Pest prediction in rice crops using convolutional neural networks

Predicción de plagas en cultivos de arroz utilizando redes neuronales convolucionales

Jaider Caldera-Nadaff 🔾
Universidad de Sucre. Sincelejo, (Colombia)
jaider.caldera@unisucrevirtual.edu.co

José Alvarez-Carrillo 🔾
Universidad de Sucre. Sincelejo, (Colombia)
josealvarez123david@gmail.com

Yasser Yañez-Velasquez 🔾
Universidad de Sucre. Sincelejo, (Colombia)
yasseryanez51@gmail.com

Resumen
Introducción: La agricultura en la región de Sucre enfrenta graves pérdidas económicas debido a la detección tardía de plagas en cultivos de arroz. La detección oportuna de plagas en cultivos agrícolas es crítica para garantizar la productividad y la seguridad alimentaria. En Sucre, Colombia, los cultivos de arroz son esenciales para la economía regional. Sin embargo, la baja tecnificación del campo dificulta la implementación de soluciones eficientes para el monitoreo de plagas. Este artículo presenta el desarrollo de una plataforma accesible que integra un modelo de redes neuronales convolucionales (CNN) para predecir plagas con alta precisión.
Objetivo: Desarrollar y validar un sistema de predicción de plagas basado en visión artificial utilizando una red neuronal convolucional entrenada desde cero
Metodología: Se recopilaron imágenes de cultivos de arroz afectados por distintas plagas. Se diseñó un modelo CNN desde cero y se entrenó en Google Colab.
Resultados: El modelo alcanzó una precisión del 94% en las pruebas de clasificación.
Conclusión: La solución propuesta permite una detección temprana, accesible y eficiente para los agricultores de Sucre, contribuyendo a la seguridad alimentaria y a la sostenibilidad del cultivo.

Palabras clave: Agricultura de precisión, arroz, plagas, redes neuronales convolucionales, visión artificial.

Abstract

Introduction: Agriculture in the Sucre region suffers severe economic losses due to delayed pest detection in rice crops. Timely detection of agricultural pests is critical to ensuring productivity and food security. In Sucre, Colombia, rice crops are essential for the regional economy. However, the low level of field technology hinders the implementation of efficient pest-monitoring solutions. This article presents the development of an accessible platform that integrates a Convolutional Neural Network (CNN) model to predict pests with high accuracy.
Objective: To develop and validate a pest prediction system based on computer vision using a Convolutional Neural Network trained from scratch.
Method: Images of rice crops affected by different pests were collected. A CNN model was designed from scratch and trained in Google Colab.
Results: The model achieved an accuracy of 94% in classification tests.
Conclusions: The proposed solution enables early, accessible, and efficient detection for farmers in Sucre, contributing to food security and crop sustainability.

Keywords: Precision agriculture, rice, pests, convolutional neural networks, computer vision.

INTRODUCTION

In rural regions such as the municipality of Majagual, Sucre, rice serves not only as the basis of the agricultural economy but also as a pillar of local food security. However, this activity is threatened by the proliferation of pests such as Brown Spot and Bacterial Leaf Blight, which cause losses exceeding 15% of annual production [1].

This paper proposes an early-pest-detection platform that leverages emerging technologies to address the lack of technology in the field. Unlike previous studies that use pre-trained models such as YOLO, this proposal uses its own convolutional model, optimized for the growing conditions in Sucre [2].

According to estimates from the United Nations (UN), the world population will reach 9.7 billion by 2050 and could peak at 10.4 billion by the middle of the 21st century [8]. This demographic growth poses significant challenges for governments seeking to ensure global food security. In 2020, around 2.4 billion people worldwide experienced moderate or severe food insecurity, with Latin America among the most affected regions [9].

In addition to this global problem, Colombia faces structural challenges that affect its development and generate social, economic, and political instability. Factors such as poverty, hunger, climate variability, and limited technological capacity have hindered progress in food security [10]. However, implementing projects to strengthen agricultural production can generate significant improvements. Nevertheless, greater state support is needed to consolidate these advances and ensure their long-term sustainability [11].

Rice cultivation is one of the most in-demand crops worldwide, but it faces multiple challenges, including weeds, pests, and diseases. In Ecuador, for example, these factors have significantly affected production. In Colombia, where rice is a high-demand product, the problem is exacerbated by many farmers' lack of knowledge about timely pest identification and management. This difficulty prevents preventive measures from being taken, leading to higher control costs when the infestation is already advanced, affecting approximately 28,000 producers and resulting in significant economic losses [12].

Rice cultivation constitutes one of the main economic and social pillars of the department of Sucre, Colombia. Nevertheless, the appearance of pests such as Brown Spot and Bacterial Leaf Blight has caused losses of up to 17% of annual production, significantly impacting the economic stability of small-scale farmers. In this context, the early detection of crop diseases through accessible and low-cost technologies represents an urgent need. Accordingly, this work presents a diagnostic model based on a convolutional neural network trained from scratch for the early identification of diseases affecting rice leaves.

RELATED WORKS

Agriculture is one of the main economic activities in the department of Sucre, with rice cultivation being one of the most representative in the region. However, this activity faces significant challenges from pests such as the fall armyworm, stink bugs, and leaf miners, which directly affect local productivity and food security. In response to this situation, various research projects have proposed technological solutions to improve pest detection and control across crops, based on computer vision, digital image processing, and artificial intelligence [24], [25].

One of the most representative studies is that of [3], which focused on implementing an automated agricultural monitoring system using drones equipped with high-resolution cameras and Random Forest-based classification algorithms. The methodology involved capturing aerial images of crops and processing them to detect damage caused by pests, such as the basket bug and red spider mite. As a result, the system achieved 100% effectiveness in detecting these pests, demonstrating that the use of artificial vision significantly improves the accuracy and speed of identifying damage to avocado crops.

Similarly, [4] developed a computer vision system to detect pest damage on Begonia leaves. The methodology involved capturing drone images and processing them with morphological filters and HSL-space segmentation. This enabled the identification and classification of pests such as grasshoppers, snails, red spiders, and leaf miners. The authors conclude that the proposed technique is effective and viable for early pest detection in this type of ornamental crop.

On the other hand, [5] presented the design and evaluation of a pest-detection model based on the YOLOv7 architecture, explicitly optimized for complex agricultural scenarios. The model, called YOLOv7-AgriPest, was trained on datasets of pest images across different crops and evaluated for accuracy and speed. The methodology included deep learning and feature extraction techniques. The results showed that the model achieved 67.23% accuracy and 60.17 FPS, indicating it is a promising tool for real-time detection of agricultural pests.

In the academic sphere, the Pontificia Universidad Javeriana (Bogotá) has conducted various research projects focused on precision agriculture. Among these, one notable study reviewed supervised learning algorithms for pest detection in rice, corn, and coffee crops [6], evaluating methods such as SVMs and artificial neural networks. The study concluded that these algorithms have high potential for application in pest monitoring, especially when integrated with data capture systems such as sensors or aerial imagery.

Additionally, in 2022, the same university evaluated the use of biocontrol agents, such as Trichoderma spp., for disease management in rice crops. This project concluded that the use of biocontrol agents is an effective and sustainable alternative to reduce agrochemical use and improve soil and crop health.

The Universidad del Valle (Cali, Colombia) led the project, which applied digital image processing techniques to improve the early identification of phytosanitary problems in crops such as cereals, fruit trees, and tubers. The methodology included image capture, segmentation, and digital analysis, significantly reducing economic losses from pests and diseases. In conclusion, the effectiveness of these digital tools in helping farmers make timely decisions was highlighted.

Finally, the Pontificia Universidad Javeriana (Cali, Colombia) developed a monitoring system to reduce the time and effort required to detect banana diseases such as Fusarium wilt and Xanthomonas wilt. By using RGB images captured by unmanned aerial vehicles (UAVs) and training deep learning models, field inspection time was reduced by approximately 25%. The results demonstrated the system's effectiveness for real-time monitoring and rapid decision-making in phytosanitary management [7].

THEORETICAL BASIS

Pest control using chemical agents remains an essential strategy for ensuring economically viable agricultural production [13]. However, excessive use of pesticides has adversely affected agricultural productivity, human health, and the environment. Modern agriculture, characterized by large-scale monocultures, has favored the emergence of more resistant and specialized pests [14]. Faced with this problem, the FAO has proposed the adoption of optimized production systems that not only increase productivity but are also sustainable and environmentally friendly, reducing environmental impact while meeting growing food demand [15].

This economic problem is not limited to the national level. Still, it is evident in productive regions such as the department of Sucre, where 69.7% of the departmental area is used for agriculture, with rice as the main crop. Despite this, the sector has experienced a decline in productivity and competitiveness due to insufficient technological investment. According to Fedearroz, farmers' net income has fallen by 22% over the last decade [16].

According to data from the National Administrative Department of Statistics [17], rice production in Sucre has decreased by 18% in the last ten years, from 320,000 tons in 2013 to 262,400 tons in 2023. This decline is associated with various factors, including increased pests and diseases that are not being effectively controlled.

In addition, the Ministry of Agriculture and Rural Development (2024) reports that losses to rice crops from pests in Colombia average 15% of annual production, equivalent to approximately 780,000 tons nationwide. In the specific case of Sucre, it is estimated that between 12% and 17% of the yearly output is affected by pests such as the sogata (Tagosodes orizicolus) and the fall armyworm (Spodoptera frugiperda).

From an economic standpoint, the decline in agricultural production has negatively affected farmers' incomes. According to [16], the average net income of rice producers in Sucre has fallen by 22% over the last decade due to low productivity and high pest-control input costs.

These indicators reflect the urgency of implementing technological solutions that enable early detection and efficient pest management, thereby improving productivity in the rice sector and strengthening food security in the region. The artificial intelligence platform proposed in this project will serve as a key tool to mitigate these impacts and optimize farmers' profitability in Sucre.

The use of systems that employ artificial intelligence has increased exponentially in recent years due to their broad applicability. These systems can read and predict variables from quantitative and/or qualitative data, as well as images, the latter being the application relevant to this project. One of the advantages of implementing this type of system is the speed of detection and the accuracy with which an artificial vision system can recognize and classify a pest in a crop [18].

To carry out this automated visual detection, one of the most effective tools is the use of convolutional neural networks (CNN), widely used for the classification of agricultural images. CNNs have proven effective for image classification in the field. Models such as YOLO, ResNet, and VGG have been used to identify pests in coffee, banana, and other crop plantations. However, their implementation often requires advanced knowledge and costly computational resources. Studies such as [19] on YOLOv7-AgriPest report high accuracy, but with complex dependencies. Thus, this project seeks to provide an accessible, practical technological solution adapted to the conditions of small rice producers in Sucre, combining modern artificial intelligence tools with a viable implementation in rural contexts.

There are precedents for applying artificial intelligence systems to different crops, including rice, as in [20]. This author proposes implementing a pest recognition system for rice crops by collecting data from user questions, which allows the possible pest affecting the crop to be matched to this data. However, this document proposes implementing a modern system that uses image recognition to enable more practical and efficient detection in a mobile application.

MATERIALS AND METHODS

The methodology implemented for the development of the recognition model is known as CRISP-DM (Cross Industry Standard Process for Data Mining), which is the most widely used methodology in data mining projects and, as in this case, in projects involving the implementation of image recognition models, as it precisely defines all the phases necessary for the completion of the project. Six phases are defined, which are: business understanding phases, data understanding phases, data preparation phases, modeling phase, evaluation phase, and finally, distribution phase [21]. This methodology is easily evidenced in Figure 1, which shows the flowchart of the methodology's implementation.
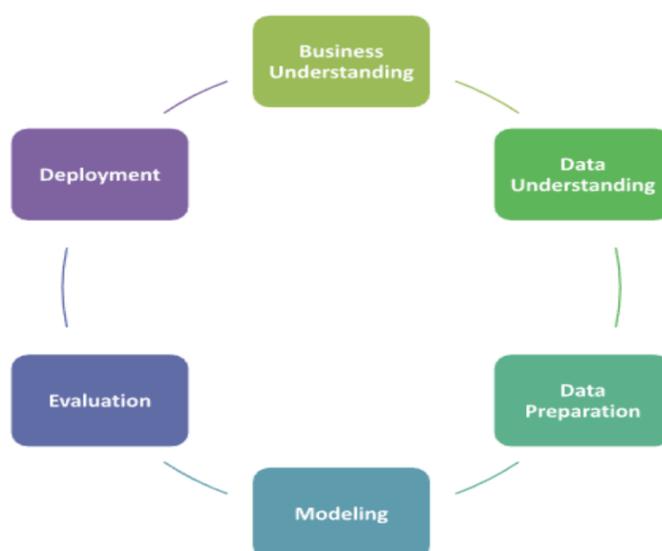

Figure 1. Flowchart of the CRISP-DM methodology. Source: Author(s)

The adoption of the CRISP-DM methodology ensured a structured, systematic approach throughout the development of the image recognition model, facilitating the traceability and reproducibility of the results. Each phase contributed to aligning the technical implementation

with the project objectives, from defining the agricultural problem to deploying the trained model for practical use. Moreover, this framework enabled iterative refinement at each stage, thereby improving data quality, model performance, and evaluation criteria, which are essential for achieving reliable, robust outcomes in applied machine learning projects [22].

Now, in the context of the issues discussed in this document:

A. Understanding the Business

Agricultural production in the Sucre region faces multiple challenges, including low adoption of technologies to optimize crop production, which affects the sector's efficiency and sustainability. One of the main problems is the difficulty of early detection and classification of pests in rice crops, which leads to significant production losses and compromises food security in the region.

Agricultural production in the Sucre region faces multiple challenges, including low adoption of technologies to optimize crop production, which affects the sector's efficiency and sustainability. One of the main problems is the difficulty of early detection and classification of pests in rice crops, which leads to significant production losses and compromises food security in the region.

If this problem is not addressed, crop losses will continue to increase, affecting the economic stability of rural communities and limiting access to food in the region. Therefore, it is necessary to implement accessible technological solutions to improve early pest detection and optimize agricultural production, ensuring the sector's sustainability.

B. Data Understanding

The images used for training and evaluating the implemented model were extracted from a public database on the Kaggle website. This dataset was chosen because it contains data on five types of diseases that can affect rice crops. We also have data on healthy crops so that the model can discern whether one of the five pests is present or not. However, although the images can catalog common diseases, there is no data obtained from the region, which is a point that should be considered for improvement in future versions of the model. Nevertheless, it can function in the same way for crops in the region.

C. Data Preparation

Continuing with the CRIPS-DM methodology, we prepare the data, which in this case is quite simple, since the dataset used already includes labeled images; that is, the images are classified and ready to train the model. Even so, for training image recognition models, specific steps must be followed, the first being to determine the size of the images the model will use. This is key, as the data input must be standardized. In addition, the size also indicates how much information the model will process and, therefore, its resource consumption [[23].

After standardizing the sizes, the images are normalized, meaning each pixel is divided by 255 so that the values range from 0 to 1, thereby ensuring there is no bias in the model. Finally, in this case, the data was split into training and evaluation sets, with an 80:20 ratio (80% for training and 20% for evaluation).

TABLE I. MODEL CLASSIFICATION REPORT TABLE.

	PRECISION	RECALL	F1-SCORE	SUPPORT
Bacterial Leaf Blight	0.94	0.93	0.94	126
Brown Spot	0.96	0.94	0.95	122
Healthy Rice Leaf	0.99	0.96	0.97	141
Leaf Blast	0.91	0.92	0.92	113
Leaf scald	0.88	0.89	0.88	119
Sheath Blight	0.93	0.97	0.95	136
Accuracy			0.94	757
Macroo avg	0.94	0.94	0.94	757
Weighted avg	0.94	0.94	0.94	757

D. Modeling

Modeling consists of the implementation and training stage of the model so that it can recognize and learn. In this case, a convolutional neural network was implemented, which is widely used due to its learning capacity and easy integration with different types of data and images, allowing for flexibility. To do this, a configuration was implemented that optimized data analysis and minimized classification errors.
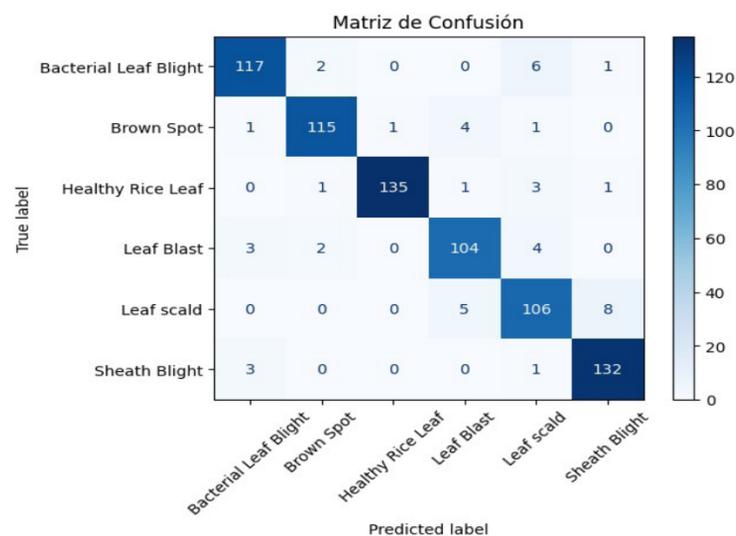

Figure 2. Confusion matrix of the DenseNet121 model trained for pest classification on rice leaves. Source: Author(s)

E. Evaluation

The model was evaluated by implementing a confusion matrix that shows how this model classifies each category, as well as false positives, providing an initial approximation of its performance. Figure 2 shows the model's clearly positive performance for each category, with no evidence of bias, indicating that training was successful.

After this, the classification report was produced, which is shown in Table IS. The overall performance achieves 94% accuracy, with balanced precision, recall, and F1 scores across the classes. These results demonstrate the model's ability to reliably differentiate between healthy leaves and those affected by pests such as Bacterial Leaf Blight, Brown Spot, Leaf Blast, Leaf Scald, and Sheath Blight.

CONCLUSIONS

The development of a convolutional model trained from scratch for the early detection of pests on rice leaves yielded highly satisfactory results, achieving 94% accuracy in classifying the primary crop diseases affecting the municipality of Majagual, Sucre. This performance demonstrates the model's ability to reliably distinguish healthy leaves from those affected by pests such as Brown Spot, Bacterial Leaf Blight, Leaf Blast, Leaf Scald, and Sheath Blight, confirming its potential as a support tool for agricultural diagnosis.

The model's effectiveness highlights the viability of applying artificial intelligence techniques in rural contexts with limited technology, providing alternatives for early detection that can help reduce losses in rice production. In addition, its implementation opens the possibility of developing accessible platforms adapted to local conditions.

Consequently, this work constitutes an initial step toward integrating computer vision-based solutions in the agricultural sector of Sucre, laying the groundwork for future developments aimed at technology transfer and the consolidation of intelligent monitoring systems for rice crops.

Furthermore, the results suggest that training a convolutional neural network from scratch, rather than relying solely on pre-trained models, can be an effective strategy for domain-specific datasets such as rice leaf disease datasets. This approach allows the model to learn relevant visual features directly from local data, improving its adaptability to regional crop conditions and disease manifestations. As a result, the proposed methodology contributes to the development of customized diagnostic systems tailored to specific agricultural environments.

Finally, future work should focus on expanding the dataset to include a broader range of environmental conditions and disease stages, and on evaluating the model's performance in

real-world field scenarios using mobile or embedded devices. Integrating the model into user-friendly applications for farmers and agricultural technicians could enhance its practical impact, promoting timely decision-making and sustainable crop management practices.

AUTHOR CONTRIBUTION

The authors' contributions to this article are as follows:

Jaider Caldera-Nadaff: Research, data analysis, visualization, writing, and editing.

José Alvarez-Carrillo: Results analysis, testbed design, data analysis, visualization, writing, and editing.

Yasser Yañez-Velasquez: Research, data analysis, visualization, writing, and editing.

The authors participated in the review of the results and approved the final version of the article.

CONFLICT OF INTERESTS

The authors declare that they have no interests or financial relationships that could have influenced this work.

REFERENCIAS

[1] Gov Sucre, "200176_pdd-sucre-tierra-de-oportunidades--interactivo--liviano-4_," Apr. 2024.

[2] B. Humán-Caceres, "Machine Learning para la detección de plagas en las hojas del tomate Abancay 2022," 2025, Accessed: Aug. 21, 2025. [Online]. Available: https://repositorio.unamba.edu.pe/handle/UNAMBA/1615

[3] R. León, M. Díaz, and L. Rodríguez, "Management of an artificial vision system for the detection of damage caused by pests in avocado crop using a drone," *Revista Ciencia y Tecnología*, vol. 16, no. 4, pp. 145–151, Nov. 2020, doi: 10.17268/rev.cyt.2020.04.14.

[4] C. A. Cáceres Flórez, O. L. Ramos Sandoval, and D. Amaya Hurtado, "Procesamiento de imágenes para reconocimiento de daños causados por plagas en el cultivo de Begonia semperflorens (flor de azúcar)," *Acta Agron*, vol. 64, no. 3, pp. 273–279, May 2015, doi: 10.15446/acag.v64n3.42657.

[5] R. Wang, K. Xiang, and B. Shao, "Research on Agricultural Pest Target Detection Method based on YOLOv7," in *2023 5th International Conference on Frontiers Technology of Information and Computer (ICFTIC)*, IEEE, Nov. 2023, pp. 505–509. doi: 10.1109/ICFTIC59930.2023.10456287.

[6] D. C. Corrales, "HACIA LA DETECCIÓN DE PLAGAS Y ENFERMEDADES EN CULTIVOS A TRAVÉS DE APRENDIZAJE SUPERVISADO," 2015, *Pontificia Universidad Javeriana*. [Online]. Available: http://hdl.handle.net/10554/26014

[7] J. Enríquez and M. Rodríguez, "Detección de enfermedades en cultivos de banano con imágenes aéreas utilizando un modelo de Deep Learning.," Jun. 2024.

[8] ONU, "Población | Naciones Unidas," https://www.un.org/es/global-issues/population. Accessed: Mar. 20, 2025. [Online]. Available: https://www.un.org/es/global-issues/population

[9] M. Garcia Bravo, *El estado de la seguridad alimentaria y la nutrición en el mundo 2023*, 58th ed., vol. 30. FAO; IFAD; UNICEF; WFP; WHO;, 2023. doi: 10.4060/cc3017es.

[10] B. Martínez, "Cuadernos Latinoamericanos de Administración," *Cuadernos Latinoamericanos de Administración*, vol. X(18), 2014, [Online]. Available: http://www.redalyc.org/articulo.oa?id=409634370001

[11] D. T. Gómez Rodríguez and M. A. Aguirre Nieto, "Seguridad alimentaria y desarrollo rural en 5 municipios del departamento del Caquetá, Colombia. Periodo 2018-2022,"

Población y Desarrollo, vol. 29, no. 57, pp. 75–93, Dec. 2023, doi: 10.18004/pdfce/2076-054x/2023.029.57.075.

[12] J. Luis *et al.*, "INGENIERO DE SISTEMAS Y COMPUTACIÓN APROBADA POR," 2021. Accessed: Mar. 23, 2025. [Online]. Available: http://hdl.handle.net/20.500.12423/3216

[13] S. Rubio, F. Alberto, and V. Castiel, "CAPÍTULO. CONTROL BIOLÓGICO DE PLAGAS Y ENFERMEDADES DE LOS CULTIVOS," 2005. Accessed: Mar. 23, 2025. [Online]. Available: https://digital.csic.es/bitstream/10261/13780/1/46.%20Rubio%20and%20Fereres,%202005.pdf

[14] D. A. Brechelt, "El Manejo Ecológico de Plagas y Enfermedades," Apr. 2004. Accessed: Mar. 23, 2025. [Online]. Available: https://enviromigration.wordpress.com/wp-content/uploads/2013/01/manejo_ecologico_de_plagas_a-bretchel.pdf

[15] Fao, "Seguridad Alimentaria y Nutricional Seguridad Alimentaria y Nutricional Seguridad Alimentaria y Nutricional Conceptos Básicos Conceptos Básicos Conceptos Básicos Programa Especial para la Seguridad Alimentaria-PESA-Centroamérica Proyecto Food Facility Honduras," Feb. 2011. Accessed: Mar. 23, 2025. [Online]. Available: https://openknowledge.fao.org/server/api/core/bitstreams/f1bb882a-b059-4368-9022-c70840d77ce5/content

[16] Fedearroz, "Fedearroz y el DANE entregaron resultados del Quinto Censo Nacional Arrocero 2023," https://www.fedearroz.com.co/es/noticias/2024/03/22/fedearroz-y-el-dane-entregaron-resultados-del-quinto-censo-nacional-arrocero-2023/?utm_source=chatgpt.com.

[17] DANE, "Quinto Censo Nacional Arrocero (5° CNA) 2023 Primera entrega (Resultados departamentales)," 2024. Accessed: Mar. 26, 2025. [Online]. Available: https://www.dane.gov.co/files/operaciones/CNA/bol-5toCNA-2023.pdf?utm_source=chatgpt.com

[18] L. Bajaña and E. Pin, "UNIVERSIDAD AGRARIA DEL ECUADOR FACULTAD DE CIENCIAS AGRARIAS," 2024, Accessed: Mar. 23, 2025. [Online]. Available: https://cia.uagraria.edu.ec/Archivos/BAJA%C3%91A%20CALLE%20LESLIE%20FIORELLA%20Y%20PIN%20GUERRERO%20ERICKA%20BRIGGITTE.pdf

[19] R. Wang, K. Xiang, and B. Shao, "Research on Agricultural Pest Target Detection Method based on YOLOv7," in *2023 5th International Conference on Frontiers Technology of Information and Computer (ICFTIC)*, 2023, pp. 505–509. doi: 10.1109/ICFTIC59930.2023.10456287.

[20] Y. M. Carbó, C. Mario, A. Echevarría, and I. R. Castillo, "PALABRAS CLAVE: arroz; diagnóstico; plagas y enfermedades; sistema experto; toma de decisiones. INTELLIGENT SYSTEM FOR THE DIAGNOSIS OF PESTS AND DISEASES IN RICE CULTIVATION," 2021. Accessed: Mar. 23, 2025. [Online]. Available: https://dialnet.unirioja.es/servlet/articulo?codigo=8164221

[21] I. Juan, M. Moine, D. Ana, S. Haedo, and D. S. Gordillo, "Estudio comparativo de metodologías para minería de datos," 2011. Accessed: Jul. 21, 2025. [Online]. Available: http://sedici.unlp.edu.ar/handle/10915/20034

[22] C. A. Mejia Rodriguez, M. A. Rincon Pinzon, L. M. Palmera Quintero, and L. M. Arevalo Vergel, "Aplicación de machine learning y metodología CRISP-DM para la clasificación precisa de severidad en casos de dengue," *REVISTA COLOMBIANA DE TECNOLOGIAS DE AVANZADA (RCTA)*, vol. 1, no. 43, pp. 78–85, Mar. 2024, doi: 10.24054/rcta.v1i43.2822.

[23] J. Montes-Bustamante, "Diabetes Predictive Model Using the CRISP-DM Process for Disease Prevention Implementing Machine Learning Modelo Predictivo de Diabetes Utilizando el Proceso CRISP-DM para la Prevención de la Enfermedad Implementando Aprendizaje Automatizado," *J. Comput. Electron. Sci.: Theory Appl*, vol. 4, no. 2, pp. 17–37, 2023, doi: 10.17981/cesta.04.02.2023.02.

[24] J. L. D. Martinez, D. Salcedo, T. Mercado, and Y. Quiñonez, "Internet de las cosas aplicado a la agricultura: estado actual y su aplicación mediante un prototipo," *RISTI –*

Revista Ibérica de Sistemas e Tecnologias de Informação, no. 53, pp. 106–121, 2024, doi: 10.17013/risti.53.106-121.

[25] M. E. A. Ochoa and J. C. B. Eljach, "Technological innovation in artisanal agriculture: Comparison of recommendation approaches to optimize marketing," *CESTA*, vol. 6, no. 1, 2025, doi: 10.17981/cesta.06.01.2025.02.

Author 1: is an electronic engineering student at the University of Sucre, Colombia. He also holds a technical degree in software development from the National Learning Service (SENA) in Colombia. His academic interests include artificial intelligence, computer vision, and machine learning applications in agriculture. https://orcid.org/0009-0009-4425-7848

Author 2: is an electronic engineering student at the University of Sucre, Colombia. His academic interests include artificial intelligence, computer vision, and machine learning applications in agriculture. http://orcid.org/0009-0007-2142-6309

Author 3: is an electronic engineering student at the University of Sucre, Colombia. His academic interests include artificial intelligence, computer vision, and machine learning applications in agriculture. https://orcid.org/0009-0001-3123-9773