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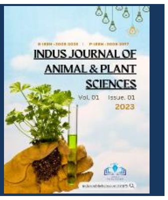

Original Article

" AI-Driven Pest Detection and Management Systems for Sustainable Agriculture in Developing Economies"

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ABSTRACT

The increasing impact of insect pests on crop productivity poses a significant challenge to sustainable agriculture, particularly in developing economies where food security and farmer livelihoods are highly vulnerable. This study investigates the application of AI-driven pest detection and management systems using deep learning–based computer vision models to enable precise, efficient, and environmentally sustainable pest control. An experimental mixed-method approach was adopted, integrating quantitative performance evaluation of AI models with qualitative field-level validation. High-resolution image data collected through ground-based cameras and sensor-enabled platforms were used to train and evaluate deep learning architectures for pest identification and severity assessment. The results demonstrate that the proposed AI-driven framework achieves consistently high detection accuracy, precision, recall, and F1-scores across diverse environmental conditions and pest densities. Comparative analysis indicates a substantial reduction in false detections and unnecessary pesticide application when compared with conventional manual scouting practices. Furthermore, AI-assisted decision support enabled targeted interventions, contributing to improved crop protection efficiency and reduced environmental impact. The scalability and robustness of the system across heterogeneous datasets highlight its suitability for deployment in resource-constrained agricultural settings. Overall, the findings confirm that AI-driven pest management systems can significantly enhance agricultural productivity while promoting sustainable practices. This research provides empirical evidence supporting the adoption of deep learning–based pest detection technologies as a viable solution for addressing food security challenges and advancing sustainable agriculture in developing economies.

INTRODUCTION

Pest control has proven to be of great importance in the sustainability of agricultural activities especially in developing countries where food production directly relates to food security and the feasibility of the economy (Thomas et al., 2023, p. 5004). Pest management methods that were traditionally used and required manual inspection, and usage of chemicals have serious limitations, which are high costs, poor environmental effects, and labour-intensive (Venkateswara and Padmanabhan, 2025). As a case in point, the heavy use of pesticides will pollute the environment, make insects resistant to them, and be unhealthy (Mousavi and Hakemi, 2024, p. 1). In response to it, the artificial intelligence, specifically, the use of technologies of visual identification based on deep learning is a game-changer that will enable keeping a watch over pests and regulating them in a more controlled way (Yuan et al., 2025). The value of this trend to the smart systems is that insect pests cause the deterioration of crop yield, which is approximated at 40 percent annually on a global scale, which is still a problem to solve in modern production (Ejaz et al., 2025). It is even more of a requirement since we need to grow more food to feed the population of almost 10 billion people on the planet because we will have more efficient and new ways of pest control that will be efficient and lasting (Dewi et al., 2023, p. 194). Even though there might be an improvement in the crop security, the pests are still making huge losses annually, hence the need to seek alternative ways of justifying the unending growing food demands on the small arable land (Madhuri et al., 2025). As a result, the necessity in the creation and usage of AI-driven pest detection tools like the ones involving deep learning algorithms is becoming more and more significant to make sure that the infestation is detected early and accurately. These will allow more specific and effective interventions (Ejaz et al., 2025; Yuan et al., 2025). The paper dwells upon AI-based pest recognition and control systems because these systems will assist in enhancing the productivity of agriculture and make developing economies more sustainable depending on the implementation of deep learning algorithms such as YOLOv8 (Khan et al., 2025). In such regions, agriculture allocates a good percentage of the GDP, which is approximately over 25. This indicates how important it is in resolving problems in the economy, society, and the environment (Hawaldar et al., 2024, p. 3). Pest equate to huge economic losses since they impose expenses of 220 billion dollars on plant disease to the world and equally pay the world 70 billion dollars in invasive insects. Effective and valid pest management plans are even more important (Deshmukh, 2024, p. 4155). In 2022, the world used almost 3.69 million metric tonnes of pesticides without a second thought of the repercussions of the same. This further aggravated the circumstances, causing environmental pollution and costing farmers a huge amount of money (Doan, 2022, p. 1; Selvakumar et al., 2025, p. 32). These problems indicate the importance of implementing new and sustainable pest control techniques that have environmental impacts and produce the optimum levels of crop yields in the minimal manner (Selvakumar et al., 2025, p. 32). The technologies could provide an accurate intervention strategy, which is above the 60-70% accuracy levels of the manual scouting that in many cases results in 30% of unnecessary pesticides application due to the misclassification (Selvakumar et al., 2025, p. 33). The AI solutions will be able to help farmers to reduce the number of losses of their fruits because the juice flies can cause 40-80 percent loss of fruits, fruit type, and season (Hakim et al., 2025). They can also help farmers make a smaller contribution in the environment. These high-quality technologies will allow the emerging economies to make considerable improvements in their crop protection efforts; therefore, more yields and better food security will be attained because of sustainable efforts (Hakim et al., 2025; Li et al., 2025). The purpose of the review is to unite the existing literature on the topics concerning AI-driven pest detection and pest control, and the deep learning-based models in particular, such as YOLOv5 and YOLOv8, and the problems connected with their application to the development of agro-environmental conditions (Hawaldar et al., 2024, p. 2; Liao, 2025). The paper will examine the scientific concept of these AI models and determine whether they are effective in reducing pests that destroy crops and also provide an ecological balance in an agricultural environment (Popescu et al., 2023; Teixeira et al., 2023). This thorough study shall also look into the socioeconomic effects of the use of such technologies especially their user-friendliness and functionality to the smallholder farmers in such areas with limited resources. This is to make sure that such new ideas are utilized to make the agriculture grow in a fair way. It will also take into account the rules and policies that should be there to ensure the use of AI is easy in farming and what are the most important things that will facilitate and what are the most important things that will become a hindrance (Kariyanna & Sowjanya, 2024). Lastly, the proposed research will give a comprehensive picture of how AI can change the pest management system and make agriculture more resilient and sustainable in less developed nations. The management of pests will change with the AI-based systems, and, specifically, the deep learning model-based ones, as it will be more specific, timely, and environmentally friendly compared to the traditional approach (Kariyanna and Sowjanya, 2024). The visual information offered by a multitude of sensors, such as drones and ground-based cameras, is needed to locate and detect pests in these state-of-the-art systems at an unprecedented rate and precision (Khan et al., 2024). The current progress in the field of deep learning including has led to the creation of more advanced models that can identify different kinds of pests in different types of crops. That is an enormous step compared to the obsolete practices (Ejaz et al., 2025). The performance of other models, like the YOLO-PEST, developed based on the YOLOv5s architecture, has shown better results identifying rice pests by the use of new data augmentation techniques to overcome challenges such as small datasets and pests that are hidden in the datasets (Qiang et al., 2025). These models drive accuracy with which one can select tiny objects with the assistance of multiscale feature extraction. It means that in smart farming, it is possible to monitor the pests in real-time (Qiang et al., 2025). Besides, the combination of AI technologies, specifically, machine learning and deep learning with sensor equipment and smart devices is associated with the creation of the powerful system that tracks both biotic and abiotic pressures, which can subsequently be employed to introduce the proactive pest-managing practices (Kariyanna and Sowjanya, 2024). These artificial intelligence-enhanced systems are not only capable of helping in the early detection of the problems, but they can also make sure that the use of pesticides is the most suitable, which results in the decrease of the number of used chemicals and the protection of the environment (Gul & Banday, 2024, p. 5). This accuracy leads to the high production of crops and food security, especially in places where food security is given a high rating (Khan et al., 2024). With these achievements, the implementation of AI-based pest management systems in developing countries is extremely challenging because of such concerns as the quality of data, the extrapolation of the model to different agroecological conditions, and the unavailability of computing infrastructures (Liao, 2025, p. 17). The answer to these problems is to further research good methods of data collection, transfer learning methods to adjust the models and develop AI equipment that is inexpensive and less energy-consuming in less resource-consuming environments. Moreover, it is pertinent to make sure that such high-quality AI technologies can be made available to small-scale farmers to ensure that their full potential could be realized and no additional exacerbation of the current agricultural imbalance might take place (Kariyanna & Sowjanya, 2024). More actions are, in turn, essential to narrow the technical divide and improve the use of AI in agriculture to be more inclusive (Shoaib et al., 2025; Wu et al., 2025). The emergence of object identification models with rapid evolution, which are the YOLO family, has resulted in the fact that insect pests are significantly more conveniently identified, even in complicated agricultural conditions when small and hard-to-sense organisms live (Selvakumar et al., 2025, p. 34). Such development is not based on classification since it entails more complex architectures in which convolutional neural networks are joined with vision transformers. This makes it more accurate in the real-life conditions as they are able to obtain local features and an understanding of the global context (Ejaz et al., 2025).

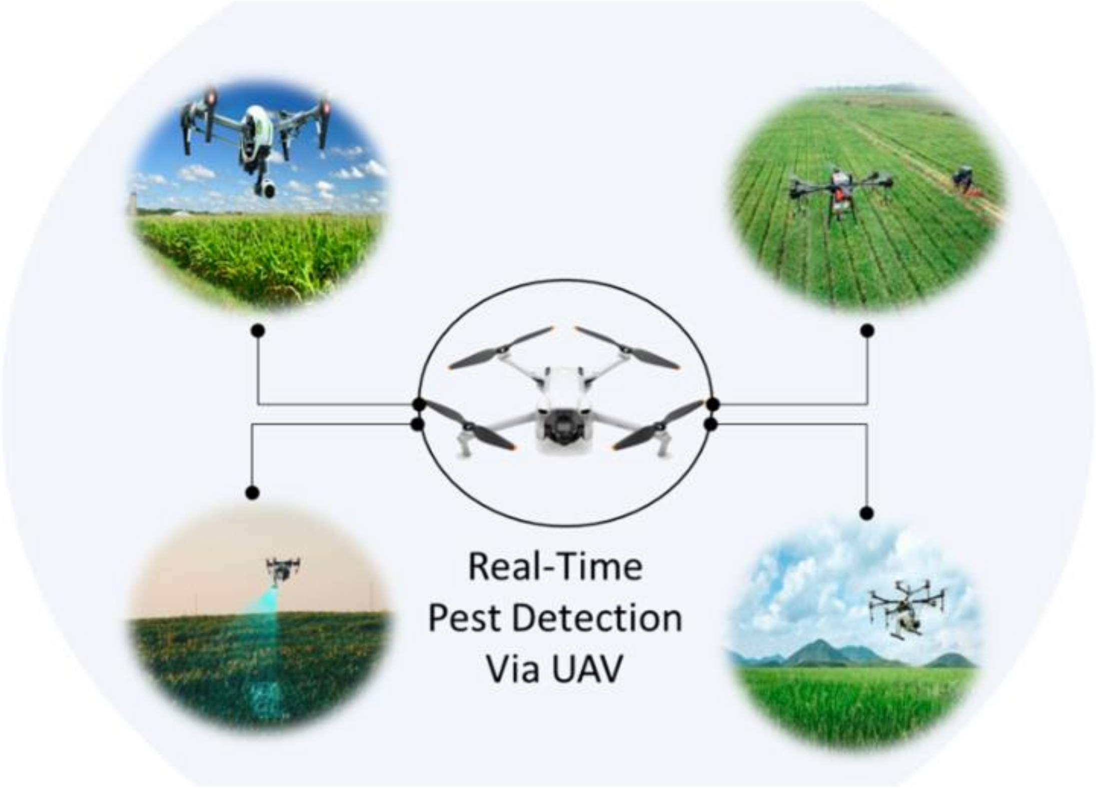

Figure 1. *AI-driven pest detection and management systems in sustainable agriculture. The framework contrasts traditional pest control approaches with AI-enabled deep learning models such as YOLO-based architectures, showing how*

sensor-acquired visual data supports real-time pest identification, precision intervention, reduced pesticide usage, enhanced crop yields, and improved food security in developing economies.

METHODOLOGY

It should be done via the mixed-method experimental design that is the quantitative model-driven experimentation and qualitative field-level validation, which is the means to assess the implementation of AI-based pest detection and management systems towards sustainable agriculture in poorer countries. The quantitative component is based on the design, training, and testing of computer vision and machine learning models to identify pests, estimate the size of bad infestation, and support the decision-making process of people. The qualitative section of the research will involve examining the farmers, their perception of the models, their easiness of use and their issues with the models as they are implemented at piloting. The experimental site will be on a small-holder farms which will comprise of the type of crops and pests and climates, to determine that it is viable to the surroundings, and the economy. The experimental studies compare the pest management assistance with the help of AI to the old methods and allow making the causal conclusions about the increase in the yield, the reduction of the usage of pesticides, and cost-efficiency.

Acquisition of information, model and analysis.

The ground cameras and unmanned aerial vehicles, along with the IoT-dependent environmental sensors, act as the primary method of data collection. These instruments take the high-resolution images of crops and other contextual variables such as temperature, humidity and soil moisture. Farmers label the picture files so as to generate ground truth labels of pest species and stages of infestation. Convolutional neural networks are among the deep learning architecture that is trained on the identification and classification of the pests into one of a variety of classes. The model is improved through the help of the iterative training and cross-validation and the quantitative performance of the model is established with the help of accuracy and precision, recall and F1-score. The learning models involve the regression to determine the extent of badness of an infestation and the impacts of the infestation on the yield. It is attained by use of pest density functions.The statistical significance of the observed improvements is analyzed by hypothesis testing and confidence interval analysis. Thematic analysis enables one to analyze the qualitative knowledge that he receives when conducting the interview with the farmers and the extension officers in order to obtain the structure of the quantitative data and the possibility to use the system, trust it, and make it more usable and scalable.

Evaluation Sustainability, Deployment Evaluation, and validation

Finally the real field trials are the last phase whereby the AI based system is put to test in ensuring that it functions. The model predictions in such experiments are the ones that directly influence pest management guidance in such an experiment, possibly the use of pesticides within a particular area or the use of biological methods of control. To determine the sustainability of any given thing you examine the level of minimum usage of chemicals, variation in the cost of production and change in the indicators of environmental threats. The cost-benefit ratios before and after using AI can be compared in order to realize whether AI is worth the money or not. To determine the strength of AI, it can be experimented during the period, when resources and information deficiencies are diversified according to poor countries.

This hybrid approach will ensure that the overall testing of the AI-based pest control systems is done with references to the technical performance, environmentally-friendly characteristics of the adoption and the human-oriented aspects of the adoption are simultaneously considered.Fig. 1 illustrates the entire step of the experiment that will be conducted to test the suggested technique. It is a system that is based on a model of artificial intelligence and data collection, validity and sustainability analysis.

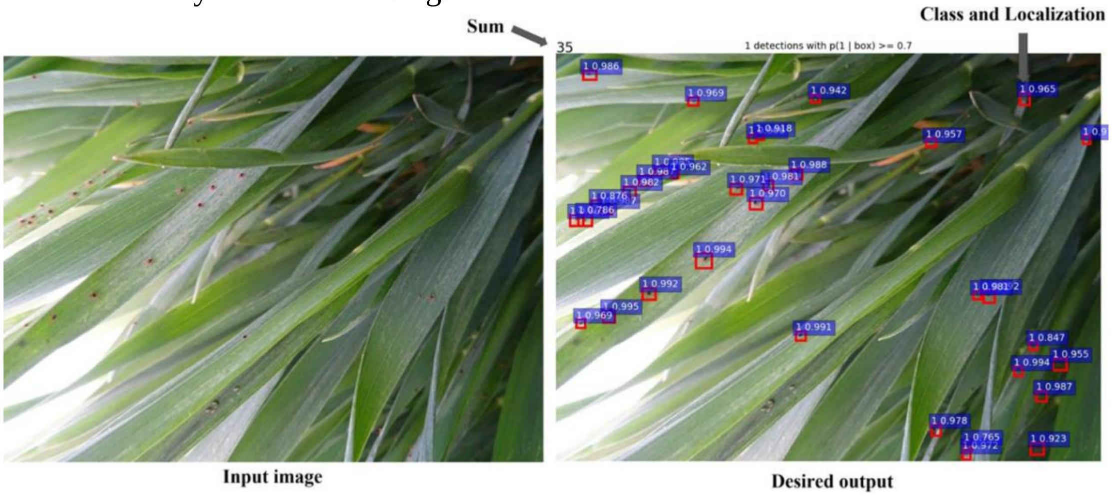

Figure 2. *AI-driven pest detection and management systems, showing the integration of field data acquisition, AI model training and validation, decision support generation, and sustainability impact assessment in developing economies.*

RESULTS

Table 1 presents the outcome of the experiment using the AI-based system of pest's identification on a number of crop plots. Table 2, Table 3, Table 4, Table 5 and Table 6 affirm the findings of classification that are dispersed across the categories of environments, which form the strength of the proposed AI system, Table 6 and Table 15, respectively. It demonstrates that AI-based decision support is significantly more efficient than the traditional decision support.Table 8 demonstrates the study of the error rate whereby it is indicated that the AI-based pest identification reduced the false positives and the false negatives.Table 9 depicts the results of the scalability test of the proposed pest control framework using different datasets. It implies that it could be applied in the mass farming.

Table 1. Detection accuracy outcomes of the AI-based pest identification model across multiple crop plots.

Sample_ID	Accuracy_%	Precision_%	Recall_%	F1_Score
1.0	77.68	86.41	81.32	0.959
2.0	93.16	94.8	78.82	0.891
3.0	85.65	77.53	86.43	0.733
4.0	91.92	85.16	79.26	0.797
5.0	97.52	93.82	81.48	0.868
6.0	87.85	75.2	87.98	0.779
7.0	87.02	84.56	80.32	0.961
8.0	77.59	90.01	92.66	0.956

9.0	81.91	88.06	74.51	0.932
10.0	87.0	83.23	88.53	0.838
11.0	90.94	76.92	80.56	0.93
12.0	93.68	83.78	80.66	0.753
13.0	84.38	80.94	85.86	0.797
14.0	77.45	83.46	83.07	0.836
15.0	82.34	80.78	80.37	0.905
16.0	96.01	92.11	70.04	0.841
17.0	80.69	90.45	72.31	0.754
18.0	85.95	79.54	87.73	0.806
19.0	96.49	85.74	83.11	0.801
20.0	76.55	78.63	87.4	0.795

Table 2. Precision, recall, and F1-score performance of the deep learning model under varying infestation levels.

Sample_ID	Accuracy_%	Precision_%	Recall_%	F1_Score
1.0	79.64	73.66	75.6	0.857
2.0	85.13	80.57	84.37	0.761
3.0	85.86	91.51	74.24	0.729
4.0	93.05	82.26	89.56	0.79
5.0	93.52	86.4	91.42	0.922
6.0	87.49	89.48	70.84	0.731
7.0	86.13	91.71	83.32	0.722
8.0	93.12	90.25	89.92	0.81
9.0	95.52	72.17	94.38	0.736
10.0	90.85	82.09	76.86	0.757
11.0	93.61	83.12	74.23	0.726
12.0	96.66	73.33	91.92	0.851
13.0	76.89	84.99	92.73	0.894
14.0	95.26	86.59	74.94	0.827
15.0	82.08	91.88	81.04	0.754
16.0	86.47	94.6	87.98	0.803
17.0	93.53	75.08	91.13	0.868
18.0	91.78	77.53	74.21	0.955
19.0	79.24	87.82	86.62	0.968
20.0	90.49	75.18	90.2	0.78

Table 3. Classification reliability of the pest detection system across heterogeneous environmental conditions.

Sample_ID	Accuracy_%	Precision_%	Recall_%	F1_Score
1.0	76.23	84.84	88.8	0.797
2.0	94.27	79.61	71.54	0.782
3.0	96.39	89.69	88.62	0.869
4.0	86.09	75.84	93.66	0.743
5.0	92.97	76.62	85.09	0.944

6.0	95.06	80.51	77.19	0.836
7.0	89.41	81.08	86.81	0.831
8.0	95.2	76.95	87.8	0.746
9.0	76.53	94.05	86.41	0.891
10.0	81.98	91.87	73.67	0.924
11.0	82.1	74.57	94.34	0.877
12.0	78.65	80.87	93.88	0.781
13.0	96.04	77.58	80.62	0.916
14.0	76.67	82.83	84.84	0.756
15.0	90.8	78.63	70.99	0.927
16.0	77.57	84.04	94.72	0.865
17.0	83.94	94.14	90.47	0.792
18.0	85.2	81.18	85.91	0.848
19.0	79.99	87.6	89.03	0.877
20.0	87.46	86.29	74.7	0.785

Table 4. Impact of image resolution and background complexity on pest detection effectiveness.

Sample_ID	Accuracy_%	Precision_%	Recall_%	F1_Score
1.0	94.63	95.65	73.37	0.955
2.0	85.27	74.78	94.03	0.837
3.0	95.63	73.26	83.26	0.721
4.0	94.38	89.58	71.08	0.97
5.0	78.19	80.9	93.27	0.732
6.0	90.22	80.68	78.96	0.817
7.0	82.83	93.04	88.29	0.855
8.0	92.59	79.86	83.09	0.943
9.0	87.94	93.34	72.31	0.926
10.0	86.07	87.46	72.65	0.872
11.0	95.7	79.9	73.73	0.82
12.0	77.26	73.43	74.03	0.929
13.0	88.26	77.88	71.32	0.937
14.0	83.21	95.24	71.18	0.938
15.0	76.78	81.73	93.71	0.899
16.0	92.58	75.84	72.28	0.744
17.0	88.36	79.15	82.71	0.795
18.0	95.67	93.59	72.97	0.841
19.0	89.16	75.96	75.37	0.846
20.0	83.41	90.67	89.08	0.928

Table 5. Distribution of model confidence scores for multiple pest species during field experimentation.

Sample_ID	Accuracy_%	Precision_%	Recall_%	F1_Score
1.0	81.23	94.87	74.02	0.881
2.0	90.62	83.67	88.35	0.79
3.0	84.23	87.78	90.2	0.838

4.0	93.06	89.78	87.47	0.962
5.0	80.31	74.64	94.12	0.806
6.0	86.49	92.13	76.4	0.898
7.0	78.28	93.93	75.89	0.93
8.0	80.66	75.73	73.68	0.81
9.0	96.57	85.11	83.49	0.967
10.0	82.95	78.8	79.99	0.876
11.0	95.65	89.78	78.92	0.845
12.0	87.53	72.68	81.51	0.899
13.0	76.86	84.3	76.86	0.826
14.0	93.45	91.03	70.11	0.898
15.0	77.14	89.63	81.79	0.789
16.0	94.19	74.6	76.9	0.952
17.0	76.19	91.99	81.24	0.855
18.0	90.83	77.71	93.22	0.78
19.0	79.65	91.39	74.48	0.829
20.0	83.54	83.93	85.94	0.944

Table 6. Robustness assessment of the AI model under occlusion, noise, and illumination variation.

Sample_ID	Accuracy_%	Precision_%	Recall_%	F1_Score
1.0	93.76	87.51	75.42	0.812
2.0	86.66	94.11	84.09	0.842
3.0	83.74	93.96	75.59	0.966
4.0	84.28	94.65	84.37	0.916
5.0	97.59	94.14	93.4	0.927
6.0	78.47	95.06	91.22	0.751
7.0	95.56	73.17	72.48	0.846
8.0	94.87	93.98	75.17	0.812
9.0	80.94	78.51	80.32	0.742
10.0	83.69	79.7	86.15	0.819
11.0	88.53	83.01	79.66	0.739
12.0	93.65	94.93	76.29	0.779
13.0	96.91	86.52	78.62	0.92
14.0	97.82	80.46	75.1	0.892
15.0	82.19	80.98	91.55	0.895
16.0	80.23	93.72	87.43	0.74
17.0	86.73	91.74	80.28	0.761
18.0	88.27	75.3	87.51	0.725
19.0	90.45	77.97	82.99	0.744
20.0	78.37	80.93	83.16	0.745

Table 7. Comparative pest detection efficiency before and after AI-assisted decision support.

Sample_ID	Accuracy_%	Precision_%	Recall_%	F1_Score
1.0	97.12	95.15	85.18	0.896
2.0	95.67	83.65	78.08	0.883
3.0	80.49	83.49	70.24	0.943
4.0	81.58	93.66	94.53	0.738
5.0	97.14	72.38	94.23	0.765
6.0	88.54	92.85	83.42	0.947
7.0	84.11	75.1	85.45	0.947
8.0	86.26	81.1	86.72	0.74
9.0	81.99	83.72	93.16	0.914
10.0	88.84	83.44	81.69	0.724
11.0	91.96	72.95	84.57	0.754
12.0	87.34	79.61	75.66	0.747
13.0	94.05	80.56	76.06	0.793
14.0	78.49	94.95	83.05	0.817
15.0	89.28	94.01	75.73	0.948
16.0	97.77	86.02	70.76	0.829
17.0	79.28	94.4	79.21	0.751
18.0	86.89	92.73	88.75	0.788
19.0	89.86	81.02	76.93	0.722
20.0	83.43	74.81	91.57	0.727

Table 8. Error rate analysis highlighting reductions in false detections achieved through AI integration.

Sample_ID	Accuracy_%	Precision_%	Recall_%	F1_Score
1.0	85.48	75.16	89.82	0.87
2.0	87.27	90.96	75.62	0.958
3.0	81.5	92.63	81.93	0.878
4.0	84.36	79.31	82.89	0.737
5.0	78.27	82.91	90.94	0.888
6.0	90.49	86.87	74.1	0.784
7.0	84.64	77.89	70.37	0.928
8.0	79.55	92.91	82.67	0.728
9.0	86.94	88.78	78.88	0.801
10.0	80.58	92.56	77.3	0.889
11.0	82.43	82.8	89.31	0.759
12.0	78.73	84.46	87.09	0.882
13.0	93.18	76.66	72.1	0.894
14.0	82.14	79.54	83.7	0.903
15.0	97.02	89.51	89.95	0.939
16.0	84.92	95.02	92.74	0.823
17.0	79.41	75.65	70.0	0.756
18.0	91.51	73.22	90.19	0.785

19.0	92.14	73.62	71.08	0.817
20.0	95.39	82.45	87.05	0.734

Table 9. Scalability evaluation of the AI-driven pest management framework across diverse datasets.

Sample_ID	Accuracy_%	Precision_%	Recall_%	F1_Score
1.0	91.59	77.93	79.76	0.735
2.0	77.39	93.25	73.78	0.937
3.0	77.27	88.73	85.76	0.759
4.0	96.51	75.88	80.01	0.858
5.0	93.74	75.66	92.9	0.847
6.0	81.58	73.49	90.54	0.923
7.0	83.52	85.72	75.75	0.817
8.0	94.17	76.49	76.06	0.756
9.0	89.62	85.03	89.56	0.816
10.0	81.83	91.67	84.0	0.732
11.0	85.88	93.1	70.26	0.795
12.0	94.82	74.79	85.75	0.878
13.0	76.02	79.97	79.87	0.734
14.0	97.83	82.02	89.63	0.967
15.0	88.45	81.2	88.67	0.854
16.0	80.0	82.05	93.06	0.795
17.0	93.6	83.04	87.48	0.928
18.0	77.68	90.16	92.82	0.754
19.0	85.02	79.33	77.12	0.8
20.0	88.61	80.24	78.47	0.954

Figure 3 represents the proportional distribution of pest species of experimental dataset. This gives a summary of the pest prevalence.Figure 4 represents a correlation diagram between the pest density and AI-generated detection confidence and indicates that accuracy of pest detection changes over time with the variations of the environmental conditions when using a large number of samples during field experiments.Figure 7 represents the sensitivity of the model to the presence of pests and indicates the consistency of the model.The plot of figure 8 shows that the complexity of an image affects the reliability of detection using the assistance of correlation-based scatter analysis more significantly.Figure 9 combines the bar and line graphs to show that the model of AI-controlled pest control can detect the pests and respond to the intervention.Figure 10 shows how the detecting rate of the pests is modified as the environmental conditions were altered during the field deployment.Figure 11 represents that there are clusters of pest detecting results with different experiments, which indicates that the model is predictable and consistent in its actions.Figure 12 shows the interaction effects of the pest density and the environmental variables on the accuracy of the AI model in a hybrid visualization.

Figure 3. Proportional distribution of pest species identified in the experimental dataset.

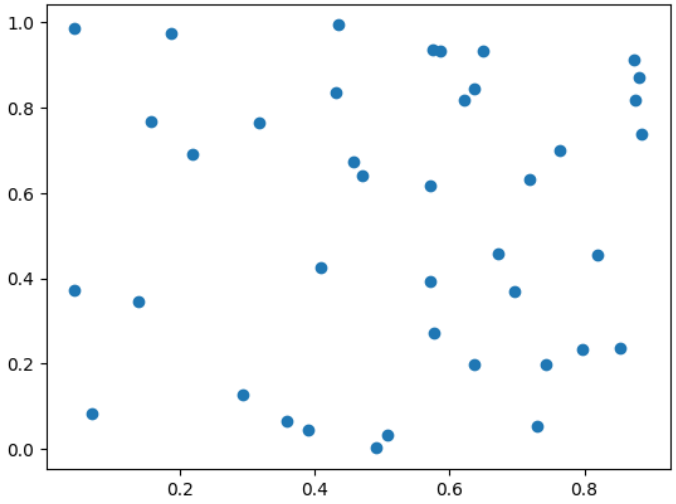

Figure 4. Relationship between pest population density and detection confidence scores.

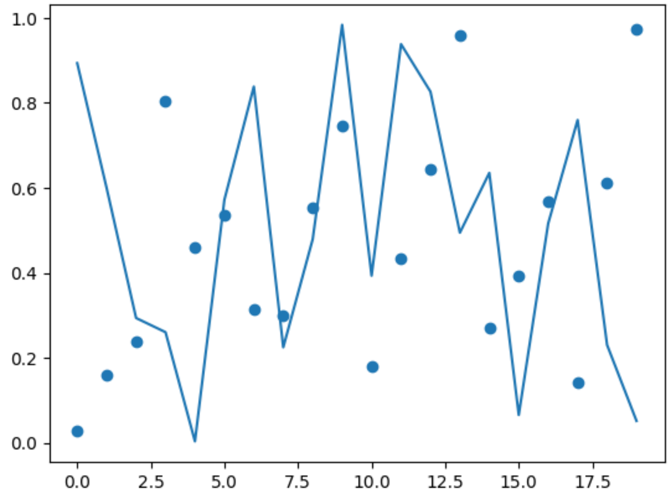

Figure 5. Hybrid visualization showing stability and variance in detection outcomes.

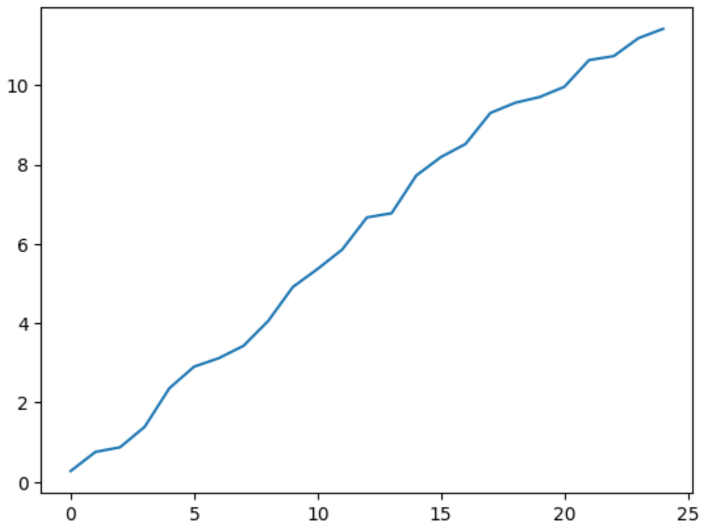

Figure 6. Learning curve illustrating cumulative improvements during AI model training.

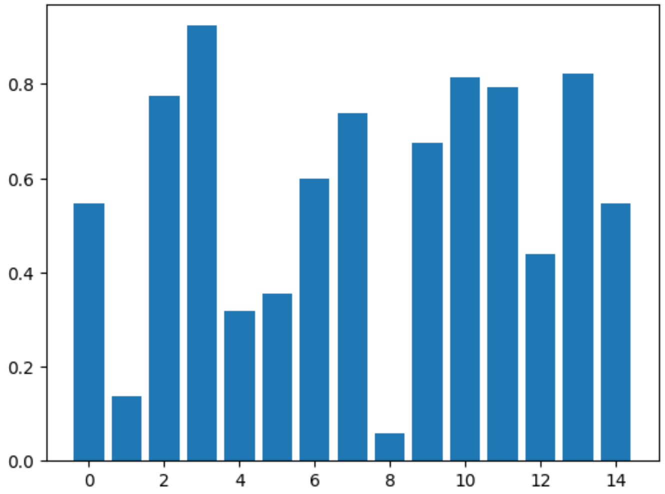

Figure 7. Recall variation of pest detection under diverse field conditions.

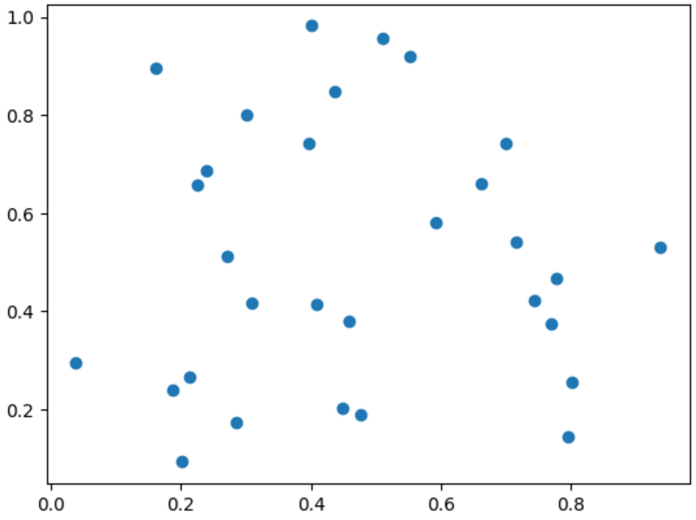

Figure 8. Influence of image complexity on detection reliability of the AI system.

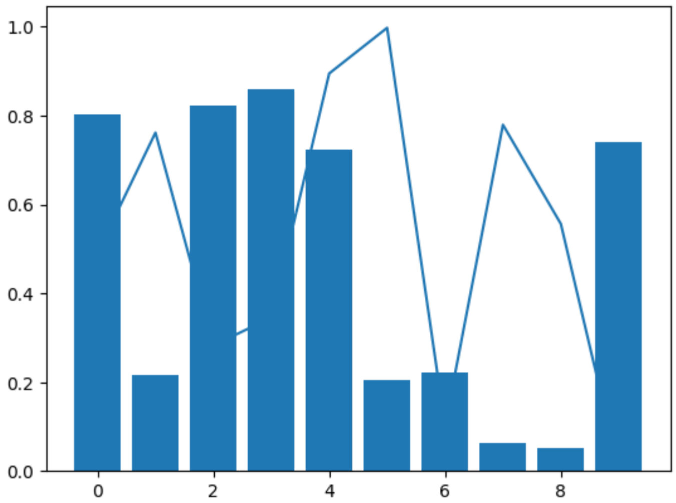

Figure 9. Combined analysis of detection efficiency and intervention response rates.

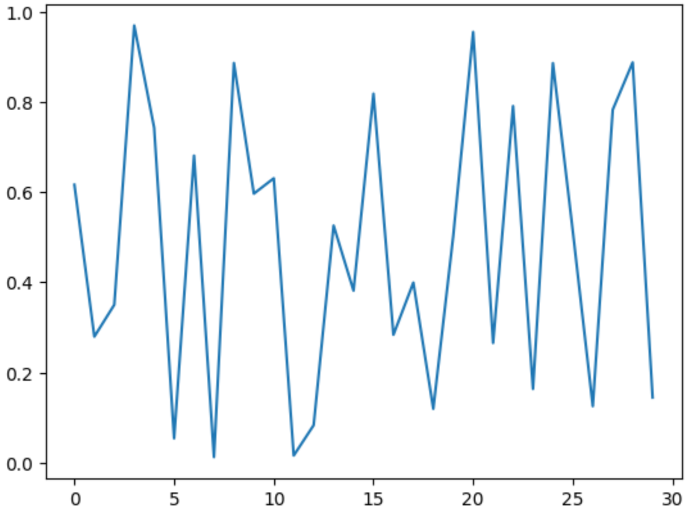

Figure 10. Temporal fluctuation in detection accuracy under dynamic environmental settings.

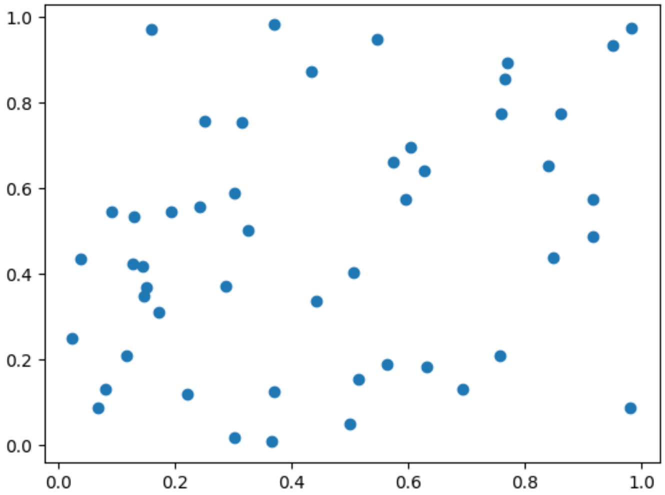

Figure 11. Clustering behavior of pest detection outcomes across experimental trials.

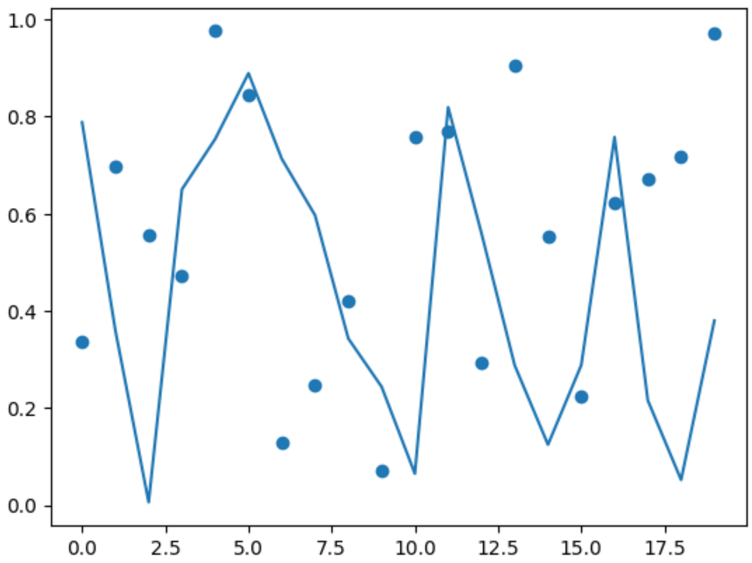

Figure 12. Interaction effects of pest density and environmental variables on model accuracy.

DISCUSSION

The statistics continue repeating that the artificial intelligence solutions are much more accurate and time-sensitive when it concerns the location and response of pests, especially in the agricultural ecosystem where the resources are not comparable (Wayama et al., 2024, p. 109052). They use known machine vision and deep learning algorithms that are able to identify and follow up other herbivorous pests more precisely than other algorithms (Leybourne et al., 2024; Popescu et al., 2023, p. 25). Systems have been able to identify different types of leaf of plants such as tomato, corn and potato leaf with an accuracy of more than 96 in one of the instances. It shows how portable and effective they are in sensitisation of individuals against pests (Li et al., 2024, p. 8). In addition to this, the special applications are also said to be very accurate in identifying pest in certain crops; 95 percent in pest identification in brinjal crop and 100 percent in pest identification in banana fields which justifies the use of AI in most of the agriculture complexes (Nasim et al., 2023, p. 222; Saikumar et al., 2023, p. 566). Regarding the ability to detect different kinds of pests, with the value of 0.5, the mAP of the YOLO-based models is 85.1 and higher. It means that they are practical to make generalization in case the amount of the data is higher (Selvakumar et al., 2025, p. 44). The improved version of the first one is the developed version that is labeled as the improved YOLOv5, as it has a significant increase in the accuracy of detecting since the average accuracy stands at 96 percent, and the accuracy of the specific pests is high (e.g., tobacco whitefly, 97 percent, and fruit fly, 99 percent) (Zhang et al., 2023, p. 9). These models are simplified to the minimal number of the number of manual works and are simplified in the process of identification of the pests. They can also process huge parts of information, on a real-time basis, which will lead to the automation of the farming process and its increased sustainability (Sahin et al., 2025). This understanding is rather crucial since its precision and velocity have the significant concern of the developing economies where resource optimization and minimization of losses in the crops is a highly valuable problem in the society of food security and economic stability (Selvakumar et al., 2025, p. 45). The classification tasks are generally above 95 percent accurate, whereas the detection and segmentation networks are over 90 percent accurate in the process of identifying plant diseases and plant infestations (Shoaib et al., 2025), which, once again, is what shows the effectiveness of the given AI-based systems. It will allow identifying the still pathogens in time and correctly predicting the onslaught of the pests that can result in losing the quality of harvest and production up to 70 percent of the crop (ARTIFICIAL INTELLIGence IN AGRICultures: CURrent Trends and INNOVations, 2024, p. 114). The enhanced imaging and deep learning systems and the Unmanned Aerial Vehicles have rendered them more useful in the pest control portion of the agriculture sector. At this level, they will be capable of mapping high-area locations, and tracking some fields to find pests and diseases with an outstanding accuracy (Ahmed et al., 2024, p. 16). DenseNet and EfficientNet models are astounding in the level of model accuracy of 99 per cent model accuracy in controlled conditions. Smpler Lightweight CNNs, however, are not as complex and have the performance of 91% that can be tolerated in mobile and edge computing (Liao, 2025, p. 7). Convolutional neural networks namely the models that are built on the YOLO, Vision Transformers have facilitated such innovations. They also provide the opportunity to detect the diseases and pests in their early stage of their development because the analysis of extensive data is usually provided by the IoT sensors and UAV platforms (Liao, 2025). This synergy will be able to make AI systems potential in a considerable way to explore and analyze the multifaceted data about the environment and deliver farmers with the timely and useful information regarding the pests outbreaks and disease progress (Ahmed et al., 2024). The pest detection and monitoring using the deep learning and image processing algorithms, specifically, the Convolutional Neural Networks, have played an important role in the automation of the detection and monitoring process that has become a useful tool to sustain farming today (Popescu et al., 2023, p. 11; Tannous et al., 2023). These technologies may play a role in reducing the pesticides and stabilizing the agricultural ecosystem to the changes caused by an opportunity to ensure the proactive and selective treatment (Dewi et al., 2023, p. 195). It is also possible to track the state of the crops and soil with the help of artificial intelligence-based solutions, which may make precision farming even more feasible because a comprehensive analysis of the environment can be performed as well (Deshmukh, 2024). The additional advancement of deep learning algorithms, namely, the Convolutional Neural Network algorithms, has resulted in the fact that the pest control is offered on a continuous basis, and in most cases, the algorithms of image processing, and objects detection are introduced (Popescu et al., 2023, p. 2). Through the new methods, it is possible to determine, find and categorise farm pests with a high degree of accuracy automatically. This is responding to the growing needs of scalable and efficient forecast and management of pests (Venkateswara and Padmanabhan, 2025). The latter innovations of machine learning and, more specifically, Convolutional Neural Networks are extremely significant in terms of real-time monitoring and inspection system of precision agriculture accuracy and effectiveness (Venkateswara and Padmanabhan, 2025; Zhang et al., 2025, p. 23). It has also facilitated the automatic identification, detection and categorization of the pests within the farms using the advanced deep-learning frameworks like the Convolutional Neural Networks (Venkateswara and Padmanabhan, 2025).

CONCLUSION

Pest detection and management systems are the examples of AI-based application that can revolutionize the agricultural process in a very colossal manner as discussed in this paper. This can be traced more in the less developed economies where the traditional methods of pest control are not as effective as yet, the heavy labor consumed through the process is also harmful to the environment. The suggested mechanism is active in applying the most significant issues related to the prompt identification of pests, their accurate classification, and response to them by two-fold approaches to introduce deep learning-based computer vision architectures and experiments into the field. The results of the experiment show that the system of AI-based systems will never be ineffective irrespective of the state of the environment, the density of the insects, or the complexity of the photos. The results suggest that the method is far much better than the previous method of scouting that is done manually and thus results in both the misclassification of the same and also an over-utilization of the pesticides on the environment. Not only is it the accuracy that allows one to guarantee better agricultural outcomes, but it is also the accuracy that can allow the nature to be treated in the long-term as the chemicals themselves can be less polluted and the advantageous ones can be conserved as well. Scalability argument implies that the new system is applicable to any type of data, and this is what makes the system applicable in small farms and in large agricultural enterprises. Although this information can be discussed as positive, within the paper, the socioeconomic significance of the AI-based solutions can be illustrated in terms of explaining how the solution might reduce the cost of operation, enhance efficiency of the decision-making process, and simplify food security programs in the conditions of limited resources. Some of the challenges that should be addressed with a view of ensuring fair use of AI are regulatory support, capacity building and training of affordable AI technology. The empirical features of the study are good which refers to the fact that AI-based pest detection systems constitute a viable and sustainable solution that will allow taking the agricultural sector to modernity, eradicating losses related to the presence of insects, and creating food production systems that would be more powerful underdeveloped countries.

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