A Survey on Detection of Alzheimer’s Disease from Brain MRI Scans

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Abstract: **Health Coder is a research project aimed at classifying Alzheimer's disease using AI and brain MRI images to help in early diagnosis. The project uses a dataset of 6400 preprocessed MRI images, each resized to 128 x 128 pixels, representing different stages of Alzheimer's. The goal is to develop an AI model that can identify the disease's progression. To achieve this, the MRI images will be preprocessed to improve their quality, reduce noise, and standardize the data. Deep learning models, trained with TensorFlow and Keras, will then classify the images into various stages of Alzheimer's. The models will be optimized for better performance, considering metrics like accuracy, precision, and recall. The performance of different models will be evaluated and compared to determine the most effective one. The results, including the MRI images, predictions, and metrics, will be visualized for easier analysis. The project will also include a detailed report summarizing the methodology, results, limitations, and possible future improvements.**

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.

Key Words: **Alzheimer’s, computer-aided diagnosis, deep learning, DenseNet121, image enhancement, MobileNetV2, Transfer learning, Conventional neural networks, CLAHE, ESRGAN.**

INTRODUCTION

The Alzheimer’s Detection and Stage Prediction System is an AI-driven medical diagnostic application designed to analyze MRI and CT scan images for the early identification and classification of Alzheimer’s disease and its progressive stages. This system employs deep learning techniques, specifically a Convolutional Neural Network (CNN), to classify brain scans into four categories: Frontotemporal Alzheimer (Glioma), Lewy Body Dementia (Meningioma), Vascular Dementia, or Safe (No Alzheimer’s detected). The project is developed using Python, TensorFlow, and Keras, ensuring high accuracy in medical image classification. It features an interactive web-based interface built with Streamlit, enabling users to upload medical images and receive real- time predictions. The backend incorporates model inference and image processing algorithms, ensuring robust performance and reliability. Additionally, the system provides detailed medical insights and treatment recommendations based on the detected condition, making it an efficient tool for early diagnosis, clinical decision-making, and proactive healthcare management. The project structure includes pre-trained models, dataset processing scripts, configuration files, and a modular architecture that supports further enhancements and scalability.

LITERATURE SURVEY

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that deteriorates cognitive functions, with MRI-based diagnosis offering a promising solution. Alwakid et al. (2024) proposed a deep learning-based approach using MobileNetV2 and DenseNet121, achieving accuracy improvements through CLAHE and ESRGAN image preprocessing techniques.

Senan et al. (2022) demonstrated that hybrid techniques combining deep learning (AlexNet, ResNet-18) and machine learning (SVM) achieved superior accuracy (95.10%) in brain tumor classification, highlighting the potential of feature extraction for robust diagnostics.

Breijyeh and Karaman (2020) provided an extensive review of AD pathology and treatments, emphasizing the multifactorial nature of the disease and exploring future directions like disease-modifying therapies. These studies collectively underscore the critical role of advanced imaging, preprocessing, and AI models in enhancing diagnostic precision for neurological disorders, particularly Alzheimer's and brain tumors.

Existing System

The existing systems for diagnosing Alzheimer's disease (AD) and related neurological disorders rely on traditional machine learning and deep learning methods. These systems use brain MRI images as inputs for classification tasks. However, they often lack robust preprocessing techniques, which limits their ability to improve image quality and resolution. Studies like Senan et al. (2022) utilize hybrid approaches combining feature extraction from deep learning models (e.g., AlexNet, ResNet-18) with classifiers like SVM to improve accuracy in brain tumor diagnosis. Similarly, earlier approaches to AD detection often depended on simpler models with limited accuracy and performance metrics. These systems, while functional, lack the integration of advanced image enhancement methods and ensemble deep learning architectures.

Proposed System

The proposed system enhances Alzheimer's diagnosis by applying advanced preprocessing techniques like CLAHE and ESRGAN to improve MRI image quality. It utilizes an ensemble of MobileNetV2 and DenseNet121 deep learning models for effective feature extraction and classification of AD stages. These enhancements lead to improved accuracy (92.34% and 89.38%) compared to traditional methods. The system also visualizes predictions and metrics, ensuring reliable and interpretable results for early detection of Alzheimer's disease.

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 analysing 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 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

Kundaram and Pathak 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. 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.

In another research, Sharma et al. 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. The suggested model achieved an accuracy of 91.75%, a specificity of 96.5%, and an F1-score of 90.25.

Al Shehri 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. 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. 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.

c. *NOVEL FRAMEWORKS AND TECHNIQUES*

Several studies introduced novel frameworks to address specific challenges in AD diagnosis. Puente-Castro et al. 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

D. ADVANCES IN FEATURE EXTRACTION AND CLASSIFICATION

Martinez-Murcia et al. 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. 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.

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.

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. 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. 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.

MobileNetV2 features a total of 19 inverted residual bottleneck layers subsequent to the initial convolution layer, which is composed of 32 filters.

DenseNet improves the effectiveness of deep learning networks by minimizing layer dependencies, which in turn enhances their overall efficiency.

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 forth is 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 , and are assigned corresponding labels from 0 to 3, as seen in Figure 1.

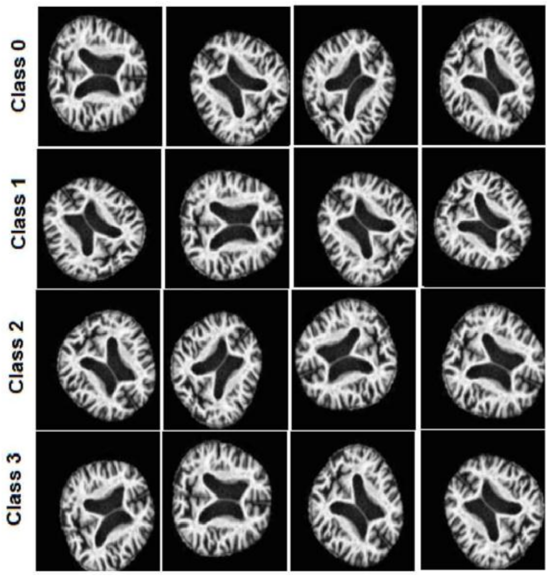

FIG 1. Different classes of AD image dataset.

B. 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 128 *128 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 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 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

$I_{SR} \leftarrow G(I_{LH})$ $D(I_H) \rightarrow 1$

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

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

$L_C(G) \leftarrow$ 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.

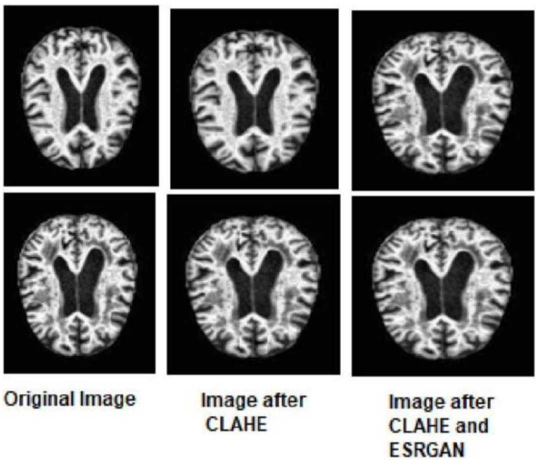

FIG 2. Processed Images of MRI after enhancement.

D. 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.

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. 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).

$$\text{Accuracy} = (1) \quad \frac{tP + tN}{tP + fP + fN + tN}$$

$$\text{Sensitivity} = (2) \quad \frac{tN}{tP + fN}$$

$$\text{Selectivity} = (3) \quad \frac{tN}{tN + fP}$$

$$\text{F1-Score} = 2 \times \frac{\overline{\text{Precision} \times \text{Recall}}}{\text{Precision} + \text{Recall}} \qquad (4)$$

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 128*128 pixels. The TensorFlow Keras 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. There sults 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

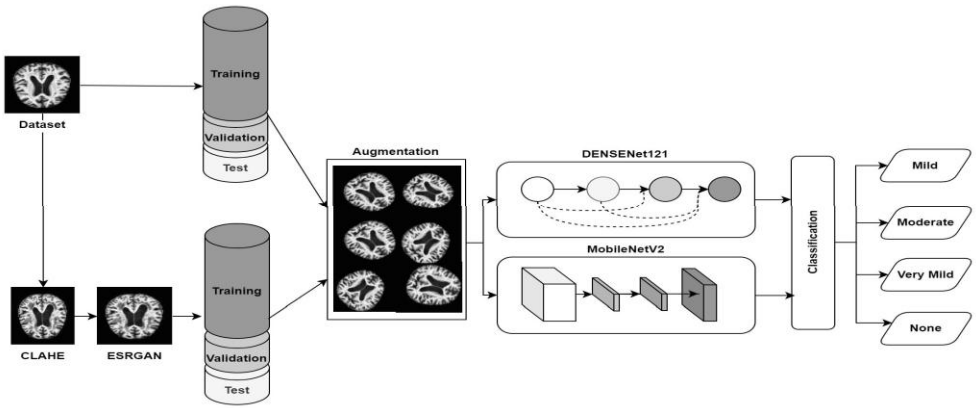

FIG 3. Proposed model with and without image enhancement.

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 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.

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%

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

	Test Accuracy	F1 score	Precision	Re
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

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

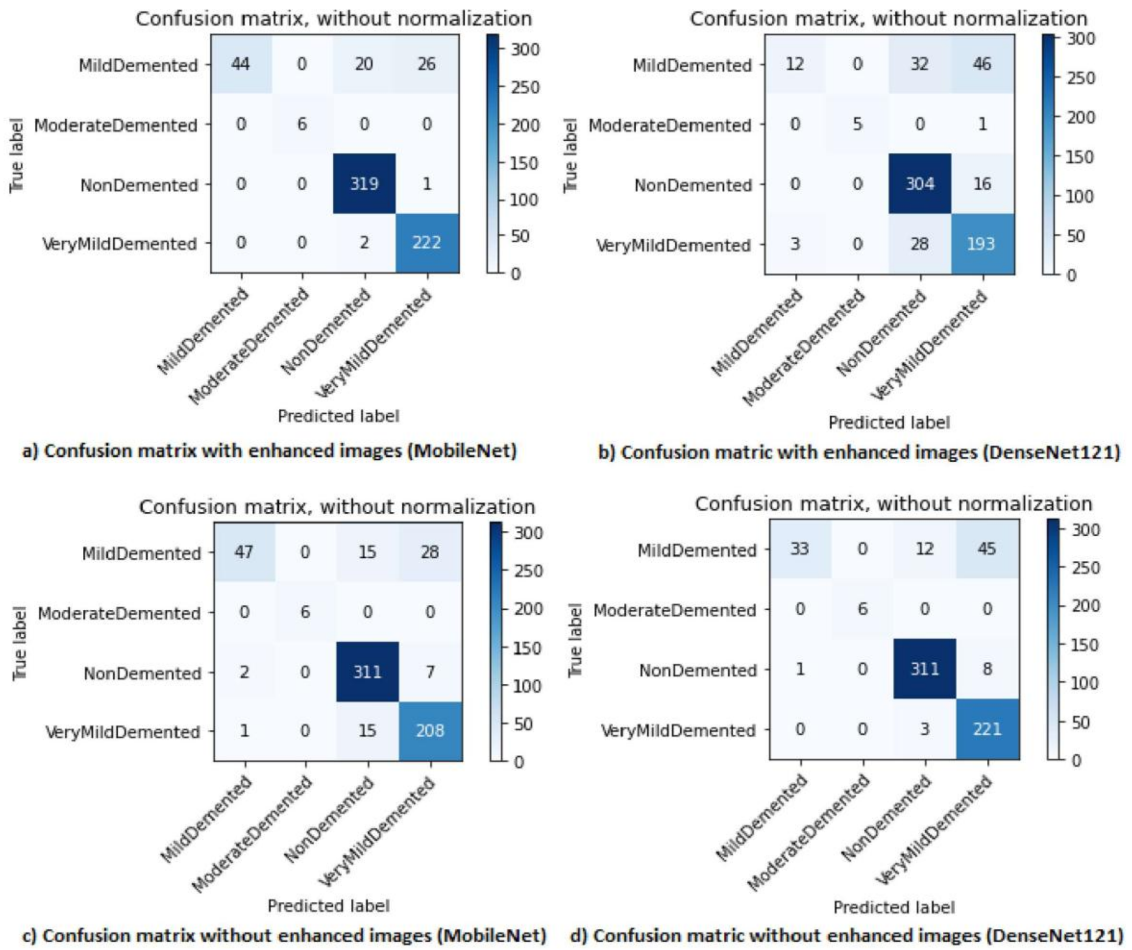

FIG 4. Confusion matrix for Mobilenet and Densenet with enhancement and without enhancement.

less distinct and clear feature representations.

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.

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 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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