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Enhancing Pest Detection: Assessing *Tuta absoluta* (Lepidoptera: Gelechiidae) Damage Intensity in Field Images through Advanced Machine Learning

Alperen Kaan BÜTÜNER[a], Yavuz Selim ŞAHİN[a], Atilla ERDİNÇ[b], Hilal ERDOĞAN[c*], Edwin LEWIS[d]

[a]*Bursa Uludağ University, Faculty of Agriculture, Department of Plant Protection, Görükle Campus, 16059 Bursa, TÜRKIYE*
[b]*Bursa Uludağ University, Faculty of Engineering, Department of Computer Engineering, Görükle Campus, 16059 Bursa, TÜRKIYE*
[c]*Bursa Uludağ University, Faculty of Agriculture, Department of Biosystems Engineering, Görükle Campus, 16059 Bursa, TÜRKIYE*
[d]*Department of Entomology, Plant Pathology and Nematology, University of Idaho, USA*

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Corresponding Author: Hilal ERDOĞAN, E-mail: hilalerdogan@uludag.edu.tr
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ABSTRACT
The tomato (*Solanum lycopersicum* (Solanaceae)) is particularly susceptible to *Tuta absoluta* (Meyrick) (Lepidoptera: Gelechiidae), a pest that directly and profoundly influences tomato yields. Consequently, the early detection of *T. absoluta* damage intensity on leaves using machine learning or artificial intelligence-based algorithms is crucial for effective pest control. In this ground-breaking study, the galleries generated by *T. absoluta* were examined via field images using the Decision Trees (DTs) algorithm, a machine learning method. The unique advantage of DTs over other algorithms is their inherent capacity to identify complex and vague shapes without the necessity of feature extraction, providing a more streamlined and effective approach. The DTs algorithm was meticulously trained using pixel values from the leaf images, leading to the classification of pixels within regions with and without galleries on the leaves. Accordingly, the gallery intensity was determined to be 9.09% and 35.77% in the test pictures. The performance of the DTs algorithm, as evidenced by a high precision and an accuracy rate of 0.98 and 0.99 respectively, testifies to its robust predictive and classification abilities. This pioneering study has far-reaching implications for the future of precision agriculture, potentially informing the development of advanced algorithms that can be integrated into autonomous vehicles. The integration of DTs in such applications, due to their unique ability to handle complex and indistinct shapes without the need for feature extraction, sets the stage for a new era of efficient and effective pest control strategies.

Keywords: Convolutional neural networks, Decision trees, Image processing, Pest management, Precision agriculture

1. Introduction

The tomato (*Solanum lycopersicum*) is a plant belonging to the Solanaceae family, and is widely cultivated worldwide due to its high nutritional value. Production is significantly increased, especially in countries such as China, India, Türkiye, Italy, the United States, and Spain. Therefore, economically, the products obtained from the tomato plant are precious, and minimizing product loss is a primary objective (Viggiani et al. 2009; González-Cabrera et al. 2011; Urbaneja et al. 2012; Veres et al. 2020). Invasive insect pests of crops cause considerable losses in agriculture (Veres et al. 2020). *Tuta absoluta* (Meyrick) (Lepidoptera: Gelechiidae), commonly called the tomato leaf miner (Lietti et al. 2005), is one of the most widely invasive pest species and has been recorded on every continent except Antarctica (Cely et al. 2010). This pest is oligophagous but is best known for the damage it causes to tomatoes (*Solanum lycopersicum* (Solanaceae), where it can cause yield losses of up to 100% (Biondi et al. 2018). *T. absoluta* damages the leaves, buds, branches, and stems, but the most important damage is the galleries formed between the two epidermis tissues (Viggiani et al. 2009). Chemical control is the most common method to manage this pest. The harmful effects of pesticides on non-target organisms have been identified by studies conducted in recent years (Urbaneja et al. 2012; Erdoğan et al. 2023). This research addresses machine learning-based *T. absoluta* gallery density as an aid to early-stage pest control. Thus, pesticides may be applied to the right location instead of the whole plant and prevent excessive use of pesticides. Early detection plays an essential role in successful pest management (Li et al. 2021). For example, yellow sticky traps are used for early detection, but this requires a lot of labour and time in the need to count the pests over the traps (Aliakbarpour & Rawi 2011). The increased use of technology in agriculture has provided new methods to acquire such data (Wolfert et al. 2017; Weersink et al. 2018; Şahin et al. 2023). In this context, the use of image processing techniques based on machine learning is an effective way to obtain agricultural data (Vibhute & Bodhe 2012; Singh et al. 2016). For instance, Ozguven & Adem (2019) employed deep learning algorithms to detect leaf spot disease in sugar beet with an accuracy rate of 95.48%. Similarly, Gerdan et al. (2023) have achieved accuracy values of up to 99.82% by employing deep learning algorithms for the detection of certain diseases observed in tomato plants.

The objective of this study was to calculate the damage intensity caused by *T. absoluta* on the tomato plant through image processing techniques based on machine learning. This is because training machine learning-based algorithms that allow data to be classified and described can provide faster, more accurate and real-time pest detection than human observation (Finger et al. 2019). Allowing us to control pests at an early stage may also contribute to the development of algorithms that can be integrated into autonomous vehicles designed within the scope of precision agriculture. In summary, this study aims to provide a faster and more accurate solution for the early-stage detection of pests and prevention of excessive pesticide use by calculating the damage caused by *Tuta absoluta* using machine learning-based image processing techniques, specifically employing the Decision Trees (DTs) method.

2. Material and Methods

2.1. Image acquisition

The study was carried out on tomato plants produced in the farmland of Bursa Uludağ University, Faculty of Agriculture (Figure 1). Adults and larvae of *T. absoluta* were collected and identified using the morphological characters (size, scale pattern, shape, colour, etc.) determined by Nayana & Kalleshwaraswamy (2015). Images of *T. absoluta* larvae damage on leaves (galleries) were recorded using a Canon EOS 700D camera with a resolution of 5184 x 3456 pixels. A total of 1000 infested leaf pictures were taken in 1 week to train the DT algorithm. Pictures were taken about 40 cm from the leaf surface. 20% of the images were allocated for training the DTs algorithm and the rest for testing.

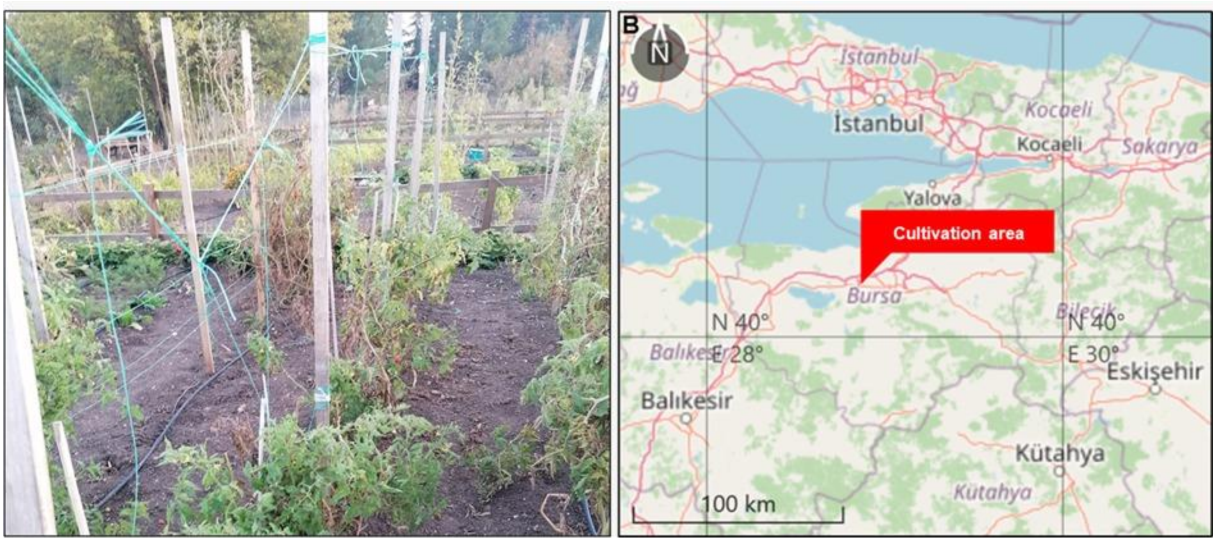

Figure 1- A: Tomato cultivation area. B: The location of the cultivation area. Location: 40°13' 38.6'' N, 28° 51' 55.8 ''E, 50 m asl

2.2. Classification by decision trees (DTs)

DTs are a non-parametric supervised machine learning algorithm (Vishnoi et al. 2021). The Classification and Regression Tree (CART) decision tree algorithms that are commonly used for detecting plant pests and disease were utilized in this study (Bhatia et al. 2020; Daniya et al. 2020; Gallardo-Romero et al. 2023; Liu et al. 2023). The matric values of the soil, galleries, healthy leaves, stems, and weeds in the original images were recorded to detect gallery intensity by DTs (Figure 2). These matrix values are made up of square pixels (image elements) arranged in columns and rows. Each digital image may contain pixel colors of different intensities. The combination of red, green, and blue creates the perception of color.

Figure 2- Matrix values of the healthy leaf (A), gallery (B), stems (C), soil (D), and weeds (E)

Matrix values were used to train and test the DTs. The classification was performed using the DTs algorithm and the precision and accuracy rate were calculated. The classification is started by creating a root node, after which the entropy value is calculated for all the data trained on the node (Adi et al. 2017; Liu et al. 2023). Galleries created by *T. absoluta* were visualized with a black tone in the test images, while a light grey tone was chosen for healthy leaf tissues. Grayscale values of the soil surface, weeds, healthy leaves, stems, and galleries from field pictures that are used for DTs training were set as in Table 1.

Table 1- Grey colours in RGB

Classifications	*R (Red)*	*G (Green)*	*B (Blue)*
Soil surface	90	90	90
Weeds	120	120	120
Stems	240	240	240
Healthy leaves	180	180	180
Galleries	0	0	0

2.3. Working diagram of decision trees algorithm

The process of using the Decision Trees (DTs) algorithm to classify matrix values in pictures of a tomato field infested by *T. absoluta*, to determine the intensity of damage caused by the pest, can be illustrated as follows:

I. Collect a dataset of images from a tomato field infested by *T. absoluta* (Figure 3)
II. Convert the images into matrix values representing the pixels in the image, including the values of the soil, galleries, healthy leaves, stems, and weeds.
III. Use the matrix values to train a DTs algorithm, in which the algorithm learns to recognize patterns in the matrix values that correspond to the presence of galleries and healthy leaves in the images. The algorithm starts by using the matrix values of the soil, galleries, healthy leaves, stems, and weeds as input features.
IV. The algorithm then builds a tree-like model by iteratively selecting the feature that best separates the data into different classes (in this case, the different matrix values of soil, galleries, healthy leaves, stems, and weeds) (Figure 4).
V. At each node of the tree, the algorithm compares the matrix values of the input feature to a threshold value and makes a decision based on whether the values are greater or less than the threshold. This splits the data into two or more subsets, each represented by a child node.

VI. The process is repeated for each child node until a stopping criterion is met, such as reaching a maximum depth or a minimum number of samples in a node.

VII. The resulting tree can be used to predict the class of new samples by traversing the tree from the root node to a leaf node.

Figure 3- Collecting a dataset of images from a tomato field infested by *T. absoluta*. Regions with galleries are shown in a red circle

In the context of detecting gallery areas, the algorithm would use the matrix values as input features and the pixel values as the output. The algorithm would then build a tree-like model that uses the matrix values to predict the pixel values. Once the gallery areas are identified, the algorithm calculates the number of pixels in those areas, which would give you the total area of the galleries in pixels.

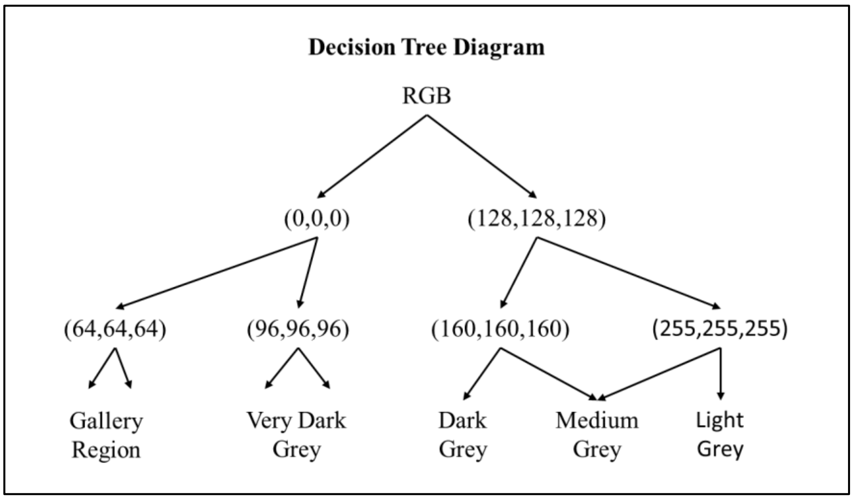

Figure 4- Selecting the feature that best separates the data into different classes

2.4. Determination of gallery intensity

T. absoluta damage intensity was determined using the DTs algorithm. The intensity was estimated by determining the pixel numbers of the areas with and without a gallery in the field images. It was calculated by the ratio of the total pigment number of the gallery-containing regions to the total pigment number of the healthy leaf regions (Goncalves et al. 2021). The intensity rate and precision are calculated by Equation (1) and Equation (2) respectively (G: Gallery area, H: healthy leaf area, I: Intensity rate (%), True Positive (TP): A True Positive is a correct identification of a positive instance in a classification task, where both the actual and predicted classes are positive. False Positive (FP): A False Positive is an incorrect identification of a negative instance as positive, where the actual class is negative, but the predicted class is positive.

$$I = \left[\frac{G}{G+H} \times 100\right] \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

3. Results

The matrix values of the soil, stems, weeds, galleries, and healthy leaves taken from the original images in the field were used in the training of DTs, which is a non-parametric supervised machine learning algorithm. During the training process, these matrix values are clustered to make comparisons on the X, Y, and Z axes using the K-Nearest Neighbor (K-Nn) method (Hamdini et al. 2021). Clustering is visualized on the X, Y, and Z-axis (Figure 5).

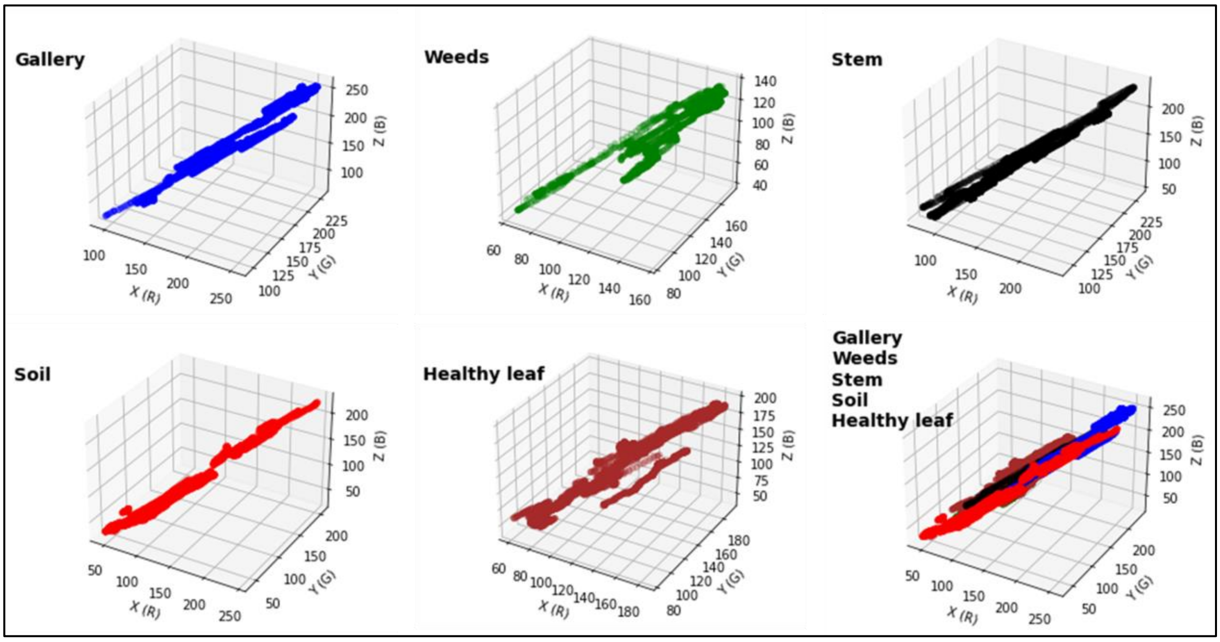

Figure 5- Clustering of RGB matrix values of healthy leaf, gallery, stems, soil, and weeds as in the original images from the field along the X, Y and Z-axes

The confusion matrix, representing the evaluation of a classification model on five distinct classes (galleries, weeds, stems, soil, and leaves), provides key insights into the model's performance. The galleries class is excellently classified with 282 577 correct predictions, while the weeds class is highly accurate but misclassified in some instances as stems (215) and soil (2,151). The stems and soil classes exhibit confusion with 239 557 and 215 108 correct predictions, respectively, and the leaves class shows high accuracy with 343 798 correct predictions. Some misclassification is observed, notably between stems and soil. The aggregate precision across these classes is 97.5%, reflecting the model's overall accuracy and highlighting areas for potential refinement in training and feature engineering (Figure 6).

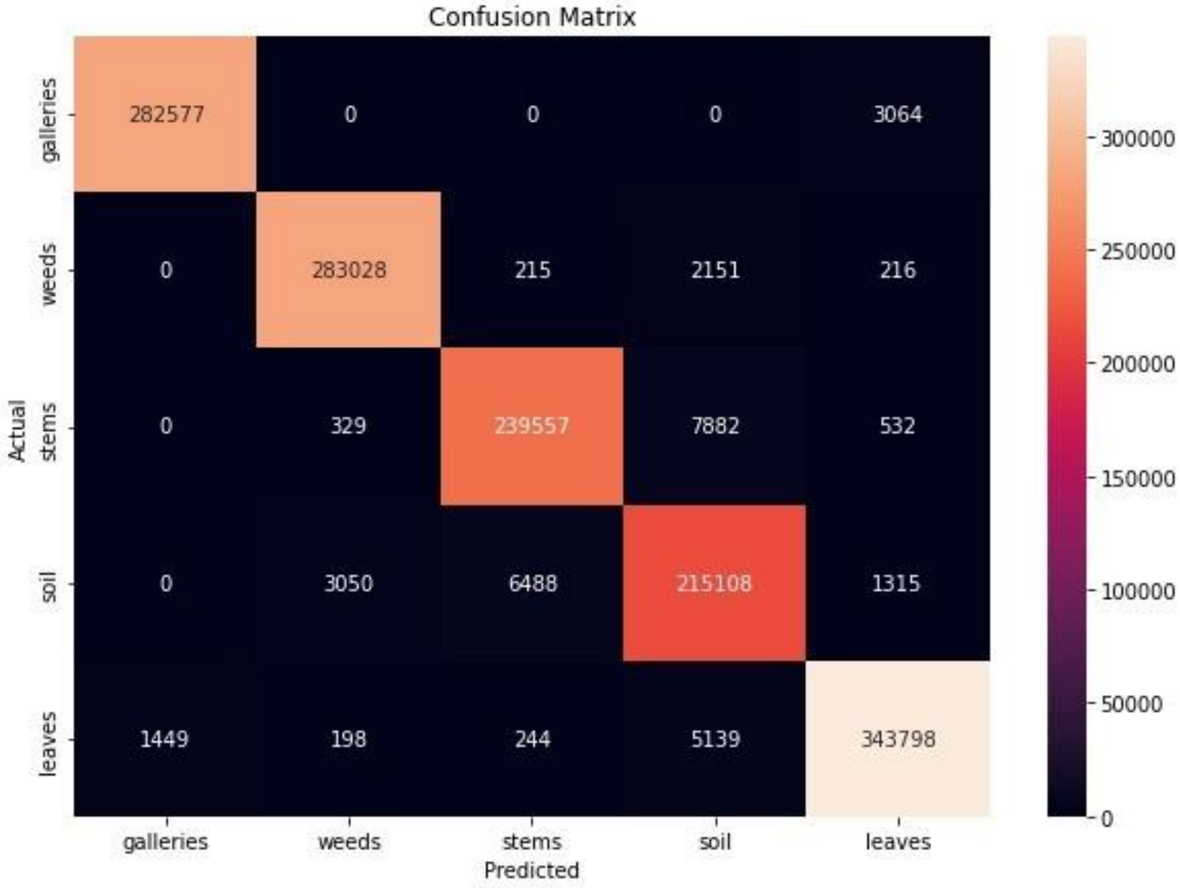

Figure 6- Confusion matrix of the classification model for the five classes (galleries, weeds, stems, soil, and leaves)

The classification model was trained and evaluated using a diverse dataset encompassing distinct classes. The evaluation metrics, including training accuracy, test accuracy, precision, recall, and F1-Score (Table 2), provide an essential understanding of the model's capability in predicting the correct classes. These metrics collectively affirm the model's robustness and predictive accuracy, reflecting a harmonious balance between the true positives and the overall number of actual positives and predictions. In this investigation, a DTs was utilized to classify various elements within an image, and the computational aspects of the methodology were assessed. The training process of the model was completed in a time of 3.08288 minutes, aligning with the theoretical time complexity of $O(n \cdot mlogm)$, where n represents the number of samples and m represents the number of features. The image prediction phase was executed in a remarkably brief span of 0.076231 seconds, corresponding to a time complexity of $O(p)$, with p denoting the total number of pixels in the image. These findings underscore the efficiency of the approach, highlighting its potential for real-time applications in the domain of image-based object recognition and categorization (Table 2).

Table 2- Evaluation metrics for the classification model, including training accuracy, test accuracy, precision, recall, and F1-Score

Training Accuracy	99%
Test Accuracy	98.7%
Precision	98%
Recall	97.54%
F1-Score	97.50%
Training Time for the Model	3.08288 minutes
Time Required for Test Image-Based Prediction	0.076231 seconds
Time Complexity for Prediction Based on Test Image	$O(p)$

Figure 7. shows the pictures used as test data in the training of the DTs algorithm; In “B”, the grayscale of image “A”, the total pixel values of Galleries and healthy leaves are 12101 and 121007, respectively. The precision and accuracy rate were determined as 0.98 and 0.99, respectively. In “D”, the grayscale of image “C”, the total pixel values of galleries and healthy leaves are 29764 and 53454, respectively. The precision and accuracy rate was determined as 0.98 and 0.98, respectively. According to the test results based on gallery intensity, 9.09% of tomato leaves were infested by *T. absoluta* in “A” while 35.77% of tomato leaves were infested by *T. absoluta* in “C”.

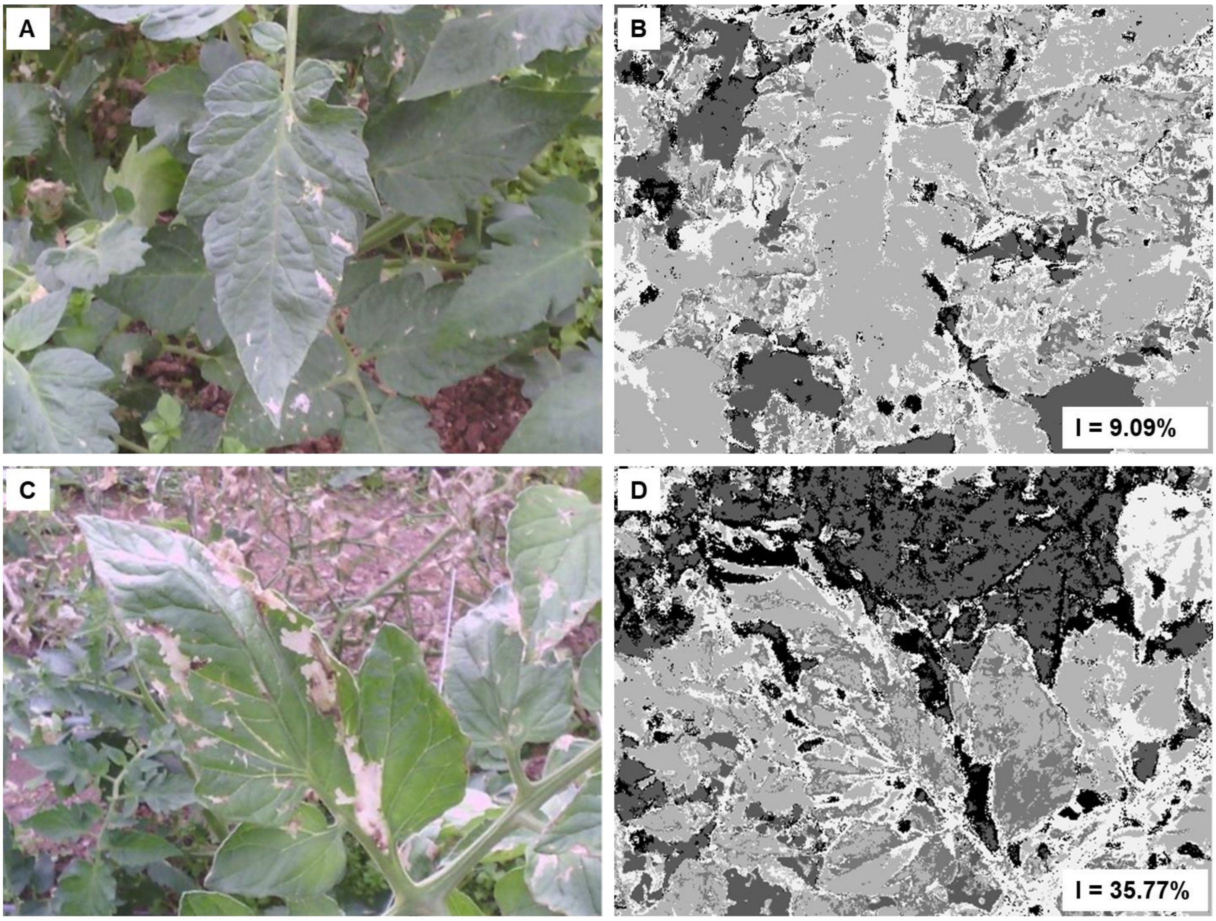

Figure 7- The test image changes to grayscale by clustering matrix values of soil, galleries, weeds, stems and healthy leaves (I = Intensity rate of galleries)

4. Discussion

Artificial Intelligence algorithms, specifically those based on Convolutional Neural Networks (CNNs), have a demonstrable effectiveness in various studies for identifying invasive pests. These methodologies offer rapid and accurate detection of agricultural pests, often surpassing the accuracy and speed of human observation (Li et al. 2022). Such algorithms facilitate the categorization and identification of data gleaned from images (Wolfert et al. 2017, Yan et al. 2021; Kiobia et al. 2023). However, the effectiveness of CNN-based models may be impeded by non-distinct object shapes in the images used for training. This complication could necessitate a larger data set for training and extend the training process (He et al. 2016; Lin et al. 2023). For instance, pests like *Cydia pomonella* and *Tuta absoluta* cause damage on leaves and fruits that may lack a distinct and stable structure. However, machine learning models like DTs are capable of classifying and learning from all the pixels of objects in images, even if those objects lack a clear shape. This property suggests that DTs might be able to discern complex shapes more effectively (Pedregosa et al. 2011; Collado & Tumibay 2023; Lin et al. 2023). Consequently, this study opted to employ the Decision Trees model, a supervised learning algorithm, instead of CNN-based models. Drawing from the work of Goncalves et al. (2021), CNN-based algorithms have shown promising results in the segmentation of necrotic leaf lesions caused by several plant disease agents, such as *Phakopsora pachyrhizi* (Soybean rust: SBR), *Pyrenophora tritici-repentis* (wheat tan spot: WTS), and *Leucoptera caffeina* (the coffee leaf miner: CLM). In the 2021 study of Goncalves et al., images were manually annotated and divided into three classes: injured leaf, healthy leaf, and leaf background. When comparing the annotated severity with the estimates, the concordance coefficients were found to be greater than 0.96, 0.98, and 0.95 for SBR, WTS, and CLM, respectively, after the leaf background was manually removed. The present study, however, approached this task from a different perspective. Rather than manually removing the background, the background elements (soil and weeds) in the field images were incorporated into the training of a Decision Trees (DTs) algorithm. This machine learning approach was employed to identify the gallery intensities created by *T. absoluta* larvae. Significantly, the algorithm was capable of detecting gallery intensities of 9.09% and 35.77% in the test images, eliminating the need for manual background removal. The precision was calculated as 0.98, indicating a high level of predictive accuracy. This suggests that machine learning models like DTs may offer a viable alternative to CNNs for pest detection, particularly in scenarios where manual background removal is impractical or undesirable. The relative strengths and weaknesses of these methods should be considered in future research and application in the field of precision agriculture. Diverse methodologies have been utilized in the context of image-based plant disease detection, as evinced by the studies conducted by Sabrol & Kumar (2016), Zou et al. (2021), and Sriwastwa et al. (2018). The approach taken by Sabrol &

Kumar (2016) enabled the determination of 78% of disease intensity in tomato plants using the Decision Trees (DTs) algorithm. The machine learning-based algorithm developed by Zou et al. (2021) facilitated the calculation of the wormhole areas ratio in broccoli seedling leaves, achieving a precision of 0.85 after manually separating the leaves from the background. Furthermore, Sriwastwa et al. (2018) deployed Otsu (1979) method's, a technique for automatic image thresholding, to perform insect detection via color-based segmentation. In contrast to these studies, the research currently under consideration embodies several distinguishing aspects. Firstly, a markedly higher precision of 0.98 was achieved, indicative of a superior predictive capability when compared to the performance reported by Zou et al. (2021). Secondly, an important deviation from prior research lies in the strategy of directly introducing background features, such as soil and weeds, into the DTs algorithm, thereby eliminating the need for manual background removal. This streamlined approach offers potential advantages over the methodologies employed by Zou et al. (2021) and Sriwastwa et al. (2018), which required manual pre-processing. In conclusion, the potency and utility of AI algorithms, notably those leveraging CNNs and DTs, have been corroborated through their crucial role in identifying and categorizing invasive pests. However, while CNNs have shown potential in similar studies, their dependence on distinct shapes within images can sometimes introduce limitations. This research spotlights the capability of DTs to tackle complex shapes more efficiently, removing the necessity for manual background elimination - an aspect that often hinders CNNs. A noteworthy achievement of this research, in comparison to previous studies, is the attainment of an exceptional precision of 0.98, indicating high predictive accuracy. This enhancement is made possible through the direct incorporation of background elements into the DTs algorithm, thereby eliminating the requirement for manual pre-processing and potentially streamlining the pest detection process. The current investigation provides an innovative viewpoint on the application of machine learning in pest detection, setting the groundwork for subsequent research. It reemphasizes the significance of choosing the most suitable algorithm, one that aptly addresses the unique challenges and requisites of each distinct case. As this exploration of varied methodologies progresses, it is expected to catalyse advancements in precision agriculture, ultimately encouraging the development of improved pest detection and disease control strategies.

5. Conclusions

This study sought an innovative method to address the problem of invasive pest detection in agriculture. Utilizing DTs as a supervised learning algorithm, the study diverged from conventional CNN-based methodologies, recognizing their limitations in handling non-distinct object shapes. By incorporating background elements, such as soil and weeds, directly into the training of the DTs algorithm, the research achieved a remarkable precision of 0.98. This indicated a high predictive accuracy, surpassing prior studies and eliminating the requirement for manual background removal, a step often essential in CNNs. The study's approach offered not only a viable alternative to CNNs for pest detection but also heralded potential advancements in precision agriculture. Significantly, this work contributes to the broader academic discourse by presenting an innovative method that aptly tackles unique challenges in pest detection. The success in utilizing DTs to detect complex shapes efficiently reemphasizes the need to consider diverse methodologies in pest detection. It sets a solid foundation for further research to develop more effective pest detection and disease control strategies.

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