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Preface

The volume CCIS 1488 contains the refereed proceedings of the International Conference on Optimization, Learning Algorithms and Applications (OL2A 2021), an event that, due to the COVID-19 pandemic, was held online.

OL2A 2021 provided a space for the research community on optimization and learning to get together and share the latest developments, trends, and techniques as well as develop new paths and collaborations. OL2A 2021 had more than 400 participants in an online environment throughout the three days of the conference (July 19–21, 2021), discussing topics associated to areas such as optimization and learning and state-of-the-art applications related to multi-objective optimization, optimization for machine learning, robotics, health informatics, data analysis, optimization and learning under uncertainty, and the Fourth Industrial Revolution.

Four special sessions were organized under the following topics: Trends in Engineering Education, Optimization in Control Systems Design, Data Visualization and Virtual Reality, and Measurements with the Internet of Things. The event had 52 accepted papers, among which 39 were full papers. All papers were carefully reviewed and selected from 134 submissions. All the reviews were carefully carried out by a Scientific Committee of 61 PhD researchers from 18 countries.

July 2021 Ana I. Pereira

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Leaf-Based Species Recognition Using Convolutional Neural Networks

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Abstract. Identifying plant species is an important activity in specie control and preservation. The identification process is carried out mainly by botanists, consisting of a comparison of already known specimens or using the aid of books, manuals or identification keys. Artificial Neural Networks have been shown to perform well in classification problems and are a suitable approach for species identification. This work uses Convolutional Neural Networks to classify tree species by leaf images. In total, 29 species were collected. This work analyzed two network models, Darknet-19 and GoogLeNet (Inception-v3), presenting a comparison between them. The Darknet and GoogLeNet models achieved recognition rates of 86.2% and 90.3%, respectively.

Keywords: Deep learning · Leaf recognition · Tree classification

1 Introduction

Sustainability is an important concern in the context of business and governments in view of nature preservation. According to Shrivastava [12], both businesses and governments play an important role in nature's preservation. The identification process of forest species is important in this context, specially in the case of endangered species. *Flora* identification is currently made by botanists by comparing with already known species or with book guidance, manuals and identification keys. This comprises simple tasks as identifying whether the plant have flowers and fruits to more complex tasks, such as identifying the plant species by observing morphological attributes. For non-professionals, this process can be long and error prone, so an automated tool would save time and, possibly, plant species. The advancements made in computation, image processing techniques and pattern recognition unveiled new ways of specie identification. Deep learning based system are promising in this field, being helpful both for the professionals and non-professionals.

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In this work, we used leaf images to train Convolutional Neural Netowrks (CNNs) for the classification task. Two models were trained: GoogLeNet (Inception-v3) and Darknet-19, both implemented using Tensorflow. These models were chosen due to their light requirements when compared to other models, allowing for use in low-cost equipment during field research. The models can be used to identify species *in natura*.

This work is organized as follows. Section 2 presents an overview of CNNs, specie identification and related works. Section 3 presents the materials and methods used to train our models. Section 4 discusses the results. Finally, Sect. 5 contains the works conclusions.

2 Background

2.1 Species Identification

In order to realize plant species classification, botanists base themselves in vegetable taxonomy, analyzing characteristic group species by morphological similarities and genetic kinship links [10]. This process generated a field in botany called dendrology, which investigates woody plants identification, distribution and classification [5]. Dendrology scope includes root types, tree sizes, pilosity, shaft, as well as diagnostic elements (color, texture and structure). The shaft is a tree trunk part free of ramifications which can be of different types, shapes and bases.

Table 1 presents leaf components. The bases of leaf variety is its division type, as there are simple leaves, which presents a single leaf lamina (Fig. 1). There are also compound leaves, which present more than one leaflet, as shown in Fig. 2.

Table 1. Leaf Characteristics

Scientific name	Description
Leaf venation	Pattern of veins in the leaf
Hairiness	Structures as hair in leaf surface
Leaf arrangement	How leaves are arranged on a twig
Stem	Plant structure that supports leaves, flowers and fruits
Stipule	A pair of small organs that may be attached to the twig on either side of the petiole
Leaf base	Part of leaf nearest to the petiole
Leaf apexes	Part of leaf farthest from petiole
Simple leaf	Leaf that has a single blade
Compound leaf	Leaf that has two or more blades that are called leaflets
Leaflets	Leaf subdivisions that are related to compound leaf
Stalk	A thin stem that supports a leaf and joints it to another part of plant tree
Rachis	Principal vein in the compound leaf, extension of stalk
Bud	A small lump from which a flower, leaf or stem develops

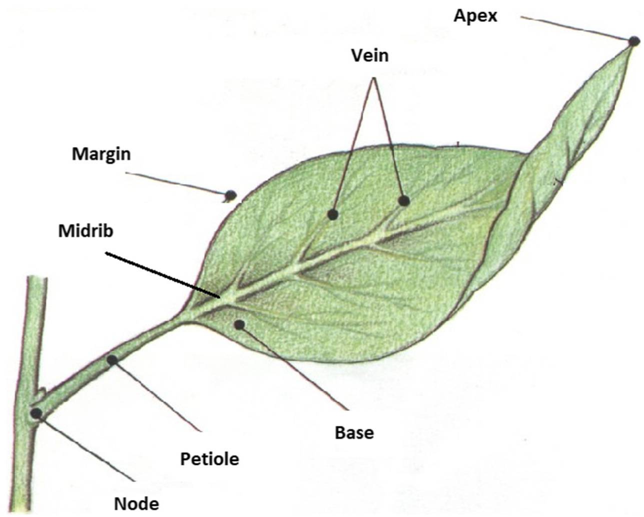

Fig. 1. Simple leaf [5]

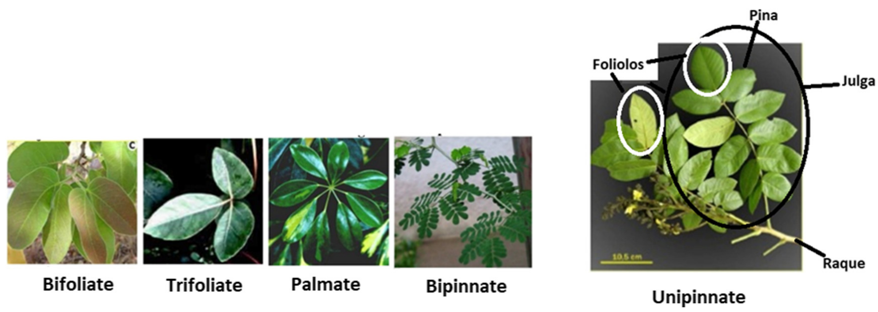

Fig. 2. Compound leaf [5]

There are other important leaf elements, which generate a wide specie variety, such as leaf shape, tip (or apex), base and margin attributes, which can be used to differentiate plant species. Leafs also can be identified according to their phyllotaxis, which are divided in four types: alternate, spiral, opposite and whorled, shown in Fig. 3. This attribute is used before leaf extraction, as it shows how leaves are organized. Other attribute is leaf venation, which is divided in pinnate, reticulate, parallel, palmate and dichotomous (Fig. 4).

All those characteristics are taken in account during species identification process and are the foundation of a widely used species identification method among botanists: dichotomous key, which is based in plant characteristics observation. Researchers compare characteristics of field extracted species with the characteristics of dichotomous keys, one by one, until matching with any of the registered species [10]. Table 2 presents a simple example using a dichotomous key to classify a leaf according to it's venation.

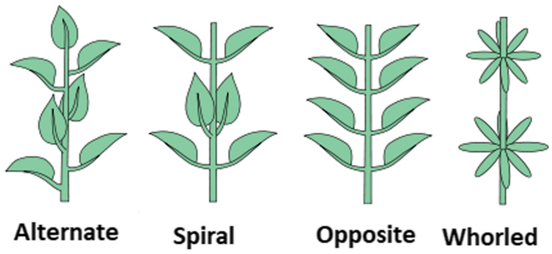

Fig. 3. Leaf phyllotaxis [5]

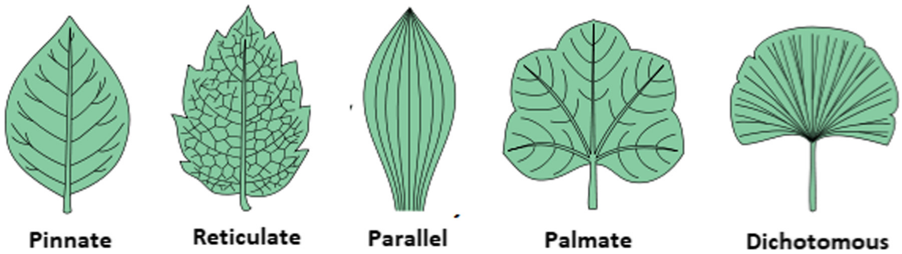

Fig. 4. Leaf venation [5] onte

Table 2. Simple dichotomous key [5]

1. Leaves with a single vein and not ramified	Single main vein
Leaves with more than a single venation	2
2. Leaves with more than a single vein and all parallel between them	Parallel
Leaves with non-parallel veins	3
3. Secondary veins originates from a main vein	Pinnate
Leaves with several main veins originating from the petiole	Palmate

This is a fairly simple example, but in many cases characteristic selection might not be trivial and plant specie identification will usually involve more than a single characteristic. An example is *Xanthosoma taioba*, which is suitable for consumption and hard to classify, as it is very similar to *Xanthosoma violaceum*, which is not suitable for consumption. In Fig. 5, it becomes clear that differing two species is not always a simple task.

Fig. 5. The real *Xanthosoma taioba* (right), and *Xanthosoma violaceum* (left) [5]

2.2 Convolutional Neural Networks

In the context of machine learning, specifically in neural networks, Convolutional Neural Networks (CNNs) are a powerful model to analyze images. CNNs are popular in image processing since they are inspired by the visual cortex. These networks are based on the idea of specialized components inside a system with specific tasks, in a similar fashion as the visual cortex observed by [16]. This architecture is composed by a sequence of layers that tries to capture a hierarchy of increasingly sophisticated representations. Besides the input layer, which normally consists of an image with width, height and color depth (RGB – red, green and blue channels), there are three typical layers: convolution layer, pooling layer and densely connected layer [15].

The first hidden layer in a CNN is usually a convolutional layer, which is composed by many feature maps (filters), capable of learning patterns as the training progresses [3]. Convolutional layers usually receive a two-dimensional or a collection of input two-dimensional and are widely used to process images. The layers are then submitted to a convolutional operation subject to parameters learned during the network training phase.

Each layer usually also performs a non-linear operation which greatly increases a model generalization capacity. This is done using an activation function. A popular function is the Rectified Linear Unit (ReLU), as it is a fast to calculate non-linear function. It replaces negative input values by zero [15]. An example as can be observed in (1), where z represents the function input (a neuron input).

$$\phi(z) = \begin{cases} 0 & z \leq 0 \\ z & z > 0 \end{cases} \tag{1}$$

After a convolution and activation function, it is common the use of a pooling layer. This technique aims to reduce the resulting matrix size, which diminishes the amount of neural network parameters to learn, contributing to avoid overfitting [15]. Max pooling is a pooling technique in which several inputs close to each other are replaced by a single value, the highest value in their neighbourhood.

Each consecutive layer are capable of representing more complex concepts than the previous layer. The last layers of a CNN usually are dense (or fully connected) layers, built on top of the convolutional layers. In case of CNNs for classification, the last layer outputs a n-dimensional vector, where n is the total number of classes and each vector element is the predicted class probability for one of the available classes [3]. For classification, it is common the use of the Softmax function, which compares each output neuron response and return the results in the form of probability. This function is presented in (2), for the stimulus z_j received by the j-nth output neuron.

$$\phi(z_j) = \frac{e^{z_j}}{\sum_k e^{z_k}} \tag{2}$$

These models are normally trained using the Backpropagation and Gradient Descent algorithms. To avoid overfitting, dropout technique can be used. Dropout approach consists on randomly removing neurons during training process [1].

2.3 Darknet

Darknet is a neural topology usually implemented in the YOLO framework. This framework allows real-time object detection and is able to identify objects in images and videos as presented in Table 3. In this work, we investigated Darknet-19, an architecture composed of 19 convolutional layers interspersed with 5 more layers that apply max-pooling [3].

This network segments input image in SxS frames, known as grids. To do this, it uses a divide and conquer strategy, making use of image segments to identify object position in addition to only identifying objects [2].

2.4 GoogLeNet

GoogLeNet is a CNN that became notorious after winning the 2014 Imagenet Competition. GoogLeNet engineer's objective was to enhance neural network computational efficiency while making it deeper and wider. The main feature in GoogLeNet is the inception module, which is based on the idea of using multiple convolutional filters [13] varying the kernel size used in the same convolutional layer. The enhanced inception module is presented in Fig. 6.

Table 3. Darknet-19 [13]

Type	Filters	Stride/Size	Output Dimension
Convolutional	32	3×3	224×224
Maxpool		$2 \times 2/2$	112×112
Convolutional	64	3×3	112×112
Maxpool		$2 \times 2/2$	56×56
Convolutional	128	3×3	56×56
Convolutional	64	1×1	56×56
Convolutional	128	3×3	56×56
Maxpool		$2 \times 2/2$	28×28
Convolutional	256	3×3	28×28
Convolutional	128	1×1	28×28
Convolutional	256	3×3	28×28
Maxpool		$2 \times 2/2$	14×14
Convolutional	512	3×3	14×14
Convolutional	256	1×1	14×14
Convolutional	512	3×3	14×14
Convolutional	512	3×3	14×14
Convolutional	256	1×1	14×14
Maxpool		$2 \times 2/2$	7×7
Convolutional	1024	3×3	7×7
Convolutional	512	1×1	7×7
Convolutional	1024	3×3	7×7
Convolutional	512	1×1	7×7
Convolutional	1024	3×3	7×7
Convolutional	1000	1×1	7×7
Avgpool		Global	1000
Softmax			

GoogLeNet is a 22 layer network, considering only convolutional layers, as shown in Table 4. The last layer uses the Softmax function to perform classification [15].

2.5 Related Work

Many solutions based on deep learning have been used in specie identification problems, due to recent results using this technique. Other strategies can also be used, based on image processing and pattern recognition. These techniques use macro and microscopic characteristics of the image. For example, [8] classifies wood applying the following image characteristics extraction techniques: color

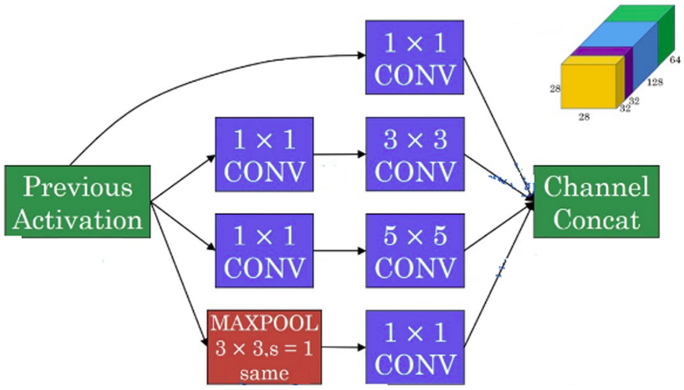

Fig. 6. Inception module [14]

Table 4. GoogLeNet's structure [13]

Type	Filters/Stride	Output Dimension
Convolution	$7 \times 7/2$	$112 \times 112 \times 64$
Max Pool	$3 \times 3/2$	$56 \times 56 \times 64$
Convolution	$3 \times 3/1$	$56 \times 56 \times 192$
Max Pool	$3 \times 3/2$	$28 \times 28 \times 192$
Inception (3a)		$28 \times 28 \times 256$
Inception (3b)		$28 \times 28 \times 480$
Max Pool	$3 \times 3/2$	$14 \times 14 \times 480$
Inception (4a)		$14 \times 14 \times 512$
Inception (4b)		$14 \times 14 \times 512$
Inception (4c)		$14 \times 14 \times 512$
Inception (4d)		$14 \times 14 \times 512$
Inception (4e)		$14 \times 14 \times 832$
Max Pool	$3 \times 3/2$	$7 \times 7 \times 832$
Inception (5a)		$7 \times 7 \times 832$
Inception (5b)		$7 \times 7 \times 1024$
Avg Pool	$7 \times 7/1$	$1 \times 1 \times 1024$
Dropout (40%)		$1 \times 1 \times 1024$
Linear		$1 \times 1 \times 1000$
Softmax		$1 \times 1 \times 1000$

analysis, GLCM (Gray-Leval Co-occurence Matrix), border histogram, fractals, LBP (Local Binary Pattern), LPQ (Local Phase Quantization) and Gabor filter. This approach resulted in a recognition rate of 99.49% among 42 species.

Another work with related theme proposes analysis and identification of plant species based in texture characteristics extraction from microscopic leaf epidermis images [7]. Texture extraction techniques were used to analyze 32 species. This approach had 96% success rate. By utilizing leaves, [11] applied image segmentation techniques for feature extraction. This was performed using the GLCM technique and feature vectors were extracted. The achieved recognition rate was around 75.4% by techniques like MLP (Multilayer Perceptron), SMO (Sequential Minimal Optimization) and LibSVM (Library for Support Vector Machines) as classifiers.

Using deep learning as main identification method, the strategy is basically to use CNNs to identify the best characteristic from the leaf to recognize a specie. From this strategy, [6] build CNNs being used for weeds control, which tries to detect a specie in the lawn. It was used 256×256 pixels images and the used architecture was AlexNet. The result was 75% precision [9].

There are other CNN approaches, [17] proposes the analysis of pictures taken from the top of farms, which demanded an extra detail preprocessing the image to enhance illumination before sending it to the network, that is composed of 5 convolutional layers with ReLU activation function and, at the end of the network, a Softmax function. Their experiment obtained 97.47% precision.

3 Method

3.1 Data Collection

Initially, leafs from 29 different species were collected. Species are listed in Sect. 4 (Table 4). For each species, 100 photos were taken on both sides. Images were obtained through the utilization of a photobooth proposed by [11]. It has 40 square centimeters and its internal contains led strips, which produces high luminosity with low energy costs. These leds can be feed using batteries or a 12 V power supply, and can be easily transported. To avoid reflexes on the images, internal walls were painted black, except for the bottom, which is white. The leaf is positioned on the bottom of the photobooth, where it is compressed by a glass pane, to keep it fixed and flat. This dataset is in the process of being public released.

After gathering enough photos, data augmentation techniques were used to artificially increase dataset size, as it is necessary to have many samples to train a Deep Neural Network. Data augmentation was done by using python 3.5.2 and Keras scripts to alter images, creating new ones. It was used Keras ImageDataGenerator class to generate new image samples from the original data, using the default values for the operations Rotation Range, Width Shift, Shear Range, Zoom Range, Horizontal and vertical Flip and Fill mode.

3.2 Training

The models were then trained with the augmented data and had their results evaluated, in order to improve performance. Both models, GoogLeNet and DarkNet19, were trained four times.

For GoogLeNet, we used the work of [13] as a reference to develop and train our network. Originally, the network was developed with batch size of 50, Reduce 1×1 of 104 and Dropout rate of 0.5.

Regarding Darknet-19, we used the python implementation Darkflow, which allow for the utilization of Darknet framework in Tensorflow [4]. Tiny-YOLO version 2 was used instead of YOLO version 3, as it was faster to train. As it was used 29 classes, the number of feature maps used in the last layer was 170, stride of size 1 and batch size of 64, following the default configuration for Tiny-YOLO version 2.

4 Tests and Results

The original dataset were divided in 5,800 images for training and 580 for test. In order to improve results, both sets were subject to augmentation, generating 34,800 images for training and 2,900 for test. The augmented dataset contains independent training and test set, as no original image from training has an augmented version in test. Similarly, augmented images in training has no version in test.

Darknet model was first trained in the original dataset during 5.000 iterations, presenting True Positive (TP) = 414, False Positive (FP) and False Negative (FN) of 166 and harmonic mean of 71.3%. After the first experiment, the model was than trained over the augmented dataset, during 18,000 iterations. Values presented by the network were TP = 2502, FP and FN of 398 and harmonic mean of 86.2%. Precision and recall were calculated for each class. Results are presented on Table 4 and Fig. 7.

GoogLeNet experiments were analogous for Darknet-19. First the model was trained over the original dataset (5,800 images for training and 580 for test). This process was performed for 2,000 iterations. The network presented TP = 461, FP and FN of 119 and harmonic mean of 79.4%. For the second experiment, (34,800 images for training and with 2,900 for validation) the iteration count was raised to 4,000. The network presented the following values: TP = 2,633, FP and FN of 267 and harmonic mean of 90.7%. Values for precision, recall and harmonic mean were also calculated per class, presented on Table 4 and Fig. 8.

In the performed experiments, GoogLeNet had a better result than Darknet. The difference between both networks in precision, recall and harmonic mean were, respectively: 4.5, 4.8 and 4.7%. GoogLeNet results are good, even with a broad and complicated dataset, as it were classified 29 classes, many of which are similar.

Analyzing results with and without data augmentation, it became clear the importance of a sufficient amount of data to work with CNNs. Differences between Darknet and GoogLeNet trained with small and sufficient amount of data was, respectively, 14.9% and 11.3%. The developed data augmentation algorithm achieved it's objective, expanding the dataset without damaging samples.

Table 5. Precision, recall and harmonic mean in details - YOLO and GoogLeNet

	Scientific Name	YOLO Precision	YOLO Recall	YOLO F1	GoogLeNet Precision	GoogLeNet Recall	GoogLeNet F1
1	*Persea Americana*	63,0%	64,2%	72,6%	73,0%	100,0%	84,3%
2	*Eriobotrya Japnica Lind*	57,0%	100%	72,6%	75,0%	100%	85,7%
3	*Psidium Rufum*	100%	80,0%	88,8%	100%	74,0%	85,1%
4	*Annona Montana*	96,0%	56,1%	70,8%	98,0%	64,0%	77,4%
5	*Annona Squamosa*	97%	100%	98,4%	100%	100%	100%
6	*Cojoba Arborea*	100%	100%	100%	100%	100%	100%
7	*Coffea*	55,0%	55,0%	55,0%	72,0%	75,0%	73,4%
8	*Pera Heteranthera*	95,0%	100%	97,4%	98,0%	82,3%	89,4%
9	*Anacardium Occidentale*	100%	100%	100%	100%	100%	100%
10	*Peltophorum dubium*	100%	84,0%	91,3%	100%	83,3%	90,9%
11	*Nectandra Megapotamica*	98%	100%	98,9%	94%	100%	96,9%
12	*Cerasus*	83,0%	89,2%	86,0%	90,0%	95,7%	92,7%
13	*Prunus Serrulata*	78,0%	100%	87,6%	91,0%	100%	95,2%
14	*Salix Babylonica*	100,0%	100%	100%	82,0%	100%	90,1%
15	*Lle Paraguariensis*	81,0%	100%	89,5%	80,0%	100%	88,8%
16	*Annona Coriácea*	94%	80,3%	86,6%	100%	94,3%	97,0%
17	*Psidium Guajava*	83,0%	76,8%	79,8%	94,0%	88,6%	91,2%
18	*Annona Muricata*	98%	91,5%	94,6%	100%	98,0%	99,0%
19	*Syzygium Cumini*	84,0%	85,7%	84,8%	97,0%	100%	98,4%
20	*Leucaena Leucocephala*	100%	100%	100%	100%	98%	99%
21	*Citrus Limon*	72%	76,5%	74,2%	76%	100%	86,3%
22	*Tibouchina Mutabilis*	100%	83,3%	90,9%	100%	90,0%	94,7%
23	*Brunfelsia Uniflora*	81,0%	81,0%	81,0%	90,0%	100,0%	94,7%
24	*Mangifera Indica*	97%	100%	98,4%	98%	79,6%	87,8%
25	*Licania Tomentosa*	61,0%	100%	75,7%	78,0%	81,2%	79,5%
26	*Dypsis Lutescens*	100%	100%	100%	100%	100%	100%
27	*Paubrasilia Echinata*	86,0%	100%	92,4%	89,0%	100%	94,1%
28	*Aspidosperma Polyneuron*	78,0%	72,2%	75,0%	82,0%	90,1%	85,8%
29	*Eugenia uniflora*	65,0%	100%	88,8%	76,0%	77,5%	78,7%

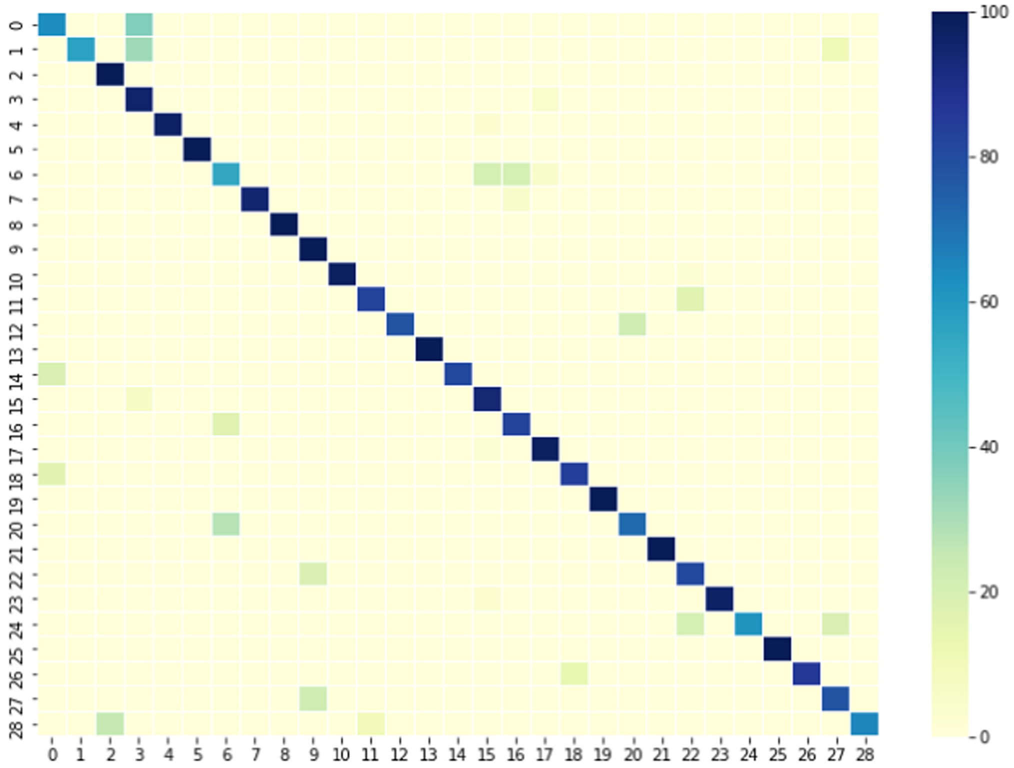

Fig. 7. Confusion Matrix Heatmap - Darknet19

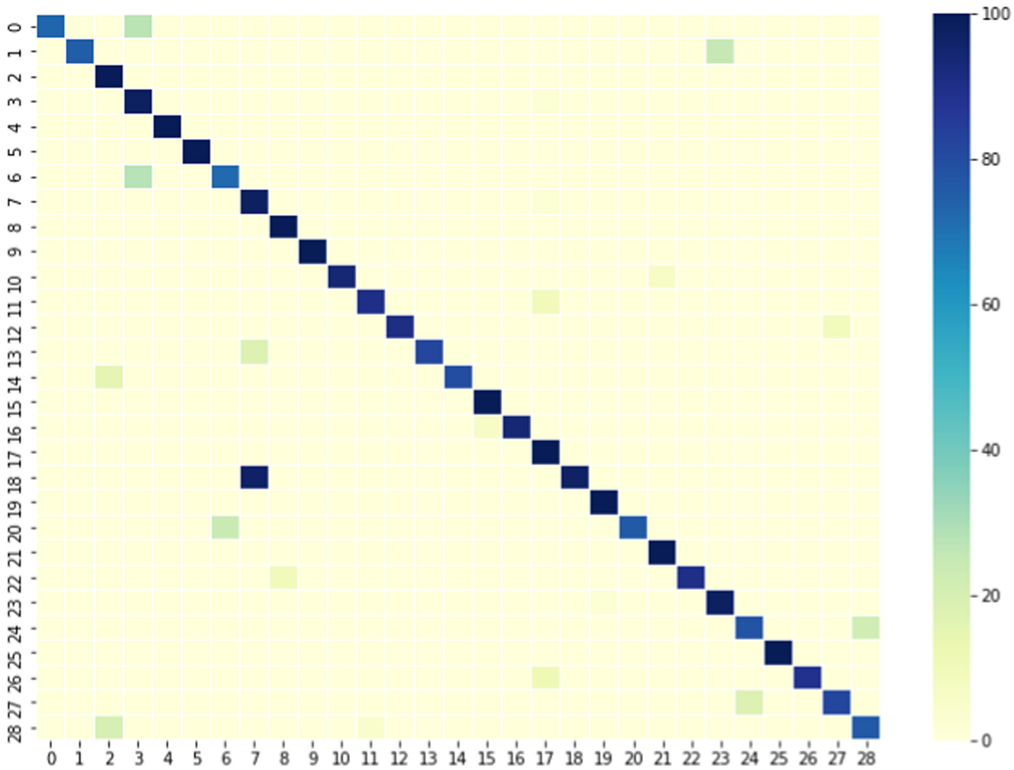

Fig. 8. Confusion Matrix Heatmap - GoogLeNet

5 Conclusions

This work presented a comparison of Darknet-19 and GoogLeNet for tree species recognition using a dataset composed by leaf images from 29 different species, reaching recognition rates of 86.2% and 90.3%, respectively. The obtained results demonstrates the viability of GoogLeNet and Darknet networks for classification. The models can be applied in field research, specially being used to identify species *in natura*.

For future works, we plan to test the models against images with leafs that were not removed from the tree. We also plan to use pre-trained Darknet networks in other platforms, as in smartphones aiming at practical uses of the model, comparing it with similar systems. YOLO have functionality for detecting objects in videos and android studio allows Tensorflow usage while associating a YOLOv2 training model. By using smartphone cameras, it is possible to develop an app to recognize plant species in video. Another suggestion would be to use the model in drones, as there is a huge amount of non registered plant species, in order to explore areas of limited access.

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