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Exploring traditional and modern techniques in fruit disease detection and classification with IoT integration: A comprehensive survey

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Abstract

Farm produce suffers greatly from fruit diseases, and scaling up the interrogation of crops is not a practical step because of manual identification. Recent trends have emerged regarding various studies on some of the recently discovered computational methodologies used for identification and classification purposes pertaining to fruit disease via application of technologies from machine learning and deep learning. In the beginning, simpler methods, such as SVM and ANN, were successful at their respective tasks but faced problems with feature extraction and generalization. However, the overall accuracy of these models increased with the introduction of newer techniques like CNNs, achieving up to 98.7% in the real-time detection model of strawberry fungal disease. This survey also indicates the possible extent of DL techniques implemented while treating issues related to the diversity of datasets and scalability of models that are necessary for further developing these technologies in agriculture. This survey provides scholars and researchers with wide-ranging information and insights into both traditional and state-of-the-art approaches to fruit disease diagnosis, this survey article can be treated as a treasured reservoir in research academia working in the domain. It provides a comprehensive framework for future research and innovation in agricultural disease control by synthesizing the existing approaches and identifying significant improvements.

Keywords: Machine learning; Fruit disease detection; Precision agriculture; Convolutional Neural Network; Real-time monitoring; Deep learning integration

1. Introduction

Fruit diseases in agriculture cause the global industry a loss of around 40% crops per year with its annual economic implications standing at $220 billion. For fruit farmers, disease can easily translate to 30-50% loss of income, increasing difficult circumstances regarding productivity and food security. With anticipated population growth to 9.7 billion by 2050, there is a growing need for efficient, large-scale fruit disease detection.

Conventional methods of detection are based on visual inspection, which is slow, subjective, and difficult to apply on a large-scale farm. Some alternative techniques that have recently been shown promising in fruit disease early detection and classification would include the use of machine learning and computer vis Conventional methods of detection are based on visual inspection, thereby slow, subjective, and not easy to apply on a large-scale farm. Emerging machine learning and computer vision algorithms clearly have much promise for the detection and classification of fruit diseases accurately and in a timely manner. Approaches like these not only bring faster accuracy and scalability but also possibilities that will lead the way toward better agricultural practice and food security.

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Detection and classification of fruit diseases are crucial for the productivity of agriculture and food security, especially at a time when food production is on demand. Fruits diseases cause reduction in yield besides severely affecting the quality of agricultural products that lead to losses and a threat to farmers' livelihood. The early diagnosis of these diseases can minimize damage and reduce production costs while increasing farmers' overall income. Traditional approaches to disease detection have relied on subjective visual inspection, which is tedious and not appropriate for large-scale farm operations.

The application of machine learning and deep learning algorithms to image processing tasks has shown a great potential in improving the accuracy and efficiency of fruit disease detection systems, which can overcome the limitations of traditional, labour-intensive methods. Thus, automated fruit disease offers the potential to reduce reliance on human experts and ensure timely interventions in agricultural practices. The application of these technologies has the potential to revolutionise agriculture by providing timely and precise diagnosis, leading to better disease management and decision-making.

Nevertheless, the currently available fruit disease datasets have certain limitations. Despite being extensive, most of the datasets lack diversity in disease types, illumination differences, and environmental circumstances. Furthermore, a lot of them are exclusive to specific fruit varieties or a small number of illnesses, which limits how broadly models developed using them may be applied. For improving model performance in real-world applications, these datasets must be continuously expanded and diversified, and they must be curated to incorporate real-world agricultural settings.

This survey paper provides a comprehensive overview of recent advancements in fruit disease detection and classification. It highlights the contributions of various researchers who have developed and applied innovative ML and DL techniques to this field. This paper talks about the issues and opportunities brought about by implementing such technologies in agricultural settings. A continuous improvement to higher accuracy at low cost is urged. Exploring the success of current approaches along with the limits, this paper aims to guide further research into future directions that are likely to spur greater adoption of such advanced technologies into agricultural practice.

This paper is divided into six main sections. Section II presents the Materials and Methodology, discussing the various datasets used and providing a flowchart outlining the general methodology. It also covers traditional techniques in fruit disease detection, machine learning approaches, and more advanced deep learning techniques. Section III explores the integration of IoT in Fruit Disease Monitoring, focusing on how IoT technologies are being employed for real-time monitoring of fruit diseases. A Comparative Analysis of Techniques is presented in Section IV, where traditional methods, machine learning algorithms, and deep learning approaches are compared based on their effectiveness, accuracy, and scalability. The Challenges and Future Scope in the detection of fruit diseases are provided in Section V to highlight the potential bottlenecks and areas for advancement. Finally, the Conclusion summarizes the conclusions and contributions drawn from this research study in Section VI.

2. Material and Methodology

2.1. Datasets

The availability of high-quality datasets is fundamental to advancing research in fruit disease detection and classification. Several specialized datasets have been developed to support the training and evaluation of machine learning and deep learning models, catering to various fruit types and their associated diseases.

One of the most extensively utilized resources is the PlantVillage dataset [1], which includes over 54,000 images of healthy and diseased plant leaves across 14 crop species, including fruits like apples, grapes, and tomatoes. This dataset has become a benchmark for evaluating the performance of different algorithms in plant pathology, particularly for fruit disease detection.

For apple disease detection, the Kaggle Plant Pathology 2020 dataset [2] is particularly significant. It contains thousands of images categorized into four classes: healthy, multiple diseases, rust, and scab. This dataset has been instrumental in developing robust models for classifying apple diseases, addressing the complexities of multi-class classification tasks.

In the case of citrus fruits, the Citrus Disease Image Gallery [3] offers a comprehensive collection of images capturing various stages of disease development in citrus plants. This dataset includes images of common diseases such as citrus greening and black spot, serving as an essential resource for researchers focused on citrus disease detection.

The Strawberry Disease Dataset [4] provides a specialised collection of images focusing on diseases affecting strawberries, such as powdery mildew and leaf blight. This dataset has been utilized to develop models capable of accurately identify these diseases, demonstrating the potential of machine learning techniques in managing fruit-specific diseases.

Similarly, the Banana Disease Dataset includes images of banana leaves [5] affected by diseases like black sigatoka and banana bunchy top virus. Researchers have used this dataset to train models aimed at the early detection and management of banana diseases, which are critical for maintaining banana crop yields.

For mango fruit diseases, the Mango Leaf Dataset and Mango Disease Dataset [6] are invaluable resources. These datasets contain images of mango leaves and fruits affected by various diseases, including anthracnose, powdery mildew, and sooty mold. They have been employed in studies to develop models that can detect and classify mango diseases, which are essential for safeguarding mango production.

These datasets, covering a broad range of fruit types and diseases, provide a solid foundation for developing and testing fruit disease detection models. The continuous expansion and curation of such datasets are vital for improving the accuracy, robustness, and generalizability of machine learning models in agricultural applications.

2.2. Fruit Disease Detection and Classification Techniques

Fruit disease identification is an important part of agricultural management since it affects both the quantity and quality of produce. Timely action can minimize crop losses and preserve the quality of output when illnesses are detected early and accurately. Fruit Disease detection is aided by the application of modern algorithms, image processing, and feature extraction while ML and DL not only improve but also automate the identification procedure. The entire process of detecting fruit diseases is described in this section, from the first image capture to the final treatment recommendations.

The flowchart depicted in Figure 1 defines the several steps within the pipeline that are expanded on throughout the processes of image processing and feature extraction for fruit disease detection. It begins with the raw acquisition of images through sensors or cameras of the fruits. It then later applies an algorithm for noise reduction to remove distortions in those images so that their quality is improvised to be further used in the pipeline. Next, there is image enhancement that boosts brightness and contrast, among others, to make critical details stand out. There is segmentation which separates diseased areas from the healthy parts of the fruit.

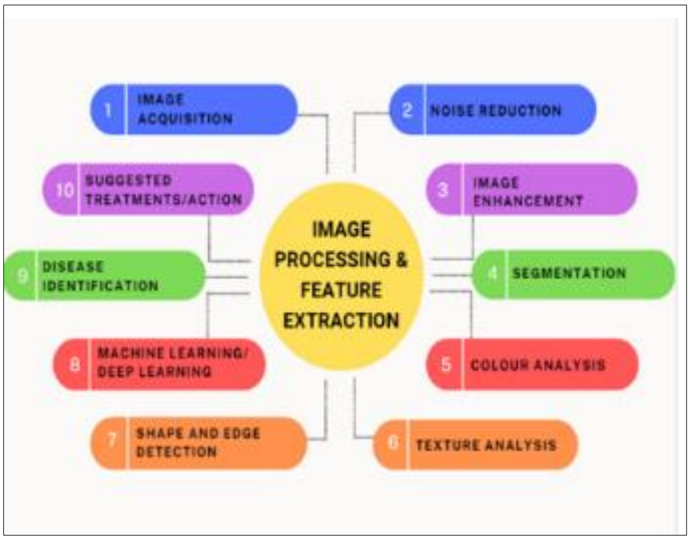

Figure 1 Steps in Fruit Disease Detection and Classification

There are more stages of colour analysis and texture analysis where the system detects the principal visual features, such as colour variation and texture patterns, suggestive of the disease. Shape and edge detection further enhance the delineation of the contours of diseased areas. The features extracted are further utilised in machine and deep learning models for enabling automatic classification of diseases, which eventually leads to more accurate and scalable outcome. The identified features lead towards disease identification where the system determines what type of disease the fruit suffers from. Finally, the system prescribes remedies or interventions that have to be used in controlling diseases diagnosed and this is a significant recommendation for agricultural management. This approach, being structured, would allow the system to provide right diagnoses about the diseases and therefore; it implies a higher response ratio in managing crop health while operating in real scenarios.

2.2.1. Traditional Techniques in Fruit Disease Detection

The traditional approaches for fruit disease detection mainly rely on the image processing techniques where segmentation and feature extraction play major roles. Various image processing techniques, using color, texture, and shape features, have been used to classify diseases like apple scab, powdery mildew, and anthracnose. These techniques include K-means clustering for image segmentation and artificial neural networks (ANN) for classification. The global and adaptive thresholding approaches have been highly used to extract regions of healthy and diseased regions according to the variation in pixel intensity. Other edge detection techniques that are frequently used are the Canny edge detector and Sobel operator to outline the boundaries of infected areas [7, 8]. Region-based approaches involving watershed transformation and region growing have also been effective for the segmentation of connected diseased regions [7, 9].

Conventional image processing methods, such as threshold-based classification, have demonstrated efficacy in the identification of diseases such as downy mildew; nonetheless, it is crucial to stress that early disease detection is necessary to minimize disease transmission and crop loss [10]. Feature extraction, checking properties like color, texture, and shape, was used to be a time-consuming process and most of the classifications were hand through metrics area, perimeter, and compactness [7,11]. While these approaches are useful, it becomes glaringly obvious how little of a scale and accuracy problem they suffer when dealing with large datasets and the complications of disease characteristics.

2.2.2. Machine Learning Approaches

Machine learning (ML) techniques have immensely automated the process of fruit disease detection, particularly in regards to segmentation, feature extraction, and classification. Classical ML algorithms applied for segmentation as well as classification of disease regions based on color and texture features include k-means clustering and decision trees [10, 12]. SVM has also been used to classify bacterial blight illness in pomegranate fruits, emphasizing the need for early intervention to prevent the disease from spreading quickly [13]. In general, it has been found to particularly distinguish between healthy and diseased fruit regions [9, 10]. For instance, blueberry rot and anthracnose leaf diseases have been successfully identified using machine learning algorithms such as RF and SVM. These have demonstrated how early diagnosis improves crop health [14].

Some of these models, feature vectors obtained from traditional techniques such as color and texture analysis. These have been recently incorporated into models such as random forests and decision trees, in which the level of automation in classification processes has been enhanced [12]. Combining feature extraction methods with ANN is also helpful in disease identification such as citrus canker and apple scab. Such a method includes color and texture analysis for fruit classification into healthy fruits or infected ones [12]. Improvements in these methods of ML cut across the need for manual intervention in disease detection processes, and they can automatically detect the disease, thus making them scalable. However, they depend on manually extracted features, thus narrowing their usability across a wide range of datasets and environmental conditions.

2.2.3. Deep Learning Approaches

Deep learning methods resulted in key advances that changed the way fruit disease detection is approached, making it even more self-driving and scalable. The methods such as CNN, LSTM, and GAN are used for detecting of black rot, early blight, and late blight. The improvements in the state of disease management were found to be significant due to the early detection [8]. CNNs, mainly U-Net and Mask R-CNN, have been utilized with the purpose of automatic segmentation of diseased regions and giving detailed outlines of the infected areas [11, 14, 15]. These developments within CNNs enable automatic feature extraction, learning color, texture, and spatial patterns directly from images and improve the accuracy in disease detection significantly [8, 14, 15]. CNN-based models have the ability to identify diseases such as powdery mildew and Gray Mold on strawberry crops, thereby giving an overview of a CNN model's ability to correlate complex patterns in disease diagnosis at an early stage for better management [11].

DL models, for example, VGGNet, ResNet, and DenseNet, have been used in disease classification. Those models attained high accuracies in classification with large datasets and learned to understand complex patterns in them [9, 11, 15]. Fine-tuning pre-trained models for specific datasets has also utilized transfer learning to achieve substantial reduction in training time and performance gains [8, 15]. In addition, sophisticated DL architectures which combine segmentation and classification into one framework thereby offer end-to-end solutions for fruit disease detection, which smoothes out the entire process to achieve efficiency in the overall process of detection [9, 13].

A self-supervised collaborative multi-network model has been developed for disease diagnosis, such as early blight and late blight, in tomato crops with improved robustness and accuracy in the detection of diseases [15]. Recent applications involve real-time disease detection on strawberries using CNNs [16, 17]. YOLOv8-based models also apply to classify ripeness and health, acknowledging a shift from the traditional manual approach to more complex automated DL models that are making better contributions in terms of accuracy, efficiency, and scalability for fruit disease detection in agricultural applications [18, 19].

Some recent researches focus on new approaches for fruit disease detection and classification. For example, studies for strawberry disease detection apply deep learning models like CNN that can identify fungal diseases in real-time for immediate indication of how the diseases spread in strawberry fields [16]. Another methodology combined the capabilities of image processing and CNN for disease identification in strawberries. The strength of the model was in real-time field identification of diseased leaves with a high probability that would, thereby, help control the spread of disease considerably [17]. Another study applied pattern recognition technology to the process of disease identification with the aim of automating this process and making agriculture management regarding diseases more efficient [20]. CNN architectures also proved that they could provide highly accurate classification and identification of diseased leaves even when minor features are distinguishing the healthy plant from the infected one [18].

Hybrid models, such as YOLOv8+ combined with image processing techniques, were utilized for strawberry ripeness classification and disease detection that contribute towards comprehensive agricultural solutions because they are concerned both with quality and disease [21]. Finally, a more general review about fruit disease detection methods confirmed the critical role of these approaches for early detection and classification, showing that early interventions help in controlling the spread of disease, increase yield, and maintain healthy crops [19].

3. IoT Integration in Fruit Disease Monitoring

A revolutionary change in agricultural methods is represented by the incorporation of the Internet of Things (IoT) in fruit disease surveillance. Farmers can now more efficiently monitor crop health and environmental conditions thanks to Internet of Things (IoT) technologies, which enable the real-time collecting and processing of data from a variety of sensors put in the field. Smart sensors are capable of measuring vital characteristics that are essential for forecasting disease outbreaks, such as temperature, humidity, soil moisture, and light intensity. Cloud-based platforms are used to process the data, and there, sophisticated algorithms are able to evaluate the data and provide farmers with useful insights. This proactive strategy improves overall productivity and sustainability in agriculture by helping to optimize resource consumption and aid in the early diagnosis of illnesses [22–23].

IoT is effective at monitoring diseases, according to recent studies. As an illustration, a system that combines machine learning algorithms with Internet of Things sensors has

been created to identify and categorize diseases in real-time, greatly accelerating the response time to possible epidemics [24]. Additionally, it has been demonstrated that combining IoT technologies with conventional farming methods can maximize crop yield and quality while reducing the need for chemical treatments [25]. IoT in agriculture could lead to completely automated systems in the future that monitor and anticipate disease risks, supporting sustainable farming methods [26].

4. Comparative Analysis of Techniques

The identification and classification of fruit diseases has advanced significantly as a result of technological breakthroughs. A wide range of methods has been explored to accurately identify and classify fruit diseases through various research papers, such as deep learning architectures, machine learning algorithms, and conventional image processing. The following table (Table 1) summarizes key studies, highlighting the authors, datasets used, models implemented, and the results achieved in terms of accuracy.

Table 1 Performance Comparison of Various Approaches in Fruit Disease Detection and Classification

Sr. no	Author	Dataset used	Model used	Result
1	Changqi Ouyang et. al (2013) [20]	Custom dataset of strawberry plants and leaves	Image Segmentation Techniques like grey morphology, the OTSU algorithm, and the mean shift segmentation algorithm and for disease classification, support vector machine (SVM) and BP neural network models are used.	Achieved 89% accuracy using SVM for strawberry disease classification.
2	Ashwini Awate et. al (2015) [12]	Grapes, Apple, Pomegranate fruits.	K-means clustering serves as the segmentation technique, while pattern matching and classification are performed using Artificial Neural Networks (ANN).	The ANN model with colour and texture analysis achieved 90% accuracy.
3	Sulakshana A. Gaikwad et. al (2017) [7]	General Fruit Datasets	K-Means clustering technique is used for the Image Segmentation and Support Vector Machine for classification	-
4	Rashmi Pawar et. Al (2017) [13]	Pomegranate Dataset	Image Processing Techniques for feature extraction and classification using Artificial Neural Networks (ANN).	The model using ANN achieved 90% accuracy in pomegranate disease classification.
5	Nikolas Lamb et. al (2020) [16]	Custom dataset of strawberry images	Convolutional Neural Network (CNN)	Achieved 95.8% accuracy in strawberry detection using CNN.
6	Benjamin Doh et. al (2019) [9]	Citrus Dataset	Artificial neural network model and the SVM.	93.12% accuracy for SVM and 88.96% accuracy for ANN is obtained for classification.
7	Shaikh Rakhshinda et. Al (2019) [10]	Apple Dataset	The employed image feature descriptors include ISADH, CCV, GLCM, CLBP, and ZM, each providing unique insights into image texture, color, and shape characteristics.	ISADH+GLCM achieved 96.07% average classification accuracy, while ISADH+CLBP+ZM reached 96.29%.
8	Cecilia Sullca et. al (2019) [14]	Blueberry Dataset	Machine learning algorithms employed include Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Random Forest. Additionally, the Convolutional Neural Network (CNN) from the field of Deep Learning is utilized.	Achieved 84% overall accuracy.
9	Yen-Chang Chen et.al (2020) [11]	Strawberry Dataset	Convolutional Neural Network (CNN)	Achieved 99.60% accuracy for feature image dataset and 98.06% accuracy is obtained for original images.
10	Yang, Guofeng et. al (2020) [15]	Tomato Dataset	LFC-Net (Location-Feedback-Classification Network), Fine-Grained Visual Categorization (FGVC), Self-Supervised Learning, and AutoML (Automated Machine Learning) and NAS (Neural Architecture Search)	Achieved 99.7% accuracy using LFC-Net model for detecting and classifying.

11	Jia-Rong Xiao et. al (2021) [18]	Custom dataset of strawberry leaves	Convolutional Neural Network (CNN)	Achieved 96.45% accuracy in detecting strawberry diseases using CNN.
12	Irfan Abbas et. al (2021) [17]	Custom dataset of strawberry leaves with fungal scorch disease symptoms	CNN models (SqueezeNet, EfficientNet-B3, VGG-16 and AlexNet)	The VGG16-based model achieved 98.7% accuracy.
13	Somya Goel et. al (2022) [8]	Multiple Fruits Dataset	Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Generative Adversarial Networks (GANs).	-
14	Sultana Banu Kazi et.al (2023) [19]	Multiple Fruit Dataset	The system utilises Convolutional Neural Networks (CNNs) for disease detection and fruit grading, alongside image processing libraries like OpenCV and scikit-image for segmentation and feature extraction, with TensorFlow, Keras, PyTorch, and scikit-learn.	Reported accuracy of CNN model of 85.86%.
15	Chenglin Wang et.al (2024) [21]	Strawberry Fruit Images Dataset	YOLOv8+ model	Achieved 98.5% accuracy.

The table offers a thorough summary of several research work carried out in the field of fruit disease detection and classification, demonstrating the advancement and variety of approaches used over time. It combines cutting-edge machine learning and deep learning models with conventional image processing methods. The accuracy of disease identification has very much increased from the early methods that used manually created features like color and texture analysis to the more current applications of convolutional neural networks (CNNs) and other complex architectures.

Some important conclusions have been drawn from the table that models like CNNs and YOLOv8+ have demonstrated impressive accuracy rates—exceeding 96% in multiple instances—especially when it comes to the diagnosis of strawberry illness. This development is a reflection of the growing dependence on deep learning methods, which enhance classification performance by automating feature extraction. The progress in diversifying datasets and increasing the complexity of models demonstrates the continuous endeavors to improve the resilience and suitability of fruit disease identification systems in real-world agricultural contexts. All things considered, these results point to bright future paths for this important field of study and research.

5. Challenges and future directions

The development of effective fruit disease detection and classification models faces variability in disease symptoms, limitations in data quality, and in model architecture, among many more. One of the primary issues is that various environmental conditions influence the appearance of disease symptoms, thereby complicating accurate detection [15]. The handcrafted attributes including color and texture present in the old models fail to communicate the richness of the patterns encompassing various diseases, thereby degrading the accuracy. Also, inadequately high-quality annotated dataset fails the model to generalize between different fruits and environmental conditions [13]. Higher computational costs and complex model architectures also characterize deep learning models, acting as a considerable barrier to deployment in real-time conditions in agriculture settings [8]. The models trained with regional data are also not generalizable and likely to cause wrongful classification because the symptoms of diseases might resemble one another [13].

Another common problem is overfitting, particularly when the models are trained on very few dataset amounts, as in the case of strawberry disease detection models [11]. Other challenges include background noise and the quality of images to increase complications in detection, particularly when symptoms are inconspicuous or could be the same when resulting from different diseases [14]. Thus, challenges increase the complexity when models have to perform multiple tasks, such as fruit grading and disease detection, requiring an exclusive feature set and model architecture for each task to be performed [27].

In essence, the following are the challenges:

- Variability in environmental conditions can alter disease symptoms, making detection more difficult.
- Handcrafted features, such as color and texture, often fail to capture the full complexity of disease patterns, leading to reduced accuracy.
- Limited access to high-quality annotated datasets hampers the model's ability to generalize across different fruits and varying conditions.
- High computational costs and complex deep learning models make real-time deployment challenging in agricultural settings.
- Models trained on region-specific data may struggle with generalization, causing misclassification when disease symptoms are similar.
- Overfitting is a common issue, especially when training models with small datasets.
- Background noise and poor image quality can obscure subtle symptoms, complicating detection.
- Managing multiple tasks, such as fruit grading and disease detection, increases complexity, as each task may require a different feature set and model structure.

However, to overcome such challenges, several future directions have been proposed. First, the extension of datasets to include more diverse fruit diseases, environmental conditions, and geographic regions will be very crucial in enhancing the models' robustness [13]. Deep learning techniques, such as CNNs, have been integrated to fully automate feature extraction, thereby improving accuracy while gradually diminishing reliance on manually crafted features [15]. In addition, using transfer learning may reduce the requirement for large annotated datasets and high computation costs [8]. For real-time application, a lightweight, adaptive model should be constructed which is sensitive to changes in environmental conditions. This can be achieved using extra sources of data like weather conditions and soil conditions [14]. Explainable AI is gaining momentum as a method of improving the transparency and trust in model predictions, especially for deployment in practical agricultural settings [8]. The future scope of work may involve exploiting data fusion techniques to include multispectral or hyperspectral images to improve the accuracy of disease detection [9]. Hybrid models integrating traditional image processing with deep learning are also very promising approaches to overcome the present approach's limitations [12]. Thus, the future scope could be:

- Expanding datasets to include a wider range of fruit diseases, environmental conditions, and geographic regions to enhance model robustness.
- Utilizing deep learning models, such as CNNs, for automatic feature extraction to improve accuracy and reduce dependence on manually crafted features.
- Implementing transfer learning to decrease the need for extensive annotated datasets and lower computational costs.
- Creating lightweight, adaptive models suitable for real-time applications that respond to changes in environmental factors by integrating additional data, such as weather and soil conditions.
- Focusing on Explainable AI to improve transparency and foster trust in model predictions for practical applications in agriculture.
- Investigating data fusion techniques, including multispectral and hyperspectral imaging, to boost detection accuracy.

In general, overcoming barriers in fruit disease detection requires advancements in deep learning, image processing, and real-time deployment. Thus, in other words, there is still the urgent emphasis of dataset enhancement, model optimization, and contextual data integration for both accuracy in detection and usability in practice in agriculture [16, 17, 18, 20, 21, 22].

6. Conclusion

The studies reviewed have demonstrated remarkable progresses in fruit disease identification and classification through various approaches of machine learning, deep learning, and image processing. Through this, every study has given new, different knowledge to counterbalance the major complications in identifying and classifying fruit diseases with enough accuracy for the boost of crop yield and sustainable agricultural practices. Through this, every study has given new, different knowledge to counterbalance the major complications in identifying and classifying fruit diseases with enough accuracy for the boost of crop yield and sustainable agricultural practices. Early works demonstrated that by combining traditional image processing techniques with other techniques from machine learning under controlled conditions, for instance, for specific fruits such as pomegranates, excellent results would be generated, while hand-crafted features seriously limited these approaches and generalised poorly across different environments.

The deep learning shift, discussed by studies such as, led to architectures like the Convolutional Neural Networks, which automatically learn complex features. It leads to higher accuracy in detection and the involvement of lesser human effort. It is an application wherein an auto/manual scalability and CNNs showcased high performance in strawberry disease detection. Besides, particular studies like are going as far as extending the application of these methods to fruits such as blueberries and tomatoes, which in reality emphasise the flexibility in the model being implemented as well as using multiple sources of data to enhance the robustness in various field conditions.

More advanced works dealt with more complex applications, such as phenotyping and fruit grading, demonstrating how the implementation of disease detection combined with quality evaluation may contribute to precision agriculture. Such researches suggest that data fusion and ensemble learning techniques should be further integrated with other approaches in order to provide a holistic solution for the complexity of real-world problems.

However, despite the remarkable development made to date, challenges at present lean more toward issues involving data diversity, model generalization, and the more stringent requirement of real-time applicability. Future research, therefore, should be aimed at the extension of these datasets with more varieties of fruits and conditions to include varied environmental setups and bring on scalable models that will utilize transfer learning, unsupervised learning, and advanced sensor technologies. Thereby, fruit disease detection systems will be able to be made more efficient and adaptable toward their operations. More efficient and sustainable agricultural practice would then ensue.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare no competing interests.

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