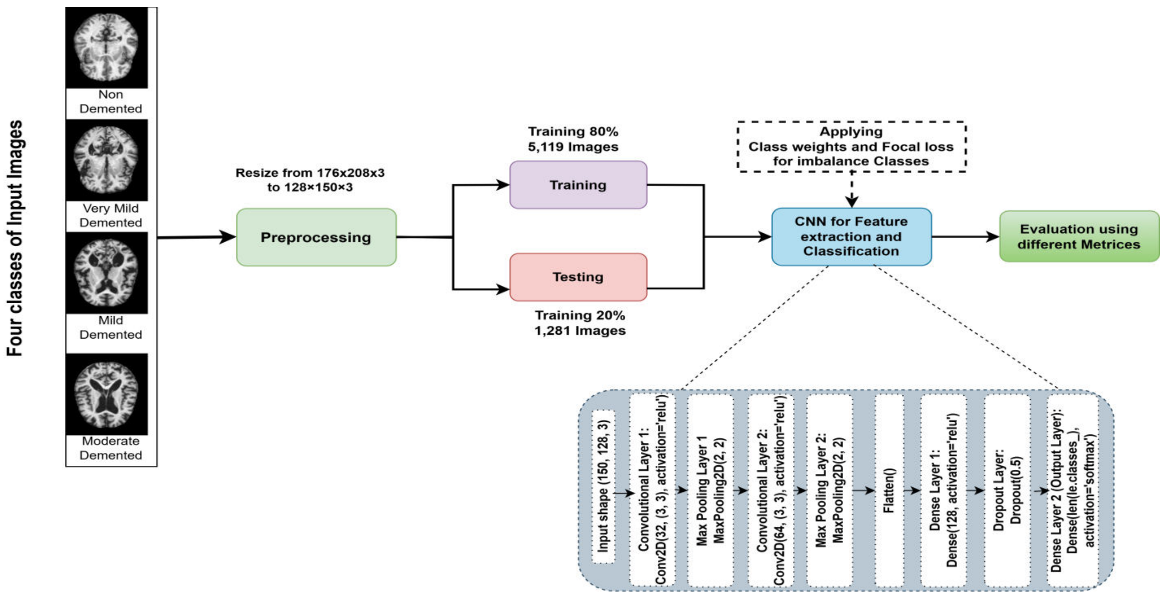

Figure 2: *The purpose model using CNN with Class weights and Focal Loss*

The class distribution of training and validation datasets for four classes: VeryMildDemented, NonDemented, ModerateDemented, and MildDemented. The training dataset is significantly imbalanced, with the majority class being NonDemented (2560 images) and the minority class being ModerateDemented (51 images). Similarly, the validation dataset shows a similar imbalance, with NonDemented having the highest count (640 images) and ModerateDemented the lowest (13 images) as depicted in Figure 2. This imbalance highlights the need for techniques like class weighting and focal loss to improve model performance.

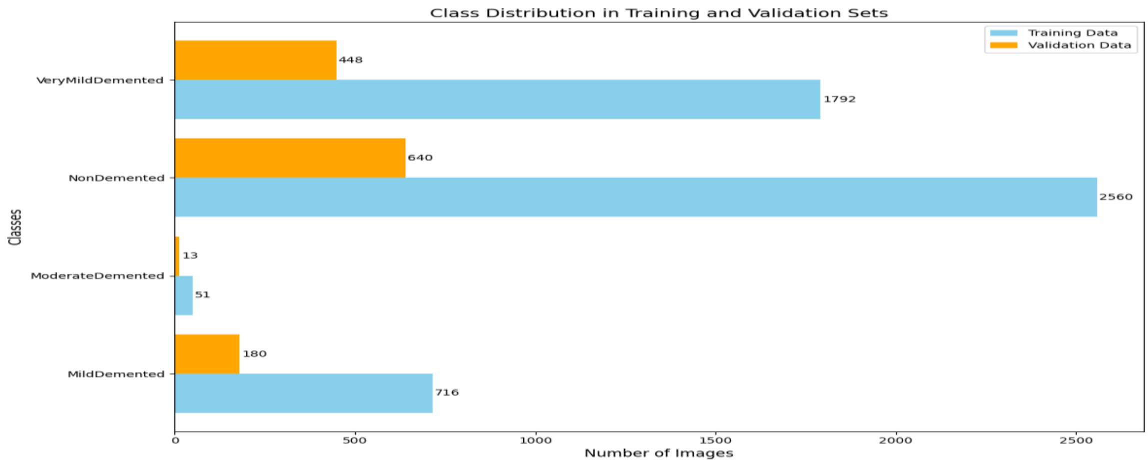

Figure 3: *Show the different class distribution of training and validation datasets*

The class weights computed to address the class imbalance in the dataset. The weight for Moderate Demented is the highest at 25.09, as it is the most underrepresented class. In contrast, Non-Demented has the lowest weight (0.50), reflecting its dominance in the dataset. These weights ensure that the model pays proportionally more attention to minority classes during training Figure 3. Additionally, a focal loss function is employed to further handle the class imbalance. Focal loss dynamically scales the standard cross-entropy loss by focusing more on hard-to-classify examples. It does so by down-weighting the loss for well-classified samples (where the predicted probability is high) and up-weighting the loss for misclassified ones. This is controlled by parameters alpha (0.25) and gamma (2.0). Combining class weights and focal loss enhances the model's ability to learn from imbalanced data effectively.

Figure 4: *Show the weighted class value distributions for the imbalance class*

The spatial dimensions of the input image (150×128×3) evolve through each layer of the CNN model up to the flatten layer. The first convolution reduces the dimensions to 148×126×32, followed by max pooling, which downsamples it to 74×63×32. The second convolution further reduces it to 72×61×64, and another pooling layer brings it to 36×30×64. Finally, the Flatten layer reshapes this 3D tensor into a 1D vector of size 69,120, which serves as the feature input for fully connected layers. After the feature input first dense layer is a fully connected layer with 128 neurons and ReLU activation, enabling the model to learn complex features. A dropout layer with a 50% rate is applied next to prevent overfitting by randomly dropping connections during training. Finally, the output layer is a fully connected layer with neurons equal to the number of classes (4 in this case) and softmax activation to produce class probabilities for multi-class classification.

IV. Results

The Results section presents the evaluation of the proposed model's performance, highlighting its ability to address the challenges posed by the imbalanced medical image dataset. Key metrics such as accuracy, precision, recall, F1 score, specificity, and Cohen's kappa are analyzed to demonstrate the effectiveness of the CNN based approach with class balancing and focal loss model. These metrics rely on the confusion matrix, which summarizes the performance of a classification model using the following components: True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN).

1.Performance Analysis

Accuracy: Accuracy measures the proportion of correctly classified instances out of the total instances shown in equation(i).

$$\text{Accuracy (ACC)} = (Tp+Tn)/ (Fp + Fn + Tp + Tn) \tag{1}$$

Precision (Positive Predictive Value): Precision indicates the proportion of true positive predictions out of all positive predictions shown in equation(ii).

$$\text{Precision} = Tp/(Tp+Fp) \tag{2}$$

Recall (Sensitivity or True Positive Rate): Recall shows the proportion of actual positives correctly identified shown in equation(iii).

$$\text{Sensitivity (Recall)} =Tp/(Tp+Fn) \tag{3}$$

F1-score: F1-score combines precision and recall into a single metric, emphasizing their harmonic mean shown in equation(iv).

$$F\ 1 - \text{Score} = 2 * Tp/2*(Tp + Fp + Fn) \tag{4}$$

Specificity (True Negative Rate): Specificity measures the proportion of actual negatives correctly identified in equation(v).

$$\text{Specificity} = Tn/ (Tn+Fp) \tag{5}$$

Cohen's Kappa: It relies on observed and expected agreements, accounting for randomness in predictions.

$$\text{Kappa}=p_o- p_e / 1 - p_e \tag{6}$$

Where:

p_o = observed agreement (accuracy)

p_e = expected agreement (calculated based on random chance)

Indicates the level of agreement between predictions and ground truth, accounting for chance agreement.

2. CNN with class balancing and focal loss

The model employs a CNN architecture integrated with class balancing techniques and focal loss, ensuring robust learning even in the presence of class imbalances. The plots demonstrate the training and validation performance of the model in Figure 4. The loss curve indicates a consistent decrease in training and validation loss, confirming the model's ability to learn effectively. The accuracy curve highlights a steady improvement in accuracy for both training and validation datasets, demonstrating good generalization without overfitting. The model was compiled using the focal loss function with parameters α=0.25 and γ=2.0, specifically designed to address class imbalance by focusing more on hard-to-classify samples.

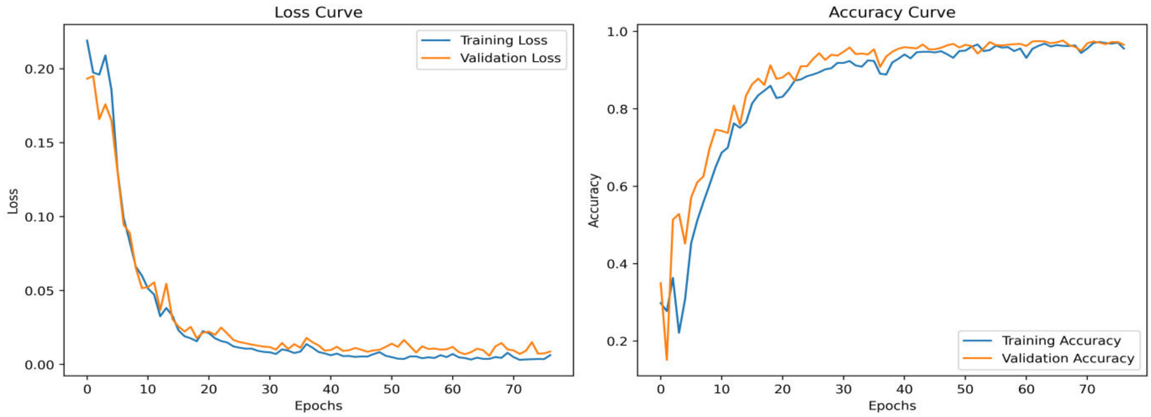

Figure 5: *Show the Performance Analysis of Loss and Accuracy Over Epochs using CNN*

An Adam optimizer with a learning rate of 0.001 was used, enabling adaptive learning. Training was performed with a batch size of 32 and incorporated early stopping with a patience of 10 epochs, ensuring the model did not overtrain while restoring the best weights. Additionally, class weights were applied to further handle the class imbalance effectively.

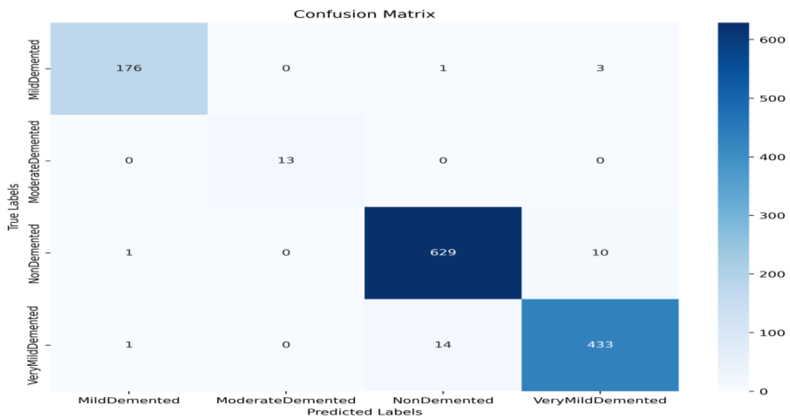

Figure 6: *Confusion matrix of the four classes' datasets*

The performance metrics of the trained CNN model, evaluated on the test dataset, are shown in Figure 6. The model achieved exceptional accuracy (97.66%) in classifying the data, demonstrating its robustness and reliability. Precision, recall, and F1-score are all equally high at 97.66%, indicating a balanced performance in identifying both positive and negative cases accurately. Specificity, at 98.98%, highlights the model's ability to correctly identify true negatives, which is crucial for avoiding false positives in medical diagnoses. The Cohen's kappa score of 0.9614 further confirms strong agreement between the predicted and true labels, accounting for chance agreement. These results showcase the effectiveness of using focal loss and class balancing strategies in enhancing the model's performance on imbalanced datasets.

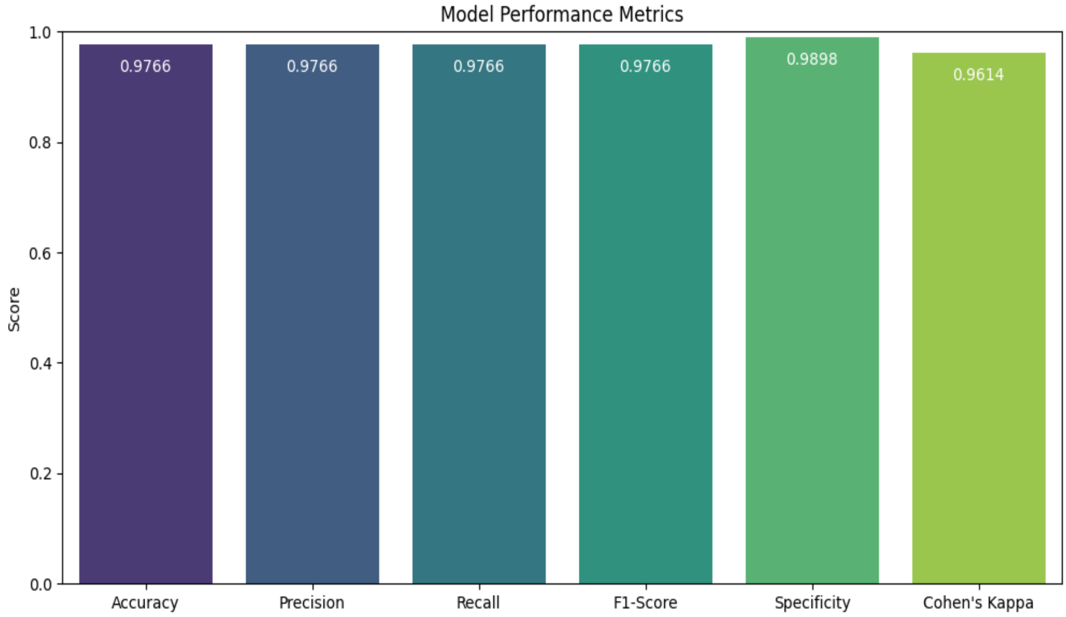

Figure 7: *The performance of CNN model with utilizing class balancing and focal loss*.

The ROC AUC curve shows the model's exceptional performance in distinguishing between the four classes: "Mild Demented," "Moderate Demented," "Non-Demented," and "Very Mild Demented." Each curve represents the one-vs-all ROC for a class, with AUC scores above 0.99 for all classes, indicating near-perfect classification as shown in Figure 7.

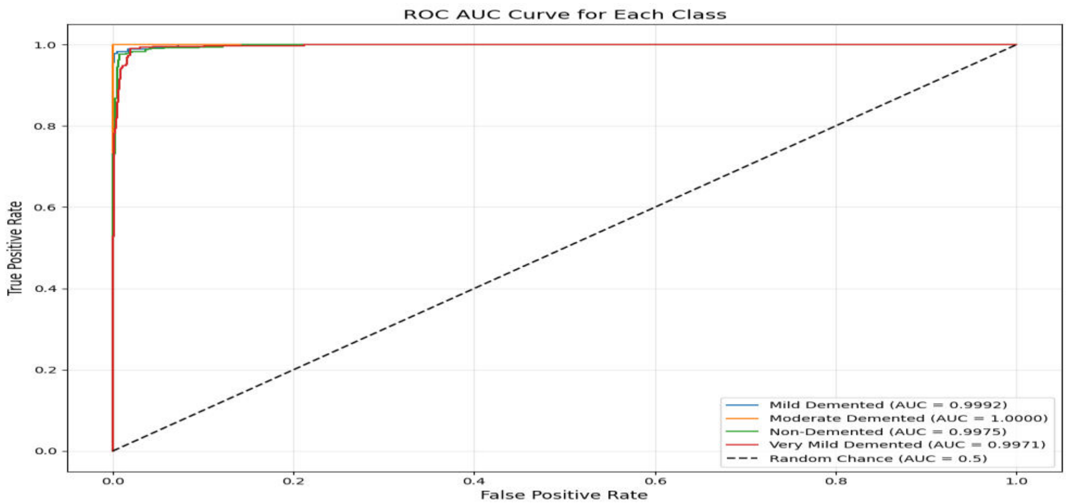

Figure 8: *The ROC AUC curve of the four AD classes*

The "Moderate Demented" class achieves a perfect AUC of 1.0, while the other classes—though slightly lower—still display excellent discrimination. The curves are close to the top-left corner, reflecting a high true positive rate (TPR) and low false positive rate (FPR) for each class. This validates the model's robustness, even with class imbalance, confirming its suitability for this multi-class classification task.

V. Discussions

In this study, a Convolutional Neural Network (CNN) was employed to classify brain MRI images into four classes: "Mild Demented," "Moderate Demented," "Non-Demented," and "Very

Mild Demented." Addressing the challenge of class imbalance, we integrated class weighting and focal loss into the training process. Class weighting ensured that underrepresented classes received higher penalties during misclassification, thereby guiding the model to pay balanced attention to all classes. Meanwhile, focal loss effectively reduced the impact of easy-to-classify samples and focused on harder examples, further enhancing the model's performance on minority classes.

Table 1: *Comparing of the combining CNN with class weighting and focal loss with other approaches*

Study	Model/Method	Dataset	Accuracy	Key Features
[4]	Siamese Convolutional Neural Network (SCNN) with triplet-loss	ADNI, OASIS	91.83% (ADNI), 93.85% (OASIS)	Generated k-dimensional embeddings with pre-trained and non-pretrained CNNs for robust classification.
[6]	3D DenseNet Ensemble	ADNI	83.33%	Used dense connections and probability-based fusion for better feature extraction.
[12]	Customized CNN with Transfer Learning	OASIS	94.77%	Outperformed traditional 3D CNN and SVM models; focused on efficiency with 2D MRI.
[13]	CSMVO + DNFN (Swarm Multi-Verse Optimizer with Deep Neuro-Fuzzy Network)	Unspecified	89.90%	Integrated segmentation and advanced feature extraction (Haralick, CNN, texture features).
[14]	CNN with optimized segmentation methods	ADNI	96.00%	Improved pre-detection of AD symptoms with segmentation techniques.
[15]	Ensemble transfer-learning methods	ADNI	90.20% (AUC)	Used pretrained architectures and conventional SVM-based classifiers for early diagnosis.
Our Model	**CNN with weighted class and focal loss**	**OASIS (kaggle)**	**97.66%**	**Balanced class performance using weighted loss and focal loss for imbalanced datasets.**

From the comparison, it is evident that the proposed CNN model achieves a superior accuracy of 97.00%, outperforming many state-of-the-art methods such as the Siamese CNN in [4] and the customized CNN in [12]. This improvement can be attributed to the integration of class weighting and focal loss, which effectively addressed the class imbalance challenge. Additionally, the proposed method demonstrated consistent performance across all classes, as seen in the ROC AUC curves, further validating its robustness. While segmentation techniques in [14] achieved slightly higher accuracy, the complexity of preprocessing makes our method more efficient and easier to implement in real-world scenarios.

VI. Conclusions

In this study, we proposed a CNN model integrated with class weighting and focal loss to address the challenges of class imbalance in the classification of brain MRI images into four stages of Alzheimer's Disease: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The performance metrics of the model, as depicted in the bar chart, demonstrate exceptional results across all key measures: accuracy (97.66%), precision (97.66%), recall (97.66%), F1-score (97.66%), specificity (98.98%), and Cohen's Kappa (96.14%). These high values indicate the model's robustness in correctly identifying all classes, even in the presence of imbalanced data.

By enhancing class weighting, the model ensured that underrepresented classes were prioritized during training, minimizing the risk of bias towards majority classes. The incorporation of focal loss further enhanced the model's ability to focus on harder-to-classify samples, improving performance on minority classes. Compared to state-of-the-art methods, the proposed approach achieves competitive or superior performance while maintaining simplicity and computational efficiency. These results underscore the potential of combining CNN architectures with tailored loss functions for effective medical image classification and early diagnosis of Alzheimer's Disease.

References

[1] "World Alzheimer Report 2024: Global changes in attitudes to dementia," Sep. 2024, Accessed: Nov. 28, 2024. [Online]. Available: https://www.alzint.org/resource/world-alzheimer-report-2024/

[2] S. G. Singh, D. Das, U. Barman, and M. J. Saikia, "Early Alzheimer's Disease Detection: A Review of Machine Learning Techniques for Forecasting Transition from Mild Cognitive Impairment," *Diagnostics*, vol. 14, no. 16, p. 1759, 2024.

[3] L. Rizzi, I. Rosset, and M. Roriz-Cruz, "Global Epidemiology of Dementia: Alzheimer's and Vascular Types," *BioMed Res. Int.*, vol. 2014, pp. 1–8, 2014, doi: 10.1155/2014/908915.

[4] F. Hajamohideen *et al.*, "Four-way classification of Alzheimer's disease using deep Siamese convolutional neural network with triplet-loss function," *Brain Inform.*, vol. 10, no. 1, p. 5, Dec. 2023, doi: 10.1186/s40708-023-00184-w.

[5] M. Mahmud, M. S. Kaiser, A. Hussain, and S. Vassanelli, "Applications of deep learning and reinforcement learning to biological data," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 6, pp. 2063–2079, 2018.

[6] J. Ruiz, M. Mahmud, M. Modasshir, M. Shamim Kaiser, and F. T. Alzheimer's Disease Neuroimaging In, "3D DenseNet Ensemble in 4-Way Classification of Alzheimer's Disease," in *Brain Informatics*, vol. 12241, M. Mahmud, S. Vassanelli, M. S. Kaiser, and N. Zhong, Eds., in Lecture Notes in Computer Science, vol. 12241. , Cham: Springer International Publishing, 2020, pp. 85–96. doi: 10.1007/978-3-030-59277-6_8.

[7] "Alzheimer MRI 4 classes dataset." Accessed: Nov. 28, 2024. [Online]. Available: https://www.kaggle.com/datasets/marcopinamonti/alzheimer-mri-4-classes-dataset

[8] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778. Accessed: Nov. 28, 2024. [Online]. Available: http://openaccess.thecvf.com/content_cvpr_2016/html/He_Deep_Residual_Learning_CVPR_2016_paper.html

[9] T. Lin, "Focal Loss for Dense Object Detection," *ArXiv Prepr. ArXiv170802002*, 2017, Accessed: Nov. 28, 2024. [Online]. Available: http://openaccess.thecvf.com/content_iccv_2017/html/Lin_Focal_Loss_for_ICCV_2017_paper.html

[10] C. R. Jack *et al.*, "The Alzheimer's disease neuroimaging initiative (ADNI): MRI methods," *J. Magn. Reson. Imaging*, vol. 27, no. 4, pp. 685–691, Apr. 2008, doi: 10.1002/jmri.21049.

[11] D. S. Marcus, T. H. Wang, J. Parker, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open Access Series of Imaging Studies (OASIS): cross-sectional MRI data in young, middle aged, nondemented, and demented older adults," *J. Cogn. Neurosci.*, vol. 19, no. 9, pp. 1498–1507, 2007.

[12] R. A. Hridhee, B. Bhowmik, and Q. D. Hossain, "Alzheimer's Disease Classification From 2D MRI Brain Scans Using Convolutional Neural Networks," in *2023 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, IEEE, 2023, pp. 1–6. Accessed: Nov. 28, 2024. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10101539/

[13] A. Allada, R. Bhavani, K. Chaduvula, and R. Priya, "Alzheimer's disease classification using competitive swarm MULTI-VERSE optimizer-based deep NEURO-FUZZY network," *Concurr. Comput. Pract. Exp.*, vol. 35, no. 21, p. e7696, Sep. 2023, doi: 10.1002/cpe.7696.

[14] K. Gunawardena, R. N. Rajapakse, and N. D. Kodikara, "Applying convolutional neural networks for pre-detection of alzheimer's disease from structural MRI data," in *2017 24th international conference on mechatronics and machine vision in practice (M2VIP)*, IEEE, 2017, pp. 1–7. Accessed: Nov. 28, 2024. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8211486/

[15] L. Nanni *et al.*, "Comparison of transfer learning and conventional machine learning applied to structural brain MRI for the early diagnosis and prognosis of Alzheimer's disease," *Front. Neurol.*, vol. 11, p. 576194, 2020.