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Plant Leaf Disease Prediction: A PLDD Net-SVM Model Proposed using Internet of Thing (IOT) and Integrated Learning Model

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Abstract:
Diseases that affect the leaves of tomato plants are the primary reason for the drastic reduction in production. As a consequence of this, it is essential to develop an intelligent detection method for illnesses that affect citrus plants. Nowadays, deep learning approaches have received encouraging results in a variety of artificial intelligence difficulties. As a result, we decided to apply these methods to the task of diagnosing diseases that can affect citrus fruit and leaf. A convolutional neural networks (CNNs) model is suggested using an integrated method in this piece of research. The Plant Leaf Diseases Diagonis (PLDD Net) – Support Vector Machine (SVM) Model that has been created has the goal of distinguishing healthy veggies and plants from fruits and leaves that have typical tomato diseases like early blight and late blight. By combining multiple different layers of data, the PLDD NET model that was introduced can extract complimentary discriminative characteristics. On the PlantVillage datasets, the SVM model was evaluated in comparison to a large number of cutting-edge deep learning models. According to the findings of the experiments, the PLDD Net-SVM model surpasses its rivals in a number of different evaluation metrics. As a result of its test accuracy of 96.55 percent, the PLDD Net-SVM model is an invaluable guide that helps for farmers who are interested in classifying tomato leaf diseases.
Keyword: Tomato leaf diseases, Support Vector Machine (SVM), convolutional neural network (CNN), deep learning.

1 Overview

The goal of agricultural research is to improve food productivity and quality while decreasing economic costs and increasing profitability [1]. Plants have a significant part in the economic growth of any state. citrus plants, which are high in vitamin C, are popular throughout the Indian subcontinent, and also in the Mideast. As a raw resources in the agricultural industry, tomato plants are used to produce a variety of various agro - food, notably jams, candies, ice creams, and confectionary [2], [3]. The process of recognising and diagnosing is subjective, error-prone, time-consuming, and costly. There will also be new diseases that appear in previously undiscovered regions where no local expertise and knowledge is available to address them [4].] Automated method for detecting leaf infections and their symptoms are need to be identified. Crop anomalies can now be spotted in real time thanks to the development of modern computer-aided techniques and sophisticated tools. For plant disease detection and diagnosis, traditional machine learning algorithms have been successful, but they are confined to the sequential image analysis tasks of segmentation, extraction of features, and pattern matching, such as employing support vector machines (SVMs), the k-nearest neighbour method, and Neural Networks (ANNs) [5–10]. In order to pick and retrieve the best apparent pathological traits, highly skilled engineers and skilled specialists must be used, that is not only random and also expensive in terms of personnel and economic center.

Specialist feature extraction and selection are considered as an important component of traditional machine learning. To train a traditional machine learning classification, a specialist must create a feature extraction algorithm that can produce a most relevant characteristics and input those features into the machine. Classification decisions are taken by learning the classifier models from data and applying what it has learned. Deep-learning algorithms, on the other hand, have recently developed excellent results [7], [9], transforming the field of images and object categorization. Deep-learning algorithms learn hierarchical structures and are learned on big datasets to get strong classification results. ImageNet [15] is one. These techniques have a long training period compared to conventional classification methods. This is because of the many data-learned factors.

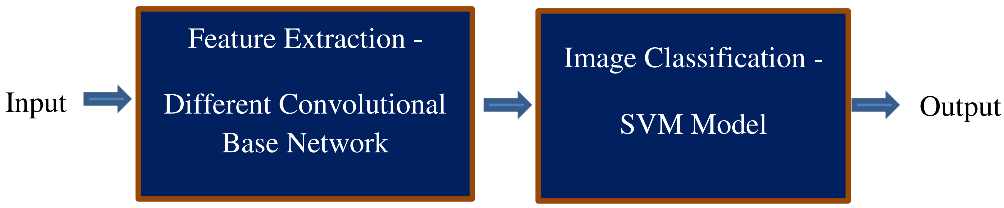

Figure 1: General CNN Architecture for Image Classification

Like other deep-learning techniques, CNN-based methods require huge datasets to obtain substantial results [17]. In other applications, the total number of the training examples is limited [18], due to the time and expertise required to obtain and label a large number of images. Generally the "data augmentation," is described as "new" data is generated from old data, or "transfer learning." CNN is a powerful alternative technique which has been frequently applied in recent years for numerous computer vision problems [1, 7, 9, 16]. CNNs have convolutional, nonlinear, pooling, fully connected, and normalising layers. Convolutional, nonlinear, and pooling layers extract features. Deep learning can automatically learn hierarchical pathology features, removing the need to manually build feature extraction and classifiers.
Computational intelligence excels in signal processing, pedestrian identification, facial recognition, road fracture detection, biological image analysis, and more. Deep learning models have achieved encouraging results in agriculture, allowing more producers and nutrition personnel detect plant illness [15], analyse weeds [16], uncover valuable seeds [17], detect insects [18], process fruit [15], etc., which has led to picture analysis. Some implementations anticipate future crop yield [19], climate circumstances [20], and field soil water content [21]. The author propose a CNN-based deep convolutional neural network for mechanized citrus fruit disease identification.
The "transferable learning" approach, established by the author [20], [21], resembles the techniques person made in ordinary life, as we don't study all from beginning but rather employ knowledge obtained in a existing activity in related current activities. We use prior knowledge to future difficulties. Isolated learning models are created for a transfer learning models can employ the gained information in another related activity, resulting in greater performance on a small data source and less training process. [22]–[26] and others studied CNN-based algorithms that used pre-trained CNN features on huge image datasets.

1.1 Background

Modern technological communication relies heavily on visuals. They're everywhere at work. Humans can comprehend photos accurately because they require natural perspective. Because we know, today's technology can equal the human brain's abilities. Computers can interpret visuals. Automatic object recognition in images is possible. Based on these data, automated classification and decision-making are conceivable. CNN is the best computational model for picture segmentation or object recognition.

1.2 Image Segmentation using Machine Learning Algorithms

Image segmentation accomplished by the use of machine learning In the fields of machine learning and computer vision, the scheme of image segmentation is an essential step. The goal of semantic segmentation is to break apart an image into meaningful sections and assign each section to a specific category using a labelling system. With the help of picture segmentation, we are able to do an unlimited number of different jobs. Examples of this include self-driving car systems, systems for detecting the background, systems for managing robots, systems for checking the quality of fruits and vegetables, systems for maintaining the quality of production lines, systems for diagnosing diseases in body cells, and so on. When segmenting an image, each pixel in the image is given a label that corresponds to a specific class. This process of assigning labels to pixels is also known as dense prediction. Let's say there are a variety of things like automobiles, trees, signals, and animals available to view in an image. Therefore, picture segmentation will categorise all trees as belonging to a single class, all animals as belonging to a single class, and all signals as belonging to a single class. When doing image segmentation, it is essential to keep in mind that it treats any two objects that are of the same kind as belonging to the same class. Through the use of instance segmentation, we are able to differentiate between objects of the same type.

1.3 Motivation

Methods of supervised machine learning and deep learning are utilised in the related works [7], [22]–[24,] on the categorization of plant leaf diseases image. The Deep learning was applied by Liu et al. [24] to the task of disease classification in plant leaf images. In addition, the neural network model suffers from some performance issues as a result of insufficient attention being paid to the selection of its parameters and layers. On the other hand, the CNN model that is suggested for classifying leaf diseases in photos of the fruit and the leaves has a various number of layers and different parameter settings than the previous algorithm. In addition, we conducted trials using several CNN model variations and compared the results to the research that served as our baseline. We propose using a CNN technique as a means of accurate disease classification based on photos of tomato leaves. The proposed method is able to diagnose a number of plant leaf diseases.

1.4 Contribution

The significant contributions of this research work is as follows:

- The dataset are pre-processed and apply image segmentation techniques and then split test and train data.
- From proposed CNN based PLDD_Net, the deep feature vectors are extracted from the different convolutional layers.
- We have extracted deep features from different layers and given as input to the SVM classification model

- The Plant Leaf Diseases Diagonis (PLDD Net) – Support Vector Machine (SVM), called as PLDD_Net-SVM Model that has been developed for distinguishing healthy and diseases leaves that have typical tomato diseases like early blight and late blight.

1.5 Region Based Segmentation

Region Based image segmentation Using some criterion as a cutoff point, it divides the items into their respective regions (s). The intensities of the image pixels are utilised in this kind of processing. It separates the regions of higher intensity into those with similar intensity and those with lower intensity. For the purpose of distinguishing, a threshold is chosen. One section is comprised of pixels with an intensity that is lower than a threshold, while another part is comprised of pixels with a value that is higher than the threshold. In a similar manner, more than one threshold can be selected, and an image can be divided into more than two areas according to the intensities of individual pixels. Using an image's pixel values as a guide, this method is the most straightforward approach to picture segmentation. This tends to make use of the facts that the pixel values of an object's edges will be very different from the pixel values of the object's background pixels. This difference might be rather significant. Therefore, in situations like these, we have the option of setting a threshold value; the difference in pixel values that are below the threshold can then be segregated in the appropriate manner. In the event that there is just one object in front of one backdrop, only one threshold value will be effective. However, in the event that there are several items or that there is overlap between the objects, we may require multiple threshold values. The term "threshold segmentation" can also be used to refer to this method. The following is a list of the benefits that come from segmenting based on region:

- Simple computations
- High speed.
- This strategy works particularly well when there is a significant difference between the object and the background..

1.6 CNN based image segmentation

In the realm of picture segmentation research, this method is currently considered to be the state of the art technology. It operates on pictures that have three dimensions—namely, height, breadth, and the number of channels—and it does so successfully. The first two dimensions give us information about the image resolution, while the third dimension represents the number of channels (RGB) or intensity levels for the red, green, and blue hues. In most cases, images that are fed into the neural network will have their size lowered in order to cut down on the amount of time required for processing and to prevent the issue of under fitting. despite the fact that if we take an image with the dimensions 224 by 224 by 3, converting it to one dimension will result in an input vector with the value 150528. Therefore, we cannot use this input vector as an input to the neural network because it is still too huge. The task of image segmentation using CNN is becoming increasingly important in today's world. In the realm of picture segmentation, this method is now considered the most advanced technology available. The primary purpose of this is to conceptually divide up an image into different parts. In situations where we need to teach an automobile to drive by itself, semantic segmentation is a beneficial tool that we can employ. We do this by using a large number of photos and manually labelling each image in accordance with the objects that are in it. For example, we might use a variety of masks to name things like trees, automobiles, signals, people, footpaths, trucks, cycles, animals, etc., and then later utilise this labelled data to train a neural network (CNN). The network will be able to recognise such items if a new image of the same kind is added to it, and it will be able to base its decisions on how to drive on the characteristics of the objects it finds in the scene. Based on the findings of a recent survey, it has been discovered that deep learning is quickly becoming an extremely significant component of image segmentation approaches and algorithms. In addition, it makes an ongoing contribution toward the goal of making the task of computer vision and autonomous surveillance systems highly trained and intelligent.

1.7 Research Paper Organization

The following outline describes the format of this article. A discussion of works that are connected to this topic kicks off the second section. In the following section, "Methods," "Dataset," and "Data Preprocessing," together with the "suggested PLDD Net-SVM Model," are all introduced in depth. In Section 4, we carry out all of the tests, discuss the shortcomings of the suggested model for deep learning, and look ahead to the work that will be done in the future. In Section 5, we talked about the talks that took place over the results. The last section of this work, Section 6, contains the conclusion of this research work and future scope.

2 Literature Survey

Plant leaf disease can be detected using cutting-edge image processing and deep learning-based techniques. The detection and classification of healthy and diseased plants, many diagnostic methods utilize a Convolutional Neural Network (CNN) with a previously trained model. For classification, Manso et al. employed a trained neural network after removing background data with segmentation [7]. Cucumber plant illnesses can be diagnosed using a combination of K-means, the state and colour of infected leaf lesions, and minimal resentment to separate diseased from healthy photos

[8]. For categorization, Yeh et al. used feature maps to highlight the most important regions while simultaneously weakening the useless related layers [9]. There are a variety of image-based and artificial intelligence-based plant disease detection methods [10].

Using the two-color elements and texture as a guide, we chose the suitable colorimetric system and parameter values for the appropriate elements [17]. K-means clustering was used to identify patterns in tomato leaves. The input selection of the feature parameters, on the other hand, has an effect on the detection accuracy. A standard backpropagation technique was used, and the model's learning rate was dynamically modified [18] to identify illness. Visible Geometric Group (VGG) used a region-based single shot multibox detector to detect the cotton plant disease proposed by [19]. For plant leaf disease diagnosis on mobile photos, a CNN model presented by Sibiya and Sumbwanyambe attained a detection accuracy of 92.85 percent [20]. For the detection of powdery mildew disease in a strawberry dataset, Shin et al. used six distinct pre-trained deep learning-based models [21]. A tomato disease detection approach based on a CNN was proposed by Karthik et al. [22]. A variety of datasets, including those from different plants [23], [24], a dataset from a peach orchard [25], and pre-trained AlexNet, were used in the detection of plant diseases in these investigations. For the identification of coffee and soybean plant diseases, ResNet was used, whereas DenseNet was used for the detection of apple leaves. Transfer learning using VGGNet was employed to develop a novel approach to multi-tasking, in which the authors extracted separate features from several datasets and trained independently for numerous related tasks on wheat and rice plant datasets. The detection accuracy of 97.13 percent was attained by Singh et al. using a multi-layer CNN for mango leaf diseases [33]. Pauropsylla illness was detected using the Internet of Things and fuzzy networks [34].

There has been a long history of research on leaf and fruit diseases. To improve the accuracy of disease diagnosis, scientists have looked into a number of approaches based on machine learning and pattern recognition. Wheat [25], rice [26], maize [27], and corn [28] are some of the crops that benefit from these cutting-edge technology. Golhani et al. [29] have described a variety of experiments including neural network algorithms for recognising and classifying diseases in images of plant leaves and fruit. Citrus canker and Huanglongbing were discovered by Wetterich et al. [30] using an SVM and a fluorescence imaging system (HLB). Citrus canker and scab were classified with 97.8% accuracy, while HLB and zinc insufficiency were classified with a 95% accuracy. [31] Padmavathi and Thangadurai [31] used the RSHE approach to better distinguish Citrus diseases from each other. The noise in the citrus photos is removed in the second stage. Citrus photos can be improved with the help of the recommended remedies. K-Means segmentation has been utilised to identify sick regions in pre-processed orange photos, as discussed by Patel et al. [32]. K-means clustering was utilised to identify sick sections of leaves, and colour and texture information were recorded. Analyzing data using the ANOVA F-test is used to identify the most important traits. Pathogens were finally discovered utilising procedures mentioned in this article. The study comprised 236 sick citrus leaves. Precision was increased by combining colour and textural features. According to the results, LDA was 84.32% accurate for colour and 81.36 percent accurate for texture in comparison to 77.12 percent and 80.93% accurate for SVM.

It was developed by Xing et al. using a convolutional network that was only moderately thickly coupled. Various CNN models were applied to a self-dataset for citrus. With an accuracy of 91.66 percent, the NIN-16 model outperformed both the SENet-16 and SENet-16 models in the test. MobileNetV2 was trained by Liu et al. [24] to classify and diagnose six prevalent citrus illnesses. MobileNetV2's ability to categorise and identify citrus diseases may be seen by comparing its model accuracy, model size, and model validation speed with those of other network models. The accuracy and speed of MobileNetV2 are equivalent to those of other network topologies. In order to identify illnesses in citrus leaves, Barman et al. [35] tested two different CNN architectures, such as MobileNet and Self-Structured (SSCNN) classifiers. With an accuracy of 92%, MobileNet CNN's maximum training accuracy occurred at epoch 10. At epoch 12, the SSCNN's training accuracy peaked at 98%, and validation accuracy reached 99 percent. For the detection of the three citrus pests mentioned above, Khanramaki et al. [36] developed an intelligent technique, convolutional neural networks. The proposed method was tested on a collection of 1774 images of orange leaves. Ten-fold cross validation was used in an experiment to gauge CNN accuracy. A 99.04 percent accuracy rate was achieved by the ensemble in comparison to other CNN algorithms. According to Kukreja and Dhiman [37], an effective and robust CNN algorithm for spotting apparent citrus fruit defects has been proposed. For comparison, the proposed approach is put up against an unaugmented, unpreprocessed dense model. An accuracy of 89.1 percent has been estimated for the model that was proposed. Data augmentation and preprocessing procedures have proven to be effective in estimating citrus crop damage. Machine vision and artificial intelligence were used by Partel et al. [38] to develop an autonomous system for monitoring ACP in groves. An insect trapping device and a camera board with a grid of cameras were utilised to gather images from the tree's branches. Using two convolutional neural networks, software was developed that can quickly and accurately identify psyllids from other insects and tree debris. Ninety-five percent accuracy and ninety-five percent recall were achieved when ACPs were detected on 90 immature citrus plants.

Most early studies had trouble boosting classification accuracy rates, even though simple ML and DL algorithms have been proved to be effective and widely utilised in crop disease prediction. Additionally, the neural network model suffers from some performance deterioration due to a lack of proper parameter and layer selection. Classification of citrus illnesses in fruit and leaf photos is made possible using a CNN model that employs a variety of layer counts and parameter values. The results of these investigations were also compared to the results of previous studies using other

CNN models. In order to correctly classify citrus illnesses from fruit and leaf pictures, we propose a CNN model with numerous layers.

3 Proposed Methodology

In this section we have demonstrate how the proposed system perform in a real-world task, such as in the classification of diseases that affect the leaves of plants. PLDD_Net – SVM models and their appropriate layers for feature characterization are the foundation of the proposed method. Pre-training CNNs may be done with big object datasets, so we take use of this. We then apply the model with the same weights in a new classification job. Pre-trained models have a number of advantages over models that have not been trained yet.

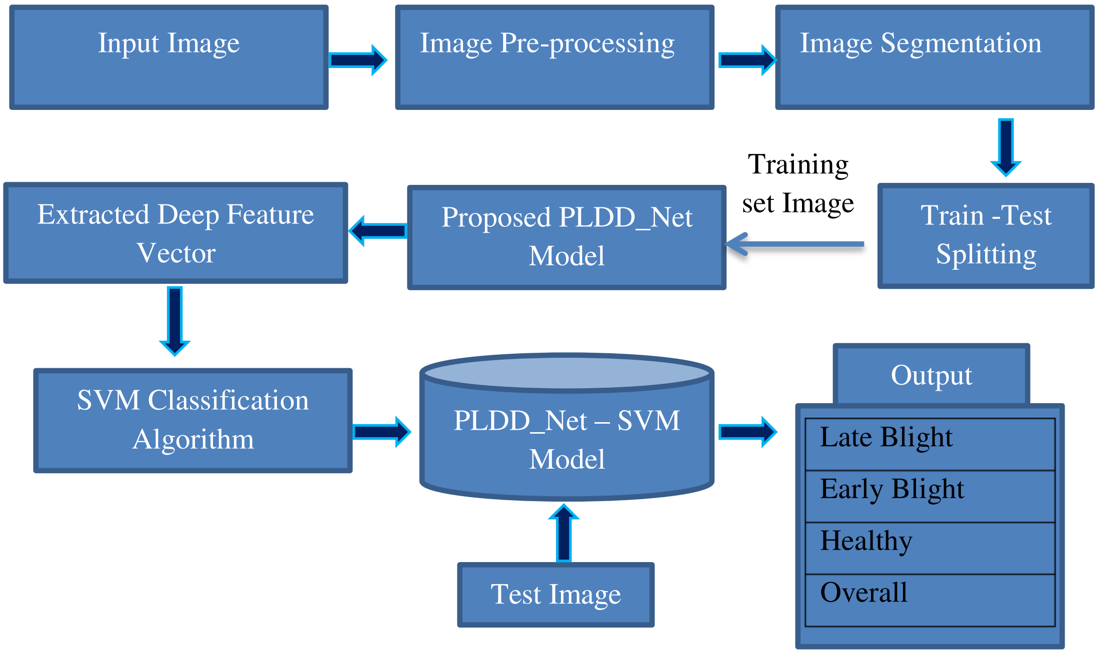

Figure 2: Architecture of Proposed PLDD_Net – SVM Model

In addition, the feature extraction process is time-efficient because the photos are only passed it through system once. For the categorization objective, relevant results can be produced from minimal datasets and no architectural handcrafting is necessary. Due to the vast datasets used to train these models, it is possible to apply previously learned patterns and characteristics to a new challenge. For the results to be meaningful, the original and the new tasks should be comparable. Even though the datasets used to build popular PLDD Net models are object-oriented and have a classification challenges because we are interested in classifying diseases leaf image. In the PLDD Net–SVM Model, the mid layers identify low-level aspects and the patterns, but only the extracted features from the final layers are now more appropriate to the beginning recognition job due of the hierarchical architecture. Figure 2 depicts the block diagram used to explain the system of leaf disease classification under consideration.

Plant leaf photos are classified using the PLDD Net model. For the Convolutional layer, images are fed in in three dimensions: height, width, and channel count. Using the first two dimensions, we know the image's resolution, and the third dimension tells us the number of channels (RGB) or the intensity levels for each of the three colours. It is common practise to minimise the size of input images before feeding them into the neural network in order to speed up processing time and avoid the problem of underfitting. If we take an image of 224x224x3 and convert it to a vector of 150528, we will still get a vector of 150528. So, this input vector is still too huge to be supplied to the neural network as a training stimulus. CNN's basic layers are as follows: Convolution layer, Activation layer, Pooling layer, Drop out Layer and Fully connected Layer.

It is possible to obtain a feature vector for each image in the dataset by using a model called PLDD Net. The extracted feature vector are given as input to the SVM with RBF kernel classifier, which is trained on 75 percent of the photos from each classification in the dataset, is used to analyze the rest of the images (25 percent). If you want to maintain weights that have been learned in the previous problem, you must delete classification layers at the end of a CNN network because they were designed to handle a larger number of courses than those in the current problem. The SVM does the classification in this study, with PLDD Net simply being employed for feature extraction. There was a possibility of using an artificial neural network (ANN) for classification but it would not have topped the SVM's performance in this case. A CNN's convolutional foundation makes it an excellent feature extractor, but a linear classifier makes it inefficient for classification, according to [37]. When dealing with more complex data, however, SVM is preferred [37] because it uses the Kernel function to transform an initial feature space into a larger space where it is possible to split data into distinct categories.

4 Experimental Setup

We conduct two separate experiments to test the method's efficacy. For starters, we look into how PLDD Net models pre-trained on big object datasets may be used for classification of leaf photos using transfer learning and what the important layers are in practise from the hierarchical PLDD Net to extract features from. Then, we utilise the results to demonstrate how leaf categorization can be used in precision agriculture to detect plant diseases.

4.1 Plant Village Dataset

For evaluation, we used the PlantVillage dataset [42], which contains healthy and diseased plant species. [43] uses the RGB photos, the grayscale**, and the segmented RGB image.**

Figure 3: Example input image from the Dataset

Figure 4: Visual Similarities of Early and Late Blight Tomato Diseases

This dataset was recorded under diverse settings, therefore plant leaves have different rotations and forms. The leaves aren't always perfectly divided from the background. We removed from the initial collection badly segmented, unrecognizable photos. We tested plant species and disease. Only healthy plant leaves were used for species identification. Fig. 3 shows example photos for each class and arrangement.

5 Discussion

This part discusses and examines the data acquired through framing experimental settings and completing several experiments to meet the research issues. We investigated several layers of PLDD Net features with SVM classifiers to recognise leaf photos as diseased. The PLDD Net-SVM model parameters for leaf disease recognition are provided in Table. We employed 1 to 6 convolutional layers under various settings. The proposed PLDD Net-SVM model with different convolutional layers and the used parameters such as number of filters = 8. 16, 32, filter size = 2, and number of

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epochs = 25 and reached the best accuracy of 96.55 percent. By increasing epochs and reducing convolutional layers, the PLDD Net-SVM model training loss score is reduced.
This experiential investigation uses accuracy, precision, recall, and F1-Score [37], [52], [53]. Thr proposed algorithms employed in this investigation resize input images to 224 224. 75% of the dataset was trained and 25% was tested. The proposed approach was tested for 25 epochs on the plant village dataset.

Table 1: Evaluation Metrics of Potato Lea Diseases Analysis using SVM

Category	Accuracy %	F1-Score %	Recall %	Precision %
Late Blight	95.70	93.19	95.11	92.13
Early Blight	94.75	96.12	94.67	97.63
Healthy	95.40	97.44	97.23	98.24
Overall	94.99	96.26	96.58	96.77

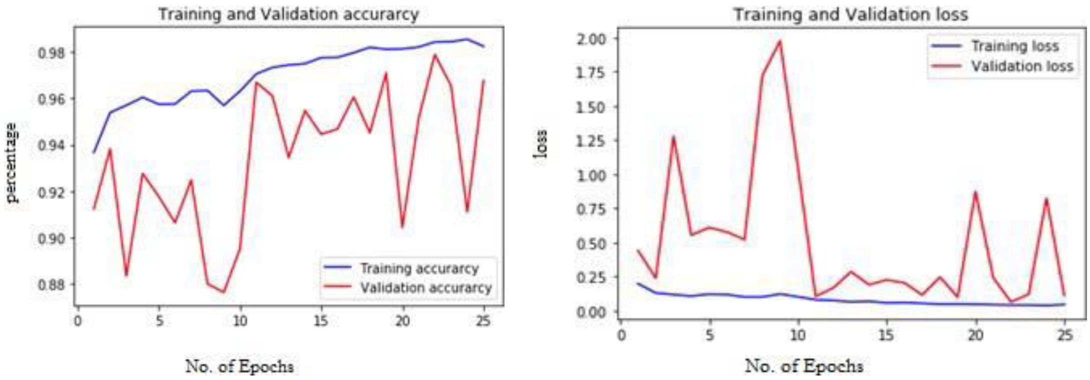

Figure 6: Loss and Accuracy for Training and Validation and Testing and Validation

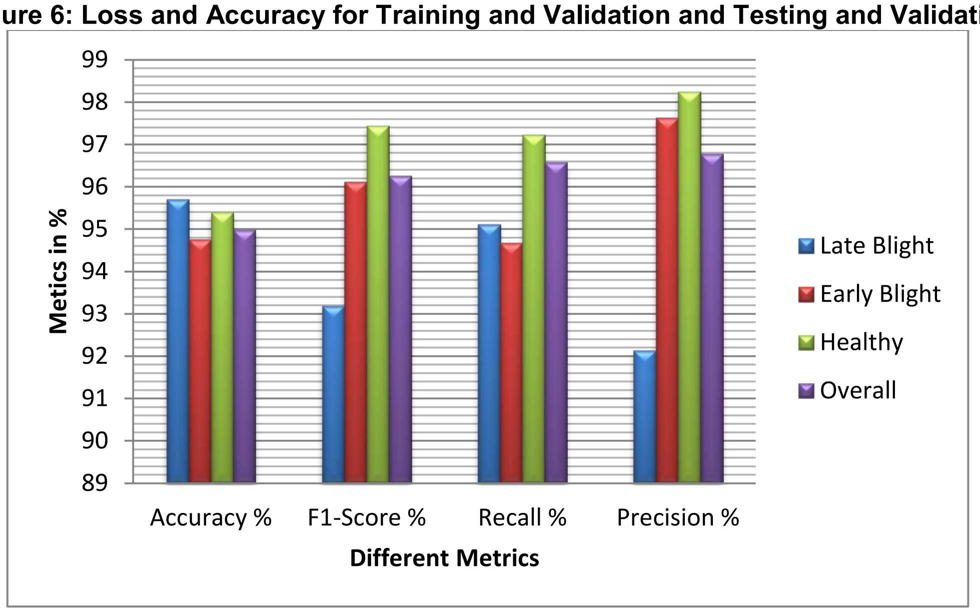

Figure 5: Levels of different evaluation metrics

The graph shows how model prediction accuracy changes with more training epochs. The number of epochs increases training and validation accuracy. Each epoch improves accuracy. The graph shows how training loss changes as the number of epochs increases.

6 Conclusion

The proposed tomato leaf diseases detection system focuses on establishing an advanced and efficient system that enables growing high yield tomatoes easier for farmers. This project tries to detect tomato leaf diseases using image processing and machine learning. The farmer can accurately detect a plant's ailment from its photograph. The suggested system has four parts: Pre-processing, Segmentation, PLDD_Net Feature extraction, Classification using SVM.
This study compares our system to others with good methodology and implementation. The suggested method generates more accurate and reliable results with easier and faster installation than existing illness detection systems. It helps farmers. The system can help the agricultural sector by improving crop production monitoring management, as agriculture is a big contributor to our country's per capita revenue.

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