Tomato Disease Detection Methods and Deep Learning Literature Review

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Introduction

Tomato disease detection draws on several approaches, from recognising visible symptoms to analysing leaf images with machine learning. Discolouration, lesions and abnormal growth can provide useful indicators, but symptoms may overlap and vary with growing conditions. This narrative review examines published work on tomato diseases, disease management, image-based detection and deep learning applications. It considers the limitations of visual assessment and the potential of computational methods to support earlier and more consistent identification. The studies use different datasets, disease categories and evaluation procedures, so their reported accuracy values are not directly comparable. The review synthesises existing research; it does not report a new experiment or a validated diagnostic system.

Tomato Diseases and Their Management

Zhang et al. (2023) [1] investigated the identification of tomato disease types and severity through fine-grained image features. Their approach uses a ResNet-50 backbone with components for object localisation, deconstruction and reconstruction, and attention-based partitioning. The localisation component identifies lesion regions without requiring additional bounding-box annotations. Deconstruction and reconstruction encourage the model to learn discriminative features rather than rely only on broad contextual information. Attention to lesion regions is intended to improve recognition. This work illustrates the distinction between identifying a disease category and assessing its degree of severity, both of which may be relevant to crop management.

Oladokun et al. (2019) [2] reviewed tomato brown rugose fruit virus (ToBRFV), including its distribution, existing knowledge and future research needs. The review describes a growing threat to tomato production and the importance of prevention and control. Understanding the virus's spread

and biological characteristics is necessary for developing effective management strategies. This study concerns disease knowledge and management rather than the evaluation of a new image classifier. It provides a useful reminder that computational detection must be understood within the broader context of plant pathology and the practical requirements of disease control.

Singh et al. (2017) [3] examined disease management through plant growth-promoting bacteria (PGPB). These organisms can support plant growth and contribute to biological control through different interactions with plants and pathogens. The review discusses mechanisms and prospects for using beneficial bacteria in tomato production. Microbial inoculants should not be described as vaccines: their functions and modes of application differ. Such approaches offer alternatives or complements to other management practices, but their performance depends on biological and environmental conditions. Their relevance to detection research lies in the connection between identifying a problem and selecting an appropriate management response.

Panno et al. (2021) [4] reviewed common and economically important tomato diseases in the Mediterranean basin. Tomato crops are affected by fungal, bacterial, phytoplasma, viral and viroid pathogens. Disease management depends on the crop's genetic characteristics, growing conditions, pathogen distribution and available control measures. Recognising symptoms and detecting pathogens early can support timely intervention. Changes in climate and production practices may also alter disease pressure. The review provides context for evaluating detection systems: a model trained on a narrow set of symptoms may not represent the full range of diseases and environmental variation encountered by growers.

Gleason and Edmunds (2005) [5] described tomato diseases and disorders encountered in gardens and greenhouses in Iowa. Their publication explains common symptoms and management responses across the growing season. Visual guidance can help growers recognise recurring problems, but visible symptoms alone may not always distinguish infectious diseases from physiological disorders. Local production conditions also affect which problems are most likely. This practical literature complements computational studies by emphasising the need for useful symptom descriptions and management context, rather than treating a classifier's output as a complete explanation of crop health.

McGovern (2015) [6] reviewed the management of tomato diseases caused by Fusarium oxysporum. Fusarium wilt (FW) and Fusarium crown and root rot (FCRR) remain important production problems. Management research includes host resistance and combinations of chemical, biological and physical measures. The pathogens and disease processes differ, so a single management method may not address both problems equally. Integrated approaches are therefore important. For detection

research, the review highlights the need to define disease categories carefully and avoid assuming that similar visible symptoms necessarily imply the same pathogen or control strategy.

Song et al. (2015) [7] investigated tomato disease resistance following inoculation with the arbuscular mycorrhizal fungus Funneliformis mosseae. The study examined responses to early blight caused by Alternaria solani. It reported changes in defence-related enzyme activity and explored the role of jasmonate signalling in mycorrhiza-induced resistance. The findings concern plant defence mechanisms rather than image classification. They illustrate how disease severity may be affected by biological interactions before an image is captured. Table 1 summarises the disease-management literature considered in this section and identifies issues relevant to interpreting detection studies.

Table 1. Tomato diseases and management research

Study	Approach or objective	Data or setting	Scope considerations
Zhang et al. (2023) [1]	Fine-grained disease type and severity identification	Tomato leaf images; ResNet-50-based modules	Performance under changing field conditions needs consideration.
Oladokun et al. (2019) [2]	Review of ToBRFV distribution and knowledge	Published plant-pathology literature	Disease knowledge and control are the focus, rather than classifier evaluation.
Singh et al. (2017) [3]	Disease management through PGPB	Biological-control literature	Effectiveness depends on plant–microbe interactions and growing conditions.
Panno et al. (2021) [4]	Important tomato diseases in the Mediterranean basin	Review of pathogens and management	Regional disease profiles may differ from those in other growing areas.
Gleason and Edmunds (2005) [5]	Symptoms and management of diseases and disorders	Practical guidance for Iowa gardens and greenhouses	Local guidance does not cover every production environment.
McGovern (2015) [6]	Management of Fusarium wilt and crown and root rot	Review of management approaches	Integrated management and pathogen distinctions remain important.

Song et al. (2015) [7]	Mycorrhiza-induced resistance to early blight	Tomato plants and Funneliformis mosseae	A biological-resistance experiment, not an image-classification system.

Image Processing and Convolutional Models

Wu et al. (2020) [8] explored data augmentation using a deep convolutional generative adversarial network (DCGAN) to improve tomato leaf disease identification. Generated images were added to original images for training GoogLeNet. The manuscript reports a top-1 average recognition accuracy of 94.33% for the described configuration. The study also used visual assessment methods, including t-SNE and a visual Turing test, to examine generated images. Augmentation can expand the apparent diversity of a training set, but the realism of generated examples and their relationship to independent test data remain important when interpreting performance.

Agarwal et al. (2020) [9] developed a compact convolutional neural network with eight hidden layers for tomato crop disease identification. The model was evaluated using PlantVillage images and compared with conventional machine-learning and pretrained models. The manuscript reports 98.4% accuracy for the proposed model and 94.9% for the best conventional method, k-nearest neighbours. VGG16 performed best among the pretrained models considered. Image preprocessing and augmentation were used to vary image conditions. These results describe the study's evaluation setting; a high score on a curated dataset does not establish equivalent performance on independent field photographs.

Karthik et al. (2020) [10] introduced residual-learning and attention-based architectures for identifying tomato leaf diseases. Residual connections support feature learning, while attention mechanisms direct the model towards informative image regions. The experiments considered early blight, late blight and leaf mould using PlantVillage data. The manuscript reports an overall accuracy of 98% on the validation data for the attention-based approach. The work demonstrates how features learned at different processing stages can contribute to classification. Its scope should nevertheless be distinguished from a system tested across every tomato disease or growing environment.

Zhou et al. (2021) [11] proposed a restructured deep residual dense network for tomato leaf disease identification. The architecture combines residual and dense connections to improve information and gradient flow while controlling the number of trainable parameters. A network originally associated with image reconstruction was adapted for classification through changes to its architecture and input

settings. The manuscript reports a top-1 average recognition accuracy of 95% on tomato images from the AI Challenger 2018 dataset. The relevant comparison is within that study's experimental protocol, rather than a direct ranking against models trained and tested on different datasets.

Liu and Wang (2020) [12] improved YOLOv3 for detecting tomato diseases and insect pests. Their modifications included bounding-box clustering, multiscale training and feature detection across image scales. The manuscript reports detection accuracy of 92.39% and a detection time below 20.39 milliseconds in the described experiment. Object detection differs from whole-image classification because it also locates affected regions. Its practical usefulness depends on both recognition and localisation, as well as the hardware and image conditions used to measure speed. Reported inference times should therefore retain their experimental context.

Liu and Wang (2020) [13] also investigated early recognition of tomato grey leaf spot using MobileNetv2-YOLOv3. Transfer learning and mix-up training were used to support generalisation, and images were evaluated under four conditions. The study compared the proposed model with Faster R-CNN and SSD using F1 score, average precision and intersection over union. The manuscript reports average values across test sets of 93.24% for F1, 91.32% for average precision and 86.98% for intersection over union. It also reports a 28 MB model and different inference speeds for GPU and CPU configurations. Hardware-specific rates should not be treated as interchangeable measurements.

Tm et al. (2018) [14] examined a LeNet-based convolutional neural network for identifying diseases in tomato leaves. The objective was to investigate a comparatively simple approach with modest computational requirements. The network learns image features and assigns an input to a disease class. The manuscript reports average accuracy between 94% and 95% for the proposed system. Simpler architectures may be relevant where computing resources are limited, but performance still depends on the range of classes, image quality and evaluation data. The study contributes to the discussion of how recognition accuracy can be balanced against computational cost.

Zhao et al. (2021) [15] proposed a deep convolutional neural network with attention components and residual blocks. The architecture was designed to learn discriminative features for tomato leaf disease diagnosis. The manuscript reports an average identification accuracy of 96.81% on the tomato dataset. It also describes a separate comparison using grape leaf images, with reported accuracy of 99.24%. The grape result concerns another dataset and should not be presented as a tomato-disease score. Attention-based models may improve feature representation, but deployment also requires consideration of complexity, image variation and practical data collection.

Qi et al. (2022) [16] investigated an improved SE-YOLOv5 model for recognising tomato virus disease. Greenhouse images were captured using a mobile phone, and an attention component was

incorporated into YOLOv5 to emphasise informative features. The manuscript reports precision of 91.07% and mAP@0.5 of 94.10% for the proposed system, alongside comparisons with YOLOv5, SSD and Faster R-CNN. These measures evaluate different aspects of detection and should not be labelled simply as a single accuracy score. Table 2 summarises this group of image-processing and convolutional-model studies; they are computational approaches rather than traditional visual diagnosis methods.

Table 2. Image-processing and convolutional-model research

Study	Approach or objective	Data or setting	Scope considerations
Wu et al. (2020) [8]	DCGAN augmentation and GoogLeNet	Original and generated leaf images	Generated-image quality and independent testing affect interpretation.
Agarwal et al. (2020) [9]	Compact CNN classification	PlantVillage tomato images	Curated-dataset results require separate field evaluation.
Karthik et al. (2020) [10]	Residual learning with attention	PlantVillage disease classes	Coverage of additional diseases and image conditions matters.
Zhou et al. (2021) [11]	Restructured residual dense network	AI Challenger 2018 tomato images	Cross-dataset performance cannot be inferred from one test score.
Liu and Wang (2020) [12]	Improved YOLOv3 disease and pest detection	Tomato images with object annotations	Object size, image resolution and speed are relevant to deployment.
Liu and Wang (2020) [13]	MobileNetv2-YOLOv3 for grey leaf spot	Images evaluated under four conditions	A disease-specific model is not evidence for every tomato disease.
Tm et al. (2018) [14]	LeNet-based disease classification	Tomato leaf disease images	Computational simplicity needs to be assessed alongside generalisation.
Zhao et al. (2021) [15]	Attention-based deep CNN	Tomato images; separate grape comparison	Scores from different crops must be distinguished.

Qi et al. (2022) [16]	SE-YOLOv5 tomato virus disease detection	Mobile-phone greenhouse images	Precision and mAP measure different aspects of detection.

Deep Learning Approaches to Disease Detection

Durmuş et al. (2017) [17] applied deep learning to tomato leaf disease identification, comparing AlexNet and SqueezeNet. Training and validation were conducted on an Nvidia Jetson TX1 using PlantVillage leaf images covering ten categories, including healthy leaves. Additional internet images were used to examine the trained networks. The work considered the prospect of running a detector on a robot in a field or greenhouse. Its practical relevance lies in combining model selection with the constraints of an embedded platform. Performance on a curated dataset and readiness for continuous operation in a changing field environment remain separate questions.

Hong et al. (2020) [18] used transfer learning for tomato disease detection and classification. Reusing a pretrained network can reduce the amount of task-specific training required, although the benefit depends on the similarity of the source and target data. The study considered healthy leaves and several disease categories. Its results contribute to the evidence on adapting established image-recognition architectures to crop health. Transfer learning should not be understood as eliminating the need for representative training and test images, particularly when a model is intended for use outside controlled acquisition conditions. The manuscript compares ResNet50, Xception, MobileNet, ShuffleNet and a DenseNet121–Xception configuration. It reports 83.68% recognition accuracy for ShuffleNet and 97.10% for the combined configuration, alongside a larger parameter requirement.

Zhang et al. (2020) [19] investigated improvements to deep-learning object detection for tomato disease. Their work addresses the recognition and localisation of disease symptoms rather than only assigning one label to an entire image. The study illustrates the importance of selecting an architecture suited to the task and the appearance of affected regions. Detection performance can be influenced by lesion size, overlapping leaves and background complexity. These considerations are relevant when comparing results with classification studies, since the outputs and evaluation criteria are not identical. The described modifications replace VGG16 with a residual feature extractor and use k-means clustering to adjust anchor boxes. The manuscript reports an improvement of 2.71 percentage points over the original Faster R-CNN in its comparison.

Ashqar and Abu-Naser (2018) [20] examined image-based tomato leaf disease detection using deep learning. Their work forms part of the early literature on learning disease-related visual features

directly from images. The approach contrasts with methods that depend entirely on manually designed features. As with other image-classification studies, the interpretation of reported performance depends on the dataset, the disease classes and the separation of training and testing data. The study is included here as evidence of the development of computational detection approaches, rather than as proof of universal field performance. The source account describes approximately 9,000 images of healthy and diseased leaves and a model intended to distinguish five disease categories.

Suryawati et al. (2018) [21] investigated deep structured convolutional neural networks for tomato disease detection. Such architectures combine successive feature-processing layers to identify patterns associated with leaf condition. Their contribution is relevant to the choice of network structure and training approach for agricultural images. Comparisons across studies require caution because differences in image preparation and evaluation can affect results as much as the architecture itself. A useful review therefore considers what was tested and under which conditions, rather than ranking models solely by their highest reported score. The comparison includes a two-convolutional-layer baseline, AlexNet with five convolutional layers, VGGNet with thirteen convolutional layers, and GoogLeNet. The manuscript reports that VGGNet performed best in the described experiment.

Hasan et al. (2019) [22] explored transfer learning for tomato leaf disease detection in precision farming. The study contributes to research on adapting pretrained image models to agricultural classification tasks. Transfer learning may be useful when specialised datasets are limited, but it still requires evaluation of the target classes and image conditions. The relevance of this work lies in its potential to reduce development effort while retaining useful feature representations. Its results should be interpreted within the original experiment and not assumed to apply to every crop, disease or deployment platform. The source describes 2,100 internet images and 500 photographs from nearby farms, with a pretrained Inception model adapted to the task. It reports accuracy of 99% when 85% of the data was used for training. Proposed drone-based spraying is a subsequent application rather than an outcome established by that score.

Tarek et al. (2022) [23] examined optimised deep learning algorithms for tomato leaf disease detection with hardware deployment. This extends the discussion beyond model training to the resources required for practical use. A deployable system must account for processing capability, memory, latency and the way images are supplied to the model. Optimisation may improve efficiency, but its effects on recognition performance also require assessment. The study is therefore relevant to understanding the trade-off between experimental model performance and the constraints of an operational device. The manuscript reports precision of 98.99% for MobileNetV3 Small and

99.81% for MobileNetV3 Large. Reported latencies are 66 ms and 50 ms on a workstation, and 251 ms and 348 ms on a Raspberry Pi 4, respectively.

Chowdhury et al. (2021) [24] investigated automatic leaf disease detection using deep learning techniques. The study contributes to the broader discussion of reliable agricultural image analysis, including the processing of leaf images and the identification of disease-related features. Reliability depends on more than obtaining a high average score: the distribution of errors and the conditions under which the system is evaluated also matter. Its inclusion provides a basis for considering how data quality, preprocessing and model design interact when a detection method is intended to support crop monitoring. The source describes 18,161 original and segmented images. Reported segmentation values are 98.66% accuracy, 98.5% intersection over union and 98.73% Dice score. It reports 99.95% and 99.12% classification accuracy for EfficientNet-B7 on binary and six-class tasks, and 99.89% for EfficientNet-B4 on a ten-class task.

Moussafir et al. (2022) [25] designed tomato leaf disease detection techniques combining a genetic algorithm and deep neural networks. The work illustrates the use of optimisation alongside learned image representations. Such combinations can support the selection of useful features or model settings, but they also need to be evaluated against appropriate baselines. The study's scope concerns tomato leaf images; extending its conclusions to other crops would require additional evidence. Its relevance here is the interaction between optimisation and classification within a disease-detection workflow. The manuscript compares seven pretrained architectures, including VGG16, ResNet50 and several EfficientNet variants, before combining two selected models through a weighted ensemble. The reported accuracy is 0.981, equivalent to 98.1%.

Wang et al. (2021) [26] examined disease detection where tomato leaves are occluded or overlap. These conditions are important because field images often differ from isolated-leaf photographs taken against simple backgrounds. The study used a self-built dataset to investigate a deep-learning approach under these more complex conditions. Its focus helps expose a limitation of evaluations that rely only on clean, unobstructed leaves. Table 3 brings together the deep-learning studies discussed in this section and identifies their different methodological emphases. The manuscript reports mAP values of 98.3%, 92.1% and 90.2% under three described conditions involving separation, occlusion and overlapping leaves, with a reported detection rate of 206 frames per second. The condition labels and hardware context should be checked in the original experiment before comparing these figures with another system.

Table 3. Deep-learning approaches to leaf disease detection

Study	Approach or objective	Data or setting	Scope considerations
Durmuş et al. (2017) [17]	AlexNet and SqueezeNet	PlantVillage and additional internet images	Embedded and field use require practical evaluation.
Hong et al. (2020) [18]	Transfer learning across CNN architectures	Tomato leaf image dataset	Model size and recognition performance need joint consideration.
Zhang et al. (2020) [19]	Improved Faster R-CNN	Annotated tomato disease images	Localisation differs from whole-image classification.
Ashqar and Abu-Naser (2018) [20]	Deep CNN disease classification	Approximately 9,000 leaf images in the source account	Controlled images may not represent all field conditions.
Suryawati et al. (2018) [21]	Comparison of CNN depths	PlantVillage images	Architecture comparisons depend on a common evaluation protocol.
Hasan et al. (2019) [22]	Transfer learning for precision farming	2,100 internet and 500 farm photographs in the source account	Precision spraying is an application prospect, not established by classification alone.
Tarek et al. (2022) [23]	Optimisation and hardware deployment	Workstation and Raspberry Pi 4 evaluations	Latency is hardware-specific.
Chowdhury et al. (2021) [24]	Segmentation and EfficientNet classification	18,161 original and segmented images in the source account	Segmentation and classification have separate performance measures.
Moussafir et al. (2022) [25]	Optimisation and ensemble deep learning	PlantVillage tomato images	Generalisability to other crops requires testing.
Wang et al. (2021) [26]	YOLOv3-tiny-IRB under occlusion and overlap	Self-built disease and pest dataset	Detection conditions affect mAP; speed needs hardware context.

Applications and Field Studies

Chen et al. (2022) [27] investigated an AlexNet-based convolutional network for tomato leaf disease detection and classification. The manuscript describes 18,345 training images and 4,585 test images, with ten labels and 64 × 64 RGB inputs. The reported configuration used the Adam optimiser, a learning rate of 0.0005, 75 epochs and a batch size of 128. Reported outcomes include approximately 98% accuracy, precision of 0.98, recall of 0.99, F1 score of 0.98 and loss of 0.1333. These measures should retain their proper names; precision is not a measure of disease severity. The reported results concern the study's model and evaluation data.

Zhao et al. (2020) [28] examined hyperspectral image reconstruction from single RGB photographs using tomato quality assessment as a case study. The work selected an HSCNN-R configuration using a mean relative absolute error loss function and evaluated reconstructed images with the corresponding metric. Images captured with a smartphone were used to estimate tomato quality characteristics, including the ratio of soluble solids to titratable acidity and a normalised anthocyanin index. This is related imaging research rather than a direct tomato disease classification experiment. Its inclusion illustrates another way in which learned image representations can support agricultural assessment.

Prabhakar et al. (2020) [29] combined deep learning with a Foldscope, a paper microscope, to assess early blight severity in tomato leaves. A ResNet101-based architecture was compared with VGG16, VGG19, GoogLeNet, AlexNet and ResNet50. The dataset included healthy leaves and different disease-severity levels. The manuscript reports 94.6% accuracy for the D-ResNet101 configuration. Severity assessment differs from merely identifying whether disease is present, since it may help describe the extent of damage. Any treatment implications still depend on agronomic context and should not be inferred from a classification score alone.

Ahmad et al. (2020) [30] studied pretrained convolutional networks for tomato leaf disease detection, including VGG16, VGG19, ResNet and Inception V3. The models were evaluated using both laboratory-style data and images collected in the field. The manuscript reports differences of roughly 10–15% across performance measures, with stronger results on the laboratory dataset. Inception V3 performed best in the described comparisons. This distinction is important: a model can perform well on controlled images and less well under field conditions. The table therefore identifies field generalisation as an issue examined by the study, rather than incorrectly claiming that field data were absent.

Fuentes et al. (2021) [31] examined tomato disease diagnosis with explicit control of hidden classes.

Their approach distinguishes control classes from target classes and evaluates the model using images from greenhouse conditions. The purpose is to investigate how learned representations respond to differences within and between classes and to new acquisition conditions. The expanded dataset described in the manuscript contains 14 classes, including five target classes. The reported mean average precision for target classes on the inference dataset is 93.37%. The terminology refers to model classes and domain conditions, not “regulator-to-board programs”, which was an erroneous phrase in the source.

Huang et al. (2023) [32] proposed FC-SNDPN for tomato leaf disease detection. A fully convolutional network based on VGG16 was used for foreground segmentation to reduce background interference. The subsequent network combines residual and dense connections with a normalisation component to improve feature learning. The manuscript reports identification accuracy of 97.59% on the augmented dataset. Separating leaves or affected regions from the background may make recognition more robust, but segmentation quality also becomes part of the overall workflow. The study therefore needs to be considered as a pipeline rather than only a final classifier.

Chipuli and Luwemba (2023) [33] developed an image-recognition approach to tomato leaf disease detection intended for a mobile application. The manuscript compares ResNet18, ResNet50, InceptionV3 and EfficientNet using images representing healthy leaves and disease categories such as bacterial spot, early blight and late blight. It reports F1 scores around 0.99 for several configurations and 0.84 for InceptionV3; these are dimensionless scores, not percentages of 0.99%. The source’s descriptions of class counts and data splits are inconsistent, so they should not be treated as a verified experimental partition. The practical aim remains field-accessible recognition through a phone interface.

Abdulridha et al. (2020) [34] used hyperspectral imaging and machine learning to identify tomato yellow leaf curl, bacterial spot and target spot. Data were collected in both laboratory and field settings, including an unmanned aerial vehicle platform. The study compared healthy and affected plants using spectral information and classification methods. The manuscript reports high classification rates, including 94%, 95% and 100% for specified laboratory comparisons and 98–100% in some later-stage or field comparisons. These values refer to different disease and acquisition conditions. The study should not be described as excluding UAV-based data, since that platform is explicitly part of its design.

Hidayatuloh et al. (2018) [35] investigated SqueezeNet for identifying tomato leaf diseases. The model was developed with a deep-learning framework and images obtained through the Indonesian Vegetable Research Institute at Lembang, West Java. The manuscript describes seven classes,

including healthy leaves, and reports average identification accuracy of 86.92%. The reference to “200 students” in the source was a wording error concerning image samples. The study demonstrates another relatively compact network approach, while the extent to which its results generalise to other locations depends on the diversity of the data and independent testing. Table 4 summarises the application studies.

Table 4. Application studies and practical evaluation

Study	Approach or objective	Data or setting	Scope considerations
Chen et al. (2022) [27]	AlexNet-based classification	18,345 training and 4,585 test images in the source account	Reported metrics concern the original evaluation.
Zhao et al. (2020) [28]	Hyperspectral reconstruction from RGB images	Tomato quality assessment	Related imaging work, not a direct disease-classification test.
Prabhakar et al. (2020) [29]	Foldscope and ResNet101 severity assessment	Healthy leaves and early blight severity categories	Severity estimates need agronomic interpretation.
Ahmad et al. (2020) [30]	Pretrained CNN comparison	Laboratory and field datasets	The study explicitly examines reduced performance on field images.
Fuentes et al. (2021) [31]	Explicit control of hidden classes	Greenhouse images with control and target classes	New acquisition conditions test robustness.
Huang et al. (2023) [32]	FC-SNDPN segmentation and recognition	Augmented tomato leaf images	The pipeline depends on both segmentation and recognition quality.
Chipuli and Luwemba (2023) [33]	Mobile-accessible recognition	Tomato leaf images and CNN comparisons	Inconsistent class and split descriptions require caution.
Abdulridha et al. (2020) [34]	Hyperspectral detection of three diseases	Laboratory and UAV-based field data	The study includes UAV sensing; platform-specific outcomes should be distinguished.

Hidayatuloh et al. (2018) [35]	SqueezeNet classification	Leaf images from Lembang, West Java	Broader geographic and environmental testing would clarify transferability.

Conclusion

The reviewed literature covers tomato pathology, biological management, image preprocessing, convolutional classification, object detection and practical deployment. Deep learning offers useful approaches to recognising visible disease patterns, but performance depends on datasets, disease categories, image conditions and evaluation procedures. Laboratory-style images often present an easier task than field photographs with complex backgrounds, occlusion or variable lighting. Severity assessment, mobile deployment and generalisation to new environments remain important research directions. Future work should report data partitions and metrics clearly, evaluate independent field data, and connect recognition outputs with appropriate plant-health expertise. These considerations are more informative than comparing isolated accuracy values across incompatible experiments.

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