A Review of Crop Pest Classification and Pesticide Recommendations Using AI Techniques

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ABSTRACT

This study presents a thorough review of existing approaches for crop pest classification and pesticide recommendation. Crop pest management has become a significant challenge in modern agriculture due to rising pest diversity, climate change, and the limitations of conventional detection and control practices. Artificial Intelligence (AI) allows automating pest identification and optimizing pesticide usage. The current study examines state-of-the-art Machine Learning (ML) and Deep Learning (DL) models, hybrid architectures, and multimodal frameworks used for pest detection and classification from image and sensor data. Additionally, the survey analyzes various knowledge-based, data-driven, and decision-support techniques employed for pesticide recommendation, highlighting their effectiveness and applicability. Crucial limitations, such as data scarcity, class imbalance, domain variations, and the need for sustainable pesticide practices, are also identified. The application of ML and DL is explored to improve the speed and accuracy of crop pest classification and pesticide recommendation, overcoming the limitations of traditional, human-dependent methods.

Keywords-crop pest classification; pesticide recommendation; Artificial Intelligence (AI); Machine Learning (ML); Deep Learning (DL)

I. INTRODUCTION

Agriculture plays a crucial role in global economic development by providing food for humans and animals and supplying raw materials for various industrial sectors. It also contributes significantly to the economies of developing countries [1]. However, the agricultural sector faces increasing pressure from several factors that affect its ability to meet future food demand. The global population is expected to have exceeded 9 billion by 2050, requiring an estimated 50–53% increase in food production by mid-century. In addition, climate change, inefficient resource use, and food waste further complicate efforts to achieve sustainable agriculture [2-4].

To address these challenges, Smart Agriculture, also known as Agriculture 4.0, has emerged as a technology-driven approach that integrates Information Technology (IT), Artificial Intelligence (AI), and Machine Learning (ML). These technologies improve agricultural processes, increase crop productivity, and reduce the use of pesticides and other hazardous substances. Precision agriculture, a key part of smart agriculture, focuses on optimizing spatial farming activities using data-driven decision-making tools [5].

AI has been widely used in agriculture for tasks such as soil and crop monitoring, predictive modeling, and agricultural robotics. AI techniques enable several applications, including pest detection, plant disease diagnosis, targeted agrochemical application, climate adaptation, nutritional optimization, and crop yield prediction. Sensor-based systems powered by AI provide farmers with accurate field data that support informed decision-making. As a result, these technologies improve productivity, enhance crop quality, and promote sustainable farming practices while reducing reliance on harmful chemical inputs [6-8].

Despite these advancements, several research gaps remain. Many studies rely on limited annotated datasets and face challenges such as class imbalance and long-tailed data distributions. In addition, models often demonstrate weak cross-domain generalization across different crops and environmental conditions. Few studies provide field-validated, end-to-end systems that integrate pest detection with pesticide recommendation. Furthermore, there is a lack of standardized benchmarks that incorporate environmental and economic factors. Issues related to model interpretability, human-in-the-loop evaluation, sustainability, resistance management, and socio-economic constraints are also insufficiently addressed.

This study presents a comprehensive review of crop pest classification and pesticide recommendation systems. It examines multimodal and hybrid architectures that combine image data, sensor data, and knowledge-based systems. Unlike previous research that focuses mainly on pest detection, the present study systematically compares different model families, including classical ML approaches, Convolutional Neural Networks (CNNs), transfer learning methods, and attention-based architectures. The present work also analyzes commonly used datasets, evaluation protocols, and deployment considerations, and outlines future research directions for developing scalable and sustainable AI-based agricultural solutions.

II. RELATED WORK

Authors in [1] reviewed AI-based pest detection and farmer advisory systems in smart agriculture. They also proposed E-Xpert Bot, an AI-driven chatbot that integrates pest detection, image segmentation, and fertilizer recommendation. This system integrates pest detection from images using Deep Learning (DL) in conjunction with k-means clustering for image segmentation, as well as functionality for fertilizer recommendation. Authors in [2] analyzed 190 studies on AI in agriculture. Their review categorized sensors, communication technologies, and AI techniques, while highlighting challenges related to data acquisition, system integration, and technology adoption. Authors in [3] reviewed AI-driven automation in agriculture, including robotic irrigation, spraying, and weed management systems. It integrates various AI methodologies, including sensor fusion, image recognition, and advanced control algorithms. From an environmental perspective, the study emphasizes the advantages of AI in reducing water and chemical inputs, improving crop yields, and mitigating ecological impacts.

Authors in [4] reviewed the integration of robotics, Internet of Things (IoT) sensors, Unmanned Aerial Vehicles (UAVs), and ML for sustainable crop protection and precision pesticide application. Their primary objective was to propose a conceptual framework that leverages IoT sensors, UAVs, and ML models to facilitate real-time monitoring and data-driven decision-making. The proposed system was demonstrated through case studies focusing on wheat and olive cultivation. Authors in [5] proposed a precision agriculture framework that integrates remote sensing imagery, vegetation indices, and ML models to estimate soil moisture. They paired spectral predictors with 69 ground samples, and used an 80/20 train-test split and GridSearchCV hyperparameter tuning. Tree-based regression models achieved the best performance with approximately 91% accuracy. Authors [6] reviewed DL for pest classification and pesticide recommendation, discussing CNNs (DenseNet, AlexNet, ResNet), transfer learning, preprocessing, evaluation, deployment, and the need for user-friendly interfaces. They proposed an integrated identification and recommendation pipeline.

Authors in [7] reviewed the role of AI in agricultural automation. They examined AI techniques, such as Artificial Neural Networks (ANNs), ML, fuzzy logic, and DL, for applications, including crop disease detection, irrigation management, and pesticide control. Key challenges, such as crop disease detection, irrigation management, and pesticide control, were addressed. Authors in [8] developed an IoT-enabled Crop Pest Recognition System (CPRS) utilizing the VGG-16 DL model. The system addressed the limitations of traditional pest detection methods by employing multi-level feature learning on the IP102 dataset. Their approach achieved an improved accuracy of 88.72% compared to existing methods. The integration of VGG-16 with IoT facilitated real-time monitoring and automated alerts to farmers, enhancing the effectiveness of pest management.

Authors in [9] presented U-SegNet, a DL architecture that integrates convolutional layers, residual blocks, and parallel attention mechanisms for multi-scale pest classification. The model was evaluated on the NBAIR, Xie1, and Xie2 datasets and achieved 93.54% accuracy on Xie2, outperforming UNet and ResNet. Hyperparameter analysis and recommendations for scalability and efficiency were also provided. Authors in [10] proposed a UAV-based crop monitoring framework using a modified YOLOv5 model with attention modules and multi-scale feature extraction. The model achieved 96% precision, 93% recall, and 95% mAP, demonstrating suitability for real-time pest detection.

Authors in [11] reviewed pest detection methods in smart agriculture and introduced an AIoT-based monitoring system integrating YOLOv3 for pest detection, and a Long Short-Term Memory (LSTM) model for pest occurrence prediction. The system achieved 90% accuracy for detecting Tessaratoma papillosa and enabled real-time monitoring through a mobile application. Authors in [12] developed a ResNet-50 DL model for identifying pests in soybean crops. Their review highlighted the challenges associated with traditional pest identification methods and the advantages of DL approaches. The model was trained on images of soybean pests and achieved high accuracy in classification.

Authors in [13] proposed the Faster-FestNet architecture, which combines Faster R-CNN with MobileNet for crop pest detection. They compared several existing models, emphasizing challenges such as image distortion handling and computational efficiency. Evaluated on the IP102 dataset, the model achieved 82.43% mAP and demonstrated improved performance compared with several conventional CNN architectures. Furthermore, when tested on a locally collected crop dataset, the model exhibited strong generalization capability. Authors [14] introduced MADN, an enhanced DenseNet model incorporating selective kernel units, representational batch normalization, and ACON activation. The model achieved higher accuracy and F1-scores than ResNet-101 and GoogLeNet on the HQIP102 dataset.

Authors in [15] proposed the lightweight Faster-PestNet framework based on MobileNet for crop pest detection. The model achieved 82.43% mAP on the IP102 dataset while maintaining computational efficiency for practical deployment. A key advantage of the proposed model is its ability to effectively handle image distortions while maintaining robust performance in pest identification and classification. Authors in [16] proposed a CNN-based system to determine whether crop pests are beneficial or harmful. By reviewing various existing pest detection techniques, they highlighted the advantages of DL approaches. Their trained model achieved 90% accuracy on a dataset of 9,500 pest images. Additionally, transfer learning using architectures, such as VGG19, Inception V3, ResNet50, and MobileNet, yielded an accuracy of 88%.

Authors in [17] evaluated ML classifiers, including Support Vector Machine (SVM), Naïve Bayes (NB), and Random Forest (RF), for crop recommendation systems using environmental and soil data. They evaluated classifiers on agricultural datasets for accuracy, precision, and recall, and presented a user-friendly decision support system incorporating environmental and soil inputs. Authors in [18] examined the historical use and classification of pesticides in relation to agricultural yield. They also explored the environmental impact of pesticides, considering factors such as degradation, migration versus sorption, volatilization, drift, and runoff. Additionally, their study highlighted the negative effects of pesticide use on water, soil, food safety, and non-target organisms.

Authors in [19] proposed a pest detection framework integrating Faster R-CNN with EfficientNet architectures. They also presented a detailed literature review on DL-based pest identification methods, emphasizing the comparative advantages of CNN and Faster R-CNN models. Using the IP102 dataset, the model achieved 99%, 96%, and 93% accuracy for datasets containing 5, 10, and 15 pest classes, respectively. Authors in [20] proposed a hybrid BiLSTM network for crop pest classification. The model integrates a pre-trained AlexNet with a BiLSTM network to combine both image-based and temporal features. The proposed model significantly improved upon traditional and existing DL methods, achieving 98.98% accuracy on 4,508 crop pest images.

Authors in [21] developed AgroAI, a crop protection system that uses a ResNet-50 model for disease detection and pesticide recommendation. The system employs a two-stage process for crop and disease identification using a ResNet-50 DL model, trained on a newly published dataset from Ghana. AgroAI integrates image recognition with a recommendation engine that provides customized pesticide suggestions based on the diagnosed disease, crop type, and prevailing environmental conditions. The system achieved 94–98% training accuracy and 84–94% validation accuracy. Authors in [22] presented a deep CNN-based pest and disease classification method using fuzzy image pre-processing and spectral graph-based segmentation. The approach improved robustness through transfer learning and data augmentation. In contrast to the common ML approaches (SVM and RF), the method is able to overcome the limitations of the datasets by using data augmentation and transfer learning to achieve similar accuracy and strong robustness.

Authors in [23] proposed the TPF-CNN model for insecticide and fertilizer recommendation. The system integrates machine vision with soil NPK sensors to support intelligent agricultural decision-making. Attention was drawn to the persistent challenges associated with the use of excessive pesticides and fertilizers, highlighting the need for precise and timely recommendation systems. Authors in [24] introduced a pest and disease detection system using transfer learning with ResNet-50 and a deep neural network. The system incorporated data augmentation to improve classification accuracy. This capability offers the potential for increased crop yields and reduced pesticide use.

Authors in [25] proposed a method leveraging transfer learning with VGG-16 and Inception ResNet-V2 CNN models. They utilized the IDADP dataset and employed data augmentation along with a weighted integration algorithm to enhance model accuracy. The proposed approach achieved an accuracy of approximately 97.71%, demonstrating superior performance compared to other methods and proving effective for crop pest identification. Authors in [26] reviewed DL methods for pest and disease detection, particularly CNN and YOLOv8 architectures. They introduced an integrated detection system to improve detection accuracy and recommendation efficiency. The system combines CNNs with YOLOv8 to enhance both the accuracy and speed of pest and disease detection, thereby facilitating timely and appropriate insecticide recommendations.

Although significant progress has been made in AI-based pest detection, several research gaps remain. Most existing studies focus primarily on pest classification using image-based DL models, while limited attention has been given to integrating pest detection with pesticide recommendation systems. In addition, many models are trained on small or imbalanced datasets, which affects their ability to generalize across different crops, environments, and geographic regions. The lack of standardized benchmark datasets and evaluation protocols also makes it difficult to compare model performance across studies. Furthermore, only a few works incorporate multimodal data sources, such as environmental sensors, weather information, and soil parameters, for comprehensive agricultural decision support. These limitations highlight the need for integrated, scalable, and field-deployable systems that combine pest detection with intelligent pesticide recommendation while considering environmental sustainability and practical agricultural constraints.

III. COMPARATIVE STUDY OF EXISTING WORKS

Table I categorizes the reviewed DL and hybrid approaches used for crop pest detection and classification. The methods are grouped into several main categories, including CNN-based architectures, YOLO-based detection models, ResNet-based techniques, domain-specific deep models, hybrid ML–DL models, multidisciplinary systems, specialized agricultural platforms, and sequence-based temporal models. Each category is further divided into subcategories based on architectural design or integration with other technologies such as IoT, robotics, transfer learning, and temporal learning models. This categorization highlights the diversity of AI approaches used in smart agriculture and provides a structured overview of existing pest detection methodologies.

TABLE I. CATEGORIZATION OF DL AND HYBRID MODELS FOR CROP PEST DETECTION AND CLASSIFICATION

Main category	Subcategory I	Subcategory II
CNN-based architectures	Basic CNN models (e.g., VGG-16)	Hybrid CNNs (e.g., with Inception)
YOLO and other detection models	YOLO variants	YOLO + other modules (e.g., IoT)
ResNet-based techniques	ResNet-only	ResNet + Extensions (e.g., DNN)
Domain-specific deep models	PestNet variants	Novel deep models (e.g., TPF-CNN)
Hybrid models (ML + DL)	ML + CNN	Fuzzy/transfer learning hybrids
Multi-disciplinary systems	IoT + ML/robotics	Smart agri platforms
Specialized tools/platforms	AI-chatbot and spraying tools	Xarvio and Drones
Sequence and temporal models	BiLSTM	YOLO + LSTM

The studies evaluated on the IP102 and related public pest datasets are listed in Table II, which shows that model architecture and dataset quality both influence pest recognition performance. Faster PestNet attained the best accuracy on IP102, suggesting an effective detection architecture, while MADN on the higher-quality HQIP102 produced lower accuracy but an intermediate F1-score, indicating a trade-off between precision/recall and dataset characteristics. The CNN ensemble delivered slightly lower accuracy, implying that ensembling alone did not surpass the specialized Faster PestNet. Overall, choosing task-tailored models and higher-quality data together offers the best prospects for improving pest classification.

TABLE II. STUDIES EVALUATED ON IP102 / RELATED PUBLIC PEST

Study	Technique / model	Dataset	Metric	Performance
[13]	Faster pestNet	IP102	Accuracy	82.43%
[14]	MADN	HQIP102	Accuracy, F1-score	75.28%, 65.46%
[15]	CNN Ensemble	IP102	Accuracy	74.13%

Table III presents IoT-based smart agriculture systems and decision-support frameworks used for crop monitoring and pest management. Table III shows diverse technological approaches for crop protection—ranging from ML/DL/IoT/robotics and AI chatbots to drones, smart monitoring, and automated spraying—each offering clear benefits such as early detection, personalized advisory, reduced chemicals, and improved resource efficiency. However, these solutions introduce trade-offs such as increased system complexity, reliance on connectivity, regional applicability limits, infrastructure needs, security vulnerabilities, and health risks. Effective deployment, therefore, requires balancing technological gains with practical constraints, robust infrastructure, and safety measures. These studies indicate that prioritizing context-specific integration and risk mitigation maximizes benefits while minimizing downsides.

A comparison of state-of-the-art crop pest detection and classification techniques is provided in Table IV. Table V presents the different AI architectures and the number of techniques used within each architecture. Table V maps eight application areas in the survey to two methodological subtypes for each category: Subtype I, the core accuracy-focused research technique, and Subtype II, the practical or deployment-oriented approach addressing real-world constraints.

These areas include crop yield assessment, soil and irrigation management, pest/weed monitoring, disease or stress detection, hybrid models, multi-object tracking, specialized architectures, and scenario or regional models. In combination, they highlight commonly used methods and datasets (e.g., IP102, Xie2, Deng, IDADP), key trade-offs between accuracy and computational efficiency, and the need for standardized benchmarks and more real-world field evaluations.

TABLE III. IoT / SMART AGRICULTURE AND DECISION SUPPORT

Study	System type	Contribution	Limitation
[1]	AI-chatbot + DL	Personalized advisory	Connectivity
[3]	Drones and robotics	Resource efficiency	Infrastructure
[4]	Smart agri system	Monitoring	Security
[7]	ML, DL, IoT, Robotics	Early detection	Complexity
[18]	Pesticide spraying	Yield improvement	Health risks

TABLE IV. COMPARISON OF STATE-OF-THE-ART CROP PEST DETECTION AND CLASSIFICATION TECHNIQUES

Study	Technique / Model	Evaluation metrics	Performance
[9]	11-layer DCNN	Recall	91.48%
		F1-score	92.98%
		Accuracy	93.54%
[10]	Modified YOLOv5	Precision	96%
		Recall	93%
		mAP	95%
[11]	YOLOv3 + k-means + LSTM + IoT	Accuracy	90%
		mAP	92%
[8]	VGG-16 + fusion model	Accuracy	88.72%
[12]	ResNet-50	Accuracy	96.25%
[16]	CNN + ML + transfer learning	Accuracy	90%
[20]	AlexNet + BiLSTM	Accuracy	98.98%
		Precision	95.98%
		Recall	96.03%
		F1-score	95.45%
[22]	Fuzzy Logic + CNN + transfer learning	Accuracy	92.6%
[23]	TPF-CNN	Accuracy	90%
[24]	ResNet-50 + DNN	Accuracy	100%
[26]	CNN + YOLOv8	Accuracy	97%
		Precision	72%

TABLE V. DIFFERENT AI ARCHITECTURES AND NUMBER OF TECHNIQUES USED IN EACH ARCHITECTURE

Category	Subtype I	Subtype II
Crop yield assessment	3	2
Soil and irrigation management	1	2
Pest/weed monitoring	1	2
Disease/stress detection	2	2
Hybrid models (ML + DL)	2	2
Multi-object tracking systems	2	1
Specialized architectures	1	2
Scenario and regional models	1	1

IV. BENEFITS AND LIMITATIONS OF AI-BASED APPROACHES

A. Benefits of AI-Based Approaches

1) High Accuracy and Efficiency

DL models, particularly CNNs, have demonstrated high accuracy—often exceeding 90%—in identifying crop pests from images, outperforming traditional methods. These models provide consistent and rapid performance, which is especially beneficial when dealing with diverse pest species and varying environmental conditions. In addition, the use of transfer learning with pre-trained models improves efficiency by reducing training time and minimizing the requirement for large datasets.

2) Precision in Pesticide Application

AI systems enable targeted pesticide recommendations based on pest type, crop variety, environmental conditions, and pest population levels. This precision reduces unnecessary pesticide usage, minimizes environmental pollution, limits pest resistance development, and decreases chemical residues on crops.

3) Early Detection and Intervention

AI-based monitoring systems facilitate early pest detection, allowing farmers to implement timely interventions before pests cause significant crop damage. Early detection is particularly important for managing invasive pest species and rapidly spreading crop diseases.

4) Accessibility and Affordability

Many AI-based solutions can be deployed on mobile devices, drones, and other digital platforms. This accessibility enables both small-scale and large-scale farmers to adopt advanced pest management technologies. As a result, AI-based systems can support scalable and sustainable agricultural practices.

B. Limitations

Key limitations and challenges faced by AI-based approaches include:

1) Data Availability and Quality

The performance of DL models depends heavily on the availability of high-quality annotated datasets. Collecting and labeling large numbers of pest images across different species and environmental conditions is both time-consuming and costly. Although data augmentation techniques can partially address this limitation, they cannot fully replace diverse real-world datasets.

2) Limited Generalizability

Models trained on specific datasets often struggle to generalize across new environments or agricultural conditions. Variations in lighting, background complexity, crop type, and climatic conditions can significantly affect model performance. Improving robustness across diverse agricultural settings remains an important research challenge.

3) High Computational Requirements

Training and deploying DL models typically require significant computational resources and specialized hardware. These requirements may limit the practical adoption of such systems in resource-constrained agricultural regions.

4) Ethical and Social Considerations

The deployment of AI in agriculture raises concerns related to data privacy, data ownership, algorithmic bias, and model transparency. Ensuring explainable AI models and responsible data management practices is significant for building trust among farmers and agricultural stakeholders.

5) Integration with Existing Agricultural Practices

For AI technologies to be widely adopted, they must integrate effectively with existing agricultural workflows. This requires the development of user-friendly interfaces, reliable field deployment strategies, and effective communication mechanisms that support farmer engagement and technology acceptance.

V. CONCLUSION AND FUTURE DIRECTIONS

This study reviewed various Artificial Intelligence (AI) techniques used for pest detection and pesticide recommendation in agriculture. Several studies have proposed different methods, contributing to more accurate and timely pest diagnosis. These AI-based approaches support experts by enabling rapid intervention, ultimately leading to improved crop yield and health.

Future research in AI-based pest detection and management should focus on several key areas. First, efficient data collection and labeling strategies should be developed to expand the availability of high-quality agricultural datasets. Second, researchers should improve the generalizability and robustness of AI models to ensure reliable performance across diverse environmental conditions. In addition, the development of computationally efficient models suitable for low-resource agricultural environments is essential. Ethical considerations, including data transparency, privacy protection, and model interpretability, should also be addressed to promote responsible AI adoption in agriculture.

Furthermore, integrating AI with other precision agriculture technologies—such as Internet of Things (IoT) sensors, robotics, and automated monitoring systems—can enable more comprehensive pest management solutions. Combining Deep Learning (DL) techniques with expert systems or rule-based decision frameworks may also enhance interpretability and improve agricultural decision-making. Finally, long-term field validation and active farmer participation will be critical for evaluating AI-based systems in real-world agricultural environments and ensuring their successful adoption.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no competing interests.

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DATA AVAILABILITY

The data presented in this study are derived from previously published articles.

AI USE AND DECLARATION OF GENERATIVE AI USE

The author used generative AI tools such as ChatGPT for assistance in language refinement and improving readability. All content was carefully reviewed and validated by the authors, who take full responsibility for the final manuscript.

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