Hybrid optimization of genetic algorithm and interior point methods for anfis-based detection of *Xanthomonas campestris*

Optimización híbrida mediante algoritmo genético y método de punto interior para la detección de Xanthomonas campestris basada en anfis

Otimização híbrida utilizando um algoritmo genético e um método de pontos interiores para a detecção de Xanthomonas campestris com base em anfisema

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Abstract

Introduction: This article presents the results of the research project entitled "Integration of Foliar Segmentation and Multivariable Analysis for the Detection of Diseases in Short-Cycle Crops Using Images," conducted at the Universidad Distrital Francisco José de Caldas in 2025.

Problem: Early symptoms of *Xanthomonas campestris* are subtle and difficult to distinguish from natural pigmentation or environmental stress using traditional visual inspection, often leading to delayed diagnosis and suboptimal disease management.

Objective: This research aims to develop an interpretable early detection system based on RGB leaf images by integrating a two-level Sugeno fuzzy inference system, an Adaptive Neuro-Fuzzy Inference System (ANFIS), and a hybrid optimization strategy to improve diagnostic accuracy and robustness.

Methodology: Cropped and standardized RGB images were transformed into the HSB color space to emphasize hue and saturation variations related to chlorosis and necrosis. At the pixel level, channel-wise membership functions and Sugeno rules generated local evidence. At the leaf level, aggregated evidence was mapped into five fuzzy memberships for binary classification. Parameter tuning combined a genetic algorithm for global exploration with an interior point method for constrained refinement. ANFIS employed hybrid learning with backpropagation and least squares estimation.

Results: Experiments on 1,685 images from 15 plant species achieved 94.23% accuracy, 92.96% precision, 95.84% sensitivity, and 92.94% specificity, with statistical consistency across 50 repetitions.

Conclusion: The proposed framework balances performance and interpretability, supporting precision agriculture.

Originality: It integrates two-level Sugeno inference, ANFIS hybrid learning, and GA–IPM optimization into a unified and interpretable model.

Limitations: Performance may be affected by background interference and very early-stage lesions.

Keywords: ANFIS; Sugeno-type fuzzy system; genetic algorithm; interior point method (IPM).

Resumen

Introducción: Este artículo presenta los resultados del proyecto de investigación titulado "Integración de Segmentación Foliar y Análisis Multivariable para la Detección de Enfermedades en Cultivos de Ciclo Corto Mediante Imágenes", desarrollado en la Universidad Distrital Francisco José de Caldas en 2025.

Problema: Los síntomas tempranos de *Xanthomonas campestris* son sutiles y difíciles de distinguir de la pigmentación natural o del estrés ambiental mediante la inspección visual tradicional, lo que con frecuencia conduce a diagnósticos tardíos y a una gestión subóptima de la enfermedad.

Objetivo: Esta investigación tiene como propósito desarrollar un sistema interpretable de detección temprana basado en imágenes RGB de hojas, integrando un sistema de inferencia difusa tipo Sugeno de dos niveles, un Sistema de Inferencia Neuro-Difuso Adaptativo (ANFIS) y una estrategia de optimización híbrida para mejorar la precisión diagnóstica y la robustez.

Metodología: Las imágenes RGB recortadas y estandarizadas fueron transformadas al espacio de color HSB para resaltar variaciones de tono y saturación asociadas con clorosis y necrosis. A nivel de píxel, funciones de pertenencia por canal y reglas Sugeno generaron evidencia local. A nivel de hoja, la evidencia agregada se mapeó en cinco funciones de pertenencia para clasificación binaria. El ajuste de parámetros combinó un algoritmo genético para exploración global y un método de punto interior para refinamiento restringido. ANFIS empleó aprendizaje híbrido mediante retropropagación y estimación por mínimos cuadrados.

Resultados: Los experimentos con 1.685 imágenes de 15 especies vegetales alcanzaron 94,23 % de exactitud, 92,96 % de precisión, 95,84 % de sensibilidad y 92,94 % de especificidad, con consistencia estadística en 50 repeticiones.

Conclusión: El marco propuesto equilibra desempeño e interpretabilidad, apoyando la agricultura de precisión.

Originalidad: Integra inferencia Sugeno de dos niveles, aprendizaje híbrido ANFIS y optimización GA–IPM en un modelo interpretable unificado.

Limitaciones: El rendimiento puede verse afectado por interferencias del fondo y lesiones en etapas muy tempranas.

Palabras clave: ANFIS; sistema difuso tipo Sugeno; algoritmo genético; método de punto interior (IPM).

Resumo

Introdução: Este artigo apresenta os resultados do projeto de pesquisa intitulado "Integração de Segmentação Foliar e Análise Multivariável para Detecção de Doenças em Culturas de Ciclo Curto Utilizando Imagens", desenvolvido na Universidade Distrital Francisco José de Caldas em 2025.

Problema: Os sintomas iniciais de Xanthomonas campestris são sutis e difíceis de distinguir da pigmentação natural ou do estresse ambiental por meio da inspeção visual tradicional, o que frequentemente leva a diagnósticos tardios e manejo inadequado da doença.

Objetivo: Esta pesquisa visa desenvolver um sistema de detecção precoce interpretável baseado em imagens RGB de folhas, integrando um sistema de inferência fuzzy do tipo Sugeno de dois níveis, um Sistema de Inferência Neuro-Fuzzy Adaptativo (ANFIS) e uma estratégia de otimização híbrida para melhorar a precisão e a robustez do diagnóstico.

Metodologia: As imagens RGB recortadas e padronizadas foram transformadas para o espaço de cores HSB para destacar as variações de matiz e saturação associadas à clorose e necrose. No nível do pixel, funções de pertinência por canal e regras de Sugeno geraram evidências locais. No nível da folha, as evidências agregadas foram mapeadas em cinco funções de pertinência para classificação binária. O ajuste de parâmetros combinou um algoritmo genético para exploração global e um método de pontos interiores para refinamento restrito. O ANFIS empregou aprendizado híbrido usando retropropagação e estimação por mínimos quadrados.

Resultados: Experimentos com 1.685 imagens de 15 espécies de plantas alcançaram 94,23% de acurácia, 92,96% de precisão, 95,84% de sensibilidade e 92,94% de especificidade, com consistência estatística em 50 repetições.

Conclusão: A estrutura proposta equilibra desempenho e interpretabilidade, apoiando a agricultura de precisão. Originalidade: Integra inferência Sugeno de dois níveis, aprendizado híbrido ANFIS e otimização GA-IPM em um modelo unificado e interpretável.

Limitações: O desempenho pode ser afetado por interferências de fundo e lesões em estágios muito iniciais.

Palavras-chave: ANFIS; sistema fuzzy tipo Sugeno; algoritmo genético; método de pontos interiores (IPM).

1. INTRODUCTION

Leaf diseases remain a critical factor contributing to yield losses and reduced commercial quality across multiple crops, particularly under production scenarios characterized by high environmental variability. Precision agriculture requires diagnostic tools that are reliable, reproducible, and cost-effective, capable of being integrated into real operational workflows and of providing actionable information with traceability for the end user [1]. Traditional visual inspection—highly dependent on expert judgment, lighting conditions, leaf orientation, and background complexity—often results in delayed or inconsistent diagnoses, underscoring the need for automated approaches that preserve both interpretability and robustness [2].

In recent years, computer vision and machine learning have enabled the development of processing pipelines that combine chromatic and spatial representations with supervised classification models. The use of color spaces such as RGB and HSB enhances features associated with chlorosis, necrosis, and mottling, while superpixel-based segmentation and photometric normalization techniques improve invariance to illumination changes [3], [4]. Directional data augmentation strategies further strengthen generalization under field conditions [5]. In parallel, multispectral and hyperspectral platforms, including those deployed on UAVs, increase sensitivity to subtle symptoms, albeit at the cost of greater operational complexity and higher implementation costs [6]–[8]. In terms of performance, significant progress has been achieved using convolutional neural network (CNN)-based segmentation and related architectures [9], as well as UNet-based approaches enhanced with deep convolutional generative adversarial networks (DCGANs) [10]. Despite these advances, challenges related to predictive uncertainty and interpretability persist, representing critical barriers to adoption in agro-industrial environments [11], [12].

The bibliometric map (Figure 1) highlights three major research axes that contextualize the field: (i) the neuro-fuzzy/ANFIS line, originating in the 1990s; (ii) the expansion of deep learning in computer vision, marked by high-impact developments during the 2010s; and (iii) the emergence of optimization metaheuristics, which gained prominence from the mid-2010s onward. The present work is positioned at the intersection of “neuro-fuzzy + hybrid optimization,” aligned with current trends toward interpretable systems supported by global search and local refinement mechanisms.

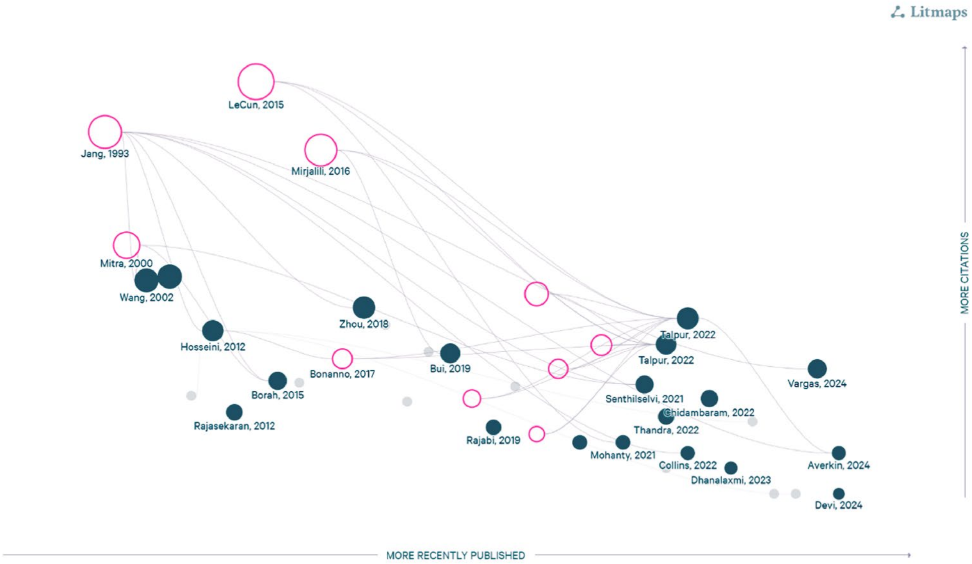

Figure 1. Bibliometric map of the literature on neuro-fuzzy/ANFIS, deep learning, and metaheuristics. Litmaps.
Source: Own work.

Recent literature supports this convergence. In texture classification, ANFIS with cluster-based initialization improves accuracy and reduces RMSE compared to conventional neural networks [13]. In edge detection, ANFIS-based approaches qualitatively outperform classical detectors such as Sobel and Roberts when evaluated using PSNR and MSE metrics [14], [15]. For noise filtering and diagnostic tasks, improvements in both accuracy and efficiency have been reported through hybrid neuro-fuzzy filters and hybrid learning strategies (e.g., Levenberg–Marquardt and least squares) [16]–[18]. Similarly, ANFIS variants optimized using swarm and colony algorithms demonstrate consistent error reductions in handwritten digit classification and other recognition tasks [19]. These findings indicate that combining clustering techniques and metaheuristics with ANFIS leads to smoother decision surfaces, improved calibration, and enhanced generalization.

Within this context, fuzzy systems—and ANFIS in particular—represent an attractive alternative by combining interpretable linguistic rules and membership functions with learning capabilities derived from real-world data [20], [21]. In parallel, hybrid optimization approaches have proven effective for tuning parameters and system topologies, ranging from metaheuristic and evolutionary techniques—including applications in agriculture and detection tasks—to deterministic methods for constrained local refinement [22]–[25]. Recent developments incorporate aggregation mechanisms such as the Sugeno integral for fuzzy classification and cluster-guided rule interpolation to construct more compact and stable systems [26], [27].

Building on this foundation, the present study proposes an interpretable framework for the detection of *Xanthomonas campestris*, integrating a two-level Sugeno fuzzy system (pixel and leaf levels), ANFIS with hybrid learning, and parameter tuning based on a genetic algorithm combined with an interior point method. The objective is to balance performance, interpretability, and practical deployment feasibility in precision agriculture applications.

2. MATERIALS AND METHODS

Dataset and Experimental Protocol

A dataset comprising 1,685 images from 15 plant species was compiled, incorporating realistic variability in illumination, orientation, background, and plant health status. To evaluate robustness and stability, a stratified 70/30 split (training/testing) was applied across 50 iterations. For each partition, the model was trained and evaluated, and the results were subsequently aggregated for statistical analysis using Student's t-test and the Kruskal–Wallis test, following established reproducibility practices in computer vision applications for agriculture [3], [4], [5], [9].

Figure 2 presents dataset examples with illumination and background variability.

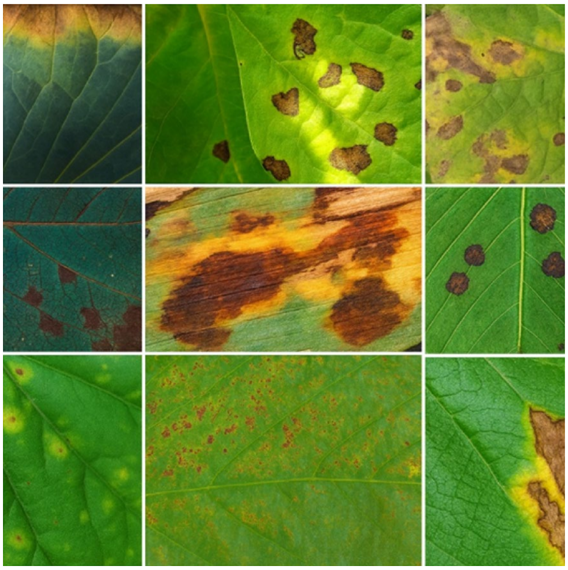

Figure 2. Dataset examples (illumination/background variability).
Source: Own work.

Pre-processing and HSB Representation

Each RGB image was cropped to maximize the leaf area, normalized per channel to mitigate exposure and color bias, and transformed into the HSB color space. This representation emphasizes hue and saturation variations associated with chlorosis and necrosis [28]. A mild smoothing filter was applied to reduce high-frequency noise without suppressing incipient lesions. The pipeline prioritizes low computational cost and explainability, avoiding reliance on more expensive multispectral or hyperspectral instrumentation in field conditions [6]–[8], [1].

The complete workflow and separation of the H, S, and B channels are illustrated in Figure 3.

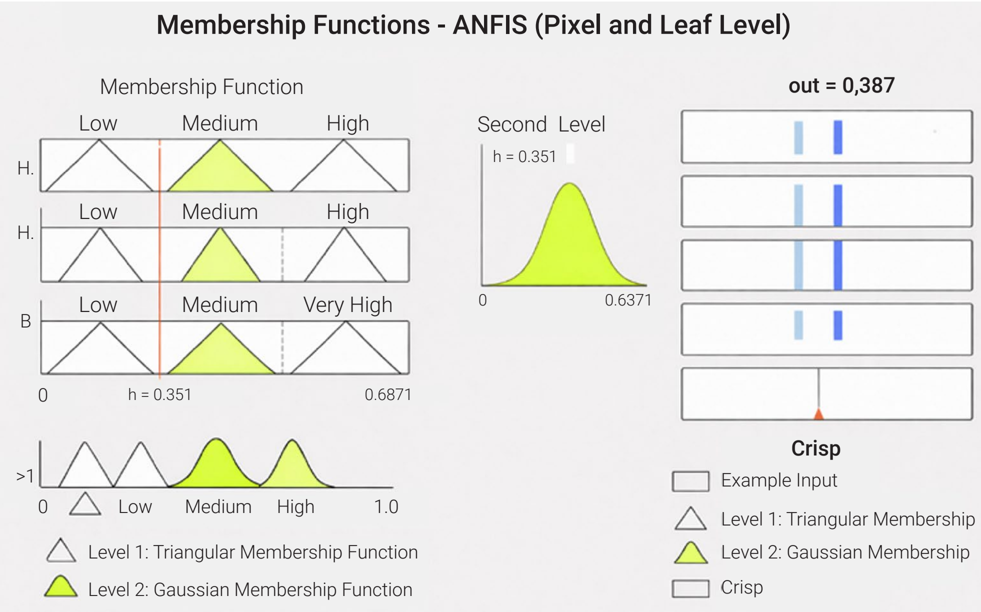

Figure 3. Pre-processing flow and H, S, B channels.
Source: Own work.

Two-Level Fuzzy System (Pixel → Leaf)

Pixel level: For each channel (H, S, B), three triangular membership functions (low/medium/high) were defined. First-order Sugeno rules combine these memberships to produce a local lesion evidence value per pixel.

Leaf level: Pixel-level evidence is aggregated (mean) over the leaf region and fed into five membership functions (very low to very high), leading to a binary decision (healthy/diseased).

Cluster-guided initialization (genfis) and manually defined rules (sugfis) were compared, analyzing their effect on inference surface smoothness and learning stability [26], [27].

The configuration and its impact on inference surfaces are illustrated in Figure 4.

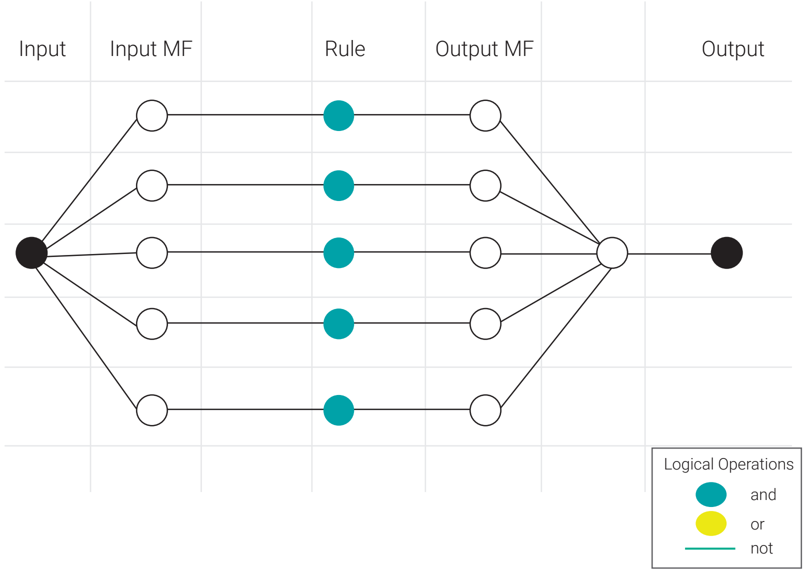

Figure 4. Initial membership functions (H, S, B) and pre-training surfaces.
Source: Own work.

ANFIS Training and Overfitting

The ANFIS model was trained using a hybrid learning strategy that combines gradient-based backpropagation for tuning premise parameters with least squares estimation for adjusting consequent parameters. This hybrid approach leverages the strengths of both optimization schemes: backpropagation enables flexible adaptation of membership function parameters, while least squares provides a stable and efficient solution for linear consequents. Training was conducted over 600 epochs, with early stopping based on validation performance to prevent unnecessary growth in model complexity and to ensure adequate generalization.

To further mitigate overfitting, L2 regularization was applied to the consequent parameters, penalizing excessively large weights and promoting smoother decision surfaces. This regularization strategy has been shown to improve stability and generalization in neuro-fuzzy systems, particularly when dealing with noisy or heterogeneous data [20], [21], [9]. Importantly, the adopted training configuration preserves the interpretability of the fuzzy rule base, as the linguistic structure of the rules remains intact while only their numerical parameters are adjusted. As a result, the model achieves a balance between expressive power and transparency, enabling both accurate predictions and meaningful inspection of the inference process.

Hybrid Optimization: Genetic Algorithm (GA) + Interior Point Method (IPM)

A hybrid GA–IPM optimization scheme was employed to fine-tune the ANFIS parameters under interpretability-preserving constraints. The Genetic Algorithm (population = 100, generations = 100, crossover rate = 0.8, elitism = 2, adaptive mutation) was responsible for the global exploration of the search space, including membership function centers, widths, and rule weights. This stochastic exploration helps avoid premature convergence and reduces sensitivity to initialization.

Subsequently, the Interior Point Method (IPM) was applied as a deterministic local optimizer to refine the best solutions obtained by the GA. IPM enforces explicit constraints on parameter ordering and admissible ranges for membership widths and decision thresholds, ensuring semantic consistency and preventing degenerate or excessively overlapping membership functions [24], [25]. The synergy between GA and IPM effectively balances exploration and exploitation, accelerates convergence, and produces smoother and more stable decision surfaces, in agreement with findings reported in hybrid optimization for computer vision and agricultural applications.

Evaluation Metrics and Statistical Analysis

Model performance was assessed using both regression- and classification-oriented metrics. During training and validation, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) were monitored to evaluate convergence behavior and detect potential overfitting. On the independent test set, classification performance was quantified using accuracy, precision, sensitivity (recall), and specificity, complemented by confusion matrix analysis.

To ensure robustness and reproducibility, the entire training–evaluation process was repeated 50 times using independent data reshuffling and stratified splits. This repetition enabled the estimation of confidence intervals and supported statistical comparisons between model variants (with and without clustering initialization; with and without IPM optimization). Student's t-test and the non-parametric Kruskal–Wallis test were employed to assess the statistical significance of the observed differences, following recommended practices for comparative evaluation in machine learning and agricultural image analysis [9], [12], [22], [23].

Hyperparameters and Configuration

Table 1 summarizes the model configuration.

Table 1. Hyperparameters and model configuration.

Component	Parameter	Value	Observation
ANFIS	Epochs	600	Early stopping via validation
ANFIS	L2 regularization	1,00E-04	Applied to consequents
Fuzzy N1	Functions per channel	3	Triangular: low/medium/high
Fuzzy N2	Membership functions	5	Very low to very high
GA	Population	100	Elitism = 2
GA	Generations	100	Crossover = 0.8; adaptive mutation
IPM	Type	Interior Point	With ordering constraints
Split	Train/Test	70/30	50 repetitions

Source: Own work.

3. RESULTS

On the test set, the best-performing configuration (ANFIS + Cluster (N1, N2) + GA + IPM) achieved an accuracy of 94.23%, a precision of 92.96%, a sensitivity of 95.84%, and a specificity of 92.94%. These values remained consistent across 50 repetitions with stratified partitioning and independent shuffling. Statistical significance tests did not reveal differences among runs (Student's t-test, $p = 0.0669$; Kruskal–Wallis, $p = 0.6421$), suggesting process stability and adequate model generalization under sampling variability [9], [12].

The training and validation MSE/RMSE curves exhibit more stable convergence for the cluster-based variant compared to manual initialization. Data-driven guidance in rule generation and initial center placement promoted smoother decision surfaces and reduced validation error, consistent with approaches based on fuzzy aggregators and cluster-informed rule construction [26], [27]. Additionally, L2 regularization contributed to effective overfitting control [9], [20], [21].

At the pixel level, an MSE of 8.30×10^{-4} was obtained, while at the leaf level the MSE reached 6.18×10^{-3} for the cluster-based configuration. The best-performing model consistently achieved an accuracy of 94.23%, a precision of 92.96%, a sensitivity of 95.84%, and a specificity of 92.94%, confirming the robustness of the proposed approach.

Table 2 summarizes the performance of the three evaluated configurations.

Table 2. Comparative performance by configuration.

Configuración	Exactitud (%)	Precisión (%)	Sensibilidad (%)	Especificidad (%)
ANFIS+Clúster + GA+IPM	94,23	92,96	95,84	92,94
ANFIS+Clúster + GA	92,57	90,9	94,6	91,1
ANFIS sin clúster + GA+IPM	91,88	90,1	93,9	90,5

Source: Own work.

4. DISCUSSION AND CONCLUSIONS

The results obtained demonstrate that the combination of interpretable fuzzy rules, ANFIS, and hybrid GA–IPM optimization constitutes a robust alternative for the detection of *Xanthomonas campestris* from RGB images transformed into the HSB color space. The first aspect to highlight is explainability. By explicitly modeling membership functions (low/medium/high per channel at the pixel level and very low to very high at the leaf level) and Sugeno rules, the decision-making process can be audited and effectively communicated to agronomists and technicians—an aspect that remains a recurrent limitation of black-box models [11]. In this regard, ANFIS acts as a bridge between interpretability and parameter learning, enabling smooth and controlled decision surfaces [20], [21]. This explainable nature not only facilitates adoption in precision agriculture but also supports the formulation of corrective actions in the field [1].

The second contribution lies in the observed robustness to illumination variability and complex backgrounds. The selection of the HSB color space increases sensitivity to hue and saturation variations associated with chlorosis and necrosis, aligning with evidence on the physiological relationship between color and plant symptoms [28]. The pixel-level stage operates as a local evidence detector which, when aggregated at the leaf level, attenuates noise and perturbations. This behavior is reflected in spatial maps consistent with leaf anatomy and pathology. Nevertheless, boundary cases were identified, including false positives (specular highlights and yellowish backgrounds) and false negatives (incipient, low-contrast lesions). For such scenarios, the use of background masks, local normalization, and—under more complex conditions—prior CNN-based segmentation (e.g., UNet with DCGAN-style augmentation) represents a practical and cost-effective improvement pathway [10], [5].

The GA–IPM coupling proved crucial in achieving a balanced exploration–exploitation trade-off, consistent with findings in agricultural and computer vision applications that report benefits from hybrid optimization strategies [24], [25], [22], [23]. Furthermore, cluster-guided initialization promoted smoother inference surfaces and lower validation error, in agreement with recent approaches that advocate rule interpolation and the use of more expressive fuzzy aggregators [27], [26].

Finally, Figure 5 provides evidence that the post-training inference surfaces preserve smooth boundaries, avoid abrupt transitions, and reflect the semantics of the fuzzy rules, which helps explain why specific chromatic patterns lead to positive or negative classifications. Overall, the experimental evidence and qualitative analysis support the conclusion that the fuzzy–neuro-fuzzy approach with hybrid optimization offers a highly favorable cost–benefit ratio, combining high predictive performance, operational explainability, and practical deployment feasibility. Nevertheless, clear opportunities for refinement remain in scenarios with strong specular reflections, occlusions, or extreme heterogeneity, where segmentation and augmentation strategies, together with the progressive incorporation of advanced fuzzy aggregators or interpolated rules, could further enhance system robustness [5], [26], [27]. Figure 5 presents the post-training inference surfaces.

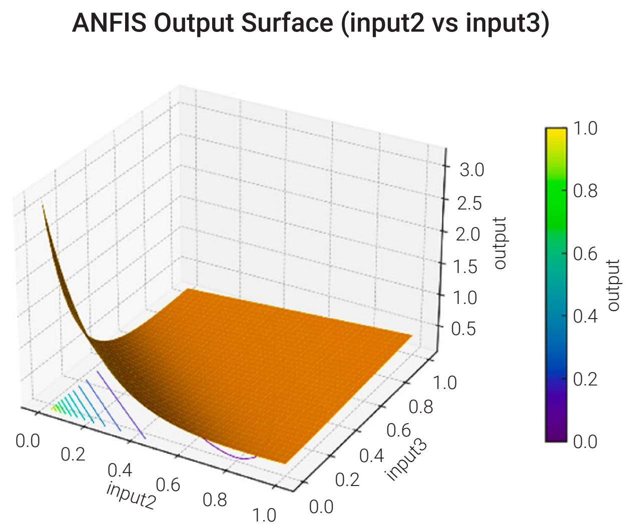

Figure 5. Post-training inference surfaces (ANFIS).
Source: Own work.

This work presents an interpretable and robust framework for the detection of *Xanthomonas campestris* that integrates: (i) a two-level Sugeno-type fuzzy system (pixel and leaf levels), (ii) ANFIS with hybrid learning, and (iii) hybrid GA–IPM optimization for constrained fine-tuning. The selection of the HSB color space, together with per-channel normalization and pixel-to-leaf aggregation, enabled the stable capture of color tonalities indicative of leaf disease. Using a dataset of 1,685 images from 15 plant species, the proposed approach achieved an accuracy of 94.23%, a precision of 92.96%, a sensitivity of 95.84%, and a specificity of 92.94%, maintaining statistical consistency across 50 repetitions. These results, together with the stability observed in the Student's t-test and Kruskal–Wallis analyses, support the generalization capability of the approach under sampling variability.

From an adoption perspective, the system provides explainability through its fuzzy rules and membership functions, which is a key requirement for precision agriculture and end-user trust. The decision-making process does not rely on a black-box mechanism, but rather on explicit linguistic relationships between hue, saturation, and symptom severity, facilitating auditing and iterative improvement. The ANFIS module ensures fine parameter adjustment without sacrificing interpretability, while GA–IPM optimization mitigates local optima and improves system calibration by enforcing constraints that preserve membership semantics. In addition, cluster-guided initialization demonstrated advantages in convergence and surface smoothness, in agreement with recent approaches based on rule interpolation and expressive fuzzy aggregators.

From a practical standpoint, the proposed pipeline relies on low-cost RGB sensors and minimal preprocessing, favoring deployment on mobile devices, greenhouses, or field environments with limited infrastructure. This approach can coexist with more sophisticated solutions—such as multispectral or hyperspectral imaging and UAV-based platforms—in scenarios where budget and logistics permit. Likewise, a prior segmentation stage based on UNet with DCGAN-style augmentation can be integrated to improve leaf lamina delineation in complex scenes, while maintaining the final decision process within the fuzzy–neuro-fuzzy domain to preserve transparency and traceability.

Three future research directions are proposed: (i) incorporating systematic background masking and local normalization into the pipeline, (ii) integrating an optional semantic segmentation stage when required by the operational context, and (iii) exploring more expressive fuzzy aggregators (e.g., the Sugeno integral) and cluster-guided interpolated rules to enhance robustness in decision boundary regions.

Overall, the proposed approach provides a balanced trade-off between predictive performance, explainability, and operational feasibility. Its modular design enables gradual adoption: it can be immediately deployed in low-cost RGB-based pipelines and progressively scaled toward more advanced configurations as needed. By integrating interpretable rules with hybrid learning and optimization strategies, the system aligns with real-world decision-making requirements in agricultural environments and establishes a solid foundation for the development of reliable, traceable, and scalable diagnostic tools in precision agriculture.

REFERENCES

[1] T. A. Shaikh, T. Rasool, and F. R. Lone, "Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming," *Computers and Electronics in Agriculture*, vol. 198, Art. no. 107119, pp. 1–29, 2022, doi: https://doi.org/10.1016/j.compag.2022.107119.

[2] R. Yadav, Y. K. Rana, and S. Nagpal, "Plant leaf disease detection and classification using particle swarm optimization," in *Lecture Notes in Computer Science*, vol. 11407, É. Renault, P. Mühlethaler, and S. Boumerdassi, Eds. Cham, Switzerland: Springer, 2019, pp. 294–306, doi: https://doi.org/10.1007/978-3-030-19945-6_21.

[3] L. Zhang, M. Xiao, J. Ma, and H. Song, "Edge detection by adaptive neuro-fuzzy inference system," in *Proc. 2nd Int. Congr. Image and Signal Processing (CISP)*, 2009, pp. 1–4, doi: https://doi.org/10.1109/CISP.2009.5304595.

[4] Y. Xiong, L. Liang, L. Wang, J. She, and M. Wu, "Identification of cash crop diseases using automatic image segmentation algorithm and deep learning with expanded dataset," *Computers and Electronics in Agriculture*, vol. 177, Art. no. 105712, pp. 1–13, 2020, doi: https://doi.org/10.1016/j.compag.2020.105712.

[5] J. Shin *et al*., "Effect of directional augmentation using supervised machine learning technologies: A case study of strawberry powdery mildew detection," *Biosystems Engineering*, vol. 194, pp. 49–60, 2020, doi: https://doi.org/10.1016/j.biosystemseng.2020.03.016.

[6] M. Kerkech, A. Hafiane, and R. Canals, "Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach," *Computers and Electronics in Agriculture*, vol. 174, Art. no. 105446, pp. 1–11, 2020, doi: https://doi.org/10.1016/j.compag.2020.105446.

[7] T. Poblete *et al*., "Detection of *Xylella fastidiosa* infection symptoms with airborne multispectral and thermal imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 162, pp. 27–40, 2020, doi: https://doi.org/10.1016/j.isprsjprs.2020.02.010.

[8] R. Van De Vijver *et al*., "In-field detection of *Alternaria solani* in potato crops using hyperspectral imaging," *Computers and Electronics in Agriculture*, vol. 168, Art. no. 105106, pp. 1–12, 2020, doi: https://doi.org/10.1016/j.compag.2019.105106.

[9] P. Sharma, Y. P. S. Berwal, and W. Ghai, "Performance analysis of deep learning CNN models for disease detection in plants using image segmentation," *Information Processing in Agriculture*, vol. 7, no. 4, pp. 566–574, 2020, doi: https://doi.org/10.1016/j.inpa.2019.11.001.

[10] S. V., A. Bhagwat, V. Laxmi, and S. Shrivastava, "A custom backbone UNet framework with DCGAN augmentation for efficient segmentation of leaf spot diseases in jasmine plant," *Journal of Computer Networks and Communications*, vol. 2024, no. 1, Art. no. 5057538, pp. 1–15, 2024, doi: https://doi.org/10.1155/2024/5057538.

[11] S. Hernández and J. L. López, "Uncertainty quantification for plant disease detection using Bayesian deep learning," *Applied Soft Computing*, vol. 96, Art. no. 106597, pp. 1–11, 2020, doi: https://doi.org/10.1016/j.asoc.2020.106597.

[12] D. Munjal *et al*., "A systematic review on the detection and classification of plant diseases using machine learning," *International Journal of Software Innovation*, vol. 11, no. 1, pp. 1–25, 2023, doi: https://doi.org/10.4018/IJSI.315657.

[13] B. A. Kuncoro and Suharjito, "Adaptive neuro-fuzzy inference system for texture image classification," in *Proc. ICACOMIT*, 2015, pp. 1–6, doi: https://doi.org/10.1109/ICACOMIT.2015.7440205.

[14] K. Bhardwaj and P. S. Mann, "Adaptive neuro-fuzzy inference system (ANFIS)-based edge detection technique," *International Journal for Science and Emerging Technologies with Latest Trends*, vol. 8, no. 1, pp. 7–13, 2013. [Online]. Available: https://www.researchgate.net/publication/281378864_Adaptive_Neuro-Fuzzy_Inference_System_ANFIS_based_edge_detection_technique

[15] L. Zhang, M. Xiao, J. Ma, and H. Song, "Edge detection by adaptive neuro-fuzzy inference system," in *Proc. 2nd Int. Congr. Image and Signal Processing (CISP)*, 2009, pp. 1–4, doi: https://doi.org/10.1109/CISP.2009.5304595.

[16] C. Hemalatha, A. P. Periasamy, and S. Muruganand, "A hybrid approach for efficient removal of impulse, Gaussian and mixed noise from highly corrupted images using adaptive neuro-fuzzy inference system (ANFIS)," *International Journal of Computer Applications*, vol. 45, no. 16, pp. 15–21, May 2012. [Online]. Available: https://research.ijcaonline.org/volume45/number16/pxc3879310.pdf

[17] M. Devi and M. Soranamageswari, “Efficient impulse noise removal using hybrid neuro-fuzzy filter,” *International Journal of Imaging Systems and Technology*, pp. 100–110, 2019, doi: https://doi.org/10.1002/ima.22324.

[18] A. M. Sagir and S. Sathasivam, “A hybridised intelligent technique for the diagnosis of medical diseases,” *Pertanika Journal of Science & Technology*, vol. 25, pp. 425–440, Apr. 2017. [Online]. Available: https://ptsldigital.ukm.my/jspui/handle/123456789/578914

[19] A. B. Bayat, “Recognition of handwritten digits using optimized adaptive neuro-fuzzy inference systems and effective features,” *Journal of Pattern Recognition and Intelligent Systems*, vol. 1, no. 2, pp. 25–37, Aug. 2013. [Online]. Available: http://paper.academicpub.org/Paper?id=14532

[20] M. Esmaili *et al*., “Assessment of ANFIS to predict production and water productivity of lettuce,” *Agricultural Water Management*, vol. 258, Art. no. 107201, pp. 1–11, 2021, doi: https://doi.org/10.1016/j.agwat.2021.107201.

[21] D. Elavarasan and P. M. Durai Raj Vincent, “Fuzzy deep learning-based crop yield prediction model,” *Neural Computing and Applications*, pp. 1–15, 2021, doi: https://doi.org/10.1007/s00521-021-05950-7.

[22] E. Omrani *et al*., “Potential of radial basis function-based support vector regression for apple disease detection,” *Measurement*, vol. 55, pp. 512–519, 2014, doi: https://doi.org/10.1016/j.measurement.2014.05.033.

[23] M. S. Mustafa *et al*., “Development of automated hybrid intelligent system for herbs plant classification,” *Neural Computing and Applications*, vol. 32, no. 15, pp. 11419–11441, 2020, doi: https://doi.org/10.1007/s00521-019-04634-7.

[24] A. Cruz *et al*., “Detection of grapevine yellows symptoms in *Vitis vinifera* L. with artificial intelligence,” *Computers and Electronics in Agriculture*, vol. 157, pp. 63–76, 2019, doi: https://doi.org/10.1016/j.compag.2018.12.028.

[25] E. Sarlaki *et al*., “Valorization of lignite wastes into humic acids,” *Renewable Energy*, vol. 163, pp. 105–122, 2021, doi: https://doi.org/10.1016/j.renene.2020.08.096.

[26] J. Wieczynski *et al*., “Application of the Sugeno integral in fuzzy rule-based classification,” *Applied Soft Computing*, vol. 167, Art. no. 112265, pp. 1–13, 2024, doi: https://doi.org/10.1016/j.asoc.2024.112265.

[27] J. Yang, T. Chen, L. Chen, and J. Zhao, "Towards a clustering guided rule interpolation for ANFIS construction," in *Proc. IEEE Int. Conf. Fuzzy Systems (FUZZ-IEEE)*, 2024, pp. 1–6, doi: https://doi.org/10.1109/FUZZ-IEEE60900.2024.10612196.

[28] T. M. Matsunaga *et al*., "Direct quantitative evaluation of disease symptoms on living plant leaves growing under natural light," *Breeding Science*, vol. 67, no. 3, pp. 316–319, 2017, doi: https://doi.org/10.1270/jsbbs.16169