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Smart Plant Leaf Disease Detection System using Internet of Thing (IOT) and PLDP Net-RF Model

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Abstract - The decline in apple yield is largely due to diseases that harm the apple's leaves. As a result, it is critical that diseases of citrus plants be detected using an intelligent detection technology. Many artificial intelligence problems can now be solved using deep learning methodologies. Consequently, we decided to use this technology to identify diseases that can impact citrus fruit and leaves. A model based on convolutional neural networks (CNNs) is proposed in this study utilising an integrated strategy. There was a need to construct a model to discriminate healthy vegetables and plants from those with typical apple leaf diseases like black rot and apple scab, therefore the Random Forest (RF) model was devised. The PLDP Net-RF model, which was introduced, may extract complementary discriminative qualities by merging many different layers of data. A number of cutting-edge deep learning models were tested against the RF model on the PlantVillage datasets. The PLDP Net-RF model outperforms its competitors in a variety of evaluation metrics, according to the results of the tests. For farmers who are concerned in detecting apple leaf diseases, the PLDP Net-RF model is a beneficial tool.

Keyword: Apple leaf diseases, Random Forest (RF), convolutional neural network (CNN), deep learning, transfer learning.

1 INTRODUCTION

Research in agricultural production is aimed at boosting yields and quality of food while lowering prices [1]. State economies rely heavily on the production of plants. Citrus trees, which contain a lot of vitamin C, are common in India and the Middle East. Raw materials from apple plants are utilised in the agricultural business to manufacture a wide range of agro-food products such as confectionery [2, 3], jams, candies, and frozen desserts. It is difficult, time-consuming, and expensive to make a correct diagnosis based on subjective, error-prone, and time-consuming information. No local experience or knowledge will be available to deal with emerging diseases that develop in previously unknown places [4]. According to the author [20], [21], "transferable learning" reflects the approaches people use in everyday life because we don't study everything from beginning to end, but rather use knowledge gained in one activity to help us in other actions. As a result, we are able to anticipate potential problems. For a transfer learning model, isolated learning models can use the learned information in another related activity, resulting in improved performance on a small data source and a shorter training time. Pretrained CNN features were employed by [22]–[26] and other researchers to analyse large image collections using CNN-based algorithms.

1.1 Background

Visuals play an important role in today's technology communication. At work, they're all over the place. When a shot is taken from a natural perspective, it can be understood by humans. It's clear to us that today's technology can outperform the human brain. Visuals can be deciphered by computers. It is possible to identify objects in photos using machine learning. Automated classification and decision-making are possible based on these data. When it comes to image segmentation and object recognition, there is no better model than CNN.

1.2 Image Segmentation using Machine Learning Algorithms

Machine learning is used to perform image segmentation. Image segmentation is an essential step in the disciplines of machine learning and computer vision. Segmenting an image into meaningful sections and assigning each portion to a particular category using a labelling system is the goal of segmentation. We can perform an infinite number of tasks using image segmentation. There are many examples, including self-driving car systems and robots controlling robots, systems for verifying the quality of fruits and vegetables, systems for maintaining the quality of production lines, and so on. For each pixel in a segmented image, the image is assigned an appropriate label. These pixel-by-pixel labels are known as dense predictions.

1.3 Region Based Segmentation

Images can be segmented using a region-based approach It separates the objects into distinct zones based on some criterion (s). This type of processing relies on the intensity of the image pixels. With it, you can distinguish between areas of higher and lower intensity inside areas of higher intensity. A threshold is chosen for the purpose of discriminating. The intensity of the pixels in one section is lower than the threshold, whereas the intensity of the pixels in the other section is higher. It is possible to divide an image into more than two sections based on the intensity of individual pixels, in the same way. The simplest method for segmenting images is to use the pixel values as a reference. An object's edges are likely to have different pixel values than the object's background pixels, which can be exploited here.

1.4 CNN based image segmentation

This technique is currently the most advanced in the field of photo segmentation research. Images with three dimensions—height, breadth, and the number of channels—are successfully processed by this algorithm. Three dimensions are used to describe the number of channels (RGB) or intensity levels for red, green and blue colours in a picture, and the first two dimensions provide us information about the image resolution. When images are fed into the neural network, they are typically reduced in size to reduce processing time and avoid the problem of underfitting. despite the fact that converting a 224 by 224 by 3 image to a one-dimensional input vector yields a 150528-bit vector. As a result, the input vector is still too large to be used as an input to the neural network. These days, the ability to segment images with CNN is more important than ever before. This method is now considered the most advanced technology in the field of picture segmentation. You can use this to break up an image into distinct sections.

1.5 Motivation

The categorization of plant leaf diseases images is done using supervised machine learning and deep learning methods [7, 22]–[24]. Liu et al. [24] used Deep learning to classify illness in plant leaf pictures. Due to a lack of attention paid to the selection of parameters and layers, the neural network model has some performance difficulties. CNN model for leaf disease classification in photographs of fruit and leaves, on the other hand, has a variable number of layers and distinct parameter settings. In addition, we tested a variety of CNN models and compared them to the research that served as our baseline. For illness classification, we propose utilising a CNN technique based on images of apple leaves. A number of leaf diseases can be diagnosed using the proposed method.

1.6 Contribution

The following are the study's major contributions: Pre-processing and picture segmentation algorithms are used to the dataset, which is then split into test and training data. The deep feature vectors are extracted from the multiple convolutional layers of the proposed CNN-based PLDP Net. To help the RF classification model, we've taken deep characteristics from several layers and fed them in. Random Forest (RF) PLDP Net-RF Model, developed to discriminate between healthy and diseased apple leaves with typical illnesses such as early blight and late blight, is known as the Plant Leaf Diseases Prediction (PLDP Net).

1.7 Research Paper Organization

This article's structure is outlined below. The second portion begins with a look at some of the related works. This section provides an overview of the "proposed PLDP Net-RF model," as well as the "methods," "dataset," and "data preprocessing" discussed previously. Section 4 includes the results of all of the tests, a discussion of the model's limitations, and a look toward the future. There was a lot of discussion concerning the outcomes in Section 5. Section 6 provides the conclusion of this study and the scope for further investigation.

2 LITERATURE SURVEY

Cutting-edge image processing and deep learning-based approaches can detect plant leaf disease. There are various diagnostic methods that use a trained Convolutional Neural Network (CNN) for the identification and categorization of healthy and damaged plants. Using a trained neural network, Manso et al. [7] used segmentation to remove background data. A combination of K-means, infected leaf lesions, and minimal resentment can be used to distinguish between diseased and healthy cucumber plants [8]. It was found that by using feature maps, Yeh et al. could better distinguish between areas of importance and non-essential layers for classification [9]. Plant disease detection approaches based on images and artificial intelligence are numerous [10].

Colorimetric systems and parameter values were selected for the relevant elements based on the two-color elements and texture [17].] [18]. The patterns in tomato leaves were discovered by the application of K-means clustering. On the other hand, the selection of feature parameters affects detection accuracy. The model's learning rate was dynamically altered [18] to identify disease using a typical backpropagation technique. One-shot multibox detection was employed by Visible Geometric Group (VGG) for the detection of the cotton plant disease proposed in [19]. In a study using smartphone photographs to diagnose plant leaf disease, Sibiya and Sumbwanyambe's CNN model achieved a detection accuracy of 92.85% [20]. Shin et al. used six different pre-trained deep learning-based models for the diagnosis of powdery mildew disease in a strawberry dataset [21].

Author [22] suggested a CNN-based method for detecting tomato illness. Plant illnesses were detected in these studies using a variety of datasets, including those from diverse plants [23], [24], and a dataset from a peach orchard [25]. Apple leaves were detected using DenseNet, while ResNet was utilised to identify coffee and soybean plant illnesses. A unique technique to multitasking was developed by the authors employing VGGNet transfer learning to extract discrete features from several datasets and train independently for numerous related tasks on wheat and rice plant datasets. For mango leaf diseases, Singh et al. used a multi-layer CNN to achieve detection accuracy of 97.13 percent

[33]. The Internet of Things and fuzzy networks were used to detect the sickness of Pauropsylla [34].

There were only somewhat densely linked convolutional networks used in its development. A citrus dataset was used to test various CNN models. The NIN-16 model outperformed the SENet-16 and SENet-16 models in the test, with an accuracy rate of 91.66 percent. Citrus diseases can be classified and diagnosed using MobileNetV2's training from [24]. Comparing MobileNetV2's model accuracy, model size, and model validation speed to those of other network models can show its capacity to classify and identify citrus diseases. MobileNetV2 has the same accuracy and speed as other network topologies. Both MobileNet and Self-Structured (SSCNN) classifiers were evaluated by Barman et al. [35] in order to identify diseases in citrus leaves. At epoch 10, MobileNet CNN's training accuracy reached a maximum of 92%. Training and validation accuracy peaked at 98 and 99 percent, respectively, at epoch 12. Convolutional neural networks (CNNs) were created by [36] for the detection of the three citrus pests listed above.

A set of 1774 photos of orange leaves was used to evaluate the new approach. A CNN accuracy experiment used a ten-fold cross validation method. In compared to previous CNN algorithms, the ensemble attained an accuracy rate of 99.04 percent. Citrus fruit flaws can be detected using a CNN algorithm, according to [37], which is both effective and robust. It is compared to an unaugmented, unprocessed dense model as a benchmark. Using the proposed approach, an accuracy of 89% has been estimated. Citrus crop damage can be estimated using data augmentation and preprocessing processes. Automated systems for monitoring ACP in groves were developed using machine vision and artificial intelligence by [38]. Camera boards with a grid of cameras were used to capture images from the tree's branches using bug traps and camera boards. Programming that can detect psyllids from other insects and tree debris was developed using two convolutional neural networks. When ACPs were found on 90 immature citrus trees, the accuracy and recall rates were 95% and 95%, respectively.

Even relatively simple ML and DL algorithms have been shown to be successful and frequently used in crop disease prediction, most early studies had difficulty increasing classification accuracy rates. Additionally, the neural network model suffers from a lack of suitable parameter and layer selection, which has a negative impact on its performance. A CNN model with various layer counts and parameter values can classify citrus diseases in fruit and leaf pictures. Results of these trials were also compared to previous studies employing CNN models that were not as accurate as the current model. We present a CNN model with multiple layers for accurately classifying citrus diseases from images of fruit and leaves.

3 PROPOSED METHODOLOGY

This section shows how the suggested system performs in a real-world task, such as the classification of plant illnesses that harm the leaves.

3.1 Plant Village Dataset

There are healthy and diseased plant species included in the PlantVillage dataset [42]. RGB photographs, grayscale images, and a segmented RGB image are all utilised in the [43] process. This dataset was collected in a variety of environments, therefore the leaves of the plants are arranged in a variety of ways. In certain cases, the leaves are not perfectly separated from the rest of the landscape. We weeded out photographs that were too disjointed and difficult to identify from the original collection. We looked at many kinds of plants and diseases. For species identification, only healthy plant leaves were used. Class and arrangement images are shown in Figure 2.

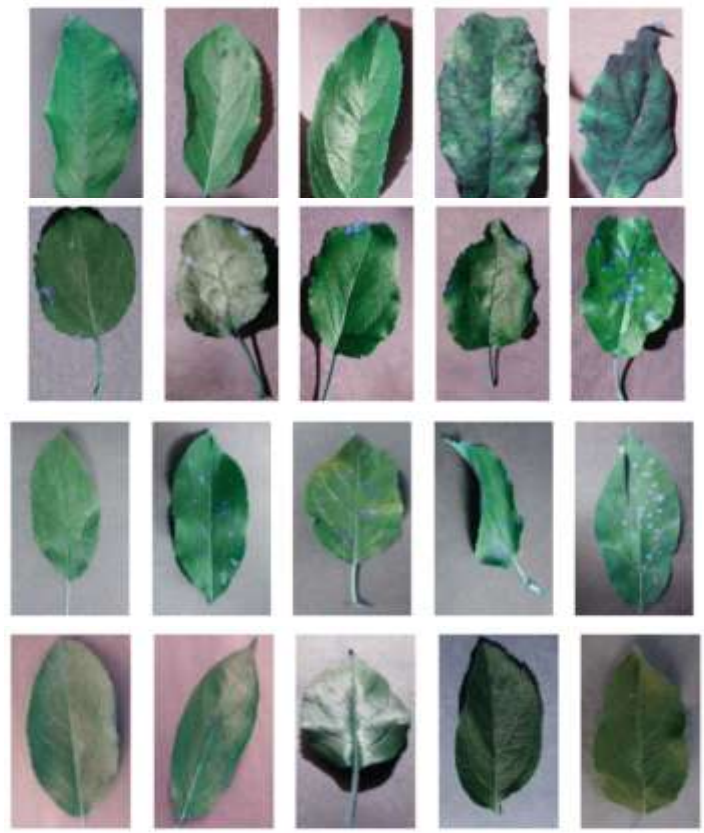

Figure 2: Example input image from the Dataset (Apple healthy and diseases leaf)

3.2 Proposed PLDP_Net – RF models

Based on the PLDP Net and its accompanying RF models, the proposed solution is developed on top of it. For pre-trained CNNs, we employ large object datasets. It is then used with the same weights on a fresh classification task. There are numerous advantages to working using pre-trained models. Features may be extracted in a short amount of time because images are only sent through the system once. The categorization process requires only a few datasets and no architectural handwork. Because of the enormous datasets used to train these models, it is possible to apply previously learned patterns and features to a new situation. If the conclusions are to be of any use, they must be based on a fair comparison of the old and new responsibilities.

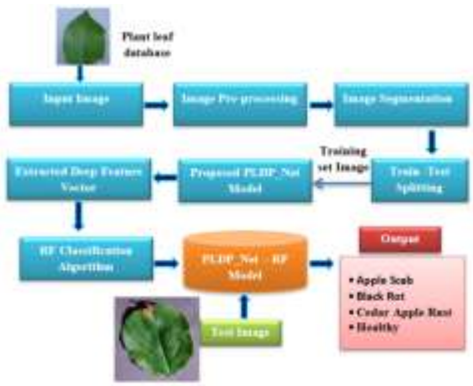

Figure 3: Architecture of Proposed PLDP_Net – RF Model

To build popular PLDD Net models, researchers use a variety of object-oriented and tough classification datasets, however for the sake of this article, we'll be focusing on photos of sick leaves. As a result of the hierarchical structure of PLDP Net – RF models, only the lowest-level traits and patterns can now be used to begin identification tasks in PLDP Net. Figure 3 shows a block schematic of the classification system for leaf diseases that we're looking at. Images of plant leaves are classified using the PLDP Net–RF models. All three dimensions of an image are taken into account when the Convolutional layer is used. First and foremost, we look at the image's width and height to figure out the image's resolution and the number of colour channels (RGB). It is common practise to reduce the image size before feeding it into a neural network in order to speed up processing and avoid underfitting. There is no difference in the final output, no matter how we change the image's dimensions. As a result, the neural network can't use this data set as a training stimulus. Following are CNN's key layers: Layers such as convolution, activation, pooling, dropout, and fully connected are all examples of these types of layers.

A feature vector for each image in the collection can be generated using the PLDP Net model. Remaining shots will be analysed using the retrieved feature vectors fed into a Random Forest classifier, which has been trained on 75% of images from each classification (25 percent). You must delete the classification layers at the end of a CNN network in order to retain the weights learned in the previous task because they were built to handle a bigger number of courses than those in the current challenge. PLDP Net handles feature extraction whereas the RF handles classification in this study. Classification could have been accomplished with an artificial neural network (ANN), but it would have fallen short of R's performance in this case. The convolutional basis of a CNN allows for an efficient feature extractor, however [37] claims that a linear classifier renders it inefficient for classification.

3.3 **Alex-Net Model**

AlexNet's eight-layer CNN consists of 5 convolution layers, 3 maximum pooling layers, and 3 fully linked layers. There are more than a million images and over 1,000 categories in the ImageNet database used to train AlexNet. It can accept photos with a high resolution of 227x227x3 pixels as input. Color images are represented by the 3 digits, and the resolution 227227 is the width and height of each individual image. It takes four steps to move an 11x11-pixel filter around in the first convolution layer. There are 256 filters in the second convolution layer, each with a 5x5 filter area and a one-step stride. The third convolution layer consists of 384 filters with a 3x3 and a single stride filter size. Using 3x3 filters with a one-step stride, 384 filters are used in the fourth convolution layer. The fifth convolution layer has 256 filters with a stride length of one and a filter size of 3x3.

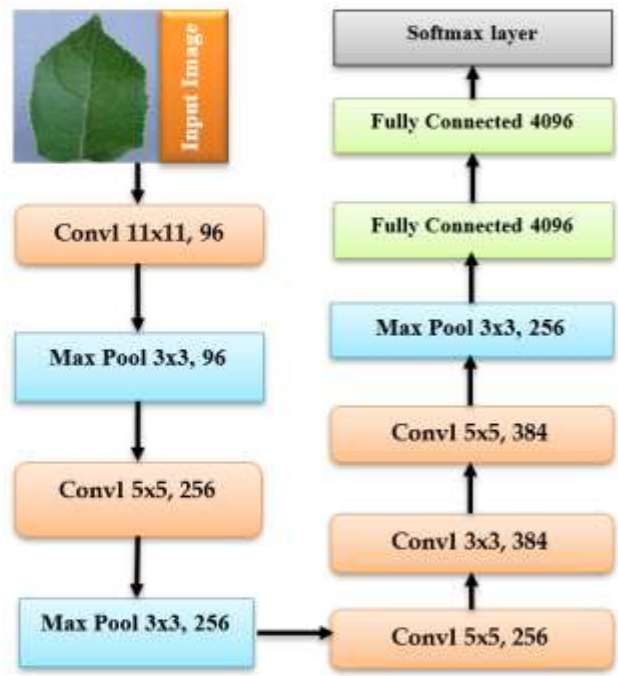

Figure 4: Architecture of Alex Net Model

Data on convolutions, filter dimensions, and stride can be found in Table 2. A 3x3 pool size is used for ReLU and max pooling in order to normalise each successive convolutional layer [29,30]. Figure 4 depicts the total setup of the AlexNet system.

3.4 VGG-16 Net Model

The Convolutional Neural Network (CNN) evolved into the Deep Convolutional Neural Network (DCNN) as a result of its development (DCNN).

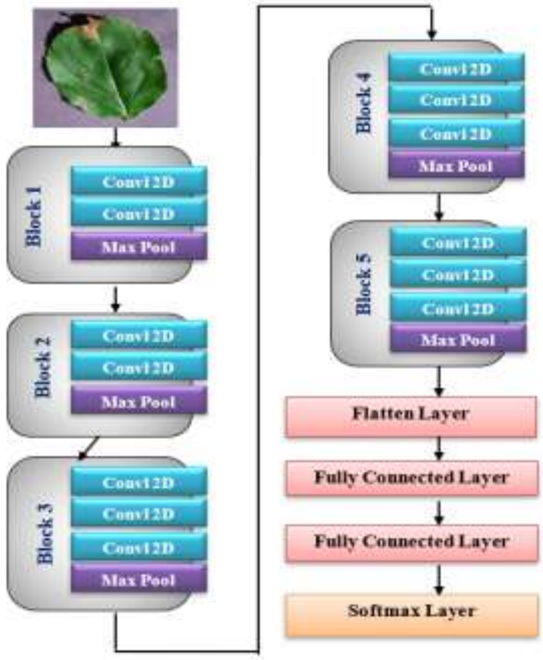

Figure 5: Workflow of VGG-16 Net deep learning architecture

AlexNet is one of the most extensively used Deep CNN models. ILSVRC-2014 competition uses VGG-16 (Visual Geometry Group), a powerful deep convolutional neural network. The VGG-16 Net model presented in Figure 5 has 13 convolutional layers, five max pooling, two fully connected layers, and one soft-max classifier. This stratum has a total of five blocks. Each of the two blocks contains two convolution layers and one pooling layer. There are three convolution and one pooling layers in the other blocks.

4 Experimental Setup

The approach is tested in two different studies. Starting with PLDP Net models trained on large object datasets, we investigate how they may be used to classify leaf pictures using transfer learning as well as which PLDP Net layers are most relevant to extract features from in practise. A leaf classification system can then be utilised in precision agriculture to identify plant illnesses.

4.1Evaluation metrics

Performance assessment measures are used to evaluate the proposed model's performance. Preciseness (Pr): To gauge how far a metric will go, precision is one of the most prevalent methods of doing so. It's a way to figure out how many events were successfully anticipated out of all those predicted. We can gauge the accuracy in this manner: $Pr = \frac{tp}{tp+fp}$ (1)

Recall (Re): The percentage of events that were correctly anticipated out of all those that occurred is known as the Remember (Re). $Re = \frac{tp}{tp+fn}$ (2)

Precision (Q): The precision of a classification is based on the number of examples that are correctly identified. In order to measure a classification system's accuracy, the percentage of valid classifications divided by the total number of classifications can be calculated. $A = \frac{tp+fp}{tp+fp+tn+fn}$ (3)

F1-Score (F): The F1-measure is used to achieve a balance between precision and recall (harmonic mean). Following is the formula for calculating an F1 score: $F = 2 \times \frac{Pr \times Re}{Pr+Re}$ (4)

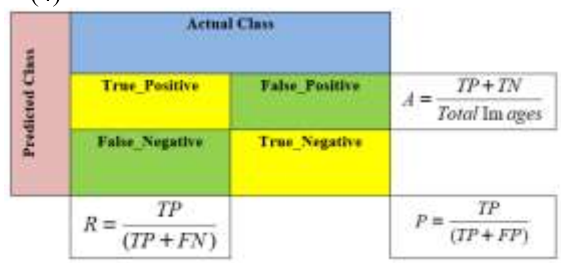

Figure 6: Formation of confusion matrix

4 DISCUSSION

It is in this section that the results of the experiments that have been carried out in order to address the research questions are discussed and examined. In order to identify images of sick leaves, we used RF classifiers to examine various PLDP Net feature layers. Table lists the PLDP Net-RF model parameters for detecting leaf disease. In varied configurations, we used one to six convolutional layers. With several convolutional layers and settings like 16, 16, 32, 2, and 20 epochs, the suggested PLDP Net-RF model achieved a maximum accuracy of 96.21%. Net-RF model training loss is decreased by increasing training epochs and decreasing convolutional layers. Accuracy, precision, recall, and F1-Score [37] are used in this experiential inquiry. Input photos are resized to 224X224 using the techniques used in this study. 70% of the dataset was used for training, but only 30% was used for testing. The proposed method was evaluated on the plant village dataset for 20 epochs.

Table 1: Evaluation Metrics of Apple Leaf Diseases Analysis using PLDP Net-RF

Category	Accur %	F1-Sc %	Reca %	Prec %
Apple Scab	95.21	93.36	95.45	92.94
Black Rot	94.74	96.14	94.12	97.61
Cedar Apple Rust	95.98	97.25	97.24	98.53
Healthy	94.54	96.96	96.57	96.75

Table 2: Traditional classifiers performance analysis

S. No.	Classifier	Accu	Prec	Reca	F1- Sc
1.	Alex Net	93.31	92.11	93.36	92.41
2.	VGG-16 Net Model	94.80	95.32	94.89	94.89
3.	PLDP_Net-RF Model	95.53	96.66	96.54	96.53

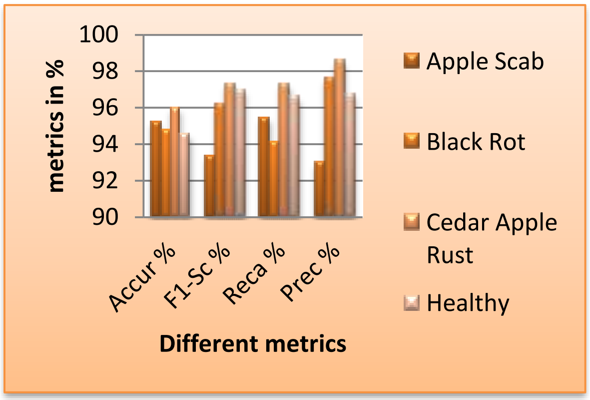

Figure 7: Levels of different evaluation metrics

The table 1 and figure 7 describes the Evaluation Metrics of Apple Leaf Diseases Analysis using PLDP Net-RF. The table 2 and figure 8 shows the comparison of traditional classifiers performance with proposed model.

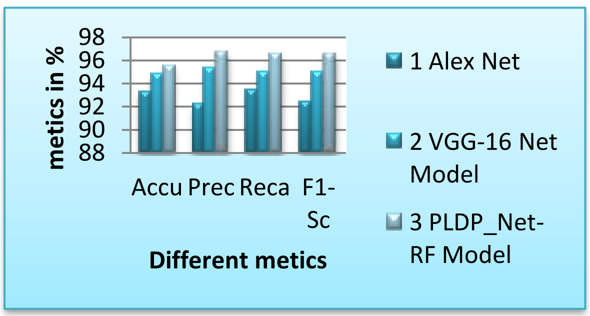

Figure 8: Comparison bar chart for proposed and traditional classifiers

6 CONCLUSION

Farmers will be able to plant high-yield apples more easily with the help of the planned apple leaf disease detection system. This study uses image processing, deep learning, and machine learning to identify apple leaf disease. From a plant's image, the farmer is able to properly identify its illness. Segmentation, PLDP Net feature extraction, and classification utilising RF are the four components of the proposed system.There are other systems that have good technique and implementation in this study that we compare to ours. The proposed technology provides more accurate and trustworthy findings than current sickness detection systems, and it is simpler and faster to implement. Farmers benefit from the use of this product. As agriculture is a significant contributor to our country's per capita income, the system can help improve crop output monitoring administration.

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