Dicle University
Journal of Engineering
https://dergipark.org.tr/tr/pub/dumf
duje.dicle.edu.tr

Research Article

Thermal Image Processing for Automatic Detection of Fusarium Root and Crown Rot Disease In Tomato Plants

Ayşin BİLGİLİ[1*]

[1:] GAP Agricultural Research Institute, Planth Health Department, Sanlıurfa, aysin.bilgili@tarimorman.gov.tr, Orcid No: 0000-0003-0801-0484.

ARTICLE INFO

Article history:

Received 10 August 2023
Received in revised form 11 October 2023
Accepted 24 October 2023
Available online 31 December 2023

Keywords:

Plant disease, thermal imaging, machine learning, tomatoes

Doi:10.24012/dumf.1340922

* Corresponding author

ABSTRACT

Plant diseases can lead to significant yield losses and economic damages, but these losses can be mitigated through early disease diagnosis. In recent times, remote sensing techniques have been widely used for early disease detection even before visible symptoms appear. This study focused on the potential of early detection of Fusarium Root and Crown Rot in Tomato Plants, which causes substantial yield losses in tomato plants, under controlled conditions using thermal images. In this research, thermal images were obtained from both disease-inoculated and disease-free control plants throughout the plant growth period under controlled conditions. These images underwent preprocessing in a computer environment, and various feature parameters related to temperature changes in both groups (such as minimum, maximum, standard deviation, and skewness) were extracted. These extracted features were then used as inputs for different machine learning techniques, including K-Nearest Neighbors (KNN), Logistic Regression (LR), and Naive Bayes (NB), to classify healthy and diseased plants. Overall, the disease-inoculated plants exhibited higher average temperatures compared to the healthy control plants. The performance of the compared machine learning techniques in distinguishing between healthy and diseased plants was found to be in the order of KNN, NB, and LR, with success rates of 72%, 68%, and 60%, respectively. This study demonstrated the potential of using combined thermal images with different machine learning techniques for early diagnosis of Fusarium Root and Crown Rot in Tomato Plants. The results show promising prospects for utilizing thermal imaging in the early detection of plant diseases, leading to better management and reduction of yield losses and economic impacts.

Introduction

Plant diseases cause significant losses in the yield and quality of cultivated crops reducing food security [1]. Globally, yield losses due to plant diseases can reach up to 20-30 percent [2],[3], depending on the type of plant and pathogen involved. However, these losses can be mitigated through early intervention and the use of advanced disease detection techniques. Traditionally, diseases have been identified using visual assessments and field surveys. Although these methods are commonly employed, they are expensive, time-consuming and more suitable for small-scale areas. Early intervention in disease management can also help reduce the inaccurate and excessive application of pesticides, offering environmental and economic benefits [4]. Consequently, research on this topic is of utmost importance [4],[5].

In recent years, the combination of remote sensing techniques and machine learning methods has become increasingly prevalent for disease detection. Remote sensing techniques offer several advantages, including quicker disease diagnoses and reduced labor requirements, particularly when dealing with large areas [1]. Spectroradiometry and satellite imagery are among the remote sensing methods that have successfully been used for the early detection of various plant diseases [6], [7].

Thermal imaging has emerged as a popular non-destructive and user-friendly technique for detecting plant diseases, applicable in both laboratory and field settings. It operates by capturing radiance in the infrared spectrum (7-12 micrometers) and translating it into visible images, enabling the detection and measurement of temperature variations in objects. The application of thermal imaging has been extensively studied in diverse fields, including agriculture [8].

Thermal imaging technology detects temperature changes in plants caused by disease or pest infestation, indicating the presence of stress in the affected region [9]. These temperature fluctuations, which can be captured effectively using thermal imaging, are a result of internal chemical changes in infected plants and cannot be observed using visual imaging methods [10]. Analyzing these thermal changes provides valuable insights for early disease prediction and offers a promising approach for disease management.

Various studies have reported the use of thermal imaging technology for pre-symptomatic identification of diseases

[1], [9], [11], [12]. In their study, Raza et al. [11] developed a machine learning system to remotely detect plants infected with the tomato powdery mildew fungus. They combined thermal and visible light image data with depth information to improve detection accuracy. The researchers extracted a novel feature set from the image data using local and global statistics, which proved effective in capturing relevant information about the plants and their infection status. By integrating these features with depth information, they achieved a significant improvement in accuracy. Moreover, their feature set not only identified plants intentionally inoculated with the fungus but also detected plants that acquired the disease through natural transmission during the experiment. Overall, their findings demonstrated the potential of this combined approach for accurately detecting diseased plants and identifying both initially infected and naturally transmitted infections.

Tomatoes are a globally cultivated vegetable, with production exceeding 187 million tons and covering an area of over 5 million hectares. Türkiye ranks as the third-largest tomato producer globally, with a production of 13,204,015 tons and an area of 181,879 hectares in 2020 [13]. Tomato cultivation takes place in open fields as well as controlled environments like greenhouses. However, tomato crops are vulnerable to root rot and soil fungal diseases, leading to significant losses. Common fungal pathogens affecting tomatoes include *Fusarium* spp., *Rhizoctonia solani,* and *Sclerotium rolfsii.* Among them, *Fusarium* species, particularly *Fusarium solani* and *Fusarium oxysporum*, are responsible for a substantial proportion of plant diseases. Vascular wilt, a disease affecting tomatoes, is caused by a pathogen that enters the plant through roots or wounds and colonizes the vascular tissue, resulting in wilting. Root and crown rot diseases, characterized by wilting, yellowing, and drying of the plant, occur during the plant's growth period in the field [14].

Fusarium wilt can cause widespread epidemics, leading to significant yield reductions, sometimes up to 100%. Hyphae of the pathogens are activated by plant root secretions, allowing them to penetrate the roots and disrupt metabolism of the plant and sap circulation. As a result, the plant experiences reduced photosynthetic activity, wilting, and eventual death, impairing its ability to absorb and transport water and nutrients.

Remote sensing techniques, including spectral methods, have been extensively studied for the early detection of *Fusarium* root and crown rot diseases in tomatoes. However, the application of thermal imaging in the detection of root diseases in tomatoes is relatively limited. Specifically, in the case of tomato plants, there is a lack of studies focusing on the use of thermal imaging for detecting *Fusarium* spp. or other root diseases.

The goal of this study was to determine the effectiveness of thermal imaging in distinguishing between diseased and healthy tomato seedlings that were inoculated with a specific pathogen. The study aimed to assess the potential of thermal imaging as a method for identifying and monitoring disease progression in tomato plants during their development stages.

Materials and methods

Climate room trial

Tomato (*Lycopersicum esculentum* L.) seedlings used in this study were grown in a climate room in the Plant Health Laboratory of GAP Agricultural Research Institute (GAPTAEM) at Sanliurfa province, Türkiye. H-2274 tomato variety sensitive to *Fusarium* spp. was used in this study. All the physical conditions of the climate room such as temperature (26◦C), humidity (60%) and lighting (16 hours of light, 8 hours of darkness) were controlled at constant level. In the pots, a 1:1 mixture of peat and perlite was employed [15].

Tomato plants have been infected with *Fusarium* spp. disease. After the *Fusarium* disease was inoculated at the rate of 10^4 cfu/gr on tomato plants [14], the presence of the pathogen was tried to be detected with a thermal camera. The diseased tomato plants were screened by comparing with the healthy plants without any treatment. In this way, two different groups of tomato plants were obtained; these are diseased and inoculated with *F. solani* and *F. oxysporum* (*Fusarium* +), and healthy and uninoculated with *Fusarium* spp. (*Fusarium* -). Each group consisted of four pots and each pot was formed from 4 tomato seedlings. From each pot five leaves were randomly selected for thermal camera measurements.

The data used in the study are the reflection values taken from the tomato leaves by the thermal camera. To symbolize classes; (F) described tomato plants inoculated with *Fusarium* and (H) described as healthy tomato plants refers that the situation is present or not present.

Experimental setup and inoculation of tomato plants

The root, crown rot and wilt fungi disease isolates used in the study were obtained from the Southeastern Anatolia Project (GAP) tomato fields and tested for their pathogenicity. Isolates with high levels of pathogenicity (*F. solani* 70 % and *F. oxysporum* 80 %) were used in testing. (Fig. 1.).

Artificial inoculation was performed by introducing fungal agar discs (2 mm in size) into autoclaved oat culture mixed with potato dextrose agar (PDA). The mixture was then allowed to grow for 2–3 weeks in an incubator. Subsequently, a 25 g/m^2 artificial culture of the fungal isolates was added to 2 kg pots containing a peat and perlite mixture in a 1:1 ratio by volume. Tomato seedlings, which were cultivated in controlled greenhouses at GAPTAEM Koruklu Research Station, were transplanted into the pots when they reached the 3–4 leaf stage, which was approximately 40–45 days after germination. Each fungus (*F. solani* and *F. oxysporum*-FORL) and the control group (non-inoculated plants) were subjected to separate experiments. The experiment followed a randomized plot design with 4 replications, and each replication contained

3 plants. Scala values used to evaluate the disease were 0-3, sensitive, moderate and resistant. The entire setup was kept in the Climate Chamber of the Plant Health Department of GAPTAEM (GAP Agricultural Research Institute Directorate) under controlled conditions, maintaining a temperature range of 24 °C – 25 °C and a humidity level of 60% throughout the

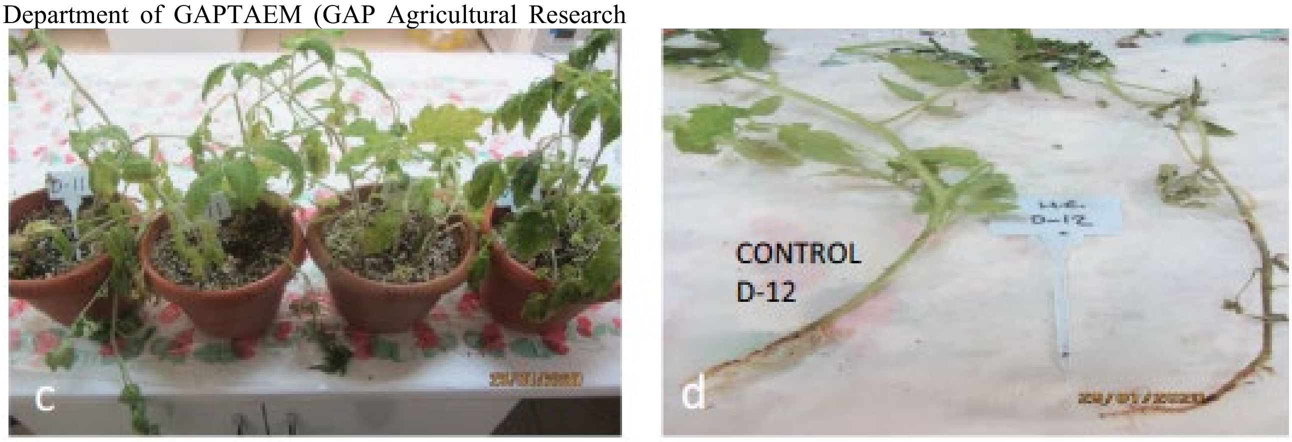

Figure 1. In the left picture-c; Furthest right pot is Healthy Control Plants with uninoculated *F. solani* (F -), the other pots from right 2. 3. and 4. pots are Diseased Plants inoculated with *F. solani* (F +). In the right picture-d; The right tomato seedling is Diseased Plant inoculated with *F. oxysporum* (F+) and the left tomato seedling is Control-*F. oxysporum* (F-).

growing season. To monitor the progression of the experiment, thermal images were taken every week for 6 weeks, starting from the date the seedlings were planted in the pots.

Table 1. Thermal imagining sampling times and the number of samples taken

Date	Control	Diseased
20.12.2019	11 Sample	12 Sample
27.12.2019	12 Sample	12 Sample
02.01.2020	12 Sample	12 Sample
09.01.2020	12 Sample	12 Sample
17.01.2020	12 Sample	12 Sample
23.01.2020	12 Sample	12 Sample

Thermal camera

The thermal camera serves as a diagnostic tool utilized across different industries to detect and measure abnormal temperatures or cold areas in specific regions. It comprises lenses and sensors designed to capture the thermal energy emitted by objects. Unlike other temperature-measuring devices, the thermal camera does not require direct contact with the equipment being assessed. Instead, it operates as an imaging system that analyzes infrared energy patterns. The camera translates this invisible infrared energy into visual representations, displaying the general structure of the image, along with colors and shapes corresponding to the infrared energy distribution. As a result, the thermal camera can identify issues that may not be visible to the naked eye, providing valuable insights into hidden problems and potential malfunctions [1], [16].

In this study, the TESTO 885 model thermal camera was used. The camera has a detector size of 320*240 pixels. The thermal information obtained is enhanced using SuperResolution technology, bringing it to a size of 640*480 pixels. The camera allows measurements with a temperature resolution of 0.03°C. Thermal imaging is recorded at a 30-degree angle. Additionally, the camera captures RGB images, but the resolution and field of view for RGB images are higher. To utilize the images taken by the camera in the software, the camera's proprietary software, IRSOFT, was used to open and obtain both the thermal and RGB images on the computer (Fig.2.).

Image Fusion of Thermal and RGB Images

The thermal camera used simultaneously captures thermal images and records RGB images. However, there are differences in the field of view, size, and resolution between the recorded thermal and RGB images. This dissimilarity complicates their combined usability during image analysis. To overcome this problem, an image alignment or registration process, known as Image Registration, is performed. With this process, the objects in the two images are brought to the same position or aligned. The image registration is carried out using a point matching method, specifically the SIFT (Scale-Invariant Feature Transform) algorithm. This algorithm ensures scale-invariant feature transformation, enabling the matching of features between the thermal and RGB images. After the thermal and RGB images are successfully aligned, the resulting image is cropped to match the size of the thermal image.

Figure 2. Thermal imagining

Plant Regions Segmentation and Obtaining Thermal Image Data of Plant Regions

Flow Diagram given in Fig.3 shows the steps in early distinguishing of root rot disease in tomatoes.

In thermal images, all temperature information in a specific area is obtained on a pixel-by-pixel basis. Therefore, processing the entire thermal image can lead to erroneous results. To address this, the plant region is detected based on RGB images, and other areas are cleared from consideration. This process involves color-based segmentation, where the RGB image is transformed into the HSI (Hue-Saturation_Intensity) color space using the expressions given in Equations given below. The resulting Hue data contains color information. For plant region detection, the Hue value within the range of 45 to 75 is selected. This range is used to identify green and related tones typically associated with plants. Using this color data, plant regions are separated from the rest of the image. The identified plant regions are then matched with the aligned thermal image. This process ensures that only the plant regions are obtained in the thermal image. It's important to note that the appearance of these regions may vary based on factors such as the leaf surface of the captured plant and the distance of imaging. These differences need to be considered while analyzing the thermal image of the plant regions.

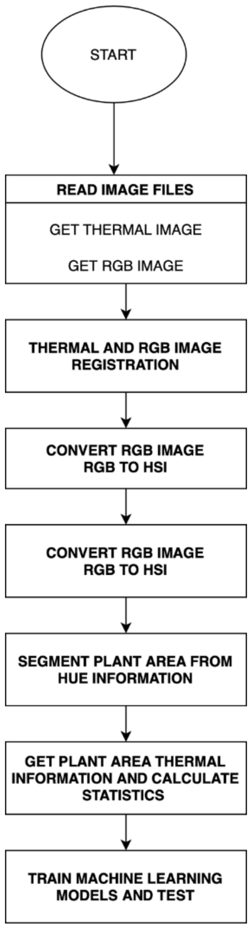

Figure 3. Flow Diagram demonstrating methodologies in early distinguishing of root rot disease in tomatoes

Initially, it is needed to begin the process of converting the RGB color space image to the HSI space by normalizing the RGB values (Equations 1 -3);

$$r = \frac{R}{R+G+B}, g = \frac{G}{R+G+B}, b = \frac{B}{R+G+B} \quad (1)$$

$$h = cos^{-1}\left\{\frac{0.5.[(r-b)+(r-b)]}{[(r-g)^2+(r-b)(g-b)]^{1/2}}\right\} \text{h€}[0,\pi] \text{ for } b \leq g \quad (2)$$

$$h = 2\pi - cos^{-1}\left\{\frac{0.5.[(r-g)+(r-b)]}{[(r-g)^2+(r-b)(g-b)]^{1/2}}\right\} \text{h€}[0,2\pi] \text{ for } b > g \quad (3)$$

s=1-3. Min (r,g,b)   s € [0,1]

i=(R+G+B)/(3•255) i € [0,1]

the h, s, and i values within the ranges [0, 360], [0, 100], and [0, 255], respectively, are calculated using the formulas: H = hx180/π, S = sx100, and I = ix255.

Extracting Features from The Thermal Data of The ROI (Region of Interest)

The thermal data of the identified plant regions serves as input data for the classification process. Statistical features are computed from the thermal image, including pixel count, maximum, minimum, mean, standard deviation, kurtosis, skewness, and moment values. By doing so, 8 feature attributes (Number of pixel, Min, Max, Mean, Standart deviation, Skewness, Kurtois, Moment) are obtained from the thermal image.

In our dataset, there are a total of 143 samples. 75% of these samples (108 samples) are used for training, while the remaining 25% (35 samples) are used for testing. The machine learning algorithms (Naive Bayes, Logistic Regression, and KNN) are trained using the 108 training samples, and then testing is performed on the 35 test samples. The obtained features are used to predict diseases using the mentioned algorithms.

The K-Nearest Neighbors (K-NN) algorithm looks at the k closest neighbors to determine the class or value of a data point. These neighbors are determined using a specific similarity metric. The parameter k represents the number of selected neighbors. In classification problems, the majority class of the neighbors is used for prediction, while in regression problems, the average value of the k nearest neighbors is used as the predicted value. K-NN is a simple algorithm that does not build a model during training, but its computational cost may increase with large datasets or a high number of features. Logistic regression is a statistical model used for classification problems. By learning the weights of independent variables in a dataset, it predicts the probability of a data point belonging to a specific class. It employs a sigmoid function to constrain these probabilities to the [0, 1] range. Usually, probabilities above a specified threshold are assigned to one class, and those below it are assigned to another. Its simplicity, speed, and interpretability make it a preferred choice, especially for binary classification problems. Naive Bayes is a machine learning algorithm based on Bayes' Theorem and is particularly employed in applications like text classification. Essentially, it operates by assuming independence between features, which is often referred to as the "naive" assumption. During the training phase, probabilities for each class are determined, and during the testing phase, the probability of belonging to a specific class is calculated using Bayes' Theorem. The class with the highest probability is then selected as the prediction.

Results and Discussion

The early diagnosis of plant diseases is crucial to mitigate economic losses caused by these diseases. In this context, remote sensing techniques have become increasingly popular. Particularly, the use of thermal images combined with machine learning techniques for the early diagnosis of diseases has been found beneficial in controlled greenhouse conditions as well as field conditions [17].

In this study, thermal images of tomato plants with root disease inoculation and healthy tomato plants without disease inoculation were obtained under controlled conditions. The research aimed to explore the potential of using thermal images for early diagnosis of the disease. By comparing thermal images between the diseased and healthy plants, the study investigated the possibility of utilizing thermal imaging as a tool for early detection of the disease. Additionally, three different machine learning classification techniques were compared in this study for the classification of healthy and diseased plants based on thermal images.

Thermal images were obtained to compare temperature changes between healthy and pathogen-inoculated diseased plants. Thermal images were captured for both healthy and

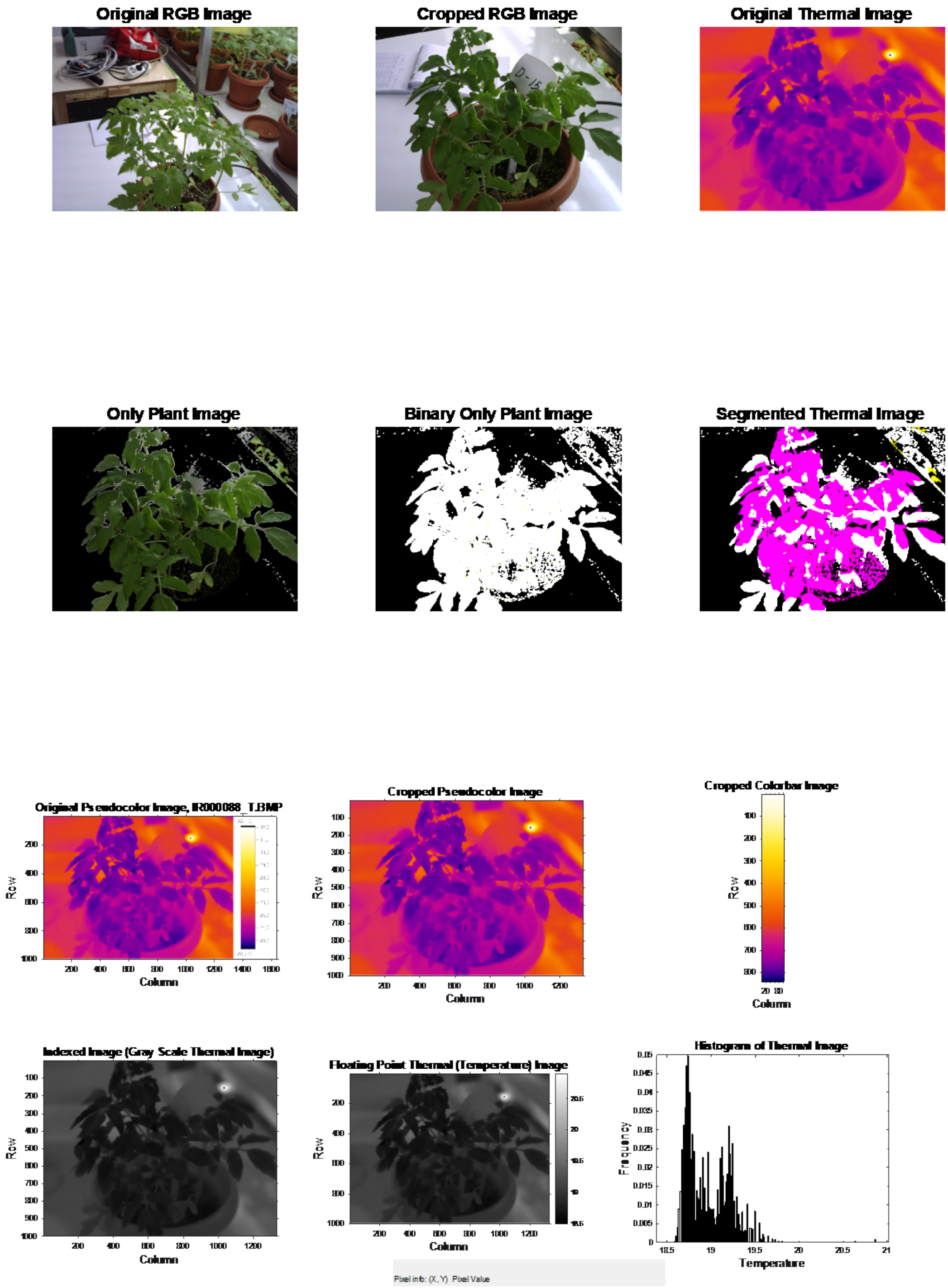

Figure 4. Pictures showing thermal and RGB images and their fusion

Table 2. The features extracted from thermal images of some plant samples.

SAMPLE	MIN	MAX	MEAN	STD_DEV	KURTOIS	SKEWNESS	MOMENT	WEEKS	CLASS	STATUS
1	18,50	20,90	20591,00	0,44	68295,00	-21943,00	-0,19	1	0	HEALTHY
8	20,90	21,90	21603,00	0,21	24835,00	-11559,00	-0,01	2	2	DISEASED
11	21,00	21,90	21632,00	0,19	24828,00	-11559,00	-0,01	2	0	HEALTHY
18	23,10	24,50	24084,00	0,29	24835,00	-11559,00	-0,03	3	2	DISEASED
29	22,10	23,70	23224,00	0,33	24835,00	-11559,00	-0,04	5	1	DISEASED
39	23,60	24,70	24373,00	0,23	24835,00	-11559,00	-0,01	6	1	DISEASED

diseased plants, and their temperature variations were compared. The table 2 presents some selected plants' statistical results regarding temperature changes. It can be observed that, generally, the average temperature values of diseased plants are higher compared to healthy plants.

Diseased plants may have higher temperatures when observed through thermal imagery due to several reasons that includes increased metabolic activity or inflammation response. Diseased plants often experience stress, which can lead to an increase in metabolic activity. The pathogen enters the plant through stomata, leading to alterations in the metabolic processes of plant tissues. This includes changes in respiration, photosynthesis, and transpiration within the plant. This heightened metabolic rate can generate more heat, causing the plant to have a higher temperature when compared to healthy plants [18]. Plants can activate defense mechanisms when they are under attack by pests or pathogens. These responses may include the release of signaling molecules or chemicals that can induce local inflammation-like reactions. These responses might elevate the temperature in the affected areas.

At a height of 50 cm from the canopy, using thermal images obtained from a thermal camera, researchers observed a decrease in leaf surface temperatures in diseased plants compared to healthy ones. However, in this study, there was an increase in temperature. The decrease in leaf surface temperature in diseased plants was attributed to the masking effect caused by fungal disease, which covers the leaf surface with spores [1]. Similarly, Awad et al. [19] found that in wheat plants artificially inoculated with pathogens under greenhouse conditions, there was a temperature decrease shortly after (around one hour later) the disease transmission. They attributed this temperature decrease to a similar cause. The high density of spores had a masking effect on the leaf surface, leading to a reduction in leaf surface temperatures in infected plants. On the other hand, researchers studying downy mildew in grapevines under field conditions observed an increase in leaf temperatures long before visible symptoms became apparent, using thermal images obtained with an infrared camera [18].

Table 3. The Accuracy assessment of distinguishing healthy and unhealthy plants based on thermal images using different machine learning techniques.

ACTUAL/ CLASSIFIED	HEALTHY/ HEALTHY	HEALTHY / UNHEALTHY	UNHEALTHY / HEALTHY	UNHEALTHY/ UNHEALTHY	ACCURACY	ERROR RATE
	TP	FP	FN	TN		
KNN	14	4	6	11	0,72	0,28
Naive Bayes	10	8	3	14	0,68	0,32
Logistic Regression	11	7	7	10	0,6	0,4

To evaluate the dependability of the classification approach, the accuracy of the classified images can be gauged using an overall accuracy metric. To calculate the overall accuracy, it involves dividing the number of correctly classified plants by the total number of plants [1].

Table 3 presents the error matrix for the classification outcomes using three different methods; KNN, Naive Bayes and Logistic regression. Among the four distinct classification methods, the KNN (k-Nearest Neighbors) technique yielded the highest classification accuracy, reaching 72%.

The Table 3 shows that disease detection can be achieved with 72% accuracy. Moreover, similar results were obtained with other methods.

Omran [1] achieved an overall success rate of 72 % in early distinguishing peanut leaf disease with varying degrees of disease using thermal imagery. The temperature difference observed between healthy and infected plants allowed the researchers to effectively differentiate between the two groups. The variations in leaf surface temperatures provided a clear distinction, enabling them to identify and discriminate healthy plants from those infected with the disease.

Synthetic data was generated using the SMOTE method. In this way the amount of data is doubled. The same results were obtained by applying statistical methods and machine learning methods. Since the results obtained were not different from the previous ones, it was seen that no advantage was gained by increasing the data.

In the study conducted by Singh et al. [17], they modeled the severity of wilting in chickpeas using RGB and thermal images, comparing different machine learning techniques. The researchers divided the dataset into two groups: the training set and the test set. The Cubist model outperformed other common machine learning models such as MARS, PLS, SVM and RF producing more successful results in comparison (with R2 value higher than 0.8).

Conclusion

The results obtained from this study demonstrated the potential of using thermal images and machine learning techniques to diagnose Fusarium root and crown rot disease in tomatoes at an early stage under controlled conditions. Overall, the ability to distinguish between healthy and diseased plants at an early stage was found to be 72%. Among the compared classification techniques, the most successful one was K-Nearest Neighbors (KNN). However, the validity of the method needs to be tested by applying the results under field conditions. Additionally, further investigations are required to examine the applicability of integrating thermal cameras into unmanned aerial vehicles (drones) and testing the method on different plant species in various field conditions. Early diagnosis of plant diseases in this manner can prevent further spread of diseases, leading to reduced economic losses and a decrease in the use of chemicals, thereby contributing to environmental pollution reduction. In conclusion, the combination of thermal imaging and machine learning techniques holds promise for the early diagnosis of Fusarium root and crown rot disease in tomatoes. The potential implementation of this approach in real-world field conditions and on other plant types warrants further exploration for effective disease management and sustainable agriculture practices.

Ethics committee approval

No ethical clearance is required for the preparation of the article.

Conflict of Interest Statement

There are no conflicts of interest involving any individuals or institutions associated with the prepared article.

Acknowledgement

I would like to thank Dr. Mehmet Emin Tenekeci for his contributions to obtaining the thermal images in the article.

References

[1] El-Sayed Ewis Omran, "Early sensing of peanut leaf spot using spectroscopy and thermal imaging", *Archives of Agronomy and Soil Science*, 63:7, 883-896, 2017.

[2] Carvajal-Yepes M, Cardwell K, Nelson A, Garrett KA, Giovani B, Saunders DGO, Kamoun S, Legg JP, Verdier V, Lessel J, Neher RA, Day R, Pardey P, Gullino ML, Records AR, Bextine B, Leach JE, Staiger S, Tohme J., "A global surveillance system for crop diseases", *Science*, vol. 364, no. 6447, pp. 1237-1239, Jun 2019.

[3] Savary S, Willocquet L, Pethybridge SJ, Esker P, McRoberts N, Nelson A. The global burden of pathogens and pests on major food crops. Nat Ecol Evol. 2019 Mar;3(3):430-439. doi: 10.1038/s41559-018-0793-y. Epub 2019 Feb 4. PMID: 30718852.

[4] J.C., Zhang, R.L., Pu, J.H., Wang, W.J., Huang, L., Yuan, J.H. Luo, "Detecting powdery mildew of winter wheat using leaf level hyperspectral measurements", *Computers and Electronics in Agriculture*, vol. 85, pp.13-23. 2012.

[5] E., Bauriegel, A., Giebel, M., Geyer, U., Schmidt, W.B. Herppich, "Early detection of Fusarium infection in wheat hyper-spectral imaging", *Computers in Agriculture*, vol. 75, pp. 304-312.

[6] K., Karadag, M.E., Tenekeci, R., Taşaltın, A. Bilgili, "Detection of pepper fusarium disease using machine learning algorithms based on spectral reflectance". *Sustainable Computing: Informatics and Systems*, vol. 28, no. 100299. 2017.

[7] A., Bilgili, A.V., Bilgili, M.E. Tenekeci, and K. Karadag, "Spectral characterization and classification of two different crown root rot and vascular wilt diseases (*Fusarium oxysporum* f.sp. *radicis lycopersici* and *Fusarium solani*) in tomato plants using different machine learning algorithms". *Eur J Plant Pathol,* vol. **165**, pp. 271–286, 2023.

[8] R. Ishimwe, K. Abutaleb, and F. Ahmed, "Applications of Thermal Imaging in Agriculture—A Review". *Advances in Remote Sensing*, **3**, 128-140.

[9] H. Erdoğan, A.K. Butuner and Y.S. Sahin," Detection of Cucurbit Powdery Mildew, Sphaerotheca Fuliginea (Schlech.) Polacci by Thermal Imaging in Field

Conditions" Scientific Paper Series Management, Economic Engineering in Agriculture and Rucal Development", 23, 1, 2023.

[10] I., Bhakta, S., Phadikar, K. Majumder, H. Mukherjee and A. Sau, "A novel plant disease prediction model based on thermal images using modified deep convolutional neural network", *Precision Agric, no:* **24**,pp. 23–39, 2023.

[11] S.A. Raza, V. Sanchez, G. Prince, J. P. Clarkson, N. M. Rajpoot, "Registration of thermal and visible light images of diseased plants using silhouette extraction in the wavelet domain," Pattern Recognition, vol. 48, no. 7, pp. 2119-2128, 2015.

[12] I.C. Hashim, A.R.M.Shariff, S.K. Bejo, F.M. Muharam, K. Ahmad and H. Hashim, " Application of thermal imaging for plant disease detection, " *IOP Conf. Series: Earth and Environmental Science,* 540, 012052.

[13], FAOSTAT World Food and Agriculture- Statistical Yearbook 2022. https://www.fao.org/3/cc2211en/cc2211en.pdf.

[14] A. Bilgili, "Determination of Root Rot Factors in GAP Region Pepper Cultivation, Molecular Characterization of the Active Pathogen and Investigation of the Efficiency of Mycorrhiza in its Control". Ph.D Thesis, Turkey, Harran University. 2017 (In Turkish).

[15] Upov. Tomato, guidelines for the conduct of tests for distinctness, uniformity and stability. 2013. Retrieved October 20, 2022, from https://www.upov.int/edocs/tgdocs/en/tg044.pdf.

[16] M., Çalışan, & İ. Türkoğlu, "Termal Kameralar Ve Uygulamaları, TMMOB Elektrik-Elektronik ve Bilgisayar Sempozyumu" 2011, Elazığ.

[17] R.N. Singh, P. Krishnan, C Bharadwaj, B. Das, "Improving prediction of chickpea wilt severity using machine learning coupled with model combination techniques under field conditions", *Ecological Informatics,* vol. 73, 101933, 2023.

[18] S. Zia-Khan,M. Kleb, N. Merkt, S. Schock, J. Müller, "Application of Infrared Imaging for Early Detection of Downy Mildew (*Plasmopara viticola*) in Grapevine", *Agriculture* **2022**, *12*, 617.

[19] Y. M. Awad, A. A. Abdullah, T. Y. Bayoumi, K. Abd-Elsalam and A. E. Hassanien, "Early detection of powdery mildew disease in wheat (triticum aestivum l.) using thermal imaging technique", *Intelligent Systems' 2014*, pp. 755-765, 2015.