Impact Analysis of Transfer Learning in CNN using different Domains

Juan Augusto Campos-Leal
Posgrado en Ciencias de la Informacion
Universidad Autonoma de Sinaloa
Culiacan, Mexico
e-mail:juan.campos@uas.edu.mx

Arturo Yee-Rendon
Facultad de Informatica Culiacan
Universidad Autonoma de Sinaloa
Culiacan, Mexico
e-mail:arturo.yee@uas.edu.mx

Ines F. Vega-Lopez
Parque de Innovacion Tecnologica
Universidad Autonoma de Sinaloa
Culiacan, Mexico
e-mail:ifvega@uas.edu.mx

Gerardo Beltran-Gutierrez
Facultad de Informatica Culiacan
Universidad Autonoma de Sinaloa
Culiacan, Mexico
e-mail:gerardo.beltran@info.uas.edu.mx

Jose Ramon Lopez-Arellano
Parque de Innovacion Tecnologica
Universidad Autonoma de Sinaloa
Culiacan, Mexico
e-mail:ramonlo@uas.edu.mx

***Abstract*—In this paper, we analyze the impact on the accuracy of CNN-based models when they use transfer learning from different source domains; a general domain (ImageNet 2012 dataset) and a specific plant domain (PlantCLEF 2018 and 2019 datasets). Transfer learning has positively impacted the accuracy of many classification models. Therefore, it has been extensively used to train deep learning-based models. For many years, the models that were trained on the ImageNet 2012 dataset have been used for transfer learning. However, thanks to the efforts of many research groups, other datasets are available for specific domains, such as birds, cars, and plants, to name a few. The models trained on these specific datasets can be used for transfer learning to deal with related domain tasks as well. In this work, we analyzed the accuracy of the models for plant species classification using digital images. We used three models previously trained on the ImageNet 2012, PlantCLEF 2018, and PlantCLEF 2019 datasets as a starting point. Our results showed that using a model trained on the PlantCLEF 2018 dataset helped to improve the model's accuracy in plant species classification. We introduced a new dataset, Mexico 80 Flower, and used a publicly available dataset, Oxford 102 Flower. The best models were those based on InceptionResNet-v2, which obtained 98.29% and 98.49% accuracies, respectively.**

***Index Terms*—CNN, Deep learning, Plant Species Classification, Transfer Learning**

I. Introduction

Convolutional neural networks (CNNs) have emerged as the most promising approach for image classification because of their ability to learn reliable and discriminative features. In recent years, transfer learning has helped to obtain more accurate CNN-based models than models trained from scratch for specific tasks. Transfer learning technique works by training a model on a source dataset, and then we use the parameter values as the initial parameter values for retrain a model on a target dataset [1] [2]. The need to use transfer learning for model training arises when there is limited training data. The limited data may be because data is scarce, the data is expensive to collect and label, or there is no more data. Generally, the models that are used for transfer learning were trained on source datasets that contain many training images. The most common dataset used for transfer learning is the ImageNet 2012 large-scale dataset. For many years, the parameter values acquired by the models trained on this dataset have been used for transfer learning. However, data availability has made it possible to build other large-scale datasets for specific domains, such as a plant domain. So, models trained on these particular datasets can be used for transfer learning to solve related domain tasks.

In this work, we analyze the accuracy of models for plant species classification using transfer learning from two domains. Plant species classification is considered a fine-grained classification problem due to high interclass similarities and high intraclass variations in this domain. We used models that were trained in two different domains for transfer learning. The first domain is the classical ImageNet 2012 dataset. This dataset contains classes such as cars, persons, animals, and buildings, to name a few. The second is a plant domain, using transfer learning from models trained on PlantCLEF 2018 and 2019 datasets, respectively. These datasets depict images of plant species in the field; each dataset contains plant species from different regions of the world. The images contain distinctive organs of the plant species, like flowers, leaves, fruits, and trunks, to name a few. We analyzed the performance of the trained models to answer the following question. What effect does model accuracy have when starting the training phase from ImageNet or PlantCLEF domains?

The main contribution of this paper is a comparative analysis of CNN-based models that use transfer learning from different source domains for plant species classification using flower images.

The rest of this paper is organized as follows. Section II describes the related work. Section III presents a detailed pipeline of the methodology used. Section IV describes the used dataset and computing environment. Section V describes the results obtained during the experimental evaluation. Finally, in Section VI we present our conclusions and state future research directions.

II. Realated work

This section describes related approaches that used transfer learning from the PlantCLEF challenges. In 2017, Ghazi *et al.* [1] used the AlexNet, GoogLeNet, and VGG-16 models for plant species classification. The models were trained from scratch and using transfer learning. Transfer learning was used from models that were trained on the LifeCLEF 2015 dataset. This dataset contains 113,205 images of 1,000 plant species native to France and neighboring countries. The authors reported 78.44% accuracy for the VGG-16 model.

In 2018, Sulc *et al.* [3] won the ExpertLifeCLEF 2018 plant classification challenge [4] using Inception-ResNet-v2 and Inception-v4 models. The challenge consisted of identifying 10,000 classes from plant species digital images. The dataset contains 1.4 million plant images. Transfer learning and data augmentation techniques were used for training. Transfer learning was used from Inception-ResNet-v2 and Inception-v4 models that were trained on the ImageNet 2012 dataset. The authors finished first place using an ensemble of 12 CNN models based on six Inception-ResNet-v2 models and six Inception-v4 models. The authors reported 88.4% *Top-1* accuracy.

In 2019, Chulif *et al.* [5] used the Inception-v4 and Inception-ResNet-v2 CNN architectures to solve the PlantCLEF 2019 plant classification challenge [6]. The challenge consists of identifying 10,000 classes of plant species from the Guiana Shield and the Amazon rainforest. The training dataset contains 434,251 images. The authors used transfer learning from models previously trained on the ImageNet 2012 dataset. The authors strategy was based on cleaning the dataset. First, they removed the duplicate images, and second, they removed additional near-duplicates based on a cosine similarity in the feature space of the last layer of Inception-v4. Finally, they removed non-plant images automatically detected using a plant binary classifier based on Inception-v4. Overall, the number of images on the dataset was reduced by nearly 42%. The authors won first place on the PlantCLEF 2019 challenge obtaining 31.60% in *Top-1* accuracy.

In 2020, Lee Lee et al. [7] investigated the impact of using transfer learning from two domains to plant disease classification. They used transfer learning from models trained on ImageNet 2012 and PlantCLEF 2015 datasets. In the experimental stage, the authors used the InceptionV3, VGG-16, and GoogeNet architectures on the Plant Village [8], IPM [9], and Bing [10] datasets. The Plant Village dataset contains 54,305 images divided into 38 classes. IPM and Bing datasets were used as test datasets. The IPM dataset contains 119 images divided into 33 classes, and the Bing dataset includes 64 images divided into 38 classes. The best accuracies were to the VGG-16 model using transfer learning from ImageNet 2012 dataset. The VGG-16 model obtained 99.00%, 44.54%, and 28.13% in *Top-1* accuracy on Plant Village, IPM, and Bing datasets, respectively.

To the best of our knowledge, there is only one published research work that analyzes the impact of transfer learning using models trained on two source domain datasets; ImageNet 2012 and PlantCLEF 2015. However, the results presented by Lee *et al.* [7] showed that when the models used transfer learning from PlantCLEF 2015 did not outperform the model that uses transfer learning from the ImageNet 2012 dataset. We argue that this is due to the fewer images on the PlantCLEF 2015 dataset and a small representation of plant species. The PlantCLEF 2015 dataset only contains 113,205 and 1,000 plant species, while the ImageNet 2012 dataset contains 1.2 million images corresponding to 1,000 classes. We know that the ImageNet 2012 dataset is not a plant domain, but the number of images per class allowed the model to learn the parameter values to classify successfully. On the other hand, we used transfer learning from the PlantCLEF 2018 and 2019 datasets in our work. These datasets have a larger number of images and considerably more classes than the PlantCLEF 2015 dataset (the PlantCLEF 2018 dataset was built with previous editions of PlantCLEF datasets). Finally, we analyzed the data distribution on the PlantCLEF datasets to explain the models results.

III. Materials and Methods

This section describes the datasets where the models used for transfer learning were trained. Furthermore, we describe the transfer learning technique used in this work. Finally, we briefly describe the CNN architectures used for training.

Figure 1 shows the diagram of our work. We used transfer learning from models previously trained on three datasets. Transfer learning was used for the Inception-v4 and Inception-ResNet-v2 models. Inception-v4 and Inception-ResNet-v2 models were retrained on two plant species datasets, one created by the authors and one publicly available dataset. We used the k-fold cross-validation technique to evaluate the results of our models during the training phase. Finally, we analyzed the models accuracies that were obtained using transfer learning from different domains.

A. Datasets for transfer learning

In this work, we used three models that were previously trained on ImageNet 2012, PlantCLEF 2018, and PlantCLEF 2019 datasets. Figure 2 shows some images examples of each dataset. We briefly describe the three datasets.

The most common dataset for transfer learning in deep learning is the ImageNet 2012 dataset [11]. This dataset contains 1.2 million images corresponding to 1,000 classes. The classes on this dataset are objects in general; examples of classes that can be found in this dataset are cars, airplanes, ships, buildings, chairs, animals, and plants, among others. The visual features of each class are very different. Therefore, this kind of classification is considered a coarse-grained classification.

The PlantCLEF 2018 dataset [4] contains 10,000 classes and up to 1.4 million plant species images. When experts validate the plant species images, they are called trusted images. There

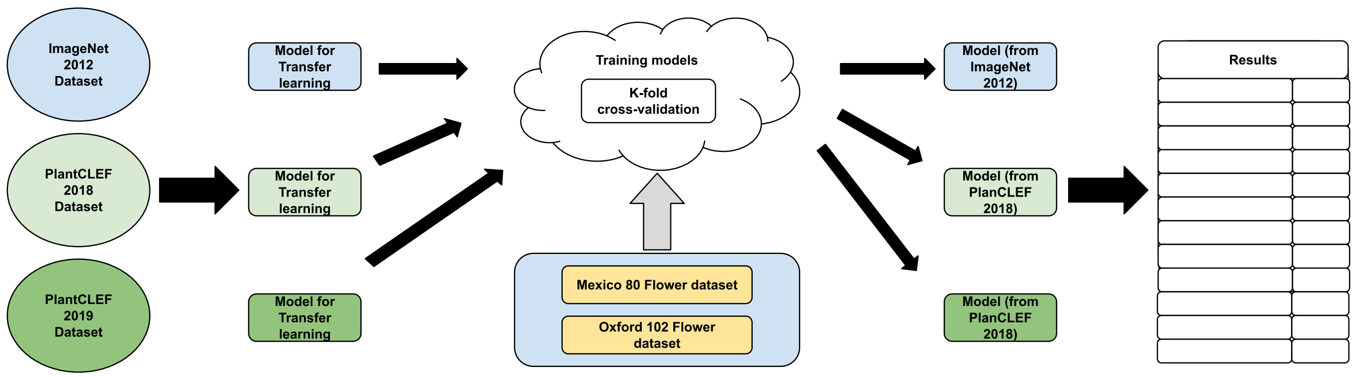
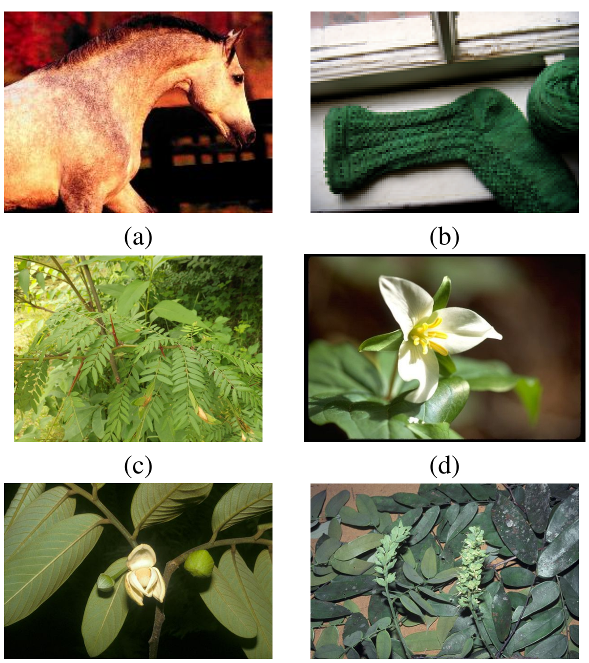


Fig. 1. General diagram of our work.



(a) (b) (c) (d) (e) (f)

Fig. 2. (a) (b) Images from the ImageNet 2012 dataset [11]. One thousand classes are identified in this challenge, and the classes are objects in general. (c) (d) Images from the PlantCLEF 2018 dataset [4]. The plant species are mostly European plant species. (e) (f) Images from the PlantCLEF 2019 dataset [6]. The plant species are mostly tropical species from South America.

are 256,288 trusted images on this dataset. The plant species are mainly located in the European and North American regions, although it also reports plant species from the rest of the world. There is a metadata file for each image containing the organ tag, like flowers, fruit, and leaves, to name a few. Most of the images are of plant species under field conditions. In this dataset, datasets from previous PlantCLEF editions were added.

The PlantCLEF 2019 dataset [6] is mainly formed with plant species from the Guiana Shield and the Amazon rainforest. This dataset contains 10,000 classes like on the PlantCLEF 2018, but the plant species are tropical. For the 2019 edition, the number of plant species images was reduced drastically to 434,251; only 58,619 are trusted images. In this dataset, the organ tag is not available. In both PlantCLEF datasets, the classification task is considered a fine-grained classification.

B. Transfer Learning

Transfer learning is the technique of using the knowledge acquired in a task and using this knowledge to solve another related task. In deep learning, this knowledge is the parameter values acquired by a trained model, so the parameter values are used as a starting point to train another classification model. In practice, models trained on ImageNet or PlantCLEF datasets are used for transfer learning. For this work, we used the fine-tuning technique during the retraining of the models. We used complete retraining of the parameter values of the models. The models that we used for transfer learning in this paper were the PlantCLEF 2018 models [1] and the PlantCLEF 2019 models [2] available for download. These models were provided by Sulc *et al.* [3] [12].

C. CNN architectures used

We used Inception-v4 and Inception-Resnet-v2 architectures in this work. Both architectures were presented by Szegedy *et al.* [13], which are based on Inception (or GoogLeNet) architecture [14]. The Inception-v4 architecture is based on a variant of the Inception module, and the Inception-ResNet-v2 architecture is another variant but with residual connections. The modules are stacked for building the architecture. The input for both architectures is a tensor of order three and size $(299, 299, 3)$ representing a color image in RGB format. The Inception-v4 architecture has 41,297,360 trainable parameters and Inception-ResNet-v2 architecture has 54,475,066 trainable parameters.

[1] http://ptak.felk.cvut.cz/personal/sulcmila/models/LifeCLEF2018/
[2] http://ptak.felk.cvut.cz/personal/sulcmila/models/LifeCLEF2019/

Fig. 3. Annotating regions of interest.

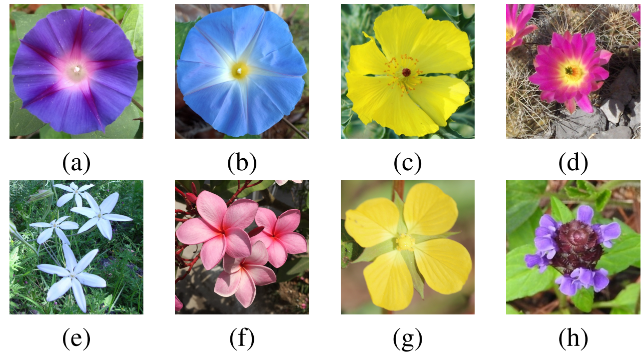


Fig. 4. Image samples from the Mexico 80 Flower dataset. (a) *Ipomoea purpurea*. (b) *Ipomoea tricolor*. (c) *Argemone mexicana*. (d) *Echinocereus pentalophus* (e) *Milla biflora*. (f) *Plumeria rubra*. (g) *Ludwigia octovalvis*. (h) *Prunella vulgaris*.

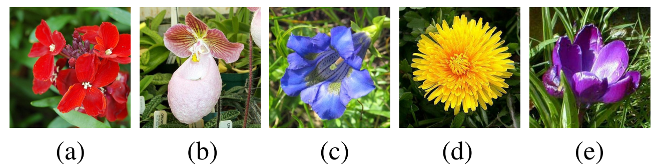


Fig. 5. Image samples from the Oxford 102 Flower dataset. (a) *wallflower*. (b) *hard-leaved pocket orchid*. (c) *stemless gentian*. (d) *common dandelion*. (e) *spring crocus*.

IV. Dataset Description and Computing Environment

This section describes the used datasets, the computing environment, and indices for evaluating the models performance.

A. *Datasets*

We used two datasets for experimentation. First, we created our own dataset, and second, we used one publicly available dataset to validate our proposal.

We created a dataset with images of the Mexican flora from two different sources. The first source was images taken by expert biologists during field expeditions in the northwest region of Mexico. The second source was images taken from Naturalista, an online social network for sharing biodiversity information [15]. All images were taken under field conditions containing background, angles, lighting, contrast, and scale variations. The dataset was constructed by regions of interest in the images collected. The regions of interest were defined in each image by annotating the flower as the distinctive organ. Some examples of the regions of interest are shown in Figure 3. The regions of interest that we annotate vary in size. Those regions of interest are always squared images to eliminate distortion in the images. This is because the inputs of the Inception-v4 and Inception-ResNet-v2 architectures are 299×299 RGB images. So, the dataset consists of 8,000 $m \times m$ color images divides into 80 plant species from the Mexican flora. Figure 4 shows some examples of images in the dataset. We used only images of flowers for this work. We will refer to this dataset as the Mexico 80 Flower dataset for the rest of this paper.

The Oxford 102 Flower [16] dataset contains 102 plant species and 8,189 images of flowers commonly found in the United Kingdom. The flower images were taken under field conditions and varied in large scale, pose, and light. Figure 5 shows some images from the Oxford 102 Flower dataset. We noticed that the images have the flowers centered in most cases. So, we preprocessed this dataset by cropping the largest inscribed square from the original image. The resulting images were used in our experimental stage.

B. *Computing environment*

We used a PC Workstation to carry on all experiments presented in this work. The workstation had an Intel Xeon W-2133 processor with 32 GB of RAM and an NVIDIA GTX 1080 Graphics Processing Card with 8 GB of memory. We used Linux Ubuntu 18.04 as the operating system. The software libraries that we used were CUDA toolkit 10.0, Keras 2.2.4, Tensorflow 1.13.1, and Python 3.6 to train the deep classification models. We used the stochastic gradient descent (SGD) training algorithm with a learning rate of 1×10^{-4} and a momentum of 0.9. We used a batch size of 16, and we defined 40 epochs for iterating. The loss function used was categorical cross-entropy.

V. Experimental Evaluation

In this section, we present the results of the models using transfer learning at a plant species classification task. We used the Inception-v4 and Inception-ResNet-v2 architectures. These architectures have been successfully used before on similar tasks [3] [12] [17] and they have been winners on the PlantCLEF 2018 and 2019 challenges [4] [6]. We trained the classification models on Mexico 80 Flower and Oxford 102 Flower datasets using 10-fold cross-validation. We trained both architectures using transfer learning from models trained on the ImageNet 2012, PlantCLEF 2018, and PlantCLEF 2019 datasets. In all cases, we completely fine-tuned the model's parameter values during the training phase. Furthermore, we used 10-fold cross-validation to ensure that the models were properly evaluated. We used the accuracy of the models as an index to compare the performance. The accuracy is the percentage of model-correct responses to the total number of samples.

In Table I, we show the accuracy of the models obtained on both Mexico 80 Flower and Oxford 102 Flower datasets.

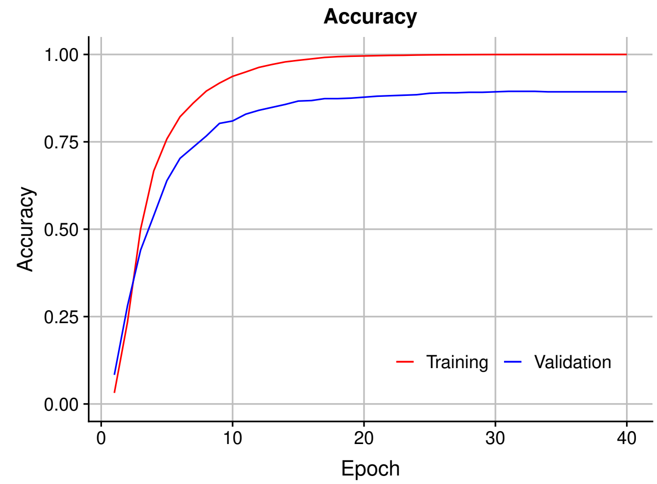
TABLE I
RESULTS OF MODELS USING TRANSFER LEARNING FROM DIFFERENT DOMAINS.

Architectures	Trained on	*Accuracy (%)* Mexico 80 Flower	*Accuracy (%)* Oxford 102 Flower
Inception-v4	ImageNet 2012	88.38	88.70
Inception-v4	PlantCLEF 2018	95.26	95.98
Inception-v4	PlantCLEF 2019	93.09	92.72
Inception-ResNet-v2	ImageNet 2012	92.89	92.37
Inception-ResNet-v2	PlantCLEF 2018	**98.29**	**98.49**
Inception-ResNet-v2	PlantCLEF 2019	97.24	97.20

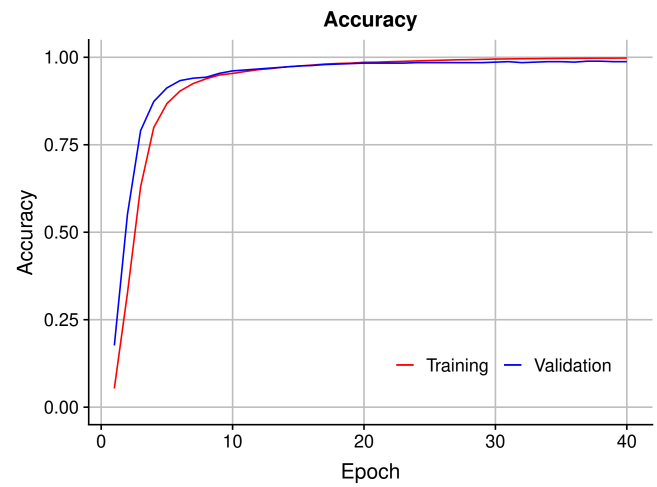
The results showed that the models that used transfer learning from the plant domain (PlantCLEF 2018 and 2019 datasets) achieved superior performance to models that used transfer learning from a general domain (ImageNet 2012 dataset). First, for Inception-v4 models, the models that used transfer learning from ImageNet 2012 dataset were outperformed by those models that used transfer learning from PlantCLEF datasets. Those results were observed in both datasets. For Mexico 80 Flower and Oxford 102 Flower datasets, the Inception-v4 models that used transfer learning from the PlantCLEF 2018 dataset reached 95.26% accuracy and 95.98% accuracy, respectively. Second, the Inception-ResNet-v2 models that used transfer learning from the PlantCLEF 2018 dataset obtained the best overall accuracy. Those models results reached 98.29% accuracy on Mexico 80 Flower dataset and 98.49% accuracy on Oxford 102 Flower dataset.

Figure 6 shows the learning curves of the best and worst accuracy of the models trained on the Mexico 80 Flower dataset. We contrasted the training phase of those models in the experimental stage. Figure 6 (a) and Figure 6 (b) show the accuracy values of the Inception-v4 and Inception-ResNet-v2 models, respectively. The Inception-v4 model used transfer learning from the ImageNet 2012 dataset, and the Inception-ResNet-v2 model used transfer learning from the PlantCLEF 2018 dataset. We observed a gap between the training accuracy and validation accuracy for the Inception-v4 model. In contrast, we did not observe a gap in the learning curves of the training accuracy and validation accuracy of the Inception-ResNet-v2 model. Because the Inception-ResNet-v2 model showed no gap between training accuracy and validation accuracy during the training, this model obtained the best result on the Mexico 80 Flower dataset.

Figure 7 shows the frequency distribution of images per class on the PlantCLEF training datasets. The PlantCLEF 2018 dataset has more images per class than the PlantCLEF 2019 dataset. The red color represents the image distribution per class on PlantCLEF 2018 dataset, and the blue color represents the image distribution per class on PlantCLEF 2019 dataset. A large number of images per class on PlantCLEF 2018 could benefit the learning of the models. Figure 8 shows the frequency distribution of the flower images on PlantCLEF datasets. We analyzed it because this paper deals with plant species classification using flower images. We show the frequency distribution of the flower images for the PlantCLEF 2018 dataset only for the subset of trusted images (images validated by experts). We observed that more than 65% of the classes have at least one flower image. We did not perform the same analysis on the PlantCLEF 2019 dataset because the organ tag was not found in the metadata files. So, we show the frequency distribution of the number of flower images on the test set. We observed that 40% of the classes have at least one flower image. In Figure 8, we show a zoom-in to compare the distribution of images per class on the PlantCLEF datasets. We know it is not a fair comparison as one set is the training set, and the other is the test set. However, we plotted the available information to get an idea of the distribution of images per class on the PlantCLEF 2019 dataset.



(a) Inception-v4 model trained on ImageNet 2012.



(b) Inception-ResNet-v2 model trained on PlantCLEF 2018.

Fig. 6. Comparison of model accuracies during the training phase using the Mexico 80 Flower dataset.

Table II shows the number of classes and images for each PlantCLEF dataset. We observed that the number of images on the PlantCLEF 2018 dataset is larger than the PlantCLEF 2019 dataset. Furthermore, the number of trusted images is larger

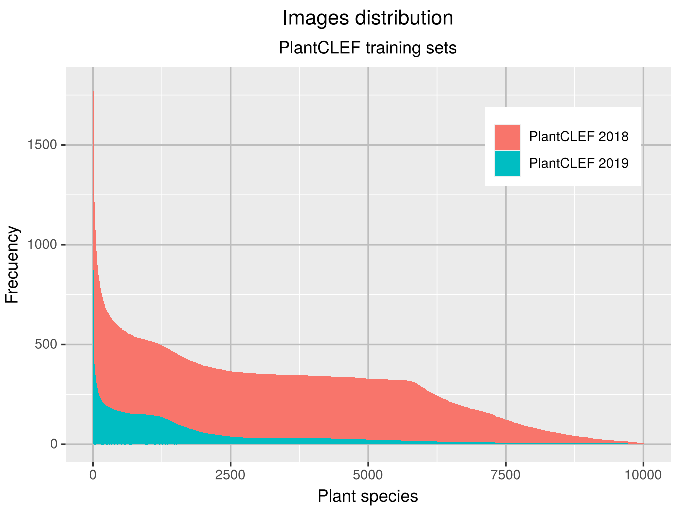


Fig. 7. Frequency distribution of plant species images on PlantCLEF 2018 and PlantCLEF 2019 training datasets.

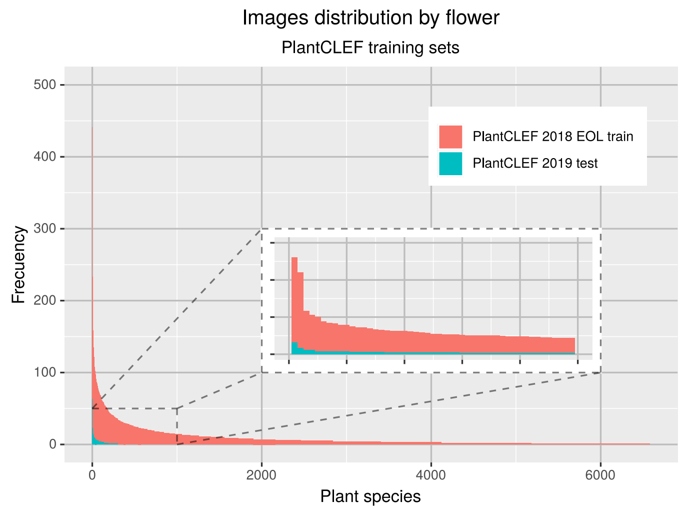


Fig. 8. Frequency distribution of plant species with flower images on PlantCLEF 2018 training set (Encyclopedia of Life) and PlantCLEF 2019 test set.

TABLE II
COMPARISON OF PLANTCLEF 2018 AND 2019 DATASETS.

Dataset	Number of Classes	Trusted images	Total images	Ratio
PlantCLEF 2018	10,000	256,288	1,400,000	1:4
PlantCLEF 2019	10,000	58,619	434,251	1:6

than the PlantCLEF 2019 dataset as well. For the PlantCLEF 2019 dataset, there are six web search images for each trusted image, while on the PlantCLEF 2018 dataset, there are only four for each trusted image. Thus, there is a larger ratio of web search images with respect to trusted images in the PlantCLEF 2019 dataset. Web search images contain duplicate, herbarium, and non-plant images. These web search images are counterproductive to learning the model and complicate the plant species classification (plant species in the field for this paper). Furthermore, we observed that the plant species on the Mexico 80 Flower dataset species are tropical as the plant species on the PlantCLEF19 dataset. However, our results show that a larger representation on the PlantCLEF18 dataset of plant species with flower images helped the models to obtain better results.

VI. CONCLUSION

In this work, we performed a comparative analysis of CNN-based models that use transfer learning from different source domains for plant species classification. The models that used transfer learning from a plant domain obtained the best results for the plant species classification using flower images. The reason is that the source and target domains are related. Furthermore, we noted that the accuracy of the models that used transfer learning from the PlantCLEF 2018 dataset was better than those that used transfer learning from the PlantCLEF 2019 dataset. We identified the following reasons. First, the number of trusted and web search images on the PlantCLEF 2019 dataset is lower than on the PlantCLEF 2018 dataset. Furthermore, the ratio of web search images is six to one on the PlantCLEF 2019 dataset. Thus, these web search images generated noise that negatively impacts the learning process of the models. Second, the distribution analysis showed that 65% of classes on the PlantCLEF 2018 have flower images. This flower representation helped the models in the plant species classification. Both datasets have the same number of classes but differ in data distribution. The PlantCLEF 2018 dataset has a larger flower image representation (trusted images) than the PlantCLEF 2019 dataset. We concluded that all those reasons play a key role for the models trained on those datasets.

For future work, we intend to evaluate the performance indices when the number of classes increases and pretend to extend the experimental evaluation to other plant datasets.

REFERENCES

[1] M. Mehdipour-Ghazi, B. A. Yanikoglu, and E. Aptoula, "Plant Identification Using Deep Neural Networks Via Optimization of Transfer Learning Parameters.," *Neurocomputing*, vol. 235, pp. 228–235, 2017.

[2] A. Kaya, A. S. Keceli, C. Catal, H. Y. Yalic, H. Temucin, and B. Tekinerdogan, "Analysis of Transfer Learning for Deep Neural Network Based Plant Classification Models.," *Computers and Electronics in Agriculture*, vol. 158, pp. 20–29, 2019.

[3] M. Sulc, L. Picek, and J. Matas, "Plant Recognition by Inception Networks with Test-time Class Prior Estimation.," in *Proceedings of the Conference and Labs of the Evaluation Forum, Avignon, France, September 10-14* (L. Cappellato, N. Ferro, J. Nie, and L. Soulier, eds.), vol. 2125 of *CEUR Workshop Proceedings*, CEUR-WS, 2018.

[4] H. Goëau, P. Bonnet, and A. Joly, "Overview of ExpertLifeCLEF 2018: How far Automated Identification Systems are from the Best Experts?," in *Proceedings of the Conference and Labs of the Evaluation Forum, Avignon, France, September 10-14* (L. Cappellato, N. Ferro, J. Nie, and L. Soulier, eds.), vol. 2125 of *CEUR Workshop Proceedings*, CEUR-WS, 2018.

[5] S. Chulif, K. J. Heng, T. W. Chan, M. A. A. Monnaf, and Y. L. Chang, "Plant identication on amazonian and guiana shield flora: NEUON submission to lifeclef 2019 plant," in *Working Notes of CLEF 2019 - Conference and Labs of the Evaluation Forum, Lugano, Switzerland, September 9-12, 2019* (L. Cappellato, N. Ferro, D. E. Losada, and H. Müller, eds.), vol. 2380 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2019.

[6] H. Goëau, P. Bonnet, and A. Joly, "Overview of LifeCLEF Plant Identification Task 2019: diving into Data Deficient Tropical Countries," in *Working Notes of CLEF 2019 - Conference and Labs of the Evaluation Forum, Lugano, Switzerland, September 9-12, 2019* (L. Cappellato, N. Ferro, D. E. Losada, and H. Müller, eds.), vol. 2380 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2019.

[7] S. H. Lee, H. Goëau, P. Bonnet, and A. Joly, "New Perspectives on Plant Disease Characterization Based on Deep Learning.," *Computers and Electronics in Agriculture*, vol. 170, 2020. https://doi.org/10.1016/j.compag.2020.105220.

[8] D. P. Hughes and M. Salathé, "An Open Access Repository of Images on Plant Health to enable the Development of Mobile Disease Diagnostics through Machine Learning and Crowdsourcing," *CoRR*, vol. abs/1511.08060, 2015.

[9] L. E. Ehler, "Integrated Pest Management (IPM): Definition, Historical Development and Implementation, and the other IPM," *Pest management science*, vol. 62, no. 9, pp. 787–789, 2006.

[10] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," *Frontiers in plant science*, vol. 7, pp. 1419–1419, 2016.

[11] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, *et al.*, "Imagenet Large Scale Visual Recognition Challenge," *International Journal of Computer Vision*, vol. 115, no. 3, pp. 211–252, 2015.

[12] L. Picek, M. Sulc, and J. Matas, "Recognition of the Amazonian flora by InceptionNetworks with Test-time Class Prior Estimation," in *Proceedings of the Conference and Labs of the Evaluation Forum, Lugano, Switzerland, September 9-12* (L. Cappellato, N. Ferro, D. E. Losada, and H. Müller, eds.), vol. 2380 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2019.

[13] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning.," in *Proceedings of the AAAI Conference on Artificial Intelligence, San Francisco, California, USA, February 4*, Association for the Advancement of Artificial Intelligence, p. 4278–4284, AAAI Press, 2017.

[14] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. E. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going Deeper with Convolutions.," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, June 7-12*, pp. 1–9, IEEE Computer Society, 2015.

[15] Naturalista, "Comisión Nacional para el Conocimiento y Uso de la Biodiversidad." http://www.naturalista.mx, 2021. Accessed: 2021-03-20.

[16] M. Nilsback and A. Zisserman, "Automated Flower Classification over a Large Number of Classes.," in *Proceedings in the Indian Conference on Computer Vision, Graphics & Image Processing, ICVGIP 2008, Bhubaneswar, India, December 16-19*, pp. 722–729, IEEE Computer Society, 2008.

[17] J. W. Lee and Y. C. Yoon, "Fine-Grained Plant Identification using Wide and Deep Learning Model.," in *Proceedings of the International Conference on Platform Technology and Service, Jeju, Korea (South), January 28-30*, pp. 1–5, IEEE Computer Society, 2019.