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# Leaky ReLU-ResNet for Plant Leaf Disease Detection: A Deep Learning Approach †

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**Abstract:** Plant diseases can result in significant yield losses, posing a threat to food security and economic stability. Deep neural networks, particularly Convolutional Neural Networks (CNNs), have shown exceptional success in image classification tasks, often surpassing human-level performance. However, conventional methods for leaf disease detection relied on manual inspection by agricultural experts, leading to limited scalability and precision. To tackle these challenges, this research introduces a novel approach called the Leaky Rectilinear Residual Network (LRRN) for plant leaf disease detection. The LRRN model comprises three key modules—data pre-processing, feature extraction, and classification. It integrates ResNet architecture with the Leaky ReLU activation function to classify plant diseases. Experimental evaluations were performed on affected plant leaf disease images from the Plant Village dataset, utilizing performance evaluation metrics to assess the proposed model. The achieved results were compared to state-of-the-art techniques, demonstrating superior accuracy (94.56%), precision (93.48%), F1-scores (92.83%), recall (93.12%), and specificity (92.58%). These findings substantiate the effectiveness of the proposed LRRN method of plant leaf disease detection.

**Keywords:** ResNet; Leaky ReLU; plant disease; deep learning; disease detection; feature extraction; pre-processing



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## 1. Introduction

Agriculture serves as the backbone of human civilization, providing sustenance and nourishment to billions of people worldwide. However, crop productivity faces significant challenges due to the emergence and spread of plant diseases [1]. Plant disease caused by pathogens, namely bacteria, fungi, viruses, and other factors, can lead to substantial yield losses, threatening food security and economic stability. Early, as well as accurate, detection of leaf diseases is crucial to mitigate their impact and ensure timely interventions for effective crop management [2]. Identifying and classifying plant leaf diseases manually a is time-consuming and labor-intensive task often prone to human errors and subjectivity. Traditional approaches to leaf disease detection relied on manual inspection by agricultural experts, which limited the scalability and precision of the process. Furthermore, these approaches struggled with handling the large data volumes generated from various crop fields and regions worldwide [3].

The advent of deep learning and its potential in image recognition opened new avenues for addressing these challenges. Deep neural networks, particularly CNNs, have demonstrated remarkable success in image classification tasks, surpassing human-level performance in many cases. However, applying standard CNNs to complex and diverse leaf disease patterns poses unique challenges [4]. The introduction of ResNet [5] marked a significant breakthrough in deep learning architecture. ResNet addresses vanishing gradient issues, which hinder the training processes of deep networks, by employing skip connections or residual blocks. Residual blocks in ResNet utilize a "shortcut" connection that adds the input directly to the output of one or more convolutional layers. This innovation not only enables the network to capture rich and complex features but also promotes better convergence and performance [6].

While ResNet effectively addresses the vanishing gradient problem, standard ReLU activation functions in deep neural networks. Neurons with negative inputs output zero and remain inactive during training, limiting their learning capacity in certain cases. To overcome this limitation, the Leaky ReLU activation function was proposed as a variant of ReLU. Leaky ReLU introduces a small negative slope (usually a small fraction like 0.01) for negative input values. The small negative slope allows the activation to be non-zero for negative inputs, ensuring the flow of gradients and preventing neurons from becoming entirely inactive [7]. The combination of ResNet and Leaky ReLU, referred to as Leaky ReLU ResNet, synergistically addresses the challenges in leaf disease detection. By incorporating Leaky ReLU activations, the model ensures better learning in the presence of negative inputs, overcoming the dying ReLU problem and promoting smooth gradient flow during training [8]. The Plant Village dataset serves as an invaluable resource for training and evaluating the Leaky ReLU ResNet model. Comprising high-resolution leaf images of multiple crops and diseases, the dataset captures the diversity of leaf disease patterns encountered in real-world agricultural settings [9].

Recently, advanced technologies in deep learning and computer vision have shown immense potential for transforming agricultural practices. One such promising application is the use of deep neural networks for plant leaf disease detection. Among various deep learning architectures, Residual Neural Network (ResNet) has emerged as a powerful and effective model for image recognition tasks [10]. This work aims to develop the potential of Leaky ReLU ResNet for the detection of plant leaf diseases, utilizing the widely used Plant Village dataset, a rich and diverse collection of leaf images infected with multiple diseases. By exploring the benefits of Leaky ReLU ResNet, this research endeavors to advance agricultural diagnostics and contribute to sustainable crop management [11]. The contribution of the work is outlined as follows:

- **Advancement in Disease Detection Accuracy:** The use of the Leaky ReLU ResNet architecture enhances accuracy. By utilizing the power of deep learning and incorporating Leaky ReLU activations, the model can effectively learn from complex and diverse leaf disease patterns, leading to improved classification performance.
- **Effective Utilization of the Plant Village Dataset:** The use of the widely used Plant Village dataset enables the training and evaluation of the Leaky ReLU ResNet model on a diverse set of leaf images infected with various diseases. The model's performance can be comprehensively assessed, showcasing its efficacy across different plant species and disease types.
- **Enhanced Crop Management and Disease Mitigation:** The accurate and early detection of leaf diseases is crucial for effective crop management and disease mitigation. The proposed model's ability to identify diseases in their early stages enables timely intervention, minimizing crop losses, as well as increasing agricultural productivity.

The paper organization of this research work is explained as follows: The literature review of plant leaf disease detection is described in Section 2, which contains certain state-of-the-art techniques related to the detection of disease using deep learning approaches, the drawbacks and challenges of the existing papers, and research gaps in this paper. Section 3 demonstrates the methodology proposed in this research paper, with different methods used to achieve high performance. The experimental discussion section is depicted in Section 4, and the experimental analysis is conducted by applying graphical representations, performance evaluations, and comparative analyses. Finally, this plant leaf disease detection paper is concluded in Section 5, which discusses future works.

## 2. Related Works

In recent years, the advent of deep learning has transformed the field of computer vision, providing powerful tools for automated disease detection. The different approaches that have been extensively explored in the literature for plant leaf disease detection are reviewed in the following section.

### 2.1. Plant Leaf Disease Detection Using Deep Learning

Various CNN architectures, such as LeNet [12] (Saleem et al.), AlexNet (Alruwaili et al.) [13], VGG (Hassan et al.) [14], GoogLeNet (Saleem et al.) [15], and DenseNet (Jiang et al.) [16], have been employed for disease classification, showcasing their potential in learning complex disease patterns. Transfer learning, where pre-trained CNNs are fine-tuned for plant disease detection, has been widely adopted to enhance model performance, as was performed by Lu et al. [17], especially when labeled data are limited. Dhaka et al.'s [18] use of benchmark datasets like Plant Village has facilitated the evaluation and comparison of different deep learning models. However, challenges persist, such as limited data availability for certain plant species and the need for interpretable AI methods to build trust in decision-making. Nevertheless, continuous research into and the innovation of deep learning approaches offer valuable tools for precision agriculture and sustainable crop management.

### 2.2. Plant Leaf Disease Detection Using ResNet

Residual Neural Networks (ResNet) have emerged as a popular choice for the detection of plant leaf disease, according to research over the past few years by Mostafa et al. [19]. ResNet's ability to train deep networks effectively, preventing vanishing gradient issues, has demonstrated its advantages in accurately classifying plant diseases from leaf images. Zhong et al. [20] have applied ResNet as a base architecture in various approaches for performing disease identification tasks. ResNet-based models have outperformed traditional CNNs in certain disease classification scenarios, highlighting their efficacy in learning complex disease patterns. Studies have utilized transfer learning techniques employed by Saeed et al. [21], fine-tuning pre-trained ResNet models, to enhance model performance with limited labeled data. The utilization of benchmark datasets, such as Plant Village and domain-specific datasets, has facilitated the evaluation and comparison of ResNet-based approaches, as utilized by Hassan et al. [22]. Despite successes, challenges remain, including addressing class imbalance in disease datasets and ensuring model interpretability for decision-making in agriculture. Nevertheless, ResNet-based approaches offer potential advancements in sustainable agriculture and disease management, contributing to improved crop yield and global food security.

## 3. Proposed Methodology for Plant Leaf Disease Detection Using Leaky ReLU-ResNet

The overall architecture of this proposed method is shown in Figure 1, which includes various modules to achieve exact plant leaf disease. Initially, the affected leaf image is obtained from the Plant Village dataset. Then, the acquired image is pre-processed, and the features are extracted and classified using the Leaky Rectilinear Residual Network. Finally, the image is categorized into two groups, namely healthy or not healthy.

### 3.1. Data Pre-Processing Phase

This mechanism is used to enhance the images' quality and make them convenient for further processing via the model. Sometimes, due to the insufficient lighting of the dataset images, the leaf disease spots may not be visible [23]. Some of the methods used in data pre-processing are described below:

- **Resizing and Scaling**: The nonuniformity of the images sometimes causes computational complexity; to solve these complexities, the images are resized to a standard size, and the uniformity is maintained in the dataset. For maintaining the value of pixels within a particular limit, the technique of scaling is used.

- **Data Augmentation**: this technique is used to expand the training set when there is a need for a large dataset, as the small training set has the issue of overfitting [24].
- **Noise Reduction**: There were artifacts or noises present in the images captured from nature. For increasing the quality of the images and reducing the noise, denoising filters can be used.

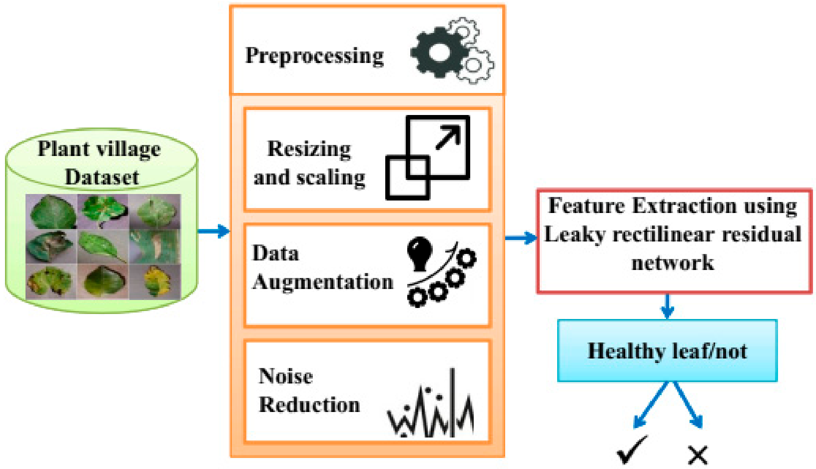


**Figure 1.** The overall architecture of the LRRN model.

*3.2. Feature Extraction and Classification Phase*

Feature extraction based on the image is the process of converting raw data into numerical features that contain the information in the raw data. These numerical features can be easily used as inputs for the machine learning algorithms. The classification and feature extraction steps are implemented by applying the LRRN model proposed in this section. It effectively extracts appropriate data properties, such as irregular color, texture, structure, and size of leaf, and accurately categorizes them based on plant leaf characteristics. The techniques employed for detecting plant leaf disease are independently clarified in the following subsections.

(1) ***ResNet*:** ResNet [25] stands for Residual Neural Network, which comprises 50 deep layers, and it is also a convolutional neural network. The ResNet model consists of five stages, which include both convolutional and identity blocks.

$$J(y) = M(y) + y \tag{1}$$

In Equation (1), $y$ signifies to the input image, $M(y)$ signifies the nonlinear layers' fitting mappings, and $J(y)$ signifies the residual mapping.

(2) ***Leaky ReLU Activation Function:*** In deep learning, ReLU is a normally applied activation function [26]. The mathematical expression of the ReLU is represented as follows:

$$\mathrm{Re}LU = \begin{cases} 0, w < 0 \\ w, w \geq 0 \end{cases} \tag{2}$$

It suggests the usage of Leaky ReLU to overcome the Dead ReLU issue related to the ReLU function. Leaky ReLU introduces a small negative slope for negative input values, allowing gradients to flow even for negative inputs. Mathematically, the Leaky ReLU activation function is defined. The mathematical formulation of the Leaky ReLU is represented as follows:

$$f(w) = \begin{cases} w, w \geq 0 \\ bw, w < 0 \end{cases} \tag{3}$$

During model training, the parameter '$b$' is unevenly produced and finally becomes a static value. When maintaining certain non-positive gradient data to avoid total loss, this process allows one-sided restraint. The Leaky ReLU is used to reshape and concatenate each layer and restricts the determination of deadly tissues in plants. The non-zero output values are generated to determine a negative input value when huge noise is obtained, and it avoids the leakage of data. The performance is enhanced by reducing the unwanted noise obtained in the image. The training of each image is performed individually for better detection.

(3) ***Proposed LRRN for Plant Leaf Disease Detection:*** The advanced technologies in deep learning and computer vision have shown enormous potential in changing agricultural practices. Among various deep learning frameworks, ResNet has emerged as a powerful and effective model for image recognition tasks. This work aims to improve the ability of LRRN to detect plant leaf diseases using the widely used Plant Village dataset, a rich and diverse collection of leaf images affected by multiple diseases. By exploring the benefits of Leaky ReLU ResNet, this study attempts to advance agriculture. The proposed LRRN-based binary classification classifies plant leaf disease detection. As a result, the detected disease in the plant leaf is accurately classified. This classification method can be integrated via two techniques, namely ResNet and the Leaky ReLU activation function. Using the classification function, the leaf detection accuracy is high. Due to some specific advantages of Leaky ReLU that can be incorporated with ResNet, such as quicker computation speed and execution, it does not need exponential solutions. ResNet is used to solve the problem of deep networks. Deep networks have many hidden layers, so they fail in network coverage and suffer from low performance and local minimum resolution. Therefore, ReLU is combined with ResNet to improve the training ability of deep networks, prevent vanishing gradient problems, and enhance the convergence and performance.

### 3.3. The Modified ResNet Model

ResNet is used to solve the problem of deep networks. Deep networks have many hidden layers, so they fail in network coverage and suffer from low performance and local minimum resolution. Leaky ReLU activity has been used to improve the detection of plant diseases by reducing the deficiency of ReLU activity. However, this does not work for non-positive inputs. The slope of the neuron never updates its weight if the value of the neuron is zero, so the neuron does not become activated. The convergence of the model is more difficult when the network has a huge number of networks. To prevent the possible loss of input information, Leaky ReLU is utilized instead of ReLU. Leaky ReLU adds an alpha parameter to the semi-axis of ReLU, resulting in a small but non-zero slope. Nodes that were previously inactive with ReLU will now adjust their weights. Therefore, ReLU is combined with ResNet to improve the training ability of deep networks, prevent vanishing gradient problems, and enhance the convergence and performance. The modified ResNet model for leaf disease classification replaces the standard ReLU activations in the original ResNet architecture with Leaky ReLU activations. This modification is applied to the convolutional layers, residual blocks, and fully connected layers throughout the network. In a Leaky ReLU ResNet, the output of each convolutional layer and the residual block is passed through the Leaky ReLU activation function instead of ReLU. The convolutional layer with Leaky ReLU is represented as follows:

$$O_C = L_R(B_N(C_{2D}(I, F, K_S) \tag{4}$$

In the above equation, $O_C$ signifies the Convolutional Layer Output, and $L_R$ and $B_N$ signify Leaky ReLU and Batch Normalization, respectively. $C_{2D}$ denotes the 2D convolution operation. The input, filters, kernel size, and strides are denoted by $I$, $F$, and $K_S$, respectively. The Batch Normalization normalizes the output of Conv2D, and Leaky ReLU applies the Leaky ReLU activation. Similarly, the residual block with Leaky ReLU is represented as follows:

$$O_R = L_R(B_N(C_{2D}(I) + C_{2D}(I))) \tag{5}$$

In the above equation, $O_R$ indicates the Residual Block Output. Here, the input is added to the output of two Conv2D layers before applying the Leaky ReLU activation. This residual connection allows the model to learn the residuals, making it easier to train deeper networks.

## 4. Experimental Results

This section explains the results achieved from this study and illustrates the effectiveness of the proposed LRRN method at detecting plant leaf diseases. The proposed LRRN method is evaluated via diverse methods, and the results are compared to existing methods such as Hybrid Random Forest Multiclass Support Vector Machine (HRF-MCSVM) [27], Multi-Feature Fusion Faster Region-based Convolutional Neural Network (MF$^3$R-CNN) [28], Optimal Mobile Network-based Convolutional Neural Network (OMN-CNN) [29], and Convolutional Neural Network-based Visual Geometry Group 19 (CNN-VGG19) [30].

**Plant Village Dataset:** The data were collected from the Plant Village dataset [31], and 24,000 observations are collected from the Plant Village dataset. This dataset was utilized to provide an efficient solution for detecting 38 different kinds of plant diseases; it covers 12 healthy plants and 26 unhealthy plants. This Plant Village dataset contains 54,303 images captured in the uniform background. The resolution of the original image is 256 $\times$ 256 pixels. The samples in the dataset were divided into training and testing in the ratio of 80:20. In the dataset collection, the potato plant has three types of disease classes, the pepper plant has two types of disease classes, the corn plant has four types of disease classes, and the grape plant has four types of disease classes.

**Plant Leaf Diseases Dataset:** The healthy and unhealthy leaf images of various plants were collected from various standard open data repositories. In total, 16 different plant species were used in the dataset to create the plant foliar disease dataset. Each plant in the dataset consists of the healthy and most common disease classes. The dataset contains 58 types of plant leaves and 1 non-leaf class. The original dataset consisted of 61,459 plant leaf and non-leaf images.

**Performance Analysis:** A performance evaluation using various performance parameters [32,33] is carried out for discussing the performances of the proposed LRRN method. Figure 2 illustrates the comparative graphical representation of the proposed LRRN method and the existing methods, such as HRF-MCSVM, MF$^3$R-CNN, OMN-CNN, and CNN-VGG19, for different evaluation measures based on plant leaf disease detection.

Figure 2a presents the graphical analysis showcasing the accuracy comparison between the proposed Leaky Rectilinear Residual Network (LRRN) method and existing techniques. The results demonstrate that the proposed approach achieved a significantly higher accuracy of 94.56%, outperforming other methods, such as HRF-MCSVM, MF3R-CNN, OMN-CNN, and CNN-VGG19, which attained lower accuracy values of 93.18%, 92.37%, 91.72%, and 90.89%, respectively. Similarly, in Figure 2b, the graphical analysis depicts the precision comparison between the proposed LRRN method and existing approaches.

Figure 2c displays the graphical analysis, comparing the recall between the proposed Leaky Rectilinear Residual Network (LRRN) approach and existing methods. The results indicate that the proposed method achieved a significantly higher recall of 93.12%, surpassing the results of the other approaches. In Figure 2d, the graphical analysis illustrates the comparison of the F1-score between the proposed LRRN approach and existing methods. The proposed method achieved a higher F1-score of 92.83%, outperforming all other approaches.

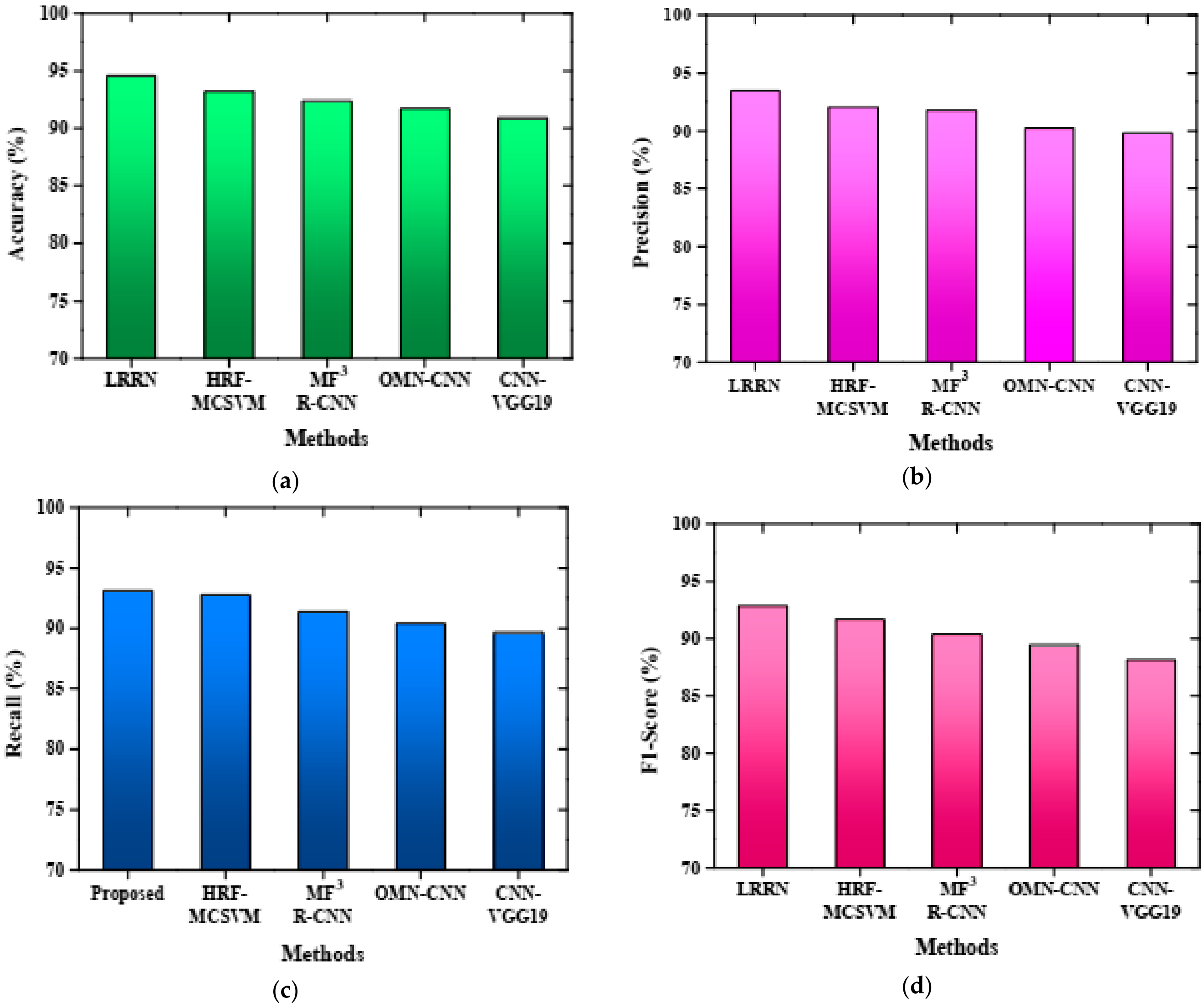


**Figure 2.** (**a**). Accuracy. (**b**). Precision. (**c**). Recall. (**d**). F1-Score.

Table 1 presents the results of the comparison between the proposed and existing approaches. The results proved that the proposed LRLR approach achieved a higher performance rate compared to the other existing approaches.

**Table 1.** Comparison results.

| Method | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | Specificity (%) |
|---|---|---|---|---|---|
| HRF-MCSVM | 93.18% | 92.03% | 91.76% | 91.69% | 91.74% |
| MF3R-CNN | 92.37% | 91.76% | 90.38% | 90.36% | 90.27% |
| OMN-CNN | 91.72% | 90.24% | 89.43% | 89.47% | 89.64% |
| CNN-VGG19 | 90.89% | 89.83% | 88.65% | 88.14% | 88.46% |
| **LRRN** | **94.56%** | **93.48%** | **93.12%** | **92.83%** | **92.58%** |

Figure 3 portrays the effectiveness of the dataset using the proposed approach. The Plant Village dataset achieved a higher performance rate compared to the plant leaf diseases dataset. The Plant Village dataset obtained a higher rate of 98.5%, and the plant leaf diseases dataset obtained a lower performance rate of 97.56%.

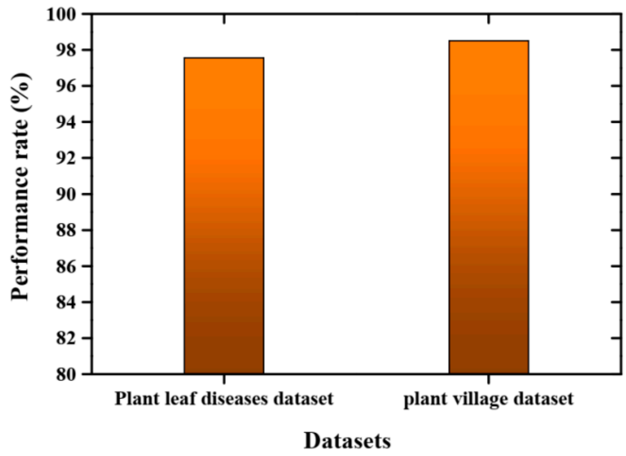


**Figure 3.** Performance analysis.

## 5. Conclusions

This work proposes a Leaky Rectilinear Residual Network (LRRN) model for the identification of plant leaf diseases using the Plant Village dataset. The performance of the proposed model is evaluated, and a comparison is made with existing methods, including HRF-MCSVM, MF3 R-CNN, OMN-CNN, and CNN-VGG19. The evaluation results demonstrate that the proposed LRRN model outperforms the existing techniques in all evaluation measures. Specifically, the proposed LRRN model achieves significantly higher values in terms of accuracy (94.56%), precision (93.48%), recall (93.12%), F1-score (93.82%), and specificity (92.58%). These results indicate the superiority of the proposed LRRN model in terms of accurately predicting plant leaf diseases, showcasing its potential for practical implementation in precision agriculture and crop management. In the future, research aims to improve robustness by addressing the challenges of a specific plant imbalance using large and comprehensive dataset collection. Additionally, efforts will be made to ensure the interpretability of the LRRN model's predictions, enabling other broader applications and helping stakeholders in the field of agriculture to understand and trust the decision-making process.

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