Evaluation of Machine Learning and Deep Learning Models for Detecting and Classifying Oidium Mangiferae on Mango Leaves

Nuvia Beltrán[1,*], Teresa Samaniego-Cobo[1], Andrés Medina[3], Johanna Sánchez[2] and Luis Rodríguez[1]

[1]*Universidad Agraria del Ecuador, Milagro, Ecuador*
[2]*Universidad Agraria del Ecuador, Guayaquil, Ecuador*
[3]*Universidad Agraria del Ecuador, Naranjal, Ecuador*

Abstract

Fungal diseases represent one of the main threats to global mango (Mangifera indica L.) production, with Oidium mangiferae, the causative agent of powdery mildew responsible for significant losses in yield and fruit quality. This study compares six machine learning and deep learning models SVM, CNN, Vision Transformer, Swin Transformer, ConvNeXt, and EfficientNet to detect and classify this leaf disease, using approximately 3,000 images of healthy and infected leaves, preprocessed through resizing, normalization, and data augmentation. Each model was evaluated using five-fold cross-validation, with accuracy, precision, recall, and F1 score as metrics. The four hybrid attention and convolutional architectures achieved the highest accuracy, led by ConvNeXt (85.02%), EfficientNet (84.60%), Vision Transformer (83.94%), and Swin Transformer (83.88%), compared to CNN (81.92%) and SVM (78.16%). A one-way ANOVA confirmed significant differences among the models ($F(5,294) = 43.83$; $p < 0.001$); however, Holm-Bonferroni correction and effect size (Cohen's d) showed that ConvNeXt, EfficientNet, and Swin Transformer are indistinguishable from the Vision Transformer, whereas SVM and CNN do differ with large effects. All six models struggled to distinguish classes of intermediate severity, with errors concentrated between adjacent stages. This indicates that modern hybrid attention and convolutional architectures offer comparable and robust performance, while SVM remains a lighter-weight but less accurate alternative. Integrating hybrid architectures and multispectral data could improve the diagnosis of leaf diseases.

Keywords

Machine Learning, Deep Learning, Comparison, Detection, Leaves, Mango

1. Introduction

The mango (Mangifera indica L.) is one of the world's most important tropical fruits [1], both for its economic value and its role in the diet. However, its production is affected by various diseases, with powdery mildew (Oidium mangiferae) being one of the most common and damaging [2, 3]. This fungal disease causes whitish spots on the leaves, reducing photosynthesis, crop yield, and fruit quality [4].

Therefore, it is important to identify Oidium Mangiferae —also known as powdery mildew—early and accurately in order to implement effective management and control strategies. Traditionally, this disease is identified through visual inspection, a method that can be subjective, time-consuming, and dependent on the farmer's experience [5, 6]. Therefore, the application of computer vision techniques is considered a viable alternative to automate diagnosis and improve the accuracy of disease stage classification [7, 8].

In this context, this study evaluates the performance of machine learning and deep learning models—specifically Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), Vision Transformer, Swin Transformer, ConvNeXt, and EfficientNet—to detect and classify the stages of Oidium mangiferae on mango leaves. Comparing these models helps identify which one offers the greatest accuracy, efficiency, and applicability in agricultural settings, contributing to the development of intelligent

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*Corresponding author.
nbeltran@uagraria.edu.ec (N. Beltrán)

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tools for the protection of mango crops.

1.1. Damage to Mango Leaves Caused by Oidium mangiferae

Mango cultivation is exposed to multiple diseases of fungal, bacterial, and viral origin. Among fungal diseases, powdery mildew stands out as one of the most common, widely distributed, and severe conditions globally, capable of causing yield losses of up to 90% [9].

The primary causative agent of powdery mildew in Mangifera indica is Oidium mangiferae (now known as Pseudoidium anacardii), belonging to the order Erysiphales. This phytopathogenic fungus preferentially colonizes young tissues, such as leaves, shoots, and panicles, where it develops a superficial mycelium with a whitish appearance and powdery texture, consisting of conidia that are easily dispersed by the wind [3]. Characteristic symptoms include the formation of a white coating on the leaf surface, progressive necrosis, leaf blade deformation, and premature defoliation in cases of severe infection. Environmental conditions that favor its development include moderate temperatures (between 10 °C and 31 °C), high relative humidity levels (60%–90%) [10], and frequent dew or fog, factors that prolong the period of leaf wetness and promote both spore germination and the fungus's penetration into plant tissues and subsequent proliferation [11].

Depending on their severity, leaf lesions can be classified into 5 classes [12]:

- **Class 1:** Healthy leaf or leaf with lesions less than or equal to 1 mm, with no mycelium present; classified as resistant.
- **Class 2:** Reddish lesions with a maximum diameter of 5 mm, with sparse mycelium, evaluated as moderately tolerant.
- **Class 3:** Lesions ranging from reddish to dark in color, with a diameter of 5 to 10 mm, accompanied by white mycelium; considered slightly tolerant.
- **Class 4:** Reddish to dark lesions 10 to 15 mm in diameter, with abundant mycelium, classified as susceptible.
- **Class 5:** Dark lesions that tend to merge, with a diameter greater than 15 mm and abundant mycelium, rated as highly susceptible.

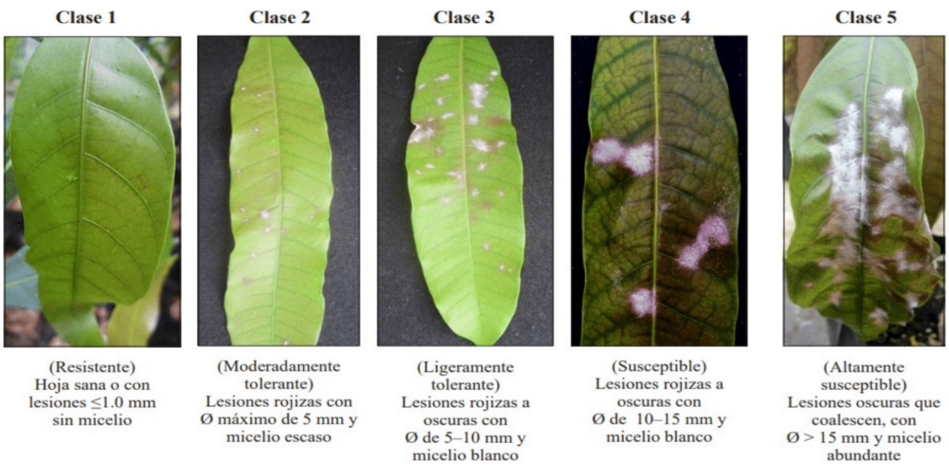

Figure 1: Classification of the severity of powdery mildew on mango leaves [12].

1.2. Computer Vision for the Detection of Foliar Diseases in Plants

The implementation of computer vision techniques enables the early and automated detection of leaf diseases by processing images of leaves and other plant parts, which is why applications based on deep neural networks, such as convolutional neural networks (CNNs) and Vision Transformers, can efficiently extract relevant features related to texture, color, and morphology in affected leaves, overcoming the limitations inherent in manual visual assessment [8, 13]. These automated solutions minimize errors resulting from human intervention, accelerate diagnostic processes, and facilitate timely interventions, thereby contributing to a reduction in production losses [7, 14]. Recent studies indicate that the accuracy of these methods is enhanced through the use of labeled databases, data augmentation techniques, and multispectral sensors [15, 16, 17], enabling their application even under field conditions with variations in lighting and background [18].

Table 1
Summary of scientific articles detailing the models used and the diseases detected on mango leaves.

Source	Year	Model Used	Disease	Accuracy
[19]	2025	CNN models: Darknet19,Xception, SqueezeNet, MobileNetv2, DenseNet201, GoogLeNet, ResNet18, VGG16, and AlexNet	Anthracnose,bacterial canker, cutting weevil damage, die-back, powdery mildew, and sooty mold.	97.4% to 99.1%
[20]	2025	YOLOv8	Anthracnose,bacterial canker, cutting weevil damage, die-back, powdery mildew, and sooty mold.	99.70%
[21]	2025	ConvNeXt and Vision Transformer (ViT) architectures	Not specified	99.87%
[22]	2024	ResNet18 CNN model	Anthracnose,bacterial canker, cutting weevil damage, die-back, powdery mildew, and sooty mold.	99.88%
[23]	2024	MSMP-CNN)	Anthracnose	98.50%
[24]	2023	lightweight convolutional neural network (LCNN)	Specifies only several diseases	98%
[25]	2023	CNN	Sternochetus mangiferae, Phytophthora spp., Fusarium spp., Ceratocystis fimbriata, Oidium mangiferae, Capnodium	100%
[26]	2022	Support Vector Machine, Gradient Boosting, Logistic Regression, XGBoost, Decision Tree, and K-Nearest Neighbor	Anthracnose, Powdery Mildew, Leaf blights, etc.	97.7%; SVM, Logistic Regression achieved an accuracy of 100%
[27]	2021	Convolutional Neural Network (CNN)	Anthracnose	70%
[28]	2021	SVM	Not specified	95.50%
[29]	2021	CNN	Anthracnose	96.16%
[30]	2021	CNN	Various diseases	98%
[31]	2020	DeNeuNet)	Anthranosis	95.35%
[32]	2020	SVM, KNN	Dag, Gomachi, Moricha, Shutimold	80%
[33]	2019	SVM	Not specified	90%
[34]	2019	Multilayer convolutional neural network (MCNN)	Anthracnose	97.13%
[35]	2017	Modified Rotation Kernel Transformation (MRKT) b	Anthracnose	98%

Feature extraction plays an essential role in improving the accuracy of leaf disease detection. The most decisive visual attributes of a diseased image—such as color, texture, and shape—can be derived using various image processing techniques [36]. However, when the symptoms of different diseases exhibit visual similarities, it becomes difficult to appropriately select the relevant features for extraction [37]. In these circumstances, deep learning approaches are better suited to automating this task [15, 38]. In this regard, convolutional neural network (CNN) models are widely used for feature extraction in plant disease identification studies, as they automatically generate feature vectors in their dense layers, avoiding the complex manual selection of attributes [38].

Classification algorithms, in turn, use these extracted features to distinguish between various diseases in plant leaves. Machine vision-based methods can be divided into two broad groups: the first relies on classical machine learning algorithms [39] (such as support vector machines, SVM) [32] that use the extracted features to improve recognition; the second is based on deep learning models, which tend to achieve better performance as the number of analyzed diseases increases [40]. Furthermore, with the emergence of Transformer-type architectures applied to images, new potential has been observed for capturing global dependencies in the image and improving feature extraction [41].

Below is a summary of studies using models for the detection of diseases in mango leaves.

According to the studies presented, these have demonstrated the effectiveness of machine learning (ML) and deep learning (DL) models in detecting mango diseases based on leaf images. The literature reviewed reveals a wide range of approaches and architectures, including deep convolutional neural networks (CNNs), vision transformers (ViTs), and traditional classifiers such as support vector machines (SVMs), k-nearest neighbors (KNN), and logistic regression. Models such as ResNet18, YOLOv8, ConvNeXt, Transformer, and MSMP-CNN achieve accuracies ranging from 97% to 100% [19], while classical models such as SVM and KNN [32] yield variable performance, ranging from 80% to 95% for KNN [32], depending on the features and the dataset used.

Despite these advances, most studies focus on the detection of anthracnose, bacterial canker, or black mildew, indicating a methodological shortcoming in the specific detection of Oidium mangiferae; or, if they do identify it, they do not classify it by class. This fungus, which causes whitish powdery spots on the leaves, can easily be confused with other fungal infections under similar lighting conditions or when the leaf texture is similar. Therefore, it is essential to evaluate the performance of different ML and DL models for its specific detection, in order to establish objective comparisons of precision, accuracy, recall, and F1 score. Consequently, this study proposes a comparative evaluation of machine learning and deep learning models (SVM, CNN, Transformer) for the detection and classification of Oidium mangiferae on mango leaves.

2. Methodology

For the comparative evaluation of the six models, the methodology was structured into five main phases described in Figure 2: data acquisition and preparation, image preprocessing, model training, result validation, and comparative performance analysis. Each stage was designed according to criteria of reproducibility and experimental consistency, ensuring the integrity and quality of the data used.

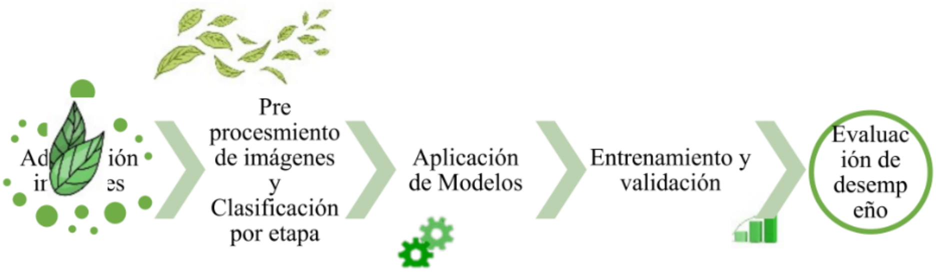

Figure 2: Phases for the comparative evaluation.

2.1. Image Acquisition

A dataset of images of mango leaves affected by Oidium mangiferae and healthy leaves was compiled from the MangoLeafBD Dataset and GitHub. The final dataset included approximately 3,000 images, balanced between healthy and infected leaves, which were reviewed and labeled by a plant pathologist to ensure labeling accuracy; furthermore, the balance between classes was a deliberate design criterion to avoid bias in training.

Table 2
Image Description by Class.

Class	Description	Images	Percentage
Class 1	Healthy leaf / Resistant	600	20%
Class 2	Moderately tolerant	600	20%
Class 3	Slightly tolerant	600	20%
Class 4	Susceptible	600	20%
Class 5	Highly susceptible	600	20%
	Total	300	100%

2.2. Image Preprocessing and Stage-by-Stage Classification

To optimize learning and ensure data set uniformity, the images were resized to 224 × 224 pixels, underwent histogram equalization to improve contrast, and had their RGB channels normalized to the range [0, 1]. Additionally, data augmentation techniques—including rotations, flips, and brightness adjustments—were applied to increase the diversity of the training dataset and reduce overfitting. To perform training, the images were classified and labeled by class based on the 5 classes identified [12]; subsequently, the dataset was divided into subsets of 70% for training, 15% for validation, and 15% for testing, following a stratified splitting strategy.

2.3. Model Implementation

Six models described in Table 3 were applied; the table also specifies the optimizer used, the number of epochs, and the learning rate.

Table 3
Image Description by Class.

Model	Loss Function	Optimizer	Batch Size	Epochs (max.)	Learning Rate
SVM	N/A	N/A	N/A	N/A	N/A
CNN	sparse_categorical_crossentropy	Adam	16	50	0.0001
Vision Transformer	sparse_categorical_crossentropy	Adam	16	80	0.001
EfficientNet	sparse_categorical_crossentropy	Adam	16	50	0.0001
ConvNeXt	sparse_categorical_crossentropy	Adam	16	50	0.0001
Swin Transformer	sparse_categorical_crossentropy	Adam	16	80	0.001

The SVM is not a neural network, so it does not use epochs, a loss function, or a learning rate. Its training is based on the SMO (Sequential Minimal Optimization) algorithm, implemented in the libsvm library. The actual hyperparameters of the model are: RBF kernel, $C = 10.0$, gamma = "scale," and class_weight = "balanced."

EfficientNet and ConvNeXt were trained from scratch, without using pre-trained weights from ImageNet; therefore, no fine-tuning was applied to these models. This was a methodological decision of the study, as both architectures are typically used with transfer learning to achieve better results. The absence of fine-tuning may have affected their generalization ability, given the limited size of the dataset used.

2.4. Performance Evaluation

For each model, the metrics of Accuracy, Precision, Recall, and F1 were calculated, taking into account both the correct identification of infected leaves and the correct classification of healthy leaves. Five-fold cross-validation was applied to ensure the robustness and stability of the results.

These metrics made it possible to analyze both the overall performance and each model's ability to correctly identify leaves infected with Oidium mangiferae, distinguishing them from healthy leaves. Specifically, accuracy reflected the total percentage of correct classifications; precision, the proportion of true positives out of all cases classified as positive; recall, the proportion of true positives detected out of all actually positive cases; and the F1 score, the balance between precision and recall.

3. Results and Discussion

To evaluate each parameter, an interface was created by integrating the models available at https://github.com/MundoCode777/Analisis-de-Cenicilla-Metodo-Mendely/tree/master, which allows users to upload images and verify the stage detected by the six models. For the evaluation, 100 images were uploaded following the procedure described below.

Figure 3: Image Upload. The interface displays the results for each model.

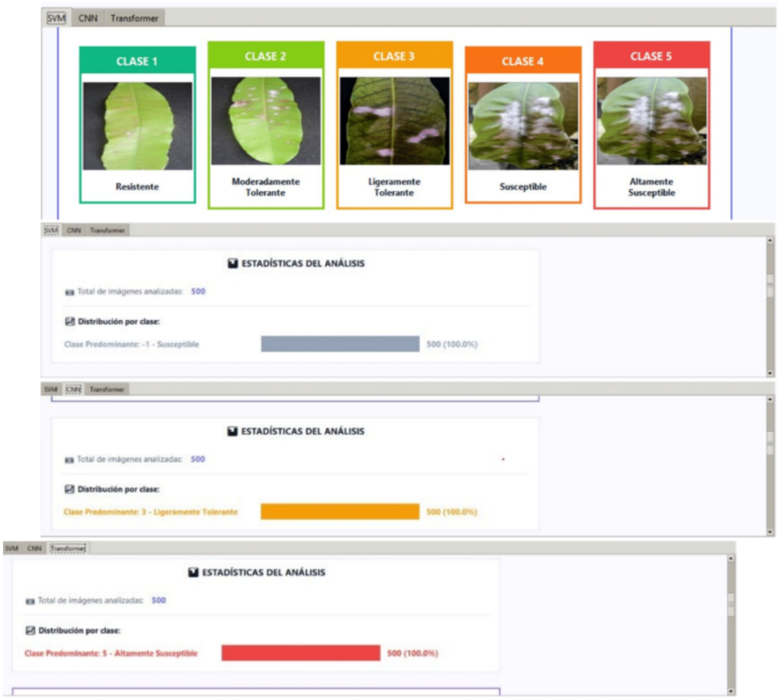

Figure 4: Prediction by Each Model. And for each model, the application calculated the metrics upon image upload.

Figure 5: Metrics display.

The overall performance of the six models showed significant differences in classifying mango leaves infected with Oidium mangiferae versus healthy leaves. ConvNeXt achieved the highest accuracy (85.02%), closely followed by EfficientNet (84.60%), Vision Transformer (83.94%), and Swin Transformer (83.88%), while CNN (81.92%) and SVM (78.16%) performed significantly worse (see Table 4).

Table 4
Parameters for Each Model.

Model	AVERAGE_ ACCURACY	ACCURACY_sd	PRECISION_ mean	PRECISION_sd	RECALL_ mean	RECALL_sd	F1_mean
SVM	0.7816	0.0268	0.7154	0.0303	0.7716	0.0268	0.7414
CNN	0.8192	0.0196	0.7542	0.0292	0.8092	0.0196	0.7750
Transformer	0.8394	0.0295	0.7846	0.0413	0.8294	0.0295	0.8040
Swin Transformer	0.8388	0.0290	0.7938	0.0333	0.8298	0.0280	0.8084
ConvNeXt	0.8502	0.0284	0.7982	0.0396	0.8402	0.0284	0.8168
EfficientNet	0.8460	0.0297	0.7906	0.0415	0.8360	0.0297	0.8106

Precision was highest for ConvNeXt ($\approx$ 79.82%), EfficientNet ($\approx$ 79.06%), Swin Transformer ($\approx$ 79.38%), and Vision Transformer ($\approx$ 78.46%), compared to 75.42% for the CNN and 71.54% for the SVM. In terms of recall, ConvNeXt detected the highest proportion of infected leaves ($\approx$ 84.02%), closely followed by the other hybrid attention/convolution models, while the SVM had the highest false-negative rate (recall $\approx$ 77.16%). The F1 score was highest for ConvNeXt (81.68%) and EfficientNet (81.06%), followed by Swin Transformer (80.84%) and Vision Transformer (80.40%), demonstrating a good balance between precision and recall in the four top-performing models, as shown in Figure 6. These results demonstrate that models with global attention can improve the classification of diseases in mango leaves [8, 41].

Table 5
Paired Student's t-test compared to the baseline model (Vision Transformer).

Model (vs. Vision Transformer)	Mean Δ	t	p	Significant?
SVM	-5.78 pp	-11.60	<0.001	Yes
CNN	-2.02 percentage points	-5.62	<0.001	Yes
Swin Transformer	-0.06 pp	-0.12	0.901	No
ConvNeXt	+1.08 pp	4.85	<0.001	Yes
EfficientNet	+0.66 pp	4.40	<0.001	Yes
SVM	-5.78 pp	-11.60	<0.001	Yes

A one-way ANOVA confirmed that these differences are statistically significant ($F(5, 294) = 43.83$; $p < 0.001$). Paired comparisons using Student's t-test against the baseline model (Vision Transformer) showed that SVM ($\Delta = -5.78$ pp; $t = -11.60$; $p < 0.001$) and CNN ($\Delta = -2.02$ pp; $t = -5.62$; $p < 0.001$) differed significantly, whereas Swin Transformer ($\Delta = -0.06$ pp; $t = -0.12$; $p = 0.901$), ConvNeXt ($\Delta = +1.08$ pp; $t = 4.85$; $p < 0.001$), and EfficientNet ($\Delta = +0.66$ pp; $t = 4.40$; $p < 0.001$)

show smaller differences, although these are statistically significant in the case of the latter two.

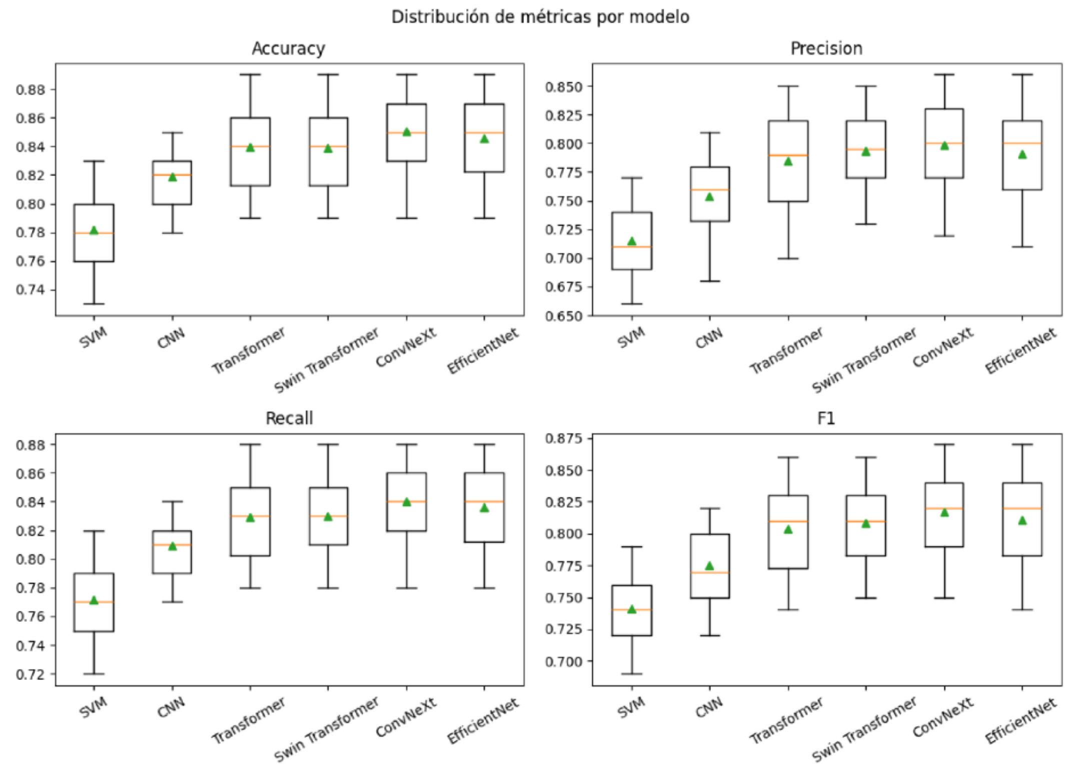

Figure 6: Distribution of metrics by model.

To verify the assumptions of the analysis, the Shapiro-Wilk test indicated that the accuracy of the SVM is consistent with a normal distribution ($W = 0.969$; $p = 0.212$), while the remaining five models deviate slightly from normality ($0.021 \leq p \leq 0.050$). The Levene test revealed heteroscedasticity among the six models ($W = 2.42$; $p = 0.036$), so independent comparisons were performed using the Welch correction.

Table 6
Model-Based Normality Test (Shapiro-Wilk)

Model	W (Shapiro-Wilk)	p	Interpretation
SVM	0.969	0.212	Compatible with normal distribution
CNN	0.945	0.021	Deviates from the norm
Vision Transformer	0.954	0.048	Deviates from the norm
Swin Transformer	0.954	0.050	Deviates from the norm
ConvNeXt	0.949	0.031	Deviates from the norm
EfficientNet	0.945	0.021	Deviates from the norm

Since statistical significance does not always reflect practical relevance, the effect size (Cohen's d) of each model was calculated relative to the Vision Transformer, with Holm-Bonferroni correction for multiple comparisons. SVM ($d = -2.05$, large effect) and CNN ($d = -0.81$, large effect) maintained significant differences after correction (adjusted $p < 0.001$ in both cases). In contrast, Swin Transformer ($d = -0.02$), ConvNeXt ($d = 0.37$) and EfficientNet ($d = 0.22$) showed small or trivial effects and were no longer statistically significant compared to the Vision Transformer after correction for multiple comparisons (adjusted $p = 0.919$, 0.196, and 0.535, respectively).

Table 7
Normality Test by Model (Shapiro-Wilk).

Model (vs. Vision Transformer)	Cohen's d	Magnitude	p (Welch)	Adjusted p(Holm)	Significant?
SVM	-2.05	Large	<0.001	<0.001	Yes
CNN	-0.81	Large	0.000119	0.000476	Yes
Swin Transformer	-0.02	Trivial	0.919	0.919	No
ConvNeXt	0.37	Small	0.065	0.196	No
EfficientNet	0.22	Small	0.268	0.535	No
SVM	-2.05	Large	<0.001	<0.001	Yes

As an additional test of robustness-given that most models deviate from normality-the nonparametric Kruskal-Wallis test was applied, which confirmed highly significant overall differences among the six models (H(5, $N = 300$) $= 114.69$; $p < 0.001$). The Mann-Whitney post-hoc test with Holm correction reproduced exactly the same pattern as the parametric analysis: no significant differences were found between Vision Transformer, Swin Transformer, ConvNeXt, and EfficientNet in any of the six cross-comparisons (all adjusted p-values > 0.32).

Table 8
Kruskal-Wallis — pairs with no significant difference (post-hoc Mann-Whitney + Holm).

Model 1	Model 2	Adjusted p-value (Holm)
Vision Transformer	Swin Transformer	0.999
Vision Transformer	ConvNeXt	0.335
Vision Transformer	EfficientNet	0.886
Swin Transformer	ConvNeXt	0.322
Swin Transformer	EfficientNet	0.886
ConvNeXt	EfficientNet	0.999

Taken together, these results indicate that, although ConvNeXt achieved the highest point accuracy, the statistical evidence does not support the claim that it robustly outperforms the other three hybrid attention-convolution architectures while SVM and CNN do exhibit significantly inferior performance, with large-magnitude effects.

4. Conclusion

The evaluations show that the four global attention and hybrid convolution architectures evaluated perform better in the detection and classification of Oidium mangiferae on mango leaves, achieving higher accuracy, precision, and a better balance between sensitivity and F1 score compared to SVM and CNN. Among these four, ConvNeXt achieved the highest point accuracy (85.02%); however, statistical analysis (ANOVA, t-test with Holm-Bonferroni correction, and Kruskal-Wallis test) found no significant differences among them, so none can be robustly considered superior to the others based on the available data.

Furthermore, it is evident that traditional models such as SVM, although faster and computationally lighter, have difficulty distinguishing between classes with similar visual features, especially in intermediate stages of the disease. In contrast, the CNN, despite its greater complexity and feature extraction capability, also failed to match the performance of the four architectures with the highest accuracy in discriminating between closely related classes; both SVM and CNN differed from these latter architectures by a large effect size (Cohen's d), a difference that remained significant even after correction for multiple comparisons.

Classification of classes 3 and 5 was consistently problematic for all six models, indicating that these categories exhibit significant morphological overlap and blurred boundaries between severity stages.

The difference in performance compared to previous studies (>97% for other diseases) is mainly explained by the greater complexity of distinguishing five continuous stages of a single disease and the variability of field capture conditions. This suggests that the very nature of the disease hinders visual discrimination; therefore, future models may benefit from strategies such as the integration of multispectral information, more aggressive data augmentation, or hybrid architectures that combine hierarchical feature extraction with global attention mechanisms.

Online Resources

https://github.com/MundoCode777/Analisis-de-Cenicilla-Metodo-Mendely

Declaration on Generative AI

During the preparation of this paper, the first author used Claude Sonnet 5.0 to search for references and DeepLM for translation.

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