Driving Gender Equality and Digital Transformation in Tuber Production through Inclusive and Smart Agriculture

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Abstract*– This project leverages strategies aimed at strengthening the participation and professional leadership of rural women in tuber crop production, driving competitiveness among smallholder farmers and unlocking value-added opportunities across Latin America and the Caribbean. By implementing smart agriculture technologies, technological training programs, and inclusive innovation strategies, the initiative promotes equal opportunities and economic autonomy for rural women. Its core solution integrates Artificial Intelligence (AI) and Internet of Things (IoT) technologies for soil characterization and market intelligence, bridging the digital divide by connecting female producers with tools traditionally out of their reach, empowering them to plan effectively, reduce post-harvest losses, and increase profitability. Guided by a commitment to social justice and environmental stewardship, the initiative also promotes the appropriation of digital solutions, such as web and mobile applications, providing real-time data access to optimize the production of potatoes and cassava in different regions of Colombia. In this work in progress, the project's justification, context, and methodology are presented, as it will be executed under a framework agreement with partner countries in Asia and the Pacific.

Keywords—Crops, IoT, AI, Potato, Cassava, gender equality, digital transformation

I. Introduction

Currently, the global agricultural sector faces multifaceted challenges that demand innovative technological solutions, particularly within the digitalization of agrifood systems. According to [1], 34% of arable land suffers from degradation due to crop expansion into low-quality soils, loss of carbon, nutrients, and biodiversity [2], [3].

Under a gender and social equity lens, this deterioration driven by monocultures and excessive inorganic fertilizers is not only an environmental crisis but a direct threat to the livelihoods, food security, and economic autonomy of rural communities, particularly impacting women who often face unequal access to resilient resources. In response to these challenges, the framework in [4] proposes strengthening capacities for the research, adoption, and ethical use of Artificial Intelligence (AI) as a key tool for social, economic, and gender-inclusive transformation. In this sense, the integration of "appropriate technologies" such as the Internet of Things (IoT) for real-time environmental data collection, alongside AI-based applications for crop geolocation, enables optimized agricultural practices, precise agronomic decision-making, and more rational use of fertilizers. However, a persistent digital divide continues to constrain the sector's modernization [5], [6], [7], and recent decomposition analyses show that gender differences in employment and labor-market participation are the single largest contributor to the digital gap between men and women across Latin America [20], a gap that is even more pronounced for rural women engaged in informal agricultural work. Consequently, the democratization of technology and the reduction of the digital gender gap must be treated as core priorities for inclusive rural development.

This approach is particularly relevant for strategic crops such as potatoes and cassava, which are essential for national food security due to their nutritional value, low production costs, and potential for diversification. Their technological transformation through AI and IoT represents a pathway to improve the income and resilience of peasant families. In 2023, in some regions of Colombia, such as Santander, which produced 104 tons of cassava, while Boyacá reached 493.5 tons of traditional potatoes, with a growing interest in more than 40 native varieties that require fewer fertilizers and contribute to food sovereignty[8], [9].

Furthermore, adopting a gender-inclusive framework addresses the critical challenge of reducing post-harvest waste, which reaches 25% in roots and tubers due to low technical capacity, inflicting severe environmental and economic losses on vulnerable producers, particularly rural women who often bear the brunt of informal labour. By promoting the production of flour and starches as viable industrial alternatives, this project seeks to add value to products currently relegated to the discard. This strategy directly strengthens the regional agro-industrial ecosystem while creating new avenues for women's entrepreneurship, leadership, and financial independence within the value chain.

The execution of this project is justified by its profound social impact on the transformation of Colombian agriculture. It fosters technology adoption in regions with low digitalization, promotes sustainable practices, and empowers farmers through strategic information and accessible tools. Beyond technical optimization, it encourages the development of high-value-added products, improving the economic livelihoods of producers and strengthening the regional agro-industrial ecosystem.

In particular, this project represents a key opportunity for the technological evolution of the Colombian agricultural sector, enhancing the productivity, sustainability, and resilience of tuber crops through an engineering approach centered on women's empowerment. Additionally, this article presents advancements in artificial intelligence applied to potato farming, specifically aimed at analyzing optimal growing conditions.

Finally, this initiative poses the following question: How does the application of AI and IoT tools—guided by gender-sensitive principles—contribute to improving the productivity, sustainability, and competitiveness of these crops while fostering social equity?

II. METHODOLOGY

Globally, the production of crops such as potatoes and cassava has seen significant growth over the last six decades. Potato production increased by 160 million tons and Cassava by 64 million. In the case of cassava, this growth has been accompanied by a surge in the export of processed products like starch, driving productivity even as harvested areas have slightly decreased [10].

In Colombia, these crops are vital for food security, serving as dietary staples and primary sources of income in rural areas[11]. Integrating ancient tubers, such as native potatoes, into current production systems offers a unique opportunity for Humanitarian Engineering to intervene by promoting these crops, bolstering seed banks, driving innovative technological alternatives through co-construction with the community, and improving their commercial competitiveness [12], [13]. Furthermore, rescuing cultural heritage and strengthening the agrifood supply with nutritionally valuable products[14], [15].

Moreover, this project seeks alignment with the Sustainable Development Goals (SDGs), given their importance in the pillars of humanitarian engineering, specifically SDG 5 (Gender Equality), SDG 8 (Decent Work and Economic Growth), and SDG 10 (Reduced Inequalities), by strengthening the leadership, technical training, and economic autonomy of rural women engaged in potato and cassava production. AI and IoT tools are positioned as enablers of this gender-inclusive transformation, helping to reduce the burden of manual crop monitoring, narrow the digital gender gap, and expand women's access to technologies, resources, and markets traditionally out of their reach[16]. It also aligns with MADR Resolution 464 of 2017[17], which promotes the peasant economy through a territorial approach to improve the sustainability and well-being of the rural population, ensuring that technological progress serves as a tool for social equity.

The methodology for this project is anchored in the Humanitarian Engineering framework, utilizing the PDCA cycle (Plan, Do, Check, Act) as a systematic tool for continuous improvement. This approach ensures that technological solutions are not only technically sound but also socially responsible, culturally appropriate, and sustainable for the farming communities of some regions in Colombia. The PDCA cycle allows for the iterative management of each stage of the process, as described below. Figure 1 graphically illustrates the phases of the PDCA cycle.



Fig 1. PDCA Cycle

The phases that the work team will be make are:

Plan: To implement artificial intelligence models aimed at identifying and analyzing potential markets—both domestic and international—for processed products (such as starches and flours), as well as using AI to analyze crop health, a detailed strategic planning phase will be carried out. This stage entails the co-design of strategies that prioritize the economic needs of small-scale producers, thereby ensuring a solid foundation for AI-driven solutions that boost the competitiveness of these agricultural products in emerging markets.

Do: During this stage, the Artificial Intelligence models are developed and implemented. Simultaneously, prototypes for products derived from potato and cassava crops (such as starches and flours) are produced. This phase focuses on creating "appropriate technology"—tools that are accessible and functional within the rural reality of the target regions.

Check: In this phase, the results generated by the models are validated through precision analysis and comparison with laboratory-level data. Crucially, this stage includes feedback from local stakeholders and farmers. This ensures that the identified markets are not only theoretically relevant but also practically accessible and beneficial to producers; it also guarantees optimal crop production, fostering an interest among women and girls in these fields to achieve real-world impact.

Strategic decisions are made based on the conducted analysis. Recommendations are formulated, and the AI models are adjusted for continuous improvement. The goal is to foster long-term community empowerment and economic resilience.

III. Technological Framework: Empowering Rural Women through Emergent Technologies

The empowerment of rural women is strengthened through the creation of collaborative networks. This project solidified the strategic positioning of women farmers as coordinators of pilot plots and managers of technology transfer. It connected three local women farmers—members of an association in Boyacá—with the project's five female engineers and researchers through mentorship and technology transfer programs. The initiative breaks with traditional governance structures in the agrifood sector and institutionalizes female leadership in decision-making and regional agricultural innovation.

The application of Artificial Intelligence (AI) constitutes a robust solution for this project, grounded in the capacity of these technologies to analyze vast volumes of complex data and identify hidden patterns. These tools are not merely technical assets but "appropriate technologies" tailored to the specific socio-environmental conditions of the agricultural landscapes in Colombia for potato and cassava crops. Unlike traditional methods based on empirical experience or reactive manual monitoring, the integration of AI allows for proactive problem-solving and personalized recommendations. When combined with the Internet of Things (IoT), these systems enable real-time resource optimization, transforming what are often costly or inefficient processes into accessible, data-driven strategies for vulnerable farming communities.

The technological ecosystem shown in Figure 2, involved in this project, offers Predictive Soil Analysis: Utilizing IoT device data to determine the most suitable lands for planting potato or cassava, ensuring long-term land health. Artificial intelligence algorithms are also used here for the early detection of diseases; this paper presents results regarding the blight caused by Phytophthora infestans in potato crops.

Resource Optimization: Reducing environmental impact by precisely managing water, fertilizers, and pesticides through advanced soil characterization; also through AI algorithms to predict healthy crops.

Market Intelligence: Identifying commercial opportunities through real-time data analysis, bridging the information gap for smallholders. Scalability and Adaptability: Ensuring that small and medium-sized producers—traditionally excluded from high-tech advancements—can benefit from these innovations.

Through gender-responsive research and the development of specific inclusion indicators, the project provides crucial scientific evidence on the impact of modernization on women's quality of life. This approach ensures that the digitalization of the agricultural sector does not deepen existing gaps, but instead serves as a tool for social justice aligned directly with the Sustainable Development Goals (SDGs 5, 8, and 10), laying the groundwork for more equitable public policies and agricultural initiatives in Latin America and the Caribbean.

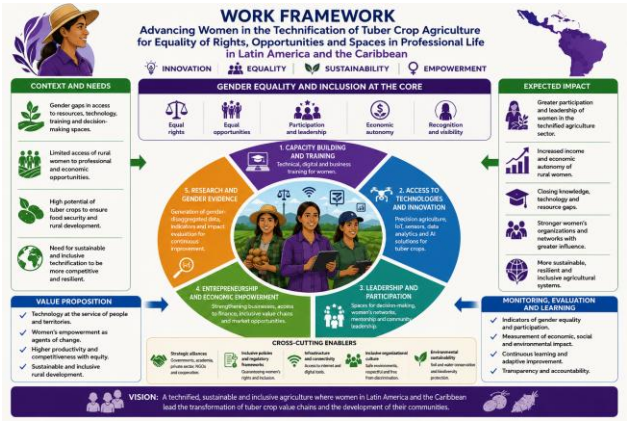


Figure 2. Framework
Note: Image generated using DaVinci AI (Hubx Studios Ltd, 2026) from a prompt.

It should be noted that the gender-disaggregated inclusion indicators referenced above form part of the project's planned monitoring and evaluation framework and have not yet been collected or measured. To date, no baseline survey, participation registry, or outcome evaluation specific to women's leadership, technology adoption, or income change has been carried out. Gathering this evidence, through structured surveys, participation records, and follow-up assessments with the rural women engaged in the project, is identified as a priority for the next phase of this work, so that the contribution of AI- and IoT-based smart agriculture to gender equality can be substantiated with empirical evidence rather than inferred from the project's design alone.

The integration of smart agriculture technologies and the certification of digital skills do not merely modernize tuber production; rather, they act as a catalyst for the financial autonomy of rural women. By linking technical training with access to digital markets and agro-industrial business models, the project transcends traditional technical assistance, enabling female producers to scale up the value chain and transform their economic roles within their communities.

Finally, this project aims to demonstrate that the implementation of AI systems, integrated with IoT technologies, represents an advanced, efficient, and highly contextualized solution for transforming tuber agriculture in Colombia. Beyond increasing productivity and sustainability, these technologies serve as a vehicle for community empowerment, providing local farmers with the knowledge and

tools necessary to overcome current agri-food challenges and achieve economic resilience.

IV. Early Detection of Late Blight Caused by Phytophthora infestans in Potato Crops: A CNN-Based Proof of Concept for Rural Women Producers

Within the framework of this project, and aligned with its commitment to bridging the digital gender gap, a computer vision proof of concept was developed to evaluate the technical feasibility of early, automated detection of late blight symptoms using deep learning, laying the groundwork for a future decision-support tool accessible to rural women producers. Additionally, the characterization of the native potato is shown.

This component of the methodology constitutes the second stage of the technological framework, following predictive soil characterization, and explores the technical foundations for what is envisioned as an 'appropriate technology': a solution that is technically robust yet transferable to the real-world conditions of rural communities in Colombia. At this stage, the pipeline constitutes a research prototype developed and validated in a controlled computational environment.

A. Native Potato Varieties in the Cundiboyacense Region

The main native potato varieties cultivated in Colombia belong to the species Solanum tuberosum spp. andigena, Solanum phureja, and *Solanum chaucha* [18]. Varieties such as *Solanum tuberosum* spp. *andigena* and *Solanum phureja* are currently being explored due to their sensory and nutritional properties, which make them suitable for the development of value-added food products. Through this project, several native potato varieties were characterized, and their denominations are presented in Figure 3.



Fig 3. Denomination of native potato varieties

Table 1 below presents the morphological characterization of the seven native potato varieties studied; this reveals considerable diversity in tuber shape, skin color, eye depth, and flesh color, based on the classification established by the International Potato Center.

TABLE 1. MORPHOLOGICAL CHARACTERIZATION OF NATIVE POTATO VARIETIES FROM THE CUNDIBOYACENSE REGION.

Variety	Morphology Characterization			
	Form	**Depth**	**Skin color**	**Pulp Color**
Yana Shungo	Compressed or flattened	Medium	Blackish	Purple - white in ring and pith
Puca Shungo	Oblong	Depth	Red - purple	Violet - yellow in ring and pith
Roja Neusa	Round	Medium	Red - purple	Yellow cream
Alcarrosa	Oblong	Medium	Red - purple	Yellow - purple in bands
Quincha	Oblong	Medium	Red - purple	Violet - yellow in bands
Valvanera	Elíptico	Medium	Red – yellow with few spots	Cream
Sangre de Toro	Oblong	Medium	Red - purple	Red - yellow in bands.

In the table, we can observe that oblong tubers predominated, while skin and flesh pigmentation ranged from cream and yellow to red, purple, and bicolored patterns, demonstrating the rich phenotypic diversity of Cundiboyacense native potatoes. These distinctive morphological traits provide reliable descriptors for digital agriculture applications, including image-based recognition systems powered by artificial intelligence and computer vision, which can facilitate automated variety identification, improve traceability, and support the conservation of native germplasm. Furthermore, the digital documentation of these phenotypic characteristics complements the traditional knowledge used by farmers—particularly rural women, who play a key role in the conservation, selection, and identification of native potato varieties. By simplifying variety identification and improving access to technical information, digital tools can strengthen women's participation in production, conservation, and

decision-making processes throughout the agricultural value chain.

B. Technofunctional properties of native potatoes

The mean values of the technofunctional properties of the native potatoes (swelling power, holding capacity of water and oil) are shown in Table 2.

TABLE 2. TECHNOFUNCTIONAL PROPERTIES OF NATIVES POTATOES

Varieties native potato	Water Holding Capacity (g/g)DM	Oil Holding Capacity (g/g)DM	Swelling Power (mL/g)DM
Yana Shungo	4.04±0.08a	2.24±0.07a	4.54±0.14a
Puca Shungo	4.61±0.18b	2.26±0.05a	5.31±0.17b
Roja Neusa	5.94±0.23c	2.22±0.04a	6.57±0.15c
Alcarrosa	3.80±0.30a	2.59±0.08b	4.29±0.35ad
Quincha Valvanera	3.40±0.26d	2.48±0.05c	3.91±0.36d
	4.56±0.13b	2.41±0.03c	5.45±0.40b
Sangre de Toro	3.42±0.03d	2.75±0.03d	4.02±0.01d

values presented like Means ± standard deviation

It was observed that Puca Shungo (4.61 g/g) and Valvanera (4.56 g/g) exhibited the highest water-holding capacity (WHC). This behavior may be attributed to the composition of the tubers, particularly their starch and fiber content, which enhance their swelling capacity (19, 21).

Regarding oil-holding capacity (OHC), the Sangre de Toro variety showed the highest values compared to the other native potato varieties evaluated. Likewise, for swelling power (SP), Puca Shungo presented the highest values.

When compared with other raw materials, native potatoes exhibited superior technofunctional properties (22). In particular, water-holding capacity and oil-holding capacity are key functional properties, as they reflect the interaction between the structural components of the food matrix, especially polysaccharides and dietary fiber, with water and lipid molecules. These interactions significantly influence ingredient behavior during processing and storage, affecting texture, stability, and sensory quality. These findings make it possible to identify varieties with greater potential to improve flavor retention and enhance the sensory characteristics of bakery products. Furthermore, the results provide relevant information for women producers and food processors in the region, supporting decision-making regarding the utilization and agro-industrial valorization of these native potato varieties

C. AI Algorithm to recognize Late blight

Late blight, caused by Phytophthora infestans, is one of the most destructive diseases affecting potato crops in Colombia, generating significant economic losses that disproportionately impact smallholder producers, particularly rural women who manage family-scale plots and lack access to timely agronomic advisory services. Traditional disease recognition relies entirely on visual inspection by the farmer, a process that is time-consuming, subjective, and often delayed until the disease has already spread to an advanced stage.

This burden falls disproportionately on rural women, who, beyond managing family-scale plots, typically carry a larger share of unpaid domestic and care work than men, leaving less time available for lengthy field inspections or for traveling to access in-person agronomic advisory services that are, in any case, less accessible to them given the employment- and technology-related gender gaps documented in the region [20]. A lightweight, smartphone-based detection pipeline, requiring only an ordinary camera phone rather than specialized sensing equipment, is therefore particularly well suited to this context: by automating a task that would otherwise demand repeated, time-consuming visual inspections, it lowers the technical and financial barrier to early disease detection precisely for the group that the literature identifies as facing the widest gap in access to digital agricultural tools.

1)Dataset Construction

A balanced image dataset of 232 samples was compiled, comprising 116 images of potato leaves exhibiting confirmed late blight symptoms and 116 images of healthy leaves (Figures 4, and 5). Images were acquired through field visits to a greenhouse facility in Boyacá and to potato crops adjacent a region where rural women represent a significant share of smallholder producers. Capture was performed using an iPhone 12 rear camera (dual 12 MP lenses) under manual ISO and exposure configuration to ensure consistent illumination across sessions. Images were stored in HEIF format to preserve quality while minimizing storage requirements, a format that would also be practical for future deployment in low-connectivity rural environments.



Figure 4. Dataset — potato crop leaves exhibiting late blight disease.



Fig 5. Dataset — healthy potato crop leaves.

All images underwent visual quality screening prior to inclusion, discarding those with insufficient resolution or ambiguous symptom presentation. The balanced class distribution (1:1 ratio) was deliberately established to prevent classifier bias toward the healthy class — a critical design decision given that missed detections of diseased leaves (false negatives) carry direct economic consequences for producers. The dataset was partitioned into a training subset (70%, n=162; 81 per class) and a validation subset (30%, n=70; 35 per class), preserving class balance across both partitions.

2)Dual-Pathway Image Segmentation Pipeline

Raw images were processed through a dual-pathway segmentation pipeline implemented in MATLAB Online, designed to isolate the necrotic lesion regions characteristic of late blight from surrounding healthy green tissue. Rather than relying on a single color transformation, the pipeline exploits two complementary representations of the same image — each capturing different chromatic properties of the lesion — whose outputs are subsequently fused through element-wise multiplication to produce a final binary mask of superior precision. The CIELAB color space was selected for both pathways due to its perceptual uniformity and its capacity to decouple luminosity (L) from chromatic information (A: red–green axis; B: blue–yellow axis), enabling robust discrimination between healthy green tissue and brownish necrotic areas even under the variable natural lighting conditions typically encountered in field environments managed by rural producers.

Pathway 1 — sRGB to CIELAB (luminosity and blue-yellow contrast)). In the first pathway, images were converted from sRGB to CIELAB using a standardized color transformation matrix. The sRGB color space, which incorporates a gamma correction curve specific to digital display devices such as the iPhone 12 camera used for image acquisition, is first linearized before conversion to CIELAB. This pathway exploits an arithmetic combination of the L (luminosity) and B (blue-yellow) components, computing LB = L + B − A, which effectively enhances the chromatic contrast between the green tissue of healthy leaves and the brownish necrotic spots of diseased ones, while simultaneously suppressing the red-green A component that introduces noise in this discrimination. The resulting grayscale LB image was thresholded using Otsu's global method, binarized, and small spurious regions below a defined area threshold were removed. The component decompositions for diseased and healthy images obtained through this pathway are shown in Figures 6 and 7, respectively.

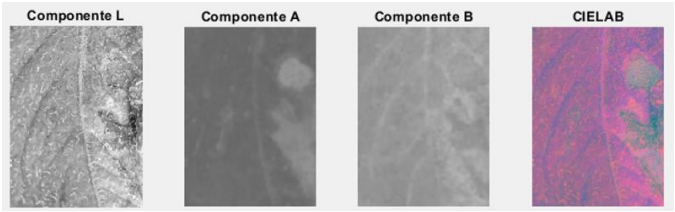


Fig 6. RGB-to-CIELAB component decomposition — diseased leaf image.

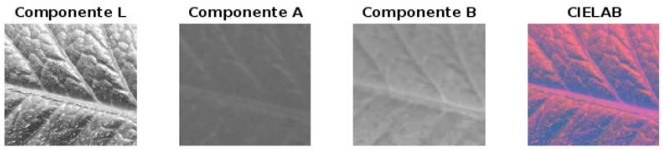


Fig 7. RGB-to-CIELAB component decomposition — healthy leaf image.

Following binarization, morphological erosion was applied to the resulting binary image using a diamond-shaped structuring element. This step is critical: the sRGB-to-CIELAB pathway, while effective at capturing lesion contrast, produces residual noise particularly in healthy leaf images — where vein structures and lighting gradients can generate spurious white regions in the binary mask. Erosion selectively removes these small isolated artifacts without affecting the larger, coherent lesion regions, significantly improving the specificity of the

mask. The output of this step — the morphologically filtered binary mask — constitutes Mask 1.

Pathway 2 — RGB to CIELAB (red-green chromatic discrimination). In the second pathway, images were converted directly from RGB to CIELAB without gamma correction. This distinction from Pathway 1 is intentional: the absence of gamma linearization alters the distribution of values in the CIELAB space, particularly in the A channel (red-green axis), producing a stronger and more direct chromatic response to the reddish-brown pigmentation of necrotic tissue caused by Phytophthora infestans. The A channel was independently extracted and binarized, generating a binary mask that specifically highlights pixels with elevated red-green chromatic contrast — precisely the color signature of late blight lesions. This mask, referred to as Mask A, is highly selective for the lesion color but does not incorporate luminosity or spatial context information. The RGB-to-CIELAB component decompositions for diseased and healthy images are shown in Figures 8 and 9.

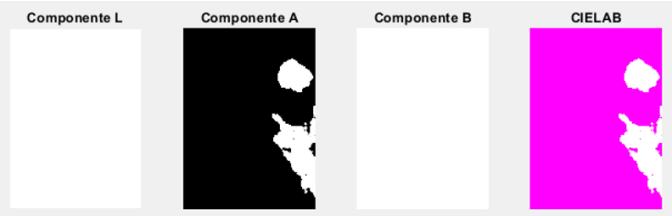


Fig 8. RGB-to-CIELAB component decomposition — diseased leaf image.

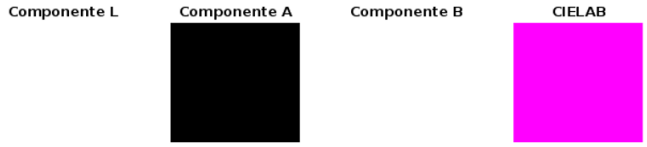


Fig 9. RGB-to-CIELAB component decomposition — healthy leaf image.

The resulting A channel binarization and LB composite images are shown in Figures 10 and 11, respectively.

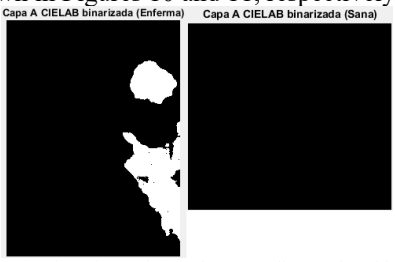


Fig 10. Binarized A channel (Mask A) — diseased and healthy leaf images

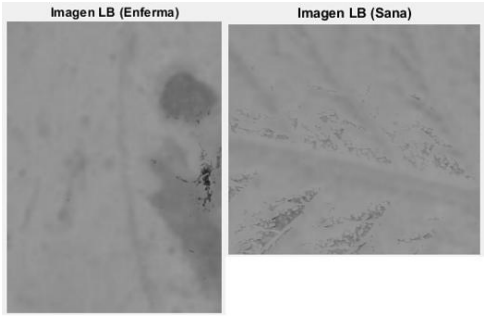


Figure 11. LB composite image — diseased and healthy leaf images

3) Mask Fusion, Edge Detection, and Final Segmentation

Fusion of Mask 1 and Mask A. The two pathways converge at the fusion step, where Mask 1 (morphologically filtered output of the sRGB-to-CIELAB pathway) and Mask A (A channel binarization from the RGB-to-CIELAB pathway) are combined through element-wise multiplication. This operation retains only those pixels that are simultaneously active in both masks - that is, pixels that exhibit both the luminosity-contrast signature captured by Pathway 1 and the red-green chromatic signature captured by Pathway 2. The rationale is straightforward: Mask 1 effectively delimits the spatial extent of the lesion region but may include low-confidence pixels at lesion boundaries; Mask A is highly color-selective but lacks spatial context. Their intersection produces a refined binary mask that is simultaneously spatially coherent and chromatically precise, substantially reducing both false positives and boundary artifacts. The resulting fused binary mask and its comparison with the intermediate morphological output are shown in Figure 12.

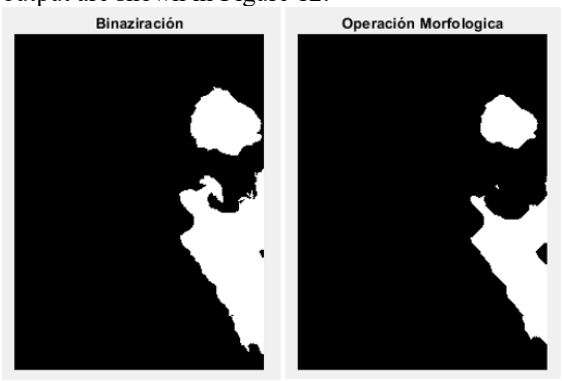


Fig 12. Intermediate binary mask (left) and fused binary mask after Mask 1 × Mask A multiplication (right) - diseased leaf.

Edge detection was then applied to the fused binary mask using the perimeter function, which identifies boundary pixels connected to at least one background pixel. The resulting edge map was overlaid on the original grayscale image, enabling visual verification that the pipeline correctly localizes the lesion region (Figure 13). This overlay serves as a quality-control step

and as an interpretable output for agronomists and extension workers supporting rural women producers in the field.

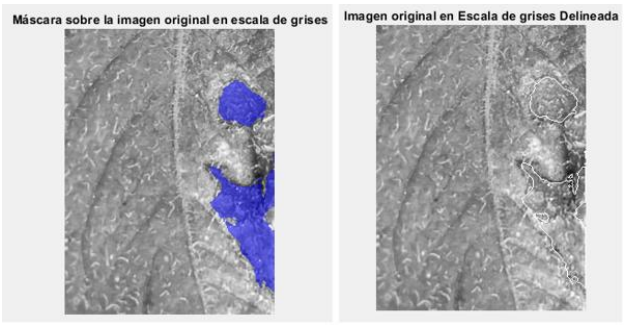


Fig 13. Edge detection overlaid on original grayscale image - verification of lesion localization.

For final segmentation, each RGB channel of the original image was multiplied element-wise by the fused binary mask, isolating pixels of interest against a black background and discarding irrelevant regions (Figure 14).



Fig 14. Final segmentation: original image (left) and color-segmented output (right).

The complete pipeline was then automated to process all 232 images, resized to a uniform 286 × 308 pixels, with segmented outputs stored in two separate directories: 'dataset/sana' for healthy images (Figure 15) and 'dataset/gota' for diseased images (Figure 16).



Fig 15. Segmented healthy potato leaf images.

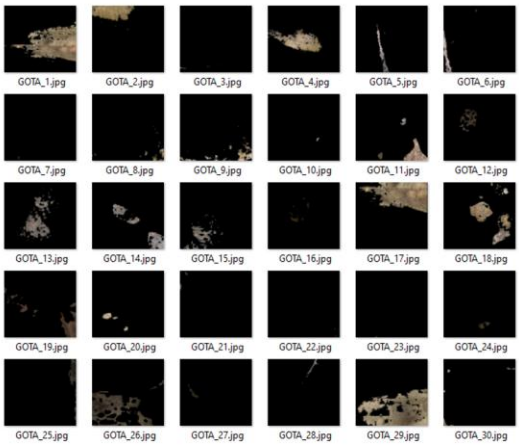


Fig 16. Segmented diseased potato leaf images.

4) CNN Architecture and Training

A Convolutional Neural Network (CNN) was designed and trained from scratch (i.e., without transfer learning) in MATLAB Online on a Windows 10 Pro 64-bit system with an Intel Core i5 processor. Input images were resized to 286 × 308 × 3 pixels. Table 3 details the resulting architecture layer by layer, including the kernel and stride configuration, the output shape after each layer, and the number of learnable parameters.

Table 3. Layer-by-layer specification of the CNN architecture used for late blight detection.

Layer	Kernel / Stride	Output Shape	Parameters
Image Input	–	286×308×3	0
Conv2D (8 filters)	3×3, stride 1, same	286×308×8	224
Batch Normalization	–	286×308×8	16
ReLU	–	286×308×8	0
Max Pooling	2×2, stride 2	143×154×8	0
Conv2D (16 filters)	3×3, stride 1, same	143×154×16	1,168
Batch Normalization	–	143×154×16	32
ReLU	–	143×154×16	0
Max Pooling	2×2, stride 2	71×77×16	0
Conv2D (32 filters)	3×3, stride 1, same	71×77×32	4,640
Batch Normalization	–	71×77×32	64
ReLU	–	71×77×32	0
Fully Connected	–	2	349,890
Softmax	–	2	0
Classification Output (cross-entropy)	–	2	0

Note: the model has 356,034 trainable parameters in total, of which 349,890 (98.3%) belong to the fully connected layer, reflecting the absence of a global pooling step before classification — a design choice that keeps the

convolutional feature extractor lightweight but leaves the parameter budget concentrated in the dense layer.

Training employed the Stochastic Gradient Descent with Momentum (SGDM) optimizer at an initial learning rate of 0.01 and a mini-batch size of 128 (MATLAB's default value, not explicitly overridden), over four epochs, with the training data shuffled every epoch and validation performed every 30 iterations. No explicit overfitting-control technique (e.g., dropout, data augmentation, or early stopping) was applied beyond batch normalization and the shallow depth of the network. The training subset (n=162) was used for parameter optimization and the validation subset (n=70) for performance evaluation (Figure 17).

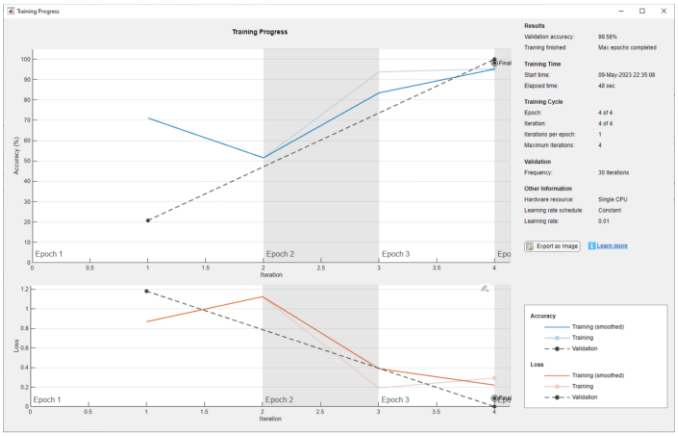


Fig 17. CNN training progress.

V. Results: Late Blight Detection - Implications for Rural Women Producers

The proposed pipeline achieved an overall classification accuracy of 98.57% on the validation subset (n=70). The confusion matrix (Figure 18) shows 35 diseased leaves correctly classified as 'gota' (true positives, TP), 34 healthy leaves correctly classified as 'sana' (true negatives, TN), 1 healthy leaf incorrectly classified as diseased (false positive, FP), and 0 diseased leaves misclassified as healthy (false negatives, FN = 0).

Table 4. Classification performance metrics on the validation subset (n=70).

Metric	Value
Precision	97.22%
Recall (Sensitivity)	100%
Specificity	97.14%
F1-score	98.59%
Accuracy	98.57%

The absence of false negatives (FN = 0) is the most agronomically significant outcome of this evaluation. In the context of smallholder potato production managed by rural women, a missed detection of late blight can lead to rapid disease spread, requiring emergency fungicide applications that account for up to 6% of total production costs, or in severe cases, the loss of up to 40% of the crop's leaf area — directly reducing yield and income. The single false positive observed (FP = 1) represents a conservative trade-off: the system errs toward caution, alerting the producer to inspect a healthy plant rather than overlooking a diseased one.

These results directly reflect the effectiveness of the dual-pathway fusion strategy: by requiring agreement between the luminosity-contrast mask (Pathway 1) and the color-selective mask (Pathway 2), the pipeline achieves a high true positive rate while keeping false negatives at zero (precisely the performance profile that would be required of an early warning tool in agricultural contexts where the cost of missed detections exceeds the cost of unnecessary inspections) validating the dual-pathway approach as a promising basis for future field deployment.

The training dynamics and final validation performance are shown in Figures 18 and 19, respectively. The model converged within four training epochs, demonstrating computational efficiency that would be compatible with periodic retraining as new field images are collected in future field validation stages involving female producers and extension workers.

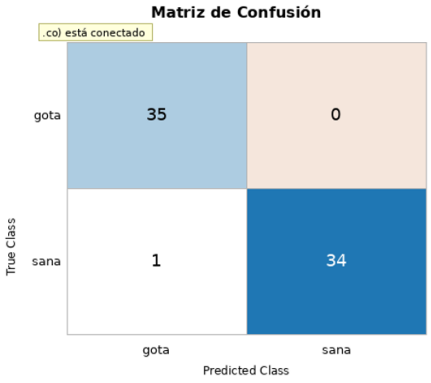


Fig 18. Confusion matrix — validation results.

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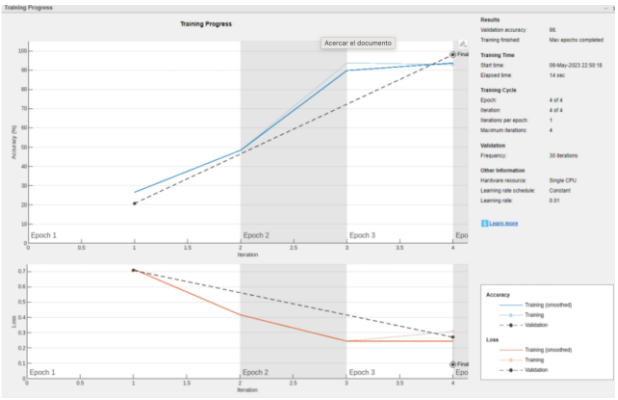


Fig 17. Learning process — accuracy 98.57%

These results demonstrate that CNN-based image classification, trained on a balanced and field-representative dataset and fed with dual-pathway CIELAB segmentation, demonstrates the technical viability of CNN-based image classification combined with dual-pathway CIELAB segmentation for early-stage detection of Phytophthora infestans. As a research prototype, this component establishes the algorithmic and methodological foundation for a future field-deployable tool that, once validated at scale and integrated (within the project's broader technological ecosystem alongside IoT-based soil characterization and AI-driven market intelligence) could contribute to closing the digital gender gap by placing data-driven crop health monitoring within reach of rural women producers, supporting proactive disease management, reduction of post-harvest losses, and informed decision-making that strengthens women's leadership, technical autonomy, and economic resilience, aligned with SDGs 5, 8, and 10.

These results should nonetheless be interpreted in light of the limited scale of the dataset. With 232 leaf images sourced from a single greenhouse facility and a single field site, the model has not yet been evaluated against the broader variability in lighting, leaf age, cultivar, and disease severity that occurs across different growing regions and seasons. No independent field-testing dataset, collected separately from the images used for training and validation, was available at this stage to assess the model's generalization performance under uncontrolled, real-world conditions. Consequently, the reported accuracy should be regarded as an upper-bound estimate obtained under controlled conditions rather than a field-validated performance figure. Expanding the dataset across multiple seasons, locations, and acquisition devices, and establishing a held-out field-testing set, are identified as priorities for the next stage of this research before the tool can be considered for deployment among rural women producers.

III. CONCLUSIONS

This project transcends technical implementation; it represents a milestone of inclusive innovation that transforms the rural ecosystem by integrating key organizations as female agents of change, generating sustainable, inclusive and scalable benefits throughout the Colombian territory.

Furthermore, this project empowers rural women through specialized training in digital tools, smart agricultural management, and innovative business models, catalyzing the recognition and strengthening of women's role in the technological and productive transformation of the agricultural sector.

The characterization of native potato varieties previously unknown in Colombia determines their ideal market use. Additionally, characterizing these varieties allows farmers to specify which tolerate extreme frosts, which survive in highly saline soils, and which require very little water. This enables them to know which potatoes to plant as regions become drier or warmer, ensuring food security.

By incorporating artificial intelligence to detect late blight, the initiative guarantees that women farmers can identify the potato disease early, leading to more profitable and sustainable value chains driven by technological traceability, thus promoting gender justice and sustainable development. The results presented in this article correspond to the crop that will serve as the foundation for cassava cultivation.

The comprehensive approach proposed demonstrates that the project delivers more than just technical results. By prioritizing the human element, it establishes installed capacities, ensures a lasting social impact, and provides valuable data for the formulation of public policies, directly contributing to sustainable and equitable rural development.

The execution of this project aims to establish research seeds, micro-enterprises, and production units led by women, directly generating local employment and economic autonomy. This aligns with the Humanitarian Engineering pillar of Community Co-design and Participation, which encourages the community to engage in data-driven decision-making, fostering leadership and collective management.

At last, this initiative will yield significant impacts and added value for productive sector organizations, academia, and peasant associations. Under a gender-inclusive and social equity framework, the project fosters institutional strengthening and generates direct benefits for the communities they support. By ensuring the active participation and leadership of rural women, the initiative guarantees that technology serves as a bridge toward social justice, gender equality, and economic resilience for the Colombian countryside as presented in Figure 19.

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