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Detection of Bean Rust (*Uromyces appendiculatus*) Disease Under Field Conditions Using Thermal Imaging

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Abstract: Among the factors causing yield losses in agricultural fields, plant diseases are known to be one of the most significant. For many years, pesticides have been used to control these diseases. However, due to the unintended toxic effects of pesticides on non-target organisms in recent years, there have been restrictions on their usage. At this point, early warning systems aiming to reduce the use of pesticides have come to the forefront. This study aims to detect bean rust disease (*Uromyces appendiculatus*) at an early stage using thermal imaging methods. Surface temperatures of healthy and infected leaves were measured at 60-minute intervals over a three-week period. Throughout this period, it was observed that the average daily temperatures of both infected and healthy leaves were below ambient temperatures. According to the obtained results, it was determined that leaves infected with the pathogen exhibited temperatures approximately 2°C lower than those of healthy leaves. Consequently, thermal imaging is considered to play a crucial role in the potential early detection of bean rust disease.

Termal Görüntüleme ile Fasulye Pası (*Uromyces appendiculatus*) Hastalığının Arazi Koşullarında Tespiti

Anahtar Kelimeler
Fasulye,
Termal görüntüleme,
Uromyces appendiculatus

Öz: Tarım alanlarında verim kayıplarına neden olan faktörler arasında bitki hastalıklarının en önemlilerinden biri olduğu bilinmektedir. Yıllardır, bu hastalıkları kontrol etmek için pestisitler kullanılmaktadır. Ancak, son yıllarda pestisitlerin istenmeyen toksik etkileri nedeniyle, bunların kullanımına yönelik kısıtlamalar getirilmiştir. Bu noktada, pestisit kullanımını azaltmayı amaçlayan erken uyarı sistemleri ön plana çıkmıştır. Bu çalışma, termal görüntüleme yöntemlerini kullanarak fasulye pas hastalığını (Etmen: *Uromyces appendiculatus*) erken bir aşamada tespit etmeyi amaçlamaktadır. Sağlıklı ve enfekte yaprakların yüzey sıcaklıkları üç haftalık bir süre boyunca 60 dakikalık aralıklarla ölçülmüştür. Bu süre boyunca hem enfekte hem de sağlıklı yaprakların ortalama günlük sıcaklıklarının çevre sıcaklıklarının altında olduğu gözlemlenmiştir. Elde edilen sonuçlara göre, patojenle enfekte yaprakların, sağlıklı yaprakların sıcaklıklarından yaklaşık olarak 2°C daha düşük olduğu belirlenmiştir. Sonuç olarak, termal görüntülemenin fasulye pasının potansiyel erken tespitinde kritik bir rol oynadığı düşünülmektedir.

1. INTRODUCTION

The increase in the world's population has led to an escalation in food demand over the years [1, 2]. This situation highlights the increasing significance of agricultural production and emphasizes measures to reduce crop losses in agricultural production. Among the most critical factors leading to product losses in agricultural production are plant diseases and pests [3-5].

Pesticides have been used for many years in the fight against plant diseases and pests. However, due to the emergence of unwanted side effects of pesticides, there have been restrictions on their usage [6, 7].

Restrictions on pesticide use have brought other alternative methods to the forefront. One of the most significant among these is precision agriculture methods. Precision agriculture aims for the right input, in the right amount, at the right place, at the right time [8, 9]. The use of precision agriculture methods is crucial in detecting diseases, especially at an early stage, before spreading throughout the entire area [10-12]. Early-stage detection without spreading throughout the entire area enables less chemical usage. In recent years, thermal imaging methods, potentially used for early disease detection, have gained prominence in this regard [13, 14].

Infrared rays are part of the electromagnetic spectrum and are emitted depending on the temperature of objects. Each object in nature has its own heat energy, invisible to the human eye, emitted into the environment. In thermal imaging systems, this heat energy is captured and, based on the degree of heat, a picture is obtained by colorizing it. It is challenging to perceive an object that has the same color as the background for RGB cameras, as they require light and color. Near Infrared (NIR), Mid-Wave Infrared (MWIR), and Long-Wave Infrared (LWIR) are distinct divisions of the infrared spectrum, which is a subset of the electromagnetic spectrum, categorized based on their applications. However, for thermal cameras, the situation is very different. Even if both objects have the same color, the difference in heat enables the object's appearance to be easily captured as an image [15]. Thermal cameras can detect infrared energy from various distances based on the sizes of their lenses without physically touching the object. Thermal cameras detect the infrared energy emitted by the object in the environment through the camera's lens and send this information to the infrared detector inside the camera for image processing [16]. As a result of these processes, the information is converted into an image that we can see. This process is called thermography, converting infrared rays into a visible image. This technique is used in many fields, especially in evaluating seedling vitality [17-19], predicting soil moisture status, estimating plant water stress, planning irrigation, identifying plants affected by diseases and pathogens [20-24], and assessing the ripeness of fruits and vegetables in agricultural activities and the food industry. Thermal imaging advantages include non-contact, rapid results, and high sensitivity [25]. Additionally, modern thermal cameras can operate at room temperature, making their usage widespread. The intensity of radiation emitted by an object is a function dependent on the surface temperature; the higher the temperature of an object, the greater the intensity of the infrared radiation emitted by the object [26]. Thermal imaging is a technique that converts the radiation emitted by an object into temperature data without physical contact. Thermal imaging methods are based on detecting the localized temperature increase or decrease resulting from the stress a plant develops in response to the infection of diseases in the area where the infection occurs. Studies have shown that it is possible to detect many diseases based on temperature differences at an early stage [24, 27-29].

Bean rust disease (*Uromyces appendiculatus* Pers. C.K.) (Pucciniales: Pucciniaceae) is a fungal disease-causing varying level of intensity, density, and yield and quality losses depending on the severity of the disease and the host reaction. This disease causes spots on the leaves, stems, and even fruits of plants [30-32]. Bean rust disease is characterized by yellow, orange, or brown spots on the upper surface of the leaves. This pathogen, which has no alternate hosts, spends all its stages on the same plant. During winter, it appears on leaves as teliospores, mostly in dark brown, and during summer, it appears as uredospores, which are red in color, seen on the leaves [33-36]. Bean rust disease spreads through spores, which can be transmitted from one plant to another through wind or irrigation. Additionally, not removing infected plant residues from the field facilitates the spread of the disease [34, 37]. This disease agent, causing yield losses in beans consumed as food worldwide, holds economic importance.

The purpose of this study is to determine the potential use of thermal imaging methods for the early diagnosis of bean rust disease in bean plants. Early diagnosis of infection will enable the control of the disease agent before spreading to all healthy plants, allowing for the application of appropriate control methods. Thus, the early detection of the disease through thermal imaging can identify the economic damage threshold at the right time and prevent excessive pesticide usage. Moreover, with thermal cameras integrated into robotic systems in subsequent studies, the density of the disease can be detected in areas where infection has started but is not visible to the naked eye, allowing for proper spraying in the right place and amount.

2. MATERIAL AND METHOD

This study was carried out in the plant production areas where bean cultivation belongs to Bursa Uludağ University TUAM Farm Directorate. The potential detection of bean rust disease on bean plants (May Magnum®) due to the stress caused by the temperature change on the plant was investigated using thermal imaging methods.

2.1. Temperature Data and Disease Diagnosis

In this study, LWIR cameras have been acknowledged as more suitable for the accurate detection of plant diseases due to their capability of determining only the temperatures emitted by the target object without being influenced by many other factors during measurement [24, 38]. Within the LWIR range (8-14 μm), most objects, including plants, exhibit high emissivity, meaning they efficiently emit infrared radiation. This high emissivity leads to more precise temperature measurements and improved thermal imaging. The study employed a portable LWIR camera with a resolution of 464 x 348 pixels and a thermal sensitivity of less than 40 millikelvin (mK) [39]. To achieve more accurate results, the emissivity was set to approximately 1, and a lens with a resolution of 0.90 m/rad pixel was utilized [24].

Measurements were conducted using a thermal camera on the leaves of both diseased and healthy plants present in an area of 250 m². Additionally, ambient temperatures were determined using a portable thermometer. Throughout the study, all thermal measurements were manually taken using a portable thermal camera (FLIR T530® Teledyne FLIR LLC, U.S.) from randomly selected diseased and healthy leaves of individual plants. The average temperatures of leaves infected by *U. appendiculatus* were monitored and recorded simultaneously with the temperatures of healthy leaf surfaces, along with the average environmental temperature. Teledyne FLIR Thermal Studio® software was employed to compute the average temperatures of leaf surfaces from thermal images. Healthy leaves were used as controls. This study was conducted during the flowering stage of bean plants.

Samples obtained from the field were processed to prepare *U. appendiculatus* disease specimens and were identified under a microscope [40-42]. A diagnostic method similar to the one used by Shaik and Steadman (1989) was employed.

2.2. Measurement Time and Distance

In the area where the study took place, thermal measurements were conducted on the leaves of both diseased and healthy plants using a thermal camera. During the temperature measurements on the leaves, environmental factors such as the intensity of sunlight can affect leaf temperatures [24, 43]. Therefore, thermal images of all labeled leaves were obtained every 60 minutes from 06:00 to 17:00 for a duration of 3 weeks (21 days). Temperature measurements were taken from 7 different points (replicates) for each hourly measurement. After 21 days, the thermal imaging process was concluded due to the healthy plants becoming infected. Additionally, a handheld thermometer was used to record ambient temperatures. The thermal imaging process was conducted manually. High-resolution (pixel) cameras and close-range shots reduce the margin of error in temperature measurements [24]. In this research, measurements were taken from a distance of 0.3 meters from the leaf surface using a thermal camera to enhance the precision of temperature measurements. All temperature measurements on the leaves were conducted at approximately the same angle (90°) and distance (0.3 m) [24, 43, 44]. The 'FLIR Thermal Studio' tool was utilized to calculate the average temperatures of infected and healthy leaf surfaces.

2.3. Statistical Analysis

The statistical analysis was conducted using data involving the daily average surface temperatures of leaves infected by *U. appendiculatus*, leaves with no infection, and concurrently measured ambient temperatures. Significant differences between temperature values were determined using variance analysis (ANOVA) employing the JMP 16.0® algorithm. Student's t-test was performed to examine average differences (at 0.05 significance level).

3. RESULTS

According to the obtained results, a decrease in temperature was observed in bean plant leaves infected with *U. appendiculatus*. Firstly, temperature values obtained from plant leaves between 06:00 and 17:00 were examined. The statistical analysis was performed by determining the average temperature values for 1, 2, and 3 weeks of ambient temperature, non-infected plant leaf temperature, and infected plant leaf temperature.

In Figure 1, although not easily noticeable to the naked eye, the area where the disease has spread is clearly depicted due to the temperature difference captured by the thermal camera. The leaf showing early-stage infection (B) was determined to have a temperature value of 9.7 ºC. This value was found to be 7.3 ºC for the infected leaf (A).

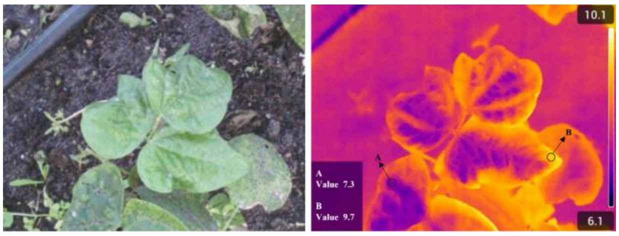

Figure 1. Temperature differences obtained using thermal imaging methods between a leaf where the infection has spread and a leaf where the infection has just started in an infected plant.

Upon examining Figure 2, a homogeneous color distribution is observed on the surface of a healthy leaf. When compared with Figure 1, both appear healthy in RGB imaging, yet in reality, Figure 1 indicates the onset and spread of the disease in those leaves.

Figure 2. Thermal image obtained from the surface of a healthy leaf.

Figure 3 displays advanced stage rust disease in the thermal and RGB images. Upon examining the results, it was observed that the obtained thermal images showed higher temperature values compared to healthy leaves (Figure 3) and leaves where the infection had just begun (Figure 1).

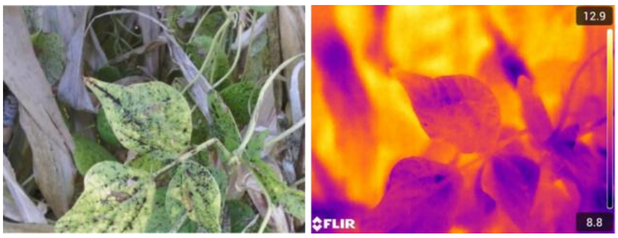

Figure 3. Thermal image of a leaf surface severely affected by infection.

According to the obtained results, at the end of the 1st, 2nd, and 3rd weeks, ambient temperature values were determined as 20.5, 21.1, and 21.3 ºC, respectively. Examining the temperature values obtained from non-infected bean leaves revealed readings of 13.42, 13.81, and 13.96 ºC, respectively. Lastly, for bean plant leaves infected with U. appendiculatus, lower values were recorded as 11.95, 12.38, and 12.61 ºC compared to the other obtained temperatures. On average, a temperature difference of 2 ºC was identified between infected and non-infected bean leaves. In some plant leaves, this temperature difference reached approximately 3 ºC (Figure 1). Upon considering all these values, statistically significant differences among the averages were obtained (Figure 4).

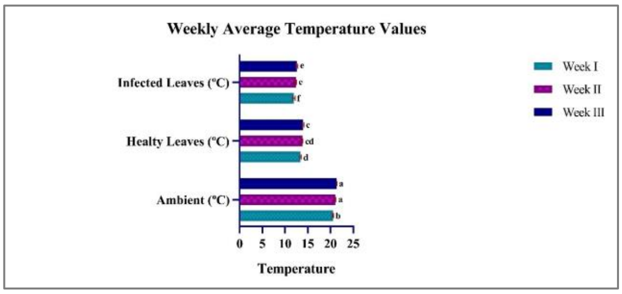

Figure 4. Average temperature values of ambient, infected, and non-infected leaves. Columns with the same letters represent no significant difference.

Throughout the three-week period, the daily average surface temperatures of infected and healthy leaves, along with the daily average ambient temperature, were statistically evaluated. The letters on top of the bars in Figure 4 indicate significant differences between the measurements (F: 806.13, df: 8;54, p <0.0001).

4. DISCUSSION AND CONCLUSION

Fungal diseases cause stress or dead in plants. This stress can affect various physiological processes in plants such as photosynthesis, respiration, and transpiration. These factors can lead to temperature changes, particularly in plant parts, especially in leaves [45-48]. Recent studies employing thermal imaging techniques have facilitated the early detection of plant diseases without spreading across the entire field [24, 49, 50]. The use of thermal imaging techniques for the detection of plant diseases, especially those not showing any symptoms in plant parts at an early stage, is becoming increasingly prevalent [38, 51]. Therefore, the aim of this study was to potentially detect bean rust using thermal imaging techniques and to determine the temperature differences caused by stress. The study revealed that bean leaves infected with *U. appendiculatus* were cooler compared to the leaves unaffected by *U. appendiculatus* infection.

Previous studies have demonstrated the effective detection of virus and fungal infections through thermal imaging. For instance, Pineda et al. [50] observed the accumulation of local salicylic acid (SA) and consequent temperature increase in plant areas exhibiting hypersensitive response (HR) to Tobacco Mosaic Virus (TMV) infection. Conversely, in the conducted study, a decrease in temperature was observed in bean leaves infected with *U. appendiculatus*. This is believed to be due to the spores formed on bean leaves, which could hinder photosynthesis. Hellebrand et al. [52] investigated the response of powdery mildew disease (*Blumeria* [syn. Erysiphe] *graminis* DC. f. sp. *tritici*) in wheat plants using thermal imaging. According to their findings, they determined an average temperature of 20.1 ºC in infected plants and 21.0 ºC in healthy, non-infected plants.

In the study conducted by Erdoğan et al. [24], the potential detection of powdery mildew (*Sphaerotheca fuliginea* Schlech. Polacci) in zucchini plants using thermal imaging methods was evaluated. Examination of the temperature values in zucchini leaves infected with *S. fuliginea* revealed an average temperature of 8.2 ºC, whereas in non-infected leaves, this value was observed to be around 10.2 ºC. The results obtained from this study align with the findings of the current research. Oerke et al. [53] investigated the potential of thermal imaging methods in detecting *Pseudoperonospora cubensis* Berk. and Curt., which causes mildew in cucumbers. Their results indicated that infected plant tissues had lower temperatures compared to non-infected plant tissues. Therefore, these findings corroborate with the results obtained from the present study.

In the study conducted by Zhu et al. [49], the temperature variations induced by stress caused by mosaic virus in tomatoes and rust diseases in wheat plants were examined. The results indicated that the mosaic virus in tomatoes led to a temperature difference ranging from 0.2°C to 1.7°C, while the rust in wheat caused a temperature variance of 0.4°C to 2°C. It was observed that with the increasing spread of the disease within the plant, there was a decrease in the temperature observed in the plants. These findings align with the outcomes of the current research. Bhakta et al. [48] integrated thermal imaging methods with Decision Trees (DTs) models, enabling the early detection of bacterial leaf blight in rice based on temperature changes in the plant. Similarly, Singh et al. [29] utilized DTs models to identify the onset of wheat yellow rust disease by detecting temperature variations in the plants at the early stages of symptoms.

Disease-causing agents, environmental conditions, time, or plant-related factors can lead to an increase or decrease in leaf surface temperature. It has been observed that these temperature changes, although not visually discernible, can be detected using thermal imaging methods. This suggests a significant potential for early disease detection. The ability to control diseases at an early stage could contribute to preventing diseases before spreading throughout the entire field, thereby reducing yield losses and benefiting the agricultural sector. Additionally, this approach may enhance environmental sustainability by reducing the use of environmentally harmful chemicals. Finally, the integration of thermal imaging methods with models such as Convolutional Neural Networks (CNN) and YOLO holds great promise for agricultural mechanization.

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