Multipath Deep Shallow Convolutional Networks for Large Scale Plant Species Identification in Wild Image

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***Abstract*—One out of five plants are threatened as evident from the IUCN Red List data. Such high rates of loss in plant species triggered to protect and conserve biodiversity. It needs extremely high identification skills obtained via intensive training and experience, even for experienced botanists it is sometimes impossible to provide a definite identification based on a single image. Automatic identification of plant species in natural scene images is one of the important however challenging research problem with various applications in the field of agriculture and botany. Recently, state-of-the-art Deep Convolutional Neural Networks have been applied to classify different species of plants however, they still suffer due to the complexity of the plant images. In this paper, we present multi-path multi deep convolutional network for the identification of plant species which feeds different versions of plant images, thus resultant model has better image presentation than traditional CNN. Comprehensive experimental evaluation on benchmark plant datasets showed that without using any pre-trained models, our proposed shallow network demonstrate very competitive performance for plant species identification. The experimental results proved that the multi-path multi CNN are highly effective for learning discriminative features.**

***Index Terms*—Plant identification, Plant species identification, Shallow network, Ensemble Learning**

I. Introduction

Plants are one of the major backbones to support not just human life, but almost all life on Earth. Current estimates of flowering plant species are approximately 420,000. However, 20% of plants on Earth are vulnerable to critically endangered according to the International Union for Conservation Nature (ICUN) Red List data. Agriculture scientist analyze plants to characterize into different species, however, categorizing plants into different classless based on visual appearance is challenging and requires expertise, thus almost impossible to identity for common public [5], [6]. Given an average of 20,000 word vocabulary of native English speaker, even teaching and learning the "taxon vocabulary" of plant is a long-term endeavor. Thus, taxonomic knowledge of plant species and their identification skills are restricted, thus, limited to number of persons today. Taxonomists are looking for efficient methods to meet identification requirements.

One of the major advantage of plant species identification is to reduce the labour and weeds spray cost by identifying and targeting weeds in field crop. Thus, improving the identification of weed in field crop has enormous economic impact in the field of agriculture. In Australian only, farmers spend more than $1.5 billion on weed control each year. However, the categorization of plant species is challenging due to complex nature of this problem i.e. high similarity between different species, large number of species, lack of expertise and annotated data. For example, there are several weeds that quite similar to field crops making it difficult to identify as shown in figure 1. Thus, automated identification of different plant species has an important implications.

Fig. 1: **Similarity between leafs of wheat and wild oats**

Image-based efficient identification methods are considered a promising approach for species identification and remains a significant obstacle towards commercial application. With the advancement of handheld devices, the ubiquity of smartphones allows us to capture the picture of different plant species and share our observations. Ideally, we can capture a picture of a plant with camera and can use it to identify species of a plant through an installed plant identification recognition application. This will help not only general public but also expert to identify the species of plant efficiently. Therefore, it is not surprising that large numbers of research studies are devoted to automate the plant species identification process. For examples, Flower101 [15] PlntNet [8] and iNaturalist [20] show the great potential of crowd-sourcing vast amounts of image data and LifeCLEF [9] is one the foremost visual image retrieval campaigns, is hosting a plant identification challenge since 2011. The LifeCLEF2019 challenge present three data-oriented challenges related to the identification and prediction of biodiversity such as bird sounds identification,

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image-based plant identification, and location-based species prediction challenge based on spatial occurrence data and environmental tensors. The interest of plant species identification will further grow in the foreseeable future due to the significant development of handheld devices cosnsit of myriad precise sensors.

To automate the identification and prediction of biodiversity, recently large numbers of research studies are devoted using deep learning that showed promising results. This paper presents a pathway for plant species identification using multi-path multi deep convolotional neural network. We perform multi-level representation through hierarchical combination of CNN features from lower-level to higher-level abstraction that results in useful visual features directly from the raw images of plant leafs. In order to validate the robustness of proposed network, we extensively evaluated on Leaf Snap and MalayaKew datasets. The key contributions of this work are

- We present multi-path multi deep convolotional neural network leveraging different kernel size that does not rely on prior learnt knowledge and showed better performance than its counter networks from both computational and accuracy perspective.
- We deployed various architectures of traditional CNN using fine-tuned transfer learning for plant species identification and compare the performance with our proposed CNN.
- We design a novel network, which feeds different versions of plant images into different CNN to learn more comprehensive features, thus resultant model has better image presentation than traditional CNN.
- Results are evaluated on two benchmark datasets and compared with state of the art method that shows considerable improvement in classification performance in comparison to not only heavy network but also with transfer learning methods.

Rest of the paper is organized as follows: Section 2 summarizes the closely related work of plant species identification using deep learning and fusion based. Section 3 describes the proposed shallow network based on multi-resolution CNN. Section 4 illustrates the experimental framework and evaluation metrics Finally, section 7 depicts the conclusion of the study.

II. Related Work

The identification and classification of plants species is an arduous task. Plant species are usually identified by morphological characteristics of leaves because leaves of the plants are the only abundant and easily available entity. By using deep and machine learning algorithms different researchers addresses their work for plant identification. Recently, many researchers focuses on the problem of identifying different diseases using deep learning and they got excellent rate for classification. Sabarinathan et al. [16] presented classification of medicinal leaves by using LeafSnap dataset. They have randomly divide the leaves from each class for training and testing subsets. 70% of the data was used for training and 30% for the testing of each leaf class. In pre-processing, leaf images were rotated to different directions and then cropped low resolution pixels for noise reduction. The shape information was extracted from the gray-scale images using edge detection. The shape features were passed to SVM for classification. By deploying CNN architecture, they have achieved 98% accuracy.

Hu et al. [7] conducted experiments on MalayaKew and LeafSnap dataset using a multi-stream convolutional neural network. An input image was down sampled to multiple low resolution images and fed to MSF-CNN for extracting discriminative features. Fusion of features between two different scales was done by a concatenation operation. Fused features were then again passed to the MSF-CNN that learns discriminative features information and aggregates the final feature for the prediction of input plant specie. In their experiments on LeafSnap, field set was randomly divided into two parts: half for training and half for testing. While in MalayaKew the three subsets MK-D1, MK-D2 and MK-D3 were partitioned into training images and testing images. 2,288 training and 528 testing images were used for MK-D1 while 34,672 training and 8800 testing samples were used for MK-D2. Mk-D3 subset is the mixture of Mk-D1 and MK-D2. They achieved 85.28% accuracy on LeafSnap dataset, 99.05% on MalayaKew-D1 and 99.82% on MalayaKew-D2 whereas 97.35% on Mk-D3 dataset respectively.

Beikmohammadi and Faez [2] used pre-trained deep CNN MobileNet for leaf classification using transfer learning techniques on two benchmark datasets, i.e. Flavia and LeafSnap. They achieved 99.6% and 90.54% accuracy on Flavia and LeafSnap datasets respectively. Pawara et al. [14] employed their comparative study on few classical feature descriptors using three datasets; AgrilPlant, LeafSnap and Folio. They split the datasets in 80% and 20% for training and test set. They combined HOG feature descriptors with KNN, and HOG-BOW with SVM and MLP classifiers and then compared them with AlexNet and GoogleNet. Using deep CNN they trained from scratch and fine-tune versions. Fine-tune versions showed best classification performance comparatively. By using AlexNet, Folio dataset achieved highest accuracy of 97.67% among three datasets while on GoogleNet AgrilPlant achieved 98.33% highest accuracy. Bodhwani et al. [3] proposed their work on LeafSnap dataset using pre-trained deep CNN ResNet50. They proposed their deep CNN methodology to learn discriminative characteristics for plant categories from leaf images and achieved 93.09% accuracy with an error rate of 24.7% on LeafSnap dataset. Choudhury et al. [4] automatic leaf recognition performed different data augmentation techniques such as translation, scale, rotation and reflection and used five different modules to evaluate the shape of leaf contours on LeafSnap dataset. For the classification of close matches to the known class they further worked on RSM (random subspace method) classifier for developing high dimensionality feature space. By using test samples their proposed method achieved 80.8% accuracy. Pankaja and Suma [13] worked on automatic recognition of

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plants species based on combining CUR decomposition and WKSR (weighted kernel sparse representation). Four different datasets, i.e., Flavia, Swedish, Original mango leaf images and LeafSnap were used in their proposed and existing methods. They evaluated experiments by comparing results of datasets with existing techniques like RF, SVM and KNN. The average classification accuracy of their proposed system is 97.45% on the LeafSnap dataset. Kalyoncu and Toygar [10] proposed their work on geometric features of leaf by using LeafSnap dataset for plant leaf recognition. In their study, an image is segmented for noise reduction and detects smaller changes along leaf blade by using contour smoothing operator. Geometric features like shape, similarity, and leaf area and margin statistics of the leaves were extracted. Extracted features were classified by using MDM (Multi-scale distance matrix) and LDC (Linear discriminant classifier) classifiers and achieved 71.6% accuracy. Thomas et al. [18] developed plant identification and recommendation system pn LeafSnap dataset using Inception-v3 through convolutional neural network. Their system achieved approximately 70% accuracy on the plant images. Lee et al. [11] conducted experiments on MalayaKew dataset by splitting it into two subsets D1 and D2. D1 extracts the shape features while, venation divergence and its variation were extracted using D2. Furthermore, extracted features were passed to the De-convolutional network for characterization of leaf images and achieved average accuracy of 99.4%. Wang et al. [22] presented Siamese network to solve a leaf classification problem with a small input size using LeafSnap dataset. Feature extraction of the images is done by a two-way convolutional neural network. The extracted features of the leaves are classified by the k-nearest neighbor (KNN) classifier. By classifying leaves in the metric space they achieved 95.75% accuracy. Barre et al. [1] developed a CNN-based Leaf-Net plant identification system to learn discriminative features from leaf images for species identification of plants. They used LeafSnap dataset for the Leaf-Net identification system and attained 86.3% accuracy using LeafSnap dataset. Too et al. [19] proposed a deep pruned nets for efficient image-based plants disease classification by working on LeafSnap dataset. They pruned DenseNet with Self-Normalization Neural Network (SNN) approach that learns 2x faster compared to the initial DenseNet architecture and achieved 86.64% accuracy performance. Lee et al. [12] experimented on MalayaKew dataset using convolution neural network and whole image was taken as input, in which foreground pixels of each leaf image were extracted using HSV color space for obtaining the venation patterns. They used two deep learning CNN i.e. CNN (convolutional neural network) and DN (Deconvolutional neural network). Pre-trained CNN was also employed to achieve plant identification while DN was utilized to detect how CNN works for identification of different plant species. By using both CNN they achieved 99.6% overall accuracy. Song et al. [17] developed a highly discriminative network and presented attention branch based convolutional neural network (ABCNN) distinguishes between the leaf features and achieved 91.43% accuracy on LeafSnap dataset. Above discussion showed that in order to automate the identification and prediction of biodiversity, recently large numbers of deep learning methods have been applied that showed promising results. Better features representation can help to improve the performance, thus in this work, we proposed to use ensemble shallow network.

III. Multi-path Multi Convolutional Neural Networks

Identification and naming of living plants is almost impossible for not only general public but also challenging task for professionals and naturalists. For experienced botanists it is sometimes difficult to provide a definite identification based on a single image, as botanists rely on other additional knowledge such as several organs at the same time, considering more than one viewing angle and taking a closer look at specific organs, combining different perspectives and organs in an automated approach is supposed to increase the accuracy of determination task. Bridging this gap is a key challenge towards enabling an effective biodiversity pant identification systems. Recently, deep learning showed promising results for the classification of plant species. Recently, state-of-the-art Deep Convolutional Neural Networks are fine-tuned to classify different species of plants however, it still suffer due to the complexity of the plant images. In order to improve the performance of automated plant species identification, we presented multi-path multi convolutional neural network via optimizing the network parameter. We have improved the feature learning and presented shallow ensemble network.

Multi-path Multi-CNN evaluates experiments on both datasets with five depth blocks of multiple CNN. Our deep feature learning architecture consists of multiple CNN blocks, max-pooling layers, flatten layer and a Softmax layer for the classification of input plant species. Each block consists of three-convolution, one batch normalization, one max-pooling layer and one dense layer making five depth CBR's. Networks are concaticated at different levels as shown in figure 2. The features extracted from one block are concatenated with the feature maps of second block using a concatenation layer. Overall concatenation results of multi-CNN are aggregated to obtain the final features to learn discriminative features for the input. Finally, the Softmax layer classifies the input plant species. Proposed Multi-CNN uses 5x5, 3×3 and then 1x1 filter size of convolution in all blocks, and also the max-pooling layer uses 3×3 filter size for the architecture. The proposed Multipath-multi-CNN architecture is shown in Figure 2. The training graph are also illustrated in the Figure 3. In order to compare the performance of multi-path multi network, we have used pre-learnt model using different network like (AlexNet, GoogleNet, VGGNet, ResNet). For both datasets, we use 80% of data as training, 10% as validation and 10% as testing. Each network is trained with number of solver and other parametric values updates corresponding to the solver and selected SGDM (stochastic gradient descent) solver as an optimal parameter for our subject studies. Momentum, L2 regularization, epochs, mini batch size, initial learn rate, and

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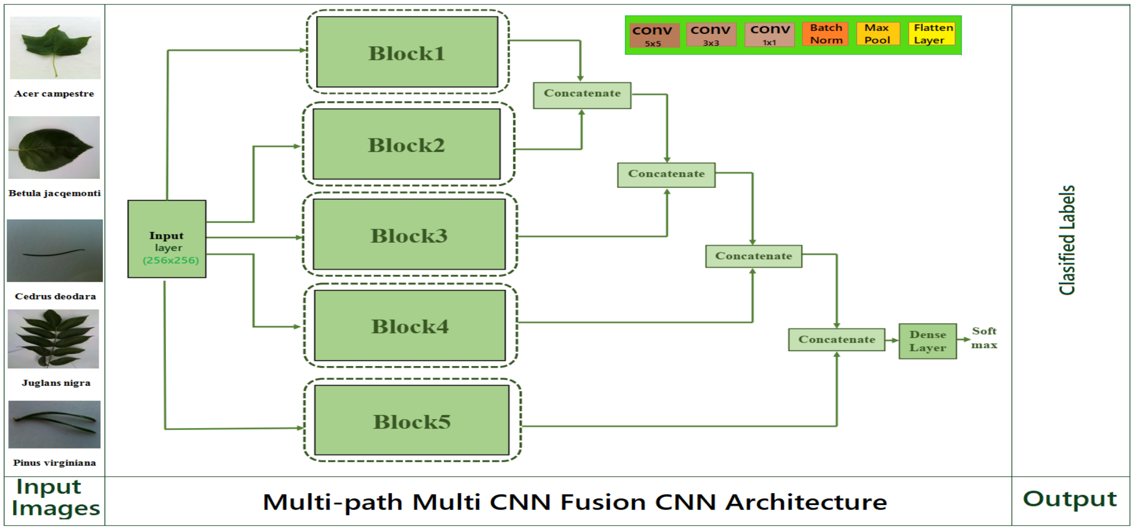

Fig. 2: **Proposed Framework of Multi-path Multi-CNN Fusion Network for Plant Species Identification**

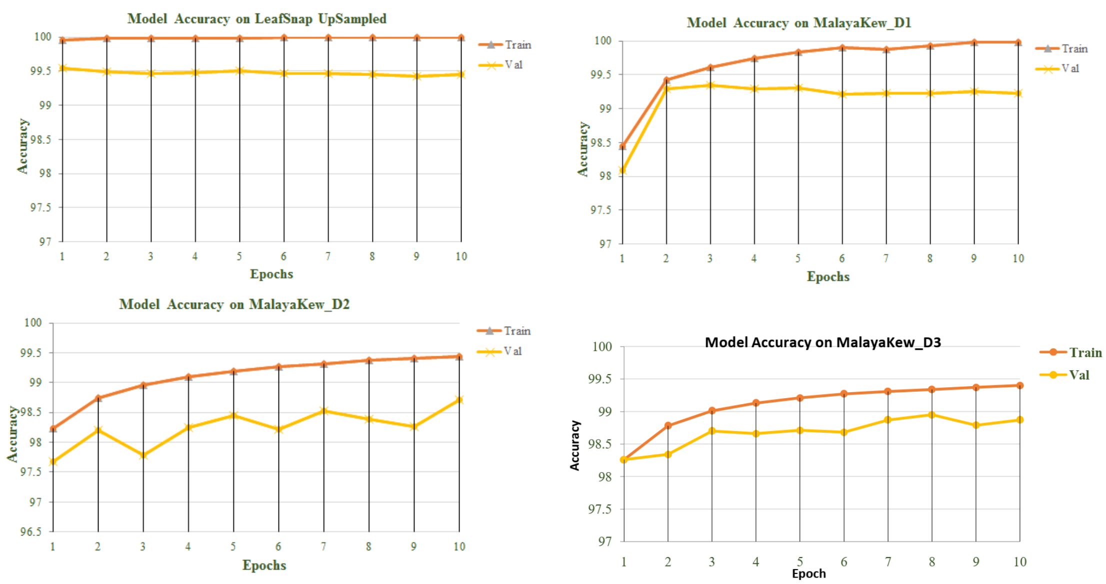

Fig. 3: Training of Proposed Multi-path Multi-CNN fusion based Model on Leaf images of LeafSnap and Malayakew datasets

validation frequency are also checked. The selected optimal values corresponding to these parameters are 0.9, 0.00054, 10, 10, 0.0001 and 300.

IV. Experiment

In this section, series of experiments have been performed to analyse the performance of proposed multi-path multi CNN network on two benchmark dataset and compared the performance with state of the art methods.

A. Datasets

In this study, we have used two common benchmark datasets. Leaf Snap dataset consists of leaf images of 185 plant species taken from North Eastern United States [21]. These images were obtained from two sources and followed by automatically generated segmentation data. First source was Smithsonian collection that comprises 23,147 lab images. Second source was mobile devices (mostly iPhones) encompasses 7719 field images. This image directory varies in sharpness, shadow, noise and illumination patterns etc. Some species samples from LeafSnap dataset are shown in Figure 4. This is an imbalance dataset because each class has different number of samples. Therefore we performed up-sampling to make the dataset balanced.

The dataset statistics are shown in Table II. MalayaKew dataset was collected at Royal Botanic garden, Kew, England for the employment of experiments [7], [11]. MalayaKew comprising of 44 species classes of plant leaves in which there are 2,288 training images and 528 testing images were used.

TABLE I: **Layers detail for proposed network for MalayaKew Dataset**

Layer type	Output Shape	Number of Parameters
InputLayer	(None, 256, 256, 3)	0
Conv2D-1	(None, 126, 126, 3)	228
Conv2D-2	(None, 62, 62, 6)	168
Conv2D-3	(None, 31, 31, 9)	63
BatchNormaization-1	(None, 31, 31, 9)	36
MaxPooling2D-1	(None, 10, 10, 9)	0
Flatten-1	(None, 900)	0
Conv2D-4	(None, 126, 126, 12)	912
Conv2D-5	(None, 62, 62, 13)	1635
Conv2D-6	(None, 31, 31, 18)	288
BatchNormaization-2	(None, 31, 31, 18)	72
MaxPooling2D-2	(None, 10, 10, 18)	0
Flatten-2	(None, 1800)	0
Conv2D-7	(None, 126, 126, 21)	1596
Conv2D-8	(None, 62, 62, 24)	4560
Conv2D-9	(None, 31, 31, 27)	675
BatchNormaization-3	(None, 31, 31, 27)	108
MaxPooling2D-3	(None, 10, 10, 27)	0
Flatten-3	(None, 2700)	0
Conv2D-10	(None,126, 126, 30)	2280
Conv2D-11	(None, 62, 62, 33)	8943
Conv2D-12	(None, 31, 31, 36)	1224
BatchNormaization-4	(None, 31, 31, 36)	144
MaxPooling2D-4	(None, 10, 10, 36)	0
Flatten-4	(None, 3600)	0
Concatenate-1	(None, 2700)	0
Concatenate-2	(None, 5400)	0
Concatenate-3	(None, 90000)	0
Dense	(None, 44)	396044

Total params: 418,976
Trainable params: 418,796
Non-trainable params: 180

Fig. 4: **Some species samples from LeafSnap dataset**

This dataset is very challenging as leaves from different classes of species have homogeneous appearance. In this each leaf image is taken as a whole in which leaf image, foreground pixels are extracted by using HSV color space. There are two (2) folders associated with this dataset i.e. D1 dataset and Dataset ground truth. D1 has segmented leaf images with size of 256×256 pixels and the number of training and testing images is 2288 and 528 respectively. Whereas ground truth

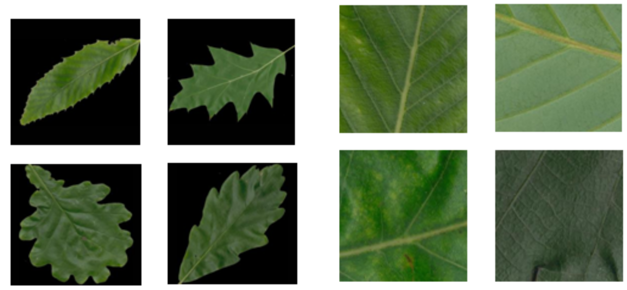

Fig. 5: Leaf images of different classes of Malayakew dataset

TABLE II: **Statistics of Datasets**

Statistics	**LeafSnap**	**MalayaKew**
Species	184	44
Images	30,866	2816
Samples per Class	183	test = 12, train = 52
classes	Imbalanced	Balanced
improve accuracy	up sampling	data augmentation
Background	Plain	Plain
Organs	Leaves	Leaves
Acquisition	Scan + photo	Scan
Life Form	Trees	Trees

consist of cropped image patches of leaf with size 256×256 pixels with 34672 and 8800 number of training and testing images. Figure 5 illustrates the original images and their patches of Malayakew dataset.

B. Results and Discussion

In this section, we analyzed and compare the performance of our proposed system with the the state-of-the-art work. We performed 10-fold cross validation. We first evaluated the proposed multi-path multi network on both datasets and compared the performance with state of the art work. We further investigated the performance of transfer learning to classify plant species. We increase the feature selection power by concatenating the features at different level, thus resultant features are best representative features compared to those of transfer learning and traditional CNN. The training graph are also illustrated in the Figure 3 and results are shown in Table III. Results showed that we have achieved significant gain in classification performance in comparison to state of the art methods. For example, (proposed/Hu et.al.) 99.38/85.28%, 99.22/99.05%, 99.84/99.82% and 98.87/97.35 on LeafSnap, MK-D1 (original), Mk-D2 (patches) and MK-D3 dataset. Our system outperforms on xyz and achieved abc% as compared to the bcd accuracy. Proposed system helps in automated identification of plant species with the improvement of results.

To further compare the performance, with transfer learning based methods, we have used the learnt weight on plain convolutional network and applied fine-tuned approach of six architectures of pre-trained CNN on both datasets. Table III summarizes the results on GoogleNet, ResNet50, ResNet101, VGG16 and VGG19. Furthermore, we have noticed that GoogLeNet showed better classification performance in com-

TABLE III: **Comparisons of Fine-tune results obtained using different deep CNN architectures and Proposed scratched MultiPath-Multi CNN fusion**

Datasets	Models	Test Accuracy(%)	Validation Accuracy(%)	Train Accuracy (%)
LeafSnap Original	AlexNet	89.05	89.02	98.2
	GoogleNet	88.65	89.39	98.23
	VGG16	**90.25**	91.67	98.65
	VGG19	89.59	89.77	99.01
	ResNet50	88.52	89.27	99.22
	ResNet101	88.25	90.66	99.45
	Proposed	**99.23**	99.48	**99.91**
LeafSnap UpSampled	AlexNet	98.37	98.41	99.77
	GoogleNet	**98.73**	98.98	99.79
	VGG16	97.43	98.05	99. 80
	VGG19	97.89	98.71	99.87
	ResNet50	97.80	97.91	99.79
	ResNet101	98.04	98.33	99.56
	Proposed	**99.38**	**99.41**	**99.97**
MalayaKew D1	AlexNet	90.53	92.86	98.45
	GoogleNet	**94.70**	94.81	98.74
	VGG16	93.18	95.45	99.52
	VGG19	93.18	94.16	99.28
	ResNet50	92.42	95.13	99.43
	ResNet101	94.70	94.84	99.48
	Proposed	99.22	**99.23**	**99.98**
MalayaKew D2	AlexNet	97.54	97.52	99.22
	GoogleNet	96.60	97.18	98.29
	VGG16	93.92	93.89	98.07
	VGG19	97.11	97.06	99.67
	ResNet50	**98.42**	98.19	99.76
	ResNet101	98.23	98.51	99.89
	Proposed	**98.71**	**98.24**	**99.1**
MalayaKew D3	AlexNet	95.32	95.48	98.22
	GoogleNet	97.08	96.60	99.01
	VGG16	95.85	95.35	97.83
	VGG19	95.06	95.18	99.36
	ResNet50	**97.60**	97.60	99.23
	ResNet101	97.58	97.29	99.63
	Proposed	**98.87**	**98.88**	**99.40**

parison to other on LeafSnap dataset whereas ResNet50 based outperform on MalayaKew D1 (original), D2 (patches) and Combined datasets. The overall results of different CNN architectures are shown in Table III. Result showed that our shallow network showed considerably better performance in comparison to pre-trained model. Comparing the relative performance of these networks, our shallow network showed significantly better performance and have less number of parameters. Thus, we conclude that although transfer learning has additional advantage of already learnt features, however, network are not suitable for such dataset. In addition, it has large number of parameters. Thus, simpler networks showed better performance and is computationally efficient networks.

We directly compare the performance of our proposed multi-path multi CNN fusion with the state of the art techniques on MalayaKew and LeafSnap datasets in table. IV.

V. Conclusion

Recently, state-of-the-art Deep Convolutional Neural Networks are fine-tuned to classify different species of plants however, it still suffer due to the complexity of the plant images. In this paper, we present developed shallow deep convolutional network for the identification of plant species which feeds different versions of plant images, thus resultant model has better image presentation than traditional CNN. Our shallow network showed considerably better performance as compared to pretrained deep learning models of AlexNet, GoogLeNet, and VGGNet. In addition, number of parameters are much smaller than pre-traind network. Comprehensive experimental evaluation on benchmark dataset showed that proposed network outperform state of the art work with overall accuracy of 99.38% and 99.22% for Leafsnap and MalayaKew datasets respectively. We found that combining multiple image perspectives depicting the same plant increases the reliability of identifying its species. We notice that accuracy is affected due to common occurrence of similar leaf contours, especially in closely related species, which could be improved including additional leaf features.

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TABLE IV: **Comparison with the state of the art techniques**

Reference	DataSet	Features	Model	Accuracy (%)
Sabarinathan et al [16]	LeafSnap	CNN based Visual	CNN	95.61
Bodhwani et al. [3]	LeafSnap	CNN based Visual	ResNet50	93.09
Song et al. [17]	LeafSnap	CNN based Visual	ABCNN	91.43
Beikmohammadi et al. [2]	LeafSnap	CNN based Visual	MobileNet	90.54
Kalyoncu and Toygar [10]	LeafSnap	Geometric and Statistical	MDM, LDC	71.6
Lee et al. [11]	MalayaKew D1 MalayaKew D2	CNN based Visual	SVM (linear) MLP	98.1
Hu et al. [7]	LeafSnap MalayaKew D1 MalayaKew D2 MalayaKew D3	CNN based Visual	MSF-CNN	85.28 99.05 99.82 97.35
Proposed Ensemble Network	LeafSnap MalayaKew D1 MalayaKew D2 MalayaKew D3	CNN based Visual	MPF-CNN	99.38 99.22 98.71 98.87

MSF-CNN: Multi Scale Fusion Convolutional Neural Network
SVM: Support Vector Machine

MLP: Multi-layer Perceptron item **MPF-CNN**: Multi Path Fusion Convolution Neural Network

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