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Agricultural plant diseases identification: From traditional approach to deep learning

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ABSTRACT

Plant disease computerization in agriculture areas an important for every country, as the population rate increases the demand for food supply also increases. Today, the significant adaption of modern techniques and tools increases the accuracy of detection the plant disease. Identifying plant diseases in an early stage can reduce their spread. Early identifying is a beginning stage to fight against disease spreading. For plenty of years, researchers have researched how to tackle the common disease effects amongst humans, animals, and plants. However, there are still many gaps are remaining to identify and explore. In recent years, there have been many researchers using Deep Learning (DL) and Transfer Learning (TL) technologies to detect agricultural diseases based on Machine Learning (ML) algorithms that were developed with the development of Artificial Intelligence (AI) technology. Many, DL architectures are carried out together with numerous diverse visualization strategies to perceive and label the features of plant diseases. Our take a look at additionally makes a specialty of how ML strategies had been moved from conventional ML to DL and additionally numerous overall performance metrics (F1-score, sensitivity, accuracy, etc) are used for the assessment of the architecture/strategies. Some challenges are figure out while identifying the plant disease detection.

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1. Introduction

Plant diseases identity is a high studies content material with inside the subject of system imaginative and prescient. It is a generation that makes use of system imaginative and prescient technique/method/gear to seize pix to determine whether or not there are sicknesses with inside the gathered plant pix [1]. The prevalence of the disease contains a poor effect on agriculture production. If the plant diseases do not appear to be recognized early time, meals scarcity can increase [2]. In latest years, disorder identity has been a decisive issue. Early diagnose is that the preliminary foundation steps for powerful difficulty and management of plant diseases, and they play an extreme position in the control of agriculture production [1,2].

Generally, each disease represents a uniquely visible pattern that can diagnose abnormal. Usually, an infected plant can show clear marks or lesions on flowers, fruits, seeds, or stems. The Primary source of identifying the diseases on plants is leaves, and most of the symptoms appear on leaves (Zhang et al., 2021).

Based on experience, the farmers can identify the disease, or agriculture experts identify on-site. Economic losses increase when farmers blindly pesticides during the disease identification process on leaves [3]. To tackle these challenges, plant disease identification with image processing methods is a hot research topic.

1.1. Traditional to deep learning

The disease identity method in a conventional manner is proven with inside Fig. 1. Dubey et al. [3] selected 3 types of apple diseases (apple scab, apple rot, and apple blotch disease) as research objects. The region of the lesion in the fruit apple was identified by K-means clustering algorithm. Pattern (CLBP), color coherence

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Fig. 1. Traditional image identification processing.

vector (CCV), local binary pattern (LBP), and global color histogram (GCH) were recognized and identified with an accuracy of 93% on a Multiclass Support Vector Machine (SVM). Singh et al. [4] used the K-means clustering with Genetic Algorithm (GA). To set unlabeled points in different dimensions in different clusters GA was used with color co-occurrence feature extraction method. Here Local homogeneity, contrast, cluster shade, energy, and cluster prominence are computed for image. GA is used in K-means and Support Vector Machine (SVM). Four disease samples are used banana, beans, lemon, rose, and with the proposed Minimum Disease Criterion (MDC) algorithm the accuracy was 93.63% and SVM with proposed algorithm accuracy reached 95.71%.

Chai et al. (2010) selected 4 kinds of tomato foliage diseases (leaf spot, early blight, leaf mold, late blight) and extracted 18 features characteristics such as color, texture, shape. Using discriminant analysis combined with bayes discriminant analysis and component analysis combined with Fisher discriminant models. Accuracy 94.71% and 98.32% reached with two methods Bayes discriminant function and principal component analysis.

Devi et al. [5] use a Support Vector Machine (SVM), K-means clustering, and Grey Level Co-occurrence Matrix (GLCM) to identify paddy leaf diseases. K-means clustering forms a group cluster of paddy leaf images. Texture feature extraction is done through GLCM, and for classification, both linear and non-linear data SVM is used. Four diseases (Bacterial, fungal, viral, and mosaic) are detected and recognized with accuracy of 98.63%.

Maity et al. [6] efficiently addressed plant disease identification. With the help of image processing, Leaf diseases were identified and processed. To identify the faulty region in a leaf, K-means clustering and Otsu's technique were used to take proper action. They have segmented the leaf images and classified them into faulty and normal regions.

Li and He (2018) to classify and identify the apple leaf diseases, Back Propagation (BP) neural network models were used. Addresses (round spot disease, speckled deciduous disease, mosaic disease, yellow leaf disease, and rust disease) 5 different kinds of diseases on an apple leaf. 92.6% average recognition accuracy reached.

1.2. Challenges

The detection of plant diseases by traditional image processing techniques has given certain results with high precision in the identification of diseases, but the following obstacles and limitations remain:

1) Identifying diseases through the traditional approach is a time-consuming process.
2) High quality of input image required to get better accuracy.
3) Continuous police work is important to diagnose the first diagnosing of the malady and forestall the unfold of the malady.
4) High cost of setting up the lab to test the results, lab tests are ruinous since collecting plant samples and bringing them to the lab for testing/analysis. In addition, shipping costs are required to send the samples to the laboratory.

Therefore, it is now to change the approach from traditional learning to deep learning to realize smart, fast, and clear-cut plant leaf disease recognition.

2. Literature review

In recent years, face recognition [9], text detection (Li et al., 2016), traffic identification (Yang et al., 2020), medical image recognition [7,8], expression recognition (Li et al., 2016), etc are some application of deep learning model. Various plant disease detection techniques related to deep learning are used in agricultural implements. Eliminate the traditional image recognition approach for identifying plant disease regions, feature extraction (texture, color, etc.), and classification, adopt the automated extracted image features and classification using deep learning methods. These properties make researchers more attention to deep learning technology in a plant's disease identification, and DL has become a new current research topic. This is due to the availability of the dataset, adapting the parallel/distributed techniques, and the training and testing development with deep neural networks.

Convolutional neural networks (CNN) a most popular part of deep neural networks that have become more popular in various machine vision tasks and show outstanding performance in image processing and classification. In 2006, Hinton and his co-author published a paper related to deep learning (DL) [10]. Deep learning is part of the most advanced systems in various disciplines, especially computer vision and automatic speech recognition (ASR). Deep learning contains multiple layers between input and output to extract high-level high-features from an image. Activation function is the introduction of nonlinearities into the output of a neuron. Activation functions perform nonlinear transformations on the input data, allowing them to learn and perform more complex tasks. Ma et al. [11] used the dataset of 14,208 symptoms image, CNN with a hidden layer is used to detect a disease from the plant cucumber. Downy mildew, anthracnose, powdery mildew, and target leaf spots four cucumber plant diseases target to identify. The accuracy of the Deep Convolutional Neural Network for both balanced and unbalanced dataset was 92.2% and 93.4%. Kawasaki et al. [12] used 800 cucumber plant disease images to train on CNN to identify disease, achieving an average accuracy of 94.9%.

Ngugi et al. [13], you presented a detailed overview of current research on the detection of plant diseases with image processing techniques (IPT). Deep learning techniques have replaced the trained surface classifier with handcrafted functions. For the identification / prediction of the first detection of diseases, and additionally for the classification of plant diseases on the idea of samples.

In this paper, to mention the previous work on the recognition of plant diseases, we offer an overview of the recent work on the identification of plant diseases with deep learning methods.

The contribution of the paper is as follows. In Section 2, we review several visualization technique used to detect the disease. In Section 3, plant disease dataset is discussed. In Section 4, some research gaps and challenges that need to be addressed.

3. Convolutional neural network layer

3.1. Without visualization methods

In [14], three different types of maize leaf diseases were identified such as northern corn leaf blight (Exserohilum), common rust (Puccinia sorghi), and gray leaf spot (Cercospora), and the results are shown with the histogram techniques. In [15], tomato leaf diseases were identified using two optimizer techniques, stochastic gradient descent (SGD) and Adam with the CNN architecture like AlexNet, GooLeNet, and ResNet. ResNet with SGD optimizer performs well with 96.51% accuracy. In [16], the LeNet architecture model was used to detect three banana leaf disease detection (healthy, black sigatoka, and black speckle). To evaluate the performance of the model in color and grayscale mode done by metrics accuracy, F1-score, recall, and precision. In [17], A total of 87,848 images were trained on five different models, including AlexNet, AlexNetOWTbn, GoogLeNet, Overfeat, and VGG, and the accuracy of the VGG model was 99.48 percent. DL models including 9 different models such as VGG16, VGG19, GoogLeNet, AlexNet, ResNet50, ResNet101, InceptionV3, InceptionResNetV2 and SqueezeNet are used with three classifiers called Support Vector Machine (SVM), Extreme Learning Machine (ELM) and K-Nearest Neighbor (KNN). The performance indicators such as sensitivity, specificity, and F1 score were compared between these models and results. Plant disease symptoms were not visualized in the above methods.

3.2. CNN layer with visualization methods

With the help of visualization techniques in deep learning, the model gets a clear understanding of plant diseases. In [18], the use of the prominence map as a visualization method to understand and classify the symptoms of plant diseases. In [19], detected 13 different types of plant diseases using CaffeNet's CNN architecture and achieved an average accuracy of 96.30%. Moreover, CNN layer visualization shown to indicate the disease region. With the help of AlexNet and Google LeNet CNN architecture, [20] identified 14 crop species and 26 diseases using public images. Leaf images consist of color, grayscale, and leaf segmented. The performance metrics evaluate considering F1-score, precision, recall, and comparison between AlexNet and GoogLeNet. Through visualization of layer spots of diseases is clearly identified. Anthracnose, downy mildew, powdery mildew, and target leaf spots four cucumber diseases were identified in (Ma J. et. al 2018). The deep convolutional neural network (DCNN) achieved accuracy 93.4% and was compared with other conventional classifiers Random Forest, support vector machines, and AlexNet models. Moreover, the image segmentation method was used to view the symptoms of diseases in the plants. In [21], banana splint complaint and pest discovery was performed by using three CNN models (ResNet-50, Commencement-V2, and MobileNet-V1) with Faster-RCNN and SSD (Single Shot sensor) sensors. According to [23], a comparison between AlexNet and GoogLeNet infrastructures for tomato factory conditions was done, which GoogLeNet performed better than the AlexNet; also, it proposed occlusion ways to fete the regions of conditions. In [24], diseases were identified and detected using VGG-FCN and VGG-CNN models in the wheat plant. Here, the visualization features of each block are shown. In [5], the k-means clustering method is used to show the spot of diseases on leaves, and also detection of fusarium was done. In [25], four grape diseases i.e. black rot, black measles, leaf blight and mites was identified by using deep learning based faster DR-IACNN model with high feature extraction. In Table 1., various CNN visualization methods are shown.

Table 1
Visualization mapping/techniques.

CNN Visualization Methods	References
Saliency map visualization	[23]
CNN layer visualization	[25]
Image segmentation method	[16]
Disease classification and detection through bounding box	[27]
Disease Prediction visualization method	[28]
Bounding box	[31]
Anchor box	[30]

For practical implementation of plant disease detection, a verified/clear-cut / background should be considered to more accurately assess the performance of the DL model. In maximum cases, the chosen datasets took into consideration simple backgrounds which aren't naturalistic situations for class and identity of the diseases [18,20,22,23], besides for some of them which have taken into consideration the authentic backgrounds [27,26]. The output of the visualization strategies utilized in numerous researches is proven in Figs. 2-14.

Disease infected image (tomato early blight) was input to CNN model and intermediate CNN layer output is shown. CNN layer output with image size is shown in each intermediate level.

In Fig. 2, visualizes the retired sub-caste affair for each sub-caste, where tomato early scar input image is reused and shown the each sub-caste affair in epitomized way.

As shown in Fig. 3, the object visualization technique was applied not only to the ImageNet data but also to the village dataset. When the feature rendering technique was applied to neurons in shallow layers (Conv1, Conv3, Conv5) of the ImageNet dataset, images containing simple patterns and textures were generated. At deeper layers (Mixed0, Mixed2, and Mixed4), the shapes became more complex and the colors more diverse, resulting in various pattern-like appearances or resemblances to objects. The objects (Mixed 6, Mixed10) were intermixed in deeper layers, creating a painting-like appearance.

To introduce scientific control into visualization, the DeepLIFT Shrikumar et al. [27] and explanation map [26] methods are used in Fig. 4. In comparison to vanilla back propagation and integrated gradients, DeepLIFT improves the specificity of lesion detection, but it is on par with guided back propagation or slightly better. With the use of GRADCAM, the explanation map method was successfully applied to the deepest layers (Mixed 0 and Conv4). In order to create an effective visualization, it is crucial to identify the right layers before applying the explanation map.

In Fig. 5, demonstrate how guided backpropagation and Grad-CAM were used on these images. Each method highlights the sheet's outline and background. By adding more images to the misclassified elements category so that the variation of leaf shapes would increase, or by preparing deleted background images for CNN training, the shape and colors of the sheet or its background could be misclassified.

In Fig. 6, the first level, the designation of the category is given to which it belongs. During the classification phase, only the image's category is known. During the second stage, the area where the disease is located for pests is defined. In the case of gray mold, a box or rectangle is marked. In the third stage, a red dot indicates the segmentation area.

Each layer is shown in its own block in Fig. 7, and the visualization shows the strongest activation for each image, starting with the first convolution layer, with properties ranging from individual pixels to simple lines to the fifth convolution layer. A block diagram of the learned features, such as the shapes and some parts of the leaves, can be seen in Fig (a). The original image size is

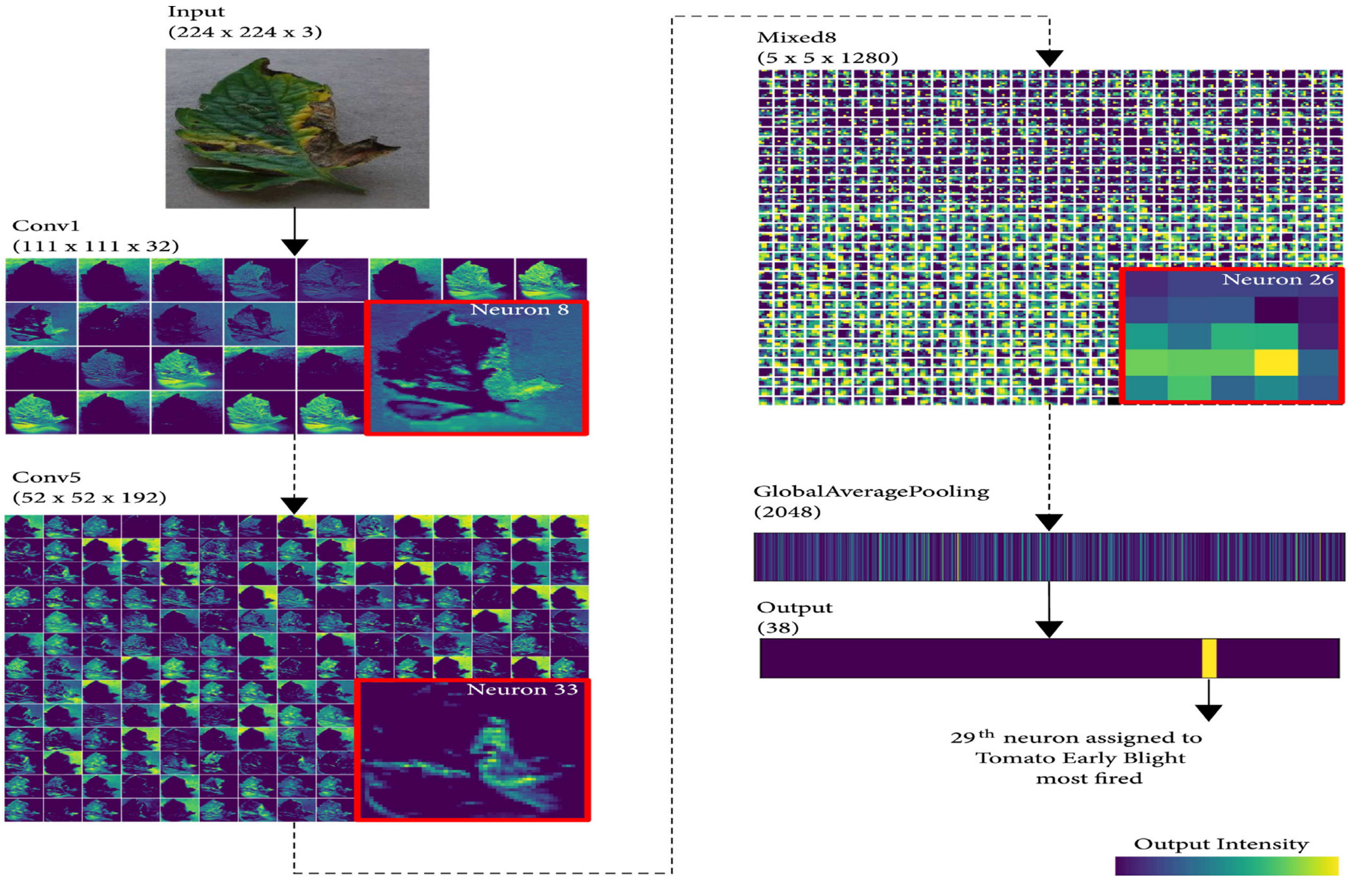

Fig. 2. CNN visualization to identify tomato disease.

256 * 256. CNN layers are displayed in Fig (b, c, d, e, f, g, h). Fig. (b, c) shows the output of the first layer, Conv1 has corrected only the first 36 answers of the filters. As shown in Figs. (d, e), the second layer's output contains only the first 36 of the 256 channels rectified, while Fig. (f) shows the output of the third layer, Conv3 (rectified, all 384 channels) and Fig. (g), the 4th layer's output, Conv4 (rectified), all 384 channels. In Figure (h) you can see the output of the fifth layer, Conv5 (corrected, all 256 channels).

Following the clustering and convolution layers of the deep lattice, Fig. 8 shows the filtered output images. In the lower right corner of each output image, the name of the corresponding layer appears.

In Fig. 9, the prominence map was never used in the classification of plant diseases. The benefits of a celebrity card are comparable to those of occlusion experiments. Helps identify symptoms of illness for users. In addition, this method is insensitive to the scattering of important areas, as the meaning of pixels is calculated analytically and is not based on pixel occlusion. There are two types of visualizations for image sheets in column 1, 4. Images in columns 2, 5 show displays without guided backpropagation. 3, 6 depict a visualization using guided back propagation.

Images go through various operations and transformation techniques; it is practical to see how the activation map looks after the first and last convolutional layer. The activation map of the leaf image is shown in both ways with background information and without background information in Fig. 10a and Fig. 10b.

We see feature maps for each image from the first to last convolutional layers by applying filters on them. We see feature maps for each image from the first to last convolutional layers by applying filters on them. The activation map for the red, green, and blue channel is shown separately in Figs. 11, 12, 13. We spot that the filters have a separate visual effect on the RGB channel.

4. Plant datasets

Plant Village is an open-source dataset available on Kaggle. The images contain a detailed description of the leaves before and after diseases affect them. In Kaggle, the Plant Village, a dataset open to the public, has now collected 54,309 images of lava plant diseases, contains 14 types of vegetables and fruits, such as apples, grapes, soybeans, apples, tomato, and corn contains total 26 diseases out of that 17 types of fungal diseases, 4 types of viral diseases and 1 type of diseases caused by mites, also includes 12 images of healthy cultivated leaves. In phytopathology, it contains 3,651 images of apple leaves including 1,399 symptoms of cedar apple rust and 1,200 symptoms of apple scab and 187 disease models and 865 healthy apple leaves. If the dataset is insufficient in other field, the authors for their research work collect real images like (coffee, tea, grapes, and guava). Table 2, Shows the dataset used by author for their work.

5. Challenges

(1) Small size problem in dataset

Deep learning methods are becoming more popular in various fields such as medical, computer vision tasks, and plant diseases. There are few sample leaf images for specific plant infections. A

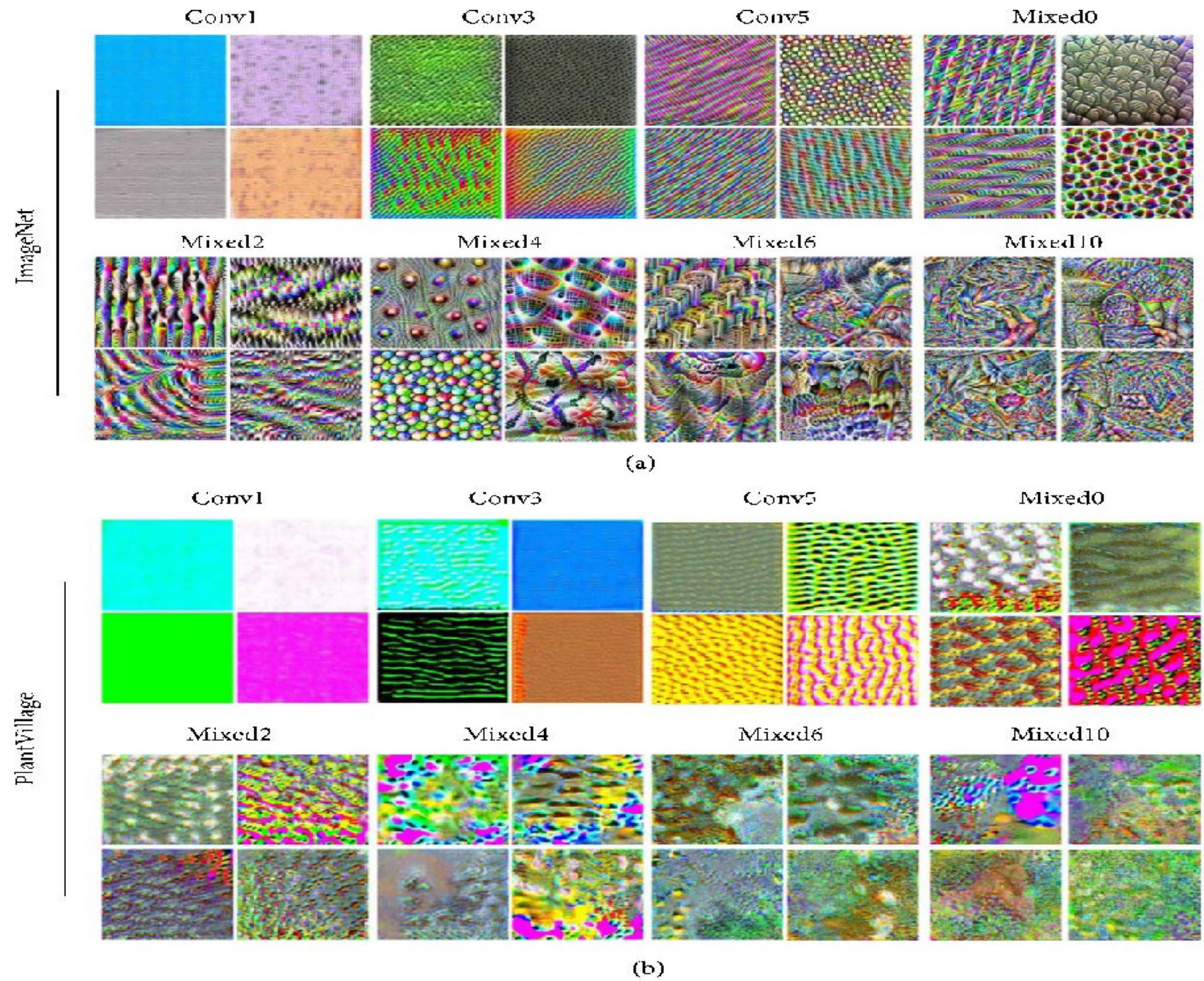

Fig. 3. Feature Visualization.

large portion of the dataset requires most of the deep learning models at the time of training due to an adequate number of images. Self-collected data sets are small and take a long time to label the data. To make the algorithms more practical, real-time images to collect. Acquisition of images is a Time-consuming process. In recent survey, the images captured through smart devices are widely used for research work. The adaption of image through smart device may help to overcome the problem related to dataset size.

(2) Early identification diseases

In order to achieve a higher level of precision, the early detection of plant diseases is essential. Due to the small size of the lesion object, the image has to be processed several times in the deep feature extraction network, which results in small objects being missing. Because of the problem of image background noise, a large, complex background can lead to more misrecognition, especially in the case of low-resolution images. To overcome the above problems, the improvement requires identifying the small object and also updating the mechanism and improving the performance of the attention mechanisms for recognizing small targets is robust. Attention mechanisms teach systems to pay attention to focus on important information and ignore irrelevant information.

(3) Performance metrics

Different performance metrics are used to evaluate different models of deep learning. Classification performance metrics such as loss, accuracy, AUC (Area under Curve), etc. Another metric are, precision, recall, specificity, sensitivity. Confusion matrix is used for find the correctness and accuracy of the model. TP (true positive), TN (true negative), FP (False positive), FN (false negative) are the terms associated with confusion matrix. TP shows the take a look at end result that successfully shows the presence of a situation.TN shows the take a look at end result that successfully shows the absence of a situation. FP shows the take a look at end result which wrongly shows that a selected situation or characteristic is present; FN shows the take a look at end result which wrongly shows that a selected situation or characteristic is absent. Accuracy is described as (TP + TN) / (TP + FP + FN + TN). To calculate precision, the ratio of the successfully superb categorized as TP/

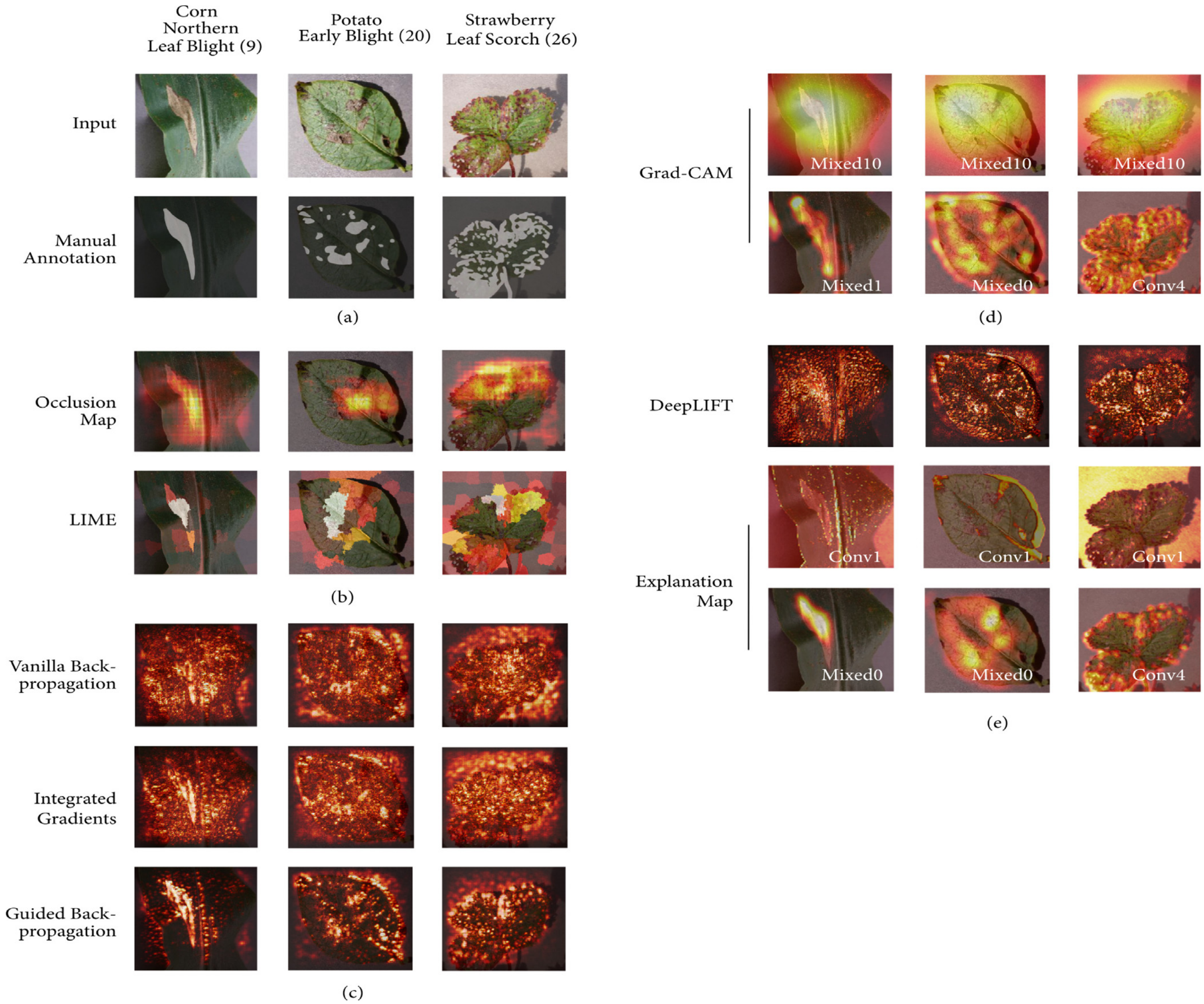

Fig. 4. Performance based visualization.

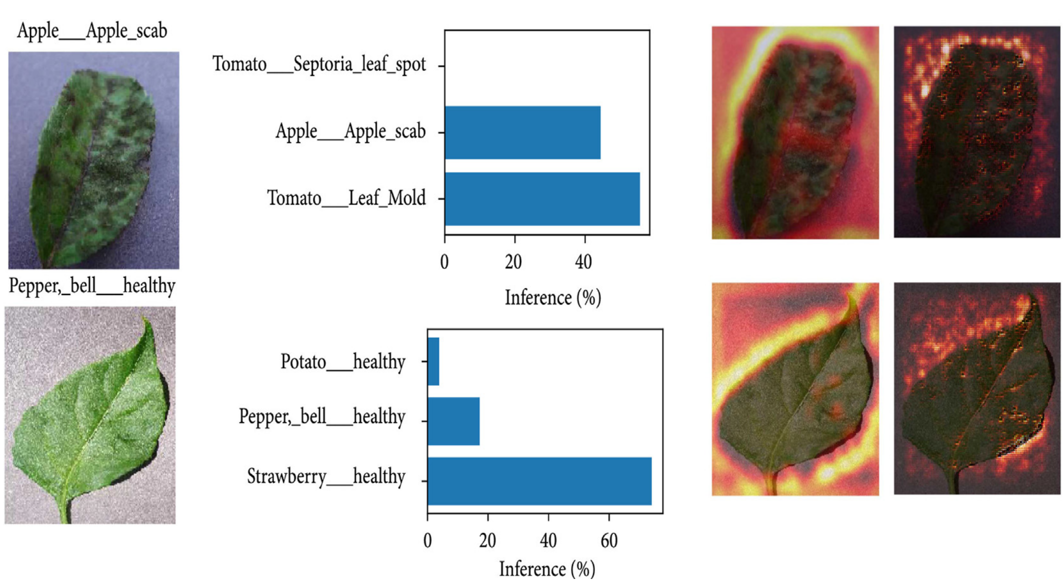

Fig. 5. Attention map.

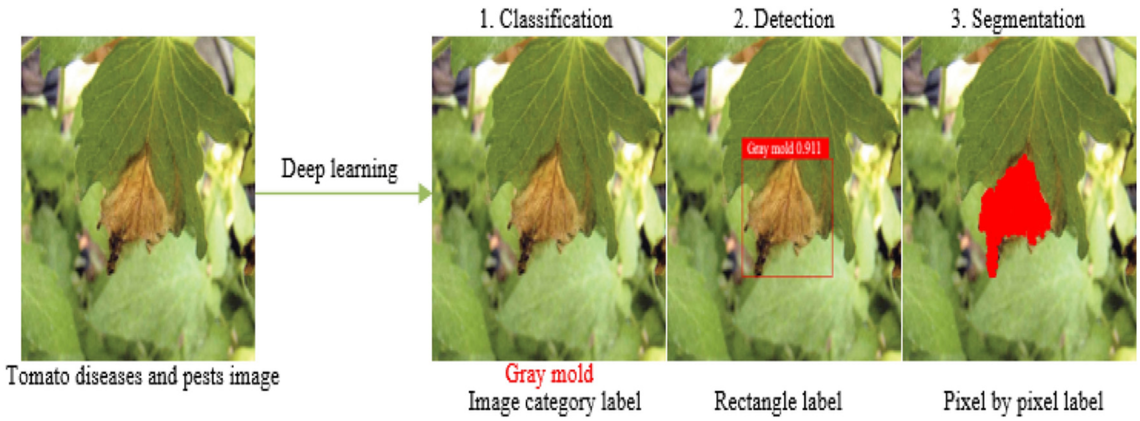

Fig. 6. Stage wise classification and detection.

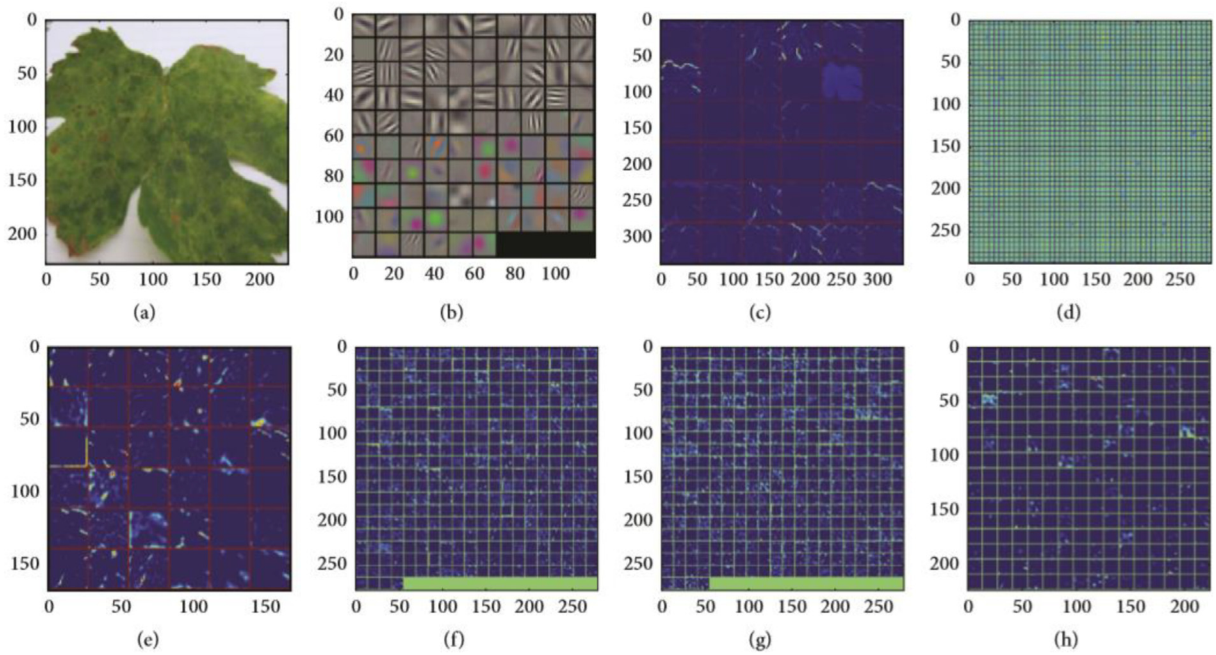

Fig. 7. Visualization of features in trained classification model.

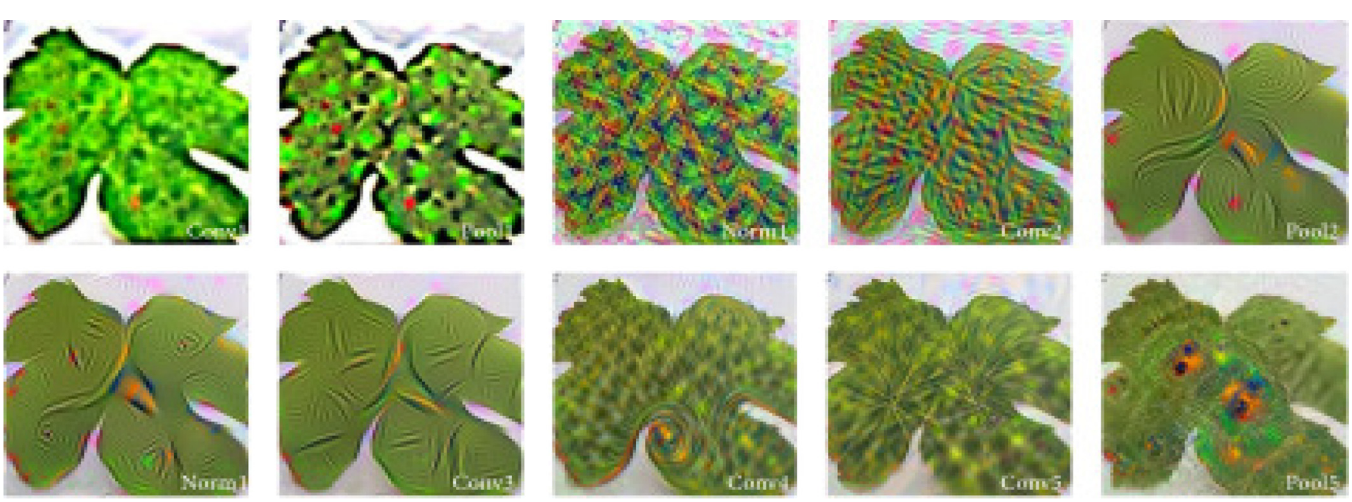

Fig. 8. Output layers images.

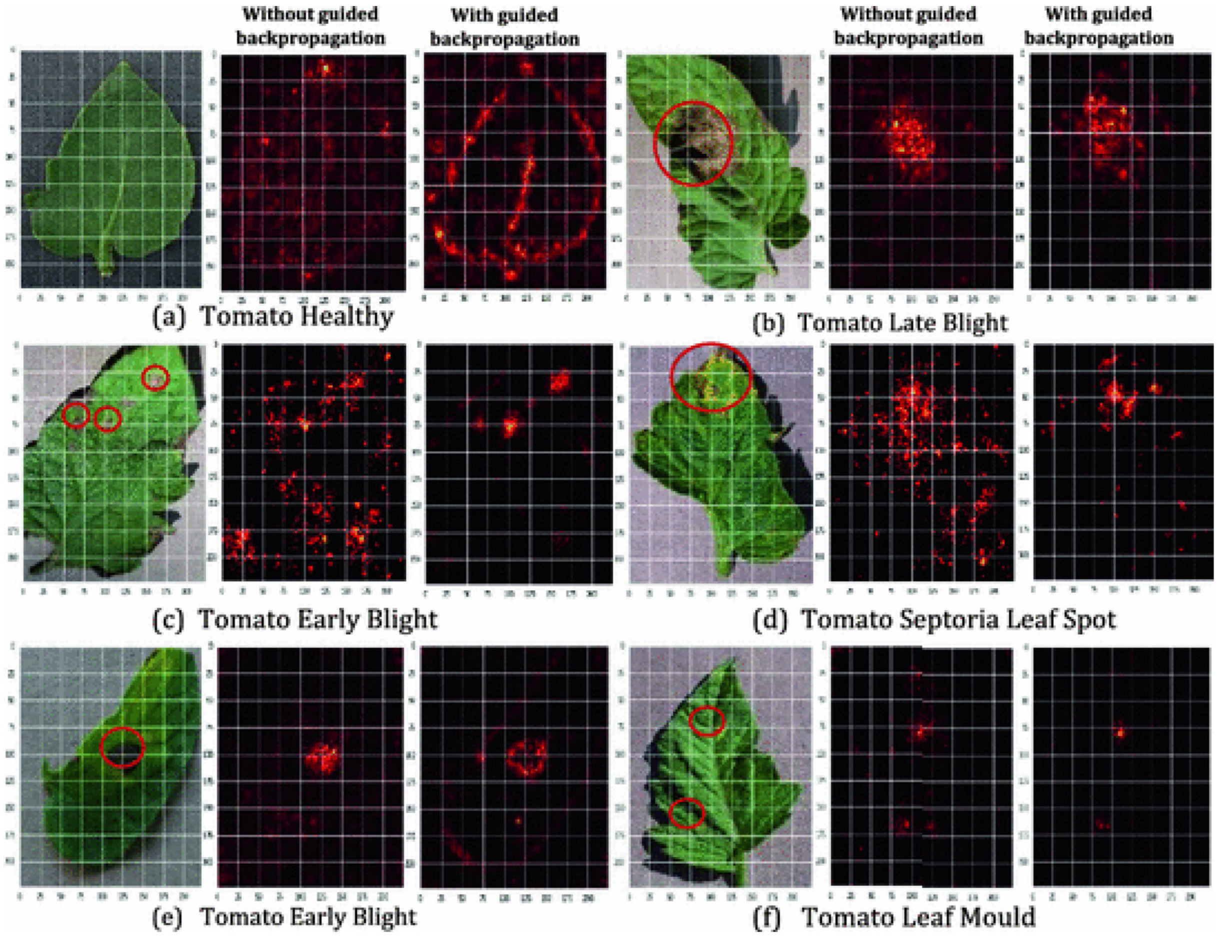

Fig. 9. Saliency map in plant diseases classification.

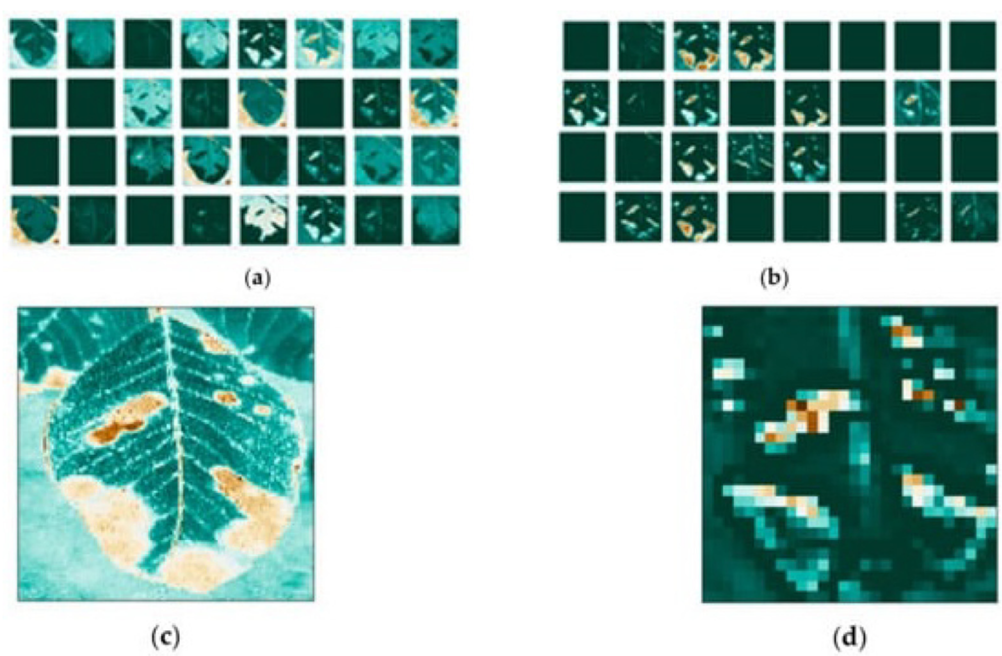

Fig. 10a. Activation maps with background.

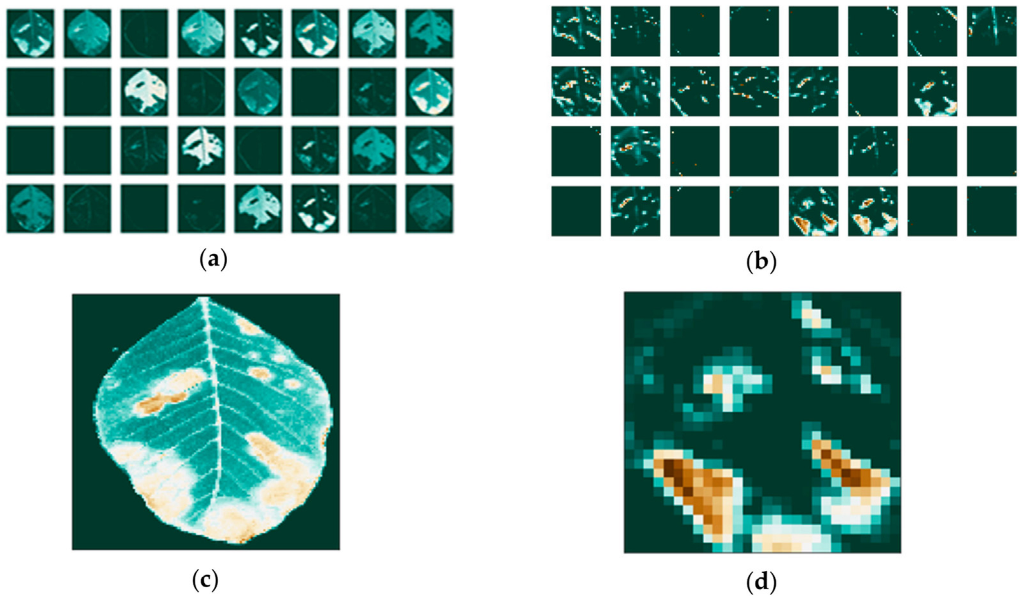

Fig. 10b. Activation maps without background.

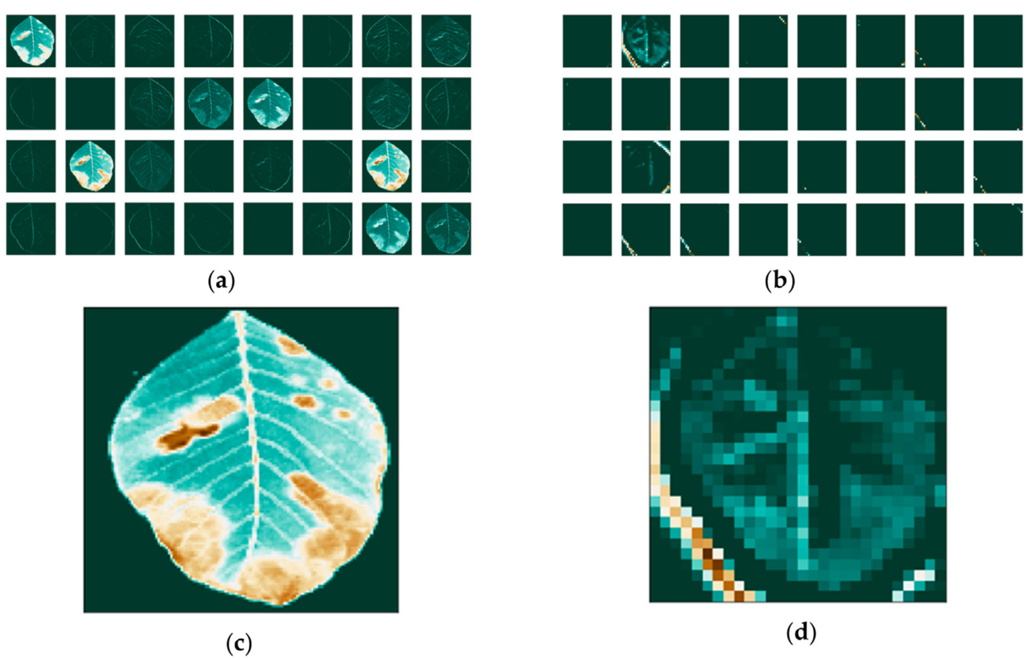

Fig. 11. Activation maps for red mode. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(TP + FP). Recall is the ratio of TP/ (TP + FN). F1 rating is the common of the precision and recall, and it's far described as 2*(recall*-precision)/ (recall + precision). Specificity is correctly negative labeled, who are healthy in real. Specificity is defined as TN/ (TN + FP).

(4) Occlusion problem

Occlusion problems are common in images, such as in illumination conditions like different lighting conditions throughout the day, evening, and night light. The clustered or textured background make hard to identify the object. Inter-class variation having different types of objects, each with their own appearance. In the last few years with the help of deep learning algorithms; some researchers have steadily identified the identification of plant diseases in occluded conditions and significant advances have been made providing a good basis for the application of plant diseases in real environments.

6. Conclusion and future direction

This document explains the path from traditional techniques to a deep learning approach to the detection/identification of plant

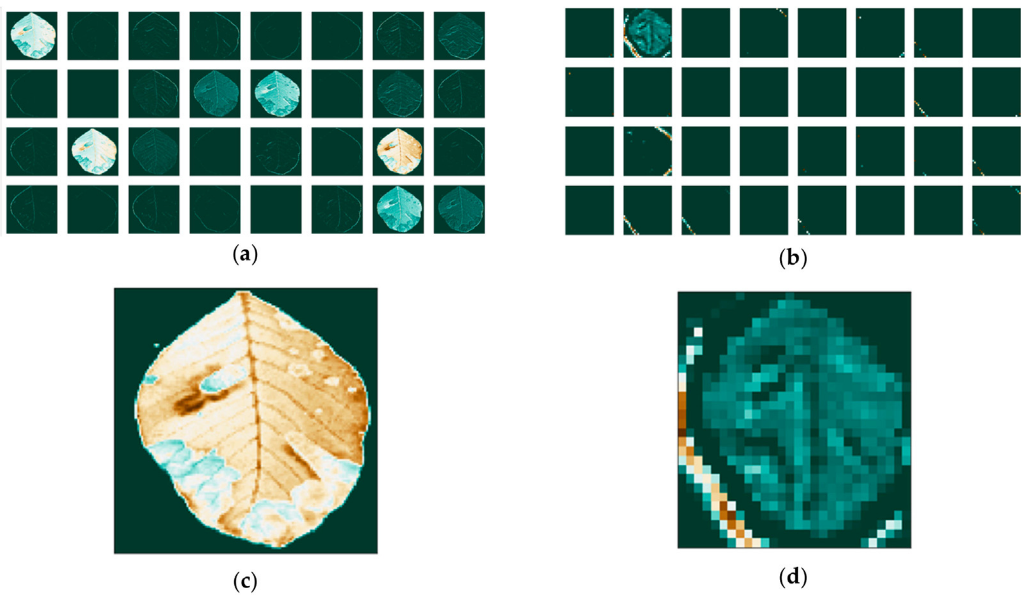

Fig. 12. Activation maps for green mode. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

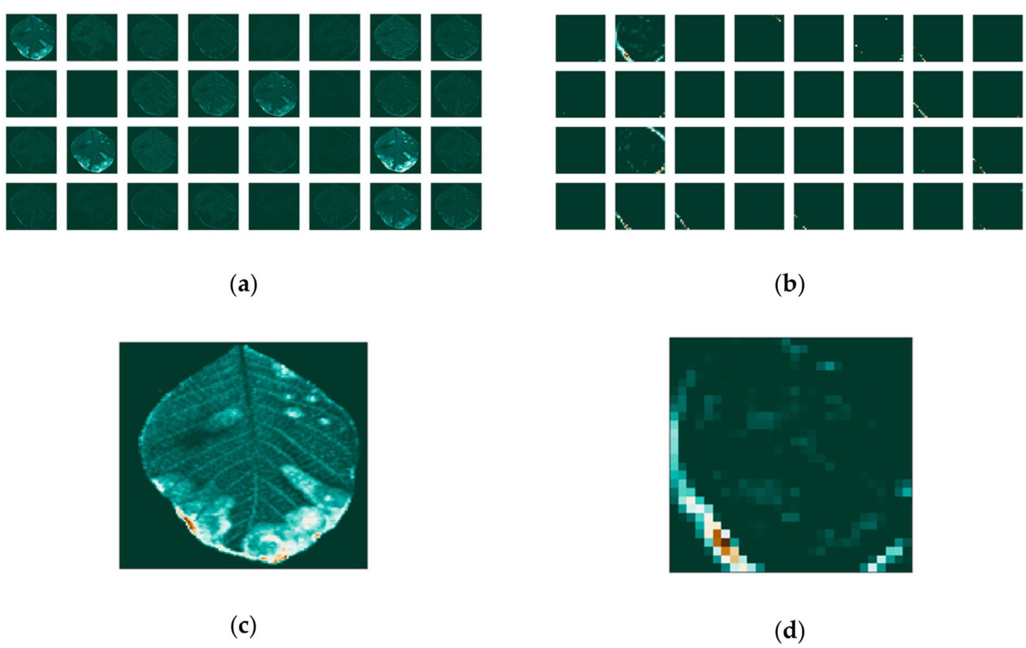

Fig. 13. Activation maps for blue mode.

diseases. A large data set on plant diseases is required when training the DL model for greater accuracy. The value of collecting large highly dispersed data sets, augmenting the data, and displaying CNN activation maps for classification accuracy. To identify the exact location of disease on leaf CNN visualization can help to locate better. In addition, many visualization techniques/mappings explain to identify symptoms of the disease. Although there has been more significant progress over the past few years, still few research gaps that should be addressed and required to implement effective techniques for plant disease detection. Few researches gaps are address:

(1) The Plant Village dataset has been used in most studies to measure the accuracy and performance of DL models. There are 54,303 healthy and unhealthy images of various types of plants with their diseases in the Plant Village dataset. Accordingly, for the practical approach, environment images should be considered.
(2) The exact location of diseases to identify on plants using visualizing methods. This will avoid the unnecessary use of pesticides.
(3) The severity of plant diseases changes as time goes on; an improved Deep learning model must be introduced to identify/detect and classify diseases from plants.

Furthermore, several techniques/mappings were summarized for recognizing the disease symptoms. Also, a comparative study is also made between machine and deep learning techniques.

Table 2
Year wise plant disease identification and detection.

Paper	Year	Dataset used	Images study	Accuracy
[36]	2003	Own	120	96
[37]	2008	Own	1478	97.80
[38]	2009	Own	400	90
[39]	2009	Own	216	97.20
[40]	2012	Own	>2000	79.5
[25]	2016	Plant village	54,306	99.35
[24]	2016	Own	4483	96.30
[41]	2016	Own	21,917	98
[42]	2017	Plant Village	3700	96
[43]	2017	Own	5000	83
[28]	2017	Plant Village	14,828	99.18
[29]	2017	Own	500	95.48
[44]	2017	Plant village and google	500	98
[45]	2017	Own	13,689	97.62
[46]	2017	Own	1796	96.7
[47]	2017	Own	400	95.85
[48]	2017	Own	299	99
[49]	2017	Own	11,670	98
[50]	2017	Through web	30,880	96.3
[51]	2018	Own	1200	96.67
[52]	2018	Plantvillage	87,848	99.53
[53]	2018	Plantvillage	50,000	96
[54]	2018	Saitama research center data set	60,000	78
[55]	2018	Plantvillage	13,262	95
[56]	2018	Soybean dataset	12,673	99.3
[57]	2018	Plantvillage	54,000	98.5
[58]	2018	Plantvillage	18,160	96.2
[59]	2019	IPPN phenotyping data set	345	90.4
[60]	2019	Powdery mildew data set	20	96.1
[61]	2019	Aerial image data set	3,000	78
[62]	2019	Sugar beet data set	155	95.5
[51]	2019	Hyperspectral image data set	111	95.7
[52]	2019	Turkey plant data set	1,965	95.6
[49]	2019	Cassava disease data set	720	79
[63]	2019	Plantvillage	9000	99.84
[53]	2019	Apple disease image data set	640	99.4
[54]	2019	Plantvillage	54,306	87
[64]	2019	Oryza sativa data set	619	91.4
[65]	2019	Own	2000	98
[56]	2020	Plantvillage	61,486	73
[66]	2020	Plantvillage	61,486	99.2
[58]	2020	Plantvillage	76,000	98
[59]	2020	Plantvillage	7,733	97.8
[60]	2021	Plantvillage	17,641	97.2
[61]	2021	Plantvillage	61,486	98.4
[62]	2021	Plantvillage	54,305	90
[67]	2022	Plantvillage	18,161	99.97
[68]	2022	Plantvillage	147,500	99.96
[69]	2022	Plantvillage	54,305	99.97
[70]	2023	Plantvillage	54,303	99.57

There were still some research gaps that should be addressed and to implement effective techniques for plant disease detection.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Mr. Jameer Kotwal reports was provided by Amity University Chhattisgarh. Mr. Jameer Kotwal reports was provided by Amity University Chhattisgarh. Mr. Jameer Kotwal reports a relationship with Amity University Chhattisgarh that includes:. Mr. Jameer Kotwal has patent licensed to Licensee. Dr. Ramgopal Kashyap Amity University Chhattisgarh Dr. Shafi Pathan World Peace University].

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