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Convolutional Neural Networks for Disease Detection in Cocoa Pod: A Roboflow Approach

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***Abstract*—This paper addresses the development of a convolutional neural network (CNN) model capable of detecting diseases in cocoa fruits, specifically black pod and moniliasis, using images collected in the field and processed with the Roboflow platform. These diseases represent a significant challenge for farmers due to the economic losses they generate, highlighting the importance of early and accurate detection. 2,000 representative images were collected, adjusted with saturation variations (+25% and -25%) and capture distances (10 cm and 30 cm), which were used to train specialized neural networks. The developed models achieved outstanding metrics, exceeding 95% accuracy and recall in the detection of both diseases in the mixed network. Among the designed networks, the network focused on black cob showed a performance higher than 96%, while the network for moniliasis obtained slightly lower, but satisfactory results of 91%, highlighting the relevance of representative data and iterative training to optimize the model performance. The conclusions highlighted the effectiveness of the model developed, the relevance of the quality and diversity of the data collected, and the positive impact that this technology can have on agricultural management.**

***Index Terms*—Deep learning, Disease detection, Cocoa, Convolutional Neural Networks**

I. Introduction

The production of cocoa *(Theobroma cacao L.)* has been a fundamental activity in world agriculture, especially in Latin America, where it is not only a significant source of economic income, but also a crop of cultural and historical relevance. Originally from the Upper Amazon, this crop has expanded to various regions of the world, consolidating itself as a key product in international markets. However, despite its economic and social importance, cocoa production faces multiple challenges that threaten its sustainability and profitability.

Among the most significant problems are fruit diseases, such as black pod *(Phytophthora palmivora)* and moniliasis *(Moniliophthora roreri)*, which cause significant economic losses by reducing both the quality and quantity of harvested fruit. These diseases represent a critical gap in efforts to maintain cocoa productivity, as traditional detection techniques, based primarily on visual inspections by farmers, are inaccurate and prone to human error. This problem highlights the need for innovative solutions that allow early and accurate identification of these diseases, ensuring a rapid and effective response to minimize damage.

Recent advances in artificial intelligence, specifically in the field of deep learning, have demonstrated their potential to address these types of agricultural challenges. CNNs have established themselves as powerful tools in image processing, allowing the detection and classification of complex patterns that are difficult to recognize by conventional methods. However, their application in the cocoa sector, particularly for the identification of fruit diseases, remains limited and presents opportunities to develop more efficient systems adapted to field conditions.

This paper addresses this knowledge gap by proposing the development of a convolutional neural network model capable of accurately and efficiently identifying the main diseases affecting cocoa fruits. This model is built through a spiral methodology, using a set of 2,000 images captured in field conditions, processed and trained on the Roboflow platform, specialized in computer vision.

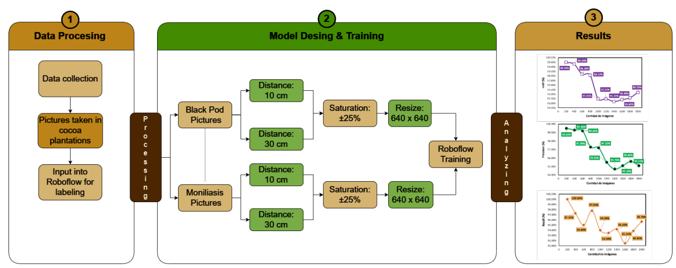

Fig. 1. Integrative image for the study

Figure 1 shows the integrative image of the model that has been proposed. This approach seeks not only to overcome the limitations of traditional methods, but also to provide a robust system that can be implemented in practical scenarios, contributing to the sustainability of the cocoa sector.

II. Context

Cacao, native to the Upper Amazon, has been cultivated in Central America and Honduras since pre-Columbian times, providing various benefits, such as food, timber and feed [1]. Today, its global consumption exceeds 4.5 million tons per year, driven not only by the chocolate industry, but also by its incorporation in sectors such as cosmetics, pharmaceuticals, and food, including innovative and healthy products [2]. As cocoa production and industrialization are diversifying, it is very important to ensure the quality of the product from cultivation to final processing.

Honduras and Central America have great potential for the cultivation and marketing of cocoa, especially in the global specialty cocoa market, thanks to the genetic attributes that distinguish their aroma and quality [1].

A. Problems of cocoa fruit diseases

Plant pathologies are a crucial challenge for agriculture, as they diminish both the production and quality of agricultural products [3]. For cocoa cultivation, there are considerable dangers from several diseases that affect trees, pods and beans, which adversely affect productivity and product quality [4]. This study focuses on two of the best known disorders: moniliasis and black pod disease.

Moniliasis, also called frosted pod or "Monilia", is distinguished by a white, powdery development on the surface of infected cocoa pods, resembling a frosted coating. This damage affects both the appearance and quality of the cocoa beans [4]. External signs generally appear between 40 and 60 days after infection, although in fresh fruits and under favorable conditions such as high humidity and temperature, this period may be shorter [5].

The black pod is caused mainly by fungi of the genus *Phytophthora*. This disease is characterized by the appearance of lesions that, if left uncontrolled, rapidly expand to transform the entire ear into a black necrotic mass. This visual change, from a healthy ear to a dark, deteriorated husk, significantly affects current and future crop yields [4]. Unlike moniliasis, black ear affects the fruit from the outside in. Although some diseased cobs may retain the seeds and mucilage apparently in good condition, it is not recommended to harvest them, as they could be contaminated with the pathogen and compromise the quality of the product [5].

B. Traditional methods of detecting cocoa diseases

Generally, pest inspection of cocoa crops is done through direct observation, identifying pests and diseases found on the pods by visual examination of the color of the fruit skin by human eyesight [6]. Historically, cocoa disease management has been based on agricultural and cultural techniques aimed at mitigating the adverse impacts of pests and diseases on plantations. Below are some traditional practices used in disease management:

Traditional agricultural practices for disease management include strategies such as crop rotation and diversification, which interrupt the life cycle of pathogens by alternating different species in the same area, reducing infestations and improving soil health. Also noteworthy is the selection of resistant varieties, where farmers choose plants that are naturally tolerant to diseases, reducing dependence on chemical pesticides and optimizing adaptation to the local environment. Finally, timely harvesting and proper storage ensure the preservation of crops through techniques such as proper drying and the use of clean, ventilated spaces, which prevent mold, pests and wastage, thus prolonging their shelf life [4].

Although these practices have proven effective in different situations, their success relies on a relentless effort by farmers and can be constrained by elements such as weather conditions conducive to fungi or the scarcity of sophisticated resources. In addition, manual identification of diseases and pests remains a costly procedure and susceptible to human error, which can delay treatment and worsen crop difficulties [7].

C. Need for technological solutions

Today, with the use of advanced technologies such as artificial intelligence, machine learning, computer vision and deep learning, defects in cocoa pods can be accurately identified and classified [8]. The choice of machine learning algorithm depends on factors such as data size and availability, accuracy and interpretation of results, training time, linearity, number of features, and model approach, whether regression, classification, or clustering [9].

CNNs are a class of deep learning networks generally used in image identification tasks. In these networks, the application of so-called convolutional layers enables hierarchical feature extraction [10]. This convolutional layer is a crucial element, as it obtains local attributes such as edges, textures and shapes, and generates feature maps through moving a set of convolutional kernels through the initial image and performing convolution operations [11].

In agriculture, CNNs stand out for their ability to generate results in seconds, allowing farmers to respond quickly with appropriate treatments or the removal of affected plants to prevent the spread of diseases or pests.

III. Methodology

A. Techniques and tools used

In this research, images were captured with a high resolution (50 MP) Motorola g54.

The Roboflow 3.0 platform was used to design three neural networks: one for detecting black cob, one for moniliasis, and a mixed network for both. Development involved loading labeled images (1,000 for each individual network and 2,000 for the mixed network), followed by structured training that achieved accuracies greater than 95%.

The object detection technique, based on CNNs, allows identifying and classifying affected areas with high accuracy, using metrics such as mAP, precision and recall. This supervised approach, supported by pre-trained models in MS COCO, stands out for its ability to locate and classify lesions in fruits, demonstrating the effectiveness of the methodology in advanced agricultural applications [12], [13].

B. Study methodology

The adapted research framework is shown in Figure 2. Each of the framework's phase steps is integral to the success of this effort:

The methodology of this study was based on [14], and followed an iterative spiral approach, starting with the collection of 2,000 images of cocoa fruits affected by black pod and moniliasis. These images were carefully selected to ensure quality and diversity, adjusting saturation levels and capturing different distances. Subsequently, they were processed and labeled in the Roboflow platform, classifying them into two classes: "*Black Pod*" and "*Monilia*". Three

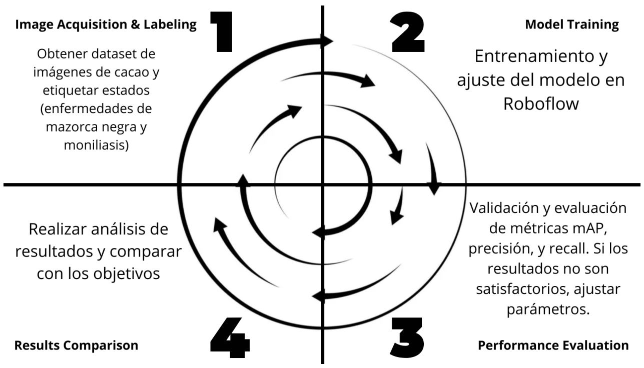

Fig. 2. Spiral Model applied in the study

CNNs were trained: two individual ones for each disease and a mixed one combining both, using batches of 120 and 100 images respectively, with multiple training cycles to optimize the model. An example annotation of the dataset from the relevant study dataset of this research is shown in Figure 3.

Fig. 3. Examples of neural network annotations

C. Evaluation metrics

Evaluation metrics are essential for measuring the effectiveness and reliability of disease detection models in cocoa. The primary metric used is the mean average precision (mAP), which combines precision and recall to evaluate the overall performance of the model in correctly classifying classes [15]. A high MAP indicates accuracy and consistency in detecting all classes.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \tag{1}$$

In addition, Precision measures the proportion of correct positive predictions, reducing false positives and avoiding unnecessary treatments.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

While recall evaluates the model's ability to identify the majority of diseased fruit, minimizing false negatives, it also evaluates the model's ability to identify the majority of diseased fruit, while minimizing false negatives [15].

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

According to [16], these metrics, widely used in datasets such as PASCAL VOC and COCO, are key to optimizing and validating the capability of models in computer vision tasks.

IV. Results

This section presents the results obtained during the development and evaluation of neural network models to detect black pod and moniliasis in cocoa fruits. Key metrics such as accuracy, recall and mAP (mean Average Precision) will be analyzed, in addition to a comparison between the individual models designed for each disease and the mixed model that integrates the detection of both pathologies.

A. Black Pod Neural Network Results

In the network plot corresponding to black pod detection in Figure 4, it is observed that the recall maintains consistently high values, reaching 99.10% at the end of the training. Accuracy, on the other hand, experiences a slight decrease, starting at 99.5% and decreasing to 96.5% with the increase of images in the dataset. The mAP, although variable, remains at high levels, ranging from 99.4% y el 98.9%, with slight fluctuations as the dataset expands.

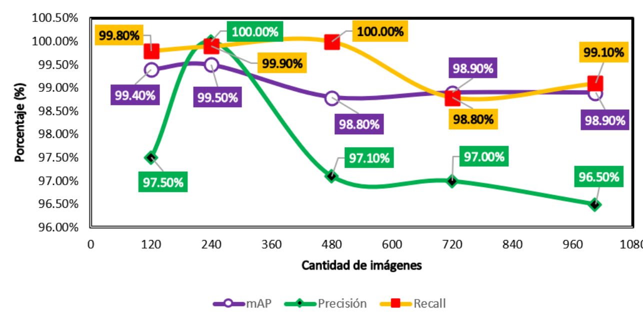

Fig. 4. Comparative graph of the final model of the black pod network

B. Moniliasis Neural Network Results

In the graph corresponding to the monilia network observed in Figure 5, it can be seen that the metrics of mAP, precision and recall experience a slight decrease as the number of images increases, starting at 99.5%, 99.8% and 100.0%, and decreasing to 91.3% in mAP and 88.7% for precision and recall, with mAP being better stabilized and being higher than 90%.

C. Mixed Neural Network

In Table I, a comparison of the results of the final Mixed Network model is presented, showing the performance in terms of the metrics mAP, precision, and recall against different numbers of training images, from 200 to 2,000. As the size of the image set increases, a slight decrease in the metrics is observed, stabilizing around 95% for precision and mAP.

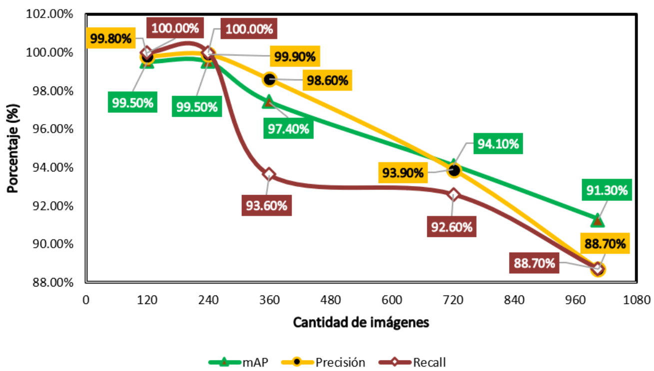

Fig. 5. Comparative graph of the final model of the Moniliasis network

TABLE I
COMPARISON OF EVALUATION METRICS

Comparison of Training Evaluation Metrics			
Training	**mAP(%)**	**Precision(%)**	**Recall(%)**
1	99.5	99.5	100.0
2	99.3	99.3	97.3
3	98.2	99.2	95.0
4	98.1	97.3	97.8
5	95.5	97.2	94.0
6	95.5	95.5	93.5
7	95.2	94.7	94.2
8	95.4	95.1	91.5
9	95.6	95.6	93.9
10	96.2	95.1	95.7

V. DISCUSSION

In this section, the results obtained are interpreted to derive meaningful conclusions in relation to the objectives of the study, incorporating critical reflections, contrasting the findings with previous research and exploring the innovative implications of the work.

A. Black Pod Network

Regarding the results obtained with the network for black pod detection, as shown in Figure 4, the graph presents metrics of mAP, precision and recall in percentage. During the first two trainings, the network showed exponential growth, indicating effective learning. However, as more images were added to the dataset, the percentages began to fluctuate and, in some cases, decrease. This suggests that it is not necessary to use an excessively large set of images; instead, it is more efficient to use a smaller, but representative, set.

Black pod disease is easier to identify because of its distinctive symptomatology: a round black spot that appears on the fruit and progressively spreads from the outside to the inside. If detected at an early stage, it is possible to save the inner fruits of the fence, although it is not recommended to do so if the disease is already advanced. The dataset includes images representing different stages of the disease, which allowed the network to learn efficiently. However, due to the simplicity of the evolution of this pathology, using a dataset that is too large may be inefficient.

Despite these observations, the network achieved outstanding results, with a mAP of 96.5%, an accuracy of 98.9% and a recall of 99.1%.

B. Moniliasis Network

As for the network intended for moniliasis detection, the results, presented in Figure 5, show a progressive decrease in the metrics of mAP, precision and recall as more images were added to the dataset, reaching values of 91.3% for mAP and 88.7% in precision and recall. This behavior can be attributed to the more complex and extensive nature of the symptomatology of this disease compared to black pod.

Unlike the latter, moniliasis develops from the inside out, making it difficult to detect, especially in early stages. Initially, the images used corresponded to intermediate and advanced stages of the disease, but as images representing all stages from early symptoms to full development were included, the network faced greater challenges in correctly identifying the disease. This is because the early stages of moniliasis are often almost imperceptible to the naked eye and require the intervention of experts or specific techniques, such as cutting a portion of the fruit, to confirm the presence of the pathology, which in some cases may only manifest as a small spot.

Despite these challenges, the network proved to be able to adequately detect the disease in general terms.

C. Mixed Network

As for the results obtained with the mixed network that combines both diseases previously mentioned, a total of 2,000 images were used, aggregated in groups of 100, and performing training every 200 images, thus completing a total of 10 trainings. Table I shows the results of the mAP metric, highlighting that the network maintained an outstanding performance with minimal drops in values, remaining above 90% at all times. In the last training, the network reached a mAP of 96.2%, evidencing a high efficiency in the detection of these diseases. Similar results are observed in the accuracy metric, although there were slight decreases, this stabilized towards the end of the process, achieving a result of 95.1% in the last training, with a minimum value of 94.7%. Regarding the recall metric, the network showed greater fluctuations compared to the other two metrics. The values ranged from a minimum of 91.5% and a maximum of 100%, finally stabilizing at 95.7% at the close of training.

It is important to note that, for this type of network, it may not be necessary to use such a large dataset. Instead, it would be more effective to use a more compact dataset that adequately represents the symptomatology of both diseases, allowing training to be optimized.

Finally, when comparing the mixed network with the results of the individual network for the detection of moniliasis, it is observed that the mixed network obtained a better performance in the class corresponding to this disease. This is due to the fact that in the development of the mixed network, the observations made in the individual network were taken into account, which allowed for more meticulous annotations.

In addition, this network was trained a total of 10 times, doubling the number of trainings performed in the individual network, which contributed to improve its detection capacity and accuracy.

Table II shows comparisons of the results obtained with those of previous studies:

TABLE II
COMPARISON OF RESULTS WITH PREVIOUS STUDIES

Comparison of results with previous studies	
Research	**Accuracy of the study (%)**
[17]	84.87
[18]	98.3
[19]	91.0
[20]	86.04
[21]	91.79
[8]	35.0
Model developed	95.1

When comparing the accuracy of the current model with previous studies, it was found that the current model showed better results on five occasions. This is due, in part, to advances in tools such as Roboflow, which simplify and optimize the training process and reduce the computational burden compared to the methods used in previous studies. In those studies, training computer vision models was more challenging because these technologies were in their early stages of development, requiring more manual processes and greater computational capacity.

In addition, it is important to note that many earlier models did not focus solely on black cob disease and moniliasis. Some addressed multiple diseases, others merely classified fruit as healthy or diseased, and some combined CNNs with other algorithms to compare their performance.

D. Future Work and Recommendations

Regarding recommendations for future work related to the topic in question, one of the most relevant findings of this study is that it is not always necessary to use large amounts of data to train neural networks. The results obtained show that, after a certain point, increasing the number of images can lead to a stabilization or even a decrease in the accuracy of the model, in addition to lengthening training times.

Therefore, it is recommended to use a more compact but representative data set that covers the diversity of different variables such as illumination level, image quality, distance and disease symptoms. This approach provides an optimal balance between quantity and quality and increases model performance without creating unnecessarily long processes. This in order to improve and enrich the networks in future work, even using lower quality cameras in terms of resolution such as minimum 800 x 600 pixels being sufficient to capture visible details of moderate size, such as spots or obvious changes in the fruit, similar to those available to growers. This approach will allow training more robust and adaptable models capable of operating in real environments where conditions are not uniform or uncontrollable, thus increasing their applicability in the agricultural sector.

For specific diseases, such as moniliasis, it is also recommended to construct representative data sets at all stages of the disease, from early symptoms to advanced stages. It is recommended to use 40% of images at early stages, 35% of intermediate stages and 25% of advanced stages, also using a 60%, to focus on morphological changes that are more complicated to identify and the remainder of the dataset on visual changes that are easier to identify. This will help form networks capable of detecting pathologies at an early stage, allowing growers to take preventive measures in time to reduce the impact of the disease on their crops.

Finally, it is important to highlight the effectiveness of using Roboflow, as this software is not only suitable for the specific areas covered by this study, but can also be used in other areas due to its versatility and advanced features. The platform offers a variety of classification and detection capabilities, as well as several pre-trained models that can be adapted to different projects according to the user's needs. Unlike tools used in previous studies, Roboflow does not require excessive computational capacity or complex programming, as its integrated model simplifies the screening and training process, making it faster and more efficient. In addition, the platform provides detailed tutorials and explanations of concepts that facilitate learning and use of the software.

VI. CONCLUSIONS

- The convolutional neural network model developed was able to successfully detect black pod and moniliasis diseases in cocoa fruits, obtaining an accuracy greater than 95% in the final tests. This demonstrates its effectiveness and ability to identify diseases.
- The collection of 2,000 representative images of affected fruits, adjusted with saturation variations (+25% and -25%) and captured at different distances (10 cm and 30 cm), allowed training a robust and adaptable model. This approach was key to ensuring that the model maintained consistent performance across various visual conditions.
- The designed neural networks achieved outstanding metrics: the network focused on black cob obtained accuracies greater than 96%, while the moniliasis network presented slightly lower results of 91%, but equally satisfactory. The mixed network managed to consolidate both detections with results greater than 95%, confirming the success of the trained model and meeting the specific objectives of adjustment and performance evaluation.

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