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IDENTIFICATION OF PLANT SPECIES THROUGH LEAF VEIN MORPHOMETRIC AND DEEP LEARNING

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Abstract

Taxonomy language is challenging to comprehend and automated knowledge is required to identify the plant species. The study focused on developing an improved deep neural network: Residual Neural Network-ResNet & and Densely Connected Convolution Network (DenseNet) for the plant identification with plant leaf vein architecture. There was a total of 44 species. Each species had 64 images, each of which was further divided into 52 images for the training data and 12 images for the test data. The Canny edge detection method was deployed to detect the vein architecture of the leaves. For ResNet and DenseNet, the 224 x 224 binary image was used. The size of the feature maps in 4 dense blocks was: 56 x 56, 28 x 28, 14 x 14, and 7 x 7, respectively. MalayaKew (MK) data set was used for the experiment. There was a total of 44 classes and images were divided into the training set and the test set. The training set contained 2288 images, with each class having 52 images. Test class contained 528 images, with each class having 12 images. After preprocessing these images, they were fed to various networks of ResNet and DenseNet. Two algorithms, Stochastic gradient descent (SGD) and Adam optimization, were used in each network. Through SGD, the model ResNet, had 26, 34, 50, 101, and 152 layers. The best accuracy achieved was 89.24% using 50 layers. DenseNet had 121, 169, and 201 layers. The best accuracy achieved was 94.20% using 169 layers. In Adam optimizer, the ResNet model had 26, 34, 50, 101, and 152 layers. The best accuracy achieved was 89.50% using 101 layers. DenseNet had 121, 169, and 201 layers. The best accuracy achieved was 95.72% using 169 layers. Overall, the best performance was achieved using Adam optimizer using the DenseNet model with 169 layers and came out to be 95.72%. This also surpassed the accuracy that was achieved using D-leaf architecture. The proposed deep learning (DL) methods were very accurate in identifying plants.

Key words: Residual neural network-resnet; Densely connected convolution network-densenet; Plant identification.

Introduction

Conservation of plant species requires plant identifications. There is a strong need to develop a rapid and robust identification system to identify the plant species that help monitor the conservation and sustainability of the ecology. The rate at which plant species are becoming extinct has a severe threat to the biodiversity of this planet. Conservation of plant species is getting inevitable and requires plant identification skills that are acquired over a while. Furthermore, the taxonomy language is challenging to comprehend. The study focused on developing an improved deep learning model for plant identification using plant leaf vein architecture. The organic life on Earth is diverse and huge (Darwin & Bynum, 2009). In biological terms, a taxon is a formal class of a living organism with its name and description. Assigning foreign species to an already defined taxon or class is called identification (Remagnino *et al.*, 2016). This study deals with plant identification. An unknown plant was assigned to a known taxon based on its affinity with other species by resembling different plant characters to assign it to a specific species name finally. The plant characteristics that were used to identify could be qualitative and quantitative. The quantitative characteristics or features can be measured or counted like the plant's height, the flower's width, the number of leaflets in the compound leaves, etc. Whereas, qualitative characteristics or features include the shape of leaves, the color of the flower, the position of the ovary, etc. There may be many plants that may belong to the same species but can have a different name. The intra-species plants can have many common characteristics. Each plant looks different. Therefore, there is a need to generalize the characteristics to assign any plant organism to the species (Govaerts, 2001; Mora *et al.*, 2011). Plant identification is a very complicated and complex task for a human being, even having good knowledge about the domains. Plant species identification is essential to monitor the ecology and conserve and maintain biodiversity (Farnsworth *et al.*, 2013). There are many avenues such as analyzing biodiversity in a specific area, checking the population of the species on the verge of extinction, evaluating the impact of changing climate conditions, environmental controlled services, and controlling the weed actions. These actions severely depend upon the correct and reliable plant identification (Elphick *et al.*, 2008). As biodiversity is impacting continuously (Ceballos *et al.,* 2015), the need for plant species identification has been increased (Hopkins & Freckleton, 2002). Considering all the limitations, taxonomists must be too demanding to move efficient and convenient methods for plant identification.

Gaston & O'Neil (2004) have suggested that digital image processing and artificial intelligence (AI) will make plant identification autonomies and tangible with the help of digital images. The research in the avenue of image processing and machine learning (ML) has brought a lot of attention in the area of plant identification. Much research has been conducted where different image processing methodologies have been used to extract the features. These features are used to train ML models that can classify the plant species (Kumar *et al.*, 2012; Joly *et al.*, 2016;

Wäldchen & Mäder, 2018; Cope *et al*., 2012). In most recent times, the dawn of deep learning (DL) has changed the course of model learning in both supervised and unsupervised mechanisms. Artificial Neural Networks (ANN) such as Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN) gave a noticeable breakthrough in the field of machine learning. These deep learning (DL) models were found remarkably well in object detection and classification. Recent studies that have used these DL models achieved remarkable improvements in identifying the plants (Pawara *et al*., 2017a; Barré *et al*., 2017; Pawara *et al*., 2017a; Liu & Kan, 2016; Xie *et al*., 2017). Traditionally, a key is used to identify the species of unknown plants. A key is a set of rules formulated to have the next statements, and by following the correct statements, one can find the correct name of the unknown plant. This key plays an important part in the flora for correctly identifying the families, genus, and species. The keys that are used in the modern age are constructed in the form of paired choices called dichotomous keys (Cope *et al.,* 2012). Each choice is divided into two parts and each part is a statement. Also, there are cases in which there are multiple choices, and some could be true or false. Initial efforts in plant identification were focused on automating these keys. Artemov (2010) and Lobanov (2007) proposed a solution of using multiple entry points rather than the single point entry points with the help of a computer program. The goal was to identify the plant species even in the absence of some of its organs. The results of the program were found accurate. They provided a good description of the features. However, some of the disadvantages were also reported in the form of missing pictures of the qualitative features. Wei Tan *et al.*, (2018) investigated the problem of plant species identification using vein morphometry. A deep learning CNN model called D-leaf was proposed. It was an alternation of AlexNet. A similar problem is addressed in (Huixian, 2020), where plant identification is performed using leaves' shape and texture features. K nearest neighbors, support vector machines, and neural networks are used to classify plants. Some other deep learning applications for various plant-related tasks include plant disease detection and identification of plant leaf stress. A comprehensive review of both these tasks is presented in (Agaraju & Chawla, 2020; Noon *et al.*, 2020).

Materials and Methods

This section presents an overview of the proposed methodology for plant species identification. The deep residual networks (DRN), dense convolutional network (DCN) architectures, and plant leaf vein architecture (LVA) were used for plant identification. Previously, ResNets have been used for plant identification by using images of the whole plant. The current research investigated plant identification via plant leaves using deep neural networks. Plant leaves can be effectively used for plant identification as they are readily available and remain consistent throughout the year. Furthermore, the vein architecture of the leaves was used as a critical feature for training and classification. The flow diagram of our proposed model and details of different deep networks used for classification are shown in (Figs 1 and 2), respectively.

Datasets: The data was obtained from the University of Malaya, Kuala Lumpur, Malaysia. This data set is commonly known as MalayaKew (MK). The locations were from the Varsity Lake (VL), main library (ML), and Dewan Tunku Canselor (DTC) hall. The images were the leaves of tropical trees that were readily available in the region. There were a total of 44 species. Each species had 64 images, each of which was further divided into 52 images for the training data and 12 images for the test data. The images were collected with the Nikon D750 model of the DSLR camera. The background of the images was black. The original images that were collected had the 6016 x 4016 resolution.

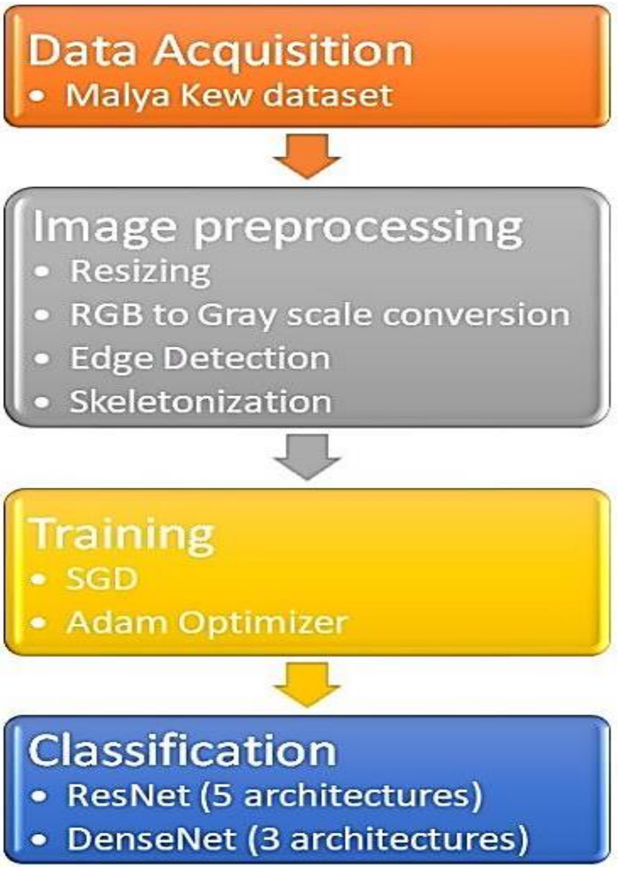

Fig. 1. Flow Diagram of Proposed Method.

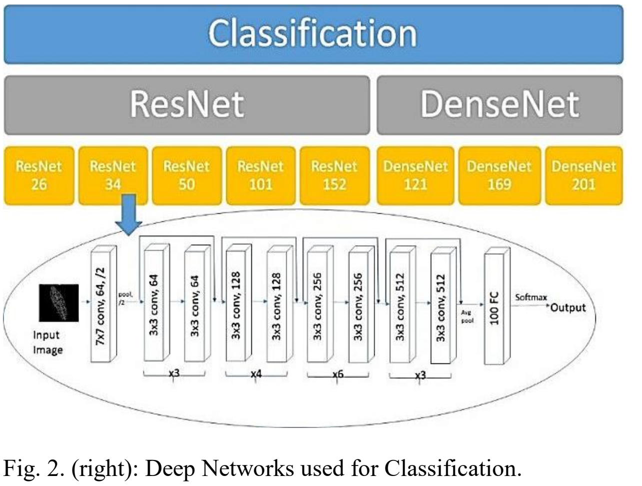

Fig. 2. (right): Deep Networks used for Classification.
Key: conv (convolution layer), fc (fully connected layer), SGD (Stochastic gradient decent)

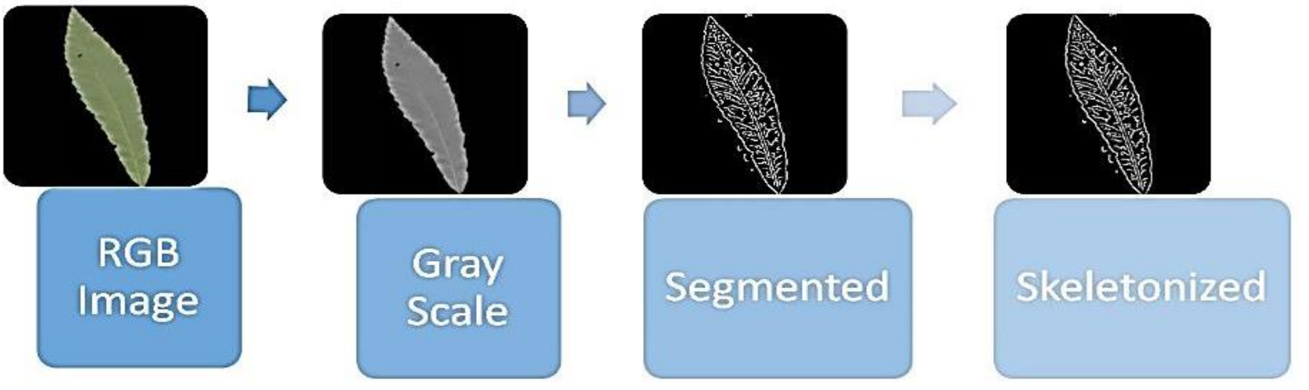

Fig. 3. Image Preprocessing Steps.

Preprocessing: Raw images were not suitable for training the network. Therefore, the resolution of the images was converted to 224 x 224. The Canny edge detection method is used to detect the vein architecture of the leaves. First, the images were converted to grayscale images from RGB images; then, canny edge detection was applied. Finally, the images were skeletonized to make sure of a clean vein architecture. An example of all these preprocessing steps is illustrated in (Fig. 3).

Network architectures: The following network architectures were used for plant identification.

Deep residual network (DRN)- Resnet: The ConvNet Convolutional neural networks (CNN) have drastically improved accuracy compared to other machine learning (ML) algorithms. To enhance its accuracy, more layers were stacked with the notion that a deeper network can extract more enriched features. After a certain number of layers, the issue of vanishing gradient appears that explodes the convergence from the start of the training. As the network goes deep, the accuracy starts to saturate and then starts dropping. Overfitting is not the reason for this degradation, but adding more layers can cause higher training errors. To counter this problem, He *et al*., (2016) proposed a solution by adding layers that have residual mapping. These networks are known as Deep Residual Neural Networks (DRNN). These networks use VGG nets, a baseline model, which add a residual block for each convolutional layer. The convolutional layer mostly uses 3 x 3 filter. Later, it down-samples the convolutional layers by keeping its stride to 2. At the end of the network, the global average pooling layer is applied with a Softmax layer that is equal to the number of classes. To make its residual counterpart, we added a skip connection between two consecutive convolutional blocks.

In this study, a 224 x 224 binary image was used. First, the input image was convolved with 7 x 7 filter, and an average pooling of 2 x 2 was applied. Then, for different network depths, there were different residual paths and architectures. These are mentioned in (Table 1). After each convolutional layer, batch normalization was applied. Another architectural change in the network named Bottleneck architecture is only used for ResNet26 and has already been used for plant identification on a different dataset. This model used less training time. The basic building block was modified to bottleneck the building block. For each residual block, rather than stacking up two layers, we used three layers with 1 x1, 3x3, and 1 x 1 convolution. The initial 1 x 1 convolution was responsible for reducing dimensions.

Densely connected convolutional networks (DenseNet): Huang *et al*., (2017) introduced DenseNet, a densely connected convolutional network, which is an improvement on ResNet. Unlike ResNet's building block, where the input of one layer is bypassed and concatenated with the output of the next layer, DenseNet has dense blocks. In each layer of the dense block, the feature maps of all preceding layers are used as input, and their *feature maps* are fed as input to all subsequent layers of the block. After concatenation, each block has a different output; therefore, a Pooling layer is used after each block to keep the size consistent for concatenation. Before this pooling layer, there were layers of batch normalization, i.e., rectified linear unit (ReLU) and convolution layer. This network ensures the maximum flow of information between the layers within a block as all layers are connected. As the number of connections in DenseNet is way more than a traditional convolution neural network, these networks are termed Densely Connected Convolutional Networks.

The data used in our experiments had a 224 x 224 image size; therefore, we used 4 dense blocks. This choice was made because the same number of dense blocks on the ImageNet data set with similar image dimensions have successfully been used. The initial layer had around 2000 feature maps were obtained by applying 7 x 7 convolutions with stride 2. Feature map" size in all the other layers can be controlled by setting k. Further, for convolution layers with size 3 x 3, zero paddings were applied to keep fixed feature map size. In the transition layer, we used 1 x1 convolution followed by 2 x 2 average pooling between two dense blocks. The global average was applied at the very end of the dense block. The sizes of the feature maps in 4 dense blocks were: 56 x 56, 28 x 28, 14 x 14, and 7 x 7, respectively. The detail of the networks used is mentioned in (Table 2). The first column in Table 1 and Table 2 specifies the types of layers. Each layer is one of these: conv (convolution layer), pooling layer, transition layer, or dense block. The second column mentions the output size of each layer, and the remaining columns give details of the block of layers for each network architecture, including the size of the convolution filter, number of input channels, and number of such layers. Finally, fc represents the fully connected layer.

Table 1. Network Architecture for ResNet.

Layer name	Output size	26-Layer	34-Layer	50-Layer	101-Layer	125-Layer
Conv1	112x112	7x7, 64, stride 2				
		3x3 max pool, stride 2				
Conv2_x	56x56	$\begin{bmatrix} 1x1 & 64 \\ 3x3 & 64 \\ 1x1 & 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3x3 & 64 \\ 3x3 & 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1x1 & 64 \\ 3x3 & 64 \\ 1x1 & 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1x1 & 64 \\ 3x3 & 64 \\ 1x1 & 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1x1 & 64 \\ 3x3 & 64 \\ 1x1 & 256 \end{bmatrix} \times 3$
Conv3_x	28x28	$\begin{bmatrix} 1x1 & 128 \\ 3x3 & 128 \\ 1x1 & 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3x3 & 128 \\ 3x3 & 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1x1 & 128 \\ 3x3 & 128 \\ 1x1 & 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1x1 & 128 \\ 3x3 & 128 \\ 1x1 & 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1x1 & 128 \\ 3x3 & 128 \\ 1x1 & 512 \end{bmatrix} \times 8$
Conv4_x	14x14	$\begin{bmatrix} 1x1 & 256 \\ 3x3 & 256 \\ 1x1 & 1024 \end{bmatrix} \times 2$	$\begin{bmatrix} 3x3 & 256 \\ 3x3 & 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1x1 & 256 \\ 3x3 & 256 \\ 1x1 & 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1x1 & 256 \\ 3x3 & 256 \\ 1x1 & 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1x1 & 256 \\ 3x3 & 256 \\ 1x1 & 1024 \end{bmatrix} \times 36$
Conv5_x	7x7	$\begin{bmatrix} 1x1 & 512 \\ 3x3 & 512 \\ 1x1 & 2048 \end{bmatrix} \times 2$	$\begin{bmatrix} 3x3 & 512 \\ 3x3 & 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1x1 & 512 \\ 3x3 & 512 \\ 1x1 & 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1x1 & 512 \\ 3x3 & 512 \\ 1x1 & 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1x1 & 512 \\ 3x3 & 512 \\ 1x1 & 2048 \end{bmatrix} \times 3$
	1x1	Average pool, 44-fc, softmax				

Key: conv (convolution layer), fc (fully connected layer)

Table 2. Network architecture for Dense Net.

Layers	Output size	Dense Net-121	Dense Net-169	Dense Net-201
Convolution	112x112	7x7, 64, stride 2		
Pooling	56x56	3x3 max pool, stride 2		
Dense Block (1)	56x56	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 6$
Transition Layer (1)	56x56	1x1 conv		
	28x28	2x2 average pool, stride 2		
Dense Block (2)	28x28	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 12$
Transition Layer (2)	28x28	1x1 conv		
	14x14	2x2 average pool, stride 2		
Dense Block (3)	14x14	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 48$
Transition Layer (3)	14x14	1x1 conv		
	7x7	2x2 average pool, stride 2		
Dense Block (4)	7x7	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1\ conv \\ 3 \times 3\ conv \end{bmatrix} \times 32$
Classification Layer	1x1	7x7 global average pool 44-fc, softmax		

Key: conv (convolution layer), fc (fully connected layer)

Results

All experiments were conducted on Google's free Cloud platform, Colaboratory. It is a free Jupyter notebook environment. It doesn't need any setup. All the library was preinstalled including Keras, TensorFlow, and Pytorch. It provides a free tesla K80 GPU for developing deep learning applications. It gives 12 GB of shared RAM. The implementation has been done in Keras with the TensorFlow backend.

Image preprocessing and skeletonization: The images were preprocessed using MATLAB. They were resized to 224 x 224 resolution. Then these RGB images were converted into grayscale. To obtain the vein architecture of the plant leaves, the Canny edge detection method was used. Then the leave images were skeletonized to get a more refined version of them. We used MalayaKew (MK) dataset for the experiment. There was a total of 44 classes and images were divided into a training set and test set.

Networks- ResNet and DenseNet: The training set contained 2288 images, with each class having 52 images. Test class contained 528 images, with each class having 12 images. After preprocessing these images, they were fed to various networks of ResNet and DenseNet. For ResNet, 26, 34, 50, 101, and 152 layers were used. DenseNet model used 121, 169, and 201 layers. The growth rate used in Dense Net was k=32. The batch size used in these experiments varied from model to model due to computational constraints and was taken as 16, 32, 64, and 128. Furthermore, two optimizers: Stochastic Gradient Descent with Momentum algorithm, decay, and Adam optimizer, were used in the following set of parameters: Decay=0.0001, Momentum = 0.9, and learning rate = 0.01. The classification accuracies of the networks using SGD (stochastic gradient descent) and adam optimizer are mentioned in (Tables 3 and 4**),** respectively. The bar charts of the same are shown in (Figs. 4 and 5).

Table 3. Accuracy using Stochastic Gradient Descent.

Architecture layers	Number of parameters (in millions)	Accuracy	Error
Res Net 26	13.9	76.05%	23.95%
Res Net 34	21.3	81.12%	18.88%
Res Net 50	23.5	89.24%	10.76%
Res Net 101	42.5	83.81%	16.19%
Res Net 152	58.5	85.38%	14.62%
Dense Net 121	6.9	91.01%	8.99%
Dense Net 169	12.5	**94.20%**	**5.8%**
Dense Net 201	18.1	87.23%	12.77%

Table 4. Accuracy using Adam Optimizer.

Architecture layers	Number of parameters (in millions)	Accuracy	Error
Res Net 26	13.9	80.31%	19.69%
Res Net 34	21.3	78.31%	21.69%
Res Net 50	23.5	88.23%	11.77%
Res Net 101	42.5	89.50%	10.5%
Res Net 152	58.5	86.29%	13.71%
Dense Net 121	6.9	92.34%	7.66%
Dense Net 169	12.5	**95.72%**	**4.28%**
Dense Net 201	18.1	89.46%	10.54%

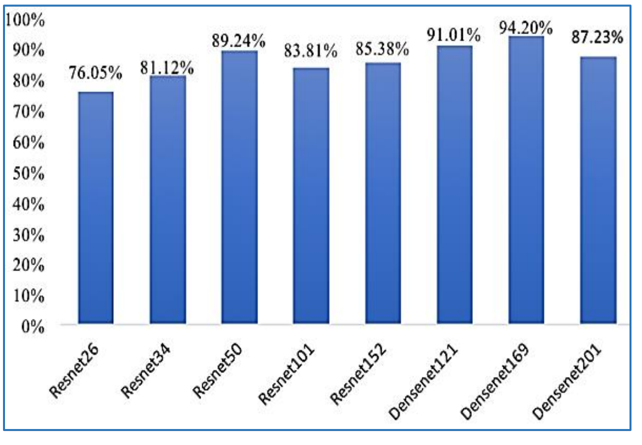

Fig. 4. Accuracy using Stochastic Gradient Descent.

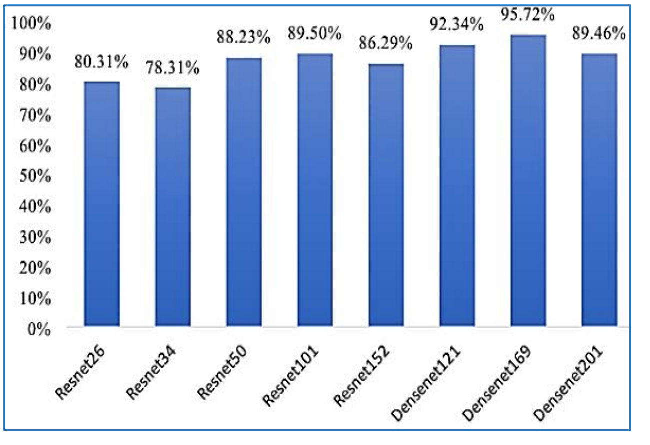

Fig. 5. Accuracy using Adam Optimizer.

Stochastic gradient descent (SGD): The model ResNet had 26, 34, 50, 101, and 152 layers through Stochastic Gradient Descent. The best accuracy achieved was 89.24% using 50 layers. The second-best accuracy achieved was 85.38% using 152 layers. Similarly, the model DenseNet had 121, 169, and 201 layers. The best accuracy achieved was 94.20% using 169 layers and the second-best accuracy was 91.01% using 121 layers. The overall best accuracy achieved using Stochastic Gradient Descent for plant species identification was 94.20%.

Adam optimizer (AO): In Adam optimizer, the ResNet model had 26, 34, 50, 101, and 152 layers. The best accuracy achieved was 89.50% using 101 layers. The second-best accuracy was achieved 88.23% by using 50 layers. Similarly, the model DenseNet had 121, 169, and 201 layers. The best accuracy achieved was 95.72% using 169 layers and the second-best accuracy was 92.34% by using 121 layers. The overall best accuracy achieved using adam optimizer for plant species identification was 95.72%. Overall, the best performance was achieved using the Adam Optimizer using the DenseNet model with 169 layers and came out to be 95.72%. This also surpassed the accuracy that was achieved using D-leaf architecture (Wei Tan *et al*., 2018). The per-class accuracy of the best models from both ResNet and DenseNet by using adam optimizer is given in (Figs. 6 and 7)**,** respectively.

Discussion

Deep learning has powerful capabilities of extracting features of the image data and then classifying it. As they have a deeper network connection, they tend to extract features more efficiently. We used Deep Learning methods for the identification of plants. This study developed an improved deep learning (DL) model for plant identification with plant leaf vein architecture. We compared different Deep Residual Neural Networks (ResNet) and Densely Connected Convolution Networks (DenseNet), through different models using a stochastic gradient descent algorithm and adam optimization. We achieved up to 96% accuracy with adam optimization using a DenseNet model with 169 layers. This also surpassed the accuracy that was achieved using D-leaf architecture (Wei Tan *et al.*, 2018). The D-leaf model identifies plant species using vein morphometry. The proposed model consists of four steps. The first step sample the data set. Several datasets have been used, including MalayaKew (MK), Flavia, and the Swedish leaf dataset. In the second step, the images were resized to 224 x 224 resolution, converted to grayscale, passed through the Sobel edge detection method, and skeletonized to obtain the clean vein architecture. Then these images were then fed to the proposed D-leaf model for classification. The model contained a total of 6 convolution layers that include convolution, ReLU (rectified linear unit), and a pooling stage for feature extraction. These features were then fed to three fully connected layers and a Softmax classification layer. Artificial Neural Networks (ANN) have been employed for the classification after the feature extraction. Such a model was found effective but relatively more straightforward with a small data set (as the number of species was less). The current study provided an improved deep learning model for plant identification by using plant leaf vein architecture. We also represented a comparison of different

Deep Residual Neural Networks (DRNN) and Densely Connected Convolution Networks (DCN) with the accuracies. We identified the plants through different models by using a stochastic gradient descent algorithm and adam optimization.

Plant leaves are the most common organ of the plant body and are readily available in all seasons. In different research works, leaf texture-like vein architecture has been used as a feature to differentiate between species. Deep learning models like convolutional neural networks have been used to identify plant species; however, the accuracy of these models can be improved considerably. Wu *et al*., (2007) worked on the problem of automated plan identification using the leaf. Their main goal was to improve feature extraction and classification. They proposed a Probabilistic Neural Network for classification and for feature extraction they used Principal Component Analysis (PCA). Cope *et al*., (2010) analyzed the problem of plant species identification using plant leaf veins. The proposed algorithm is based on a Genetic Algorithm and Ant colony optimization for vein extraction. The classifier can extract the primary and secondary veins with only very little noise. Jamil *et al*., (2015) investigated the problem of automatic plant identification by emphasizing the leaf's shape. The main goal was to determine the effectiveness of shape as a critical feature. They used the AdaBoost classifier to train the features extracted from the images of seven species. Yanikoglu *et al*., (2014) investigated the challenges involved due to the variation of light, pose, and orientation of leaf images. Aakif *et al*., (2015) identified the problem of plant species classification based on their leaves. The proposed solution used morphological features like aspect ratio, eccentricity roundness, convex hull, their novel shape defining feature, and Fourier descriptor. For classification, they used artificial neural networks (ANN) and used different combinations of features to study the impact on the accuracy of the model. Adinugroho *et al*., (2018) proposed a neural network for the identification of plant species by including the characteristics of leaves of the plant for 15 species. After preprocessing, 31 features were extracted using the characteristics of leaves, i.e., shape, color, and texture. These extracted features are fed as an input to the neural network. Larese *et al*., (2012) proposed an automatic algorithm for the classification of legume leaves by taking leaf venation patterns and excluding the color, texture, and shape of the leaves. Sun *et al*., (2017) proposed a Deep Residual Network to improve the accuracy of image classification. The model consists of a convolution layer, max pool layer, and a bottleneck residual block layer. They used full-plant images, but sometimes endangered species do not have the whole plant available, so leaf recognition comes in handy in such situations.

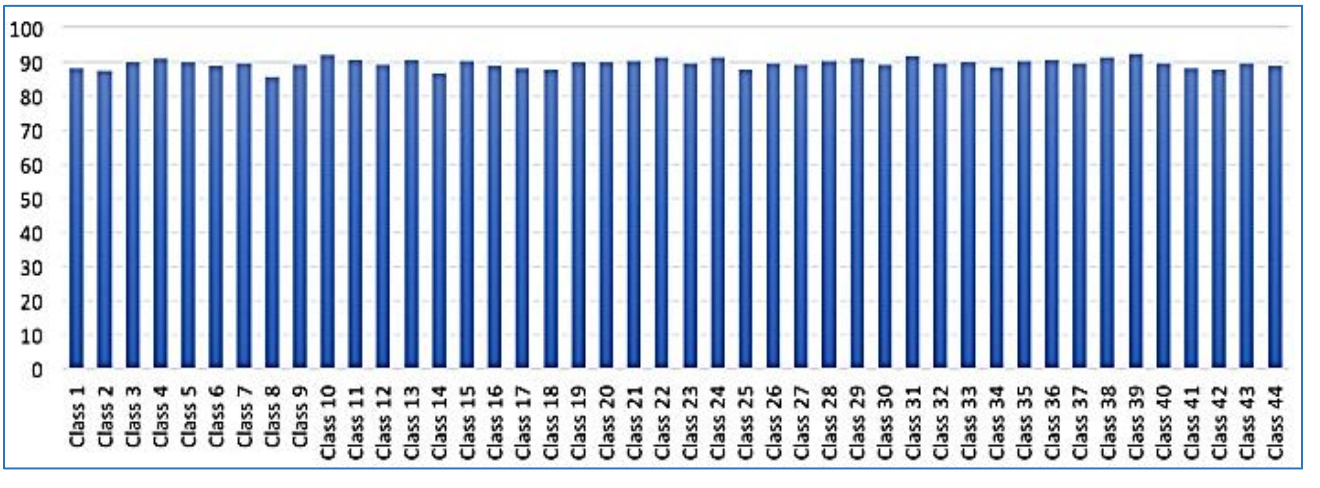

Fig. 6. Per class accuracy of Res Net 101 with an average accuracy of 89.50% using Stochastic Gradient Descent.

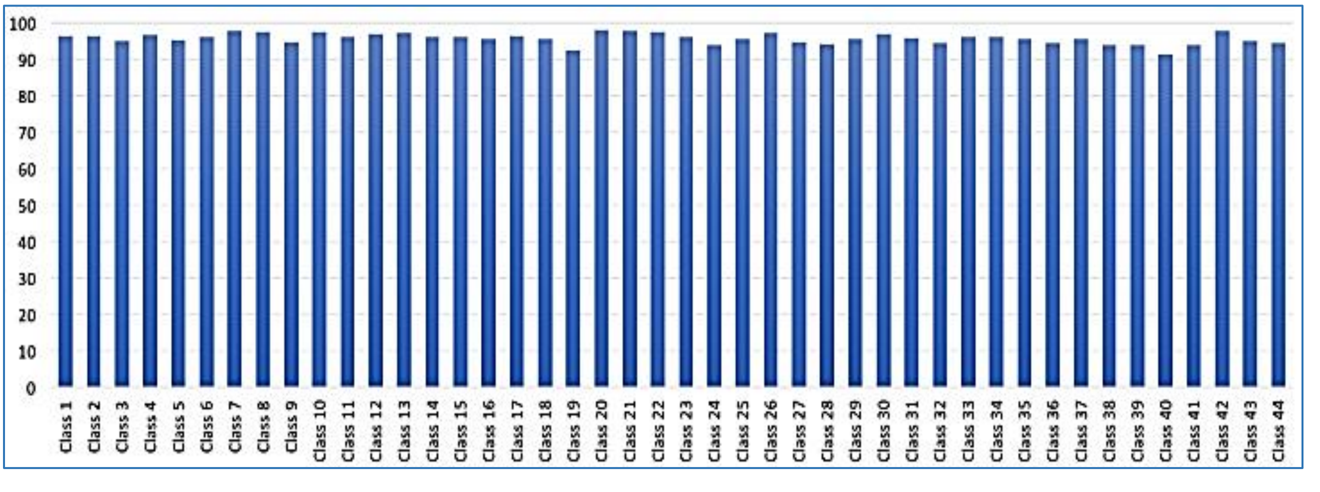

Fig. 7. Per class accuracy of Dense Net 169 with an average accuracy of 95.72% using Adam optimizer.

Zhang *et al.,* (2021) developed the MFCIS (Multi-feature Combined Cultivar Identification System)-that incorporates multiple leaf morphological information obtained using persistent homology. The classification accuracy after score-level fusion was 91.4 percent, which was much higher than the accuracy when each development period was utilized individually or when all growth periods were merged (Zhang *et al.,* 2021). Mary Sobha & Thomas (2020) employed VGG16 CNN to extract features from simple and complex leaf pictures. For feature extraction and classification of actual complicated background pictures, a transfer trained VGG16 CNN was employed. VGG16 CNN models are used to extract and classify features from original (model1) and patch (model2) pictures independently. Using complicated backdrop leaf pictures, their suggested fusion model demonstrated 98.6 percent accuracy in model evaluation and 90 percent accuracy in plant identification. Sachar & Kumar (2021) used transfer learning to assess the feature extraction skills of the VGG-16, Xception, MobileNetV2, and DenseNet121 architectures using freely accessible Swedish, Flavia, and MalayaKew leaf picture datasets. The requested feature extractor models' assessments and comparisons were supplied. DenseNet121 obtained maximum accuracy of 100 percent, 99 percent, and 92.4 percent on the three datasets, respectively.

Conclusion and Future work

Plant identification has been a significant area of research for many decades as it plays a significant role in biodiversity conservation. Many plant species are getting extinct day by day, and there is a need to build a common knowledge base that could identify the plant species. This has been greatly simplified by automated methods. Machine learning algorithms learn information from several photos and predict the proper outcome. The deep learning models used to identify the species of plants in this study were the ResNet, and DenseNet. The optimizers used were adam optimization and Stochastic Gradient Descent. Overall, the best performance was achieved using Adam optimization using the DenseNet model with 169 layers and came out to be 95.72%. This is higher as compared to the state-of-the-art methods. The deep learning (DL) methods were found very accurate to employ to have a better and exact plant identification. As future work, we aim to test our DDN-based model on various datasets from different regions of the world. We wish to incorporate plant features such as stems and branches in addition to leaves in our model to improve its accuracy. Furthermore, we intend to enhance our model by tuning the hyperparameters of current deep nets and deploying new emerging deep neural nets. There is also a need to carry out a detailed and comprehensive study for comparing different traditional and deep neural network-based models for plant identification on various real-world datasets.

Limitation: The proposed research model for plant identification is tested on one dataset namely MalayaKew, so it may suffer from the sample bias. Scientists have shown that big data combined with the best machine learning techniques and DNN-based models can give intuitive insights. However, we do not have vast data of leaves for plant identification. We can use the emerging GANs, which are composed of two deep neural nets, to generate substantial synthetic data for plant identification models.

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