

Citrus Diseases Detection & Classification using DL and ML Models: A Systematic Review

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Abstract Citrus diseases are a major challenge in agricultural production because they can reduce crop yield, fruit quality, and farmers’ economic returns. Early and accurate detection of diseases is therefore essential for effective crop management and sustainable citrus production. Traditional disease identification methods mainly depend on visual inspection and expert knowledge, which can be time-consuming, subjective, and difficult to apply on a large scale. This systematic review examines the application of **Deep Learning (DL) and Machine Learning (ML) models for citrus disease detection and classification**. The review analyses recent studies focusing on image processing, conventional machine learning algorithms, Convolutional Neural Networks (CNNs), transfer learning, YOLO-based object detection, attention mechanisms, ensemble learning, and Vision Transformers. It compares commonly used datasets, preprocessing techniques, model architectures, evaluation metrics, and reported classification or detection performance. The findings indicate that DL models generally provide higher accuracy and stronger feature-learning capabilities than traditional ML approaches, while lightweight and YOLO-based models offer greater potential for real-time agricultural applications. However, challenges remain concerning limited and imbalanced datasets, complex field backgrounds, variations in lighting and disease symptoms, early-stage disease identification, computational requirements, and model generalisation across different citrus varieties and geographical locations. The review identifies these research gaps and highlights future opportunities for developing robust, lightweight, explainable, and field-deployable AI systems for automated citrus disease detection and classification.

Keywords: Citrus Diseases; Deep Learning; Machine Learning; Disease Detection; Disease Classification; Convolutional Neural Networks; YOLO; Transfer Learning; Computer Vision; Precision Agriculture.

I INTRODUCTION

Citrus is an economically important fruit crop cultivated widely for fresh consumption, processing, and international trade. However, citrus production is seriously affected by diseases caused by fungi, bacteria, viruses, insects, and other environmental factors. Diseases such as citrus Huanglongbing (HLB), canker, black spot, scab, anthracnose, and greasy spot can adversely affect plant health, fruit quality, productivity, and farmers’ income. Early and accurate identification of disease symptoms is therefore essential for timely intervention and

effective disease management. Recent research has increasingly explored computer vision and artificial intelligence as alternatives to conventional visual inspection, which can be labor-intensive, subjective, and dependent on expert knowledge. The rapid development of machine learning (ML) and deep learning (DL) has created new possibilities for automated citrus disease detection and classification [1-3]. Traditional ML approaches generally require manually designed features related to colour, texture, shape, and lesion characteristics, whereas DL models can automatically learn discriminative features directly from images. CNN-based architectures have consequently become widely used for plant-disease classification because of their ability to extract hierarchical visual features. Recent research has also demonstrated the application of transfer learning, ensemble models, object-detection networks, and attention mechanisms to improve disease-recognition performance[2].

Recent 2024 research demonstrates the rapid advancement of lightweight and high-performance detection models. [3] Developed a YOLOv8n-based citrus leaf disease detection model incorporating cross-domain dynamic attention, pruning, and knowledge distillation. Their model was specifically designed to address small disease targets, complex orchard backgrounds, uneven illumination, and leaf obstruction, while achieving a lightweight configuration suitable for real-time detection. Similarly, [4] proposed YOLOv8-GABNet for citrus disease and nutrient-deficiency recognition. The model incorporated lightweight convolution, weighted BiFPN, and global-to-local spatial aggregation to improve multiscale feature extraction and recognition in complex backgrounds.

The literature has also moved beyond conventional CNN architectures toward hybrid CNN–Transformer approaches. A 2024 study on an improved FasterViT model combined the local feature-learning capability of CNNs with the global representation capability of Vision Transformers. This approach was designed to improve the recognition of complex morphological and textural characteristics of citrus diseases, particularly when image datasets are relatively small. In another 2024 study, a transfer-learning and ensemble-based model-fusion network achieved high performance for distinguishing healthy and diseased citrus leaves and for classifying multiple diseases, pests, and nutrient deficiencies [5].

The increasing performance reported by individual studies demonstrates the potential of DL for automated citrus disease diagnosis. For example, [6] developed a deep-learning framework using data augmentation, transfer learning, and feature selection, reporting high classification performance using citrus leaf images. Their study highlights the value of automated image analysis for reducing the limitations of manual disease diagnosis. JCBI However, high accuracy on individual datasets does not necessarily guarantee reliable performance under real agricultural conditions[7]. Differences in illumination, camera angle, disease severity, background complexity, citrus variety, and geographic location can substantially affect model generalisation.

A major concern identified in the 2024 literature is the limited availability and diversity of labelled citrus disease datasets. [8] In their review of 25 studies, identified limited datasets, class imbalance, insufficient evaluation of augmentation methods, and difficulties in real-world implementation as important challenges. The authors emphasised the need for larger and more diverse datasets and more rigorous evaluation of models under practical agricultural

conditions. IJISRT These limitations demonstrate that future research should not focus exclusively on increasing classification accuracy but should also consider robustness, computational efficiency, explainability, and deployment capability[9].

Therefore, the present systematic review, “Citrus Diseases Detection & Classification using DL and ML Models: A Systematic Review,” examines the evolution of ML and DL techniques used for citrus disease detection and classification. The review focuses on the datasets, preprocessing approaches, feature-extraction methods, ML/DL architectures, evaluation metrics, reported performance, and limitations of existing studies. Particular attention is given to CNN, transfer learning, YOLO-based object detection, attention mechanisms, ensemble learning, and transformer-based approaches[10]. By systematically synthesising the available evidence, the study aims to identify methodological trends, compare existing approaches, highlight research gaps, and provide directions for developing more accurate, lightweight, generalisable, and field-deployable citrus disease detection systems[10-12].

Table:1 Major Citrus Diseases and Their Characteristics

Citrus Disease	Causal Agent	Major Symptoms	Affected Plant Part	Importance for AI/DL Detection
Citrus Huanglongbing (HLB/Greening)	<i>Candidatus Liberibacter spp.</i>	Blotchy mottling, yellow shoots, small and poorly coloured fruits	Leaves, shoots, fruits	Irregular symptoms make automated image-based detection challenging
Citrus Canker	<i>Xanthomonas citri subsp. citri</i>	Raised corky lesions surrounded by yellow halos	Leaves, fruits, stems	Distinct lesions make CNN and YOLO-based detection suitable
Citrus Black Spot	<i>Phyllosticta citricarpa</i>	Dark circular spots and lesions on fruit and leaves	Fruits, leaves	Small lesions require high-resolution image analysis
Citrus Scab	<i>Elsinoë fawcettii</i> / <i>Elsinoë australis</i>	Raised, rough, corky lesions and wart-like growth	Leaves, fruits, young shoots	Texture-based and CNN approaches can identify characteristic lesions
Citrus Anthracnose	<i>Colletotrichum spp.</i>	Brown or dark necrotic lesions, leaf spots and fruit decay	Leaves, fruits, twigs	Similar symptoms to other fungal diseases create classification challenges

Citrus Melanose	<i>Diaporthe citri</i>	Small dark brown to black spots with rough texture	Leaves, fruits, twigs	Fine lesion patterns require effective feature extraction
Citrus Greasy Spot	<i>Zasmidium citri-griseum</i>	Yellowish leaf spots that develop into dark, greasy-looking lesions	Mainly leaves	Colour and texture features are useful for automated classification
Citrus Alternaria Brown Spot	<i>Alternaria alternata</i>	Brown necrotic spots surrounded by yellow halos	Leaves, fruits, shoots	Early-stage symptoms can be difficult to distinguish automatically
Citrus Tristeza	Citrus tristeza virus (CTV)	Leaf decline, stem pitting, reduced growth and yield	Leaves, stems, roots	Virus symptoms are often indirect, making image-only detection difficult
Citrus Sooty Mold	Sooty-mould fungi associated with honeydew-producing insects	Black fungal coating on leaves and fruit surfaces	Leaves, fruits	Surface colour information can support computer-vision detection

Table 1 presents the major diseases affecting citrus crops and their characteristics, including the causal agent, major symptoms, affected plant parts, and relevance to AI- and deep-learning-based detection. The table covers important bacterial, fungal, viral, and surface-associated diseases such as Huanglongbing (HLB), citrus canker, citrus black spot, citrus scab, anthracnose, melanose, greasy spot, Alternaria brown spot, tristeza, and sooty mold. The differences in symptoms, lesion characteristics, colour, texture, and affected plant parts demonstrate why automated image-based disease detection requires effective feature extraction and classification techniques. The information provides a biological basis for selecting appropriate computer-vision, machine-learning, and deep-learning methods for citrus disease identification.

Table:2 Disease Categories for the Systematic Review

Category	Examples	Suitable AI/DL Approaches
Bacterial diseases	Citrus canker, HLB	CNN, YOLO, Vision Transformer
Fungal diseases	Black spot, scab, anthracnose, melanose, greasy spot	CNN, ResNet, DenseNet, EfficientNet
Viral diseases	Citrus tristeza	CNN, transfer learning, multimodal models

Surface/secondary diseases	Sooty mold	CNN, image segmentation, object detection
Multiple-disease classification	Healthy + several citrus diseases	CNN, YOLO, ensemble learning, Vision Transformer

Table 2 presents the major diseases affecting citrus plants, their causal agents, common symptoms, affected plant parts, and their relevance to artificial intelligence (AI)-based detection. The table covers important bacterial, fungal, and viral diseases, including Huanglongbing (HLB), citrus canker, black spot, scab, anthracnose, melanose, greasy spot, and tristeza. It shows that citrus diseases produce diverse visual symptoms, such as leaf discoloration, necrotic spots, corky lesions, mottling, and fruit damage. These variations create challenges for automated disease recognition and require effective image-processing and feature-extraction techniques. The table therefore provides a foundation for selecting appropriate **machine learning (ML), convolutional neural network (CNN), YOLO, transfer-learning, and Vision Transformer (ViT)** approaches for citrus disease detection and classification.

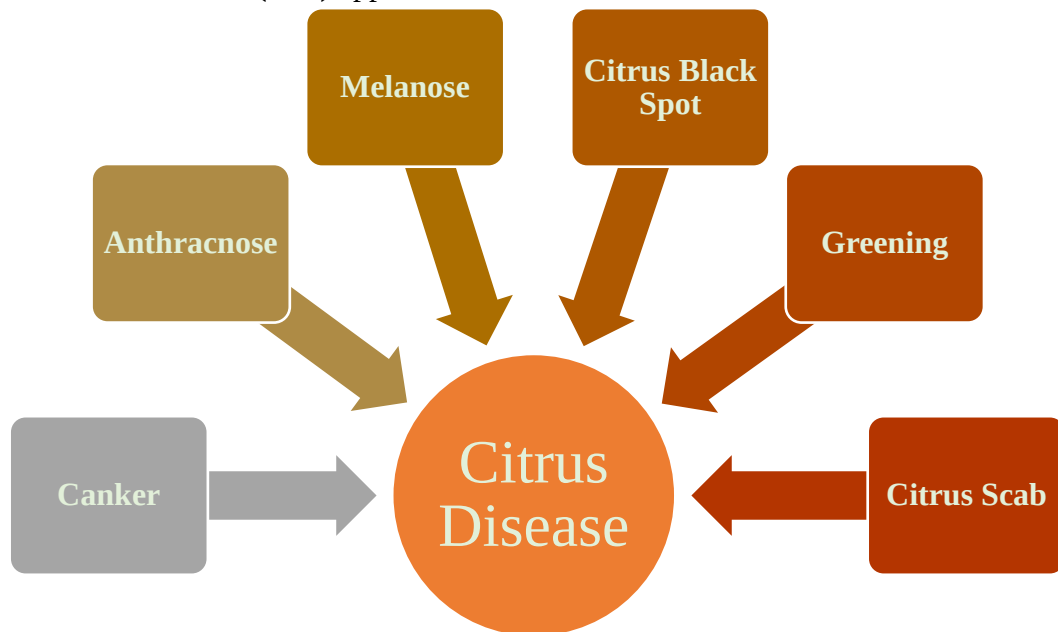


Figure 1 different types of citrus disease

Major Challenges in Disease Detection and Fruit Grading of Citrus based on Machine Vision-Machine vision, which integrates cameras, processing gear, and software algorithms, allows for the automation of regular visual inspection tasks. With machine vision, these include location, identification, verification, measurement, and flaw detection. The fundamental purpose of machine vision in this crop is to detect defects (diseases), classify diseases and citrus fruit kinds, and evaluate fruit quality and size. (1) Optical consistency; (2) separation of the disease from the background; (3) the presence of irrelevant features; and (4) the absence of big datasets are significant challenges in citrus disease identification and diagnosis. [13-15]

Machine vision mainly relies on preprocessing to improve the optical consistency of the incoming images. Included in the preparatory procedures are image enhancement, color space conversion, image resizing, and image filtering. Many challenges, including lighting, brightness, and contrast issues, can therefore be eliminated. These factors have a direct effect on the accuracy of disease classification [16]. For the identification of plant diseases, numerous preprocessing techniques are utilized. They include image enhancement, scaling, image correction, and the elimination of shadows. Segmentation is the second primary process for separating the disease's fragments [17]. Color change, substantial diversity in colors, changing lighting circumstances, variations in the size of the sick portion, the volume of fruits, and estimation of disease area and fruit size are some of the most typical obstacles for segmenting diseased parts in an image [18].

Due to these flaws, the accuracy of detection and grading is weakened, and the system as a whole suffers. Using various methods, such as K-means and thresholding, crop disease diagnosis and fruit grading are possible. Preprocessing and segmentation techniques assist with crop defect classification. In order to evaluate illness and fruit grades, feature extraction and categorization are also required. An essential objective of feature extraction methods is to diagnose diseases based on the texture, size, and color of lesions. Dealing with challenges such as enormous dimensions of extracted features, irrelevant information, lengthy computation durations, redundant data, and changeable lighting conditions and characteristics that are not invariant under scaling and rotation are phases of the feature extraction process. As each disease has a specific hue that is utilized to identify it, the majority of studies concentrate on color. Other properties, such as texture and shape, contribute in the detection of disease in agricultural plants [19]. The conclusion of machine learning is classification. In agricultural operations, SVM, KNN, and ANN [20] are frequently employed for disease classification and fruit grading. The main cause of the classifier's low performance is the lack of feature selection and feature reduction algorithms. Figure 2 depicts the machine learning technique to disease detection and fruit grading. Recently, there has been a great deal of interest in machine learning regarding deep learning (DL) (ML). When applied to big datasets, deep learning (DL) enhances agriculture's precision and productivity. Similar to ANN, DL provides a hierarchical data representation in the form of convolutions. Deep learning is defined by the automated extraction of features from raw data (DL)[21]. Hence, DL solves complex problems more rapidly and with fewer errors. DL techniques are not used in the literature for citrus disease classification for a

number of important reasons, including the availability of a big dataset. A huge number of data points are needed to train a machine learning model. Other plants, including apple, tomato, and general plant leaves, are classified [22-23]. Figure 2 displays the typical deep learning methodology for disease identification, as well as the citrus crop's fruit grading. Taking into account all demanding elements and available methodologies, these two approaches are more attentive for disease detection. The most suited strategies for generating high dimension feature vectors from a short dataset are the feature fusion techniques. Thus, citrus disease diagnosis and fruit grading performance may be improved[24]

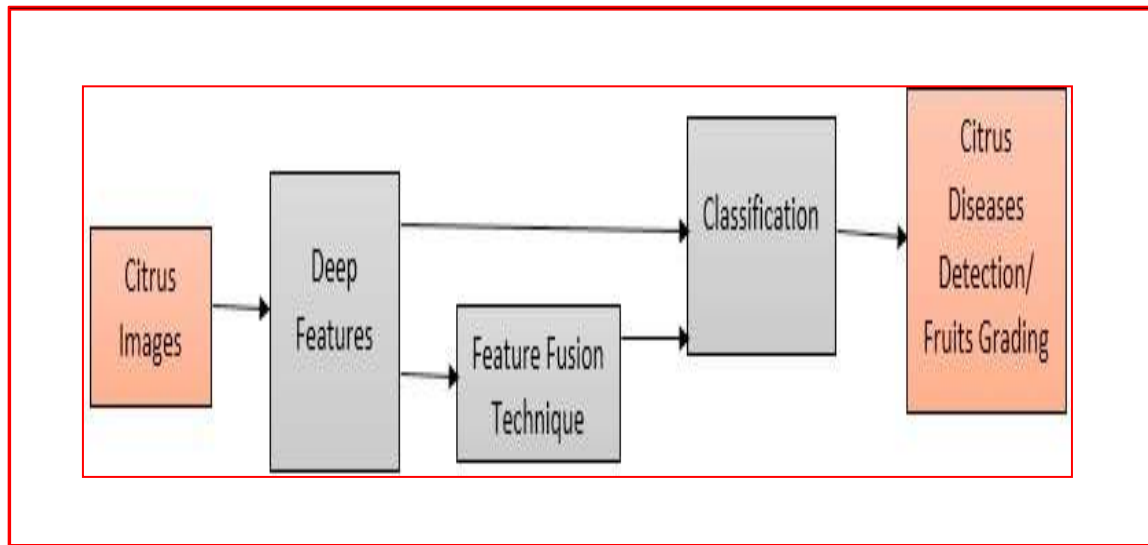


Figure 2. Framework based on Deep Learning.

II RELATED WORK

[25] Developed an enhanced lightweight deep-learning model, YOLOv8-GABNet, for the recognition of citrus diseases and nutrient deficiencies. The study addressed major challenges associated with disease detection, including complex backgrounds, leaf occlusion, and the need for computationally efficient models. The authors incorporated improved feature extraction and attention mechanisms into the YOLOv8 architecture to enhance detection performance. Their findings demonstrated the potential of lightweight object-detection models for practical citrus disease monitoring, particularly where computational resources are limited. However, further validation using larger datasets and diverse field environments is required to establish the model's generalization capability.

[26] Proposed a lightweight citrus leaf disease detection model based on YOLOv8n and cross-domain dynamic attention. The study focused on diseases such as anthracnose, scab, and greasy spot, which can be difficult to identify because of small lesions, uneven illumination, occlusion, and complex orchard backgrounds. The proposed YOLOv8n-CDDA model incorporated attention mechanisms, pruning, and knowledge distillation to reduce computational requirements while maintaining detection effectiveness. The model achieved a parameter size of only 0.8 million and operated at approximately 45 frames per second, indicating strong potential for real-time agricultural applications.

[27] investigated citrus disease detection using an innovative deep-learning approach combined with a hybrid meta-heuristic optimisation technique. The study used a citrus leaf disease image dataset and demonstrated how deep-learning models can automatically learn disease-related visual features while optimisation techniques can improve model performance. The research contributes to the growing application of intelligent image-recognition systems for citrus disease diagnosis. However, the authors' reliance on image datasets highlights the continuing need for more diverse, field-based images representing different lighting conditions, disease stages, citrus varieties, and geographical locations.

[28] Compared four advanced deep-learning architectures—EfficientNetB0, ResNet50, DenseNet121, and InceptionV3—for citrus disease classification. Their dataset contained 759 images representing nine disease and healthy classes, including black spot, canker, greening, scab, and melanose. The study demonstrated that advanced CNN architectures can achieve very high classification performance and can effectively distinguish different citrus disease categories. The findings support the suitability of transfer-learning-based CNN models for automated citrus disease diagnosis. Nevertheless, the relatively limited dataset size indicates a need for further testing using larger and independently collected field datasets. Nature

[29] proposed a hybrid multi-optimizer approach combining Convolutional Neural Networks (CNN) and Gradient Boosting (GB) for citrus fruit disease prediction. The research highlighted the limitations of conventional manual inspection and investigated automated image-based prediction using deep-learning and machine-learning techniques. By integrating CNN-based feature learning with machine-learning optimisation, the study demonstrated the potential of hybrid models for improving citrus fruit disease prediction. The study also indicates that combining different learning approaches may provide an alternative to relying exclusively on a single deep-learning architecture. Springer Link

[30] introduced YOLOV8-CMS for automated citrus leaf disease classification and grading. Unlike studies that focus only on identifying whether a plant is diseased, this research also considered disease grading, making the approach more relevant for practical crop-management decisions. The model was designed to improve feature extraction and accurately identify disease symptoms from citrus leaf images. The study demonstrates the increasing movement of citrus disease research from simple classification toward integrated detection and severity assessment. However, additional research is required to assess its robustness across different citrus species, disease stages, and uncontrolled orchard environments.

Citrus disease detection based on dilated reparameterisation and a shared parameter head [31]proposed YOLOv8n-DE to address the difficulties caused by diverse lesion patterns and complex orchard environments. The model incorporated dilated reparameterisation for improved feature extraction and a shared detection head to improve parameter efficiency. The study reported 97.6% classification accuracy, 91.8% recall, and 97.3% mAP, demonstrating the potential of lightweight YOLO-based architectures for citrus disease detection. An important contribution of the research is its evaluation using both public and orchard-collected datasets, although further testing across wider geographic and environmental conditions would strengthen its generalisability[32].

[33] proposed a multi-stage deep ensemble-learning framework incorporating Vision Transformers for citrus disease classification. The study used actual-field images of oranges and lemons, making it particularly relevant to real-world agricultural applications. The approach combined CNN-based learning, ensemble techniques, and Vision Transformers to improve early disease diagnosis. The research demonstrates the transition from conventional CNN models toward more advanced hybrid and transformer-based architectures. However, the computational complexity of such models and their suitability for low-resource agricultural devices remain important areas for future research.

[34] Developed YOLO-Citrus, a lightweight and efficient model for citrus leaf disease detection in complex agricultural environments. The researchers used YOLOv11s as the basis and introduced architectural improvements to address issues such as complex backgrounds and difficult disease symptoms. The study is particularly significant because it focuses not only on detection accuracy but also on computational efficiency, which is important for real-time deployment in agricultural environments. Nevertheless, additional validation across different citrus varieties, geographic regions, environmental conditions, and disease severity levels is necessary before widespread field deployment[35-40].

The 2025 multi-component CNN study investigated citrus disease detection using a large dataset of approximately 12,000 citrus leaf and fruit images. The researchers developed a Multi-Component CNN (MC-CNN) approach to detect important diseases such as black spot, canker, and greening. The study reported performance of up to 97.75%, indicating that CNN-based models can provide robust disease classification when trained using sufficiently large image datasets. Compared with studies based on smaller datasets, this research highlights the importance of dataset scale for developing models that can better handle real-world variability.

III METHODOLOGY

- The purpose of this systematic review is to provide an overview of the various machine-learning and deep learning algorithms employed in the diagnosis of citrus fruit diseases using photographs of sick citrus trees. The review technique consists of the following steps.
- Data Collection
- Searched databases
Science Direct, Scopus, Springer, ACM (Association for Computing Machinery), and IEEE (Institute of Electrical and Electronics Engineers) were utilized to analyze this body of literature (IEEE Explore Digital Library). This survey utilized the years 2000 to 2020 as its time frame.

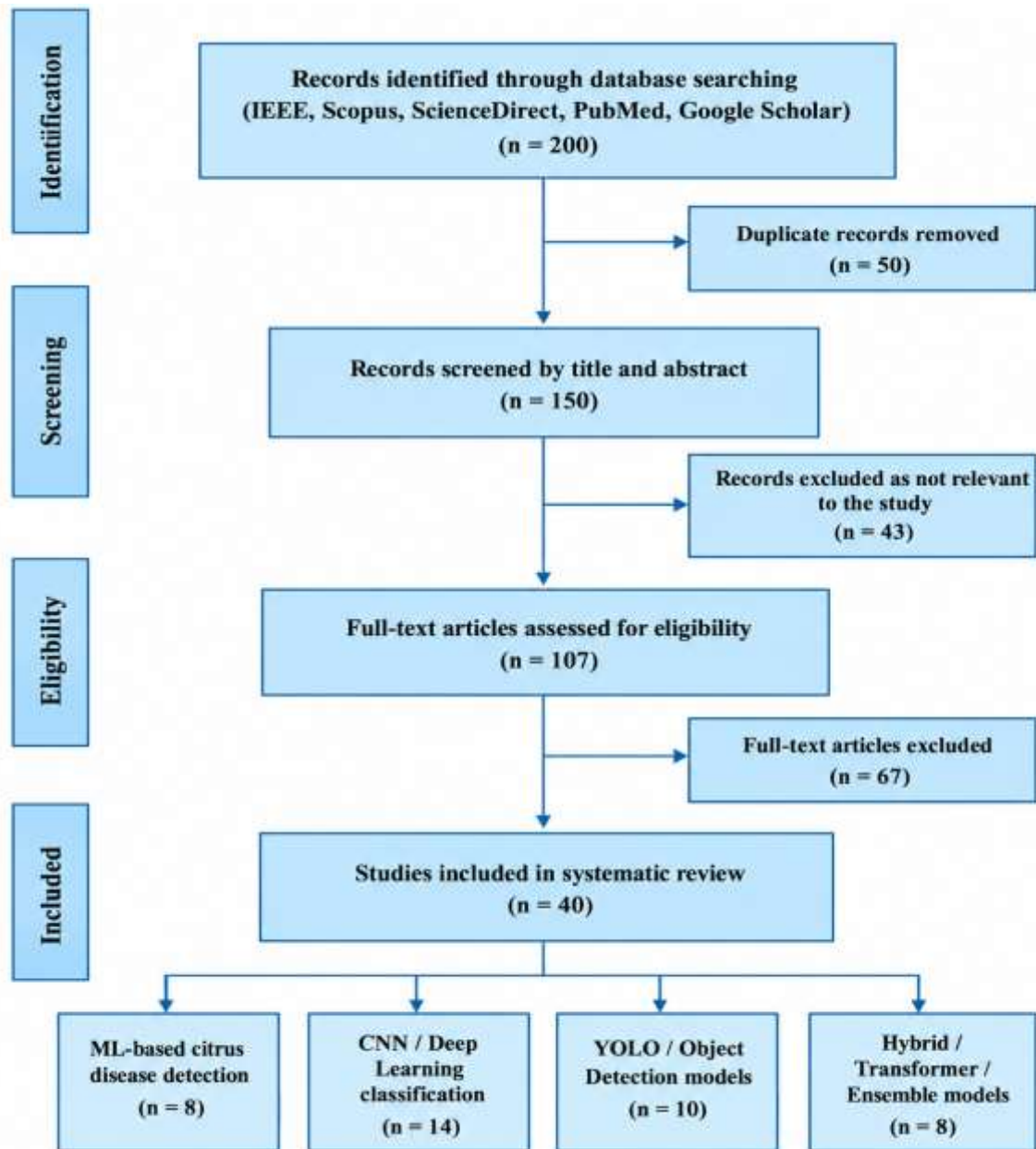


Figure 3: PRISMA Flow Diagram for the Systematic Review of Citrus Disease Detection and Classification

The figure presents the PRISMA-based study selection process used for the systematic review of citrus disease detection and classification using machine learning and deep learning techniques. Initially, 200 records were identified through database searches of IEEE, Scopus, ScienceDirect, PubMed, and Google Scholar. After removing 50 duplicate records, 150 studies remained for title and abstract screening. During the screening stage, 43 records were excluded because they were not relevant to the research topic, leaving 107 full-text articles for eligibility assessment. Following detailed full-text evaluation, 67 articles were excluded based on the eligibility criteria. Finally, 40 studies were included in

the systematic review. These selected studies were further classified into four major research categories: ML-based citrus disease detection (8 studies), CNN/deep learning classification (14 studies), YOLO/object detection models (10 studies), and hybrid, transformer, and ensemble models (8 studies). Thus, the figure demonstrates the systematic and transparent process used to identify, screen, assess, and select the studies included in the review.

VI CONCLUSION

This paper looks at almost all papers published between 2010 and 2022 that deal with citrus diseases and how to grade fruit. This survey gives information about the signs of citrus diseases. Also, the techniques that the researcher used to understand citrus diseases and grade the fruit are looked at. These include image processing, machine learning, and deep learning. The pros and cons of the current state of the art are shown in a table. This paper also gives a brief overview of techniques for pre-processing, segmentation, feature extraction, and classification. Most of the time, a hybrid approach is suggested for automatically predicting citrus diseases and grading them. Deep learning and machine learning are both parts of the hybrid approach. Researchers in this field might also be very interested in an attempt to make such a system. In this survey, different ways of using image processing to find out what kind of disease is affecting a plant are talked about. This survey has four main steps, such as preprocessing, segmentation, feature extraction, and classification. The comparison is made for each step based on how it is done, how well it works, and what its pros and cons are. From the results of the survey, we can say that preprocessing techniques help improve the accuracy of segmentation. Also, we think that Kmeans is the most popular method for dividing up plants that have been infected. Also, the texture features are the most important for showing disease in an image, and both SVM and NN use these features. So, they need to work on making a system that works quickly, accurately, and automatically to find diseases on citrus leaves that haven't been affected. This paper does a comparison of the different kinds of Convolutional Neural Network and Deep Learning models used to find and classify different rice plant diseases. It does this by looking at research from the last five years that was published in an internationally indexed journal. This article also goes into detail about the different kinds of data sources. After this study, we found that most researchers were able to find citrus diseases more accurately when they used the Convolutional Neural Network model of Deep Learning. The goal of this research is to look at all of the different Deep Learning models and find the best one for getting better accuracy and precision.

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