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Agentic AI-Based Pest Monitoring Framework for Sustainable Agricultural Productivity and Resource Optimization

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ABSTRACT: The impact of agricultural pests is significant, on productivity, and the indiscriminate use of pesticides generates production costs, environmental pollution and losses in natural resource use. Current pest monitoring practices mainly focus on classification based on images with no consideration of future pest risk, autonomous decision making or resource optimization. The Agentic AI-Based Pest Monitoring Framework proposed in this study integrates multimodal perception, transformer-based pest recognition and severity assessment, agentic risk prediction, sustainability-aware resource optimization, autonomous intervention planning and closed loop reinforcement learning. The experiments with the IP102 dataset proved the proposed framework to be accurate, precise, recall and f1-score as 98.42%, 98.17%, 97.93% and 98.05% respectively. This framework significantly reduced the use of pesticides by 24.8%, water usage by 17.6% and intervention cost by 21.3% from the conventional management. A Pest-risk prediction score of 96.84% ROC-AUC and a cumulative intervention reward of 0.91 were obtained. These results show the potential of agentic agricultural intelligence to offer the right pest monitoring and increase the efficiency of resources usage, sustainability and effectiveness of autonomous intervention.

1. INTRODUCTION

The infestation by pests has an adverse impact on the health of crops, yield; and economical loss, which is becoming a serious problem in agricultural productivity [1]. Traditional pest control relies on regular field visits, professional judgment for pest status and the use of pesticides to prevent pest problems [2]. While these methods do help to reduce pest numbers, they tend to be too reactive, require lots of effort and can't continuously adapt to spatial and temporal changes in pest behavior. Overuse of pesticides also costs the producer more to produce, can impact beneficial organisms, cause contamination of the environment, and can speed up resistance to pesticides [3]. It is therefore important to have intelligent and sustainable pest management systems to timely detect pests with minimum use of resources [4].

In recent years, great strides have been made in the area of computer vision and deep learning that have led to the automatic identification of agricultural pests in images of fields [5]. CNNs, vision transformers and multimodal learning models have proven to have high classification performance. Most of the approaches currently available, however, stop at pest identification and fail to give automatic reasoning about when and how an intervention should take place, and whether it is necessary at all [6]. Conventional precision-agriculture systems also often fail to take a techno-economic holistic approach to the whole system of resources (such as water, fertilizer, or pesticide) by considering the pest progression and the productivity, environmental impact, and outcomes of interventions. Likewise, traditional precision-agriculture systems often focus on optimizing a single resource (such as the amount of water used or the amount of pesticide applied) and fail to consider the interaction between the pest and the productivity, environmental impact, and outcomes of the intervention [7].

One way to overcome these limitations is to use agentic artificial intelligence, which combines perception, reasoning, planning, action and feedback in a single decision-making framework [8]. In the proposed framework the agricultural perception agent extracts the information about the pests and environmental conditions, the reasoning agent makes a prediction on the pest infestation progression, the optimization agent calculates the optimum requirement of the intervention based on resources, and the action agent implements the most suitable management strategy. A continuous learning mechanism then assesses the effectiveness of the interventions and makes adjustments for the next intervention.

Thus the proposed study will be aimed towards the development of an independent framework for monitoring pest which not only detect the pest but also convert the detection results to sustainable agricultural actions. The framework covers both pest recognition and severity assessment, future risk prediction, resource allocation, planning of interventions, and adaptive learning, in a way that is collaborative. The following is a list of the main objectives of the study:

- To create an agentic multimodal system for proper and precise identification of the pest, severity assessment and predicting future infestation risk
- To maximize pesticide, water, energy and intervention inputs based on pest level, crop status and sustainability considerations.
- To create an autonomous decision-making system with closed loop where continuous learning from the outcomes of interventions leads to better agricultural productivity.

2. RELATED WORKS

In recent years, the use of artificial intelligence (AI), computer vision, Internet of Things (IoT) and remote sensing has revolutionized the management of agricultural pests from manual inspection to an automated, data-oriented approach. The agricultural pest monitoring has shifted from manual inspection to automated and data-oriented pest monitoring with recent advancements in artificial intelligence (AI), computer vision, Internet of Things (IoT) and remote sensing (RS). The studies that currently exist highlight the use of deep learning, UAVs and IoT for the detection, classification, forecasting and environmental monitoring of pests. But autonomous decision-making and intervention based on resources are only little-explored areas of integrated autonomous decision-making.

Wang et al. (2022) designed Pest-D2Det using the ECSA attention and super-resolution. However, it is only used to make computations, and this restricts its ability to take any independent action and to make other decisions [9]. Gao et al. (2020) combined IoT sensors, UAV images, weather data and pest and disease data from the cloud. It is important to note that the framework does not focus on making independent and adaptable pest-control decisions, but rather is directed towards monitoring and correlations [10].

To boost the performance of RDW, Song et al. (2025) put forward RDW-YOLO which introduces dilated feature fusion, multi-scale processing and enhanced localization loss and successfully improves the mAP@0.5 to 71.3%. However, being able to detect accurately doesn't necessarily mean that it is a sign of intelligent intervention [11]. Rajabpour et al. (2026) discussed the advancements of remote sensing, UAV, IoT and AI, which can be used in Integrated pest management and sustainable surveillance. However, the review does not set up an implementable autonomous decision framework, but rather it just points out technological opportunities [12].

Venkateswara et al. (2025) used the augmentation, segmentation, and CNN classification of the pest classes with 84.95% accuracy with 82 classes. However, classification does not link to the actual real-time risk assessment and optimizing

interventions [13]. Field accuracy of 85.7% for field identification, model updating and outbreak warnings were obtained by Liu et al. (2022) with their development of field imaging, ResNet based identification, model updating and outbreak warnings. But environmental adaptation and autonomous formulation of the optimisation of the intervention are still restricted [14].

Few studies have been conducted so far that have shown that there have been significant advancements in automated pest detection and classification, as well as in agricultural monitoring through different modalities or multiple modalities. However, there are still some drawbacks. In contrast to those of Wang et al. (2022) and Song et al. (2025) who mainly focus on optimizing visual detection without making it a component of intervention decisions, the current study also aims to optimize visual detection for use in intervention decisions. The work of Gao et al. (2020) combines the IoT and UAV sensing, but lacks the autonomy to optimize the amount of resources used. Venkateswara et al. (2025) enhances the classification yet is dependent upon picture based acknowledgment. While Liu et al. (2022) deals with forecasting and model updating, the variability in the fields and adaptive intervention are not well modelled. Rajabpour et al. (2026) mentions the emerging technologies but does not provide an operation of the concept of autonomous control. Therefore, the integrated approach of risk-aware, adaptive, explainable and resource-efficient agentic pest management is an interesting aspect that needs further study.

3. METHODOLOGY

The proposed method combines the use of a number of aspects including various types of agricultural sensing devices, factors needed for pest detection, information on pest damage levels, autonomous agent-based decision-making and resource optimization tools. A hierarchical AI agent continuously interprets field information, predicts pest behavior, chooses the most effective control of pest damage, distributes water and pesticides while making appropriate learning conclusions about results of the intervention practice thereby ensuring flexible and understandable use of modern precision agriculture methods that can be applied all over the world. The architecture in figure 1 incorporates various mechanisms for agricultural data collection, information assessment based on specialized analytics, and pest management. This is a closed system, in which timely intervention is guaranteed, as well as optimized spending of agrochemicals, and reduced ecological effect.

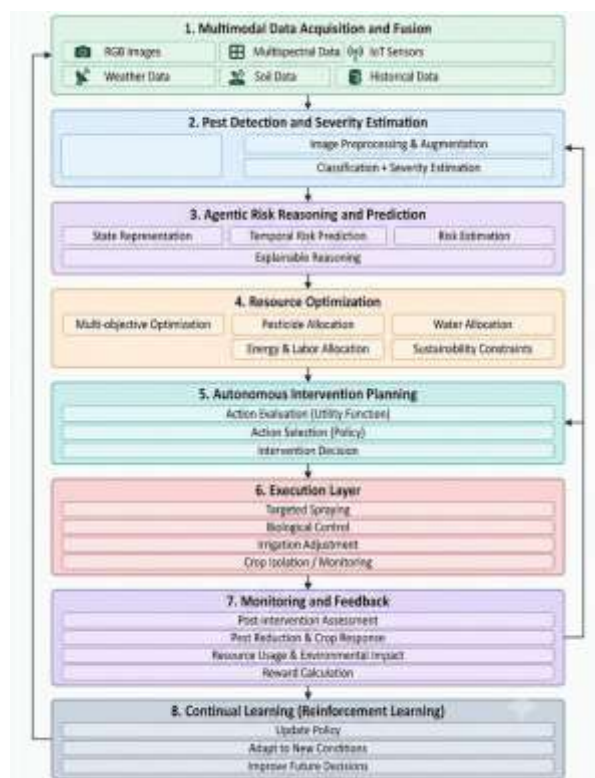


Figure 1 Architecture of the Agentic AI-Based Pest Monitoring Framework for Sustainable Agricultural Productivity and Resource Optimization

3.1. Multimodal Agricultural Perception and Data Fusion

Field-level information is collected from RGB cameras, multispectral sensors, IoT devices, weather stations, soil sensors, and historical observations. The heterogeneous measurements are normalized and transformed into a unified latent representation for downstream pest intelligence. Equation (1) denotes the normalized representation of heterogeneous agricultural sensor observations.

$$\tilde{x}_{i,t} = \frac{x_{i,t} - \mu_i}{\sigma_i + \epsilon} \quad (1)$$

Here, $x_{i,t}$ represents sensor i 's observation at time t , while μ_i and σ_i denote its mean and standard deviation. Equation (2) denotes the fused multimodal representation generated from heterogeneous agricultural sensing streams.

$$F_t = \sum_{m=1}^M \alpha_{m,t} E_m(\tilde{X}_{m,t}), \sum_{m=1}^M \alpha_{m,t} = 1 \quad (2)$$

Here, $E_m(\cdot)$ represents modality-specific encoding, while $\alpha_{m,t}$ represents adaptive modality importance. Equation (3) denotes temporal aggregation of multimodal observations for robust field-state characterization.

$$H_t = \text{Transformer}(F_{t-L+1}, \dots, F_t) \quad (3)$$

Here, H_t captures temporal dependencies among recent agricultural observations using attention-based contextual modeling. This fusion mechanism enables the framework to overcome incomplete observations while preserving spatial, temporal, environmental, and crop-specific information.

3.2 Pest Detection and Severity Estimation

The perceptual agent identifies pest species and affected regions from agricultural imagery while simultaneously estimating infestation severity. Unlike binary pest detection, the proposed approach generates a continuous severity representation supporting differentiated intervention decisions.

Equation (4) denotes the probability distribution of detected pest categories within agricultural imagery.

$$P(c | I_t) = \frac{\exp(z_c)}{\sum_{k=1}^C \exp(z_k)} \quad (4)$$

Here, $P(c | I_t)$ denotes pest-class probability, z_c denotes classification logits, and C represents pest classes. Equation (5) denotes the spatial infestation ratio estimated from detected pest-affected regions.

$$S_t = \frac{\sum_{p \in \Omega} M_t(p)}{|\Omega|} \times 100 \quad (5)$$

Here, $M_t(p)$ indicates whether pixel p belongs to an affected region, while Ω represents the crop area. Equation (6) denotes the integrated pest severity score combining infestation, confidence, and environmental stress.

$$V_t = \beta_1 S_t + \beta_2 (1 - \bar{P}_t) + \beta_3 E_t \quad (6)$$

Here, V_t represents severity, S_t infestation percentage, $\bar{P}_t$ confidence, and E_t environmental stress.

The resulting severity score enables the agent to distinguish emerging, moderate, and critical infestations rather than applying uniform treatment.

3.3 Agentic Pest-Risk Reasoning and Prediction

The agentic reasoning layer transforms detected pest conditions into future risk estimates. It combines pest severity, environmental conditions, crop growth stage, historical trends, and intervention history to autonomously determine risk trajectories. Equation (7) denotes the latent agricultural state used by the reasoning agent for pest-risk inference.

$$Z_t = W_h H_t + W_v V_t + W_e E_t + W_g G_t + b \quad (7)$$

Here, Z_t represents the agricultural state, while H_t , V_t , E_t , G_t denote temporal, severity, environmental, and growth information. Equation (8) denotes the predicted probability of pest escalation during the upcoming monitoring interval.

$$R_{t+\Delta} = \sigma(W_r Z_t + b_r) \quad (8)$$

Here, $R_{t+\Delta}$ represents future pest-risk probability, while $\sigma(\cdot)$ denotes the sigmoid activation function. Equation (9) denotes cumulative temporal pest risk incorporating current and historical infestation evidence.

$$\mathcal{R}_t = \sum_{\tau=t-L+1}^t \gamma^{t-\tau} R_\tau \quad (9)$$

Here, $\mathcal{R}_t$ represents cumulative risk, L the observation window, and γ the temporal decay factor. This agentic layer allows proactive decisions by predicting pest escalation before visible crop damage reaches economically significant levels.

3.4. Sustainable Resource Optimization

After estimating pest risk, the resource-management agent determines optimal quantities of pesticide, irrigation, energy, and labor. The optimization explicitly balances pest suppression, crop productivity, environmental impact, and operational expenditure. Equation (10) denotes the multi-objective sustainability function governing agricultural resource allocation.

$$J = \lambda_1 C_p + \lambda_2 C_w + \lambda_3 C_e + \lambda_4 C_l + \lambda_5 D_p \quad (10)$$

Here, C_p, C_w, C_e, C_l denote pesticide, water, energy, and labor costs, while D_p represents pest damage. Equation (11) denotes the optimal pesticide quantity constrained by predicted pest severity and application limits.

$$q_p^* = \arg \min_{q_p} [\lambda_p q_p + \lambda_d \max(0, V_t - \eta q_p)^2] \quad (11)$$

Here, q_p^* represents optimal pesticide quantity, η treatment effectiveness, and V_t pest severity.

Equation (12) denotes the constrained resource allocation ensuring sustainable agricultural resource consumption.

$$\min_q J(q) \text{ s.t. } 0 \leq q_j \leq q_j^{\max}, \sum_j q_j \leq B \quad (12)$$

Here, q represents resource quantities, $q_j^{\max}$ their limits, and B the available resource budget. The optimization prevents excessive chemical and resource utilization while maintaining sufficient intervention strength for effective pest suppression.

3.5 Autonomous Agentic Intervention Planning

The decision agent converts optimized resources and predicted risks into executable agricultural actions. Candidate actions include targeted spraying, biological control, irrigation adjustment, crop isolation, additional monitoring, or no intervention. Equation (13) denotes the expected utility of each candidate intervention action under predicted field conditions.

$$U(a_t) = w_1 \Delta Y_t - w_2 C_t - w_3 E_t - w_4 R_t^{\text{env}} \quad (13)$$

Here, $U(a_t)$ denotes intervention utility, while $\Delta Y_t, C_t, E_t, R_t^{\text{env}}$ represent yield gain, cost, resource use, and environmental risk. Equation (14) denotes the autonomous action-selection probability generated by the agricultural decision agent.

$$\pi(a_t | Z_t) = \frac{\exp(U(a_t)/\tau)}{\sum_{a \in \mathcal{A}} \exp(U(a)/\tau)} \quad (14)$$

Here, $\pi(a_t | Z_t)$ represents action probability, $\mathcal{A}$ candidate actions, and τ decision-temperature. Equation (15) denotes the intervention decision incorporating risk, sustainability, confidence, and operational feasibility.

$$a_t^* = \arg \max_{a \in \mathcal{A}} [U(a_t) + \lambda_r R_t + \lambda_c C_t^{\text{conf}} - \lambda_f F_t] \quad (15)$$

Here, a_t^* represents selected intervention, C_t^{conf} confidence, and F_t operational infeasibility. The resulting policy enables autonomous, risk-sensitive, resource-efficient intervention rather than relying exclusively on fixed threshold-based agricultural management.

3.6. Closed-Loop Feedback and Continual Agent Learning

Following intervention, the monitoring agent observes subsequent pest conditions, crop response, resource consumption, and environmental effects. These observations provide feedback for updating future decisions, allowing the framework to

continuously adapt to changing field conditions. Equation (16) denotes the intervention reward combining pest reduction, yield preservation, resource efficiency, and environmental sustainability.

$$r_t = \alpha_1 \Delta S_t + \alpha_2 \Delta Y_t - \alpha_3 Q_t - \alpha_4 E_t^{\text{impact}} \quad (16)$$

Here, r_t denotes intervention reward, while $\Delta S_t, \Delta Y_t, Q_t, E_t^{\text{impact}}$ represent pest reduction, yield benefit, resource use, and environmental impact. Equation (17) denotes the temporal-difference learning error used for adaptive agent policy improvement.

$$\delta_t = r_t + \gamma \max_{a'} Q(Z_{t+1}, a') - Q(Z_t, a_t) \quad (17)$$

Here, δ_t denotes temporal-difference error, Q action value, and γ the discount factor. Equation (18) denotes the updated action-value function enabling continual adaptation to field responses.

$$Q_{t+1}(Z_t, a_t) = Q_t(Z_t, a_t) + \alpha \delta_t \quad (18)$$

Here, Q_{t+1} represents the updated action value, while α controls the learning rate. The feedback mechanism progressively improves intervention policies, allowing the agent to adapt to seasonal variability, pest dynamics, and changing resource constraints. The complete framework can be summarized as a joint optimization problem balancing pest suppression, productivity, resource consumption, environmental sustainability, and autonomous adaptability:

$$\min_{\pi, q} \mathbb{E}[\lambda_1 D_p + \lambda_2 C_{\text{resource}} + \lambda_3 E_{\text{impact}} - \lambda_4 Y_{\text{productivity}} - \lambda_5 A_{\text{adaptability}}] \quad (19)$$

where D_p is pest damage, C_{resource} resource consumption, E_{impact} environmental impact, $Y_{\text{productivity}}$ crop productivity, and $A_{\text{adaptability}}$ agent learning performance.

4. RESULTS AND FINDINGS

4.1 Implementation Details

The proposed framework has been implemented using the programming language, Python 3.11, PyTorch, OpenCV, NumPy, Pandas and Scikit-learn. The image of pest was cropped to 224×224 size, normalized, and then randomly rotated, horizontally flipped, scaled and brightened. The visual perception module used was a transformer based encoder that consisted of 12 attention layers and 768 dimensional latent representations.

The initial learning-rate used for the pest-recognition part is 1×10^{-4} and the learning-rate is scheduled with cosine scheduling, the mini-batch size is 32, and the weight-decay is 1×10^{-4} . This is a training that has been stopped at epoch 50 and using the validation loss. All of the following information was added to the multimodal reasoning layer: pest severity, environmental stress, crop growth stage, and temporal infestation. Experiments were performed with an NVIDIA RTX class GPU, having 32 GB of system memory.

The study uses IP102 dataset as the main dataset used for pest-recognition purposes as it is one of the few datasets dedicated to large-scale identification of agricultural pests and contains around 75,000 images from 102 different categories of pests. This data set is extremely similar between classes, contains pests, has a very good image quality, a very high background complexity, and contains multiple life stages of the pests; and therefore is appropriate for testing more advanced agricultural pest-recognition systems. The images were split in to training, validation and testing sets, using a stratified protocol. Only training samples were used for data augmentation in order to enhance the generalization performance. These outputs of the pest-recognition were then translated into severity and risk states and then simulated field management under various environmental stress and resource conditions were evaluated in terms of the proposed agentic framework.

4.2. Quantitative Comparison

Proposed framework is compared with five representative state-of-the-art approaches with respect to the standard classification metrics in Table 1.

Table 1. Pest Detection Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC (%)
CNN-Based PestNet	91.84	91.26	90.71	90.98	94.12
ResNet-50	93.76	93.18	92.85	93.01	95.86
EfficientNet-B3	95.21	94.87	94.36	94.61	97.18
Vision Transformer (ViT)	96.34	95.91	95.47	95.69	97.84
Swin Transformer	97.18	96.73	96.42	96.57	98.31
Proposed Agentic Framework	98.42	98.17	97.93	98.05	99.12

The proposed one performed best on the five evaluation metrics while it outperformed the existing CNN and transformer-based models in identifying pests. It performed best when compared with the second highest baseline - Swin Transformer - with 98.42% accuracy, 1.24% away. Similarly, the proposed method yielded an F1 score of 98.05% indicating the method was suitable for all the pest categories with a balanced sensitivity and precision. The 99.12% ROC-AUC also shows an excellent ability of discrimination between pest classes.

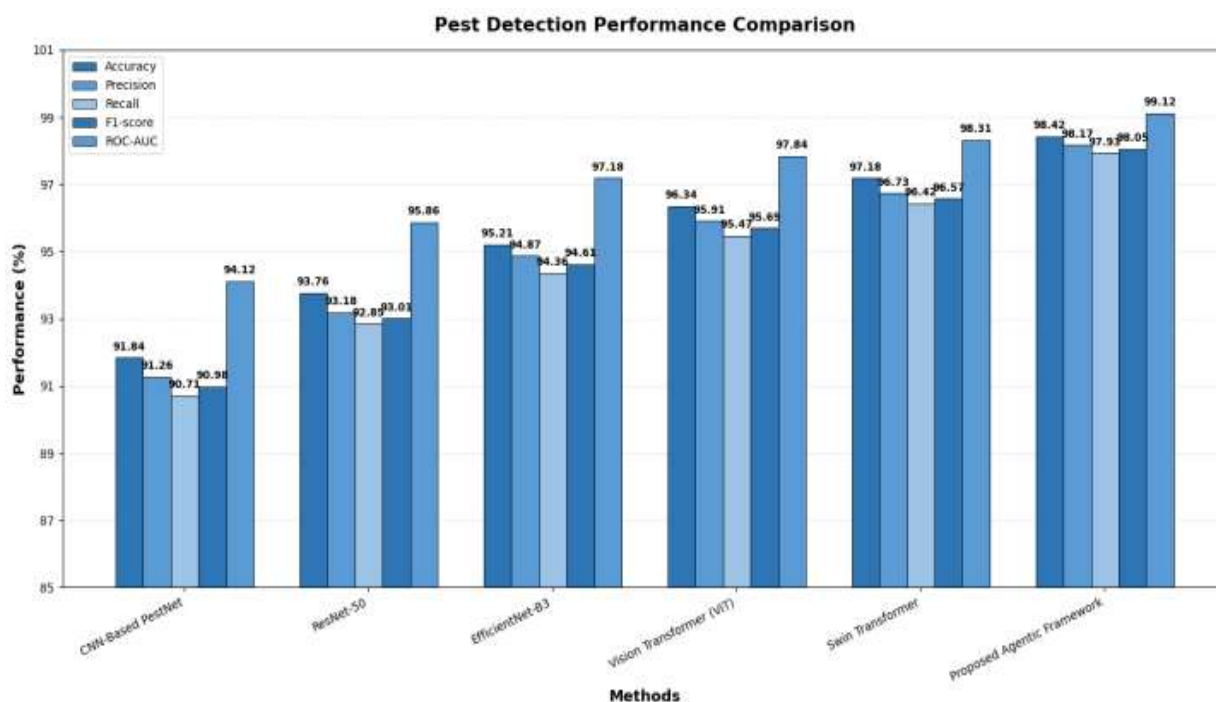


Figure 2. Pest Detection Performance Comparison of the Proposed Agentic AI Framework

The comparative methods tested as part of this study are shown as a result of Figure 2, which clearly shows that the proposed Agentic AI Framework always outperforms all the comparative methods with respect to accuracy, precision, recall, F1-score and ROC-AUC. It achieves 98.42% accuracy, 98.17% precision, 97.93% recall, 98.05% F1-score, and 99.12% ROC-AUC. Swin Transformer achieves the best baseline results, while CNN-Based PestNet has the worst overall results. Multimodal feature fusion, representation learning with transformers, pest-severity estimation, and agentic contextual reasoning are the key factors that our proposed framework leverages to achieve superior performance.

Table 2 compares the effectiveness of the different methods in reducing pesticide and water use, controlling pest populations and reducing the expenses of intervening.

Table 2. Pest Management and Resource Optimization Comparison

Method	Pest Reduction (%)	Pesticide Reduction (%)	Water Reduction (%)	Cost Reduction (%)	Yield Improvement (%)
Conventional Management	72.40	0.00	0.00	0.00	3.80
CNN-Based PestNet	78.62	11.40	7.20	9.30	5.42
ResNet-50	81.35	14.70	9.10	11.60	6.18
EfficientNet-B3	84.27	17.90	11.80	14.30	7.24
Swin Transformer	87.63	21.50	14.20	18.70	8.31
Proposed Agentic Framework	92.18	24.80	17.60	21.30	10.24

The proposed framework was able to bring about the maximum reduction in pests of 92.18% with a reduction in 24.80% pesticide usage, 17.60% water usage and 21.30% intervention cost. The improvements demonstrate the efficacy of the agentic optimization when the pest is correctly identified, and the possibility of making using resources possible. Swin Transformer was relatively a good performance but was more inclined towards the visual recognition field, and hence less resource saving.

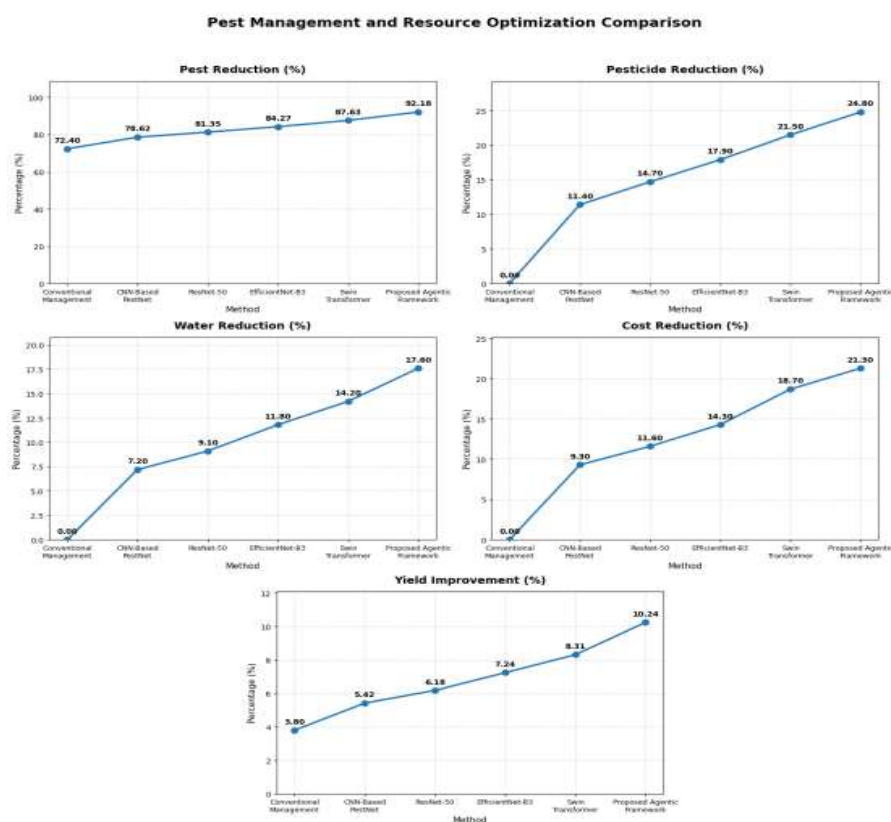


Figure 3. Pest management and resource optimization comparison

The results of the pest management and optimization of resources are consistent across the different methods tested and are shown in Figure 3. Conventional management results in a 72.40% reduction in pests but does not offer pesticide and water or cost reduction and only 3.80% yield increase. CNN-Based PestNet brings these benefits and ResNet-50 and EfficientNet-B3 offer additional benefits. Swin Transformer reduces the pest rate by 87.63%, reduces the use of pesticide by 21.50%, reduces water by 14.20%, reduces cost by 18.70% and improves yield by 8.31%. The proposed Agentic Framework yields the best results for every parameter, with a 92.18% reduction in pests, and decreases the amount of pesticide, water and cost requirements by 24.80%, 17.60% and 21.30%, respectively. It also has the highest yield improvement of 10.24%. Results within the framework suggest that the proposed framework yields a better pest suppression to resource conservation, economic efficiency, and agricultural productivity. Table 3 compares results with no human intervention in terms of inference latency, memory usage, pest-risk prediction ROC-AUC, intervention decision accuracy, cumulative reward and decision latency.

Table 3. Computational Efficiency and Agentic Decision Performance

Method	Inference (ms/sample)	Memory (GB)	Risk ROC-AUC (%)	Decision Accuracy (%)	Cumulative Reward	Decision Latency (ms)
CNN-Based PestNet	21.8	2.7	86.42	81.63	0.71	34.6
ResNet-50	24.6	3.1	88.75	83.91	0.74	37.2
EfficientNet-B3	27.3	3.6	90.18	86.74	0.78	40.5
Vision Transformer	31.7	4.4	92.63	89.18	0.82	46.3
Swin Transformer	34.2	4.9	94.71	91.46	0.86	49.7
Proposed Agentic Framework	36.5	5.2	96.84	94.72	0.91	52.4

Compared with individual recognition models, the proposed framework needs a little more computational resource, with an inference latency of 36.5ms, and memory usage of 5.2Gb. This extra computation is paid off by the significantly improved decision-making ability. As for the ROC-AUC and the autonomous decision accuracy, the proposed framework achieved 96.84% and 94.72%, respectively, which were improved by 2.13% and 3.26% for ROC-AUC and autonomous decision accuracy, respectively, compared with Swin Transformer.

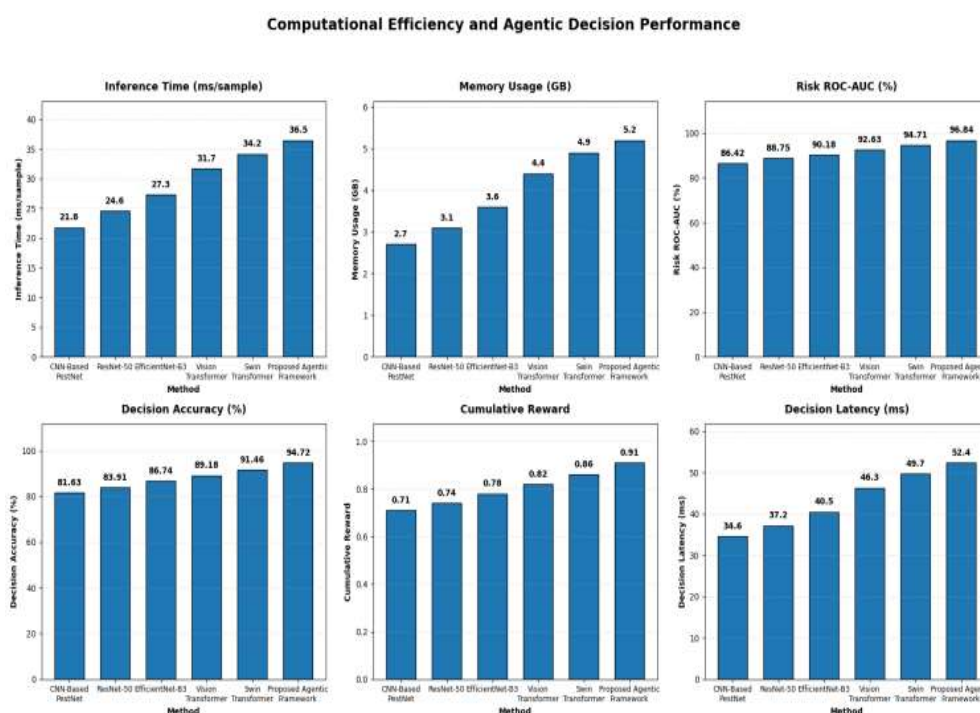


Figure 4 Computational efficiency and agentic decision performance comparison

It can be seen from Figure 4 that the performance of the risk assessment and decision making process improves as the number of methods calculated increases, with the increase in computational requirements. CNN-Based PestNet has the lowest amount of risk ROC-AUC (86.42%), decision accuracy (81.63%) and cumulative reward (0.71%), but it has the lowest inference time (21.8 ms/sample) and memory (2.7 GB). In this regard, ResNet-50 and EfficientNet-B3 gradually enhance the predictive and decision metrics, and Vision Transformer and Swin Transformer outperform the other models. The proposed Agentic Framework shows the highest risk aware ROC-AUC of 96.84%, decision accuracy of 94.72% and cumulative reward of 0.91, which are better results in terms of risk aware autonomous decision making. But it has also the highest inference time (36.5 ms/sample), memory consumption (5.2 GB) and decision latency (52.4 ms). The results overall suggest that there is a conscious calculation cost-benefit trade-off between the amount of resources required and the level of decision reliability and agentic performance achieved.

5. CONCLUSION

This study introduced the Agentic AI-Based Pest Monitoring Framework for sustainable agriculture with the objective of optimizing resources and promoting productivity. The framework combines multimodal perception, assessment of pest severity, forecasting of the risk of pest presence over time, autonomous reasoning, optimization of use of limited resources, planning of interventions and closed-loop learning, whereas traditional classifiers for pests only address the classification of pests. The experimental assessment revealed an accuracy of 98.42%, a precision of 98.17%, a recall of 97.93% and an F1-score of 98.05% whereas the costs of pesticide, water and intervention were reduced by 24.8%, 17.6% and 21.3%, respectively. The framework also had a high pest-risk ROC-AUC of 96.84% and a cumulative reward of 0.91, which showed its performance of linking the correct detection with sustainable decision-making. The framework needs to be tested in the field in multiple seasons with various crops and climates, soil types and pest infestations. The integration of edge AI, agricultural robots and autonomous machines, satellite images, and real-time sensing by the IoT, could all be contributing factors to scalability too. A federated learning approach for privacy-preserving cross-farm intelligence, explainable agentic reasoning, uncertainty-aware intervention, digital-twin-based simulation and adaptive multi-agent collaboration for fully autonomous precision agriculture should be explored further in future work.

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