Transfer Learning Models for the Plant Disease Detection

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Abstract - Digital Image Processing based Multimedia system has become a basic component of information field. Detecting the infected plants in exact way and on time is challenging task to get exact horticulture. Preventing the excessively waste of monetary and different assets prompts gains the solid efficiency. The essential task is to prevent the infections in the varied climate so that the ailments are diagnosed ahead of time and precisely. The diagnosis of diseases happened on plants is carried out utilizing a few techniques. The plant disease detection technique is proposed in this research work. The proposed model is based on transfer learning which is the combination of VGG16 and CNN. The proposed model is implemented in python and results is analyzed in terms of accuracy, precision and recall.

Keywords - Plant disease, transfer learning, VGG16, CNN

I. INTRODUCTION

The issue connected with safeguarding the plant straightforwardly alludes to the problem related to environmental variations and feasible horticulture. As indicated by researchers, the climate change prompts adjust the improvement stages and the sizes of microorganism development. The explanation which prompts cause this intricacy is a basic broad pace of transmission of infections in plant in existing situation when contrasted with the prior one. The districts, at which this sort of circumstance is happened and local mastery is inaccessible to manage these problems, are more inclined to new ailments [1]. Detecting the infected plants in exact way and on time is challenging task to get exact horticulture. Preventing the excessively waste of monetary and different assets prompts gains the solid efficiency. The essential task is to prevent the infections in the varied climate so that the ailments are diagnosed ahead of time and precisely. The diagnosis of diseases happened on plants is carried out utilizing a few techniques. The side effects of certain diseases are not showed up anyway their influence should be visible later on [2]. In this way, an upgraded analysis is put forward in handling these kinds of conditions. Some sort of show is acquired from different infections visually. A CAD system is planned for diagnosing the diseases relying on the noticed and pictorial side effects of plants.

An approach took on in horticultural fields is known as CVS. Such an approach is valuable to arrange the fruits and perceive the food items [3]. This purpose is achieved by processing the image, characterizing the grains, diagnosing the weeds and a few other comparative errands are completed. The pictures are caught from digital cameras and the strategies are embraced so that these pictures are processed. The viable DIP systems like color analysis and thresholding are executed with the purpose of detecting the disorders. The viral, contagious and bacteriological diseases, the early and late scorch are regularly noticed messes on plants [4]. The images are processed for diagnosing the ailments of plants in different stages like image acquisition, to pre-process and segment the images, separating the elements and arranging them. Figure 2 illustrates a general procedure to diagnose the plant disorders.

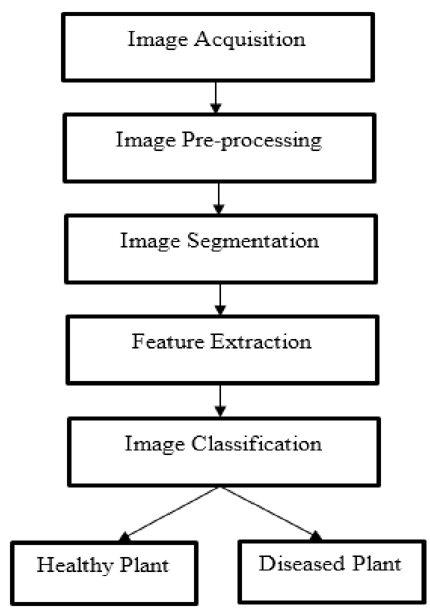

Figure 2: Plant Disease Detection based on Image Processing [5]

Each stage of the presented technique to diagnose the infections occurred on plant is characterized as:

The initial stage is image acquisition in which a powerful framework of diagnosing ailments of plant is created depended on the images which are captured from particular natural circumstances, for example, illumination conditions [6]. The dataset is created based on various pictures of assorted resolutions. The pictures are generated within the improvement periods of a plant. Secondly, various tasks are directed on the pictures utilizing the strategies to pre-process the image so that image is improved or the critical information is separated [7]. It conveys a few procedures for eliminating the noise from the pictures or different items. The superfluous region of a picture is taken out and the extensive regions are obtained in the wake when the images are cropped. Thirdly, the significant process in critical situations is of segmenting the pictures in order to localize and place the infected plants [8]. Consequently, this procedure assists in detaching the sign information from the location and segment the image into a some non-covering, dramatic regions. RoI is used to define the infected region of leaves. The significant emphasis is on segmenting the leaf, suffered from infection, in an image for distinguishing the diseased portion from the healthy one [9]. The feature extraction process is utilized for transforming the unprocessed data into huge pictures for a classifier. Its major intend is to compress the images of huge size for assessing the abstract credits that suggests a numerical delineation of the image is comprised of information for classifying the data such as figure, texture or color. Ordinarily, the farming experts plan the traits that are valuable for extricating attributes in a lengthy run and an actual system [10]. The following stage called image classification, is emphasized on classifying the images as per their objective credits. The chief underline is on creating and executing the classifiers. The most common way of removing credits leads to generate a vector in the output. This vector is planned to a confidence score utilizing a classifier [11]. Various methods are utilized for classifying an image, that are characterized as: Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Random Forest (RF), etc.

SVM is exploited for producing a hyperplane because of the contribution of positive and negative patterns in the ideal decision taken in the preparation test. The initial samples are disengaged from latter ones and the distance in the midst of 2 samples is extended from the plane with the purpose of improving the validity of segregation utilizing this method [12]. It guarantees that the classification of precision of the objective is done. KNN is a traditional and basic strategy that is effective in classifying the data. The results produced from K-NN are much of the time viewed as promising. This algorithm additionally helps in improving the customary strategy subsequent to incorporating earlier information in it [13]. Each unlabeled case is characterized among its k-NNs in the preparation set using the majority label. Random Forest (RF) is developed by integrating various DT methods. Subsequently, a tree is made with the segregating credits for each level of the tree via decision tree [14]. The principles of this approach are huge in accomplishing expectations on indefinite data. Decision Tree (DT) is an effective algorithm to classify the data effectively. The major goal of this approach is to coordinate a wide range of circumstances to choose the data with the assistance of tree arrangement [15]. This model is assessed utilizing the quantity of trees with regard to accuracy. It results in categorizing the little datasets in successful way. Logistic Regression (LR) is an efficient method, implemented to remove some gathering of weighted ascribes from the info, accomplish the logs and coordinate them linearly [16]. It is a discriminative classification method that is often adopted to forecast the likelihood in regards to event of an occasion. To accomplish it, the fundamental stage is to make the data powerful towards a logistic function.

II. LITERATURE REVIEW

M. Sardogan et.al, (2018) suggested using a CNN (Conventional Neural Network) algorithm and LVQ (Learning Vector Quantization) focused technique to recognize and categorize illnesses in tomato plant leaves [17]. After feature extraction, images were automatically categorized using CNN modeling. The color information was used to categorize the different types of diseases that could be found in plant leaves. According to RGB components, this system applied filters to three channels. The output feature vector from the convolutional section was used by the LVQ algorithm to train the network. The experiments were run on an open-source dataset that included 500 images of tomato plant leaves and 4 disease symptoms. The test findings demonstrated that the methods offered made it possible to precisely and quickly locate four different illnesses on tomato leaves.

Adedoja et.al (2019) introduced a DL-based method to identify plant diseases from photos of leaves [18]. TL model was utilized for this. The Convolutional Neural Networks (CNN) technique was used in conjunction with the NASNet design. The new technique was then trained and tested using a dataset known as the PlantVillage Project. This collection contains several photos of plant leaves with a wide range of parasite status and location in plants. The experiment's findings demonstrated that the new algorithm could distinguish between photos of plants that were healthy and those that were afflicted by illness. Furthermore, it was determined that this algorithm's accuracy was approximately 93.82%.

P. Jiang et.al (2019) formulated a sophisticated ConvNet (convolutional neural network) technique to identify apple leaf illnesses [19]. A database dubbed ALDD (Apple Leaf Disease Dataset) was made up of complex photographs captured in the field and in laboratories. A unique apple leaf disease detection system employing Deep-CNN was developed using the Google LeNet inception structure and rainbow concatenation. In order to train the INARSSD model to detect apple leaf illnesses, a dataset of 26,377 photos of infectious apple leaves was employed. According to the proof of concept, the developed algorithm produced 78.80% mAP.

P. Wspanialy, et.al (2020) developed a novel AI system to automatically identify different illnesses, find infections that hadn't been seen before, and gauge the severity of infections across all leaves [20]. Most effectively, infections brought on by bacteria and fungi used proportional area metrics to gauge the severity of the illness. However, a number of systemic illnesses brought on by insects and viruses were best treated by ordinal classes. The nine different varieties of tomato diseases from the Plant Village tomato dataset were utilized in this study to test and train the classifier model and show how different leaf attributes affect disease detection. By incorporating the model into a computerized measurement design, lowering costs and measuring bias, and enhancing precision and greenhouse coverage, it was possible to actually put the study' findings into practice.

Z. Iqbal, et.al (2018) gave a thorough taxonomy of diseases on citrus leaves [21]. The difficulties encountered at each step were first discussed. The accuracy of the identification and classification activities was significantly impacted by these difficulties. Additionally, a comprehensive case study of automated disease detection and categorization techniques was provided by this paper. Finally, several pre-processing, segmentation, feature extraction, feature selection, and classification techniques were investigated. The case study's findings demonstrated that automated detection and classification methods for Citrus planta infections are still in their infancy. In order to automate every step of disease identification and classification, more tools have to be included.

A. Waheed, et.al (2020) discussed that to recognize and categorize illness in maize plants, DenseNet, an upgraded dense CNN architecture, was developed [22]. In this study, a method was proposed for keeping track of the health of crops utilizing DL. The formulated architecture's correctness was calculated to be 98.06%. In addition, this architecture used less important metrics than traditional ConvNets (convolutional neural networks). Based on two quality criteria, the proposed design was contrasted with existing CNN architectures. This comparison research showed that the defined architecture had performance that was substantially equal to that of the common ConvNet architecture.

S. Mishra, et.al (2020) suggested a useful DCNN-based technique for maize plant leaf disease diagnosis [23]. On a system with a graphics processing unit, pooling combinations and hyper-parameters were modified to improve deep ConvNet performance. The suggested system's amount of metrics was also improved to make it acceptable for real-time estimation. Convolutional Neural Network (CNN) hardware blocks from the Intel Movidius Neural Compute Stick were combined with the Raspberry Pi 3 to implement this previously trained, highly suggested architecture. The suggested framework demonstrated its viability in identifying illnesses in the leaves of maize plants with an accuracy of about 88.46%.

Z. Lin, et.al (2019) constructed a unified convolutional neural network (CNN) called matrix-based convolutional neural network (M-bCNN) to detect disaeses occurred on plants [24]. The convolutional kernel matrix was this model's key component. This model's convolutional layers were organized in parallel as a matrix. These layers, as opposed to the frequently used plain networks, can effectively increase the model's data streams, neurons, and connection channels by adding adequate metrics. To conduct the test, pictures of wheat leaf infection were used. In this study, 16,652 photos made up the dataset. This data collection was gathered in the Shandong province of China. The developed architecture achieved training and test accuracy of 96.5 and 90.1%, respectively.

E. C. Tetila, et.al (2019) examined several network weights for the purpose of robotically detecting infection in soybean leaves [25]. These weights were assigned to pictures of several soybean plant leaves. These photos were taken straight from a small, low-cost UAV (Unmanned Aerial Vehicle). Four deep neural network models were examined in this work to reach a high level of accuracy. This work uses a variety of fine-tuning (FT) and transfer learning metrics to achieve this. The network was trained using data augmentation and rejecting to combat the overfitting issue. The SLIC approach was used in the presented method to segment the high-altitude images of plant leaves. A dataset utilized in this study was created using data from actual flying studies. Tools for computer vision were used to test this dataset. The outcomes demonstrated that the detection accuracy can be effectively increased by using fine-tuned measures.

X. Liu, et.al (2021) developed a fresh large-scale plant illness dataset with 220,592 photos and 271 different plant disease categories [26]. To show the degree of difference in each patch, the weights of all split patches from each image were first calculated based on the cluster distribution of these patches. Each loss was then given a particular weight in order to learn the discriminative illness component of each patch-label pair. The network that was trained via loss reweighting was then used to extract patch characteristics. Long short-term memory (LSTM) was used to encrypt the weighted patch feature string and create an inclusive representation of the features. The appropriateness of the developed methodology was confirmed through tests on this dataset and other freely available datasets.

III. RESEARCH METHODOLOGY

In plant disease detection, the major concern is the identification of infections on the leaves of plants. The whole cycle of this process has the three phases which are pre-processing, feature extraction and classification. In the pre-processing phase, the noise will be removed from the image. The machine learning and deep learning are techniques of artificial intelligence which are popularly used for the classification. The Proposed Model is the transfer learning model which is the combination of VGG16 and CNN. The various phases of proposed model are explained below: -

1. Input image and Pre-process: - The image is taken as input and input image will be pre-processed using Gaussian filter. The Gaussian filter will reduce noise from the image This filter makes images non-blurry and is also known as a smoothing operator. This filter eradicates intrinsically present fine image details. Its impulse response refers to a Gaussian function which outlines the probability distribution of the noise. This filter efficiently removes Gaussian noise. It is a non-uniform, linear and low pass filter with a Gaussian function of a given standard deviation.

2. Segmentation: - The technique of snake segmentation will be applied which can segment the part from the image. The Snake segmentation technique is inspired from the raster scan due to which it will cover maximum edges of the image The Snake active contour model actually sets a parameterized initial contour curve in the image space, and establishes an energy functional that characterizes the shape of the region based on the internal energy and external energy. The internal energy is determined by the characteristics of the curve itself. Such as the definition of curvature, curve length, etc., the external energy is defined by the characteristics related to the image. By minimizing the energy functional, the initial contour curve $C(s) = (x(s), y(s), s \in [0,1])$ continuously converges to the boundary of the target area under the constraints of the inner and outer energies:

$$E(C) = \int_0^1 \alpha E_{int}\big(C(s)\big) + E_{img}\Big(C(s) + \gamma E_{con}\big(C(s)\big)\Big)\, ds$$

Among them, the energy function is composed of three parts: E_{int}represents internal energy, which can ensure the smoothness and regularity of the curve; E_{img}represents image energy, which is set according to desired target position characteristics such as edges; E_{con}represents constrained energy, generally a curve The length and curvature are determined. The main advantage of the Snake active contour model is that it comprehensively considers the geometric constraints. Regardless of the quality of the image, smooth and closed boundaries can always be extracted, but the algorithm still has some shortcomings, among which the more difficult to overcome is that it depends on the initial contour. The position, shape and number of control points can only achieve the desired effect if a suitable initial contour is selected.

4. Classification: To prediction the disease type model of transfer learning is applied which is the combination of VGG16 and CNN model. The VGG16 is used as the base model over which CNN model is used for the training.

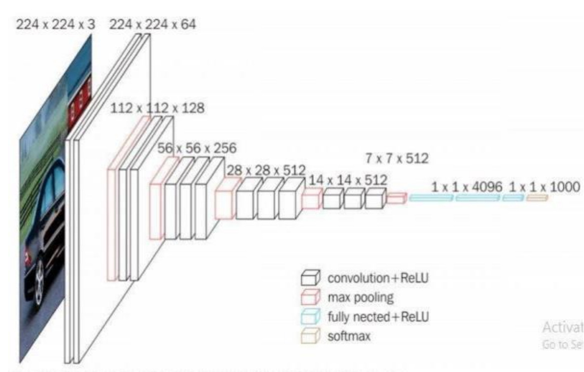

Figure 5: VGG16 Model Architecture

Following are the various specifications of VGG16 Model: -

1. The 16 in VGG16 refers to 16 layers that have weights. In VGG16 there are thirteen convolutional layers, five Max Pooling layers, and three Dense layers which sum up to 21 layers but it has only sixteen weight layers i.e., learnable parameters layer.

2. VGG16 takes input tensor size as 224, 244 with 3 RGB channel

3. Most unique thing about VGG16 is that instead of having a large number of hyper-parameters they focused on having

convolution layers of 3x3 filter with stride 1 and always used the same padding and maxpool layer of 2x2 filter of stride 2.

4. The convolution and max pool layers are consistently arranged throughout the whole architecture

5. Conv-1 Layer has 64 number of filters, Conv-2 has 128 filters, Conv-3 has 256 filters, Conv 4 and Conv 5 has 512 filters.

6. Three Fully-Connected (FC) layers follow a stack of convolutional layers: the first two has 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer.

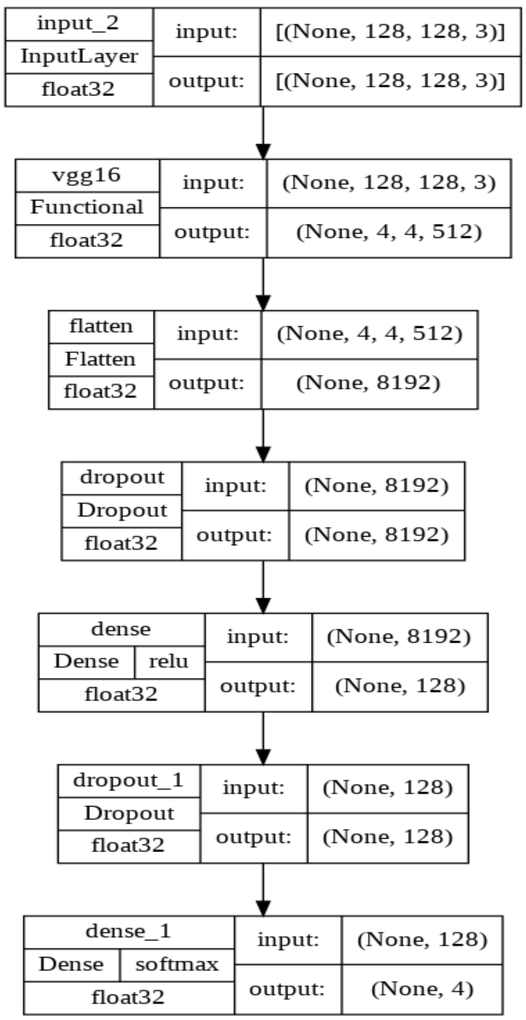

Figure 5: Proposed Transfer Learning Model

IV. RESULT AND DISCUSSION

Python is a high-level programming language that places a strong focus on readability, dynamic semantics, and object-oriented capabilities. It is frequently used as a scripting language to link various components and for quick application development. Python's simple syntax encourages code modularity and reuse by supporting modules and packages while lowering the cost of program maintenance. On most major systems, the Python interpreter and extensive standard library are accessible for free in source or binary form. The Python API is utilized by applications such as GIMP, Inkscape, Blender, and Autodesk Maya to enhance their functionality.

4.1. Dataset Description

The experiment conducted on the developed model involves using the Plant Village dataset. This dataset is publicly available and provides comprehensive information about various plants and their associated contagions. Imagery in the dataset is labeled with the corresponding disease type it represents.

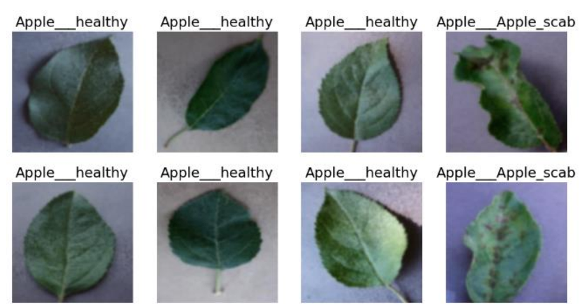

Figure 4.1: Input images

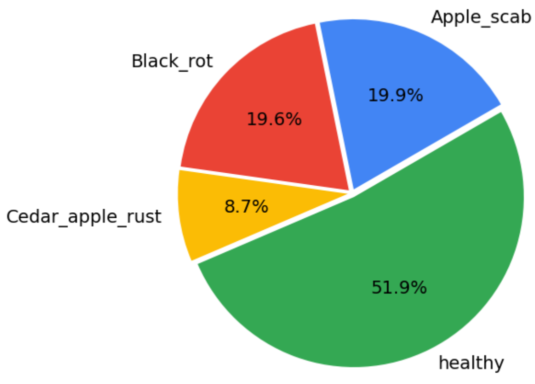

Figure 4.2 Class distribution

As shown in figure 4.2, the dataset has four classes which are cedar apple rust, black rot, apple scab and healthy. The dataset distribution is with their percentage is shown in terms of percentage.

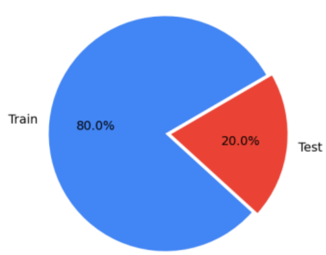

Figure 4.3 Training and test data

As shown in figure 4.3, the percentage of training and test data is illustrated. The training data is 80 percent and test data is 20 percent

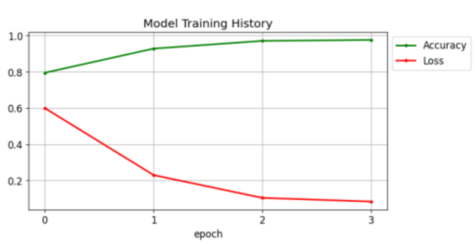

Figure 4.4. Model training information

As shown in figure 4.4, the model training and loss is illustrated in the figure. It is analyzed that training accuracy is achieved upto 96 percent

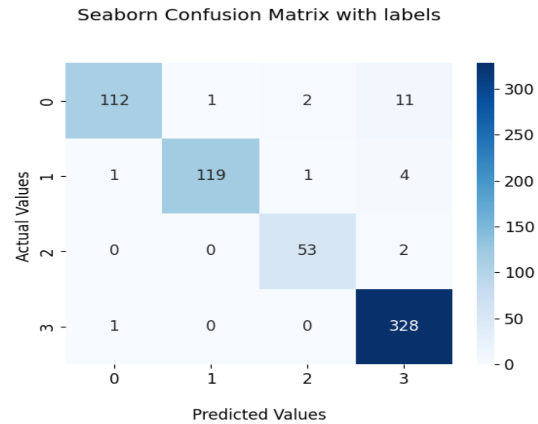

Figure 4.5 Confusion Matrix

As shown in figure 4.5, the proposed model is tested on the test data. The confusion matrix is plotted with the true positive, true negative, false positive and false negative values.

4.2 Result Analysis

a. Accuracy: Accuracy is a widely used metric for evaluating the performance of a program. It measures the proportion of correctly classified samples out of the total number of samples. Mathematically, it can be represented as:

$$A_i = \frac{t}{n} \cdot 100$$

In this equation, t denotes the count of samples that are correctly classified, while n represents the total number of samples.

b. Precision: Precision is a performance metric that quantifies the ratio of accurately predicted positive cases to the total number of predicted positive cases.

Precision= TP/TP+FP

c. Recall: Recall, also referred to as sensitivity in psychology, is a performance measure that evaluates the proportion of true positive cases that are accurately predicted as positives. It provides an indication of how well the positive prediction rule (+P) covers the true positive cases.

Recall= TP/TP+FN

Table 1 illustrates a comparative analysis of the KNN (K-Nearest Neighbors) and voting classifier models based on their accuracy, precision, and recall. The metrics are presented as percentage values.

Table 1: Performance Analysis

Model	Accuracy	Precision	Recall
Random Forest	66 Percent	56 Percent	66 Percent
SVM	77.59 Percent	78 Percent	78 Percent
KNN	69.88 Percent	70 Percent	70 Percent
Proposed Model	91 Percent	91.2 Percent	92 Percent

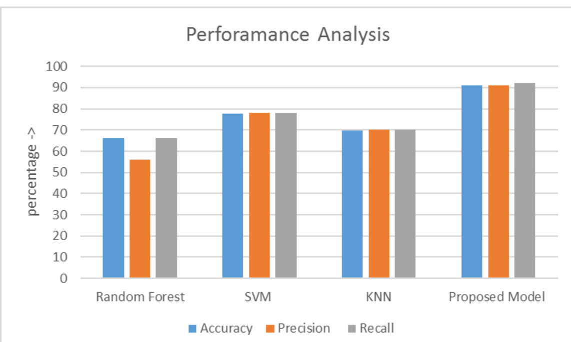

Fig 4.5 Performance Analysis

The results of the contrast among the proposed methodology, the voting classification algorithm, and the current method, KNN classification, is shown in Figure 4.5. According to the analysis, the proposed method performed better for forecasting plant illnesses than the current method with respect to of precision, recall, and accuracy.

V. CONCLUSION

Finding illnesses in plant leaves is the major goal of this activity. In the past, plant disease detection was done manually using microscopes. However, this approach is time-consuming and impractical for large-scale detection. Digital image processing techniques, coupled with machine learning algorithms, allow plant pathologists to detect diseases from digital photographs of plant leaves. The proposed approach in this work utilizes digital image processing methods and a voting-based architecture for disease detection. Digital cameras have been used to capture the photos, and image processing methods are then used to extract the necessary features. In this research work transfer learning model is applied for the plant disease detection. The proposed model achieve accuracy of 92 percent which is approx. 8 percent higher than existing models

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