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RESEARCH ARTICLE

Improving Alzheimer's Detection With Deep Learning and Image Processing Techniques

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ABSTRACT Alzheimer's Disease (AD) is characterized by the gradual degeneration and decline of brain cells, leading to irreversible neurological changes. This study investigates advanced image enhancement techniques for improving AD diagnosis using brain MRI. The methods used include CLAHE (Contrast Limited Adaptive Histogram Equalization) to enhance local image contrast and ESRGAN (Enhanced Super-Resolution Generative Adversarial Networks) to improve image resolution. These preprocessing methods improve MRI images and classification accuracy. An ensemble model of MobileNetV2 and DenseNet121, two efficient deep-learning models with feature extraction capabilities, were used as classifiers. This approach addresses challenges in AD diagnosis by leveraging deep learning for more accurate classification of brain tissue images. The model achieved an accuracy of 80.31% for MobileNetV2 and 89.22% for DenseNet121 when no enhancements were utilized. The model achieved accuracies of 92.34% and 89.38% for MobileNetV2 and DenseNet121, respectively, when enhancement methods were utilized, indicating strong dependability with the Kaggle dataset of MRI images. These findings underscore the efficacy of advanced image processing and deep learning in the early and accurate detection of Alzheimer's disease.

INDEX TERMS Alzheimer's, computer-aided diagnosis, deep learning, DenseNet121, image enhancement, MobileNetV2, transfer learning.

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurological disorder marked by the gradual degeneration of brain cells, leading to impairments in memory, cognition, behavior, and daily functioning [1], [2]. Symptoms include memory loss, decreased motivation, personality changes, and impaired decision-making abilities [3], [4]. Diagnosing AD involves a thorough assessment including physical and neurological examinations, medical history reviews, and cognitive tests such as the mini-mental state examination. While no cure exists, early detection is vital for slowing disease progression and enabling timely intervention [5], [6], [7], [8].

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Due to its outstanding spatial resolution and capacity to differentiate between various brain tissues, Magnetic Resonance Imaging (MRI) is essential in the diagnosis of AD [9]. MRI can identify AD-related brain atrophy, a key diagnostic marker [10]. Despite its benefits, MRI is challenged by factors such as motion artifacts, high costs, limited accessibility, and the need for advanced data analysis [11], [12]. Manual interpretation of MRI is also prone to variability among observers, which can affect diagnostic accuracy [13].

To address these challenges, there has been an increasing focus on automated prediction and classification methods. Machine Learning (ML) and Deep Learning (DL) approaches have shown promise in improving diagnostic accuracy and efficiency. DL methods, such as Support Vector

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Machine (SVM) and Learning Vector Quantization-SVM (LVQ-SVM), are particularly effective in classifying brain images and detecting AD [9]. These techniques can analyze large datasets and extract complex features that traditional ML methods may miss [5], [14].

However, traditional ML approaches often struggle with large volumes of data and manual analysis remains time-consuming and error-prone. To overcome these limitations, DL techniques offer more consistent results by identifying novel patterns and improving diagnostic precision [15], [16]. Ensemble DL methods have gained traction in various medical imaging applications, demonstrating significant improvements in diagnostic capabilities [12], [17].

This study proposes an approach for AD diagnosis that integrates image enhancement techniques with DL classification. We investigate the impact of preprocessing brain MRI images with Contrast-Limited Adaptive Histogram Equalization (CLAHE) [18] and Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) before classification [12]. We compare two scenarios: one with enhanced images and one with original, unenhanced images. DenseNet-121 and MobileNetV2 are used to train the models on images from the Kaggle dataset. Our primary objective is to assess the effectiveness of image enhancement in improving AD detection accuracy and to explore how DL techniques can address current diagnostic challenges. The primary contribution of this paper is as follows:

- This study uses enhanced images from the Kaggle collection and significantly improves AD detection accuracy.
- The reliability and efficiency of the proposed model are evaluated carefully by comparative study. The evaluation measures include accuracy, precision, confusion matrix, recall, top-n accuracy, and the F1-score as assessment parameters.
- The study has reliable foundations as the proposed ensembled DL model is trained using the existing Kaggle data collection.
- The results of this study indicated improvement in the performance of the proposed model in detecting Alzheimer's disease by conducting a comparative analysis of enhanced and original images.

The rest of the article is organized as follows. Section II presents relevant literature on CADs used for the detection of AD. Section III explains the proposed methodology and dataset. Section IV details the experimental evaluation. Results are presented in section V along with a detailed discussion. Section VI concludes the work along with future directions.

II. RELATED WORK

Recent research has increasingly focused on leveraging DL techniques within computer-aided systems for the diagnosis of AD. These approaches aim to enhance early detection and intervention strategies by analyzing medical imaging modalities like MRI. This review discusses various studies and their contributions to advancing AD diagnosis through DL.

A. DEEP LEARNING METHODS FOR AD DIAGNOSIS

Several studies have utilized Deep Learning (DL) techniques to improve AD diagnosis using MRI. Murugan [19] proposed a Convolutional Neural Network (CNN) framework to identify distinctive features associated with AD from MRI scans. Their DEMentia NETwork (DEMNET) achieved an accuracy of 95.23%, an Area Under Curve (AUC) of 97%, and a Cohen's Kappa value of 0.93, outperforming previous methods. This study highlights the potential of CNNs in enhancing diagnostic precision despite challenges such as class imbalance in MRI datasets.

Kundaram and Pathak [20] explored a Deep Convolutional Neural Network (DCNN) for classifying AD into three categories: AD, mild cognitive impairment, and normal control. Their DCNN model, implemented using Spyder software with Keras and TensorFlow, achieved an accuracy of 98.57%, demonstrating significant improvement over earlier approaches and extending the methodology to broader illness classification phases.

Sharma et al. [21] examined the use of CNNs, incorporating the VGG16 feature extractor for AD detection through MRI analysis. Their model achieved varying accuracy across two datasets, with a peak accuracy of 90.4% for the first dataset and 71.1% for the second. This study underscores the impact of different datasets on model performance and the importance of dataset quality in achieving reliable results.

In another research, Sharma et al. [22] introduced a hybrid artificial intelligence (AI) model that integrated Transfer Learning (TL) with a permutation-based machine learning (ML) voting classifier. The model was partitioned into two primary stages. Firstly, two transfer learning (TL) models, namely DenseNet-121 and DenseNet-201, were employed to extract features. Secondly, three separate ML classifiers, specifically Naïve Bayes, Support Vector Machine (SVM) and XGBoost were used for classification. An evaluation of the classifier's final findings was conducted by permuting the voting process. The suggested model achieved an accuracy of 91.75%, a specificity of 96.5%, and an F1-score of 90.25.

Al Shehri [23] presented a solution that utilizes deep learning techniques, specifically DenseNet-169 and ResNet-50 CNN architectures, to diagnose and classify Alzheimer's disease. The proposed model categorized AD into different stages based on dementia severity. The design of DenseNet-169 shown exceptional performance in both the training and testing domains. The DenseNet-169 model achieved training and testing accuracy values of 0.977 and 0.8382, respectively. In contrast, the ResNet-50 model maintained accuracy values of 0.8870 and 0.8192. The suggested approach showed its feasibility in the real-time analysis and categorization of AD.

B. ENHANCEMENTS IN MRI ANALYSIS

Several researchers have focused on improving MRI analysis through advanced DL techniques. An et al. [24] developed a deep ensemble learning framework combining multiple sparse autoencoders and a deep belief network. Their approach demonstrated a 4% higher classification accuracy compared to six prominent ensemble techniques, emphasizing the effectiveness of combining multiple data sources and classifiers for improved diagnostic accuracy.

Helaly et al. [15] used Transfer Learning (TL) with pre-trained models like VGG19 for classifying AD stages. Their study achieved accuracies of 93.61% and 95.17% for 2D and 3D multi-class AD stages, respectively, highlighting the benefits of TL in enhancing diagnostic performance.

Venugopalan et al. [25] proposed a multimodal DL model that combined MRI, genetic, and clinical data to classify AD. Their approach used stacked denoising autoencoders for feature extraction and CNNs for imaging data analysis. The study demonstrated that DL models outperformed shallow models and effectively identified key brain features associated with AD.

C. NOVEL FRAMEWORKS AND TECHNIQUES

Several studies introduced novel frameworks to address specific challenges in AD diagnosis. Puente-Castro et al. [26] developed a system using TL techniques for automated AD detection from MRI scans. Their framework, utilizing sagittal-plane MRIs, showed comparable efficacy to other MRI planes and demonstrated the potential of sagittal MRIs in early AD detection.

Rashid et al. [27] introduced Biceph-Net, a resilient framework for diagnosing AD using 2D MRI scans. Biceph-Net achieved high accuracy rates, including 100% for distinguishing normal cognitive function from AD and 97.8% for differentiating AD stages. This framework highlighted improvements in computational efficiency and diagnostic precision.

D. ADVANCES IN FEATURE EXTRACTION AND CLASSIFICATION

Martinez-Murcia et al. [28] employed convolutional autoencoders for extracting abstract features from MRI scans. Their approach combined neuropsychological test scores with MRI data, achieving over 80% classification accuracy for AD diagnosis and highlighting the effectiveness of deep autoencoders in feature extraction.

Zhu et al. [29] proposed the Dual Attention Multi-Instance DL Network (DA-MIDL) for detecting AD using structural MRI. DA-MIDL utilized spatial attention blocks and multi-instance learning pooling to enhance feature extraction and classification accuracy. Their model outperformed various state-of-the-art techniques, demonstrating improvements in detecting diseased regions and generalizability.

After analyzing the results of the studies on identifying and diagnosing AD, it is clear that there are still many gaps that need further investigation. The above studies have shown that pre-trained DL models can achieve impressive trustworthiness. In addition, the majority of these experiments focused on training DL models using unprocessed images, which restricted the potential for the classification network to be scaled up. The current study integrates various layers into the architecture of pre-trained models to develop a concise model for identifying Alzheimer's disease, effectively addressing these issues. Consequently, the suggested proposed model demonstrates enhanced medical diagnosis and effectiveness.

III. PROPOSED METHODOLOGY

Accurately diagnosing AD is a persistent difficulty in the field of medical imaging. While MRI is a valuable technique for detecting brain disorders associated with AD, the constraints of resolution and contrast often impede the accurate discernment and categorization of AD. This section explains the preliminary techniques for image enhancement and deep learning classifiers used in this study, along with their rationale for selection for this study. Afterward, it describes the dataset used for training and testing. In the next phase, the workings of image enhancement techniques are explained, followed by the use of DL classifiers for AD classification.

A. PRELIMINARY TECHNIQUES

This section investigates advanced image-enhancing algorithms such as CLAHE and ESRGAN. These techniques increase the quality of MRI images before they are transmitted to classifiers. This section explains the methodologies used for image improvement and examines the classifiers utilized to classify improved images.

CLAHE is a medical imaging technique utilized to improve the visibility of disease diagnosis-critical, refined image features [18]. CLAHE optimizes image contrast in a flexible and precise manner, ensuring that vital details remain unaffected by variations in tissue thickness. Furthermore, implementing the ESRGAN method substantially enhances the quality of the medial image [12]. ESRGAN enhances the complexity and accuracy of medical image quality. Both of these approaches work together to improve the diagnostic capabilities of medical imaging. The quality enhancement features of CLAHE and ESRGAN help accurately assess and predict chronic illnesses like AD.

CLAHE and ESRGAN image enhancement algorithms were used in this work because of their efficacy in enhancing MRI images, which often exhibit low contrast and resolution. CLAHE selectively focuses on smaller areas of an image by utilizing its contrast capability to improve the visibility of brain tissues without introducing extra noise. Equally, ESRGAN enhances the image resolution, facilitating more effective feature extraction in the classification layers. Both image enhancement methods are beneficial for the precise and efficient prediction of Alzheimer's disease in humans.

DL techniques play a pivotal role in the classification of AD from MRI scans, particularly when coupled with

image enhancement methods. Utilizing existing datasets requires meticulous preprocessing to ensure data integrity and accuracy. The DenseNet121 and MobileNetV2 techniques are used because of their effectiveness in extracting intricate features from MRI images, enabling precise disease detection. DenseNet121 densely connected layers facilitate efficient information propagation, while MobileNetV2 lightweight architecture is adept at handling computational constraints without compromising performance. Leveraging these techniques promises enhanced accuracy and reliability in AD diagnosis, paving the way for more effective treatment strategies and improved patient outcomes.

The MobileNet architecture was developed utilizing depthwise separable convolution. The traditional two-dimensional convolution operation concurrently executes convolution across both spatial and depth dimensions, ultimately yielding a singular output channel. The process of depthwise convolution entails the division of input images and filters into distinct channels, followed by the execution of convolution operations between each channel and its respective filter channel. Subsequent to the generation of the filtered output channels, these channels are reconstructed into a cohesive stack. In separable depthwise convolution, the output channels that have been stacked undergo additional processing through 1×1 convolution, often referred to as pointwise convolution, in order to amalgamate the stacked output channels into a singular channel. The depthwise separable convolution yields a result that is equivalent to that of the standard convolution; however, it enhances efficiency by diminishing the number of factors engaged in the process.

MobileNetV2 features a total of 19 inverted residual bottleneck layers subsequent to the initial convolution layer, which is composed of 32 filters. The network culminates in a pointwise convolution, resulting in an output characterized by dimensions of $7\times7\times1280$ pixels. A residual block creates a connection between the beginning and the end of a convolutional block through the implementation of a skip-connection. This connection fulfills the objective of conveying information to the more profound strata of the network. In a conventional residual block, it is observed that the initial and terminal layers of the convolutional block generally exhibit a higher number of channels in comparison to the intermediate layers.

DenseNet improves the effectiveness of deep learning networks by minimizing layer dependencies, which in turn enhances their overall efficiency. The primary layer of DenseNet exhibits interconnections with the second, third, fourth layers, and so on, whereas the subsequent layer maintains interconnections with the third, fourth, and fifth layers. The principal objective is to enhance the transmission of data across the different tiers of the organization. Each layer within the system acquires input from the layers that precede it and offers direction to the layers that follow, thereby ensuring the continuity of information flow.

B. DATASET DESCRIPTION

The research has carefully chosen a dataset containing an ample number of high-quality images to utilize. The AD dataset from Kaggle was utilized for this research. The dataset has over 5000 images, categorized into several classifications based on the degree of Alzheimer's disease, including mild, extremely mild, none, and moderate. The MRI images are classified into four phases, ranging from moderate (0) to none (3), and are assigned corresponding labels from 0 to 3, as seen in Figure 1. Similar to any other dataset, the images and the labels will display a certain level of random variation. The provided images may display a range of flaws, including but not limited to distorted features, blurriness, inadequate brightness, and other similar difficulties. The images were acquired by individuals using various MRI machines at many clinics over a prolonged duration. This varied assortment enhances the extensive scope of the entire set. The dataset was partitioned into three segments, with an 80:10:10 ratio for the training, validation, and testing divisions.



FIGURE 1. Different classes of AD image dataset.

C. IMAGE ENHANCEMENT

Alzheimer's MRI images are often collected from diverse sources utilizing various techniques.Given the considerable intensity fluctuations present in the images utilized by the proposed methodology, it became essential to improve the quality of Alzheimer's MRI images and reduce various types of interference through the application of CLAHE and ESRGAN, as illustrated in Figure 2. All images across all scenarios are resized to a resolution of 224 × 224 x 3 to suit the input requirements of the learning model optimally. Given the wide range of pixel intensities in each image, the data has been standardized to fall within the range of (-1) to (1) to ensure consistency and eliminate interference. The clip limit parameter was fine-tuned to control the

enhancement of bright regions. Mobilenet and DenseNet121 parameters fine-tuning included the learning rate and a number of training iterations to improve the accuracy of MRI image classification. Data enhancement techniques like ESRGAN and CLAHE were applied to the given dataset per algorithms 1 and 2, explained below.

Algorithm 1 CLAHE-Based Preprocessing

Input: Image I, Block B, Histogram Equalization $\mathcal{E}$, Clipped Histogram $C\mathcal{E}$, Clipped Image CI, Processed Image PI
Output: Processed Image PI
Start
Set $PI \leftarrow \emptyset$
Let I be the MRI dataset
for each block B in I **do**
  Extract block B_i from I
  $\mathcal{E}_i \leftarrow \text{HistogramEqualizer}(B_i)$
  $C\mathcal{E}_i \leftarrow \text{Clip}(\mathcal{E}_i)$
  $CI \leftarrow \text{CDF}(C\mathcal{E}_i)$
  $PI \leftarrow \text{Recombine}(CI, PI)$
end for
Stop

Algorithm 2 ESRGAN-Based Preprocessing

Input:
G = Generator, D = Discriminator,E = Exception, I_{LH} = Low Resolution Image, I_H = High Resolution Image, I_{SR} = Super Resolved Image, L_{ad} = Adversarial Loss, L_p = Perceptual Loss, L_C = Content Loss, $\lambda_p, \lambda_{ad}, \lambda_C$ = Hyperparameters for Balancing
Start
Let I_L and I_H be the input dataset
$I_{SR} \leftarrow G(I_{LH})$
$D(I_H) \rightarrow 1$
$D(I_{SR}) \rightarrow 0$
$L_{ad}(G) \leftarrow E_{I_{LH}}\left[\log\left(1 - D(G(I_{LH}))\right)\right]$
$L_C(G) \leftarrow \text{ContentLoss}(I_H, G(I_{LH}))$
$L_p(G) \leftarrow \text{PerceptualLoss}(I_H, G(I_{LH}))$
$L_G(G) \leftarrow \lambda_{ad} \cdot L_{ad}(G) + \lambda_C \cdot L_C(G) + \lambda_p \cdot L_p(G)$
Train G
Stop

Implementing CLAHE and ESRGAN addresses the problem of inadequate contrast and resolution. The CLAHE method guarantees the elimination of noise and the enhancement of contrast. Likewise, the high-resolution images obtained using ESRGAN guarantee the accurate capture of intricate features included within the images. The rationale for selecting these image enchantment approaches mostly lies in their importance in enhancing MRI images necessary to classify healthy and diseased brain tissue. The optimization of input images for an ensemble model of deep learning models has enhanced both the detection capacity and precision.

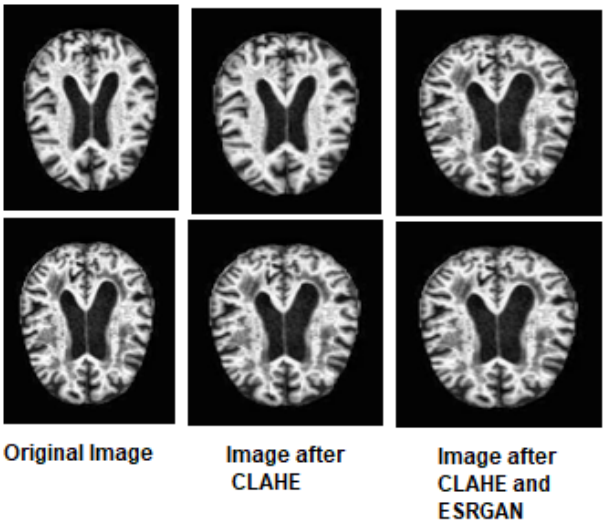


FIGURE 2. Processed Images of MRI after enhancement.

D. DL MODELS

The AD diagnosis from MRI images necessitates implementing various procedures within an ensemble model that combines MobileNetV2 and DenseNet121 architectures. Each procedure contributes to the overall effectiveness of the diagnostic framework. The image enhancement and preprocessing aim to improve the distinction between different elements in the images and enhance the clarity of their details, thereby increasing their diagnostic utility. By enhancing image perception of subtle features in brain tissues with specific regard to AD, image enhancement played a pivotal role in better feature extraction, thereby avoiding misclassification. Better quality input data for deep learning models resulted from these upgraded images, which eventually improved prediction accuracy. Following the enhancement of MRI images, the feature extraction process is a key step in the diagnostic framework. This process, performed using both the MobileNetV2 and DenseNet121 frameworks, is crucial for capturing and representing high-level and low-level image characteristics relevant to AD pathology. MobileNetV2 and DenseNet121, known for their lightweight convolutional and densely connected layers, respectively, allow for the extraction of a broad range of information from the input MRI images.

In the MobileNetV2 architecture, the inverted residual block is designed in such a way that the linked layers have a lower number of channels compared to the layers in between. This results in a significant reduction in the number of parameters when compared to the regular residual block.

The DenseNet improves the efficiency of deep learning networks by minimizing layer dependencies and enhancing their efficacy. The primary layer of DenseNet is connected to the second, third, fourth, etc. layers, while the succeeding layer is connected to the third, fourth, fifth, etc. layers. The objective is to optimize the transmission of data between different levels within the company. In order to sustain

the flow of information, each layer in the system takes input from the previous levels and offers guidance to the succeeding layers.

DenseNet has two necessary layers besides the convolutional and pooling layers. These dense blocks and layers help transition between stages or levels. Different filters in DenseBlocks enhance channel components.DenseNet starts with convolutional operations and pooling. The process has dense block, progress, change, thick square, and characterization layers. Dense blocks have two convolutions, one 1×1 and one 3×3. The event occurs multiple times in dense blocks 1, 2, and 3, with 24 and 16 repeats in block 4. Each thick layer has two convolution operations: one with a 1 X 1 kernel for conventional feature extraction and one with a 3 X 3 kernel to minimize feature depth or channel count. The input features, dense layers, and growth rate determine the number of feature-maps after each dense block. To reduce channels, a layer or block is added between two thick blocks.

A unified feature representation for each MRI image is created by concatenating the features derived from MobileNetV2 and DenseNet121. This integrative approach ensures a comprehensive representation of the MRI image characteristics, leveraging the strengths of both architectures to enhance the classification process's discriminative capacity. Prior to generating ultimate predictions, the ensemble model undergoes rigorous training using annotated data. This stage entails establishing the associations between the extracted characteristics and the relevant AD diagnoses. Once training is complete, the proposed ensemble model is used to predict the likelihood of AD presence or severity for each MRI image in the dataset. The two different scenarios were trained and tested, one where we applied enhancement on the images and the other where we used the original images as shown in Figure 3.

Predictions can assist in the process of clinical decision-making about the diagnosis of AD and the treatment of patients. This method has the capacity to enhance accuracy and usefulness in the assessment of neurodegenerative disorders. The final predictions have four labels: Mild, Very mild, and None. The effectiveness of both scenarios was estimated through different experiments.

The deep learning ensemble technique utilized MobileNetV2 and DesneNe121 to leverage the combined capabilities of both models. The MobileNetV2 model is used for feature extraction, whereas deep learning targets the intricate aspects of interconnected structures. The ensemble model MobileNetV2 accepts preprocessed MRI images as input and utilizes high-resolution and improved images to analyze the features. In contrast, DenseNet121 uses dense connections to extract richer patterns from these images.

IV. EXPERIMENTAL EVALUATION

This section outlines the practices used in evaluating the efficacy of the study and its definitive results. Classifier accuracy stands as a dominant metric used to assess the performance of classification models [30]. This parameter uses True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) instances out of all instances (N) to calculate accuracy. This matrix is derived by dividing the total count of correctly identified instances by the percentage of valid instances, as expressed by Equation (1). Evaluation of image classification accuracy conventionally includes metrics such as sensitivity and specificity. Specificity, as presented by Equation (2), amends with the enhanced accuracy in labeling a greater number of images. Utilizing Equation (3), a quantification was conducted to determine the extent of linear correlation exhibited by images within the dataset [31]. A higher F1-score implies a heightened likelihood of the system rendering accurate predictions. The evaluation of a system's efficacy requires consideration beyond mere accuracy and sensitivity, as denoted by Equation (4) capturing the formula for computing the F1-score [32]. The effectiveness of the proposed model is dependent upon the correspondence of one of the N predictions with the actual label.

$$\text{Accuracy} = \frac{tP + tN}{tP + fP + fN + tN} \tag{1}$$

$$\text{Sensitivity} = \frac{tN}{tP + fN} \tag{2}$$

$$\text{Selectivity} = \frac{tN}{tN + fP} \tag{3}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

A. EXPERIMENTAL SETUP

The proposed ensemble model underwent validation using the Kaggle dataset, and its performance was compared against established best practices. Adhering to the recommended training protocol, 80% of the data was allocated for training, 10% for testing, and 10% for validation purposes. During training, images were resized to a resolution of 224×224 x 3 pixels. The TensorFlow Keras application of the proposed system was assessed using an Intel PC equipped with 8 GB of RAM and RTX3060 GPU. Simulation was conducted over 50 epochs, with the learning rate ranging between 1E x $10\hat{3}$, 1E x $10\hat{4}$, and 1E x $10\hat{5}$. Batch sizes varied from 2 to 64, incremented by a factor of 2, with 10 patience steps and a momentum of 0.90. To diversify our anti-infective strategies, a ''batching'' technique was applied to evenly distribute AD classes within the Kaggle dataset.

V. RESULTS AND DISCUSSION

This section offers a comprehensive analysis of the experimental results for both scenarios. The results have been extensively assessed using recognized evaluation criteria. During our inquiry, we methodically employed MobileNetV2, an advanced DL framework, to differentiate AD in MRI scans obtained from the Kaggle dataset. In order to strengthen the model's capacity for differentiation, we incorporated sophisticated image enhancement techniques such as CLAHE

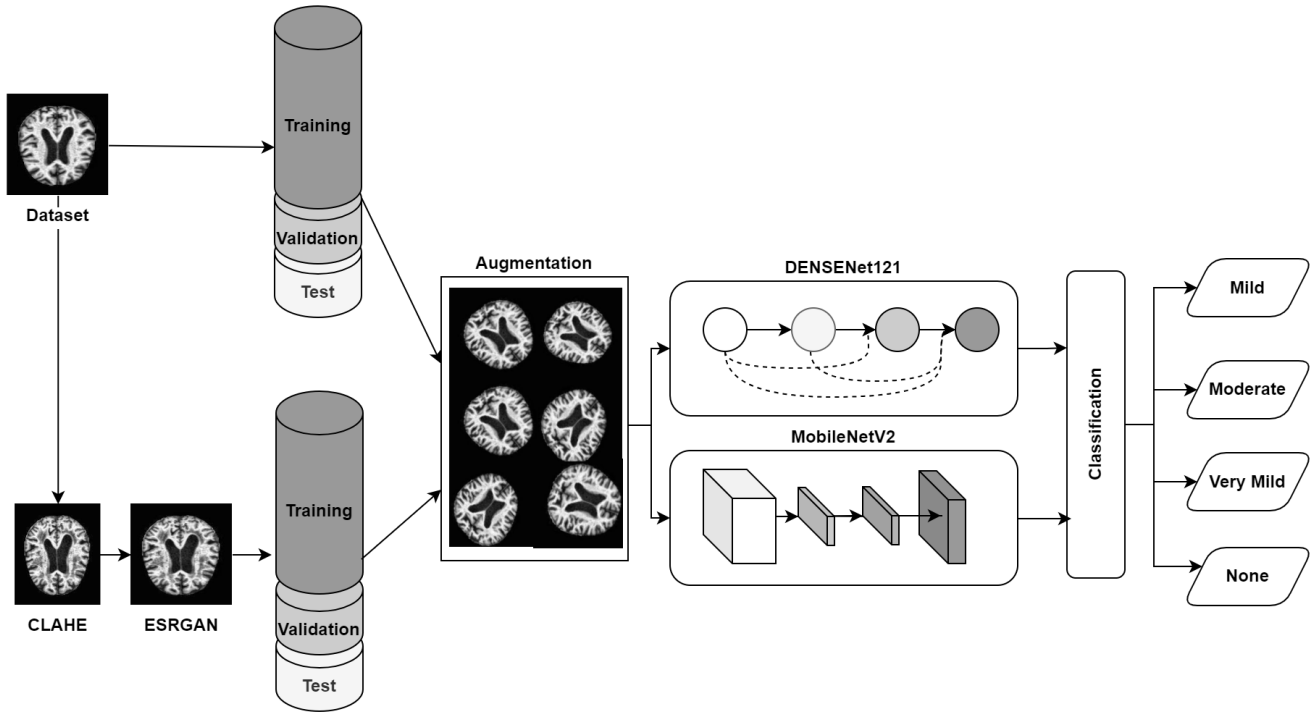


FIGURE 3. Proposed model with and without image enhancement.

TABLE 1. MobileNetV2 Comparison of performance with and without enhancements.

	Test Accuracy	F1 score	Precision	Recall
With enhancements	92.34%	92.3%	93%	92%
Without enhancements	80.31%	80.3%	80%	80%

and ESRGAN. The integration of various approaches was intended to enhance the image quality and highlight significant characteristics, hence permitting a more precise detection of diseases.

The DL ensemble AD detection model was evaluated by using the MobileNetV2 classifier on the enhanced MRI images. The results indicate a significant level of precision and resilience in the diagnostic framework. The achieved test accuracy of 0.9234 indicates that the model successfully classified 92.34% of the test images. In addition, the model demonstrated a remarkable top-2 accuracy of 0.9469 and a top-3 accuracy of 0.9906. The results emphasize the model's outstanding performance, especially when assessing the top two or three predictions, as shown in Table 1. The notable enhancement in accuracy values indicates that the preprocessing phases, specifically ESRGAN and CLAHE, have significantly improved the clarity and differentiation of the MRI images. This improvement in image quality has directly contributed to the model's enhanced ability to identify AD accurately.

Additional evaluation indicators provide more proof of the model's efficacy. The F1 score, a statistic that takes into account both precision and recall, attained a value of 0.9234. This suggests an even performance in terms of accuracy, precision, and recall. The accuracy number of 0.93 signifies a notable degree of precision, with 93% of the model's positive predictions being accurate. Similarly, the recall score of 0.92 signifies that the model correctly identified 92% of the actual positive cases. The findings highlight the remarkable skills of the MobileNetV2 classifier in accurately distinguishing AD from improved MRI images. The improved image quality and efficient feature extraction capabilities of MobileNetV2 contribute to the high precision and recall values, resulting in more precise and dependable classification.

The MobileNetV2 classifier achieved a test accuracy of 0.8031 when applied to unenhanced MRI images. This indicates that around 80.31% of the test images were correctly classified. The precision of the highest two forecasts was 0.9016, but the precision of the highest three forecasts was 0.9906. This suggests that the model exhibits satisfactory performance while making several predictions, but its total accuracy is significantly lower in comparison to the situation where improved images are used. The F1 score of the test, which is 0.8031, suggests a somewhat balanced performance with slightly poorer precision and recall. The values for both precision and recall were recorded as 0.80. The data clearly shows that the model's ability to reliably and consistently identify AD is impaired when the preprocessing enhancements are not used.

A precision value of 0.80 signifies that 80% of the positive predictions made by the model were correct, but a recall value of 0.80 indicates that the model successfully detected 80% of the actual positive cases. The equilibrium between precision and recall in this instance signifies a moderate degree of effectiveness. However, it also brings attention to the limitations of the model's accuracy in classifying

TABLE 2. DenseNet121 Comparison of performance with and without enhancements.

	Test Accuracy	F1 score	Precision	Recall
With enhancements	89.38%	89.3%	90%	89%
Without enhancements	89.22%	89.2%	91%	89%

AD without image enhancement. The lower precision and recall, in comparison to the enhanced scenario, highlight the difficulties presented by the inherent variability and quality of the raw MRI images, which likely contribute to less distinct and clear feature representations.

Upon reviewing the results of the MobileNetV2 classifier, it becomes clear that there are significant improvements when image enhancing techniques are employed. By employing preprocessing techniques like ESRGAN and CLAHE, the test accuracy significantly increased from 0.8031 to 0.9234. This notable enhancement serves as evidence of the effectiveness of these measures in improving both the quality of the image and the accuracy of the diagnosis. The top-2 accuracy has seen a substantial enhancement, increasing from 0.9016 to 0.9469. This indicates a more robust performance in circumstances that require more certain forecasts. The parameters of accuracy, recall, and F1 score shown substantial enhancement. At first, their values were 0.8031, 0.80, and 0.80, respectively. Nevertheless, with the improvement of the images, these metrics increased to 0.9234, 0.93, and 0.92. This suggests that the improved images were essential in facilitating more accurate and reliable categorization.

The comparison results highlight the substantial significance of image preprocessing in the identification of Alzheimer's disease using deep learning models. Enhanced image quality leads to improved clarity and more prominent features, allowing the MobileNetV2 classifier to achieve higher accuracy and dependability. The significant advancements in many metrics underscore the necessity of employing image enhancing techniques to overcome the inherent limitations of raw MRI data and achieve more precise diagnostic outcomes.

The application of the DenseNet121 classifier on improved MRI scans yielded a test accuracy of 0.8938, indicating that the model correctly identified 89.38% of the test images. The model obtained an amazing top-2 accuracy score of 0.9531 and a faultless top-3 accuracy score of 1.0000, demonstrating its exceptional performance in assessing the best two or three predictions. The elevated accuracy values demonstrate that the implementation of image preprocessing approaches, such as ESRGAN and CLAHE, significantly improved the quality and distinction of the MRI images, as seen in Table 2. This enhancement allowed the DenseNet121 model to more effectively collect and depict crucial attributes associated with AD, leading to more precise categorizations.

Further supporting the model's effectiveness, the test F1 score was also 0.8938, reflecting a balanced performance in terms of precision and recall. The precision of 0.90 indicates that 90% of the positive predictions were correct, while the recall of 0.89 signifies that the model successfully identified 89% of the actual positive cases. These high precision and recall values underscore the robustness of the DenseNet121 classifier in detecting AD from enhanced MRI images. The dense connections within the DenseNet121 architecture facilitate the extraction of comprehensive feature representations, which, combined with the improved image clarity from preprocessing, enhance the model's ability to distinguish between AD and non-AD cases with high accuracy and reliability.

The DenseNet121 classifier, when trained on unenhanced MRI images, achieved a test accuracy of 0.8922. This indicates that the model effectively classified 89. The method achieved a recognition rate of 89.22% for the test images. The accuracy for the top-2 predictions was 0.9422, while the accuracy for the top-3 predictions was a perfect 1.0000. Upon analyzing the top predictions, it becomes evident that the models' performance is commendable. It is worth noting that the model achieved impressive results without the need for any image enhancement. All the F1 scores, including the test F1 score, the overall F1 score, and the F1 scores of each class, are 0.8922 indicates a fair performance, demonstrating a commendable balance between precision and recall. Specifically, the precision was 0.91, signifying that 91 of the positive predictions were accurate, while the recall was 0. The model's accuracy rate indicates that it achieved an 89% success rate in correctly identifying the positive cases. These metrics reflect the inherent strengths of the DenseNet121 architecture, which utilizes densely connected layers to extract rich and diverse features from the MRI images. Despite the lack of image enhancement, the model's architecture allows it to maintain high levels of precision and recall, underscoring its capability to effectively capture and represent important characteristics associated with AD.

Comparing the results of the DenseNet121 classifier with and without image enhancement reveals subtle yet important differences. With enhancement, the test accuracy was 0.8938 compared to 0.8922 without enhancement, showing a slight improvement. The top-2 accuracy increased from 0.9422 to 0.9531 with enhancement, and both scenarios achieved a perfect top-3 accuracy of 1.0000. The F1 score remained consistent, with a minor increase from 0.8922 to 0.8938 when enhancement was applied. Interestingly, precision was slightly higher without enhancement at 0.91 compared to 0.90 with enhancement, while recall remained the same at 0.89 in both scenarios.

These comparisons demonstrate that the DenseNet121 model achieves impressive performance even without any enhancements. However, the preprocessing steps offered by ESRGAN and CLAHE still provide slight improvements in accuracy and top-2 predictions. There may be a slight decrease in precision when using enhancement, which could be attributed to the introduction of new features that may not always have a positive impact on classification. However, the overall effect on performance is minimal. It can be inferred

that DenseNet121 is quite resilient on its own. However, the incorporation of image enhancement techniques can yield further advantages, specifically in enhancing specific metrics and ultimately improving the diagnostic process as a whole.

The performance disparities observed between DenseNet121 and MobileNetV2, with and without image enhancement, can be attributed to the inherent strengths and interdependencies of their respective architectures. The impressive performance of DenseNet121, regardless of image enhancement, highlights its remarkable capability to extract intricate and detailed features using its densely connected layers. This architecture enables the understanding of intricate patterns and connections within the data, establishing a solid basis for precise classification, even when the input images are not enhanced through preprocessing. However, the significant improvement of MobileNetV2 when used with enhanced images emphasizes the importance of image quality in order to optimize its efficiency.

MobileNetV2, a model tailored for lightweight applications, places a strong emphasis on computational efficiency and speed. However, this focus on efficiency may occasionally limit its ability to perform deep feature extraction. Preprocessing techniques such as ESRGAN and CLAHE are essential in addressing these limitations by enhancing image clarity and detail. This, in turn, enables MobileNetV2 to attain greater accuracy and reliability in its predictions.

The disparity in performances indicates that DenseNet121 possesses inherent versatility and resilience, rendering it suitable for a wider array of diagnostic scenarios, especially in settings where image quality may not always be regulated or assured. On the other hand, the performance of MobileNetV2 greatly improves with preprocessing. This suggests that it is most suitable for situations where there are limited computational resources but high-quality imaging and reliable preprocessing techniques are accessible. This philosophical perspective highlights the significance of selecting models that are in line with the particular requirements and limitations of the diagnostic situation. Although DenseNet121 is a versatile option, MobileNetV2's efficiency can be effectively utilized in situations where reliable preprocessing is possible. This allows for optimized resource utilization without sacrificing diagnostic accuracy. Therefore, when deciding between these models, it is important to take into account the various technological, operational, and contextual factors that are present in the diagnostic environment.

The 4×4 confusion matrix is being analyzed to identify different classifications within the dataset. The MobileNet model is used for this analysis, as depicted in Figures 4a and 4b. The higher values of TN and FN demonstrate the model's effectiveness in correctly identifying instances of this class as negatives (true negatives), but also highlight its limitations in accurately detecting instances of the class that were mistakenly overlooked (false negatives). However, the component known as true positive (TP) for a different class indicates the model's ability to accurately detect instances of that specific class (true positives). On the other hand, when there is a higher presence of the remaining grid, it suggests that there are lower numerical values. This is a sign of false positive (FP) and false negative (FN) instances across different classes. These instances indicate that the model may be prone to misclassifications and errors, which calls for additional research and potential strategies to enhance the overall accuracy and reliability of the classification. The results and performance matrix demonstrate the collaborative impact of utilizing the DenseNet121 architecture, which encourages the reuse of features and the flow of gradients in conjunction with CLAHE and ESRGAN. CLAHE operates by analyzing the histograms of images and then equalizing them within specific localized regions. This function enhances the local contrast and improves its visibility. Simultaneously, ESRGAN enhances image quality by utilizing generative adversarial networks. This feature enhances the quality of images by increasing the level of detail, resulting in high-resolution visuals. It achieves this by effectively improving the classifier's ability to distinguish between different elements. These results further demonstrate the proposed model's effectiveness in accurately identifying AD instances from MRI images. This enhances the interpretability of MRI images and improves the classifier's ability to distinguish between different cases. The proposed model's features provide a more reliable diagnostic of AD in a real clinical environment.

Based on the data presented in Figure 4c and 4d, it is evident that the model has successfully identified a significant number of instances accurately, as indicated by the higher values in the diagonal cells. Based on the confusion matrix, it appears that DenseNet121 performs well in accurately recognizing instances of this class (true negatives). However, it struggles to detect instances where the class is present but not identified by the model (false negatives). Given the relative values of false positive instances compared to true positives and false negatives, it is evident that the model has a lower likelihood of predicting misclassified instances, as shown in Figure 4. The pattern observed in these confusion matrices suggests that the proposed model performs strongly in identifying classes associated with AD stages. The proposed model seems to be encountering difficulties with errors and misclassification problems.

A. COMPARISON WITH EXISTING APPROACHES

The proposed approach is compared with existing techniques for assessing efficacy in terms of accuracy. According to the results presented in Table 3, the proposed methodology outperforms previous methods in terms of both effectiveness and efficiency while using same dataset. The effectiveness of this methodology is compared to that of comparable approaches. The proposed model demonstrates superior efficiency compared to the previous top techniques. The proposed model, which utilizes MobileNetV2 and DenseNet121 with enhancements, achieves higher accuracy due to its optimized feature representation architecture and ability to

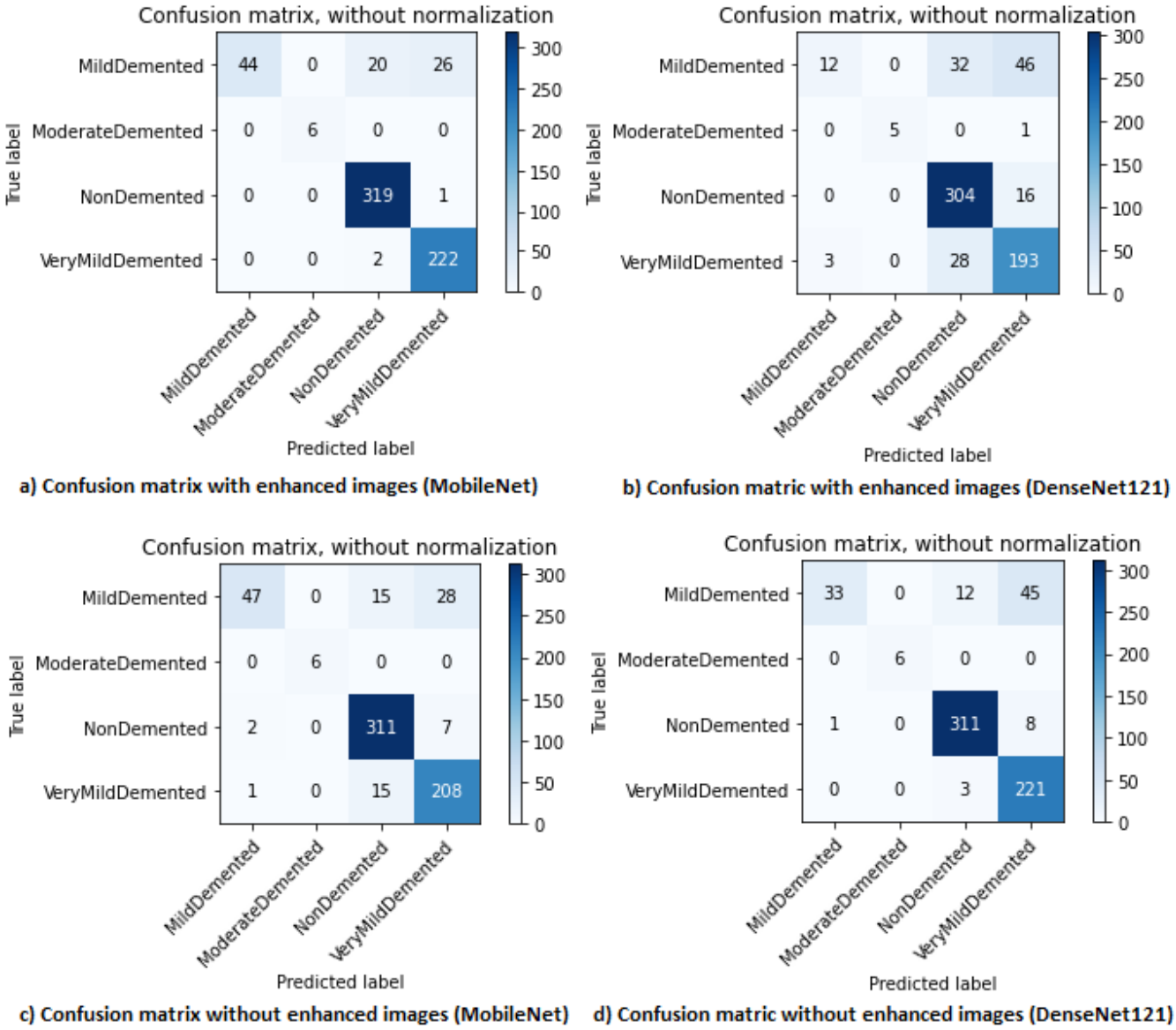


FIGURE 4. Confusion matrix for Mobilenet and Densenet with enhancement and without enhancement.

generalize the provided dataset. In addition, the utilization of data preparation techniques such as enhancements aids in decreasing the complexity of MobileNetV2 and renders it appropriate for the specific dataset employed in this research endeavor. In comparison to the state-of-the-art (SOTA) model indicated in Table 3, MobileNetv2 significantly narrows the performance difference. This showcases its ability to achieve high accuracy while maintaining efficiency due to its streamlined training and reduced computing complexity.

Ultimately, the incorporation of image enhancement techniques has been instrumental in enhancing the precision and dependability of Alzheimer's disease detection through deep learning models. The comparison between MobileNetV2 and DenseNet121 reveals the importance of preprocessing in improving model performance, offering valuable insights for enhancing diagnostic accuracy in real clinical settings.

TABLE 3. Comparison of different techniques on various datasets.

Reference	Technique	Accuracy
[23]	ResNet50 and DenseNet169	83.82%
[33]	VGG19	70.3%
[22]	DenseNet	91.75%
Proposed	Mobilenetv2 with enhancement	92.34%
	DenseNet121 with enhancement	89.38%
	Mobilenetv2 without enhancement	80.31%
	DenseNet121 without enhancement	89.22%

Despite the outstanding performance of the proposed model, there exist some limitations that can be achieved in the future. The constraints of the MobileNV2 network lie in its restrictions on the size of feasible models and the need for precise parameter adjustment. On the other hand, the primary drawback of DenseNet121 is the potential loss of

critical features caused by the bottleneck approach employed in DenseBlocks. This might result in poor convergence and overfitting. In addition, when the depth and width of the network design expand, DenseNet121 may necessitate a significant amount of processing resources.

VI. CONCLUSION

The field of medical imaging has been significantly influenced by the application of DL, as it has enabled the identification and analysis of intricate patterns and features that are essential for precise diagnosis. This study makes an effort to utilize the image enhancement on the MRI image dataset available at Kaggle data to improve the prediction of early AD categorization and detection. The objective is to develop a more effective result prediction method that can be utilized in primary care settings. This work presents two distinct scenarios for classification, employing a DL method with enhancement and without enhancements. The novelty of this work lies in its explanation of using preprocessing approaches like ESRGAN and CLAHE that can improve AD diagnosis precision. This work explores the capacity of DL models to improve the identification of AD, especially when used in conjunction with efficient image preprocessing approaches. The findings demonstrated that the DenseNet121 model had exceptional performance irrespective of image enhancement, attaining a test accuracy of 0.8938 with enhancement and 0.8922 without enhancement. In contrast, MobileNetV2 demonstrated a significant enhancement when using improved images, resulting in a test accuracy of 0.9234, compared to 0.8031 without enhancement. The results emphasize the influence of image quality on the precision of diagnosis, especially for models such as MobileNetV2 that greatly improve their performance with improved image sharpness and level of detail. Subsequent research could prioritize the improvement of these DL models by integrating many types of data, such as merging MRI with other imaging techniques or including genetic and clinical data to better the accuracy of diagnosis. In addition, the advancement of the discipline could be furthered by the development of more intricate preprocessing algorithms that are customized to meet specific diagnostic requirements, as well as by investigating the implementation of these improved models in real-world clinical environments. By further integrating technical breakthroughs with clinical needs, future research can significantly impact the timely and precise detection of Alzheimer's Disease, thereby enhancing patient outcomes.

In our future work, we suggest using sophisticated hyperparameter optimization strategies to tackle the limitations of MobileNetV2. Additionally, we aim to investigate hybrid architectures that merge DenseNet with other models to alleviate feature loss and minimize overfitting. In addition, the model's generalization capabilities on varied datasets might be further improved by implementing more advanced data augmentation procedures.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The dataset is available at https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images/data.

Conflicts Of Interest: The authors declare no conflicts of interest.

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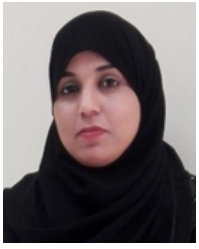


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