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A PRISMA-guided systematic review of artificial intelligence techniques for fruit diseases detection

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ABSTRACT

Fruit diseases pose a serious challenge to agricultural productivity and require effective and prompt detection strategies. Traditional techniques based on manual observation are often limited by subjectivity and delay, creating a strong need for automated solutions. Deep learning and artificial intelligence (AI) have become revolutionary technologies in detecting fruit diseases, which can be correctly classified and diagnosed at an early stage in various agricultural environments. This study conducts a systematic literature review guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to summarize the recent achievements in the field. Unlike prior reviews focused on fruit grading, this work centers on pathological diagnosis. Our initial search across Scopus and Web of Science databases yielded 876 records. After applying inclusion and exclusion criteria, 31 primary studies published between January 2024 and August 2025 were selected. These papers were further analyzed to obtain three core areas, namely recent methods, ongoing challenges, and future research directions. Recent methods demonstrated strong progress with attention mechanisms, transformer hybrids, and YOLO-based detectors specifically optimized for real-time use on mobile phones and drones. However, practical application is heavily hindered by data scarcity and poor cross-domain generalization. In addition, moving these systems from the lab to the farm is often restricted by hardware limitations and a lack of explainable AI. Thus, future research must prioritize diverse, multi-site datasets and ensure that model outputs make practical sense to agronomists. This review consolidates these findings to help researchers build scalable, interpretable, and field-ready disease detection tools.

Contribution/Originality: This paper presents the first PRISMA-guided systematic review on AI-based fruit disease detection. By analyzing 31 recent studies, we analyzed the recent methods, ongoing challenges, and future research directions.

1. INTRODUCTION

Fruit-disease detection artificial intelligence (AI) solutions [1-4] are now at the nexus of food engineering, food safety, and food supply-chain management. World food security heavily depends on agricultural productivity, and fruit crops are an important factor in human nutrition, economic stability, and export markets. Nevertheless, fruit production is continuously threatened by diseases caused by fungi, bacteria, viruses, and pests [5-11]. The conventional methods of detection are based on human-eye evaluation, which is prone to inconsistency, delays, and subjectivity [12-14]. The application of artificial intelligence (AI), encompassing machine learning (ML), deep learning (DL), and computer vision, provides automated and efficient detection of fruit diseases through image analysis in laboratory or field conditions [15-18]. Such technologies are consistent with the goals of precision agriculture by providing early identification, reducing unnecessary application of pesticides, and maximizing productivity, which is highly pertinent in multidisciplinary food engineering, food safety, food supply-chain management, agricultural informatics, and sustainable agriculture [19, 20].

The last several years have witnessed a rapid increase in literature on AI-based fruit analysis. Encouraging performance has been demonstrated with convolutional neural networks (CNNs) and pretrained networks, including ResNet, EfficientNet, MobileNet, YOLO variants, and transformer-based networks [21-23]. However, the shift of general AI application in agriculture, including sorting, grading, and general quality inspection, to fruit-specific pathology presents different challenges. Although the general AI vision systems are very effective when evaluating surface damage or ripeness, disease diagnosis needs models to detect complex and nuanced pathological conditions that are caused by fungi, bacteria, and viruses. This difference is essential, and though numerous automated systems have been successfully applied in generalized attacks on physical damage, disease pathology can require examination of subtle textural, morphological, and color changes, which require specific data, architectures, and deployment strategies. In turn, a systematic synthesis that exclusively focuses on the specifics of fruit disease detection is needed to fill this gap. Indicatively, Espinoza et al. [19] conducted a review of the application of classical CNNs, R-CNN, YOLO, and visual transformers in the analysis of fruits and revealed that methodological trends and challenges include color variability, labeling challenges, and high computation cost. In a similar vein, Rojas et al. [20] provided a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-based systematic review [24] of artificial vision systems to analyze fruit inspection and classification, where preprocessing methods and prevalence of RGB imaging and deep learning are used. Nevertheless, their analysis focused on sorting, grading, and quality checks instead of diagnosing diseases, thus giving a limited understanding of the fruit pathology.

Despite ongoing progress, there are a number of limitations. The majority of works are devoted to the detection of fruit damage instead of the diagnosis of the disease. As an example, Safari et al. [25] surveyed automated detection of fruit damage with segmentation, ML, and DL, and mentioned the necessity of mobile deployment and occlusion management. Corceiro et al. [26] focused on the general area of AI on weeds, diseases, and fruits, but due to the extensive area, little attention was given to the specifics of detecting fruit diseases. Dhiman et al. [27] aimed at citrus disease through the feature extraction approach with the various imaging modalities and ML/DL classifiers with a focus on noise and segmentation issues. Rojas et al. [20] also performed a PRISMA-based review of fruit inspection systems, but instead of disease-specific diagnosis, they focused on general quality assessment activities like ripeness, damage, and grading. Together, these reviews demonstrate significant progress in methodology and areas of application, but usually do not contain the fruit-disease-specific synthesis systematically organized and needed. Table 1 presents an overview of these recent review studies, their scope, methods, and limitations to demonstrate the need for the current study.

Table 1. Summary of existing review studies on AI in fruit and agricultural analysis.

Reference	Scope / Topic	Methods / Techniques Analyzed	Limitations (Research Gap)
Espinoza et al. [19]	Fruit analysis using deep learning.	Classical CNNs, R-CNN, YOLO, visual transformers.	General fruit analysis; not exclusively dedicated to disease diagnosis.
Rojas et al. [20]	Fruit inspection and classification (PRISMA review).	Artificial vision systems, RGB imaging, deep learning.	Emphasizes sorting, grading, and quality inspection over pathological disease diagnosis.
Safari, et al. [25]	Automated fruit damage detection.	Segmentation, ML, DL.	Focuses on general physical damage rather than specific disease diagnosis.
Corceiro, et al. [26]	AI for weeds, diseases, and fruits.	General AI.	The scope is too broad, limiting the specific focus on fruit disease detection.
Dhiman, et al. [27]	Citrus disease detection.	Feature extraction (various imaging modalities), ML/DL classifiers.	Lacks generalizable insights across multiple fruit types (restricted to citrus).

This article differs from previous works in several critical ways. Although the current reviews, like the ones by Safari et al. [25] and Corceiro et al. [26], offer generalized descriptions of AI in fruit and crop applications, they lack a systematic synthesis focused on fruit diseases. Likewise, Dhiman et al. [27] specialized in citrus fruits but could not make a general observation of various types of fruits. In addition, although Rojas et al. [20] followed PRISMA guidelines in a systematic review of vision systems for fruit inspection, their primary objective was quality control, grading, and classification, not the diagnosis of pathological conditions. In contrast, the present review applies a PRISMA-guided methodology explicitly to AI-based fruit disease detection, offering a more focused and relevant synthesis. The objective of this article is to provide a systematic literature review of fruit disease detection using AI, which has direct implications for food security and sustainable production. Specifically, the article seeks to identify recent AI-based methodologies in disease detection; to identify challenges at the data, imaging, and deployment levels; and to propose future research directions emphasizing robustness, explainability, and scalability. This fruit-disease-specific focus, combined with a PRISMA methodology, establishes a unique contribution distinct from earlier inspection-focused or broadly scoped reviews. Figure 1 displays a conceptual framework of the transition between general applications of AI in agriculture towards the narrower topic of fruit disease pathology and the subsequent themes of this systematic literature review.

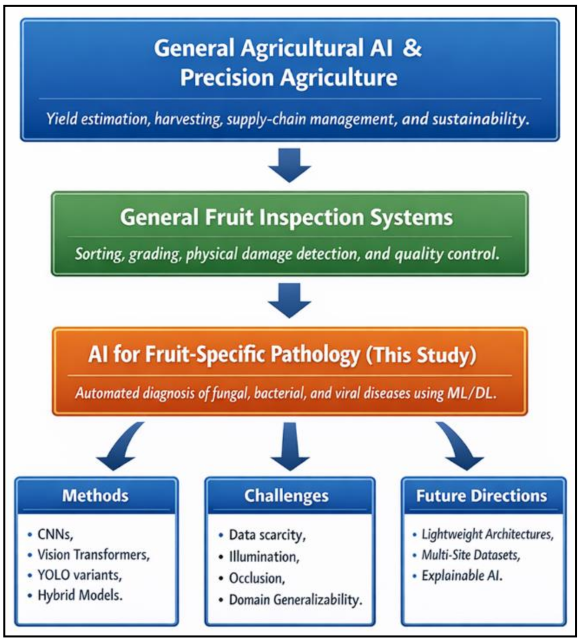

Figure 1. Conceptual framework.

As demonstrated in Figure 1, this research suggests a conceptual framework that narrows down these general agricultural applications to the narrower field of disease pathology. This difference is crucial; disease diagnosis requires examination of subtle changes in textures, morphologies, and colors, which require particular data, architectures, and deployment plans. Therefore, a systematic synthesis that is specifically focused on this niche is needed, and it should be organized under three main themes, i.e., methodological improvements, challenges, and future directions.

2. RESEARCH QUESTIONS

Research questions help organize information from different studies. They create a clear framework for grouping study results. According to this framework, analysis becomes easier when drawing logical and valid conclusions. Good questions remove confusion and keep the review focused on important issues. Clear questions help maintain rigorous attention on important problems. The results become more relevant when this focus itself is used. Further, this approach makes the findings more applicable. Having clear research questions makes the SLR process more transparent and easier to reproduce. When the research steps are well-documented, other researchers can follow the same procedure and verify that the findings hold.

Moreover, they can also use this work to study related topics in their own fields. For this reason, this step is regarded as the most important task at the planning stage and continues to be essential to the entire review methodology [28].

The present review aims to investigate the current state of artificial intelligence for fruit disease detection. To ensure systematic formulation of the research questions, the PICo framework was applied. This approach is commonly used in qualitative research and provides a structured way of developing focused questions [29]. PICo stands for Population, Interest, and Context. Population refers to the group or dataset under study, identifying the specific entities that the review is concerned with, such as images of fruits showing symptoms of disease. Interest is the general phenomenon under consideration, which here is the use of artificial intelligence methods to detect disease. Context is related to the setting where the population and interest lie, which could be farmland, garden, laboratory conditions where pictures are taken and processed. Based on the PICO framework, this paper will answer three research questions.

- Among fruit-disease image data, what AI methods have been most recently designed to detect fruit disease?
- What are the key data, imaging, and deployment limitations to the accuracy and generalizability of AI-based fruit disease detection?
- Which methodological and system-level improvements must be made in the future to realize robust, explainable, and real-time scalable fruit disease detection in heterogeneous environments and for stakeholders?

3. MATERIAL AND METHODS

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) is considered an international standard and promotes transparency, completeness, and consistency throughout the systematic review process [24]. This framework enhances the reliability and rigor of the analysis as it provides a systematic basis for identifying, screening, and including relevant studies. The method also focuses on quality studies, such as randomized studies, which are regarded as helpful in minimizing bias and enhancing the evidence base. The PRISMA approach is especially useful in conducting reviews of studies on artificial intelligence to detect fruit diseases. The field of research in food engineering, agricultural informatics, and AI is rapidly expanding, and the variety of studies is increasing, with different studies focusing on different methods and with varying quality.

The lack of a clear and consistent review process would result in the loss of important evidence or unequally assessed evidence, which would undermine the general conclusions. PRISMA offers a formalized system that will contribute to locating and evaluating studies regarding datasets, algorithms, and real-world applications in a systematic and methodical manner. This strategy not only highlights the work done but also pinpoints limitations to methodologies, data problems, and future research requirements that are essential in enhancing AI's contribution to sustainable agriculture. To conduct a systematic literature review using PRISMA on artificial intelligence to detect fruit diseases, we have selected two popular academic databases, namely Web of Science (WoS) and Scopus, because of their large scope of coverage and established credibility.

The PRISMA approach has four key steps, namely identification, screening, eligibility assessment, and data extraction to analyze the results. These are steps that are easy to follow in any research project. In the identification phase, researchers are bound to find relevant research by searching databases thoroughly. Besides, they analyze reference lists and refer to subject experts in order to locate further sources. This is done through a systematic search of various academic databases. What we are witnessing is that the screening process is done by checking the acquired records against predetermined standards to eliminate only poor-quality and irrelevant studies. This step provides that only relevant and high-quality research is to be included in the analysis. This makes sure that there is proper quality as far as the selection of research is concerned. During the eligibility phase, we review the rest of the studies to ensure that they satisfy the inclusion criteria. The next phase is the data-collecting phase, where important data in the selected research article is collected and merged into a comprehensive dataset. This process will ensure that the review employs appropriate methods and that it produces evidence that can be applied to inform research and practice.

3.1. Identification

The systematic literature review process began with the identification of literature that could be applied to the development of the fruit disease detector based on artificial intelligence. It started with the meticulous choice of primary keywords and recognition of relevant ones with the help of dictionaries, thesauri, encyclopedias, and past academic sources. On the basis of such resources, the detailed search strings were created and used in two big academic databases, Web of Science and Scopus, as displayed in Table 2. The asterisk (*) used in the search strings acts as a wildcard or truncation symbol to retrieve all word variations and endings of the root term (e.g., fruit* retrieves fruit, fruits; imag* retrieves image, images, imaging). The stage of the review resulted in the generation of 723 records in Scopus and 153 records in Web of Science, and a total of 876 publications, which were deemed to be pertinent to the subject area.

Table 2. The search string.

Scopus	TITLE-ABS-KEY ((fruit*) AND (imag*) AND (disease*) AND (detect*) AND (“artificial intelligence" OR "machine learning" OR "deep learning")) AND PUBYEAR > 2023 AND PUBYEAR < 2026 AND (LIMIT-TO (LANGUAGE, "English")) Date of Access: 25 August 2025
WoS	(fruit*) AND (imag*) AND (disease*) AND (detect*) AND ("artificial intelligence" OR "machine learning" OR "deep learning") (Topic) and 2025 or 2024 (Publication Years) Date of Access: 25 August 2025

3.2. Screening

The screening phase played a crucial part in the systematic review process, where all the identified studies were thoroughly investigated in order to confirm their relevance and consistency with the already established research questions. This was done to make sure that only literature that had direct relevance to artificial intelligence in detecting fruit diseases was retained in order to proceed with the analysis. At this point, 604 publications were eliminated, and 272 studies met the initial inclusion criteria (Table 3). The first criterion was that publications should be within the area of the core of agricultural science, biological science, computer science, and engineering, as they are the major source of knowledge on the research topic. Other documents that were not included in these categories included book reviews, book series, conference proceedings, chapters, and other secondary sources. Other criteria limited the review to publications in English that were published between 1 January 2024 and 25 August 2025. This stage also eliminated 61 duplicated records to ensure that the records were accurate and not redundant.

Table 3. The inclusion and exclusion criteria.

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline	1st January 2024 – 25th August 2025	< 2024
Literature type	Journal (Research Article)	Conference, Book, Review
Subject area	Agricultural Science, Biological Science, Computer Science, Engineering	Besides Agricultural Science, Biological Science, Computer Science, and Engineering
Publication stage	Final	In Press

3.3. Eligibility

The third step, the eligibility phase, was the preparation of 211 articles to be further evaluated. These steps were followed to verify the title and key contents of each article and to ensure that it met the predetermined inclusion criteria and that it aligned with the research objectives of artificial intelligence in fruit disease detection. One hundred and eighty articles were filtered off due to a lack of relevance to the research area, the titles were not relevant, or the abstracts lacked any relevance to the objectives of this research. Following this screening, 31 articles passed all the requirements and were kept in the final review. The PRISMA protocol involves the following steps of the selection process, which is summarized in Figure 2 and demonstrates how the initial identification led to the inclusion of 31 eligible studies to be analyzed.

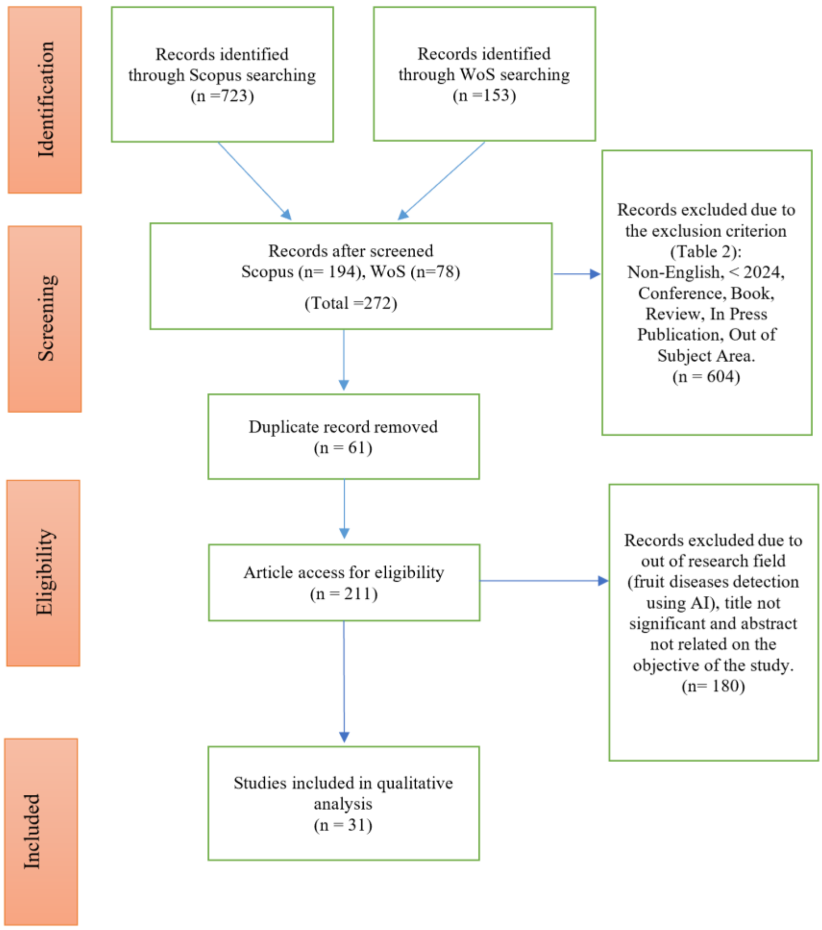

Figure 2. Flow diagram of the proposed searching study.

3.4. Data Extraction and Analysis

To analyze the chosen literature, we used an integrative analysis approach. The approach enables the systematic synthesis of qualitative, quantitative, and mixed-methods research orientations into coherent, overarching themes. This mode of analysis is quite different than the existing studies in the field. Whereas past reviews tended to use traditional narrative or bibliometric methods to conduct an overarching survey of agricultural AI (e.g., general fruit damage, ripeness, or crop monitoring), our review is highly thematic and limited to fruit disease pathology. We used a PRISMA-supported extraction framework to selectively extract and synthesize the data under three pillars: methodological architecture, challenges in real-world deployments, and future directions at the system level. This systematic thematic extraction avoids the dilution of the results, unlike the earlier studies, which, along with the general quality grading and sorting activities, combined pathological diagnosis with them. Its goal is to identify shared themes with regard to artificial intelligence in identifying fruit diseases. Further, such recurrent patterns enable us to comprehend the contemporary focus of research in this area. This was done by first extracting data from the selected studies, and it served as the foundation for the creation of themes. The review helps in depicting the process in which 31 articles were identified and reviewed to make the findings in connection with the research questions (Figure 2). We critically examined the procedures and findings of both studies. The results were assessed appropriately.

As mentioned in the research methodology, the method of analysis was also enhanced by having the author and co-author work together on extraction and interpretation. This is done to increase the reliability of the research and make it accurate and consistent. The team collaborated to structure the data and further to create themes with the help of the evidence itself. This can minimize personal bias and also make sure that when developing the balanced themes, multiple points of view are taken into account. This collaborative practice also allowed cross-validation of interpretations, thus strengthening the consistency of the results. The outcome is also an indication of a comprehensive analysis of all research and the expertise of the team. This method obviously results in more credible and open results. To capture all the observations, reflections, and notes, a detailed log was kept according to the analysis process. All findings and thoughts were documented in this log. In addition, it was necessary to collaborate with co-authors to further develop the thematic framework. In cases where real differences occurred regarding the interpretation of the data, the researchers discussed them until they came to an agreement on the interpretation.

4. RESULTS AND FINDINGS

This part reveals the results of the systematic review, and in particular, the review of the chosen studies and the synthesis of the information regarding the identified themes. In accordance with the PRISMA protocol, thirty-one (31) primary studies (PS) were retrieved following the last eligibility step and reviewed in detail in accordance with the formulated search strategy. Table 4 presents the number and publication details of the selected PS, including their respective database sources. These papers are the empirical basis of answering the three research questions that we designed in this review: (1) among fruit-disease image data, what AI methods have been most recently designed to detect fruit disease? (2) What are the key data, imaging, and deployment limitations to the accuracy and generalizability of AI-based fruit disease detection? (3) Which methodological and system-level improvements must be made in the future to realize robust, explainable, and real-time scalable fruit disease detection in heterogeneous environments and stakeholders?

The findings were arranged into three themes that were identified to organize the evidence: Methods, Challenges, and Future Directions. The first theme shows the recent methodological practices and technical solutions used to develop AI models to detect fruit diseases, both machine learning and deep learning models. The second theme is concerned with the data-related, imaging, and deployment issues that limit the model's generalizability and performance in actual agricultural environments. The third theme is a synthesis of how things can be improved and what future opportunities there are to further develop AI systems that are capable of providing more reliable, interpretable, and scalable solutions to agricultural situations. Collectively, these themes offer a full picture of the present research status, limitations that still exist, and the directions that must be taken to increase the contribution of artificial intelligence to detecting fruit diseases.

Table 4. Number and details of Primary Studies (PS) Database.

PS	Authors	Title	Journal/year	Scopus	WoS
PS1	Sandhi, et al. [30]	Multi-architecture CNN Framework with MBConv-SE optimization for fruit disease classification	Applied Fruit Science 2025	/	/
PS2	Kaushik, et al. [31]	Vision transformer-capsule network for orange quality inspection: Ripeness and black spot disease detection	Applied Fruit Science 2025	/	/
PS3	Shibu, et al. [32]	A hybrid transformer-based approach for arecanut disease prediction	SSRG International Journal of Electronics and Communication Engineering 2025	/	
PS4	Sudjud, et al. [33]	Development of Cocoa Pod Rot disease identification model using you only look once (YOLO-v9)	Mathematical Modelling of Engineering Problems 2025	/	
PS5	Said and Jawale [34]	Design of an iterative method for enhanced disease detection and feature selection using particle swarm optimization, genetic algorithms, and convolutional neural networks	Evolving Systems 2025	/	/
PS6	Srinivasan, et al. [35]	DBA-ViNet: an effective deep learning framework for fruit disease detection and classification using explainable AI	BMC Plant Biology 2025	/	/
PS7	Huang, et al. [36]	Implementing transfer learning for citrus Huanglongbing disease detection across different datasets using a neural network	Computers and Electronics in Agriculture 2025	/	
PS8	He, et al. [37]	Passion fruit disease detection using a sparse parallel attention mechanism and optical sensing	Agriculture (Switzerland) 2025	/	/
PS9	Wen, et al. [38]	Apple disease detection and classification using random forest (One-vs-All)	EAI Endorsed Transactions on AI and Robotics 2025	/	
PS10	Li, et al. [39]	RF-YOLOv7: A model for the detection of poor-quality grapes in natural environments	Agriculture (Switzerland) 2025	/	/
PS11	Venkatesh, et al. [40]	Strawberry disease detection using adaptive deep residual network	Journal of Phytopathology 2025	/	
PS12	Chen, et al. [41]	LFA-YOLO: Detection of lychee fruit anthracnose based on UAV images and deep learning	Applied Engineering in Agriculture 2024	/	/

PS	Authors	Title	Journal/year	Scopus	WoS
PS13	Raouhi, et al. [42]	Optimizing olive disease classification through transfer learning with unmanned aerial vehicle imagery	International Journal of Electrical and Computer Engineering 2024	/	
PS14	Javidan, et al. [43]	Diagnosing the spores of tomato fungal diseases using microscopic image processing and machine learning	Multimedia Tools and Applications 2024	/	
PS15	Makni, et al. [44]	Intelligent inspection and quality control of table olives	Journal of Applied Research and Technology 2024	/	
PS16	Mora, et al. [45]	From pixels to plant health: accurate detection of banana Xanthomonas wilt in complex African landscapes using high-resolution UAV images and deep learning	Discover Applied Sciences 2024	/	
PS17	Sajitha, et al. [46]	A deep learning approach to detect diseases in pomegranate fruits via a hybrid optimal attention capsule network	Ecological Informatics 2024	/	
PS18	Sameera and Deshpande [47]	Efficient early-stage disease detection in pomegranate (Punica granatum) using convolutional neural networks optimized by the honey badger optimization algorithm	Cogent Food and Agriculture 2024	/	/
PS19	Van Tran, et al. [48]	Designing a mobile application for identifying strawberry diseases with YOLOv8 model integration	International Journal of Advanced Computer Science and Applications 2024	/	/
PS20	Kalaivani and Saravanan [49]	A CONV-EGBDNN model for the classification and detection of mango diseases on diseased mango images utilizing transfer learning	Engineering, Technology, and Applied Science Research 2024	/	
PS21	Tewari, et al. [50]	Automatic guava disease detection using different deep learning approaches	Multimedia Tools and Applications 2024	/	
PS22	Uygun and Ozguven [51]	Real-time detection of shot-hole disease in cherry fruit using deep learning techniques via smartphone	Applied Fruit Science 2024	/	/
PS23	Pakruddin and Hemavathy [52]	Development of a pomegranate fruit disease detection and classification model using deep learning	Indian Journal of Agricultural Research 2024	/	
PS24	Upadhyay and Gupta [53]	Diagnosis of fungi-affected apple crop disease using an improved ResNeXt deep learning model	Multimedia Tools and Applications 2024	/	/
PS25	Pawar, et al. [54]	Fruit disease detection and classification using machine learning and deep learning techniques	International Journal of Intelligent Systems and Applications in Engineering 2024	/	
PS26	Shah, et al. [55]	FuzzyShallow: A framework of deep shallow neural networks	Measurement: Journal of the	/	

PS	Authors	Title	Journal/year	Scopus	WoS
		and modified tree growth optimization for agriculture land cover and fruit disease recognition from remote sensing and digital imaging	International Measurement Confederation 2024		
PS27	Hashan, et al. [56]	Guava fruit disease identification based on an improved convolutional neural network	International Journal of Electrical and Computer Engineering 2024	/	
PS28	Hassan, et al. [57]	Highly efficient machine learning approach for automatic disease and color classification of olive fruits	IEEE Access 2024	/	
PS29	Selvanarayanan, et al. [58]	Early Detection of Colletotrichum kahawae disease in coffee cherry based on computer vision techniques	CMES - Computer Modeling in Engineering and Sciences 2024	/	
PS30	Sundaramoorthi and Kamarasan [59]	Enhancing tomato fruit disease detection using dung beetle optimization with a deep transfer learning-based feature fusion model	International Journal of Engineering Trends and Technology 2024	/	
PS31	Patel and Patil [60]	An intelligent grading system for automated identification and classification of banana fruit diseases using a deep neural network	International Journal of Computing and Digital Systems 2024	/	

4.1. Methods

The recent studies can be divided into two broad fields: image-level classification and object detection. CNNs remain at the core of classification, although more recent designs tend to have finer structures and attention-based features. As an example, multi-branch CNNs with MBConv-SE blocks have shown that one can enhance the accuracy of fruit disease recognition without the need to incur much higher computational cost [30]. Vision Transformers are also getting traction; a study that used a ViT with a Capsule Network to grade oranges and detect black spots claimed that capsule routing assists in preserving part-whole relationships that a conventional attention model can overlook [31]. Hybrid models of this type have been experimented with for arecanut disease prediction, with transformer encoders combined with convolutional layers to learn on smaller datasets [32]. Residual networks have also been adapted by researchers to individual crops, including a deep residual network specific to strawberries [40] and an improved ResNeXt architecture to detect apple fungi [53]. All in all, these studies outperform the conventional CNN implementations by integrating attention, capsule, and residual architecture to deal with texture-rich disease patterns in a subtle manner [30-32, 40, 53].

The research on object detection aims at localization, counting, and early detection in crowded environments. This lane is dominated by several YOLO families with personalized heads or loss functions for small, occluded targets. A YOLO-v9 setup has been used to detect cocoa pod rot [33], poor grape quality with an RF-YOLOv7 variant that adds random-forest-like refinement [39], and lychee anthracnose on UAV images with an LFA-YOLO design that uses aerial perspectives [41]. An applied orientation can be seen in mobile deployments: a YOLOv8 pipeline has been embedded into an Android app to detect strawberry diseases [48], and a phone-based, real-time detector has been described to detect shot-hole disease in cherries [51]. A landscape-scale complementary UAV pipeline demonstrates that high-resolution orthomosaics can be analyzed to indicate symptomatic plants before human scouting [45]. These detection-first approaches address the operational need of directing users to where to look, rather than what class is where [33, 39, 41, 45, 48, 51].

In conjunction with deep detectors and classifiers, a stream of hybrid and classical learning is still ongoing to address settings with limited labels or limited hardware. A fuzzy-shallow neural model that combines deep characteristics and lightweight learners has been tested on remote-sensing and traditional imagery of fruit diseases and seeks to trade off throughput and simpler tuning [55]. Comparisons of classical and deep methods on an end-to-end basis highlight the persistence of the usefulness of tree ensembles and margin-based learners under some regimes [36, 54]. Microscopy-scale pipelines of tomato spores are based on conventional image processing and machine learning to use morphological features that are challenging to generic backbones [43]. Training aided by optimization is also discussed, e.g., genetic algorithms with CNNs to search hyper-parameters [34] and meta-heuristics like honey-badger optimization to enhance early detection in pomegranate [47]. The multi-attribute decision pipelines under industrial constraints are extended by quality inspection and grading operations: table-olive inspection systems and olive fruit color disease classification [44, 57]. These integrated methods provide practitioners with additional choices to operate with, particularly when they have inconsistent data, varied imaging circumstances, and restricted resources [34, 38, 43, 44, 47, 54, 55, 57].

Figure 3 represents a heat map to visualize these trends of methodologies systematically by showing the adoption of AI technology in different types of fruits that were found in the primary studies. The mapping shows that there are different application patterns according to the needs of operation. As an example, regular Convolutional Neural Networks (CNNs) and residual networks are the current standard of the baseline in nearly all fruit types since they are strong in the classification of images at the image level. YOLO variants and object detection systems, on the other hand, are strongly focused on complex canopy fruits (grapes, lychee, and cocoa) where localizing small, occluded lesions in a natural orchard setting is the main problem. In the meantime, Classical Machine Learning and hybrid optimization are used more commonly on crops such as olives and apples, where the quality inspection or microscopy regime of hardware constraints determines the need to use lightweight or feature-engineered models.

Fruit Category	CNNs & Residual Networks	YOLO & Object Detection	Vision Transformers & Attention	Classical ML & Hybrids
Pomegranate	2	0	1	0
Olive	1	0	0	2
Apple	1	0	0	1
Banana	2	0	0	0
Strawberry	1	1	0	0
Tomato	1	0	0	1
Citrus / Orange	1	0	1	0
Grape / Lychee / Cocoa	0	3	0	0
Others (Mango, Guava, etc.)	6	0	3	3

Number of Studies:	lowest				highest

Figure 3. Heat map of technology adoption trends across fruit types.

4.2. Challenges

One of the main problems that is present throughout these studies is insufficient data and the disproportion (imbalance) between classes. In detecting apple fungus, e.g., a fine-tuned ResNeXt model demonstrates how difficult it is to train stable models on small datasets, which leads to the application of data augmentation and disciplined dataset splitting [53]. Other works on fuzzy-shallow hybrids indicate that even simple models can be effective in cases where there is limited data or when labels are missing or erratic [55]. Transfer learning is considered to be critical in the case of citrus Huanglongbing as the source and target data usually vary in terms of lighting and imaging configuration, and thus pretraining on similar data is more effective than random initialization [36]. Other problems of this sort are also evident in the UAV-based olive disease detection models, where aerial images are very different than those taken at the lab [42]. Studies on tomato spore classification using microscopes also indicate that at high magnifications, the size of classes is too small to allow large neural networks to generalize with no additional feature engineering [43]. All of these data limitations affect not only the choice of models, but also their training and testing [36, 42, 43, 53, 55].

The other significant challenge is the ever-evolving reality in the real-world fields. Natural orchards tend to cause such issues as uneven lighting, shadows, and disorganized backgrounds. Grape quality detection and anthracnose detection of lychee using UAV images both demonstrate the ability of leaves and branches to produce occlusions and confounding textures [39, 41]. The high-resolution UAV mosaics of diseased plants also demonstrate that variations in canopy structure and camera angles can be used to distort patterns of features, complicating the establishment of reliable detection thresholds [45]. Other concerns are motion blur, sensor noise, and fast processing requirements when real-time analysis is performed with smartphones, restricting the complexity of the model [51]. Transfer learning in citrus HLB detection also indicates that models that have been trained on clean datasets cannot work similarly in the field because of the differences in domains [36]. All these results indicate that addressing the issue of lighting variation, occlusion, and background noise must be one of the main design objectives, rather than an after-the-fact consideration [36, 39, 41, 45, 51].

The common constraints encountered during lab-to-farm migration include deployment and compute constraints. Mobile applications using YOLOv8 or phone-based detectors should be able to satisfy latency constraints and maintain recall of small lesions on fruit skin [48, 51]. Multi-branch CNNs trained on MBConv SE emphasize a design trend in which architectural efficiency is explicitly emphasized to enable agricultural platforms using few GPUs [30]. There are still systems that use traditional machine learning or shallow hybrid models due to their simplicity in training and maintenance within the constraints of agricultural IT systems [54, 55]. Although more complex architectures are used, the addition of explainable AI components tends to add processing time, necessitating additional optimization to maintain real-time performance in the field [35]. Such constraints have implications on the selection of the model as well as the amount of money that can be allocated to label data and the frequency of new data collection in real operation [30, 35, 48, 51, 54, 55].

4.3. Future Directions

Several key insights can be drawn from these studies. To begin with, there is a clear need for larger, higher-quality datasets with well-structured training and validation splits that encompass diverse seasons and regions. Research on citrus disease detection reveals that while transfer learning is beneficial, true domain adaptation remains necessary to address variations between datasets [36]. Work on UAV-based olive disease detection also highlights the ongoing gap between aerial and ground imagery, underscoring the importance of collecting data at multiple resolutions with consistent labelling methods [42]. Similarly, UAV mapping of banana plant health suggests building datasets gradually across growth stages, allowing models to learn how symptoms develop over time instead of treating them as static categories [45]. These observations are consistent with findings in apple, pomegranate, and guava studies, where limited and imbalanced datasets have been shown to reduce model reliability [47, 53, 56]. Moving forward, data augmentation should be combined with collection strategies that intentionally capture differences in lighting, occlusion, plant variety, and sensor type [36, 42, 45].

Another trend indicates the growing use of attention-based and hybrid models, which are designed to handle texture and scale variations more effectively. Approaches that merge Vision Transformers with Capsule Networks, or other transformer–CNN hybrids, reflect an interest in combining broad contextual understanding with fine-grained feature encoding that avoids misleading correlations [31, 32]. Explainability components, which are already part of many plant disease models, could be enhanced to deliver practical insights for agriculture, such as highlighting lesion areas or generating maps linked to known symptom types, while maintaining low computational costs [35]. Lightweight designs, such as fuzzy–shallow networks, offer practical solutions for settings with limited resources, and ensembles that combine traditional and deep models can help manage noisy labels [54, 55]. Optimization-driven training methods, including genetic and meta-heuristic searches, could also replace trial-and-error tuning for selecting hyperparameters and data augmentation strategies [34, 47]. Overall, the evidence suggests a balanced direction: keep models simple and interpretable but integrate attention and structure where they provide clear benefits [31, 32, 35, 54, 55].

A third direction focuses on how AI models can be more effectively deployed in real-world field conditions. This involves building a structured system that incorporates model compression techniques, such as quantization or pruning, on-device data caching, and semi-supervised updates that learn from user input. Early examples include mobile detectors for cherries and a YOLOv8-based model for strawberries, both of which demonstrate how smartphone applications can seamlessly integrate into everyday workflows [48, 51]. UAV-based systems for lychee and olive disease detection also demonstrate that combining data collection and inference is possible when models are tuned to factors like flight height, image resolution, and motion blur [41, 42]. Studies on grape detection in natural environments further emphasize the importance of handling false positives and applying temporal smoothing to maintain steady frame-by-frame predictions [39]. Compact CNN architectures with SE or MBConv units appear well-suited for these cases, especially where speed is critical and internet access is limited [30]. Altogether, these strategies outline a path toward dependable, scalable field systems that can move from small test plots to large commercial orchards without losing performance [30, 39, 41, 42, 48, 51].

5. DISCUSSION

There are three technical tendencies that are observed in the 31 primary studies. Firstly, image-level diagnosis is still being developed with a backbone meticulously engineered and attention-like modules. Multi-branch CNNs: MBConv with SE units achieve high accuracy at moderate compute levels, and crop-adaptive residual networks (adaptive ResNet/ResNeXt) are tasked with fine-grained recognition of subtle symptoms [30, 40, 53]. Transformer signals exist, although predominantly in the hybrid form; transformer-based arecanut predictors and the Vision Transformer with Capsule concepts of orange quality are examples of attempts to stabilize learning and maintain part-whole relationships [31, 32]. Second, YOLO derivatives are superior in object detection on real-scene objects: the cocoa pod rot using the YOLO-v9 structure, grape quality using the RF-YOLOv7, and lychee anthracnose using the UAV view with the LFA-YOLO variant [33, 39, 41]. Third, deployment-oriented pipelines have become a norm, with an YOLOv8 Android app to detect strawberry diseases, smartphone detector to detect cherry shot-hole, and UAV-scale map to detect banana health, demonstrating that end to end capture to inference stacks are becoming a reality [45, 48, 51]. Concurrently, hybrid or classical solutions are still useful where data or hardware is limited; such as fuzzy, shallow frameworks, tree ensembles of apple disease, and feature-engineered microscopy of tomato spores, are frequently tuned by meta-heuristic or genetic methods [34, 38, 43, 47, 55].

The selected three themes are consistent with the way the literature gathers around the issues of what gets built, what prevents performance, and what the next thing should be built. The methods used are a balanced answer to small or distorted data sets, as well as to operational limitations in orchards. Smaller CNNs with SE/MBConv and crop-tuned residual imply a smaller capacity is favored, whereas hybrid transformer designs imply a slow upgrading route that blends the global information with convolutional inductive bias instead of an outright replacement [30-

32]. This high concentration of YOLO families justifies a pragmatic bias to where in scanning and sorting lines; localized lesions and spot defects in scrappy foliage demand detectors that can be maintained stable in the face of occlusions, luminance variations, and background-textures [33, 39, 41]. Apple fungi and pomegranate early detection reports confirm the reason why classical or hybrid pipelines continue to be used: heavy end-to-end models are penalized by limited sampling, label noise, or microscopy regimes; hence, lighter learners and engineered features continue to provide value [43, 47, 53]. Lastly, the deployment of mobile and UAVs demonstrates that the budget of latencies and the memory of platforms are now defining the design of algorithms; efficiency-first backbones and pruned detection heads are not only selected to achieve accuracy but also predictable real-time characteristics in the field [30, 48, 51].

Application designers are able to map operational goals to method families with more definite rules of thumb. Image-level classifiers that use compact attention (SE/MBConv) or residual variants are an expedient default when the task is at the intake belts to perform triage or grading; they have been shown to yield trustworthy gains with minimal user-provided accelerators [30, 40, 53]. YOLO-based small-object-focused detectors with tuned loss heads and anchors are appropriate for orchard scouting and counting under clutter, and with a vision system such as a UAV acquisition or a handheld phone can be used; such designs are demonstrated on lychee anthracnose and poor-quality grapes [39, 41, 51]. In situations where computing is limited or where labels are few, hybrid and classical paths can be reasonable, such as fuzzy-shallow combinations and tree ensembles, perhaps supplemented by genetic or meta-heuristic exploration to tune hyperparameters [34, 38, 55]. Explainable modules could be given priority to extension services and QA teams (e.g., class-activation maps or lesion proposals in explainable frameworks) provided overhead does not exceed latency goals [35, 48, 51]. A realistic workflow through various farms would be to combine capture and feedback with a loop: cell phone/UAV acquisition, on-camera/near edge inference, light human verification, and periodic refresh using hard-curated hard negatives of past seasons [41, 48, 51].

Data governance must shift to planned acquisition across seasons, cultivars, and geographies, with explicit cross-domain validation splits to instigate truthful measurement under shift; cross-dataset transfer to citrus and UAV-borne pipelines to lychee and olive already underscores the importance of the latter [36, 41, 42]. It is possible to develop models that combine attention with efficient convolution with their model development, e.g., transformer-CNN fusions or capsule-assisted attention of texture-rich lesions, but with quantization or pruning in mind in phones and edge boards [30-32]. The approaches to label efficiency should be systematically tested, such as semi-/self-supervision, active learning and meta-heuristic tuning, also used in the context of early detection and hyperparameter search, which has already been tested [34, 47, 55]. Compared to the minimal-to-maximal split of train-validation splits, error taxonomy by size and occlusion of objects, and deployment measures like frames-per-second and memory-footprint should enhance comparability in the studies according to field constraints in phone and UAV applications [41, 48, 51]. Lastly, explainability study ought to connect the outputs to agronomic activities and symptom ontology rather than just generic saliency, which will turn around decision support faster supply chains and extension initiatives [35, 44, 57].

Heterogeneity in evaluation protocols and variable reporting depth limits the synthesis, and a more powerful benchmark design remains needed. Certain inferences are based on an abstracted description as opposed to the same setup of experiment, which may conceal other confounders like various light regimes, cultivars or optics. However, it seems that converged signals are strong: small attention-enhanced CNNs and custom YOLO variants are reliable baselines in current bottlenecks; cross-domain generalization and label efficiency are the two key bottlenecks; deployment-first engineering balances latency, memory, and interpretability, which is critical to real-world adoption [30, 31, 39]. The findings can be utilized in future work to (a) curate multi-season, multi-site data with published cross-domain splits, (b) test domain adaptation and continual learning on UAV and phone captures, and (c) bridge the gap between model output and field action using explainability and agronomic ontologies [36, 41, 51]. The most promising pattern to consider in the near-term in an operational setting is a looped pipeline wiring together acquisition, inference, human verification, and periodic retraining with hard-negative mining as proposed in strawberry, cherry, and vineyard case studies [39, 48, 51].

6. CONCLUSION

The current synthesis proposes to perform a PRISMA-based review of artificial-intelligence systems to detect fruit disease, structured around three questions: what are the recent AI computational methods; what are the limitations to performance due to data, imaging, and deployability; and what methodological and system-level directions can make the systems more robust, explainable, and capable of working at scale. Two method families are predominant across the corpus screened. Compact convolutional networks with capacity-efficient modules (such as squeeze-and-excitation and MBConv blocks), crop-tuned residual backbones, and selective application of transformer components or capsule mechanisms are used to advance image-level diagnosis to capture global context and part-whole structure. Localization at the object level is motivated by tailored YOLO derivatives and associated detectors that emphasize sensitivity to small targets, occlusion management, and the ability to operate in cluttered foliage and unstable lighting conditions. Segmentation is presented in the form of a complementary track in which the extent or severity of lesions should be quantified. The practice of validation is heterogeneous, but patterns can be observed: transfer learning is prevalent, k-fold or hold-out protocols are the norm, and cross-dataset testing is becoming increasingly popular to investigate generalization. Hybrid and classical configurations (e.g., handcrafted features with tree ensembles or margin-based learners, and meta-heuristic optimization of hyperparameters) are also still applicable in situations where labels are limited, microscopy is a bottleneck, or hardware is tight. Viewed in a bigger picture, the field is slowly transforming from proof-of-concept classification to full stacks that connect on-device inference, lightweight explainability, human-in-the-loop verification, and data capture (UAV or smartphone).

This review is a synthesis of existing approaches that unites existing methods, determines the major challenges, and offers practical guidelines for future work. The general results indicate that there is a definite rule: model selection must correspond to the purpose. Compact classifiers with focused attention, such as those used in sorting and quality checks, are effective; orchard monitoring and counting can be done with detectors specialized to small objects and sensitive to the UAV height, image resolution, or mobile sensor configuration. Lightweight segmentation models are better at measuring lesion areas. There are common challenges in studies, such as limited and uneven data, shifts between farms or seasons, non-uniform lighting, occlusions, the cost of labelling, and constraints of hardware on speed and memory. Out of these lessons, there are lessons to be learned. A few simple rules can guide system designers to align goals with technical decisions: plan for the smallest target and most challenging lighting conditions, provide cross-domain validation, report on accuracy and performance metrics such as processing speed and model size, employ explainability tools that give real agricultural insights, not just visual maps, and maintain an update loop that adds difficult examples and updates models regularly.

There are a number of directions that deserve priority in future research. The data management should cover a variety of seasons and locations, with well-defined cross-domain splits and open and standardized protocols, so that the results of various studies can be compared in a fair and accurate way. Therefore, label-efficient learning methods, e.g., semi-supervised, self-supervised, and active learning, require more work as well, especially when it is too expensive or time-consuming to label every pixel. The domain adaptation and continual learning must be adequately tested on real-world data streams of UAVs and smartphones to address actual distribution changes, not merely fine-tuning. Thus, computer engineering-wise, the methods of model compression, pruning, and quantization should be viewed as design options, not an afterthought, and energy consumption and field performance should be given special consideration. More importantly, this review makes a direct contribution to the research in the field of computer engineering by providing a hardware-software co-design blueprint of agricultural AI. This study informs engineers about how to create systems that effectively balance high diagnostic quality with the hard computational, memory, and energy limits of real-world deployments by focusing on the integration of lightweight architectural backbones and edge-computing optimizations on platforms with latency-constrained UAV and smartphone platforms.

It would also enhance research transparency to provide short model summaries of how the studies split their data, what type of errors (by object size or occlusion) they have, how fast they are, what memory they use, and what scripts they can be re-run. There are limitations to this review, primarily because of variations in study methods and reporting styles, making strict meta-analysis difficult. Nevertheless, the fact that the same results are obtained in various types of fruits, sensors, and environments indicates that the field is maturing. On the whole, this work contributes to the formulation of a viable roadmap to further development: start with compact, attention-enhanced CNNs and specialized detectors as strong foundations; conduct solid cross-domain tests to understand the reliability in the real world; connect explainability to meaningful agricultural decisions; and create feedback-driven systems that can be improved over time. Combined, these measures can assist in transforming AI-based fruit disease detection, which is just in its early stages, into reliable, scalable tools to address crop management, quality enhancement, and food supply chain resilience.

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