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Deep learning based multi disease classification of plant leaves using light weight residual architecture

Muniyandi Sadhasivam[1], Manoharan Kalaiselvi Geetha[1], James Gladson Maria Britto[2]
[1]Department of Computer Science and Engineering, Annamalai University, Annamalai Nagar, India
[2]Department of Computer Science and Engineering, Malla Reddy College of Engineering, Hyderabad, India

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ABSTRACT

Plant diseases can severely impact crop yields, posing a major risk to worldwide food stability. Prompt and precise identification of these diseases is crucial for early intervention and efficient crop administration. This paper introduces an innovative method for detecting plant leaf diseases using residual networks (ResNets) and the PlantVillage dataset. To develop light weight residual (LWR) architecture, five convolutional layers are interleaved with five max-pooling layers, making up the architecture of ten layers. The number of filters in the convolutional layers is gradually increased from 32 to 64 and up to 512 with a 3×3 kernel. A fully connected layer is the last layer of the network which provides the classification of leaf diseases The LWR architecture is trained and evaluated using the PlantVillage dataset, a broad collection of annotated images. This dataset serves as the basis for the system. The findings of the experiments provide evidence that the suggested system has higher accuracy, sensitivity, and specificity measures. The use of residual networks in LWR architecture improves the capability of the model to acquire complicated representations, which in turn enables a more precise differentiation between healthy and unhealthy plant leaves.

Corresponding Author:

Muniyandi Sadhasivam
Department of Computer Science and Engineering, Annamalai University
Tamilnadu, India
Email: msadhasivam156@gmail.com

1. INTRODUCTION

Computer vision (CV) focuses on devising methods to enable computers to perceive and understand the information contained in visual data, such as images and signals. Typically, this involves developing techniques that aim to imitate human visual systems. One method of comprehending the content of digital images is by extracting a description, which may pertain to various things present in the image [1]. CV is an interdisciplinary domain incorporating components from artificial intelligence, pattern recognition, and mainly image processing [2]. It often employs a blend of specialized methodologies and generic learning algorithms to analyze and understand visual data.

Machine learning refers to the use of computer systems that possess the ability to learn and adjust their behavior without explicit instructions or rules. This is accomplished by using algorithms and statistical models to analyze and forecast data within an input. In broad terms, machine learning techniques are classified into supervised learning and unsupervised learning. In supervised learning, the machine learning model employs an algorithm that can establish a correlation between an input variable x and an output variable y. The algorithm learns the correct labels of the training samples using a training dataset containing input sample labels. Unsupervised learning refers to the process in which a machine learning model acquires the ability to identify and differentiate patterns from a set of data with no assigned labels. Semi-supervised learning is a family of machine learning approaches that can handle a small number of labeled data.

Image classification is a key problem in CV that involves using supervised learning to categorize unstructured input, such as images, into predetermined classes or labels [3]. These labels are provided throughout the training phase. Historically, image classification methods relied on manually designed features, which required extensive expertise in the field and exhibited limited capacity to adapt to other domains. Deep learning (DL) has been used in recent years to tackle practical issues. DL is a machine learning method that involves many steps of non-linear information processing in hierarchical structures to identify patterns and learn features. DL employs an artificial neural network (ANN), a model designed to imitate the human brain, to acquire intricate characteristics and patterns from input data. A deep convolutional neural network (DCNN) [4] is a DL model designed to handle unstructured data inputs, like images and videos.

Detecting plant leaf disease is crucial for advancing sustainable agriculture, guaranteeing food security, and reducing the ecological consequences of agricultural methods. Prompt identification and focused intervention are fundamental to efficient disease control programs [5]. This paper presents an approach for leaf disease detection using a residual approach based DCNN model. In machine learning, specifically within the domain of neural networks, the word "residual" often pertains to residual learning or the use of residual networks. Residual networks include shortcut connections, known as "skip connections", which enable the model to learn residual functions. This architectural advancement has shown to be very useful in enhancing the training of extremely deep neural networks [6].

2. RELATED WORKS

Ant colony optimization (ACO) with CNN system is developed for leaf disease identification and classification in [7]. After preprocessing using median filters, the diseased areas are segmented and ACO-CNN based system is used for the classification. A DL system that detects pest and disease of mung beans is addressed in [8]. Transfer learning, which is able to provide a highly accuracy for quick and easy pest and disease identification is employed. Image based DL for plant infection recognition is depicted in [9]. At first, the leaves of affected crops are selected and then labeling them according to the disease pattern. The pixel-based procedures are used to enhance the classification accuracy. A detailed analysis of the existing works on leaf disease-based models established on DL is provided in [10]. DCNN, CNN, remaining skip network-based super-resolution for leaf disease recognition are some of the DL models discussed along with their advantages and limitations of these models.

An automatic plant leaf damage detection system is described in study [11]. The dense network (DenseNet) model is used for the classification. A detailed review of fungal and bacterial plant disease recognition and categorization is discussed in [12]. These studies are arranged based on the crop type, DL, and the dataset used for experiments. The possibilities of using machine learning algorithms to diagnose plant diseases are discussed in [13]. Four types of crops, such as tomatoes, rice, potatoes, and apples are taken into consideration, and an in-depth analysis is provided for the stages involved in the detection and categorization of plant diseases via machine learning and DL methods. A lightweight DL solution is discussed in [14] based on the vision transformer (ViT). Along with the ViT, classical CNN and the mixture of CNN and ViT have been deployed to classify plant diseases.

A study of CNN models using different datasets, number of images, and number of classes is illustrated in [15]. Residual networks (ResNet)-34-based faster residual CNN (RCNN) based classification of diseases that affect tomato plant leaf is described in [16]. The first step is to develop annotations for images suspected of being diseased to identify the region of interest (ROI). In the subsequent stage, ResNet-34 is employed with the convolutional block attention module as a feature extractor module of Faster-RCNN to remove the deep features. Over the last five years, DL methods have been utilized in the agriculture domain. The most significant contributions and challenges are discussed in [17] based on many agricultural factors monitored by the internet of things (IoT).

A lightweight CNN is described in [18] to diagnosis agricultural diseases via plant-leaf images. It has 6 million parameters, considerably fewer than the state-of-the-art algorithms. A CNN containing 19 convolutional layers is designed in [19] to accurately and effectively classify diseases caused by Marsonina coronaria and Apple scab from apple leaves. Three apple tree diseases such as black rot, fish scale disease, and snow apple rust are discussed in [20]. It uses the Yolo-v5 model along with stable information based on an auto-encoder. An end-to-end DL model to recognize vigorous and diseased corn plant leaves is discussed in [21]. The model makes use of two CNNs, DenseNet121 and efficientnetb0, for effective classification.

A hybrid deep-spatio-temporal model is formulated in [22] to detect medicinal plant diseases. Firefly heuristic-driven fuzzy C-means clustering retrieves ROI-specific regions from individual color planes such as red, green and blue (RGB). It uses gray-level co-occurrence matrix-based features and AlexNet transferable network technologies. A sequential model is used for the classification task in [23]. It uses Adam's optimization strategy since it has maximum global convergence. A CNN approach is employed for mango leaf disease detection in [24]. This system makes use of transfer learning in DenseNet201 [25], InceptionResNetV2, InceptionV3 [26], ResNet50 [27], ResNet152V2, and Xception [28], in order to get a higher level of accuracy from the selected images. A computer-assisted CNN along with a camera is used to identify citrus plant diseases in [29]. Many techniques are developed to raise and develop the quality of agricultural production and prevent the disease from spreading further by detecting it at an earlier stage.

3. METHODS AND MATERIALS

The significant aim of this research is to propose a light weight residual (LWR) architecture for identifying plant leaf diseases. This method uses DL residual networks, and the extensive PlantVillage dataset. Figure 1 shows the proposed LWR architecture for plant disease detection using plant leaves without residual approach and Figure 2 shows the system with residual approach.

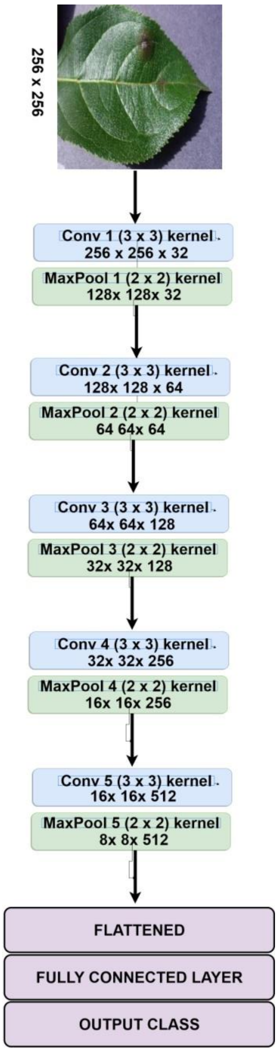


Figure 1. Proposed architecture for plant disease detection using plant leaves

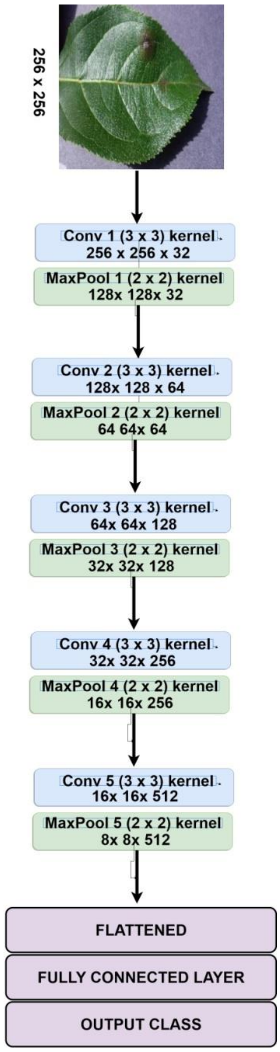


Figure 2. Proposed LWR architecture with residual approach for plant disease detection using plant leaves

The neural network architecture is a CNN developed specifically for plant leaf disease categorization. Five convolutional layers are interleaved with five max-pooling layers, making up the ten layers of this structure. The number of filters in the convolutional layers gradually raises from 32 to 64 and up to 512. The kernels in these layers are 3×3. Following each convolutional layer, max-pooling layers with 2×2 kernels are added, which helps to reduce the spatial dimensions. A fully connected layer is the last layer which provides the classification of leaf diseases. This layer has an input size of 32786 and an output size depends on the number of leaf diseases for a particular plant. For efficient feature extraction and classification, this architecture is designed to progressively decrease the spatial resolution of the input images while increasing the images' depth.

The correlation between the number of layers in a neural network and the degree of accuracy is well recognized. Nevertheless, the number of extra layers that may be included is restricted, and these additional layers should be capable of learning the requisite information for approximating both basic and complex functions. However, including this supplementary layer inside the network presents many challenges, including vanishing gradients and the curse of dimensionality. Hence, instead of including supplementary layers, it is feasible to circumvent the training process of certain levels by using residual connections. Figure 3 shows the residual connection between the layers. The definition of residue $R(x)$ is defined as (1).

$$R(x) = H(x) - x \tag{1}$$

It can be seen from (1) that the residual network learns from $R(x)$ whereas a conventional system learns from $H(x)$. The neuron structure in LWR architecture has two fundamental building blocks; activation and activation function. The activation block calculates the output sent to the neuron; the function that does this computing is called the activation function. In a typical neuron, the activation is calculated as the weighted sum of the neuron's inputs, and the activation function may take the form of a rectified linear unit (ReLU). Figure 4 shows the original neuron structure.

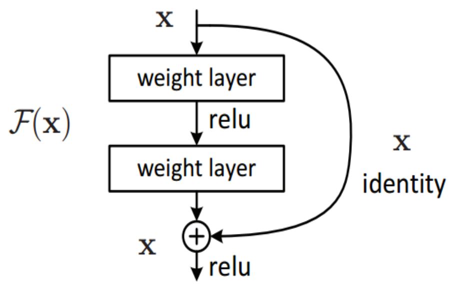


Figure 3. Residual connection

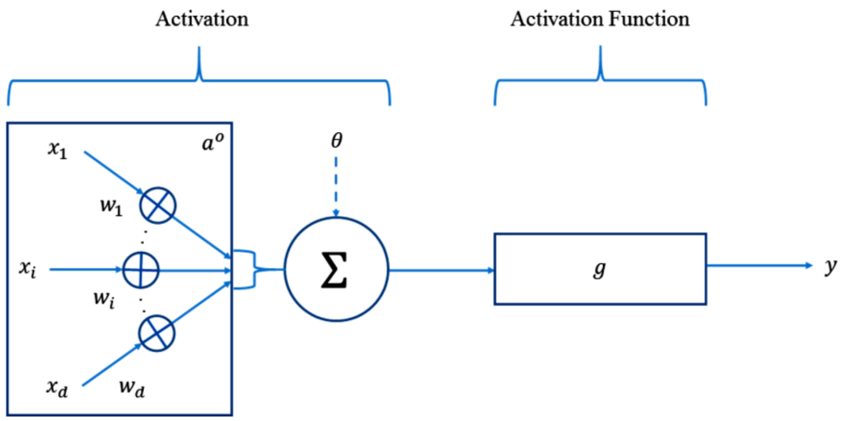


Figure 4. Neuron structure in LWR architecture

In machine learning, feature vectors are applied to mathematically characterize the symbolic qualities of an image that are denoted to as features. The term "feature space" denotes to the vector space associated with these vectors. As a result, the feature space incorporates all of the ANN input signals. These input signals are weighted and summated (along with an optional threshold for the original neuron types) to provide the neuron's activation. The activation function called as the transfer function, which develops the neuron's output. It receives the activation as its input. The activation function and the activation are the two fundamental components that make up a neuron, which is why the neuron is considered a composite function.

It is clearly observed from Figure 3 that the activation of the neuron receives its input in the form of the feature space formed by the input vectors (features from the CNN). The activation sums up the weighted inputs for each and every conceivable combination of weighted input types. The mathematical equation that depicts the original neuron is written in (2), where g is the activation function and $a^o = \left(\sum_{i=1}^{d} x_i w_i + \theta\right)$ is the "sum-of-the-weights" activation. This equation is the mathematical representation of the original neuron. In the initial state of the neuron's feature space, each input contributes an equal amount to the activation of the neuron.

$$y^o = g\left(\sum_{i=1}^{d} x_i w_i + \theta\right) \tag{2}$$

In this activation, the input vector $x = [x_1, \ldots . x_d]$ is multiplied with the weight vector $w^o = \begin{bmatrix} w_1 \\ . \\ . \\ w_d \end{bmatrix}$ and an optimal threshold (θ) is added before being sent to the activation function. The ReLU activation function is revealed in Figure 5. It illustrates that the ReLU function for eternity returns the same positive integer values, and that it always returns zero for negative integer values. Hence, this function is less susceptible to the vanishing gradient issue.

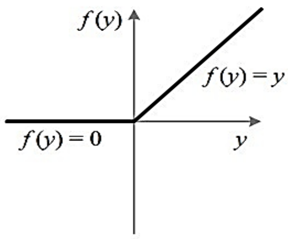


Figure 5. ReLU function

4. RESULTS AND DISCUSSION

The construction of a reliable plant leaf disease detection system may benefit from the inclusion of a large number of annotated images, which contribute to the creation of a dataset that is both rich and diverse. The LWR architecture uses PlantVillage dataset [30] contains a broad variety of plant species, diseases, and environmental circumstances, which helps to improve the model's capacity to generalize to a variety of diverse situations. A comprehensive foundation for the development of a universal and scalable plant leaf disease detection model is provided by this dataset. The PlantVillage project, which is directed by academics at Penn State University, is responsible for compiling and maintaining the PlantVillage dataset. It makes use of technology, such as computer vision and machine learning, in order to provide assistance to farmers in the diagnosis and management of conditions that affect plants. The PlantVillage database is chosen due to the following reasons: i) diverse plant species and diseases, ii) images captured in real-world conditions, iii) large and varied dataset, and iv) public availability. During the process of training and assessing the proposed model, the PlantVillage dataset is a very helpful resource. The collection contains 54,303 leaf images, 15,084 of which are healthy and 39,221 of which are diseased. These leaf images are classified into 38 groups according to the species and their respective diseases. There are some examples of images taken from the PlantVillage dataset shown in Figure 6. Figure 6(a) shows the healthy and diseased apple leaves, and the strawberry leaves are shown in Figure 6(b). Figure 6(c) shows the peach leaves, and grape and cherry leaves are shown in Figure 6(d) and Figure 6(e) respectively.

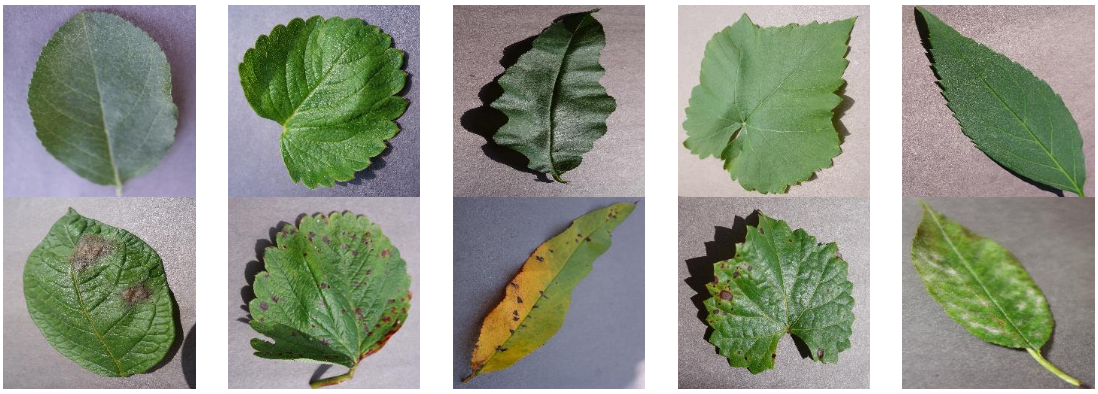
The system's operation is measured utilizing classification accuracy, and dropout regularization (0.8) is employed with a random split technique to split the dataset into training (70%) and testing (30%). The performance metrics are as (3)-(5):

$$\text{Precision} = TP/(TP + FP) \tag{3}$$

$$\text{Accuracy} = (TP + TN)/(TP + FP + FN + TN) \tag{4}$$

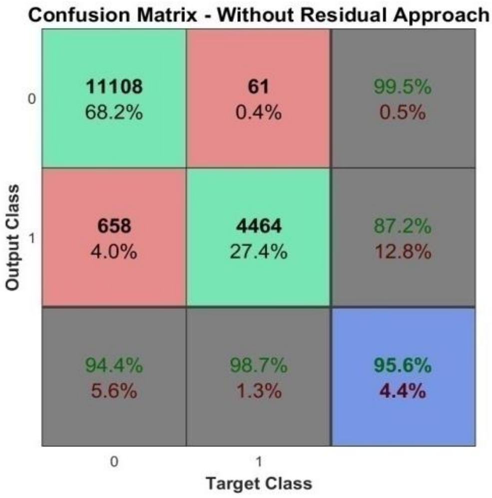
$$\text{Recall} = TP/(TP + FN) \tag{5}$$

here TP represents the number of correctly classified diseased leaves, FP is the number of misclassified healthy leaves, FN is the number of misclassified diseased leaves and TN is the number of correctly classified healthy leaves. The LWR architecture is initially tested for binary classification using all leaf images in the database. Figure 7 explains the obtained confusion matrix for binary classification with Figure 7(a) shows the obtained confusion matrix without using residual approach and the result of using residual approach is shown in Figure 7(b).

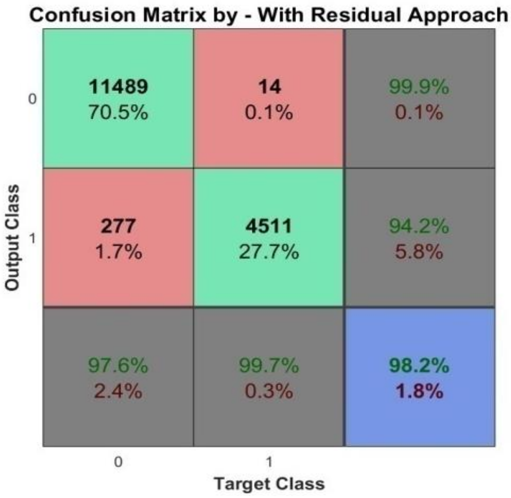


(a) (b) (c) (d) (e)

Figure 6. Sample images: healthy (top row) and diseased (bottom row) of (a) apple, (b) strawberry, (c) peach, (d) grape and (e) cherry



(a)



(b)

Figure 7. Confusion matrix for binary classification (a) without residual approach and (b) with residual approach

Figure 6 demonstrates that the system with residual setting provides more accurate results than a conventional system. The residual approach provides 98.2% average accuracy whereas it is 95.6% by the conventional system. It is also inferred that the classification accuracy of residual-based systems for normal and diseased leaves is ~3% higher than the conventional system. Each plant leaf is considered for classification to analyze the system further. From the dataset, five different plant leaves such as apple, grape, strawberry, peach, and cherry are considered. Among them strawberry, peach, and cherry have only two types of leaves (normal and diseased) and apple and grape have four types of leaves (normal and three types of diseases). Thus, the LWR architecture is tested for binary and multiclass classification using only a residual approach. Table 1 establishes the number of training and testing samples used for classifying leaves of strawberry, peach, and cherry plants. Table 2 shows the obtained confusion matrices for classifying strawberry, peach, and cherry plants.

Table 1. Number of samples used for classifying leaves of strawberry, peach, and cherry plants

Plant type	Number of samples						
	#normal	#diseased	#total	#training normal	#training diseased	#testing normal	#testing diseased
Strawberry	456	1,109	1,565	319	776	137	333
Peach	360	2,297	2,657	252	1,608	108	689
Cherry	854	1,052	1,906	598	736	256	316

Table 2. Performance of the proposed leaf disease classification system for strawberry, peach, and cherry

Plant type	Confusion matrix				Performance metrics		
	True positive	False negative	True negative	False positive	Accuracy	Recall	Precision
Strawberry	326	7	130	7	97.02	97.90	97.90
Peach	676	13	101	7	97.49	98.11	98.98
Cherry	309	7	252	4	98.08	97.78	98.72

Table 2 explains that the LWR architecture has performed well across all three plant kinds. The model's capacity to accurately classify the plant leaves is shown constantly, with an average accuracy of 97.53%. The high recall values for each class, which range from 97.78% to 98.11%, demonstrate that the model successfully captures the majority of occurrences of real positives, hence reducing the likelihood of false negatives. Furthermore, the accuracy percentages, which range from 97.90% to 98.98%, emphasize the model's precision in properly detecting positive predictions while simultaneously decreasing the number of false positives. This combination of high accuracy, recall, and precision highlights the model's capacity to successfully recognize between the many species of plants, making it a dependable instrument for tasks involving plant categorization. Table 3 demonstrates the number of images of every disease for apple and grape plants used for multi-classification. Table 4 shows the obtained confusion matrices for classifying strawberry, peach, and cherry plants. Based on the confusion matrix, the performance measures are computed and are shown in Table 5.

Table 3. Number of samples used for classifying leaves of grape and apple plants

Grape plant disease	#samples	#training	#testing	Apple plant disease	#samples	#training	#testing
Healthy	423	296	127	Healthy	1,645	1,152	493
Esca	1,383	968	415	Cedar	275	193	82
Black rot	1,180	826	354	Black rot	621	435	186
Blight	1,076	753	323	Scab	630	441	189

Table 4. Confusion matrices obtained for grape and apple plants

Grape	Predicted Class				Apple	Predicted Class			
Actual	Healthy	Esca	Black Rot	Blight	Actual	Healthy	Cedar	Black Rot	Scab
Healthy	118	2	4	3	Healthy	481	5	3	4
Esca	4	400	5	6	Cedar	3	72	3	4
Black rot	4	5	341	4	Black rot	6	4	171	5
Blight	6	5	8	304	Scab	4	5	4	176

Table 5. Performance of the proposed leaf disease classification system for grape and apple plants

Grape	Performance measure			Apple	Performance measure		
	Accuracy	Recall	Precision		Accuracy	Recall	Precision
Healthy	98.11	92.91	89.39	Healthy	97.37	97.57	97.37
Esca	97.79	96.39	97.09	Cedar	97.47	87.80	83.72
Black rot	97.54	96.33	95.25	Black rot	97.37	91.94	94.48
Blight	97.37	94.12	95.90	Scab	97.26	93.12	93.12

Across a wide range of different plant diseases affecting grape and apple plants, the performance measurements in Table 5 demonstrated that a high degree of accuracy is obtained for their classification. The proposed model exhibits outstanding accuracy rates that range from 97.26% to 98.11%. The recall and precision rates are consistently high, except for the cedar disease in apple plant, due to the minimum number of images for training the network. Overall, the sophisticated examination of performance metrics highlights the overall excellence of the model to establish a balance between accuracy and precision across the different plant categories.

5. CONCLUSION

The LWR architecture discussed in this paper contributes to develop an automated plant disease detection system, which provides farmers and other agricultural stakeholders with a dependable and scalable solution. The efficiency of the suggested model, in conjunction with the exploitation of the PlantVillage dataset, underlines its potential for real-world applications in precision agriculture, which contributes to the management of crops in a sustainable manner and to the security of food supplies throughout the globe. The LWR architecture makes use of a DCNN architecture based on residual connections. Residual networks are much more successful than deep neural networks when training deep neural networks. This design enables the model with the capability to recognize detailed characteristics and patterns that are related to various plant diseases. The main limitation of the proposed system is that it classifies the strawberry, peach, and cherry grape and apple plant diseases only and the system's performance will be analyzed for all plant diseases in the near future.

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BIOGRAPHIES OF AUTHORS

Muniyandi Sadhasivam **is** assistant professor at computer science and engineering, SRM Institute of Technology, India. He is pursuing PhD degree in computer science and engineering at Annamalai University. His research area is image processing. He has completed his master of engineering at Annamalai university, bachelor of engineering at Anna University. He received state first award in Tamil Nadu Government in India. He has been working as assistant professor at computer science and engineering since 2012. He published a book 'Computer Graphics'. He published a patent and also granted a patent. He has attended national and international conferences. He can be contacted at email: msadhasivam156@gmail.com.

Manoharan Kalaiselvi Geetha is working as professor at Annamalai university in Computer Science and Engineering Department in India. she Holds a PhD degree in computer science and engineering with specialization in artificial intelligence, machine learning, image and video processing. She guided and awarded PhD for six students and she guiding five research scholars currently. She completed two research projects wroth of twenty-four lakhs and above. She attended more than sixteen national conferences and fifteen international conferences. She has teaching experience more than 29 years. She is life time member of ISTE and CSI. She published more than 75 international journals and five national journals. She published three Books in well reputed Publication. She can be contacted at email: geesiv@gmail.com.

James Gladson Maria Britto is working as a professor computer science and Engineering Department in Malla Reddy College of Engineering, India. He completed his PhD in Manonmaniam Sundaranar University India. He has more than 15 years teaching experience. He published a book named "Computer Graphics". He attended more than 15 international conferences and ten national conferences. He published 10 international journals and two patents. He attended many FDP and seminar in various reputed institutions. He also a journal editor for BEIESP-Blue Eyes Intelligence Engineering and Sciences Publication Pvt Ltd from January 2018. He can be contacted at email: gmbrittocse@gmail.com.