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RESUMEN

Contexto: El maíz es uno de los cultivos más importantes a nivel mundial por su aporte a la seguridad alimentaria y a la economía agrícola, Sin embargo, las enfermedades foliares representan una amenaza creciente para su rendimiento. La identificación temprana es fundamental, en este contexto las técnicas de Inteligencia Artificial (IA) especialmente el aprendizaje profundo (Deep Learning), se está aplicando con éxito debido a su capacidad de analizar grandes volúmenes de imágenes. **Métodos:** Se construyó un dataset de 1079 imágenes de hojas de maíz y se evaluaron cuatro algoritmos preentrenados, junto con un modelo entrenado con arquitectura propia en dos escenarios: clasificación binaria (healthy vs. unhealthy) y multiclase (Stenocarpella, Roya común, Bipolaris, mancha de asfalto y saludable). Para el desarrollo del estudio, se siguió la metodología CRISP-ML. **Resultados:** En clasificación binaria, InceptionV3 alcanzó una precisión (accuracy) del 100%, el modelo Red Neuronal Convolucional (CNN) propuesto con pocas capas también alcanzo un 97 % de accuracy y 93 % en F1-score. Para la clasificación multiclase, DenseNet201 alcanzó el mejor rendimiento con 91% de accuracy. **Conclusiones:** estos resultados evidencian el potencial del aprendizaje profundo para la detección automatizada de enfermedades foliares del cultivo de maíz. Ofreciendo herramientas prometedoras para la agricultura 4.0.

Palabras clave: Redes neuronales convolucionales, Aprendizaje profundo, Inteligencia artificial, Enfermedades de maíz.

ABSTRACT

Context: Maize is one of the most important crops worldwide for its contribution to food security and the agricultural economy. However, foliar diseases represent a growing threat to its yield. Early identification is fundamental; in this context, Artificial Intelligence (AI) techniques, especially Deep Learning, are being applied successfully due to their capacity to analyze large volumes of images. **Methods:** A dataset of 1079 images of maize leaves was constructed, and four pre-trained algorithms were evaluated, along with a model trained with a custom architecture, in two scenarios: binary classification (healthy vs. unhealthy) and multi-class (Stenocarpella, Common rust, Bipolaris, tar spot, and healthy). The study followed the CRISP-ML methodology. **Results:** In binary classification, InceptionV3 reached 100% accuracy. The proposed Convolutional Neural Network (CNN) model with few layers also reached 97% accuracy and a 93% F1-score. For multi-class classification, DenseNet201 achieved the best performance with 91% accuracy. **Conclusions:** These results demonstrate the potential of deep learning for the automated detection of foliar diseases in maize crops, offering promising tools for Agriculture 4.0.

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Keywords: Convolutional neural network, deep learning, artificial intelligence, corn diseases.

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INTRODUCTION

Corn is one of the most relevant crops worldwide, not only because of its role in food security but also due to its contribution to agricultural economies (FAO, 2023), In this context, Ecuador is no exception, agriculture is a key sector in the national economy, representing 8.2 % of Gross Domestic Product (GDP) and generating employment for a significant portion of the rural population (Banco Central del Ecuador [BCE], 2021). Within this category, hard yellow corn is a crop of great economic and social importance (Zambrano & Arias, 2021), with provinces such as Guayas, Los Rios and Manabí leading its production (Palacios et al., 2023). In 2024, national corn yield reached 1.2 million tons and Manabí stood out by allocating 30.7 % of its agricultural land surface to this crop (Instituto Nacional de Estadística y Censos [INEC], 2024).

However, despite its relevance, corn farming faces the threat of fungi, viruses, and bacteria that can affect its development and yield (Román et al., 2018). Estrada (2021) adds that, in Ecuador, the number of disease cases affecting the foliar area have increased in recent years. Among these diseases are northern leaf blight, leaf spot, common rust, and asphalt stain or tar spot. According to a study carried out by Mayorga (2017), in coastal production areas, including Manabí, diseases known as leaf spots including *Diplodia* have incidence levels of up to 99.56 %, which highlights the seriousness of the problem.

This increase in foliar diseases highlights a critical issue, having certainty about the type of disease affecting the plants is important in agriculture, as it creates better decision making to avoid serious negative effects. Currently, it is estimated that 65 % of the agricultural sector lacks technology applied to plant health (Tamayo et al., 2024). As a result, incorrect treatments are often applied due to a lack of knowledge. This not only puts the health of crops at risk, but also impacts the productivity and profitability of the agricultural sector, this is why the implementation of faster and more effective solutions becomes necessary.

To face these challenges, data-driven agriculture has emerged as an innovative solution. Recent research points out that the integration of machine learning (ML) and *deep learning* (DL) models into precision agriculture enables the analysis of large amounts of data to improve decision-making (Bhat & Huang, 2021), In this context, the use of deep learning models for disease recognition in crops represents an alternative to overcome limitations such as the subjectivity and slowness of manual diagnoses, the difficulty of scaling monitoring across large agricultural areas, and the lack of early symptom detection (Lebrini et al., 2024).

The ability of CNN to analyze images and detect complex patterns makes them ideal for this task, enabling automated and accurate diagnosis. This approach is not new, Shoaib et al. in their study (Shoaib et al., 2023), conducted a literature review of publications from 2015 to 2022. From approximately 50 articles, they concluded that the experiments discussed in the study demonstrate the effectiveness of using these techniques to improve the accuracy and efficiency of plant disease detection.

In the field crop disease classification, advances in deep learning algorithms have shown great promise to surpass conventional methods. Diverse research studies have compared these approaches in crops such as tomato and corn, achieving positive results. In the study presented by Tan et al. (2021) diverse Machine Learning and Deep Learning algorithms were compared for disease classification in tomato crops, in which images from the PlantVillage dataset were used. Results proved that deep neural networks, such as ResNet34, outperformed traditional ML algorithms reaching 99.7 % accuracy, while other ML methods such as Support Vector Machine (SVM) and k-nearest neighbors (kNN) did not reach such high performance. These findings

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highlight the advantage that deep learning poses, eliminating the need to manually extract features and significantly improve results in comparison with more conventional approaches. Authors Li & Lai (2019) support this claim, as their study shows that the deep learning method is more accurate and stable in image recognition.

Similarly, Fraiwan et al. (2022) achieved an accuracy of 98.6 % classifying three common corn diseases (northern blight, common rust, and *Cercospora leaf spot*) using convolutional neural networks without the need of image processing. These results confirm that artificial intelligence can outmatch traditional diagnosis methods, especially in areas with limited access to experts in agriculture. In another study, Ma et al. (2022) proposed a deep transfer Convolutional Neural Network (CNN) was introduced to identify foliar diseases in corn, specifically gray leaf spot, common rust, and northern leaf blight. Models such as ResNet and MobileNet were utilized, achieving a high accuracy of up to 99.48 % and 98.69 %, subsequently.

Likewise, Amin et al. (2022) developed a model to identify diseases in corn leaves by combining EfficientNetB0 and DenseNet121 through feature fusion, achieving an accuracy of 98.56 %. This approach surpassed more complex models like ResNet152 (98.37 %) and InceptionV3 (96.26 %), proving that it is possible to reach higher precision without the need for more computational capacity. Researchers implemented data augmentation techniques to improve the model's generalization, confirming that the strategic combination of neural networks and optimized image processing can offer efficient solutions for agricultural diagnosis under real-world conditions. On the other hand, Hu et al. (2020), developed a model based on GoogLeNet optimized with transfer learning and data augmentation was developed. A 97.6 % of precision was reached identifying four types of diseases in corn leaves (gray leaf spot, common rust, northern blight, and healthy leaves), outperforming the original model and other networks such as ResNet18 and VGG16/19 by 5.9 %. The study demonstrated that fine-tuning pre-trained networks with specific techniques significantly improves the diagnosis of illnesses in crops.

In a similar study, Da Rocha et al. (2021) evaluated Three state-of-the-art CNN architectures for classifying diseases in corn leaves were evaluated, applying Bayesian hyperparameter optimization, data augmentation, and fine-tuning. The validated models through five- folds cross-validation on the PlantVillage dataset, reached a peak of 97 % accuracy, verifying the effectiveness of these techniques. Finally, Haque et al. (2023) developed a 15-layered convolutional neural network was developed to identify diseases in corn crops. This was done using 3,852 images from the PlantVillage repository, including gray leaf spot, common rust, northern blight, and healthy leaves. The proposed model showed a 3.2 % higher performance than the best pre-trained network (DenseNet121), while using three times fewer trainable settings.

According to the mentioned research, convolutional neural networks (CNN) have obtained satisfactory results in recognizing illnesses in corn leaves. Yet, none of the studies report on tar spot (*Phyllachora maydis*) , Bipolaris (*Bipolaris maydis*), Stenocarpella (*Diplodia leaf Streak*), diseases of economic importance in the country. Therefore, the current research proposes the development of a classifying diseases in corn leaves model using Convolutional Neural Networks (CNNs) and Deep Learning techniques, based on pictures and locally collected datasets, with the aim of optimizing disease diagnosis through early detection and improving crop productivity.

To achieve this objective, the article is structured as follows: Section II presents the materials and methods applied in this research, including the collection and preparation of the local dataset, as well as the configuration and training of the Convolutional Neural Network (CNN) models. Section III describes and analyzes the results obtained in the binary and multi-class classification experiments, comparing the performance of the different deep learning architectures. Finally, Section IV presents the main conclusions, highlighting the practical contributions of this study to precision agriculture and the potential of deep learning for the early and precise detection of foliar diseases in maize crops.

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II. MATERIALS AND METHODS

For this research applied the first five phases (total of six phases) of the CRISP-ML methodology (Studer et al., 2021), starting with understanding the problem and data up to implementation and monitoring. Each phase was adapted to the context of this research, securing a rigorous analysis of corn leaf image data and an adequate optimization of the Convolutional Neural Network (CNN) model.

A. Business (Phase 1) and data understanding (Phase 2)

The need for improving the diagnosis of foliar diseases in corn was identified, more specifically those with economic relevance in Ecuador, such as, Stenocarpella (*Diplodia leaf Streak*) whose symptoms begin with small lesions, round or oval in shape, ranging in color from dark brown to cinnamon. As the disease advances, lesions expand parallelly along the leaf and the chlorotic zones around the lesion become more prominent (Liu et al., 2025). Common rust (*Southern Rust)* can appear as small ovals, densely accumulated, of a brown-orange color, they almost exclusively present on the top surface of leaves. As southern rust pustules age, they turn dark brown to black, often forming dark halos around the original pustule (Chang et al., 2025). Bipolaris (*Bipolaris maydis*), injuries tend to be wider or oval shaped, with well-defined borders, initially, the lesions can have yellow or light green color, but they advance to shades of brown, dark brown or black as the disease progresses (Meshram et al., 2022). Asphalt stain or tar spot (*Phyllachora maydis*) produces small shiny black spots over the leaf, these spots have oval or round shape of a size ranging from 0.5 to 2.0 mm diameter (Coyoy et al., 2024).

In this phase of the dataset, three experimental plots of land were collected, located in the in the cantons: Bolivar, Chone, and Tosagua in the province of Manabí, Ecuador, identified as plots N1, N2, and N3 accordingly. Pictures were captured using an iPhone 13 smartphone ensuring that every image is taken using the same device to maintain consistency in quality and conditions (using default camera application). The shots were done keeping consistent conditions, ensuring they were taken at the same time of day (09:00am to 10:00 am) and from a height and distance (15-20 cm approximately), with the goal of minimizing potential biases. This dataset is publicly available on Mendeley Data (Murillo Parraga & Silva Villafuerte, 2025).

B. Data preparation (Phase 3)

The complete data set includes samples of healthy leaves and four persistent diseases in the region: Stenocarpella (*Diplodia leaf Streak*), common rust (*Southern Rust*), Bipolaris (*Bipolaris maydis*) y asphalt stain or tar spot (*Phyllachora maydis*). The dataset consists of 1079 images manually annotated by experts in phytopathology. Table 1 lists the details of the dataset.

Table 1. Distribution of the image dataset

N°	Disease Name	Total
1	Stenocarpella (*Diplodia leaf Streak*)	227
2	Common rust (*Southern Rust*)	200
3	Bipolaris (*Bipolaris maydis*)	220
4	asphalt stain or Tar spot (*Phyllachora*	200
5	Healthy	232
	Total	1079

Source: Authors

The dataset was divided into two subsets with 70% for training and 30% for validation, an evidence-based practice that enhances the model's ability to learn useful representations without compromising the assessment of its generalization (Nguyen et al., 2021). This split was performed using the train_test_split function from

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the scikit-learn library, applying stratification based on the target variable (Binary_Numeric or Multiclass_Numeric, depending on the classification scenario) to preserve the proportional representation of each class in both subsets. The dataset presented a slight natural imbalance among the classes, but this distribution was maintained to reflect real-world field conditions. All images were resized to 128 × 128 pixels and normalized to the [0, 1] range before training.

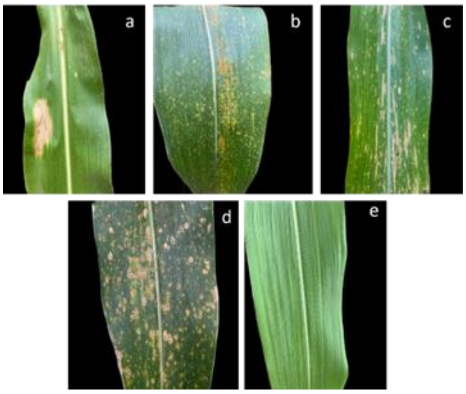

Figure. 1. Sample images from the four disease classes and the healthy one: (a) stenocarpella, (b) common rust, (c) bipolaris, (d) Tar spot, (e) healthy.
Source: Authors

C. Modeling (Phase 4)

The model that was implemented uses a custom CNN architecture that processes previously resized images to 128×128 pixels. The network consist of: a starting convolutional layer with 3×3 (ReLU) filters which inputs tensors in (128,128,3) shape, two convolutional blocks with 256 filters (3×3, ReLU) braided with max-pooling operations (2×2); and a classifier composed of a dense layer (256 neurons, ReLU) and a linear output layer for 5 classes (4 diseases + healthy). The training was conducted during 20 seasons using Adam optimizer, with validation performed from an independent dataset. The process was implemented in Python using the TensorFlow/Keras, scikit-learn, NumPy, and Pandas libraries, which ensures reproducibility and computational consistency. See Figure 2 for more details.

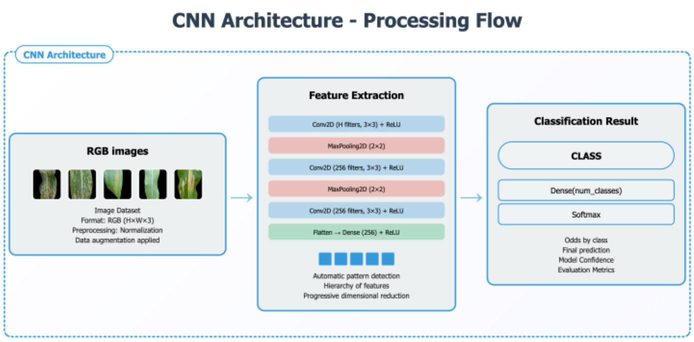

Figure. 2. Architecture of the implemented custom CNN.

Source: Authors

Additionally, to compare the performance of the custom CNN against well-established image classification architectures, five pre-trained models were included in the evaluation on the dataset: EfficientNetV2S (M. Tan & Le, 2021), DenseNet201 (Huang et al., 2017), InceptionV3 (Szegedy et al., 2016), ResNet50 (He et al., 2016), y VGG16 (Simonyan & Zisserman, 2014). Each one of these models were trained using transfer

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learning techniques, replacing their original output layers for a more compact five-nodes layer according to the four diseases and healthy leaves. Moreover, all the models were trained under controlled conditions with respect to the number of epochs, Adam optimizer and input size of 128×128 pixels.

D. Evaluation (Phase 5)

The metrics that were used to assess the performance of CNN models are shown in the equations (1) to (4). They include true positives (*TP*), images of correctly classified diseased leaves; false negatives (*FN*), cases of disease falsely identified as healthy; false positives (*FP*), healthy leaves classified as diseased; and true negatives (*TN*), images of correctly identified healthy leaves (Saeed et al., 2021). Sensitivity measures the capacity of the model to detect diseases affected by the *FN*; a high sensitivity means an accurate recognition of affected leaves, although it might include *FP*. The specificity evaluates the correct identification of healthy leaves under the influence of *FP*. Finally, the F1-score allows a balance between accuracy and sensitivity (Tharwat, 2020).

$$Accuracy = \frac{TP + TN}{P + N} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

$$F1 - Score = \frac{2.TP}{2.TP+FP+FN} \quad (4)$$

In binary assessment of scenario 1, a true positive *TP* happens when a healthy leaf is predicted to be inside the healthy class, while in multiclass assessment of scenario 2 a *TP* is considered when the model accurately identifies the specific disease that affects the leaf.

RESULTS AND DISCUSSION

In this section results will be presented, initially comparative assessments were carried out with different image sizes 64×64, 128×128, and 256×256 pixels. Size 128×128 yielded the best results, therefore the following data is presented using the aforementioned configurations.

Binary evaluation

The best results were obtained with models EfficientNetV2s and InceptionV3 (See Figure 3), both showing 100 % accuracy, these findings match previous research where EfficientNet had the best performance, achieving a 97.5 % accuracy determining whether the leaves were healthy or not (Arefin et al., 2023). Authors pointed out that EfficientNet's compound scaling and attention mechanisms capture detailed and discriminative features, supporting its high applicability in practical agriculture. Another model that approached a similar value was VGG16 achieving a 98 % accuracy. The CNN model with few layers also delivered positive results with 97 % accuracy and 93 % in F1-score. This is consistent with a previous study that evaluated a lightweight CNN and validated their efficacy as a multifunctional tool by individually classifying healthy and infected categories of each crop, getting 99.74 %, 82.67 %, and 97.5 % accuracy for corn, rice, and wheat respectively (Verma et al., 2024). Because of its lightweight and the output values make it a viable option for real-time disease detection in crops, even in environments with limited resources.

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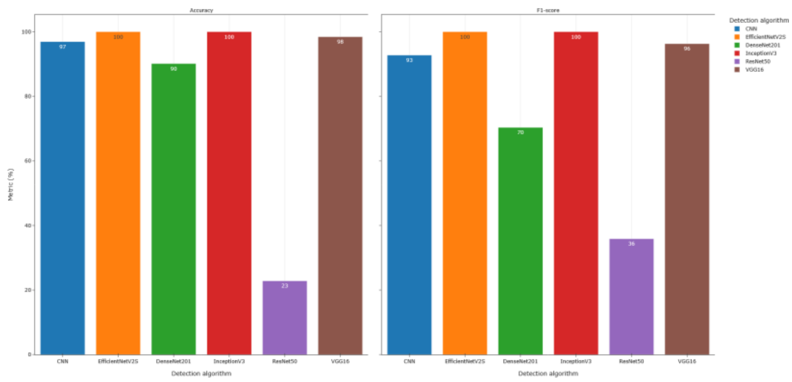

Figure 3. Accuracy and F1 score results of six deep learning architectures evaluated in binary classification of corn leaf diseases.

Source: Authors

Multiclass assessment

Figure 4 shows that in the multiclass evaluation scenario, the data exhibit greater variability across classes. Generally, the DenseNet201 model achieved better results with a 100 % accuracy in healthy class detection; 98 % in common rust; 87 % in stenocarpella; 83 % in asphalt stain; and 88 % bipolaris. Another model that yielded close results was EfficientNetV2S showing a 100 % accuracy detecting the healthy class; 92 % common rust; 93 % stenocarpella; 70 % asphalt stain; and 91 % bipolaris.

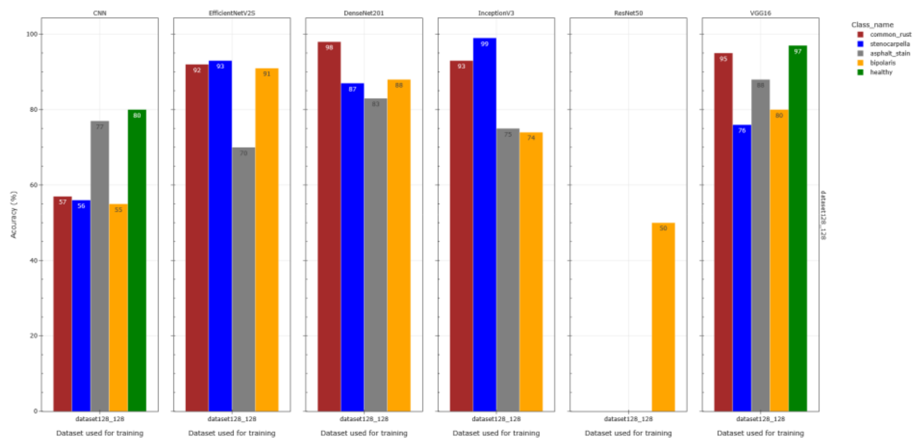

Figure 4. Accuracy results of six deep learning architectures evaluated in multiclass classification of corn leaf diseases.

Source: Authors

Figure 5 presents the confusion matrices corresponding to the six models analyzed for the multiclass classification of maize leaf diseases (Healthy, Stenocarpella, Common Rust, Bipolaris, and Asphalt Spot). The diagonal cells reflect correct predictions, while off-diagonal positions indicate misclassifications among visually similar categories. Recurring confusions are observed between Stenocarpella and Bipolaris, as well as between Common Rust and Asphalt Spot. The DenseNet201 and EfficientNetV2S models show a higher concentration of values along the main diagonal, indicating better discriminative and generalization capability. In contrast, ResNet50 showed a bias towards some predominant classes (Healthy and Bipolaris).

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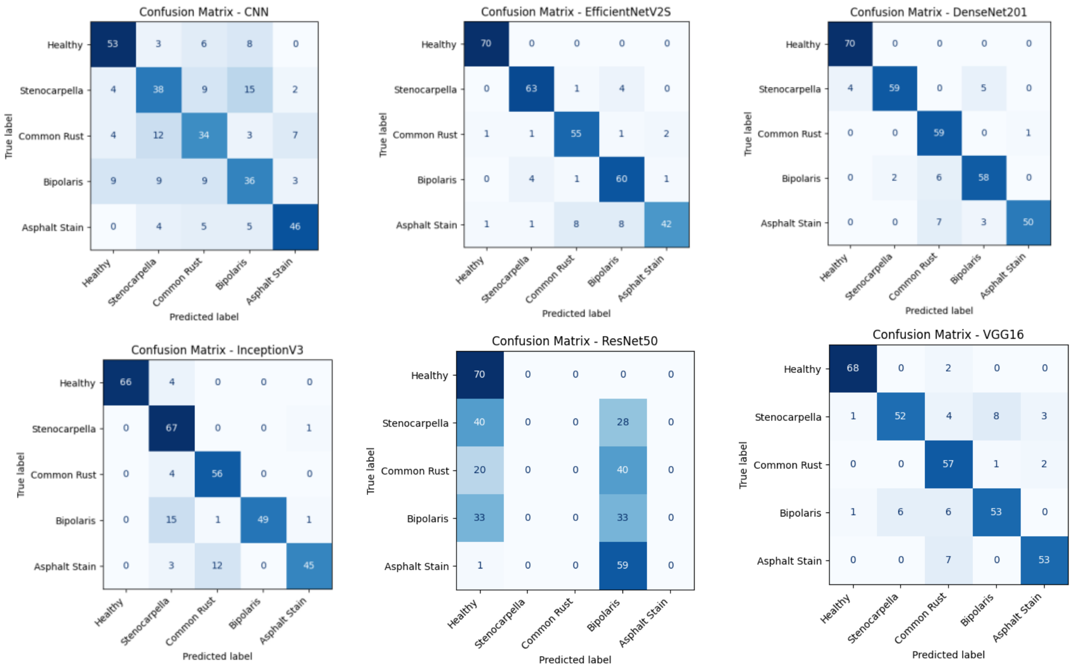

Figure 5. Confusion matrices for CNN, EfficientNetV2S, DenseNet201, InceptionV3, ResNet50 and VGG16 models.
Source: Authors

The results of this research, where DenseNet201 yielded better results classifying corn diseases (common rust 98 %, bipolaris 88 %) agree with recent findings in which the model reached 97 % accuracy detecting common rust (Fraiwan et al., 2022), attributing this success to its ability to capture microscopic features of the pustules. This behavior is replicated in the obtained results (98 %), validating the model's robustness for this class. The advantage that EfficientNetV2S offers in stenocarpella (93 % vs. 87 % from DenseNet201) matches with the research that highlighted its efficiency in detecting well defined circular patterns (Rajeena P. P et al., 2023), which is a main feature of this class (Liu et al., 2025). As it is shown in Table 2, the analysis of variance (ANOVA) revealed statistically significant differences among the six deep learning architectures evaluated for multiclass classification of diseases in corn leaves.

Table 2. Analysis of variance (ANOVA) results for the performance of deep learning architectures.

Source of variation	Sum of squares	Degrees of freedom	F	p-value
Architectures	0.832053	5	1664	1.31E-16
Residual	0.0012	12		
Total	0.833253	17		

Source: Authors

The post hoc test with Turkey HSD (see Table 3) indicated that DenseNet201 reached the highest accuracy, although without significant statistical differences with EfficientNetV2S, which suggests a similar performance between both models, in contrast with all other architectures. It is worth noting that EfficientNetV2S also shared statistics with VGG16 and InceptionV3, showing a similar performance among them. These relationships are visualized in Figure 6 through a bar chart labeled with letters, where architectures marked with the same letters do not present significant differences.

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Table 3. Tukey HSD post-hoc analysis for six deep learning architectures in corn ($\alpha = 0.05$)

Comparison	Av.Diff	p-value	Sig (p<0.05)
CNN vs DenseNet201	0.2747	<0.0001	*
CNN vs EfficientNetV2S	0.2562	<0.0001	*
CNN vs InceptionV3	0.2346	<0.0001	*
CNN vs ResNet50	-0.3210	<0.0001	*
CNN vs VGG16	0.2346	<0.0001	*
DenseNet201 vs EfficientNetV2S	-0.0185	0.2784	-
DenseNet201 vs InceptionV3	-0.0401	0.0037	*
DenseNet201 vs ResNet50	-0.5957	<0.0001	*
DenseNet201 vs VGG16	-0.0401	0.0037	*
EfficientNetV2S vs InceptionV3	-0.0216	0.1591	-
EfficientNetV2S vs ResNet50	-0.5772	<0.0001	*
EfficientNetV2S vs VGG16	-0.0216	0.1591	-
InceptionV3 vs ResNet50	-0.5556	<0.0001	*
InceptionV3 vs VGG16	0.0000	1.000	-
ResNet50 vs VGG16	0.5556	<0.0001	*

Source: Authors

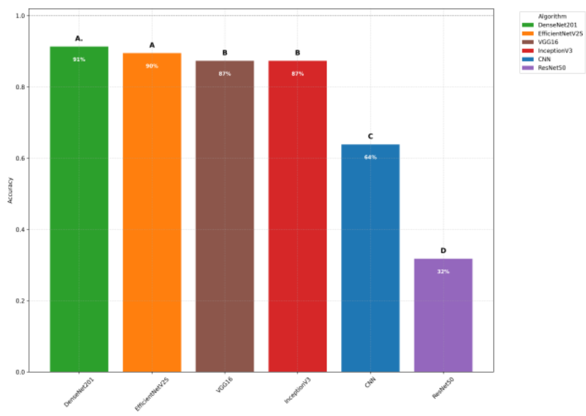

Figure 6. Comparison of disease classification models in corn in statistical groups.
Source: Authors

The results of this study in which DenseNet201 and EfficientNetV2S showed a comparable performance ($\alpha = 0.05$) in classifying corn diseases partially align with similar research proving that DenseNet121, which has a similar architecture that DenseNet201, reached a 98.45% accuracy on the PlantVillage dataset (Baldota et al., 2021), validating the efficacy of densely connected architectures. Baldota et al. (2021) developed an EANet based on EfficientNetV2 which achieved a 99.89 % accuracy, explaining the high performance of efficiency architectures in this study. On the other hand, Amin et al. (2022) proved that merging EfficientNet and DenseNet outmatched complex models such as ResNet152. Nonetheless, the results obtained in this study indicate that DenseNet201, on its own, is competitive in performance without the need for a merger.

These comparisons reveal that, while hybrid and attention-based solutions offer maximum accuracy, well-selected and individual architectures such as DenseNet201 or EfficientNetV2S can achieve competitive results with lower computational complexity. This is particularly valuable for agricultural implementations with resource constraints. Regardless, both models displayed limitations in asphalt stain (*Phyllachora maydis*) suggesting the need to improve irregular texture recognition using attention-based or data augmentation techniques as proposed by (Kumar et al., 2022). Additionally, Figure 6 represents the location of N1 plantation,

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selected as a representative study unit. The orthomosaic allows for the precise visualization of the collected pictures.

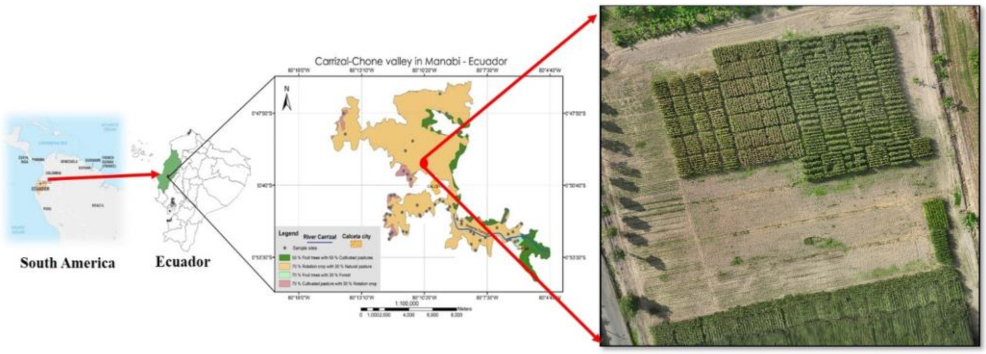

Figure 7. Aerial mosaic and location of the plantation N1.
Source: Authors

Figure 7 shows the spatial distribution of the detected diseases in corn crops. Panel (a) depicts the layout of the simples within the plantation, differentiated by color according to their category, while panel (b) displays the results of the multiclass classification, spatially highlighting both correctly identified samples and those with classification errors.

Figure 8. (a) Spatial visualization of the GPS location of samples in plantation N1. Healthy: [green]; stenocarpella: [blue]; Bipolaris: [orange]; common rust: [red]; Asphalt stain: [white]. (b) Graphical visualization of the GPS location of samples in plantation N1. From the results of the multiclass classification: green: correctly classified; red: incorrectly classified.

Source: Authors

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CONCLUSIONS

Agriculture is one of the main pillars upon which the country's economy relies, both in terms of economic aspects and food security, and the loss of crops due to plant diseases is an important factor contributing to the reduction of crop yields. Based on several previous experiments, it has been shown that CNNs perform well

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in detecting various plant diseases. In this study, several different deep learning models were trained to classify some nationally significant diseases in corn. The custom CNN, despite being a simple structure, showed competitive performance in the binary classification scenario, suggesting its potential for implementation in environments with limited computational resources, which is essential in the agricultural field. On the other hand, the use of pre-trained models has a significant improvement for the classification of disease images in corn leaves. In the multi-class scenario, DenseNet201 and EfficientNetV2S stood out with accuracies exceeding 90 %. Additionally, the study created a valuable local dataset that covers relevant diseases for the country, including (*Diplodia leaf Streak*), (*Bipolaris maydis*), and (*Phyllachora maydis*), which are not found in global databases. This resource paves the way for future research work and the deployment of tools tailored to the local agricultural context.

Despite these promising results, certain limitations must be acknowledged. The dataset contained a moderate number of samples, which may limit model generalization. Based on these findings, the following future recommendations are proposed: expand the dataset with images captured under diverse environmental conditions and at different stages of disease progression to better represent symptom variability; apply data balancing and augmentation techniques to enhance model robustness and minimize bias; and integrate these models into mobile or UAV-based monitoring systems to enable real-time and large-scale disease surveillance, thereby strengthening precision agriculture and sustainable crop management in tropical regions.

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