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CNN Approaches for Classification of Indian Leaf Species Using Smartphones

M. Vilasini[1, *] and P. Ramamoorthy[2]

Abstract: Leaf species identification leads to multitude of societal applications. There is enormous research in the lines of plant identification using pattern recognition. With the help of robust algorithms for leaf identification, rural medicine has the potential to reappear as like the previous decades. This paper discusses CNN based approaches for Indian leaf species identification from white background using smartphones. Variations of CNN models over the features like traditional shape, texture, color and venation apart from the other miniature features of uniformity of edge patterns, leaf tip, margin and other statistical features are explored for efficient leaf classification.

Keywords: Deep learning, CNN, classification, transfer learning, prewitt edge detection.

1 Introduction

Leaf detection and classification is fundamental to agriculture, forestry, rural medicine and other commercial applications. Precision agriculture demands plant leaf disease diagnosis for automatic weed identification [Ahmad, Muhammad, Ahmad et al. (2018); Bakhshipour and Jafari (2018); Bakhshipour, Jafari, Nassiri et al. (2017); Dos Santos Ferreira, Freitas, da silva et al. (2017)]; Environment and Forestry needs solutions for automatic tree species identification [Bakhshipour, Jafari, Nassiri et al. (2017); Ghasab, Khamis, Mohammad et al. (2015); Goyal and Kumar (2018); Mouine, Yahiaoui and Verroust-Blondet (2012); Mouine, Yahiaoui, Verroust-Blondet et al. (2013c); Mzoughi, Yahiaoui and Boujemaa (2013); Pahalawatta (2008); Yahiaoui, Mzoughi, Boujemaa et al. (2012)]; rural medicine [Ahmad, Muhammad, Ahmad et al. (2018); Pornpanomchai, Rimdusit, Tanasap et al. (2011)] involves recognition of plant species for deciding upon the suitability of consumption. Freshness of leaves is an important trait for processing tea leaves.

The problems in all of the above areas rely upon leaf classification to a larger extent. By taking advantage of the leaf features, advanced machine learning algorithms could be applied for automatic leaf detection. Most of the existing literature on leaf classification focused largely on shape, texture and color based features. Inspite of the presence of various big datasets [Dobrescu, Valerio and Tsaftaris (2017)] on leaf classification

[1] KPR Institute of Engineering and Technology, Coimbatore, 641407, India.

[2] Adithiya Institute of Engineering and Technology, Coimbatore, 641107, India.

[*] Corresponding Author: M. Vilasini. Email: vilasiniaddress@gmail.com.

research, ensembling the learning over high dimensional features of leaf image data is less addressed. This paper proposes deep learning based approaches for plant leaf classification using large feature set for Indian leaf species.

2 Related work

There are many different methods for leaf image classification, Wu et al. [Wu, Yang, Chen et al. (2008)] adopted multi-spectral image techniques for categorizing green leaves. The idea was to use the entropy value of green tea leaf images as texture features. With full training, a support vector machine (SVM) with radial basis function (RBF): kernel successfully identifies the class labels than raw RBF. In addition, a principal component analysis (PCA) at the input of SVM will again improve the classification accuracy [Chen, Zhao, Fang et al. (2007); Palacios-Morillo, Alcazer, de Pablos et al. (2013)]. Linear discriminant analysis (LDA) was also used in combination with PCA [Chen, Zhao, Cai et al. (2008)]. Texture estimation [Borah, Hines and Bhuyan (2007)] is another convincing yet causal research that primarily would contribute to effective leaf classification. Additionally apart from texture features [Chen, Zhao, Cai et al. (2008)], other features like shape, color, venation etc. were also used for improving the classification.

Texture based classification algorithms have been well explored in the recent past. Li et al. [Li, Kwok, Zhu et al. (2003)], Fernando et al. (2013)], scale-invariant feature transform (SIFT) [Liu, Liu, Sun et al. (2014)], Gray level co-occurrence matrix (GLCM), Local Binary Pattern [Ojala, Pietikainen and Maenpaa (2002)], LBP-GLCM [Tang, Su, Er et al. (2015)], wavelet transform and Gabor filter are to name a few. Various improvements to LBP descriptors have also been proposed [Liao, Law, Chung et al. (2005); Heikkilä, Pietikainen and Schmid (2009); Ahonen and Pietikainen (2007); Zhao, Jia, Hu et al. (2013)].

Recently, various deep learning based plant leaf identification methods have been discussed in the literature. Liu et al. [Liu, Zhu, Zhang et al. (2015)] applied a traditional CNN for feature extraction to apply over SVM for leaf classification. Grinblat et al. [Grinblat, Uzal, Larese et al. (2016)] used vein pattern segmentation at the input of CNN for better classification accuracy. The chosen features of CNN were validated by a deconvolutional network [Shelhamer, Long and Darrell (2017)] in most literature.

Alternatively, layers of CNN are also utilized for effective feature learning. Two CNN Lee et al. [Lee, Chan and Mayo (2017)] is a two-stream CNN which learns features on whole and patch images. Multiscale CNN (MSCNN) Du et al. [Du and Gao (2017); Rasti, Rebbani, Mehridehnavi et al. (2017)] are comprised of multiple different scale feature learning layers. MSF-CNN Hu et al. [Hu, Chen, Yang et al. (2017)] is a slighter modification to MSCNN that, the learnt features are not mapped at the end, instead, the features are fused at every intermediate step such that subsequent meta-information arising from intermediate fusing would also contribute to feature learning.

Automated leaf image detection literature involves statistical feature matching approaches [Arbelaez, Marie, Fowlkes et al. (2010); Dollár and Zitnick (2014), Konishi, Yuille, Coughlan et al. (2003)] for appropriate edge detection. More semantic edge boundaries shall be identified using [Arbelaez, Marie, Fowlkes et al. (2010)] which is learned over very large datasets [Shen, Wang, Wang et al. (2015); Xie and Tu (2017)]. Color and shape feature analysis has been extensively applied over leaf detection literature [Wang, Yang, Tian et al. (2007)]. Active polygons Bell et al. [Bell and Dee (2019), Rabatel, Manh, Aldon et al. (2001)] and active contours [Mishra, Fieguth, Clausi et al. (2010); Qiangqiang, Zhicheng, Weidong et al. (2015)] are noteworthy to mention. Histograms [Pape and Klukas (2014)] are widely used for background image separation. For faster detection, leaves required to have a plain white background. Overlapping leaves are also dealth with in literature [Pape and Klukas (2014); Soares and Jacobs (2013); Wang and Min (2012)].

Deep CNNs have been proposed for leaf counting applications [Aich and Stavness (2017); Dobrescu, Valerio and Tsaftaris (2017)]. Pyramid CNN [Morris (2018)] seeks to combine statistical boundary detection approaches [Arbelaez, Marie, Fowlkes et al. (2010); Dollár and Zitnick (2014); Kirk, Anderson, Thomson et al. (2009)], and CNN based boundary detection algorithms [Shen, Wang, Wang et al. (2015); Xie and Tu (2017)] with additional advanced CNN architectures [Newell, Yang, Deng et al. (2016)] for dense leaves segmentation. However, it does not involve testing the dataset in wild forestry. Though leaf boundary detection in dense setup was successful including approaches for closed-boundary leaf segmentation, it was not convincing for leaves possessing internal textures. Also, strong additional cues were necessary for achieving high precision.

Colour characteristics were predominantly used to distinguish green plants away from soil for leaf area estimation purposes [Rasmussen, Norremark, Bibby et al. (2007); Meyer and Neto (2008), Kirk, Anderson, Thomson et al. (2009)]. Cues like ExG (Excess Green Index) and ExR (Excess Red Index) provided a clear contrast between plants and soil, and has been widely used in separating plants from non-plants [Zheng, Zhang, Wang et al. (2009); Burgos-Artizzu, Ribeiro, Guijarro et al. (2011); Guerrero, Pajares, Montalvo et al. (2011)]. Colour Index of Vegetation Extraction (CIVE) was proposed for measuring growth status of crops. Other combined indices derived upon primary color cues were also proposed [Meyer and Neto (2008); Guijarro, Pajares, Riomoros et al. (2011); Burgos-Artizzu, Ribeiro, Guijarro et al. (2011); Guerrero, Pajares, Montalvo et al. (2011)].

Alternate algorithms using Mean-Shift methods upon Back Propagation Neural Network MS-BPNN [Zheng, Zhang, Wang et al. (2009)] and Fisher Linear Discriminant (FLD) [Zheng, Shi, Zhang et al. (2010)] proved to improve the quality of segmentation. Other methods like Affinity Propagation-Hue Intensity (AP-HI) [Yu, Cao, Wu et al. (2013)] and Decision Tree based Segmentation (DTSM) [Guo, Rage, Ninomiya et al. (2013)] were also proposed. [Bai, Cao, Yu et al. (2014)] used Particle Swarm Optimization (PSO) based k-means for Lab colour space based clustering. Ye et al. [Ye, Cao, Yu et al. (2015)] introduced crop image extraction methods for varying illuminations.

Other features like leaf tip [Xie and Tu (2017); Mzoughi, Yahiaoui, Boujemaa et al. (2012b); Tekkesinoglu, Rahim, Rehman et al. (2014)], leaf base [Xie and Tu (2017); Mzoughi, Yahiaoui, Boujemaa et al. (2012b); Tekkesinoglu, Rahim, Rehman et al. (2014); Larese, Baya, Craviotto et al. (2014)], leaf petiole [Mouine, Yahiaoui, Verroust-Blondet et al. (2012); Mouine, Yahiaoui, Verroust-Blondet et al. (2013a); Mouine, Yahiaoui, Verroust-Blondet et al. (2013c); Mouine, Yahiaoui, Verroust-Blondet et al. (2013b); Pahalawatta (2008); Gouveia, Filipe, Reis et al. (1997):] are also considered for leaf image classification [Hati and Sajeevan (2013); AbJabal, Hamid, Shuib et al. (2013); Priya, Balasaravanan, Thanamani et al. (2012); Fern, Sulong, Rahim et al. (2014);

Narayan and Subbarayan (2014); Petchsri, Boonkered, Baum et al. (2012); Pornpanomchai, Supapattranon, Siriwisesokul et al. (2011); An, Palmer, Baker et al. (2016); Jelínková, Tremblay, DesRochers et al. (2014)]. Texture analysis was combined with shape above margin and base for better classification [Mzoughi, Yahiaoui, Boujemaa et al. (2013)]. Venation of leaves [Larese, Baya, Craviotto et al. (2014)] was also analysed. Extensive research on applying deep learning for automated plant species identification is found in the last decade. AlexNet [Krizhevsky, Sutskever, Hinton et al. (2012); Lee, Chan, Mayo et al. (2017); Lee, Chan, Wilkin et al. (2015); Shen, Wang, Wang et al. (2015)], ResNet [He, Zhang, Ren et al. (2016); Sun, Liu, Wang et al. (2017):], FractalNet [Larsson, Marrie and Shakhnarovich (2016)], DenseNet [Huang, Liu, Van der Maaten et al. (2017)], SqueezeNet [Iandola, Han, Moskewicz et al. (2016)] and other CNN architectures [Yu, Cao, Wu et al. (2013); Barré, Stover, Miller et al. (2017)] have transformed automatic leaf classification research into remarkable dimensions.

Leaf segmentation approaches combined with edge classification is yet another alternative approach for leaf identification. Paper et al. [Paper and Klukas (2014)] applied 3D histograms for pixel level classification and robust leaf edge detection [Pape and Klukas (2015)]. Vukadinovic et al. [Vukadinovic and Polder (2015)] use neural network based pixel classification techniques for background separation, and proceed with watershed segmentation approaches for segmenting leaves. Yin et al. [Yin, Liu, Chen et al. (2014); Ye, Cao, Yu et al. (2015)] uses chamfer matching techniques. Super pixel approach [Shen, Wang, Wang et al. (2015)] is also proposed for color-based and watershed based leaf segmentation. Plant phenotyping is the recent method for leaf identification which uses deep learning [An, Palmer, Baker et al. (2016); Pound, Atkinson, Townsend et al. (2017); Scharr, Minervini, French et al. (2016)]. Romero-Paredes et al. [Romero-Paredes and Philip Hilaire Sean Torr (2016)] and [Ren and Zemel (2017)] propose another remarkable progress in leaf identification research. They use RNN models which remember the previously identified leaves. Basically leaf edge detection approaches works with counting the leaves and establishing the leaf area of a growing plant. Shallow CNN [Bell and Dee (2019)] is used to distinguish plant edges from leaf edges. Canny edge detection is applied before region-based segmentation. These sequence of approaches help in better elimination of occluded leaf images. The literature on plant species detection also shown in Tab. 1.

Table 1: Literature on Plant species detection

No.	Feature extracted & feature set selection	Datasets used	Classifier	Accuracy
1	Boundary based feature, moments feature and colour of leaves [Gopal, Reddy and Gayatri (2012)]	Own dataset with 100 leaves (10 per species)	Dissimilarity measures	92%
2	Shape, vein colour and texture features combined with Zernike Moments [Kulkarni, Rai, Jahagirdar et al. (2013)]	Flavia Dataset	RBPNN (Radial basis proba- bilistic neural network)	93.82 %
3	Local Binary Pattern to extract leaf texture [Prasvita and Herdiyeni (2013)]	Own dataset (30 species of In- donesian medicinal plants)	Probabilistic Neural Network	NA
4	Shape and texture features Gabor filter and GLCM. [Chaki and Parekh Bhattacharya (2015)]	Own dataset (930 images di- vided into 31 classes)	A neuro-fuzzy controller and a feed-forward back-propagation Multi-Layered Perceptron	NA
5	Moment invariant, convexity, perimeter ratio, multi scale distance matrix, average margin distance, marginstatistic [Kalyoncu and Toygar (2015)]	Flavia dataset, leaf Snap	Linear Discriminant Classifier	Flavia dataset(94%)
6	Combination of shape colour, texture, morphology feature [Ghasab, Khamis, Mohammad et al. (2015)]	Flavia dataset	SVM	96.25%.
7	PCNN. [Wang, Zhaobin, Xiaoguang et al. (2016)]	Flavia dataset, Mew2012 dataset (middle Europe), ICL dataset(China)	SVM (Support Vector Machine)	Flavia (96.97%), MEW (91.20%), ICL (91.56%)
8	Pre-processing & Morphological feature (Aspect Ratio, Eccentricity, Roundness, Convex Hull), Shape Defining Feature, Fourier Descriptor [Aakif and Khan (2015)]	Flavia dataset, ICL dataset	ANN (Artificial Neural Net- work) with back propagation. Sigmoid function is used as a transfer function.	Shape feature (68%), FD (77.8%), SDF (83.6%), all combined (96%)
9	Raw leaf data. [Lee, Chan, Zhang et al. (2017)]	Malaya Kew (MK) dataset	De-CNN, MLP, SVM	Dataset (D1) MLP (97.7%) SVM (98.1%) Dataset (D2) MLP (99.5%): SVM (99.3%):

There are hundreds of literature available for plant leaf detection, however, very few discusses automatic plant leaf detection using smartphones. Leafsnap [Gouveia, Filipe, Reis et al. (1997)] is the foremost application developed for ios smartphones. For Android smartphones, recently various applications are attempted [Borah and Bhuyan (2003); Gill, Kumar and Agarwal (2013); Heikkilä, Pietikäinen, Schmid et al. (2009)]. But mostly the images are pre-processed which is not practically useful. More advanced feature learning approaches [Cerutti, Tougne, Vacavant et al. (2011), Grinblat, Uzal, Larese et al. (2016); Laddi, Sharma, Kumar et al. (2013)] are needed to learn from natural raw leaf images. Combination of CNN with SVM proves to be more beneficial in feature learning [LeCun, Bengio and Hinton et al. (2010); Li, Nie, Qiu et al. (2011); Simon and Rodner (2015); Wu, Bao, Xu et al. (2007)] and classification [Li, Nie, Qiu et al. (2011); Simon and Rodner (2015); Wu, Bao, Xu et al. (2007)]. Considering the progress of above literature, this paper proposes various approaches for Indian leaf species identification using deep learning.

3 Automated identification of leaf species

The idea is to classify the plant species after proper edge detection and segmentation. The proposed work utilizes a cluster of edge detection algorithms which is discussed in the next subsection shown in Fig. 1 (1-14).

3.1 Prewitt edge detection

Prewitt is a discrete differentiation operator, which computes the gradient approximation of image intensities. In other words, the prewitt operator calculates the point-wise image intensity to capture the smooth variation of leaf image changes at any direction. Horizontal and Vertical intensities are calculated which are then examined for the direction which has the largest possible intensity variations. The operator uses 3×3 kernels one each for horizontal and vertical directional changes. For the leaf image, assuming are the two gradient vectors of horizontal and vertical directions respectively, the resulting gradient approximation is given by Eq. (1). The direction of gradient is given by Eq. (2).

$$G = \sqrt{G_x^2 + G_y^2} \tag{1}$$

$$\Theta = \alpha \tan^2(G_y, G_x) \tag{2}$$


Fig. (1)


Fig. (2)


Fig. (3)

Fig. (4)

Fig. (5)

Fig. (6)

Fig. (7)

Fig. (8)

Fig. (9)

Fig. (10)

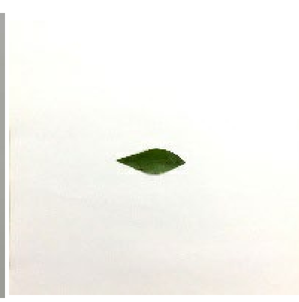

Fig. (11)

Fig. (12)

Fig. (13)

Fig. (14)

Figure 1: Original Leaf images (1) Pipal (2) Nerium (3) Asoka (4) Crown (5) Hibiscus (6) Mango (7) Betel (8) Jackfruit (9) Cannonball (10) Neem (11) Curryleaf (12) Moringa (13) Mint (14) Lemon

3.2 Sobel edge detection and laplacian edge detection approaches

The conventional Sobel edge detector and Laplacian edge detector is also applied for leaf edge and vein segmentation. The outcome of sobel operator and laplacian operator is averaged with prewitt edge detection and the skeleton of leaf is obtained for further classification.

3.3 K-Nearest neighbor classification

The edge detected leaf images are subjected to classification using k-NN approach. The PSNR value for each image is multiplied by 100 and taken as input to the k-NN code. The k-NN uses Manhattan distance to find the K nearest neighbors and takes a majority vote to classify a particular image. Extra values are taken for normalization and it does not affect the k-NN calculation as same values are used for each dataset, hence distance between them is 0. Leaves of Pipal, Nerium, Neem, Ashoka, Crown flower, Cannonball tree, Hibiscus, Mango, Mint, Lemon, Moringa, Betel, Jackfruit and Curry Tree were clicked in smartphone (android): and were considered for examination. Ten positional variations for each species were captured in mobile phone camera under white background. The algorithm resulted at 72% accuracy for detecting 9 leaf species' positions and 79% accuracy for detecting all 14 leaf species.

Structural Similarity values indicated poorer recognition accuracy upon various positions and an overall PSNR evaluated to better values for leaves of Crown flower, Cannonball tree, where lower PSNR values evaluated to worst evaluation for Curry Leaves. The reason is that the dataset consisted of Neem leaves which is close to Curry leaves' structure and shape; However crown flower and cannonball tree flowers have distinct characteristics in color, shape, vein and texture which resulted in much higher accuracies.

3.4 SVM classification without edge detection

The fundamental approach for classification using SVM is adopted here. 14 Indian leaf species were examined using basic SVM. Fig. 2. shows the SVM classification accuracy of Nerium across other species without edge detection. It is interesting to note that Nerium is misclassified as Mango and Neem at various experiments. This emphasizes the need for edge detection before classification. Accuracy of other species before edge detection is also presented in Figs. 3-16. Though the detection is reasonably high the misclassification is also high.

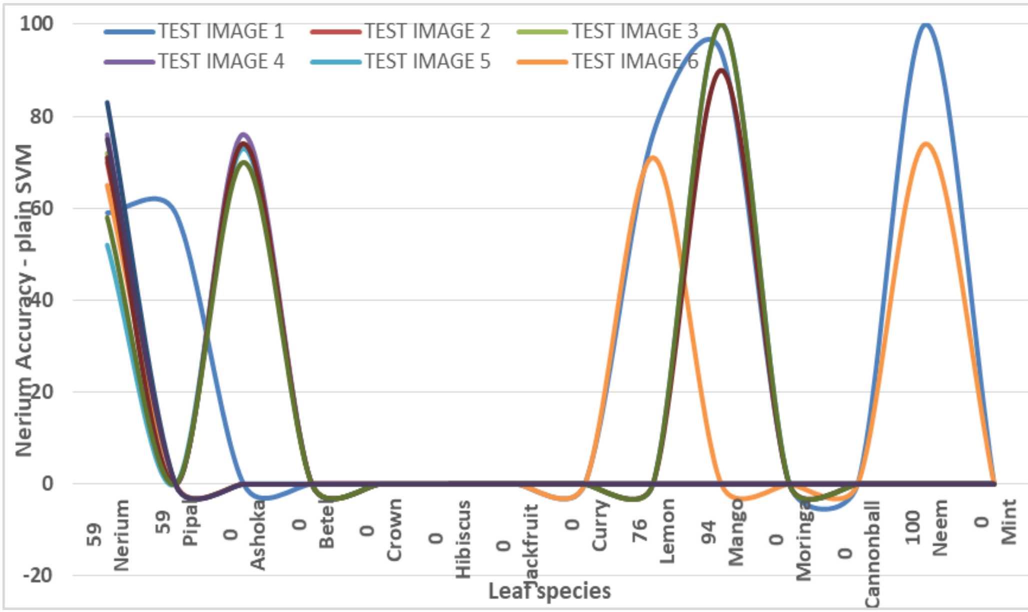

Figure 2: Nerium Accuracy across dataset-plain SVM without edge detection

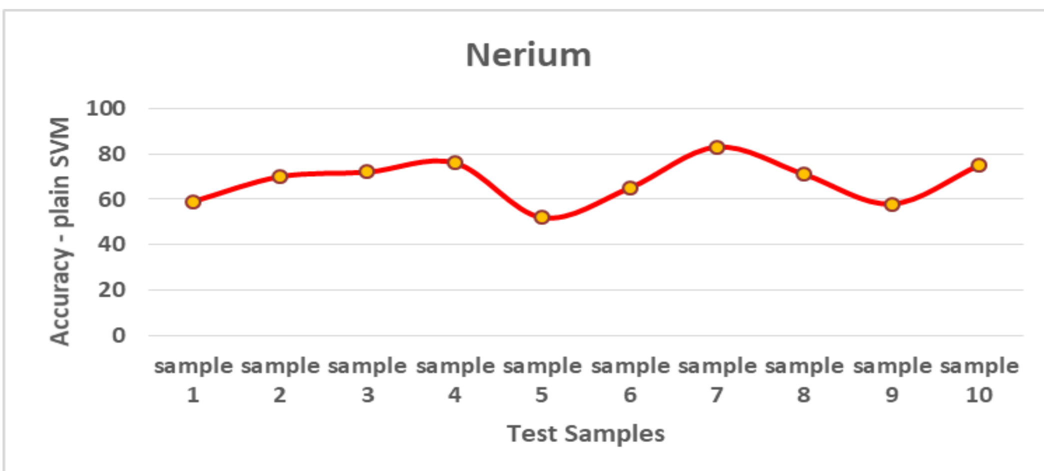

Figure 3: Nerium Accuracy-plain SVM without edge detection

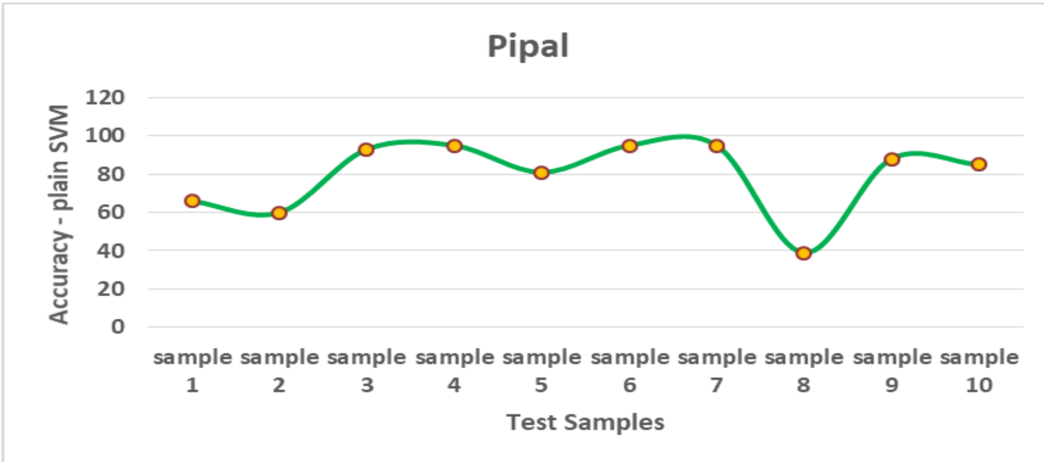

Figure 4: Pipal Accuracy-plain SVM without edge detection

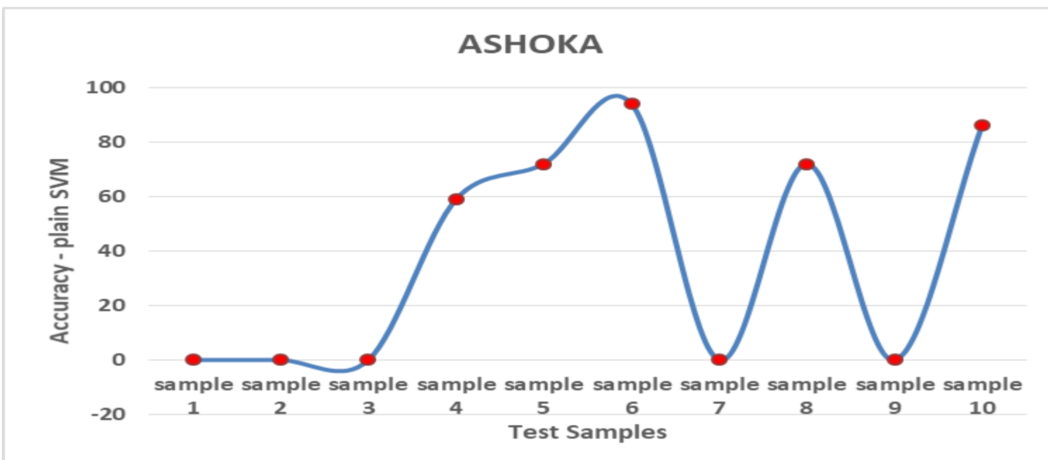

Figure 5: Ashoka Accuracy-plain SVM without edge detection

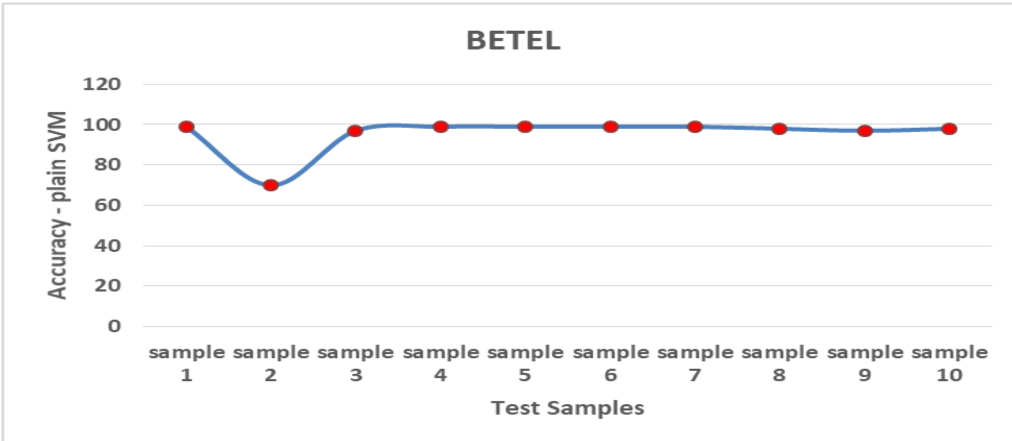

Figure 6: Betel Accuracy-plain SVM without edge detection

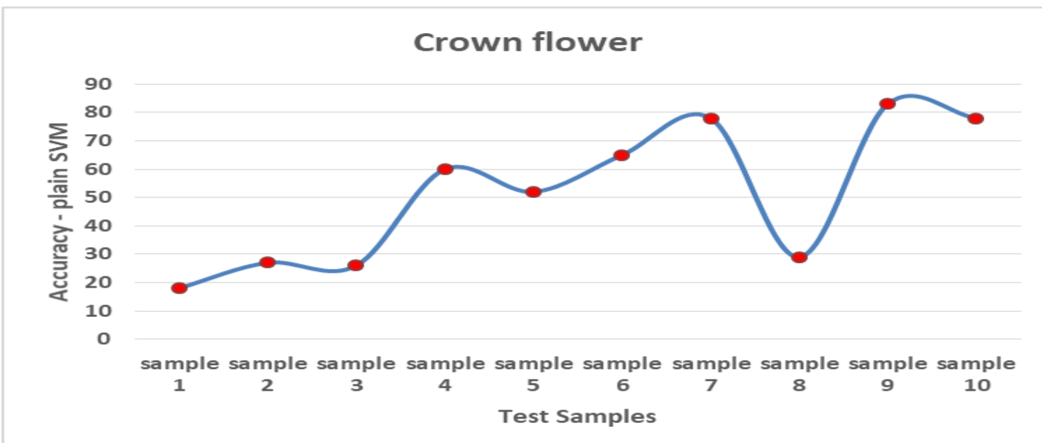

Figure 7: Crown Accuracy-plain SVM without edge detection

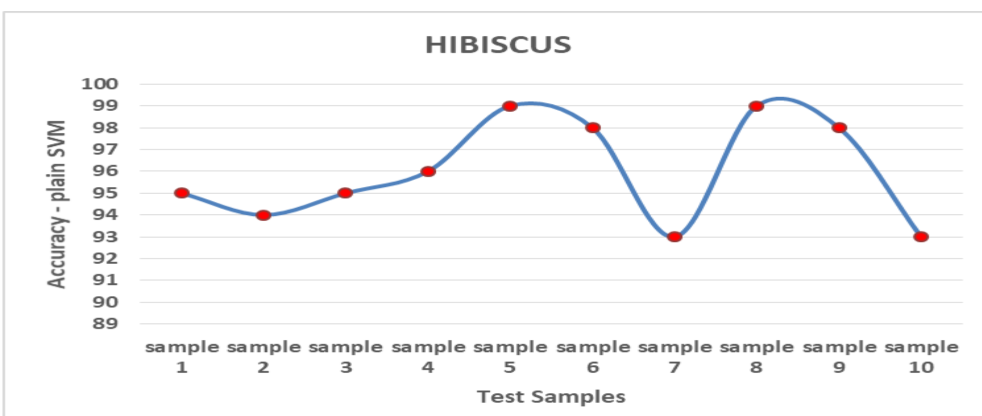

Figure 8: Hibiscus Accuracy-plain SVM without edge detection

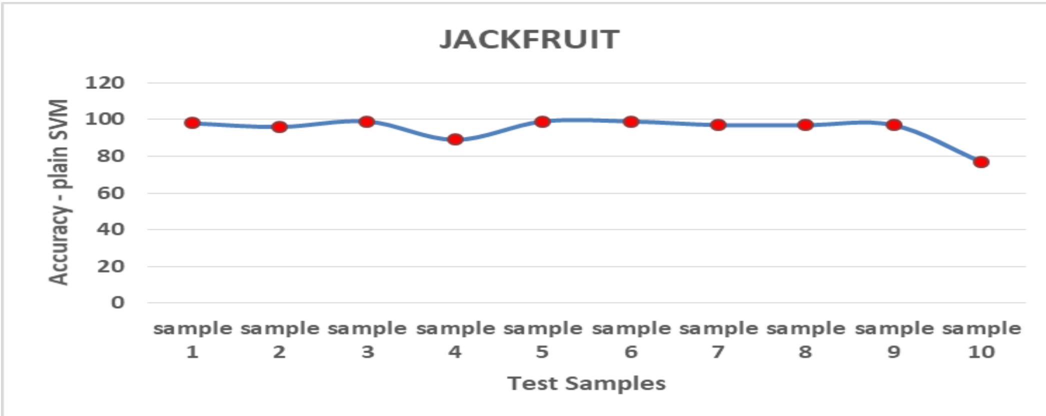

Figure 9: Jackfruit Accuracy-plain SVM without edge detection

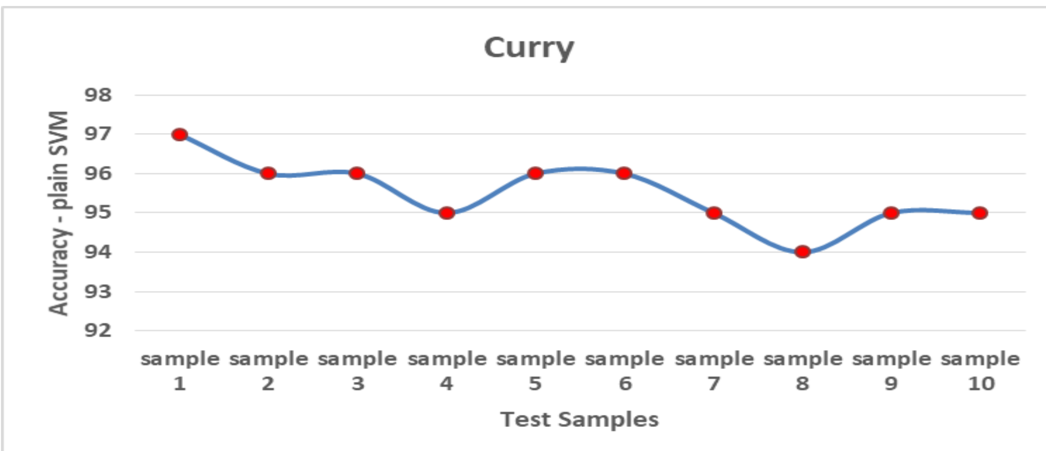

Figure 10: Curry Accuracy-plain SVM without edge detection

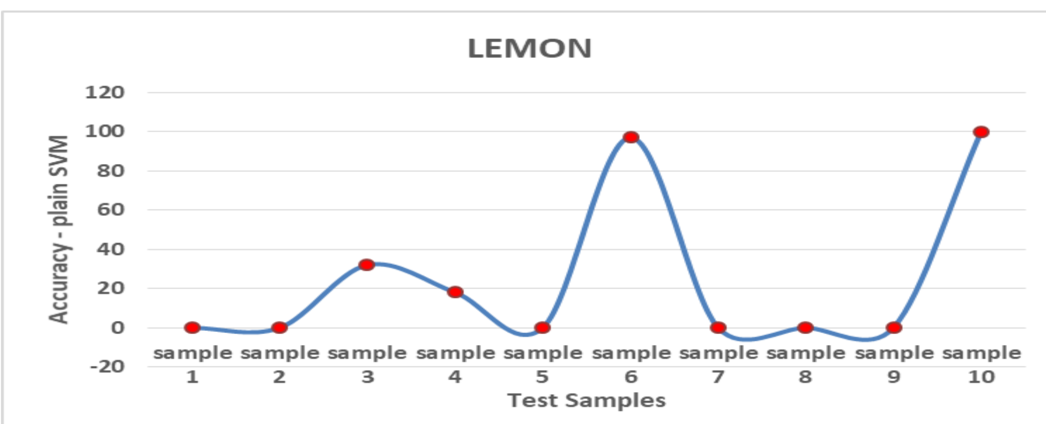

Figure 11: Lemon Accuracy– plain SVM without edge detection

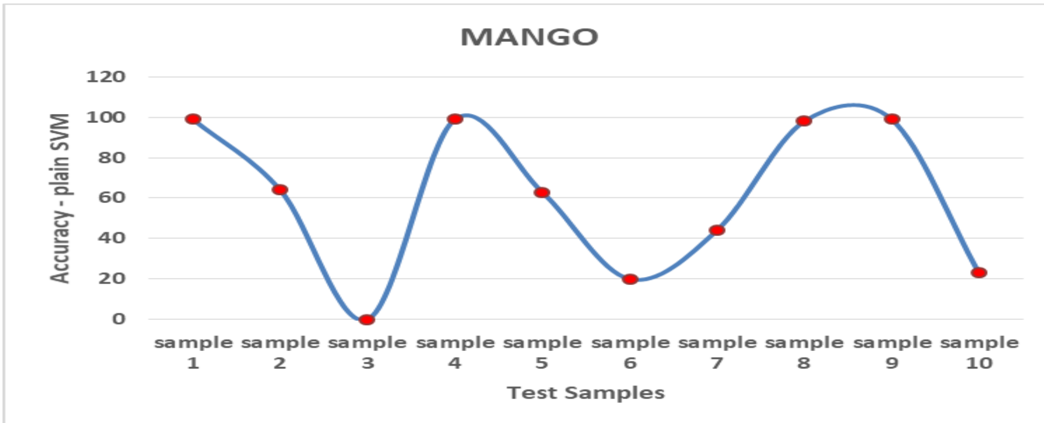

Figure 12: Mango Accuracy-plain SVM without edge detection

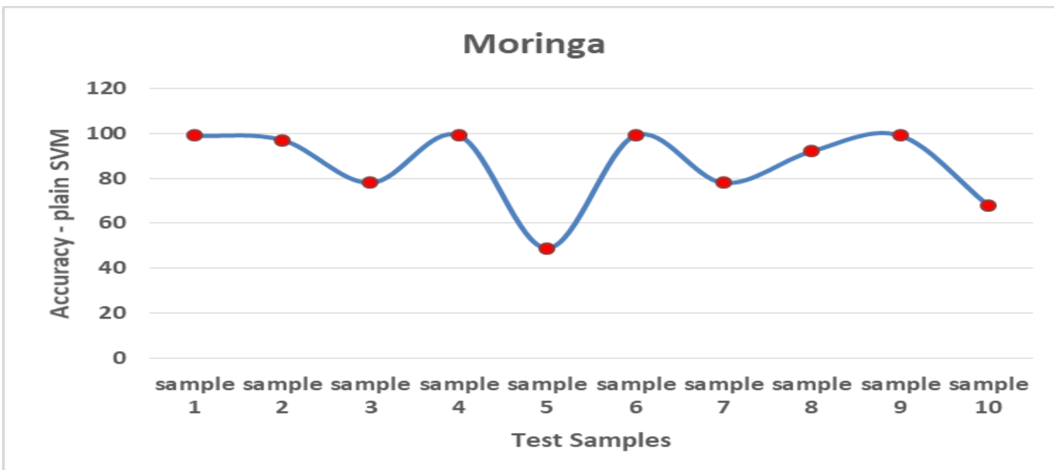

Figure 13: Moringa Accuracy-plain SVM without edge detection

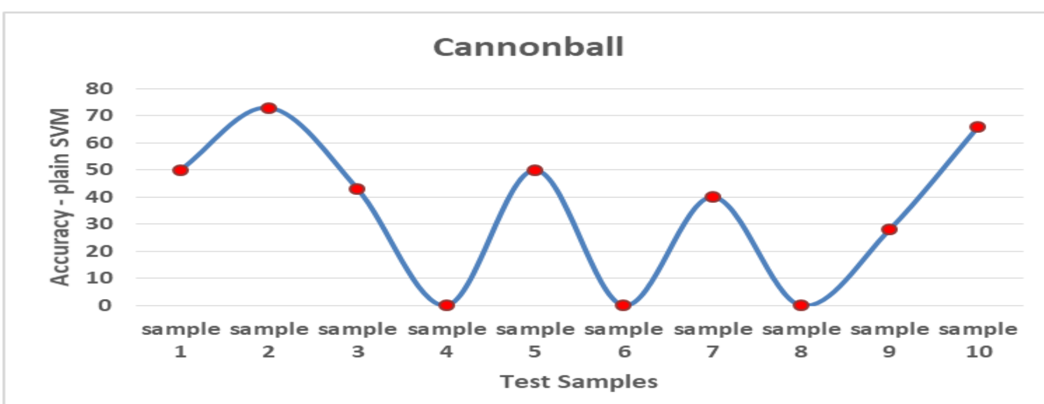

Figure 14: Cannonball Accuracy-plain SVM without edge detection

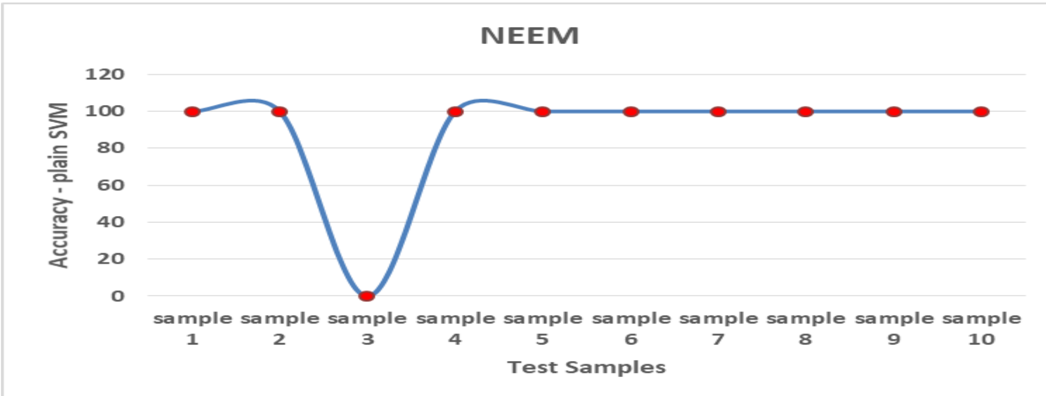

Figure 15: Neem Accuracy-plain SVM without edge detection

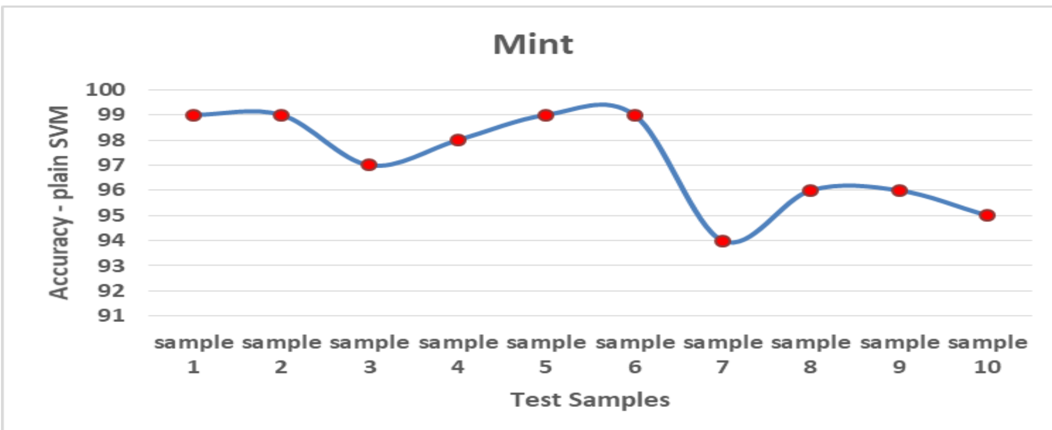

Figure 16: Mint Accuracy-plain SVM without edge detection

3.5 Deep learning based approaches

We have also explored the possibility of k-NN, SVM in pre-training with ANN. The results are promising when compared to all earlier approaches. Firstly, we defined 2 different preprocessing functions using openCV package. The first one is called image to feature vector, to resize the image and then flatten the image into a list of row pixel. The second one is called extract color histogram, to extract a 3D color histogram from the HSV color spacing using cv2.normalize and then flatten the result. We use 85% of the dataset as train set, and 15% as the test set. Finally we applied the KNN, SVM for pre-training and ANN to evaluate the data.

Table 2: Raw pixel and Histogram accuracy

Dataset Labels	k-NN raw pixel	k-NN Histogram	ANN raw pixel	ANN Histogram
2	k=9, 66.67%	k=9, 63.33%	58.33%	66.67%

5	k=11, 30.67%	k=11,32.67%	17.33%	36.67%
10	k=17, 27%	k=17, 22.33%	7.33%	24.67%

In k-NN, the raw pixel accuracy and histogram accuracy are relatively same. In 5 labels sub-dataset the histogram accuracy is a little bit higher than raw pixel, but overall, the raw pixel shows better result. In ANN classifier, the raw pixel accuracy is much lower than histogram accuracy. For the whole dataset (10 labels), the raw pixel accuracy is even lower than random guessing. Based on the results, we found that in order to improve the accuracy listed in Tab. 2, its necessary to use some deep learning method.

In addition we have implemented leaf detection with MLP (Multi-layer perceptron). (MLP) models were successfully used for image recognition, due to the full connectivity between nodes they suffer from the curse of dimensionality and thus do not scale well to higher resolution images. So in this part we built a CNN using deep learning frame work by Google - Tensor Flow. Tensor Flow defines the CNN architecture as a stack of distinct layers that transform the input volume into an output volume (e.g. holding the class scores): through a differentiable function. We assumed the first layer to hold the images, followed by 3 Convolutional layers with 2 x 2 max-pooling and Rectified Linear Unit (ReLU). The input is a 4-dim tensor with the following dimensions: Image number, Y-axis of each image, X-axis of each image, Channels of each image. The output is another 4-dim tensor with the following dimensions: Image number, same as input, Y-axis of each image. If 2x2 pooling is used, then the height and width of the input images is divided by 2, X-axis of each image, Channels produced by the convolutional filters. The 2 Fully-Connected Layers were built at the end of the network. The input is a 2-dim tensor of shape [num_images, num_inputs]. The output is a 2-dim tensor of shape [num_images, num_outputs].

However to connect Convolutional layers and Fully-Connected Layers a Flatten Layer is needed to reduce the 4-dim tensor to 2-dim which can be used as input to the fully-connected layer. The very end of CNN is always a softmax layer which normalize the output from Fully-connected layer so that each element is limited between 0 and 1 and all the elements sum to 1. To optimize the training Cost function is used i.e., cross entropy. The Optimization Method is Adam Optimizer () which is an advanced form of Gradient Descent.

Table 3: Results of CNN for various dataset labels

Dataset Labels	CNN
2	71.9%
5	56.2%
10	43.9%

Further we have explored yet another variation of CNN. We attempted at retraining the last layer of a pre-trained deep neural network called Inception V3, also provided by Tensor Flow. Inception V3 is trained for the ImageNet Large Visual Recognition Challenge using the data from 2012. This is a standard task in computer vision, where models try to classify entire images into 1000 classes, like “Zebra”, “Dalmatian”, and

"Dishwasher". In order to retrain this pre-trained network, we ensured that our own dataset is not already pertained. Modern object recognition models have millions of parameters and can take weeks to fully train. Transfer learning is a technique that shortcuts a lot of this work by taking a fully-trained model for a set of categories like ImageNet, and retrains from the existing weights for new classes, the results in Tab. 3.

Though it is not as good as a full training run, this is surprisingly effective for many applications, and can be run in as little as thirty minutes on a laptop, without requiring a GPU. First from the pre-trained model, the old top layer is removed, and a new layer is trained on the dataset. None of the leaf images were involved in pre-training. The magic of transfer learning is that lower layers that have been trained to distinguish between some objects can be reused for many recognition tasks without any alteration. The script runs with 4,000 training steps. Each step chooses ten images at random from the training set, finds their bottlenecks from the cache, and feeds them into the final layer to get predictions. Those predictions are then compared against the actual labels to update the final layer's weights through the back-propagation process.

Table 4: Results of CNN (softmax) for various dataset labels

Dataset Labels	CNN
2	100%
5	92%
10	88%

In CNN based models we attempted at examining the CNN model with sigmoid as well. The detection accuracy shown in Tab. 4. is well appreciable when compared to earlier models like k-NN and SVM. However, the models were subjected to sample image edge detection before feature learning and classification. Binary CNNs were used in sigmoid variation. The CNN models were subjected to pre-training with plain SVM discussed in earlier section. 20 epochs were planned and the validation loss and accuracy are obtained. Almost up to 12 epochs the validation loss is reduced to 50% as compared to training loss in Figs. 17-20.The validation loss increases after 19 epochs. Therefore a stopping criteria of 20 epochs is chosen for the proposed work. The validation accuracy for every iteration per epoch is also presented in Figs. 21-22. Fig. 23 presents the accuracy of leaf identification of Binary CNN without pre-training. The detection is much lower when compared to pre-training which supports the fact that pre-training using the proposed methods improves the CNN classification accuracy in Fig. 24.

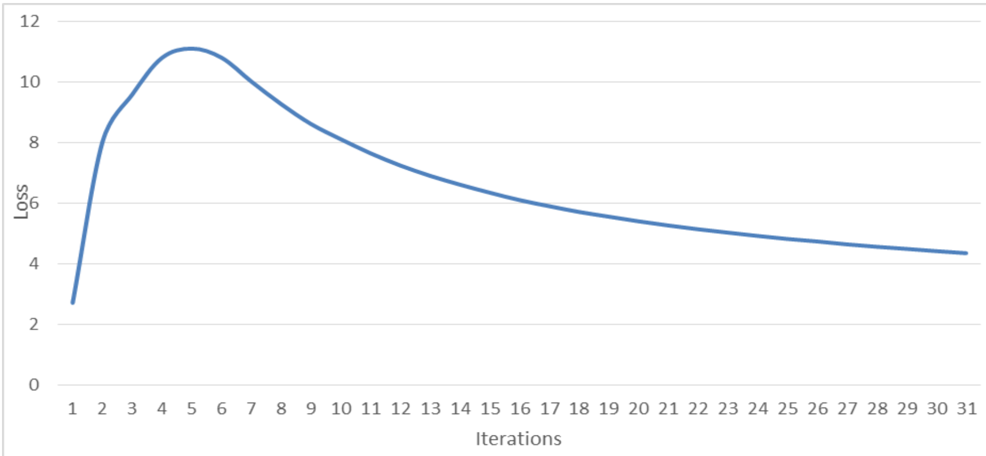

Figure 17: Validation Loss-Epoch 1

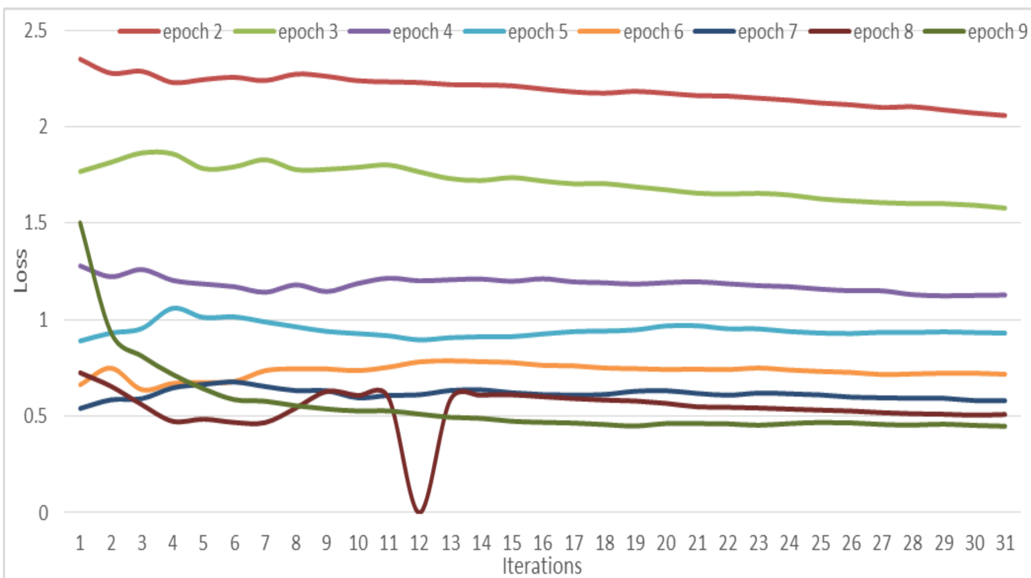

Figure 18: Validation Loss-Epoch 2 to Epoch 9

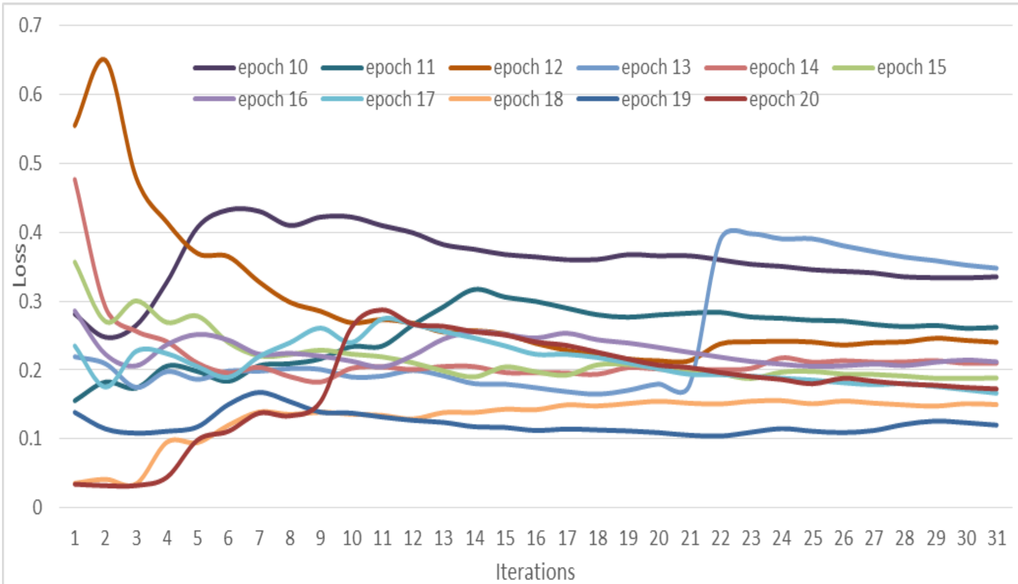

Figure 19: Validation Loss-Epoch 10 to Epoch 20

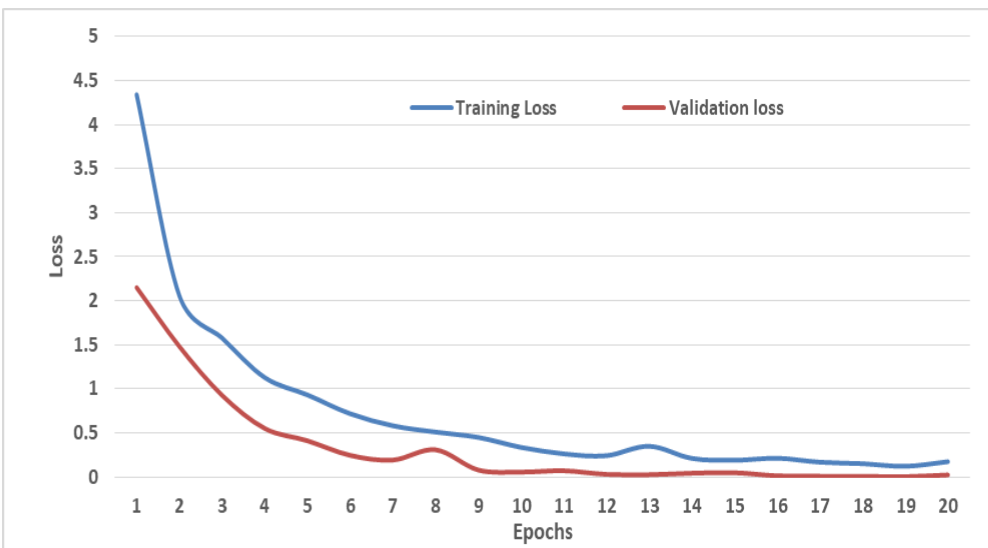

Figure 20: Comparison of Training Loss *vs.* Validation Loss

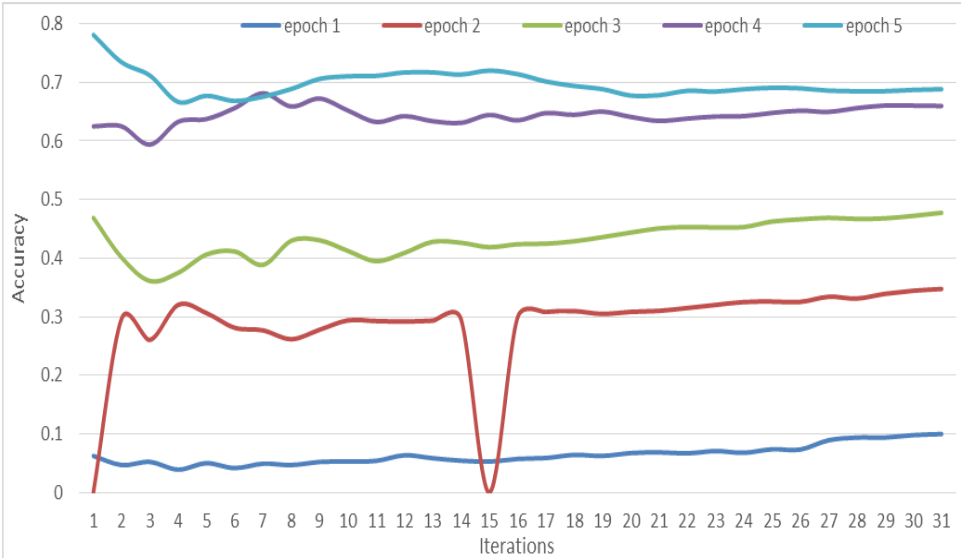

Figure 21: Accuracy of Binary CNN-Sigmoid across iterations/epochs (1-5): -across all species

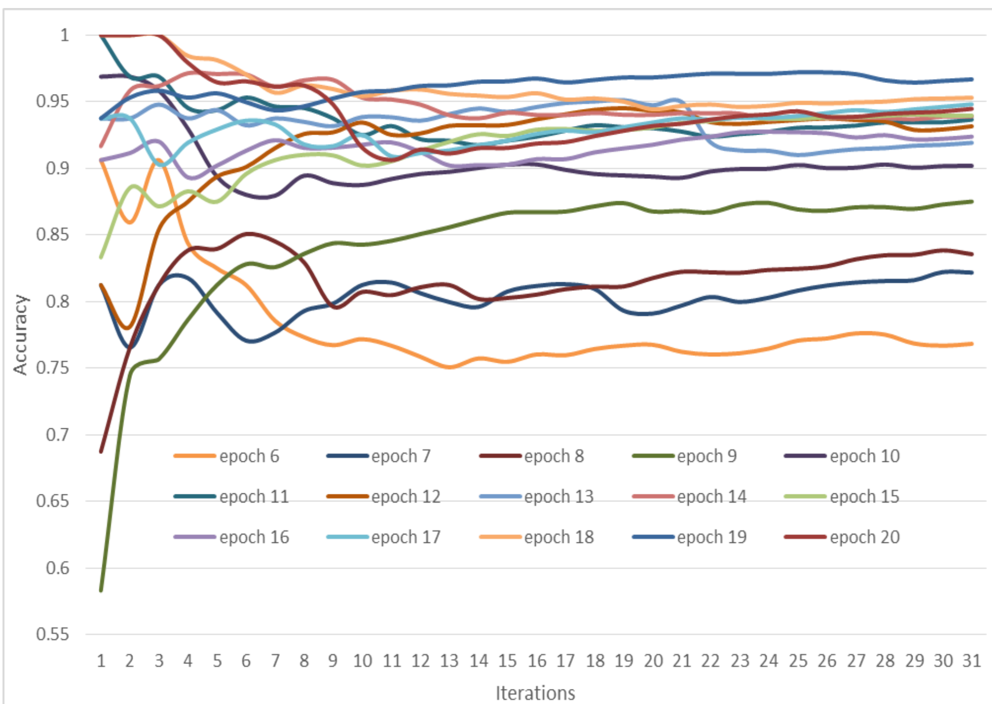

Figure 22: Accuracy of Binary CNN-Sigmoid across iterations/epochs (6-20): -across all species

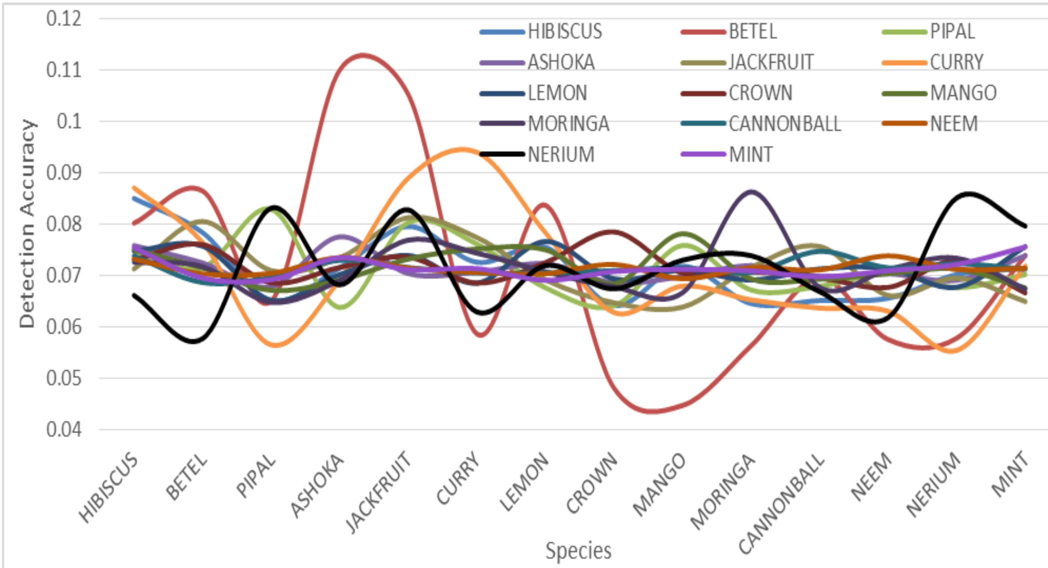

Figure 23: Accuracy of Binary CNN without pre-training across all species

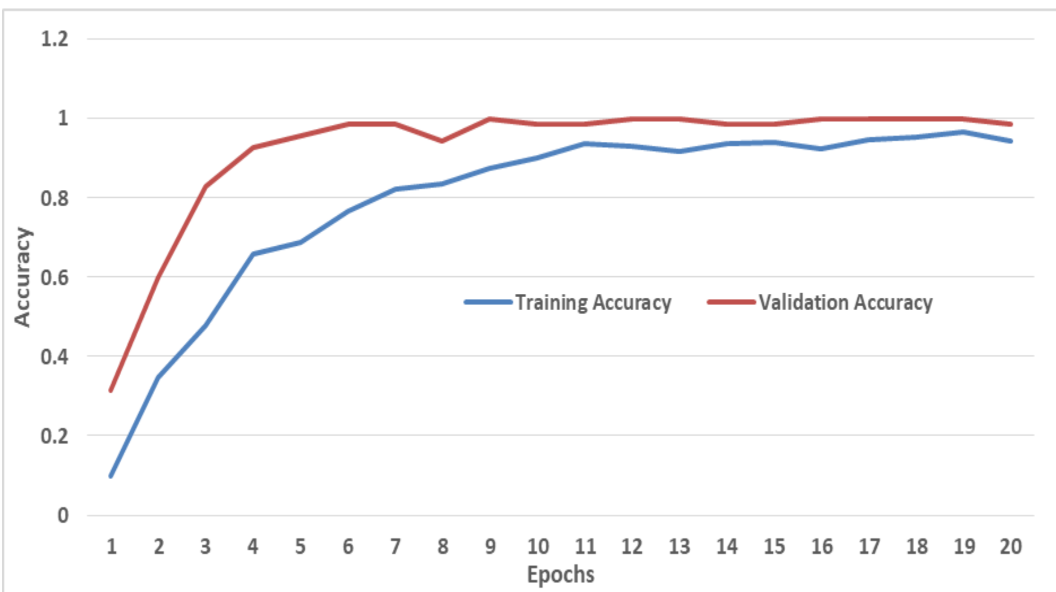

Figure 24: Comparison of training accuracy *vs.* validation accuracy-pre-trained binary CNN

4 Conclusion and future work

The paper proposes CNN based approaches for detecting Indian leaf species. The experiments were conducted with pre-training and edge detection. CNN is experimented with softmax as well as sigmoid layer. The results validate that with proper edge detection and pre-training, binary CNN with sigmoid is able to detect the leaf species more accurately. In future, more exploration of fast and robust CNNs with multiple deep layers would support real-time leaf detection using smartphones.

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