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Review Paper

Application of infrared thermal imaging in the field of biosystems engineering in Iran

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ABSTRACT

Thermal imaging is a useful remote temperature monitoring tool that combines infrared thermometry and imaging technology. The technique is widely used to study temperature and surface-related properties of objects. Therefore, both internal and external properties of objects are assessed by the technique. Thermal imagers are installed on satellites, drones, ground stations, and tables to acquire thermal images. Biological engineering requires new engineering knowledge and technologies to increase technical and economic productivity and reduce environmental impacts in agriculture, natural resources, and food sectors. Due to the high abilities and advantages of the method, it has been widely applied to solve problems in agriculture, natural resources, and food. The literature review shows high accuracy of the thermal imaging technique (70-100%) in detecting various goals in these fields. This study aims to introduce thermal imaging and describe its applications in agriculture, natural resources, and food sectors in Iran. Future trends of the technique's applications have been presented in the study.

1. Introduction

Food security is one of the most important issues in the world. Agriculture, natural resources, and the food industry are among the first sectors related to this issue (Sajadipour and Kheiralipour, 2024). Also, these sectors must respond to new challenges, such as climate change, drought, and other environmental problems, and the growing demand for food due to the increasing population and enhancing welfare level (Nti et al., 2023; FAO, 2022). Moving towards sustainable food production, according to its aspects, including technical, environmental, social, and economic, and using new technologies will promote food security (Kheiralipour et al., 2022). Researchers in the fields of agriculture, natural resources, and food sectors are looking for efficient solutions to increase production and reduce costs and environmental impacts (Kheiralipour, 2021). Biosystems engineering is a field that utilizes beneficial technologies in agriculture, natural resources, and the food sectors (Kheiralipour and Jayas, 2024). In this context, sensor-based technologies offer effective tools by minimizing input consumption, optimizing processes, and promoting environmentally friendly practices (Mwinuka et al., 2021; Alphonce et al., 2014).

Imaging is one of these technologies, widely used in various production processes. It captures both visible and invisible electromagnetic waves and converts them into meaningful images (Vadivambal and Jayas, 2016; Kheiralipour et al., 2018; Kheiralipour and Jayas, 2023; Kheiralipour et al., 2023a). This technology is used as an effective tool to analyze various parameters of objects with high accuracy, reliability, speed, and low cost (Vibhute and Bodhe, 2012; Nti et al., 2023).

Infrared thermal imaging (TI) or thermography is an imaging method with high ability and advantages that has many applications in various fields, including agriculture, natural resources, and food sectors (Pineda et al., 2020; Bhole and Kumar, 2020; Ismail et al., 2022; Liu et al., 2025). TI is now applied to monitor livestock body temperature, plant and soil moisture distribution, crop water stress, irrigation planning, physiological status and stress in animals, inflammation or injury detection, disease diagnosis in plants, crop damage assessment, seed germination capability, maturity level, health and vitality of crops, soil salinity, nutrient levels, yield estimation, field monitoring, and system evaluation (Kheiralipour et al., 2011a; Doosti Irani et al., 2013; Yousefzadeh and Abbaspourfard, 2015; Samadzadeh and Gohari, 2016). Considering the capabilities and advantages of TI, the aim of the present study is to review the applications of this method in agriculture, natural resources, and food sectors in Iran.

2. Thermal Imaging

In TI, thermal images (thermograms) of objects are produced based on their thermal radiation in the infrared range (8-14 µm) (Kheiralipour et al., 2018). TI systems map the temperature distribution of objects based on emitted energy and convert it into temperature data (Stokton and Lucas, 2012). TI is a non-destructive method with high speed, remarkable accuracy, and low cost. The TI technique is an advanced technique of thermometry. In this method, remote infrared thermometry integrates with imaging technology to provide a non-contact measuring tool. To this end, TI cameras include an infrared detector to provide a pseudo image by receiving thermal radiation, i.e., infrared wavelengths band from 8000 to 14000 nm. Figure 1 illustrates the schematic operation of an infrared TI camera. Infrared radiation emitted from the surface of an object is first focused by a lens and passed through a filter that selects

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specific wavelengths. The filtered radiation is then received by an infrared detector, which converts it into electrical signals. These signals are subsequently amplified, processed, and visualized as a thermal image (thermogram). This non-contact temperature measurement system is widely used in biosystems engineering and precision agriculture for monitoring plant stress and environmental conditions.

Objects with a temperature higher than absolute zero emit infrared or heat radiation that is invisible. although the emitted radiation changes with temperature, it remains invisible to the human eye. A thermal imager receives the radiation emitted from objects by the camera sensor and converts it to a visible thermal image. The imager includes a special lens that focuses infrared radiation on its sensor, made up of many small pixels, called microbolometers. A thermal imager uses microbolometers that convert infrared radiation received by each pixel into electrical signals and send them to the camera's processor. The processor calculates the temperature of each pixel and then assigns the proper color for each pixel based on the calculated temperatures (red or white for hot pixels and blue or black for cold pixels). The processor creates a thermal image based on the colored pixels and displays it on the camera screen. The advantage of the thermal image is depicting the temperature difference between different points of the objects and the surrounding environment. In a thermal image, the color of each pixel represents the temperature corresponding to that point of the object. TI cameras are evaluated based on thermal sensitivity, scanning speed, and image resolution (Kheiralipour et al., 2018).

Figure 2 presents a systematic overview of the TI workflow, encompassing five essential stages: initial setup, fine-tuning of operational parameters, image acquisition, data interpretation, and final documentation. Adhering meticulously to each of these steps is critical to ensure the accuracy, reliability, and analytical value of the thermal data collected—especially in applications requiring precise temperature diagnostics and environmental monitoring. As seen in Figure 2, the thermal camera is turned on, and date, time, language, and units are configured in the first setup. In the next step, the lens focus, the emissivity coefficient of the target object, and color palettes are adjusted. In step 3, the camera must be held steady, the view must be cleared, and then the capture button must be pressed. Then, thermal images are interpreted and analyzed to determine temperature readings. In the final step, the images are saved, the findings are recorded, and further analysis is conducted.

Thermal images can be obtained in indoor and outdoor conditions for several goals. The images are captured by thermal cameras installed on tables, ground stations, drones, and satellites, and in also handheld cameras are also used in different conditions (Sajadipour and Kheiralipour, 2024). As TI is used to study different properties of objects beyond their surface temperature, the acquired thermal images are processed. Figure 3 shows the steps of thermal image processing including reading the thermal images, converting the images to grayscale or separating image channels (R, G, and B), segmenting the images by detecting edges or cropping the target areas, filling image gaps caused by dead pixels, extraction of color, texture or shape features, selecting the most relevant features, and predicting and classifying the data (Kheiralipour et al., 2018).

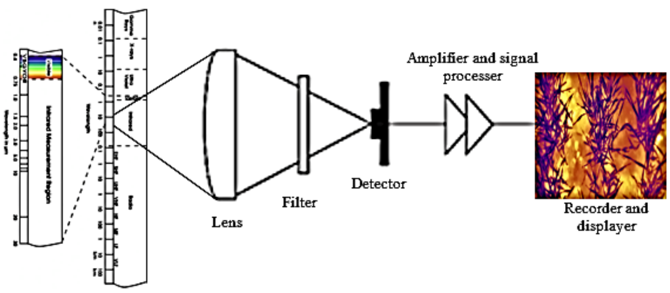

Figure 1. The schematic of a thermal imager

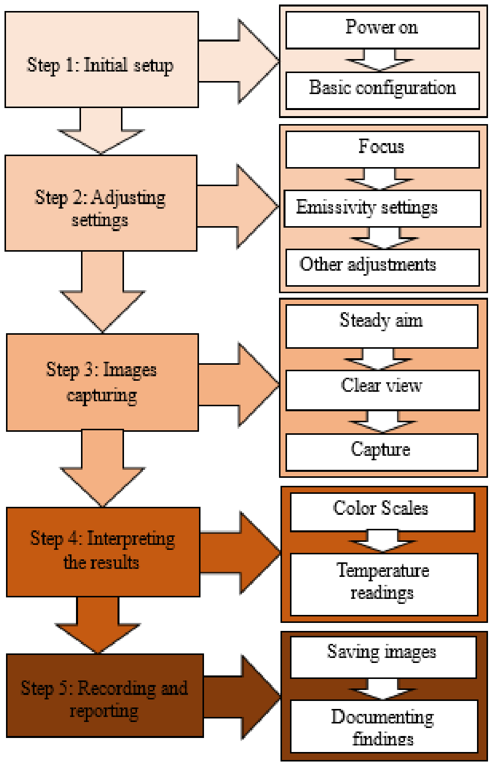

Figure 2. The steps of thermal imaging

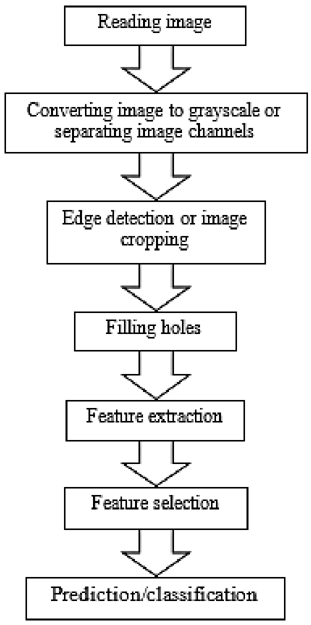

Figure 3. Thermal image processing steps.

Compared to contact measurement methods, TI provides a remote strategy to measure all points of objects' temperature (surface temperature), simultaneously (Kheiralipour et al., 2023b; GST-IR, 2023). As TI captures the infrared radiation emitted from objects and different factors and properties of objects affect the amount of energy emitted by them, the technique is used to measure not only the surface temperature of objects, but also to investigate all properties of objects related to the emitted infrared wave from them, such as color, texture, and defect. Therefore, TI can assess other factors, i.e., internal and external physical and chemical properties, of objects that lead to changes in the radiant energy of objects (Kheiralipour et al., 2018). Although other imaging techniques, such as visible and hyperspectral imaging, are used to assess physical and chemical properties of objects, these methods cannot evaluate temperature-based changes in objects.

However, this technology has limitations and challenges, such as the necessity of using heating or cooling processes in active TI, which may damage the objects and lead to unwanted changes. Ambient temperature affects the results of TI, which is almost uncontrollable. Thermal imagers relatively low resolution compared to visible cameras. To measure the temperature or another property of an object, the object's emissivity coefficient must be adjusted in the camera. Therefore, another challenge is the absence of an emission coefficient table for most agricultural materials that need to be measured (Kheiralipour et al., 2018).

3. Applications of Thermal Imaging

Due to its high advantages, TI is widely used in various fields. Table 1 lists the applications of TI in agriculture, natural resources, and food in Iran. The accuracies of the studies are different (up to 100%).

4. Agriculture

TI has been used in different agricultural sectors for a variety of purposes (Samadzadeh and Gohari, 2016; Kheiralipour et al., 2018). TI has been applied to detect tea diseases (Yang et al., 2019), evaluate drought tolerance in lentil plants (Ishimiwe et al., 2014), detect bruises in apples (Xing et al., 2007; Doosti-Irani et al., 2017), enable early detection of date palm weevils (Ali Ahmad et al., 2019), and distinguish between different pineapple cultivars (Rud et al., 2015). In Iran, this technology has been used to identify fungal infections in potato tubers, diagnose diseases in grape leaves, detect fungal infections in pistachio kernels, and assess drought stress in olive trees.

4.1. Detection of drought stress

The researchers used TI to investigate drought stress in olive trees as a criterion for managing irrigation schedules and reducing water consumption, because leaf surface temperature can be an indicator of drought stress and water needs. The researchers recorded thermal images of olive trees at five levels of low irrigation and three trees per level. During the imaging, wet and dry references were placed in the camera's field of view. The results showed that the accuracy of TI reached 83% (Shoa et al., 2015).

4.2. Disease detection

In plant production fields, detection of grape leaf diseases has been reported in the early stages of growth using the TI technique. Researchers recorded thermal images of infected grape leaves grown under controlled greenhouse conditions on days 1, 2, 4, and 7 post-infections. The leaves in the images were identified using the active contour algorithm for edge detection. Five classification methods were applied to distinguish between healthy and infected leaves, and the best results were obtained using the support vector machine model, with a classification accuracy of 69.2% and an F1 score of 74.9% (Kurd et al., 2016).

In livestock production, TI has been used for early detection of mastitis (Coskun and Aytekin, 2021; Golzarian et al., 2017), detection of foot disease in livestock (Ajuda et al., 2014), and detection of honey quality (Kibar, 2023). Researchers have used thermography to diagnose Holstein cow mastitis. Although the diagnosis accuracy was relatively low (57.3%), it is possible to diagnose mastitis by improving imaging conditions, such as reducing the effects of ambient light and cleaning the breast skin (Golzarian et al., 2017).

4.3. Identifying fruit ripeness

The ability of active thermography in the classification of ripe and unripe white mulberry fruits has been investigated. Temperature changes of mulberry samples were used for classification using the principal component analysis (PCA) method in MATLAB software. The results showed that this method has a 90% accuracy in differentiating between ripe and unripe berries (Heidari et al., 2019). In future research, the TI technique could be applied in Iran to assess animal body temperature as a criterion for diagnosing disease in livestock and poultry and determining the quality of animal products such as meat, dairy, and honey.

5. Natural Resources

The TI technique has been applied for forest fire prevention (Gong and Chen, 2020; Carta et al., 2023) and for detecting vegetation cover and assessing water stress in rangelands (Neinavaz et al., 2021). This technique has also been used in various applications within Iran's natural resources sector.

Table 1. Application of thermal imaging in different fields

Thermal imaging type	Goal	Camera model	Accuracy	Reference
Passive	Vegetation and land use detection in Ardakan and Mook regions	Landsat TM	-	Alavipanh et al. (2001)
Passive	Land surface temperature	Landsat TM	-	Alavipnah et al. (2007)
Active	Detection of Aspergillus flavus in pistachio kernels	TI160	86–100%	Kheiralipour et al. (2012)
Passive	Quality control of agricultural products	FLIR ThermaCAM	-	Dousti Irani et al. (2013)
Active	Bruise detection in apples over time	-		Doosti-Irani et al. (2014)
Passive	Disease detection in plants	FLIR SC620	-	Yousefzadeh and Abbaspourfard (2015)
Passive	Drought stress detection in olive trees		83%	Shoa et al. (2015)
Passive	Early detection of grape leaf disease	-	69.2%	Kurd et al. (2016)
Passive	Seed germination and crop maturity assessment	FLIR B335	-	Samadzadeh and Gohari (2016)
Active	Detection of Fusarium solani in potato tubers	-	88–98.5%	Farokhzad et al. (2016)
Passive	Mastitis detection in Holstein cows	-	57.3%	Golzarian et al. (2017)
Active	Classification of ripe/unripe white mulberry using PCA	-	90%	Heidari et al. (2019)
Active	Bruise detection in red apples	-	100%	Hajali Oghli and Ahmadi Moghaddam (2019)
Passive	Detection of water stress in greenhouse cucumber	FLIR E60.	-	Ghasemi et al. (2020)
Passive	Subsurface space identification in carbonate rocks	-	-	Jalali and Kazemi (2020)
Passive	Climate control in commercial greenhouses	FLIR T420	-	Bahrami and Amani (2021)
Passive	Tree canopy detection using deep learning	-	-	Moradi et al. (2022)
Passive	Tree canopy detection using deep learning	-	-	Moradi et al. (2022)
Active	Detection of bruises in fruits	-	-	Yousefi et al. (2023)

5.1. Land surface temperature

A study has been conducted on the land surface temperature in the Lut Desert, Iran, using remote sensing TI. Landsat TM thermal images were used, and field surveys were performed to measure actual surface temperatures in the study area. Based on the results, they reported that land surface temperatures increased from wet, saline, desert pavements, yardangs, and sand marshes (Alavipnah et al., 2007).

5.2. Identifying land cover

The researchers used remote sensing satellite imaging in the thermal range to identify vegetation and land use. They investigated two areas, including Ardakan, located in Yazd province, characterized by sparse vegetation, extreme desert conditions, and high soil salinity, and Mook forested mountainous region in Fars province, with rainfed lands and orchards with rainfed lands and orchards. Landsat TM satellite images were analyzed for the two regions in September and October 1990, respectively. Maximum likelihood classification was applied using TM6 band combinations. They reported that the TM heat band can detect vegetation and land use status; however, operational geographical and climatic conditions influence thermal image results and must be considered during interpretation (Alavipanh et al., 2001).

Since TI is able to show trees in hidden areas based on their temperature difference with the surrounding environment, researchers have used TI techniques to identify trees. They installed a camera on a drone to capture thermal images and also used a visual imaging method to extract the characteristics of the trees. The researchers analyzed the images using deep learning algorithms and reported that the analysis based on the combination of images of the visual-thermal-normalized digital surface model was more accurate than other images (visual images, thermal images, and visual-thermal image combinations). They reported that the root mean square error in estimating the area and diameter of the tree canopy ranged between 0.21-0.24 and 0.08-0.11 (Moradi et al., 2022).

5.3. Subsurface space detection

Thermal images from ETM+ and ASTER sensors have been used to identify the Earth's subsurface. The researchers used the digital elevation model and its derivatives, as well as other environmental data. influencing land surface temperature. Using satellite image processing software, data management, integration of spatial information and modeling, ILWIS (ITC Institute of the Netherlands) were able to identify thermal anomalies related to the intrinsic conditions of carbonate rocks and prepare a spatial distribution map of areas with subsurface spaces in the study area (Shiramin, Azarshahr, Iran) validated these findings using field observations, exploration well logs, and geological records (Jalali and Kazemi, 2020). In future research, this method could be used in Iran to evaluate rangelands and forests for forest fire prevention, ecosystem monitoring, and sustainable management of rangelands and deserts.

6. Food

6.1. Detecting infection

In Iran, TI technology has been used to detect fungal KK11 and R5 isolates of *Aspergillus flavus* in pistachio kernels. Thermal images of pistachio kernels were taken before heating, after heating at 90 °C for 90 s, and after cooling. They used an emissivity coefficient of 0.95 for the TI of pistachio kernels. To analyze the selected features, linear discriminant analysis, quadratic discriminant analysis, ANN, support vector machines (SVM), and threshold-based classification methods were used. The researchers achieved high accuracy (0.86-100) in distinguishing healthy pistachios from fungus-contaminated pistachios (Kheiralipour et al., 2013; 2015).

The TI method has been effective in detecting *Fusarium solani* in potato tubers during storage. The researchers recorded thermal images of healthy and fungus-infected potato tubers at different stages of 1 to 7 days after infection, using a thermal camera and a heating box under different heating-cooling treatments. They reported that a temperature of 90 °C and a cooling time of 40 seconds were the optimal conditions for TI. After extracting statistical features from the images. LDA, QDA, SVM, and ANN were used to classify the data. High classification accuracy (88.00 to 98.50) reported in their study demonstrated the efficiency of TI for detecting fungal diseases in potato tubers (Farokhzad et al., 2016; 2020; 2024).

6.2. Detecting fruit bruise

The variation in apple tissue temperature has been studied using TI (Doosti-Irani et al., 2016). The researchers reported that the amount of yellowing in visible images decreased over time until about 15 days after crushing, but then it increased. The temperature of the tissue in the thermal images was cooler than the healthy tissue up to 48 hours after crushing, while during this time, the color changes are not visible to the naked eye. After 48 hours, the crushed tissue appeared as a bruised area in the visible images. Maintained a temperature similar to the healthy tissue for 96 hours after crushing, but after that, it was 0.5 to 1 °C warmer than the healthy tissue, after 360 hours, due to the increase in the yellowing index and the change in the color of the crushed tissue from bruised to white, the effectiveness of visual imaging in detecting the crushed tissue decreased (Doosti-Irani et al., 2014). In another study, crushing in red delicious apples was detected using active TI and an ANN with 100% accuracy (Hajali Oghli and Ahmadi Moghaddam, 2019).

6.3. Detecting adulteration

TI was used to identify adulteration in pure ground beef samples containing ground chicken gizzard and sheep lungs. For this purpose, the researchers used active TI, and two thermal stimulation techniques-heating and cooling. Deep learning algorithms were employed to analyze the thermal images. The active TI method was able to detect impurities at concentrations as low as 5% of chicken gizzard and sheep lungs in beef. The accuracy of active TI was reported to be 98% using the heating method and 84% using the cooling method (Bahmani et al., 2024). In Iran, the TI technique can be applied in the future to assess the food quality, ensure proper food processing and packaging integrity, and also monitor storage conditions of different food products.

7. Conclusions

TI is widely used in different studies for detecting different goals in Biosystems engineering, contributing to enhanced productivity in agriculture, natural resources, and the food industry. As a non-destructive, rapid, and precise monitoring tool, TI has demonstrated effectiveness in postharvest quality assessment, greenhouse climate control, and precision irrigation through the detection of subtle temperature variations on crop surfaces. Its integration into agricultural practices offers significant potential for enhancing productivity, sustainability, and early stress detection.

The capabilities and advantages of this method have led to various applications in agriculture, natural resources, and food sectors around the world. This method has been used in Iran to detect water stress, adulteration in meat products, diseases in crops and animals, and postharvest attributes of food products. TI can be used in future research in Iran in various fields of agriculture, natural resources, and the food industry. However, several limitations must be addressed to enable broader adoption. Environmental factors such as ambient light, humidity, and airflow can affect measurement accuracy. Additionally, the high cost of TI equipment, the need for meticulous calibration, and the requirement for specialized expertise in data interpretation present practical challenges. To overcome these barriers, future research should focus on developing advanced image processing techniques and incorporating machine learning algorithms to improve detection accuracy. Designing cost-effective TI systems would facilitate wider field deployment, particularly in farms and cold storage facilities. Moreover, integrating TI with complementary technologies such as hyperspectral imaging or spectrometry could provide more comprehensive diagnostic insights. Evaluating system performance under diverse climatic conditions across Iran is also essential to ensure reliability and scalability in real-world agricultural environments.

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