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ORIGINAL ARTICLE

Real-time detection and identification of plant leaf diseases using convolutional neural networks on an embedded platform

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Abstract
Early identification of crop disease can aid the farmers to take timely precautions and countermeasures for its removal. In this paper, a real-time system to identify the type of disease present in a crop based on leaf images using machine learning is proposed. A deep convolutional neural network architecture is proposed to classify the crop disease, and a single shot detector is used for identification and localization of the leaf. These models are deployed on an embedded hardware, Nvidia Jetson TX1, for real-time in-field plant disease detection and identification. The disease classification accuracy achieved is around 96.88%, and the classification results are compared with existing convolutional neural network architectures. Also, the high success rate of the proposed system in the actual field test makes the proposed system a completely deployable system.

Keywords Convolutional neural network · Crop diseases identification · Embedded Platform · Machine Learning · Precision Agriculture · Real-time detection

1 Introduction

Agriculture being an important sector in Indian economy [43] contributes to around 15.87% of the country's GDP [43], and it nearly employs the nation's 54.15% of the workforce. Though considerable progress has been made in this sector over the past decades, damage due to pests and diseases in crops remains a prime concern. This not only affects the yield, incurring a loss to the farmer, but also impacts the overall population, health, livelihood and economy as a whole. However, if the crop diseases can be detected and identified properly, corrective measures to control its spread and loss of yield can be employed.

In developing countries like India, the primary identification of crop disease is done by visual observation by the farmer, where proper diagnosis of the disease usually depends on the skill, experience and ability of the farmer. There always underlies a risk of incorrect identification of the disease as it becomes a case of subjective analysis. Sometimes, the plant pathologists or agronomists may even fail to correctly identify the disease, leading to improper counter measures. This poses a major challenge for correct diagnosis of crop disease, so as to provide timely treatment and save crop damage. The recent advancements in artificial intelligence and machine learning and their ability to accurately identify and differentiate between patterns and structural analogies from images are gaining popularity in the field of precision agriculture and management.

Machine learning-based approaches have been employed to diagnose the disease present in a crop. However, their extent and scope are limited to identification of the type of disease in the crop. In this paper, we not only use machine learning to correctly identify the crop disease, but also deploy this on an embedded platform and perform real-time processing for leaf detection and disease identification. The complete idea of this work is to provide a disease detection system on

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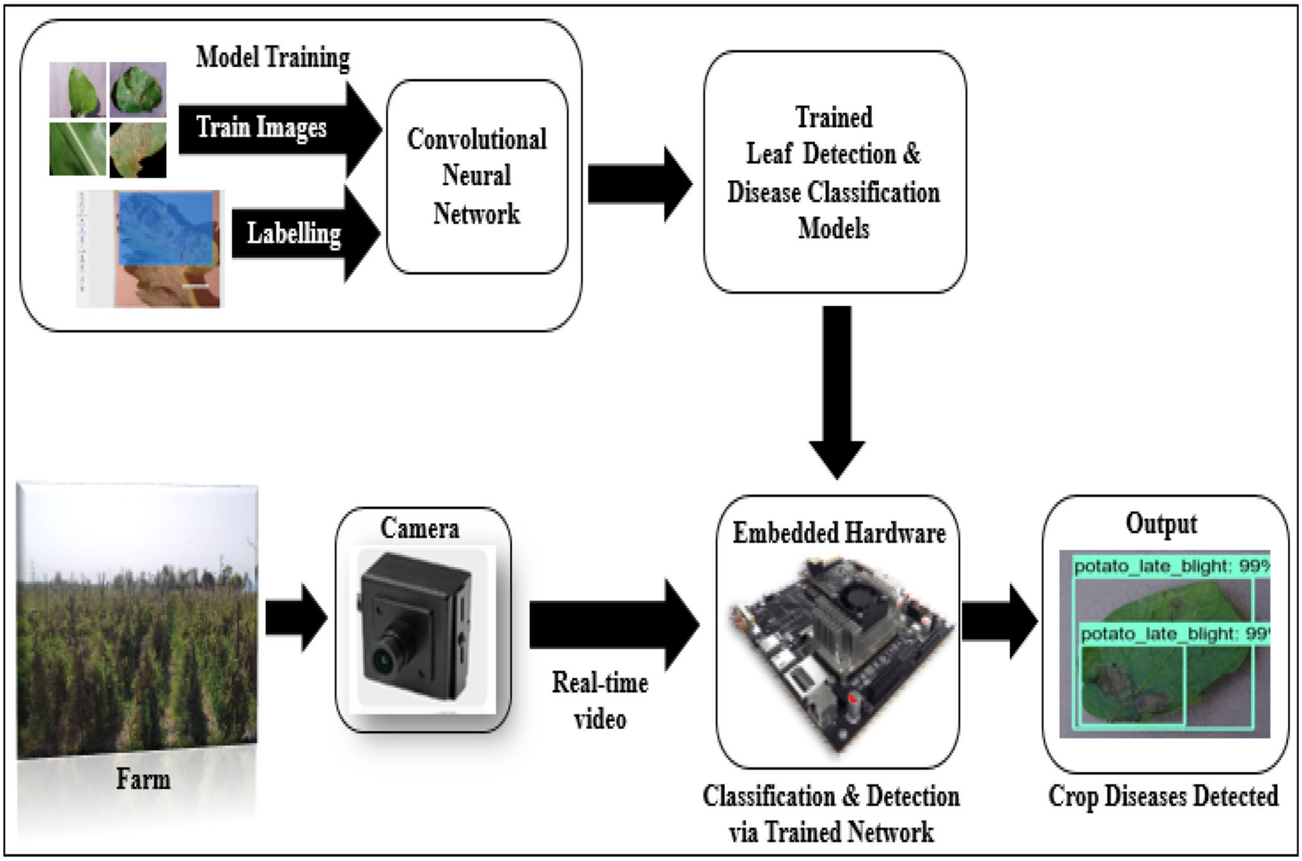


Fig. 1 Block diagram of the complete crop disease detection system

a handheld device, which the farmer can use in the field and get real-time identification of the crop disease.

The objective of this paper is to propose an automatic agriculture crop disease diagnosis system that detects the leaves from real-time video frames captured in-field by a camera attached to a handheld embedded device and identify the type of disease present in the crop using a deep convolutional neural network. Figure 1 presents the block diagram of the complete system. To detect the location of the leaf in field, single shot detector (SSD) is used and a convolutional neural network architecture is designed and trained to classify the crop disease. The complete detection and identification architecture is ported on Nvidia's Jetson TX1 to process the data. To perform real-time disease diagnosis in field, a handheld device is designed, which integrates a camera that takes real-time input from the field and gives to the Nvidia's Jetson TX1, which detects the leaf and detects the type of disease present in the crop. As the device being a compact, handy instrument, this embedded hardware will facilitate the farmer for timely and accurate diagnosis of the disease in the crop. The advantage of the complete system is real-time processing by a mobile device, which can work efficiently and give accurate diagnosis despite of varying illumination conditions, complex background and surrounding area such as other leaves, soil, orientation of the leaf or camera angle or image quality.

The main contributions of this paper are as follows:

- A deep learning-based real-time localization of leaves and identification crop disease from those leaves, which outperforms existing conventional CNN architectures.
- Real-time detection of crop diseases using input from leaf video captured by a camera, processed on an embedded hardware.
- An integration of the crop disease identification on a handheld embedded device to achieve real-time, in-field diagnosis of the disease.

The rest of the paper is organized as follows. A brief overview of the work reported in the literature for plant disease identification using various machine learning approaches is described in Sect. 2. Section 3 describes the model for leaf detection and then presents the architecture of the proposed model for plant disease identification from infected leaves. The results demonstrating the effectiveness of implementation of the proposed approach are presented and compared with existing architectures in Sect. 4, and Sect. 5 gives the conclusion.

2 Related work

For centuries, food loss due to crop infections from pathogens such as bacteria, virus and fungi is a vital issue that needs to be addressed across the globe. So to ensure agricultural sustainability, crop disease detection at an early stage can drastically reduce the yield loss as well as economic loss. There are several methods to detect disease based on localization of its occurrence in the crop, like leaf, node or stem. This paper deals with identification of the crop disease by examining the effect of the diseases on the leaves.

Diseases in plants can be broadly detected by direct and indirect methods [11]. Direct detection includes molecular analysis of the plant, giving higher throughput. However, direct detection requires large samples for identification. Indirect methods detect the disease in plants by observing and exploiting the plant stress and volatile profile [11]. The most extensively used indirect methods include thermography, fluorescence imaging and hyperspectral techniques [6]. Infection in the plant due to pathogens can cause loss of water in plants, which leads to temperature changes in the plant leaves [27]. These differences in the surface temperature of plant leaves can be found using thermographic imaging [11]. Here, the color difference in the leaf is captured by the thermographic cameras. However, this method is sensitive to changing environmental conditions and lacks specificity toward certain diseases [11]. Fluorescence imaging measures chlorophyll fluorescence in a leaf as a function of incident light. Leaf rust in wheat leaves was detected by analyzing the spatial and temporal variations in chlorophyll fluorescence at 470 nm using this method by [24]. Similarly, Plasmopara Viticola infection in grapevine leaves was also detected by fluorescence imaging in [8].

These scientific techniques still require human efforts to process the leaves for disease detection. In order to non-invasively detect the plant disease and automate the complete process, digital image processing techniques were used on leaf images. The ability of image processing approaches to segment, cluster, classify data or regions in an image came as an advantage for classifying between healthy and unhealthy leaves, discriminating the affected area, detection and identification of the disease. Arivazhagan et al. [5] detected the healthy and unhealthy regions in leaves using image segmentation and fed color co-occurrence as features to support vector machine (SVM) classifier and detected early scorch, spots, fungal and bacterial diseases in nearly 30 native plants from 500 images. Singh [37] used segmentation with genetic algorithm to detect the damage in leaves due to spread of various diseases. Zhang et al. [48] used k-means clustering to segment the disease leaf images, extracted shape and color features and then used sparse representation to classify diseased images of cucumber leaves.

With rapidly changing technical areas, the involvement of artificial intelligence (AI) in agriculture and vegetation can contribute to sustainable development. The evolution of AI has taken place so rapidly that in less than a century, AI has found its application in almost all the fields. Subsequently, due to the recent advancements in field of machine learning, various machine learning approaches and convolutional neural network architectures have been applied to detect and identify the diseases in plants. Amara et al. [3] used a deep learning-based approach to classify diseases in banana leaves using CNN-based LeNet architecture to recognize two banana leaf diseases under varying conditions of illumination, background, resolution, size and orientation. Kawasaki et al. [21] proposed a CNN-based approach to classify disease from cucumber leaves. Sladojevic et al. [38] used a CNN to identify 13 types of plant diseases from leaf images in five crops. Mohanty et al. [32] employed two CNN approaches based on AlexNet and GoogLeNet, to distinguish 26 diseases included in 14 crops using the PlantVillage dataset. Fuentes et al. [13] used deep learning-based method for detection of diseases in tomato plants by combining meta-architectures faster region-based convolutional neural network (Faster R-CNN), region-based fully convolutional network (R-FCN) and single shot multibox detector (SSD) with VGG net and residual network (ResNet). Lu et al. [30] detected 10 common rice diseases by using a CNN from leaf and stem images. Lu et al. [29] proposed an automatic in-field diagnosis system that identified diseases in wheat images using VGG-FCN-VD16 and VGG-FCN-S. Ferentinos [12] trained various CNN models like AlexNet, GoogLeNet and VGG to identify healthy and infected leaves from 25 different plants. Geetharamani [15] proposed a leaf disease identification model using a deep convolutional neural network (Deep CNN) to classify plant diseases from 13 different plant leaves. Durmus et al. [10] deployed convolution neural network on hardware platform Nvidia Jetson TX1 successfully. Table 1 presents a comparative analysis of the various methods and implementation in the literature to detect the plant disease from leaf images of various crops using machine learning approaches.

Based on this literature survey, it is observed that the ability of machine learning to extract and identify features from the input data can be further explored for efficient detection and identification of diseases in plant leaves. Architectures of convolutional neural networks are trained and tested on the available dataset for disease classification in the plants. However, hardly any research work had been reported to work on in-field images and detect in real time, given the actual complex field conditions. Also, the majority of the works are limited to simulation-based outcomes. We have proposed a real-time in-field convolutional neural network-

Table 1 Analysis of various algorithms & architectures

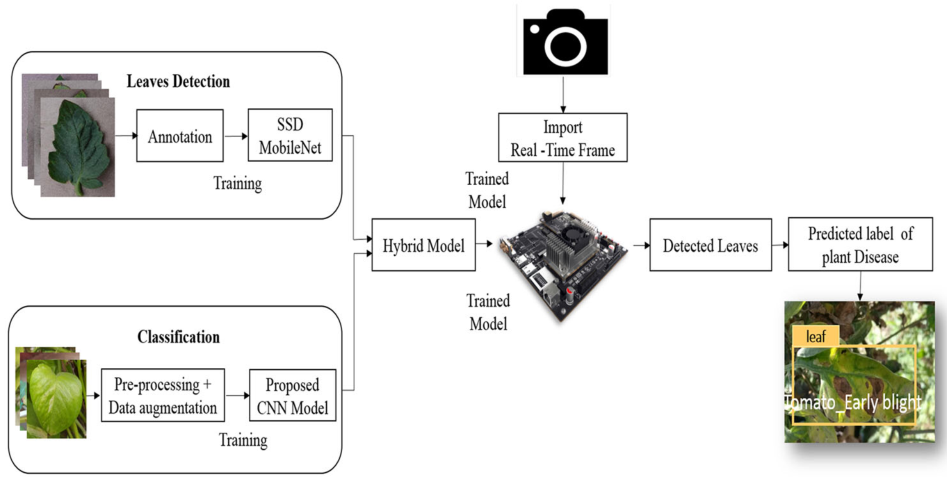
Sr. No	Author	Crop	Dataset details	Models architectures	Outcomes
1.	[1]	Grape Tomato Orange Apple	54,306 images from PlantVillage dataset	NASNet CNN	93.82% accuracy
2.	[31]	Coffee	159 images of Coffee Leaves	CNN	95.00% accuracy
3.	[15]	Apple Tomato Cherry Potato	61,486 images with 39 different classes	Deep CNN	96.46% classification accuracy
4.	[20]	Apple	26,377 leaf images of Apple diseases	VGG-INCEP (VGGNet + Inception) network as CNN	Detection performance reaches 78.80% mAP
5.	[49]	Maize	500 images from PlantVillage and Google	GoogLeNet (inception modules) as convolutional neural network	Average identification accuracy 98.90%
6.	[12]	Apple Banana Blueberry Cherry Maize	87,848 images of 25 different plants with 58 distinct classes	AlexNetOWTBn and VGG architectures as a CNN	99.53% success rate achieved
7.	[22]	Raspberry Soybean Squash Strawberry Tomato	54,309 images from PlantVillage dataset	Five layered convolutional neural networks	95.05% accuracy
8.	[3]	Banana	3700 Banana images from PlantVillage dataset	LeNet Architecture as a convolutional neural network	95.55% accuracy
9.	[30]	Rice	500 natural images of rice disease and healthy rice leaves	CNN	95.48% accuracy
10.	[10]	Tomato	Tomato leaf images from the PlantVillage dataset	CNN AlexNet and SqueezeNet Architectures	94.30% accuracy
11.	[16]	Legume	866 leaf Legume images	DL/CNN	98.8% accuracy for five CNN layers
12.	[38]	Pear Cherry Peach Apple	4483 original images taken from the available Internet sources	CaffeNet as CNNs	Achieved precision between 91% and 98%
13.	[21]	Cucumber	800 Cucumber leaf images	CNNs	94.9% accuracy
14.	[14]	Cucumber	7520 Cucumber leaf images	CNNs	Average of 82.3% accuracy
15.	[33]	Apple	2539 images from 6 known disorders	CNNs	Achieved a 97.3% accuracy
16.	[35]	Corn	8506 images of corn leaves from 4 categories	Proposed CNN architecture	97.09% accuracy
17.	[25]	Tomato Corn Apple	54,306 images from PlantVillage dataset	CNNs	89.83% accuracy
18.	[44]	Tomato	18,160 Tomato images from PlantVillage dataset	Convolutional neural network model as LeNet	Achieved an average accuracy of 94-95%
19.	[19]	Guava	2705 images of Guava	AlexNet	98.74% Average accuracy
20.	[45]	Tomato Corn Cherry Grape Apple	54,305 images from PlantVillage dataset	CNNs	Validation accuracy 95.81%
21.	[36]	Tomato	500 images of tomato leaves	CNNs/LVQ	86% accuracy

based models for plant disease identification system that not only detects the leaves in the field, irrespective of their background, orientation, size or cluster, but also classifies the type of disease from the leaf. Also, identification is not limited to a single disease, but multiple diseases present on single or multiple leaves are efficiently identified. The complete system is ported on an embedded hardware Nvidia Jetson TX1, making it a portable and easy to use system.

3 Proposed approach

The implementation of the complete system is basically divided into two sections, one for leaf detection and the other for disease identification. For leaf detection, initially, we have created the leaf dataset by capturing the images of multiple leaves having different shapes, sizes, orientations and backgrounds. These leaf images were then manually annotated and used as input to train the single shot detector (SSD) model for detection of leaves from the input image. This trained SSD

Fig. 2 Implementation flow of the proposed system



model outputs the area where the leaves are detected in the image through bounding boxes over the leaves. After successful detection of the leaves in the image, for the further prediction of the crop disease from leaf images, a convolutional neural network (CNN) architecture is proposed. For this disease classification model, we have used the PlantVillage dataset from which healthy and infected leaf images are preprocessed and then proposed CNN architecture described in Sect. 3.2 is trained. This trained model predicts the diseases present in the plant through leaf images provided to the model.

To develop the real-time system for detection and identification of the plant disease from leaves, a hybrid approach is proposed, which combines both, the trained leaf detection model and the disease classification model. With this model, multiple diseases can be identified on single as well as multiple leaves at same instance of time. In this approach, first the leaves are detected using the SSD leaf detection model which outputs bounding box coordinates for every leaf captured by the camera image. Using these coordinates, each leaf from the image is cropped and resized and then passed through the disease classification model which processes these leaf images and predicts the diseases infected on the plant leaf. Further, these models are then deployed on embedded hardware for real-time execution in the field. A camera is attached to an embedded hardware which captures real-time video of the plant, and these video frames are first fed to this hybrid model which first detects the leaves and then predicts the diseases on the leaves through the approach described above. Figure 2 presents the implementation flow of the complete process.

3.1 Leaf detection

Before identifying the disease present in a leaf, it is important to detect the location of the leaf in the field of view of the camera. The existing approaches in the literature, as discussed in Sect. 2, have been identifying the disease present on a single leaf, based on the training by the available dataset. However, these techniques would fail when deployed in-field, as identifying the disease assuming a single leaf to be present on any crop would be illogical. It is necessary to have a model that can identify multiple leaves on a plant and accurately locate them for disease detection. Hence, the first task undertaken by us was to correctly detect the leaves, in real time, on the plant. For this, we used the object detection model, single shot detector [28] to detect multiple leaves on a plant. Mobilenet [18] was used as the base network for SSD. We chose the Mobilenet V1 as we were intending to run our disease detection algorithm on the embedded platform. The inference speed for Mobilenet V1 is 30 ms, which is very low as compared to other existing object detection models like Faster R-CNN [40] and YOLO [42]. Multiscale feature maps and convolutional predictors at each feature layers with default bounding boxes allow us to detect leaves of multiple scales very effectively with reliable accuracy. SSD's simple method encapsulates all predictions in one network also effectively reduces the time for each prediction. This makes it very attractive for embedded platforms. This would also increase our processing speed when deployed on an embedded hardware. The SSD Mobilenet detects the leaves and creates a bounding box across it and predicts the coordinates of the bounding box.

3.2 Diseases classification

To efficiently classify the crop diseases from leaves, we propose our own machine learning model which is inspired by the Inception model [41]. Instead of using only one kernel of fixed size, Inception extends this idea by introducing kernels of multiple sizes at each layer and concatenating their outputs. The main idea behind Inception module is factor-

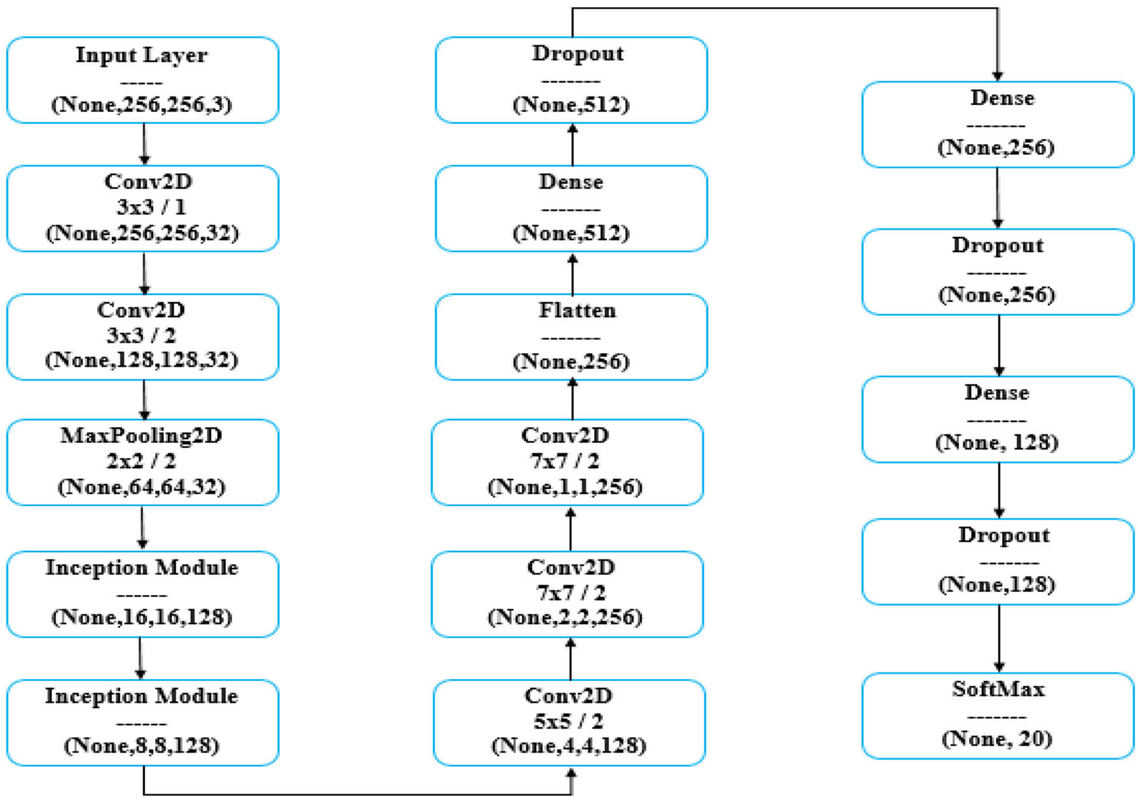


Fig. 3 Architecture of the proposed leaf disease classification model, which has 6,076,980 parameters

izing the convolutional operation into smaller convolutions. For example, factorizing the 5x5 convolutional layer into two 3x3 convolutional layers saves computation power but provides same effect.

Using this concept of Inception module, we have designed our own CNN architecture for classification of the plant diseases. The architecture of our proposed model is shown in Fig. 3. The proposed disease classification model uses convolutional neural network-based architecture to first extract visual features from images and then perform classification using fully connected neural networks. The model first uses convolutional layers to extract the low-level features of the input image such as lines, edges and patterns present in the leaf image. After the convolutional layer, we have added the Pooling Layer, which reduces the spatial dimension. This layer is responsible for reducing the variations, and it computes the maximum value of the feature over the specific region on an image. These layers even help for faster convergence with processing invariant features. Layers before the Inception module are responsible for extracting low-level features which may be common in all leaf images. The Inception module uses convolutional layers of different kernel sizes on the same feature maps which are responsible for extracting different levels of features from the same maps. Hence, the Inception module here extracts the granular level features to high-level features using different sizes of kernels and also fuses this information at the end. Visual representations generated in the form of feature maps are converted to vector by flattening them. These representation vectors represent each image in the lower-dimensional feature space where they can be easily classified by fully connected neural networks. Fully connected neural networks use a Softmax classifier to convert scores generated by neurons of the fully connected layer to the probability distribution of disease classes, where the class having the highest probability is considered as a prediction of disease class. To initialize the weights of the network, He normal [17] method is used where distribution of weights depends upon the size of the previous layer. He normal initialization helps with gradient vanishing and exploding problem and also helps the cost function to reach global minimum faster. For every neuron, exponential linear unit [ELU] [7] is used as an activation function. As a regularization method to make the model less prone to overfitting, dropout [39] with rate 0.5 is used in a fully connected network.

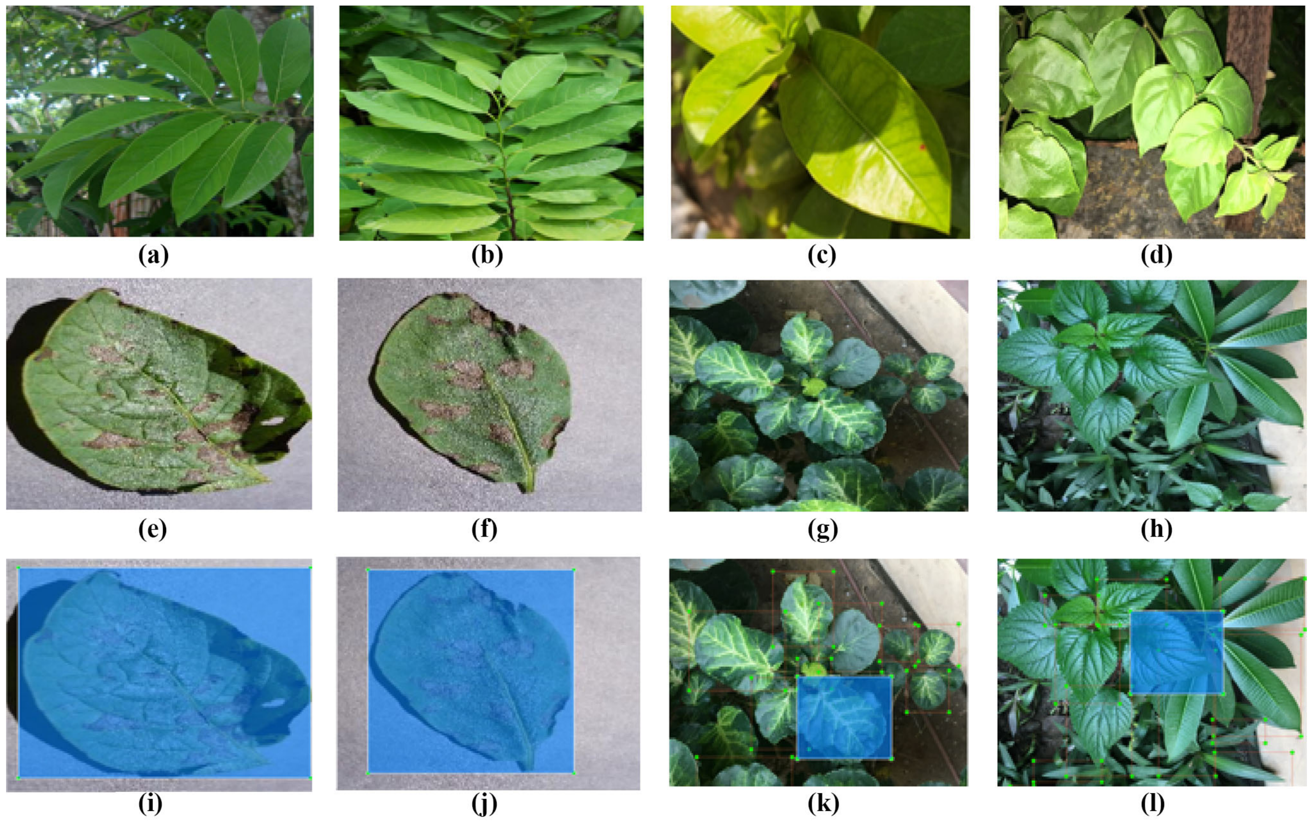


Fig. 4 Sample images from the dataset for leaf detection. (**a**)–(**d**) Captured from the University campus; (**e**) and (**f**) images from PlantVillage dataset; (**g**) and (**h**) images taken from the Internet; (**i**)–(**l**) annotation of leaves from images (**e**)–(**h**), respectively

3.3 Embedded platform

The models for leaf detection and disease classification are combined sequentially, generating a hybrid model, which is then ported on Nvidia's Jetson TX1 for real-time testing on field. Nvidia® Jetson TX1 has a quad-core ARM processor, 256 cores CUDA Maxwell GPU, 4GB LPDDR4 RAM, 16GB eMMC storage. Jetson TX1 was used to test the disease classification model and leaves detection model described in previous subsections.

4 Experimental results

4.1 Dataset details

The training and testing of both, the leaf detection model and disease classification model, were done on images from PlantVillage dataset as well as images collected by us manually, for making the models robust. These trained models were deployed on the embedded platform Nvidia Jetson TX1, and the final testing of the proposed hybrid model was done on a real farm.

4.1.1 Leaf detection

In order to train our leaf detection model, we prepared the dataset containing the images of leaves of various sizes, colors and species. We collected 338 leaf images from our University campus at a different time of day using an HD camera. This ensured that the images had variations in the illumination, size, quantity in cluster and various features with random background and brightness. Sample images for the dataset are shown in Fig. 4a–d. To have a variation of illumination and exposure, these images were clicked at different hours of the day. The image (a) was captured in the morning at 8:00 am, (b) at 11:00 am, (c) in the noon at 4:00 pm and (d) in the late evening at 8:00 pm. In order to increase the spontaneity of the data, we downloaded 52 leaf images available online from Google using the Python library. These images were chosen such that they had multiple leaves in them so to ensure that the leaf detection model was able to detect multiple leaves from the single image. Sample images are shown in Fig. 4g, h. These images were of the plants other than those considered for disease classification. We randomly took 111 images from PlantVillage dataset so that the leaf detection algorithm can get famil-

Table 2 Dataset details of healthy and infected leaves considered and their corresponding class label

Class label	Class name	Number of images
0	Apple scab	630
1	Apple black rot	621
2	Cedar Apple rust	275
3	Apple healthy	1645
4	Corn Cercospora gray leaf spot	513
5	Corn common rust	1192
6	Corn healthy	1162
7	Corn northern leaf blight	985
8	Potato early blight	1000
9	Potato healthy	152
10	Potato late blight	1000
11	Tomato bacterial spot	2127
12	Tomato early blight	1000
13	Tomato healthy	1591
14	Tomato late blight	1909
15	Tomato leaf mold	952
16	Tomato Septoria leaf spot	1771
17	Tomato spider mites	1676
18	Tomato target spot	1404
19	Tomato mosaic virus	373
	Total images	21,978

iarized with the images of leaves affected with diseases. Figure 4e and f shows these diseased leaf images. Thus, we created a dataset of 501 images containing variations in orientation, size, illumination, background and clustering of leaves. We need to manually annotate the area of images containing leaves to train the object detection algorithm. In the annotation process, we aim to label the class and area of leaves with bounding boxes. LabelImg [46] tool was used to draw bounding boxes over leaves, and XML files were generated containing coordinates for every bounding box in each image. Annotated sample images from the dataset are shown in Fig. 4i–l.

4.1.2 Disease classification

A rich dataset was required to create a deep learning model to detect plant diseases. For training the disease classification model, we used the PlantVillage dataset [32] which contains the images of disease-affected plants and healthy plants of various plant species. From this dataset, we have considered healthy and infected leaf images of 4 crops, namely corn, apple, potato and tomato, thereby producing 20 different classes in total. Table 2 presents the plants considered and the disease type for each plant, along with the class label assigned to each type and the number of images present in each class. Every class is either a healthy or infected leaf class defined by its label. Some sample images for the visualization from the PlantVillage dataset are shown in Fig. 5. The dataset for classification was divided into train, validation and test set in a ratio of 80%, 10% and 10%, respectively.

4.1.3 In-field dataset

To check the robustness and accuracy of the proposed leaf disease identification CNN architecture, we tested it in a tomato farm in real time. Some sample images captured from the field are shown in Fig. 6. Frames from real-time video taken from the field were fed to the trained detection and classification models ported on Jetson TX1 to first detect the leaves in real time and then predict the disease in the leaves.

4.2 Training and testing

4.2.1 Leaves detection

We performed our experiments on the system with Intel® core™ i5-8300H CPU@ 2.3 GHz(8 cores) and Nvidia® GTX 1050 ti 4 GB VRAM using CUDA® parallel processing library and TensorFlow framework. The dataset for leaf detection was divided into 90% for training and 10% for testing. Data augmentation techniques such as randomly flipping the image horizontally, adding random brightness and random image crops were applied to make the model less prone to overfitting. Our aim was to minimize the localization loss for the bounding box and classification loss for leaves. We used the pre-trained SSD on the COCO dataset [26] and trained on our dataset for 75000 steps. SSD uses non-max suppression to reduce the false-positive cases by only selecting the predicted box having IOU (intersection over union) >0.5 with the ground truth box. After training, the model was evaluated on test set images. The hyperparameters used for the training of the proposed leaf detection model are mentioned in Table 3.

4.2.2 Disease classification

Data augmentation techniques such as brightness, flipping image left-right and flipping up-down randomly were done on the images during training to make the model less prone to overfitting and also helped in making the model more robust. This proposed model consists of nearly 6M (million) parameters which are nearly one-tenth less compared to AlexNet [23], and also, it provides relatively higher accuracy compared to AlexNet. The hyperparameters chosen for the training are shown in Table 4. The learning rate was initially set to 10e-3, and it decays exponentially after every epoch. The learning curves for this classification model, i.e., number

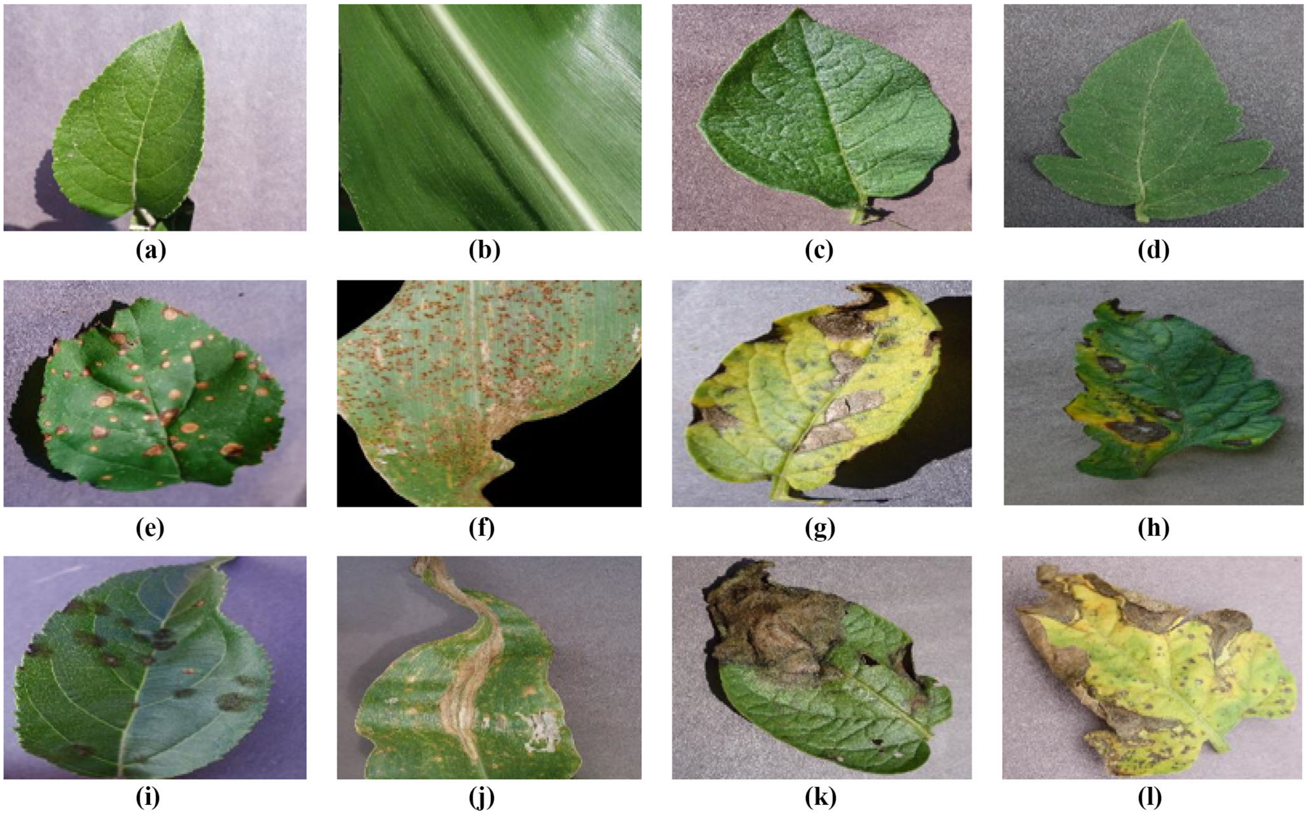


Fig. 5 Sample images of healthy and diseased leaves from the PlantVillage dataset for disease classification. **a** Apple healthy; **b** corn healthy; **c** potato healthy; **d** tomato healthy; **e** apple black rot; **f** corn common rust; **g** potato early blight; **h** tomato early blight; **i** apple scab; **j** corn (maize) northern leaf blight; **k** potato late blight; **l** tomato Septoria leaf spot

Fig. 6 Sample images from the field used for testing

Table 3 Hyperparameters of the leaf detection model

Hyperparameters	Value
Learning rate	0.004
Exponential decay	5000 steps with decay factor 0.95
Optimizer	Rms-prop
Batch size	8
Number of steps	75000

Table 4 Hyperparameters of the leaf disease classification model

Hyperparameters	Value
Learning rate	10e-3
Exponential decay	Decay factor 0.95
Optimizer	SGD
Epochs	100
Dropout rate	0.5
Kernel initializer	He Normal

of epochs vs loss and accuracy with respect to the number of epochs, are shown in Figs. 7 and 8, respectively. From these curves, it can be observed that the loss reduces with increasing epochs and hence it is evident that the proposed neural network architecture is efficient in learning the training data for disease classification, with less error rate.

4.2.3 Proposed hybrid model

We combined both, the leaves detection model and the disease classification model, to detect the leaves and classify the disease present within each leaf. During real-time detection, every video frame is fed into the leaf detection model which was described in Sect. 3.1. The model outputs the predicted coordinates for bounding boxes containing each leaf. Using these coordinates, each leaf image is cropped from the video frame and fed into the disease classifier described in Sect. 3.2 which classifies each leaf image as one of the 20 classes mentioned in Table 2. This process is repeated for all video frames, and disease detection in real time is achieved.

4.3 Results

4.3.1 Leaves detection results

For the leaves detection model described in Sect. 3.1, the mean average precision (mAP) of 0.4062 was obtained at 0.5 IOU. Table 5 presents the results for the leaf detection model. Figure 9 shows the output of leaves detection in real time. It can be seen that multiple leaves in the same frame, of different sizes and orientations, are accurately detected by the model despite the background condition.

4.3.2 Disease classification results

After the training of the proposed classification model for 100 epochs, the categorical accuracy achieved was 96.88%. The equations to calculate the precision, recall and F1-score for the model are shown below. Table 6 consists of the model testing parameters values calculated using the mentioned equations. Our proposed model has around 6M parameters, way too less compared to AlexNet which has around 62M parameters. Table 7 presents the comparison of accuracy for the disease classification of our proposed model with existing conventional CNN architectures. The comparative results show that the proposed model achieves an accuracy of 96.88%, which is much better in comparison with other architectures like SqueezeNet, AlexNet and DenseNet which achieve an accuracy of 94.67%, 95.53% and 96.59%, respectively. The performance of two reported CNN architectures [45] and [15] is also compared in terms of accuracy, and the proposed model outperforms in comparison with the respective accuracy of 95.81% and 96.46% achieved by them.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{1}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{2}$$

$$F1 - \text{Score} = 2 \cdot \frac{\text{Recall} \cdot \text{Precision}}{\text{Recall} + \text{Precision}} \tag{3}$$

Confusion matrix shows the predicted values over the true values on the test data set. The confusion matrix for our proposed disease classification model for all the 20 classes of healthy and unhealthy leaves using true positives and false negatives is shown in Fig. 10, where the misclassifications are highlighted in red color. It can be seen from the confusion matrix that the proposed model predicts the plant diseases very accurately, with minor misclassifications. However, misclassification between two classes of diseases in corn, i.e., Corn Cercospora gray leaf spot and Corn northern leaf blight, is observed. Corn Cercospora gray leaf spot is caused by the fungus Cercospora zeae-maydis. It causes pinpoint lesions on the leaf, surrounded by yellow halos initially [47]. At this stage, it can be difficult to correctly identify the disease [9], but as lesions mature, they elongate into narrow, rectangular, brown to gray spots. Due to this reason, Corn Cercospora gray leaf spot can be confused with symptoms of other foliar diseases particularly with northern leaf blight [4], which are long tan colored lesions on the leaf. This could be a reason for misclassification among these two classes of diseases by the proposed model. Figure 11a and b shows the sample images of corn leaves infected with gray leaf spot and

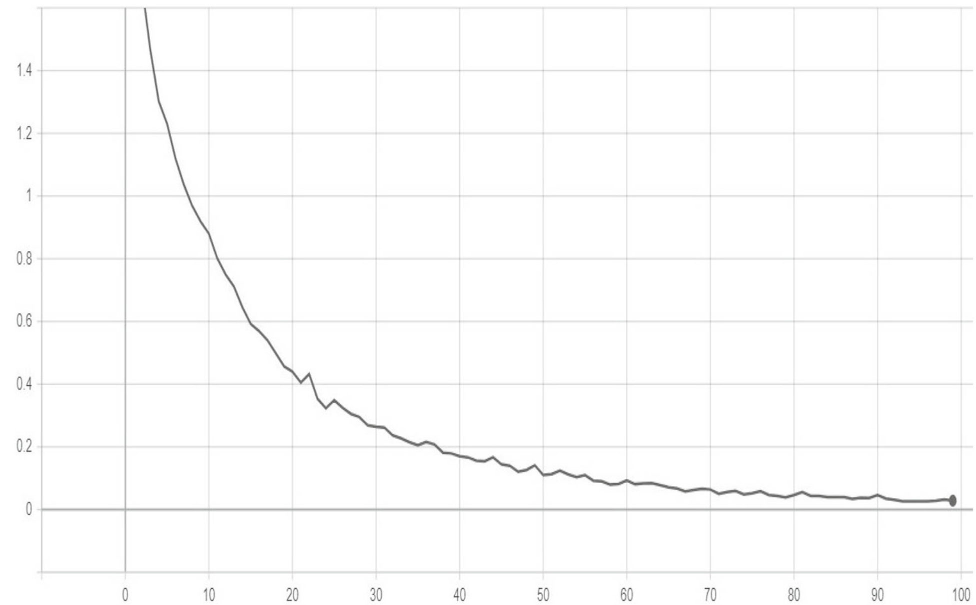


Fig. 7 Loss vs epoch curve for proposed leaf disease classification model

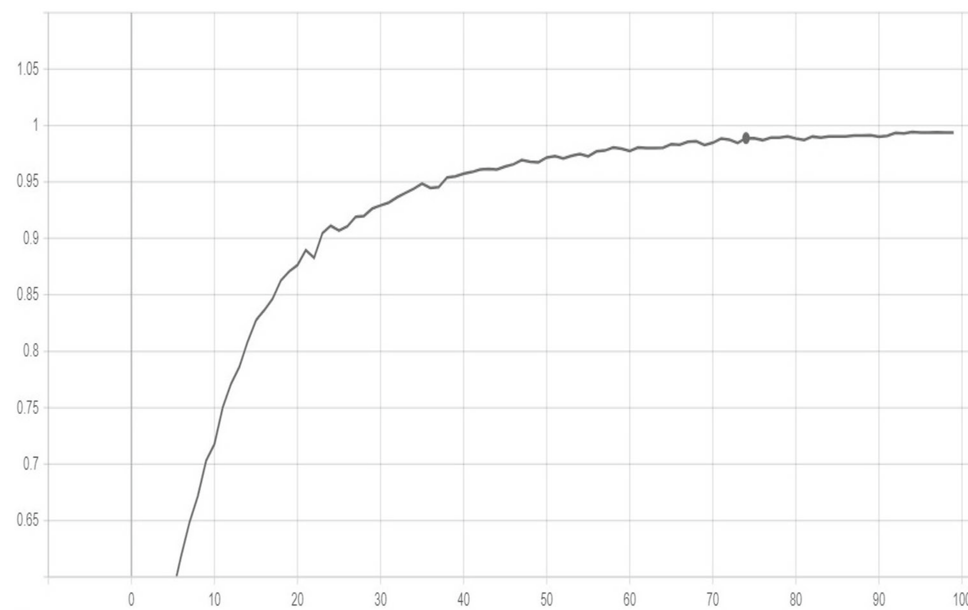


Fig. 8 Accuracy vs epoch curve for proposed leaf disease classification model

northern leaf. Another misclassification is observed between the classes late blight in tomato and late blight in potato. Late blight, a disease caused due to fungal pathogen, Phytophthora infestans, is a common and serious disease infecting tomato and potato plants [34]. The symptoms of this disease are formation of dark blackish-brown, water-soaked lesions (spots) on the leaves [2]. Since late blight is a common disease in tomato and potato, it affects the leaves in the same fashion. This is also evident from the images of infected potato and tomato leaves shown in Fig. 11c and d, respectively, and hence could have resulted in wrong class predication. Apart from this, the proposed model has shown promising results in identifying similar diseases like tomato late blight and tomato leaf mold, both which cause large dark spots on the leaf.

Table 5 Results of real-time leaf detection

Test parameter	Value
Mean average precision (mAP@0.5 IOU)	0.4062
Classification loss	5.53
Localization loss	1.082

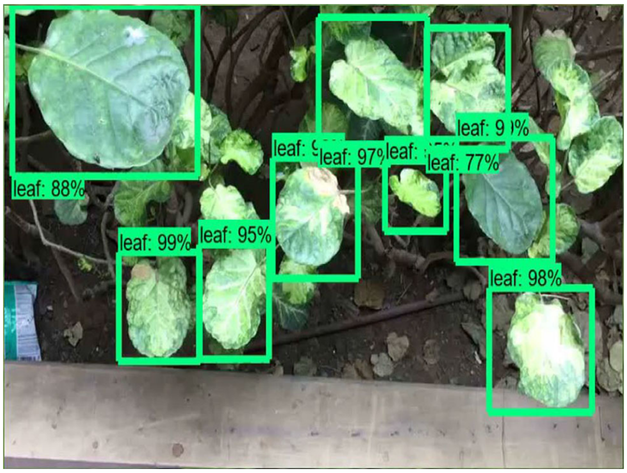


Fig. 9 Real-time leaves detection result

Table 6 Classification/model performance report

Evaluation metrics	value
Precision	93.78 %
Recall	94.91 %
Accuracy	96.88 %
F1-score	95.34%
Epochs	100
No. of parameters	6,076,980

Table 7 Comparison of disease classification models

Model	Accuracy
SqueezeNet	94.67 %
AlexNet	95.53 %
DenseNet	96.59 %
CNN model by [45]	95.81 %
CNN model by [15]	96.46 %
Proposed CNN model	96.88 %

4.3.3 In-field testing results

Nvidia Jetson TX1 was used to do field testing of the proposed plant disease identification system. The leaf detection and disease classification models were deployed on Jetson TX1. The effectiveness of the leaf detection and disease identification model was tested by taking the system to a tomato field. During real-time testing, it was observed that the system took on an average around 3 ms for detection of the leaves and identification of the disease present on the leaves, providing a quick and effective prediction of the disease.

To evaluate the disease detection accuracy of the proposed system, we designed an experiment for quantitative analysis in the field. To validate our detection results, we had taken the assistance of the farmer looking after that field and also an agronomist. The steps of the experimental procedure and methodology employed for testing were as follows: We picked up one area in the field where the tomato plant leaves showed the presence of disease and did the setup for the testing. For the setup, we connected the camera to the Jetson TX1 hardware, on which the detection model was already loaded, and gave the real-time video feed for the leaf detection and disease classification. The outcome of this model was the detected disease class displayed on the bounding box of the detected leaf. The model was efficient in detecting healthy as well as diseased leaves and was also able to display the presence of multiple diseases on the leaves. These identified diseases in the form of classified outputs of the model were then confirmed by the farmer as well as the agronomist. Their identification revealed that the diseases classification results by our model were near to 97.00% accurate. It was observed that model was able to efficiently detect the diseases on the leaves in the field of view of the camera. Figure 12 shows the results on real-time field testing, where leaves affected by the tomato early blight and late blight disease are accurately identified by the proposed system. Also, the system is efficient in distinguishing healthy and infected leaves with high accuracy. The proposed model not only detected multiple leaves infected by different diseases in the same frame efficiently, but was also capable of accurately identifying multiple diseases present on the same leaf. The efficient detection in real field also proves that the proposed model is robust against conditions like weather, background, soil and illumination.

5 Conclusions

Detection of diseases in crops is of utmost importance to minimize the loss of crops and getting higher yield by providing suitable pesticides. In this paper, a complete framework for real-time disease identification in a crop is presented. A new CNN architecture is proposed for identification and classification on 20 different healthy and diseased leaves of 4 different plants. From the experimental results, it can be concluded that the proposed CNN architecture performs well in classification of diseases from leaves, giving an accuracy around 96.88%, higher as compared to the accuracy achieved by existing architectures. The leaf detection and disease classification models are deployed on Nvidia Jetson TX1 to perform real-time disease detection in the field. The proposed system is not only efficient in detecting multiple leaves in the field for disease identification, but is also highly accurate in identifying multiple diseases simultaneously from the leaves. The performance of the system is validated in real

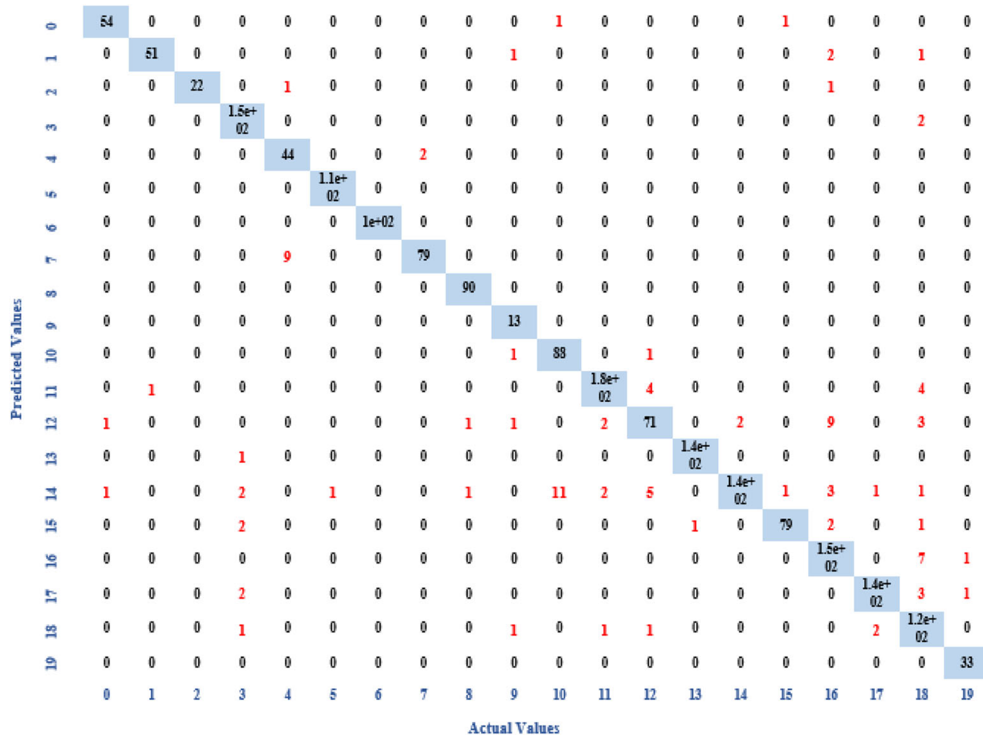


Fig. 10 Confusion matrix of the proposed disease classification model

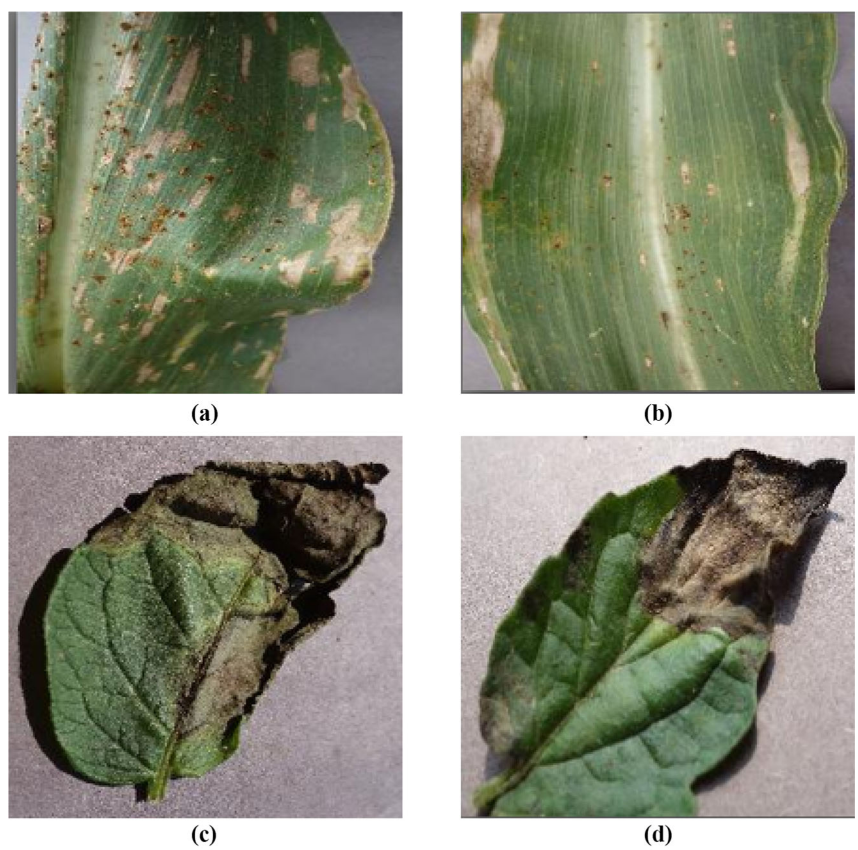
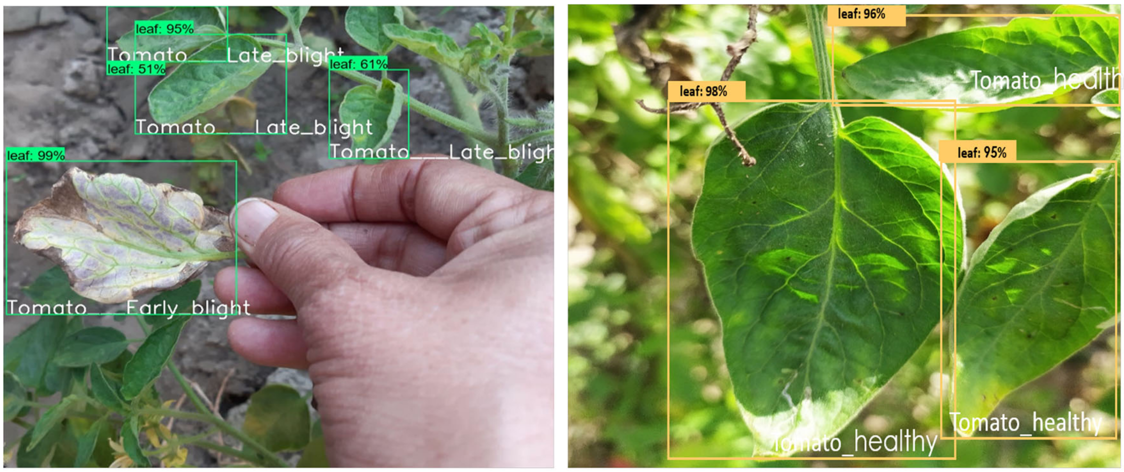


Fig. 11 Example of sample images of classes with incorrect classification. **a** Corn Cercospora gray leaf spot; **b** corn northern leaf blight; **c** potato late blight and **d** tomato late blight



(a) **(b)**

Fig. 12 In-field testing of the proposed system. The leaves of tomato are detected with accuracy mentioned in green color, forming a similar color bounding box around the leaf. **a** The identified disease; here early and late blight is also mentioned near the leaf (in white caption); **b** identification of healthy tomato leaves, without diseases

field, and it is robust under varied conditions of illumination, size, orientation of the leaf, soil and background conditions. This work can be further extended for more crops and plants with different diseases.

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