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Deep Learning and YOLOv10 architecture to detect Cercospora nicotianae and Alternaria alternata diseases in tobacco crops

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Abstract

In this research, a mobile application based on machine learning was developed to detect and control diseases caused by Cercospora nicotianae and Alternaria alternata on the leaves of the tobacco plant at the Tabacalfa tobacco company in the Ventanas canton. The application used inductive and deductive methods to gather information from various sources and analyze tobacco leaf image data to train with the Roboflow application and 253 images. The results showed that the model's performance improved with training iterations, with metrics such as recall, mAP50, and precision indicating the model's high ability to accurately identify and classify the types of diseases Alternaria alternata and Cercospora nicotianae in tobacco leaves by images. The model with a higher confidence threshold is considered to have better overall performance, with a higher precision-recall curve. In addition to the application of a satisfaction survey to 70 individuals, which revealed a positive user interface, clear navigation, and optimal functionality for detecting diseases in tobacco plants. In addition, an application of technologies such as deep learning and YOLOv10 is praised for a high satisfaction level of 97.14% among the respondents. In conclusion, it is evident that the mobile application has significant economic benefits, as it can reduce crop losses and improve productivity, working conditions, job satisfaction, and reduce the use of pesticides.

Keywords: Mobile application, machine learning, YOLOv10, tobacco plant, Cercospora nicotianae, Alternaria alternate.

1.Introduction

Tobacco cultivation in the Ventanas canton, Ecuador, is crucial for the local economy. However, pests such as *Cercospora nicotianae* and *Alternaria alternata* affect agricultural yields, leading to production losses (Ali MY, et al., 2023). To address this issue, a mobile application is proposed that uses artificial intelligence techniques such as Deep Learning (Yinghua Li et al., 2025). The application will be developed in the Android Studio environment, offering an Android device emulator, compatibility with operating systems like Windows, MacOS, and Linux, and the Dart programming language with the open-source Flutter framework (Aung, et al., 2024). An object detection model using Yolo (You Only Look Once) will be implemented to identify pests in tobacco plants, allowing farmers to take pictures of tobacco leaves with specific symptoms (Lin J, et al., 2023; R. N. Ariwa et al., 2024).
The Ventanas canton, a key economic area for tobacco planting, faces significant pests such as *Cercospora nicotianae* and *Alternaria alternata*, causing considerable losses in agricultural production. This research highlights the need for innovative technological solutions for the early and effective detection of these diseases in tobacco crops (Nguyen, C., 2021). The proposed mobile application, based on artificial intelligence techniques such as Deep Learning and the Yolo

object detection model, aims to improve management and efficiency in early pest detection. The application, developed in Android Studio with the open-source Flutter framework, enables farmers to detect and differentiate diseases in tobacco leaves using a pre-trained neural network. This not only contributes to technological advancement in agriculture but also enhances the sanitary management of tobacco crops, ensuring economic viability and long-term environmental sustainability.

Tabacalfa, a tobacco company in the Ventanas canton, has developed a mobile application using Deep Learning technology and the YOLOv10 model to improve the detection of diseases such as *Cercospora nicotianae* and *Alternaria alternata* (Shava, J., 2021). The application will allow farmers and technicians to capture images of affected tobacco leaves and receive real-time diagnoses (Mohammad Mustafa, 2023). The machine learning algorithms will analyze specific patterns, providing precise and objective detection regardless of the user's experience (Sarker, I.H., 2021). This will improve farmers' response capabilities and reduce reliance on physical experts. The application is expected to minimize damage to tobacco crops, improving profitability and sustainability in the agricultural industry. The initiative combines advanced technology with the urgent needs of agriculture, promoting efficient and sustainable disease management practices in specific crops like tobacco.

Therefore, this scientific paper begins with the application of machine learning techniques in the detection of diseases in agricultural tobacco crops. Then, a mobile application was developed to train the detection algorithm for both healthy and infected areas of tobacco leaves by *Cercospora nicotianae* and *Alternaria alternata*. Finally, acceptance tests of the mobile application and evaluation of user satisfaction perceptions were carried out to correct any errors before its release.

Methodology

This research involved transitioning from an extensive bibliographic development to field research, employing inductive and deductive methods to collect information on tobacco crop diseases using an artificial intelligence approach. The bibliographic research involved gathering and analyzing existing information from various sources, such as books, academic articles, and electronic publications. The field research involved participant observation, interviews, and analysis. The inductive method was used to analyze data from field observations and tobacco leaf images, identifying patterns and common features for disease detection. The deductive method was used to draw conclusions from general principles of artificial intelligence and learning, using general knowledge about object detection models like YOLOv10 to develop the mobile application.

This study was based on the use of models that set a new standard in detection by optimizing their architecture. The YOLOv10 model, developed by researchers from Tsinghua University (Hussain & Khanam, 2024; Wang et al., 2024), is an evolution of the YOLO series for real-time object detection, addressing problems such as NMS and architectural inefficiencies (Yibo Sun, Zhe Sun & Weitong Chen, 2024).

In addition, the Roboflow application (Qinjie et al., 2022) was used, within which a total of 253 images were selected for training the app. Of these, 222 images were used for training (Figure 1), 21 images were assigned to a validation set, and 10 were used for the test set.

Figure 1. Image records for training, validation, and testing.

Results

3.1. Initial training test of the algorithm

The image shows multiple leaves with areas marked in red rectangles, labeled with the numbers "0" and "1". These numbers represent different categories, such as "non-infected" and "infected" respectively, or different types of infections. In the top left leaf, the "0" mark indicates a small spot in the center of the rectangle, representing an early infection of *Cercospora nicotianae*. On the other hand, the top right leaf shows a "1" mark with a larger and more defined spot, indicating an infection of *Alternaria alternata*.

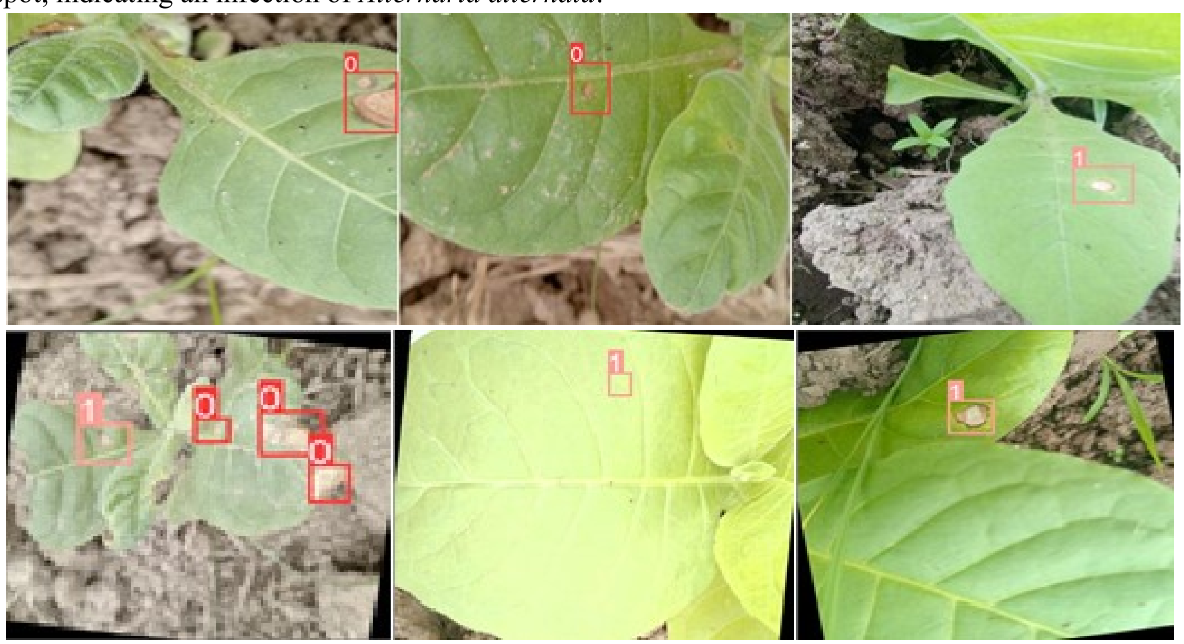

Figure 2. Identification of infection with the algorithm and training images.

3.2. Classification and training of the algorithm with test data

This image presents four sections of tobacco leaves, each with areas marked and labeled with specific disease names: Cercospora nicotianae and Alternaria alternata.

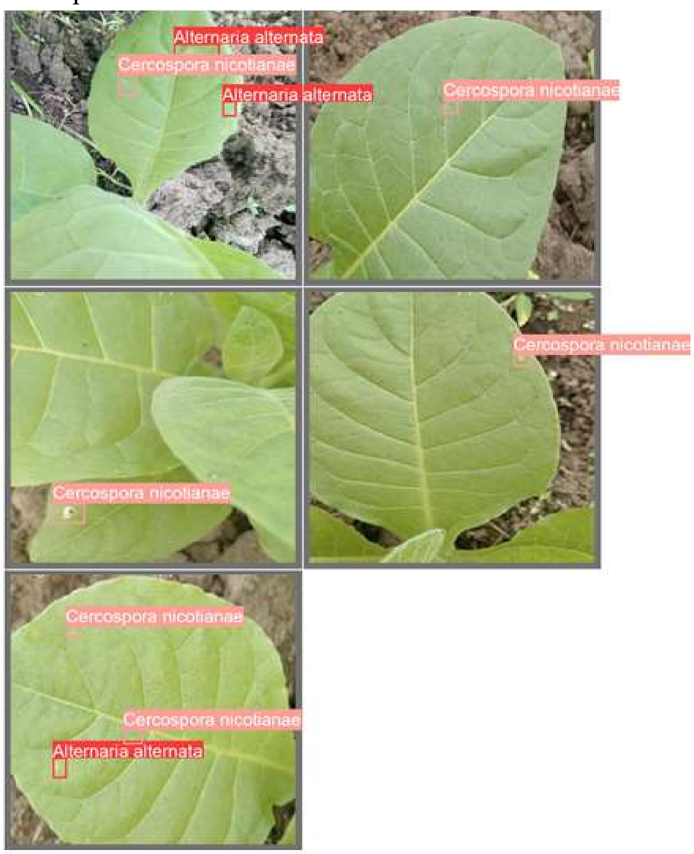

Figure 3. Classification of the infection type on tobacco leaves for training data.

3.3. Third classification and training of the algorithm with test data

This image presents multiple tobacco leaves arranged in a grid format. Each leaf is labeled with the diseases Alternaria alternata and Cercospora nicotianae, along with numerical values indicating the severity or percentage of infection.

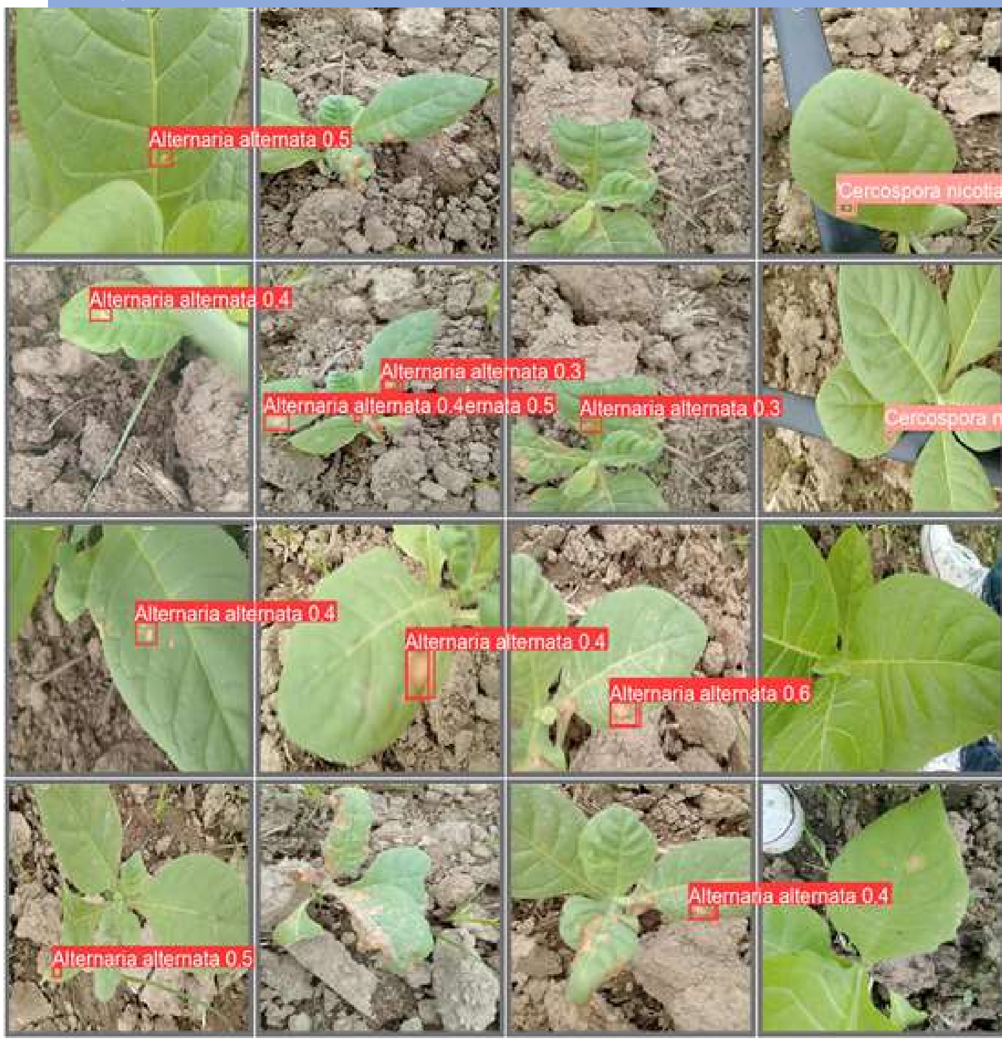

Figure 4. Classification of the type of infection in tobacco leaves for test data.

3.4. Graphs and metrics on training results

This section presents the findings in terms of different graphical representations. It highlights the performance metrics obtained from a Deep Learning model throughout the various iterations in the training process. The metrics considered in the graphical representations of Figure 5 are: Recall (B), which quantifies the model's ability to correctly identify elements of a class. The metric mAP50 (B) expresses the model's average precision at a 50% Intersection over Union (IoU) threshold. The metric mAP50-95 (B) expresses the model's average precision at different Intersection over Union thresholds, ranging from 50% to 95% IoU. The Precision (B) metric determines the proportion of correct predictions made by the model.

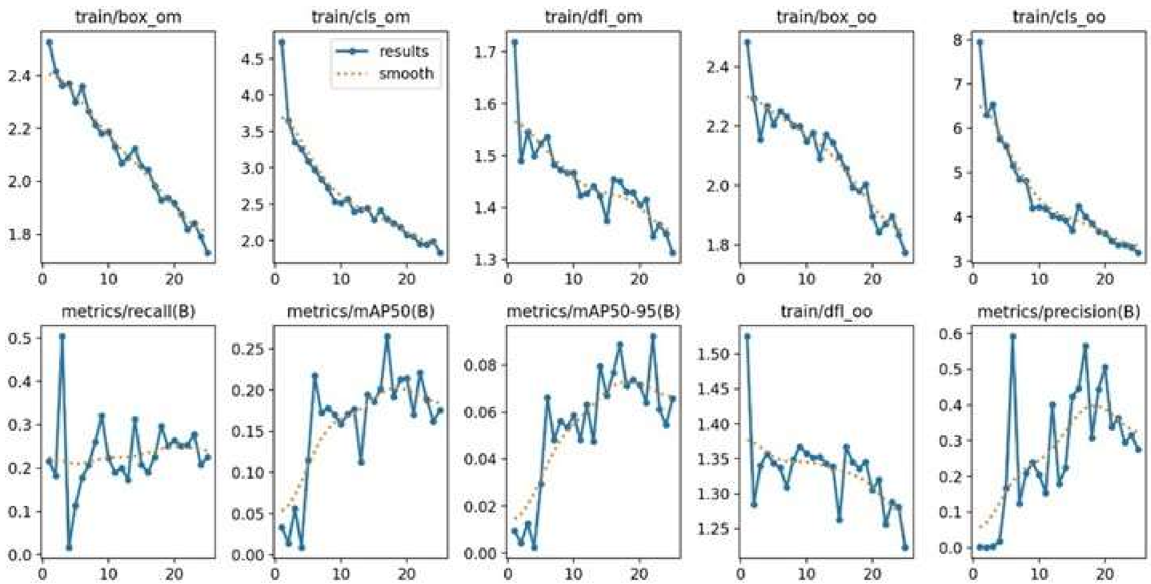

Figure 5. Metrics obtained with training data.

Each graph presented in Figure 5 shows the evolution of the metrics for performance across training iterations, with actual values represented by the blue line and the smoothed series represented by the dashed line. This allows for the analysis of how the model's performance improves as training progresses and enables the adjustment of training hyperparameters during the process to enhance its performance.

In this context, we proceed to present and describe the underlying implications of the Recall-Confidence curve (also known as the ROC curve) for a binary classification model (Figure 6). This Recall-Confidence curve represents a graphical tool used to evaluate the performance of a classification model and assist in selecting the most appropriate classification threshold. The description of this graph indicates that the x-axis represents the model's confidence level, i.e., the probability or classification score assigned to each element. The y-axis represents sensitivity or the true positive rate (Recall), which measures the model's ability to correctly identify elements of a class.

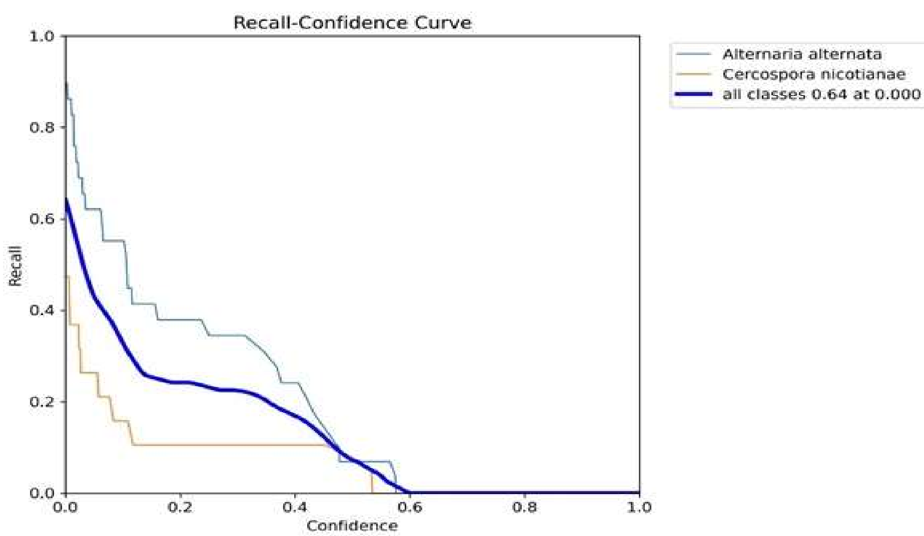

Figure 6. Recall-Confidence Curve.

These curves represent the model's performance in correctly classifying the Alternaria alternata class (Figure 6), as they allow evaluating the balance between the model's ability to correctly identify the elements of a class and the classification score assigned to each element. Indeed, the closer the curve is to the upper left corner, the better the model's performance, as it will have a high confidence level with a high classification rate and few false negatives.

In a specific context where high precision is required, a higher confidence threshold can be chosen, which will likely sacrifice the model's ability to correctly classify a class; however, it will improve the reliability of the predictions. Therefore, evaluating Figure 7 determines the precision-recall curve for classification models of different images in Alternaria alternata 0.377 and Cercospora nicotianae 0.153. It also reflects the metric in the classification model for all cases (All classes 0.265 mAP@0.5).

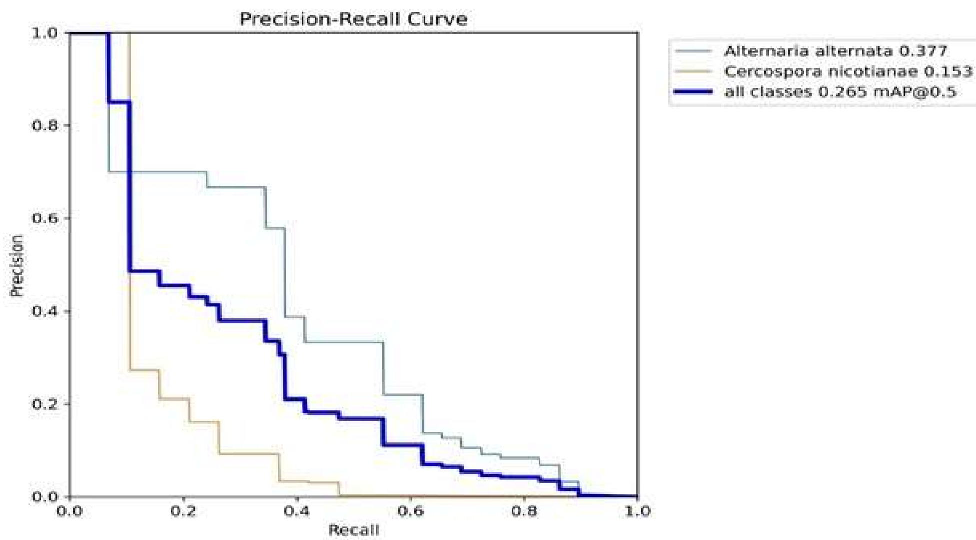

Figure 7. Precision-Recall Curve.

In Figure 7, it can be observed that the "Alternaria alternata" classification model has a characteristic value of 0.377, representing the best overall performance, with a curve that is closer to the top-right corner of the graph, indicating a better combination of precision and recall. The other two models have lower curves, suggesting worse performance in comparison.

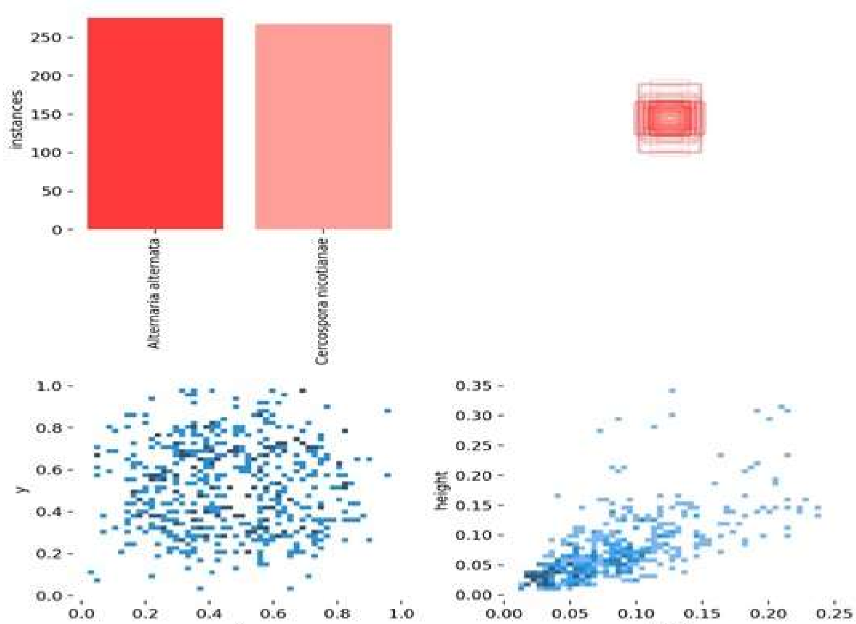

Figure 8. Representation of labels for infection dispersion, height and width metrics in tobacco leaves, and infection type in the crops.

Figure 8 contains multiple graphs that show different aspects of a dataset. Descriptive aspects include the higher prevalence of diseases in tobacco leaves of the "Alternaria alternata" type compared to "Cercospora nicotianae." Additionally, a homogeneous dispersion of the combined presence of both diseases in tobacco leaves is observed, and it is established that as the leaf height and width decrease, there is a higher prevalence of "Cercospora nicotianae."

On the other hand, Figure 9 presents a normalized confusion matrix for the binary classification model. This confusion matrix is a tool used to evaluate the performance of a classification model, showing how the model behaves when classifying elements from a dataset.

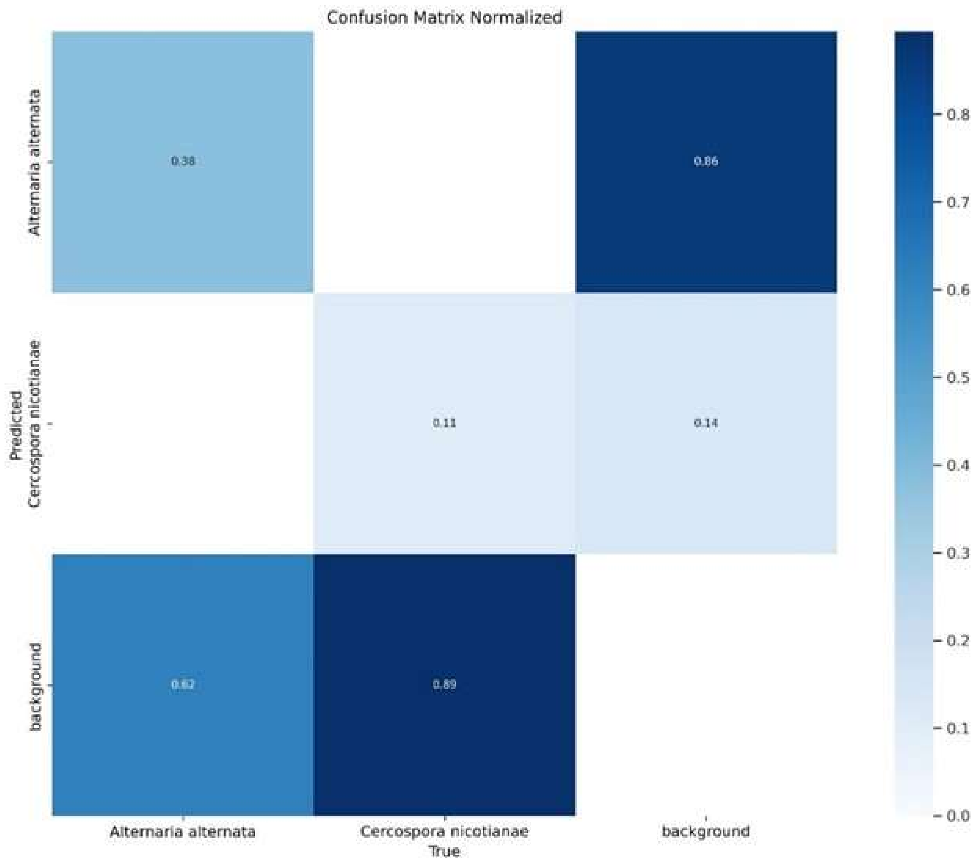

Figure 9. Confusion matrix for infection type in tobacco crop leaves.

In this case, the confusion matrix is normalized, meaning that the values in this matrix represent proportions or probabilities rather than absolute counts. The elements on the main diagonal (0.86 and 0.62) represent the model's accuracy for each class based on the disease background, i.e., the proportion of elements correctly classified for each class. The elements outside the main diagonal represent classification errors, where the model confuses one class with another. On the other hand, the value of 0.38 indicates that the model incorrectly classifies 38% of the "Alternaria alternata" cases, and a value of 0.11 indicates an incorrect classification of 11% of the cases belonging to the "Cercospora nicotianae" disease.

3.5. Customer Satisfaction

Evaluation A satisfaction survey was conducted about the application, which was reviewed by most of the respondents, including employees of the company and students from the Information Systems and Agronomy departments at the Technical University of Cotopaxi. The survey revealed that the user interface design was largely positive, with 91.43%

of respondents having a positive or very positive impression. The navigation and clarity of the application were also well received, with 94.28% of respondents finding it clear and easy to navigate. The functionality of the application for detecting diseases in tobacco plants was largely positive, with 91.43% of respondents finding it very clear or clear. The application of technologies like Deep Learning and YOLO was overwhelmingly positive, with 97.14% of respondents considering it very innovative. The responsiveness of the application in image analysis was also very positive, with 95.71% of respondents describing it as very responsive or fast. The utility of the application for businesses in the agricultural sector was also highly positive: 98.57% of respondents stated that it could be useful or definitely useful.

Table 1. Perceptions of the application.

Questions	Categories	Frequency
What was your initial impression of the user interface design of the application?	Very positive	48
	Positive	16
	Neutral	6
	Negative	0
	Very negative	0
How would you rate the clarity and ease of navigation within the application based on the demonstration?	Very clear and easy to navigate	39
	Clear and easy to navigate	27
	Neutral	4
	Somewhat confusing	0
	Very confusing	0
How well does the application function (detection of diseases in tobacco plants)?	Very clear	45
	Clear	19
	Neutral	4
	Somewhat confusing	1
	Very confusing	1
How innovative did you find the use of technologies like Deep Learning and YOLO for disease detection in plants?	Very innovative	49
	Innovative	19
	Neutral	2
	Not very innovative	0
	Not innovative at all	0
How did you perceive the response speed of the application in image analysis during the demonstration?	Very fast	42
	Fast	25
	Neutral	3
	Slow	0
	Very slow	0

4. Discussion

The mobile application for detecting diseases in tobacco plants, using advanced technologies such as Deep Learning and YOLO, has significantly impacted the agricultural sector (Airam, D. & Irving, P., 2024; Shradha Verma et al., 2019; Xiong, et al., 2024), particularly Tabacalfa in the Ventanas canton. The application improves efficiency and accuracy in detecting diseases such as Cercospora nicotianae and Alternaria alternata, potentially reducing crop losses and increasing productivity (Muhammad, 2024). The application also has economic benefits, as it prevents significant losses in tobacco production and positions Tabacalfa and the Ventanas canton as pioneers in implementing advanced agricultural technologies for traditional infection classification through images in tobacco crops (Manju B. & Sonali G., 2024). It also enhances the working conditions of farmers and technicians, leading to higher job satisfaction and quality of life. The application also has positive environmental implications, as it reduces the need for preventive pesticide applications.

5. Conclusion

The mobile application for detecting diseases in tobacco crops has been developed using machine learning techniques, specifically Deep Learning and YOLO, to create an innovative tool. The application has received high user satisfaction, indicating an optimal balance between functionality and accessibility. The algorithm, trained with Cercospora nicotianae and Alternaria alternata, recognizes healthy and infected areas from various images. The acceptance tests have yielded positive results, indicating good performance before launch. This user response validates the work done and predicts continued adoption and use of the application by the company. The success of the application is a testament to the innovative nature of machine learning in the agricultural sector.

Further research is recommended to expand the application and detect tobacco and other crop diseases, thus improving its agricultural utility. Regular updates to the training dataset and measures to protect the intellectual property of the algorithm are also recommended.

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