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A Survey On Detection Of Alzheimer's Disease From Brain MRI Scans

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Abstract

Alzheimer's disease (AD) is a progressive neurological disorder that affects memory, cognition, and brain structure. Accurate and early diagnosis is essential for effective treatment and clinical decision-making. This paper presents a deep learning–based framework for automated detection and stage classification of Alzheimer's disease using brain Magnetic Resonance Imaging (MRI) scans. A dataset containing approximately 6,400 MRI images was utilized and categorized into four stages of disease severity. Image preprocessing techniques, including Contrast Limited Adaptive Histogram Equalization (CLAHE) and Enhanced Super-Resolution Generative Adversarial Network (ESRGAN), were applied to improve contrast and resolution. An ensemble classification model combining MobileNetV2 and DenseNet121 architectures was implemented using TensorFlow and Keras. The performance of the system was evaluated using accuracy, precision, recall, and F1-score metrics. Experimental results demonstrate that the proposed approach improves classification performance and provides reliable detection of Alzheimer's disease stages. The system offers a computationally efficient and scalable solution for computer-aided medical diagnosis.

Keywords: Alzheimer's disease, MRI, Deep learning, MobileNetV2, DenseNet121, Image enhancement, CLAHE, ESRGAN, Classification

I. INTRODUCTION

Alzheimer's disease is a neurodegenerative disorder characterized by progressive cognitive decline and structural deterioration of brain tissues. It is one of the most common causes of dementia and significantly affects memory, thinking ability, and daily functioning. Early identification of Alzheimer's disease plays a critical role in slowing disease progression and improving patient management.

Magnetic Resonance Imaging (MRI) is widely used for analyzing structural changes in the brain associated with Alzheimer's disease. However, manual interpretation of MRI images is time-consuming and may lead to inconsistent results. Artificial intelligence, particularly deep learning, has emerged as an effective solution for automated medical image analysis.

Convolutional Neural Networks (CNNs) have demonstrated strong capability in extracting meaningful features from medical images. Transfer learning models such as MobileNetV2 and DenseNet121 provide efficient feature extraction and improved classification performance. In addition, image enhancement techniques such as CLAHE and ESRGAN improve image quality and assist deep learning models in extracting relevant features.

This paper proposes an ensemble deep learning framework for automatic detection and stage classification of

Alzheimer's disease using MRI scans. The proposed system integrates preprocessing, feature extraction, classification, and performance evaluation to achieve reliable diagnostic results.

II. LITERATURE REVIEW

Recent studies have explored deep learning techniques for automated Alzheimer's disease detection using MRI images. Convolutional Neural Networks have shown promising results in identifying structural abnormalities associated with the disease.

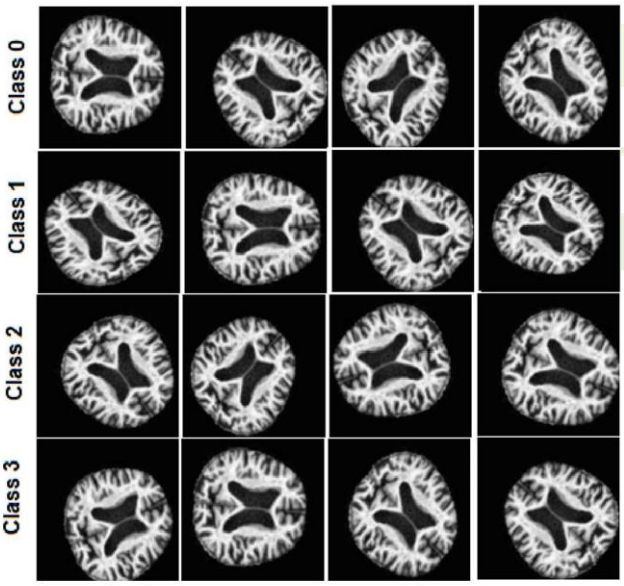
Murugan et al. developed a CNN-based model capable of extracting disease-related features from MRI scans and achieved high diagnostic accuracy. Similarly, Kundaram and Pathak proposed a deep convolutional neural network for classifying Alzheimer's disease into multiple stages, demonstrating improved classification performance.

Transfer learning approaches have also been widely used. Sharma et al. applied pretrained CNN models such as VGG16

FIG 1. Different classes of AD image dataset.

for Alzheimer's disease classification and reported improved

feature extraction efficiency. Ensemble learning methods combining multiple deep learning models have further



enhanced classification accuracy and robustness.

Recent research has also emphasized the importance of image enhancement techniques. CLAHE improves contrast in medical images, while ESRGAN enhances spatial resolution. These preprocessing techniques help improve feature visibility and classification performance.

Overall, deep learning combined with image enhancement has significantly improved the effectiveness of automated Alzheimer's disease detection systems.

III. EXISTING SYSTEM

Existing Alzheimer's disease detection systems primarily rely on traditional machine learning and deep learning models for MRI classification. These approaches use feature extraction and classification algorithms to detect disease stages.

However, many existing methods do not include advanced image enhancement techniques, which limits their ability to improve image quality. In addition, single-model architectures may not provide optimal classification performance. These limitations reduce overall diagnostic accuracy and reliability.

IV. PROPOSED METHODOLOGY

The proposed methodology presents an automated framework for detecting and classifying Alzheimer's disease using brain MRI images. The system integrates image preprocessing, enhancement, deep learning–based feature extraction, and classification to improve diagnostic accuracy and reliability. The overall workflow consists of multiple stages, as illustrated below.

A. Dataset Collection

The first stage involves collecting MRI brain images from a publicly available dataset. The dataset contains images representing different stages of Alzheimer's disease, including Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia. These images serve as input to the proposed system. The dataset is divided into training, validation, and testing sets to ensure proper model training and performance evaluation.

B. Image Preprocessing

In this stage, the MRI images are prepared for deep learning model input. Since MRI images may have different sizes and intensity variations, preprocessing is required to standardize them. All images are resized to a fixed resolution of 128×128 pixels to match the input dimensions required by the neural network. Additionally, pixel values are normalized to improve training stability and reduce computational complexity. This step ensures uniformity across the dataset and improves the efficiency of the learning process.

C. Image Enhancement Using CLAHE and ESRGAN

Medical images often suffer from low contrast and limited resolution, which can affect feature extraction. To address this issue, two image enhancement techniques are applied:

CLAHE (Contrast Limited Adaptive Histogram Equalization):CLAHE improves the contrast of MRI images by enhancing local regions while preventing excessive noise amplification. This technique helps highlight important brain structures and improves feature visibility.

ESRGAN (Enhanced Super-Resolution Generative Adversarial Network):ESRGAN enhances image resolution by reconstructing high-quality images from low-resolution inputs. This technique improves spatial details and enables the deep learning model to capture more accurate features.

The combination of CLAHE and ESRGAN improves overall image quality and enhances classification performance.

Algorithm 1 CLAHE-Based Preprocessing

Input: Image I, Block B, Histogram Equalization E, Clipped Histogram CE, 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

$E_i \leftarrow$ Histogram Equalizer(B_i)

$CE_i \leftarrow$ Clip(E_i)

CI $\leftarrow$ CDF(CE_i)

PI $\leftarrow$ Recombine(CI,PI)

end for

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

ISR $\leftarrow$
G(ILH) $D(I_H)$
$\rightarrow 1$

$D(I_{SR}) \rightarrow 0$

$L_{ad}(G) \leftarrow E_{ILH} \log(1 - D(G(I_{LH})))$

$L_C(G) \leftarrow$ Content Loss(I_H,$G(I_{LH})$)

$L_p(G) \leftarrow$ Perceptual Loss(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 this 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.

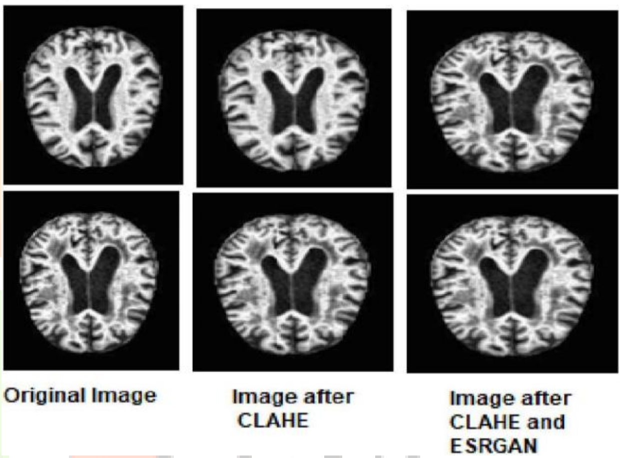


FIG 2. Processed Images of MRI after enhancement.

D. Feature Extraction Using Deep Learning Models

Feature extraction is performed using two pretrained convolutional neural network architectures: MobileNetV2 and DenseNet121.

MobileNetV2:MobileNetV2 is a lightweight deep learning model designed for efficient computation. It uses depthwise separable convolutions and inverted residual blocks to extract important features while reducing computational cost.

DenseNet121:DenseNet121 improves feature learning by connecting each layer to all previous layers. This architecture enhances information flow, reduces feature loss, and improves classification accuracy.

These models automatically extract relevant features from MRI images without manual intervention.

E. Classification and Performance Evaluation

After feature extraction, the extracted features are used for classification. The ensemble model combines predictions from MobileNetV2 and DenseNet121 to improve classification accuracy and robustness.

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. 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

$$1.\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$2.\text{Sensitivity} = \frac{TP}{TP+FN}$$

$$3.\text{Selectivity} = \frac{TN}{TN+FP}$$

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

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 128*128 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 103ˆ, 1E x 104ˆ, and 1E x 105ˆ. 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.

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 and ESRGAN.

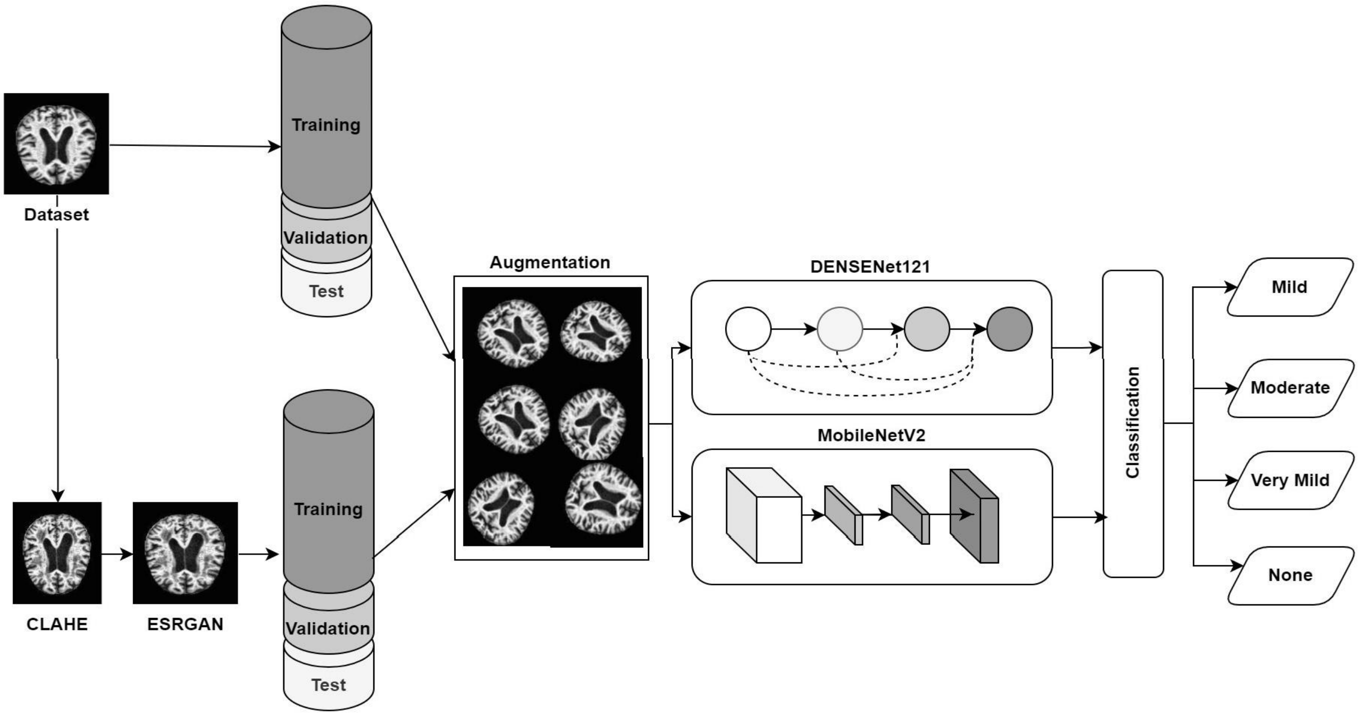


FIG 3. Proposed model with and without image enhancement.

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

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%

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.

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%

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 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. Despite the outstanding performance of the proposed model, there exist some limitations that can be achieved in the future.

TABLE 3. Comparison of different techniques on various datasets.

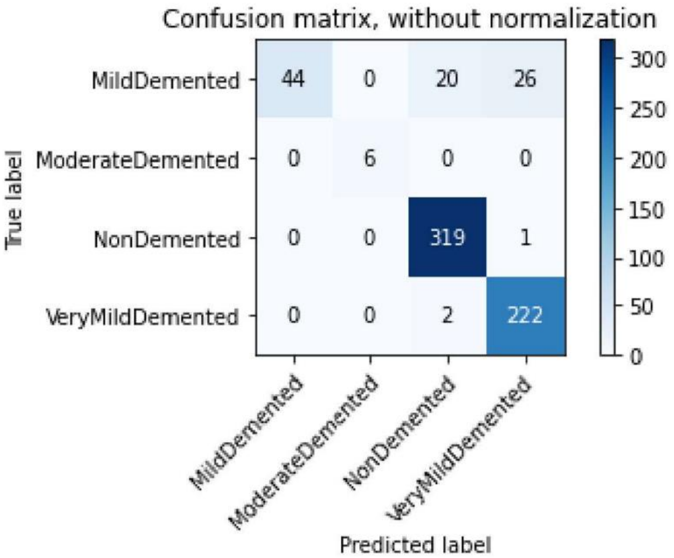
Reference	Technique	Accuracy
[23]	ResNet50 and DenseNet169	83.82%
[33]	VGG19	70.3%
[22]	DenseNet	91.75%
Proposed	Mobilenetv2 with enhancement	92.34%
	DenseNet121 with enhancement	89.38%
	Mobilenetv2 without enhancement	80.31%
	DenseNet121 without enhancement	89.22%

Despite the outstanding performance of the proposed model, there exist some limitations that can be achieved in the future.

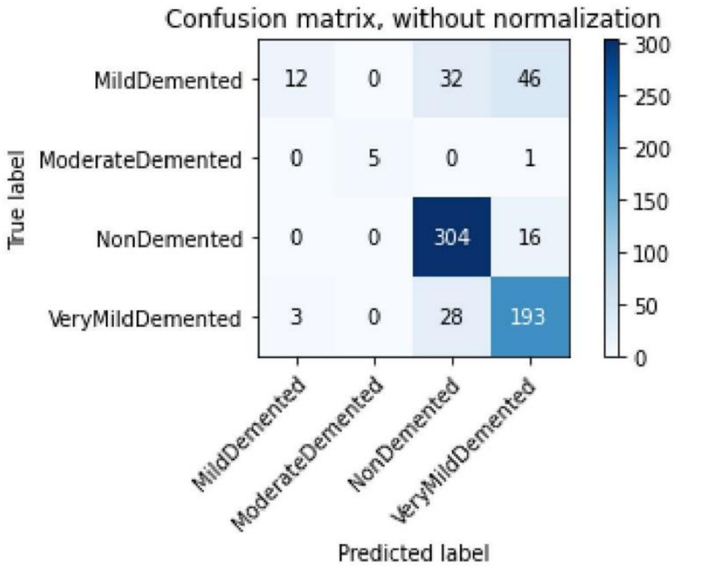
CONCLUSION

The field of medical imaging has been significantly influenced by the application of DL, as it has enabled the

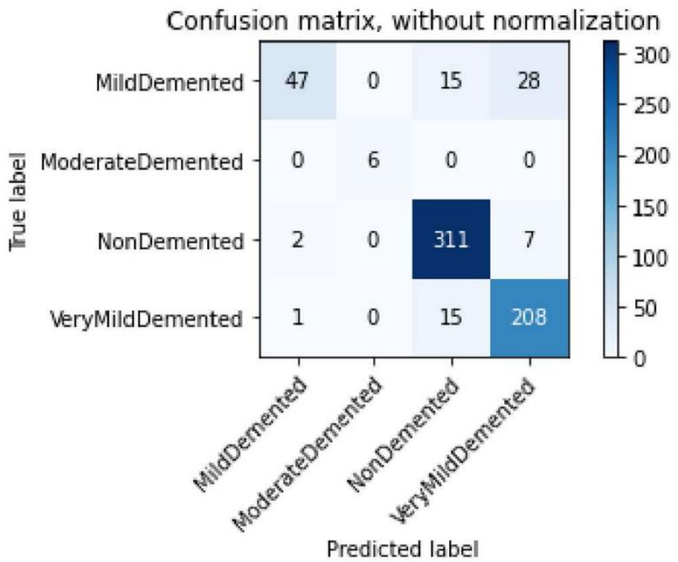
FIG 4. Confusion matrix for Mobilenet and Densenet with enhancement and without enhancement.



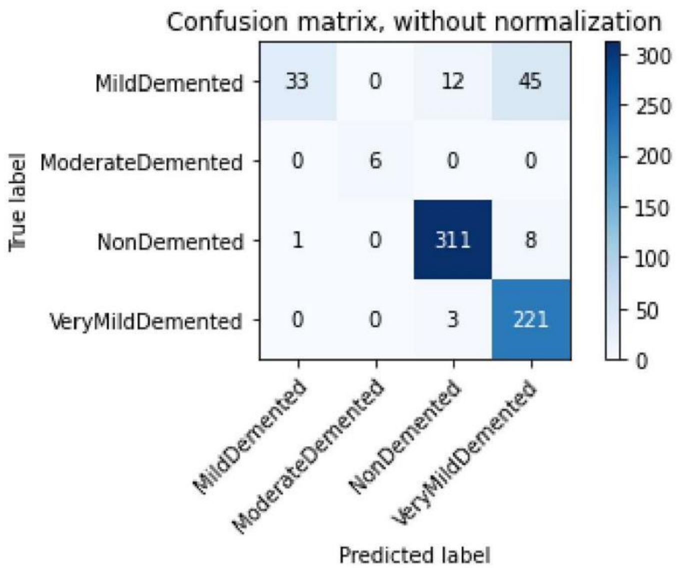
a) Confusion matrix with enhanced images (MobileNet)



b) Confusion matric with enhanced images (DenseNet121)



c) Confusion matrix without enhanced images (MobileNet)



d) Confusion matric without enhanced images (DenseNet121) 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 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.

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