IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 6, December 2025, pp. 4722~4730
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i6.pp4722-4730

Early detection of tar spot disease in *Zea mays* using hyperspectral reflectance and machine learning

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Article Info

Article history:

Received Jun 27, 2024
Revised Aug 27, 2025
Accepted Oct 16, 2025

Keywords:

Machine learning classification
Phyllachora maydis
Spectral signature
Tar spot
Zea mays

ABSTRACT

Ensuring food security and meeting the economic needs of farmers and nations depend heavily on detecting and preventing crop yield losses. Early detection of tar spot caused by *Phyllachora maydis* is crucial to implementing efficient mitigation actions in the earliest stages of infestation. Currently, visual methods are used for detection, which require extensive training and experience from the operator. However, remote sensing techniques can be used to detect tar spot infestation through the selection of wavelengths present in the maize plant spectral signature. This research proposes using machine learning techniques and logistic regression to determine the first stage of tar spot infestation. The results show that the logistic regression model is the most suitable for detecting this first stage, and the k-nearest neighbors classification (KNNC) and random forest classification (RFC) algorithms generate the best classification results. This approach can significantly reduce costs in terms of time, labor, and subjective analysis.

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1. INTRODUCTION

Tar spot, named after the dark-brown lesions [1], is currently one of the main foliar diseases of maize in several Latin American countries [2], [3]. As of 2015 in the United States, the first report of disease occurrence was given [4], [5]. The loss of grain yield caused by the tar spot complex (TSC) can be as high as 51%, contingent upon the level of vulnerability of corn genotypes and the existence of specific environmental factors that promote the growth of this disease [6]. In the year 2021, the occurrence of tar spot led to a substantial reduction in grain production, amounting to a loss of approximately 5.88 million metric tons. This detrimental effect on crop yield had significant economic implications for the United States, resulting in a financial impact of approximately US$1.25 billion. Consequently, there was a noticeable decline in grain output, amounting to a decrease of approximately 1.44%. This disease is caused by an association of two fungi: *Phyllachora maydis* and *Monographella maydis,* along with the hyperparasitic fungus *Coniothyrium phyllachorae* [7]. Although there is currently limited comprehension regarding the mode of interaction occurring between vulnerable maize genotypes and the pathogens, it is evident that the combined effect resulting from their interaction holds significant relevance. This is primarily due to the consequential economic impact it has on grain yield [8].

The primary indications of the ailment are apparent on the plant's leaves, which can become withered in a span of fewer than eight days, because of the merging of wounds caused by various types of fungi and attributed to the creation of a harmful substance [6]. Each of the fungi causes a specific symptomatology: *Phyllachora maydis* initiates with small, shiny, bulging, oval or circular dark spots with a diameter of 0.5 to 2 mm, *Monographella maydis* produces dark spots which are surrounded by a straw-colored halo that is already necrotic tissue; this fungus is the one that causes the most damage, causing the burned appearance of the foliage, it can appear two to three days after *P. maydis* and *Coniotrhyrium phyllachorae*: It is a hyperparasitic fungus that its mechanism is still unknown [8]. Initial symptoms have additionally been documented to manifest as diminutive chlorotic lesions one-week post-infection, succeeded by circular brown to black stromata (indications) dispersed throughout the upper and lower leaf exteriors, occasionally merging into bands. On occasion, stromas may be encircled by a necrotic halo, bestowing upon the lesion a "fisheye" semblance [5], [9], [10]. The disease generally occurs in tropical and subtropical areas, in mountainous, cool and humid areas, which are located between 1300 to 2300 meters above sea level and have favorable environmental conditions for the development of pathogens such as monthly temperatures of 17 to 22 °C, relative humidity greater than 75%, leaf spray in the morning and evening hours, high nitrogen fertilization and low luminosity, all the conditions mentioned above help to favor the potential and rapid development of the pathology [11].

Plant disease evaluation, including the process of both identification and quantification, has traditionally been carried out by highly skilled individuals, either in the field of agricultural cultivation or in the domain of scientific investigation [12]. One of the predominant techniques for gauging the severity of a disease involves the utilization of logarithmic scales presented in diagrammatic form. These scales entail depicting a sequence of plants or plant components exhibiting disease symptoms across a spectrum of intensities. The methodology is rooted in the Weber-Fechner law, positing that the perceptual acuity of damage corresponds proportionally to the logarithm of the stimulus, up to a 50% severity threshold. Beyond this threshold, the correlation becomes inversely proportional to the logarithm of the stimulus, determined by the quantity of remaining healthy tissue [13]. Nonetheless, the visual evaluation of diseases is vulnerable to subjectivity and potential errors stemming from human raters, encompassing discrepancies in skill levels, value preferences, the numerical and size aspects of lesions in relation to the affected area, the intricacy of symptoms, and timing considerations [14]. Furthermore, the process is resource-intensive, demanding both time and financial investment for the training of personnel and the refinement of accuracy in visual assessments. Digital phenotyping technologies present a prospect for augmenting the objectivity and efficiency of detecting and quantifying plant diseases [12].

Recent intensive research has unveiled novel sensor-based approaches for the detection, identification, and quantification of plant diseases. These sensors analyze the optical characteristics of plants across diverse regions of the electromagnetic spectrum, leveraging information beyond the visible range [15]. These methods facilitate the early detection of alterations in plant physiology attributed to biotic stresses, as diseases can induce changes in tissue color, leaf morphology, transpiration rate, canopy structure, and plant density. Moreover, they allow for the assessment of variations in the interaction between solar radiation and plants [16].

Various platforms, including smartphones, robots, airplanes, unmanned aircraft systems (UASs), and satellites, have been utilized for data acquisition in the realm of plant disease detection [17], [18]. Among these platforms, UASs garner notable attention from researchers and producers due to their efficient data acquisition, deployment flexibility, and relatively lower costs compared to imaging methods involving robots, airplanes, and satellites [9], [12], [16], [19]. Complementing these platforms, diverse sensors and imagers, such as red-green-blue or RGB [20], multispectral [12], hyperspectral, and thermal cameras, are employed for data collection. Machine learning algorithms are commonly employed to automatically identify, classify, and quantify plant diseases using the collected data or extracted features [12], [16], [17]. The purpose of this study is to propose methodologies that allow for the early detection of tar spot disease caused by *Phyllachora maydis* in maize, to generate mitigation actions that prevent significant losses in crop yield.

2. MATERIALS AND METHODS

2.1. Definition of the experimental plots

The experimental plots were implemented in the Santagueda Village, municipality of Palestina (Colombia). The characteristics of the area are, average temperature of 25.8 °C, altitude of 1,010 meters above sea level, annual average precipitation of 2,200 mm and relative humidity of 76%. A homogeneous lot of approximately one hectare was used. Yellow maize hybrid ATL 200 plants were sown at 80 cm between rows, with 7 seeds per square meter. An integrated pest and disease management was carried out to eliminate external factors in the experiment.

2.2. Spectral signatures capture

The FLAME-T-VIS-NIR Spectrometer with a range of 350 to 1000 nm and an optical resolution of 1.5 nm was used to take spectral signatures. Calibration was performed with a calibration target of 99% reflectance and a dark object of minimum reflectance, to reduce noise in the reflectance of each measurement. Subsequently, sampling plants were identified, and their spectral signature was taken at a 45º angle, avoiding shadow formation, that is, allowing direct sunlight to shine on the surface of the leaves. Between 6 and 10 spectral signatures were taken from each sample, distributed equally between low and high leaves, and then averaged for each type of sample.

2.3. Tar spot severity evaluation

The diagrammatic scale proposed by [13] was used for the evaluation of disease severity of the tar spot disease. Based on the area affected by the pathogen on the leaves, and by visual comparison with the scale, the severity class was defined in the leaves of the plant (see Figure 1). The objective of this study is to determine the moment when the crop is affected by the pathogen. In this sense, the classification requirements focus on establishing the earliest moment of contagion (class 1) to initiate treatment and avoid losses in yield.

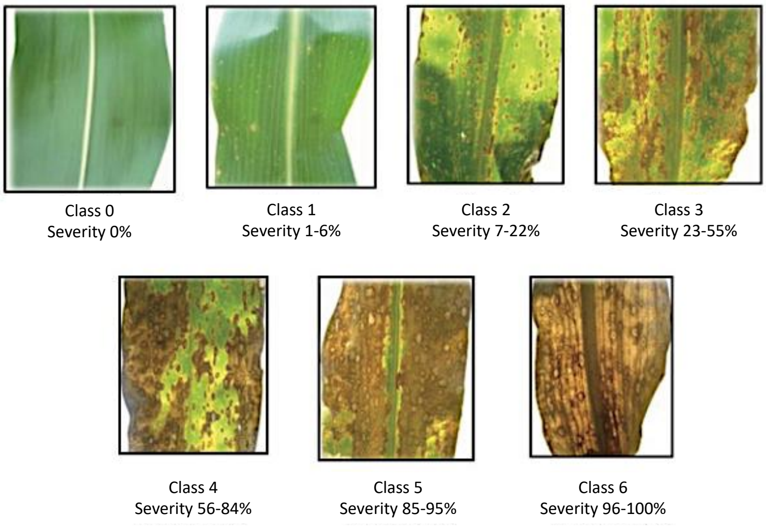


Figure 1. Diagrammatic severity scale for the tar stain complex in maize [13]

2.4. Data analysis

Once spectral signatures were collected, the data was extracted and loaded in Excel (Microsoft® Excel for MAC v16.63) for preprocessing of the spectral signatures. Initially, the edges of the signatures were removed, resulting in signatures between 400 to 900 nm. Subsequently, the signatures were smoothed and normalized to eliminate noise, and finally, the signatures of the same severity were averaged to obtain a single reference signature per severity. Then, with classes 0 and 1, machine learning models were applied to define the best classification model that allows for early identification of the disease before it can cause irreparable damage to crop yields. Additionally, a logistic regression model was evaluated for classification, considering that a dichotomous categorical variable is to be classified.

2.5. Machine learning classification algorithms

To determine the best machine learning classification model that responded to the research objective, eight classification algorithms were executed: boosting classification (BC), decision tree classification (DTC), k-nearest neighbors classification (KNNC), linear discriminant classification (LDC), neural network classification (NNC), random forest classification (RFC), and support vector machine classification (SVMC) [21]–[23]. Additionally, the logistic regression model was analyzed, considering the need to classify two possibilities of the plant's state (class 0 and class 1). The R (R 4.2.2 GUI 1.79 Big Sur ARM build (8160) and RStudio v2023.03.0+386 (2023.03.0+386)) [24] and JASP (v0.17.1 Apple Silicon) [25] software was used to execute the models. The hyperparameters for the machine learning models in the

JASP software were automatically adjusted by the software in its programming. Assumptions and data integrity were checked in R software using Anderson Darling tests.

2.6. Model performance

Principal component analysis (PCA) was performed on the complete spectral signature obtained from each plant to determine the most suitable wavelengths for training the machine learning algorithms. The filtered database containing the PCA wavelengths was randomly divided into 80% training data and 20% test data. Several performance criteria were selected: accuracy, precision, recall, F1-score, and area under curve (AUC). Furthermore, the model's performance was evaluated using receiver operating characteristics (ROC) curves as a criterion. ROC curves depict the relationship between the true positive rate (TPR) and the false positive rate (FPR), which reflects the sensitivity and specificity. As sensitivity increases, specificity decreases and vice versa. A curve closer to the upper left corner of the graph indicates higher accuracy of the algorithm. Conversely, a curve closer to the diagonal (45°) indicates a performance accuracy that is no better than guessing. For the logistic regression model, using the same wavelengths determined with PCA, the best model is calculated using the backward elimination method.

3. RESULTS AND DISCUSSION

The results allow us to determine that the best algorithm for detecting the second level of infestation is KNNC followed by SVMC in terms of accuracy, precision, and recall. In terms of AUC the best result is obtained with RFC, while the best F1 is obtained with the KNNC algorithm (Table 1). The results in Table 1 can be corroborated with the ROC curves in Figure 2. In Figure 2(f) the best performing curves are RFC, and Figure 2(c) KNNC as they are the closest to the upper left part of the plot. The weakest performance as a function of ROC curves and AUC was for the NNC, SVMC, and DTC algorithms (see Figures 2(e), 2(g), and 2(b) respectively). In Figures 2(a) and 2(d) are the case of BC and LDC algorithms, the response is intermediate.

Table 1. Model performance of the seven classifiers

Model	Accuracy	Precision	Recall	AUC	F1
BC	0.680	0.627	0.680	0.802	0.583
DTC	0.760	0.751	0.760	0.675	0.742
KNNC	0.780	0.773	0.780	0.812	0.767
LDC	0.760	0.751	0.760	0.805	0.742
NNC	0.720	0.702	0.720	0.595	0.688
RFC	0.740	0.735	0.740	0.814	0.704
SVMC	0.760	0.758	0.790	0.658	0.773

For the logistic regression model, based on the backward model, six wavelengths were established as the ideal ones (see the first column of Table 2). With these characteristics for the logistic regression model, the confusion matrix shows the results summarized in Table 3. Table 3 presents the results in the form of a confusion matrix with an accuracy of 83.46%, this metric refers to the dispersion of the set of values obtained from repeated measurements of a magnitude. The recall or sensitivity and specificity are two values that indicate the capacity of our estimator to discriminate the positive cases from the negative ones, in the case of the logistic regression model the values obtained are 91.39% and 61.76% respectively. The performance metrics of the logistic regression model are presented in Table 4, while the estimates plots are shown in Figure 3 with a 95% confidence interval. Figure 4 illustrates the performance of the logistic regression model from the ROC curve with satisfactory results for the classification of the first two pest infestation stages.

Table 2. Logistic regression model summary

Parameter	Estimate	Standard error	z	Wald test		
				Wald statistic	df	p
(Intercept)	20.271	5.736	3.534	12.490	1	< .001***
625.12	54.595	14.547	3.753	14.084	1	< .001***
698.819	95.218	36.037	2.642	6.981	1	0.008**
703.083	-156.034	37.569	-4.153	17.250	1	< .001***
722.749	53.637	9.187	5.838	34.085	1	< .001***
762.496	-21.486	3.789	-5.670	32.152	1	< .001***
889.68	-16.518	6.404	-2.579	6.652	1	0.010**
(Intercept)	20.271	5.736	3.534	12.490	1	< .001***

Note. SEVERITY level '3%' coded as class 1.

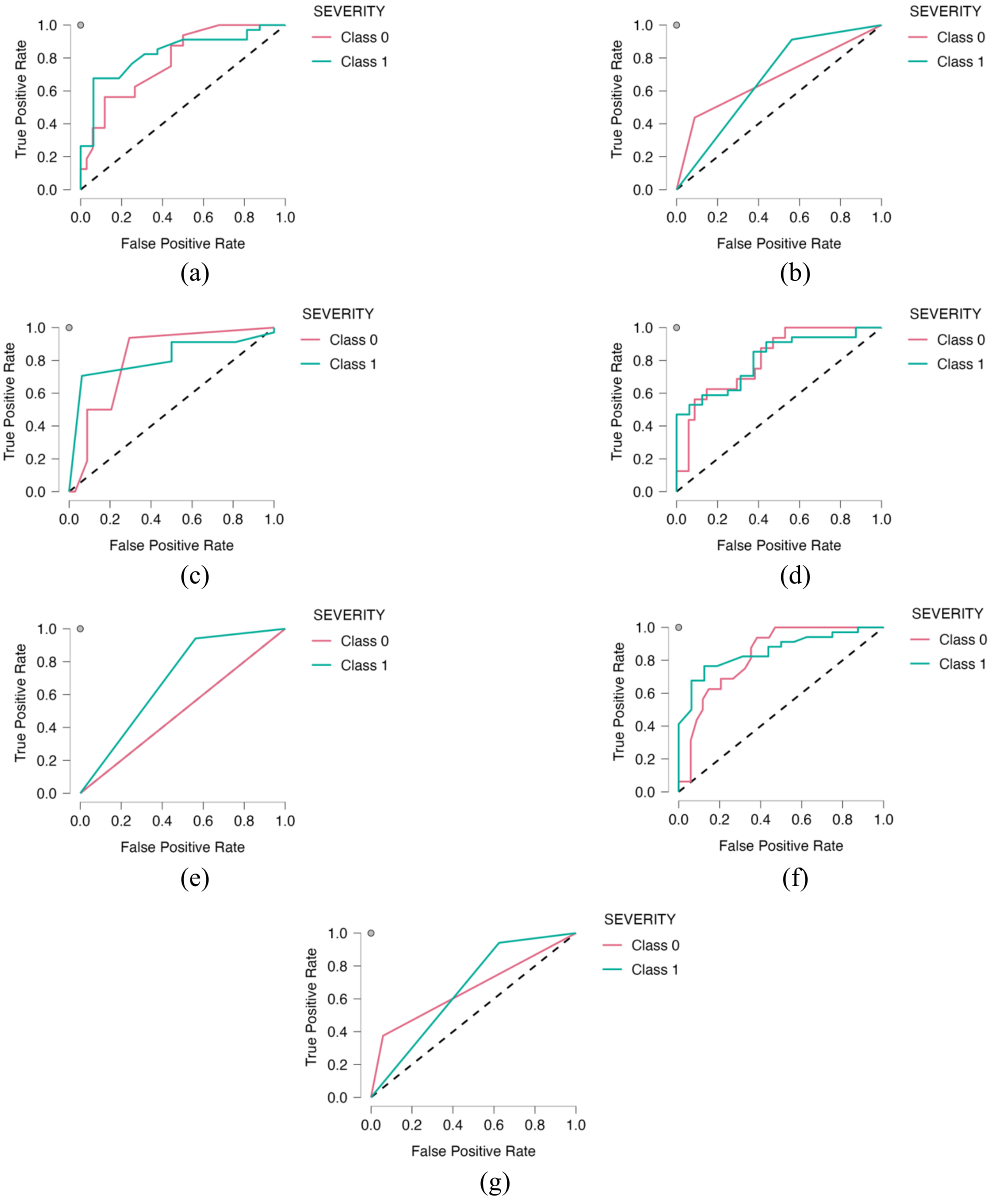
Table 3. Confusion matrix for the logistic regression model

Observed	Predicted		% Correct
	Class 0	Class 1	
Class 0	42	26	61.765
Class 1	16	170	91.398
Overall % correct			83.465

Note. The cut-off value is set to 0.5

Table 4. Logistic regression model summary

Performance metric	Value
Accuracy	0.835
AUC	0.902
Sensitivity	0.914
Specificity	0.618
Precision	0.867
F-measure	0.890
Brier score	0.113
H-measure	0.515



(a) (b) (c) (d) (e) (f) (g)

Figure 2. ROC curves plots for the seven classifiers: (a) BC, (b) DTC, (c) KNNC, (d) LDC, (e) NNC, (f) RFC, and (g) SVMC

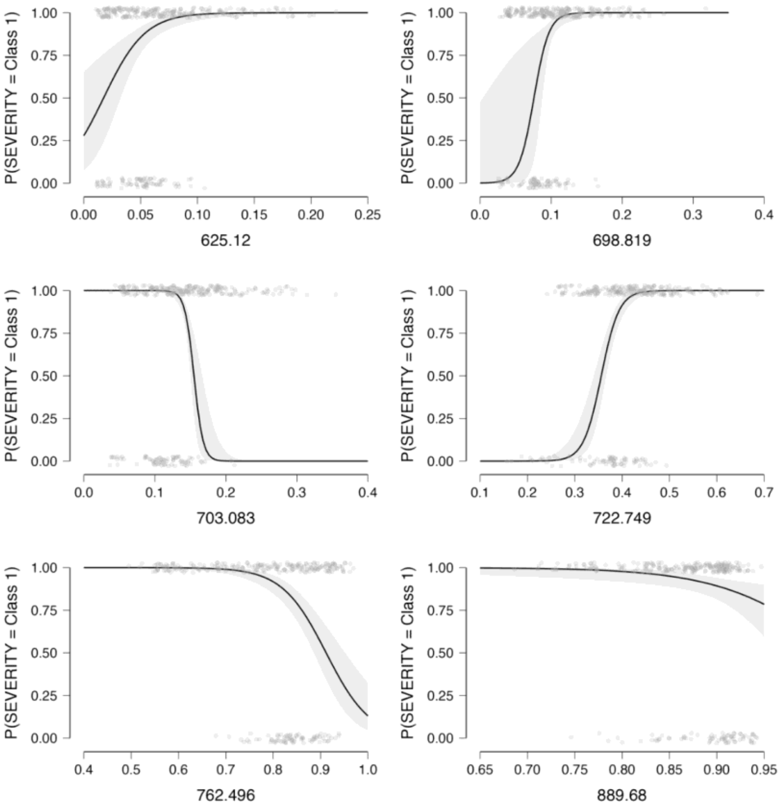


Figure 3. Conditional estimates plots with a 95% confidence interval for the logistic regression

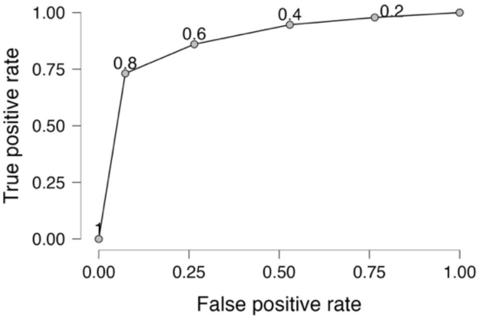


Figure 4. Performance of the logistic regression model

In the literature review conducted for this research, it has been observed that the detection and characterization of tar spot infection levels are still carried out using visual techniques [13], which require highly trained personnel and time-consuming fieldwork for sampling. The visual detection model for tar spot proposes 7 levels ranging from "class 0" with no presence of the disease to "class 6" indicating total vegetative loss of the plant [13]. However, late detection of infestation can lead to significant economic losses in the crop, as the disease progresses rapidly after "class 2" infestation, making control more challenging. It should also be noted that visual detection is a sampling process, and in large crop areas, incorrect detections can occur as it is impossible to visualize the entire plant population. In this regard, the detection of the initial "class 1" stage of infestation is of utmost importance for the crop management process, but, detecting the first stages of tar spot infestation by *Phyllachora maydis* visually can be a subjective process for an untrained or inexperienced eye [12]. Therefore, proposing remote sensing-based solutions that allow for early and easy detection of infestation is crucial for the profitability of maize cultivation.

The ML methods proposed in this study allow for the classification of the first two levels (class 0 and class 1) with an accuracy between 68% and 78%, with KNNC and RFC models showing the best

AUC. The logistic regression method based on spectral signatures allows for the classification of the first level of infestation (class 1) with a TPR (sensitivity) of 91.4% and an overall accuracy of 83.5%, making it the best model for predictions in this experiment. These results enable effective infestation control actions to be taken at a time when classifications that could not be efficiently detected visually (class 1) are identified.

The present study successfully establishes a processing pipeline for hyperspectral reflectance signatures to accurately detect tar spot disease in field trials. The advantages and the need for a first-level infestation determination model were discussed using two machine learning models and one logistic regression model, comparing their performance metrics. The logistic regression model showed the best performance for detecting the first level of infestation "class 1" while having lower computational cost compared to the machine learning models. The performance metrics of the three proposed models were calculated following the recommendations of [21]. Improvements and advancements in infestation detection can be achieved using airborne multispectral sensors. Finally, it is important to highlight that the proposed method is objective and eliminates the subjectivity of the evaluator and the need for extensive prior field experience. Considering the arguments presented, we conclude that tar spot detection using multispectral methods supported by numerical calculations is a potential tool for determining the first level of infestation in field conditions. It has been demonstrated that this technology can replace the laborious work of visual scoring by providing reliable parameters efficiently. The presented approach can be transferred to agricultural practice for decision-making in integrated pest management.

4. CONCLUSION

Detecting the first stage of tar spot infestation by *Phyllachora maydis* visually can be a subjective process for an untrained or inexperienced eye. Therefore, proposing remote sensing-based solutions that allow for early and easy detection of infestation is crucial for the profitability of maize cultivation. The machine learning methods proposed in this study allow for the classification of the first two levels (class 0 and class 1) with an accuracy between 68% and 78%, with KNNC and RFC models showing the best AUC. The logistic regression method based on spectral signatures allows for the classification of the first level of infestation (class 1) with a TPR (sensitivity) of 91.4% and an overall accuracy of 83.5%, making it the best model for predictions in this experiment. These results enable effective infestation control actions to be taken at a time when classifications that could not be efficiently detected visually (class 1) are identified. Future work would allow the optimization of classification algorithms based on cross-validation models and the use of high-resolution imagery as remote sensing tools to improve infestation classification processes.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Oscar Cardona-Morales	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓
Oscar López-Naranjo	✓				✓	✓			✓	✓			✓	
Freddy Eliseo Hernandez-Jorge	✓				✓	✓			✓	✓			✓	✓
Yeison Alberto Garcés-Gómez		✓	✓	✓	✓			✓	✓	✓	✓			✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [YAG], upon reasonable request.

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