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ORIGINAL ARTICLE

Leaf species and disease classification using multiscale parallel deep CNN architecture

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Abstract

Plant species are often affected by conquering biotic strains and for sustainable yield more emphasis can be on the novel mitigation measures rather than traditional methods. Plant diseases are witnessed by visible effect on the leaf like the detectable change in color, texture or shape. Categorizing leaf diseases poses challenges like intensity of the disease in the leaf, resolution of the image, shot category and complex background. Literature reports myriads of architecture employing Convolutional Neural Networks for generating models that assist in detecting plant disease. This research work has merged responses from customized filters (Law's Mask) that well define the texture pattern and learnable filters to ensure adaptive learning. Depending upon the stages of diseases in leaves, the defects occur at varying scales and at varying locations of leaves. Thus, rather than single deep stream of network, a specialized parallel multiscale stream with learnable filters that extract inherent attributes are utilized for improved performance. Experimental evaluation of the proposed methodology with end to end training on Plant Village dataset with 39 classes gives 99.17% for plant species classification and 98.61% for disease classification. For data Repository of Leaf Images with 12 species, 97.16% for plant species classification and 90.02% for leaf disease classification. MepcoTropicLeaf an Indian Ayurvedic Leaf dataset with 50 species is experimented using the proposed algorithm and reported with 90.86% of classification accuracy.

Keywords Plant leaf disease · Convolutional neural network · Multiscale architecture · Law's mask

1 Introduction

Plant diseases such as rusts, mildews, and blights have serious impact on the country's economic situation. Although leaves are commonly observed part of the plant it is critical to diagnose plant diseases at an early stage. To effectively diagnose plant disease, a plant pathologist must have good observation skills and be able to recognize distinctive patterns on leaves. The variety of plants, fluctuations in the development of plant diseases as a result of climate change and the rapid spread of disease has a high impact on the plant leaf disease classification. Agronomists rely on professional and sophisticated technologies that can reliably diagnose plant disease automatically. Artificial intelligence advancements have cleared the road for the development of automated systems that can diagnose diseases faster and with greater accuracy. Higher accuracy with less prediction time prove superiority of one system over another.

The majority of plant diseases are caused by fungi, viruses, bacteria, and some nematodes. A noticeable change in color or shape of the leaf, wilting, scabs, moldy coatings, rusts, and blotches in response to the pathogen are some of the symptoms of plant disease. Tomato powdery mildew, for example, starts with pale yellow patches on the leaves. The patches quickly become covered in white spores, giving the leaves the appearance of being powdered with flour. The pale sections of the leaves turn dark and shrivel as the fungal illness progresses, becoming dry and brittle.

The modules for computer vision-based plant disease classification includes pre-processing steps like segregating the defect regions, extracting relevant features and

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classifying it using machine learning algorithms. The spatial discriminative features for leaves defect detection include color, texture and shape features. Further, the features can be extracted from transform domain like Wavelet Transform, Gabor Transform, Ridgelet Transform, Curvelet Transform etc. Rather than using single features, combination of multiple features gives better performance in terms of classification accuracy. As the dimensionality of the features are more, to avoid overfitting and redundancy feature selection algorithms that increase system recognition accuracy is used. The popularly used plant disease classification methods include Random Forest, support vector machine and its variants.

Apart from the usual challenges in image classification task like illumination, visual quality resulting in extracting irrelevant features, the challenges specific to plant leaf defect classification are as follows: a) Most symptoms don't have clear boundaries, instead blending into normal tissue or defected tissue over time thus, difficult to classify between healthy and diseased tissue. b) Disease's characteristics vary depending on its stage of development and the location of the leaf. c) Hybrid symptoms due to different diseases can arise at the same leaf is difficult to discern. d) Different diseases might have very similar symptoms, prompting researchers to rely on minute differences to diagnose them. The motivation of this research is to overcome limitations of identifying disease features in complex environment.

The contributions of this paper in detecting plant leaf diseases are summarized as below:

- The intensity of the leaf disease occurs at varying scales the proposed pyramidal representation effectively captures the features of the region of interest.
- Parallel networks with varying number of convolution and pooling layers to automatically learn and recognize the most discriminative features from the scratch.
- Deep network architecture by merging customized filters and learnable filters at initial stage, vividly improves classification accuracy.

The paper is structured as follows: Sect. 2 summarizes related work on Plant Leaf Disease Recognition using handcrafted and deep learning-based methods. Section 3 describes the proposed method for leaf category / leaf disease recognition in detail. Comprehensive experimental research on Plant Leaf Disease Recognition detailed in Sect. 4. The concluding remarks of this paper are given in Sect. 5.

2 Literature survey

Plant diseases cause major crop production losses around the world, hence extensive research has been performed to improve crop monitoring and disease identification processes. The modules included for plant leaf disease classification includes pre-processing for contrast enhancement, effective segmentation for identifying healthy region and infected region and features like texture features, shape, roundness are used for identifying the disease categories.

Arivazhagan et al. [1] used texture statistics extracted from the diseases region and experimented on the leaf like Banana, Beans, Jackfruit, Lemon, Mango, Potato, Tomato, and Sapota. Ahmed et al. [2] extracted 6 color features and 22 texture features after segmenting the diseased region of the image and classified using Support Vector Machines. For classifying tomato leaf diseases, Tan et al. [3] extracted 52 texture features using Local Binary Pattern (LBP) and Grey Level Co-Occurrence Matrix (GLCM), and 105 color features using color moment and color histogram methods, and reported that combining color and GLCM features yielded the best results. Omeer and Deshmukh [4] used Continuous Wavelet Analysis and Principal Component Analysis for features reduction and regularized and guided regularized random forest to discriminate between five invasive plant species.

With sophisticated hardware and Graphical Processing Units (GPUs) paved the way for deep learning architectures that can process raw data without the need for handcrafted features. Saleem et al. [5] presented a brief review on the deep learning-based approaches for the detection of plant diseases. Moreover, many visualization techniques/mappings were summarized to recognize the symptoms of diseases. Grinblat et al. [6] used CNN for plant image recognition with leaf vein patterns as input for classifying three leguminous plant species. Ma et al. [7] used a deep CNN to conduct symptom-wise recognition of four cucumber diseases (i.e., downy mildew, anthracnose, powdery mildew, and target leaf spots). The symptom images were segmented from cucumber leaf images captured under field conditions and recognition accuracy of 93.4% is obtained.

Qiu et al. [8] employed ResNet for feature extraction to detect the Fusarium head blight wheat disease areas, and reported the average accuracy of 92.01% on test data. Ahmad et al. [9] employed four different pretraining convolution neural networks VGG19, VGG16, ResNet, and Inception V3 by fine-tuning parameters and found Inception V3 had the best performance from their experimentation. Jiang et al. [10] used the Mean Shift algorithm to segment four kinds of rice disease spot at first, and then extract shape feature by artificial calculation and CNN extracts color feature, at last, the SVM classifier was used to identify the diseases, and the results showed that the CNN used segmentation algorithm accuracy was 92.75%, the accuracy was 82.26% without the segmentation algorithm, and the accuracy of the CNN in combination with the SVM model was 96.8%. Liang et al. [11] established a dataset contains 2906 of the positive samples and 2902 of the negative samples to identify rice blasts. And the experimental results showed that the senior characteristics extracted from CNN than the traditional manual extraction of local binary pattern histogram (LBPH) and wavelet transform (Haar-WT) had better identification and effectiveness.

Chen et al. [12] modified VGGNet and inception module to perform maize and rice leaf disease classification and experimented on Plant Village dataset and reported 91.83% accuracy. Mohanty et al. [13] classified plant diseases using pretrained models like AlexNet and GoogLeNet and training from the scartch. From their experimentation they reported, they obtained 99.35% classification accuracy with transfer learning by Googlenet on Plant Village Dataset. Too et al. [14] used CNN models such as VGG16, Inception V4, ResNet50, ResNet101, Resnet152 and DenseNets 121. They reported that DenseNet model performs better than other models with no signs of overfitting and performance deterioration and highest test accuracy of 99.75%. Geetharamani and Pandian [15] trained the 9-layer CNN architecture in the PlantVillage dataset with augmentation techniques and achieved 96.46% classification accuracy on the Plant Village dataset.

Ferentinos [16] made the classification of 58 different diseases of 25 different plant species using 87,848 images with AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat and VGG architectures. VGG architecture used in the study gave the highest accuracy with 99.53%. Arsenovic et al. [17] created PlantDisease dataset, which is an expanded version of the PlantVillage dataset and contains 79,265 images. Two-stage PlantDiseaseNet model is proposed for classification it classifies plant species from leaves in the first stage, it classifies the leaf disease in the second stage. The model they proposed achieved 93.67% accuracy in the Plant Disease dataset. Nanehkaran et al. [18] proposed a new model for the detection of plant diseases, including image segmentation and image classification stages. They proposed a hue, saturation and intensity-based and LAB-based hybrid segmentation algorithm in the image segmentation phase and used CNN model in the classification phase. Chen et al. [19] proposed a new model for the detection of plant diseases called MobileNet-Beta by expanding the pre-trained MobileNetV2 model with the classification Activation Map. Tan and Le [20] proposes EfficientNet deep learning architecture for the classification of plant diseases.

Saeed et al. [21] extracted deep features using a pre-trained VGG19 and PLS-based parallel fusion method is used to combine the features and the most discriminant features are finally plugged into the ensemble baggage tree classifier for final recognition. Atila et al. [22] used EfficientNet deep learning architecture on Plant Village dataset and achieved the highest values of 99.97% accuracy with augmented datasets. Chen et al. [23] introduced the self-organizing data mining technology and proposed a novel GMDH-Logistic method for the automatic detection and classification of plant leaf diseases. Argüeso et al. [24] used Inception V3 network was fine-tuned in the source domain to learn general plant leaf characteristics. FSL using Siamese networks and Triplet loss was used and compared to classical fine-tuning transfer learning.

Researchers used set of discriminative features like edges, vein patterns, histogram features, local binary pattern and color moments for plant leaf disease classification. Handcrafted features are features that get tested and hand-picked by the researchers and must require domain knowledge else the model may fail. Because learned features are extracted automatically to solve a specific task, they are extremely effective at it. In fact deep learning models that perform feature extraction and classification outperform models that classify manually extracted features by a large margin. In many cases, these features are only good for classifying the data and have no real-world interpretation. They are only good for the task that they were trained for. In most of the researches, transfer learning is used for plant disease classification. The main benefits of transfer learning include the saving of resources and improved efficiency when training new models. It can also help with training models when only unlabelled datasets are available, as the bulk of the model will be pre-trained. A more generalized approach to machine problem solving, leveraging different algorithms to solve new challenges. Thus, this research aims at utilizing both handcrafted and learnable features for plant disease classification.

3 Proposed methodology

The deep architecture proposed for plant leaf disease recognition capable of extracting features at varying scales is shown in Fig. 1. The architecture is made up of a series of layers that accept an image of size $m \times n \times d$ (height (m), width (n), and number of channels (d)) as input and forecast class probabilities at the output. The parallel architecture processes the input leaf images of size $m \times n$ and it's scaled down versions $(\frac{m}{2} \times \frac{n}{2})$ and $(\frac{m}{4} \times \frac{n}{4})$. Since the

1	4	6	4	1	-1	-2	0	2	1	-1	0	2	0	-1	1	-4	6	-4	1	-1	2	0	-2	-1
4	16	24	16	4	-4	-8	0	8	4	-4	0	8	0	-4	4	-16	24	-16	4	-4	8	0	-8	-4
6	24	36	24	6	-6	-12	0	12	6	-6	0	12	0	-6	6	-24	36	-24	6	-6	12	0	-12	-6
4	16	24	16	4	-4	-8	0	8	4	-4	0	8	0	-4	4	-16	24	-16	4	-4	8	0	-8	-4
1	4	6	4	1	-1	-2	0	2	1	-1	0	2	0	-1	1	-4	6	-4	1	-1	2	0	-2	-1
-1	-4	-6	-4	-1	1	2	0	-2	-1	1	0	-2	0	1	-1	4	-6	4	-1	1	-2	0	2	1
-2	-8	-12	-8	-2	2	4	0	-4	-2	2	0	-4	0	2	-2	8	-12	8	-2	2	-4	0	4	2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	8	12	8	2	-2	-4	0	4	2	-2	0	4	0	-2	2	-8	12	-8	2	-2	4	0	-4	-2
1	4	6	4	1	-1	-2	0	2	1	-1	0	2	0	-1	1	-4	6	-4	1	-1	2	0	-2	-1
-1	-4	-6	-4	-1	1	2	0	-2	-1	1	0	-2	0	1	-1	4	-6	4	-1	1	-2	0	2	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	8	12	8	2	-2	-4	0	4	2	-2	0	4	0	-2	2	-8	12	-8	2	-2	4	0	-4	-2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
-1	-4	-6	-4	-1	1	2	0	-2	-1	1	0	-2	0	1	-1	4	-6	4	-1	1	-2	0	2	1
1	4	6	4	1	-1	-2	0	2	1	-1	0	2	0	-1	1	-4	6	-4	1	-1	2	0	-2	-1
-4	-16	-24	-16	-4	4	8	0	-8	-4	4	0	-8	0	4	-4	16	-24	16	-4	4	-8	0	8	4
6	24	36	24	6	-6	-12	0	12	6	-6	0	12	0	-6	6	-24	36	-24	6	-6	12	0	-12	-6
-4	-16	-24	-16	-4	4	8	0	-8	-4	4	0	-8	0	4	-4	16	-24	16	-4	4	-8	0	8	4
1	4	6	4	1	-1	-2	0	2	1	-1	0	2	0	-1	1	-4	6	-4	1	-1	2	0	-2	-1
-1	-4	-6	-4	-1	1	2	0	-2	-1	1	0	-2	0	1	-1	4	-6	4	-1	1	-2	0	2	1
2	8	12	8	2	-2	-4	0	4	2	-2	0	4	0	-2	2	-8	12	-8	2	-2	4	0	-4	-2
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
-2	-8	-12	-8	-2	2	4	0	-4	-2	2	0	-4	0	2	-2	8	-12	8	-2	2	-4	0	4	2
-1	-4	-6	-4	-1	1	2	0	-2	-1	1	0	-2	0	1	-1	4	-6	4	-1	1	-2	0	2	1

Fig. 1 Law's Kernel of size 5 × 5 used as Customized Filter

leaf is of varying size and the region of interest, i.e., defect in the leaf region varies from tiny spots to blotches and to significant change like withered leaf the deep network is tailored with Convolutional, ReLu and maxpooling layers that enables to extract scale invariant features. The six parallel streams of the architecture are designed by reducing the size of the input image and the number of convolutional layers connected with it, allowing the fusion layer to receive feature maps of the same size. The input leaf image used for analysis is the size (128, 128, 3). Here, parallel streams are trained from the scratch with progressively reduced input size by the factor of 2 thus the Stream 1 and Stream 2 receives the input of size 128 × 128 × 3 pixels, Stream 3 and Stream 4 receives the input of size 64 × 64 × 3 pixels and Stream 5 and Stream 6 receives the input of size 64 × 64 × 3 pixels. The number of convolution and pooling layers of each streams are engineered to keep the size of the input feature maps to the fusion layers fixed.

Symptoms of an unhealthy plant are expressed as visible changes in its color and appearance of the leaf. When making a diagnosis, description of color can be a useful tool, such as the yellowing of leaves associated with chlorosis and in the later stage the areas on the leaf are bleached and nearly transparent.

Laws' mask [25] is a traditional technique for extraction of texture feature whose main approach is toward filtering of images with five types of one-dimensional masks, namely level, edge, spot, ripple, and wave.

L5 (Level)	[1 4 6 4 1]
E5 (Edge)	[− 1 − 2 0 2 1]
S5 (Spot)	[− 1 0 2 0 − 1]
R5 (Ripple)	[1 − 46 − 41]
W5 (Wave)	[− 1 2 0 − 2 − 1]

The 25 filters used at the initial layer of customized stream are shown in Fig. 2. Thus, the weights of the initial convolutional layers of stream 1, Stream 3 and Stream 5 are handcrafted so as to detect texture features from the image using Law's mask [25]. Deep learning seeks to automatically learn features from data at several levels of abstraction and translates input to output without relying on human-crafted features.

Thus, at the first convolutional layer, the fusion of stream with tailored weights and learnable weights sought to improve performance characteristics. All CNNs in this study were trained by optimizing the cross-entropy objective function with an initial learning rate of 0.001 and a momentum of 0.9. A minibatch's size has been set to 28 with 30 epochs.

4 Results and discussion

The performance of the proposed methodology is experimented using Plant village dataset [26], data repository of leaf images [27] and MepcoTropicLeaf [28] (for leaf species classification) the results are discussed in this section.

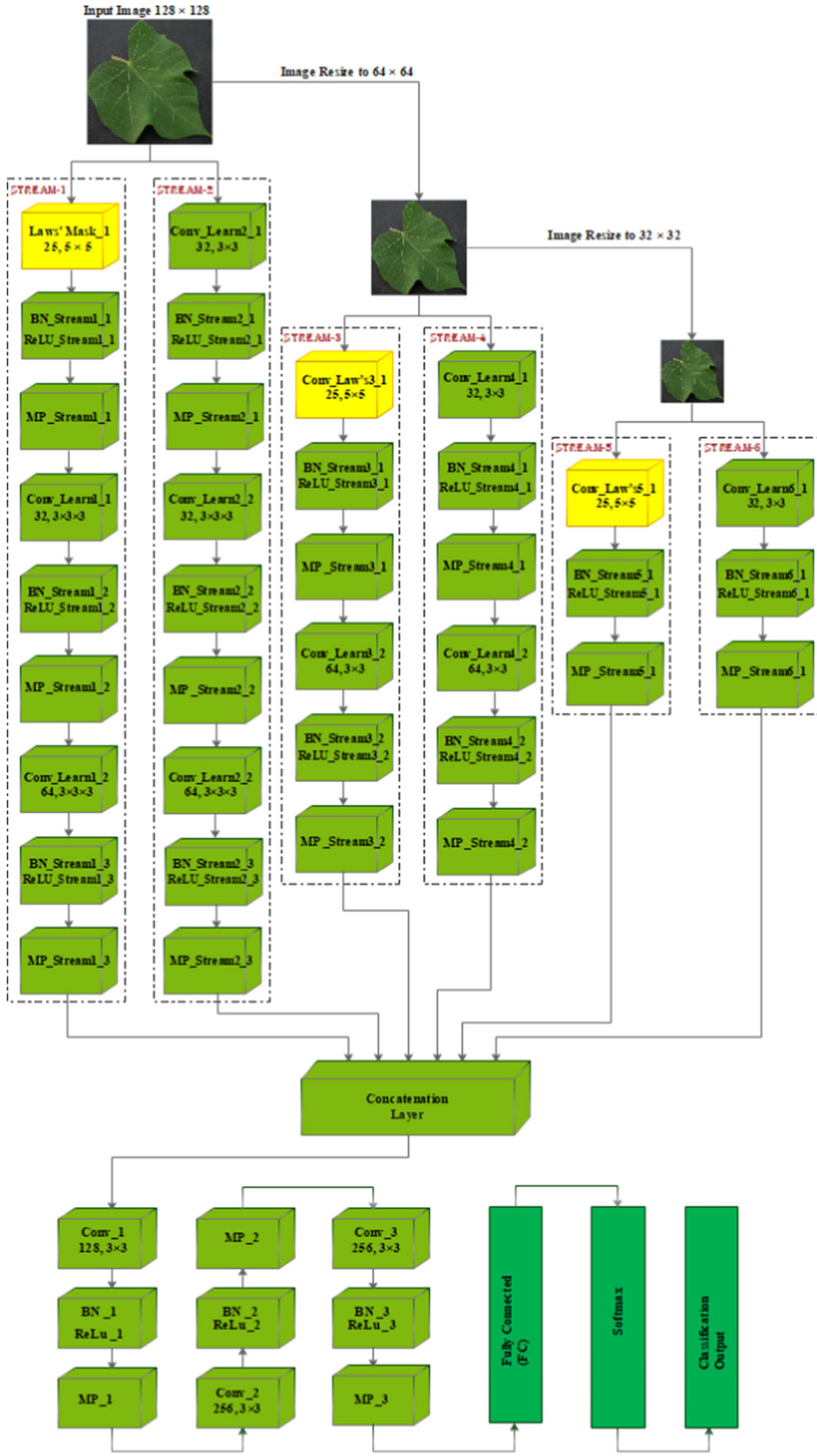

Fig. 2 Proposed Architecture for Leaf Species / Leaf Disease Classification

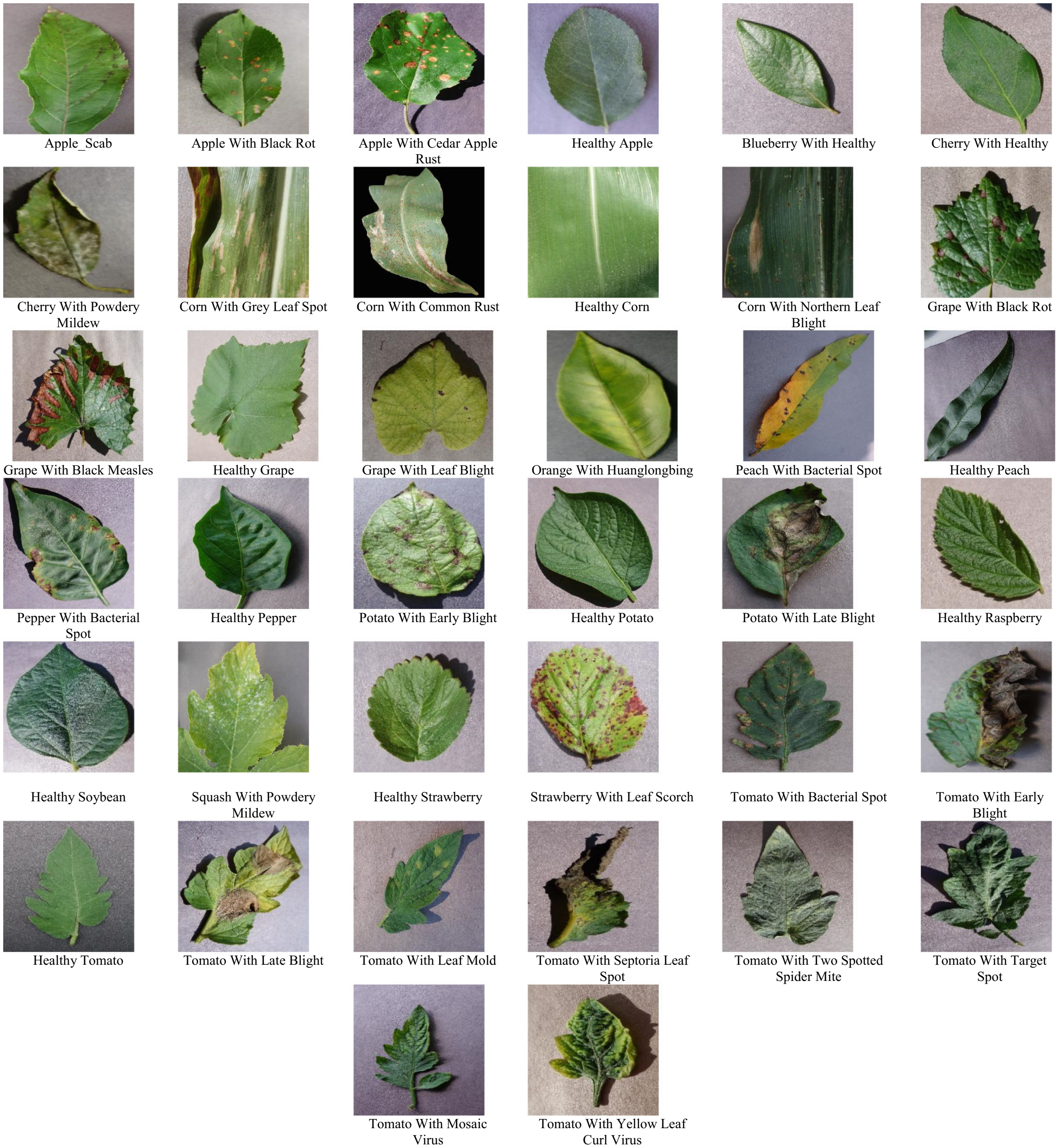

Fig. 3 Sample Images from Plant village dataset

4.1 Database details

4.1.1 Plant village dataset

[26] has totally of 61,486 augmented images belonging to 14 species and grouped under 38 categories and 1 class of background images. Each class may have single or multiple sub categories. For example, there are no sub-categories available for Blueberry, Orange, Raspberry, Soybean, and Squash. For the other classes, the sub-categories may vary from 2 to 10. For example, Cherry has only 2 sub-categories Cherry with powdery mildew & Cherry with healthy whereas, tomato has 10 subcategories named as Tomato with bacterial spot, Tomato with early blight, Healthy

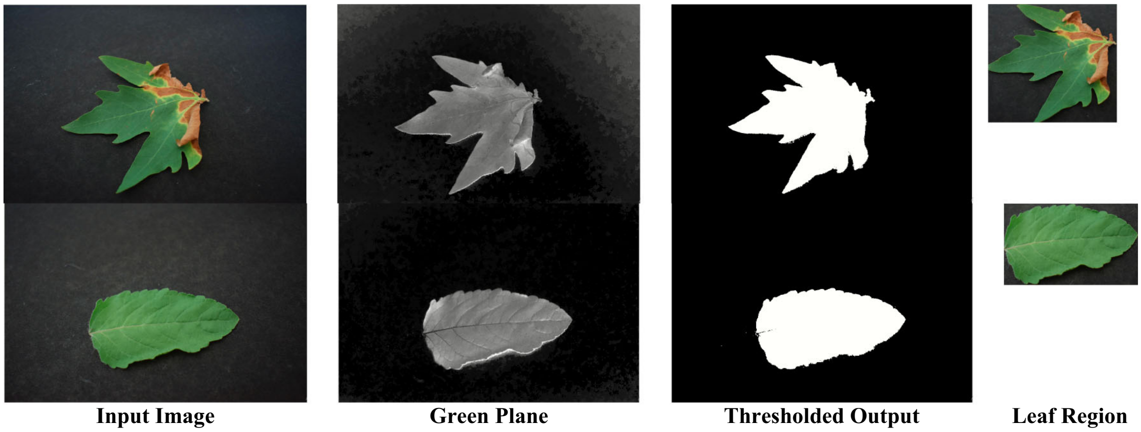

Fig. 4 Extracting Leaf Region and removing background

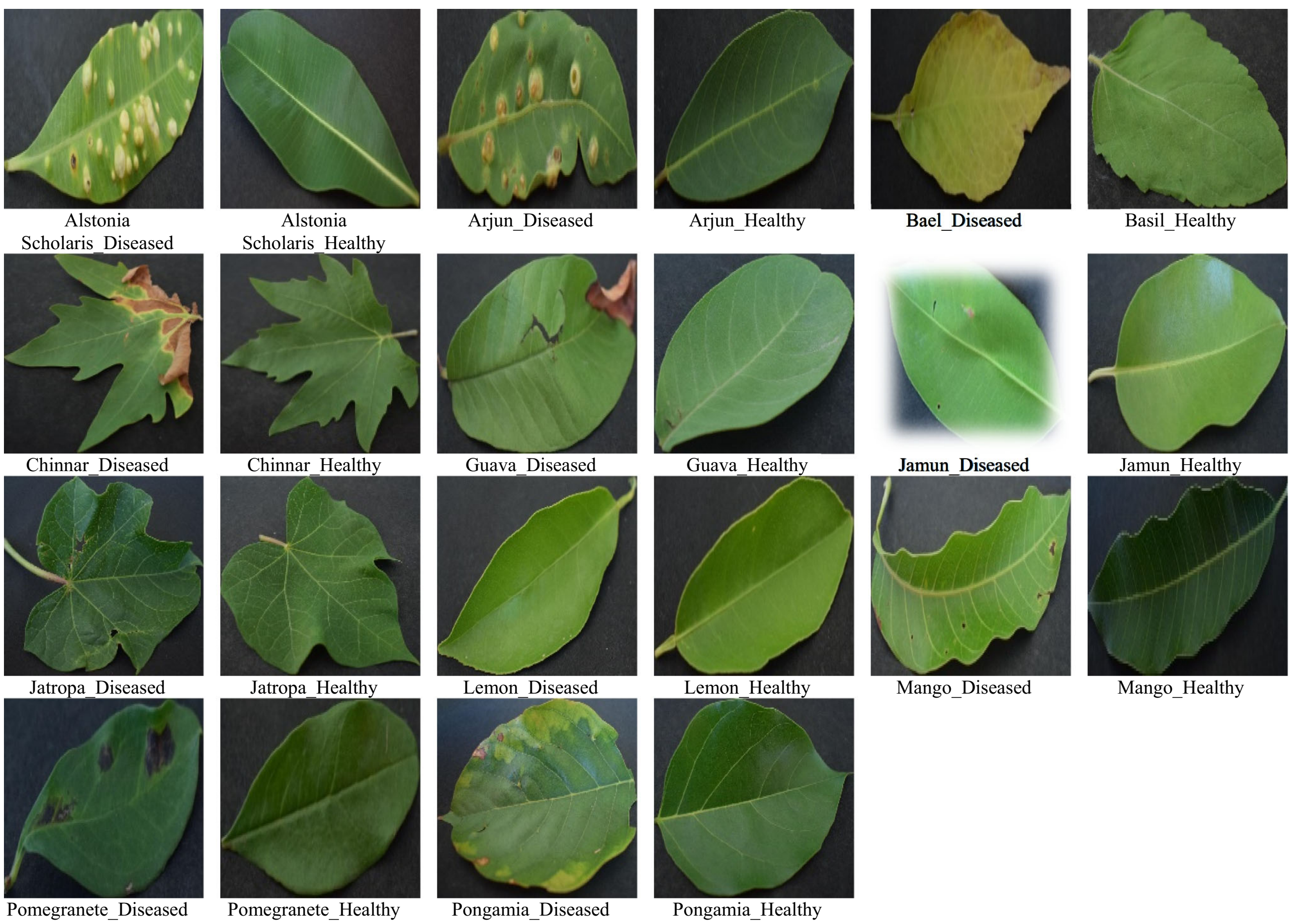

Fig. 5 Healthy and Diseased Leaf Image Samples from Data repository of leaf image

tomato, Tomato with late blight, Tomato with leaf mold, Tomato with Septoria leaf spot, Tomato with two spotted spider mite, Tomato with target spot, Tomato with mosaic virus and Tomato with yellow leaf curl virus. The sample images of each class are presented in Fig. 3.

4.1.2 Data repository of leaf image

[27] consists of 4503 images under Twelve species of plants named as Mango, Arjun, Alstonia Scholaris, Guava, Bael, Jamun, Jatropha, Pongamia Pinnata, Basil, Pomegranate, Lemon, and Chinar with healthy and diseased

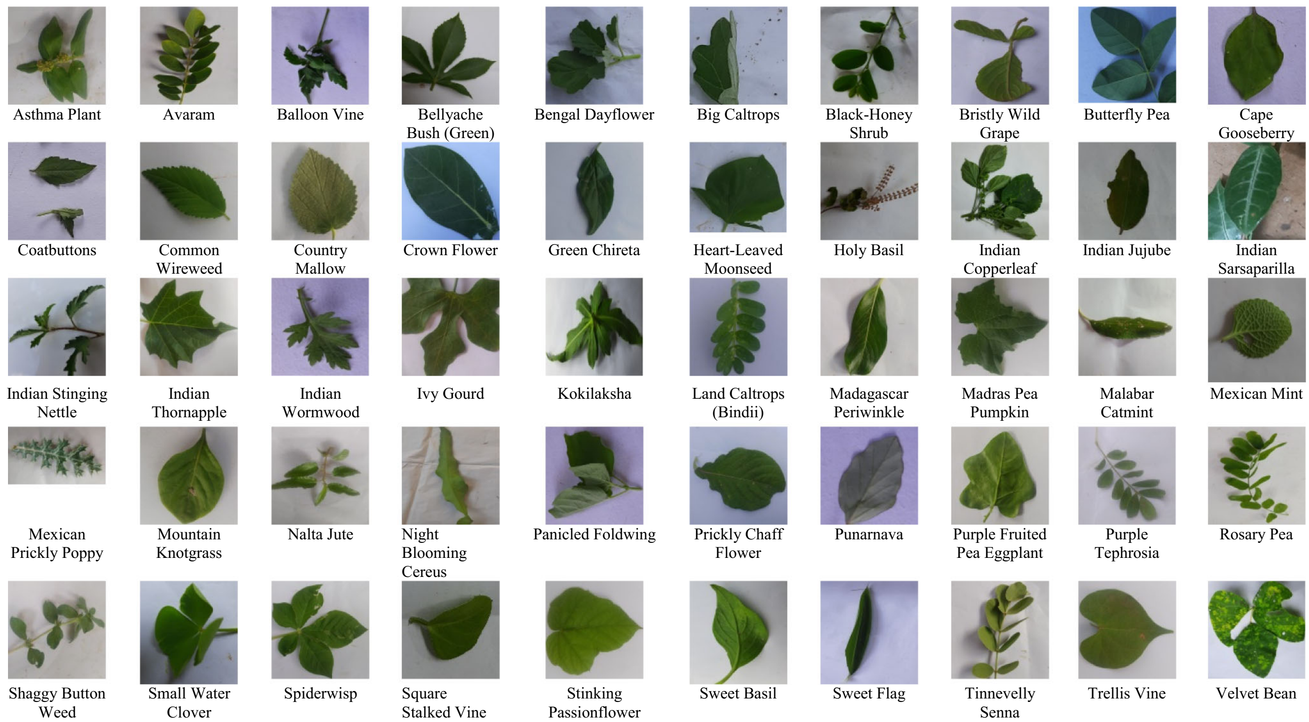

Fig. 6 Sample Leaf Images from MepcoTropicLeaf database

condition. The background from the leaf images are removed by thresholding the green plane of the image as shown in Fig. 4. Figure 5 shows a healthy and diseased leaf image sample of each species from data repository of leaf.

MepcoTropicLeaf [28] has 50 different species of herbal plants with not less than 50 images under each category and sample images from MepcoTropicLeaf database is shown in Fig. 6.

4.2 Visualizing feature maps generated by customized and learnable filters at first layer

Visualizing feature maps of CNN give deep understanding of the features learned by the filters as a result of convolution. The vein patterns are clearly evident in the filtered output from the customized filters (Law's Mask), and the distinctive changes in the diseased leaves, such as edges and spots, may be visualized. Using the learnable filters, characteristics such as color and shape of leaf as well as for diseased leaf characteristics such as region with changed color or leaf rolling are learned (Fig. 7).

4.3 Plant leaf species classification

For plant species classification, each species consists of healthy and diseased leaves are considered. Table 1 shows the classification rate by considering 75% of the samples for training and remaining 25% for testing. From Table 1, it is inferred that, the samples from Alstonia species has leaf galls that are better learned by Fused Customized and Learnable stream (Stream 5 & Stream 6) which is the scaled down version of the input. The galls developed on the upper surface of the leaf has greenish-yellow to brownish pimples and thus Fused Multiscale Customized Streams and with Fused Multiscale Learnable Streams too gives the same result. Leaf species like Arjun, Bael, Basil, Jamun, Mango and pongamia yields noble outcome when the customized and learnable filters are fused together at the input scale of 128 $\times$ 128. Whereas for Guava leaves are affected by rust which is are small circular or oval, orange pustules on the upper surface of infected leaves better learned by stream 3 & Stream 4, i.e., with the scaled down version of the input. Lemon leaves shows light tan in color and better described by the scaled down streams (stream 3 &4 combined and Stream 5 & Stream 6 combined). Pomegranate, mango reports good results when the features from all streams are fused together. Jatropa, Chinar color has slightly pale and may show purpling or reddening of leaves hence Fused Multiscale Customized Streams performs better.

In Table 1 in leaf species classification using fused customized and learnable stream (Stream 1 & Stream 2) reports best accuracy among all other combinations. Thus, for that specific combination Rank 1 accuracy is 97.16%,

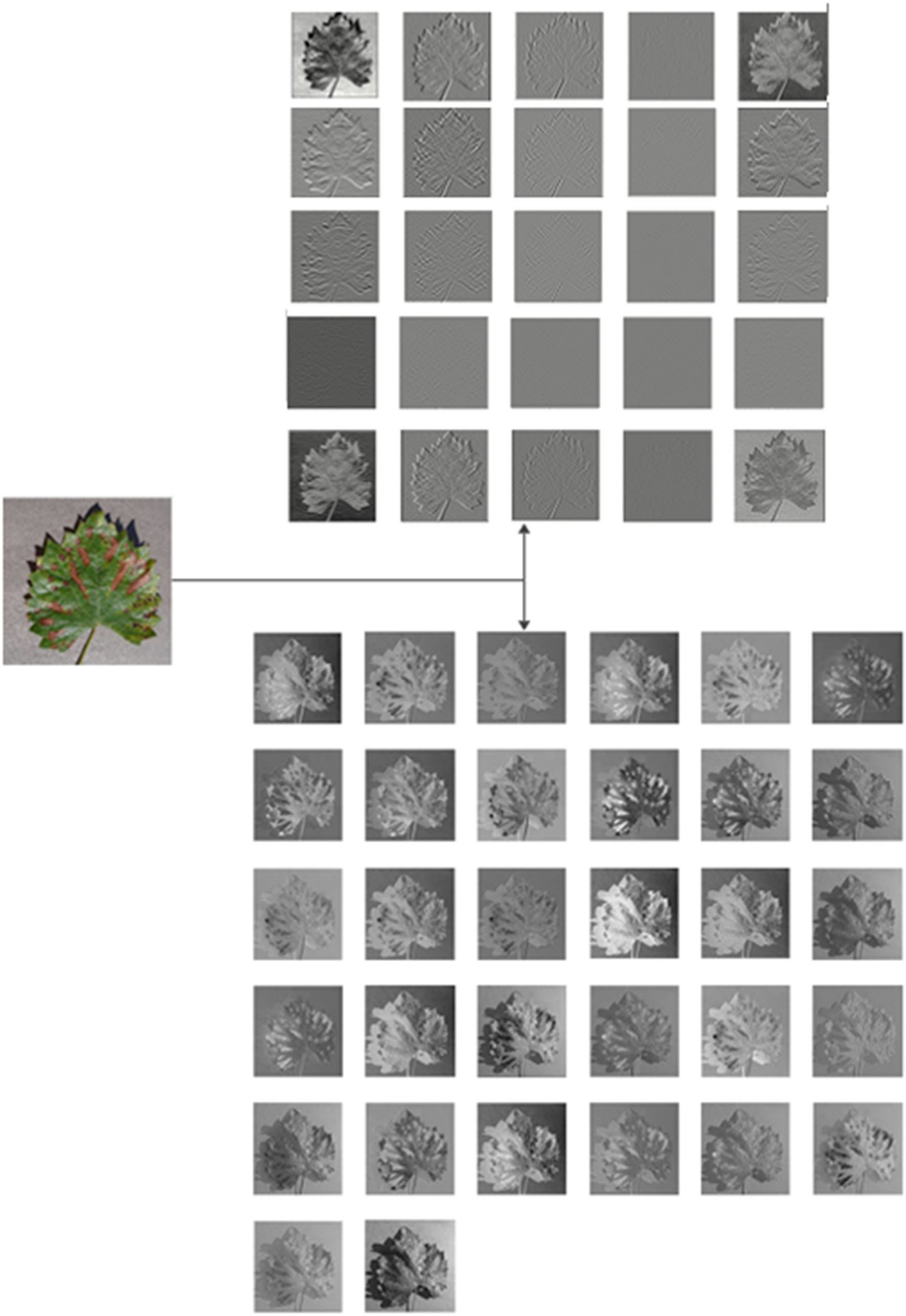

Fig. 7 Feature Maps generated by Customized and Learnable Filters

Table 1 Leaf species classification for data repository of leaf image

Name of the plant Species	Number of leaf images	Classification Accuracy (%)					
		Fused Multiscale Customized and Learnable Streams	Fused Multiscale Customized Streams	Fused Multiscale Learnable Streams	Fused Customized and Learnable stream (Stream 1 & Stream 2)	Fused Customized and Learnable stream (Stream 3 & Stream 4)	Fused Customized and Learnable stream (Stream 5 & Stream 6)
Alstonia	433	89.81	**95.37**	**95.37**	93.52	92.59	**95.37**
Arjun	452	95.58	93.81	92.04	**98.23**	94.69	92.92
Bael	118	89.66	89.66	86.21	**96.55**	89.66	93.10
Basil	149	94.59	**100**	97.3	**100**	**100**	**100**
Gauva	419	97.14	96.19	97.14	95.24	**100**	96.19
Jamun	624	95.51	96.15	95.51	**98.08**	**98.08**	96.79
Jatropha	257	**100**	95.31	**100**	98.44	96.88	95.31
Lemon	236	96.61	96.61	86.44	96.61	**98.31**	**98.31**
Mango	435	**99.08**	95.41	98.17	**99.08**	96.33	97.25
Pomegranate	559	**99.29**	**99.29**	95.71	97.86	98.57	97.14
Pongamia Pinnata	598	96.64	93.29	93.29	**97.99**	95.97	95.97
Chinar	223	98.21	**100**	96.43	92.86	94.64	96.43
Total Number of Images / Average Recognition Rate	4503	96.01	95.92	94.47	**97.16**	96.31	96.23

The bold symbols reflect the fields having higher recognition rate

Rank 2 accuracy is 99.29% and Rank 3 accuracy is 99.56%. For example, while classifying Alstonia Scholaris species, the first three probabilities are 0.7543, 0.1453 and 0.0316 and the corresponding classes are Mango, Alstonia Scholaris and Bael. Thus, the first highest probability maps to mango (misclassified), whereas the second largest value corresponds to the correct class Alstonia Scholaris.

From Table 2, it is evident that Apple and Corn leaf species has brown leaf spot, small patches of white or grey powdery masses hence fused stream 3 & stream 4 performs better. Blueberry, Cherry strawberry, Orange and Tomato leaves are better defined by combining shape and vein structures hence Stream 1 & stream2 combined together achieves enhanced results. Potato and Raspberry leaf species are better defined by stream 3 & stream 4. For the categories Soybean, Squash Background Grape Pepper combining all the 6 streams yield good results.

From Table 2, Fused Customized and Learnable stream (Stream 3 & Stream 4) gives better results thus Rank 1 classification gives 99.17% accuracy and 99.79% & 99.95% for Rank 2 and Rank 3.

From Table 3, it is evident that combining the feature maps from all the 6 streams results in the classification rate of 90.86%. But Holy Basil and Mountain Knotgrass pull down the recognition accuracy. As Holy Basil and Mountain Knotgrass leaves shows great variations, i.e., leaves with flower, multiple leaves at varying size etc.

4.4 Leaf disease classification

From Table 4, it is observed that, Apple with scab, Potato with early blight, healthy strawberry with Stream 2 & Stream 3 as leaf spots turn dark brown to black, get bigger and grow together and leaf spots often form along the leaf veins. Grape with leaf blight, tomato with yellow leaf curl virus, tomato with two spotted spider mite, healthy tomato the defects occur at all scales hence fused features from all 6 streams works good. Tomato with late blight, tomato with leaf mold, healthy soybean healthy pepper with 3 scales of learnable streams fused together as the leaves have large, dark brown blotches with a green gray edge and it is not confined by major leaf veins. Tomato with target spot, tomato with early blight, tomato with septoria leaf spot, healthy potato, potato with late blight, healthy raspberry, apple with black rot, cherry with powdery mildew corn with grey leaf spot corn with northern leaf blight grape with black measles with all 6 streams and 3 learnable streams. Healthy grape, orange with huanglongbing, peach with bacterial spot tomato with bacterial spot, healthy cherry, grape with black rot with Stream 1 & Stream 2, i.e.,

Table 2 Leaf species classification for plant village database

Name of the plant Species	Number of leaf images	Classification Accuracy (%)					
		Fused Multiscale Customized and Learnable Streams	Fused Multiscale Customized Streams	Fused Multiscale Learnable Streams	Fused Customized and Learnable stream (Stream 1 & Stream 2)	Fused Customized and Learnable stream (Stream 3 & Stream 4)	Fused Customized and Learnable stream (Stream 5 & Stream 6)
Apple	4645	97.16	95.00	94.49	97.42	**99.40**	97.59
Background	1143	**98.60**	95.80	95.45	97.55	97.90	97.20
Blueberry	1502	98.93	99.20	97.60	**99.73**	99.20	99.47
Cherry	2052	98.83	96.10	94.54	**99.03**	97.08	98.05
Corn	4354	99.91	99.54	98.90	99.91	**100**	99.91
Grape	4639	**100**	99.66	98.62	99.91	99.74	99.66
Orange	5507	99.93	99.78	**100**	**100**	99.93	99.78
Peach	3297	99.20	95.20	99.20	**100**	**100**	98.00
Pepper	2478	**99.19**	97.90	97.09	98.38	98.71	96.61
Potato	3000	96.27	97.47	94.13	98.53	**99.07**	96.53
Raspberry	1000	**100**	98.80	94.40	98.00	**100**	99.20
Soybean	5090	**99.69**	99.53	98.98	99.53	99.14	99.37
Squash	1835	**100**	99.78	99.78	99.56	99.56	97.60
Strawberry	2109	99.05	97.53	97.53	**99.24**	98.67	99.24
Tomato	18,835	99.55	99.26	**99.53**	**99.53**	99.09	98.85
Total Number of Images / Average	61,486	99.09	98.04	97.35	99.09	**99.17**	98.47

The bold symbols reflect the fields having higher recognition rate

with customized and learnable filters with scale of size 128 $\times$ 128. Apple with cedar apple rust corn with common rust, blueberry with healthy strawberry with leaf scorch with all 6 Streams and with scale down stream 3 & 4. Pepper with bacterial spot with 6 Streams, 3 streams, Stream 1 + Stream2. Healthy corn with 6 Streams, Stream 1 + Stream 2 and Stream 3 + Stream 4. Tomato with mosaic virus with 3 streams of learnable filters and with Stream 3 + Stream 4.

From Table 4, it is observed that Fused Multiscale Customized and Learnable stream gives 98.61% accuracy and Rank 2 gives 99.77% accuracy and 99.92% for Rank 3. For example, when one of the test input is from Apple_scab category the probability classification scores are 0.4966 for Corn_Northern_Leaf_Blight, 0.3614 for Peach_Bacterial_spot and 0.0305 for Apple_scab.

From Table 5, the following observations are made: Alstonia Scholaris_Healthy, Arjun_Healthy, Bael_Diseased, Lemon_Healthy works well with all 6 streams and with customized and learnable filters with scale of size 128 $\times$ 128. In the database no diseased Basil leaves are available Basil_Healthy Basil leaves are glossy and oval-shaped, with smooth or slightly toothed edges 100% in all cases. For Alstonia Scholaris_Diseased, Guava_Diseased, Jamun_Diseased, Jatropa_Diseased the spots on leaves may vary from specks to big patches thus fused customized filters across scales performs better. Arjun_Diseased, Guava_Healthy, Lemon_Diseased, Pomegranete_Diseased Chinnar_Diseased are learned by fusion of customized and learnable filters with scale of size 64 $\times$ 64 as leaf spots can vary in size, shapes and colors depending on the age and type of the cause or pathogen. Pongamia_Diseased and Pongamia_Healthy gives 100% classification rate with Stream 1 &2. Lemon diseased reports classification accuracy of 73.58% as confusion occurs between healthy lemon leaves and diseased leaves.

From Table 5, Fused multiscale customized and learnable stream gives 90.02% accuracy and Rank 2 gives 97.42% accuracy and 98.75% for Rank 3.

Tables 6 and 7 show the species specific leaf disease classification and it is observed that, the Average Classification Rate by Species Specific Disease Classification is higher than classifying without species specific.

Table 8 displays the comparison of classification accuracy reported in the literature for classifying diseases corresponding to the specific species, i.e., disease classification in apple and tomato individually and with all 39 categories in the database. The proposed method trains

Table 3 Leaf species classification for MepcoTrophicLeaf database

Name of the plant species	Classification accuracy (%)					
	Fused multiscale customized and learnable streams	Fused multiscale customized streams	Fused multiscale learnable streams	Fused customized and learnable stream (stream 1 & stream 2)	Fused customized and learnable stream (stream 3 & stream 4)	Fused customized and learnable stream (stream 5 & stream 6)
Asthma plant	**90.00**	70.00	65.00	85.00	85.00	65.00
Avaram	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Balloon vine	**96.77**	83.87	77.42	80.65	80.65	87.10
Bellyache bush (Green)	95.00	95.00	95.00	**100.00**	95.00	90.00
Benghal Dayflower	78.57	71.43	42.86	**92.86**	71.43	50.00
Big caltrops	87.50	**93.75**	62.50	**93.75**	87.50	87.50
Black-Honey shrub	**92.31**	**92.31**	57.69	84.62	**92.31**	84.62
Bristly wild grape	87.50	75.00	75.00	**100.00**	87.50	93.75
Butterfly pea	**69.23**	**69.23**	**69.23**	53.85	61.54	61.54
Cape gooseberry	**86.67**	93.33	66.67	80.00	96.67	56.67
Common wireweed	80.00	**100.00**	**100.00**	86.67	**100.00**	93.33
Country mallow	**100.00**	**100.00**	88.24	**100.00**	94.12	**100.00**
Crown flower	**100.00**	93.75	93.75	**100.00**	**100.00**	**100.00**
Green chireta	82.35	**100.00**	82.35	82.35	94.12	94.12
Holy basil	69.23	**84.62**	76.92	76.92	**84.62**	76.92
Indian copperleaf	74.19	87.10	70.97	74.19	**87.10**	74.19
Indian jujube	**100.00**	81.25	68.75	81.25	93.75	93.75
Indian sarsaparilla	95.24	90.48	90.48	**100.00**	95.24	85.71
Indian stinging nettle	92.31	96.15	80.77	**100.00**	**100.00**	**100.00**
Indian thornapple	85.71	**92.86**	85.71	**92.86**	**92.86**	85.71
Indian wormwood	82.35	88.24	82.35	**94.12**	**94.12**	**94.12**
Ivy Gourd	**100.00**	92.31	76.92	92.31	92.31	76.92
Kokilaksha	**100.00**	86.67	73.33	86.67	**100.00**	93.33
Land caltrops (Bindii)	**100.00**	**100.00**	87.50	**100.00**	93.75	**100.00**
Madagascar periwinkle	92.86	**100.00**	92.86	**100.00**	85.71	78.57
Madras pea pumpkin	92.31	92.31	**100.00**	84.62	92.31	69.23
Malabar catmint	**100.00**	93.75	68.75	93.75	93.75	93.75
Mexican mint	**100.00**	73.08	92.31	92.31	92.31	88.46
Mexican prickly poppy	**92.86**	**92.86**	**92.86**	**92.86**	**92.86**	**92.86**
mountain Knotgrass	78.95	68.42	73.68	**84.21**	**84.21**	78.95

Table 3 (continued)

Name of the plant species	Classification accuracy (%)					
	Fused multiscale customized and learnable streams	Fused multiscale customized streams	Fused multiscale learnable streams	Fused customized and learnable stream (stream 1 & stream 2)	Fused customized and learnable stream (stream 3 & stream 4)	Fused customized and learnable stream (stream 5 & stream 6)
Nalta jute	**94.44**	88.89	77.78	**94.44**	88.89	88.89
Night blooming cereus	92.31	84.62	84.62	**100.00**	84.62	92.31
Panicled Foldwing	**76.47**	41.18	35.29	70.59	52.94	52.94
Prickly chaff flower	**100.00**	**100.00**	76.92	**100.00**	**100.00**	**100.00**
Punarnava	84.21	**89.47**	36.84	**89.47**	84.21	73.68
Purple fruited pea eggplant	94.12	88.24	88.24	**100.00**	88.24	94.12
Purple tephrosia	93.33	**100.00**	**100.00**	93.33	**100.00**	**100.00**
Rosary pea	**100.00**	**100.00**	81.25	**100.00**	93.75	93.75
Shaggy button weed	**93.75**	75.00	75.00	81.25	87.50	62.50
Small water clover	**100.00**	85.71	85.71	**100.00**	92.86	92.86
Spiderwisp	**100.00**	78.57	92.86	**100.00**	92.86	**100.00**
Square stalked Vine	82.50	87.50	90.00	**95.00**	92.50	92.50
Stinking passionflower	**100.00**	93.75	56.25	75.00	93.75	93.75
Sweet basil	90.32	96.77	93.55	96.77	**100.00**	83.87
Sweet flag	**100.00**	94.74	89.47	94.74	94.74	94.74
Tinnevelly senna	76.92	**100.00**	76.92	92.31	76.92	76.92
Trellis vine	92.86	**100.00**	92.86	92.86	92.86	85.71
Velvet bean	88.89	88.89	83.33	88.89	**94.44**	88.89
Coatbuttons	**93.33**	86.67	86.67	86.67	86.67	53.33
Heart-Leaved moonseed	87.50	97.92	**100.00**	97.92	93.75	85.42
Average	**90.86**	88.71	79.87	90.70	90.24	85.05

The bold symbols reflect the fields having higher recognition rate

the data from the scratch whereas the over performing models presented in Table 8 are with transfer learning.

From Table 8, it is observed that, for apple leaf compare with the state of the art work with pre-trained networks the proposed architecture shows 8% increase in the classification accuracy. For tomato, comparing with deep networks like Dense net, inception net etc., by transfer learning the proposed architecture gives comparable results. Similarly, for classifying all the 39 categories from Plant Village Database, the trending deeplearning architectures like efficientnet, inceptionnet, Googlenet and Mobilenet excels the proposed architecture in minimal value.

For Plant species classification, using MepcoTrophic database Ahila et. al. [27] used 6 layers of CNN architecture and reports 87.25% accuracy for batch size of 19 and 300 epochs. Whereas, the proposed architecture reports 90.86% accuracy for classifying the entire 50 species of the above database.

Table 4 Leaf disease classification for plant village database

Name of the plant Species	Number of leaf images	Classification Accuracy (%)					
		Fused Multiscale Customized and Learnable Streams	Fused Multiscale Customized Streams	Fused Multiscale Learnable Streams	Fused Customized and Learnable stream (Stream 1 & Stream 2)	Fused Customized and Learnable stream (Stream 3 & Stream 4)	Fused Customized and Learnable stream (Stream 5 & Stream 6)
Apple with scab	1000	93.60	93.60	66.00	91.60	**94.40**	90.00
Apple with black rot	1000	97.20	**100**	96.00	98.40	98.80	95.20
Apple with cedar apple rust	1000	**100**	99.60	94.00	99.60	**100**	99.20
Healthy apple	1645	**98.54**	98.30	94.40	**98.54**	97.81	96.59
Background	1143	**98.60**	**98.60**	93.71	96.50	97.55	97.90
Blueberry with healthy	1502	**99.73**	**99.73**	97.87	99.20	**99.73**	98.40
Cherry with powdery mildew	1052	99.24	**100**	96.58	99.62	99.24	98.10
Cherry with healthy	1000	96.00	98.00	95.60	**98.40**	97.20	96.00
Corn with grey leaf spot	1000	**96.00**	**96.80**	70.00	96.40	94.80	**96.80**
Corn with common rust	1192	**100**	99.66	98.99	99.66	**100**	97.99
Corn with northern leaf blight	1000	92.00	92.40	**95.20**	88.00	90.80	70.00
Healthy corn	1162	**100**	99.31	99.31	**100**	**100**	99.31
Grape with black rot	1180	98.64	97.97	91.19	99.32	**98.98**	92.88
Grape with black measles	1383	99.71	**100**	95.09	99.42	97.98	97.40
Grape with leaf blight	1076	100.00	99.26	98.88	**99.63**	99.26	97.40
Healthy grape	1000	99.20	98.80	96.40	**100**	99.20	98.80
Orange with huanglongbing	5507	99.93	99.85	99.78	**100**	99.85	99.78
Peach with bacterial spot	2297	99.48	98.08	96.34	**99.65**	98.08	97.39
Healthy peach	1000	**100**	99.20	96.80	**100**	99.60	98.00
Pepper with bacterial spot	1000	**98.40**	**98.40**	90.40	**98.40**	97.60	96.00
Healthy pepper	1478	**99.73**	98.64	97.56	99.19	99.46	96.75
Potato with early blight	1000	98.80	98.80	92.80	98.40	**99.60**	97.60
Healthy potato	1000	94.80	**98.80**	85.60	94.40	96.40	94.80
Potato with late blight	1000	98.00	**99.20**	92.80	98.00	97.60	96.00
Healthy raspberry	1000	98.80	**99.60**	91.20	96.80	**99.60**	97.60
Healthy soybean	5090	**99.76**	99.37	99.06	99.06	99.53	98.19
Squash with powdery mildew	1835	**100**	99.56	99.56	**100**	99.56	99.56

Table 4 (continued)

Name of the plant Species	Number of leaf images	Classification Accuracy (%)					
		Fused Multiscale Customized and Learnable Streams	Fused Multiscale Customized Streams	Fused Multiscale Learnable Streams	Fused Customized and Learnable stream (Stream 1 & Stream 2)	Fused Customized and Learnable stream (Stream 3 & Stream 4)	Fused Customized and Learnable stream (Stream 5 & Stream 6)
Healthy strawberry	1000	98.92	99.28	86.64	99.64	**100**	97.11
Strawberry with leaf scorch	1109	**100**	**100**	96.40	99.20	**100**	98.00
Tomato with bacterial spot	2127	99.06	98.50	95.49	**99.25**	98.31	96.62
Tomato with early blight	1000	86.40	**89.20**	57.60	88.00	83.60	82.00
Healthy tomato	1591	**96.86**	95.39	90.99	95.18	95.60	91.40
Tomato with late blight	1909	**98.40**	96.80	75.60	94.80	98.00	89.60
Tomato with leaf mold	1000	**98.65**	97.97	75.17	95.71	97.52	93.45
Tomato with septoria leaf spot	1771	97.61	**99.28**	92.60	98.33	98.09	95.47
Tomato with two spotted spider mite	1676	**95.73**	92.88	88.60	94.30	95.44	94.30
Tomato with target spot	1404	99.85	**99.93**	96.94	99.70	99.85	99.40
Tomato with mosaic virus	1000	99.60	**100**	88.00	97.60	**100**	97.60
Tomato With yellow leaf curl virus	5357	**100**	99.50	97.99	99.75	99.50	98.74
Average	**61,486**	**98.61**	98.54	93.24	98.20	98.34	96.25

The bold symbols reflect the fields having higher recognition rate

5 Conclusion

In this paper, unified model with six parallel CNNs learning the discriminative features from pyramidal decomposition of the input leaf image is proposed. Learning from the individual streams by customized and learnable filters that complements each other leads to performance enhancement. The customized filers (Law's Mask) is preferred for extraction of texture feature that well defines level, edge, spot, ripple, and wave patterns. The combination of these mask is used for getting discriminative information. Learnable filters are randomly initialized based on the data and here the color and shape characteristics are well learned at the initial stages. Experimental studies were conducted using augmented versions of the PlantVillage dataset, Data repository of leaf image and MepcoTrophicLeaf database. From the experimentation, it is observed that leaf with small brown spots and burned

Table 5 Leaf disease classification for data repository of leaf image

Name of the plant species	Classification accuracy (%)					
	Fused multiscale customized and learnable streams	Fused multiscale customized streams	Fused multiscale learnable streams	Fused customized and learnable stream (stream 1 & stream 2)	Fused customized and learnable stream (stream 3 & stream 4)	Fused customized and learnable stream (stream 5 & stream 6)
Alstonia Scholaris_Diseased	84.13	**98.41**	80.95	88.89	95.24	90.48
Alstonia Scholaris_Healthy	**93.33**	86.67	80.00	**93.33**	82.22	84.44
Arjun_Diseased	86.21	84.48	74.14	82.76	**93.10**	87.93
Arjun_Healthy	**96.36**	90.91	90.91	**96.36**	80.00	78.18
Bael_Diseased	**100**	93.10	96.55	**100**	93.10	96.55
Basil_Healthy	**100**	**100**	**100**	**100**	**100**	**100**
Guava_Diseased	88.57	**91.43**	85.71	82.86	82.86	85.71
Guava_Healthy	95.65	95.65	88.41	97.10	**98.55**	91.30
Jamun_Diseased	89.53	**93.02**	90.70	84.88	84.88	87.21
Jamun_Healthy	91.43	75.71	88.57	**92.86**	85.71	84.29
Jatropa_Diseased	70.97	**90.32**	67.74	67.74	67.74	74.19
Jatropa_Healthy	87.88	**90.91**	75.76	**90.91**	81.82	72.73
Lemon_Diseased	**73.68**	68.42	57.89	57.89	31.58	63.16
Lemon_Healthy	**90.00**	87.50	77.50	87.50	**90.00**	82.50
Mango_Diseased	**100**	90.91	96.97	96.97	93.94	95.45
Mango_Healthy	95.24	90.48	90.48	**97.62**	**97.62**	92.86
Pomegranete_Diseased	86.76	89.71	67.65	83.82	**91.18**	88.24
Pomegranete_Healthy	90.28	97.22	90.28	**98.61**	94.44	80.56
Pongamia_Diseased	94.20	94.20	88.41	**100**	97.10	92.75
Pongamia_Healthy	98.75	93.75	96.25	**100**	97.50	96.25
Chinnar_Diseased	86.67	**96.67**	80.00	66.67	90.00	80.00
Chinnar_Healthy	80.77	80.77	80.77	84.62	**88.46**	**88.46**
	90.02	90.01	83.89	88.70	87.14	86.06

The bold symbols reflect the fields having higher recognition rate

Table 6 Species specific leaf disease classification for data repository of leaf image

Plant species	Plant diseased category	Classification rate (%) as per Table 5	Average classification rate per species as per Table 5	Classification rate by species specific disease classification	Average classification rate by species specific disease classification
Alstonia	Alstonia Scholaris_Diseased	84.13	88.73	93.65	**96.83**
	Alstonia Scholaris_Healthy	93.33		100.00	
Arjun	Arjun_Diseased	86.21	91.29	94.83	**93.78**
	Arjun_Healthy	96.36		92.73	
Guava	Guava_Diseased	88.57	92.11	91.43	**94.27**
	Guava_Healthy	95.65		97.10	
Jamun	Jamun_Diseased	89.53	90.48	89.53	**92.62**
	Jamun_Healthy	91.43		95.71	
Jatropa	Jatropa_Diseased	70.97	79.43	96.77	**93.84**
	Jatropa_Healthy	87.88		90.91	
Lemon	Lemon_Diseased	73.68	81.84	94.74	**94.87**
	Lemon_Healthy	90.00		95.00	
Mango	Mango_Diseased	100.00	97.62	98.48	**98.05**
	Mango_Healthy	95.24		97.62	
Pomegranate	Pomegranete_Diseased	86.76	88.52	88.24	**91.34**
	Pomegranete_Healthy	90.28		94.44	
Pongamia	Pongamia_Diseased	94.20	96.48	100.00	**99.38**
	Pongamia_Healthy	98.75		98.75	
Chinnar	Chinnar_Diseased	86.67	83.72	93.33	**92.82**
	Chinnar_Healthy	80.77		92.31	

The bold symbols reflect the fields having higher recognition rate

Table 7 Species specific leaf disease classification for PlantVillage database

Plant species	Plant diseased category	Classification rate (%) as per Table 4	Average classification rate per species as per Table 4	Classification rate by species specific disease classification	Average classification rate by species specific disease classification
Apple	Apple with scab	93.60	97.335	96.80	**98.92**
	Apple with black rot	97.20		99.60	
	Apple with cedar apple rust	100		100.00	
	Healthy apple	98.54		99.27	
Cherry	Cherry with powdery mildew	99.24	97.62	99.62	**99.81**
	Cherry with healthy	96.00		100.00	
Corn	Corn with grey leaf spot	96.00	97	98.4	**97.415**
	Corn with common rust	100		99.66	
	Corn with northern leaf blight	92.00		91.6	
	Healthy corn	100		100	
Grape	Grape with black rot	98.64	**99.39**	98.98	99.22
	Grape with black measles	99.71		98.27	
	Grape with leaf blight	100.00		99.63	
	Healthy grape	99.20		100.00	
Peach	Peach with bacterial spot	99.48	99.74	99.73	**99.865**
	Healthy peach	100		100	
Pepper	Pepper with bacterial spot	98.40	99.065	99.20	**99.465**
	Healthy pepper	99.73		99.73	
Potato	Potato with early blight	98.80	97.2	98.4	**99.2**
	Healthy potato	94.80		99.6	
	Potato with late blight	98.00		99.6	
Strawberry	Healthy strawberry	98.92	99.46	100	**100**
	Strawberry with leaf scorch	100		100	

Table 7 (continued)

Plant species	Plant diseased category	Classification rate (%) as per Table 4	Average classification rate per species as per Table 4	Classification rate by species specific disease classification	Average classification rate by species specific disease classification
Tomato	Tomato with bacterial spot	99.06	97.216	98.87	**97.381**
	Tomato with early blight	86.40		87.40	
	Healthy tomato	96.86		97.06	
	Tomato with late blight	98.40		95.60	
	Tomato with leaf mold	98.65		98.42	
	Tomato with septoria leaf spot	97.61		98.81	
	Tomato with two spotted spider mite	95.73		97.87	
	Tomato with target spot	99.85		99.78	
	Tomato with mosaic virus	99.60		100.00	
	Tomato with yellow leaf curl virus	100		100.00	

The bold symbols reflect the fields having higher recognition rate

tips/edges is better learned by the stream with customized and learnable filters at lower scale (32 × 32). Leaves with small yellowing brown patches are learned by customized and learnable filters at mid-scale (64 × 64) and brown to dark brown or black colored spots with yellow halo are learned by customized and learnable filters at higher scale (128 × 128). From the experimental results, it is observed that the proposed algorithm gives better accuracy as compared with the state of the art methods. Plant pathologists and farmers will be able to promptly diagnose plant diseases and take the appropriate measures it they are deployed as mobile applications.

Table 8 Comparison with the state of the art methods for PlantVillage database

Species	Author	Methodology	Classification rate
Apple	Wang et. al. [29]	VGG16	90.4
		VGG19	90
		Inception-v3	83
		ResNet50	80
	Proposed methodology	Six Stream Parallel Learning using learnable and customized filter	**98.91**
Tomato	Brahimi et. al. [30]	GoogleNet	99.18
		AlexNet	98.66
	Bhatt et al. [31]	ResNet-50	99.7
		Xception	98.6
		Inception-v3	98.4
	Zhang et al. [32]	ResNet	97.28
	Rangarajan et al. [33]	VGG16	97.29
		AlexNet	97.49
	Chowdhury et al. [34]	DenseNet201	98.05
	Tm et al. [35]	LeNet	94.85
	Mohit et al. [36]	CNN	91.2
	H. Durmuş et al.[37]	AlexNet and then SqueezeNet	95.5
	Proposed methodology	Six stream parallel learning using learnable and customized filter	97.38
Species not specified (all 39 classes)	Mohanty et al. [13]	Alexnet	98.91
		Googlenet	99.21
	Ahmed and Gopireddy [38]	CNN	93.6
	Hassan et al. [39]	InceptionV3	98.42
		InceptionResNetV2	99.11
		MobileNetV2	97.02
		EfficientNetB0	99.56
	Too et al. [14]	DenseNets-121	99.75
	Chen et al.[12]	MobileNet-Beta	99.94
	Geetharamani and Pandian [15]	9-layer CNN model	96.46
	Atila et al. [22]	EffcientNet B4	99.97
	Saleem et al. [5]	Xception model	99.81
	Proposed methodology	Six stream parallel learning using learnable and customized filter	98.61

The bold symbols reflect the fields having higher recognition rate

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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