IDENTIFICATION OF DISEASES AND LESIONS IN THE COFFEE LEAF USING A CONVOLUTIONAL MODEL

Fredy H. Martínez S., Holman Montiel A. and Edwar Jacinto G.
Facultad Tecnológica, Universidad Distrital Francisco José de Caldas, Bogotá D.C., Colombia
E-Mail: fhmartinezs@udistrital.edu.co

ABSTRACT

The planting and commercialization of coffee is an important source of economic resources and commercial dynamizer for many developing countries, particularly with economies that are strongly dependent on agricultural production, as is the case of Colombia. Coffee is the most important export product of the country and enjoys a high reputation for its quality and flavor. Although the country has done a lot of research to develop the sector, investment in technology is very low, and most of its cultivation for export (of the highest quality) is done by small coffee families without a high degree of technology, and without major resources to access it. The quality of the coffee bean is strongly sensitive to various diseases induced by environmental conditions, fungi, bacteria, and insects, which directly and strongly affects the economic income of the entire production chain and the country. In many cases the diseases are rapidly transmitted, causing great economic losses. A quick and reliable diagnosis would have an immediate effect on reducing losses, which is why the development of a low-cost embedded system capable of making reliable diagnoses in the hands of peasant farmers is proposed. In this article, we propose the development of a software model capable of identifying in real-time the possible disease of a plant from an image of a leaf. For this, we use a DenseNet convolutional neural network trained with 1250 images corresponding to five categories that include the most important diseases of the plant. Laboratory tests show that the proposed model is capable of operating on a low-cost embedded system with a high-performance rate by correctly categorizing the plant's leaves against an unknown set.

Keywords: cercospora coffeicola, convolutional neural network, coffee leaf miner, coffee leaf rust, deep neural network, densenet, image processing, phoma leaf spot.

1. INTRODUCTION

Colombian coffee enjoys great importance in the international markets, not only because it is one of the countries with the highest production and exportation, but also because Colombian coffee has characteristics that make it stand out, such as its excellent quality and its soft flavor [1]. The importance of coffee is so great that it has been the main source of foreign exchange for the country with 5.3 of the Gross Domestic Product (GDP) and with a production of one million fifty thousand sacks by January 2020. However, its cultivation is mainly carried out by low-income coffee families, with very little access to technologies that help reduce the effect of the plagues that affect the plant [2, 3]. While real-time image processing can be computationally expensive [4, 5], a low-cost artificial system reduces costs for damage and care of the plant because farming families can access these tools at low cost and use them to reduce the spread of disease and artificial intelligence strategies can increase crop performance if they are made accessible to people with modest education and purchasing power [6, 7].

The production and conservation of quality coffee are very difficult for small producers [8]. In Colombia, only Arabic coffees are cultivated, which differ from the Canephora coffees (Robusta coffees) because they are soft, and of greater acceptance in the world market. The harvest is mostly done by small coffee-growing families of medium and low profile. Some plagues attack and make the plant sick, reducing the production and affecting the quality and flavor [9, 10]. These problems have increased considerably in the last decades worldwide, which has affected quality and quantity indicators [11]. Among the most important pests that affect the coffee plant are Coffee Leaf Rust (CLR) [12, 13, 14], the Coffee Borer Beetle (*Hypothenemus Hampei*) [15], the Coffee Leaf Miner (*Leucoptera Coffeella*) [15], the Citrus Mealybug (*Planococcus Citri*), the Coffee Stem, and Root Borer (*Plagiohammus Colombiensis*), and the red spider. Also of importance are the Iron Spot (*Cercospora Coffeicola*) [16], the Lint Disease (*Corticium Koleroga*), the Cock's Eye (*Mycena Citricolor*) [17, 18], and the Anthracnose (*Colletotrichum Coffeanum*) [19]. The varieties of Arabic found in Colombia are Tipica (susceptible to CLR), Borbón, Maragogipe, Tabi (resistant to CLR), Caturra (susceptible to CLR), and Colombia variety (resistant to CLR).

Another important factor that negatively affects the cultivation of coffee, and that favors the propagation of plagues and their diseases, is related to the climatic variations of the planting areas [20, 21]. These climatic variations in addition to affecting the growth of the plants tend to increase the aggressiveness of the pests [22]. It has been observed that height affects the intensity of CLR aggression, which is greater in the lower areas with higher temperatures [23, 24].

Prevention and timely diagnosis are essential to stop the advance of pests [25]. Identifying pests at an early stage of infection greatly increases the chances of successful treatment. There are methods for determining the diseases of any plant, such as taking samples of vegetative tissue to a specialized laboratory or bringing an expert agronomist to the crop site. In any of these cases, the disadvantages for the farmer are centered on the time needed to obtain the results and the costs involved. This is why the design of autonomous systems using artificial vision and pattern recognition techniques, as well as some classification algorithms, has been considered for the development of preliminary diagnostic tasks [26, 27, 28]. In this way, the coffee grower can identify the possible disease, its propagation, and with experts and specialists coordinate more quickly and with less cost the correct treatment [29, 30].

Several of the diseases and plagues that are threatening the cultivation of coffee also produce visually detectable effects [5]. The visible effects have been studied as possible indicators of their presence, thanks to the fact that they present specific characteristics [31]. Among these specific characteristics are abnormal coloring of the leaves, deformation of the leaves, and signs of dehydration. These particular characteristics can be used for the process of diagnosis of the disease, or in the opposite case, to diagnose the plant as healthy. RLC is considered by many to be the most severe disease of the coffee crop since it causes the premature fall of the leaves, leading to the death of the plant. The disease has caused great production losses in countries in Asia, Africa, and the Americas. Once the disease appears and establishes itself in a place, it has not been possible to eradicate it, despite multiple strategies implemented by the producing families [32]. It is characterized by pale spots on the underside of the leaves that over time become large yellow or orange spots with the presence of a yellow powder (the spores of the fungus) [33].

In the case of the Cock's Eye disease (*Mycena Citricolor*), small circular or oval spots are observed, slightly sunken, with a diameter of 6-10 mm on the leaves [17, 18]. The lesions start as dark brown spots with an undefined border, which when reaching their final size present a well-marked border, with little or no chlorosis around them, and can be light brown, grayish, or reddish-brown, with a papery and dry appearance.

Iron Spot (*Cercospora Coffeicola*) is another important disease that attacks coffee cultivation. It is caused by a fungus that affects the plant in various stages, beginning in the nursery [16]. It is visually characterized by brown spots with a yellowish halo that contrasts with the normal leaf tissue. As the disease progresses, the size of the spot increases, causing the tissue to die. The most serious damage occurs to the fruit, but also affects the leaves. It is transmitted by the fungus *Cercospora Coffeicola*, and its spot is particularly prevalent in the nursery and on unshaded coffee plantations. In the fruits the infection starts through wounds or exposure to the sun forming lesions similar to those on the leaves, but which eventually stop being circular to become elongated and dark.

Each disease produces characteristic damage to the plant. These damages visually generate geometrical and colorimetric parameters that can be identified through digital image processing [34, 35]. One of the most powerful strategies for image categorization is the convolutional neural networks, which have demonstrated to have a very high capacity to identify information in unknown images after training with categorized cases [36, 37]. Therefore, it is possible to use a neural model to design an embedded, autonomous, and low-cost system capable of identifying in real-time diseases of the coffee plant leaves [38].

2. PROBLEM FORMULATION

This research seeks to develop an autonomous model, based on deep neural networks, for the identification of diseases in the coffee plant from color images of the plant's leaves. The intention is that the neuronal model can be implemented on a low-cost embedded system, which is why the tool must have a low computational requirement (both in processing and storage hardware) that allows it to run in real-time on a small development board. These restrictions are imposed as a condition for its possible massification among family coffee growers.

To design the model, the most frequent diseases that cause the most damage to the plant and coffee production were selected. For these images, we used public databases categorized by experts in the plant [39]. We used 1250 images with a size of each of 2048x1024 pixels, corresponding to Arabica coffee leaves separated into five categories, each category with 250 images. The number of images in each category was kept the same (250) to avoid bias in the model. The label for each of the categories is taken from the name of the folder containing the images of the category (Figure-1). The first category (category 1) corresponds to healthy leaves, the other four categories correspond to leaves affected by four common plant diseases (each leaf has only one of the diseases): Coffee Leaf Miner (CLM, category 2), Coffee Leaf Rust (CLR, category 3), Phoma Leaf Spot (*Phoma Tarda*, category 4), and Iron Spot (*Cercospora Coffeicola*, category 5). Figures 2 to 6 show the detail of the images in each of the categories.

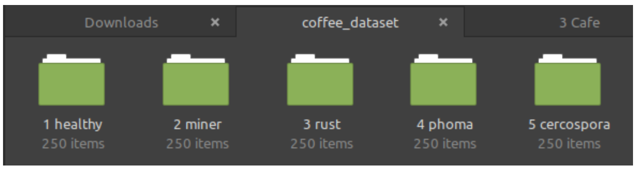


Figure-1. Dataset and labels for each category used for training and model validation.

The leaves are framed in the figure horizontally, regardless of the orientation of the petiole (sometimes to the right and sometimes to the left). Before training the model, the images will be pre-processed using segmentation and labeling filters to remove the background of the image and keep only the leaf. Color adjustment filters will also be used to enhance the images. In this way, we seek to ensure that each image has the visual information that a human expert would identify. The same processing is applied to the images used in the training as well as those used for model validation.

VOL. 17, NO. 8, APRIL 2022 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

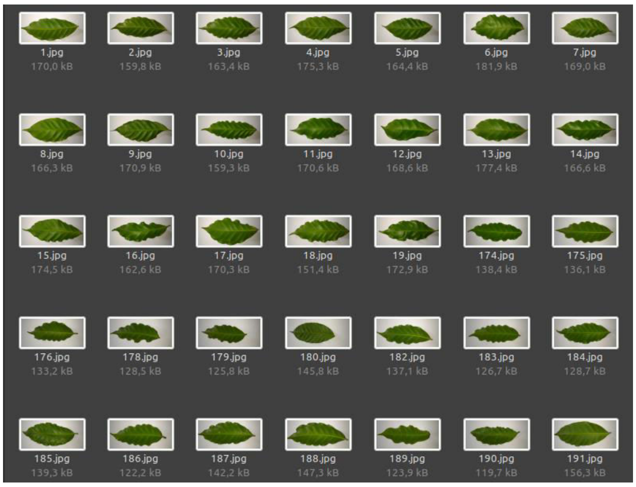


Figure-2. Sample of the images corresponding to category 1: healthy leaves.

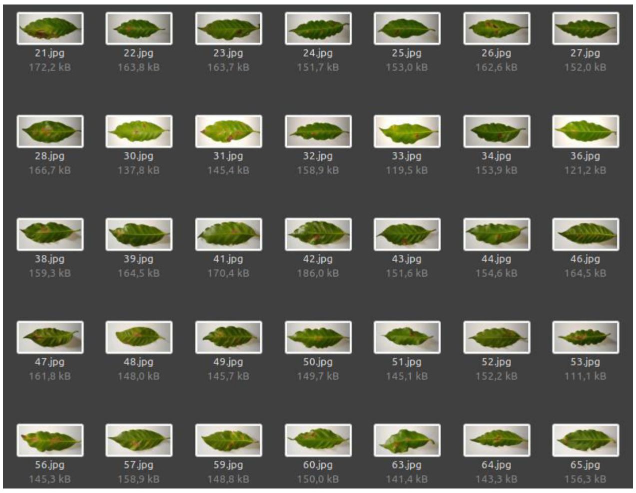


Figure-3. Sample of the images corresponding to category 2: Coffee Leaf Miner (CLM).

The use of a DenseNet (Dense Convolutional Network) type convolutional neural network is proposed as a deep learning architecture. Convolutional neural networks have convolution layers (convolution filters) that have the effect of filtering the image with a previously trained kernel capable of detecting primitive features such as lines or curves. Over several layers, the neural network learns to identify these features along with the training dataset. The DenseNet architecture stands out among convolutional topologies because of its dense structure that leads to a lower number of adjustable parameters compared to other networks such as ResNet (Residual Neural Network), with equal or superior performance. This characteristic is achieved thanks to its design; the topology of the network contemplates short connections from the previous layers which have been observed to increase its accuracy. Figure-7 shows a section of a DenseNet network where the jumps between layers are detailed.

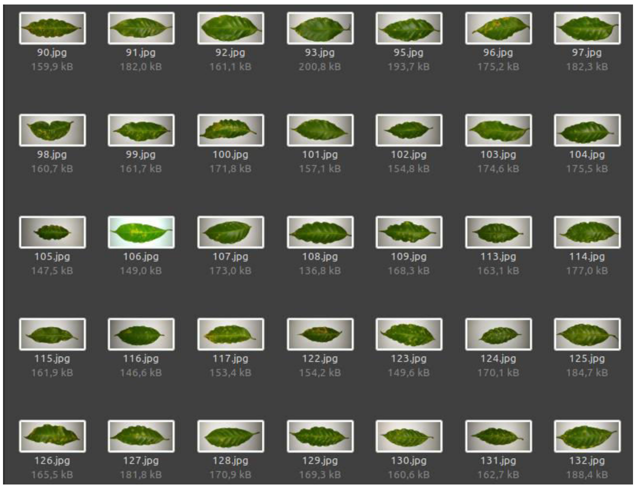


Figure-4. Sample of the images corresponding to category 3: Coffee Leaf Rust (CLR).

Figure-5. Sample of the images corresponding to category 4: Phoma Leaf Spot (*Phoma Tarda*).

The secret of this model lies in its dense connection structure, thanks to which it achieves a considerable reduction in the number of parameters to be adjusted while increasing its categorization capacity compared to other topologies such as ResNet (Residual Neural Network). In a convolutional neural network, different convolution layers are applied to the image to identify high-level features, in the DenseNet network this is taken a step further, each layer of the network receives additional inputs from the previous layers, and at the same time sends outputs to the subsequent layers of the network. Consequently, it can be said that each layer of a DenseNet receives the accumulated knowledge from the previous layers.

ARPN Journal of Engineering and Applied Sciences

Figure-6. Sample of the images corresponding to category 5: Iron Spot (*Cercospora Coffeicola*).

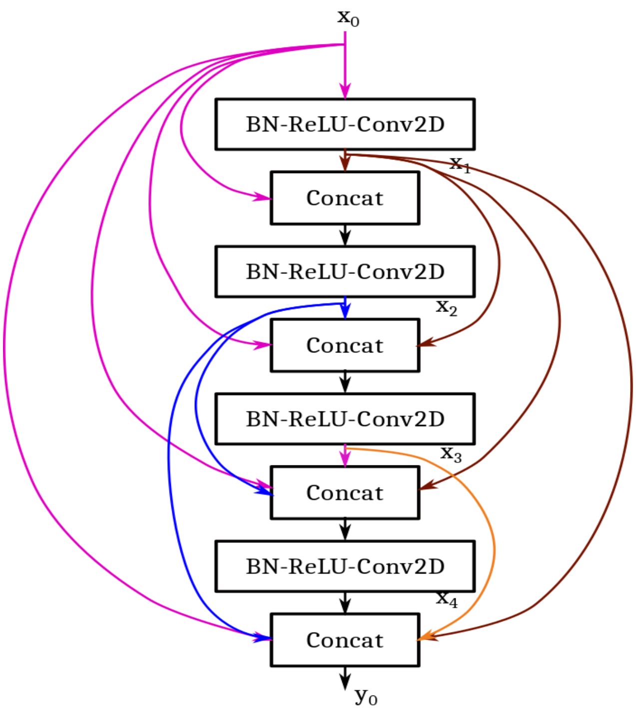


Figure-7. Densely Connected Convolutional Network (DenseNet) architecture.

3. MATERIALS AND METHODS

We selected Arrow Electronics' DragonBoard 410c development board as the platform to evaluate the performance of our neural model as an embedded system. We chose this board for both cost and performance. This board has a Qualcomm APQ8016e 64-bit quad-core processor, Wi-Fi, Bluetooth, and GPS connectivity, and support for Windows 10 IoT Core, Android 5.1, and Debian 8.0. To evaluate the performance of our model, we use Keras 2.4.3 and Tensorflow 2.3.0 installed above Linux Debian OS. Additionally, we used numpy 1.18.5, scipy 1.4.1, scikit-learn 0.22.2, Pillow 7.0.0, glob2 0.7, matplotlib 3.2.2, cv2 4.1.2.30, seaborn 0.11.0, and pandas 1.1.2.

The images in the dataset were filtered to remove the background, center the leaf on the image, and improve its color level. Also, they were randomly mixed within the stack to improve the performance of the network. To facilitate training and reduce resource consumption, the images were scaled to 224x224 pixels in RGB format (default image size in DenseNet121 architecture, Figure-8). Although the aspect ratio of the images was altered, this does not alter the visual information related to the images, but it does facilitate the design of the neural network.

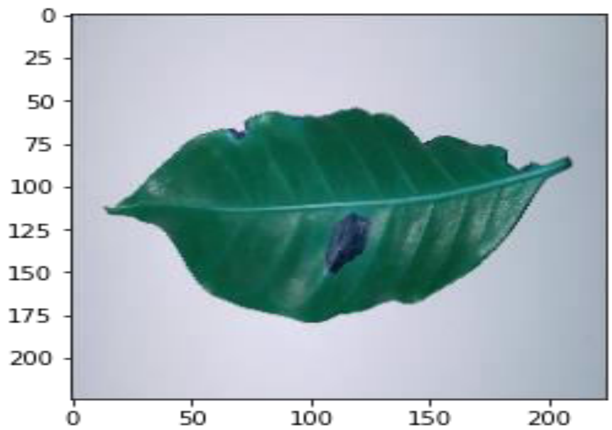
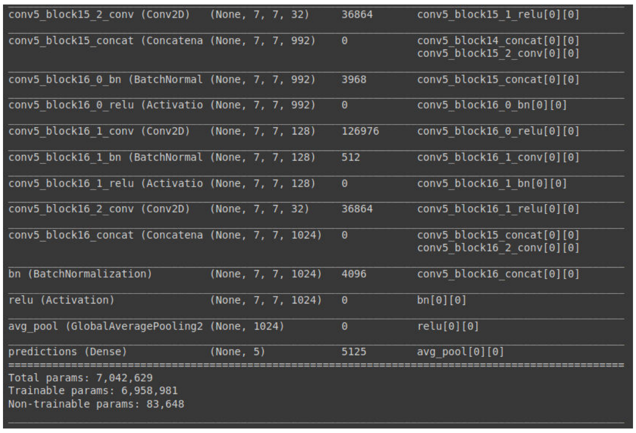


Figure-8. Image of the dataset after segmentation, labeling, filtering and scaling.

For neural network training, the color matrices of the images, which make up the input parameters, were normalized to color depths in the range of zero to one. Besides, the 1250 images were randomly separated into two groups, the first group with 80% of the images (1000 images) for neural network training, and a second group with the remaining 20% (250 images) for model validation purposes. For the design of the network structure, the size of the input images is taken into account, 224*224*3 = 150,528, which defines the total number of input nodes. The number of output nodes is defined by the number of network categories, which in our case are five categories, so five output nodes. In the output, a one-hot coding structure was defined to define these five output categories. The neural network has a depth of 121 layers (DenseNet121), which corresponds to one of the standard topologies of the DenseNet network. The network has a total of 7,042,629 parameters, of which 6,958,981 were adjusted during training (Figure-9). These layers are distributed in a 5+(6+12+24+16)*2=121 structure, where 5 is (convolutional, pooling) + 3 transition layers + classification layer. Multiplication by 2 is done because each dense block has two layers (1x1 convolutional and 3x3 convolutional).

VOL. 17, NO. 8, APRIL 2022 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com



conv5_block15_2_conv (Conv2D)	(None, 7, 7, 32)	36864	conv5_block15_1_relu[0][0]
conv5_block15_concat (Concatena	(None, 7, 7, 992)	0	conv5_block14_concat[0][0] conv5_block15_2_conv[0][0]
conv5_block16_0_bn (BatchNormal	(None, 7, 7, 992)	3968	conv5_block15_concat[0][0]
conv5_block16_0_relu (Activatio	(None, 7, 7, 992)	0	conv5_block16_0_bn[0][0]
conv5_block16_1_conv (Conv2D)	(None, 7, 7, 128)	126976	conv5_block16_0_relu[0][0]
conv5_block16_1_bn (BatchNormal	(None, 7, 7, 128)	512	conv5_block16_1_conv[0][0]
conv5_block16_1_relu (Activatio	(None, 7, 7, 128)	0	conv5_block16_1_bn[0][0]
conv5_block16_2_conv (Conv2D)	(None, 7, 7, 32)	36864	conv5_block16_1_relu[0][0]
conv5_block16_concat (Concatena	(None, 7, 7, 1024)	0	conv5_block15_concat[0][0] conv5_block16_2_conv[0][0]
bn (BatchNormalization)	(None, 7, 7, 1024)	4096	conv5_block16_concat[0][0]
relu (Activation)	(None, 7, 7, 1024)	0	bn[0][0]
avg_pool (GlobalAveragePooling2	(None, 1024)	0	relu[0][0]
predictions (Dense)	(None, 5)	5125	avg_pool[0][0]

Total params: 7,042,629
Trainable params: 6,958,981
Non-trainable params: 83,648

Figure-9. Detail of network parameters and structure of its last layers.

As optimization function in the model, we use the stochastic gradient descent function. In the optimization we use as error measure the categorical cross-entropy function. During the training, we calculated in each epoch the values of accuracy (or hit rate) and MSE (mean quadratic errors) metrics to observe the performance of the network throughout the training. The final model was trained over 30 epochs with a batch size of 32. Throughout the training, the accuracy increased from 59.6% to 94.9% for the training data. The final accuracy for the validation data was 72.0%.

4. RESULTS AND DISCUSSIONS

Figure-10 shows the behavior of the trained model. The error produced by the training data is continuously reduced during the 30 epochs. An equivalent behavior is observed in the accuracy of the training data, which increases continuously throughout the training process. The behavior of the validation data is not so uniform, but an overall reduction of the error is observed at the end of the training process (1.9 to 0.4). Despite this, the accuracy of the validation data does have a uniform behavior, increasing continuously throughout the training process. The results show that it is possible to further increase the performance of the model by final tuning. It is also clear that the model is viable for the classification of coffee leaves.

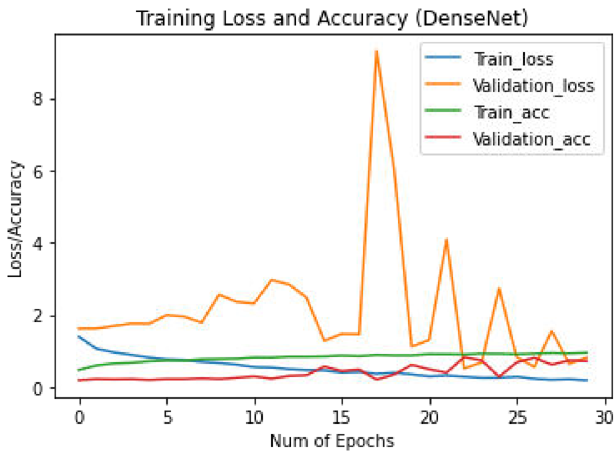


Figure-10. Model behavior based on training and validation data.

The confusion matrix provides a quick image of the model's classification capability. We calculate the confusion matrix for our model using the images from the validation group (unknown images for the model) and assign a heatmap with light colors for the highest number of true positives, and dark colors for the opposite cases (Figure-11). The diagonal of the curve clearly shows that the model correctly classifies most of the unknown images. For example, for the healthy leaves' category, 41 of the images were correctly classified in the first category. However, the color of category 3 (CLR) is very dark (only 23 images out of 51 were correctly sorted).

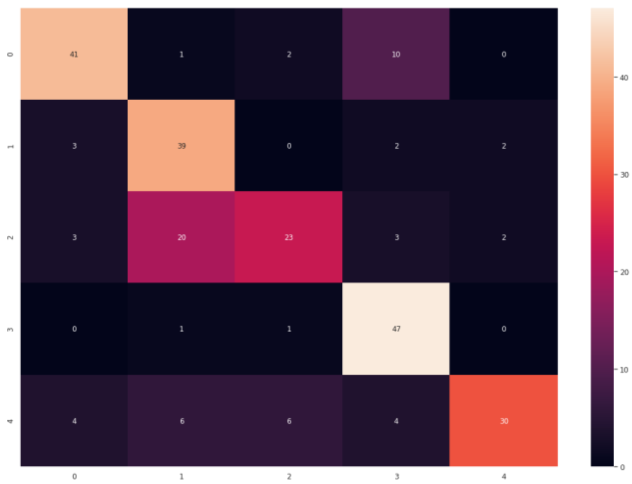


Figure-11. Confusion matrix.

To evaluate the performance of the model in a specific way, we calculate the accuracy, recall, f1-score, and support metrics for each of the categories with the validation images (the 250 unknown images for the model, Figure-12). The average accuracy of the model (percentage of correct positive predictions among all positive predictions) was 74%, with an exceptional classification of diseased leaves with Iron Spot (88% accuracy) and healthy leaves (80% accuracy). However, the classification of diseased leaves with Coffee Leaf

VOL. 17, NO. 8, APRIL 2022 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

Miner was considerably low (58% accuracy). The values of recall, f1-score, and support show similar results to those shown by the accuracy, in the case of recall (percentage of correct positive predictions among all positive predictions that could have been made) some measure of the wrong positive predictions is presented, in this case, the average value drops a little to 72%, which is very similar to the accuracy value, but the recall for the leaves that are sick with Iron Spot drops to 60%, and the value for the leaves that are sick with Coffee Leaf Miner goes up to 85%, that is, it is much more wrong in the first case than in the second. The f1-score corresponds to the harmonic mean of accuracy and recall, so the above peaks are averaged out at 71%.

	precision	recall	f1-score	support
0	0.80	0.76	0.78	54
1	0.58	0.85	0.69	46
2	0.72	0.45	0.55	51
3	0.71	0.96	0.82	49
4	0.88	0.60	0.71	50
accuracy			0.72	250
macro avg	0.74	0.72	0.71	250
weighted avg	0.74	0.72	0.71	250

Figure-12. Model metrics.

We also calculated the ROC curve (Receiver Operating Characteristic) of the neural model (Figures 13 and 14). This curve graphically shows the sensitivity of the model (ratio of true positives to the ratio of false positives) to variations in the discrimination threshold between categories. In this sense, high average values (0.93) and high values per category (0.86 to 0.95) of true positives versus false positives are observed.

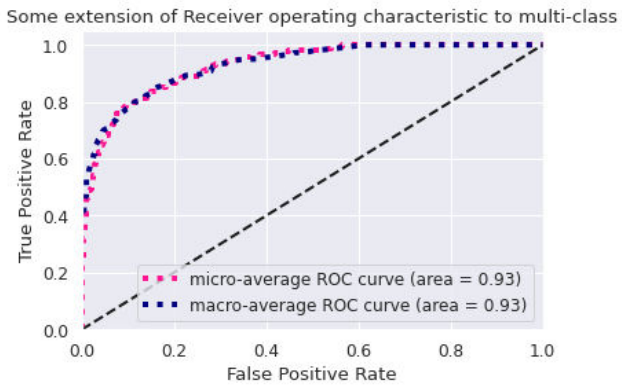


Figure-13. ROC curve (average behavior).

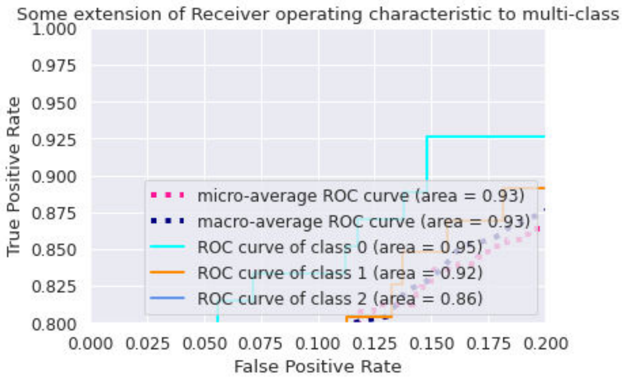


Figure-14. ROC curve (behavior by class).

5. CONCLUSIONS

In this article, we present the design and tuning of a classification model based on convolutional neural networks for the rapid and low-cost classification of diseases in the coffee plant leaf. Coffee is an export product of great importance for the Colombian economy, as well as for other tropical countries such as Brazil, Vietnam, Indonesia, Uganda, Mexico, and Peru. Despite this, its cultivation is largely developed by small coffee-growing families with little access to modern technologies. This constitutes a great weakness of the economic model since diseases in the plants can be late or incorrectly diagnosed, which facilitates the propagation of the disease, and therefore the reduction in quality and quantity of the product. Eradication costs, along with reduced sales and export revenues, strongly affect the production chain and the country's income. As an alternative to support coffee growers in the early diagnosis of common diseases, the development of an autonomous low-cost system that can be used directly by the farmer and that allows the categorization of the disease of a plant from the photograph of the leaves is proposed. For the design of the classification model, we selected four high impact diseases for this crop: Coffee Leaf Miner (CLM), Coffee Leaf Rust (CLR), Phoma Leaf Spot (*Phoma Tarda*), and Iron Spot (*Cercospora Coffeicola*). Healthy leaves were also assigned a category. These diseases produce visible damage in the coffee leaf that can be identified and classified by image processing. In this sense, we selected a deep neural network type DenseNet (Dense Convolutional Network) to identify and learn the characteristics of the leaves and their diseases. This neural network was selected due to its high performance and lower number of parameters compared to other topologies such as ResNet. The architecture of the DenseNet network was adjusted for input images of 224x224 pixels in RGB format, 121 layers of depth (DenseNet121), and five output categories. The database was made up of 250 images in each category, and 80% of them were used for training (1000 images) and 20% for model validation. The training was carried out over 30 epochs taking care not to over-adjust the network. To fine-tune the parameters, the error was evaluated using the categorical cross-entropy function, and optimized using the stochastic gradient descent function. The final accuracy achieved by the model was 94.9% for the training data and 74% for the validation data (images unknown to the model). This model was implemented on a DragonBoard 410c from Arrow Electronics, running a Debian OS. Preliminary results show low resource consumption, low cost, and acceptable performance for real-world implementation.

ACKNOWLEDGEMENT

This work was supported by the Universidad Distrital Francisco José de Caldas, in part through CIDC, and partly by the Facultad Tecnológica. The views expressed in this paper are not necessarily endorsed by Universidad Distrital. The authors thank the research group ARMOS for the evaluation carried out on prototypes of ideas and strategies.

REFERENCES

[1] D. Bebber, À. Castillo and S. Gurr. 2016. Modelling coffee leaf rust risk in Colombia with climate reanalysis data. Philosophical Transactions of the Royal Society B: Biological Sciences, 371(1709). doi:10.1098/rstb.2015.0458.

[2] J. Avelino, M. Cristancho, S. Georgiou, P. Imbach, L. Aguilar, G. Bornemann, P. Läderach, F. Anzueto, A. Hruska and C. Morales. 2015. The coffee rust crises in Colombia and Central America (2008–2013): Impacts, plausible causes and proposed solutions. Food Security, 7(2): 303-321. doi:10.1007/s12571-015-0446-9.

[3] D. Velásquez, A. Sánchez, S. Sarmiento, M. Toro, M. Maiza and B. Sierra. 2020. A method for detecting coffee leaf rust through wireless sensor networks, remote sensing, and deep learning: Case study of the Caturra variety in Colombia. Applied Sciences (Switzerland), 10(2). doi:10.3390/app10020697.

[4] A. Mengistu, S. Mengistu and D. Melesew. 2018. An automatic coffee plant diseases identification using hybrid approaches of image processing and decision tree. Indonesian Journal of Electrical Engineering and Computer Science, 9(3): 806-811. doi:10.11591/ijeecs.v9.i3.pp806-811.

[5] A. Sánchez and S. Arguijo. 2018. Análisis de imágenes multiespectrales para la detección de cultivos y detección de plagas y enfermedades en la producción de café. Research in Computing Science, 147(7): 309-317. ISSN 1870-4069.

[6] A. Cadena, E. Peña and F. Martínez. 2016. Desarrollo de prototipo de quadrotor con sistema de comunicación inalámbrica bidireccional. Tekhnê, 13(1): 13-30. ISSN 1692-8407.

[7] B. Ortega, R. Biswal and E. DelaCruz. 2019. Detección de enfermedades en el sector agrícola utilizando Inteligencia Artificial. Research in Computing Science, 148(7): 419-427. ISSN 1870-4069.

[8] R. Cerda, J. Avelino, C. Gary, P. Tixier, E. Lechevallier and C. Allinne. 2017. Primary and secondary yield losses caused by pests and diseases: Assessment and modeling in coffee. PLoS ONE, 12(1). doi:10.1371/journal.pone.0169133.

[9] S. Brinate, L. Martins, G. Pereira, V. Cunha, A. de Jesus, J. do Amaral, W. de Jesus and M. Tomaz. 2015. Copper can influences growth, disease control and production in arabica coffee trees. Australian Journal of Crop Science, 9(7): 678-683.

[10] L. Belan, W. de Jesus, A. de Souza, L. Zambolim, J. Filho, D. Barbosa and W. Moraes. 2020. Management of coffee leaf rust in Coffea canephora based on disease monitoring reduces fungicide use and management cost. European Journal of Plant Pathology, 156(3): 683-694. doi: 10.1007/s10658-019-01917-6.

[11] L. de Sousa, M. da Silva and J. Costa. 2018. Leaf-associated bacterial microbiota of coffee and its correlation with manganese and calcium levels on leaves. Genetics and Molecular Biology, 41(2): 455-465. doi:10.1590/1678-4685-gmb-2017-0255.

[12] S. Brinate, L. Martins, W. Rodrigues, T. Colodetti, V. Cunha, G. Rosa, W. Junior and M. Tomaz. 2015. Influence of copper sources on the management of leaf rust, growth and crop yield of Arabica coffee. Journal of Food, Agriculture and Environment, 13(2): 184-189.

[13] Z. Hajian-Forooshani, I. Salinas, E. Jiménez, I. Perfecto and J. Vandermeer. 2016. Impact of regionally distinct agroecosystem communities on the potential for autonomous control of the coffee leaf rust. Environmental Entomology, 45(6): 1521-1526. doi:10.1093/ee/nvw125.

[14] L. Ehrenbergerová, A. Kučera, E. Cienciala, J. Trochta and D. Volařík. 2018. Identifying key factors affecting coffee leaf rust incidence in agroforestry plantations in Peru. Agroforestry Systems, 92(6): 1551-1565. doi:10.1007/s10457-017-0101-x.

[15] L. de Oliveira and G. de Souza. 2020. Models for simulating the frequency of pests and diseases of Coffea arabica L. International Journal of Biometeorology, 64(7): 1063-1084. doi:10.1007/s00484-020-01881-5.

[16] S. Arteaga and D. Espinoza. 2019. Eficacia de dos productos a base de trichoderma, en tres dosis de aplicación para el control de la mancha de hierro (cercospora coffeicola), en café (coffea canephora) variedad robusta a nivel de vivero en el Cantón Francisco de Orellana provincia de Orellana. Caribeña de Ciencias Sociales: 1-24. ISSN 2254-7630.

[17] K. Zamora, L. Castro, A. Wang, L. Arauz and L. Uribe. 2017. Uso potencial de lixiviados y tés de vermicompost en el control del ojo de gallo del cafeto Mycena citricolor. Agronomía Costarricense, 41(1): 33-51.

[18] J. Silva, M. Resende, A. Monteiro, M. Pádua, L. Guerra-Guimarães, F. Medeiros, S. Martins and D. Botelho. 2019. Resistance inducers applied alone or in association with fungicide for the management of leaf rust and brown eye spot of coffee under field conditions. Journal of Phytopathology, 167(7-8): 430-439. doi:10.1111/jph.12814.

[19] B. Zewdie, A. Tack, G. Adugna, S. Nemomissa and K. Hylander. 2020. Patterns and drivers of fungal disease communities on Arabica coffee along a management gradient. Basic and Applied Ecology, 47: 95-106. doi:10.1016/j.baae.2020.05.002.

[20] I. Merle, P. Tixier, E. Virginio, C. Cilas and J. Avelino. 2020. Forecast models of coffee leaf rust symptoms and signs based on identified microclimatic combinations in coffee-based agroforestry systems in Costa Rica. Crop Protection, 130. doi:10.1016/j.cropro.2019.105046.

[21] K. Belachew, G. Senbeta, W. Garedew, R. Barreto and E. Del Ponte. 2020. Altitude is the main driver of coffee leaf rust epidemics: A large-scale survey in Ethiopia. Tropical Plant Pathology, 45(5): 511-521. doi:10.1007/s40858-020-00383-4.

[22] F. Hinnah, P. Sentelhas, C. Meira and R. Paiva. 2018. Weather-based coffee leaf rust apparent infection rate modeling. International Journal of Biometeorology, 62(10): 1847-1860. doi:10.1007/s00484-018-1587-2.

[23] G. Daba, K. Helsen, G. Berecha, B. Lievens, A. Debela and O. Honnay. 2019. Seasonal and altitudinal differences in coffee leaf rust epidemics on coffee berry disease-resistant varieties in Southwest Ethiopia. Tropical Plant Pathology, 44(3): 244-250. doi:10.1007/s40858-018-0271-8.

[24] T. Liebig, F. Ribeyre, P. Läderach, H. Poehling, P. van Asten and J. Avelino. 2019. Interactive effects of altitude, microclimate and shading system on coffee leaf rust. Journal of Plant Interactions, 14(1): 407-415. doi:10.1080/17429145.2019.1643934.

[25] S. McCook and J. Vandermeer. 2015. The Big Rust and the Red Queen: Long-term perspectives on coffee rust research. Phytopathology, 105(9): 1164-1173. doi:10.1094/PHYTO-04-15-0085-RVW.

[26] K. Lewis, M. Quioc and J. Espineli. 2020. Image processing techniques and data mining algorithms for coffee plant's leaves classification. International Journal of Advanced Trends in Computer Science and Engineering, 9(2): 1101-1106. doi:10.30534/ijatcse/2020/31922020.

[27] I. de Sousa, M. Nascimento, G. Silva, A. Nascimento, C. Cruz, F. Silva, D. de Almeida, K. Pestana, C. Azevedo, L. Zambolim and E. Caixeta. 2020. Genomic prediction of leaf rust resistance to arabica coffee using machine learning algorithms. Scientia Agricola, 78(4): 1-8. doi:10.1590/1678-992x-2020-0021.

[28] F. Montalbo and A. Hernandez. 2020. Classifying barako coffee leaf diseases using deep convolutional models. International Journal of Advances in Intelligent Informatics, 6(2): 197–209. doi:10.26555/ijain.v6i2.495.

[29] L. Rodrigues, G. Sera, O. Filho, L. Beriam and I. de Almeida. 2017. First report of mixed infection by Pseudomonas syringae pathovars garcae and tabaci on coffee plantations. Bragantia, 76(4): 543-549. doi:10.1590/1678-4499.2016.399.

[30] A. Chemura, O. Mutanga, M. Sibanda and P. Chidoko. 2018. Machine learning prediction of coffee rust severity on leaves using spectroradiometer data. Tropical Plant Pathology, 43(2): 117-127. doi:10.1007/s40858-017-0187-8.

[31] N. Thiep, K. Soytong, N. Oanh and P. Hung. 2019. Study on nematodes (Pratylenchus spp.) on Arabica

coffee in the Northwestern Vietnam. International Journal of Agricultural Technology, 15(4): 675-684.

[32] L. Belan, L. Belan, A. da Matta, C. Gonçalves, F. Alves, W. Cintra and W. Moraes. 2020. Standard area diagram with color photographs to estimate the severity of coffee leaf rust in Coffea canephora. Crop Protection, 130. doi:10.1016/j.cropro.2020.105077.

[33] A. Chemura, O. Mutanga and T. Dube. 2017. Separability of coffee leaf rust infection levels with machine learning methods at Sentinel-2 MSI spectral resolutions. Precision Agriculture, 18(5): 859-881. doi:10.1007/s11119-016-9495-0.

[34] J. Cepeda and M. Pereira. 2004. Identificación de formas geométricas y colores mediante procesamiento y reconocimiento de imágenes. Tekhnê, 2(1): 9-17. ISSN 1692-8407.

[35] C. Cortes, J. Leguizamon and E. Jacinto. 2015. Sistema de procesamiento de imágenes vasculares infrarrojas para aplicación en dispositivos biométricos de control de acceso. Tekhnê, 12(1): 13-22. ISSN 1692-8407.

[36] F. Martínez and F. Martinez. 2020. Evaluation of deep neural network architectures in the identification of bone fissures. TELKOMNIKA (Telecommunication Computing Electronics and Control), 18: 807. doi:10.12928/telkomnika.v18i2.14754.

[37] F. Martínez, F. Martinez and E. Jacinto. 2020. Performance Evaluation of the NASNet Convolutional Network in the Automatic Identification of COVID-19. International Journal on Advanced Science, Engineering and Information Technology, 10: 662. doi:10.18517/ijaseit.10.2.11446.

[38] F. Martínez and A. Rendón. 2020. Identifier of human emotions based on convolutional neural network for assistant robot. TELKOMNIKA (Telecommunication Computing Electronics and Control), 18: 1499. doi:10.12928/telkomnika.v18i3.14777.

[39] J. Esgario, R. Krohling and J. Ventura. 2020. Deep learning for classification and severity estimation of coffee leaf biotic stress. Computers and Electronics in Agriculture, 169(105162): 1-9. doi:10.1016/j.compag.2019.105162.