Application of supervised models and infrared thermography in the identification of mechanical injuries in guava

Aplicación de los modelos supervisados y la termografía infrarroja en la identificación de lesiones mecánicas en la guayaba

Aplicação de modelos supervisionados e termografia infravermelha na identificação de lesões mecânicas em goiaba

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Abstract

Introduction: This article is the result of the research entitled "Application of supervised models and infrared thermography in the identification of mechanical damage in guava," conducted at the University of Cartagena, Colombia, in 2025.

Problem: In agroindustry, fruit classification is based on visual inspection or limited automated systems, making early detection of mechanical damage difficult and leading to economic losses due to post-harvest deterioration, particularly in climacteric fruits such as guava.

Objective: To evaluate the fitting performance of six supervised learning models on a dataset of thermographic images of healthy guavas and guavas with mechanical damage.

Methodology: An adaptation of the CRISP-DM methodology was applied: F1. Business and data understanding, F2. Data preparation, F3. Modeling, and F4. Evaluation and deployment.

Results: Six models were evaluated using cross-validation on 84 thermographic images of healthy and mechanically damaged guavas. Random Forest achieved accuracy, precision, and recall metrics above 0.82 using original images, whereas SVM exceeded 0.85 when cropped images were used.

Conclusion: The feasibility of integrating infrared thermography and supervised learning techniques into automated agroindustrial systems for fruit damage detection is demonstrated.

Originality: A novel approach is proposed based on the integration of infrared thermography and machine learning techniques for the classification of guava fruits with mechanical damage.

Limitations: Image contour segmentation was required to improve model performance, introducing an additional preprocessing stage.

Keywords: machine learning; infrared thermography; guava; mechanical damage.

Resumen

Introducción: El artículo es producto de la investigación "Aplicación de los modelos supervisados y la termografía infrarroja en la identificación de lesiones mecánicas en la guayaba", desarrollada en la Universidad de Cartagena, Colombia, en el año 2025.

Problema: En la agroindustria, la clasificación de frutos se basa en la inspección visual o en sistemas automatizados limitados, lo que dificulta la detección temprana de lesiones mecánicas y genera pérdidas económicas por deterioro poscosecha, especialmente en frutos climatéricos como la guayaba.

Objetivo: Evaluar la capacidad de ajuste de seis modelos de aprendizaje supervisado sobre un conjunto de datos de imágenes termográficas de guayabas sanas y con lesiones mecánicas.

Metodología: Se realizó una adaptación de la metodología CRISP-DM: F1. Entendimiento del negocio y de los datos, F2. Preparación de los datos, F3. Modelado, y F4. Evaluación y despliegue.

Resultados: Se evaluaron seis modelos mediante validación cruzada sobre 84 imágenes termográficas de guayabas sanas y lesionadas. Se observó que Random Forest alcanzó métricas de accuracy, precision y recall superiores a 0.82 con imágenes originales, mientras que SVM superó 0.85 al emplear imágenes recortadas.

Conclusión: Se evidencia la factibilidad de integrar la termografía infrarroja y el aprendizaje supervisado en sistemas automatizados agroindustriales para la detección de lesiones en frutos.

Originalidad: Se propone un enfoque centrado en la combinación de técnicas de termografía infrarroja y aprendizaje automático para la clasificación de frutos de guayaba con lesiones.

Limitaciones: Fue necesario segmentar el contorno de las imágenes para mejorar el ajuste, lo que implicó una etapa adicional de preprocesamiento.

Palabras clave: aprendizaje automático; termografía infrarroja; guayaba; lesión mecánica.

Resumo

Introdução: Este artigo é produto do projeto de pesquisa "Aplicação de modelos supervisionados e termografia infravermelha na identificação de danos mecânicos em goiaba", realizado na Universidade de Cartagena, Colômbia, em 2025.

Problema: Na agroindústria, a classificação de frutas é baseada na inspeção visual ou em sistemas automatizados limitados, o que dificulta a detecção precoce de danos mecânicos e gera perdas econômicas devido à deterioração pós-colheita, especialmente em frutas climatéricas como a goiaba.

Objetivo: Avaliar o ajuste de seis modelos de aprendizado supervisionado em um conjunto de dados de imagens termográficas de goiabas sadias e goiabas com danos mecânicos.

Metodologia: Foi realizada uma adaptação da metodologia CRISP-DM: F1. Compreensão do negócio e dos dados, F2. Preparação dos dados, F3. Modelagem e F4. Avaliação e implantação.

Resultados: Seis modelos foram avaliados utilizando validação cruzada em 84 imagens termográficas de goiabas sadias e danificadas. O Random Forest alcançou métricas de acurácia, precisão e recall superiores a 0,82 com imagens originais, enquanto o SVM ultrapassou 0,85 ao usar imagens recortadas.

Conclusão: A viabilidade de integrar termografia infravermelha e aprendizado supervisionado em sistemas agroindustriais automatizados para detecção de lesões em frutas é evidente.

Originalidade: Uma abordagem focada na combinação de técnicas de termografia infravermelha e aprendizado de máquina é proposta para classificar goiabas com lesões.

Limitações: A segmentação do contorno da imagem foi necessária para melhorar o ajuste, o que exigiu uma etapa adicional de pré-processamento.

Palavras-chave: aprendizado de máquina; termografia infravermelha; goiaba; lesão mecânica.

1. INTRODUCTION

Guava (*Psidium guajava* L.) is a seasonal fruit native to Central America and the Caribbean, belonging to the Myrtaceae family and holding significant commercial importance in more than 70 countries worldwide [1]. In the Colombian context, its production is intended for both fresh consumption and agroindustrial processing into various derivatives from the fruit, seeds, and leaves. It is therefore relevant for food security and the rural economy, particularly in producing regions such as the Caribbean and the Andean zone [2]–[4].

In climacteric fruits such as guava, mechanical injuries caused by impact, compression, and cutting result in irreversible damage and compromise the commercial value of the product [5], [6]. These injuries accelerate the ripening process, leading to senescence, reducing the time to consumer maturity, increasing dehydration, and ultimately causing decay and loss of nutritional value [7]. This condition contributes to the inherently short shelf life of climacteric fruits, resulting in significant postharvest losses [8], [9].

In Colombia, according to the National Planning Department (NPD), food losses during postharvest, storage, and transportation reach 40.4%. In the fruit and vegetable sector, of the 10.4 million tons available annually, 58% is lost, and 28% of these losses occur at the level of supermarkets, stores, marketplaces, and households [10]. According to the Food and Agriculture Organization of the United Nations (FAO), food waste affects the sustainability of food systems, threatens food security by reducing both local and global availability, and impacts the income of producers and retailers, thereby contributing to price increases. Additionally, the inefficient use of natural resources and waste generation negatively affect the environment [11]. In this context, it is necessary to implement alternatives for postharvest monitoring of climacteric fruits to reduce losses. A viable option is infrared thermography, a non-invasive analytical tool that does not require physical contact with the sample and can therefore be used in food analysis without causing damage or contamination, preserving food safety [12]–[14].

Several studies have applied infrared thermography to fruits for different purposes, with some integrating thermal imaging and machine learning approaches. For example, [15] used thermographic images to predict freshness in Roma VF tomatoes stored for five days at room temperature, concluding that tomatoes exhibit extended shelf life and are recommended for consumption when, after five days, their mean temperature drops below 31 °C. Similarly, [13] employed thermography to assess ripening stages in fruits such as avocado and kiwi, which do not exhibit color changes during maturation, demonstrating that thermal imaging is effective in detecting ripening due to variations in specific heat reflected in temperature changes captured by the camera. Likewise, [5] captured thermographic images of guavas with induced lesions, enabling a clear distinction between bruised and healthy tissue under three temperature conditions. In a related study, [16] detected bruises in strawberries using thermal imaging and classified them with a convolutional neural network (CNN), achieving an accuracy of 0.98. Similarly, [17] identified bruises in guava, pomegranate, and apple using thermographic imaging combined with K-means clustering, achieving the highest effectiveness with guava and demonstrating the reliability of this approach for non-destructive agricultural inspection.

Building on these contributions, the relevance of research on the identification of mechanical injuries in fruits using thermographic imaging is evident. However, in the specific case of guava, previous studies have mainly applied unsupervised learning techniques, leaving the implementation of supervised classification models as an open research challenge. In this context, the present study evaluates the fitting performance of different supervised learning models (KNN, Random Forest, Decision

Trees, Logistic Regression, AdaBoost, and SVM) using a dataset of thermographic images of healthy guavas and guavas with induced mechanical injuries. This approach opens the possibility for the future development of automated systems for detecting mechanical damage in fruits within agroindustrial contexts, as models trained on labeled datasets can subsequently classify new input data [18], [19]. Furthermore, by employing open-source software for machine learning workflow design—specifically Orange Data Mining [20]—this methodology can be implemented without the need for costly proprietary tools or advanced technical expertise, which is particularly advantageous for developing countries such as Colombia [21]. Consequently, within the food industry (primary production, processing plants, supermarkets, stores, and marketplaces), such tools facilitate fruit selection processes, enabling prioritization for commercialization or use in by-product production, thereby reducing postharvest losses.

The remainder of this article is organized as follows: Section 2 describes the methodological phases guiding the development of this research. Section 3 presents the results obtained from the training and evaluation of supervised learning models using performance metrics on datasets with cropped and uncropped images. Finally, Section 4 discusses the findings and presents the conclusions derived from this study.

2. MATERIALS AND METHODS

For the development of this research, an adaptation of the CRISP-DM methodology into four phases was carried out: P1. Business and data understanding, P2. Data preparation, P3. Modeling, and P4. Evaluation and deployment. This methodology was selected because it defines a clear and flexible structure that can be easily adapted to the specific needs of the computer vision field, thereby allowing the organization of complex tasks such as image acquisition and processing, as well as the training of detection models, while ensuring that each stage is well documented and aligned with the objectives of this domain [22], [23], [24].

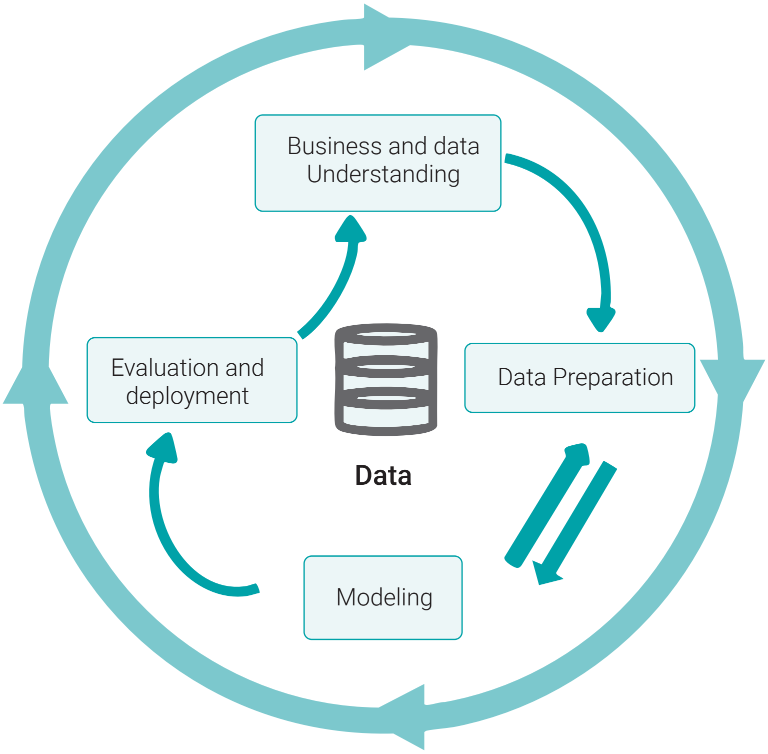
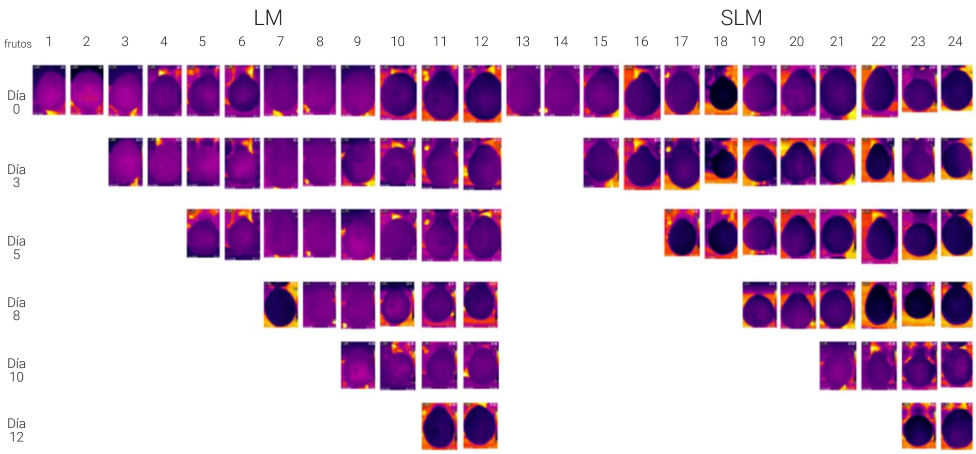


Figure 1. Adaptation of the CRISP-DM Methodology.
Source: own work

In Phase 1 of the methodology, a Guide T-120 thermal camera with a thermal sensitivity of ≤ 45 mK and an accuracy of ±2 °C or ±2% was used to capture 84 thermographic images of guavas, taken at a height of 15 cm. These included guavas with and without mechanical damage induced by the impact of a pendulum specifically designed for this purpose. The samples were stored for 12 days at 5 °C on a plate that held them in place and kept them separated, thus preventing physical contact. In this way, 42 images of fruits with mechanical injury and 42 without injury were generated, as shown in Figure 2, and these were used for training the classification models under consideration. Class balance was taken into account, since imbalanced datasets often lead to bias toward the majority class, causing models to predict the class with more observations, which may result in high overall accuracy but poor performance in correctly identifying the minority class [25], [26], [27].



Note. LM (samples with mechanical damage), SLM (samples without mechanical damage)

Figure 2. Captured thermographic images.
Source: own work

Subsequently, in Phase 2 of the methodology, the thermographic images were preprocessed for the construction of the dataset. First, using the Python OpenCV library, the images were resized to a resolution of 50×50 with three RGB channels, and each image was then flattened into a one-dimensional array of 7,500 positions by leveraging the functionality provided by the Python NumPy library. Based on this, a matrix of 7,500 columns and 84 rows was created (42 rows corresponding to guava images with mechanical damage and 42 without), to which a binary label column was added. In this way, the first 42 rows were assigned a label of 1, representing samples with induced mechanical injury, while the remaining 42 rows were assigned a label of 0, representing samples without injury. From this matrix, a Pandas DataFrame was generated, with its first five rows presented in Table 1.

Table 1. Experimental dataset with uncropped thermographic images

	C1	C2	C3	C4	…	C7497	C7498	C7499	C7500	Label
0	20	1	72	6	…	140	148	1	147	1
1	53	1	101	24	…	109	74	0	117	1
2	156	1	149	74	…	122	108	0	130	1
3	41	1	94	12	…	146	144	0	144	1
4	91	0	119	43	…	111	205	25	84	1
5 rows x 7501 columns										

Source: own work

In the same way, based on the 84 images, a process similar to the one used for the construction of the dataset in Table 1 was carried out; however, in this case, an additional step was performed consisting of cropping the region of interest from each image. Specifically, for each thermographic image, the rectangle enclosing the guava—with or without mechanical damage—was selected. Thus, Table 2 presents the first five rows of the dataset obtained from the cropped images, formatted as a Pandas DataFrame.

Table 2. Experimental dataset with cropped thermographic images

	C1	C2	C3	C4	...	C7497	C7498	C7499	C7500	Label
0	23	0	85	23	...	141	193	13	131	1
1	2	0	39	2	...	214	214	37	78	1
2	38	1	97	40	...	141	141	0	144	1
3	143	0	144	148	...	149	149	0	146	1
4	171	0	159	172	...	154	154	3	152	1
5 rows x 7501 columns										

Source: own work

Subsequently, based on the two constructed datasets, the machine learning workflow was implemented using the open-source tool Orange Data Mining (Demsar et al., 2013). Through this platform, data from both datasets were loaded, followed by sampling using 5-fold cross-validation. Thereafter, six supervised learning models (KNN, Logistic Regression, Decision Trees, Support Vector Machines, AdaBoost, and Random Forest) were trained and evaluated using performance metrics derived from the confusion matrix. Orange Data Mining was selected because it is based on visual programming and provides a wide range of machine learning algorithms, enabling the creation of data analysis workflows in a simple and flexible manner, thus making the approach accessible to professionals from diverse fields of knowledge [28]–[31].

Finally, in Phase 4 of the methodology, a comparative analysis was conducted using the metrics of accuracy, precision, and recall, all derived from the confusion matrix of each classification model. This analysis made it possible to identify the models with the best performance in detecting guava fruits with mechanical injuries.

3. RESULTS

The results are introduced with a description of the machine learning workflow generated in the Orange Data Mining tool [20], which was applied to the two working datasets (original images and cropped images) and is presented in detail in Figure 3.

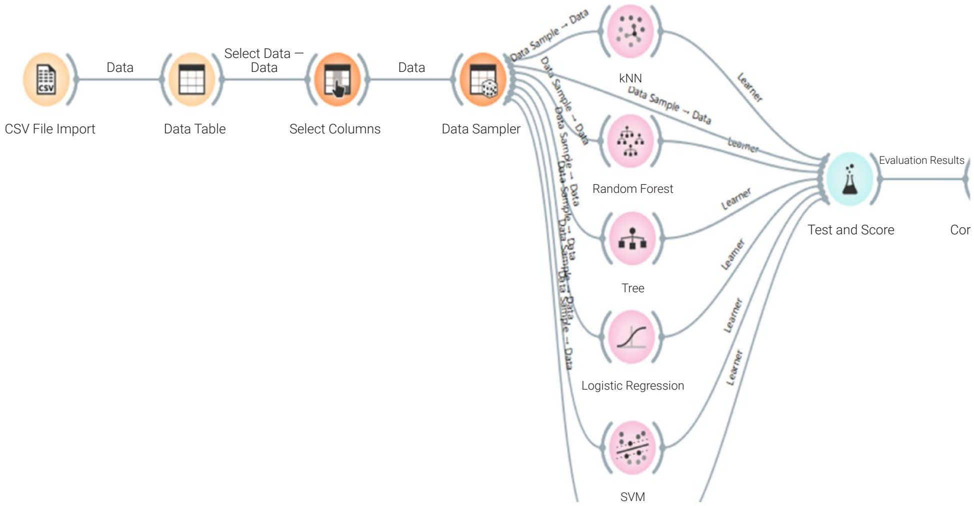


Figure 3. Machine learning workflow implemented using the Orange Data Mining tool.
Source: own work

In Figure 3, the machine learning workflow shows that the dataset is initially loaded through the component "CSV File Import," which allows the incorporation of the .CSV file containing the thermographic image data described in Tables 1 and 2. Subsequently, once the dataset is loaded, its structure of rows and columns can be visualized using the "Data Table" component. In the same manner, after verifying the data, the attributes or independent variables (X), as well as the labels or dependent variables (y), were selected using the "Select Columns" component. Furthermore, data sampling was performed using the "Data Sampler" component, applying 5-fold cross-validation, which enables a robust evaluation of the classification models through multiple iterations with different training and testing sets [32], [33]. After sampling, the six classification models were trained using their corresponding components, configuring different hyperparameters. Likewise, to evaluate the fitting performance of the models through the metrics of accuracy, precision, and recall, the "Test and Scores" component was used. Finally, the visualization of the confusion matrix for each model was carried out using the "Confusion Matrix" component.

Once data sampling was completed using cross-validation, the training and evaluation of the six supervised learning models were conducted. In this context, Table 3 presents the results of each model's fitting performance using the original thermographic images, considering the metrics of accuracy, precision, and recall. The accuracy metric is defined as the proportion of correct predictions made by a classifier over the entire test set. Precision indicates how effectively the classifier identifies true positive cases, reflecting its ability to correctly label positive instances; for example, a model with a precision of 0.84 correctly predicts positive cases 84% of the time. On the other hand, the recall metric, also known as sensitivity or true positive rate, measures the ability of a model to correctly identify true positives, answering the question: of all actual positive cases, what proportion is correctly identified? Thus, a high recall indicates that the number of true positives is relatively higher than the number of false negatives, whereas a low recall indicates the opposite [34]–[37].

Table 3. Performance of the models with the uncropped image dataset.

Model	Accuracy	Precision	Recall
KNN	0.687	0.708	0.687
Random Forest	0.821	0.822	0.821
Tree	0.761	0.765	0.761
Logistic Regression	0.761	0.761	0.761
SVM	0.791	0.800	0.791
AdaBoost	0.731	0.734	0.731

Source: work.

From the results in Table 3, it can be observed that the SVM and Random Forest models achieved the best balance and the highest values across the three evaluated metrics, with scores above 79%, whereas the KNN and AdaBoost models obtained the lowest performance among the six models, with values ranging between 0.69 and 0.73. In this regard, the Random Forest model stood out as the most effective for identifying mechanical damage in guava thermographic images, demonstrating consistent performance across all metrics, with an accuracy of 0.821, a precision of 0.822, and a recall of 0.82. This indicates that the model is suitable for distinguishing between images with and without mechanical damage.

The results presented in Table 3 are more clearly visualized in the bar chart shown in Figure 4, where the superior performance of the Random Forest and SVM models across the three evaluated metrics is evident. Despite this, with the exception of the KNN model, the remaining five models achieved performance levels above 70% in all three metrics, highlighting the relevance of both the machine learning models and the dataset used.

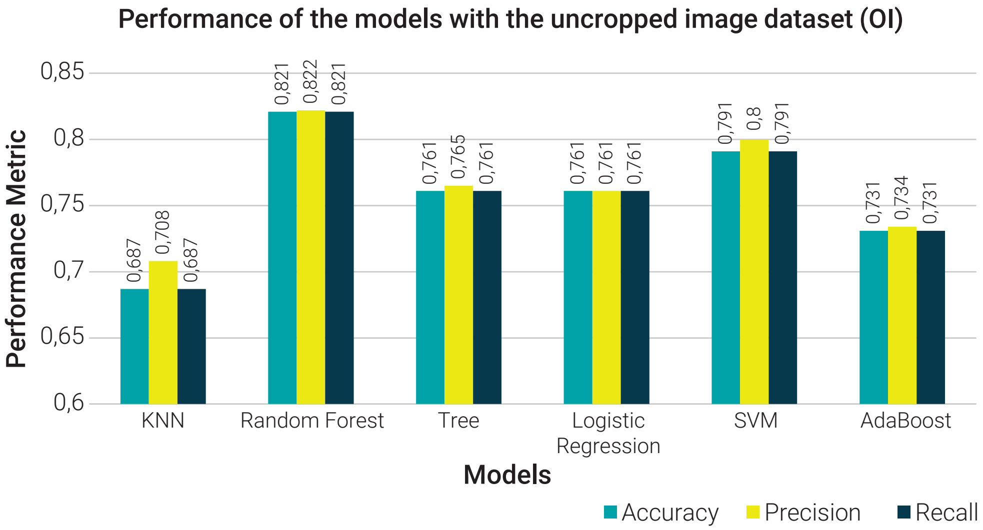


Figure 4. Performance chart of the models with the uncropped image dataset.
Source: own work

When the classification models were trained using the thermographic images cropped to the fruit silhouette, it was observed that the SVM model, with hyperparameters similar to those used with the previous dataset, achieved the highest performance among the six models, with an accuracy of 0.851, a precision of 0.862, and a recall of 0.851 (see Table 4). This model stood out in comparison with AdaBoost, which also showed good performance but with slightly lower values of 0.836, 0.838, and 0.836, respectively. In the same vein, the Random Forest model, which had achieved the highest performance with the uncropped images, ranked third in this case, maintaining results similar to those obtained with the original thermographic images (accuracy of 0.821, precision of 0.822, and recall of 0.821). On the other hand, the KNN and logistic regression models showed the lowest performances, with metric values ranging between 0.70 and 0.73.

Table 4. Performance of the models with the cropped image dataset

Model	Accuracy	Precision	Recall
KNN	0.701	0.730	0.701
Random Forest	0.821	0.822	0.821
Tree	0.731	0.734	0.731
Logistic Regression	0.746	0.749	0.746
SVM	0.851	0.862	0.851
AdaBoost	0.836	0.838	0.836

Source: own work

The above results are more clearly visualized in Figure 5, which presents a bar chart of each model's performance across the three evaluated metrics. As shown in Figure 5, although all models achieved performance above 0.7, the SVM model consistently reached values above 0.85 in all three metrics, demonstrating a strong balance in distinguishing images with mechanical damage from those without. In this way, the SVM model outperformed the Random Forest model trained with the original dataset. This finding indicates that the modified dataset—obtained by cropping the thermographic images to the fruit silhouette—proved to be more suitable for differentiating between guava images with and without mechanical damage using supervised learning models.

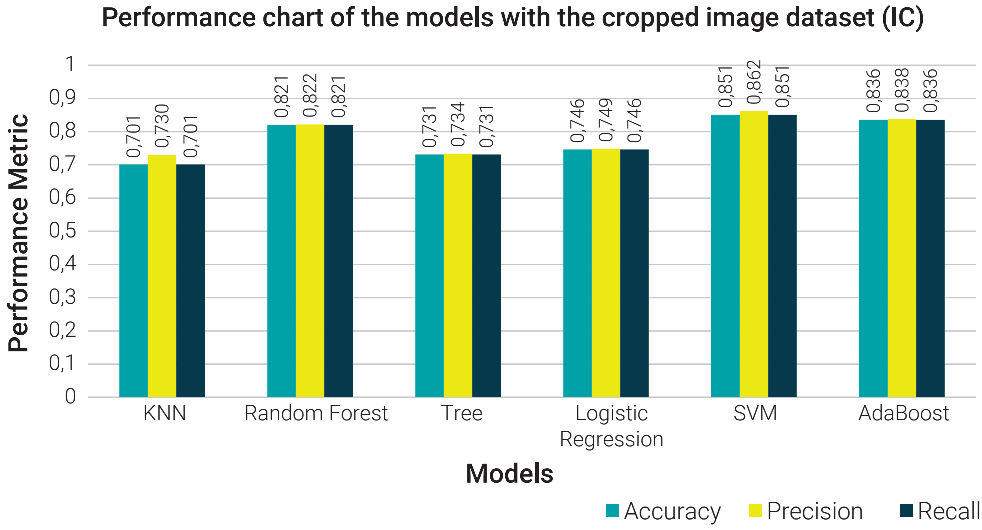


Figure 5. Performance chart of the models with the cropped image dataset.
Source: Own work

The relevance of the dataset with cropped images is more clearly illustrated in Figure 6, which compares the three best-performing models obtained with the uncropped dataset and the cropped thermographic image dataset. It can be observed that, although the Random Forest model achieved the best performance and balance with the original dataset, it ranked third when using the modified dataset, showing comparable results but being outperformed by the SVM and AdaBoost models, both of which achieved values above 0.83 across all three metrics.

In this regard, it is important to highlight that the three best-performing models using the modified dataset reached scores above 0.82, indicating strong differentiation capability between images with and without mechanical damage. In contrast, with the original dataset, only the Random Forest model achieved performance above

0.8, while the SVM and Tree models showed greater variability across the three metrics, with values ranging between 0.76 and 0.8. These findings suggest that the three top-performing models obtained with the cropped image dataset (SVM, AdaBoost, and Random Forest) represent reliable alternatives for implementation in automation applications within the agroindustrial sector.

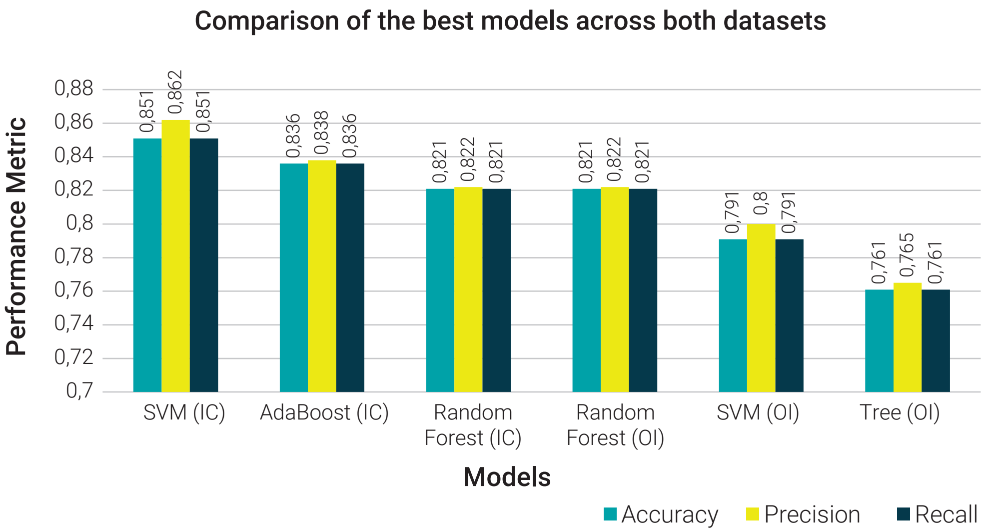


Figure 6. Comparison of the best models across both datasets.
Own elaboration

Finally, comparing the results obtained by the Random Forest model with the original dataset and the SVM model with the cropped image dataset, Figure 7 presents the confusion matrices generated for each model using the cross-validation approach. These matrices compare the actual target values with the values predicted by the machine learning model, thereby providing the basis for evaluating the performance of a classification model [38], [39].

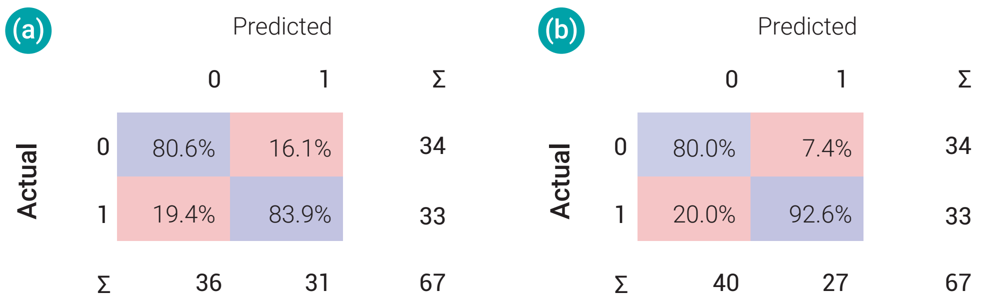


Figure 7. Confusion Matrices: (a) Random Forest on uncropped images, (b) SVM on cropped images
Source: own work

From matrix (a) in Figure 7, it can be observed that the Random Forest model, trained with the original thermographic image dataset, correctly classified 80.6% of the instances corresponding to images without mechanical damage (label 0) and 83.9% of those with mechanical damage (label 1). Similarly, 16.1% of the cases corresponded to false positives, that is, images without mechanical damage incorrectly classified as damaged, while 19.4% corresponded to false negatives, representing damaged images classified as undamaged.

Likewise, matrix (b) shows that the SVM model, applied to the cropped thermographic image dataset, achieved 80.0% accuracy in classifying images without mechanical damage and 92.6% accuracy in identifying damaged images. In this case, the error rates decreased to 7.4% false positives and 20.0% false negatives, demonstrating a substantial improvement in the correct detection of mechanical damage. This highlights the importance of preprocessing strategies using libraries such as OpenCV, NumPy, and Pandas. In summary, the performance of the SVM model on the cropped dataset is superior, particularly in the identification of damaged images, suggesting that preprocessing through cropping enhances class discrimination.

4. DISCUSSION AND CONCLUSIONS

The contribution of this study lies in the use of thermographic images combined with machine learning models, specifically supervised learning models, for the identification of mechanical damage in guava during postharvest, as a competitive alternative for the implementation of automated systems in the agroindustrial sector. In this regard, it was found that, when experimenting with two datasets of thermographic images (uncropped and cropped to the fruit contour), the Random Forest and SVM models achieved the best performance in terms of accuracy, precision, and recall, with values above 0.82 and 0.85, respectively. This strong classification capability in distinguishing images with and without mechanical damage highlights the relevance of the proposed approach. In this sense, the results obtained contribute to the existing body of research [5], [13], [15], [40], in which thermographic imaging was used for the identification of lesions in guava and apples, prediction of fungal growth in strawberries, freshness assessment in tomatoes, and detection of ripening stages in fruits such as avocado and kiwi, without considering the advantages of machine learning for automating damage detection.

In addition, the practical viability of infrared thermography combined with supervised learning models is evident as a non-destructive, non-contact, and scalable tool for postharvest quality control, ensuring food safety by avoiding physical handling.

Unlike traditional visual inspection methods, the proposed approach minimizes operator bias and reduces dependence on subjective human judgment, while enabling early detection of mechanical injuries that may not be visible to the naked eye. This represents a significant advancement in improving decision-making processes related to harvesting, storage, transportation, and commercialization within the guava supply chain.

Experimentation with the dataset of original thermographic images allowed the conclusion that the Random Forest model was the most effective according to the metrics of accuracy, precision, and recall. Similarly, experimentation with the dataset of thermographic images cropped to the fruit silhouette showed that three of the evaluated models (SVM, AdaBoost, and Random Forest) achieved performance above 0.82 across all three metrics, indicating that any of these methods may be suitable for implementation in production environments due to their strong performance in differentiating images with mechanical damage. However, the SVM model stands out as a particularly competitive option, achieving performance levels above 0.85 across all metrics. Therefore, both the evaluated models and the experimental dataset are appropriate and can serve as a reference for the implementation of automated real-time detection systems. Nevertheless, it is important to note that the best results were obtained with cropped images, which implies that, for process automation, a prior segmentation stage of the fruit boundaries in thermographic images is required.

One of the fundamental phases of this research was the preprocessing of thermographic images, a critical step in constructing a high-quality dataset that enables optimal performance of supervised learning models. In this study, preprocessing included cropping, normalized resizing, flattening, and labeling of the images, resulting in a dataset that allowed three of the six evaluated supervised learning models (SVM, AdaBoost, and Random Forest) to achieve high performance. This was made possible through the use of functionalities provided by open-source Python libraries such as OpenCV and Pandas.

The preprocessing strategy applied to thermographic images also contributes to reducing noise and variability associated with image acquisition, such as differences in size and orientation. By standardizing the input data, the study ensured a fair comparison among the models, improving their generalization capability, which is a fundamental requirement for the implementation of automated inspection systems under real agroindustrial conditions.

For the adoption and extrapolation of the proposed approach in industry, it is important to emphasize the use of open-source libraries and technologies, which enable research centers, universities, and companies to easily replicate both the machine learning workflow and the preprocessing stages. In this regard, the OpenCV library facilitated image reading and normalized resizing, while the NumPy library enabled the flattening of images into one-dimensional arrays of uniform size. The Pandas library was used for labeling dataset observations and exporting the dataset for experimentation. Finally, the Orange Data Mining software [20] allowed the visual implementation of the complete machine learning workflow on the constructed dataset, with the added advantage of applying a robust cross-validation approach.

As future work derived from this research, the following approaches are proposed: (a) evaluating the performance of the models applied to thermographic image analysis, considering exclusively the mapped thermal information rather than the color component; (b) analyzing the effectiveness of neural network-based classification models for both the color image dataset and the mapped thermal information dataset; and (c) extending the proposed approach to the identification of mechanical damage in fruits other than guava.

Furthermore, future studies could address the limitations associated with implementing infrared thermography using real-time supervised models, as well as evaluate model robustness under varying environmental conditions.

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