Banana Leaf Disease Classification System Using Convolutional Neural Networks

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***Abstract*—This article presents the development of a disease classification system for banana plantations using Convolutional Neural Networks (CNN). The main objective is to assist producers in the early identification of diseases such as Sigatoka, Cordana, and Pestalotiopsis, which compromise production and cause financial losses. The methodology involves processing images of banana leaves to enable the classification of crop conditions, using a dataset extracted from the Banana Leaf Spot Diseases (BananaLSD) dataset. The proposed model was trained and validated using various hyperparameters to optimize disease detection performance. Performance evaluation used confusion matrices alongside precision, recall, and F1 score metrics to assess the performance of the designed classification system. The best result was obtained by combining CNN with the application of the SVM post-processing technique, achieving an overall accuracy of 89%, considering the classes cordana, healthy, pestalotiopsis, and sigatoka.**

***Index Terms*—Convolutional Neural Networks, Disease Identification, Processing Images, BananaLSD, Banana Plantations**

I. Introduction

The western Bahia region is one of the largest banana-producing areas in Brazil, with a particular emphasis on the municipality of Bom Jesus da Lapa (BA), which until mid-2018 was the title of the country's largest banana producer, with an annual production of approximately 170,000 tons [1]. The Formoso Irrigation District plays a crucial role in the agricultural development of the region by facilitating the channeling of water from the Corrente River and improving local productivity. Within the irrigated area, the Formoso A project was implemented, with 8,372.70 irrigable hectares, along with the Formoso H project, which covers 4,343 hectares [2].

Currently, approximately 800 producers invest in technology, infrastructure, and innovative cultivation methods to optimize production. However, banana cultivation faces significant challenges due to the incidence of various diseases. Among the most notable are Yellow Sigatoka and Black Sigatoka, caused by fungi that produce leaf spots, alter photosynthesis, and reduce productivity. Furthermore, Panama disease, also of fungal origin, affects the plant's vascular system, leading to the death of banana trees [3]. These adverse conditions directly impact agricultural production, causing losses for producers.

Although there are various preventive measures to reduce the incidence of problems in plantations, many producers do not have access to conventional identification methods, which generally involve the work of specialists and laboratory analyzes [4].

An effective alternative to minimize the time and cost of this process is the use of technology-based tools based on computational intelligence (CI), which are a viable solution for disease detection [5]. In this context, the adoption of CI enables optimization of the diagnosis, making it faster and more accessible to producers.

Currently, various studies are working to develop automated devices based on image processing techniques to support the identification of diseases that affect banana crops [6]. In this context, Deep Learning (DL) algorithms and computer vision stand out, as they are capable of recognizing patterns in image data sets of these diseases, enhancing diagnostic accuracy [7]. The prediction and detection of diseases in banana leaves is highlighted in the study by [8], which employs convolutional neural networks combined with feature extraction techniques to improve the identification of issues in this crop. Panama wilt disease was identified with 91.56% accuracy, 91.61% precision, 88.56% recall, and an F1-score of 81.56% in the study conducted by [9], using a machine learning approach.

Given the above, this research aims to develop an automatic classification system to allow the identification of pathologies such as Cordana, Sigatoka, and Pestalotiopsis. Earlyection of these diseases helps prevent their spread in the plantation, reducing the risk of crop losses and the production of low-quality fruits. Thus, for the processing and detection of banana leaf images, a classification system was proposed using a Convolutional Neural Network (CNN) combined with post-processing techniques such as Random Forest and Support Vector Machine.

II. Proposed Methodology

The good performance of banana plantations depends directly on the health of the leaves, which must be free from diseases. For this reason, early identification of these issues is crucial, enabling the adoption of effective and preventive measures. Traditional crop evaluation relies on manual detection, which requires time and specialized technical knowledge. Therefore, the adoption of automated systems can significantly accelerate this process, making it more efficient and accessible [10].

A. Contextualization of Diseases

This research focuses on three major banana leaf diseases: Sigatoka, Cordana, and Pestalotiopsis. These affect banana crops and compromise both fruit production and quality. Plantations can suffer from the spread of these pathologies, which can cause irreparable damage. Figures 1 and 2 illustrate the manifestation of these diseases on banana leaves, with the healthy leaf condition also presented.

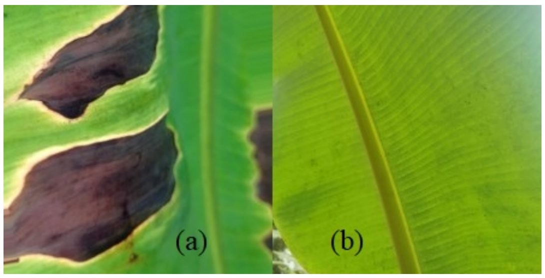

Fig. 1. Illustration of classes: a) cordana b) healthy.

Cordana is a fungal disease caused mainly by the fungus Cordana musae. Although considered less aggressive than other foliar diseases, such as Sigatoka, it can negatively impact banana productivity by compromising leaf health. The most characteristic symptoms are associated with severe infections that cause partial or total drying of the leaves. This leaf damage reduces the active photosynthetic area, affecting fruit development and the overall vigor of the bunch [11]. The disease cycle begins with the dispersal of fungal spores, which occurs through wind, rain splashes, and the use of contaminated tools. The main conditions that favor the infection and spread of Cordana are high relative humidity, elevated temperatures, and the presence of infected plant debris in the field.

The control of Cordana involves integrated practices such as the removal of infected leaves and crop residues, improved ventilation of the banana plantation through proper spacing, rational use of fungicides, and constant monitoring for early detection.

Sigatoka, also known as leaf spot disease, is one of the main diseases affecting banana plants. It is caused by fungi of the genus Mycosphaerella, with Yellow Sigatoka caused by Mycosphaerella musicola—the first form of the disease to be identified—and Black Sigatoka caused by Mycosphaerella fijiensis, which is more aggressive and destructive, affecting a wider range of banana varieties and causing greater production losses. The symptoms of Sigatoka include yellow spots on older leaves, which gradually turn brown and necrotic [11]. Disease progression leads to premature leaf death, significantly reducing the plant's photosynthetic capacity.

The control of Sigatoka remains a continuous challenge for banana producers. Management strategies include the use of fungicides, cultural practices such as removing infected leaves, and improving ventilation within the plantation canopy.

Pestalotiopsis is a disease caused by fungi of the genus Pestalotiopsis, Pestalotiopsis musarum being the most notable species, affecting mainly the leaves and fruits of banana plants. Although less well known than other foliar diseases, Pestalotiopsis can significantly compromise production quality, especially in the post-harvest phase [12]. The pathogen spreads through spores from infected plant material, disseminated by wind, water splashes, and contaminated tools. Disease development is favored by conditions of high relative humidity and elevated temperatures, as well as by wounds on leaves and fruits caused by insects, improper management practices, or adverse climatic factors. Typical symptoms include dark brown leaf spots, usually with well-defined edges and yellowish or gray centers. In fruits, the infection manifests itself as sunken lesions that progress to superficial or deep rot, reducing the commercial quality and market value of the fruit [13].

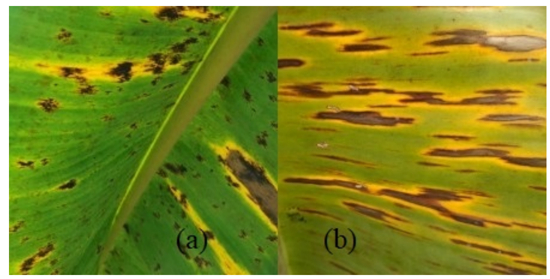

Fig. 2. Illustration of the classes: a) pestalotiopsis b) sigatoka.

B. Dataset Description

The Banana Leaf Spot Disease dataset was used for this research [14]. During the data preparation phase, the images were standardized to a 224x224 pixel format, a resolution frequently used for image classification problems. To enrich the dataset, augmentation techniques were applied. The main processes applied to the images were [15]:

- Cropping: Random crops were applied. In addition to reducing the input size, this technique also adds images with different proportions by extracting central fragments from each image.
- Horizontal Inversion: This inversion is safe for this scenario as it does not affect the meaning of the label, unlike cases involving text recognition.
- Translation: Offers similar effects to cropping but preserves the original spatial dimensions of the image.
- Shearing: Distorts the image along a specific axis. It is primarily used to create or correct perception angles.
- Rotate Shearing: Similar to shearing, but also applies a rotation to the image.
- Linear Contrast Adjustment: This is the only color space transformation performed. It is applied to correct lighting biases (images that are too bright or too dark), a common challenge in image identification.
- Gaussian Blur: Applying blur to images makes the deep learning model more tolerant to images with motion blur during the testing phase.

Table I shows the class distribution of the dataset used in this work [15].

TABLE I
DATASET DISTRIBUTION BY CLASS FOR ORIGINAL AND AUGMENTED IMAGES

Class	Original Images	Augmented Images
cordana	162	400
Healthy	129	400
pestalotiopsis	173	400
sigatoka	473	400
Total	**937**	**1600**

1) Data Preprocessing Stage: The dataset is organized into folders, with subdirectories representing the classes. Using the glob library, the code employs an iterative routine that:

- Lists the images contained in the training and testing folders;
- Reads the images using the function cv2.imread, ensuring the capture of color channels through the IMREAD_COLOR parameter;
- Resizes each image to a fixed size of 128×128 pixels, which is essential to ensure uniform input to the model;
- Converts the color space from BGR to RGB, ensuring consistency with the standard used in deep learning frameworks.

After this process, the sets of images and their corresponding labels are encapsulated into NumPy arrays. The preprocessing stage also involves label encoding (converting textual data into integers) using the LabelEncoder from the Scikit-learn library, followed by one-hot encoding to prepare the data for network training. Additionally, the pixel values of the images are normalized to the [0, 1] range, a common practice to reduce scale bias and improve performance during network training.

C. Classification System

This research proposed the development of a convolutional neural network aimed at classifying images related to the health conditions of banana crops. CNNs are particularly well-suited for applications involving image and video processing, although it has also been successfully applied in experiments involving temporal signals [16].

The algorithm was implemented using the Python programming language and the Spyder integrated development environment (IDE). Initially, it was necessary to import essential libraries for data processing and visualization (such as NumPy, Matplotlib, OpenCV, and Seaborn) as well as Keras modules for building the model (including Sequential, Model, convolutional layers, and pooling layers).

1) Model Architecture: The model is built using a sequential architecture, where feature extraction is performed through convolutional layers and auxiliary operations. Notable components include:

- Convolutional Layers (Conv2D): These are added progressively, starting with 32 filters and then expanding to 64 filters, applying a sigmoid activation function at each step. The filters operate on the images with a kernel size of 3 and use padding with a ”same” strategy to preserve the spatial dimensions of the inputs.
- Normalization and Pooling: In each block of operations, BatchNormalization is applied, which contributes to training stability. Additionally, MaxPooling2D layers reduce the spatial dimensions of the activations, facilitating the extraction of the most relevant patterns and decreasing computational complexity.
- Flatten and Dense Layers: After feature extraction through convolutional operations, the data is flattened and fed into a dense layer with 128 neurons. The output layer has 4 neurons, whose softmax activation enables multi-class classification.

The model compilation uses the RMSprop optimizer and the categorical_crossentropy loss function, which is suitable for classification problems where the outputs are represented in one-hot format. During training, the model's performance is monitored in terms of accuracy and loss, allowing evaluation of both training and validation data. The architecture implemented in this work is illustrated in Figure 3.

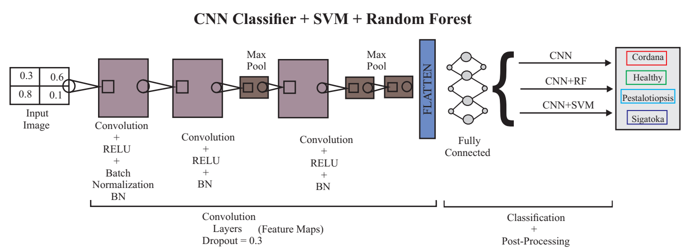

Fig. 3. CNN architecture implemented.

2) Training and Evaluation: The model is trained over 100 epochs, allowing for iterative parameter adjustments and enabling visualization of the model's behavior through plots of loss and accuracy values. Matplotlib functions generate two charts that illustrate:

- The evolution of loss during training and validation, highlighting the minimization of losses over time;
- The variation in accuracy for both datasets makes it easier to identify potential signs of overfitting or underfitting.

After training, the model undergoes a prediction phase on the test dataset. The resulting predictions are compared with the actual labels through the generation of a confusion matrix, which provides a detailed visualization of the model's performance for each class, using Seaborn for enhanced graphical representation.

It is worth noting that the use of this neural network architecture is justified by its ability to extract relevant information from the analyzed images [17]. Thus, to obtain the parameters for the designed classification system, it was necessary to evaluate the convergence process during the training and validation stages. This procedure was carried out by adjusting the network, particularly the number of epochs and batch size, which were configured to achieve the best accuracy results. This monitoring enabled the identification of the most suitable parameters for the methodology proposed in this study.

D. *Methodology for Results Evaluation*

The neural network's performance metrics were calculated based on the confusion matrix, allowing for a detailed analysis of the classifier's effectiveness in each category.

The confusion matrix summarizes the correct and incorrect predictions across classes. The sum of the elements in each row i that are outside the main diagonal corresponds to the False Positives (FP) for $class_i$, representing the number of times the model predicted $class_i$ when it belonged to other classes. Conversely, the sum of the elements in each column j that are outside the main diagonal represents the False Negatives (FN) for $class_j$, indicating instances of $class_j$ that were incorrectly classified as other classes. The True Negatives (TN) are the sum of the remaining elements after excluding the row and column of $class_i$ [18].

Other performance measures can be derived from the confusion matrix to extract information about the developed classifier. Accuracy (Cf) represents the overall performance of the model, indicating the proportion of correct classifications relative to the total number of classifications (Equation 1). Confusion or error (Ac) can be calculated using Equation 2, which reflects the ratio of incorrect classifications to the total number of classifications [19].

$$Ac = \frac{\sum_{i=1}^{m} n_{i,j}}{\sum_{i=1}^{m} \sum_{j=1}^{m} n_{i,j}} \tag{1}$$

$$Cf = 1 - Ac \tag{2}$$

Precision is a metric related to the efficiency of the model in correctly identifying the positive samples present. It is based on the following equation:

$$Precisao = \frac{TP}{TP + FP} \tag{3}$$

- TP - *True positive*.
- FP *False Positive*.

Equation (3) represents an average calculated across all positive values, whether true or false.

Recall, on the other hand, shows the proportion of true positive values regarding the total number of positive samples. This allows for evaluating the model's ability to correctly identify these positive samples. Mathematically:

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

The evaluation using the F1-Score consists of combining the values of precision and recall in a balanced way, merging both metrics into a single one for classifying the positive values present (Equation 5).

$$F1\text{-}Score = \frac{2(\text{Precisão} \cdot \text{Recall})}{\text{Precisão} + \text{Recall}} \tag{5}$$

III. Results

The results are presented in three stages. Initially, the classification system is evaluated considering the CNN. The subsequent analyses make use of post-processing techniques. In this case, Random Forest (CNN+RF) and Support Vector Machine (CNN+SVM) were used. The neural network training considered 80% of the banana leaf image data, with the remaining 10% used for testing and 10% for validation. All models were trained using 100 epochs and a batch size of 32.

The training procedure was executed multiple times to mitigate the risk of biased outcomes. The results reported correspond to the average performance measured on the test dataset. For each classifier design iteration, the images composing the training, validation, and test sets were randomly selected before the initialization phase.

A. *Classification System Performance Using CNN*

The classification system was designed to detect diseases on banana leaves. These pathologies are responsible for triggering various issues in the plantation, leading to production losses and reduced fruit quality. Initially, a convolutional neural network was used to extract features from images of this crop. The results are presented according to the confusion matrix shown in Table II. The classifier exhibited limited performance in distinguishing between the involved classes. The Sigatoka disease was identified with 100% accuracy, however, the other classes achieved only 35%, 35%, and 15% for Cordana, Healthy, and Pestalotiopsis, respectively. It is noteworthy that the Cordana and Healthy classes were misclassified as Sigatoka, with misclassification rates of 65% and 60%, respectively.

TABLE II
CONFUSION MATRIX (IN %) FOR THE CLASSES CORDANA, HEALTHY, PESTALOTIOPSIS, AND SIGATOKA, BASED ON THE CNN CLASSIFIER FED WITH BANANA LEAF IMAGES.

CNN		Predicted Class			
		cordana (%)	**Healthy (%)**	**pestalotiopsis (%)**	**sigatoka (%)**
Actual Class	**cordana**	35,0	0,0	0,0	65,0
	Healthy	5,0	35,0	0,0	60,0
	pestalotiopsis	0,0	60,0	15,0	25,0
	sigatoka	0,0	0,0	0,0	100,0

Table III presents additional metrics considered in the evaluation of the designed system. It is worth noting that the class Pestalotiopsis achieved the highest precision in disease discrimination (100%), while Sigatoka obtained the best recall value (100%). The Figure 4 summarizes the results found after evaluating precision, recall, and f1-score.

B. *Classification System Performance Using CNN + Random Forest*

Given the low class discrimination efficiency observed in the previous configuration, post-processing techniques were evaluated. These were combined with the designed convolutional neural network in an attempt to improve disease identification. Initially, the Random Forest algorithm was used, showing better overall class discrimination efficiency compared to the methodology previously proposed using only CNN. In

TABLE III
PERFORMANCE EVALUATION OF THE CLASSIFICATION SYSTEM USING CNN.

Class	*Precision*	*Recall*	*f1-score*
Cordana	0,88	0,35	0,50
Healthy	0,37	0,35	0,36
Pestalotiopsis	1,00	0,15	0,26
Sigatoka	0,40	1,00	0,57
accuracy = 0,46± 1,2			

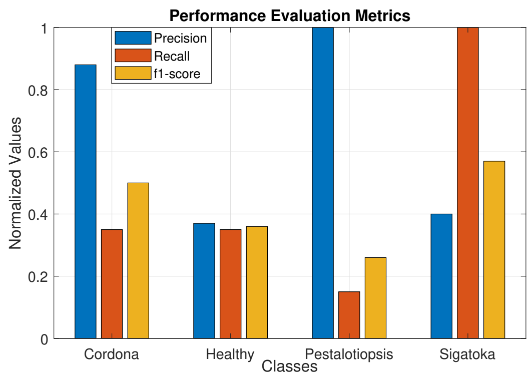

Fig. 4. Performance Evaluation Metrics for the classes Cordana, Healthy, Pestalotiopsis, and Sigatoka.

this case, the accuracy increased from 46% to 69%, with notable improvements in the detection of Cordana, Healthy, and Pestalotiopsis diseases. However, the Sigatoka class got a drop in detection, decreasing from 100% to 70%. Despite these improvements over the previous configuration, the model still showed reduced class discrimination, with detection errors reaching up to 70%, principally when the classifier identified the Healthy class instead of the Pestalotiopsis disease. These results are presented in Table IV.

TABLE IV
CONFUSION MATRIX (IN %) FOR THE CLASSES CORDANA, HEALTHY, PESTALOTIOPSIS, AND SIGATOKA, BASED ON THE CNN CLASSIFIER + *Random Forest* FED WITH BANANA LEAF IMAGES.

CNN + *Random Forest*		Predicted Class			
		cordana (%)	Healthy (%)	pestalotiopsis (%)	sigatoka (%)
Actual Class	cordana	95,0	0,0	0,0	5,0
	Healthy	15,0	80,0	5,0	0,0
	pestalotiopsis	0,0	70,0	30,0	0,0
	sigatoka	5,0	0,0	25,0	70,0

Table V presents some metrics used to evaluate the performance of the classification system using CNN + Random Forest. A significant drop in the precision of the Pestalotiopsis class is observed, which previously was 100%, but has now decreased to 50%. The Sigatoka disease showed the highest precision value (93%), while Cordana achieved the best recall (95%). The Figure 5 summarizes the results found after evaluating precision, recall and f1-score.

TABLE V
PERFORMANCE EVALUATION OF THE CLASSIFICATION SYSTEM USING CNN + *Random Forest*.

Classes	*Precision*	*Recall*	*f1-score*
cordana	0,83	0,95	0,88
Healthy	0,53	0,80	0,64
pestalotiopsis	0,50	0,30	0,38
sigatoka	0,93	0,70	0,80
accuracy = 0,69± 1,2			

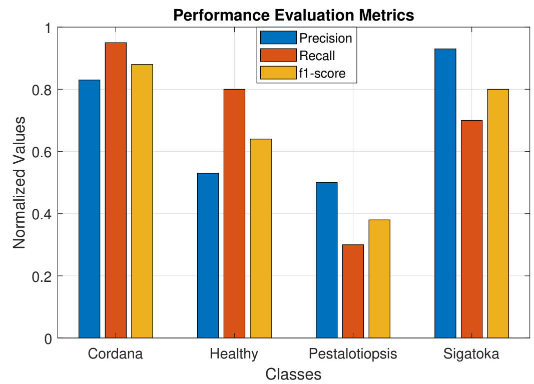

Fig. 5. Performance Evaluation Metrics for the classes Cordana, Healthy, Pestalotiopsis, and Sigatoka.

C. Classification System Performance Using CNN + Support Vector Machine

The Support Vector Machine algorithm was implemented in conjunction with the convolutional neural network. The results proved to be promising. As shown in Table VI, the classes Cordana, Healthy, and Sigatoka were identified without errors. The disease Pestalotiopsis, however, achieved only 55% accuracy, being confused with the Healthy class, which accounts for 45% of the misclassification. These rates affected the precision of the Healthy class, the recall of the Pestalotiopsis disease, and the overall class discrimination (accuracy), as observed in Table VII. Notably, the Cordana and Sigatoka classes achieved 100% in the precision, recall, and f1-score metrics. The Figure 6 summarizes the results found after evaluating precision, recall and f1-score.

TABLE VI
CONFUSION MATRIX (IN %) FOR THE CLASSES CORDANA, HEALTHY, PESTALOTIOPSIS, AND SIGATOKA, BASED ON THE CNN CLASSIFIER + *Support Vector Machine* FED WITH BANANA LEAF IMAGES.

CNN + *Support Vector Machine*		Predicted Class			
		cordana (%)	Healthy (%)	pestalotiopsis (%)	sigatoka (%)
Actual Class	cordana	100,0	0,0	0,0	0,0
	Healthy	0,0	100,0	0,0	0,0
	pestalotiopsis	0,0	45,0	55,0	0,0
	sigatoka	0,0	0,0	0,0	100,0

D. Final Considerations

Technological tools aimed at automating the process of identifying agricultural issues are essential for improving efficiency and ensuring product quality. This research focused

TABLE VII
PERFORMANCE EVALUATION OF THE CLASSIFICATION SYSTEM USING CNN + SVM.

Class	***Precision***	***Recall***	***f1-score***
cordana	1,00	1,00	1,00
Healthy	0,69	1,00	0,82
pestalotiopsis	1,00	0,55	0,71
sigatoka	1,00	1,00	1,00
accuracy = 0,89± 1,2			

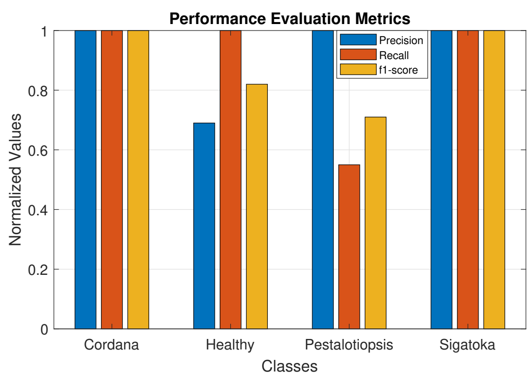

Fig. 6. Performance Evaluation Metrics for the classes Cordana, Healthy, Pestalotiopsis, and Sigatoka.

on the application of a convolutional neural network, combined with post-processing techniques (Random Forest and SVM), to identify pathologies in banana plantations, namely: Cordana, Healthy, Pestalotiopsis, and Sigatoka. The results showed high efficiency in discriminating between the Cordana, Healthy, and Sigatoka classes. The overall performance of the best model achieved a precision and total accuracy of 92% and 89%, respectively.

The classification system designed showed difficulty in identifying the Pestalotiopsis disease, which was incorrectly detected in 45% of the test cases, being confused with the healthy class. For this study, this rate is particularly concerning, since when a pathology is identified as healthy, no corrective actions are taken, which compromises the crop. Imbalances in the image samples may have contributed to this result, as a reduced amount of data from the healthy class was used to train the model. Another important aspect is that Pestalotiopsis infection, in its early stages, presents subtle symptoms such as small, slightly altered spots that closely resemble the natural appearance of healthy leaves.

IV. CONCLUSION

This research presented a disease detection system for banana crops. The proposed methodology involved a convolutional neural network combined with post-processing techniques (Random Forest and Support Vector Machine). The performance of the proposed model was evaluated using a confusion matrix and metrics such as accuracy, precision, recall, and F1-score. The results showed good performance in disease classification when combining CNN with Support Vector Machine. The diseases Cordana, Healthy, and Sigatoka were identified without errors. However, the Pestalotiopsis class was misclassified as Healthy, showing a 45% error. This rate is undesirable for this application because when a disease is classified as Healthy, no corrective action is taken, which harms the plantation and fruit development. On the other hand, it can be said that our methodology demonstrates promising results in discriminating some of the diseases evaluated in this work, as success was achieved in the evaluation of the other three classes. Future evaluations intend to use other information processing techniques to reduce confusion between diseased and healthy classes. After the classification system adjustment phase, the implementation of a pre-trained network embedded in a microcontroller will be proposed. This device will be incorporated into a drone for monitoring banana plantations in the Formoso Project, located in the city of Bom Jesus da Lapa, western Bahia.

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