



Deep Learning-based Classification of Tomato Leaf Diseases

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ABSTRACT

Background: In the Indian economy agriculture plays important role. Many of the crops are damaged due to diseases, therefore plant leaf disease detection at early stage is important. Tomatoes are the second most consumed vegetable in Indian households, with a rank second largest producer and consumption in world. Tomatoes are of economically important crop in India with large scale cultivation. Yet, unfavourable environmental factors tend to cause numerous diseases due to bacteria, fungi and viruses that infect different plant parts. These diseases cause the yield to be lower, leading to heavy economic losses for the farmers. For effective disease management, it is important to detect the disease in early stage using the advanced techniques for maximising the yielding of crop.

Methods: In the proposed approach, tomato leaf images were first enhanced using CLAHE to improve local contrast, after that data augmentation to increase dataset diversity. Four transfer learning models based on pretrained CNN architecture: VGG16, VGG19, ResNet50 and MobileNetV2, were used as fixed feature extractors, where the pre-trained layers were fixed and newly added classification layers were trained for tomato leaf disease classification. Although transfer learning has been widely applied for tomato leaf disease classification, comparative investigations on the effect of CLAHE-enhanced images across different pre-trained architectures remain limited. This study shows performance of these four CNN architectures under identical preprocessing and training conditions to analyze the influence of CLAHE-based contrast enhancement on disease feature representation and classification performance.

Result: The outcomes of experimental results shows strong classification performance on the plant village dataset for detection of tomato leaf disease, achieving best accuracies of 93.75%, 95.75%, 86.38% and 98.54% using the VGG16, VGG19, ResNet50 and MobileNetV2 models respectively.

Key words: CLAHE, MobileNetV2, ResNet50, VGG16, VGG19.

INTRODUCTION

Detecting plant diseases is of the utmost importance as it paves the way for preventing crop diseases and maintaining the crop quality. Tomato is economically important crop, representing a fair share of dietary needs (Sundararaman *et al.*, 2023). It is among the most widely cultivated horticultural crops. Tomatoes are versatile and hence valuable in many food applications. Tomatoes has rich source of nutrients like vitamin C, vitamin K and antioxidants. Usually, tomatoes are grown throughout the summer season but can be grown throughout the year. However, the diversity of diseases attacking the foliar parts of this plant along with other tissues has threatened both productivity and economic viability in tomato farming (Sundararaman *et al.*, 2023; Attallah, 2023). Generally diseases produced from a different pathogens such as fungi, bacteria and viruses (Kaur *et al.*, 2023) and manifest various symptoms; hence, yield loss and economic hardship among farmers cannot be ignored (Attallah *et al.*, 2023; Pandiyaraju *et al.*, 2024). This investigation considers the most prevalent tomato leaf diseases, as shown in Fig 1 a, b, c, d, e respectively. Disease identification rely heavily on expert visual inspection, which are time-consuming, often subjective and not readily scalable to large-scale agricultural operations (Debnath *et al.*, 2023; Chowdhury *et al.*, 2021). Traditional method depends on the on human observers are inefficient, have poor scalability and are unreliable. To address this challenge, different image

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processing and computer vision techniques have been employed for the automated analysis of plant diseases (Schar *et al.*, 2017; Al Farid *et al.*, 2022). In addition, machine learning-based intelligent systems have been developed to enable automatic disease detection that provide timely intervention and improved crop management practices that contribute to enhanced agricultural productivity (Islam *et al.*, 2022).

Deep learning (DL) is a subfield of artificial intelligence and this has drastically transformed the character of image analysis and classification procedures (Wagle and Harikrishnan, 2021; Zhang *et al.*, 2018). DL architecture, in general and the convolutional neural network (CNN) in particular, are self-learning in obtaining complex patterns and features from data in images which may lead to developing dependable and efficient strategies in the identification of diseases on the leaves of the tomato (Wagle and Harikrishnan, 2021; Zhou *et al.*, 2021). Many studies have proven the success of CNNs in classifying a wide range of plant diseases, including those of tomato leaves (Attallah *et al.*, 2023; Wagle and Harikrishnan, 2021). For leaf image classification deep learning CNN model are always better choice as compared to conventional ML algorithms as it is computationally efficient, providing highest accuracy and faster processing times. CNN are useful to automatically detect important features from the input images without manual feature extraction or human supervision. This allows them to learn hierarchical patterns and complex structures in the data, making them highly effective for leaf classification. Performance of the model can be improve by image enhancement and augmentation technique.

For the purpose of giving the accurate and efficient method in detecting and predicting the development of tomato leaf diseases. For image enhancement contrast limited adaptive histogram equalization (CLAHE) is use and augmentation technique use to expand the dataset. After that CNN architectures such as VGG16, VGG19, ResNet50 and MobileNetV2 are used for the disease classification.

Plant village dataset is use in this study for comparing different transfer learning (TL) architectures by using identical preprocessing and training conditions. Although the extensive research on tomato leaf disease classification using transfer learning, most existing studies focuses on evaluating individual CNN architectures or proposing new architectures. Limited research has been given to systematically investigating the impact of CLAHE-based image enhancement across multiple pre-trained architectures under identical experimental settings. This study addresses this gap by providing a comprehensive comparative analysis of VGG16, VGG19, ResNet50 and

MobileNetV2, highlighting how contrast enhancement influences feature extraction and classification performance.

Major contributions of this work are:

1. A systematic evaluation of CLAHE-based contrast enhancement for tomato leaf disease classification using four different TL architectures.
 2. An analysis of how image enhancement and augmentation affect feature learning and classification performance.
- A comparative study of lightweight MobileNetV2 and deep architectures: VGG16, VGG19 and ResNet50 under identical training conditions.
3. An investigation into architecture-specific behavior for tomato disease recognition, highlighting the strengths and limitations of each model.

The organization of paper as follows:

The literature review section provides prior research in the field of identification and classification plant disease. The proposed methodology section provides the propose methodology for the classification of tomato leaf disease. The results and discussion section provides an analysis of work. Lastly, the conclusion section summarizes the study.

Literature survey

The traditional methods for detection of plant disease are mainly based on the texture, shape, color and other features of the disease spots for extraction. The technique has low identification efficiency since it relies on a vast amount of expert knowledge in agricultural diseases. Now artificial intelligence (Rangarajan *et al.*, 2018) has proved to be very effective in upgrading the discipline of plant science, ML and DL strategies have emerged as the two most popularly explored methodologies for the detection plant diseases. Most of the existing methods for plant disease analysis are based on disease classification (Mane and Rangarajan, 2017; Patil and More, 2025). Mehta *et al.* (2025) presented reviews on by using DL frameworks to perform plant disease classification, thereby powering smart farming operations. Nigam and Jain (2020) have evaluated a wide variety of deep learning algorithms for plant disease detection and identification. It was found by them that CV, ML and DL applications greatly increased classification

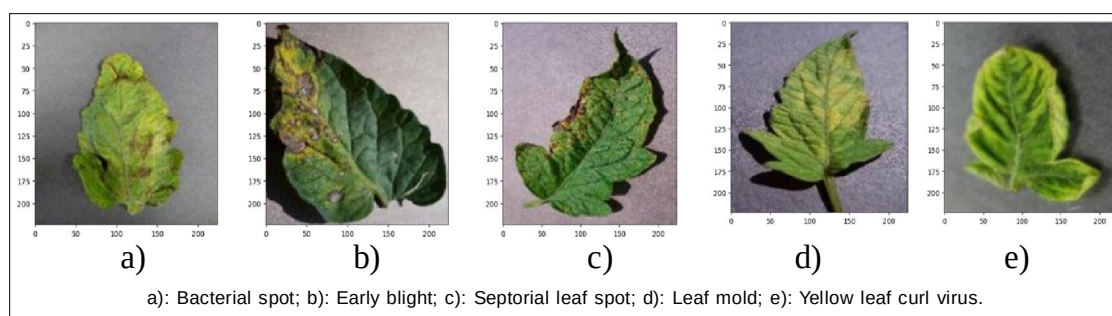


Fig 1: Tomato leaf diseases.

accuracies, which led to more intelligent decision-making in agricultural applications. This section reviews recent and prominent studies focusing on automatic disease identification systems, focusing on novel, design-oriented frameworks and their applications to overcome challenges in this area of study.

Tm *et al.* (2018) proposed three-phase methodology, which is the collection of images of tomato leaf from plant village dataset, data pre-processing with normalization and disease classification using a modified LeNet CNN. The proposed model obtained accuracy of 94-95% that surpassed the AlexNet and GoogleNet models. ResNet (Ahmad *et al.*, 2020) has more layers of convolution than VGG16, which means it can better extract the details of objects. Its layer-skipping structure skips layers and overcomes the gradient vanishing problem due to deep stacking. VGG16 fails to extract detailed features for tomato leaf diseases (Aversano *et al.*, 2020). The deep residual network uses feed-forward neural network residual connections such that layer outputs become inputs to subsequent layers, hence improving efficiency without adding any variables or considerably increasing computation time.

Deng *et al.* (2021) utilized generative adversarial networks (GANs) to augment the dataset and trained different network and evaluating their performance on a test set. Kanda *et al.* (2022) described the use of four diversity levels: Depth size, discriminative learning rates, training-validation split ratios and batch sizes. It reached F1 score:99.5%, surpassing the performance of most existing tomato leaf disease recognition methods. Further testing is conducted on the Flavia leaf image dataset to obtain a 99.23% F1 score, signifying the reliability and efficiency of the proposed approach. Peng *et al.* (2023) has described a new classification network for tomato leaf disease that combines the dense inception MobileNet-V2 with a parallel convolutional block attention module. The original images of five tomato leaf diseases were expanded to 8190 using data augmentation from 1256. An improved bilateral filtering and threshold function algorithm IBFTF was proposed to effectively filter noise out. While Dense Inception focuses on most intra-class variability but negligible inter-class differences, the PCBAM enhanced MobileNet-V2 minimizes the effects of background complexity. Empirical experiments show that the DIMPCNET achieves an accuracy of 94.44% with an F1-score of 0.9475. Siddiky *et al.* (2024) applied the deep learning and image processing to enhance the detection of diseases and, therefore, food security. Five models were applied: MobileNet, ResNet50V2, Xception, InceptionV3 and VGG19. The five models were trained on 83,568 images of tomato leaves. The best validation accuracy was achieved by MobileNet at 91%, followed by the others. Chowdhury *et al.* (2021) applied EfficientNet for tomato leaf disease classification in three scenarios: Two-class (healthy vs. unhealthy), six-class labels (segmented) and ten-class labels. The Adam optimizer achieved 99% accuracy for this

task. Tan *et al.* (2021) compared traditional machine learning techniques including KNN, SVM and RF with deep learning architectures like AlexNet, VGG16, ResNet34, EfficientNet and MobileNetV2 on the plant village dataset. Classical approach methods have achieved the accuracies between 82.10%-91.00%, whereas the deep learning model achieved the highest accuracy between 91.20% to 99.70% . Sharma *et al.* (2025) proposed deep learning ensemble model based on MobileNetV2 and ResNet50 is presented for classifying the tomato leaf diseases. By training it on a Kaggle dataset consisting of 11,000 images covering 10 disease classes, the model was able to achieve state-of-the-art performance with 99.91% test accuracy. Adding layers and merging of feature maps improved the ability to extract features and reduce false classifications. This strategy enables the early detection of plant diseases, by reducing crop losses and promoting smart and sustainable agricultural practices. Vinothini *et al.* (2025) developed a transfer learning-based deep learning model for the classification of tomato leaf diseases. In both the balanced setup and imbalanced setup, 4 models (AlexNet, LeNet-5, DenseNet-121 and InceptionV3) were trained using different sampling methods. The enhanced AlexNet-based model presented the best performance with accuracy, precision, recall and F1-score of 95%. This system provided a dependable means for early disease identification to help enable efficient crop management and sustainable agriculture practice. Mezenner *et al.* (2025) proposed a novel fuzzy aggregation-based CNN ensemble model for tomato leaf disease classification. First, five deep learning models VGG16, ResNet152V2, MobileNetV2, InceptionV3 and DenseNet201 are pre-trained separately where different feature extractors of each model are used. These models are aggregated via a newly proposed fuzzy Max-Sum integral derived from the fuzzy convex combination operator.

MATERIALS AND METHODS

The experimental work was carried out at the MPSTME Shirpur, Maharashtra. The study utilized the publicly available PlantVillage dataset for tomato leaf disease classification. The experimental work was conducted during the period from May 2025 to December 2025. Diseases of tomato leaves considerably reduce agricultural productivity, causing substantial economic problems to the growers. In this context, we highlight the critical necessity of timely and accurate disease diagnosis by using proposed architecture as shown in Fig 2.

The proposed method comprises the following components:

Dataset and pre-processing

This study utilized a dataset comprising images of tomato plants affected by various diseases, serving as a valuable foundation for analysis and research. For this work Plant village dataset (PlantVillage, 2024) is used that is available on Kaggle. We choose tomato leaves images of 6 classes. Class 0: Bacterial spot, Class 1: Early blight, Class 2:

Healthy, Class 3: Septoril leaf spot, Class 4: Leaf mold, Class 5: Yellow leaf curl virus, there count is as shown in Fig 3, out of this 7245 images used for training, 1355 images used for validation and 448 images used for testing.

Pre-processing of the images is important step before to applying the actual model, as it helps to further improve the effectiveness of the model. In this work CLAHE is used as described in Algorithm 1. This technique applied on all images in the dataset. It enhances disease features like spots, discoloration, or blight, making them more prominent, reduces the effects of uneven lighting in image and help to improves model performance, especially for models relying on color and texture features. Fig 4 shows tomato leaf images before and after applying CLAHE for each class. This approach was chosen since tomato leaf disease is usually described

through various changes in texture, coloring and lesion boundaries, which may not be sufficiently reflected in the image itself. The use of CLAHE will help improve the local contrast of an image without over-amplifying the noise present.

When we are working with limited data size data augment helps to increase the size of the original dataset. This approach helps strengthen the model's ability to generalize effectively, reduce overfitting and speed up the training. The data augmentation was only done on the training dataset, not on the validation and test datasets, in order to measure the performance of the model precisely. The same technique had been proved repeatedly to be enhancing the performance of deep learning models and their generalization. The augmentations that were done by using height shift, width shift, rotation

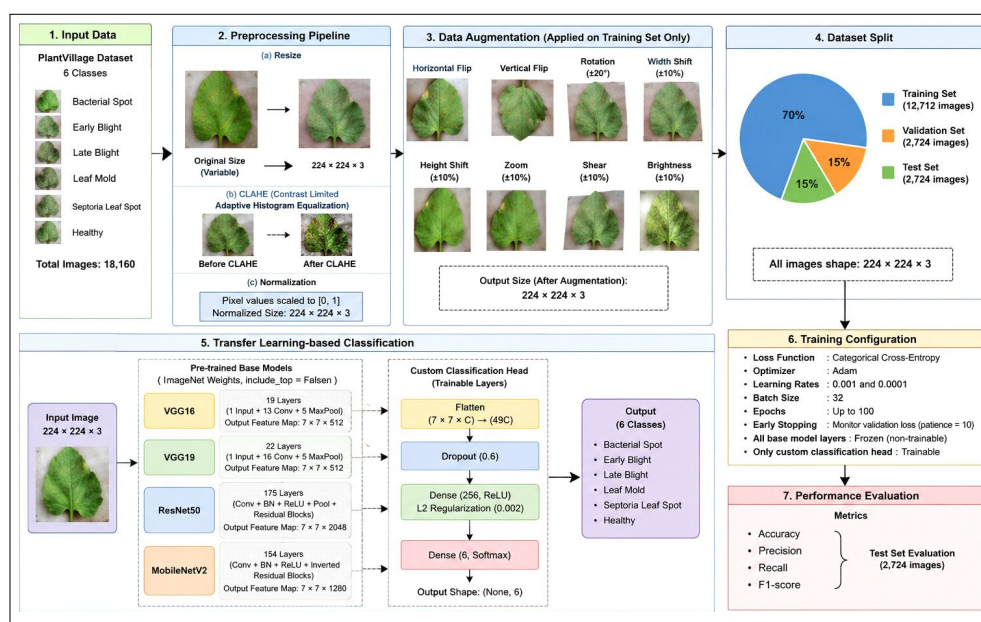


Fig 2: Overall architecture of proposed approach.

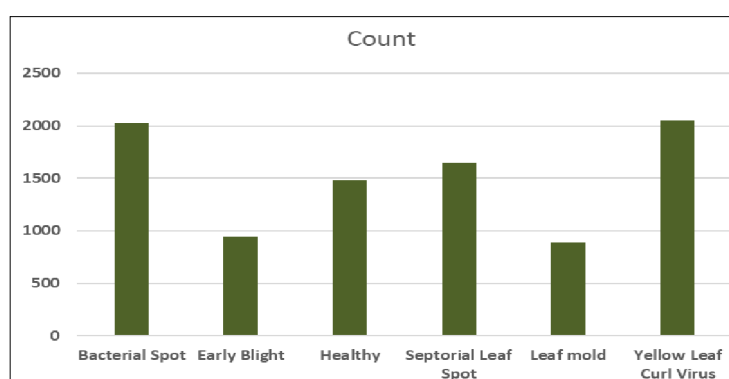


Fig 3: Class wise image count in original dataset.

and zooming. After augmentation training images increases from 7245 to 26658.

Algorithm 1: CLAHE algorithm.

Input

I: Input image.

N: Number of tiles per row and column ($N \times N$).

Cliplimit: Maximum allowed histogram count before clipping.

NB: Number of bins for histogram.

1. Initialize parameters

Divide the image I into ($N \times N$).

$T_{i,j}$ = The tile at position (i, j).

2. For each tile $T_{i,j}$

Calculate histogram $H_{i,j}$ of the tile using NB bins.

Clip the histogram

If any bin $H_{i,j}(k) > \text{cliplimit}$, redistribute excess counts equally to all bins while maintaining the total count.

Normalize the histogram:

$$H_{i,j}^{\text{norm}}(k) = \frac{H_{i,j}(k)}{\sum_{k=0}^{NB-1} H_{i,j}(k)}$$

Calculate the cumulative distribution function (CDF):

$$\text{CDF}_{i,j}(k) = \sum_{i=0}^k H_{i,j}^{\text{norm}}(i)$$

Map the pixel values of $T_{i,j}$ to the enhanced range:

$$P_{\text{new}} = \lfloor \text{CDF}_{i,j}(\text{Pold}) \cdot (NB - 1) \rfloor$$

Where,

Pold= The original pixel value.

P_{new} = The enhanced value.

3. Perform interpolation

Use bilinear interpolation:

$$I_{\text{enhanced}}(x, y) = w_1 \cdot T_{i,j} + w_2 \cdot T_{i+1,j} + w_3 \cdot T_{i,j+1} + w_4 \cdot T_{i+1,j+1}$$

Where,

w_1, w_2, w_3, w_4 = The weights based on the relative distance of (x, y) to the centers of the neighboring tiles.

4. Output: I_{enhanced} : Enhanced image

Deep learning architectures

We employed four pre-trained CNN architectures-VGG16, VGG19, ResNet50 and MobileNetV2-for tomato leaf disease classification. The pre-trained models were initialized with ImageNet weights using the include_top=False configuration, which removes the original ImageNet classification layer while retaining the convolutional feature extraction layers. Transfer learning was adopted to leverage the generic visual features learned from the large-scale ImageNet dataset. To preserve the generic visual features learned during pre-training and reduce computational complexity, all layers of the pre-trained base networks were frozen during training. Specifically, the VGG16 base model consisted of 19 layers (1 input layer, 13 convolutional layers and 5 max-pooling layers), while the VGG19 base model consisted of 22 layers (1 input layer, 16 convolutional layers and 5 max-pooling layers), all of which were set as non-trainable. Similarly, the complete pre-trained base networks of ResNet50 (175 layers) and MobileNetV2 (154 layers), comprising convolutional, batch normalization, activation, pooling and residual/inverted residual layers, were entirely frozen. Consequently, only the newly added classification head, consisting of a Flatten layer, a Dropout layer (0.6), a Dense

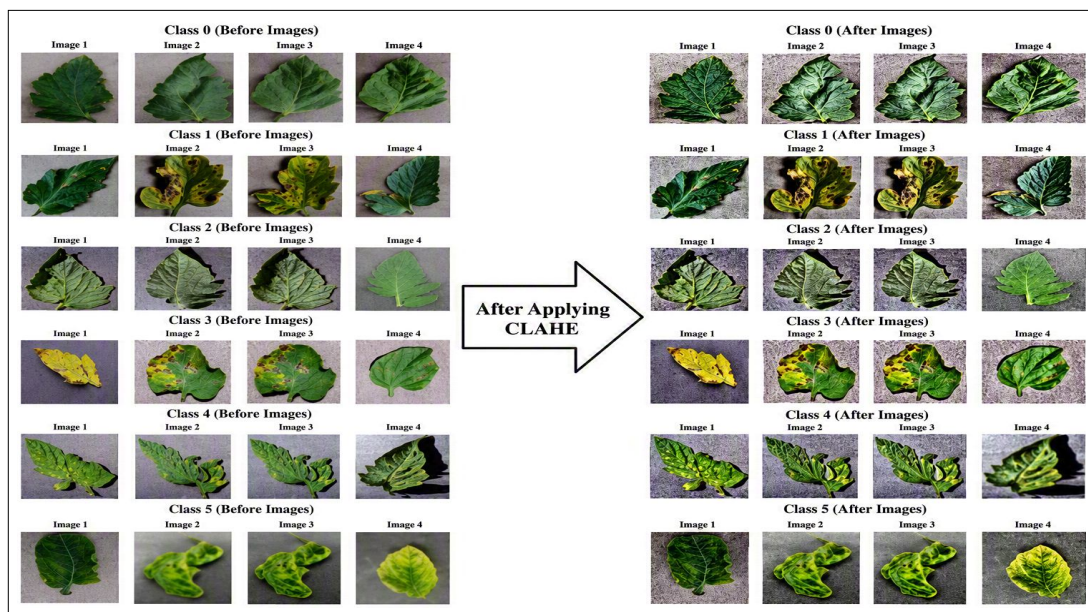


Fig 4: Before and after applying CLAHE.

layer with 256 neurons using ReLU activation and L2 regularization (0.002) and a Softmax output layer with six neurons, was trained using the tomato leaf dataset. For each architecture, a custom classification head was appended to the frozen base network. The classification head consisted of a flatten layer, followed by a dropout layer with a dropout rate of 0.6 to reduce overfitting. A fully connected dense layer with 256 neurons, ReLU activation function and L2 regularization was added to improve feature learning and enhance model generalization. Finally, a Softmax output layer with six neurons was used to classify the tomato leaf images into the six disease categories. For training, Adam optimizer was chosen with the learning rates: 0.001 and 0.0001 to observe the impact of varied optimization techniques. With the learning rate of 0.001, the training process converges quickly; however, the use of learning rate 0.0001 provides slow updates to the weights. Due to the fact that the task is about multi-class classification, the categorical cross-entropy loss function was utilized. Each model was trained for a maximum of 100 epochs with early stopping to prevent overfitting. Model performance was evaluated on the test dataset using accuracy, precision, recall and F1-score and the results of all four architectures were compared to identify the most effective model for tomato leaf disease classification.

RESULTS AND DISCUSSION

This work assesses the performance of different fine-tuned pre-trained models for the classification of tomato leaf diseases, CLAHE for pre-processing and data augmentation methods to improve the dataset. Table 1 and 2 illustrate the performance of four CNN architectures-VGG16, VGG19, ResNet50 and MobileNetV2-on a classification task with varying learning rates LR=0.001 and 0.0001 respectively. The performance is measured using three common metrics: Precision, recall and F1-score, on six classes. Table 3 shows the accuracy comparison of CNN models at different learning rates. All model shows outstanding performance at LR=0.001. VGG 16, VGG19, ResNet50 and MobileNetV2 achieved 93.75 %, 95.75%, 86.38% and 98.54% accuracy.

From the above experiment findings, it is clear that deep learning models that have been pretrained are highly effective in detecting tomato leaf diseases. The application of CLAHE pre-processing led to increased image contrast, feature extraction and overall model performance. Data augmentation was applied to solve the problem of imbalanced classes in the data set, hence increasing the overall robustness of the model. From among the models tested, the MobileNetV2 model proved to be the most effective, recording high accuracy and F1-scores.

VGG19 also performed well, especially at high learning rates, showing its capability to work in high precision applications. ResNet50 worked as a feature extractor and could not adapt its deep residual features to the tomato leaf disease dataset, which may have resulted in

Table 1: Performance measure (LR =0.001).

Class	VGG16			VGG19			ResNet 50			MobileNetV2		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
0	0.97	0.97	0.97	0.97	0.99	0.98	0.96	0.85	0.9	0.99	0.99	0.99
1	0.97	0.83	0.89	0.91	0.87	0.89	0.85	0.48	0.61	0.94	0.96	0.95
2	0.93	0.97	0.95	0.97	0.97	0.97	0.91	0.96	0.93	0.97	0.97	0.97
3	0.86	0.99	0.92	0.95	0.96	0.96	0.78	0.95	0.86	0.96	0.99	0.98
4	0.93	0.86	0.89	0.93	0.93	0.93	0.86	0.73	0.79	0.98	0.95	0.97
5	0.97	0.92	0.94	0.97	0.96	0.97	0.84	0.97	0.9	0.99	0.97	0.98

Table 2: Performance measure (LR =0.0001).

Class	VGG16			VGG19			ResNet 50			MobileNetV2		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
0	0.97	0.95	0.96	0.96	0.95	0.96	0.82	0.86	0.84	0.99	0.96	0.97
1	0.89	0.87	0.88	0.83	0.87	0.85	0.49	0.41	0.45	0.94	0.98	0.96
2	0.91	0.96	0.93	0.86	0.99	0.92	0.89	0.89	0.89	0.97	0.99	0.98
3	0.86	0.98	0.91	0.96	0.93	0.94	0.69	0.9	0.78	0.95	0.96	0.96
4	0.92	0.82	0.87	0.98	0.95	0.97	0.96	0.57	0.71	0.93	0.95	0.94
5	0.97	0.9	0.93	0.98	0.9	0.94	0.91	0.86	0.88	0.99	0.97	0.98

Table 3: Accuracy comparison.

Models	LR=0.001	LR=0.0001
VGG16	93.75	92.41
VGG19	95.75	93.3
ResNet50	86.38	79.91
MobileNetV2	98.54	96.87

underfitting and reduced classification performance. ResNet50 functioned as a fixed feature extractor and could not adapt its deep residual features to the tomato leaf disease dataset, which may have resulted in underfitting and reduced classification performance. Learning rate was equally critical in optimizing the model as well. High learning rates were found to give better performance in all cases, showing faster optimization without overfitting, while low learning rates gave poorer performances especially with minority classes.

CONCLUSION

The present work highlights the classification of tomato leaf diseases using DL algorithms which is essential in prevention of agriculture losses. CLAHE technique used for pre-processing and data augmentation techniques for expanding the dataset. The suggested method achieved impressive levels of classification accuracy. MobileNetV2 algorithm provided the best results by obtaining accuracy level of 98.54% which makes it extremely suitable for low resource settings such as mobile devices.

Even though the promising results were obtained in this research, there are certain limitations of this research. Experiments were conducted on the PlantVillage dataset which consists of laboratory acquired images and thus does not entirely represent the variety of images in a real-life agricultural setting. Further research will include conducting experiments on tomato leaf datasets obtained in the field, studying the influence of partial fine-tuning of high layers, using explainable artificial intelligence methods such as Grad-CAM to increase the model interpretability.

Conflict of interest

The authors declare no conflicts of interest of any kind.

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