Journal of Information Systems & Information Technology (JISIT)
ISSN: 2478-0677; Vol. 6 No.1 2021; [Pages 84 - 95]

A Transfer Learning Classification Prototype Model for Sri Lankan Trees

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Abstract: Automatic classification of the trees from images or videos is difficult, due to its large variety of species. Identifying and classifying tree types requires agricultural experts and botanists. The technology is moving fast so the people are running towards growth so they become more urbanized and forget about nature. We have lost valuable tree species due to the forest firing without knowing its name. It's difficult to identify trees by the naked eye because of their variation in orientation, the shape of the leaves, and the viewpoint. Next-generation people mostly will forget the importance of the trees. So there is a need for a system to recognize trees. In this experiment, we acquired 2,500 images of 25 different types of trees inside South Eastern University of Sri Lanka premises. We focused on analyzing the performance of the pre-trained deep learning models. Therefore, we specifically use transfer learning by leveraging pre-trained deep learning models. The evaluated architectures are VGG16, VGG19, Xception, InceptionV3, and MobileNet. The performance of each classification model is assessed in terms of validation accuracy. In our experiment, MobileNet achieves a validation accuracy score of 87.20% and outperforms other pre-trained models. Trees must be classified into identifiable classes for us to have a clear, organized way of identifying the diverse array of trees that inhabit the planet. We did not find any similar research work on identifying/ classifying trees in Sri Lanka using image processing-based machine learning. This MobileNet architecture could be used to deploy the final web-based application solution and mobile-based application. Also, it took a smaller number of epochs which is 4 to reach the higher validation accuracy. Because of the lightweight nature of the MobileNet architecture model, it has performed better than others.

Keywords: *Trees Classification; Convolutional Neural Network; Deep Learning; Transfer Learning*

 [RECEIVED: 10TH SEPTEMBER, 2021; REVISED AND ACCEPTED: 30 TH DECEMBER, 2021]

1. Introduction

Sri Lanka has 704 species of common trees and shrubs of flora under 95 families [1]. Technology is moving fast, the people are running towards growth, so they become more urbanized and forget about nature. There are around 280 types of trees have been identified in Sri Lanka as endangered species [2] and 297 plant species were listed in the threatened red list by the world bank [3]. We have lost valuable tree species due to the forest firing without knowing its name. It's difficult to identify trees by the naked eye because of their variation in orientation, the shape of the leaves, and the viewpoint. Next-generation people mostly will forget the importance of the trees. So, there is a need for a system to recognize trees. Agricultural experts identify tree species by analyzing their different aspects. Mainly focusing on visible characteristics. It's a tedious thing for normal people to categorize the species. In the past few years, the rapid growth of machine learning has been shown very good results in computer vision and plant identification.

Also, it has come to know that there are no automated plant identification tools are available in Sri Lanka until the day this research has been conducted. So, the main purpose of this research was to create a best performing machine learning-based automated tree identification tool and deploy it in a web-based application where the public can access it, they can feed an image of the tree to be identified and the application would suggest the name with the prediction probability. But this requires a lot of effort to collect all the images of the available trees on the island. Therefore, this study is a limited version of a prototype model with 25 species available on the premises of the South Eastern University of Sri Lanka and this prototype can be expanded to a large industrial scale in the future for public use. Considering the earlier works plants were identified by their leaves, flowers, and fruits. Those images were acquired with clean backgrounds. However, classifying trees type is a tedious task because the images were captured not in the controlled background it has some noises. Categorizing natural images can be extremely difficult due to their complex background, shadows, objects, etc. Therefore, there is a need for an automated system to identify trees from natural images. For human beings, it's easy to only focus on a particular object but machines need to train for this task.

Deep learning, a subfield of artificial intelligence has been successfully applied in various applications. Such as medical image classification, text to speech translation, object detection, natural language processing, computer vision, etc. Moreover, it has been applied in agriculture, business, and industrial applications. Training a deep learning model from scratch needs a large amount of dataset, high processing power, and long processing time. With the help of transfer learning, we can overcome the aforementioned problems [4]. Fig. 1 shows the transfer learning process. Transfer learning is a popular method because experiments gave high accuracy with less amount of data size, it dramatically reduces training time and computes resources [4]. Transfer learning is flexible allowing the pre-trained models to be used as a classifier, standalone feature extractor, integrated feature extractor, and used to weight initialization. To classify new images with the trained model we can use as a classifier and to extract relevant features from images we can use the full or half portion of the pre-trained model as a standalone feature extractor, the full or half portion of the pre-trained model is integrated with another model and also during the training process the layers of the pre-trained models are frozen if we want to use as integrated feature extractor, and weight initialization is integrating pre-trained models with new models and also layers of the pre-trained models were trained during the process.

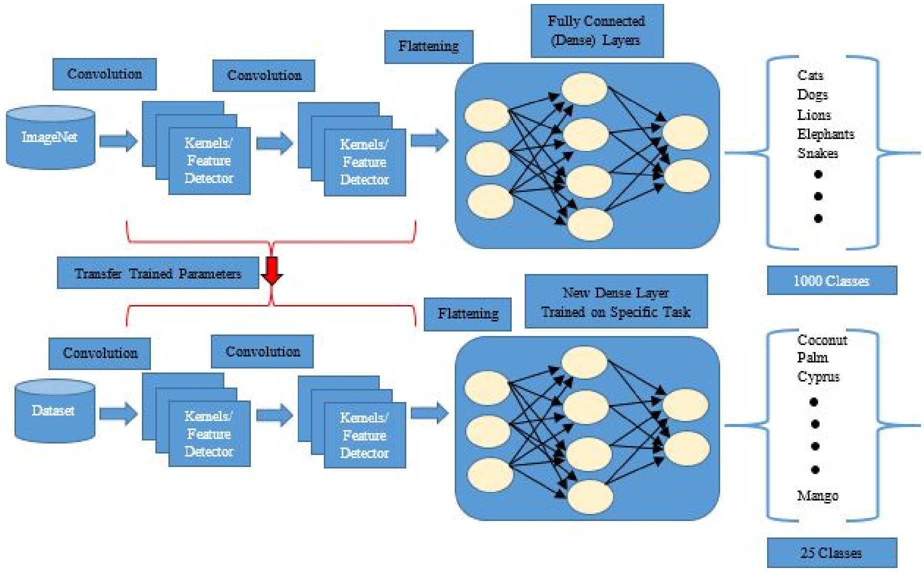

Fig. 1: Transfer Learning Process

2. Literature Review

2.1 Convolutional Neural Networks (CNN)

CNNs are specifically used for image classification tasks. CNN became very famous with the popularity of GPU [5]. CNN trained with using high-performance GPU for image classification applications resulted in better accuracy [6]. It gives the test error rate of 0.35%, 2.53%, and 19.51% for the image classification tasks digit recognition (MNIST), 3D object recognition (NORM), and natural images (CIFAR10). Modified National Institute of Standards and Technology (MNIST) dataset consists of 60,000 small square, 28×28 pixel grayscale images of handwritten single digits. CIFAR10 dataset has 60,000 color images with 32×32 pixels. ImageNet is a database consisting of over 15 million labeled high-quality images with around 22,000 classes [7]. ImageNet Large Scale Visual Recognition Challenge (ILSVRC) uses a subsection of the ImageNet database of around 1000 categories. In all, there are nearly 1.2 million training images, 50,000 validation images, and 100,000 testing images. AlexNet is the first CNN architecture that won in the competition. AlexNet has 5 convolutional layers, 3 fully connected layers, and ReLU as the activation function. ZFNet a new architecture was introduced using the same architecture of AlexNet but tuning some of its hyperparameters and it gives more accuracy than the AlexNet [8]. ResNet [9], ResNet50 [9], Xception [10], VGG16 [11], VGG19 [11], InceptionV3 [12], and MobileNet [13] are some of the deep convolutional neural network architecture that gives better accuracy in the ImageNet competition. And these are some of the well-known transfer learning model architectures which can be used for image

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classification tasks and we have compared the performance of each model in this research except AlexNet, ResNet, and ResNet(50).

2.2 Plant Classification

Several experiments are conducted in plant classification using traditional machine learning algorithms, deep learning, and combining both methods. Plant classification has been conducted based on the characteristics of leaf, fruit, and flower. BJFU100 dataset, Swedish leaf dataset, ICL (Intelligent Computing Laboratory) leaf dataset, LifeCLEF plant dataset, Flavia dataset, and Folio dataset are used for plant classification. The evaluation of technology and research on plant recognition helps to develop mobile applications such as Pl@ntNet [14], LeafSnap [15], or Flower Recognition app [16] from Microsoft Garage to identify plants. Plant detection and localization, plant segmentation, leaf segmentation, leaf counting, and leaf detection are available under phenotyping datasets [17]. Some of the USA and Canada-based plant species are available under the UCI repository [18]. This dataset was collected and maintained by the Department of Agriculture, USA.

It is identified that the reported work on tree recognition over Sri Lankan species is sparse and no machine learning-based automated tools or tree databases are available in Sri Lanka. An experiment was conducted using the traditional feature extraction method combined with the machine learning classification algorithm K-nearest neighbor [19]. They have used the following digital image processing techniques namely rotation, gray scaling, thresholding, opening operations, inverse threshold, edge filtering, and edge extraction. From the processed images they have extracted the following information they are convex hull information, morphological information, distance maps, and color histogram. They used this model to find out the accuracy for their dataset called Folio it obtained 87.2% for the Flavia dataset it obtained 91.1%. The images of the Folio dataset were taken from the farm of the University of Mauritius and nearby locations. The dataset consists of 32 different species in each type they have collected 20 different pictures. We can classify an object based on its color and shape. Multiscale distance matrix (MDM) a shape descriptor was proposed and tested for two famous datasets namely, ICL (Intelligent Computing Laboratory) leaf dataset and the Swedish leaf dataset [20]. Swedish leaf dataset contains 15 different Swedish tree species, with 75 images per class label and ICL Leaf dataset images were collected at the Botanical Garden of Hefei, Anhui Province of China by the members of Intelligent Computing Laboratory (ICL) in Institute of Intelligent Machines, Chinese Academy of Sciences. The ICL Leaf database consists of 6000 plant leaf images from 200 species, in which each class has 30 images.

The rapid developments in deep learning have made promising results in plant identification. Traditional machine learning algorithms and handcrafted feature extracting methods from images is time-consuming, rely on expertise to a certain extent, and has a deficient generalization to big data. Therefore, conventional shallow machine learning methods of plant identification are not suitable for images with huge species and complex backgrounds. Deep learning has been applied to the agricultural field including investigations of plant disease, pests, and species classification.

Transfer learning approach was conducted on the LifeCLEF plant dataset. LifeCLEF 2015 dataset contains 91,758 labeled images of 1000 species and the testing dataset contains 21,466 images with the very challenging varying condition of backgrounds. They fine-tuned the hyperparameters such as batch size and training iterations of the following pre-trained models, they are AlexNet, GoogleNet, and VGGNet in the results section they analyzed their performance [21]. A 26-layer residual network model was proposed for plant identification. They have used Flavia and BJFU100 datasets. BJFU100 dataset is captured by mobile phone in natural surroundings. The dataset consists of 10,000 images of ornamental plant species on the Beijing Forestry University campus. They have considered 18, 26, 34, and 50 layers in deep residual networks. They achieved 99.65% accuracy with the ResNet model for the Flavia dataset and 91.78% for the BJFU dataset.

The image classification process consists of mainly three steps. They are image preprocessing, feature extraction, and classification. An experiment was conducted with two different approaches [22]. Feature extraction such as shape, texture features, and color features was carried out using traditional methods and also using deep learning methods. In traditional methods, they used Local Binary Pattern and Haralick to extract features. In the deep learning method, they used pre-trained CNN models namely VGG16, VGG19, InceptionV3, and Inception ResNetV2. After that, the classification is done using shallow machine learning algorithms namely Logistic Regression, K-Nearest Neighbor (KNN), Classification and Regression Tree (CART), Random Forest classifier, Bagging Classifier, and Naive Bayes. They achieved an accuracy of 96.53%, 96.25%, and 99.41% for Folio, Flavia, Swedish leaf datasets using VGG19 for feature extraction and Logistic Regression as a classifier. Reference [23] experimentally proved that deep learning models give better accuracy than traditional machine learning models. An efficient method was presented using the transfer learning method for the plant classification, which first uses a pre-trained model for learning leaf characteristics from the input data, and then they used a logistic regression algorithm as a classifier [24]. The method was tested with the Flavia dataset and Leaf Snap dataset. The respective models achieved an accuracy of 99.6% and 90.54%. Convolutional recurrent neural networks (C-RNNs) are proposed for observation-centered plant identification to overcome the limitations of image-centered identification [25]. The C-RNN model has two components. CNN is the backbone for extracting features from images, and the recurrent neural network (RNN) cells are built to synthesize multiview features from each image for final prediction. Different combinations of CNN and RNN have been experimented with. Results from their experiment show that the combination of MobileNet and Gated Recurrent Unit (GRU) is the best trade-off of classification accuracy and computational overhead on the Flavia dataset.

Plant species identification helps in the detection of weed and the classification of plant disease. In the past decade, there have been lots of research conducted on plant leaf disease detection using traditional machine learning method, deep learning, and combining both methods. Also, numerous research works are carried out using features such as shape, texture, color, morphological or physiological features. Here we carried out the deep learning method known as transfer learning.

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3. Methodology

In computer vision, many deep convolutional neural network architectures have been introduced for object detection and image classification. Fig. 2 shows the working flow of our experiment. In this work, five of the most used deep learning networks (VGG16, VGG19, InceptionV3, MobileNet, and Xception) are examined for tree types classification with a smaller amount of dataset using transfer learning, and the results are discussed comprehensively. The aforementioned models are publicly available so there is no need for training the model again from scratch. Keras API has all pre-trained model weights. Table 1 shows the details of the pre-trained models.

Fig. 2: Classifier Model

Our approach in this work is downloading the weights of the pre-trained models and without changing its convolutional base layers only made changes in the last layers and it has been replaced with the output layer which is equal to the number of classes, in this case, its 25 and addition to that softmax layer is added after that the models were trained with augmented images.

Table 1. Details of pre-trained models.

Model	Parameters (Millions)	Size (MB)	Input Image Size
VGG16	138.4	528	224×224
VGG19	143.7	549	224×224
Inception V3	23.8	92	224×224
Mobile Net	4.3	16	224×224
Xception	22.9	88	229×229

3.1 Dataset

Our image database contains a total of 2,500 images with 25 different tree types and in each type 100. Table 2 shows the common name and biological names of the trees in our dataset. The images were captured using 13 MP mobile cameras with different positions and validated by agricultural experts. We did photograph the images of trees that are located on our campus premises. Pictures of 25 plants were collected as initial prototype development. This dataset can be expanded in the future as per our requirements. We photographed the images of trees that are located on our campus premises. Images were captured under different light conditions, different backgrounds, viewpoints, and different positions (Fig. 3). Gathered images were renamed based on their classes. After that, we randomly split the dataset such that 70% for training and 20% for testing, and 10% for validation. The obtained images were resized according to the input size of each model when they are given for training.

Table 2. Details of the Dataset

Class Name	Common Name	Biological Name
Plant - 01	Bougainvillea	Bougainvillea glabra
Plant - 02	Coconut	Cocos nucifera
Plant - 03	Monterey Cypress	Cypressus macrocarpa
Plant - 04	African mahogany	Khaya senegalensis
Plant - 05	Neem / Nim tree	Azadirachta indica
Plant - 06	Mango tree	Magnifera indica
Plant - 07	Cuban royal palm	Roystonea regia
Plant - 08	Plant_A	-
Plant - 09	Tamarind	Tamarindus Indica
Plant - 10	Cordia	Cordia
Plant - 11	Pashu padauk	Pterocarpus indicus
Plant - 12	Asian palmyra palm	Borassus flabelifer
Plant - 13	Cassava	Manioc esculenta
Plant - 14	Jack tree	Artocarpus heterophyllus
Plant - 15	Ceylon satinwood	Chloroxylon swietenia
Plant - 16	Plant_B	-
Plant - 17	Kelat paya	Syzygium campanulatum
Plant - 18	Plant_C	-
Plant - 19	Indian banyan	Ficus benghalensis
Plant - 20	Country almond	Terminalia catappa
Plant - 21	Indian fig tree	Ficus racemose
Plant - 22	Cashew tree	Anacardium accidentale
Plant - 23	Date palm	Phoenix dactylifera
Plant - 24	False ashoka	Polyalthia longifolia
Plant - 25	Plant_D	-

3.2 Models

The performance of the following models was analyzed in this experiment.

VGG Net

VGG Net is considered to be one of the finest vision model architectures to date. VGG16 has 16 and 19 convolutional layers, the complexity increases comparing the initial versions of CNN models like LeNET. VGG16 has a uniform architecture. VGG16 has 138 million parameters which are certainly difficult to handle. There are 13 convolution layers and 5 max-pool layers. All convolution kernels are of size 3×3 with stride 1, padding the same and all max-pooling kernels are of size 2×2 with stride 2. Hidden layers have ReLU as the activation function.

Xception

The Xception model was introduced in 2016 [8]. Xception network has fewer parameters and high accuracy. Xception sports the smallest weight serialization at only 88MB. The Xception architecture surpassed the VGG-16, ResNet50, ResNet101, ResNet152, and Inception-V3 on ImageNet.

Fig. 3: Thumbnails of all 25 tree species from the dataset

Inception V3

The base manifestations of this architecture were named GoogLeNet, other versions with improvement on these models have simply been called Inception vN where N refers to the version number. There are 04 versions. Inception V3 introduces sparsely connected network architecture it gives better accuracy compared to fully connected layers. The

Journal of Information Systems & Information Technology (JISIT)
ISSN: 2478-0677; Vol. 6 No.1 2021; [Pages 84 - 95]

inception layer is a combination of 1×1, 3×3, and 5×5 convolutional layers. The output from these convolutional layers is concatenated into a single vector and fed into the next layer. Inception V2 talks about batch normalization and Inception V3 talks about the factorization ideas.

MobileNet

To achieve higher accuracy in computer vision models they should be in deeper architecture. The deeper models are hard to utilize. To overcome this problem MobileNet was introduced. MobileNet is small, latency, and resulted in good accuracy. MobileNet - V1 and MobileNet - V2 are two versions of MobileNet. MobileNet uses depth-wise separable convolution layers.

3.3 Image Processing

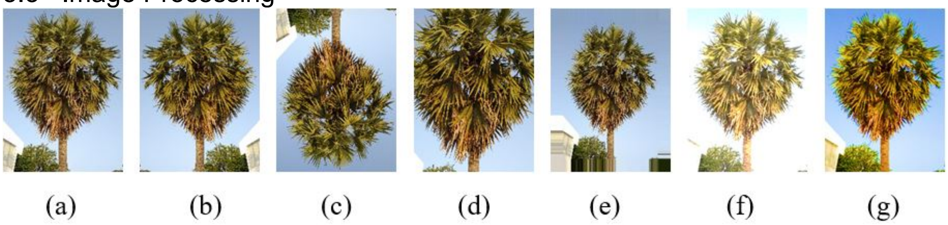

Fig. 4: Results of the Augmentation process. (a) Original Image; (b) Horizontal Flipping; (c) Vertical Flipping; (d) Zoom In; (e) Zoom Out; (f) Brightness Enhancement; (g) Sharpness Enhancement

Deep neural networks need lots of data to learn. Data augmentation helps to increase the dataset size and model generalizability. We can simply define data augmentation as a process of increasing the size of the dataset by artificially creating variations in the dataset. The motivation behind data augmentation is to prevent overfitting. Overfitting refers to a phenomenon when a deep learning model with high capacity exactly models the train data since they don’t generalize test data. Fig. 4 shows the different augmented images. The following are the basic data augmentation techniques namely horizontal and vertical flips, zooming, sharpness, and brightness correction. Points outside the boundaries of the input are filled with reflecting mode.

4. Results and Discussions

4.1 Experiment Setup

Google Colaboratory or Google Colab was the integrated development environment used for experimenting with virtual GPU. This setup runs entirely in the cloud. Specifications are 1xTesla K80, 2496 CUDA cores, compute 3.7, 12 GB (11.439 GB usable) GDDR5 VRAM.

4.2 Training

For every experiment, the models are evaluated by test accuracy. The performance of each model with accuracy and loss was graphically plotted. Models are trained of up to 05

Journal of Information Systems & Information Technology (JISIT)
ISSN: 2478-0677; Vol. 6 No.1 2021; [Pages 84 - 95]

epochs, with 55 iterations per epoch. The hyper-parameters in the neural network are kept unchanged for all experiments. All the networks are trained with Adaptive Moment Estimation (Adam), we trained the network with the Batch size of 32. The learning rate was set to 0.001 for all network models. We did data augmentation. ReLU activation was used. Fig. 5 shows the training and test accuracy.

4.3 Results of the experiment

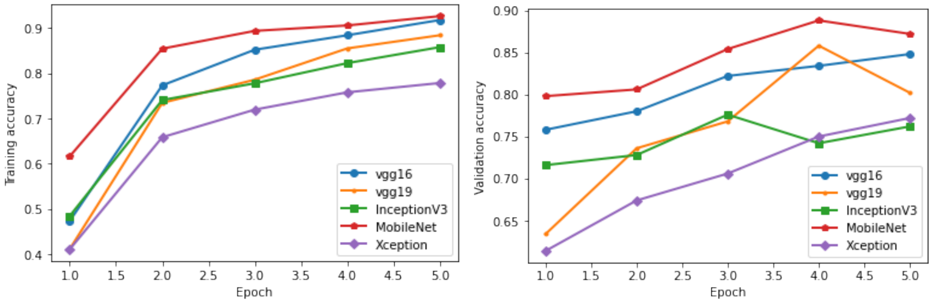

Fig. 5: Training and Validation Accuracy

The first graph illustrates the accuracy of the training dataset and the other graph shows the accuracy of the validation dataset. The training accuracy of all five models is increasing while the number of epochs increases. VGG16 and MobileNet performed well compared with the other three models for training data. Similarly, testing accuracy is also higher in VGG16 and MobileNet architecture models. Even though the accuracy is increasing while increasing the number of epochs, the maximum number of epochs was tested is 5 due to the limited resource availability in the laboratory which we have used Google colab free version which we can continue to use for up to 12 hours. It took almost 12 hours to run 5 epochs for an architecture. Validation accuracy values indicate that the VGG19 model and Inception V3 are prone to model overfitting because the training accuracy is always increasing while increasing the number of epochs but the validation accuracy is reduced after an optimum point. Optimum points for VGG19 are 4 and for Inception, V3 is 3. And further, it shows that Inception V3 performs better than VGG 19 at a lower number of epochs where it is not the case while at a higher number of epochs. The best model among the five is MobileNet which shows a higher validation accuracy at 4 number epochs and the accuracy value is decreasing while the number of epochs is increasing beyond 4. But this is conclusion is limited since we could not be able to visualize the accuracy values after 5 numbers epochs.

MobileNet is one of the lightweight architecture models which is very suitable for mobile applications. It has a reduced network size and a smaller number of parameters. So, it can be faster than other architecture models.

5. Conclusion

This study proposed a method for classifying tree types by analyzing the performance of pre-trained models. With the help of transfer learning, we solved the problem of having a huge dataset of images for training. This proposed method was carried out using 5 deep learning architectures. Namely VGG16, VGG19, InceptionV3, MobileNet, and Xception. We compared the accuracy of each model by setting epochs 5 during the training phase. MobileNet architecture outperforms other state-of-the-art models. It gives an accuracy of 87.20%. Moreover, further fine-tuning of hyperparameters and using different optimizers might better improve the accuracy of the models. In future work, we will be expanding our database by more tree species.

These trees are not necessarily belonging or are native to Sri Lanka, but some of them could be, but it's not part of our scope to identify the trees whether they are native to the country or not. Our scope is to develop a machine learning-based automated software application to identify the trees automatically which are available in Sri Lanka. This study is currently limited to 25 tree species that are available on the university premises. And this application can be considered as a prototype. This could be expanded to a greater number of species available around the country in the future. This will require a significant amount of physical and resource requirements. And we have a plan to explore them in the future. Moreover, some of the new images which are unknown or unseen by the system of the same trained types of trees can be fed to the system, and based on that our prediction model can be further evaluated and updated. A web-based and mobile application could be developed for public use in the future with an extensive number of tree species.

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