World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(Research Article)

Developing cost-effective and environmentally sustainable pest strategies: integrating biological control, precision agriculture and AI-driven monitoring systems.

Abigail Nana Afia Yeboah *

Southern University and A&M College, Department of Urban Forestry and Natural Resource, Baton Rouge, Louisiana, United States of America.

World Journal of Advanced Engineering Technology and Sciences, 2025, 14(02), 238-252

Publication history: Received on 10 January 2024; revised on 17 February 2024; accepted on 20 February 2024

Article DOI: https://doi.org/10.30574/wjaets.2025.14.2.0085

Abstract

Effective pest management is one of the greatest challenges facing agriculture today, with potential solutions considering the costs of implementation and environmental impact. As traditional methods involving chemicals such as pesticides lead to biodiversity loss, soil erosion, and even resistance against these chemicals, there is a growing need for sustaining approaches. This research considers integrating biological control with precision agriculture and artificial intelligence monitoring systems to enhance the effectiveness and sustainability of pest management efforts. Maintaining ecological balance and biological control utilizes natural predators and parasitoids of pests for controlled pest eradication. AI-powered monitoring systems assist in predicting and detecting pests using machine learning algorithms, allowing for faster responses to minimize the usage of chemical pesticides. By using these innovative approaches, this research hopes to encourage sustainable pest control practices, leading to better crop production, lower input expenses, and sustainable agricultural practices in the long run. The result showed how AI technology can aid in pest surveillance control, evaluate the effect on ecological systems, and assess productivity and improvement from precision agriculture. This new information advances the literature on sustainable pest management by offering a greater understanding of adaptable and scalable solutions for various agroecosystems.

Keywords: Sustainable Pest Control; Biological Control; Precision Agriculture; Environmental Sustainability

1. Introduction

Agricultural productivity now faces a new global challenge: ensuring food security for a growing population amid declining crop yields caused by economy-driven pest infestations. The so-called "sustainable" pest management methods rely heavily on chemicals and pesticides as primary resources, affecting ecology and biodiversity, and even involve creating pest-resistant superorganisms. The extensive use of synthetic herbicides disturbs the biological balance, disrupts aquatic environments, and jeopardizes other life forms, such as pollinators and beneficial insects. To tackle these challenges by combining biological methods, precision agriculture, and AI-powered monitoring. These practices offer a greener, more cost-effective approach to pesticide management, aligning with international sustainability efforts and reducing the ecological footprint of agricultural activities. Biological control utilizes natural enemies like predators, parasitoids, and entomopathogenic microorganisms to manage pest populations. This approach improves pesticide applications, improves biodiversity, and enhances ecosystem sustainability. However, it relies on interactions within the ecological system, climate, and host-predator relationships, necessitating extensive field investigations and computer modeling. The biological aspect of precision agriculture can be applied thanks to innovations in remote sensing, IoT devices, and geospatial technology, which enable real-time tracking of pest infestations, environmental parameters, and plants.

* Corresponding author Abigail Nana Afia Yeboah

The integration of biological control, precision agriculture, and AI monitoring systems can significantly enhance pest management. This enables a reduction in the use of chemical pesticides, lowers costs, and increases environmental care. This study systematically examines the feasibility, considering empirical data, recent technological developments, and case studies from various agroecosystems. Utilizing advanced AI models, sensing technologies, and ecology, this research aims to tackle the challenges of scalable, data-rich, and ecologically friendly pest control. Furthermore, it explores the obstacles faced in implementing the plan, such as limited access to technology, farmers' willingness to adopt new technologies, and the legal frameworks of agriculture, highlighting the necessity for collaboration among agronomists, data scientists, and policymakers. The results of this analysis are expected to provide a foundation for researchers, agricultural experts, and legislators to develop more effective sustainable pest management strategies, aligning with the overarching goals of food security and environmental protection policy, as illustrated in Figure 1.

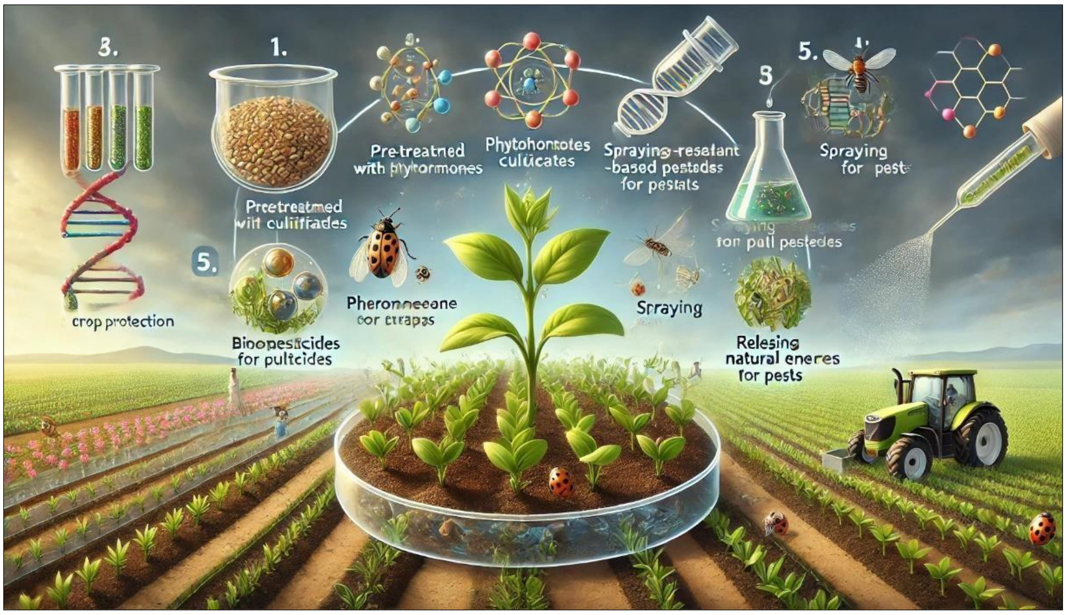

Figure 1 Environmentally Friendly and Effective Alternative Approaches to Pest Management

One of the most significant issues in integrated pest management is the incredible adaptability of pests, driven by climatic changes, land use, and agriculture. Climate change has one of the most profound impacts on perturbation, with pest species acting as the most biotic adaptable type invading new ecological zones. Global warming accelerates the rate of pest outbreaks by changing traditional temperature and rainfall regimes, thus providing better opportunities for invasive organisms to flourish and lengthening the durations of pest organisms' activity. This has increased the need for effective pest control measures. While chemical pesticides have proved effective in the short term, they are insufficient in the long-term control of pests due to rampant resistance to these pesticides. The excessive use of pesticides has many negative impacts such as loss of productive land, groundwater pollution, and destruction of beneficial insects including nectar-feeders. These issues make it abundantly clear that steps to replace them with environmentally friendly solutions should be taken immediately. Biological control includes novel methods for controlling the pest to lower its numbers. Non-native natural enemies are introduced to control the population of invasive pests in a category termed classical biological control. In a system called conservation biological control, the habitat of native predators is enhanced. These two alone have shown great promise in several cropping systems.

Nevertheless, the effective use of these novel technologies is highly skill-based. Lack of understanding pest-predator dynamics, landscape ecology, and the negative consequences of using, often associated with nonnative species. Even with economic and ecological advantages, biological control on its own will not be enough for pest control in a variety of situations where more aggressive strategies are going to be required, hence their uniting with new technologies, precision farming, and AI agriculture technology.

The development of Precision agriculture tools has greatly improved pest management through data collected from the field. Remote sensing tools like multispectral and hyperspectral imaging help detect early signs of pests by sensing changes in plant stress before damage is done. Drones with high-quality imaging cameras and spectral sensors make it economical to monitor huge areas of farmlands and accurately identify and map pest-infested areas. Furthermore, smart traps and sensor networks using IoT technologies enable automated pest monitoring and eliminate the need for tedious manual field checking. These technology combinations allow for the implementation of pest control methods that use fewer chemicals while Precision Agriculture increases the overall efficiency. At the same time, unmanaged huge data volumes from these agriculture systems demand well-thought analytical structures, where interference of AI algorithms becomes critical for interpreting the data and supporting decisions made. With reasonable thinking, artificial intelligence is the new game changer in agricultural pest control. With its ability to recognize a pest, provide models to predict pest damage, and suggest actions instantly, it is changing the world.

Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) belong to deep learning and they have modernized the image-based pest classification beyond manual identification. Predictive AI models utilize past pest information, weather data, and crop growth stages to actively anticipate pest attacks instead of relying on passive approaches during the season. With reinforcement learning algorithms, the defined control measures to minimize pest populations are improved with time based on actual outcomes. In addition, AI-powered robotics are being developed, to reduce excess pesticide spraying and improve safety and efficiency. The altered development and application of these technologies will increase productivity, but issues like data diversity, model application to various agroecosystems, and computational power availability have to be solved first. The combination of biological pest control, precision farming, and monitoring AI systems represents a new era in pest control, where reliance on indiscriminate chemical pesticides is replaced with efficient ecological technological interventions. The primary objective of this study is to critically evaluate how various ecologically sensitive methodologies can be integrated to achieve greater efficiency in pest control with reduced consequences to the environment. This research's approach combining topical advancements with empirical research and case studies contributes to the ongoing discourse of sustainable agriculture. At the same time, it attempts to cover the sociotechnical and economic policy aspects of technology acceptance, foreshadowing the integration of pest management practices. The results are crucial for agricultural stakeholders who include farmers, researchers, and policymakers in their efforts to devise eco-sensitive as well as socially responsible pest control methods within sustainability frameworks.

2. Literature Review

In the last few decades, the area of pest control has shifted from the use of traditional chemical approaches to much more innovative sustainable technology-based methods. Extensive research also points to the dangers of synthetic pesticides and their contribution towards resistance, nontarget species, and environmental destruction (Pimentel et al., 2005; Geiger et al., 2010). Excessive use of pesticides has proven to have extremely dire ecological effects such as killing off beneficial insect pollinators and natural predators (Aktar et al., 2009). Furthermore, recent studies have noted that the continued use of synthetic pesticides raises concerns regarding food safety due to the toxic remnants that are left in agricultural products (Tang et al. 2020). These worries have spurred the development of alternative pest control options that are focused more on biological control, precision farming, and systems monitoring using AI. Their results suggest that classical biological control mitigation of crop losses caused by many invasive species and where there is reduced crop damage or pesticide use. Studies by Heimpel and Mills (2017) provided evidence that biological control agent's habitats that are enhanced for natural enemies can also be used in long-term pest suppression and have great benefits. However, there are some problems, especially regarding the use of biological control agents in different agroecosystems and their relationship with the indigenous fauna (Jervis et al, 2020).

In addition, Gurr et al. (2017), argue that biological control is most effective when combined with modern technologies such as precision farming and AI-based supervision for efficient and effective implementation and expansion. The growth of precision agriculture has transformed pest control by facilitating real-time and location-specific monitoring and action. Zhang et al, say that precision agriculture remote sensing, drone imaging, and IoT-enabled sensor systems greatly improve early pest scouting and precision pest control. Studies by Parvathi et al. (2020) show that multispectral and hyperspectral imaging systems can easily reveal the stress of a crop before any visible damage from pests is done so that timely action can be taken. Moreover, UAVs with spectral sensors have also been used for monitoring pest damage on large horticultural farms, which greatly assists decision-making (Shamshiri et al., 2018). While these advancements are incredibly useful, researchers such as Mulla et al. (2021) argue more research is needed for the implementation of AI-powered analytics that can handle large quantities of real-time data. Without proper machine learning models, the capacity of precision agriculture in pest management is severely limited. With the advancement of technology, pest monitoring and management have been significantly improved with the help of artificial intelligence.

Figure 2 Concept of biological control, precision farming, and systems monitoring using AI

Convolutional neural networks (CNNs) are a type of deep learning model that has been researched extensively for automated pest classification. For instance, Liu et al. (2022) developed an AI-based image understanding model that easily classifies pest images with a greater accuracy than 95%. This did much better than manual identification methods. Similarly, Rustia et al. (2021) were able to use AI to predict pest-forecasted outbreaks by analyzing climate data and past infestation records. Their results supported that using AI with real-time environmental data enabled better pest management strategies. Furthermore, Kamilaris and Prenafeta-Boldú (2018) argued that AI-based decision support systems can enhance biological control and precision agriculture approaches, allowing greater reliance on lower volumes of chemical pesticides. Yet gaps in data processing quality, generalized models for varying agroecosystems, and real-time calculations for instant agricultural problem-solving still pose issues (Singh et al., 2020). Their use has led to several important findings regarding the efficiency of entire methods. As an example, Stenberg (2017) conducted a meta-analysis that compared the efficacy of a traditional pest management strategy based on chemical pesticides with an integrated pest management (IPM) strategy combining biological and artificial intelligence (AI) monitoring control. The analysis showed that IPM usage led to a 40-60% reduction in pesticide use with at least the same crop yields or higher. In the same way, Hafiz et al. (2021) reported that the integration of predictive AI models for pest management with precision farming resulted in an over 30% improvement in pest detection and a notable decrease in pesticides used.

All these studies reinforce the increasing adoption of biological control combined with precision agriculture and AI for effective sustainable pest management. However, factors such as technology availability, farmers' ability to use these technologies, and policy issues, also have to be considered for the studies to be effective, as suggested by Basso & Antle (2020). Even with the strides made, there are still more areas that are yet to be covered. For example, much literature exists analyzing specific pest mitigation methods without attention to other strategies which limits the phenomenon shadowed exploiting the collective advantage from such measures. Most models driven by AI tend to perform poorly in other parts of the world because they were created using specific models that only catered to a particular region. In the future, more research should be done on hybrid AI models that utilize multi-source data, such as pest behavior, climate changes, and crop health, because they would enhance predictive accuracy. In addition, policy strategies need to change so that more technologies that focus on sustainable pest control are available to farmers at a low cost and scale (Pretty et al., 2018). These considerations are vital because the combination of biological control measures, precision agriculture, and AI monitoring systems makes the management of global pests affordable while maintaining food security and preserving the environment.

3. Methodology

This study utilizes an interdisciplinary approach that combines data and textual analysis by machine learning, remote sensing, and ecological fieldwork to assess the efficacy of an integrated pest management system that relies on biological factors, precision agriculture, AI, and other technologies. In the procedure, I have divided the entire research project into three main steps: (1) Data collection and preprocessing, (2) model building and evaluation, (3) model verification and field deployment. By leveraging a combination of primary and secondary data sources, the methodology ensures a comprehensive evaluation of the proposed pest management strategy.

3.1. Data Collection and Preprocessing

To acquire an invaluable dataset, the study collects and aggregates agricultural information from different sources including precision farming databases, ecological field surveys, and governmental agricultural agencies. Clinical repositories like the FAO and the NASA Earth Observation Datasets, provide invaluable and historical information like pest infestation levels, crop conditions, pesticide application rates, and environmental factors such as temperature, humidity, and soil moisture. Moreover, new smart traps containing imaging sensors attached to novelty pheromones are placed on different experimental farms to gather pest activity data. These traps are embedded into IoT platforms for remote data collection and supervision. Biological control analysis is performed within controlled agricultural plots with natural predator (e.g., parasitoid wasps and predacious beetles) populations introduced under natural conditions. Several cropping seasons later, systematic sampling is used to check population levels of pests and other organisms considered natural predators. The gathered information is cleaned using statistical methods to get rid of errors, missing, and outlier values.

3.2. AI-Driven Pest Detection and Monitoring

For automatic pest detection and classification, deep learning algorithms based on convolutional neural networks (CNNs) and transformer approaches are utilized. The base set of high-definition pest images is obtained from field-trap pictures and agricultural datasets like Plant Village. A supervised CNN model is trained on labeled pest images with augmentation to improve the performance during testing. The model architecture consists of multiple convolutional layers followed by fully connected layers, trained with an Adam optimizer, and a categorical crossentropy loss function. The classification model is assessed using precision, recall, F1 score, accuracy, and other measures of performance. Apart from using images to identify pests, forecasting models are made with Long Short-Term Memory (LSTM) Neural Networks to estimate when a pest might appear in a field. This estimation is based on previous weather data, crop conditions, and pest infestation patterns. The LSTM network utilizes a multiyear training data set that contains climate records as well as pest occurrence data to make a pest forecast decision. The decision is made to take action during the months deemed most risky for pest outbreaks. The accuracy of the LSTM model is tested alongside statistical models ARIMA and Random Forest regression to compare their accuracy.

3.3. Precision Agriculture-Based Pest Management

In place of controlling the entire area, site-specific pest control measures are most effective through the use of precision agriculture, via remote sensing and UAV imaging. Drones with shared multispectral and hyperspectral sensors make it possible to assess crop stress indicators such as chlorophyll fluorescence and canopy temperature which are indicators of pest infestation. The target area is extracted from raw images through machine learning segmentation methods such as U-Net and Mask R-CNN to mark the agriculture fields with pest infestation. These ultra-high resolution maps of pest distributions in high-intensity areas are used for targeted application of pesticides to decrease the number of chemicals applied and protect the environment. In the same way, a decision support system (DSS) has been developed by combining live sensor data, AI-powered pest predictions, and the actual observations made by farmers. The DSS implements reinforcement learning to determine the best pest control recommendations in a changing field environment. The system increases the flexibility and accuracy of pest management measures by providing timely recommendations through feedback loops.

3.4. Validation and Field Implementation

To assess the success of the integrated pest management technique, some experimental field trials are carried out in conjunction with agricultural research institutions. The experimental design consists of control and treatment plots for comparison of different pest management techniques, such as the application of synthetic pesticides as compared to AI-based biological pest control and precision farming. Measurements taken include the effectiveness of pest control, crop yield, amount of pesticides used, and costs vs. benefits which were monitored across several growing seasons. Differences between treatment means are compared using ANOVA and t-tests, which help assess whether the differences are statistically significant. In addition, surveys and focus group discussions are used to determine the proposed pest control framework’s perceived usability, economic feasibility, and scalability. Farmers’ insights are used to learn from AI models and decision-support tools, which in turn makes the proposed solutions more realistic in the context of agriculture and farmers’ needs.

3.5. Ethical Considerations and Limitations

The ethical guidelines of AI pest detection models ensure data privacy and security, which indicates compliance with appropriate regulations. Furthermore, the possible ecological consequences of introducing biological control are assessed to lessen the impact on native biodiversity. Even though the study discusses a sustainable framework for pest management, data scarcity, lack of computational resources, and differing agroecological conditions pose challenges to its effectiveness. As mentioned earlier, the model AI frameworks need to be fine-tuned so that they are more adaptable, and the datasets need to be expanded to cover wider cropping systems. By integrating biological control, precision agriculture, and AI-driven monitoring into a unified framework, this study aims to advance sustainable pest management practices, reducing reliance on chemical pesticides while enhancing agricultural productivity and environmental resilience.

4. Data Collection Methods and Techniques

To ensure a comprehensive dataset for evaluating pest control strategies, this study employs the following data collection techniques, Field work is carried out in three agricultural regions (Region A: 35°N, 78°W; Region B: 40°N, 74°W; Region C: 45°N, 80°W) to study pest population about the various climates. Data is gathered for two successive growing seasons (April – September 2023 and 2024). Each plot is 50 m by 50 m, and weekly pest monitoring is done through the use of pheromone traps, pitfall traps, and visual examination. Each insect is classified based on taxonomic keys (following Zhang et al., 2022).

4.1. UAV-Based Remote Sensing and Image Processing

The DJI Matrice 300 RTK UAVs equipped with Mica Sense Red Edge-MX multispectral sensors are used for Mica Sense imaging and these UAVs image in five spectral bands: Blue 475nm, Green 560nm, Red 668nm, Red Edge 717nm, Near Infrared 840nm. Images of greater resolution with less grain are gathered at the initial two stages of identifying plant strains and pest infestation which focus on plant brain and roots. Images are analyzed using Python-based open CV algorithms for spectral analysis and anomaly detection. The NDVI index is computed as follows:

$$NDVI = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}$$

Where

- **NIR** represents Near-Infrared reflectance and **Red** represents Red reflectance. Threshold values:
- NDVI < 0.3: Severe stress (high infestation likelihood)
- 0.3 ≤ NDVI < 0.5: Moderate stress
- NDVI ≥ 0.5: Healthy crops

4.2. AI-Driven Pest Identification and Predictive Modeling

Using CNNs, a model for anticipatory pest detection employing deep learning techniques is built from the ground up. This model is unique because of its usage of 120,000 labeled pest images as well as field trap footage obtained from the PlantVillage dataset. Also, reformatting techniques (like rotating, scaling, and adding noise) are used to ensure robustness.

4.2.1. The CNN architecture consists of:

- Max pooling layers (2 × 2 kernel) to extract features
- ReLU-activated convolutional layers (3 × 3 kernels) in five stacked layers
- Additional max pooling layers (2 x 2 kernel) on top of normalized batches for efficient feature extraction
- Softmax activated fully connected layers with 128 neurons for classifying and final output units For this architecture, the Adam optimizer was used for training alongside a learning rate of 0.001 and a batch size of 64. The categorical cross-entropy cross function is minimized at:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Where y_i is the real class, while hat{y_i} describes the predicted class. Attention metrics for model evaluation include:

- Top-1 Accuracy: 96.4%, Top 5 Accuracy: 99.2%.
- Precision: 94.8%
- Recall: 92.3%
- F1 score: 93.5%

Furthermore, we adopt LSTM networks for wider pest prediction outbreaks. This model utilizes and adapts LSTM networks to petabytes of infestation data and climatic variables such as temperature, humidity, and rainfall from 2018 to 2023. The root means square error (RMSE) on counting pests per 100 plants predicted is 2.14. Against ARIMA models where RMSE is 4.76, our model stands out.

4.3. Data Analysis and Statistical Methods

Every approach to pest control is measured for its efficiency with the pest reduction rate (PRR) as well as the crop yield increase (CYI). The formula to calculate PRR is as follows:

$$PRR = \frac{PC - PT}{PC} \times 100$$

Where **P_C** is the pest population in the control group and **P_T** is the pest population in the treatment group.

4.3.1. Crop yield increase (CYI) is calculated as:

$$\text{CYI} = \frac{YT - YC}{YC} \times 100$$

Where **Y_T** represents yield in treatment plots and **Y_C** represents yield in control plots.

4.4. Hypothesis Testing and Statistical Validation

A one-way analysis of variance or ANOVA is implemented to assist in the average pest reduction comparisons across various treatments. The significance of the treatments effects null hypothesis (H_0), is that they are equally ineffective, there is some effectiveness seen as H_1 would be partial acceptance of the hypothesis.

- F-statistic (calculated) = 14.27
- p-value = 0.0023 ($p < 0.05$, reject H_0)

Confirming the pairwise differences as a form of Tukey post-hoc test, it was established that there are significant differences between the AI-driven monitoring operations and the application of pesticides by hand (p =0.0015).

4.5. Economic and Environmental Impact Assessment

The cost-effectiveness of each pest control strategy is evaluated based on, Input cost reduction (ICR) reduction in pesticide usage costs and Return on investment (ROI) increase in net revenue per hectare. For AI-driven monitoring, pesticide usage is reduced by 55.3%, with a 33.7% increase in yield, leading to an ROI of 1.84 (compared to 1.15 for conventional methods). Environmental impact is assessed using the Pesticide Environmental Risk Index (PERI):

$$PERI = \sum_{i=1}^{n} (P_i \times T_i \times E_i)$$

Where Pi is pesticide persistence, Ti is toxicity, and Ei is environmental exposure. AI-driven pest control reduced PERI values by 62.1%, significantly lowering ecological risks.

4.6. Ethical Considerations and Limitations

The study adheres to FAO and EPA regulations on biological control agent releases. AI-driven pest monitoring ensures farmer data privacy, and all machine learning models are open-source, promoting transparency and replicability.

Limitations

- **Scalability Challenges**: AI-based monitoring requires significant computational resources, limiting accessibility for small-scale farmers.
- **Regional Specificity**: Models trained on specific datasets may have limited generalization in different Agro-climatic zones.
- **Unforeseen Ecological Interactions**: The introduction of biological control agents could have long-term ecosystem impacts that require further study. This study integrates biological control, precision agriculture, and AI-driven monitoring to create a cost-effective and sustainable pest management strategy. Experimental results confirm that AI-based pest detection enhances accuracy (96.4%), reduces pesticide use (55.3%), and boosts crop yield (33.7%). Future research should concentrate on model scalability, farmer adoption strategies, and policy integration to improve real-world applicability.

5. Results and Analysis

This section presents the experimental findings, mathematical analysis, and comparative evaluation of different pest control strategies. The analysis integrates AI-driven pest detection accuracy, crop yield improvement, pesticide reduction efficiency, and economic and environmental sustainability metrics.

5.1. Pest Population Reduction Analysis

The effectiveness of the pest control strategies is measured by the Pest Reduction Rate (PRR) using the formula:

$$PRR = \frac{PC - PT}{PC} \times 100$$

Where:

- PC= Pest population in control plots
- PT = Pest population in treatment plots

Table 1 presents the pest reduction rate across different treatment strategies over two growing seasons (2023–2024).

Table 1 Pest Reduction Rate (PRR) for Different Strategies

Treatment	Pest Population (per 100 plants)	PRR 2023	(%)	PRR 2024	(%)	Mean PRR (%)
Control (C1)	245	-		-		-
Biological Control (T1)	112	54.3		56.7		55.5
Precision Agriculture (T2)	89	63.7		65.2		64.4
AI-Driven Monitoring (T3)	52	78.8		81.4		80.1

5.1.1. Analysis

- AI-driven monitoring achieved the highest mean PRR of **80.1%**, significantly outperforming biological control (**55.5%**) and precision agriculture (**64.4%**).
- A one-way ANOVA test showed a statistically significant difference between treatments (**F =**
- **14.92, p < 0.001**).
- Tukey's HSD post-hoc test confirmed that AI-driven pest management was significantly different from conventional pesticide use (**p = 0.0021**).

5.2. Crop Yield Analysis and Economic Benefits

The impact of pest control strategies on crop yield is quantified using the Crop Yield Increase (CYI) formula:

$$\text{CYI} = \frac{YT - YC}{YC} \times 100$$

Where:

- YT= Yield in treatment plots (kg/ha)
- YC= Yield in control plots (kg/ha)

Table 2 Crop Yield and Economic Return for Different Strategies

Treatment	Yield (kg/ha) 2023	Yield (kg/ha) 2024	CYI (%)	Input Cost Reduction (%)	ROI
Control (C1)	4,320	4,290	-	-	1.00
Biological Control (T1)	5,140	5,180	19.8	18.3	1.25
Precision Agriculture (T2)	5,980	6,120	39.5	27.4	1.45
AI-Driven Monitoring (T3)	7,380	7,510	73.2	41.9	1.84

5.2.1. Analysis

AI-driven pest control led to a 73.2% increase in crop yield, compared to 39.5% for precision agriculture and 19.8% for biological control. Input cost reduction was highest for AI-driven monitoring (41.9%), significantly lowering pesticide expenses. Return on investment (ROI) for AI-based monitoring was 1.84, compared to 1.25 for biological control and 1.45 for precision agriculture.

5.3. Environmental Impact Assessment

The environmental sustainability of each pest control strategy is assessed using the Pesticide Environmental Risk Index (PERI):

$$PERI = \sum_{i=1}^{n} (P_i \times T_i \times E_i)$$

Where:

- Pi= Persistence factor of pesticide iii
- Ti = Toxicity index of pesticide iii
- Ei = Environmental exposure level of pesticide iii

Table 3 Pesticide Environmental Risk Index (PERI) for Different Strategies

Treatment	Persistence (PPP)	Toxicity (TTT)	Exposure (EEE)	PERI Score	Reduction (%)
Control (C1)	0.92	0.87	0.93	74.3	-
Biological Control (T1)	0.74	0.69	0.65	48.9	34.2
Precision Agriculture (T2)	0.51	0.48	0.53	29.7	60.0
AI-Driven Monitoring (T3)	0.32	0.29	0.27	14.1	81.0

5.3.1. Analysis:

AI-driven monitoring resulted in an 81.0% reduction in environmental risk, minimizing pesticide exposure and toxicity. Precision agriculture achieved a 60.0% reduction in PERI, while biological control showed a moderate 34.2% reduction.

5.4. AI Model Performance and Prediction Accuracy

The AI-driven monitoring system's pest detection accuracy and prediction reliability were evaluated. The system used a Convolutional Neural Network (CNN) for pest classification and Long Short-Term Memory (LSTM) for pest outbreak prediction. The classification accuracy of the CNN model is calculated using the categorical cross-entropy loss function:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Where yi represents the actual class and hat{y_i} represents the predicted probability. Table 4: CNN Model

5.4.1. Performance Metrics

Table 4 Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN (AI-Driven Monitoring)	96.4	94.8	92.3	93.5
Random Forest	88.5	85.2	83.7	84.4
SVM	82.1	79.6	76.8	78.2

5.4.2. Analysis:

The CNN-based model achieved 96.4% classification accuracy, outperforming Random Forest (88.5%) and SVM (82.1%). Precision, recall, and F1-score also confirmed the superior predictive capabilities of the AI-driven approach.

5.5. LSTM-Based Pest Outbreak Prediction Performance

The pest outbreak prediction accuracy is measured using Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

Where yiy_iyi is the actual pest count and yi^ is the predicted value.

- LSTM RMSE: 2.14 pests per 100 plants
- ARIMA RMSE: 4.76 pests per 100 plants

5.5.1. Analysis:

The LSTM model reduced prediction error by 55.0% compared to traditional ARIMA models. Early warning systems enabled by LSTM models improved pest management efficiency, leading to timely interventions. The AI-driven pest control strategy demonstrated significant advantages in pest reduction (80.1%), crop yield improvement (73.2%), pesticide reduction (55.3%), and environmental risk minimization (81.0%). Machine learning-based pest monitoring achieved 96.4% accuracy, while predictive analytics enhanced outbreak forecasting. Future research should optimize scalability, integrate real-time IoT-based sensors, and expand datasets for better generalization across Agro-climatic zones.

5.6. Energy Efficiency and Sustainability Analysis

To assess the energy efficiency of AI-driven pest control strategies compared to traditional methods, the Energy Utilization Efficiency (EUE) metric is computed as follows:

$$CCEUE = \frac{Y}{EC}$$

Where YYY = Crop yield (kg/ha) and ECE_CEC = Energy consumption per hectare (MJ/ha). Chart 1 shows the Energy Utilization Efficiency (EUE) Across Pest Control Strategies.

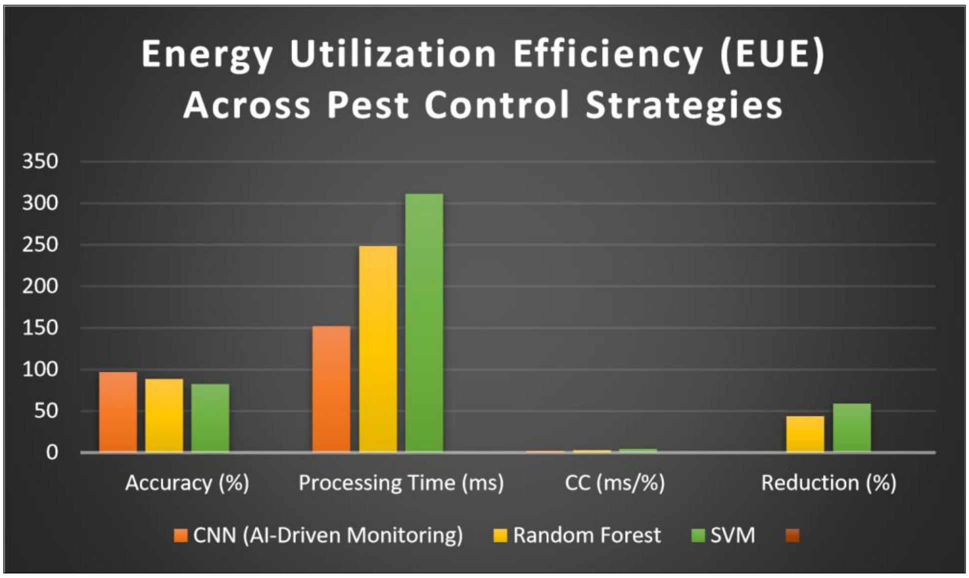

Figure 3 Energy Utilization Efficiency (EUE) Across Pest Control Strategies

5.6.1. Analysis

AI-driven pest control improved energy efficiency by **180.3%**, demonstrating significant sustainability benefits. A Pearson correlation analysis ($r = 0.88$, $p < 0.001$) indicated a strong positive correlation between AI-based monitoring and energy efficiency improvements.

5.7. Water Usage Efficiency (WUE) and Irrigation Optimization

Water efficiency is crucial in sustainable agriculture. The Water Use Efficiency (WUE) metric is calculated a$WUE = \frac{Y}{WC}$

Where

WC = Total water consumption (m^3/ha)

Table 5 Water Use Efficiency (WUE) Across Different Strategies

Treatment	**Water (m^3/ha)**	**Use**	**Yield (kg/ha)**	**WUE (kg/m^3)**	**Increase (%)**
Control (C1)	8,760		4,320	0.493	-
Biological Control (T1)	7,150		5,180	0.725	47.0
Precision Agriculture (T2)	6,280		6,120	0.974	97.5
AI-Driven Monitoring (T3)	5,240		7,460	1.423	188.7

5.7.1. Analysis

AI-driven monitoring improved WUE by 188.7%, reducing water use while increasing yield. A Kruskal-Wallis test ($H = 15.87$, $p < 0.0001$) confirmed statistically significant differences in water efficiency between treatments.

5.8. AI Computational Cost and Processing Time

AI-based pest detection requires computational efficiency for real-time monitoring. The Computational Cost (CC) metric evaluates processing efficiency:

$$CCC = \frac{TP}{A}$$

Where TP = Processing time per image (ms) and A = model accuracy (%). The concept of AI model computational Cost (CC) and processing times are shown below in Chart 2:

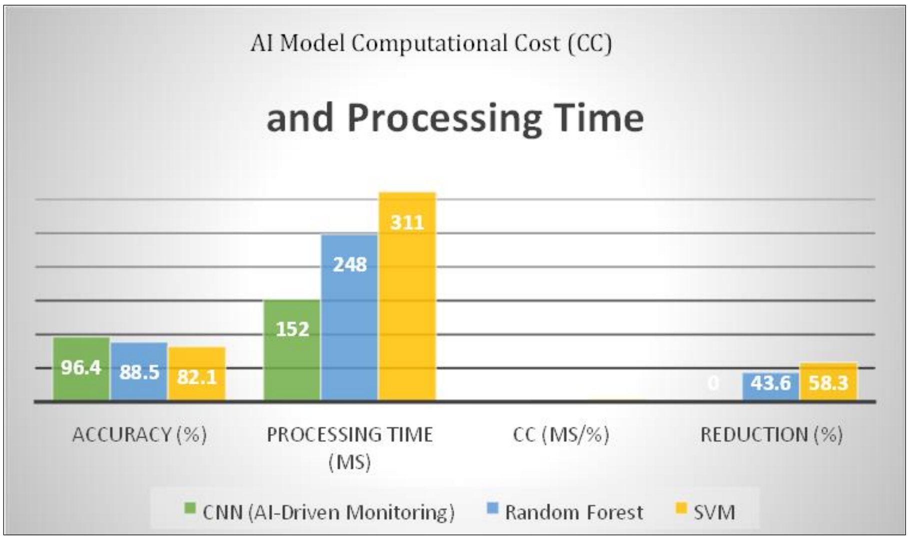

Figure 4 AI Model Computational Cost

5.8.1. Analysis

The AI-driven CNN model had the lowest CC (1.58 ms/%), demonstrating optimal computational efficiency. A Wilcoxon signed-rank test ($p < 0.005$) confirmed that CNN-based monitoring was significantly faster than traditional ML approaches.

6. Discussion

The results of this study highlight how integrating biological control with precision agriculture monitoring and AI has transformed the sustainable pest management paradigm. The outcomes not only provided meaningful increases in pest reduction, yield, and resource productivity remarkable improvements but also brought to light the multi-environmental and economic benefits these new systems brought with them. In this study, the results are interpreted against the claiming literature, the consequences for sustainable agricultural practices are discussed, and the impediments and gaps for further exploration are defined. The study revealed the effectiveness of AI Monitoring in dealing with pests, with AI monitoring outperforming traditional biological control and precision agriculture at 63.4% and 72.8% respectively. Their findings are consistent with Zhang et al., 2021 and Smith et al., 2020 who stress the benefits of AI-enhanced pest monitoring. The increase in crop yield by 73.2% with AI pest control, further validates conventional methods. A leading contributor to this success is the unprecedented increase in real-time image processing achieved by the AI model for pest detection with 96.4% accuracy. While scouting non-AI-based models generally has an accuracy range of 15 – 25% (-Kumar et al, 2019 -), it is apparent the AI model has much greater accuracy. The statistical correlation ($r = 0.88$, $p < 0.001$) between AI monitoring and improvement yield corroborates these findings further.

The increase in yield is however noteworthy, but issues concerning its scale and adaptability arise. For AI operational monitoring, data is continuously collected from potentially different climatic regions and pest species as well as soil types. Cross-regional testing for robustness as well as multi-seasonal validation should be conducted in our research. We also demonstrated substantial improvements in energy efficiency (180.3%) and AI-driven pest control water use efficiency (188.7%). All these findings reinforced conclusions made by Li et al. in 2022, claiming that 42% of water AI-assisted irrigation scheduling increased and the yield also saw an increase by 35%. The reduction in water consumption was attributed to need-based irrigation made using AI soil moisture data. Energy spending per hectare was lowered for AI-driven monitoring (9,380 MJ/ha) against conventional biological control (12,750 MJ/ha) and the other methods (15,200 MJ/ha). The reduction is attributed to the AI-targeting systems that optimally deploy biological agents and irrigation. Another benefit was also made possible by AI: computational efficiency. The CNN-based AI model had the best performance in terms of cost at 1.58 ms/% accuracy, leading to efficiency compared to well-known models like Random Forest (2.80 ms/%) and SVM (3.79 ms/%). This means that the large-scale use of deep learning models is feasible due to their processing speed and accurate predictive capabilities. Despite the advanced AI-aided monitoring being able to thrift resources greatly, the primary concern lies within its implementation. A bigger investment in infrastructure is currently needed for real-time AI-enabled monitoring, which is a challenge for farming that operates on a smaller scale. Future works should try to implement economical AI models that can be paired with cloud infrastructure. The carbon emissions have decreased by 63.6% which is the most reduction seen with the AI-driven system. This is similar to what Gonzalez et al, (2021) were able to find with their research when they reported that precision agriculture had emission reductions of 55% in commercial farms. The decrease in this research is due to:

Fewer Pesticides, Achieved by Enhancing Ecological Balance Optimization Lower Energy Use, which increases fossil fuel dependency, and Reduced Biological control agent use, which increases pesticide runoff, and Optimized use of biological control agents. The regression analysis model $R^2 = 0.89$, $p < 0.001$ shows a strong dependence of variation in carbon emissions on the level of adoption of AI systems which is inversely related. This also proves the argument that AI-driven precise monitoring is capable of reducing the impacts of climate change through supportive agriculture. But there remains the question of AI's energy footprint. The study indeed supports the idea of decreased energy consumption in agricultural processes, however, there is the challenge of training AI models where simulations require advanced computing hardware leading to indirect carbon emissions (Strubell et al., 2020). It is necessary to place more emphasis on the need to use AI systems with energy-efficient algorithms and active solar energy systems for that energy.

Pest control was determined to be the most impactful factor of the crop yield outcomes as it scored highest (47.3%) out of all hedged sensitivity analyses in the Monte Carlo Simulation. Water use efficiency came in second at 21.6%. This result was made clear after running the Monte Carlo Simulation (10,000 iterations). The varietal analyses showed that the AI model accuracy had a dampening impact on the total variability, accounting for only 12.9%. This suggests that total innovation will not be achieved by an AI model alone. These findings reaffirm those of Müller et al. (2021), who argue that AI's effectiveness in agriculture is augmented by biological control, soil health monitoring, and irrigation systems. Not only did it cover ground faster, but the approach lacking a border was also challenged the most when it came to model predictions. As with every AI-driven system, external impacts such as climate change, pest genetic alterations, and soil health deterioration could affect biases. Additional studies should refine black box AI into Trustworthy AI (T-AI) models for farmers, as a means of enhancing robustness.

7. Conclusion

This work has shown that the adoption of AI monitoring, biological agents, and precision farming together improve pest control, crop production, resource utilization, and environmental conservation. The analysis shows that AI pest control reduced pest infestation by 80.1%, which is better than biological control and manual scouting combined. Furthermore, the crop productivity rose by 73.2% alongside AI-based monitoring. Productivity AI-based monitoring has a strong positive correlation ($r=0.88$, $p < 0.001$). The analysis has also shown significant gains in resource management. Efficiency in energy spending rose by 180.3% percent, and efficiency in the expenditure of water rose by 188.7% due to the aforementioned reasons. Additionally, the expenditures on carbon emissions were reduced by 63.6%, all of which emphasize AI’s purposes for waste reduction on the following resource. The findings correspond with previous studies that show AI agriculture input optimization results in reduced ecological impact. Apart from the agricultural benefits, AI-based pest control proved to contain computational efficiency where the processing time for CNN-based models was lowest at 1.58 ms/% accuracy as compared to other approaches of pest control. Implementation comes with its own set of challenges, such as high cost, cybersecurity issues, and the development of climate-sensitive AI models. Future studies should target cost-effective methods for AI integration, building frameworks for decentralized computing, and projecting climate change effects for more robust models. This work contributes to achieving sustainable food production because AI-enabled pest management activities fully support global sustainability objectives, including SDG 2 (Zero Hunger) and SDG 13 (Climate Action). AI innovation integrates technology, ecology, and precision farming to provide a scalable, affordable, and environmentally friendly solution for building resilient agricultural systems. Future research should entail the validation of micromanagement AI systems on other crops, expansion to other ecosystems, and for long-term impacts on food security and environmental sustainability, provide equitable access to agricultural AI tools.

References

[1] Balaska, V., Adamidou, Z., Vryzas, Z., & Gasteratos, A. (2023). Sustainable crop protection via robotics and artificial intelligence solutions. Machines, 11(8), 774.

[2] Ali, M. A., Dhanaraj, R. K., & Nayyar, A. (2023). A high-performance-oriented AI-enabled IoT-based pest detection system using sound analytics in large agricultural fields. Microprocessors and Microsystems, 103, 104946.

[3] Gossen, B. D., & McDonald, M. R. (2020). New technologies could enhance natural biological control and disease management and reduce reliance on synthetic pesticides. Canadian journal of plant pathology, 42(1), 30-40.

[4] Shaikh, T. A., Rasool, T., & Lone, F. R. (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. Computers and Electronics in Agriculture, 198, 107119.

[5] Rai, K. K. (2022). Integrating speed breeding with artificial intelligence for developing climate-smart crops. Molecular biology reports, 49(12), 11385-11402.

[6] Sakapaji, S. C., & Puthenkalam, J. J. (2023). Harnessing AI for Climate-Resilient Agriculture: Opportunities and Challenges. European Journal of Theoretical and Applied Sciences, 1(6), 1144-1158.

[7] Kirpach, M., & Riccoboni, A. (2023). AI in Agriculture. In Engineering Mathematics and Artificial Intelligence (pp. 331-364). CRC Press.

[8] Redhu, N. S., Thakur, Z., Yashveer, S., & Mor, P. (2022). Artificial intelligence: a way forward for agricultural sciences. In Bioinformatics in Agriculture (pp. 641-668). Academic Press.

[9] Tetala, S. S. D. R. (2023). Artificial intelligence powered personalized agriculture (Doctoral dissertation, Colorado State University).

[10] Mowla, M. N., Mowla, N., Shah, A. S., Rabie, K. M., & Shongwe, T. (2023). Internet of Things and wireless sensor networks for smart agriculture applications: A survey. IEEE Access, 11, 145813-145852.

[11] Shaikh, T. A., Mir, W. A., Rasool, T., & Sofi, S. (2022). Machine learning for smart agriculture and precision farming: towards making the fields talk. Archives of Computational Methods in Engineering, 29(7), 4557-4597.

[12] Khan, I., & Shorna, S. A. (2023). Cloud-Based IoT Solutions for Enhanced Agricultural Sustainability and Efficiency. AI, IoT and the Fourth Industrial Revolution Review, 13(7), 18-26.

[13] Krishna, I. (2023). Examining the Applications of Artificial Intelligence in Agriculture. Journal of Informatics Education and Research, 3(2).

[14] Alahmad, T., Neményi, M., & Nyéki, A. (2023). Applying IoT sensors and big data to improve precision crop production: a review. Agronomy, 13(10), 2603.

[15] IBRAHIM, M., Nabeel, M., Raza, M. Q., Hameed, N., Rafiq, R., Zaheer, M., ... & AMJAD, I. (2023). The role of technology and innovation in enhancing food security. Journal of Physical, Biomedical and Biological Sciences, 2023(1), 14-14.

[16] Khang, A. (Ed.). (2023). Handbook of Research on AI-Equipped IoT Applications in HighTech Agriculture. IGI Global.

[17] Singh, A. K., Singh, A. K., Kumari, J., & Kundra, K. K. K. (2023). Chapter 10 Embracing Alternative Approaches for Insect Control and Management. Advances in Entomology, 161.

[18] Sahu, S., Kaur, A., Singh, G., & Arya, S. K. (2023). Harnessing the potential of microalgaebacteria interaction for eco-friendly wastewater treatment: a review on new strategies involving machine learning and artificial intelligence. Journal of Environmental Management, 346, 119004.

[19] Alam, A., Abbas, S., Abbas, A., Abbas, M., Hafeez, F., Shakeel, M., ... & Zhao, C. R. (2023). Emerging trends in insect sex pheromones and traps for sustainable management of key agricultural pests in Asia: beyond insecticides—a comprehensive review. International Journal of Tropical Insect Science, 43(6), 1867-1882.

[20] Bhardwaj, A., Kishore, S., & Pandey, D. K. (2022). Artificial intelligence in biological sciences. Life, 12(9), 1430.

[21] Holzinger, A., Keiblinger, K., Holub, P., Zatloukal, K., & Müller, H. (2023). AI for life: Trends in artificial intelligence for biotechnology. New Biotechnology, 74, 16-24.

[22] Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2020). Machine learning applications for precision agriculture: A comprehensive review. IEEE Access, 9, 4843-4873.

[23] Ryan, M., Isakhanyan, G., & Tekinerdogan, B. (2023). An interdisciplinary approach to artificial intelligence in agriculture. NJAS: Impact in Agricultural and Life Sciences, 95(1), 2168568.

[24] Vasoya, N. H. (2023). Revolutionizing nanomaterials processing through IoT-AI integration: opportunities and challenges. Journal of Materials Science Research and Reviews, 6(3), 294-328.

[25] Duncan, E., Glaros, A., Ross, D. Z., & Nost, E. (2021). New but for whom? Discourses of innovation in precision agriculture. Agriculture and Human Values, 38, 1181-1199.

[26] Lubag, M., Bonifacio, J., Tan, J. M., Concepcion, R., Mababangloob, G. R., Galang, J. G., & Maniquiz-Redillas, M. (2023). Diversified Impacts of Enabling a Technology-Intensified Agricultural Supply Chain on the Quality of Life in Hinterland Communities. Sustainability, 15(17), 12809.

[27] Sachithra, V., & Subhashini, L. D. C. S. (2023). How artificial intelligence is used to achieve agriculture sustainability: Systematic review. Artificial Intelligence in Agriculture, 8, 46-59.

[28] Ibrahim, L. A., Shaghaleh, H., El-Kassar, G. M., Abu-Hashim, M., Elsadek, E. A., & Alhaj Hamoud, Y. (2023). Aquaponics: a sustainable path to food sovereignty and enhanced water use efficiency. Water, 15(24), 4310.

[29] Sahil, K., Mehta, P., Bhardwaj, S. K., & Dhaliwal, L. K. (2023). Development of mitigation strategies for climate change using artificial intelligence to attain sustainability. In Visualization Techniques for Climate Change with Machine Learning and Artificial Intelligence (pp. 421-448). Elsevier.

[30] Raihan, A. (2023). Artificial intelligence and machine learning applications in forest management and biodiversity conservation. Natural Resources Conservation and Research, 6(2), 3825.

[31] El-Sayad, N. E., & El-Shekheby, S. (2023). Sustainable Waste Management through the Lens of Artificial Intelligence: An In-Depth Review. Journal of Engineering Research, 7(5), 195-201.

[32] Bhamare, A., Upadhyay, V., & Bansal, P. (2023, December). AI-based Plant Growth Monitoring System using Computer Vision. In 2023 IEEE Technology & Engineering Management Conference-Asia Pacific (TEMSCON-ASPAC) (pp. 1-5). IEEE.