Drone-Based Sensing and Imaging for Fruit Crop Monitoring: A Review

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Abstract

The global fruit production industry has been suffering from numerous problems in the yield, quality, and food safety context. The use of drone-based sensing and imaging technologies has emerged as a promising approach for monitoring fruit crops, enabling real-time assessment of crop health, growth, and development. Monitoring fruit crops helps identify areas of improvement and makes decisions based on data. This review focuses on the various sensor technologies utilized in drone-based fruit crop monitoring, including RGB, multispectral, hyperspectral, thermal, and LiDAR sensors. The applications of these sensors are discussed, including yield estimation and prediction, crop growth monitoring, disease detection and diagnosis, pest detection and management, nutrient deficiency detection, and water stress monitoring. The review highlights the advantages and limitations of each sensor technology, as well as the challenges associated with data processing and analysis. Case studies demonstrate the effectiveness of drone-based sensing and imaging in fruit crop monitoring, and future directions are discussed, including the integration of sensor technologies with other precision agriculture tools and the development of specialized sensors and cameras. Standardization and best practices are emphasized as crucial for the widespread adoption of drone-based sensing and imaging in fruit crop monitoring.

1. Introduction

The global fruit production industry has faced various challenges in terms of optimum yield, quality, and food safety. Fruit crop monitoring is an important task for identifying possible issues, making data-driven decisions, and implementing precision agriculture practices (Zhang et al., 2020). Precise monitoring will allow farmers to detect the early signs of stress, disease, and pests and reduce yield losses and environmental impact (Gomez et al., 2020). Timely monitoring allows farmers to detect potential problems, make data-driven decisions, and apply precision agriculture practices. Fruit production around the world faces several challenges in ensuring optimum yield, quality, and food safety.

Fruit crop monitoring plays an essential role in pointing out possible issues, data-based decisions, and precision agriculture practice implementation by Zhang et al. (2020).

Correct monitoring gives a farmer a chance to discover the earliest signs of stress, diseases, or pests that eventually cause lesser losses and also lesser impact on the environment, as identified by Gomez et al. 2020). Timely monitoring enables farmers to pinpoint potential problems, make data-driven decisions, and employ precision agriculture.

Traditional methods of fruit crop monitoring rely highly on manual inspection, ground-based sensors, and satellite images. Manual observation is the mainstay of traditional agricultural monitoring techniques, which have drawbacks including being costly, labor-intensive, and they are very prone to errors (Karmakar et al., 2023). This is because it limits the inspector's ability to examine a smaller sample of crops from a smaller region of fields in a given amount of time. The inspectors are also specialists in a particular agricultural procedure. To examine various processes or to cover a larger area, more inspectors have to be hired. Nevertheless, it raises costs (Dorj et al., 2017). It will then be a result of the quality of knowledge and expertise of the inspector. Therefore, it might come up with less successful outcomes containing critical mistakes (Bargoti and Underwood, 2017).

Remote sensing technology is currently considered a tool with great potential to improve intelligent and precise agricultural processes with the introduction of Unmanned Aerial Vehicles (UAVs) (Rejeb et al., 2022). According to Eskandari et al. (2020), UAVs are drones or remotely piloted aerial systems equipped with advanced equipment, such as multispectral cameras, sensors, and communication devices with decision-making intelligence, for data collection and perception, decision-making, and action performance. Overcoming the drawbacks of conventional monitoring, drone-based sensing and imaging have become useful instruments for precision agriculture (Sankaran et al., 2015). Precision agriculture, in combination with drone technology, offers monitoring of extensive areas, reduction in labor costs, and enhanced decision-making (Rejeb et al., 2022). Drones equipped with different sensors and cameras provide critical data about crop health, growth, and development. This is a comprehensive review of drone-based sensing and imaging for the monitoring of fruit crops based on principles, technologies, applications, advantages, challenges, and future direction. This review aims to synthesize the existing research on the effectiveness of drone-based sensing and imaging in fruit crop monitoring.

2. Drone Platforms and Sensors

Drone platforms are very significant for fruit crop monitoring, as they offer numerous types according to specific applications (Zhang et al., 2020). Fixed-wing drones have airplane like designs, thus they are used in large agricultural areas. Equipped with long-range capability and a stable flight pattern, such drones are ideal for mapping expansive fields, monitoring crop health, and assessing general farm conditions (Vinodhini, 2024)). Rotary-wing drones, like quadcopters, are more agile and can hover, making them ideal for smaller, complex orchard environments (Sankaran *et al.,* 2015). Hybrid drones have a fixed-wing and rotary-wing combination, providing versatility. Sensor selection is vital for successful fruit crop monitoring.

Drones offer an exciting opportunity to track crop fields with high spatial and temporal resolution remote sensing to enhance water stress management in irrigation. Farmers have historically depended on soil moisture measurements and weather conditions to detect crop water status for irrigation scheduling (Awais *et. al, 2022*). RGB cameras are utilized for high-resolution photography (Candiago *et al*., 2015), whereas multispectral cameras capture reflectance data over specific wavelengths (Matese *et al*., 2015). Hyperspectral cameras offer detailed spectral information, and this can be used for the detection of minor changes in crop health (Gomez et al., 2020). Thermal cameras are used to detect temperature variations that can indicate the presence of water stress or illness (Lottes *et al.,* 2017). LiDAR sensors offer high-resolution 3D models of orchards, enabling crop height and density analysis (Rasmussen *et al*., 2016).

The quality of data, in great measure, is affected by camera systems and configurations. The use of single-camera setups is appropriate for simple monitoring tasks, while multi-camera configurations allow for the simultaneous capture of data from multiple angles (Toth *et al.,* 2019). Stereo camera systems offer 3D imaging capabilities, improving spatial awareness (Zhang *et al*., 2020); some drones integrate multiple sensor types, allowing for comprehensive data collection; efficient sensor-drone integration ensures smooth data collection and processing; this integration includes sensor calibration, synchronization, and data fusion techniques (Sankaran *et al*., 2015); advanced drone platforms frequently have modular designs that make it simple to swap out or upgrade sensors; integration also takes communication protocols, power management, and data storage into consideration.

The choice of drone platform and the sensor suite mainly depends on monitoring objectives, orchard features, and environmental conditions (Gomez *et al*., 2020). For example, to detect fruit and count the number, RGB imaging at a high resolution might be acceptable, while for disease diagnosis or analysis of nutrient deficiency, one may need multispectral or hyperspectral imaging.

3. Applications in Fruit Crop Monitoring

Drone-based sensing and imaging have numerous applications in fruit crop monitoring, enhancing the efficiency and accuracy of agricultural practices.

3.1. Yield Estimation and Prediction, Crop Growth Monitoring:

Drones mounted with RGB, multispectral, and hyperspectral cameras provide accurate yield estimation and forecast (Gomez *et al*., 2020). Crop growth, height, density, and vigor can be monitored by assessing vegetation indicators such as NDVI and EVI (Matese *et al.*, 2015). This information allows for more informed judgments on pruning, thinning, and harvesting. Additionally, drone-based 3D model using LiDAR and photogrammetry permits the accurate assessment of crop height and density (Rasmussen *et al*., 2016).

3.2. Disease Detection and Diagnosis, Pest Detection and Management

Drones are useful in detecting fungal, bacterial, and viral diseases such as powdery mildew and citrus canker (Candiago *et al*., 2015). Hyperspectral imaging identifies subtle changes in spectral reflectance, indicating disease presence (Gomez et al., 2020). In the same way, thermal cameras installed in drones detect temperature variations, which helps in pest management (Lottes et al., 2017). For example, thermal imaging detects areas with increased insect activity, allowing for targeted pesticide application.

Drones detect fungal, bacterial, and viral diseases like powdery mildew and citrus canker (Candiago et al. 2015). Hyperspectral imaging detects even slight variations in spectral reflection, indicating the presence of illness (Gomez *et a*l., 2020). Conversely, a drone with a thermal camera will detect temperature differentials and aid in the management of pests (Lottes et al., 2017). For instance, thermal imaging shows areas of high activity of insects so that targeted pesticide application can be provided.

3.3. Nutrient Deficiency Detection and Water Stress Monitoring:

Over the past decade, vegetation characterization has been identified as an important indicator for understanding ecosystem adaptation to environmental change (Lioubimtseva and Henebry, 2009). Precise estimation of plant nutrient needs based on leaf optical properties such as fluorescence, reflectance, and transmittance is also gaining wide attention in agriculture (Mee et. al., 2016). This has been facilitated by development of various sensing techniques. Among all nutrients, nitrogen appears most frequently as a comparative element in most research-based studies on nutrient uptake dynamics and patterns due to its high relative content in the form of proteins in chlorophyll and enzymes. Multispectral and hyperspectral imaging have emerged as the most reliable and important quantification techniques of biochemistry of vegetation (Asner *et al*., 2015; Singh *et al.,* 2015; Wang *et al*., 2020) and have, therefore, the great potential to monitor nutrient status of crops (He *et al.,* 2016; Mahajan *et al*., 2017).

Drone-based thermal imaging measures water stress and identifies regions that require irrigation changes (Zhang et al., 2020). This enables more efficient irrigation scheduling, avoiding water waste and maintaining maximum crop growth. Growers can embrace precision agriculture practices by combining these applications, which increase crop output, reduce pesticide use, and promote sustainable agriculture.

4. Image Processing and Analysis Techniques

Effective image processing and analysis are important to extract valuable information essential for useful information derivation from drone-acquired images in fruit crop monitoring. This section discusses various techniques employed in image examines the many approaches used in picture processing and analysis.

Image preprocessing is an important pre-processing step for preparing images ready for analysis. Registration is an essential step in getting images in a position to be analysed. Registration is the process of aligning multiple images taken several pictures collected at different times or angles to form a single, holistic image (Gonzalez and woods, 2017). Filtering methods like Gaussian or median filtering reduce noise and enhance image quality while enhancing image quality (Jensen *et al*., 2000). Normalization helps maintain consistency in intensity and contrast of images so that one can compare across images (Liu *et al*., 2018). Fruit crop monitoring employs OBIA very extensively.

OBIA involves segmenting images into meaningful objects, such as individual trees or fruit, and extracting relevant features (Blaschke *et al.,* 2014). This approach enables precise analysis of crop health, growth, and development. OBIA can easily identify the alterations in the size, shape, and color of tree canopies, thereby indicating stress or presence of disease (Hossain *et al*., 2019). The implementation of machine learning-based methods for image analysis to monitor fruit crops is now progressively increasing every day. For instance, some of the classifying algorithms that can ensure precise recognition of crop type, growth phases, as well as the existence of diseases include Models such as SVM, Random Forest Classifier, Naive Bayes, ANN, CNN, and their variants (Bhargava and Bansal, 2021).

Continuous factors like fruit quality and yield are predicted by regression methods (Gomez et al., 2020). Large datasets are necessary for the training and validation of these algorithms. In fruit crop monitoring, image analysis has been transformed by deep learning approaches. According to Kamilaris *et al.* (2018), CNN shows great effectiveness in picture categorization as well as object recognition tasks. LSTM networks and RNN check spatial and temporal patterns in image sequences (Xu et al., 2020).

These methods enable one to automatically detect minute changes in crop development as well as health. Data integration and fusion combine information from sources like drone-acquired images, weather data, and soil sensors. This integrated approach allows one to have a comprehensive insight into crop growth, development, and response to environmental factors (Zhang et al., 2020). Techniques in data fusion, such as PCA and ICA, reduce the dimensionality of data and enhance efficiency in analysis (Liu et al., 2018).

5. Case studies and examples

5.1 Apple Yield Estimation using Drone-Based RGB Imaging

A study conducted in Washington State, USA, drone-based RGB imaging was utilized to estimate apple yield (Gomez *et al.*, 2020). The researchers employed object-based image analysis (OBIA) to segment images into individual trees and extract features related to yield. Results showed a strong correlation between drone-estimated yield and actual yield (R2 = 0.85). This study demonstrated the potential of drone-based RGB imaging for accurate yield estimation in apple orchards.

5.2. Citrus Disease Detection Using Multispectral Imaging

Candiago *et al*. (2015) employed multispectral imaging to identify Huanglongbing or citrus greening disease caused by a bacteria *Candidatus liberibacter*. Images were captured by using a camera mounted on the drone and machine learning classification was performed for distinguishing healthy from diseased trees. With 92% accuracy of detection, the results have been demonstrated for the efficacy of early detection of diseases using multispectral imaging in citrus orchards.

1.3. Grapevine Water Stress Monitoring using Thermal Imaging

A study in Italy used thermal imaging to track water stress in grapevines (Matese *et al*., 2015). Thermal images taken by drones were analyzed to detect temperature changes that could be indicative of water stress. The results indicated a high correlation between the thermal indices and the levels of water stress (R2 = 0.90). This study proved the potential of thermal imaging in precision irrigation management in grapevine cultivation.

5.4. Mango Fruit Detection and Counting with LIDAR

Scientists in Australia used LIDAR (Light Detection and Ranging) to detect and count mango fruit (Turner et al., 2015). LIDAR point clouds were analysed to identify fruit and estimate yield. The results indicated an accuracy of 95% in fruit detection and counting. The study proved the efficiency of LIDAR for yield estimation in mango orchards.

6. Challenges and Limitations

Although drone-based sensing and imaging of fruit crops hold much promises, there are still various challenges and limitations.

6.1. Weather Conditions

Weather conditions are significantly found to have impacts on drone operations and data quality. Wind, rain, and extreme temperatures can compromise drone stability, sensor accuracy, and image quality (Toth *et al.,* 2019). Sunlight variability also affects image quality, with harsh sunlight causing saturation and shadows (Gomez *et al*., 2020). Researchers have proposed strategies to mitigate weather-related issues, such as using weather-resistant drones and adjusting flight schedules (Zhang *et al*., 2020).

6.2. Sensor Calibration and Validation

Sensor calibration and validation are important to ensure proper data collection. However, sensor drift, noise, and variability can degrade the quality of data collected (Matese *et al*., 2015). Calibration processes are tedious and need specialized equipment (Candiago *et al*., 2015). Validation methods such as ground-truthing are very important to validate the accuracy of sensors (Turner *et al*., 2015).

6.3. Data Processing and Analysis Complexity

Data processing and analysis are an essential part of drone-based sensing and imaging. However, there exist challenges in processing vast data sets, noise handling and errors, and extracting meaningful information from this data (Liu *et al*., 2018). Advanced algorithms and machine learning techniques can help with overcoming these challenges but necessitate heavy computational resources and skillset knowledge (Kamilaris *et al.,* 2018).

6.4. Regulatory Frameworks and Privacy Concerns

Regulatory frameworks that govern the use of drones vary globally, thus causing uncertainty and liabilities for users (European Union Aviation Safety Agency, 2020). Data collection and storage, therefore, pose privacy issues that need to be taken into consideration (NOAA, 2017). The researcher must adhere to the regulation and privacy concerns by having transparent data handling practices.

6.5. Cost-Effectiveness and Scalability

Cost-effectiveness and scalability are essential for large-scale adoption. Drone-based sensing and imaging can be costly, especially when high-resolution sensors and complex analytics are used (Lottes et al., 2017). Scalability becomes a problem when drone-based solutions are applied to large agricultural operations (Gomez et al., 2020). Some researchers are working on finding cost-effective alternatives, such as using low-cost sensors and exploiting existing infrastructure.

7. Future Directions

The development of drone-based sensing and imaging has many future directions that have the potential to enhance fruit crop monitoring.

7.1. Integration with Other Technologies

Integration with emerging technologies such as Internet of Things (IoT), robotics, and Artificial Intelligence (AI) will transform fruit crop monitoring (Kamilaris *et al*., 2018). IoT sensors can provide real-time soil moisture and temperature data, while robotics can automate pruning and harvesting tasks (Liu *et al*., 2019). AI-powered analytics can optimize data analysis, predictive modeling, and decision-making (Gomez et al., 2020).

7.2. Development of Specialized Sensors and Cameras

Sensor and camera technology have the potential and can offer improved data quality and resolution. Specific sensors for targeted stresses, diseases, or nutrient deficiencies will enhance monitoring accuracies (Matese *et al.,* 2015). High-resolution cameras with new spectral ranges (hyperspectral, multispectral) provide insights into crop health and growth (Candiago *et al*., 2015).

7.3 Better Data Analysis and Decision Support Systems

Next-generation data analysis and decision support systems will be able to make more informed decisions. Advanced machine learning algorithms will improve predictive modeling, anomaly detection, and recommendation systems (Kamilaris *et al*., 2018). Cloud-based platforms will allow for data sharing, collaboration, and integration with other agricultural systems (Liu *et al*., 2019).

7.4. Expanded Applications

Drone-based sensing and imaging will extend beyond crop monitoring to precision irrigation, fertilization, and pest management. Precision irrigation systems will apply water according to soil moisture and crop water stress (Zhang *et al*., 2020). Drone-based fertilization will allow targeted nutrient application, minimizing waste and environmental impact (Gomez *et al.,* 2019).

7.5. Standardization and Best Practices

Standardization and best practices can only be achieved through this wide-scale adoption. Standardization of protocols in drone operation, data collection, and analysis will ensure consistency and allow comparability among studies (Toth *et al*., 2019). Best practices development for data management, storage, and sharing will boost collaboration and innovation (Federal Aviation Administration, 2020).

Disclaimer (Artificial intelligence):

Authors hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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