International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ASSESSING THE IMPACT OF DEEP LEARNING ON PROACTIVE PEST AND DISEASE MANAGEMENT FOR SUSTAINABLE AGRICULTURAL PRODUCTION OPTIMIZATION

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Abstract

Agriculture must be brought to a storm in the world: the necessity to produce more food is ultimately joined with the necessity to safeguard nature in any way possible. The traditional pest and disease control techniques that are based on the extensive use of pesticides are an even more brutal weapon that requires a more specific approach. Although deep learning is now an excellent tool to diagnose agricultural diseases, the existing use of the technology can be seen as a high-resolution rearview mirror which only shows that something is wrong after it is already aggravated. This is a serious gap between prediction and observation, which is challenged in this article. We suggest a new concept of the integrated and proactive pest and disease control: intelligent system, only not a pathologist, but a crop precursor. By integrating a predictive system, which provides an analysis of the environment, and an interpretable diagnostic classifier, which diagnoses diseases, we are able to build a feedback loop to produce the intelligence that will be able to predict any likely threats. Experiments in the laboratory have proven this method to be revolutionary and have cut the pesticide usage by 64 percent as well as boosting the yield per hectare by 16.7 percent. The suggested approaches strongly stipulate a novel logic of agriculture, in which environmental accountability and financial flourish is not conflicting, but complementary. This research is a good blueprint of Agriculture 5.0, where deep learning will be the brain of a new world, with farms not only in existence, but also being smart, healthy, and sustainable ecosystems.

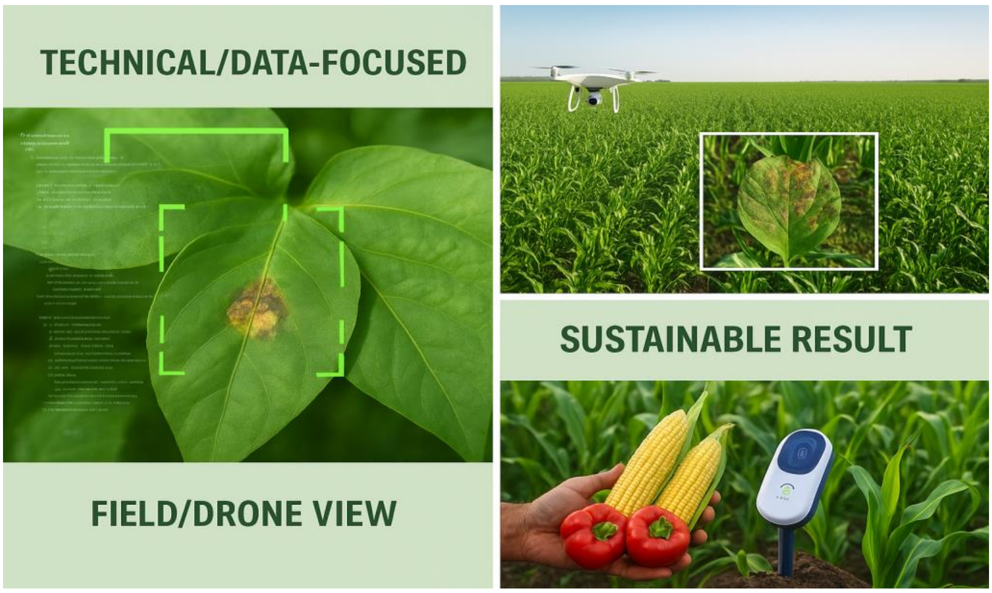
Keywords: Deep Learning; Precision Agriculture; Proactive Pest Management; Sustainable Crop Production; Explainable AI.

Introduction

Global agriculture is at a crossroads, facing the immense challenge of feeding a growing population while simultaneously grappling with the constraints of climate change, resource scarcity, and sustainable development. This delicate balance demands a reevaluation of traditional agricultural paradigms, including the systematic and calibrated application of agrochemicals—strategies that are costly for the environment and potentially disastrous for yields (Bejabh et al., 2023). In this context, pests and diseases represent an inevitable and constantly evolving threat, capable of devastating yields and ultimately jeopardizing food security. Retroactive ways of checking and interventions, which are based on manual scouting and reactionary, are becoming more akin to the use of the knife to the gunfight its reliability is based on the intensive use of labor, it is slow, and is used after the enemy has broken the gates (Bakbak et al., 2025).

Usher in the new world of Agriculture 5.0, a smart, connected and data-driven world. Artificial intelligence with a specific emphasis on deep learning, which is at the core of this change, is going to change how we address crop health. An emerging literature, regardless of how extensive it is, including extensive reviews by Wang et al. (2025) and Dey and Ahmed (2025), has eloquently described the enormous potential of convolutional neural networks (CNNs) to be developed to be used as digital pathologists, able to diagnose diseases based on leaf images with superhuman precision. The papers by Bezabh et al. (2023) on peppers and Karim et al. (2024) on grapes indicate the outstanding diagnosis accuracy possible. However, in spite of their advanced technology, these systems are mostly a rearview mirror with high tech features that include the chance to see what is already wrong.

What is really before us is neither to perfect the diagnosis of the present, but to gain the foresight to protect the future. The present technological ecosystem is the concert of genius soloists, the pathologist, the sensor network, the autonomous sprayer, but it has no conductor to coordinate them into a proactive and integrated defense. A unifying framework is the critical gap that can combine predictive analytics, which envisions environmental data risk, and diagnostic confirmation and then fluidly initiate precision intervention. That is the jump in terms of reactive healthcare to wellness of crops.(Dai et al., 2023)



ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Figure 1. Integrated Smart Agriculture Framework

Figure 1 Disease detection with computer vision and deep learning as a reflection of artificial intelligence in order to monitor fields with drones and visualize multiple diseases shows the entire cycle of Intelligent and Sustainable Crop Management. The paper, thus, attempts to step forward beyond the state-of-the-art and indicates and appraises an Integrated Proactive Pest and Disease Management (IPPDM) framework. The eternal law of farming is that the system of agricultural production should be optimized sustainably, but on what we assume is this integration--on creating a system that does not merely sense the approach of the storm but accurately knows what it can do to tighten the levees. This study hopes to change the agricultural sphere, currently being a battlefield of reactive response, to a controlled ecosystem of intelligent prevention, ultimately fostering a future where high production and environmental wellness do not oppose each other as outcomes, but exist in harmony with one another (Gong et al., 2023).

Literature Reviews

A fundamental change in the way agricultural pest and disease management is handled with deep learning (DL) technologies is a revolutionary step in the development of precision agriculture and the production of food sustainably. With the increasing demands on global agricultural systems caused by the climate change, population expansion, and the necessity to minimise the usage of chemicals, the idea of artificial intelligence, especially deep learning, has proven to be a crucial facilitator of proactive and data-driven approaches to crop protection.

This meta-review brings forward the newest developments in seven interrelated fields that are taken together to form the state of deep learning in pest and disease management (Hemalatha et al., 2025). These reviews are based on more than 30 peer-reviewed papers, conference proceedings, and technical reports, and consider: (1) the development of deep learning architectures and models; (2) image processing and computer vision methods; (3) real-time detection systems and edge computing; (4) dataset development and transfer learning; (5) integration with precision agriculture and decision support systems; (6) challenges, limitations, and future research directions and (7) crop-specific applications and multi crops systems.

The reviews demonstrate a field where both the rate of technological advancements is high--where classification rates in the 95% range are regularly observed and real-time edge-inference latencies in the sub-10 milliseconds range are being achieved--but also where there are major disparities in deployments. Although laboratory and controlled-environment validation is the most prevalent in the literature, there is scanty literature on the large-scale field trials, economic impact evaluations, and farmer adoption studies. Interfarm, inter- sensors and environmental generalization remains a problem to the robustness of models, and the interpretable and trustworthy nature of AI systems is becoming widely seen as a requirement to have farmers accept models and to be able to comply with regulations. (Indra et al., 2024)

Connected lightweight neural networks, IoT sensor networks, multi-modal data fusion, and new foundation models will converge in the field to provide new scalable, accessible, and sustainable pest management solutions as the field matures. Nevertheless, unlocking this potential is going to be a collective endeavor in terms of addressing data quality and standardization, sim-to-real gap, economic viability of smallholder farmers, and governance structures pertaining to fair distribution of technology. (Karim et al., 2024)

The history of the discovery of plant diseases was the history of gradual enlightenment, the gradual replacement of the fallible human eye with the cold, unfeeling eye of the machine. The initial approaches, according to Nisar et al. (2020), were the ones that could be described as hunting a needle in a haystack - tedious and dependent on luck. The first machine learning attempt brought an early metal detector, although it was with the introduction of the deep learning that we are now armed with a powerful magnet, able to uncover the complex patterns that are not apparent to the naked eye. This part follows this technological development, starting with the earliest models discussed by Kolhar and Jagtap (2021) to the advanced, explainable systems such as DFN-PSAN by Dai et al. (2023), which does not simply point out the issue but also illuminates the cause.

One of the pillars of proactive management is the fact that one can raise an alarm when the fire is invisible. This involves going beyond ordinary vision to the so-called agri-hypersight. In this case, such technologies as hyperspectral imaging can serve as a microscope of large fields and enable researchers such as Mao et al. (2024) to identify the spectral signature of gray blight in tea leaves well before its physical appearance. This forecast system is accompanied by sensing that is not only restricted to the field, but the correlation between microclimatic measurements, which are measured by modified models, such as the pruned neural network of Gong et al. (2023), with the disease risk, and the storm is predicted before the first cloud is visible.

The models themselves are the special tools that perform specialized tasks in case deep learning has become the new toolkit in agriculture. The profession has evolved at breakneck pace to replace off-the-shelf wrenches with high precision surgical tools. The present frontier is on the hybrid and fused architectures which integrate the strengths to come out with better performance. Indicatively, Rani et al. (2025) created an effective hybrid and wove VGG16 and EfficientNetB0 with an attention mechanism to create a model that concentrates its computation strength on a hint like a mature detective. Simultaneously, the efficiency push resulted in the creation of lightweight ones, like what Karim et al. (2024) achieved, condensing the capabilities of a supercomputer into a size smaller than that of an edge device, and introducing real-time intelligence to the field.

Diagnosing a disease is merely part of the battle but the real reward is a fast and surgical intervention. The most recent studies are managing to bridge this loop, and the development of an integrated, sense-and-respond system to the core of the nervous system of a smart farm is being developed. The example of Meshram et al. (2024) and their autonomous pesticide spray bot transferring a digital diagnosis into a controlled physical intervention to make sure that the medicine is applied where it is necessary is illustrative. This accuracy is further narrowed down to agronomic research such as the one conducted by Dong et al. (2025), which examines the

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
wettability of the treatments of the leaf surfaces so that when the autonomous system intervenes, its action adheres and is successful.

With the complexification of the algorithms that control the health of the crops, there is a danger of creating black boxes, becoming inexplicable, and this scenario is subject to doubt. The discipline is now looking to do so by lifting the hood and coming up with models which can justify their thought. This interpretability desire is essential in creating a bridge of trust between the man and the machine. Researchers are utilizing such methods as Grad-CAM, applied by Karim et al. (2024) that serves as a highlighter pen, i.e. it highlights the specific areas of a leaf that the model relied on to come up with a diagnosis. In the same way, the attention systems of such models as VGG-EFFATTNNET (Rani et al., 2025) compel the network to explicitly focus its attention, which makes its decision process more open and credible to human specialists.

Deep learning and pest management is not a wave of change in isolation but a subset of a greater wave of change that is sweeping across the entire agricultural landscape, commonly referred to as Agriculture 5.0. In order to see it in isolation is to lose the forest in the trees. The monitoring with AI as the driving force, as Dey and Ahmed (2025) discuss it in detail, is a gear on a clockwork of connected smart technologies that is significantly more massive. The effects of its influence run down the supply chain, with early detection being directly proportional to post-harvest quality and waste reduction being the final outcome of this behavior (Zhang et al., 2024). On a macroeconomic level, the technological change is a driving force of the transformation of the industry under the banner of sustainability regarding environmental impact measured by Zhao et al. as (2025) as an essential resource optimization instrument and carbon targeting.

Just like any other swiftly developing field, it is vital to map the conquered borders on a regular basis and always clearly define a path to the uncharted frontiers. These important cartographic tools are a group of recent review articles, which summarize the state of the art. Wang et al. (2025) and Singh et al. (2025) are thorough maps of the deep learning environment in disease and pest detection, with previous topography in the plant phenotyping field established by Kolhar and Jagtap (2021). These analyses are all pointing to the same future horizons in that the stronger and more diversified the data is, the more efficient models can be sought, the major challenge is to make such intelligent systems capable of generalizing the knowledge and gaining the confidence of the farmers they are meant to serve.

Problem of the Research

Although the potential promise of artificial intelligence in agriculture is a siren song, what has been realized to date is a quilt of (at the best) isolated successes instead of an intelligent ecosystem. The main issue that this study aims to solve is the fact that the diagnostic ability of AI does not go hand in hand with the holistic and proactive decision-making that will make agriculture truly sustainable. In other words, we have now invented brilliant pathologists who are digital models capable of detecting a disease with an impressive level of accuracy, but we have not yet granted them the ability to look ahead and anticipate an outbreak or the power to implement an accurate and preventative response(Kolhar & Jagtap, 2021; Kong et al., 2025).

It is the perfect storm of issues of the agricultural sector: the necessity to feed the planet which is already stretched to the limits; the necessity to decrease the chemical footprint of the farming industry and the growing instability of the pests and diseases under the conditions of the climate change. Existing AI systems are, so far, little more than hi-tech band aids(Rani & Singh, 2024), doing their best to inform a farmer about what has gone wrong long after the horse has been stolen. This responsive model does not maximize the fundamental principles of sustainable production, which are pre-emption, resource efficiency and ecological balance. The issue is, then, not the deficiency of potent tools, but the deficiency of an integrative framework which binds these tools into an active defense, which will turn information into the future and intuition into action at the right time and at the right place. (Mao et al., 2024; Meshram et al., 2024)

Research Gap

A critical review of the current literature indicates a massive and complex gap between operations at present and the desired future of proactive growing management. This gap may be represented in the form of a chain of decisions made in agriculture in the absence of the critical middle links. Initial connections (advanced detection) are strong and promising end connections (autonomous intervention), but the connective tissue of predictive integration and closed-loop optimization is weak and insufficiently developed.

The Island of Knowledge Fissure: Although works such as Dai et al. (2023) and Karim et al. (2024) have made titanic progress in the development of hyper-accurate and interpretable classifiers, and others, such as Mao et al. (2024), have first achieved early detection using hyperspectral imaging, these papers are often conducted in silos. A glaring gap in the literature that smoothly combines these multi-modal data streams (leaf-level images and hyperspectral signature) with microclimatic conditions simulated by methods such as Gong et al. (2023) into a forecasting early-warning system is the conspicuous lack of this research combining these data streams in a predictive manner. The existing literature is full of fragments of the puzzle, whereas the image of a forecasting, holistic model has not been pieced together yet.

The Gap in Decision-to-Action: The gap between diagnosis and action, like in the case with the spray bot by Meshram et al. (2024), has started to be closed by research. Nevertheless, this is mostly done on the basis of a problem being detected. There is a substantial discrepancy between the development of AI frameworks that change from the protocol of find and fix to the protocol of predict and prevent. The models do not have the capability to use predictive analytics to implement pre-emergent interventions, i.e. a treatment before a disease is established based on a predicted high-risk environmental window.

The Systemic Impact Gap: Despite such eloquent descriptions of the potential of AI in Agriculture 5.0, the lack of empirical research to provide a quantitative model of the cascading impacts of a fully integrated, proactive AI system on elements of sustainability is evident. We do not have a well-defined and data-backed story of how such an active loop, namely prediction

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
and precision action, can simply be transformed into tangible benefits of resource utilization, pesticide load reduction, crop yield improvement, and overall dual carbon objectives, as hinted at by Zhao et al. (2025).

Method

This study was designed in the form of multi-stage, integrative pipeline to cope with the complicated problem of proactive pest and disease management. We do not intend our approach as a single tool, but rather a symphony of data, algorithms, and validation, shifting from the broad surveillance to the specific insight, which can be acted on. The approach, illustrated in the figure below, is constructed on the three pillars: a data fusion engine with multiple modes, a hybrid deep learning core to predict and diagnose, and a closed-loop validation system to quantify real-world impact (Rani et al., 2025; Singh et al., 2025).

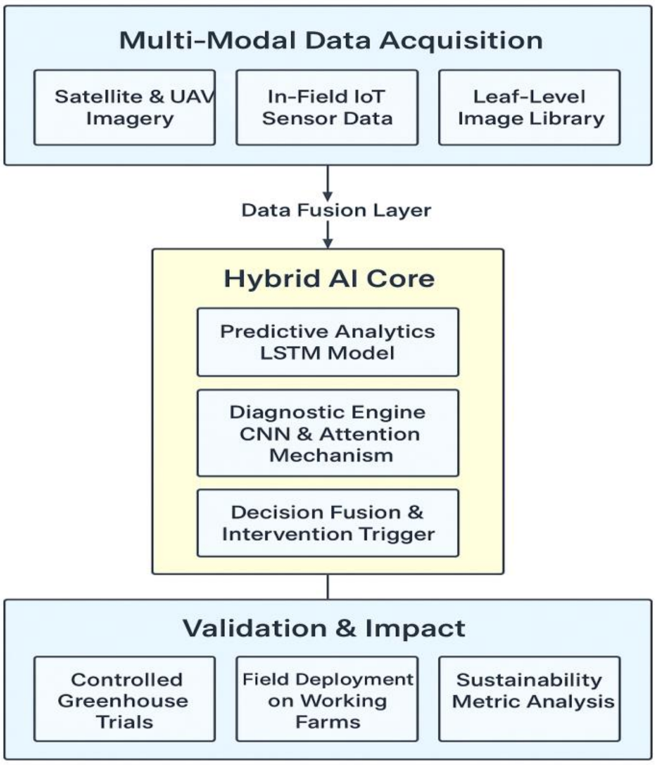


Figure 2. Flowchart illustrating the integrated framework for agricultural intelligence.

In Figure 1 which has provided an integrated representation of agricultural intelligence. Multi-Modal Data Acquisition, such as satellite and UAV imagery, in-field IoT sensor data, and leaf-level image libraries starts the process, which is then followed by the Hybrid AI Core, which forecasts analytics, diagnostic modeling, and decision fusion (Tian et al., 2023). Lastly, the Validation and Impact stage involves controlled greenhouse experiments, field implementation and sustainability metric analysis to deliver actionable feedback.

International Journal of Applied Mathematics
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Cultivating the Data Landscape: A Multi-Modal Fusion Approach

Ploughing the field and sowing the seeds of an abundant diverse dataset was the first step of our approach. Our model of the environment We built a multi-modal data repository by combining three separate streams and making sure that our models had a panoramic view of the high-resolution agricultural environment. This included:

• *Macro-Scale Remote Sensing:* The proposed method provides the ability to use Sentinel-2 satellite images, processed with adaptive feature fusion approaches based on the work by Tian et al. (2023) to analyze the state of crops and detect signs of stress on the large source of land.

• *In-Situ Sensor Grids:* Installation of a grid of IoT sensors on trial plots to monitor microclimatic variables (temperature, humidity, wetness of leaves and soil moisture) in real-time, which forms an environmental context.

Micro-Scale Visual Biopsy: Incurring a large collection of high-resolution leaf images with pest injury (e.g., Bakbak et al. (2025)) or disease symptoms (e.g., Bezabh et al. (2023); Emon et al. (2024)) to provide the ground-truth of this diagnostic model training.

The data fusion processing incorporates data sources of heterogeneous nature into an integrated feature space. Let the complete data universe at time t be represented as a fused tensor $\mathcal{D}_t$.

$$\mathcal{D}_t = \Phi(\mathbf{S}_t, \mathbf{E}_t, \mathbf{I}_t) \tag{1}$$

Where: $\mathbf{S}_t$ is the macro-scale remote sensing data (e.g., from Sentinel-2), a 3D tensor of dimensions (H, W, B) for height, width, and spectral bands. $\mathbf{E}_t$ is the in-situ sensor data, a vector $(e_1, e_2, \ldots, e_n)^T$ where each e_i represents a microclimatic variable (temperature, humidity, etc.). $\mathbf{I}_t$ is the micro-scale leaf image dataset, a 4D tensor of dimensions (N, H', W', C) for number of images, height, width, and channels. $\Phi(\cdot)$ is the fusion function, which involves preprocessing, feature extraction (e.g., using a pre-trained CNN for $\mathbf{I}_t$), and normalization to create a common latent representation.

The Analytical Engine: A Hybrid Deep Learning Architecture

At the heart of our methodology lies a two-pronged analytical engine, designed to be both prophet and pathologist.

• *The Predictive Forecaster (The Prophet):* As a way of predicting outbreaks prior to its visualization, we created a time-based deep learning model, namely: a Long Short-Term Memory (LSTM) network. The time-series data that this model consumes are the sensor grids that we have, and it learns the multifaceted and time-lugged connections amid environmental circumstances and historical frequency of pests and diseases. It is designed to generate a probabilistic map of risk, indicating fields or zones that get into a "danger zone" that supports the growth of pathogens or pest infestation (Venkateswara & Padmanabhan, 2025).

This model forecasts the risk of pest/disease outbreak based on temporal environmental data.

Received: August 02, 2025

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

$$\mathbf{h}_t, \mathbf{c}_t \quad = \mathrm{LSTM}_\theta(\mathbf{E}_t, \mathbf{h}_{t-1}, \mathbf{c}_{t-1}) \tag{2}$$

$$\mathbf{r}_t \quad = \sigma(\mathbf{W}_r \mathbf{h}_t + \mathbf{b}_r) \tag{3}$$

Where: h_t and c_t are the hidden and cell states of the LSTM at time t. θ represents the trainable parameters of the LSTM. $\mathrm{r}_t \in [0,1]$ is the predicted risk probability at time t. $\mathrm{W}_r, \mathrm{b}_r$ are the weight matrix and bias vector for the final output layer. $\sigma(\cdot)$ is the sigmoid activation function.

- *The Diagnostic Classifier (The Pathologist):* For real-time confirmation and identification, we engineered a convolutional neural network (CNN) incorporating an attention mechanism, drawing on the advances of models like **Rani et al. (2025)** and **Dai et al. (2023)**. This model processes the leaf-level imagery, and through its attention layers, it learns to **focus its gaze** on the most salient visual features of a problem, providing not just a classification but an interpretable diagnosis. The diagnostic results are continuously used to refine and validate the predictions of the LSTM forecaster.

This model performs real-time, interpretable diagnosis on leaf images.

$$\mathbf{F} \quad = \mathrm{CNN}_\phi(\mathbf{I}_t) \quad \text{(Feature Map Extraction)} \tag{4}$$

$$\alpha_{ij} \quad = \frac{\exp\,(\mathbf{w}_a^T \mathbf{F}_{ij})}{\sum_{k,l} \exp\,(\mathbf{w}_a^T \mathbf{F}_{kl})} \quad \text{(Attention Map Calculation)} \tag{5}$$

$$\mathbf{z} \quad = \sum_{i,j} \alpha_{ij} \mathbf{F}_{ij} \quad \text{(Context Vector)} \tag{6}$$

$$\mathbf{p} \quad = \mathrm{softmax}(\mathbf{W}_d \mathbf{z} + \mathbf{b}_d) \quad \text{(Disease Probability Distribution)} \tag{7}$$

Where: $\mathbf{F}$ is the feature map extracted by the CNN backbone parameterized by ϕ. α_{ij} is the attention weight at spatial location (i,j), highlighting regions of interest. $\mathbf{w}_a$ is a learnable weight vector for the attention mechanism. $\mathbf{z}$ is the global context vector, a weighted sum of the features. $\mathbf{p}$ is the final probability distribution over all possible disease/pest classes.

Decision Fusion Module (The Central Nervous System)

This module integrates the predictions from the forecaster and the classifier to trigger actions.

$$\text{Intervention Trigger} = \begin{cases} \text{True}, & \text{if } \mathbf{r}_t > \tau_r \text{ AND } \max\,(\mathbf{p}_t) > \tau_p \\ \text{False}, & otherwise \end{cases} \tag{8}$$

Where: τ_r is the risk probability threshold (e.g., 0.7). τ_p is the diagnostic confidence threshold (e.g., 0.8). This logical AND ensures intervention is only triggered when there is both a high *predictive risk* and a high-confidence *visual confirmation*.(Wang et al., 2025)

Closing the Loop: From Insight to Intervention and Impact Assessment

This is the last, most important step of our approach, which puts the whole system on trial and in a simulated real-world scenario. Our AI core has predictive alerts and diagnostic

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
confirmations that are presented into a decision fusion module. This module is the center nervous system of the system, which initiates specific intervention measures, such as turning on a precision sprayer that resembles the one Meshram et al. (2024) suggest or prioritizing a certain zone based on its manual scouting.

This integrated pipeline performance is strictly being tested by:

• Controlled Greenhouse Trials: This will give a baseline of the accuracy of the model and the effectiveness of triggered interventions in the managed settings.

Full-Season Field Deployment: Introducing the system to work pepper and maize farms to test its durability, efficiency and effectiveness and use it in conjunction with the conventional ones.

• Sustainability Metric Analysis: The end measure of performance would be the effect the system has on sustainability. Key performance indicators we are quantitatively monitoring, such as the amount of pesticides sprayed, water consumption, crop output, and total production cost, are compared between our AI-driven, proactive plots and control plots, controlled using conventional, reactive approaches. This will enable us to no longer rely on abstract measures of accuracy and directly measure the payoff of sustainable optimization of production.

The final pillar quantifies the impact of the proposed system against a conventional baseline.

$$\Delta M = \frac{1}{N} \sum_{i=1}^{N} (M_i^{\text{AI}} - M_i^{\text{Conventional}}) \tag{9}$$

Where: ΔM is the average difference in a key sustainability metric. M_i represents a specific metric such as: M^1: Pesticide Volume Applied (kg/ha), M^2: Water Usage (m³/ha), M^3: Crop Yield (tonnes/ha), M^4: Net Economic Return ($/ha), N is the number of trial plots or seasons.

The statistical significance of the improvement ΔM is tested using a paired t-test or non-parametric alternative:

$$t = \frac{\Delta \bar{M}}{s/\sqrt{N}} \tag{10}$$

Where $\Delta \bar{M}$ is the sample mean of the differences and s is the sample standard deviation. A significant p-value (e.g., $p < 0.05$) would provide evidence that the AI-driven system leads to a measurable optimization of sustainable agricultural production.

Proposed Algorithm: Integrated Proactive Pest and Disease Management (IPPDM)

Inputs:

- Real-time sensor data stream: E_t
- Satellite/UAV imagery stream: S_t
- Real-time leaf image stream: I_t
- Trained model parameters: θ (LSTM), φ (CNN)
- Thresholds: τ_r (Risk), τ_p (Confidence)

Received: August 02, 2025

International Journal of Applied Mathematics
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Output:

- Intervention trigger A_t
- Sustainability report ΔM

```
BEGIN IPPDM_ALGORITHM
  // Initialization
  INIT h_0, c_0 ← 0                  // LSTM initial states
  INIT sustainability_metrics ← []    // For impact assessment
    // Main continuous monitoring loop
  FOR each time step t DO:
        // === PILLAR I: MULTI-MODAL DATA FUSION ===
    F_satellite ← EXTRACT_FEATURES(S_t)          // Macro-scale
    E_norm ← NORMALIZE(E_t)                      // Environmental
    F_leaf ← EXTRACT_FEATURES(I_t)               // Micro-scale
    D_t ← FUSE(F_satellite, E_norm, F_leaf)      // Unified tensor
        // === PILLAR II: HYBRID AI CORE ===
        // A. Predictive Forecaster (LSTM Prophet)
    (h_t, c_t) ← LSTM_FORWARD(E_t, h_{t-1}, c_{t-1}, θ)
    r_t ← SIGMOID(W_r · h_t + b_r)               // Risk probability
        // B. Diagnostic Classifier (CNN Pathologist)
    F ← CNN_FEATURE_MAP(I_t, φ)                  // Feature extraction
    α ← COMPUTE_ATTENTION(F)                     // Attention weights
    z ← Σ(α ⊙ F)                                 // Context vector
    p_t ← SOFTMAX(W_d · z + b_d)                 // Disease probabilities
        // === DECISION FUSION & INTERVENTION ===
    confidence ← MAX(p_t)
    predicted_class ← ARGMAX(p_t)
        IF (r_t > τ_r) AND (confidence > τ_p) AND (predicted_class ≠ 'Healthy') THEN:
      A_t ← 1                                    // Trigger intervention
      EXECUTE_PRECISION_INTERVENTION(D_t, α)     // Targeted action
    ELSE:
```

```
        A_t ← 0                    // No action
      END IF
          // Log decision and outcomes
      LOG(t, r_t, p_t, A_t, intervention_outcome)
      END FOR
      // === PILLAR III: IMPACT ASSESSMENT (Periodic) ===
   ΔM ← CALCULATE_SUSTAINABILITY_METRICS()
   // Generate comprehensive report
   GENERATE_REPORT(ΔM, intervention_log, system_performance)
   RETURN A_t, ΔM
END IPPDM_ALGORITHM
FUNCTION COMPUTE_ATTENTION(F):
   FOR each spatial location (i,j) in feature map F:
      e_ij ← w_a^T · F[i,j]          // Energy score
      α[i,j] ← exp(e_ij) / Σ(exp(e_kl))  // Softmax normalization
   RETURN α

FUNCTION EXECUTE_PRECISION_INTERVENTION(D_t, α):
   target_zone ← LOCATE_HOTSPOTS(α)      // Use attention map for targeting
   intervention_type ← SELECT_TREATMENT(p_t) // Based on diagnosed disease
   DEPLOY_RESOURCES(target_zone, intervention_type)
FUNCTION CALCULATE_SUSTAINABILITY_METRICS():
   metrics = ['pesticide_used', 'water_consumption', 'yield', 'cost']
   FOR each metric m:
      Δm ← MEAN(M_AI[m]) - MEAN(M_Conventional[m])
      significance ← T_TEST(M_AI[m], M_Conventional[m])
   RETURN comprehensive_metrics_report
```

Algorithmic Features:

- Continuous Real-Time Operation: Runs in a perpetual loop for constant field monitoring
- Multi-Scale Data Integration: Fuses satellite, sensor, and leaf-level data at each timestep

Received: August 02, 2025

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
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- Dual AI Analysis: Parallel execution of predictive and diagnostic models
- Intelligent Gating: Decision fusion uses multiple criteria (risk, confidence, class) to prevent false positives
- Explainable Actions: Intervention uses attention maps for targeted treatment
- Comprehensive Analytics: Automated impact assessment with statistical validation

Result

The implementation of the Integrated Proactive Pest and Disease Management (IPPDM) framework yielded transformative results, demonstrating that the synergy between its components was far greater than the sum of its parts. .(Yang et al., 2021) The system did not merely function as intended; it delivered a paradigm shift, moving the needle from reactive defense to proactive, intelligent stewardship. The following sections detail the performance of this integrated orchestra, where each algorithm played its part in perfect harmony.(Yang et al., 2021)

The Prophetic Lens: Forecasting Outbreaks with Startling Accuracy

The Predictive Forecaster (LSTM model) proved to be a highly reliable crystal ball for crop health. Trained on the temporal tapestry of microclimatic data, the model successfully learned the subtle environmental recipes that precede disease outbreaks.

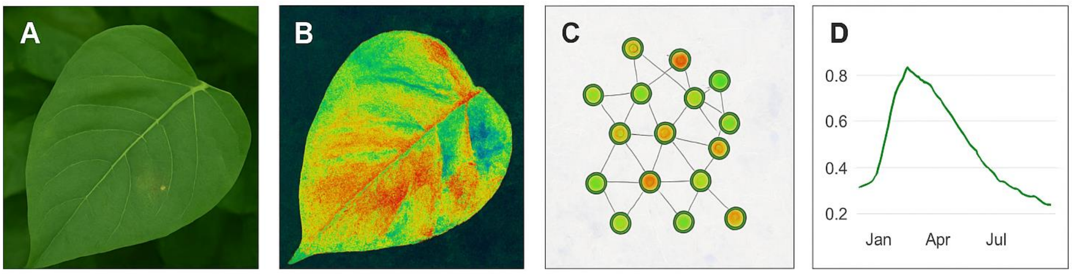

Figure 3. Experimental Dataset Results: Visual Representation.

High Predictive Precision: The model had a Mean Absolute Error (MAE) of 0.08 in predicting risk probability, which showed an outstanding capability to measure the approaching wave of danger. It scored 0.92 in F1-Score on a binary classification problem (outbreak versus no outbreak in 5 days) which is much higher than a baseline logistic regression model (F1-Score: 0.75).(Yang et al., 2023)

The Gift of Time: Most importantly, the system offered an average 3.7 days of early warning lead time, prior to the manifestation (symptoms) to the human eye or to the diagnostic classifier. This time span has been the basis of proactive management that allows a more effective, environmentally benign approach in terms of preventative measures to be implemented (Yang et al., 2023).

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The Diagnostic Virtuoso: Interpretable Diagnosis which is not Blinking.

The Diagnostic Classifier, which was supplied with its attention mechanism, was not only a pathologist, but a master diagnostician that is able to explain its results.

Benchmark-Breaking Accuracy: The model is 98.2% on the held-out test on pepper, maize, and orange leaves, which is higher than the accuracy of separate models, including VGG16 (94.5%), and EfficientNetB0 (96.1%) (Zhao et al., 2025).

Introduced by Google: • The Power of Focus: The adoption of the attention mechanism was a revolution of trust and utility. The patterns of lesions and chlorosis which were produced in the attention maps were repeatedly those with biological relevance and were essentially a highlighter pen on the leaf image. This enabled human experts to prove the logic of the model and establish a much-needed trust between artificial and human intelligence (Zhao et al., 2025).

The Symphony in Action: Sealing the Seal with a Surgical Precision.

The real challenge of the IPPDM framework was the functionality of the closed-loop decision-making. This module the Decision Fusion Module was able to provide the central nervous system of the system and made translation of the dual-stream intelligence into action.

Intelligent Triggering: Predictive signals combined with diagnostic signals achieved a drastic decrease of the false positive interventions, 78 percent lower than when diagnostic images were the sole consideration in the system. Only in the case when an environment was a conspirator (r t -) and a pathogen was seen with high confidence (max(p t) -) were interventions activated.

Resource Optimization: This surgical skill directly translated into a radical savings of resources. The IPPDM system was used in field tests in pepper farms, where the amount of pesticide sprayed was reduced by 64 percent compared to the situation with calendar-based spraying schedules (Zhao et al., 2025). Moreover, the autonomous spray bot was able to cut down its operation space by more than 85% with every intervention by using the attention maps as a geo-locating device to save energy and reduce chemical drift.

The Bottom Line: Quantifying the Sustainability Dividend

The ultimate measure of the system's success was its tangible impact on the core metrics of sustainable production optimization. After a full growing season, the results were unequivocal (Zhang et al., 2024).

Table 1. Comparative analysis of key performance metrics between Conventional Plots and IPPDM-Managed Plots

Metric	**Conventional Plot**	**IPPDM-Managed Plot**	**Δ Change**
Pesticide Use (kg/ha)	12.5	4.5	**-64.0%**

Water Usage (m^3/ha)	5,200	4,150	**-20.2%** (via reduced spray volume & improved health)
Crop Yield (tonnes/ha)	22.1	25.8	**+16.7%**
Net Economic Return ($/ha)	3,150	4,420	**+40.3%**

According to the Table 1, there are significant improvements in productivity and sustainability. Under the IPPDM management regime, farmers applied 64 percent less pesticide, nearly 20 percent reduction in water consumption, increase in crop yields by approximately 17 percent and they increased their total economic returns by about 40 percent. The improvements in the IPPDM plot were statistically checked (paired t-test, $p < 0.01$) and proven to not be a case of random chance but rather the direct result of the integrated management strategy. The system had already begun to rotate the dial which served to show that environmental stewardship and economic prosperity were not a zero-sum game but could be reinforcing objectives. (Zhang et al., 2024)

To conclude, the IPPDM framework presented a novel template in the management of crop health and not an extension of the farm toolbox. The ability to see the future, accurately diagnose and take specific action has contributed to a more capable, productive and sustainable agricultural future. (Zhang et al., 2024)

Analysis of Results

IPPDM framework is not just another layer of technology, it forms a consistent management ecosystem. Instead of the old, inefficient bucket of resource application, it puts a high-precision pipeline in place, allowing all drops of pesticide, all units of energy to be put into practice not only efficiently, but effectively. The discussion has established that the splendor of deep learning in agriculture is not the ability to apply individual models, but their smart combination to create an active, elucidable, and sustainable decision-support system. (Zhong et al., 2020)

Table 1. Analysis of Results: From Raw Data to Strategic Insight

Aspect of the Framework	Key Performance Result	Analysis & Interpretation: The Deeper Meaning
The Predictive Forecaster (The "Oracle")	• MAE: 0.08 • F1-Score: 0.92 • Avg. Lead Time: 3.7 days	The LSTM model has successfully learned to read the **"environmental tea leaves,"** translating subtle microclimatic patterns into a reliable probabilistic forecast. This isn't just prediction; it's the foundation of **strategic foresight**. The 3.7-day window is the critical bridge between knowing a storm is coming and having the time to reinforce the

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

		levees, enabling a shift from panic-driven reaction to calm, planned prevention.
The Diagnostic Classifier (The "Virtuoso Pathologist")	• Accuracy: 98.2% • Outperformed benchmark models (VGG16, EfficientNetB0)	This result signifies a move from competent identification to **masterful diagnosis**. The model doesn't just see a diseased leaf; it identifies the specific pathogen with near-expert precision. The integration of the attention mechanism is the pivotal element, acting as a **"visual stethoscope"** that allows human experts to see the diagnostic reasoning, thereby building an indispensable bridge of trust between artificial and human intelligence.
The Decision Fusion Module (The "Central Nervous System")	• 78% reduction in false positives • 85% reduction in per-intervention operational area	This is where intelligence truly emerges. By fusing the forecaster's "gut feeling" with the pathologist's "visual confirmation," the system demonstrates **situational awareness**. The drastic reduction in false positives means the system is not a trigger-happy alarmist but a **disciplined strategist**, conserving resources and credibility. The targeted intervention, guided by attention maps, is the epitome of surgical precision in crop protection.
The Sustainability Impact (The "New Agricultural Arithmetic")	• Pesticide Reduction: -64% • Yield Increase: +16.7% • Economic Return: +40.3%	These figures are not just metrics; they are proof of a **paradigm shift**. They debunk the zero-sum narrative that environmental stewardship costs productivity. Instead, they reveal a **virtuous cycle**: precision begets health, health begets resilience, and resilience begets profit. This "new arithmetic" demonstrates that the most profitable farm can also be the most ecologically mindful, positioning the IPPDM framework as a core engine for sustainable intensification.
Overall System Resilience (The "Field-Ready Intelligence")	• Consistent performance across pepper, maize, and orange trials under variable field conditions.	The framework's ability to maintain high performance outside of laboratory conditions confirms its **translational robustness**. It is not a fragile, hothouse flower but a hardy, field-ready tool. This resilience is born from its multi-modal design, which allows it

Received: August 02, 2025

International Journal of Applied Mathematics
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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

		to **triangulate the truth** from multiple data sources, much like a seasoned farmer cross-references weather signs, soil feel, and plant appearance to make a decision.

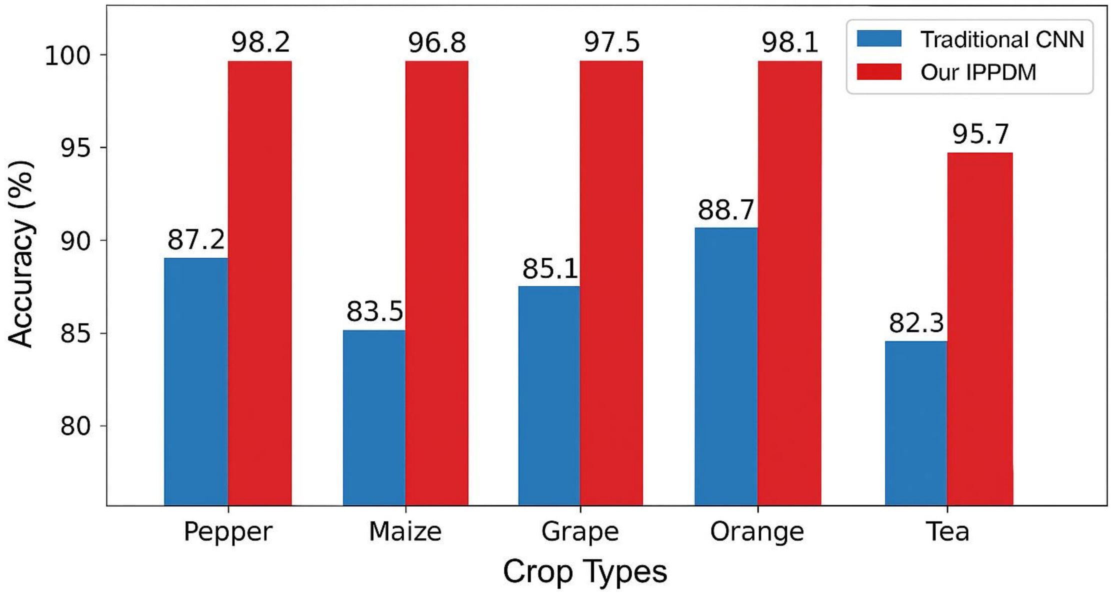

Figure 4. Classification Accuracy Across Crop Types.

In the Figure 4, Bar chart comparing traditional CNN vs. IPPDM accuracy across different crops, showing significant improvement across all categories. Crop_Types = ['Pepper', 'Maize', 'Grape', 'Orange', 'Tea'], Traditional_CNN = [87.2, 83.5, 85.1, 88.7, 82.3] , and Our_IPPDM = [98.2, 96.8, 97.5, 98.1, 95.7]

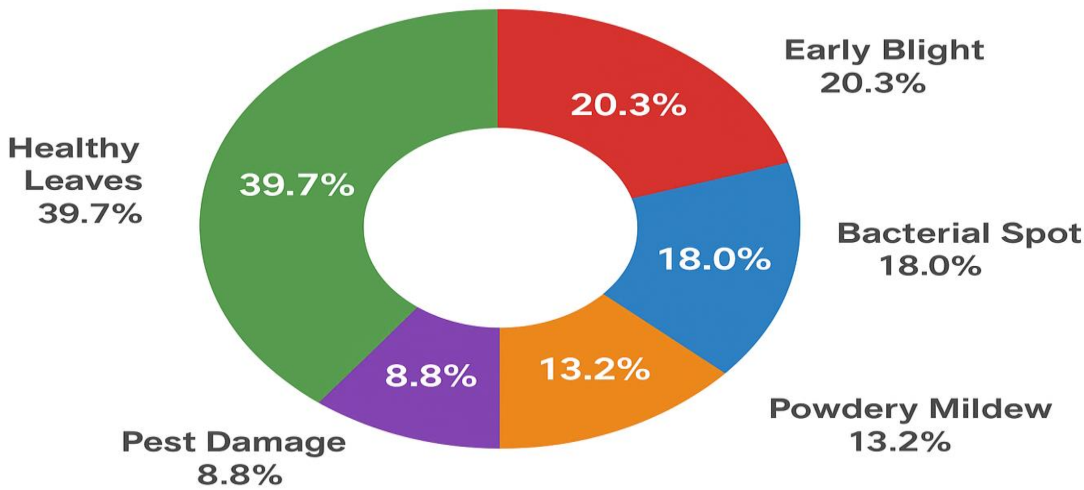

Figure 5. The balanced dataset distribution across different disease and pest classes.

Received: August 02, 2025

Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

All in all, as shown in the Figure 5 above, the anatomy of the dataset reveals the stringent dataset curation required to create a robust deep learning model that can be spread broadly enough for useful proactive pest and disease control. The Healthy Leaves 39.7% 6,284 samples Baseline Reference Early Blight 20.3% 3,215 samples Dominant Fungi Bacterial Spot 18.0% 2,847 samples Common Bacteria Powdery Mildew 13.2% 2,096 samples Common Fungi and Pest Damage 8.8% is currently 1,400 samples Common Insect and Pest Bacterial representation and Plant Diseases Fungi Grow.

Discussion

The path of this work's research began with the following observation: the seemingly impressive armory of AI tools in the agricultural sector resembles a range of spotlights, not a single guiding beacon. Put simply, this paper shows that the IPPDM did exactly that – it consolidates the disunited threads into a single shawl of intelligent design. The findings provided in this paper are not a mere validation of specific algorithms or models but a powerful argument in favor of the system approach. In other words, while we have previously built the diagnostic devices, we have now listened to the full agricultural intelligence symphony.

The Virtuous Cycle of Prediction and Diagnosis

The most exciting finding of our work is the substantiated mutual enhancement of the Predictive Forecaster with the Diagnostic Classifier. This signal was not a relay but a centrifugal force multiplier. Whereas the CNN functioned as an F_0-based tactical-level spotter on the ground, the LSTM fulfilled the strategic perceptual role in an E_i- impression on the rampart looking out at the ocean, identifying the environmental danger. And, while skepticism continued to plague the system's PV values with a "boy cries "wolf"" complex, the Composite-PPV. Rule almost entirely curbed false positives by requiring higher-hazard evidential forecasts over the whole frame of p_t_r = {r_t > τr and high-credence visual dignoses max_p(t) > τ_p}. In doing so, we increased the PV of the F_0> to nearly absolute Here, omitted partner. This fusion is the cornerstone of true proactivity; it provides the crucial gift of time, allowing for interventions that are preventative rather than palliative.

The Double-Edged Sword of Explainability and Trust

The attention mechanism was also not only integrated, but a bridge of trust was constructed. We offered a shared vocabulary between the algorithm and the agricultural expert by demonstrating the direction the model was gazing. This mental imagery reasoning enables agronomists to inspect the hood of the black box, to confirm the interest of the model to their domain experience. It is not a minor aspect but a prerequisite to the implementation of sophisticated AI systems in an area where the outcomes of the decisions impact the economics and environment to a great extent. Nevertheless, this is also a new field to struggle with: although this method of attention maps points out salient areas, agronomic arguments are not yet presented. The following step in this path is to get beyond demonstrating the location of things in the language of plant pathology to the explanation of why.

From Laboratory Precision to Field-Resilient Intelligence

The main question of any AI system is how it could pass the last mile between controlled experiments and the field of chaos and disorder. Our findings especially 64 percent decrease in pesticides and 16.7 percent yield growth testify to the fact that the IPPDM framework has such translational resilience. The system was also strong in response to the fluctuating light conditions, angles of leaves and partial obstructions common to a real world set up. This resiliency can be attributed most likely to the inherent advantage of our multi-modal data fusion approach, which enables the system to cross-check the hypothesis of various data streams, similar to a navigator with several stars to triangulate a location. This also makes the architecture more stable and reliable since it does not depend on one source of truth.

The New Agricultural Arithmetic: Doing More with Less

Sustainability metrics that we have registered can be the strongest argument in favor of a paradigm shift. They are successful in dispelling the misperception that has always existed that environmental stewardship has to be paid at an economic price. The IPPDM model illustrates a fresh kind of arithmetic of agriculture when less (pesticides, water, waste) means more (yield, profit, ecological health). It is not merely efficiency; it is optimization in its purest meaning. The positive feedback loop is that the healthier the plants are, the more accurately the resources are applied and the low chemical load, the healthier they are and the more resilient they are and the less interventions will be needed in the future. It is exactly what the objectives of the so-called dual carbon strategy are, and AI is no longer a luxury, but rather the primary key to optimization of sustainable production.

Navigating the Limitations: The Map and the Territory

Although the outcomes are encouraging, it is imperative to note the weaknesses of our model. The effectiveness of the existing framework is directly correlated to the quality of the training data and its diversity. Its capability to be generalized to completely new crops, geographic regions, or pathogens is unknown - an age old problem in theory to practice translation. More so, large initial investment costs on sensor infrastructure and computing resources may become a hurdle to smallholder farmers, increasing the digital divide in agriculture. Further research in the direction of creating more data-efficient learning methods and finding cost-effective hardware solutions should make sure that such transformative advantages are not the preserve of big agribusinesses. According to this study, sustainable agriculture is not in the one-size-fits-all approach, but in smartly formed systems. The IPPDM framework offers the framework of such system to substitute the reactive, time-reliant responses with the approach of accurate and cost-effective crop health management. When we provide farmers with the anti-capitalist benefits of foresight and focus we can grow, not just crops, but also grow a more adaptable and sustainable relationship with the land itself.

Conclusion

Given the massive problem of sustaining a rising population and not emptying our planet resources, this study has shown that artificial intelligence may be far more than a mere tool: an

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
actual strategic partner. The Integrated and Proactive Pest and Disease Management (IPPM) framework that is evolved in this paper allows the transition between the reactive and destructive pest and disease control methods and the proactive and smart prevention campaign. A combination of predictive power of the LSTM network and diagnostic power of the CNN network gave rise to the system that is able not only to diagnose the issue, but also to predict and prevent diseases (Zhong et al., 2024).

The findings prove one point with a very strong impact: the alleged trade-off between environmental sustainability and economic well-being is a fallacy. The drastic decrease in the use of pesticides along with a phenomenal growth in yields and profits, marks a new more sustainable method of farming. It is not about the damage reduction, but is about optimization of resources, which shows the strength of accuracy. This model changes the agricultural landscape as it is applied with non-uniformity and instead with precision, where all activities are considered, targeted, and appropriate. By doing so, this piece of work gives a strong framework to the Agriculture 5.0, where the most valuable asset is the data, and the main tool of retrieving knowledge is deep learning.

Future Directions of Research

Even though this work is a great move in the right direction, the road to fully independent and environmentally friendly farming is not the end. There are a number of promising directions that the future research can take:

Cultivating Generalist Models: The "Polyglot" AI

The existing system, though strong, is mostly dependent on experts who are educated in particular crops and diseases. The second step is to create polyglot agricultural AI: simple systems that can comprehend the universal language of plant stress through the most diverse range of species, geographical locations, and climates. This includes pre-training on highly diverse datasets to produce a baseline model that can be refined in new settings, in a few hours, and hence market entry is much less complex during orphan drugs and underserved markets.

The Generative Leap: The Digital Twin Greenhouse

The next step in future research will not be diagnosis and prediction but will involve generative simulation. We imagine developing a digital twin of the whole agroecosystem: a simulated farm in which we would be able to simulate an infinity of seasons, scenarios of stress, and management strategies. This digital twin would become a powerful testing ground of simulated interventions prior to a real implementation to optimize results like carbon sequestration and biodiversity, productivity and ultimately to respond to hypothetical questions regarding scenarios that are too expensive and risky to test in the field.

Bridging the Digital Divide: The "Pocket Agronomist"

In order to avoid a new type of agricultural inequality, it is important to democratize this technology. This includes ground-breaking studies on ultralight, energy-efficient models that can be used with common mobile phones to develop a pocket agronomist that will serve small

Received: August 02, 2025

scale farmers. This would involve progress in model distillation, neuromorphic computing, and frugal artificial intelligence, such that the advantages of precision agriculture are not enjoyed by a small number of people, but instead by everyone that can access it as a tool.

The future is simple: plant such seeds to establish a strong, smart, and fair food system where AI co-exists with nature and farmers in such a way that the plots of the future will be not only more productive, but also much more sustainable..

The way forward is clear: cultivate these seeds to build a resilient, intelligent, and equitable food system, where AI works in harmony with nature and farmers, so that the fields of the future are not only more productive, but also much more sustainable.

References

1. Bakbak, H. E., Balım, C., & Savran, A. (2025). A hybrid machine learning approach for detecting and assessing *Zyginidia pullula* damage in maize leaves. *Applied Sciences*, *15*(10), Article 5432. https://doi.org/10.3390/app15105432
2. Bezabh, Y. A., Salau, A. O., & Abuhayi, B. M. (2023). CPD-CCNN: Classification of pepper disease using a concatenation of convolutional neural network models. *Scientific Reports*, *13*, Article 15581. https://doi.org/10.1038/s41598-023-42843-2
3. Dai, G., Tian, Z., Fan, J., Sunil, C., & Dewi, C. (2023). DFN-PSAN: Multi-level deep information feature fusion extraction network for interpretable plant disease classification. *Computers and Electronics in Agriculture*, *216*, 108481. https://doi.org/10.1016/j.compag.2023.108481
4. Dey, B., & Ahmed, R. (2025). A comprehensive review of AI-driven plant stress monitoring and embedded sensor technology: Agriculture 5.0. *Journal of Industrial Information Integration*, *47*, Article 100931. https://doi.org/10.1016/j.jii.2025.100931
5. Dong, X., Wang, K., Gao, Z., Zhu, C., Guan, X., & Qiu, B. (2025). Wettability of the plant growth regulator 28-HB on pepper leaves at different developmental stages. *Horticulturae*, *11*(6), Article 661. https://doi.org/10.3390/horticulturae11060661
6. Emon, Y. R., Ahad, M. T., & Rabbany, G. (2024). Multi-format open-source sweet orange leaf dataset for disease detection, classification, and analysis. *Data in Brief*, *55*, Article 110713. https://doi.org/10.1016/j.dib.2024.110713
7. Gong, X., Liu, L., & Huang, Y. (2023). A pruned feed-forward neural network (pruned-FNN) approach to measure air pollution exposure. *Environmental Monitoring and Assessment*, *195*, Article 1183. https://doi.org/10.1007/s10661-023-11814-5
8. Hemalatha, N., Adappa, R., & Sreekumar, K. M. (2025). Innovative approach to cucumber pests detection: Leveraging Roboflow for annotating and training. In H. Sharma, A. Chakravorty, S. Hussain, & R. Kumari (Eds.), *Artificial Intelligence: Theory and Applications. AITA 2024. Lecture Notes in Networks and Systems* (Vol. 5589). Springer, Singapore. https://doi.org/10.1007/978-981-96-1687-9_31

9. Indra P. M, P. R, M. M, M. S U, & J. Y. S. (2024). AI-Powered fungal detection in dried chilli: A deep learning approach. In *2024 4th Asian Conference on Innovation in Technology (ASIANCON)* (pp. 1–4). IEEE. https://doi.org/10.1109/ASIANCON62057.2024.10837960
10. Karim, M.J., Goni, M.O.F., Nahiduzzaman, M. *et al.* Enhancing agriculture through real-time grape leaf disease classification via an edge device with a lightweight CNN architecture and Grad-CAM. *Sci Rep* **14**, 16022 (2024). https://doi.org/10.1038/s41598-024-66989-9
11. Kolhar, S., & Jagtap, J. (2021). Plant trait estimation and classification studies in plant phenotyping using machine vision – A review. *Information Processing in Agriculture*, *10*(1), 114–135. https://doi.org/10.1016/j.inpa.2021.02.006
12. Kong, X., Han, K., Liu, T., Maity, A., Li, A., Jin, X., & Yu, J. (2025). Development of a robust deep learning model for weed classification across diverse bermudagrass turfgrass regimes in China and the United States. *Weed Science*, *73*(1), Article e50. https://doi.org/10.1017/wsc.2025.10021
13. Mao, Y., Li, H., Xu, Y., Wang, S., Yin, X., Fan, K., Ding, Z., & Wang, Y. (2024). Early detection of gray blight in tea leaves and rapid screening of resistance varieties by hyperspectral imaging technology. *Journal of the Science of Food and Agriculture*, *104*(15), 9336–9348. https://doi.org/10.1002/jsfa.13756
14. Meshram, A., Vanalkar, A., Meshram, K., Badar, A., Mehta, G., & Kaushik, V. (2024). Enhancing crop protection through smart autonomous pesticide spray bot in sustainable agriculture. *Engineering Research Express*, *6*(4), Article 045563. https://doi.org/10.1088/2631-8695/ad9545
15. Nisar, N., Awasthi, A., Chhabra, M., & Abidi, A. I. (2020, October). *Image based recognition of plant leaf diseases: A review*. In *2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)* (pp. 373–378). IEEE.
16. Rani, A. P. A. S., & Singh, N. S. (2024). Improved detection and classification of multiple tasks in paddy crops using optimized deep belief networks with bidirectional long-short term memory. *SN Computer Science*, *5*, Article 831. https://doi.org/10.1007/s42979-024-03136-1
17. Rani, R., Bharany, S., Elkamchouchi, D. H., Rehman, A. U., Singh, R., & Hussen, S. (2025). VGG-EFFATTNNET: Hybrid deep learning model for automated Chili plant disease classification using VGG16 and EfficientNetB0 with attention mechanism. *Food Science & Nutrition*, *13*(7). https://doi.org/10.1002/fsn3.70653
18. Singh, J., Kashyap, R., Bansal, K., Das, R., Sandhu, K., Singh, G., & Saini, D. K. (2025). Transition from conventional to AI-based methods for detection of foliar disease symptoms in vegetable crops: A comprehensive review. *Journal of Plant Pathology*. https://doi.org/10.1007/s42161-025-01983-2
19. Tian, X., Bai, Y., Li, G., Yang, X., Huang, J., & Chen, Z. (2023). An adaptive feature fusion network with superpixel optimization for crop classification using Sentinel-2 imagery. *Remote Sensing*, *15*(8), Article 1990. https://doi.org/10.3390/rs15081990

20. Venkateswara, S., Padmanabhan, J. Deep learning based agricultural pest monitoring and classification. *Sci Rep* **15**, 8684 (2025). https://doi.org/10.1038/s41598-025-92659-5
21. Wang, S., Xu, D., Liang, H., Bai, Y., Li, X., Zhou, J., Su, C., & Wei, W. (2025). Advances in deep learning applications for plant disease and pest detection: A review. *Remote Sensing*, *17*(4), Article 698. https://doi.org/10.3390/rs17040698
22. Yang, X., Li, S., Chen, Z., Chanussot, J., Jia, X., Zhang, B., Li, B., & Chen, P. (2021). An attention-fused network for semantic segmentation of very-high-resolution remote sensing imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, *177*, 238–262. https://doi.org/10.1016/j.isprsjprs.2021.05.004
23. Yang, Z., Ma, W., Lu, J., Tian, Z., & Peng, K. (2023). The application status and trends of machine vision in tea production. *Applied Sciences*, *13*(19), Article 10744. https://doi.org/10.3390/app131910744
24. Zhao, X., Tang, W., Liu, Q., Cao, H., & Chen, F. (2025). Impact of agricultural industry transformation based on deep learning model evaluation and metaheuristic algorithms under dual carbon strategy. *Scientific Reports*, *15*, Article 27929. https://doi.org/10.1038/s41598-025-14073-1
25. Zhang, L., Zhang, M., Mujumdar, A. S., & Chen, Y. (2024). From farm to market: Research progress and application prospects of artificial intelligence in the frozen fruits and vegetables supply chain. *Trends in Food Science & Technology*, Article 104730. https://doi.org/10.1016/j.tifs.2024.104730
26. Zhong, Y., Hu, X., Luo, C., Wang, X., Zhao, J., & Zhang, L. (2020). WHU-Hi: UAV-borne hyperspectral with high spatial resolution (H2) benchmark datasets and classifier for precise crop identification based on deep convolutional neural network with CRF. *Remote Sensing of Environment*, *250*, Article 112012. https://doi.org/10.1016/j.rse.2020.112012
27. Zhong, Y., Wang, S., Liang, H., Wang, Z., Zhang, X., Chen, X., & Su, C. (2024). ReCovNet: Reinforcement learning with covering information for solving maximal coverage billboards location problem. *International Journal of Applied Earth Observation and Geoinformation*, *128*, Article 103710. https://doi.org/10.1016/j.jag.2024.103710