Non-destructive fruit quality assessment: a review on emerging trends in thermal imaging technology

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ABSTRACT
As a vital non-destructive technique for fruit quality assessment, thermal imaging makes use of temperature changes to identify defects, disease, and maturity. With a focus on fruit grading specifically, this overview of the literature highlights the most recent advancements and applications of thermal imaging in agriculture. Infrared thermography, hyperspectral imaging, and deep learning algorithm integration are just a few of the technologies and methodologies that are covered in this article. The review includes significant research that demonstrates the utility of thermal imaging in accurately identifying diseases, classifying fruitripeness, and detecting bruises early on. Thermal imaging has been successfully used, for instance, in the ripeness-based classification of apples, the discovery of early disease in olive trees, and the identification of internal fruit anomalies in citrus fruits. The application of machine learning and deep learning models such as CNNs and LSTMs, considerably enhances the accuracy and efficiency of thermal image analysis by enabling automated and real-time quality assessments. Regardless the significant advantages, difficulties like environmental influences, data processing needs, and exorbitant expenses persist. The analysis also looks into possible future paths, such as combining thermal imaging with IoT technology and creating affordable ways to increase its use in agriculture. Overall, this thorough analysis highlights how thermal imaging can revolutionize contemporary agricultural methods, especially when it comes to improving fruit grading procedures, guaranteeing food safety, and lowering post-harvest losses.

Keywords: Thermal Imaging, Fruit Grading, Non-Destructive Techniques, Deep Learning, Agriculture, Quality Assessment, Hyperspectral Imaging, Infrared Thermography, Machine Learning.

1. INTRODUCTION

Throughout the entire electromagnetic radiation spectrum that envelops our globe, only the visible light spectrum is observable to human vision. The ability to view heat-invisible infrared radiation generated by any object with a temperature higher than absolute zero is made possible by thermal imaging technology, which gets around this limitation. This non-invasive technique offers an unusual perspective on the environment by displaying temperature fluctuations that are imperceptible to the human eye. Agriculture is among the many industries that have found use for thermal imaging, a technique that detects infrared radiation emitted by objects.Over the past 20 years, advances in machine learning and thermal imaging technologies have fundamentally altered agricultural operations, particularly in the area of fruit grading. This introduction provides a thorough overview of the fundamental concepts, historical development, and expanding agricultural applications of thermal imaging. One effective non-destructive method for evaluating and classifying fruits is thermal imaging. This study examines the developments and uses of thermal imaging in fruit grading, emphasizing significant research, approaches, and the incorporation of machine learning strategies to improve precision and effectiveness. The use of thermal imaging in agriculture seems to have a promising future with lots of room for expansion. By combining thermal imaging with IoT devices and precision agriculture technology, real-time monitoring and decision-making can be enhanced.

A comprehensive picture of crop health can be obtained by combiningthermal imaging with multi- and hyper-spectral imaging, and powerful machine learningmodels can enhance the precision and dependability of thermal image analysiseven more [2]. This literature review aims to offer a thorough examination of the mostrecent advancements and developing patterns in the use of thermal imaging technologyfor fruit grading. The evaluation will include several aspects of thermal imaging, such as how it works with other technologies and how it impacts the agriculture sector, particularly in terms of assessing fruit quality. It will examine a review of current developments in thermal imaging sensors, cameras, and associated hardware. investigation of the application of thermal imaging to evaluate fruit moisture content, internal flaws, and freshness. The presenting of case studies illustrating the useful uses of thermal imaging in diverse agricultural contexts is another main emphasis of the review. Identification of the technical difficulties—such as data interpretation, calibration problems, and environmental influences—that come with using thermal imaging to grade fruit.Further sections cover topics such as identifying developing trends in thermal imaging technology and its uses in agriculture, future research prospects, and recommendations for future research to fill in existing gaps and improve the efficiency of thermal imaging for fruit grading.

1.1. Importance of Fruit Grading

Fruit grading is a crucial procedure in the agriculture sector that evaluates and guarantees fruit quality prior to consumer consumption. By only providing fruits that satisfy particular quality criteria, accurate grading preserves the market value of the product, minimizes post-harvest losses, and ensures customer satisfaction. Fruit has traditionally been graded by professional labourers' by tactile and visual inspection. Unfortunately, the grading process is inconsistent and inefficient because this system is time-consuming, laborious, and subject to human error.

1.2. Overview of Thermal Imaging Technology

In several industries, including agriculture, thermal imaging technology has becomean effective non-invasive and non-destructive inspection tool. Infrared radiation fromobjects is captured by thermal cameras and transformed into temperature data thatcan be shown as pictures. The temperature changes on the items' surface are visible inthese thermal photos, which offer important information about their inside state. Thermalimaging, as opposed to visible light imaging, can identify internal flaws, moisturecontent, and other qualitycharacteristics that are not evident from the outside.

1.3. Statement of the Problem and Research Objectives

Despite recent advancements in the field, the application of thermal imaging in fruit grading has not yet been completely explored and perfected. Because traditional fruit grading systems are unable to provide a comprehensive evaluation of internal quality aspects, they often result in significant post-harvest losses and poor consumer satisfaction. It is necessary to use sophisticated techniques that can accurately and consistently assess fruits based on both internal and external quality parameters. Examining the most current developments and creative concepts in the application of thermal imaging to fruit grading is the aim of this study of the literature. The following are the review's specific goals:

- Provide comprehensive overview of thermal imaging technology which offers adetailed understanding of the principles and advancements in thermal imagingtechnology.
- Examine the efficacy of thermal imaging in fruit grading, considering the impact on the accuracy and consistency of fruit quality assessment.
- Investigate how fruit grading procedures are improved by integrating thermal imaging with IoT devices and machine learning algorithms.
- Examine how thermal imaging is integrated with IoT and machine learning.
- Identify and talk about the drawbacks and restrictions of thermal imaging, emphasizing the operational, financial, and technological difficulties that come with using it to grade fruit as well as new patterns and potential areas for future study.
- It will support researchers to identify new trends in thermal imaging technology andpropose areas for future research. The paper is organized to give a detailed, chronologicalsummary of the developments in thermal imaging for fruit grading. The sectionsare organized as follows:
- **Historical Review:** Describes the development and context of thermal imaging technology in agriculture during the last 30 years, emphasizing significant turning points and breakthroughs.
- **Technological Foundations:** Examines recent developments in sensor technology as well as the fundamentals of thermal imaging**.**
- **Thermal Imaging Applications in Fruit Grading:** This paper looks at how thermal imaging can be used to evaluate interior quality, find flaws, and compare results with more conventional grading techniques.
- **Integration with IoT, Machine Learning and Deep Learning:** Explains how deeplearning, machine learning, IoT, and thermal imaging work together to improve fruitgrading. The integration of thermal imaging with other technologies is also covered.

- **Research Gaps:** Examines the research gaps that need to be filled.
- **Challenges and Limitations:** Identifies the technical, economic, and operationalchallenges of implementing thermal imaging in fruit grading.
- **Conclusion and Future scope:** Summarizes the key findings and implications forthe agricultural industry. Highlights emerging trends and suggests future researchdirections to enhance the effectiveness of thermal imaging in agriculture.

By addressing these objectives and organizing the content systematically, this literaturereview aims to contribute to the understanding and advancement of thermalimaging technology in fruit grading, providing insights into its potential to revolutionizeagricultural practices.

2. Historical Review Context And Development

Thermal imaging, initially developed for military and industrial applications, hasfound significant utility in agricultural practices. The technology's ability to detecttemperature variations has made it particularly useful for assessing fruit quality,identifying defects, and ensuring optimal storage conditions. The foundation for thermalimaging was laid in 1800 with the accidental discovery of infrared radiation byastronomer Sir William Herschel [3]. While experimenting with sunlight and thermometers,he observed a temperature increase beyond the visible spectrum. Thisgroundbreaking discovery paved the way for future developments in thermal imagingtechnology. Gerald C Holst et.al provided an early comprehensive overview of thermalimaging, discussing its principles and applications. Although the primary focus wason industrial and military uses, the foundation laid by this work facilitated later agriculturalapplications [4]. The story of thermal imaging is a fascinating journey thatstretches back centuries, intricately linked to our evolving understanding of heat andradiation. Here's a detailed exploration of the key milestones and figures that shapedthis technology:

2.1. Early Developments (1990s - Early 2000s)

Early in the 1990s, thermal imagingin agriculture started to receive notice, mostly as a means of tracking environmentalfactors and plant health. Infrared thermography was the primary tool used in earlyresearch to track temperature changes in crops and identify water stress. These groundbreaking studies showed that thermal imaging might be a non-invasive diagnostic tool, which paved the way for its application in evaluating fruit quality.

1. Water Stress Detection: Previous research showed that thermal imaging could distinguish temperature differences brought on by variations in transpiration rates, which allowed for the detection of water stress in crops. Idso et al.'s (1990) research demonstrated how infrared thermometry might be used to monitor crop water stress, which laid the groundwork for later, more sophisticated agricultural applications.
2. Thermal Imaging in Horticulture: To evaluate the maturity and quality of crops, researchers started looking into the application of thermal imaging in horticulture. Research on the thermal characteristics of apples and their relationship to ripeness by Schirrmann and Giebel (1998) demonstrated the possibility of thermal imaging in fruit grading.

2.2. Advancements in Technology (2000s - 2010s)

The 2000s saw significantadvancements in thermal imaging technology, including improvements in sensor resolution,sensitivity, and affordability. These technological advancements facilitatedmore widespread adoption and experimental applications in agriculture, particularly
in fruit quality assessment.

1. **High-Resolution Thermal Cameras:** Accurate and detailed imaging of fruit surfaces was made possible by the invention of high-resolution thermal cameras. High-resolution thermal imaging was used in a study by Baranowski et al. (2008) to find early bruises in apples, proving that technology is useful for locating internal flaws that are not apparent from the outside.
2. **Integration with Multispectral Imaging:** Comprehensive evaluations of fruit quality were made possible by combining thermal imaging with additional spectral imaging methods, such as hyperspectral and multispectral imaging. Menesatti et al. (2009) conducted studies that combined thermal and hyperspectral imaging to analyze the internal quality and maturity of fruits, greatly improving the accuracy of quality evaluations.
3. **Automation and Machine Learning:** The incorporation of machine learningalgorithms into thermal imaging systems marked a significant advancement.Automated fruit grading systems leveraging thermal imaging and machine learningwere developed to classify fruits based on their thermal signatures. Researchby Gat et al. (2010) highlighted the use of neural networks to analyse thermalimages of citrus fruits, achieving high classification accuracy.

2.3. Recent Innovations and Trends (2010s - 2020s):

Due to developments in IoT, AI, and data analytics, there has been a notable upsurge in the past ten years in the study and use of thermal imaging for fruit grading. The capabilities and uses of thermal imaging for agriculture have increased thanks to these advancements.

1. IoT Integration: Real-time data collection and tracking have been made possible by the integration of thermal imaging with IoT devices. IoT-enabled thermal cameras can reduce post-harvest losses and provide timely insights by continuously monitoring fruit quality in storage facilities and during transit. Research by Zhou et al. (2023) and Garcia-Tejero et al. (2011) showed how useful IoT-integrated thermal imaging devices are for agricultural applications [5].

2. Advanced AI Algorithms: The use of modern artificial intelligence (AI) methods, such as convolutional neural networks (CNNs) and deep learning, has improved the precision and effectiveness of thermal imaging systems. The MangoYOLO model was created by Koirala et al. (2019) using a combination of CNNs and thermal imaging to precisely categorize mangoes according to their ripeness and quality.

3. Commercial Applications and Field Studies: Commercial uses of thermal imaging for fruit grading have grown in the last few years. Thermal imaging technology is becoming more widely used by businesses and agricultural organizations for inventory management and quality control. Case studies and field investigations, like those conducted by Kuzy et al. (2023) and Cetin et al. (2024), offer useful perspectives on the advantages and difficulties of applying thermal imaging in actual agricultural environments.

Thermal imaging technology has advanced over the last 30 years from being acutting-edge research tool to an essential part of contemporary agriculture methods.Thanks to developments in sensor technology, IoT and AI integration, and successfulcommercial applications, thermal imaging has become a potent non-invasiveapproach for evaluating fruit quality. The use of thermal imaging in agriculture isexpected to grow as studies tackle new problems and open up previously unchartedterritory. This will lead to innovations and improve the precision and efficiency offruit grading procedures. The future of thermal imaging seems quite bright. Artificialintelligence will soon be integrated for real-time analysis and anomaly identification,opening up even more possibilities. Additionally, advancements in microbolometertechnology portend the creation of even more powerful and versatile thermal cameras[6]. Sir William Herschel, who discovered infrared radiation, John Baird, whoinvented the first thermal imaging system, and researchers from Texas Instruments,Hughes Aircraft, Honeywell, Philips, and EEV, which made pyroelectric Vidicontubes, as well as the Raytheon Research Team, who made ferroelectric detectors,are important figures in the field of thermal imaging. A significant leap forwardcame in the 1960s with the development of single-element detectors by researchers atTexas Instruments, Hughes Aircraft, and Honeywell [7]. These detectors could scana scene and produce a linear image, offering a substantial improvement over earliermechanical scanning system. The 1970s witnessed the development of the pyroelectricvidicon tube by Philips and EEV, a crucial advancement that improved thermalimaging capabilities [8, 9]. Raytheon's research team made a significant breakthroughin 1978 by patenting ferroelectric detectors utilizing Barium StrontiumTitanate (BST). These detectors boasted superior sensitivity compared to existingtechnologies, paving the way for the development of more sophisticated and powerfulthermal cameras. With advancements in technology leading to reduced costsand improved functionalities, the 1980s marked the beginning of thermal imaging'sentry into the commercial sector. The rise of World War II (1930s-1950s) spurredsignificant advancements in thermal imaging technology. Research efforts in Europeand the United States focused on improving image resolution and functionality fornight time reconnaissance and weapon targeting [10, 11].

3. Technological Foundations, Conclusion And Future Scope

Thermography, another name for thermal imaging, is a method of producing imagesbased on temperaturevariations on an object's surface using infrared light. As anobject's temperature changes, it releases infrared radiation, which thermal cameraspick up to create thermal images. The primary principles of thermal imaging include:

Infrared Radiation: Objects emit infrared radiation when their temperature is above absolute zero, with the intensity of this radiation increasing as the temperature rises.

Emissivity: Emissivity refers to an object's capacity to emit infrared energy, with different materials having varying emissivity values. These differences can impact the accuracy of thermal imaging.

Thermal Contrast: Thermal contrast arises from the temperature difference between an object and its surroundings. This contrast is essential for identifying anomalies or variations within the object.

Thermal imaging works by converting detected infrared radiation into electrical signals. These signals are then processed to create a visual map of temperature distribution, revealing temperature differences that are not visible to the naked eye. This makes thermal imaging an effective tool for non-invasive quality assessment.

3.1. The Core Principle

The core principle of thermal imaging is based on the fact that all objects emit electromagnetic energy due to their temperature. This energy is primarily radiated in the infrared range of the spectrum, which cannot be seen by the human eye. The amount of infrared radiation an object emits is directly linked to its temperature—hotter objects produce stronger infrared radiation, while cooler objects emit less. [12].

3.2. Recent Advancements in Sensor Technology ThermalCameras: Capturing the Invisible

Thermal cameras are specialized instruments used to measure and identify infraredradiation. Thermal camerasdon't need an external light source to work, in contrastto conventional cameras that record visible lightreflected from objects. The incominginfrared radiation is converted into an electrical signal by an array of infrared detectorshoused within them. After that, this data is processed to create a thermogram,which is a colorful image that shows temperature fluctuations visually. In a thermogram,objects that are hotter (usually yellow, orange, or red) look brighter, while thosethat are colder (usually blue, purple, or black) appear darker [13]. Recent advancementsin thermal sensor technology have significantly improved the resolution andaccuracy of thermal imaging devices. The FLIR C5 thermal camera (FLIR Systems,2024) is an example of a modern, compact thermal camera with high spatial resolutionand sensitivity, making it suitable for detailed fruit quality assessments [14]. The fieldof thermal imaging for fruit grading is constantly evolving, with researchers exploringnovel techniques to improve accuracy, efficiency, and address existing limitations[15]. Significant improvements in thermal imaging sensor technology over the last fewdecades have raised the resolution, sensitivity, and cost of thermal cameras, increasingtheir usefulness and accessibility for agricultural applications.

- **High-Resolution Sensors:** Contemporary thermal cameras feature advanced sensors with high resolution, enabling the capture of detailed thermal images. This increased resolution enhances the ability to identify subtle temperature differences and smaller imperfections in fruits. Research by Baranowski et al. highlighted the success of high-resolution thermal imaging in identifying early bruising in apples [16].
- **Improved Sensitivity:** Advances in sensor sensitivity have enabled thermal camerasto detect minutetemperature differences. This improvement is critical for identifyingsubtle internal defects and variations in fruit quality. Enhanced sensitivity has beena focal point of research, as highlighted in works by Lu, Y et al., which combinedhyperspectral and thermal imaging for comprehensive quality assessment [17].
- **Affordable and Portable Devices:** The development of affordable and portablethermal imaging devices has facilitated their widespread adoption in agriculture.Compact thermal cameras, such as the FLIR C5, offer high performance at a lowercost, making them accessible to small and medium-sized agricultural enterprises[14]. The model of thermal camera, which is compact for the use of image collectionis shown below 1

Figure 1:FLIR C5 Thermal CameraThermal Resolution: 160 × 120 pixels. Temperature Range: -20°C to 400°C. Accuracy: ±3°C or ±3\% of reading. Field of View: 54° × 42° [67]

Figure 2: Various models of thermal imaging cameras[66]

- **Integration with Smartphones:**Recent advancements have also seen the integrationof thermal imaging sensors with smartphones, allowing for convenient and on-thegomonitoring. These devices, like the FLIR ONE, can be attached to smartphones,providing farmers with an easy-to-use tool for assessing fruit quality in the field.Ishimwe R et al. explore the diverse applications of thermal imaging technology in agriculture. Their paper discusses how thermal imaging can be utilized to monitor crop health, detect pest issues, identify water stress, and assess the ripeness and quality of fruits.They go through the current state of thermal imagingtechnology, how it works with cutting edge machine learning algorithms, and whatobstacles and practical difficulties exist in actual agricultural applications. The studyoffers insights on potential future paths for this field's research and development aswell. [18]. A modular hyperspectral thermal imaging camera with a large field of view,a low false positive rate, and no need for cryogenic cooling of the optical componentsis described in the patent [19]. The patent discloses an upgraded thermal imaging systemthat is built into a facepieceassembly and enables the wearer to detect infraredobjects that would not normally be visible because they are radiating heat energy. Athermal imaging camera with enhanced durability and ergonomic features is describedin the patent. These features include a handle that serves as the centre of gravity,resilient material around projecting parts, a seamless housing that is water-resistant,support for camera components that are not directly attached, a dual battery systemthat enables hot swapping, and the capacity to be set upright on a level surface [20].

Figure 3: Thermal Camera for Android,Sobtoe H2F Thermal Imager, Thermal Imaging Camera,160X120 IR High Resolution, 5°F~1122°F Temperature Range,50mk Thermal Sensitivity,Applied to Circuit Inspection[64]

Figure 4: Thermal Camera for iOS, Xinfrared T2S Plus, InfiRay Sensor, 8mm Adjustable Macro Lens, 25Hz, 256x192 IR, Infrared Thermal Imager with Image Enhancement Technology for Industry, Circuit Boards Detect [65]

3.3 Applications of thermal imaging in fruit grading

Thermal imaging offers precise applications in fruit grading, crop health monitoring, soil assessment, disease and pest detection, and water stress analysis. By detecting temperature variations, thermal imaging identifies areas of water stress within a field, optimizing irrigation schedules through deep learning models [21]. The FLIR C5 thermal camera, equipped with a high-resolution sensor (160 x 120 pixels) and a sensitivity of ≤70mK, detects subtle temperature differences on fruit surfaces. This capability is vital for identifying variations that correspond to different ripeness stages or internal defects, supporting real-time assessment and decision-making during fieldwork or post-harvest processing [22,23].

1. Detection of Ripeness and Quality

Thermal images captured by the FLIR C5 are instrumental in assessing fruit ripeness and internal quality. As fruits ripen, they emit metabolic heat detectable as temperature variations on their surfaces. The FLIR C5's high-resolution thermal imaging classifies fruits into different ripeness stages, allowing for better sorting and grading processes. Baranowski et al. used thermal imaging to classify apples based on ripeness by detecting temperature changes linked to metabolic heat at various stages [24]. Similarly, Emmanuel Ekene Okere et al. applied thermal imaging to assess citrus fruit quality, identifying internal defects such as cavities and bruises critical for maintaining quality during storage and transportation. Garc´ıa-Tejero et al. provide a comprehensive overview of non-destructive imaging techniques like thermal imaging, hyperspectral imaging, and MRI, emphasizing their role in ensuring food safety, improving marketability, and reducing post-harvest losses. They also discuss integrating these techniques with advanced data analysis methods, such as machine learning and computer vision, to enhance quality assessment accuracy and efficiency.

K. Kurinji et al. developed a method to predict banana ripeness using thermal imaging and deep learning, achieving a training accuracy of 96.46% and a testing accuracy of 97.7%. They employed MATLAB 2023a and the Deep Learning Toolbox, experimenting with pre-trained CNN models like ResNet, SqueezeNet, DarkNet, and GoogLeNet. The study showed the best results with ResNet-50 and a 0.25 learning rate, with potential for further improvement using more advanced models [26]. Abid Hussain et al. review recent non-destructive imaging techniques for evaluating fruit ripening and maturity stages. Additionally, various segmentation techniques, discussed in another study, are useful before feature extraction and can enhance machine learning algorithms like SVM and random forest [27,28].

2. Detection of Defects and Diseases

Calderón et al. utilized thermal imaging to detect red palm weevil infestations in palm trees, demonstrating its ability to identify internal defects and infestations by detecting temperature differences caused by pests or diseases [29]. García-Tejero et al. applied thermal imaging to detect water stress in plants, showcasing how this technique can monitor crop health, a principle that extends to fruit trees where water stress impacts fruit quality and yield [25]. Thermal imaging identifies internal defects, such as bruises, cavities, and rot, by detecting temperature anomalies on the fruit surface. The FLIR C5 thermal camera captures these anomalies, providing insights into internal quality without cutting open the fruit.

Rishabh Sachan et al. conducted a study using deep learning and thermal imaging to detect and classify paddy leaf diseases. The researchers used a FLIR E8 camera to capture images of healthy and diseased paddy leaves. They then preprocessed and resized these images to 224x224 pixels and split the dataset for training, validation, and testing. The team developed a convolutional neural network (CNN) model with Conv2D, ReLU activation, and max pooling layers, optimized using TensorFlow's data pipeline. They also explored transfer learning with pre-trained models like ResNet152V2, Inception V3, VGG19, and MobileNetV2. The study highlighted challenges, including limited high-resolution thermal image data and noise within the thermal images [30].

Daddy Budiman et al. proposed a method to generate reconstructed thermal images from visible images using a Generative Adversarial Network (GAN) architecture. This deep learning approach involves a generator network that maps input noise to the target IR image space and a discriminator network that distinguishes between real and generated IR images. They trained the network by generating the discriminator for both visible (RGB) and IR images, adjusting parameters like sampling blocks, filter size, weight initialization, and normalization layers to enhance the generator's performance [31].

Mahnoor Khalid et al. conducted an in-depth study on using thermal imaging and numerical data to detect plant stress. They used two plants in the study, one under normal conditions and the other under stress, applying OpenCV for thermal image preprocessing. The research explored two key approaches: feature extraction from thermal images and segmentation using deep learning. They also created a dataset combining thermal images, CWSI index, and soil moisture, training a supervised neural network model to detect water stress in plants [32].

Deep learning models can learn to recognize thermal patterns associated with specific plant diseases or pest infestations, enabling early detection and timely intervention. Early detection is vital in reducing agricultural losses. Calderón et al. successfully identified red palm weevil infestations in palm trees using thermal imaging to detect temperature anomalies caused by larval activity, allowing for prompt action [29]. Prashar et al. emphasized the application of infrared thermography for high-throughput phenotyping, which helps detect plant diseases by monitoring temperature variations [33].

Dhanashree Jawale et al. presented an automated system that uses a thermal camera and image processing algorithms to detect bruises in apples, addressing the high cost and inconsistencies of manual fruit grading. They used a thermal camera to capture images, preprocess them to remove noise, and segment the images using techniques like k-means clustering and Otsu's method. The study employed a Support Vector Machine (SVM) classifier to categorize the images into bruised and non-bruised. Although the study focused on a limited number of fruit samples, the authors suggest expanding the research to include more types of bruises and other fruits. They also propose enhancing the system to make it more robust for broader applications [34].

Thermal imaging can rapidly and non-destructively detect up to 100% of apple bruises by identifying surface temperature differences between bruised and sound tissues, resulting from differences in thermal diffusivity rather than emissivity. The study involved 45 apples of three varieties (Red Delicious, Fuji, and McIntosh) with known densities. The apples were bruised by dropping them from a height of 0.46 m onto a concrete floor, then held at 26°C and 50% RH for 48 hours. Researchers imaged the apples using a ThermaCam PM390 infrared camera during heating and cooling treatments. The apples were refrigerated at 3°C for at least three hours before imaging, with each apple being imaged for three minutes during the assigned treatment [35, 36].

Thermal imaging also helps detect various leaf diseases. Rajasree Rajamohanan et al. classified tomato leaf diseases using a YOLO v5 deep learning model on a field dataset. They captured images of tomato leaves in different farms in Tamil Nadu and Kerala using a cell phone and categorized them as healthy or diseased. The YOLO v5 model demonstrated an impressive accuracy rate of 93% on the test dataset, offering farmers a quick way to detect diseases and take appropriate action [37].

3. Non-Destructive Quality Assessment

Prashar et al. demonstrated the use of infrared thermography as a high-throughput tool for field phenotyping. While their study primarily focused on crop research, they highlighted the non-destructive nature of thermal imaging, making it ideal for assessing the internal quality of fruits without causing damage. Smith et al. conducted a comprehensive review of thermal imaging applications in agriculture, discussing various use cases, including fruit grading. Their study emphasized the potential of thermal imaging to enhance the accuracy and efficiency of quality assessment processes [18, 38].

Hulya Cakmak et al. evaluated the ripening and maturity stages in fruits and vegetables using non-destructive imaging techniques. Their study explored the effectiveness of different imaging modalities in accurately assessing the physiological state of horticultural produce. They clarified the distinction between ripening and maturity, noting that maturity refers to the stage when a fruit reaches physiological development, while ripening involves biochemical changes post-maturation. Understanding these stages is crucial for optimizing harvest times and ensuring quality during storage and distribution. The authors applied Convolutional Neural Networks (CNNs) to analyze images and classify fruits based on their ripeness and maturity levels. They used statistical methods and pattern recognition to interpret imaging data and correlate it with ripening stages. For instance, they assessed tomato ripeness using hyperspectral imaging combined with machine learning, achieving high accuracy in classifying different ripeness stages. In addition, they performed apple maturity detection by employing NIR imaging to measure internal qualities like firmness and sugar content, providing reliable indicators of maturity. Lastly, they conducted citrus fruit analysis by integrating thermal and hyperspectral imaging to detect early signs of spoilage and internal defects [39].

3.4 Integration with IoT, machine learning and deep learning

IoT sensors integrated with thermal cameras can detect temperature fluctuations that may indicate pest infestations, diseases, or water stress, enabling continuous monitoring of crop health. By pinpointing areas that require more or less water, this integration supports precise irrigation management, optimizes resource use, and boosts crop yields. Machine learning algorithms can analyze thermal images captured by the FLIR C5 to enhance the accuracy and automation of fruit quality assessment. For example, Convolutional Neural Networks (CNNs) can be trained to classify ripeness stages or identify specific internal defects based on thermal images. The FLIR C5's compact size and portability make it suitable for both field applications (e.g., assessing fruit directly on trees) and post-harvest applications (e.g., monitoring fruit in storage) [40].

Kamilaris et al. surveyed the use of deep learning in agriculture, including applications of thermal imaging. Their research demonstrated that integrating machine learning algorithms with thermal imaging data significantly improves the accuracy of detecting fruit ripeness, defects, and diseases. Koirala et al. developed the MangoYOLO deep learning model for real-time fruit detection and load estimation. Their study showed that combining thermal imaging with CNNs can automate the grading process and enhance accuracy. The FLIR C5 includes software and connectivity options that facilitate the integration of thermal imaging data with other quality assessment systems [1].

IoT connects various tools and sensors to the internet, enabling real-time data collection and analysis. By merging thermal imaging with IoT devices, one can continually monitor fruit quality in storage and transit. IoT-enabled thermal cameras send real-time alerts about temperature anomalies, helping to reduce post-harvest losses and prevent rotting. Garcia-Tejero et al. highlighted the benefits of integrating IoT with thermal imaging for agricultural applications [40].

Supervised machine learning algorithms, such as Support Vector Machines (SVM) and Random Forests, classify fruits based on thermal image features [42]. These models learn to differentiate between quality classes (e.g., ripe, unripe, bruised) using training data [43, 44]. Deep learning models, particularly CNNs, analyze thermal images for automated fruit grading. These models identify patterns and features that correlate with fruit quality attributes. For instance, Koirala et al.'s MangoYOLO model combines thermal imaging with machine learning to accurately classify fruits based on ripeness and quality [21].

Traditional methods extract basic features from thermal images, like average temperature or temperature distribution patterns. Recent advancements focus on advanced feature extraction techniques, such as texture analysis, which examines spatial variations in temperature across the fruit surface to reveal subtle defects or ripeness variations. Deep learning models can automatically learn complex and informative features directly from raw thermal images, potentially surpassing handcrafted features [46]. CNNs, in particular, excel at image processing tasks, automatically extracting relevant features from thermal images, such as temperature patterns related to disease, ripeness, or water stress. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks analyze sequences of thermal images over time to capture temporal changes in temperature patterns. CNNs can be trained to detect subtle temperature variations that might indicate early disease or pest infestations. Deep learning models achieve high accuracy in image classification and anomaly detection, often outperforming traditional methods [47, 48]. These models handle complex and high-dimensional data effectively, making them suitable for analyzing detailed information in thermal images. By staying updated with the latest advancements, researchers can develop more effective and efficient fruit grading systems using thermal imaging technology [49]. Deep learning facilitates the automation of thermal image analysis, reducing manual inspection and enabling real-time monitoring. Trained models can process large volumes of thermal images quickly, making them ideal for large-scale agricultural operations. Automated systems using deep learning can monitor entire orchards, detecting water stress or disease in real-time and sending alerts to farmers. For example, thermal imaging can analyze water stress in sunflower leaves [51]. Such technology allows for comprehensive monitoring of entire plants. Integrating data from multiple imaging modalities, including visible light images, hyperspectral images, and environmental sensors, can enhance the overall assessment of fruit and vegetable quality. Combining thermal and hyperspectral imaging data can improve the detection of specific diseases that may not be apparent in thermal images alone [52, 53].

3.5 Integration with Other Technologies

The integration of thermal imaging with technologies such as machine learning, deep learning, and the Internet of Things (IoT) has significantly expanded its applications in fruit grading.

i) Multi-Spectral and Hyper-Spectral Imaging

Combining thermal imaging with multi-spectral and hyperspectral imaging enhances the assessment of fruit quality. These techniques capture data across various wavelengths, providing insights into both surface and internal quality attributes. Research by Ye et al. demonstrated the advantages of merging thermal and hyperspectral imaging for non-destructive quality evaluation. This approach captures detailed spectral information about the fruit, allowing analysis of internal properties like sugar content and firmness [54]. Applications include chemical composition analysis, which evaluates sugar content, moisture levels, and pigment concentrations. Although hyperspectral imaging has advanced significantly in assessing horticultural product quality and safety over the past two decades, its commercial use has been limited by speed and cost. However, future developments in imaging technologies and computational methods are expected to facilitate broader industry applications. Yuzhen Lu et al. outlined the essential components of a hyperspectral imaging system, including light sources, wavelength dispersive elements, and area-array detectors [55]. The system employs various image acquisition methods such as point-scanning, line-scanning, area-scanning, and snapshot. It also utilizes sensing modes like reflectance, transmittance, fluorescence, and Raman. Key preprocessing techniques include radiometric correction, noise reduction, and artifact removal, while image analysis involves enhancement, segmentation, and texture analysis. This technology allows for early disease detection and the assessment of quality attributes such as firmness and texture. Combining thermal and visible-light cameras enables simultaneous analysis of thermal properties and external features, such as size, shape, and color defects [56].

ii) Magnetic Resonance Imaging (MRI)

Magnetic resonance imaging (MRI) enables non-invasive evaluation of the internal structure and composition of fruits and vegetables, including water distribution and cellular structure. MRI allows detailed observation of internal features, such as internal rot, voids, and bruising, without destructive testing. It aids in assessing ripeness and maturity by examining internal structures and water distribution. This capability supports consistent quality throughout the supply chain and helps optimize harvest timing [57].

iii) Integration with Automated Systems and Robotics

Integrating thermal imaging with automated systems and robotics has further enhanced its role in fruit grading. Automated sorting lines equipped with thermal cameras and robotic arms efficiently grade and sort fruits based on their thermal signatures. This automation reduces labour costs and increases grading throughput, as evidenced by recent studies on commercial applications of thermal imaging technology.

In summary, advancements in sensor technology, integration with other imaging techniques, and developments in machine learning and IoT have greatly expanded the use of thermal imaging in fruit grading. These innovations make thermal imaging a powerful tool for accurate, non-invasive quality monitoring, contributing to more efficient agriculture and reduced post-harvest losses.

3.6 Advantages and research gaps of thermal imaging

Thermal imaging presents several advantages compared to traditional visible-light imaging:

1. Day and Night Operation:

Thermal cameras operate effectively in complete darkness, fog, smoke, or other obscuring conditions where traditional cameras may struggle [13].

2. Temperature Measurement:

Thermal imaging enables non-invasive remote measurement of surface temperatures. This feature is valuable in applications ranging from industrial inspections to medical diagnostics [58].

3. Visualization of Heat Patterns:

Thermal imaging reveals hidden temperature variations that are not visible to the naked eye. This capability allows for early detection of potential issues in buildings, machinery, and the human body. Developments in detector sensitivity, image processing algorithms, and miniaturization are making new and interesting applications of thermal imaging technology possible. Over time, thermal imaging is expected to become increasingly significant across various industrial, scientific, and everyday applications.

Kyungjae Lee et al. propose a novel method to enhance thermal images using a convolutional neural network (CNN) trained in the brightness domain. The residual learning technique within this network significantly improves thermal image quality, making the method applicable to various practical uses. Extensive experiments and comparisons with state-of-the-art methods show that the brightness domain approach outperforms others [59]. Data augmentation techniques, such as rotation, scaling, and flipping, further enhance the network's performance. The brightness domain method substantially improves thermal image quality, achieving the highest performance among all compared techniques.

Mojgan Madadikhaljan et al. propose a pipeline for georeferencing thermal satellite images. This pipeline employs a deep learning network to classify land cover types in the images and compares these classifications to reference land cover maps to determine the image's location. The pipeline successfully geolocates 75% of test images with an error of less than 10 pixels. The methodology includes:

- Using deep learning models for binary and multi-class land cover classification.
- Matching projected land cover maps to reference maps using template matching.
- Restricting the search area to a buffer around the satellite navigation system's coarse geolocation.
- Employing cross-correlation coefficient template matching to find the most similar reference map section.
- Using a weighted decision-making process that prioritizes high-performing classification models.

Training involves:

- Applying Dice Loss along with Cross-Entropy Loss to address class imbalances.
- Conducting experiments with a batch size of 64 for 300 epochs.

Mojgan Madadikhaljan et al. also explore the performance difference between region-specific models and non-region-aware models, finding that region-aware models perform better [60].

Article provides an overview of thermal imaging systems, their real-time applications across various fields such as agriculture, medical diagnostics, human detection, and facial expression analysis. Thermal imaging systems use passive sensors to detect and capture infrared radiation emitted by objects. According to Planck's law, the spectrum of this radiation shifts to shorter wavelengths as temperature increases. Two primary detectors used in uncooled thermal cameras are ferroelectric and microbolometer, with microbolometers being more sensitive and offering advantages over ferroelectric sensors [61].

Mritunjay Rai et al. identify several limitations in current thermal imaging systems, including the lack of textural information, reflections of thermal radiation, and the need for affordable, high-resolution thermal cameras with optical zoom and wide-angle lenses. Additionally, the absence of standardized calibration methods for thermal sensors with other types of sensors poses a challenge.

Thermal imaging has evolved significantly since the discovery of infrared radiation, transforming from a military tool into a versatile technology with diverse applications in scientific, industrial, and societal domains. As technology progresses, further exciting advancements are anticipated. Thermal imaging provides real-time monitoring and quick decision-making through continuous data collection and analysis. It offers a non-invasive means of assessing conditions without physical contact. IoT integration enhances operational efficiency by providing precise insights. However, the system also faces challenges, such as managing the vast amounts of data generated and addressing high initial setup costs for IoT and thermal imaging equipment. Ensuring data security is crucial to prevent unauthorized access and breaches

3.6.1 Research gaps

Although thermal imaging has shown to be a useful technique in agriculture, a numberof research gaps must be filled before its full potential can be realized. Future researchmust focus on standardizing protocols, minimizing environmental effects, integratingwith other imaging modalities, developing data processing techniques, cutting costs,and investigating new applications. By filling in these gaps, thermal imaging willbecome more accurate, more accessible, and more useful in modern agricultural operations.This will improve crop management, fruit quality assessment, and sustainablefarming.

1. New Applications in Agriculture:
Exploring novel applications of thermal imagingin agriculture, such as soil moisture content analysis, livestock health monitoring,and precision irrigation scheduling. Research should also investigate the long-termimpacts of thermal imaging on agricultural productivity and sustainability. Prasharet al. explored the use of infrared thermography for phenotyping, suggesting otherpotential applications inagriculture [33].

2. Real-Time Monitoring and IoT Integration:
While thermal imaging is valuable forreal-time monitoring, integrating it with IoT systems for continuous data collectionand analysis remains underexplored. Developing IoT-enabled thermal imaging systemsthat can transmit data in real-time to centralized platforms for analysis. Thisincludes creating efficient data management systems that can handle large volumesof thermal data and provide actionable insights for farmers. Zhang et al. discussedthe potential of integrating small unmanned aerial systems with IoT for precisionagriculture [1].

3. Cost and Accessibility:
High-resolution thermal cameras remain relatively expensive,limiting their accessibility to small-scale farmers and researchers with limitedbudgets. Research into the development of cost-effective thermal imaging solutionswithout compromising accuracy. This includes exploring alternativematerials andmanufacturing processes for thermal sensors, as well as the potential for low-cost,portable thermal imaging devices. Sinha et al. addressed the economic challengesof implementing advanced imaging technologies in agriculture [62].

4. Data Processing and Machine Learning:
Processing and analyzing thermal images demand substantial computational resources and expertise. Current machine learning models, while effective, often face challenges with the high-dimensional and complex nature of thermal data. Researchers need to develop more efficient and robust machine learning algorithms specifically designed for thermal imaging data. This involves exploring deep learning models capable of addressing the unique challenges posed by thermal data, such as noise, low contrast, and high dimensionality. Furthermore, creating large, annotated datasets is essential for effectively training these models.
Kamilaris et al. highlight the integration of deep learning in agriculture and address the challenges associated with processing thermal imaging data. Koirala et al. demonstrate the potential of deep learning models, such as MangoYOLO, for real-time fruit detection and grading. [41].

5. Fusion with other imaging modalities issue:
While thermal imaging providesvaluable information about temperature variations, it often needs to be combinedwith other imaging modalities to obtain a comprehensive assessment of crophealth and fruit quality. Research into the integration of thermal imaging withmulti-spectral and hyper-spectral imaging. Developing data fusion techniques thatcombine information from different imaging sources to enhance the overall accuracyand reliability of agricultural assessments. Calder´on et al. demonstrated thebenefits of combining hyperspectral and thermal imagery for disease detection [29].Wang et al. explored the potential of integrating thermal infrared remote sensingwith other imaging technologies.

6. Lack of standardized protocols:
There is a lack of standardized protocols forcapturing and analysing thermal images in agricultural settings. Variations inequipment, environmental conditions, and methodologies can lead to inconsistentresults. Developing universally accepted calibration methods and standardized protocolsforthermal imaging in agriculture. This includes guidelines for image capture,processing, and interpretation toensure consistency and comparability across differentstudies and applications. Iv´an Francisco Garc´ıa-Tejero et al. emphasized theneed for careful calibration to mitigate environmental effects on thermal imagingaccuracy [25]. Sugiura et al. discussed the challenges in standardizing dataprocessing for thermal images [63].

3.7 Conclusion and future scope
This section explains conclusion of the thermal imaging in various areas and futurescope in agricultural section.

3.7.1 Conclusion

For non-destructive fruit grading, thermal imaging has shown to be an invaluable toolwith substantial benefits in automation, efficiency, and accuracy. Thermal imagingcan improve fruit quality assessment by detecting ripeness, flaws, and diseases moreaccurately by combining with cutting-edge machine learning approaches. Despite challenges such as environmental conditions, data processing, and costs, advancements in sensor technology and data analysis are poised to reveal new applications for thermal imaging in agriculture. Integrating deep learning with thermal imaging significantly enhances its capabilities, offering improved accuracy, greater automation, and the ability to combine data from multiple sources for more comprehensive analysis.Deep learning for thermal imaging is a useful tool for contemporaryagricultural operations, helping to more effectively and efficiently monitor and managecrops despite its obstacles. Future applications of thermal imaging could be furtherexpanded by continued improvements in deep learning algorithms and technology.

3.7.2 Future Scope

i) Integration with IoT and Precision Agriculture:

Real-time monitoring and decisionmakingcan be improved by integrating thermal imaging with Internet of Things(IoT) devices and precision agriculture technology. With the use of Internet ofThings-enabled thermal cameras, agricultural techniques can become more preciseandresponsive by sending data for analysis to centralized systems [1].

ii) Multi-Spectral and Hyper-Spectral Imaging:

A thorough understanding of crophealth can be obtained by combining thermal imaging with multi- and hyperspectralimaging. By collecting data at various wavelengths, multispectral imagingcan provide insights into the physiology and stress conditions of plants. Even morespectral resolution is possible with hyper-spectral imaging, making it possible toidentify minute variations in plant health [2].

iii) Advanced Machine Learning Models:

The accuracy and dependability of thermalimage analysis can be further increased by the creation of more complexmachine learning models, such as CNNs and Long Short-Term Memory (LSTM)networks. These models can identify intricate patterns in thermal data, improvingcategorization and forecasting [40].

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