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Optimized convolutional neural network model for plant species identification from leaf images using computer vision

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Abstract

In recent works of computer science, especially in the fields of image processing and pattern recognition techniques with machine learning, considerable focus is given to plant taxonomy which enhances the abilities of people to recognize plant species. This paper presents a method that analyzes color images of leaves using a type of Convolutional Neural Network to recognize plant species. The proposed Neural Network consists of four convolutional layers followed by two Fully-Connected layers and a final soft-max layer to offer a feature representation for different plant species. Four max-pooling layers are performed over a 2×2 pixel window with stride 2. Results on five plant datasets viz. Leaf snap (52 plant species), UCI leaf (40 plant species), PlantVillage (38 plant species), Flavia (32 plant species) and Swedish (15 plant species) are tabulated that demonstrate the remarkable performance of the proposed deep neural network when compared to the state of art methods.

Keywords Plant species identification · Convolutional Neural Network · Leaf snap · UCI · Plant village · Flavia · Swedish

1 Introduction

Plants are the backbone of life on earth, as they provide food and oxygen to humans and many other creatures. Plants provide a lot including balance of ecological system, used in production of drugs, causing rain fall etc. Hence, there is a need to identify plant species that requires understanding of plants and their species. Identifying plant species will be useful to drug industry to invent new drugs and improve the quality of existing ones. Inventing plant species also improves the balance in the ecosystem and agricultural productivity and sustainability. Botanists are much concerned about the variations of leaf characteristics as it enables them to carry out a comparative analysis on plants (Manasa et al., 2019; Turkoglu & Hanbay, 2019; Zhu et al., 2019).

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Recognition of plant species from leaf images is a challenging computer vision task (Manasa et al., 2019; Turkoglu & Hanbay, 2019; Zhu et al., 2019). The major challenge in plant identification is due to many parts of the plant are diverse in nature with high intra class and few inter class variations. The recent research works on automatic plant species identification has given good results, yet to necessity of good models are required to build. The traditional classification models preprocess the data to eliminate complex background and they suffer from problems like degradation and vanishing gradient. Hence, an approach that overcome the pitfalls of the state-of-the-art models need to be proposed.

The rest of the paper is organized as follows. Section 2 presents a review of related work. The details of feature extraction and CNN used are described in Sect. 3. The datasets used are discussed in Sect. 4. Experimental results are reported in Sect. 5. Finally, a conclusion is drawn in Sect. 6.

2 Literature survey

This section presents a brief review of recent progress in the area of plant identification. Plant recognition is usually done based on different organs of plant species.

Dyrmann et al. (2016) presents a method of recognizing plant species using color images. They had used a CNN built from scratch. The model is trained on 10,413 images of 22 crop species that are at early growth stages. This model later tested with part of theses considered images.

Fan et al. (2018) presented a new approach for detecting tobacco plants using DNN. In this approach authors used Unmanned Aerial Vehicles (UAVs) mechanism for collecting images with high spatial resolution. Here authors followed three phase mechanism. The proposed mechanism has shown the good efficiency for detection of tobacco plants.

Grinblat et al. (2016) proposed novel mechanism for identification of plant from its leaf veins using DCNN particularly for white/red/soy bean. This proposed model has shown the good accuracy for considered datasets.

Hu et al. (2018) proposed a plant recognizing model using Multi Scale Fusion(MSF)-CNN from plant leafs. In this approach, authors have given the low resolution images as input for train the model. In the second case they train the model with different scaled images.

Jeon and Rhee (2017) proposed a model for leaves classification using CNN by adjusting depth of GoogleNet. Then each model performance is evaluated by considering leaves damage.

Kaya et al. (2019) analyzed four plant species classification models of transfer learning for DNN. Their investigations demonstrated that the considered models automatically identified the plant species with good accuracy.

Lee et al. (2015) in their work considered 44 different plant species located at Royal Botanical Gardens of Britain. Unsupervised features are studied using convolutional neural networks (CNN). They had also applied a visualization technique to gain more intuition on the chosen features. The visualization technique is based on Deconvolutional networks (DN). Each of the plant species is uniquely represented using venations of different order. Results obtained found to show good consistency and accuracy compared to state-of-the art methods.

Manasa et al. (2019) classified plants considering their leaf structure. The acquired images are preprocessed through the processes, resizing, image enhancement, shadow removal and background removal. When multiple leaves surround a leaf, Watershed algorithm is used for image segmentation to separate each leaf. This method can accurately classify eight different species of plants using neural network. The final results of this method are customized, brief yet informative.

Ghazi et al. (2017) identifying different performance affected factors of DNN. For this purpose, they had

Table 1 Different algorithms analysis

Authors	Description	Future perception
Dyrmann et al. (2016)	This method is used to identify from color plant leaf images	Neural network methods are required to use to increase the recognition rate
Fan et al. (2018)	This method is used to recognize the plants using DNN	More layers are needed to be added to increase the recognition rate
Grinblat et al. (2016)	This method is used to recognize the plants species using CNN	Deep Neural network methods are required to use to increase the recognition rate
Hu et al. (2018)	This method is used to recognize the plants using MSF-CNN	It is needed to increase the recognition rate
Jeon and Rhee (2017)	This method is used to classify the plant leaves with CNN	It is needed to increase the classification rate
Kaya et al. (2019)	This method is used to classify the plant leaves with transfer learning	It is needed to increase the classification rate
Lee et al. (2015)	This method is used to identify the plant leaves with CNN	It is needed to increase the identification rate
Manasa et al. (2019)	This method is used to classify the plant leaves with NN	More layers are needed to be added to increase the recognition rate
Ghazi et al. (2017)	This method is used to identify the plant leaves with DNN	It is needed to increase the identification rate
Turkoglu and Hanbay (2019)	This method is used to recognize the plant leaves with LBP	It is needed to increase the recognition rate
Zhang et al. (2015)	This method is used to recognize the plant leaves with ConvNet	It is needed to increase the recognition rate
Zhu et al. (2018)	This method is used to identify plant leaf images using CNN	More layers are needed to be added to increase the recognition rate
Zhu et al. (2019)	This method is used to identify plant leaf images using DCNN	It is needed to increase the recognition rate
Reyes et al. (2015)	This method is used to identify plant using CNN	DNN is required to increase the recognition rate

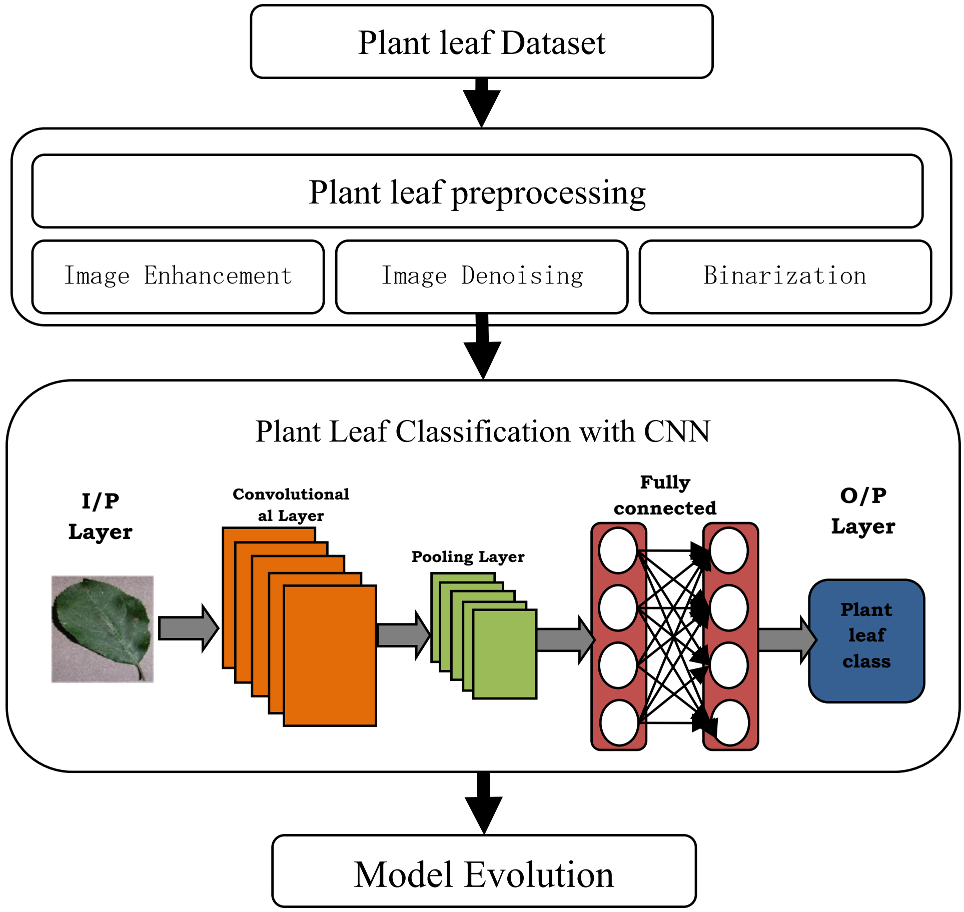


Fig. 1 Structure of the process of plant species identification with CNN

developed a method to identify plant species captured in an image using DCNN. The factors considered are applied on three popular deep learning networks, viz., AlexNet, GoogLeNet, and VGGNet for performance evaluation.

Turkoglu and Hanbay (2019) proposed a method to recognize plant leaves by extracting texture features from images. They had followed an approach based on LBP (Local Binary Pattern). Their method uses R and G color channels of an image in contrast to the original LBP which converts color images to gray ones. In addition, the robustness of the proposed method had been evaluated against noise measures such as Gaussian and salt & pepper. Later, Extreme Learning Machine (ELM) method is applied to classify and test the features obtained from the proposed method.

Zhang et al. (2015) developed a ConvNet consisting of seven layers for leaf recognition using data ugmentation. First, the dataset had been enlarged with same labeling using multiform transformations like rotation, ranslation etc. This technique had significantly reduced the degree of model over fitting and enhanced the generalization ability of the ConvNets which in turn improves the performance of ConvNets. Shapes of leaves are obtained by sharpening the images applying a random parameter. This method resembles edge detection, a technique useful in image classification. Later, the augmented leaves data had been classified using a trained a deep convolutional neural network. Three groups of test sets were used. This method is proved to be quite effective and feasible.

Zhu et al. (2018) employed a different method of plant identification from leaf images. In this method discriminative features are extracted from plant leaf using DL. The deep CNN used by them consists of sixteen convolutional layers. Following the convolutional layers are 3-FC layers followed by a final soft-max layer, finally this network model offers self learning.

Zhu et al. (2019) presented two-way attention model called family first & max-sum with DCNN for plant taxonomy recognition. This model avoids conflict of family labels and given better classification accuracy.

Reyes et al. (2015) proposed a novel model for plant identification with DL. This model is trained with 1.8 million plant images by considering transfer learning.

The actual comparison and analysis of these methods are described in Table 1.

3 Materials and methods

In our work, we had implemented an efficient framework based on CNN for identifying plant species using leaf images. The proposed model has four steps: data collection, feature extraction, CNN model creation, and model evaluation and model is presented in Fig. 1, its details are described in this section.

3.1 Data collection

In this phase, we had collected the plant leaf images from various data resources viz. Leaf snap data, UCI Leaf, PlantVillage, Flavia and Swedish datasets. The images from these datasets are used for train,validate and test the proposed model.

3.1.1 Plant leaf preprocessing

Generally images have variations in intensity. By eliminating such variations or poor contrast, we can get an enhanced image and be able to extract some useful information from the image. Hence, image preprocessing is done using image enhancement, image denoising and binarization.

3.1.2 Image enhancement

It transforms the RGB image to color space. The input image is resized and then the image will be converted into a suitable color space from which we can easily extracted the required information. Grayscale images facilitate efficient extraction of features when compared to color images. Hence, the input RGB image is converted into a grey-level image using Eq. 1.

$$Y = \left(x_1 \times R\right) + \left(x_2 \times G\right) + \left(x_3 \times B\right) \tag{1}$$

where Y represents the gray value equivalent of the color pixel, R,G,B represents the Red, Green and the Blue components of a pixel and x_1, x_2, x_3 are predefined values in the color image respectively.

3.1.3 Image denoising

Next phase after image enhancement is to remove shadows and undesired perturbations like impulse noises from images. These irregularities may affect the computation of leaf feature values. Any feature of size smaller than Structure Element (SE) may be treated as noise.

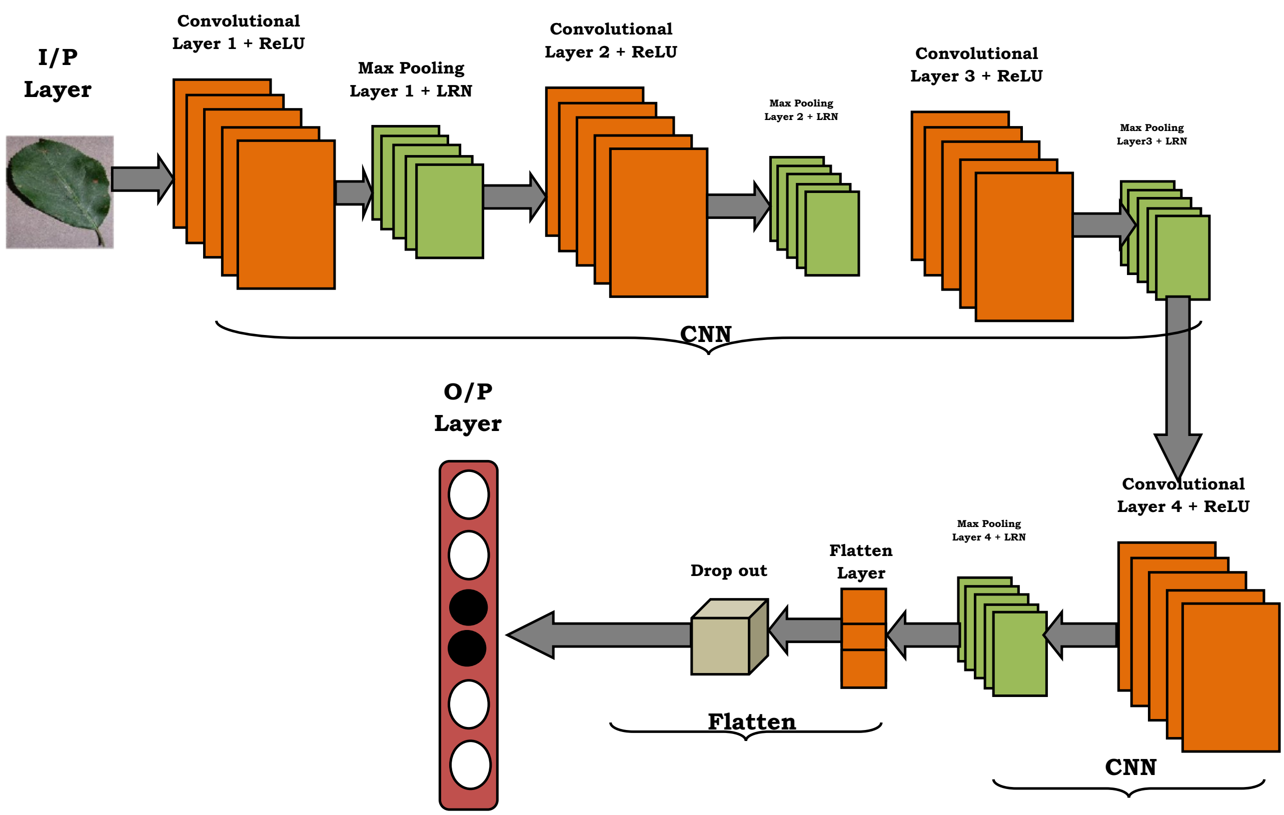


Fig. 2 Convolutional structure

3.1.4 Image segmentation

It is a process, where every pixel present in an image is assigned a label so that pixels of same label shares the visual characteristics. Thresholding is a technique normally used to isolate the background or foreground of an image. The segmentation results depend on the selection of correct threshold value. There are various methods available but each has its own limitations and advantages in terms of applicability and suitability. Each threshold technique works best for certain set of images.

3.2 Feature extraction

The leaf images are classified based on the morphological shape and texture features.

3.2.1 Morphological shape features

A set of morphological features viz. Smooth factor, Form factor, Narrow factor, Perimeter ratio of diameter and Vein features are computed for training feature data set.

3.2.1.1 Smooth factor Image smoothness is measured by the effect of noise on the image area. It is the ratio between leaf image area smoothed by 5×5 rectangular average filter and the one smoothed by 2×2 rectangular average filter.

3.2.1.2 Form factor It is represented as $4\pi\frac{\mathrm{A}}{\mathrm{P}}2$ where A is area of the leaf and P is the perimeter of the leaf margin.

3.2.1.3 Narrow factor It is the ratio of the diameter D and physiological length. $LF = \frac{D}{LP}$.

Table 2 Trained parameters and layers of 2D-CNN

Layer(type)	Output shape	Parameters
conv_1 (Conv2D)	(None, 200, 200, 32)	896
maxpool_1 (MaxPooling2D)	(None, 100, 100, 32)	0
conv_2 (Conv2D)	(None, 100, 100, 64)	18496
maxpool_2 (MaxPooling2D)	(None, 50, 50, 64)	0
conv_3 (Conv2D)	(None, 50, 50, 128)	73856
maxpool_3 (MaxPooling2D)	(None, 25, 25, 128)	0
conv_4 (Conv2D)	(None, 25, 25, 128)	147584
maxpool_4 (MaxPooling2D)	(None, 12, 12, 128)	0
flatten_2 (Flatten)	(None, 18, 432)	0
dropout_2 (Dropout)	(None, 18, 432)	0
dense_1 (Dense)	(None, 512)	9437696
dense_2 (Dense)	(None, 256)	131328
output (Dense)	(None, 40)	10280

3.2.1.4 Perimeter ratio of diameter It is represented as $\frac{P}{D}$, where P is perimeter of the leaf and D is diameter of the leaf.

3.2.1.5 Vein features Each leaf can be uniquely identified by its veins. The background information is subtracted and only the vein patterns are extracted by applying morphological opening operation.

3.2.2 Texture features

A texture based Local Vector Pattern has been proposed to extract the texture features of leaf images. This pattern exhibits high variance between inter class images such as robust against aging of images, illumination changes and other such factors. The Local Vector Pattern of size 200×200 is computed and stored as a training feature dataset with reduced dimension. The feature set for all input images are computed and stored as s feature data set which can be given as the input to the classifier to train the data set.

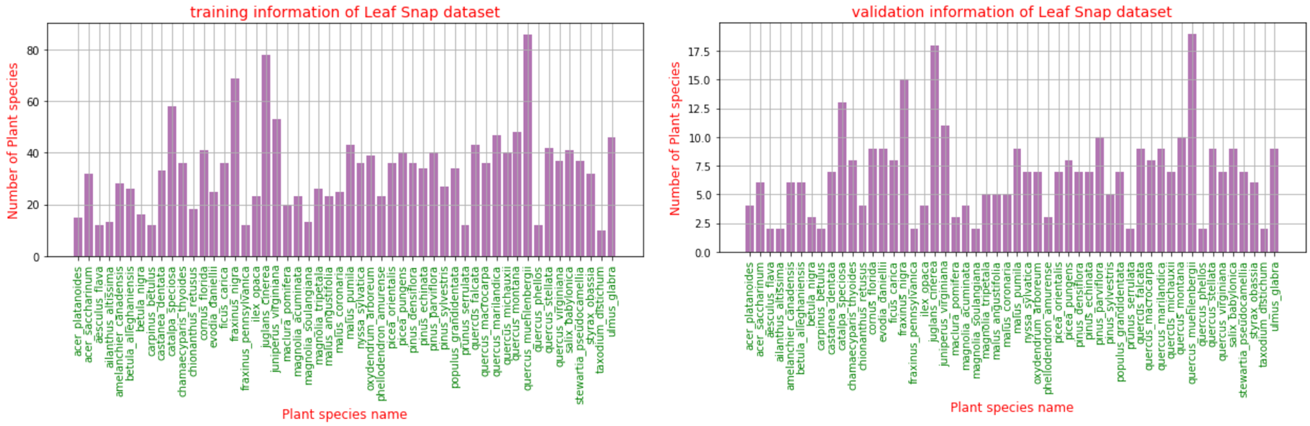
3.3 Plant leaf classification with CNN

The proposed CNN model architecture is depicted in the third part of Fig. 1. The proposed CNN model contains three layers (An input layer, hidden layers (including convolutional, pooling and fully connected layers), and an output layer) which are Shown in Fig. 2. CNN had been applied in numerous fields and had given accurate results. In our work, plant leaf image dataset is input to the CNN. The proposed CNN predicts plant species using their leaf image features as the input data. The dataset is a collection of color images of leaves of various plants with 200×200 pixels. The proposed model is then trained with CNN.

To improve the performance of the CNN model, we used diverse parameters are used and after that leaf image is considered as input. CNN is used in our model because it extracting maximum possible features from the leaf images rather than other models. The use of more number of hidden layers facilitates extraction of more hidden features so that plant species can be identified easily. In our work, we used

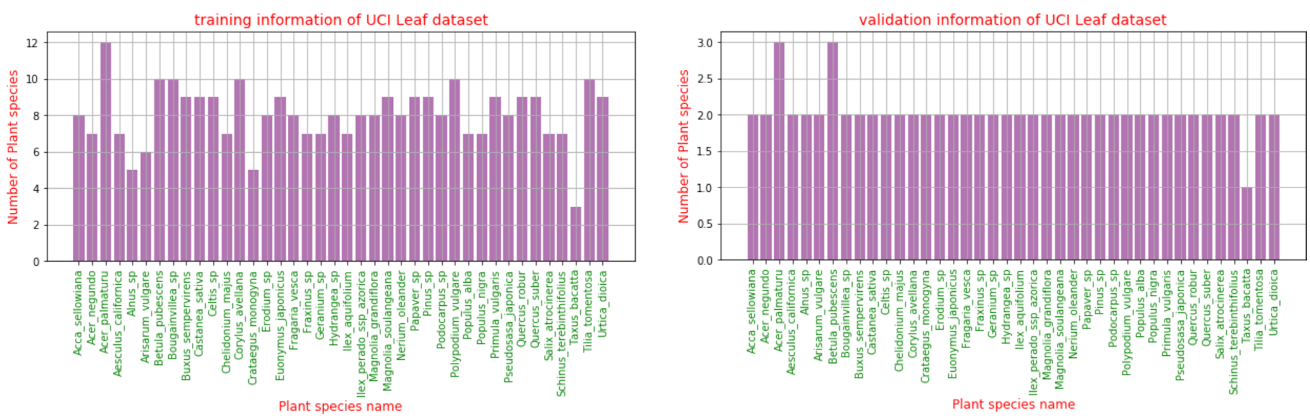
Table 3 Datasets properties

Dataset name	Number of classes	Number of plant leaf images	Plant leaf color	Size
Leaf Snap	52	2130	RGB	200×200
UCI Leaf	40	443	RGB	200×200
Plant Village	38	54,305	RGB	200×200
Flavia	32	1907	RGB	200×200
Swedish leaf	15	1125	RGB	200×200



(a) Leaf Snap dataset Training information **(b)** Leaf Snap dataset validation information

Fig. 3 **a** Leaf Snap dataset Training information. **b** Leaf Snap dataset validation information



(a) UCI Leaf dataset Training information **(b)** UCI Leaf dataset validation information

Fig. 4 **a** UCI Leaf dataset Training information. **b** UCI Leaf dataset validation information

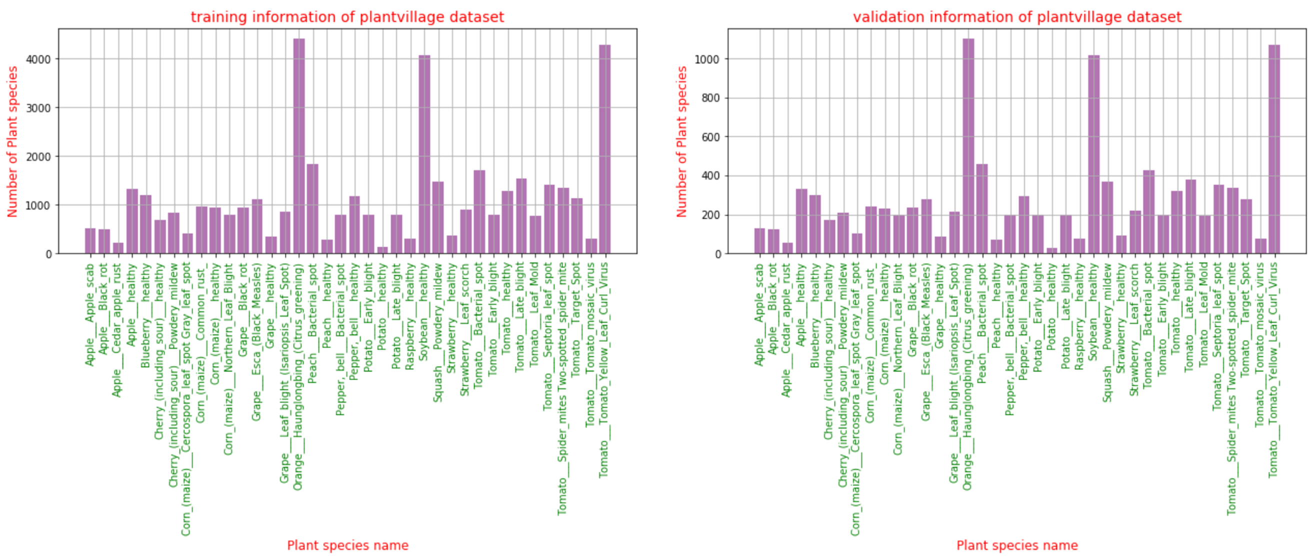
five filter layers (with 32, 64, 128, 256, and 512 filters) and each filter has three different kernel sizes.

3.3.1 Multiple hidden layers for deep neural networks

Hidden layers are existed in the network immediately after the i/p layers, that generates matrices to read/extract/learn features from image. These layers has no.of sub layers with diverse shape and parameters. Sub layers used convolutional logic, max pooling & also Fully Connected(FC) layers with different no.of filters. The number of layers and parameters used in our model determines its quality. In our proposed CNN model first layers kernel size is 32×32 that means features are stored and learned with matrices of size 32×32. Training is repeated by taking bias and weights from previous layer. In our model, max pooling is performed by stride of size 2 with selection of max value. The stride of size 2 is used to reduce the processing time in each next layer. The o/p is calculated using Eq. 2.

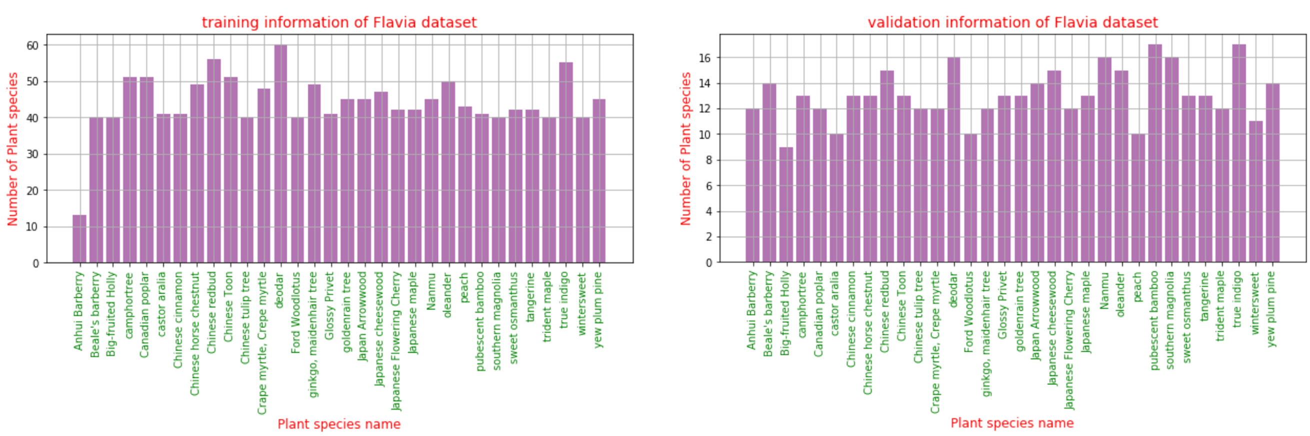
$$os = \frac{w - k + 2p}{s} + 1 \tag{2}$$

where w is size of i/p, k is size of the filter, p is the padding & s is the size of stride.



(a) PlantVillage dataset Training information **(b)** PlantVillage dataset validation information

Fig. 5 **a** PlantVillage dataset Training information. **b** PlantVillage dataset validation information



(a) Flavia dataset Training information **(b)** Flavia dataset validation information

Fig. 6 **a** Flavia dataset Training information. **b** Flavia dataset validation information

3.3.2 Output layers

A flatten layer forms the first layer of output layers. Every node in first layer has connection with flatten layer. A flatten layer which is included before the FC layers that converts the i/p matrix to vector. In this network we are added two FC layers, in this every node has connection with every in node in the earlier layer, and this FC layers are played the crucial role in last phase of the network. This structure allows the model to learn more and perform better. The first fully-connected layer is connected to the output layer via the second layer. In addition, a dropout layer is inserted which enhances the accuracy of the results of the model and it also help in preventing the problem of model over fitting. The model randomly deactivates neurons with a probability p in the dropout layer. Dropout value had been tuned (from 0 to 1) to reduce computing time for the next layers so that the training will be faster. Each convolutional operation is followed by an additional non-linear operation called ReLU (Rectified Linear Unit). The ReLU output function is defined using Eq. 3:

$$f(x) = \max(0, x) \tag{3}$$

where x is the no. of i/p to the NN. A softmax is a function which is used to calculate the probability for each possible output of the model. The softmax function is defined by Eq. 4:

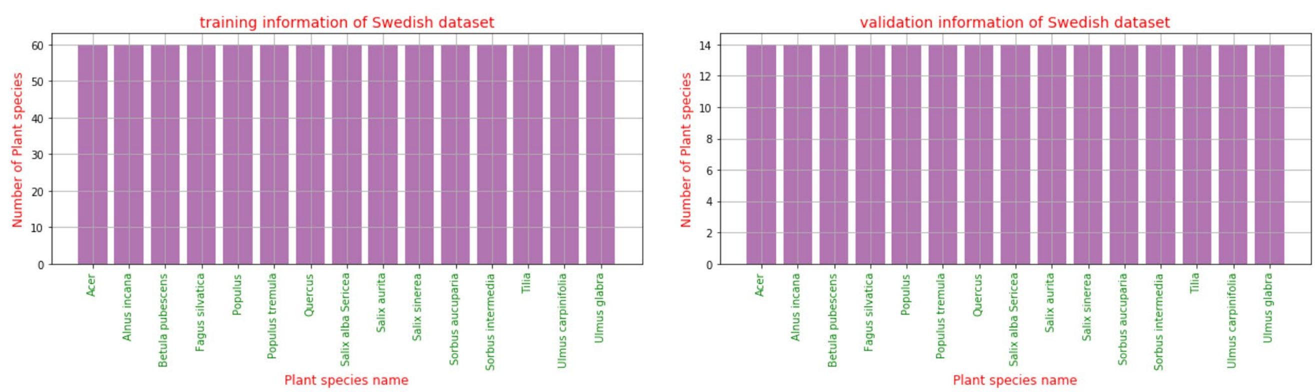
Fig. 8 **a** Accuracy values for Training and validation of 100 epochs for Leaf Snap Dataset. **b** Training and validation loss values of 100 epochs for Leaf Snap Dataset. **c** Accuracy values for Training and validation of 150 epochs for Leaf Snap Dataset. **d** Training and validation loss values of 150 epochs for Leaf Snap Dataset. **e** Accuracy values for Training and validation of 200 epochs for Leaf Snap Dataset. **f** Training and validation loss values of 200 epochs for Leaf Snap Dataset

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}} \tag{4}$$

where z is the input vector of K-dimensional, $\sigma(z)$ has range (0, 1) of real values. 9,820,136 parameters are there in the proposed CNN model, the actual description is given in Table 2.

3.4 Model evaluation

The key idea of proposed model is to predict the plant species using CNN model. The model is initially trained for each data set by applying cross/k-fold validation. By employing hyper-parameter optimization of cross/k-fold, best model is found. Accuracy is used as measure for performance evaluation of the model because the considered datasets are unbalanced.



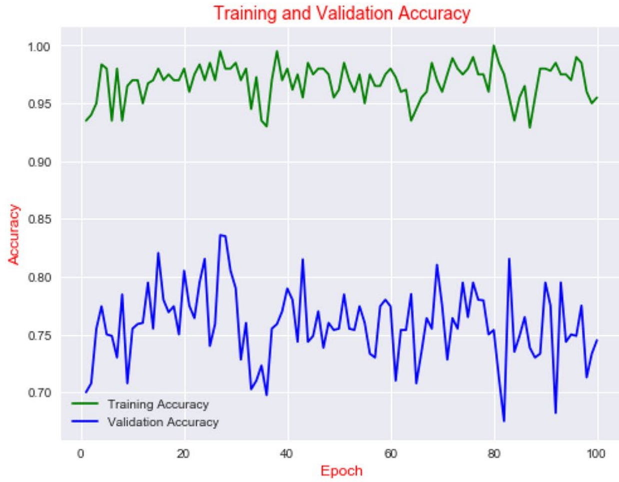
(a) Swedish dataset Training information

(b) Swedish dataset validation information

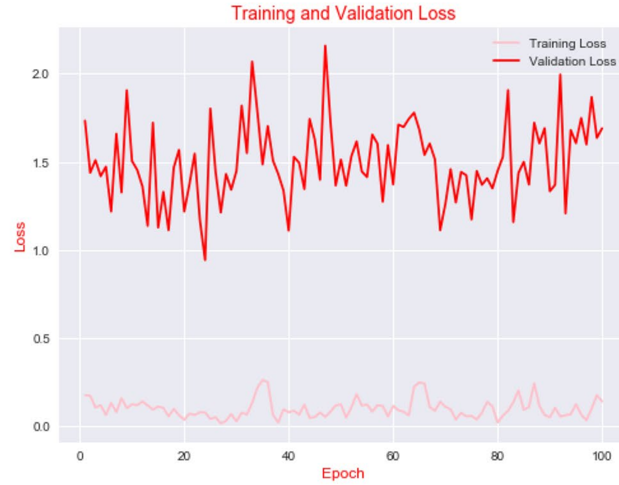
Fig. 7 **a** Swedish dataset Training information. **b** Swedish dataset validation information

Table 4 Train and validation datasets accuracy of CNN model for Leaf Snap, UCI Leaf, PlantVillage, Flavia and Swedish leaf plant species

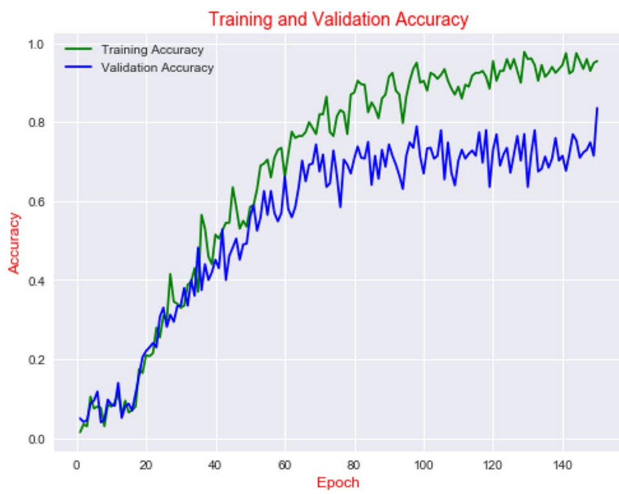
# Epochs	100		150		200	
Dataset name	Train	Valid	Train	Valid	Train	Valid
Leaf Snap	1.0	0.835	0.978	0.835	0.979	0.810
UCI Leaf	1.0	0.641	1.0	0.641	1.0	0.654
Plant Village	0.8	0.8	0.889	0.909	0.899	0.869
Flavia	1.0	0.795	1.0	0.774	1.0	0.784
Swedish leaf	1.0	0.942	1.0	0.947	1.0	0.968



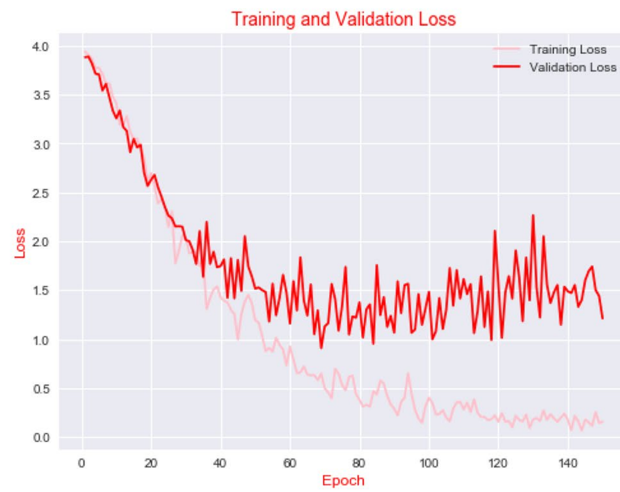
(a) Accuracy values for Training & validation of 100 epochs for Leaf Snap Dataset



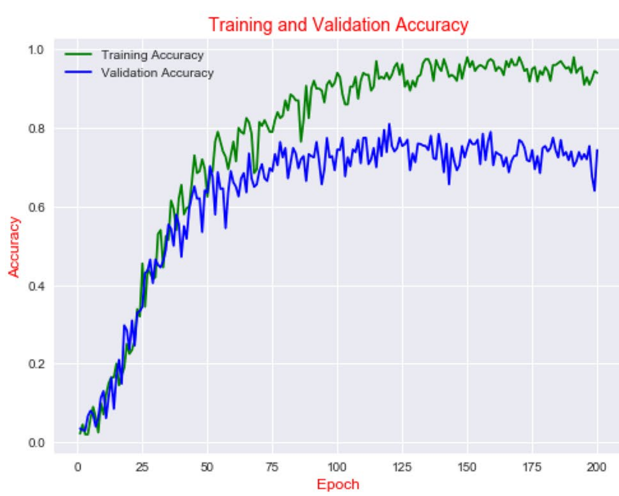
(b) Training & validation loss values of 100 epochs for Leaf Snap Dataset



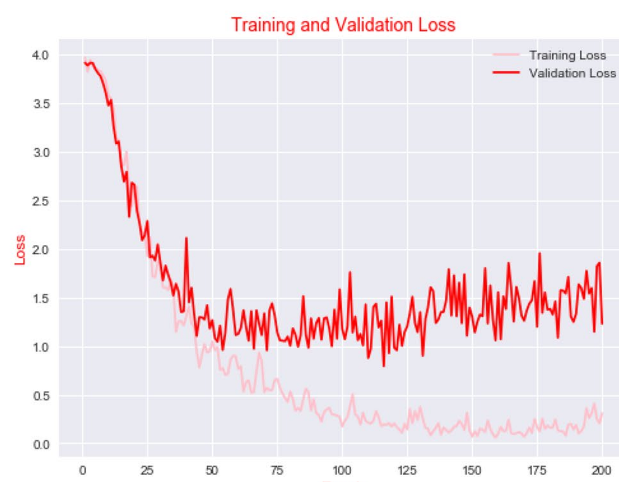
(c) Accuracy values for Training & validation of 150 epochs for Leaf Snap Dataset



(d) Training & validation loss values of 150 epochs for Leaf Snap Dataset

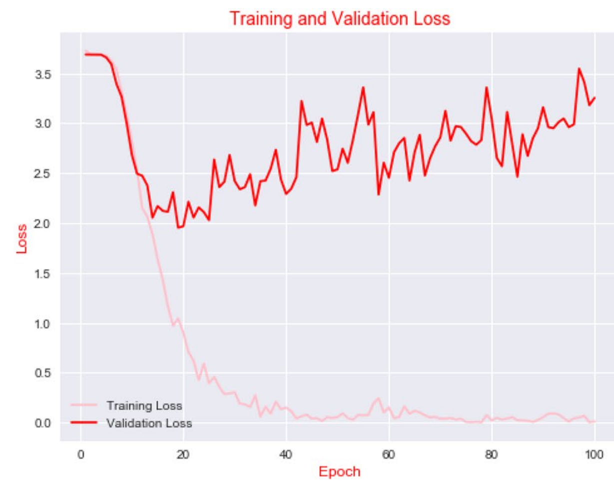


(e) Accuracy values for Training & validation of 200 epochs for Leaf Snap Dataset



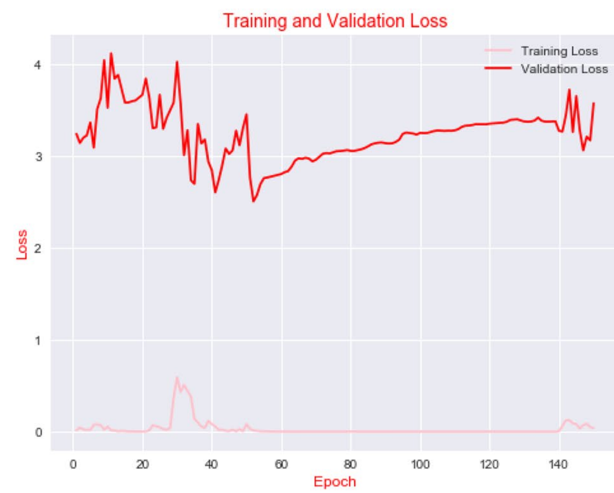
(f) Training & validation loss values of 200 epochs for Leaf Snap Dataset

(a) Accuracy values for Training & validation of 100 epochs for UCI leaf Dataset

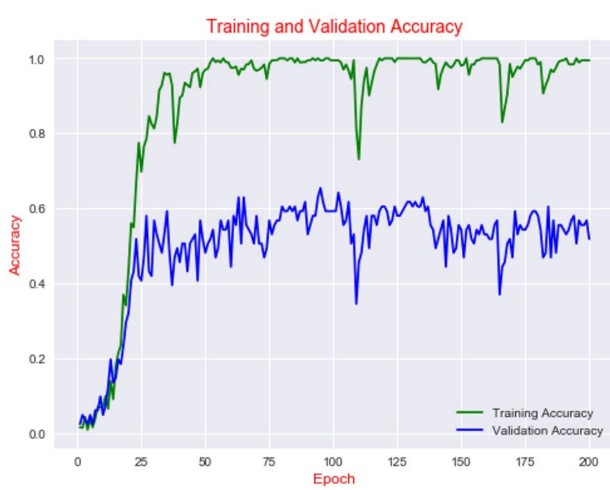


(b) Training & validation loss values of 100 epochs for UCI leaf Dataset

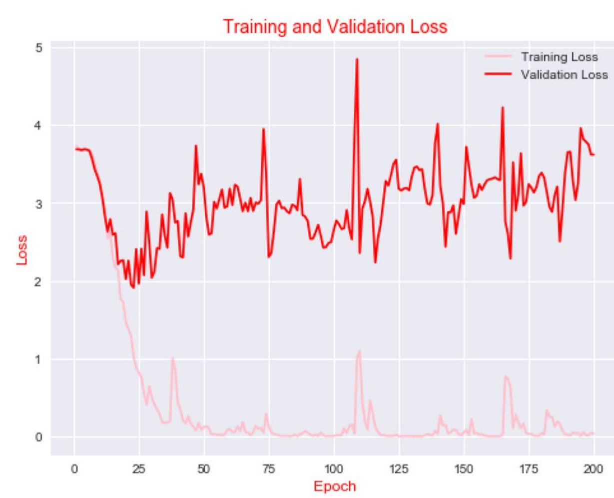
(c) Accuracy values for Training & validation of 150 epochs for UCI leaf Dataset



(d) Training & validation loss values of 150 epochs for UCI leaf Dataset



(e) Accuracy values for Training & validation of 200 epochs for UCI leaf Dataset



(f) Training & validation loss values of 200 epochs for UCI leaf Dataset

◂**Fig. 9** **a** Accuracy values for Training and validation of 100 epochs for UCI leaf Dataset. **b** Training and validation loss values of 100 epochs for UCI leaf Dataset. **c** Accuracy values for Training and validation of 150 epochs for UCI leaf Dataset. **d** Training and validation loss values of 150 epochs for UCI leaf Dataset. **e** Accuracy values for Training and validation of 200 epochs for UCI leaf Dataset. **f** Training and validation loss values of 200 epochs for UCI leaf Dataset

4 Dataset

In this paper, we used five publicly available plant datasets called Leaf Snap, UCI Leaf, Plant Village, Flavia and Swedish leaf. The properties of the datasets are presented in Table 3.

4.1 Leaf Snap

It is plant leaf dataset designed and developed by Kumar et al., (2012) from Columbia University. It has 52 plant species categories, 2130 images. This dataset is collected by mobile app from plants by discarding non leaf images, by segmentation of untextured background with multiple scales. The plant species of each 52 categories are depicted in graphical representation shown in Fig. 3a and b.

4.2 UCI leaf

This dataset is designed and created by Silva et al. (2013) from Universidade do Porto. It has 40 plant species categories, 443 images. This dataset is collected with shape, texture from digital images of 40 different plant species. The plant species of each 40 categories are depicted in graphical representation shown in Fig. 4a and b.

4.3 Plant village

This dataset is designed and created by Mohanty et al. (2016). It is having 38 plant species categories, 54,305 images. It is new hybrid dataset which consists of color, area and density. The plant species of each 38 categories are depicted in graphical representation shown in Fig. 5a and b.

4.4 Flavia

This dataset is designed and created by Wu et al. (2007). It is having 32 plant species categories, 1907 images. It is having leaf images of high constrained with white background. The plant species of each 32 categories are depicted in graphical representation shown in Fig. 6a and b.

4.5 Swedish leaf

It is designed and developed by Söderkvist (2001), Kumar et al. (2021), and Kumar and Rao (2017) from computer vision laboratory. It is having 15 plant species categories, 1125 images. These plant images are scanned with plain background. The plant species of each 15 categories are depicted in graphical representation shown in Fig. 7a and b.

5 Results and discussion

Our experimentation is based on a CNN structure, running on i7 processor, 16 GB RAM. In this paper, we had considered five datasets for evaluating our model. Every dataset is split into two parts in percentage of 80 and 20 criteria for training & validation respectively.

Leaf snap dataset consists of 2130 images which includes 52 plant categories (shown in Table 10). We split these images into two parts: 1704 for training and 426 for validation.

UCI Leaf dataset consists of 442 images which includes 40 plant categories (shown in Table 8). We split these images into two parts: 354 for training and 88 for validation.

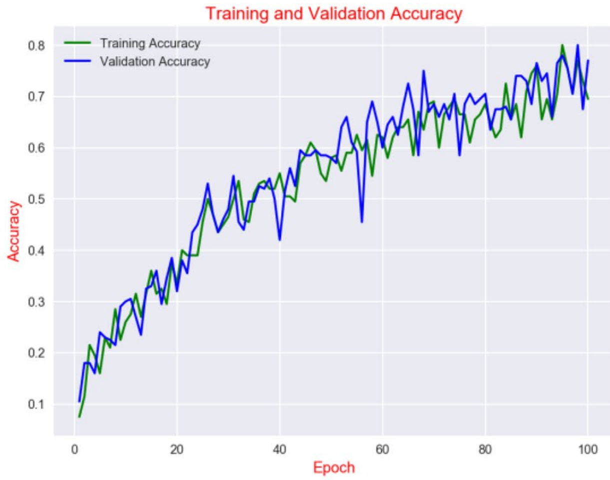
PlantVillage dataset consists of 54,305 images which includes 38 plant categories (shown in Table 9). We split these images into two parts: 43,445 for training and 10,860 for validation.

Flavia dataset consists of 1907 images which includes 32 plant categories (shown in Table 6). We split these images into two parts: 1526 for training and 381 for validation.

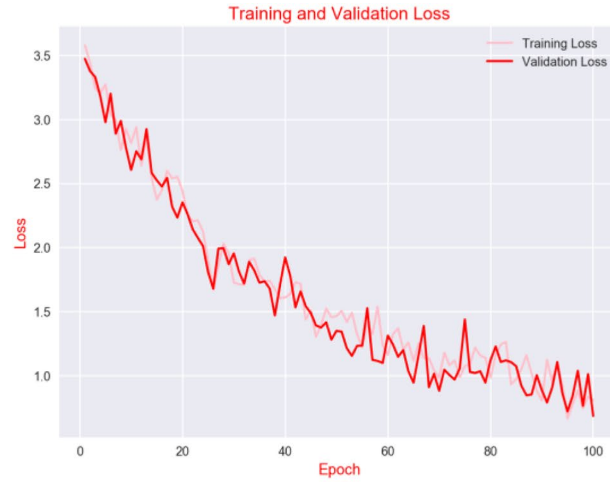
Swedish dataset consists of 1125 images which includes 15 plant categories (shown in Table 7). We split these images into two parts: 900 for training and 225 for validation.

For comparison of results, three testing strategies are deployed. They are, 100 epochs, 150 epochs and 200 epochs.

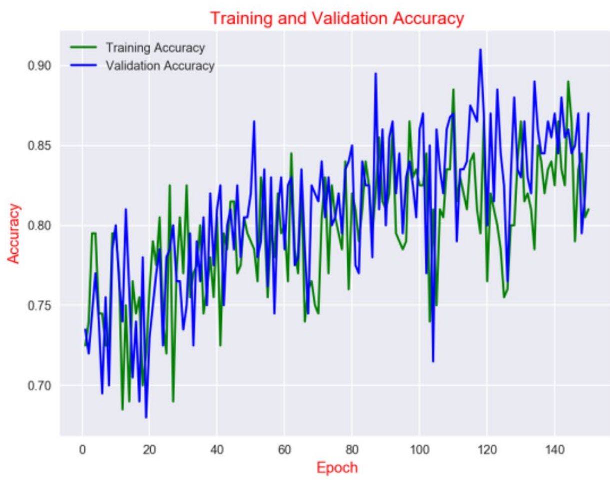
We compared the accuracy influenced by the depth and epochs of the CNN models. Using the training and validation datasets, the results are tabulated in Table 4. The experimental results indicate that the depth & epochs of the structure can affect the accuracy of the model. The performance drops as the number of epochs reduces. The reason is that by decreasing the number of epochs in training, the ability of the model to represent the complex dependencies between data tends to reduce. While we increase the number of epochs in validation, accuracy also increases in the three strategies. Following plots shows training and validation accuracy and loss for 100,150 and 200 epochs respectively



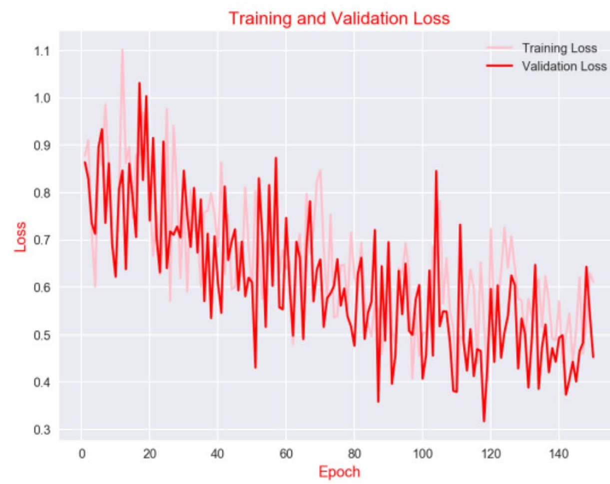
(a) Accuracy values for Training & validation of 100 epochs for PlantVillage Dataset



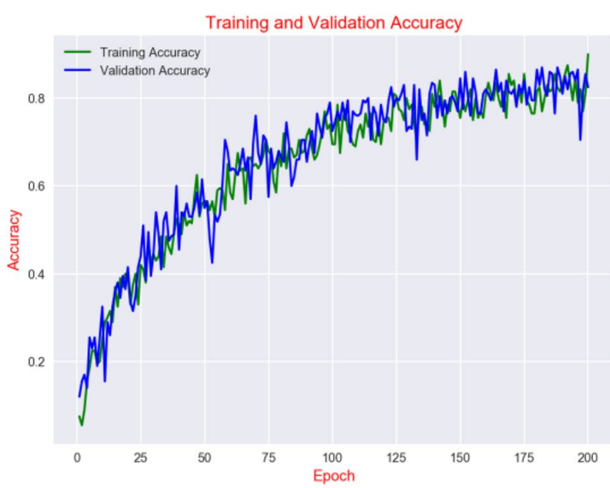
(b) Training & validation loss values of 100 epochs for PlantVillage Dataset



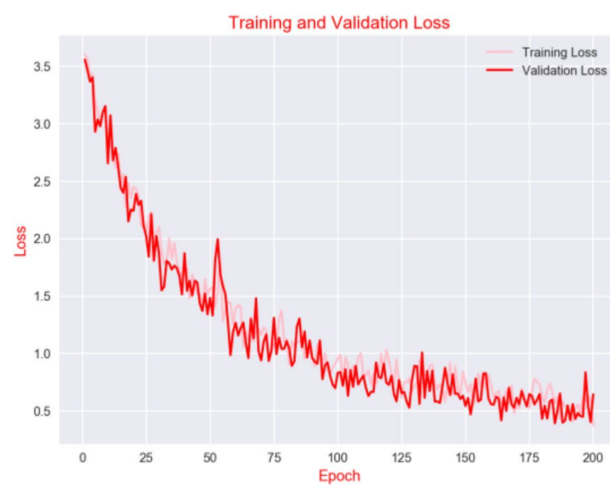
(c) Accuracy values for Training & validation of 150 epochs for PlantVillage Dataset



(d) Training & validation loss values of 150 epochs for PlantVillage Dataset



(e) Accuracy values for Training & validation of 200 epochs for PlantVillage Dataset



(f) Training & validation loss values of 200 epochs for PlantVillage Dataset

Fig. 10 **a** Accuracy values for Training and validation of 100 epochs for PlantVillage Dataset. **b** Training and validation loss values of 100 epochs for PlantVillage Dataset. **c** Accuracy values for Training and validation of 150 epochs for PlantVillage Dataset. **d** Training and validation loss values of 150 epochs for PlantVillage Dataset. **e** Accuracy values for Training and validation of 200 epochs for PlantVillage Dataset. **f** Training and validation loss values of 200 epochs for PlantVillage Dataset

for each of the five data sets mentioned above. In general, if number of epochs increases, accuracy increases and loss decreases. It can be obsererved from the plots corresponding to each data set.

Figure 8a–f shows the Leaf snap Dataset Accuracy values for Training and validation, Training and validation loss values for 100, 150 and 200 epochs repsectively. From Fig. 8a, c, and e, it is clearly observed that, the number of epochs increases from 100 to 150, 150 to 200, accuracy also increases for both training and validation datasets. From Fig. 8b, d, and f, it is also observed that the number of epochs increases from 100 to 150, 150 to 200, the loss will drops for both training and validation datasets.

Figure 9a–f has shown the UCI Leaf Dataset Accuracy values for Training & validation, Training and validation loss values for 100, 150 and 200 epochs repsectively. From Fig. 9a, c, and e, it is clearly observed that, the number of epochs increases from 100 to 150, 150 to 200, accuracy also increases for both training and validation datasets. From Figure 9b, d, and f, it is also observed that the number of epochs increases from 100 to 150, 150 to 200, the loss will drops for both training and validation datasets.

Figure 10a–f has shown the PlantVillage Dataset Accuracy values for Training and validation, Training and validation loss values for 100, 150 and 200 epochs respectively. From Fig. 10a, c, and e, it is clearly observed that, the number of epochs increases from 100 to 150, 150 to 200, accuracy also increases for both training and validation datasets. From Fig. 10b, d, and f, it is also observed that the number of epochs increases from 100 to 150, 150 to 200, the loss will drops for both training and validation datasets.

Figure 11a–f has shown the Flavia Dataset Accuracy values for Training and validation, Training and validation loss values for 100, 150 and 200 epochs respectively. From Fig. 11a, c, and e, it is clearly observed that, the number of epochs increases from 100 to 150, 150 to 200, accuracy also increases for both training and validation datasets. From Fig. 11b, d, and f, it is also observed that the number of epochs increases from 100 to 150, 150 to 200, the loss will drops for both training and validation datasets.

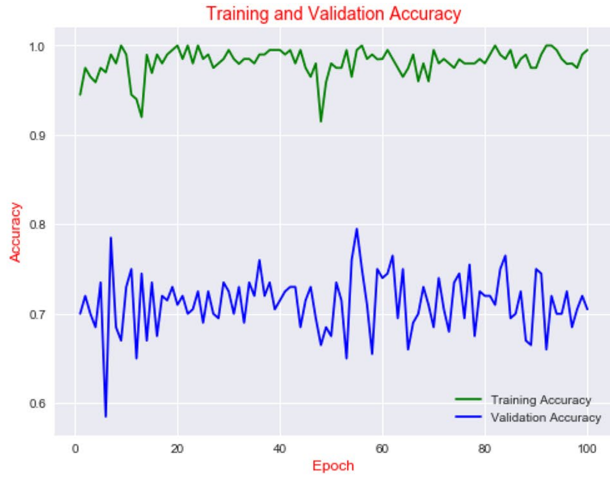
Figure 12a–f has shown the Swedish Dataset Accuracy values for Training and validation, Training and validation loss values for 100, 150 and 200 epochs respectively. From Fig. 12a, c, and e, it is clearly observed that, the number of epochs increases from 100 to 150, 150 to 200, accuracy also increases for both training and validation datasets. From Fig. 12b, d, and f, it is also observed that the number of epochs increases from 100 to 150, 150 to 200, the loss will drops for both training and validation datasets.

The Table 5 represents the different mechanisms accuracy for Flavia, Swedish leaf, UCI Leaf, Plant Village, Leaf Snap datasets. The accuracy measures of these datasets are depicted in Fig. 13. From the Fig. 13, it is observed that proposed model expresses good accuracy for all above mentioned datasets. It is also observed that experiment results have shown that the depth of the structure and number of epochs can considerably affect the accuracy. Performance like accuracy, precision, recall will drops sharply if we reduce the number of layers in the proposed model. The reason for this is that the small layers model structure has limited capability to signify the complex enslavement between data that deeply disintegrate the ability of the model.

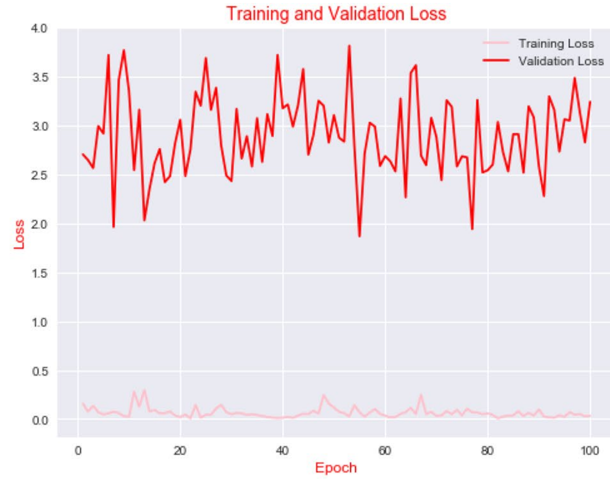
Table 6 has shown the accuracy of different existing models and proposed method. According to Table 6, the accuracy of proposed method has shown the good accuracy measures compared to the state-of-the-art models. While compared to other methods, the proposed method is capable of extract the features called Morphological Shape Features(Smooth factor, Form factor, Narrow factor, Perimeter ratio of diameter, Vein features) and Texture Features of raw data automatically. Therefore, it can discover the most essential difference or correlation in them.

Table 6 represents the precision, recall measures of existing and proposed methods. These values are depicted in Fig. 14. From the Fig. 14a it is observed that proposed method has shown the good precision values for all most all the datasets. From the Fig. 14b it is also observed that recall is also shown good values for all datasets when compared to state of art methods.

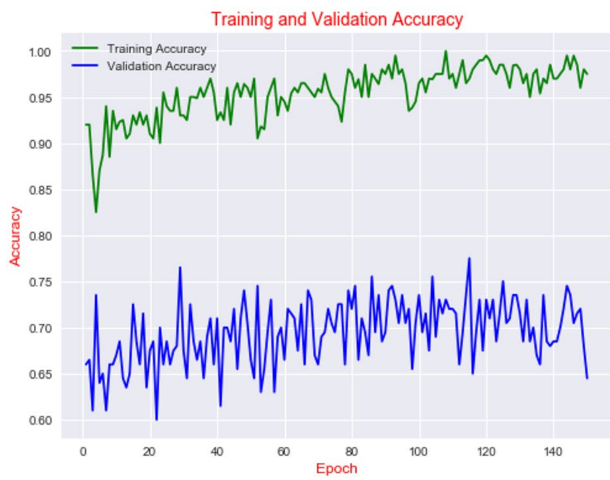
For testing the model, we considered single image from each plant species.



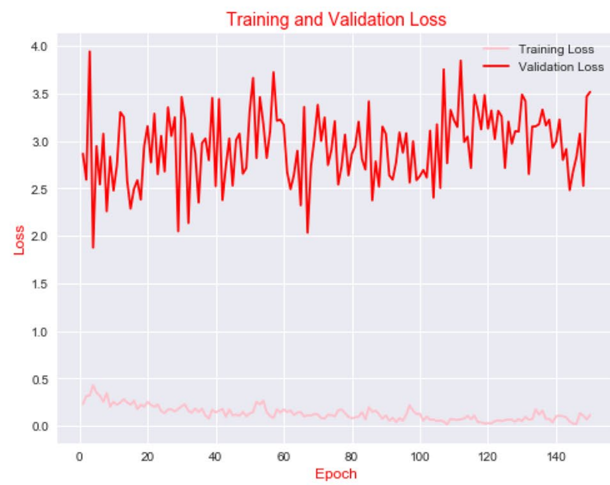
(a) Accuracy values for Training & validation of 100 epochs for Flavia Dataset



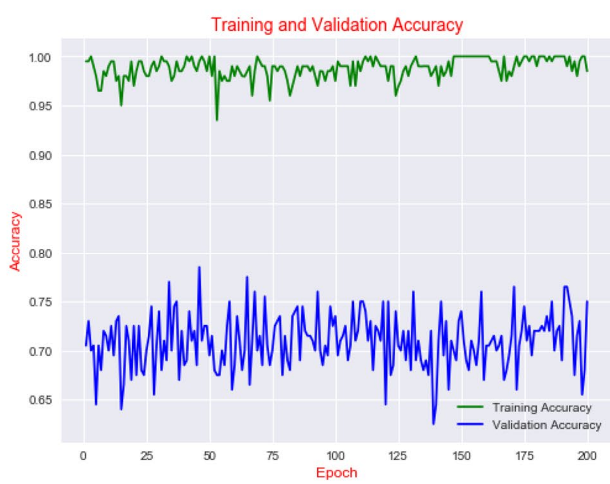
(b) Training & validation loss values of 100 epochs for Flavia Dataset



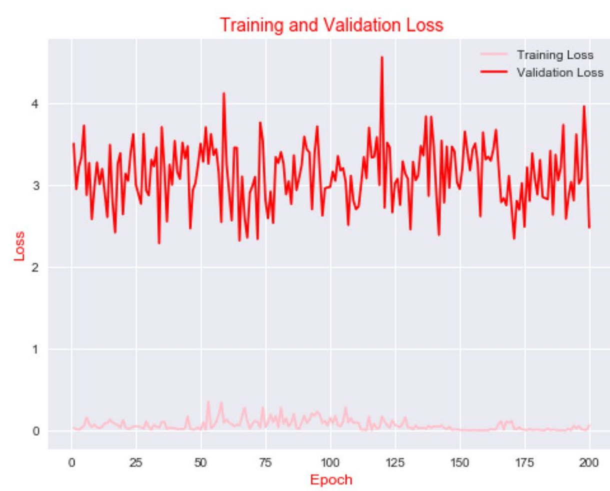
(c) Accuracy values for Training & validation of 150 epochs for Flavia Dataset



(d) Training & validation loss values of 150 epochs for Flavia Dataset



(e) Accuracy values for Training & validation of 200 epochs for Flavia Dataset



(f) Training & validation loss values of 200 epochs for Flavia Dataset

◂**Fig. 11** **a** Accuracy values for Training and validation of 100 epochs for Flavia Dataset. **b** Training and validation loss values of 100 epochs for Flavia Dataset. **c** Accuracy values for Training and validation of 150 epochs for Flavia Dataset. **d** Training and validation loss values of 150 epochs for Flavia Dataset. **e** Accuracy values for Training and validation of 200 epochs for Flavia Dataset. **f** Training and validation loss values of 200 epochs for Flavia Dataset

Leaf snap dataset had 52 categories, so we had considered 52 plant leaf images for testing dataset. These 52 testing leaf images are given as input to our CNN model and actual and predicted classes of Leaf snap dataset are shown in Table 7 and are depicted in Fig. 15a–c for 100, 150 and 200 epochs respectively**.**

From the Table 7 and Fig. 15a–c, it is observed that 18 plant species are wrongly predicted for 100 epochs, 16 species are wrongly predicted for 150 epochs, 15 species are wrongly predicted for 200 epochs.

UCI Leaf dataset had 40 categories; hence we had considered 40 plant leaf images for testing dataset. These 40 testing leaf images are given as input to our CNN model and actual and predicted classes of Flavia dataset are shown in Table 8 and are depicted in Fig. 16a–c for 100, 150 and 200 epochs respectively**.**

From the Table 8 and Fig. 16a–c, it is observed that 18 plant species are wrongly predicted for 100 epochs, 13 species are wrongly predicted for 150 epochs, 16 species are wrongly predicted for 200 epochs.

PlantVillage dataset had 38 categories; hence we had considered 38 plant leaf images for testing dataset. These 38 testing leaf images are given as input to our CNN model and actual and predicted classes of Flavia dataset are shown in Table 9 and are depicted in Fig. 17a–c for 100, 150 and 200 epochs respectively.

From the Table 9 and Fig. 17a–c, it is observed that 12 plant species are wrongly predicted for 100 epochs, 10 species are wrongly predicted for 150 epochs, 8 species are wrongly predicted for 200 epochs.

Flavia dataset had 32 categories; hence we had considered 32 plant leaf images for testing dataset. These 38 testing leaf images are given as input to our CNN model and actual and predicted classes of Flavia dataset are shown in Table 10 and are depicted in Fig. 18a–c for 100, 150 and 200 epochs respectively**.**

From the Table 10 and Fig. 18a–c, it is observed that 13 plant species are wrongly predicted for 100 epochs, 10 species are wrongly predicted for 150 epochs, 17 species are wrongly predicted for 200 epochs.

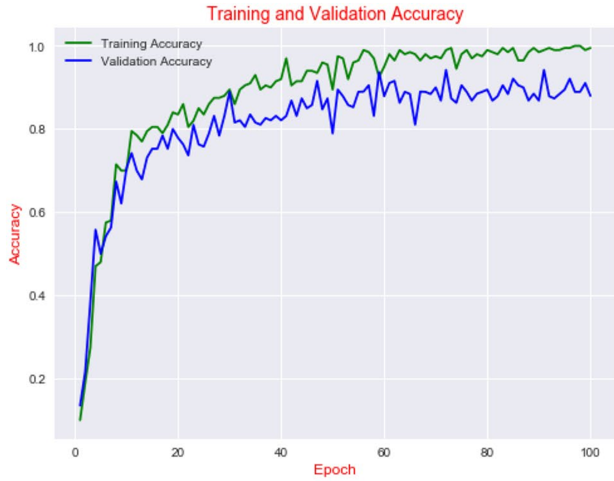
Swedish dataset had 15 categories; hence we had considered 38 plant leaf images for testing dataset. These 38 testing leaf images are given as input to our CNN model and actual and predicted classes of Flavia dataset are shown in Table 11 and are depicted in Fig. 19a–c for 100, 150 and 200 epochs respectively**.**

From the Table 8 and Fig. 19a–c, it is observed that one plant species is wrongly predicted for 100 and 150 epochs, two species for 200 epochs.

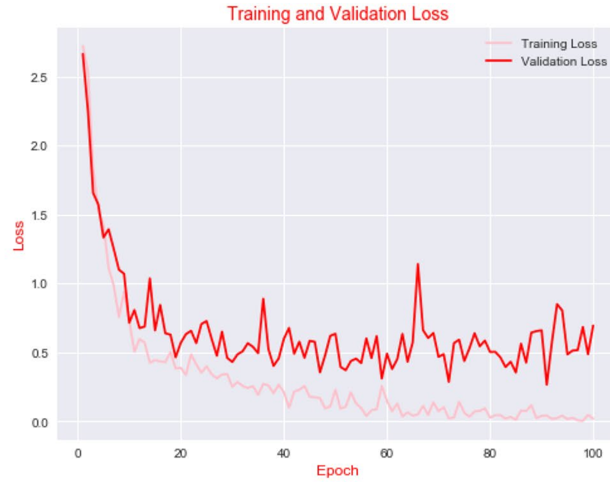
Root Mean Square Error (RMSE) is also one of the important measures for measuring the models performance in addition to accuracy, precision and recall. It is calculated by Eq. 5.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(actual - predicted)}{N}} \tag{5}$$

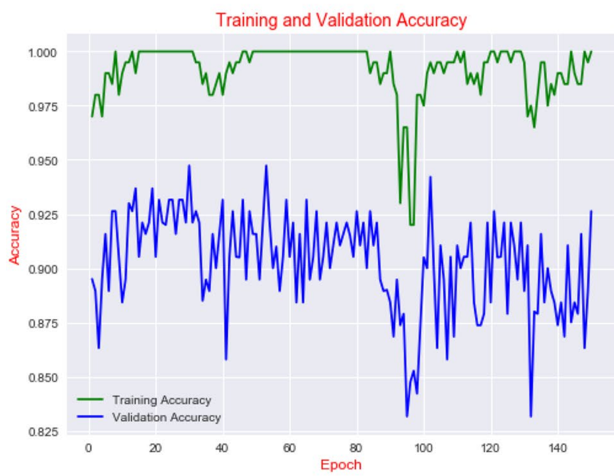
The actual and predicted values not matched cases are predicted in Table 12. The RMSE values for five datasets related to 100, 150 and 200 epochs are presented in Table 13. From the Table 13, it is clearly observed that RMSE values are very less for all most all the cases of all the datasets, so according to RMSE rule our model is well fitted for all Leaf Snap, UCI Leaf, Plant Village, Flavia, and Swedish leaf datasets.



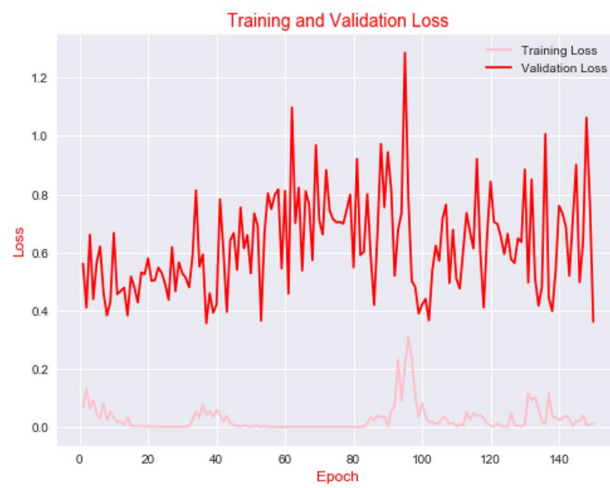
(a) Accuracy values for Training & validation of 100 epochs for Swedish leaf Dataset



(b) Training & validation loss values of 100 epochs for Swedish leaf Dataset

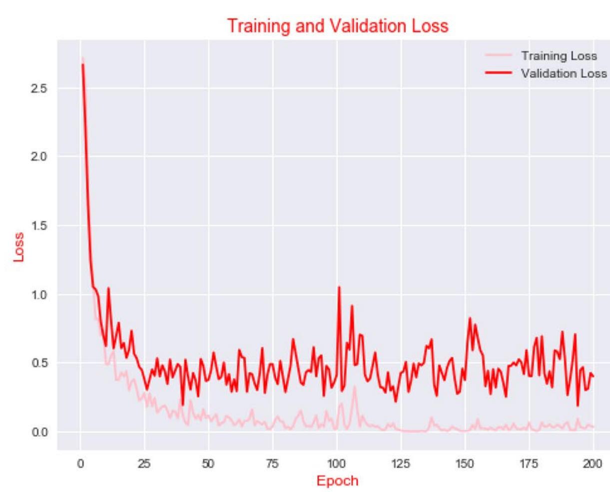


(c) Accuracy values for Training & validation of 150 epochs for Swedish leaf Dataset



(d) Training & validation loss values of 150 epochs for Swedish leaf Dataset

(e) Accuracy values for Training & validation of 200 epochs for Swedish leaf Dataset



(f) Training & validation loss values of 200 epochs for Swedish leaf Dataset

◂**Fig. 12** **a** Accuracy values for Training and validation of 100 epochs for Swedish leaf Dataset. **b** Training and validation loss values of 100 epochs for Swedish leaf Dataset. **c** Accuracy values for Training and validation of 150 epochs for Swedish leaf Dataset. **d** Training and validation loss values of 150 epochs for Swedish leaf Dataset. **e** Accuracy values for Training and validation of 200 epochs for Swedish leaf Dataset. **f** Training and validation loss values of 200 epochs for Swedish leaf Dataset

Table 5 Comparison of accuracy of proposed method with existing methods

Dataset name	Two-way attention model in Zhu et al. (2019)	LBP in Turkoglu and Hanbay (2019)	NN in Manasa et al. (2019)	MSF-CNN in Hu et al. (2018)	NN in Jeon and Rhee (2017)	NN in Zhang et al. (2015)	Proposed
Flavia	0.85	0.825	0.79	0.87	0.89	0.895	1.0
Swedish leaf	0.82	0.81	0.8	0.88	0.895	0.887	1.0
UCI Leaf	0.83	0.815	0.81	0.875	0.885	0.875	1.0
Plant Village	0.81	0.8	0.78	0.86	0.87	0.865	0.8999999
Leaf Snap	0.845	0.835	0.81	0.868	0.899	0.89	0.97999

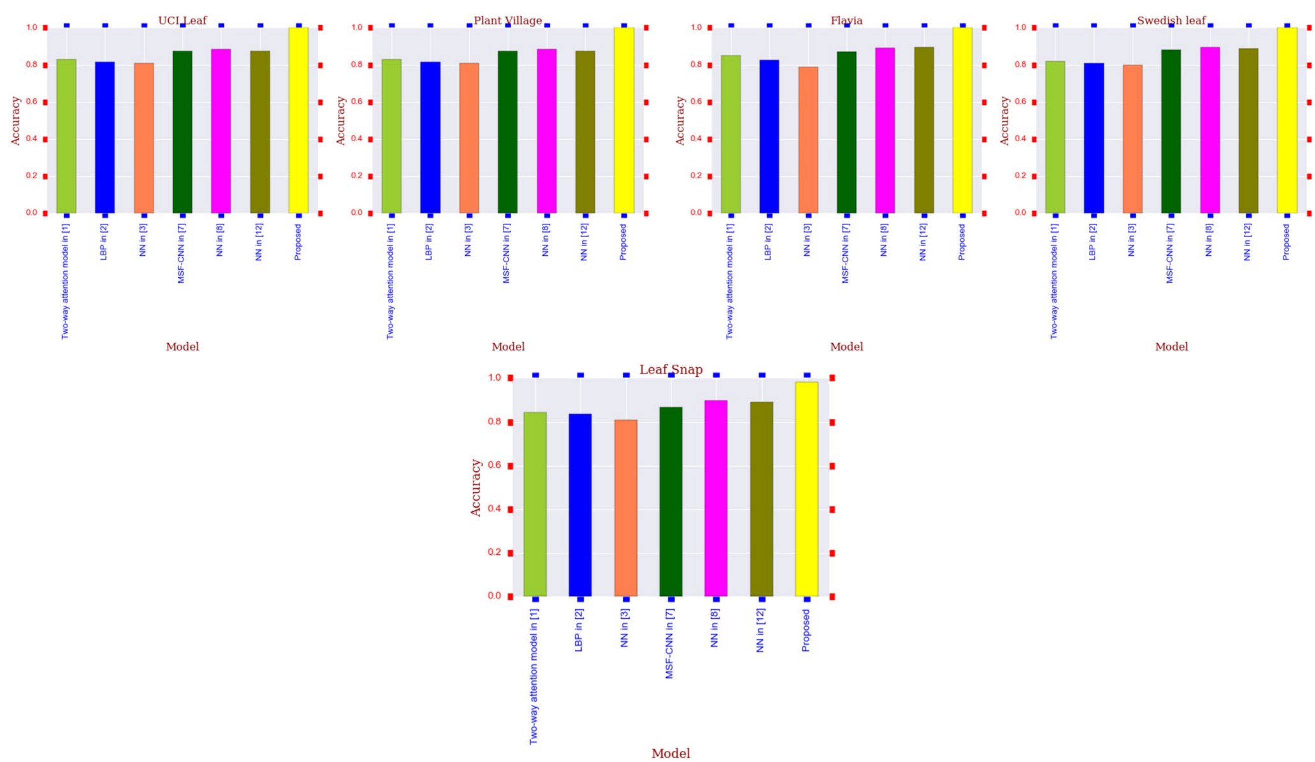


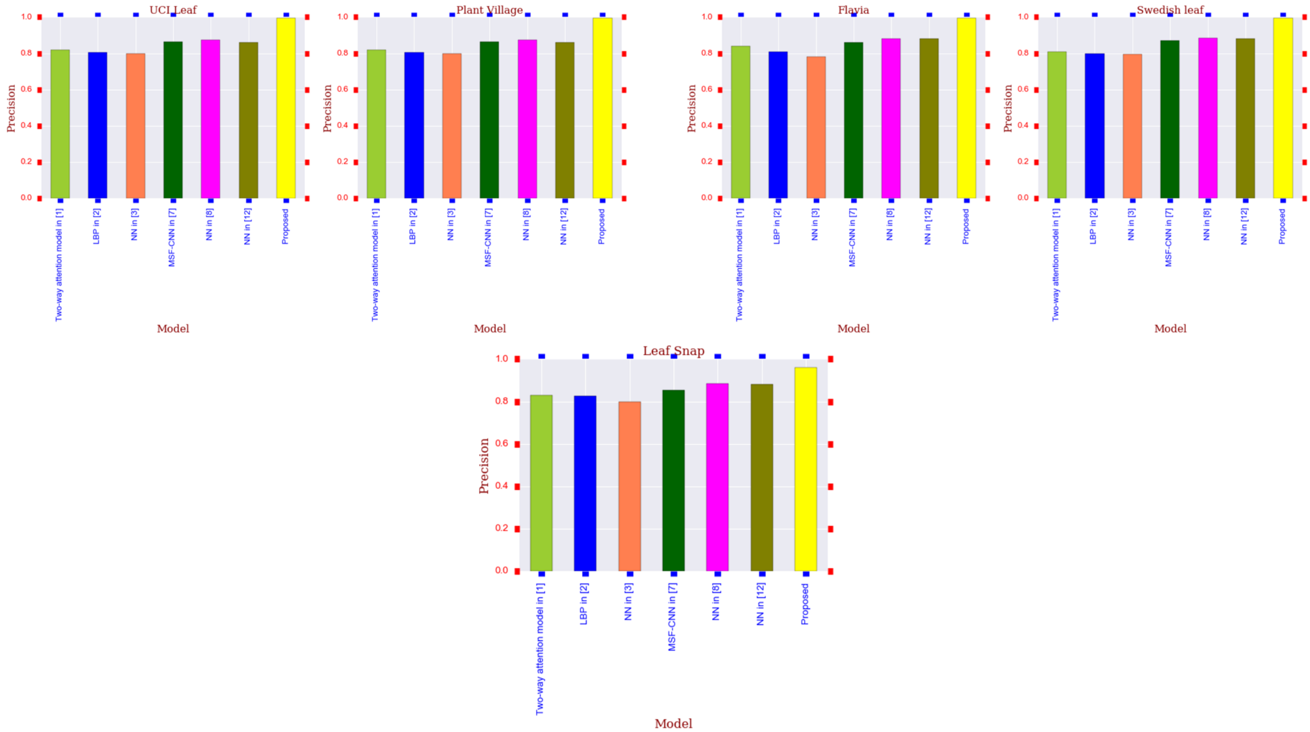
Fig. 13 Accuracy of existing and proposed models

Table 6 Precision and Recall comparison of proposed method with existing methods

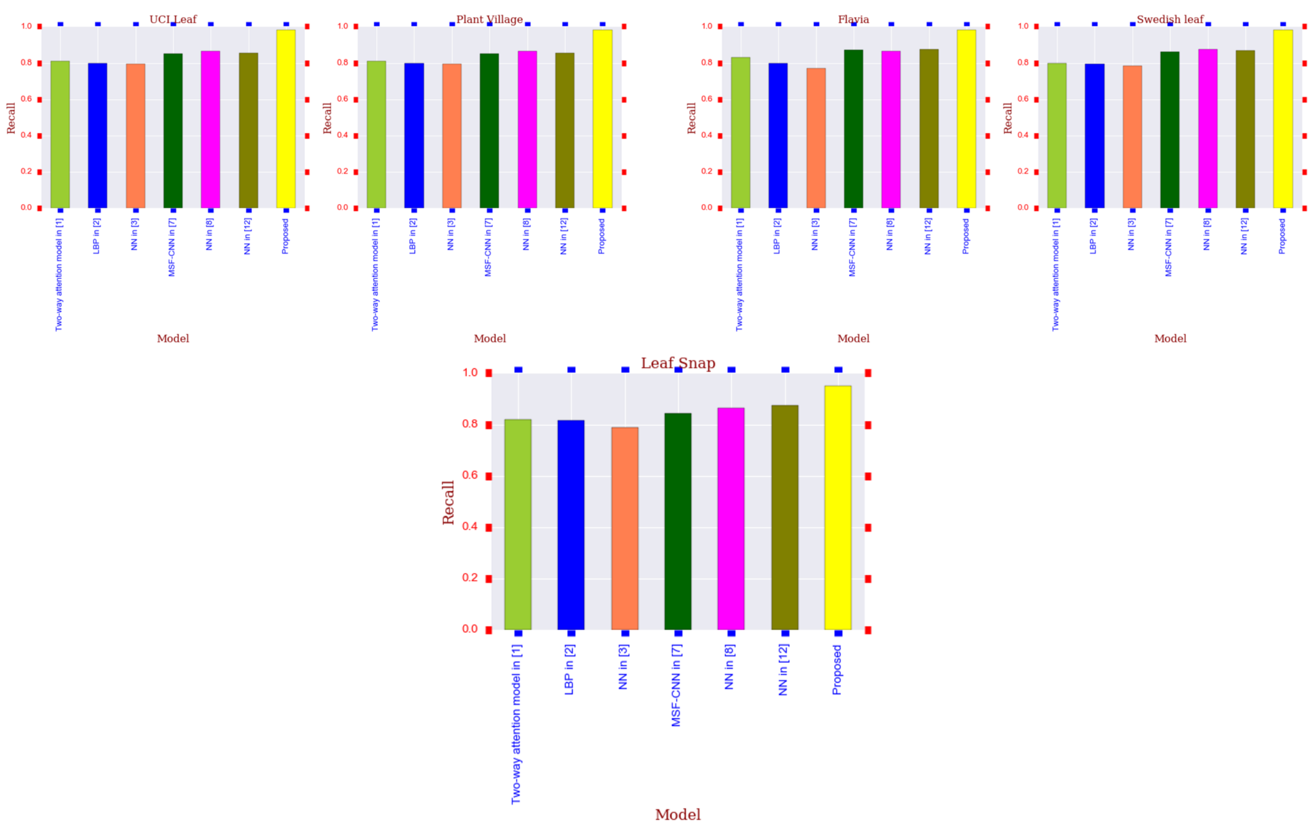
Dataset name	Two-way attention model in Zhu et al. (2019)		LBP in Turkoglu and Hanbay (2019)		NN in Manasa et al. (2019)		MSF-CNN in Hu et al. (2018)		NN in Jeon and Rhee (2017)		NN in Zhang et al. (2015)		Proposed	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Flavia	0.84	0.83	0.81	0.8	0.78	0.77	0.86	0.87	0.88	0.865	0.88	0.875	0.995	0.98
Swedish leaf	0.81	0.8	0.8	0.795	0.795	0.785	0.87	0.86	0.885	0.875	0.88	0.868	0.995	0.98
UCI Leaf	0.82	0.81	0.805	0.8	0.8	0.795	0.864	0.85	0.875	0.865	0.86	0.855	0.995	0.98
Plant Village	0.8	0.79	0.79	0.784	0.77	0.76	0.853	0.84	0.86	0.855	0.85	0.845	0.885	0.87
Leaf Snap	0.83	0.82	0.825	0.815	0.8	0.79	0.854	0.845	0.885	0.865	0.88	0.875	0.96	0.95

6 Conclusions

In this paper we proposed a model for identification of plants using DCNN. In the proposed model, we used a new training strategy, that learn complete layers point to point from plant images data. For testing the CNN model, we considered five plant species leaf image datasets called Leaf snap, UCI leaf, PlantVillage, Flavia and Swedish. We concluded that our CNN model provides better representation of features than the hand crafted features. We have also justified that our model has shown the good performance for identification of plants using proposed number of layers by ReLU in the network for all considered plant species datasets. From the Table 5 and 6, we also concluded that proposed system has shown better values for accuracy, recall and precision while compared with state of art models. We are evaluating hybrid CNN architecture in future by adopting other learning mechanisms like hashing and Zero-Shot.



(a) Precision values of existing and proposed models



(b) Recall values of existing and proposed models

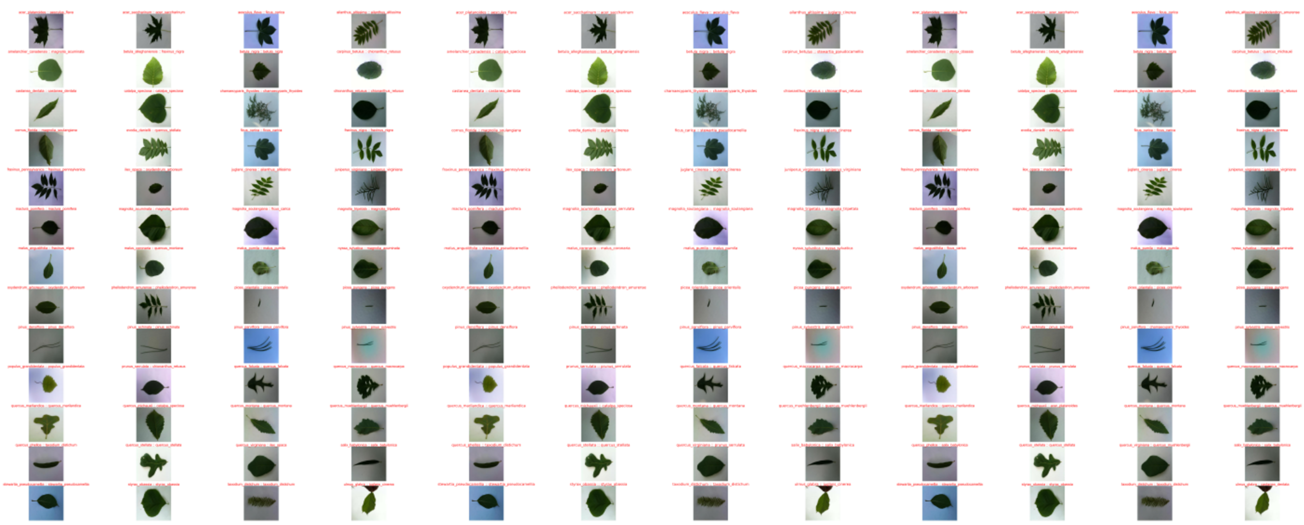
Fig. 14 **a** Precision values of existing and proposed models. **b** Recall values of existing and proposed models

Table 7 Plant species class prediction actual vs predicted for *Leaf snap Dataset*

Actual	Predicted		
	# 100 of Epochs	# 150 of Epochs	# 200 of Epochs
acer_platanoides	aesculus_flava	aesculus_flava	aesculus_flava
acer_saccharinum	acer_saccharinum	acer_saccharinum	acer_saccharinum
aesculus_flava	ficus_carica	aesculus_flava	ficus_carica
ailanthus_altissima	ailanthus_altissima	juglans_cinerea	phellodendron_amurense
amelanchier_canadensis	magnolia_acuminata	catalpa_speciosa	styrax_obassia
betula_alleghaniensis	fraxinus_nigra	betula_alleghaniensis	betula_alleghaniensis
betula_nigra	betula_nigra	betula_nigra	betula_nigra
carpinus_betulus	chionanthus_retusus	stewartia_pseudocamellia	quercus_michauxii
castanea_dentata	castanea_dentata	castanea_dentata	castanea_dentata
catalpa_speciosa	catalpa_speciosa	catalpa_speciosa	catalpa_speciosa
chamaecyparis_thyoides	chamaecyparis_thyoides	chamaecyparis_thyoides	chamaecyparis_thyoides
chionanthus_retusus	chionanthus_retusus	chionanthus_retusus	chionanthus_retusus
cornus_florida	magnolia_soulangiana	magnolia_soulangiana	magnolia_soulangiana
evodia_daniellii	quercus_stellata	juglans_cinerea	evodia_daniellii
ficus_carica	ficus_carica	stewartia_pseudocamellia	ficus_carica
fraxinus_nigra	fraxinus_nigra	juglans_cinerea	juglans_cinerea
fraxinus_pennsylvanica	fraxinus_pennsylvanica	fraxinus_pennsylvanica	fraxinus_pennsylvanica
ilex_opaca	oxydendrum_arboreum	oxydendrum_arboreum	maclura_pomifera
juglans_cinerea	ailanthus_altissima	ailanthus_altissima	juglans_cinerea
juniperus_virginiana	juniperus_virginiana	juniperus_virginiana	juniperus_virginiana
maclura_pomifera	maclura_pomifera	maclura_pomifera	maclura_pomifera
magnolia_acuminata	magnolia_acuminata	prunus_serrulata	magnolia_acuminata
magnolia_soulangiana	ficus_carica	magnolia_soulangiana	magnolia_soulangiana
magnolia_tripetala	magnolia_tripetala	magnolia_tripetala	magnolia_tripetala
malus_angustifolia	fraxinus_nigra	stewartia_pseudocamellia	ficus_carica
malus_coronaria	quercus_montana	malus_coronaria	quercus_montana
malus_pumila	malus_pumila	malus_pumila	malus_pumila
nyssa_sylvatica	magnolia_acuminata	nyssa_sylvatica	magnolia_acuminata
oxydendrum_arboreum	oxydendrum_arboreum	oxydendrum_arboreum	oxydendrum_arboreum
phellodendron_amurense	phellodendron_amurense	phellodendron_amurense	phellodendron_amurense
picea_orientalis	picea_orientalis	picea_orientalis	picea_orientalis
picea_pungens	picea_pungens	picea_pungens	picea_pungens
pinus_densiflora	pinus_densiflora	pinus_densiflora	pinus_densiflora
pinus_echinata	pinus_echinata	pinus_echinata	pinus_echinata
pinus_parviflora	pinus_parviflora	pinus_parviflora	chamaecyparis_thyoides
pinus_sylvestris	pinus_sylvestris	pinus_sylvestris	pinus_sylvestris
populus_grandidentata	populus_grandidentata	populus_grandidentata	populus_grandidentata
prunus_serrulata	chionanthus_retusus	prunus_serrulata	prunus_serrulata
quercus_falcata	quercus_falcata	quercus_falcata	quercus_falcata
quercus_macrocarpa	quercus_macrocarpa	quercus_macrocarpa	quercus_macrocarpa
quercus_marilandica	quercus_marilandica	quercus_marilandica	quercus_marilandica
quercus_michauxii	catalpa_speciosa	catalpa_speciosa	acer_platanoides
quercus_montana	quercus_montana	quercus_montana	quercus_montana
quercus_muehlenbergii	quercus_muehlenbergii	quercus_muehlenbergii	quercus_muehlenbergii
quercus_phellos	taxodium_distichum	taxodium_distichum	salix_babylonica
quercus_stellata	quercus_stellata	quercus_stellata	quercus_stellata
quercus_virginiana	ilex_opaca	prunus_serrulata	quercus_muehlenbergii
salix_babylonica	salix_babylonica	salix_babylonica	salix_babylonica

Table 7 (continued)

Actual	Predicted		
	# 100 of Epochs	# 150 of Epochs	# 200 of Epochs
stewartia_pseudocamellia	stewartia_pseudocamellia	stewartia_pseudocamellia	stewartia_pseudocamellia
styrax_obassia	styrax_obassia	styrax_obassia	styrax_obassia
taxodium_distichum	taxodium_distichum	taxodium_distichum	taxodium_distichum
ulmus_glabra	juglans_cinerea	juglans_cinerea	castanea_dentata



(a) Plant species class prediction Actual vs Predicted for **Leaf snap Dataset for 100 epochs**

(b) Plant species class prediction Actual vs Predicted for **Leaf snap Dataset for 150 epochs**

(c) Plant species class prediction Actual vs Predicted for **Leaf snap Dataset for 200 epochs**

Fig. 15 **a** Plant species class prediction Actual vs Predicted for *Leaf snap Dataset for 100 epochs. b* Plant species class prediction Actual vs Predicted for *Leaf snap Dataset for 150 epochs*. **c** Plant species class prediction Actual vs Predicted for *Leaf snap Dataset for 200 epochs*

(a) Plant species class prediction Actual vs Predicted for UCI **Leaf Dataset for 100 epochs**

(b) Plant species class prediction Actual vs Predicted for UCI **Leaf Dataset for 150 epochs**

(c) Plant species class prediction Actual vs Predicted for UCI **Leaf Dataset for 200 epochs**

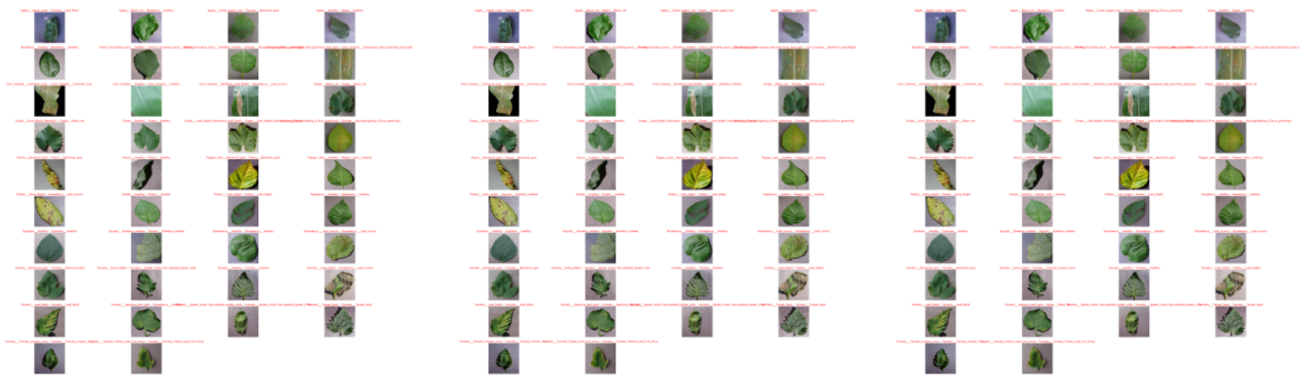
Fig. 16 **a** Plant species class prediction Actual vs Predicted for UCI *Leaf Dataset for 100 epochs*. **b** Plant species class prediction Actual vs Predicted for UCI *Leaf Dataset for 150 epochs*. **c** Plant species class prediction Actual vs Predicted for UCI *Leaf Dataset for 200 epochs*

Table 8 Plant species name actual and prediction for *UCI Leaf dataset*

Actual	Predicted		
	# 100 of Epochs	# 150 of Epochs	# 200 of Epochs
Acca sellowiana	Acca sellowiana	Acca sellowiana	Acca sellowiana
Acer negundo	Acer negundo	Crataegus monogyna	Acer negundo
Acer palmaturu	Acer palmaturu	Acer palmaturu	Acer palmaturu
Aesculus californica	Geranium sp	Geranium sp	Aesculus californica
Alnus sp	Alnus sp	Alnus sp	Alnus sp
Arisarum vulgare	Arisarum vulgare	Arisarum vulgare	Arisarum vulgare
Betula pubescens	Polypodium vulgare	Betula pubescens	Betula pubescens
Bougainvillea sp	Populus nigra	Populus nigra	Bougainvillea sp
Buxus sempervirens	Buxus sempervirens	Buxus sempervirens	Buxus sempervirens
Castanea sativa	Corylus avellana	Corylus avellana	Corylus avellana
Celtis sp	Celtis sp	Celtis sp	Celtis sp
Chelidonium majus	Chelidonium majus	Chelidonium majus	Chelidonium majus
Corylus avellana	Corylus avellana	Bougainvillea sp	Acer negundo
Crataegus monogyna	Fraxinus sp	Fraxinus sp	Quercus suber
Erodium sp	Buxus sempervirens	Buxus sempervirens	Buxus sempervirens
Euonymus japonicus	Acca sellowiana	Ilex perado ssp azorica	Ilex perado ssp azorica
Fragaria vesca	Populus nigra	Populus nigra	Populus nigra
Fraxinus sp	Fraxinus sp	Fraxinus sp	Fraxinus sp
Geranium sp	Geranium sp	Geranium sp	Fragaria vesca
Hydrangea sp	Hydrangea sp	Hydrangea sp	Hydrangea sp
Ilex aquifolium	Ilex aquifolium	Ilex aquifolium	Ilex aquifolium
Ilex perado ssp azorica	Populus nigra	Populus nigra	Buxus sempervirens
Magnolia grandiflora	Primula vulgaris	Primula vulgaris	Primula vulgaris
Magnolia soulangeana	Castanea sativa	Castanea sativa	Primula vulgaris
Nerium oleander	Nerium oleander	Nerium oleander	Nerium oleander
Papaver sp	Papaver sp	Papaver sp	Papaver sp
Pinus sp	Pinus sp	Pinus sp	Pinus sp
Podocarpus sp	Podocarpus sp	Pseudosasa japonica	Pseudosasa japonica
Polypodium vulgare	Polypodium vulgare	Polypodium vulgare	Polypodium vulgare
Populus alba	Polypodium vulgare	Podocarpus sp	Taxus bacatta
Populus nigra	Populus nigra	Populus nigra	Populus nigra
Primula vulgaris	Acca sellowiana	Celtis sp	Buxus sempervirens
Pseudosasa japonica	Pseudosasa japonica	Pseudosasa japonica	Pseudosasa japonica
Quercus robur	Alnus sp	Quercus robur	Quercus robur
Quercus suber	Fraxinus sp	Fraxinus sp	Quercus suber
Salix atrocinerea	Castanea sativa	Salix atrocinerea	Corylus avellana
Schinus terebinthifolius	Schinus terebinthifolius	Schinus terebinthifolius	Schinus terebinthifolius
Taxus bacatta	Ilex perado ssp azorica	Corylus avellana	Corylus avellana
Tilia tomentosa	Tilia tomentosa	Tilia tomentosa	Tilia tomentosa
Urtica dioica	Betula pubescens	Acer negundo	Bougainvillea sp

Table 9 Plant species name actual and prediction for *PlantVillage Dataset*

Actual	Predicted		
	# 100 of Epochs	# 150 of Epochs	# 200 of Epochs
Apple___Apple_scab	Tomato___Leaf_Mold	Tomato___Leaf_Mold	Apple___healthy
Apple___Black_rot	Blueberry___healthy	Apple___Black_rot	Blueberry___healthy
Apple___Cedar_apple_rust	Tomato___Bacterial_spot	Apple___Cedar_apple_rust	Blueberry___healthy
Apple___healthy	Apple___healthy	Apple___healthy	Apple___healthy
Blueberry___healthy	Blueberry___healthy	Tomato___Target_Spot	Blueberry___healthy
Cherry_(including_sour)___Powdery_mildew	Orange___Haunglongbing_(Citrus_greening)	Cherry_(including_sour)___Powdery_mildew	Cherry_(including_sour)___Powdery_mildew
Cherry_(including_sour)___healthy	Cherry_(including_sour)___healthy	Cherry_(including_sour)___healthy	Cherry_(including_sour)___healthy
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	orn_(maize)___Northern_Leaf_Blight	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Corn_(maize)___Common_rust_	Corn_(maize)___Common_rust_	Corn_(maize)___Common_rust_	Corn_(maize)___Common_rust_
Corn_(maize)___healthy	Corn_(maize)___healthy	Corn_(maize)___healthy	Corn_(maize)___healthy
Corn_(maize)___Northern_Leaf_Blight	Strawberry___Leaf_scorch	Squash___Powdery_mildew	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Grape___Black_rot	Grape_Black_rot	Tomato___Bacterial_spot	Grape___Black_rot
Grape___Esca_(Black_Measles)	Grape___Black_rot	Grape___Black_rot	Grape___Black_rot
Grape___healthy	Grape___healthy	Grape___healthy	Grape___healthy
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Orange___Haunglongbing_(Citrus_greening)	Orange___Haunglongbing_(Citrus_greening)	Orange___Haunglongbing_(Citrus_greening)	Orange___Haunglongbing_(Citrus_greening)
Peach___Bacterial_spot	Peach___Bacterial_spot	Peach___Bacterial_spot	Peach___Bacterial_spot
Peach___healthy	Peach___healthy	Peach___healthy	Peach___healthy
Pepper,_bell___Bacterial_spot	Peach___Bacterial_spot	Pepper,_bell___Bacterial_spot	Pepper,_bell___Bacterial_spot
Pepper,_bell___healthy	Pepper,_bell___healthy	Pepper,_bell___healthy	Pepper,_bell___healthy
Potato___Early_blight	Strawberry___Leaf_scorch	Squash___Powdery_mildew	Potato___Early_blight
Potato___Late_blight	Potato___Late_blight	Potato___Late_blight	Potato___Late_blight
Potato___healthy	Potato___healthy	Potato___healthy	Potato___healthy
Raspberry___healthy	Raspberry___healthy	Pepper,_bell___healthy	Raspberry___healthy
Soybean___healthy	Soybean___healthy	Soybean___healthy	Soybean___healthy
Squash___Powdery_mildew	Squash___Powdery_mildew	Squash___Powdery_mildew	Squash___Powdery_mildew
Strawberry___Leaf_scorch	Strawberry___Leaf_scorch	Strawberry___Leaf_scorch	Strawberry___Leaf_scorch
Strawberry___healthy	Strawberry___healthy	Strawberry___healthy	Strawberry___healthy
Tomato___Bacterial_spot	Tomato___Bacterial_spot	Tomato___Bacterial_spot	Tomato___Bacterial_spot
Tomato___Early_blight	Tomato___Spider_mites Two-spotted_spider_mite	Tomato___Spider_mites Two-spotted_spider_mite	Tomato___Tomato_mosaic_virus
Tomato___healthy	Tomato___healthy	Tomato___healthy	Tomato___healthy
Tomato___Late_blight	Strawberry___Leaf_scorch	Potato___Late_blight	Potato___Late_blight
Tomato___Leaf_Mold	Tomato___Leaf_Mold	Tomato___Leaf_Mold	Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot	Strawberry___healthy	Tomato___Septoria_leaf_spot	Apple___Black_rot
Tomato___Spider_mites Two-spotted_spider_mite	Tomato___Spider_mites Two-spotted_spider_mite	Tomato___Spider_mites Two-spotted_spider_mite	Tomato___Spider_mites Two-spotted_spider_mite
Tomato___Target_Spot	Tomato___Target_Spot	Tomato___Target_Spot	Tomato___Target_Spot
Tomato___Tomato_mosaic_virus	Tomato___Tomato_mosaic_virus	Tomato___Tomato_mosaic_virus	Tomato___Tomato_mosaic_virus
Tomato___Tomato_Yellow_Leaf_Curl_Virus	Tomato___Tomato_Yellow_Leaf_Curl_Virus	Tomato___Tomato_Yellow_Leaf_Curl_Virus	Tomato___Tomato_Yellow_Leaf_Curl_Virus

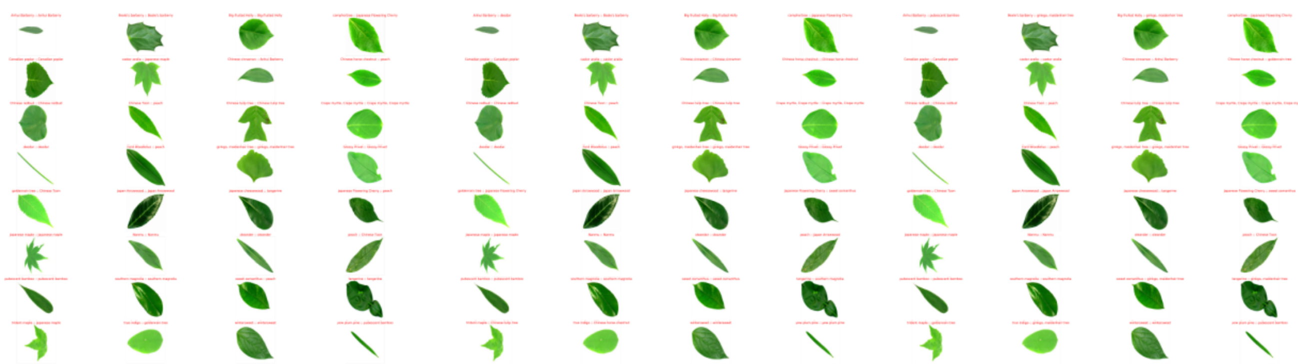


(a) Plant species class prediction Actual vs Predicted for **PlantVillage Dataset for 100 epochs**

(b) Plant species class prediction Actual vs Predicted for **PlantVillage Dataset for 150 epochs**

(c) Plant species class prediction Actual vs Predicted for **PlantVillage Dataset for 200 epochs**

Fig. 17 **a** Plant species class prediction Actual vs Predicted for *PlantVillage Dataset for 100 epochs*. **b** Plant species class prediction Actual vs Predicted for *PlantVillage Dataset for 150 epochs*. **c** Plant species class prediction Actual vs Predicted for *PlantVillage Dataset for 200 epochs*



(a) Plant species class prediction Actual vs Predicted for **Flavia Dataset for 100 epochs**

(b) Plant species class prediction Actual vs Predicted for **Flavia Dataset for 150 epochs**

(c) Plant species class prediction Actual vs Predicted for **Flavia Dataset for 200 epochs**

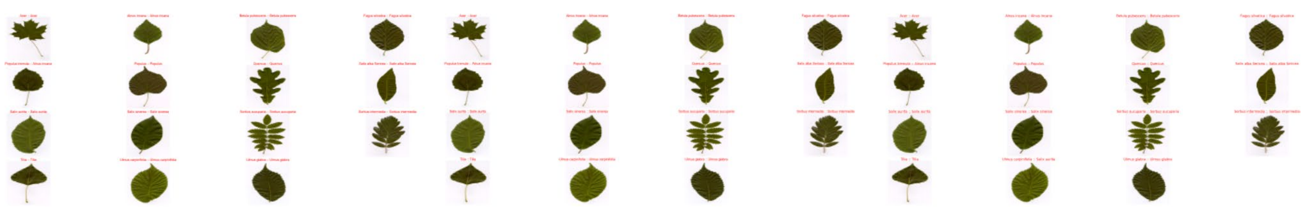
Fig. 18 **a** Plant species class prediction Actual vs Predicted for *Flavia Dataset for 100 epochs*. **b** Plant species class prediction Actual vs Predicted for *Flavia Dataset for 150 epochs*. **c** Plant species class prediction Actual vs Predicted for *Flavia Dataset for 200 epochs*

Table 10 Plant species name actual and prediction for *Flavia dataset*

Actual	Predicted		
	# 100 of Epochs	# 150 of Epochs	# 200 of Epochs
Anhui Barberry	Anhui Barberry	deodar	pubescent bamboo
Beale's barberry	Beale's barberry	Beale's barberry	ginkgo, maidenhair tree
Big-fruited Holly	Big-fruited Holly	Big-fruited Holly	ginkgo, maidenhair tree
camphortree	Japanese Flowering Cherry	Japanese Flowering Cherry	Japanese Flowering Cherry
Canadian poplar	Canadian poplar	Canadian poplar	Canadian poplar
castor aralia	Japanese maple	castor aralia	castor aralia
Chinese cinnamon	Anhui Barberry	Chinese cinnamon	Anhui Barberry
Chinese horse chestnut	peach	Chinese horse chestnut	goldenrain tree
Chinese redbud	Chinese redbud	Chinese redbud	Chinese redbud
Chinese Toon	peach	peach	peach
Chinese tulip tree	Chinese tulip tree	Chinese tulip tree	Chinese tulip tree
Crape myrtle, Crepe myrtle	Crape myrtle, Crepe myrtle	Crape myrtle, Crepe myrtle	Crape myrtle, Crepe myrtle
deodar	deodar	deodar	deodar
Ford Woodlotus	peach	peach	peach
ginkgo, maidenhair tree	ginkgo, maidenhair tree	ginkgo, maidenhair tree	ginkgo, maidenhair tree
Glossy Privet	Glossy Privet	Glossy Privet	Glossy Privet
goldenrain tree	Chinese Toon	Japanese Flowering Cherry	Chinese Toon
Japan Arrowwood	Japan Arrowwood	Japan Arrowwood	Japan Arrowwood
Japanese cheesewood	tangerine	tangerine	tangerine
Japanese Flowering Cherry	peach	sweet osmanthus	sweet osmanthus
Japanese maple	Japanese maple	Japanese maple	Japanese maple
Nanmu	Nanmu	Nanmu	Nanmu
oleander	oleander	oleander	oleander
peach	Chinese Toon	Japan Arrowwood	Chinese Toon
pubescent bamboo	pubescent bamboo	pubescent bamboo	pubescent bamboo
southern magnolia	southern magnolia	southern magnolia	southern magnolia
sweet osmanthus	peach	sweet osmanthus	ginkgo, maidenhair tree
tangerine	tangerine	southern magnolia	ginkgo, maidenhair tree
trident maple	trident maple	Chinese tulip tree	goldenrain tree
true indigo	goldenrain tree	Chinese horse chestnut	ginkgo, maidenhair tree
wintersweet	wintersweet	wintersweet	wintersweet
yew plum pine	pubescent bamboo	yew plum pine	pubescent bamboo

Table 11 Plant species name Actual and Prediction for *Swedish dataset*

Actual	Predicted		
	# 100 of Epochs	# 150 of Epochs	# 200 of Epochs
Acer	Acer	Acer	Acer
Alnus incana	Alnus incana	Alnus incana	Alnus incana
Betula pubescens	Betula pubescens	Betula pubescens	Betula pubescens
Fagus silvatica	Fagus silvatica	Fagus silvatica	Fagus silvatica
Populus	Populus	Populus	Populus
Populus tremula	Alnus incana	Alnus incana	Alnus incana
Quercus	Quercus	Quercus	Quercus
Salix alba 'Sericea'	Salix alba 'Sericea'	Salix alba 'Sericea'	Salix alba 'Sericea'
Salix aurita	Salix aurita	Salix aurita	Salix aurita
Salix sinerea	Salix sinerea	Salix sinerea	Salix sinerea
Sorbus aucuparia	Sorbus aucuparia	Sorbus aucuparia	Sorbus aucuparia
Sorbus intermedia	Sorbus intermedia	Sorbus intermedia	Sorbus intermedia
Tilia	Tilia	Tilia	Tilia
Ulmus carpinifolia	Ulmus carpinifolia	Ulmus carpinifolia	Salix aurita
Ulmus glabra	Ulmus glabra	Ulmus glabra	Ulmus glabra



(a) Plant species class prediction Actual vs Predicted for **Swedish Dataset for 100 epochs**

(b) Plant species class prediction Actual vs Predicted for **Swedish Dataset for 150 epochs**

(c) Plant species class prediction Actual vs Predicted for **Swedish Dataset for 200 epochs**

Fig. 19 **a** Plant species class prediction Actual vs Predicted for *Swedish Dataset for 100 epochs*. **b** Plant species class prediction Actual vs Predicted for *Swedish Dataset for 150 epochs*. **c** Plant species class prediction Actual vs Predicted for *Swedish Dataset for 200 epochs*

Table 12 The actual and predicted values not matched cases

# Epochs	# of not matched cases		
	# 100 of Epochs	# 150 of Epochs	# 200 of Epochs
Leaf Snap	18	16	15
UCI Leaf	18	13	16
Plant Village	12	10	8
Flavia	13	10	17
Swedish leaf	1	2	2

Table 13 The RMSE values of five datasets related to 100, 150 and 200 epochs

# Epochs	# of not matched cases		
	# 100 of Epochs	# 150 of Epochs	# 200 of Epochs
Leaf Snap	0.392	0.339	0.537
UCI Leaf	0.670	0.570	0.632
Plant Village	0.561	0.512	0.458
Flavia	0.637	0.559	0.728
Swedish leaf	0.258	0.258	0.365

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