A Machine Learning Model for the Diagnosis of Coffee Diseases

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***Abstract*—The growing and marketing of coffee is an important source of economic resources for many countries, especially those with economies dependent on agricultural production, as is the case of Colombia. Although the country has done a lot of research to develop the sector, the truth is that most of its cultivation is carried out by small coffee families without a high degree of technology, and without major resources to access it. The quality of the coffee bean is highly sensitive to diverse diseases related to environmental conditions, fungi, bacteria, and insects, which directly and strongly affect the economic income of the entire production chain. In many cases the diseases are transmitted rapidly, causing great economic losses. A quick and reliable diagnosis would have an immediate effect on reducing losses. In this sense, this research advances the development of an embedded system based on machine learning capable of performing on-site diagnoses by untrained personnel but taking advantage of the know-how of expert coffee growers. Such a system seeks to instrument the visual characteristics of the most common plant diseases on low-cost, robust, and highly reliable hardware. We identified a deep network architecture with high performance in disease categorization and adjusted the hyperparameters of the model to maximize its characterization capacity without incurring overfitting problems. The prototype was evaluated in the laboratory on real plants for recognized disease cases, tests that matched the performance of the model validation dataset.**

Keywords*—*Cercospora Coffeicola; convolutional neural network; coffee leaf miner; coffee leaf rust; deep learning; image processing; phoma leaf spot

I. Introduction

For developing countries, agriculture is one of the most important economic sectors, both for foreign exchange earnings and for ensuring the food sustainability of their citizens. Colombian coffee enjoys great importance in the international markets because 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], 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 [5], [6].

The production and conservation of quality coffee are very difficult for small producers [7]. 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 [8]. These problems have increased considerably in the last decades worldwide, which has affected quality and quantity indicators [9]. Among the most important pests that affect the coffee plant are Coffee Leaf Rust (CLR) [10], the Coffee Borer Beetle (Hypothenemus Hampei) [11], the Coffee Leaf Miner (Leucoptera Coffeella) [11], 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) [12], the Lint Disease (Corticium Koleroga), the Cock's Eye (Mycena Citricolor) [13], and the Anthracnose (Colletotrichum Coffeanum) [14]. 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 [15], [16]. These climatic variations in addition to affecting the growth of the plants tend to increase the aggressiveness of the pests [17]. It has been observed that height affects the intensity of CLR aggression, which is greater in the lower areas with higher temperatures [18], [19].

Prevention and timely diagnosis are essential to stop the advance of pests [20]. 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 [21], [22]. 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 [23], [24].

Several of the diseases and plagues that are threatening the cultivation of coffee also produce visually detectable effects [25]. The visible effects have been studied as possible indicators of their presence, thanks to the fact that they present specific characteristics [26]. 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 [27]. 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) [28].

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 [29], [13]. 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 [12]. 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 [30], [31]. 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 [32], [33]. 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 [34].

The rest of this article is organized as follows. Section II describes the functional characteristics of the embedded system and the working environment of the equipment, which define the design profile of the system. Section III describes the model developed for the detection of anomalies in the coffee leaf, as well as the characteristics of the hardware used, and its configuration. The results that demonstrate the behavior of the classification model are given in Section IV, and in Section V the conclusions of the research and development are presented.

II. Problem Statement

The sustainability of agriculture depends on many factors, including the ability to reduce food losses due to infections caused by bacteria, viruses, and fungi. In this sense, early detection of crop diseases drastically reduces the spread of illnesses, and therefore economic losses. Solution strategies should be developed focusing not only on the nature of the crop in question but also on the social conditions under which production takes place. Our research focuses on the identification of diseases common to the coffee plant, which is why we sought to develop a system that could examine in real-time the leaf of the plant, the place where diseases can be identified. This system aims to detect possible changes in the leaf of the plant that could signal an infection.

The objective of this research is to develop an embedded system for the autonomous and on-site diagnosis of coffee diseases. Other important features of the system include low cost and ease of operation. Among the design features, the need for autonomous operation stands out given the impossibility of connection for the deployment of complex models. In addition to these features, portability and high performance also limit the hardware characteristics to be used.

Among the machine learning schemes evaluated as automatic categorization schemes, those based on deep networks presented the highest values in the evaluation metrics. Consequently, a deep model that can be run in real-time on limited processing hardware should be chosen for implementation. Such a system should have a digital camera for image capture, and the appropriate framework for digital processing. The categorization model must extract the image parameters with the diseases to be identified, so a specific dataset for the problem is required. It should also facilitate the interpretation of results by the user, so the images captured by the user should be labeled according to the diagnosis (Fig. 1).

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. We used 1250 images with a size of each of 2048×1024 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 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). Fig. 2 show the detail of the images in each of the categories.

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 (Fig. 3). The system must have a visual

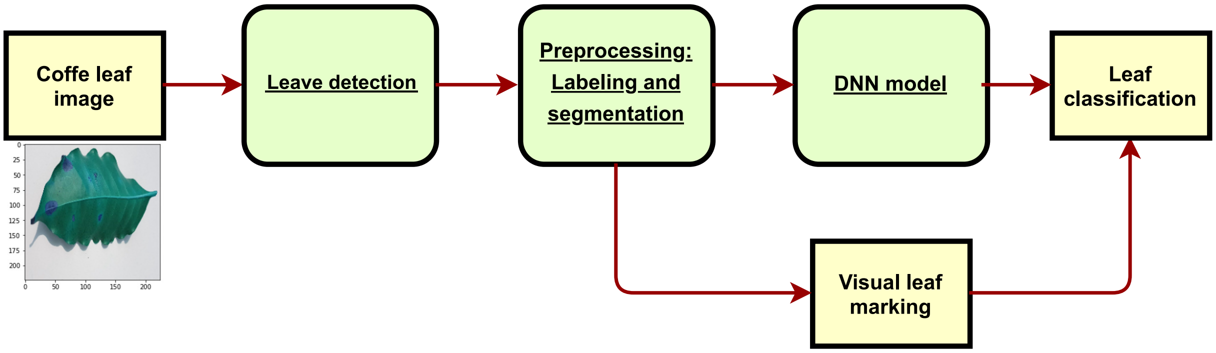

Fig. 1. Pipeline of the Proposed Embedded System.

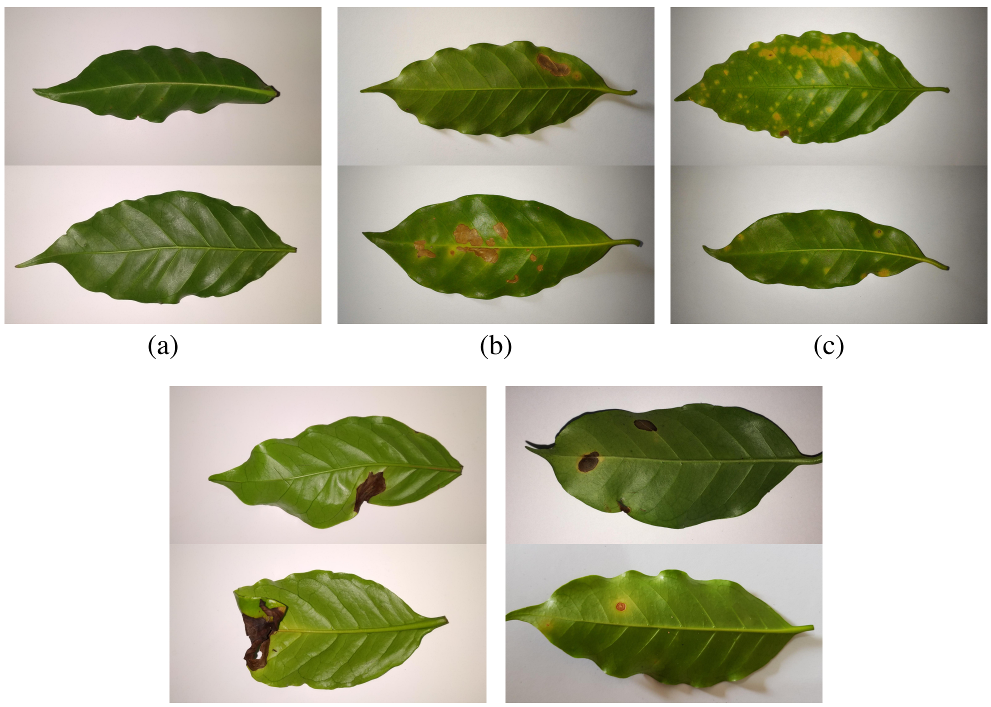

Fig. 2. Sample Images from the Dataset. (a) Healthy Leaves, (b) Coffee Leaf Miner (CLM), (c) Coffee Leaf Rust (CLR), (d) Phoma Leaf Spot (*Phoma Tarda*) and (e) Iron Spot (*Cercospora Coffeicola*)

output in which the user can observe the damage identified on the leaf in real-time. In principle, a screen should be available in which this image is constructed by superimposing on the frame captured by the camera the information related to this labeling and the information related to the categorization.

Among the possible deep models, the best performance was obtained with the ResNet (Residual Neural Network). 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 data set. The ResNet50 architecture is selected as the topology given its smaller comparative size (fewer parameters), and high initial test results. This feature is achieved thanks to its design, the network topology contemplates short forward connections from the previous layers, which has been observed to increase its accuracy.

III. Methods

The system is composed of three processing modules: leaf detection unit, preprocessing unit, and DNN (Deep Neural Network) based model (Fig. 1). These modules are sequential, the output of one functions as input to the next. The first one corresponds to a set of filters applied to the input image that seeks to identify the morphological characteristics of the leaf in the video frames. These filters look for leaf shape regardless of orientation or background, but prioritize shapes of relative size to the frame, thus requiring the user to focus on individual plant leaves. These initial filters reduce processing

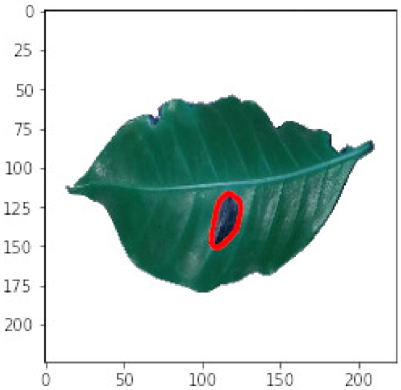

Fig. 3. Image after Segmentation, Labeling, Filtering and Scaling.

requirements by identifying an area in which the second module's preprocessing is applied. The preprocessing module receives as input an area in the frame on which segmentation and labeling are applied to identify areas of the region with characteristics different from those expected in a healthy leaf. This information is transferred to the output screen for user documentation but is also used to precisely delimit the region containing the leaf, which feeds the next module. Finally, this information enters the DNN module, which propagates the network in the trained model, and defines the most likely disease. This information is also displayed on the screen for the user.

The ResNet network was trained with public images corresponding to different databases. The selection of the images considered criteria related to the effect of the disease in the region of interest, the severity of leaf damage, and image capture conditions (real environment and/or laboratory). The images in the dataset were filtered to remove the background, center the leaf on the image, and improve its color level [35]. 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 256 $\times$ 256 pixels in RGB format. 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.

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, $256\times256\times3$ = 196,608, 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 ResNet50 model is a variant of ResNet with a total of 48 convolution layers, along with 1 MaxPool layer and 1 Average Pool layer. The network has a total of 23,597,957 parameters, of which 23,544,837 were adjusted during training. Of these parameters, 10245 corresponded to the dense output network. As optimization function in the model, we use the stochastic gradient descent function. In the optimization we use as error measure the categorical hinge 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 300 epochs with a batch size of 32. Throughout the training, the accuracy increased from 23.3% to 96.5% for the training data.

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.

IV. Result and Discussion

The performance of the model was evaluated based on the behavior of the categorization system with the validation images, in this way it was possible to quantify the performance under ideal conditions. The final tests of the prototype were performed in the laboratory with leaves collected directly in the field by the research group. These tests allowed validation of the detection and preprocessing modules.

For the case of the final DNN model tuned for implementation, training was performed over 300 epochs, and accuracy (Fig. 4) and loss values (Fig. 5) were recorded for both training and validation data. The error produced by the training data is continuously reduced throughout the whole process, reaching a final value of 0.07. An equivalent behavior is observed for the accuracy of the training data, which increases continuously throughout the training process from 23.3% to 96.5%. The behavior of the validation data is not as uniform, but an overall reduction of the error at the end of the training process is observed, which although it is lower than that achieved by the training data, keeps decreasing in parallel, guaranteeing the non-existence of overfitting (final loss value of 0.56). The accuracy of the validation data also has a uniformly increasing behavior, parallel to the training data, increasing continuously throughout the training process (final value of 71.5%). These data, while not guaranteeing a perfect classification, do provide for the application of an adequate classification of the analyzed images.

The confusion matrix provides a quick picture of the classification capability of the model as it explicitly shows when one category is confused with another. This allows working separately with different types of error, as well as calculating different model performance metrics. 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

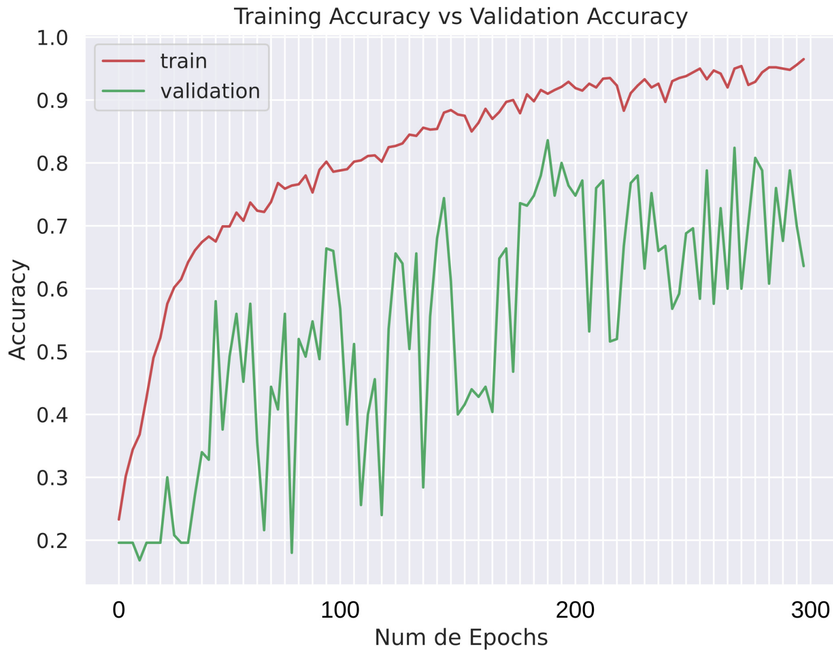

Fig. 4. Model Behavior: Training Accuracy vs Validation Accuracy.

positives, and dark colors for the opposite cases (Fig. 6). The diagonal of the curve clearly shows that the model correctly classifies most of the unknown images. For example, for the healthy leaves' category, 22 of the images were correctly classified in the first category, and for the CLM category, the best performing category, 45 of the images were correctly classified.

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). The average precision of the model (percentage of correct positive predictions among all positive predictions) was 73%, with an exceptional classification of diseased leaves with Phoma Leaf Spot (84% precision) and healthy leaves (92% precision). However, the classification of diseased leaves with Coffee Leaf Rust was considerably low (42% precision). The values of recall and f1-score show similar results to those shown by the precision, 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 64%, which is very similar to the precision value, but the recall for the leaves that are healthy drops to 41%, and the value for the leaves that are sick with Coffee Leaf Rust goes up to 88%. The f1-score corresponds to the harmonic mean of precision and recall, so the above peaks are averaged out at 64%. For the classification model of our project, these values are good enough to support the development of the prototype.

We also calculated the ROC curve (Receiver Operating Characteristic) of the neural model (Fig. 7). 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 (0.87) and high values per category (0.85 to 0.93) of true positives versus false positives are observed.

Laboratory tests of the prototype showed not only the correct operation of the classification model within the metric margins but also how the leaf detection and preprocessing modules facilitate the work of the deep model. The need to evaluate the impact of these modules on the overall performance of the system is raised in future work. The capability of the DragonBoard 410c development board to run the software in real-time will also be verified.

V. Conclusion

Early and on-site detection of diseases in coffee crops is of great importance to avoid harvest losses, and to schedule the correct spraying processes. In this sense, in this work, we propose an embedded system based on machine learning for the detection of diseases in the coffee plant. This system is intended to be used directly in crops by farmers without technical knowledge, so its design, in addition to the characteristics of the plant and its diseases, considers aspects of use, cost, and performance. These characteristics of the system constitute the major contribution of the authors in the research.

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 ResNet (Residual Neural 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, including other larger ResNet models. The architecture of the

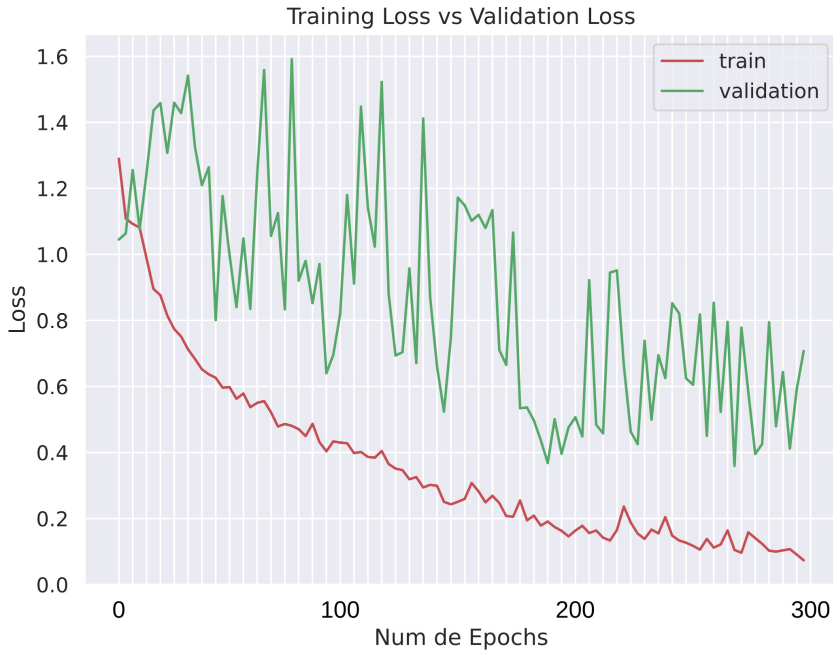

Fig. 5. Model Behavior: Training Loss vs Validation Loss.

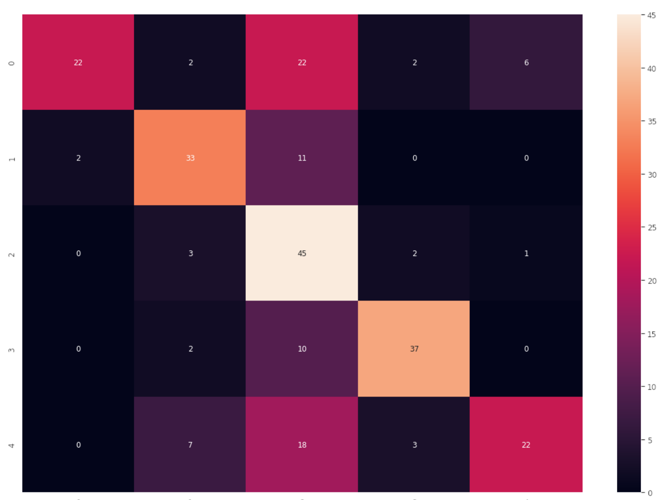

Fig. 6. Confusion Matrix.

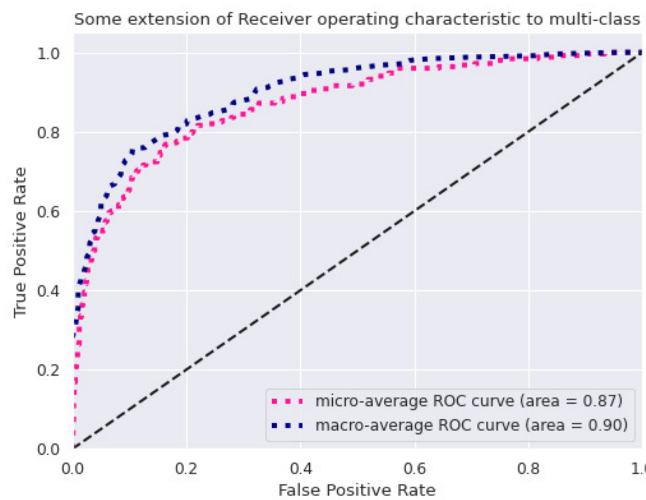

Fig. 7. ROC Curve.

ResNet network was adjusted for input images of 256×256 pixels in RGB format, 50 layers of depth (ResNet50), 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 300 epochs taking care not to overfitting the network. To fine-tune the parameters, the error was evaluated using the categorical hinge function, and optimized using the stochastic gradient descent function. The final accuracy achieved by the model was 96.5% for the training data and 63.6% 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 and acceptable performance for real-world implementation. Detection of diseased leaves exceeds 91% of cases, and correct disease identification is 64% in the worst case. Research continues to strengthen the training database, apply further fine-tuning to the hyperparameters, and evaluate the impact on the performance of the digital image processing modules.

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