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Artificial Intelligence-Driven Economic Threshold Prediction for Sustainable Pest Management in Agroecosystems

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Abstract: Economic Threshold (ET) and Economic Injury Level (EIL) are fundamental concepts in Integrated Pest Management (IPM), providing scientific guidance for determining when pest control measures become economically justified. However, conventional threshold estimation methods often rely on empirical observations, fixed decision rules, and historical field experiments, limiting their ability to respond to dynamic agroecosystems characterized by changing climatic conditions, pest population variability, and fluctuating economic factors. Recent advances in Artificial Intelligence (AI) have created new opportunities for developing intelligent, adaptive, and data-driven approaches for predicting economic thresholds with greater accuracy and efficiency. This review examines the current state of AI applications in predicting economic thresholds for pest management across diverse agroecosystems. The paper first discusses the evolution of economic threshold-based pest management and reviews existing literature on conventional and AI-assisted approaches. Subsequently, recent developments in machine learning, deep learning, reinforcement learning, explainable artificial intelligence, and hybrid AI models are critically analyzed with respect to their capability to forecast pest populations, assess crop damage, estimate yield losses, and support threshold-based decision-making. The review further highlights practical applications of AI in cereal, oilseed, horticultural, plantation, greenhouse, and precision agriculture systems. Current challenges, including limited availability of standardized datasets, model interpretability, regional variability, and climate-induced uncertainty, are also discussed, together with emerging research opportunities involving multimodal data fusion, edge AI, digital twins, and autonomous decision support systems.

Keywords: Artificial Intelligence; Economic Threshold; Economic Injury Level; Integrated Pest Management; Machine Learning; Deep Learning; Precision Agriculture; Pest Prediction; Decision Support Systems; Sustainable Agriculture.

I. Introduction

Agriculture is fundamental to global food security, economic development, and environmental sustainability. As the global population continues to increase, agricultural production systems are under mounting pressure to produce higher crop yields while minimizing environmental degradation and ensuring the efficient utilization of natural resources. Among the numerous factors limiting

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agricultural productivity, insect pests remain one of the most significant biotic constraints, causing substantial yield losses and economic damage across a wide range of cropping systems [1]. It has been estimated that insect pests, together with diseases and weeds, account for a considerable proportion of annual crop losses worldwide, thereby threatening food availability, farmers' livelihoods, and the sustainability of agroecosystems. Conventional pest management has historically relied on calendar-based pesticide applications or visual field scouting to determine when control measures should be implemented. Although these approaches have contributed to improved crop protection, they frequently result in excessive pesticide use, increased production costs, pesticide resistance, environmental contamination, and adverse impacts on beneficial organisms [2]. The indiscriminate application of chemical pesticides has also raised concerns regarding food safety, biodiversity conservation, and ecosystem health. Consequently, there has been a growing emphasis on developing sustainable pest management strategies that balance effective pest suppression with economic profitability and environmental protection.

Integrated Pest Management (IPM) has emerged as one of the most effective and environmentally responsible approaches for managing agricultural pests. Rather than relying exclusively on chemical pesticides, IPM integrates biological, cultural, mechanical, physical, and chemical control measures based on continuous monitoring of pest populations and crop conditions [3]. A central component of IPM is the concept of the Economic Injury Level (EIL) and the Economic Threshold (ET)**,** which provide scientifically established criteria for determining when pest control actions become economically justified. These concepts enable farmers to avoid unnecessary pesticide applications by recommending interventions only when expected crop losses exceed the costs of control. Accurate estimation of economic thresholds therefore plays a pivotal role in maximizing crop profitability while reducing environmental impacts.

Artificial Intelligence (AI) has become one of the most transformative technologies in modern agriculture because of its ability to analyze high-dimensional datasets, identify complex nonlinear relationships, and generate accurate predictive models. Machine learning algorithms, deep learning architectures, ensemble learning techniques, reinforcement learning approaches, and explainable artificial intelligence have demonstrated remarkable performance in applications such as pest identification, disease diagnosis, crop classification, yield prediction, weather forecasting, precision spraying, and autonomous agricultural robotics [4]. More recently, AI has shown significant potential for predicting pest population dynamics and estimating economic thresholds by integrating biological, environmental, agronomic, and economic variables into unified predictive frameworks. Unlike conventional threshold estimation methods, AI-based models can continuously learn from historical and real-time observations, adapt to changing environmental conditions, and improve prediction accuracy through iterative model optimization. These capabilities enable the development of dynamic economic threshold prediction systems that account for temporal variability, spatial heterogeneity, and evolving pest populations. Moreover, the incorporation of explainable AI techniques enhances the transparency and interpretability of prediction models, thereby increasing user confidence and supporting practical adoption by farmers, agricultural advisors, and policymakers.

II. Literature Review

A. Evolution of Economic Threshold-Based Pest Management

The concept of economic threshold-based pest management has evolved significantly over the past several decades, shifting agricultural pest control from routine pesticide applications toward scientifically informed decision-making. Early pest management practices primarily relied on fixed spraying schedules, where pesticides were applied at predetermined intervals regardless of pest population density or anticipated crop damage. Although such approaches initially contributed to improved crop productivity, they frequently resulted in excessive pesticide use, increased production costs, environmental contamination, and the rapid development of pesticide resistance. These limitations stimulated the development of economic decision-making frameworks that considered both pest biology and crop economics. The introduction of the Economic Injury Level (EIL) and the Economic Threshold (ET) represented a major milestone in Integrated Pest Management (IPM). These concepts established quantitative criteria for determining when pest populations become economically damaging and when control measures should be initiated to prevent unacceptable yield losses. Over time, researchers incorporated additional biological, environmental, and agronomic variables into threshold estimation, including crop growth stage, pest developmental biology, weather conditions, natural enemy populations, and regional cultivation practices [5].

B. Conventional Models for Economic Injury Level and Economic Threshold Estimation

Traditional approaches for estimating Economic Injury Levels and Economic Thresholds have generally relied on statistical analyses, regression

models, field experiments, expert knowledge, and empirical observations collected across multiple growing seasons [6]. These models establish mathematical relationships between pest density and expected yield loss while incorporating economic variables such as crop market value, pesticide cost, and application expenses. Many threshold recommendations remain crop- and region-specific because pest behavior and crop responses vary considerably across environmental conditions. Although conventional models have been successfully adopted for numerous agricultural systems, they exhibit several inherent limitations [7]. Most assume relatively stable environmental conditions and linear relationships among variables, making them less effective under rapidly changing climatic conditions or complex agroecosystems. Furthermore, these approaches often require extensive field experimentation, periodic recalibration, and expert interpretation before implementation. Their inability to continuously adapt to dynamic pest populations and environmental variability has encouraged researchers to investigate data-driven predictive approaches capable of generating more flexible and adaptive threshold estimates.

C. Artificial Intelligence Applications in Pest Detection and Monitoring

Artificial intelligence has transformed pest monitoring by enabling automated detection, identification, and surveillance using large-scale agricultural datasets. Machine learning and computer vision algorithms can process images collected from smartphones, unmanned aerial vehicles, satellites, and smart traps to identify pest species with high accuracy while substantially reducing manual scouting efforts [8]. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in recognizing insect species, classifying infestation severity, and distinguishing visually similar pests under varying field conditions. Beyond image-based detection, AI has also been integrated with Internet of Things (IoT) devices, wireless sensor networks, and environmental monitoring systems to enable continuous surveillance of pest populations. Smart pheromone traps equipped with cameras and embedded processors automatically count insect populations and transmit observations to cloud-based analytical platforms for real-time monitoring [9]. These developments have significantly improved the temporal and spatial resolution of pest surveillance, providing high-quality datasets that support predictive modeling and threshold estimation.

D. AI-Based Decision Support Systems for Integrated Pest Management

Decision Support Systems (DSS) integrate data acquisition, predictive analytics, and recommendation engines to assist farmers in selecting appropriate pest management strategies. Artificial intelligence has significantly enhanced these systems by enabling automated analysis of heterogeneous agricultural datasets collected from weather stations, IoT sensors, remote sensing platforms, and field observations [10]. AI-driven DSS can continuously evaluate pest populations, forecast infestation risks, estimate potential yield losses, and recommend economically justified intervention strategies.Modern AI-based DSS increasingly employ cloud computing, edge computing, and mobile technologies to deliver real-time recommendations directly to farmers. These platforms support precision agriculture by enabling location-specific pesticide applications that minimize unnecessary chemical use while maximizing economic returns [11]. The integration of AI with DSS represents an important advancement toward intelligent, adaptive, and sustainable pest management.

E. Machine Learning for Pest Population Forecasting

Predicting future pest populations is a critical component of economic threshold estimation because management decisions depend on anticipated rather than current infestation levels. Machine learning techniques have increasingly been adopted to forecast pest outbreaks by learning complex relationships among environmental variables, crop characteristics, and historical pest incidence. Algorithms such as Decision Trees, Random Forests, Support Vector Machines, Gradient Boosting Machines, XGBoost, and LightGBM have demonstrated strong predictive capabilities across diverse agricultural environments [12].

Unlike traditional regression-based forecasting models, machine learning algorithms effectively capture nonlinear interactions among temperature, humidity, rainfall, vegetation indices, crop phenology, soil properties, and historical infestation records. Ensemble learning methods further improve predictive accuracy by combining multiple models and reducing overfitting. These capabilities allow machine learning models to generate more reliable forecasts of pest emergence, seasonal population dynamics, and infestation risk, thereby providing valuable information for economic threshold prediction.

F. Deep Learning for Crop Health and Pest Damage Assessment

Recent advances in deep learning have substantially improved automated crop health assessment and pest damage quantification. Convolutional Neural Networks have become the dominant architecture for extracting hierarchical image features from leaf images, canopy photographs, UAV imagery, and multispectral satellite observations. These models accurately identify pest infestation symptoms, estimate damaged leaf area, classify disease severity, and monitor crop health over large agricultural landscapes [13].

Temporal deep learning architectures, including Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and Transformer-based models, extend these capabilities by analyzing sequential weather observations, crop growth patterns, and historical pest populations. Such models enable early prediction of pest outbreaks before visible crop damage occurs, thereby supporting proactive intervention strategies. Deep learning has therefore become an essential component of intelligent agricultural systems designed to estimate both biological damage and its associated economic consequences.

III. Artificial Intelligence Technologies for Economic Threshold Prediction

Artificial Intelligence (AI) has become one of the most influential technologies in precision agriculture, enabling intelligent analysis of complex agricultural datasets for improved decision-making. In pest management, AI extends beyond automatic pest identification by supporting prediction of pest population dynamics, crop damage, yield loss, and ultimately the estimation of Economic Injury Levels (EIL) and Economic Thresholds (ET). Unlike conventional statistical models, AI algorithms can capture nonlinear interactions among biological, environmental, climatic, and economic variables, allowing the development of adaptive threshold prediction models capable of responding to continuously changing agroecosystem conditions.

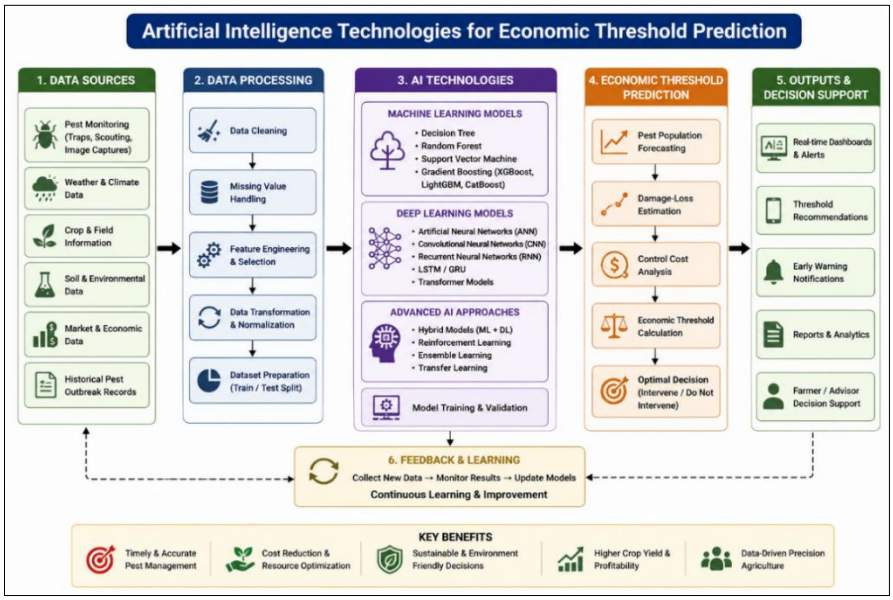


Figure 1. Artificial Intelligence Technologies for Economic Threshold Prediction.

Recent advances in machine learning, deep learning, reinforcement learning, and explainable artificial intelligence have substantially improved predictive accuracy while reducing dependence on manual field observations. These technologies process heterogeneous datasets collected from weather stations, IoT sensors, unmanned aerial vehicles (UAVs), satellite imagery, smart insect traps, crop growth monitoring systems, and historical pest records. The integration of these diverse information sources enables AI models to estimate when pest populations are likely to exceed economically acceptable limits and recommend timely intervention strategies that maximize crop profitability while minimizing pesticide use.

A. Machine Learning Algorithms

Machine learning (ML) algorithms have become widely adopted for predicting pest occurrence, infestation severity, and crop yield losses because of their ability to learn complex relationships directly from historical agricultural data. Supervised learning techniques establish predictive models using labelled observations that relate environmental conditions and pest populations to crop damage or economic outcomes. These models

continuously improve their predictive capability as larger and more diverse datasets become available.

Decision Trees represent one of the earliest machine learning techniques applied to agricultural decision support because of their simplicity and interpretability. Tree-based models recursively partition agricultural datasets according to influential variables such as temperature, humidity, rainfall, crop growth stage, pest density, and vegetation indices, producing transparent decision rules that can support threshold estimation.

Random Forest algorithms extend Decision Trees by combining predictions from multiple trees generated through bootstrap sampling and random feature selection. This ensemble strategy reduces overfitting while improving robustness and generalization. Random Forest models have demonstrated strong performance in pest outbreak forecasting because they effectively capture nonlinear interactions among climatic, biological, and agronomic variables while remaining relatively insensitive to missing data and measurement noise.

Support Vector Machines (SVMs) have also been extensively employed for agricultural classification and regression tasks. Their capability to construct optimal separating hyperplanes enables accurate discrimination between economically safe and economically damaging pest populations. Kernel-based SVM models further improve performance when dealing with nonlinear agricultural datasets, making them valuable for threshold classification problems.

Gradient Boosting algorithms, including XGBoost, LightGBM, CatBoost, and AdaBoost, have recently become dominant predictive techniques due to their exceptional accuracy and computational efficiency. These algorithms iteratively minimize prediction errors by sequentially constructing optimized decision trees that emphasize difficult observations. Their ability to model highly nonlinear relationships among weather conditions, crop characteristics, pest populations, and economic variables makes them particularly suitable for dynamic economic threshold prediction.

B. Deep Learning Models

Deep learning has significantly advanced agricultural intelligence by automatically learning hierarchical feature representations from large and complex datasets. Unlike conventional machine learning algorithms that depend heavily on manually engineered features, deep neural networks learn discriminative patterns directly from raw images, sensor observations, and temporal sequences.

Convolutional Neural Networks (CNNs) have become the dominant architecture for image-based pest recognition and crop damage assessment. These networks automatically extract spatial features from RGB images, hyperspectral imagery, multispectral satellite observations, and UAV-acquired photographs to identify insect species, quantify infestation severity, and estimate crop damage. Accurate assessment of pest-induced damage provides essential information for estimating economic losses and determining intervention thresholds.

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, are highly effective for modelling temporal agricultural processes. By analyzing historical weather observations, seasonal pest populations, crop growth stages, and previous infestation records, these networks can forecast future pest outbreaks before significant crop damage occurs. Such predictive capabilities enable proactive implementation of economic threshold-based pest management strategies.

Transformer architectures have recently attracted considerable attention because of their ability to capture long-range dependencies within sequential agricultural datasets. Attention mechanisms allow Transformers to identify the most influential environmental and biological variables affecting pest development, improving forecasting performance under complex climatic conditions. As increasingly large agricultural datasets become available, Transformer-based models are expected to play a significant role in future threshold prediction systems.

C. Reinforcement Learning Approaches

Reinforcement Learning (RL) represents an emerging paradigm for sequential agricultural decision-making in which intelligent agents learn optimal pest management strategies through repeated interaction with agricultural environments. Rather than relying exclusively on historical observations, RL continuously adapts management policies according to rewards associated with crop productivity, economic returns, pesticide costs, and environmental sustainability.

Within economic threshold prediction, reinforcement learning agents evaluate alternative intervention strategies by balancing immediate control costs against future economic losses resulting from pest population growth. State variables typically include pest density, crop developmental stage, weather conditions, natural enemy abundance, and expected market value, while actions correspond to alternative management decisions such as pesticide application, biological control, mechanical intervention, or continued monitoring.

D. Explainable Artificial Intelligence (XAI)

As artificial intelligence models become increasingly complex, understanding the reasoning behind their predictions has become essential for practical adoption within agriculture. Farmers, agricultural advisors, and policymakers require transparent explanations regarding why particular intervention recommendations are generated before integrating AI into routine management decisions.

Explainable Artificial Intelligence (XAI) addresses this challenge by identifying the relative importance of input variables contributing to model predictions. Popular approaches include SHAP (Shapley Additive Explanations), Local Interpretable Model-Agnostic Explanations (LIME), permutation feature importance, attention visualization, and counterfactual explanations.

E. Hybrid and Ensemble Learning Models

Recent research increasingly emphasizes hybrid AI models that integrate complementary computational techniques to overcome the limitations of individual algorithms. Ensemble learning combines predictions from multiple base models to improve robustness, reduce variance, and enhance predictive accuracy across diverse agricultural environments.

Common ensemble strategies include Random Forest, Gradient Boosting, XGBoost, LightGBM, stacking, voting classifiers, and blending techniques. These approaches frequently outperform single algorithms because they exploit complementary predictive strengths while reducing susceptibility to overfitting.

Hybrid AI systems further integrate deep learning, fuzzy logic, Bayesian inference, optimization algorithms, evolutionary computation, and expert knowledge. For example, CNN-LSTM architectures combine spatial image analysis with temporal forecasting, while fuzzy-neural systems incorporate uncertainty associated with pest biology and environmental variability. Bayesian machine learning models additionally provide probabilistic estimates of economic thresholds that better represent uncertainty within agricultural decision-making.

F. Comparative Analysis of AI Algorithms

The existing literature demonstrates that no single artificial intelligence algorithm consistently outperforms all others across every agricultural application. Machine learning algorithms generally provide excellent interpretability and computational efficiency for structured agricultural datasets, whereas deep learning models achieve superior performance when analysing large image collections and complex temporal sequences. Reinforcement learning offers adaptive optimization capabilities for sequential pest management decisions, while explainable AI improves transparency and user confidence. Hybrid and ensemble models frequently achieve the highest predictive accuracy by combining complementary strengths of multiple computational techniques.

Table 1. Comparative Characteristics of AI Algorithms for Economic Threshold Prediction

Algorithm	Prediction Accuracy	Interpretability	Training Speed	Overall Suitability
Decision Tree	7.5	10.0	9.8	6.9
Random Forest	9.2	8.4	7.5	8.7
Support Vector Machine	8.8	6.5	6.7	7.2
Artificial Neural Network	9.0	4.8	5.6	8.0
CNN	9.6	4.5	5.0	8.9
LSTM	9.5	4.2	4.8	9.0
GRU	9.3	4.5	6.2	8.8
Transformer	9.8	3.8	4.2	9.4
XGBoost	9.8	7.8	8.6	9.4

LightGBM	9.7	7.5	9.4	9.3
CatBoost	9.6	7.6	8.2	9.2
Reinforcement Learning	9.1	3.5	3.8	8.6
Hybrid AI Models	9.9	6.8	6.5	9.8

Table 1 presents a comparative evaluation of widely used artificial intelligence algorithms based on four key characteristics that influence their applicability to economic threshold prediction in pest management, namely prediction accuracy, interpretability, training speed, and overall suitability. Ensemble learning techniques such as XGBoost**,** LightGBM**,** and CatBoost demonstrate consistently high predictive performance owing to their ability to model complex nonlinear relationships while efficiently handling heterogeneous agricultural datasets. Transformer and LSTM models also exhibit excellent predictive capability, particularly for dynamic pest forecasting, although their training speed is comparatively lower due to greater computational complexity. In contrast, Decision Tree algorithms provide the highest interpretability and fastest training, making them attractive for transparent decision support despite relatively lower predictive accuracy. Deep learning models such as CNN and ANN achieve high accuracy but generally require larger training datasets and greater computational resources. Hybrid AI models combine the complementary strengths of multiple algorithms and consequently achieve the highest overall suitability, highlighting their potential for developing accurate, reliable, and adaptive economic threshold prediction systems for precision agriculture.

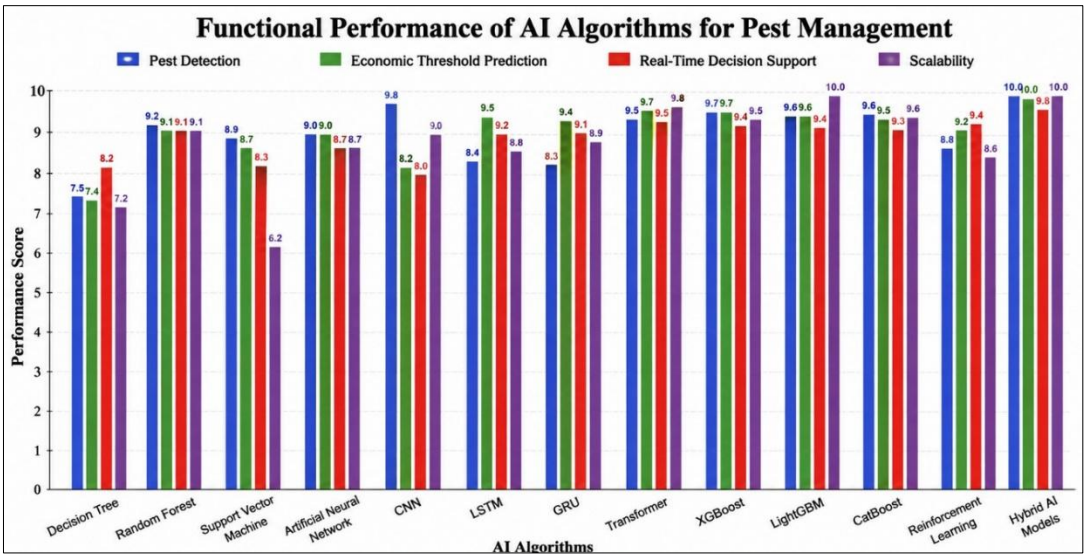


Figure 2. Functional Performance of AI Algorithms for Pest Management

Figure 2. compares the functional performance of AI algorithms across four critical applications in intelligent pest management: pest detection, economic threshold prediction, real-time decision support, and scalability. Image-based deep learning models, particularly **CNN**, achieve superior performance in automated pest detection due to their exceptional capability to extract visual features from crop images, UAV imagery, and remote sensing data. Ensemble learning methods such as XGBoost and LightGBM demonstrate outstanding effectiveness in economic threshold prediction by integrating multiple environmental, biological, and economic variables into accurate predictive models. Transformer**,** LSTM**,** and Reinforcement Learning algorithms provide excellent real-time decision support by effectively analyzing sequential pest dynamics and continuously adapting management strategies under changing environmental conditions. Furthermore, Hybrid AI models consistently outperform individual algorithms across all evaluated criteria by combining strengths such as image analysis, temporal learning, and robust prediction, making them the most promising approach for next-generation AI-driven economic

threshold prediction and sustainable integrated pest management systems.

Future research is expected to increasingly focus on multimodal AI frameworks capable of simultaneously processing environmental observations, pest surveillance data, crop phenology, remote sensing imagery, and economic information to generate dynamic, location-specific Economic Threshold predictions. Such intelligent systems will play a central role in sustainable Integrated Pest Management by reducing unnecessary pesticide applications, minimizing production costs, improving crop productivity, and supporting environmentally responsible agricultural practices.

IV. Applications of AI-Based Economic Threshold Prediction

Artificial intelligence has significantly expanded the capabilities of modern pest management by enabling crop-specific prediction of pest outbreaks, crop damage, and economic thresholds. Unlike conventional pest management strategies that rely on generalized recommendations, AI-driven systems utilize crop characteristics, pest biology, climatic variables, and economic information to generate location-specific and time-sensitive intervention recommendations. These intelligent approaches support sustainable Integrated Pest Management (IPM) by minimizing unnecessary pesticide applications while maintaining crop productivity and profitability. Recent research demonstrates that AI technologies are increasingly being deployed across diverse agroecosystems, ranging from cereal crops to protected cultivation systems.

A. Cereal Crop Protection

Cereal crops, including rice, wheat, maize, barley, and sorghum, constitute the primary food source for a large proportion of the global population. These crops are frequently affected by insect pests such as stem borers, armyworms, aphids, planthoppers, leafhoppers, and fall armyworms, which can cause substantial reductions in grain yield and quality. Traditional pest management in cereal production often depends on routine pesticide applications or manual scouting, which may not accurately reflect rapidly changing pest populations.

B. Oilseed Crop Protection

Oilseed crops, including soybean, sunflower, rapeseed, mustard, and groundnut, are vulnerable to numerous insect pests throughout their growth cycle. Pest infestations reduce seed yield, oil quality, and overall market value, making timely intervention essential for profitable production.

C. Fruit and Vegetable Crop Protection

Fruit and vegetable production involves high-value crops that require intensive pest monitoring because even minor infestations may significantly reduce market quality. Crops such as tomato, potato, cucumber, pepper, citrus, mango, apple, grape, and banana are susceptible to diverse insect pests whose populations fluctuate rapidly under changing environmental conditions.

D. Plantation and Cash Crops

Plantation crops such as tea, coffee, cocoa, sugarcane, cotton, coconut, rubber, and oil palm represent major economic commodities in many countries. Their long production cycles and extensive cultivation areas make continuous pest surveillance particularly challenging using conventional methods.

E. Greenhouse and Protected Cultivation

Protected cultivation systems provide highly controlled growing environments that enhance crop productivity but may also create favorable conditions for rapid pest population growth. Because greenhouse pests can spread quickly under stable environmental conditions, early detection and timely intervention are critical for preventing severe economic losses.

F. Precision Agriculture and Smart Farming Systems

Precision agriculture represents one of the most significant applications of artificial intelligence in modern crop production. By integrating GPS technologies, IoT devices, UAVs, satellite imagery, autonomous machinery, and cloud computing platforms, precision agriculture enables site-specific management of agricultural inputs according to local field variability.

5. Challenges and Future Research Directions

The rapid advancement of artificial intelligence has significantly improved pest monitoring, outbreak forecasting, crop health assessment, and decision support systems for precision agriculture. Despite these achievements, the application of AI for predicting Economic Injury Levels (EIL) and Economic Thresholds (ET) remains in its early stages. Current research has demonstrated promising predictive capabilities; however, several scientific, technical, economic, and operational challenges continue to limit large-scale adoption. Addressing these limitations is essential for developing robust, adaptive, and trustworthy AI systems capable of supporting sustainable Integrated Pest Management (IPM). This section discusses the major challenges

facing AI-driven economic threshold prediction and outlines future research directions that may accelerate the development of intelligent pest management systems.

A. Data Availability and Standardization

Artificial intelligence models rely heavily on large, diverse, and high-quality datasets for accurate prediction. However, agricultural datasets remain fragmented across research institutions, government agencies, commercial organizations, and regional monitoring programs. Most available datasets focus on pest identification or disease classification rather than economic threshold estimation, resulting in limited training data for predictive models.

Furthermore, differences in data collection protocols, pest sampling techniques, environmental measurements, spatial resolution, and annotation standards make it difficult to integrate datasets collected from different regions. Missing values, noisy observations, class imbalance, and inconsistent labeling further reduce model reliability. Future research should emphasize standardized data collection protocols, open agricultural databases, interoperable data formats, and collaborative international repositories that facilitate model development and benchmarking across diverse agroecosystems.

B. Dynamic Economic Threshold Prediction under Climate Change

Conventional Economic Threshold models were developed under relatively stable climatic conditions and often assume predictable pest population dynamics. However, global climate change has altered insect distribution, reproduction, migration patterns, seasonal emergence, and host–pest interactions. Increasing temperatures, irregular rainfall, drought events, and changing humidity patterns are modifying pest behavior, making static threshold recommendations less reliable.

Artificial intelligence offers significant potential for developing adaptive threshold prediction systems capable of continuously updating recommendations according to changing environmental conditions. Future AI models should integrate climate projections, seasonal weather forecasts, crop phenology, and long-term ecological observations to estimate dynamic Economic Thresholds that remain effective under evolving climatic scenarios. Such adaptive systems will improve resilience and sustainability in future agricultural production systems.

C. Explainability and Trustworthy Artificial Intelligence

Although deep learning models frequently achieve superior predictive accuracy, many operate as "black-box" systems whose internal decision-making processes are difficult to interpret. Farmers, extension specialists, and policymakers are often reluctant to adopt recommendations that cannot be clearly explained or scientifically justified.

Developing trustworthy AI therefore represents an important research priority. Explainable Artificial Intelligence (XAI) techniques such as SHAP, LIME, feature attribution methods, attention visualization, and counterfactual explanations should be integrated into economic threshold prediction models to identify the variables influencing intervention decisions. Transparent AI systems will increase user confidence, facilitate scientific validation, support regulatory approval, and encourage wider adoption of intelligent decision-support technologies in agriculture.

D. Edge AI and Real-Time Pest Monitoring

Many agricultural production systems are located in remote rural regions where internet connectivity and cloud computing infrastructure remain limited. Consequently, cloud-based AI systems may experience communication delays that reduce their effectiveness for real-time pest management.

Edge Artificial Intelligence provides a promising solution by enabling predictive models to operate directly on local devices such as smartphones, smart insect traps, agricultural robots, IoT gateways, and UAV platforms. Processing data locally reduces communication latency, minimizes bandwidth requirements, enhances data privacy, and enables immediate pest management recommendations. Future research should focus on lightweight AI architectures, model compression techniques, efficient neural network optimization, and energy-efficient hardware capable of supporting real-time economic threshold prediction under field conditions.

E. Digital Twins and Autonomous Pest Management

Digital Twin technology has emerged as an innovative approach for creating virtual representations of agricultural fields that continuously synchronize with real-world observations. By integrating IoT sensors, weather stations, remote sensing platforms, and crop simulation models, digital twins provide a dynamic

digital environment for monitoring crop growth, pest populations, and environmental conditions.

Artificial intelligence integrated within digital twins can simulate multiple pest management scenarios, evaluate expected economic outcomes, and recommend optimal intervention strategies before field implementation. Coupled with autonomous agricultural robots, unmanned aerial vehicles, and precision spraying systems, digital twins may enable fully autonomous pest management capable of continuously adapting to changing agroecosystem conditions. Such intelligent ecosystems represent a promising direction for future precision agriculture.

F. Integration of IoT, UAVs, and Satellite Data

Modern precision agriculture generates enormous volumes of heterogeneous information through Internet of Things sensors, unmanned aerial vehicles, satellite imagery, weather stations, automated insect traps, and mobile applications. Although each technology independently contributes valuable information, effective integration of these diverse data sources remains a significant challenge.

Future research should focus on multimodal artificial intelligence capable of combining spatial, temporal, environmental, biological, and economic information into unified predictive frameworks. Graph Neural Networks, Transformer architectures, multimodal deep learning, and attention-based fusion techniques offer promising approaches for integrating heterogeneous agricultural datasets. Such comprehensive data fusion is expected to substantially improve prediction accuracy, robustness, and scalability across different crops and production systems.

G. Future Research Opportunities

Artificial intelligence for economic threshold prediction remains a rapidly evolving research field with numerous opportunities for innovation. Future investigations should move beyond conventional pest forecasting toward intelligent decision-support systems capable of simultaneously considering pest biology, crop physiology, environmental variability, economic profitability, and ecological sustainability. The development of adaptive AI frameworks that continuously learn from new observations will significantly improve prediction reliability across different agroecosystems.

Emerging technologies including foundation models, generative artificial intelligence, federated learning, transfer learning, graph neural networks, digital twins, autonomous agricultural robotics, and multimodal learning are expected to transform future pest management systems. In addition, integrating AI with biological control strategies, ecological modelling, climate forecasting, and precision pesticide application will support more sustainable and environmentally responsible agricultural practices. Collaborative efforts among agronomists, entomologists, economists, computer scientists, remote sensing specialists, and policymakers will be essential for developing standardized datasets, robust evaluation frameworks, and practical decision-support platforms that facilitate widespread adoption.

C. Conclusion

Artificial intelligence (AI) has emerged as a transformative technology for advancing economic threshold-based pest management by enabling intelligent, data-driven, and adaptive decision-making. Unlike conventional threshold estimation methods that rely on fixed empirical relationships and periodic field observations, AI models can integrate diverse datasets, including weather variables, pest population dynamics, crop phenology, remote sensing imagery, IoT sensor data, and economic parameters, to generate accurate and dynamic predictions of Economic Injury Levels (EIL) and Economic Thresholds (ET). This capability supports timely interventions that minimize crop losses while reducing unnecessary pesticide applications and production costs. This review highlighted the evolution of economic threshold concepts, recent advances in AI technologies, and their applications across various agroecosystems. Machine learning, deep learning, reinforcement learning, explainable AI, and hybrid models have demonstrated considerable potential for improving pest forecasting, crop damage assessment, and intelligent decision support. Furthermore, AI-enabled systems integrated with precision agriculture technologies facilitate site-specific pest management, enhance resource-use efficiency, and contribute to environmentally sustainable farming practices.

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