Journal of Computer Science and Cybernetics, V.39, N.3 (2023), 223–235
DOI no 10.15625/1813-9663/18144

A PLANT RECOGNITION APPROACH USING HIGH RESOLUTION NETWORK

DANG NGAN HA[1], HIEU TRUNG HUYNH[2,*]

[1] *Vietnamese-German University, Binh Duong, Viet Nam*
[2] *Industrial University of Ho Chi Minh city, Ho Chi Minh city, Viet Nam*

Abstract. Plant species recognition plays an important role in agriculture, the pharmaceutical industry, and conservation. The traditional approaches may take days and have difficulties for non-experts. Several computer vision-based models have been proposed, which can partially assist and speed up the plant recognition process. Thanks to the development of data collection and computational systems, the models based on machine learning have considerably improved their performance in the last decades. In this paper, we present a model for plant recognition in Southeast Asia based on the high-resolution network. The evaluation is carried out on a public dataset consisting of 26 different species in Southeast Asia. It shows high accuracy in recognition.

Keywords. Plant classification; High-resolution network; Deep learning.

1. INTRODUCTION

The medicinal plant and conservation of natural resources have received increasing attention in recent years and depend greatly on identifying species. Species information can provide important characteristics. The manual methods were based on human intuition which is time-consuming, imprecise, and frustrating for non-experts due to the usage of words from the botanical major. The recognition methods based on machine learning and image processing techniques have been investigated by research communities. Digital image techniques may easily capture the leaf shape and venation of plants, which can provide crucial properties for recognition. For convenience of usage, the images could be received from the built-in camera in a mobile device. They have opened research directions in plant identification based on image processing techniques, computer vision, artificial intelligence, and machine learning.

One of the approaches based on computer vision for identifying the tree class from the leaf image was introduced by Oska JOS [1]. The different descriptors that describe the different features of leaves are compared. The dataset is from a joint project between Linkoping University and the Swedish Museum of Natural History. Gaston and O'Neill [2] proposed a method to identify plants and speed up the identification process by using computer vision and search engine. Wu S et al. [3] proposed an approach for leaf recognition by using a probabilistic neural network. Its performance was evaluated on a dataset of leaves collected from the campus of Nanjing University and the Sun Yat-Sen arboretum, Nanking. Most of

*Corresponding author.
E-mail addresses: 14328@student.vgu.edu.vn (N.H Dang); hthieu@iuh.edu.vn (T.H Huynh);

them are common plants of the Yangtze Delta, China. How an extent combination of features can improve the performance of flower classification was investigated by ZA Nilsback [4, 5] The approaches were evaluated on a challenging database of flower images. In addition, a 103-class flower dataset was introduced. An approach for the classification of leaf images with a complicated background was proposed by Sonali Agrawala et al. [6]. This method consists of three steps including leaf segmentation from the complicated background image, feature extraction of morphological and texture, and leaf recognition by using multilevel classification. The proposed method could attain an accuracy of 94%.

Recently, following the advances in deep learning the performance of image recognizers has improved considerably [7–9]. In deep learning, the abstract and composite representation can be learned from each level. In the image recognition application, the raw input images are processed through layers to extract the features before being input into a recognizer. The success of deep learning models trained with supervision is typically contributed from large datasets of annotated images. For plant recognition, some datasets are available including PlantCLEL [10–15], Pl@ntNet [16], iNaturalist [17], etc., which allowed constructing challenges for classification training and evaluation. Several models have been proposed for plant recognition. However, they are not fully developed, and the datasets used in these studies are still heavily regional, and species oriented.

In this study, we investigate plant recognition by using the high-resolution neural network, which offers semantically richer and spatially more precise representation. The experiments are validated on the Bali26 dataset with 26 different plant species collected from the Southeast Asia region [18]. The proposed approach is promising with an accuracy of 100% on the test set.

This paper is the extended version of one presented at CIIA2022 [19]. The rest of the paper consists of three sections. The related works are presented in Section 2, Section 3 describes the model for plant recognition, the experiments are presented in Section 4, and finally, Section 5 is the conclusion.

2. RELATED WORKS

Traditional approaches for identifying species by biologists is to use field guides and dichotomous keys. The field guides utilize images and textual descriptions of unknown species. Dichotomous keys generate a decision tree based on the features of the organism. These approaches have limitations such as difficulty in searching or questioning people who a non-expertise is. These issues have been overcome by the electronic tools including online or handheld device applications [20–22].

Early methods for automatic recognition were based on the leaf shape [23]. Methods for classifying the images of chrysanthemum leaves were proposed by Mokhtarian and Abbasi [24]. Saitoh and Kaneko [25] introduced a method based on neural networks to identify wild-flowers by using their shape and color. A method based on shape descriptions and contexts was presented by Ling and Jacobs [26]. Wang et al. [27] introduced an approach based on the centroid-contour distance combined with more standard and global descriptions of shape. Felzenszwalb and Schwarts [28] proposed a hierarchical shape algorithm for plant classification. Another method based on the leaf shape was proposed by Peter N. Belhumeur et al. [29]. Most leaf recognition methods based on the shape of scanned leaves have the limitation in the "in the wild" scenario due to the uniform background requirements [30].

Following the advances of artificial intelligence (AI) over the last years, the performance of AI-based recognizers for world flora has improved considerably. Several deep neural network (DNN) architectures have been developed. A broad range of convolutional neural networks (CNN) and transformer-based models are evaluated to validate the recognition capabilities of different feature extractors. The commonly used baselines include ResNet-50 [31], ResNet-101, Inception-v4, and Inception-ResNet-v2. The CNN-based models can identify 10,000 plant species from Europe and North America and 10,000 species from the Guiana Shield and the Amazonia with an accuracy of approximately 90 and 40%, respectively [30]. Mads Dyrmann et al. [32] proposed a method that relied on DNN. The experiments were validated on 22 species. The transfer learning from large-scale datasets to domain-specific datasets was introduced by Cui et al. [33]. Zheng et al. [34] proposed the trilinear attention sampling network that generates attention maps relying on inter-channel relationships. Malik et al. [35] proposed an approach based on Inception, MobileNet, and ResNet architectures. In 2017, Lasseck proposed a model that relied on three architectures including GoogLeNet, ResNet-152, and ResNeXt-101-64x4d. The model can attain the best accuracy of 88.5% on PlantCLEF2017 [36]. An approach based on Inception-ResNet-v2 and Inception-v4 was proposed by Sulc and Matas [37]. It can obtain the best accuracy of 88.4% on PlantCLEF2018.

In this paper, a method for plant recognition from the Southeast Asia region is developed. The model is based on deep learning architecture with high-resolution features.

3. THE MODEL FOR PLANT RECOGNITION

Deep convolutional neural networks CNNs have received considerable attention and can obtain state-of-the art results in several applications. Many network architectures have been proposed for object recognition, some reputed architectures are VGG [38], GoogLeNet [39], EfficientNet [40], AlexNet [41], and ResNet [31]. These architectures offer a low-resolution representation for image recognition. The medium-resolution representation can be handled by architectures including DeconvNet [42], SegNet [43], and U-Net [44]. In some applications, the high-resolution representation may give better performance. An architecture for maintaining the high-resolution representation in image processing was proposed by J Wang et al. [45]. It has reported promising results in problems such as object detection, classification, and semantic segmentation.

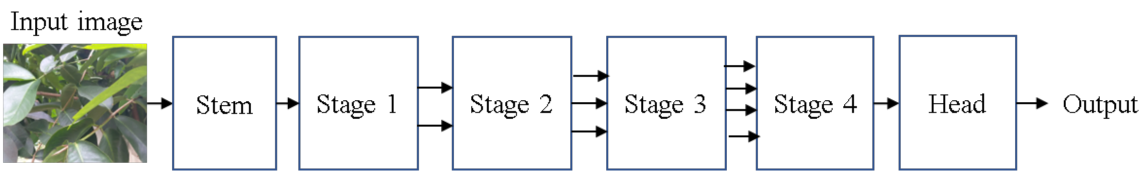


Figure 1: The overall architecture for plant recognition

The overall architecture for plant recognition based on a high-resolution representation is depicted in Figure 1. It consists of multiple stages with parallelly connected streams to maintain the resolution representations. Firstly, the input image is fed into a stem consisting of two convolutional blocks. Each convolutional block includes a stride-2 3×3 convolution to decrease the resolution to 1/4, its output is passed into a batch normalization and a rectified linear unit. The output from the stem is then processed by the main body of a high-resolution network which consists of four stages, each stage has three main components including transition, multi-resolution convolution, and fusion as shown in Figure 2.

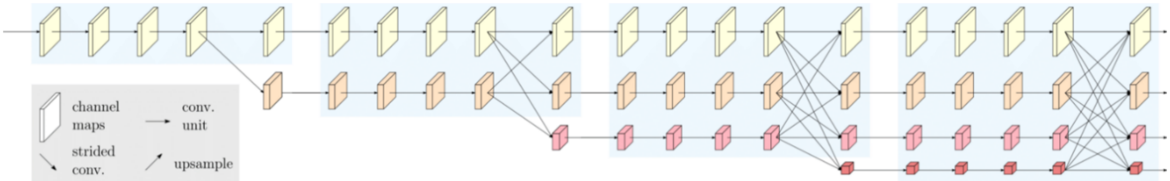


Figure 2: Components of a high-resolution network [45]

The main goal of the transition component is to add a high-to-low resolution. Let R_{ji} be the representation of the i-th resolution index at the j-th stage. The representation in the next stage is determined by

$$R_{j+1i} = \begin{cases} R_{ji} & \text{if } i \leq j \\ f_{j+1}\left(R_{jj}\right) & \text{otherwise,} \end{cases} \tag{1}$$

where, f_{j+1} is a transitional function. In this study, the transitional function is corresponding to the downsampling of the input representation R through stride-2 3×3 convolutions. Note that we can downsample at 2× size by using multiple stride-2 3×3 convolutions. An example of transition from the third stage to the fourth stage is illustrated in Figure 3.

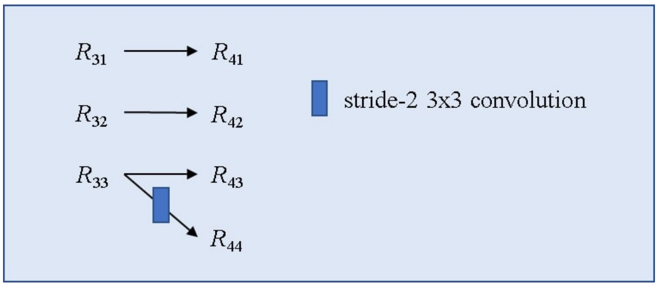


Figure 3: Transition component from the third stage to the fourth stage. The representation in the fourth stage is determined by R_{4i}=R_{3i} for $i \leq 3$ and R_{44}=$f_4\left(R_{33}\right)$, where f_4 is implemented by downsampling using the stride-2 3×3 convolutions.

The multi-resolution consists of multi-streams of four blocks. Each block has the architecture as shown in Figure 4, which consists of 3×3 and 1x1 convolutions followed by batch normalization. The streams are parallelly connected and contain the resolutions from the previous stages. Therefore, it can maintain the high-resolution representations throughout the entire process to generate reliable high-resolution representations having high position sensitivity.

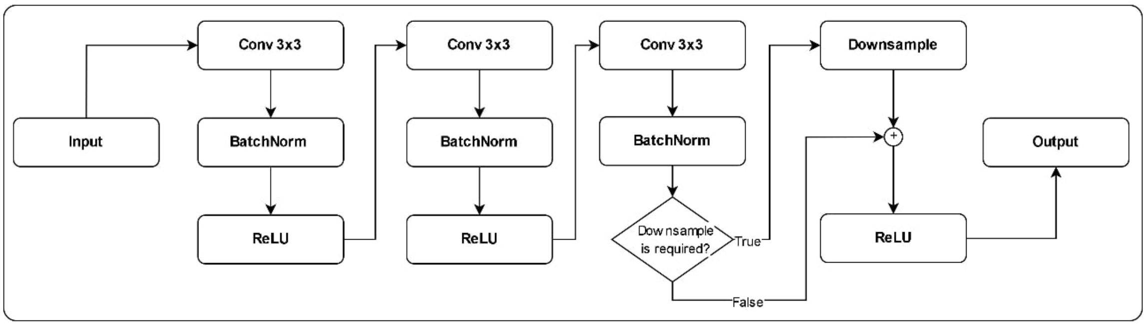


Figure 4: The architecture of a block in a stream

The main goal of the fusion component is to exchange data across representations with different resolutions. The output representation at the i-th index is computed by

$$R_i = \sum_j f_j\left(R_j\right), \tag{2}$$

where R_j is the j-th representation and f_j is a fusion function. The selection of this function relies on the input and output resolution, which is expressed through indexes:

(1) If $j = i,\ f_j(R) = R$;

(2) If $j < i,\ f_{ji}(R)$ is a function to downsample R by using $i - j$ stride-2 3×3 convolutions;

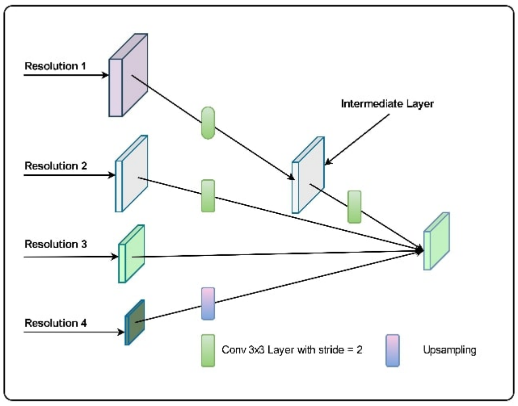
(3) If $j > i,\ f_j(R)$ is a function to upsample R by using the bilinear interpolation followed by a 1×1 convolution for aligning the number of channels.

An illustration of aggregating data from different resolutions is depicted in Figure 5. In Figure 5a, the third representation is generated by $R_3 = f_1\left(R_L\right) + f_2\left(R_2\right) + R_3 + f_4\left(R_4\right)$, in which f_1 is implemented by 2 stride-2 3×3 convolutions, f_2 is implemented by one stride-2 3×3 convolution, and f_4 is implemented by the bilinear interpolation followed by a 1×1 convolution. The Figure 5b is the second representation generated by aggregating data from resolutions 1,2,3, and 4 similar to the third representation except for the difference in the number of intermediate layers for downsampling from resolution 1 and upsampling from resolutions 3 and 4.

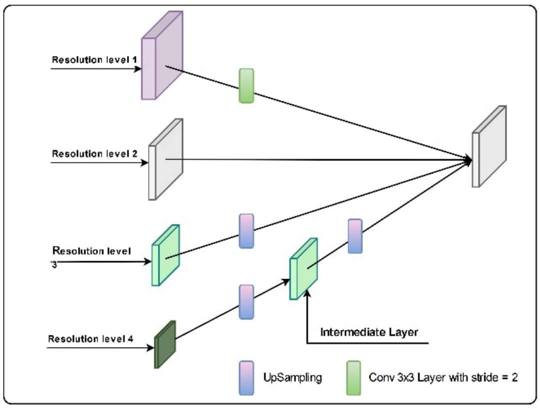
The architecture in our implementation consists of four stages. The first stage contains four residual blocks, each block consists of a bottleneck unit with a width of 64 followed by a 3×3 convolution, which resizes the width of feature maps. The number of branches in the second, third, and fourth stages respectively, is two, three, and four. Each branch includes four residual blocks including two 3×3 convolutions, batch normalization, and the rectified linear unit. The number of channels corresponding to the four resolutions are C, $2C$, $4C$, and $8C$, respectively.

4. EXPERIMENTAL RESULTS

We evaluate the performance of plant recognition on the Bali26 dataset [46, 47] which consists of 26 categories of ethnobotanically significant seeds, fruits, plants, and trees. The



(a) Generating the third representation



(b) Generating the second representation

Figure 5: Aggregating data from different resolutions

Figure 6: Typical images from the Bali26 dataset

number of images is from 1000 to 2500 for each category. This dataset was generated from late February to May 2020 [18, 46]. All images in the dataset are collected from the Island of Bali in the vicinity of Ubud, specifically in the villages of Penglipuran, Kerta, Jatiluwih, Buahan, Sekaan, and Bayung Gede. In comparison to the ImageNet dataset, the images in Bali26 have a higher information richness of the deliriously lush flora. The collection process was performed by a team of members collecting data in the wild, in a constrained location, and over a short period. The images with the size of 1080×1920 in JPG format were captured by data collectors in the field using high-definition mobile phones. Some typical images are shown in Figure 6, and a summary of plant categories including common name, ethnobotany, and scientific name is given in Table 1.

Table 1: A summary of plant categories from the Bali26 dataset [19]

No.	**Common name**	**Ethnobotany**	**Scientific name**
1	Bamboo	Cooked shoots could be added to vegetable soups	Gigantochloa apus
2	Banana	The core stems could be added to vegetable soups	Musa x paradisiaca
3	Cacao	Powder of seeds powder can be used for inducing relaxation	Theobroma cacao
4	Coffee arabica	Powder of seeds can be used for inducing relaxation	Coffea canephora
5	Dragon fruit	Ripe fruit eaten fresh; Fruits can be used for processing or religious offerings	Hylocereus costaricensis
6	Durian	Fruits can be used for processing or religious offerings	Durio zibethinus
7	Elephant foot yam (Suweg)	Tuberous roots can be used as staple food	Amorphophallus paeoniifolius
8	Frangipani	The flowers can be used in religious offerings; The Flower juice can be applied to the skin for smallpox	Plumeria alba
9	Guava	Ripe Fruit can be used in religious offerings or eaten fresh.	Psidium guajava
10	Indonesian cinnamon	Decoction of leaves and barks can be used for hypertension, fever, heartburn, sore throat, cough, and to stimulate the appetite; Barks can be used as spices.	Cinnamomum burmanii
11	Jackfruit	Leaf decoction can be used for diarrhea; Cooked fruit and seeds can be added to vegetable soups.	Artocarpus heterophyllus
12	Lychee	Fruits can be used eaten fresh, for drying, or for religious offerings.	Litchi chinensis
13	Mango	Decoction of leaves can be used for hypertension and diabetes	Mangifera indica
14	Mangosteen	Ripe fruit can be eaten fresh, or used in religious offerings	Garcinia mangostana

15	Nilam	The leaves can be used for rheumatic, dysentery, headache, and as diuretic	Pogostemon cablin
16	Papaya	Young leaves and cooked fruit can be added to vegetable soups	Carica papaya
17	Passiflora	Ripe fruit can be eaten fresh	Passiflora edulis
18	Sawo	Ripe Fruit can be used in religious offerings or eaten fresh	Manilkara zapota
19	Snake fruit	Ripe Fruit can be used in religious offerings or eaten fresh	Salacca zalacca
20	Star fruit	Juice of leaves can be used for heartburn; Cooked fruit and leaves can be added to vegetable soups	Averrhoa carambola
21	Sugarplum	Boiled fruit is edible; Boiled inner stems can be eaten as a staple food; Root decoction can be used for urolithiasis; Leaves can be used in religious offerings	Arenga pinnata
22	Taro	Cooked leaves can be added to vegetable soups; Boiled tuberous roots can be eaten as a staple food.	Colocasia esculenta
23	Vanilla	Fruit powder can be used as vanilla flavoring	Vanilla planifolia
24	Water guava	Ripe fruit can be eaten fresh	Syzygium aqueum
25	White pepper	Seeds powder can be used as spice	Piper nigrum
26	Zodiac	Leaves can be used for mosquito repellent	Evodia sauveolens

Table 2: The recognition results from the testing set

No.	**Category**	**# Images**	**No.**	**Category**	**# Images**
1	Cinnamon	136	14	Suweg	132
2	Dragon fruit	234	15	Sawo	136
3	Jack fruit	297	16	Banana	191
4	Mango	149	17	Mangosteen	180
5	Nilam	138	18	Durian	271
6	Papaya	183	19	Snake fruit	130
7	Passiflora	151	20	Bamboo	214
8	Vanilla	217	21	Coffee arabica	149
9	Water guava	205	22	Lychee	124
10	White pepper	157	23	Sugar palm	140
11	Star fruit	189	24	Frangipani	174
12	Taro	177	25	Guava	215
13	Zodiac	148	26	Cacao	187

The proposed scheme was implemented by using Python 3.7 programming language and PyTorch machine learning framework on Ubuntu 18.04 operating system. The hardware configuration of CPU Intel® Xeon® Quad-core 2.9 GHz, RAM of 16GB, GPU GeForce GTX 2080ti with 16GB, and HDD of 1TB was used. The hyperparameters were selected based on try-and-error and previous publications. The Adam optimizer was used. The batch size, learning rate, momentum, and epochs were 32, 0.05, 0.9, and 50, respectively.

The model was pretrained on the ImageNet dataset, then trained on the Bali26 dataset. The performance is evaluated on the criterion of accuracy. The testing set corresponding to 26 categories is given in Table 2. The overall accuracy is highly impressive, which is 100% for the testing set.

The high-resolution input images can require the high-resolution network model which may result in more memory. There are several models for identifying plants, they are evaluated on different datasets. The DNN model proposed by Mads Dyrmann et al. (Dyr16) was evaluated on 22 species. The architectures based on GoogLeNet, ResNet-152, and ResNeXt-101-64×4d can attain the best accuracy of 88.5% on PlantCLEF2017. The model based on Inception-ResNet-v2 and Inception-v4 can attain the best accuracy of 88.4% on PlantCLEF2018. In our study, most of the features in the dataset are fruits, leaves, and whole trees. The model based on the high-resolution architecture can attain an impressive accuracy of 100% on the test set of Bali26.

5. CONCLUSIONS

Identifying plant information plays an important role in not only agriculture but also medicine. Several models have been developed relying on image processing techniques and machine learning. They can attain promising results. However, they are validated on datasets collected from some specific regions. In this paper, an approach based on the high-resolution network is proposed and evaluated on a dataset consisting of 26 different species in Southeast Asia. The accuracy of the testing set is impressive. By training the model with more datasets for plant identification, we believe that the trained model can contribute to a variety of applications, especially in the pharmaceutical industry. In addition, plant identification may contribute to disease detection in plants to help solve agricultural problems.

REFERENCES

[1] O. Söderkvist, "Computer vision classification of leaves from swedish trees," in *Dissertation*, Independent thesis Advanced level, 2001.

[2] K. Gaston and M. O'Neill, "Automated species identification: Why not?" *Philos Trans R Soc Lond B Biol Sci.*, vol. 359, pp. 655–667, 2004.

[3] S. G. Wu, F. S. Bao, E. Y. Xu, Y.-X. Wang, Y.-F. Chang, and Q.-L. Xiang, "A leaf recognition algorithm for plant classification using probabilistic neural network," in *2007 IEEE International Symposium on Signal Processing and Information Technology*, 2007, pp. 11–16. DOI: 10.1109/ISSPIT.2007.4458016.

[4] M.-E. Nilsback and A. Zisserman, "A visual vocabulary for flower classification," in *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, vol. 2, 2006, pp. 1447–1454. DOI: 10.1109/CVPR.2006.42.

[5] M.-E. Nilsback and A. Zisserman, "Automated flower classification over a large number of classes," in *2008 Sixth Indian Conference on Computer Vision, Graphics Image Processing*, 2008, pp. 722–729. DOI: 10.1109/ICVGIP.2008.47.

[6] M. A. K. Sonali Agrawala A. S. Jalala, "Plant identification using leaf image analysis," 2018. DOI: http://dx.doi.org/10.2139/ssrn.3170725.

[7] M. M. Ghazi, B. Yanikoglu, and E. Aptoula, "Plant identification using deep neural networks via optimization of transfer learning parameters," *Neurocomputing*, vol. 235, pp. 228–235, 2017.

[8] S. T. H. Pierre Bonnet Hervé Goëau, M. Lasseck, M. Šulc, *et al.*, "Plant identification: Experts vs. machines in the era of deep learning," in *Multimedia Tools and Applications for Environmental & Biodiversity Informatics*. Springer International Publishing, 2018, pp. 131–149.

[9] L. Picek, M. Šulc, and J. Matas, "Recognition of the amazonian flora by inception networks with test-time class prior estimation cmp submission to plantclef 2019," 2019. [Online]. Available: https://api.semanticscholar.org/CorpusID:201707612.

[10] H. Goëau, P. Bonnet, and A. Joly, "Plant identification in an open-world (lifeclef 2016)," in *Conference and Labs of the Evaluation Forum*, 2016. [Online]. Available: https://api.semanticscholar.org/CorpusID:292341.

[11] H. Goëau, P. Bonnet, and A. Joly, "Plant identification based on noisy web data: The amazing performance of deep learning (lifeclef 2017)," in *Conference and Labs of the Evaluation Forum*, 2017. [Online]. Available: https://api.semanticscholar.org/CorpusID:6480972.

[12] H. Goëau, P. Bonnet, and A. Joly, "Overview of expertlifeclef 2018: How far automated identification systems are from the best experts?" In *Conference and Labs of the Evaluation Forum*, 2018. [Online]. Available: https://api.semanticscholar.org/CorpusID:51942763.

[13] H. Goëau, P. Bonnet, and A. Joly, "Overview of lifeclef plant identification task 2019: Diving into data deficient tropical countries," in *Conference and Labs of the Evaluation Forum*, 2019. [Online]. Available: https://api.semanticscholar.org/CorpusID:198488668.

[14] H. Goëau, P. Bonnet, and A. Joly, "Overview of lifeclef plant identification task 2020," Thessaloniki, 2020. [Online]. Available: https://ceur-ws.org/Vol-2696/paper_140.pdf.

[15] H. Goëau, P. Bonnet, and A. Joly, "Overview of plantclef 2021: Cross-domain plant identification," in *Conference and Labs of the Evaluation Forum*, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:237297929.

[16] C. Garcin, A. Joly, P. Bonnet, *et al.*, "Pl@ntnet-300k: A plant image dataset with high label ambiguity and a long-tailed distribution," in *NeurIPS Datasets and Benchmarks*, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:244906850.

[17] i. C. Datasets. "Inaturalist competition datasets." (2021), [Online]. Available: http://www.k-jahn.de/files/bibtex.xslhttp://www.k-jahn.de/files/bibtex.xsl (visited on 2023).

[18] Adoy101, C. Wang, HenryVu, N. G. Nhu, and S. Ali. "Classification of plants of southeast asia." (2022), [Online]. Available: https://kaggle.com/competitions/classification-of-plants-of-southeast-asia.

[19] D. N. Ha, T. H. Ngoc, and H. T. Huynh, "Plant classification in southeast asia using high resolution network," in *CIIA2022*, Ho Chi Minh, 2022.

[20] M. Edwards and D. R. Morse, "The potential for computer-aided identification in biodiversity research," *Trends in Ecology Evolution*, vol. 10, no. 4, pp. 153–158, 1995, ISSN: 0169-5347. DOI: https://doi.org/10.1016/S0169-5347(00)89026-6.

[21] R. Pankhurst, *Practical taxonomic computing*. Cambridge: Cambridge University Press, 1991.

[22] R. Stevenson, W. Haber, and R. Morris, "Electronic field guides and user communities in the eco-informatics revolution," *Conservation Ecology*, vol. 7, no. 1, 2003. [Online]. Available: https://www.ecologyandsociety.org/vol7/iss1/art3/.

[23] M.-E. Nilsback and A. Zisserman, "A visual vocabulary for flower classification," in *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, vol. 2, 2006, pp. 1447–1454. DOI: 10.1109/CVPR.2006.42.

[24] F. Mokhtarian and S. Abbasi, "Matching shapes with self-intersections:application to leaf classification," *IEEE Transactions on Image Processing*, vol. 13, no. 5, pp. 653–661, 2004. DOI: 10.1109/TIP.2004.826126.

[25] T. Saitoh and T. Kaneko, "Automatic recognition of wild flowers," in *Proceedings 15th International Conference on Pattern Recognition. ICPR-2000*, vol. 2, 2000, 507–510 vol.2. DOI: 10.1109/ICPR.2000.906123.

[26] H. Ling and D. W. Jacobs, "Shape classification using the inner-distance," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 2, pp. 286–299, 2007. DOI: 10.1109/TPAMI.2007.41.

[27] Z. Wang, Z. Chi, and D. Feng, "Shape based leaf image retrieval," *IEE Proceedings - Vision, Image, and Signal Processing*, vol. 150, no. 1, p. 34, 2003. DOI: 10.1049/ip-vis:20030160.

[28] P. F. Felzenszwalb and J. D. Schwartz, "Hierarchical matching of deformable shapes," in *2007 IEEE Conference on Computer Vision and Pattern Recognition*, 2007, pp. 1–8. DOI: 10.1109/CVPR.2007.383018.

[29] P. N. Belhumeur, D. Chen, S. Feiner, *et al.*, "Searching the world's herbaria: A system for visual identification of plant species," in *Lecture Notes in Computer Science*, Springer Berlin Heidelberg, 2008, pp. 116–129. DOI: 10.1007/978-3-540-88693-8_9.

[30] L. Picek, Y. P. Milan Šulc, and J. Matas, "Plant recognition by AI: Deep neural nets, transformers, and kNN in deep embeddings," *Frontiers in Plant Science*, vol. 13, 2022. DOI: 10.3389/fpls.2022.787527.

[31] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778. DOI: 10.1109/CVPR.2016.90.

[32] M. Dyrmann, H. Karstoft, and H. S. Midtiby, "Plant species classification using deep convolutional neural network," *Biosystems Engineering*, vol. 151, pp. 72–80, 2016, ISSN: 1537-5110. DOI: https://doi.org/10.1016/j.biosystemseng.2016.08.024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1537511016301465.

[33] Y. Cui, Y. Song, C. Sun, A. Howard, and S. Belongie, *Large scale fine-grained categorization and domain-specific transfer learning*, 2018. DOI: 10.48550/ARXIV.1806.06193.

[34] H. Zheng, J. Fu, Z. Zha, and J. Luo, "Looking for the devil in the details: Learning trilinear attention sampling network for fine-grained image recognition," in *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Los Alamitos, CA, USA: IEEE Computer Society, 2019, pp. 5007–5016. DOI: 10.1109/CVPR.2019.00515. [Online]. Available: https://doi.ieeecomputersociety.org/10.1109/CVPR.2019.00515.

[35] O. A. Malik, M. Faisal, and B. R. Hussein, "Ensemble deep learning models for fine-grained plant species identification," in *2021 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, 2021, pp. 1–6. DOI: 10.1109/CSDE53843.2021.9718387.

[36] M. Lasseck, "Image-based plant species identification with deep convolutional neural networks," in *Conference and Labs of the Evaluation Forum*, 2017. [Online]. Available: https://api.semanticscholar.org/CorpusID:12717795.

[37] M. Šulc and J. Matas, "Fine-grained recognition of plants from images," *Plant Methods*, vol. 13, no. 1, 2017. DOI: 10.1186/s13007-017-0265-4.

[38] K. Simonyan and A. Zisserman, *Very deep convolutional networks for large-scale image recognition*, 2014. DOI: 10.48550/ARXIV.1409.1556.

[39] C. Szegedy, W. Liu, Y. Jia, *et al.*, "Going deeper with convolutions," in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, 2015. DOI: 10.1109/cvpr.2015.7298594.

[40] M. Tan and Q. V. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks," 2019. DOI: 10.48550/ARXIV.1905.11946.

[41] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems*, F. Pereira, C. Burges, L. Bottou, and K. Weinberger, Eds., vol. 25, Curran Associates, Inc., 2012. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf.

[42] H. Noh, S. Hong, and B. Han, *Learning deconvolution network for semantic segmentation*, 2015. DOI: 10.48550/ARXIV.1505.04366.

[43] V. Badrinarayanan, A. Kendall, and R. Cipolla, "Segnet: A deep convolutional encoder-decoder architecture for image segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 12, pp. 2481–2495, 2017. DOI: 10.1109/TPAMI.2016.2644615.

[44] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Lecture Notes in Computer Science*, Springer International Publishing, 2015, pp. 234–241. DOI: 10.1007/978-3-319-24574-4_28.

[45] J. Wang, K. Sun, T. Cheng, *et al.*, *Deep high-resolution representation learning for visual recognition*, 2019. DOI: 10.48550/ARXIV.1908.07919.

[46] M. Böhlen and W. Sujarwo, "Return to bali," in *2020 Second International Conference on Transdisciplinary AI (TransAI)*, 2020, pp. 92–95. DOI: 10.1109/TransAI49837.2020.00020.

[47] M. Böhlen and W. Sujarwo, "Machine learning in ethnobotany," in *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2020, pp. 108–113. DOI: 10.1109/SMC42975.2020.9283069.

Received on March 04, 2023
Accepted on June 25, 2023