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Promoting Environmental Sustainability through Artificial Intelligence: A Systematic Review of Detection, Prevention, and Treatment Applications in Houseplants and Home Greenhouses

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Abstract

Ornamental houseplants and home greenhouses, as part of urban agriculture and indoor cultivation, are playing a growing role in environmental sustainability, household food security, indoor air quality, and urban well-being. This review asked how far the existing literature has actually moved beyond reactive disease detection toward a complete cycle of intelligent and sustainable plant protection — one that also covers early prediction, treatment decision support, and deployment in users' real homes. Following PRISMA 2020, the researchers analyzed 55 primary studies published between 2015 and 2025. Thematic coding produced 23 codes across 9 categories and 4 dimensions: disease detection (64%), prediction and early warning (18%), treatment support (9%), and home/greenhouse deployment (7%). The reported accuracy reached 95–99% in laboratory settings but fell to 70–85% once models were tested in real environments. We identified five structural gaps: a strong bias toward reactive over preventive approaches, a persistent laboratory-to-reality accuracy gap, an almost complete absence of data for indoor ornamental species, no use whatsoever of large language models for treatment guidance, and a weak theoretical connection to sustainable agriculture and Integrated Pest Management (IPM) principles. Future work should prioritize lightweight, generalizable models that integrate with environmental sensing under an IPM framework, thereby translating technical accuracy into measurable sustainability outcomes.

Keywords

Houseplants, Home Greenhouse, Plant Disease Detection, Deep Learning, Environmental Sustainability, Sustainable Agriculture.

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Introduction

The sustainable management of indoor plants — a category that encompasses decorative ornamentals, edible herbs, and medicinal species alike — sits at the intersection of urban environmental sustainability and the growing movement toward home-based food and plant cultivation. Indoor cultivation contributes directly to several UN Sustainable Development Goals including SDG 11 (Sustainable Cities and Communities) through urban greening and reduced heat-island effects, and SDG 15 (Life on Land) through the support of urban biodiversity and the conservation of functionally significant plant species. Beyond aesthetics, houseplants and home greenhouse crops measurably improve indoor air quality, lower concentrations of volatile organic compounds, help regulate humidity, and support mental well-being (Liu et al., 2022; Shen et al., 2025; Wang et al., 2025). As more households take up indoor cultivation, exposure to biotic and abiotic stress has grown alongside it (Kohli et al., 2020).

Among indoor plants, medicinal and functional species deserve particular attention from a sustainability standpoint. Plants such as aloe vera, lavender, rosemary, mint, and various aromatic herbs are increasingly cultivated indoors for their pharmacological and culinary value (Daughtrey & Buitenhuis, 2020; Kohli et al., 2020). Disease-driven loss of these plants represents not merely an aesthetic setback but a loss of functional biomass that the user would otherwise replace through purchase often involving supply chains with higher environmental footprints. AI-assisted health monitoring that prevents such loss, through early warning, targeted intervention, and minimal chemical use, thus carries a direct environmental sustainability benefit beyond the individual household (Yang et al., 2026). Strengthening the AI toolbox for indoor medicinal plant conservation is therefore an environmental imperative, not merely a convenience.

Fungal and bacterial pathogens, pests, and physiological disorders remain the principal threats to plant health in indoor settings, producing yellowing leaves, fungal spotting, root rot, stunted growth, and, left untreated, plant death. Indoor conditions such as high humidity, limited light, poor ventilation, inconsistent watering create an environment well suited to powdery mildew, root rot, and a handful of recurring pests (Cañadas et al., 2017; Daughtrey & Buitenhuis, 2020; Romero et al., 2022). Most plant owners are not trained in plant pathology, so early symptoms often go unnoticed until intervention is no longer effective (Liu & Wang, 2021; Pacal et al., 2024). Visual inspection by a non-expert is slow, subjective, and a poor fit for the kind of continuous monitoring these conditions demand (Khan et al., 2025; Mohanty et al., 2016).

This problem is part of a larger sustainability question. Sustainable agriculture aims to balance productivity, ecosystem health, and social well-being (FAO, 2018). In urban and indoor cultivation, reducing chemical intervention is an important sustainability goal. Improving the timing of disease control is another area where artificial intelligence could make a measurable contribution. Recent work confirms that AI-driven early detection can reduce fungicide and pesticide application in commercial settings (Park et al., 2026; Yang et al., 2026).

AI methods applied to plant disease have gone through roughly three phases. Early

work used classical machine learning support vector machines, decision trees, and random forests built on hand-crafted visual features (Liu & Wang, 2021). Convolutional neural networks followed, with architectures such as AlexNet, VGG, ResNet, and DenseNet learning features directly from raw pixels and substantially improving accuracy (Ferentinos, 2018; He et al., 2016; Mohanty et al., 2016; Saleem et al., 2020). More recently, Vision Transformers, hybrid CNN-Transformer models, and approaches built around large language models have begun to define the leading edge of the field (Aboelenin et al., 2025; Prommakhot et al., 2025; Shandilya et al., 2025; Shawon et al., 2026; Subhan et al., 2026).

A useful comparative frame is provided by four recent systematic reviews in adjacent territory. Geiser et al. (2023) pointed to the gap between laboratory detection performance and what happens once a system is deployed. Pacal et al. (2024), reviewing 160 studies from 2020 to 2024 in field-based agriculture, argued for lightweight, mobile-friendly models. Upadhyay et al. (2025) and Shawon et al. (2026) both found that most studies still lean heavily on the PlantVillage dataset and agricultural crops. Yang et al. (2026) further confirmed that multimodal AI systems hold promise for sustainable crop protection but remain untested in indoor ornamental contexts. The present review has a narrow focus on indoor ornamental and medicinal species. It covers the full T1-to-T4 protection cycle. It also identifies a gap that has not been highlighted in previous reviews: there is currently no standardized dataset for this target environment.

The aim of this review is to critically assess how far the existing literature has moved past reactive detection toward the full cycle of intelligent, sustainability-oriented protection for houseplants and home greenhouses. The main research question is: to what extent has the literature addressed the complete protection cycle including early prediction and warning, treatment decision support, and deployment in a user's actual home rather than detection alone, and how do these dimensions contribute to sustainable plant management? Four sub-questions examine the dominant approaches and architectures used, the distribution of studies across the four core protection functions, the scientific and practical gaps that remain, and where future research should go.

This study contributes in four ways: a systematic review specifically focused on AI for intelligent protection of houseplants and home greenhouses in a sustainability context; a detailed thematic coding scheme with 23 codes for organizing this literature; identification of the structural gaps separating laboratory performance from real-world sustainability outcomes; and a research agenda for preventive, multimodal, generalizable, and user-centered systems.

Literature Review

AI in Ornamental and Medicinal Plant Identification and Monitoring

Indoor cultivation encompasses a wide range of plant types, from purely decorative species such as ficus, philodendron, and orchid to functionally significant plants including aloe vera, lavender, rosemary, and various aromatic herbs used for medicinal and culinary purposes. Despite the growing interest in sustainable indoor cultivation, dedicated AI

research on ornamental and medicinal indoor species remains thin compared to the volume of work on staple agricultural crops (Kohli et al., 2020; Liu et al., 2022).

Early efforts to automate plant identification drew on morphological feature extraction from leaf images, relying on shape descriptors, color histograms, and texture measures processed by classical classifiers like support vector machines (Liu & Wang, 2021). The arrival of deep convolutional architectures and transfer learning lowered data requirements sufficiently to make disease detection tractable for species with limited training samples (Chiang et al., 2020; Kim et al., 2018). Nonetheless, the species covered in these models have remained overwhelmingly agricultural. A systematic inventory of benchmark datasets confirmed that common indoor ornamentals such as ficus, maranta, and pothos appear in none of the publicly available reference collections (Bellary et al., 2025).

Medicinal plants present a related but distinct challenge. Beyond disease detection, their conservation value means that accurate identification is itself a safety concern (Daughtrey & Buitenhuis, 2020). A small body of work has applied CNN-based classifiers to medicinal herb identification, but these studies have typically been conducted under controlled photographic conditions and have not addressed continuous health monitoring over time. The gap between single-point identification and ongoing health surveillance is a recurring limitation.

Environmental Sustainability and Artificial Intelligence in Plant Management

The relationship between AI and environmental sustainability has been articulated most clearly in the precision agriculture literature, where AI-driven disease detection has been linked to measurable reductions in fungicide and pesticide application, lower water consumption, and reduced soil contamination (FAO, 2018; Romero et al., 2022; Yang et al., 2026). These gains rest on a straightforward mechanism: earlier and more accurate detection allows for targeted, minimal intervention rather than prophylactic blanket treatment. The same logic applies to indoor cultivation. For example, a home user who receives an early warning of powdery mildew risk can adjust humidity and airflow. This may reduce the need for chemical sprays (Bicamumakuba et al., 2025; Cañadas et al., 2017).

This sustainability argument, however, has rarely been operationalized in the indoor plant AI literature. The majority of studies reported accuracy metrics without any measurement of downstream environmental outcomes such as pesticide reduction, plant survival rate, or resource efficiency (Ferentinos, 2018; Mohanty et al., 2016). Establishing the causal pathway from AI prediction to sustainable management action is an unresolved challenge that this review treats as a central gap.

From a broader perspective, indoor cultivation itself carries environmental co-benefits such as improved indoor air quality, urban heat island mitigation through green walls and vertical gardens, and promotion of biodiversity in built environments that are rarely acknowledged in the AI plant health literature (Liu et al., 2020; Shen et al., 2025). Integrating these dimensions would situate AI-assisted plant care within the wider discourse on urban environmental sustainability and the UN Sustainable Development Goals.

AI Applications in Plant Disease Detection and Management

The mainstream of AI plant health research organizes into three successive phases. The first phase (2015-2018) was characterized by classical machine learning applied to hand-crafted image features. The introduction of the PlantVillage dataset (Mohanty et al., 2016) marked a turning point, enabling training and evaluation of deep models at scale. The second phase (2018-2022) was dominated by CNNs trained on PlantVillage, achieving reported accuracy of 95-99% on held-out test sets (Ferentinos, 2018; He et al., 2016; Saleem et al., 2020). The critical limitation of high accuracy on test splits that did not transfer to real deployment remained largely unaddressed throughout this phase. Chen et al. (2020) and Shafay et al. (2025) both documented accuracy drops of 15-25 percentage points moving from laboratory images to photographs taken by non-expert users in home environments.

The third phase (2022 onward) has introduced Vision Transformers (Barman et al., 2024; Shandilya et al., 2025), hybrid CNN-Transformer models (Aboelenin et al., 2025; Prommakhot et al., 2025), and early explorations of large language model integration (Ma et al., 2025; Shawon et al., 2026; Subhan et al., 2026). These developments have improved accuracy further under controlled conditions, but the fundamental data problem of the near-total absence of training data for indoor ornamental species has not been solved by architectural innovation alone (Park et al., 2026).

Beyond detection, a smaller body of work has explored prediction and early warning through environmental sensor networks (e.g., Bicamumakuba et al., 2025; Romero et al., 2022), automated climate control as a prevention strategy (e.g., Cañadas et al., 2017), and explainable AI to make model output interpretable to non-expert users (e.g., González-Rodríguez et al., 2024; Nigar et al., 2024). No published study has yet integrated early environmental prediction, detection, and natural-language treatment recommendation into a single system designed for home deployment.

Prior Systematic Reviews and the Positioning of the Present Study

Four systematic reviews form the immediate comparative context for this study. Geiser et al. (2023) identified a persistent gap between laboratory performance and field deployment. Pacal et al. (2024) who surveyed 160 deep learning studies, concluded that lightweight, mobile-deployable models are urgently needed, and noted that PlantVillage underpins the majority of reported accuracy figures. Upadhyay et al. (2025) confirmed the dominance of agricultural crop species and the near-absence of indoor plant studies. Shawon et al. (2026) found that most federated learning approaches still rely on the same agricultural benchmark datasets.

Three observations distinguish the present review from these predecessors. First, all four prior reviews worked with the existing datasets; the present review's central finding is that no standardized dataset exists for indoor ornamental or medicinal plants. Second, none of the prior reviews examined the complete protection cycle from detection through prediction, treatment decision support, and home deployment. Third, none positioned their findings within an IPM framework, the theoretical lens most

directly applicable to sustainable, minimal-intervention plant care.

Methodology

This review follows the PRISMA 2020 guidelines (Page et al., 2021).

Search Strategy

The researchers searched Scopus and Web of Science for publications between January 1, 2015 and April 30, 2025. The complete Boolean search string applied in Scopus was: ("indoor plant" OR "houseplant" OR "ornamental plant" OR "potted plant" OR "home greenhouse" OR "indoor garden" OR "urban farming" OR "controlled environment agriculture" OR "vertical garden") AND ("plant disease detection" OR "plant pest detection" OR "plant health monitoring" OR "disease prediction" OR "early warning" OR "leaf disease" OR "fungal infection plant" OR "pest infestation") AND ("deep learning" OR "machine learning" OR "artificial intelligence" OR "CNN" OR "convolutional neural network" OR "vision transformer" OR "YOLO" OR "transfer learning" OR "GAN" OR "IoT" OR "sensor fusion" OR "decision support" OR "computer vision"). An identical string structure was applied in Web of Science. The search was conducted on April 30, 2025. Results were limited to English-language articles published in peer-reviewed journals. No document-type filter was applied at the search stage. Duplicates were first removed automatically within each platform's export tool, then a second manual cross-database pass was conducted after merging the two export files, yielding 163 unique records.

Inclusion and Exclusion Criteria

We included peer-reviewed studies that applied AI methods to detecting, predicting, or managing plant disease and pests, and that addressed houseplants, ornamentals, potted plants, home greenhouses, controlled indoor environments, OR commercial greenhouse settings where the authors explicitly discussed applicability to home or small-scale greenhouse contexts. Studies from general agricultural contexts were retained only where their methodology was directly applicable to indoor or home greenhouse settings. He et al. (2016) introduced the ResNet architecture that underpins the majority of subsequent indoor plant disease models. Its inclusion is methodologically necessary for tracing the architectural lineage of the field. Varghese et al. (2025) and Mitta (2023) were included under the same logic. All three are clearly labelled in Table 1 under "Domain Classification: General agricultural methodological comparison". Studies with no connection stated or inferable to enclosed cultivation environments were excluded at the full-text stage. The systematic reviews identified through the same search were set aside from the primary analysis and used only in the Discussion and Literature Review as points of comparison.

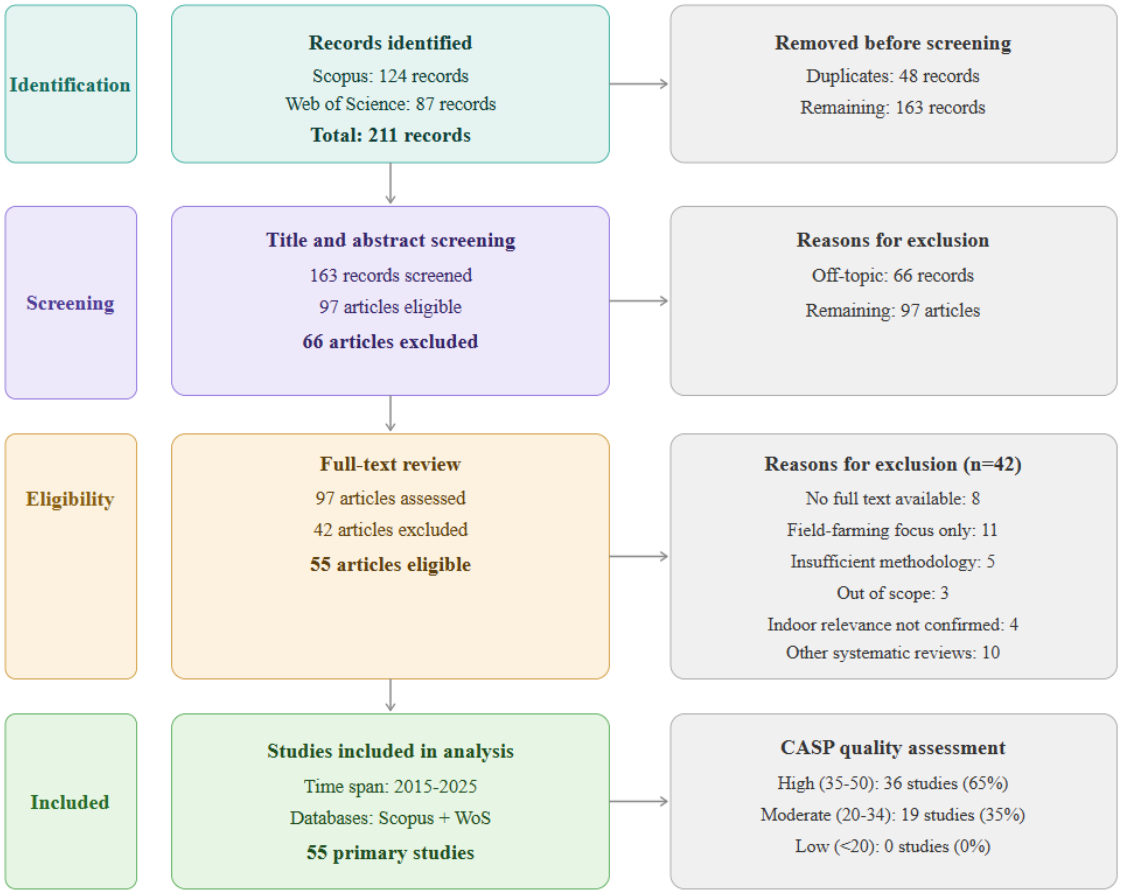
The Study Selection and PRISMA Flow

The search returned 211 records including 124 from Scopus and 87 from Web of Science. After removing 48 duplicates, 163 unique records went to title-and-abstract screening. This left 97 articles for full-text review.

At full-text review, 42 studies were excluded: eight lacked an accessible full text in a reputable database; eleven addressed exclusively open-field agricultural crops with no indoor or greenhouse content despite relevant terminology in the abstract; five were excluded for insufficiently described methods that precluded quality assessment; three fell outside scope entirely (one examined human disease using plant images as auxiliary input, two addressed remote sensing at landscape scale with no connection to indoor cultivation); four studies including Mohiuddin and Yousuf (n.d.), Slišković et al. (2011), Osman and Speekenbrink (2012), and Lew et al. (2019) could not be confirmed as relating to houseplants or home greenhouses after close full-text reading; and ten were systematic reviews whose findings were used as comparison points in the Literature Review and Discussion rather than as primary evidence. This yielded 55 primary studies for analysis.

One of the included studies was published in 2026 (Shawon et al., 2026). This article was retrieved as an online-first publication indexed in Web of Science prior to the April 30, 2025 search cutoff and was therefore included within the review window. Its formal volume and issue date reflects the publication schedule of the journal rather than the date of online availability and indexing.

Figure 1.
The PRISMA 2020 Flow Diagram Showing Identification, Screening, Eligibility Assessment, and Final Selection of Studies (Page et al., 2021)



(Source: The Researcher's Findings)

Quality Assessment

The study quality was assessed with the CASP checklist (CASP, 2018) across 10 criteria. Each criterion is scored 1–5, for a maximum of 50. Two key metrics used throughout this review are defined here at first use: F1-score is the harmonic mean of precision and recall, used as a balanced accuracy metric for classification tasks with imbalanced classes; AUC (Area Under the Receiver Operating Characteristic Curve) is a threshold-independent measure of a model's ability to discriminate between classes, where a value of 1.0 indicates perfect discrimination. We classified studies as High (35–50), Moderate (20–34), or Low (below 20), and treated a score of 35 or above as the threshold for use as primary evidence. Of the 55 studies, 36 (65%) scored High and 19 (35%) scored Moderate; none fell into the Low band.

Table 1 lists the structural characteristics and CASP score for all 55 studies. A "Domain Classification" column has been added to explicitly identify each study as: (a) directly indoor/home ornamental, (b) controlled greenhouse with transferable methods, or (c) general agricultural included for methodological comparison only. "Input Type" indicates the general kind of data the model receives. "Real-World Test" indicates whether the study evaluated performance outside the controlled laboratory conditions.

The columns in Table 1 are defined as follows. Theme indicates which of the four review dimensions the study primarily addresses (T1 = disease and pest detection; T2 = prediction and early warning; T3 = treatment management and support; T4 = deployment in home and greenhouse settings); studies covering more than one dimension carry a combined code such as T1+T4. Environment and Plant Domain describes the deployment setting and the type of plant species studied. Input Type refers to the form of data fed into the AI model image, sensor signal, text, or a combination. Data Source specifies the origin of that data, for example a controlled laboratory camera, a real-world smartphone, IoT sensors recording temperature or humidity, or synthetically generated images. Architecture refers to the AI method or model used, such as CNN (Convolutional Neural Network), ViT (Vision Transformer), LSTM (Long Short-Term Memory network), GAN (Generative Adversarial Network), or classical machine learning algorithms such as SVM and Random Forest. Domain Classification labels each study explicitly as: (a) directly indoor or home ornamental, (b) controlled greenhouse with methods transferable to the home context, or (c) general agricultural retained for methodological comparison only. Real-World Test records whether the study evaluated the model performance under conditions outside a controlled laboratory (Yes/No).

Table 1.
The Characteristics and Quality Assessment of Selected Studies (n = 55)

#	Reference	Theme	Environment & Plant Domain	Input Type	Data Source	Architecture	Real-World Test
1	Mohanty et al. (2016)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	CNN	No
2	Ferentinos (2018)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	Deep CNN	No
3	He et al. (2016)	T1	Open field, general	Image	General-purpose camera (RGB)	ResNet	No
4	Saleem et al. (2020)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	CNN	No
5	Chen et al. (2020)	T1	Home greenhouse, agricultural	Image	Diverse cameras (RGB)	Transfer Learning	Yes
6	Bakr et al. (2022)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	DenseNet	No
7	Karthikeyan & Raja (2023)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	DenseNet+ Transfer	No
8	Archana et al. (2023)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	ResNet	No
9	Hanif et al. (2024)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	ResNet/Inception/SVM	No
10	Pandian et al. (2022)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	Deep CNN	No
11	Kim et al. (2018)	T1	Apartment, ornamental	Image	Controlled camera (RGB)	Transfer Learning	No
12	Sumaya et al. (2024)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	AlexNet/VGG/ResNet	No
13	Shandilya et al. (2025)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	CNN+ViT	No
14	Prommakhot et al. (2025)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	CNN-Transformer	No
15	Aboelenin et al. (2025)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	CNN-ViT	No
16	Barman et al. (2024)	T1	Home greenhouse, agricultural	Image	Real-world camera (RGB)	ViT+mobile	Yes
17	Parez et al. (2023)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	Efficient ViT	No
18	Nazki et al. (2019)	T1	Home greenhouse, agricultural	Image	Synthetic image (GAN)	GAN+CNN	No
19	Douarre et al. (2019)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	CNN+Data Augmentation	No
20	Padmanabhuni & Gera (2022)	T1	Home greenhouse, agricultural	Image	Synthetic image (GAN)	MILGAN	No
21	Ullah et al. (2025)	T1	Home greenhouse, agricultural	Image	Synthetic image (GAN)	GAN	No
22	Yoon & Lee (2025)	T1	Apartment, ornamental	Image	Synthetic image (Diffusion)	Diffusion+CNN	Yes
23	Shafay et al. (2025)	T1+T4	Home greenhouse, agricultural	Image	Real-world camera (RGB)	CNN/Transformer	Yes

24	Khan et al. (2025)	T1	Home greenhouse, agricultural	Image	Controlled camera (RGB)	DenseNet+ Attention	No
25	Nyawose et al. (2025)	T1	Home greenhouse, agricultural	Image	Diverse cameras (RGB)	YOLO/ML	No
26	Varghese et al. (2025)	T1	Open field, agricultural	Image + sensor data	Camera and environmental sensor	CNN-Transforme r+GAN	No
27	Mitta (2023)	T1	Open field, agricultural	Image + sensor data	Camera and environmental sensor	CNN-LSTM	No
28	Bellary et al. (2025)	T1+T4	Apartment, ornamental	Image	Real-world camera (RGB)	CNN+machi ne vision	Yes
29	Elanchezhian et al. (2020)	T1	Home greenhouse, agricultural	Sensor data	IoT sensor (temperature, humidity, CO_2)	ML comparativ e	No
30	Chiang et al. (2020)	T1	Apartment, ornamental	Image	Home camera (RGB)	—	No
31	Parrales-Bravo et al. (2024)	T1	Open field, agricultural	Sensor data	Time-series environmental sensors	Time series analysis	No
32	Shafi et al. (2020)	T2	Home greenhouse, agricultural	Image + sensor data	Camera and IoT sensor	ML+IoT	No
33	Romero et al. (2022)	T2	Home greenhouse, agricultural	Sensor data	Environmental sensor (temperature, humidity)	ML environme ntal	No
34	Bicamumakuba et al. (2025)	T2+T3	Home smart greenhouse, agricultural	Sensor data	IoT sensor (temperature, humidity, CO_2, light)	ML+IoT	No
35	Fenu & Malloci (2021)	T2	Home greenhouse, agricultural	Sensor data	Time-series climate sensors	LSTM/RF/S VM	No
36	Eraliev & Lee (2023)	T2	Home hydroponic greenhouse, agricultural	Sensor data	IoT sensor and time series	LSTM/ CNN	No
37	Hosseini Monjezi et al. (2023)	T2	Home greenhouse, agricultural	Sensor data	IoT sensor (temperature, humidity, radiation)	ANN+ sensitivity	No
38	Lin (2024)	T2	Home greenhouse, agricultural	Sensor data	Time-series climate sensors	LSTM/GRU /Transform er	No
39	Yan et al. (2025)	T2	Home greenhouse, agricultural	Sensor data	IoT sensor (temperature, humidity)	ANN	No
40	Berdugo et al. (2014)	T2	Home greenhouse, agricultural	Image + sensor data	Spectral camera + sensor	ML+ sensor fusion	Yes
41	Zhu et al. (2025)	T2	Home greenhouse, agricultural	Image + sensor data	Spectrometer + soil moisture sensor	ML multi-sensor	No
42	Aviles Toledo et al. (2024)	T2	Home greenhouse, agricultural	Image + sensor data	Camera and environmental sensor	CNN+ Attention	No

43	Shen et al. (2025)	T2	Apartment, ornamental	Sensor data	IoT sensor (temperature, humidity)	ML regression	Yes
44	Nigar et al. (2024)	T3	Home greenhouse, agricultural	Image	Controlled camera (RGB)	CNN+ Grad-CAM	No
45	González-Rodríguez et al. (2024)	T3	Home greenhouse, agricultural	Image	Diverse cameras (RGB)	CNN+XAI	No
46	Christakakis et al. (2024)	T3+T4	Apartment, ornamental	Image	Real-world camera (RGB)	CNN mobile	Yes
47	Arzuaga et al. (2024)	T3	Home greenhouse, agricultural	Image	Real-world camera (RGB)	CNN mobile	Yes
48	Cañadas et al. (2017)	T2+T3	Home greenhouse, agricultural	Sensor data	IoT sensor (temperature, humidity, CO_2)	ML+ decision support system	Yes
49	Daughtrey & Buitenhuis (2020)	T3	Home greenhouse, ornamental	—	Controlled review	IPM framework	No
50	Ma et al. (2025)	T1+T3	Home greenhouse, agricultural	Descriptive text	User text report	LLM-assisted	No
51	Afzal et al. (2024)	T1+T4	Apartment, ornamental	Image	Real-world camera (RGB)	CNN+3D	Yes
52	Kohli et al. (2020)	T2+T4	Apartment, ornamental	Sensor data	IoT sensor (temperature, humidity, light)	ML+ IoT	Yes
53	Liu et al. (2020)	T4	Apartment, ornamental (green wall)	Sensor data	IoT sensor (temperature, humidity, light)	ML anomaly detection	Yes
54	Shagol et al. (2018)	T4	Apartment, ornamental	Sensor data	IoT sensor (light intensity)	ML+IoT	No
55	Zhou et al. (2022)	T4	Apartment, ornamental (multi-story)	Image + sensor data	Camera and environmental sensor	CNN multi-sensor	No

(Source: The Researcher's Findings)

Thematic Coding Approach

The thematic coding followed the framework proposed by Braun and Clarke (2006). Four dimensions were defined based on the disease management cycle in sustainable agriculture: disease and pest detection (T1), prediction and early warning (T2), treatment management and support (T3), and deployment in home and greenhouse context (T4). These four dimensions track the IPM framework, which treats prevention, monitoring, detection, and intervention as the core pillars of sustainable disease management (Daughtrey & Buitenhuis, 2020). The keyword co-occurrence analysis was conducted in VOSviewer (van Eck & Waltman, 2010).

Findings

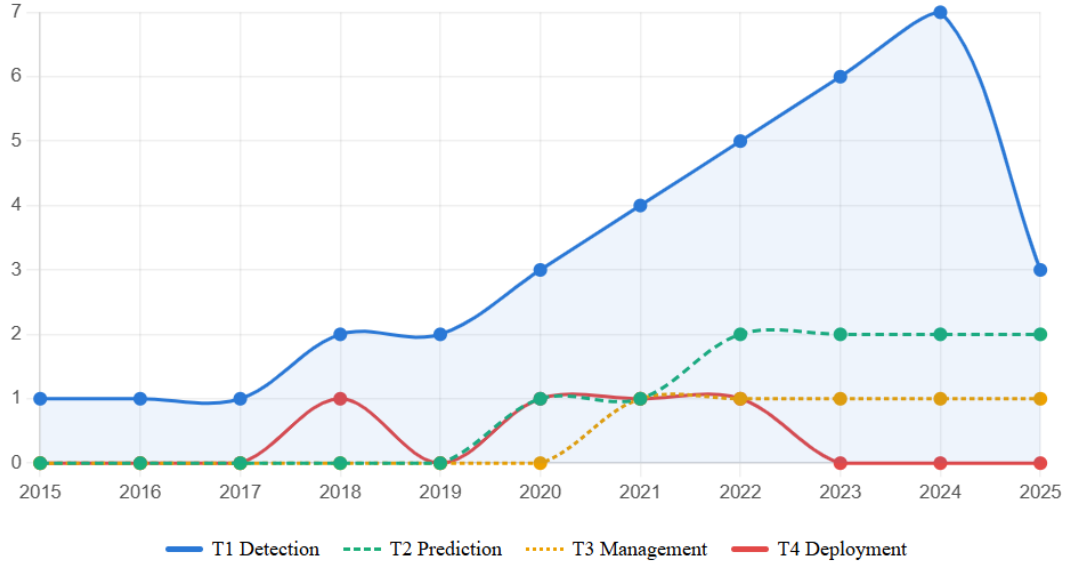
As defined in the methodology, the four dimensions of this review are: T1 (disease and pest detection), T2 (prediction and early warning), T3 (treatment management and support), and T4 (deployment in home and greenhouse settings). The distribution by theme is lopsided: T1 accounts for 35 studies (64%), T2 accounts for 10 studies (18%), T3 for 5 studies (9%), and T4 for 4 studies (7%).

Table 2.
Studies with Multi-dimensional Coverage

Reference	Dimensions	Description
Bellary et al. (2025)	T1+T4	Disease detection in a real home environment
Christakakis et al. (2024)	T3+T4	User interface and home deployment
Kohli et al. (2020)	T2+T4	IoT monitoring and home deployment
Cañadas et al. (2017)	T2+T3	Climate-based warning and decision support
Bicamumakuba et al. (2025)	T2+T3	Smart control and prediction
Nigar et al. (2024)	T1+T3	Detection and XAI for the user
Afzal et al. (2024)	T1+T4	Detection and 3D home modeling
Shafay et al. (2025)	T1+T4	Detection and mobile deployment
Ma et al. (2025)	T1+T3	LLM-supported detection and treatment recommendation

Note: T1 = Disease and pest detection; T2 = Prediction and early warning; T3 = Treatment management and support; T4 = Deployment in home and greenhouse settings. Studies with a combined code (e.g., T1+T4) address two dimensions simultaneously.
(Source: The Researcher's Findings)

Figure 2.
Distribution of Studies by the Four Main Dimensions and Publication Trend over Time



(Source: The Researcher's Findings)

Thematic Coding: The Full Code Set

The coding produced 23 codes across 9 categories and 4 dimensions, detailed in Table 3. The table has been reorganized to group codes first by dimension (T1–T4) and then by category, with each category accompanied by a brief definitional note in the table footnote. For each code, we tracked: (a) Conceptual Code (short label), (b) Empirical Finding (what the reviewed studies show), (c) Identified Limitation, and (d) Research Implication — clearly distinguishing between these four elements throughout.

The headline finding in T1 (35 studies, 64%) is a genuine contradiction: 31 studies reported laboratory accuracy above 95%, yet only 8 studies tested both laboratory and real-world settings and every one showed a 10-25 percentage point decline. In other words, 73% of studies reported strong accuracy without checking whether it holds

outside the lab. A related problem: 27 studies relied on PlantVillage, yet 12 explicitly noted that it contains no ornamental species, meaning 44% of the studies using this dataset knew about its core weakness and used it regardless. Architectural progress from CNN to ViT (n = 19) happened with no parallel change in the underlying data, leaving more complex models with the same generalizability problem.

In T2 (10 studies, 18%), the only quantitative preventive signal in the whole literature usable at home was humidity above 80% with temperatures of 18-25°C something a basic IoT sensor could flag 24-48 hours before symptoms appear (Romero et al., 2022). All time-series modeling studies were run in commercial greenhouses.

In T3 (5 studies, 9%), the most consequential finding is Row 16 of Table 3: n = 0 for LLM-based treatment recommendation, the only complete gap across all 23 codes. Row 13 showed just two studies linking climate control to pesticide substitution within an IPM frame, with no quantified reduction reported by either.

In T4 (4 studies, 7%), Row 21 (n = 6) is the most frequent code: models trained on PlantVillage were not prepared for real home imaging conditions directly traceable to Row 3's PlantVillage reliance in T1. Pest coverage for enclosed environments stayed under 10% across the literature.

Table 3.
Thematic Coding of the 23 Codes across Four Dimensions (n = 55)

Row	Dimension	Category	Concept/Code	Main Challenge in Literature	Risk Related to Sustainable Agriculture	Count	Sample References
1	T1	Accuracy-centeredness	Exclusive focus on accuracy, F1-score, and AUC, without practical evaluation	73% of studies reported high accuracy but never tested the real-world environment	Apparent success that collapses on deployment; wasted research effort	28	(Mohanty et al., 2016; Ferentinos, 2018; Shafay et al., 2025)
2	T1	Accuracy-centeredness	Reporting accuracy above 95% under controlled laboratory conditions	None of these 31 studies measured pesticide reduction, productivity, or user satisfaction	High laboratory accuracy with no clear bearing on real pesticide reduction, since sustainability outcomes go unmeasured	31	(Chen et al., 2020; Mohanty et al., 2016; He et al., 2016)
3	T1	Limited generalizability	Heavy reliance on PlantVillage, which contained no indoor ornamental species	60% of studies used PlantVillage; 44% of these acknowledged its limitations and used it anyway	Models that simply don't work for ficus, orchid, or philodendron — a structural species gap	27	(Mohanty et al., 2016; Bellary et al., 2025; Nazki et al., 2019)
4	T1	Limited generalizability	Common ornamental species missing from reference datasets entirely	None of the reviewed studies documented a common indoor ornamental in PlantVillage	The houseplant market still had no dedicated dataset of its own	12	(Bellary et al., 2025; Shafay et al., 2025; Yoon & Lee, 2025)

5	T1	Laboratory-reality gap	A 10-25 percentage point accuracy drop moving from controlled to real conditions	Only 8 studies tested both settings, and all showed a substantial decline	Home users ended up with a system that simply underperformed in practice	8	(Shafay et al., 2025; Chen et al., 2020; Bellary et al., 2025)
6	T1	Architectural evolution	Progression from classical CNN to CNN-Transformer with no corresponding change in data	Architectural sophistication was advancing while the dataset problem stayed untouched	Resources poured into model complexity instead of the actual bottleneck — data	19	(Shandilya et al., 2025; Prommakhot et al., 2025; Barman et al., 2024)
7	T2	Environmental modeling	IoT sensor data were used to predict disease-favorable conditions before symptoms appear	This preventive approach covered only 18% of the literature	Without prediction, late intervention was the default outcome	7	(Romero et al., 2022; Bicamumakuba et al., 2025; Shafi et al., 2020)
8	T2	Environmental modeling	Humidity above 80% combined with 18-25°C as a predictor of powdery mildew risk	Validated only in commercial greenhouses; never tested at home	A parameter that could give 24-48 hours of advance warning, barely used	3	(Romero et al., 2022; Bicamumakuba et al., 2025; Cañadas et al., 2017)
9	T2	Pre-symptomatic spectral imaging	Detecting leaf biochemical changes via spectroscopy before symptoms were visible	Accurate, but required equipment well beyond a typical household budget	Precise technology that stayed out of reach; actual cost never reported	3	(Berdugo et al., 2014; Zhu et al., 2025)
10	T2	Pre-symptomatic spectral imaging	Spectrometer equipment limitations and distance from home applicability	No study offered a cost-benefit comparison against the home use	Without that economic picture, it was hard for anyone to make a policy case	4	(Berdugo et al., 2014; Shafi et al., 2020)
11	T2	Time-series modeling	LSTM, GRU, and ANN were used to predict greenhouse temperature and humidity for preventive climate control	All conducted in commercial greenhouses; nothing validated at home	A promising preventive use of IoT with no proof it worked in an actual house	5	(Eraliev & Lee, 2023; Lin, 2024; Yan et al., 2025)
12	T3	Climate decision support	Automated greenhouse climate control to reduce the fungal disease risk	Effective in principle, but disease reduction was never quantified	A claim of replacing pesticides that nobody has actually measured	3	(Cañadas et al., 2017; Bicamumakuba et al., 2025)
13	T3	Climate decision	Smart climate adjustment as a	Only 2 studies linked this to	Without quantified	2	(Cañadas et al., 2017;

		support	pesticide substitute within an IPM framework	IPM explicitly	pesticide reduction, the sustainability claim was just a claim		Daughtrey & Buitenhuis, 2020)
14	T3	User interpretability	Grad-CAM and XAI were used to build non-expert trust in model output	The positive effect was documented, but never measured quantitatively	Without measuring trust, interface design had no real benchmark	4	(Nigar et al., 2024; González-Rodríguez et al., 2024; Christakakis et al., 2024)
15	T3	User interpretability	Simpler interfaces were designed to improve the quality of home users' input data	Helped with data quality, but still did not produce a treatment recommendation in plain language	The user saw a diagnosis but was left not knowing what to actually do	2	(Christakakis et al., 2024; Arzuaga et al., 2024)
16 ★	T3	Absence of LLM-based treatment recommendation	No study has used a large language model to generate natural-language treatment advice	The only complete gap (n = 0) in the entire literature — the largest unfilled opportunity	The home user was left to translate a diagnosis into action alone, with high room for error	0	(Complete gap identified in this review)
17	T3	Treatment decision support	IPM as the theoretical foundation for IPM in ornamental greenhouses	The most fitting framework available, yet explicitly used in under 10% of studies	Without IPM, the field had no real way to claim these systems are sustainable	3	(Daughtrey & Buitenhuis, 2020; Cañadas et al., 2017)
18	T4	Species gap	No reference dataset for common enclosed-environment pests (mealybugs, spider mites, whiteflies)	Common household pests appeared in no benchmark dataset	Systems untrained on these pests simply could not be deployed at home	4	(Cañadas et al., 2017; Bicamumakuba et al., 2025)
19	T4	Species gap	Coverage of enclosed-environment pests stayed under 10% across the literature	Fewer than 10% of studies addressed these pests at all	Home users faced pests no system has ever seen	5	(Bellary et al., 2025; Liu et al., 2020; Kohli et al., 2020)
20	T4	Imaging gap	Variable lighting, cluttered backgrounds, and inconsistent angles in smartphone photos at home	Laboratory models were never trained for these conditions	The 10-25% accuracy drop at home traced directly back to this gap	5	(Bellary et al., 2025; Shafay et al., 2025; Christakakis et al., 2024)

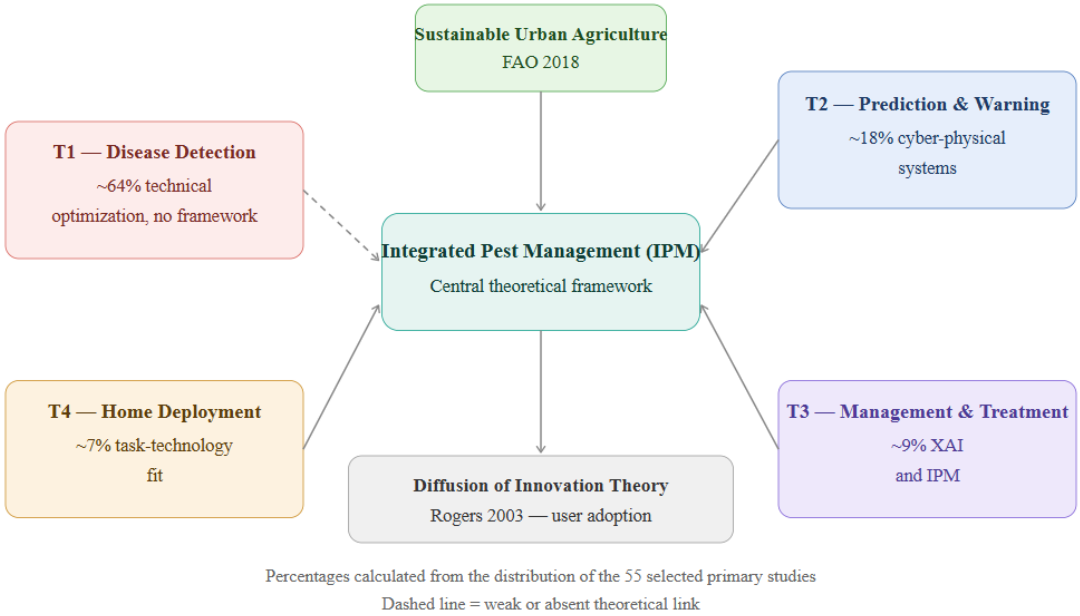
21	T4	Imaging gap	Models trained on PlantVillage simply were not ready for real home imaging conditions	The single most frequent code in T4; a direct consequence of the dataset choice made in T1	A causal chain — laboratory data choices in T1 produced poor home performance in T4	6	(Bellary et al., 2025; Chen et al., 2020; Shafay et al., 2025)
22	T4	User empowerment	Pairing environmental monitoring with smart mobile alerts to support home users	The most encouraging T4 finding, but documented in only 3 studies	A genuinely practical path forward, still well below its potential	3	(Kohli et al., 2020; Afzal et al., 2024; Liu et al., 2020)
23	T4	User adoption	Little attention to task-technology fit or what drives non-expert adoption	Adoption rates among home users were never reported	A system can be technically sound and still fail in practice if nobody adopts it	2	(Christakakis et al., 2024; Kohli et al., 2020)

★ Row 16: the only code with a complete gap (n = 0) among the 23 codes identified.
(Source: The Researcher's Findings)

Four implicit theoretical orientations emerged from the analysis of the 55 studies, shown in Figure 3. The figure was constructed by the authors based on the thematic coding results in Table 3 and was not reproduced from any existing source. It places IPM at the centre because, as argued throughout this review, IPM is the theoretical framework most directly applicable to sustainable, minimal-intervention indoor plant care. The four review dimensions (T1–T4) are positioned around this centre according to the theoretical tradition each dimension draws on: T1 studies predominantly adopted a technical optimization logic with no explicit theoretical framework (indicated by the dashed line); T2 studies implicitly followed a cyber-physical systems logic in which the physical sensor data is translated into digital decisions; T3 studies aligned most closely with IPM principles; and T4 studies drew on task-technology fit theory, which evaluates whether a system matches the capabilities and expectations of its intended user. The outer nodes including Sustainable Urban Agriculture (FAO, 2018) and Diffusion of Innovation Theory (Rogers, 2003) represent the broader theoretical traditions within which the IPM cycle acquires meaning in the home cultivation context. The percentages in each dimension node reflect the proportion of the 55 primary studies assigned to that dimension.

Figure 3 was constructed by the authors as an original analytical synthesis of the thematic coding findings; it does not reproduce any existing model from the literature but maps the theoretical landscape of the reviewed field as revealed by the coding process.

Figure 3.
Distribution of Theoretical Orientations across the 55 Selected Primary Studies



The figure was constructed by the authors based on the thematic coding results (Table 3). Solid lines indicate an explicit or direct theoretical connection identified in the reviewed studies; dashed lines indicate a weak or absent theoretical link. Percentages reflect the proportion of the 55 primary studies assigned to each dimension: T1 (disease detection) ≈ 64%, T2 (prediction and early warning) ≈ 18%, T3 (treatment management) ≈ 9%, T4 (home deployment) ≈ 7%. This figure is an original contribution of the present review and does not reproduce any pre-existing theoretical model.
(Source: The Researcher's Findings)

Discussion and Conclusion

Taken together, the 55 studies showed that this literature has not really achieved what the field or environmental sustainability needs. It remained, for the most part, limited to reactive detection, with no empirically measured link to sustainability outcomes. Three theoretical frameworks helped explain what is missing. The IPM framework put prevention ahead of reaction and positioned detection as a failure mode of a system that did not prevent effectively (Daughtrey & Buitenhuis, 2020). Diffusion of Innovation Theory predicted that technologies without a clear relative advantage for the end user will struggle to be adopted (Rogers, 2003). The task-technology fit model centered the actual expectations of a non-expert user rather than the technical capabilities of the system (Goodhue & Thompson, 1995). Together, these three frameworks pointed toward five priority research directions: building standardized datasets for common indoor ornamentals; developing IoT-based early warning systems; building lightweight, mobile-deployable models; exploring large language models for natural-language treatment guidance as a gap entirely unfilled; and explicitly grounding development in IPM principles to connect technical performance to measurable sustainability outcomes.

T1's 63% dominance showed the field is still trapped in reactive logic. The 64% dominance of T1 is not simply a distributional observation it reflected a deeper paradigmatic choice. The field has implicitly adopted a diagnostic frame borrowed from clinical medicine: identify the problem, then treat it. IPM, by contrast, treated detection

as a last resort, the failure mode of a prevention system that did not work. That these two logics have not been reconciled in the literature is itself an interpretive finding. It suggested that researchers are importing methods from crop pathology without importing the management philosophy that gives those methods meaning in a sustainable agriculture context. From an IPM standpoint, common fungal infections in enclosed spaces often reach an advanced stage by the time visible symptoms appear, by which point effective intervention is already difficult (Romero et al., 2022). The laboratory-to-reality accuracy gap is not a minor technical wrinkle. It points to something more fundamental: resources were being invested in model complexity rather than the actual bottleneck, which was data.

Figure 4.
The Coverage Matrix of the Five Structural Gaps across the Four Themes

High Moderate Low Complete (n=0) Not applicable

Structural Gap	T1 Detection	T2 Prediction	T3 Management	T4 Deployment
Dominance of reactive over preventive	High	Moderate	Low	Low
Laboratory-to-reality gap	High	Moderate	Low	High
Lack of data for ornamental species	High	—	—	High
Absence of LLM in treatment support ★	—	—	Complete	—
Weak link to IPM	High	Moderate	Moderate	High

★ The only gap with complete absence (n=0) in the literature. Cells marked "—" indicate the gap is not applicable to that dimension.

(Source: The Researcher's Findings)

The five structural gaps are traced below:

Gap 1: Dominance of reactive over preventive approaches. The split T1 at 64%, T2 at 18%, T3 at 9%, T4 at 7% sits at odds with IPM principles. Romero et al. (2022) showed that humidity above 80% with 18-25°C significantly raises powdery mildew risk, providing the kind of signal that a basic IoT system could potentially use to generate a 24–48-hour warning. Yet only 18% of the literature has adopted this preventive approach, and no study has measured whether any AI-assisted approach has actually reduced the pesticide use in an indoor home setting.

Gap 2: Absence of data for indoor ornamental and medicinal species. Common ornamentals such as ficus, orchid, philodendron, maranta, and cactus appeared in no benchmark dataset, and pests specific to enclosed environments such as mealybugs, spider mites, and whiteflies were addressed in fewer than 10% of studies. Bellary et al. (2025) found that models trained on PlantVillage take a real performance hit once tested at home. Shafay et al. (2025) documented a 15-25 percentage point drop moving from laboratory to real-world conditions. The actual fix here is collecting real data, not

generating more synthetic data, since GAN-based approaches reproduce the statistical patterns of the original dataset (Nazki et al., 2019; Ullah et al., 2025; Yoon & Lee, 2025).

Gap 3: Absence of a usable decision-support framework. Roughly 70% of T1 studies operated without an explicit theoretical framework. Without IPM, key sustainability questions went unanswered: did the system lead to reduced pesticide use? Was the disease caught early enough to matter?

Gap 4: Complete absence of LLMs in treatment support. According to Table 3, Row 16, n = 0: no study has used a large language model to give plant owners natural-language treatment advice. Christakakis et al. (2024) found that non-expert users respond best to simple interfaces; a recommendation such as "trim the lower leaves, hold off watering for three days" would likely matter far more in practice than a probability score.

Gap 5: Limited attention to non-expert user experience. Fewer than 10% of studies engaged seriously with the home-user dimension. Kohli et al. (2020) showed that pairing environmental monitoring with smart alerts genuinely helps users care for their plants representing a practical yet under-exploited path toward closing this gap and realizing the actual sustainability benefits.

Theoretical and Practical Implications

First, it extends IPM theory from field-scale to indoor domestic settings, demonstrating that the prevention–monitoring–detection–intervention cycle is both applicable and necessary in the home context as a setting that IPM scholarship has not previously addressed systematically. The review showed empirically that, without this theoretical anchor, the field defaults to detection-only approaches that deliver no measurable sustainability benefit.

Second, it applies Rogers's (2003) diffusion of innovation framework to explain adoption barriers among non-expert home users, a population largely overlooked in the plant health technology adoption literature. Technologies that offer reactive detection without actionable treatment guidance fail the relative advantage criterion that drives adoption and diffusion. This provides a theoretical explanation for why, despite high laboratory accuracy, home deployment accounted for only 7% of the literature.

Third, it introduces the task-technology fit model (Goodhue & Thompson, 1995) as a necessary evaluation lens for AI plant health tools, arguing that technical accuracy alone is an insufficient performance criterion when the end user is a non-expert expecting actionable, plain-language output from a smartphone interface. This reframes the evaluation problem for the field: the question is not only "how accurate is the model?" but "does the system fit the task and capabilities of the intended user, and does its use lead to sustainable management outcomes?"

Researchers are directed to five concrete priorities: standardized datasets for common indoor ornamentals and medicinal species; IoT-based early warning systems validated in real home environments; lightweight on-device models tested under home imaging conditions; LLM-based treatment guidance integrated with IPM principles; and explicit measurement of sustainability outcomes such as pesticide reduction and plant survival rate. The framework architecture (Figure 5) provides a blueprint for how these priorities connect across data, processing, and user layers.

Figure 5.
The Architecture of the Integrated Framework for Intelligent Houseplant Protection



(Source: The Researcher's Findings)

Practitioners and developers building AI plant health tools should note that laboratory accuracy is a poor proxy for user value in this setting. Products claiming high accuracy should be required to demonstrate performance under real home imaging conditions such as variable light, cluttered backgrounds, non-expert camera angles before commercial release. The framework proposed here offers a design template for systems that move beyond detection toward the full sustainable management cycle.

Policymakers and regulators can draw on this review's finding that no AI plant health study has measured the pesticide reduction outcomes. This issue points to a regulatory gap: there are currently no standards requiring AI plant health tools to demonstrate the sustainability outcomes, and no incentives for developers to measure them. Establishing such standards would accelerate the field's alignment with SDG 11 and SDG 15, and provide a meaningful basis for public procurement and subsidy decisions related to urban agriculture technology.

The plant owners and urban agriculture practitioners should be cautious about the

commercial AI plant health tools. Despite the high reported accuracy, none of the 55 studies reviewed here has demonstrated reliable performance in an actual home environment across a range of common ornamental or medicinal species. Tools based on IoT environmental monitoring of humidity, temperature, and CO_2 currently offer more robustly demonstrated preventive value for home use than image-based detection tools whose training data contains none of the species or pests the home user is likely to encounter.

All in all, these gaps and priorities point toward an integrated architecture that ties data collection, AI processing, and user interaction into a single sustainability-oriented chain (Figure 5; Table 6). Such a framework would combine leaf imagery, environmental sensing, and user care-history data (data layer); lightweight, home-validated detection, prediction, and IPM-grounded decision-support models (processing layer); and a mobile interface delivering LLM-based, plain-language treatment guidance and smart alerts (user layer). The single complete gap across all 23 codes –LLM-based treatment recommendation– sits precisely at the point in this chain where a diagnosis would otherwise be translated into action for a non-expert user, making it the most consequential unfilled opportunity identified by this review.

Table 6.
The Components of the Integrated Framework

Layer	Component	Technology	Status in the Literature	Gap	Research Priority
Data	Leaf image	RGB image from a mobile camera	Available	No ornamental species represented	A dedicated houseplant dataset
Data	Environmental sensor	Multi-sensor IoT (temperature, humidity, light, CO_2)	Available in commercial greenhouses	Not transferred to home use	A low-cost IoT setup for home users
Data	Care history	User behavioral data	Absent	Complete gap	Collecting user behavioral data
Processing	T1 detection	Lightweight CNN and ViT	Advanced, but laboratory-bound	Laboratory-to-reality gap	A lightweight model that runs on a smartphone
Processing	T2 prediction	ML and climate time series	Commercial greenhouse only	Not transferred to home use	Generalizing to real home and home-greenhouse settings
Processing	T3 decision support	XAI and IPM	Still rudimentary	No real IPM framework in place	Explicit integration with IPM
Processing	T4 deployment	Mobile and edge computing	Early prototypes only	The home environment isn't yet ready for this	Field testing in actual homes and home greenhouses
User	Mobile interface	Simple user interface	Available, but incomplete	Adoption never measured	Measuring adoption among non-expert users
User	Treatment recommendation	Natural-language LLM	Absent (n = 0)	Complete gap	An LLM built around IPM principles
User	Smart warning	IoT notification	Early prototypes only	Limited deployment	Wider deployment for home users

(Source: The Researcher's Findings)

As Table 6 shows, the single complete gap across all 23 codes –LLM-based treatment recommendation– sits precisely at the point in this chain where a diagnosis would otherwise be translated into action for a non-expert user, making it the most consequential unfilled opportunity identified by this review.

Limitations and Future Studies Suggestions

This review has several limitations. First, the search was restricted to Scopus and Web of Science and to English-language, peer-reviewed journal articles; relevant work indexed only in other databases, in conference proceedings, or in non-English literature may have been missed. Second, thematic coding was not independently cross-validated by a second reviewer, which may introduce a degree of subjectivity. Third, the review window closed at April 30, 2025, and relevant work published after this date was not captured. Finally, because so few studies directly target indoor ornamental or medicinal species, some conclusions particularly the complete absence of LLM-based treatment support described an evidence gap rather than a comparison across a mature body of work.

Building on the five structural gaps identified, future studies should prioritize: (1) standardized, publicly available datasets for common indoor ornamental and medicinal species; (2) validating IoT-based early-warning models in real home conditions; (3) lightweight, mobile-deployable architectures tested under home imaging conditions; (4) large language models for IPM-grounded treatment guidance; and (5) direct measurement of sustainability outcomes such as pesticide reduction and plant survival rate.

Based on 55 primary studies published between 2015 and 2025, this review found that the literature on intelligent and sustainable protection of houseplants and home greenhouses remains largely focused on reactive detection, and that the complete intelligent-protection cycle particularly its connection to measurable environmental sustainability outcomes has yet to be fully realized. Thematic coding identified 23 codes across 9 categories and 4 dimensions, and the distribution T1 at 63% against just 7% for T4 is itself evidence of this structural imbalance.

Five core gaps emerged, each capturing a different facet of the problem: a preference for reactive over preventive approaches, almost no data for indoor ornamental or medicinal species, a meaningful 10-25 percentage point gap between laboratory and real-world accuracy, a complete absence of LLMs in treatment decision support (n = 0), and limited attention to what non-expert users actually need. Together, these point to a field that has made real technical progress in deep learning architecture without a corresponding shift in how data is collected, how systems are evaluated, or how sustainability outcomes are measured.

The clearest contribution of this review is showing that no standardized dataset exists for this target environment, and that this absence is a structural condition not a minor oversight that prevents the field from realizing the environmental sustainability benefits that AI-assisted plant protection could offer. The five research priorities outlined in this study –standardized datasets for indoor ornamental and medicinal species, IoT early warning systems, lightweight on-device models, LLM-based treatment guidance, and explicit IPM integration– together define the path from high laboratory

accuracy to genuine, measurable sustainability benefits in homes, urban gardens, and indoor medicinal plant cultivation.

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