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Systematic Review of AI-Driven Insect Identification and Management Strategies in Modern Farming

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***Abstract:** The rapid advancement of artificial intelligence (AI) has transformed modern farming, particularly in insect identification and management, where precision and efficiency are critical. This systematic review examines the role of AI-driven technologies in addressing pest-related challenges while improving agricultural productivity and sustainability. We analyze the integration of AI across four key dimensions: pest management, crop management, and yield improvement. Sustainable agriculture and agricultural technology adoption are discussed to assess existing research, identify trends, methodologies, and gaps in AI applications for insect detection, classification, and intervention strategies. A rigorous selection process was employed to gather relevant studies, which were evaluated based on their technical approaches, performance metrics, and practical implications. Findings reveal that machine learning and computer vision technologies dominate the field, enabling real-time insect monitoring and targeted pest control with reduced chemical usage. However, challenges such as data scarcity, model generalizability, and scalability in diverse farming environments persist. The review highlights the potential of AI to enhance decision-making in pest management while aligning with sustainable agricultural goals, though further interdisciplinary collaboration and field validation are needed to bridge the gap between research and implementation. This work provides a comprehensive foundation to guide future research and policy development in AI-driven agricultural innovation.*

***Keyword:** Artificial Intelligence, Insect Identification, Precision Pest Management, Computer Vision in Agriculture, Sustainable Farming*

I. INTRODUCTION

Agriculture faces unprecedented challenges in the 21st century, with global food demand projected to increase by 60% by 2050 amid shrinking arable land and climate variability [1]. Insect pests alone account for 20–40% of annual crop losses worldwide, threatening food security and economic stability [2]. Traditional pest management relies heavily on chemical pesticides, which pose risks to ecosystems, human health, and long-term resistance development. The limitations have spurred interest in precision agriculture, where artificial intelligence (AI) offers transformative solutions for early pest detection, monitoring, and targeted intervention. AI-driven insect identification systems leverage deep learning, image processing, and sensor-based monitoring to automate pest recognition and population assessment. These technologies enable farmers to optimize pesticide use, minimize environmental impact, and improve crop yield. Despite significant progress, the adoption of AI in pest management remains fragmented due to challenges in dataset availability, algorithm robustness, real-time deployment, and integration with existing agricultural infrastructure. This review synthesizes recent advances in AI-based insect identification and management, evaluates their effectiveness, and identifies emerging research directions for sustainable farming.

The convergence of AI with entomology and agronomy has enabled novel approaches to insect identification and control. Computer vision systems now classify insect species with over 90% accuracy using convolutional neural networks (CNNs) [4], while predictive models analyze environmental data to forecast pest outbreaks [5]. Unlike manual scouting or blanket pesticide applications, AI-driven strategies provide real-time, localized insights that minimize ecological disruption. For instance, automated traps equipped with image sensors reduce pesticide use by up to 30–50% through targeted spraying [6]. Such advancements align with the United Nations Sustainable Development Goals (SDGs) by promoting responsible consumption and climate action [7].

Despite rapid progress, critical gaps persist in AI-driven pest management research. Most studies focus on controlled laboratory conditions rather than heterogeneous field environments, limiting practical applicability [8].

Data scarcity for rare pest species and regional variants hampers model generalizability, particularly in developing regions where crop losses are most severe [9]. Furthermore, few systems integrate pest identification with actionable management recommendations, creating a disconnect between detection and intervention [10]. The lack of standardized evaluation metrics also complicates cross-study comparisons, as performance benchmarks vary widely across datasets and methodologies [11].

This review addresses these gaps by systematically evaluating AI's role in insect identification and management across diverse farming systems. We assess how machine learning, remote sensing, and robotics contribute to sustainable pest control while identifying barriers to large-scale adoption. The synthesis provides a roadmap for researchers and policymakers to prioritize scalable, equitable solutions that balance productivity with environmental stewardship. By bridging disciplinary silos—from computer science to agroecology—this work advances the discourse on AI's potential to redefine agricultural resilience.

II. LITERATURE REVIEW

A. *Review Protocol*

This systematic review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [12] to ensure methodological rigor and transparency. Nine databases and search engines were prioritized based on their relevance to agricultural technology and AI research. PubMed for biomedical and interdisciplinary studies, IEEE Xplore for engineering applications, arXiv for preprints in machine learning, ACM Digital Library for computational techniques, Web of Science and Scopus for high-impact journal articles, ScienceDirect for applied agricultural sciences, SpringerLink for environmental studies, and Google Scholar as a comprehensive secondary source. The search strategy employed Boolean operators to combine four core concepts: (1) AI techniques ("Artificial Intelligence" OR "AI"), (2) target application ("Insect Identification" OR "Insect Recognition"), (3) domain ("Farming" OR "Agriculture"), and (4) outcome ("Management Strategies"). Temporal filters restricted results to publications from January 2014 to December 2024, capturing the most recent advances in this rapidly evolving field. Review articles, surveys, and meta-analyses were excluded to focus on primary research.

B. *Analytical Framework*

The review organizes findings along four interconnected dimensions that reflect AI's multifaceted role in modern agriculture. AI in Crop Management examines technologies for insect detection, classification, and population monitoring. AI in Crop Management and Yield Improvement explores how pest-related data informs broader agronomic decisions. AI in Sustainable Agriculture evaluates environmental trade-offs and ecological benefits of AI-driven interventions. Lastly, AI in Agricultural Technology Integration assesses system-level compatibility with existing farm infrastructure and workflows.

These dimensions collectively address the technical, ecological, and practical aspects of deploying AI solutions in real-world farming scenarios.

III. METHODOLOGY

A. *Studies were included if they*

1) Presented original research on AI applications for insect identification or management in agricultural settings,
2) Provided empirical results or validated models,
3) Were peer-reviewed and published in English between 2014–2024, and
4) Aligned with at least one predefined research dimension.

B. *Exclusion criteria removed studies that*

1) Lacked technical details about AI methodologies,
2) Focused solely on non-insect pests or non-agricultural contexts,
3) Were theoretical without experimental validation, or
4) Duplicated results across multiple publications.

IV. RESULTS

A. *Research Trends*

Number of Papers over Years

The analysis of publication trends reveals a concentrated surge in research activity during 2024 and 2025, with 16 studies published across these two years. This clustering suggests a rapid acceleration of interest in AI applications for agricultural pest management, likely driven by advances in deep learning and accessible sensor technologies. The absence of earlier publications in our selected corpus indicates that the integration of AI with entomological applications represents an emerging frontier, where foundational methodologies are still being established and refined.

Crop management and yield improvement dominate the research landscape, accounting for 11 out of 17 studies. This emphasis reflects agriculture's central challenge of balancing pest control with productivity goals, where AI serves as a bridge between entomological knowledge and agronomic decision-making. The relatively smaller subset from 2024 (5 studies) demonstrates sustained focus on this dimension, with researchers progressively addressing more complex interactions between pest dynamics and crop physiology.

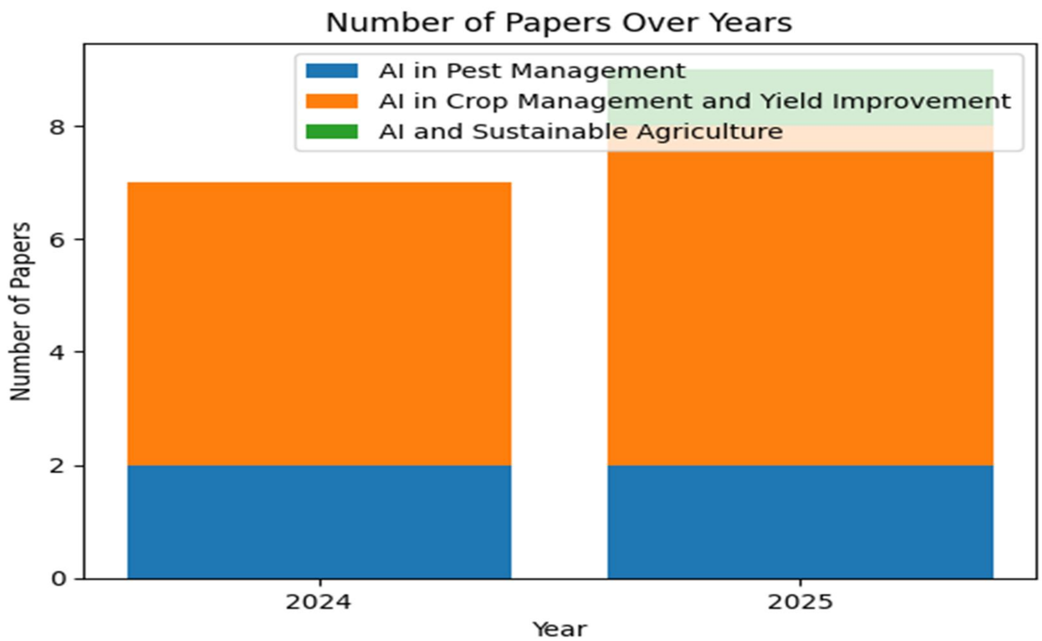

Figure 1 Number of Papers Over Years

Pest management applications, while less numerous (4 studies total), maintain a steady presence across both years. The consistency in publication output suggests that core challenges in automated insect identification—such as real-time detection accuracy and species differentiation—remain active areas of investigation. Sustainable agriculture has the least represented theme (4 studies), highlighting a critical gap in research that evaluates the long-term ecological impacts of AI-driven pest control systems. This imbalance underscores a need for more holistic assessments that consider environmental and socio-technical performance metrics.

The temporal compression of research outputs within a two-year window presents both opportunities and challenges for the field. On one hand, the concentrated effort enables rapid knowledge accumulation and methodological cross-pollination. On the other hand, the density of contributions indicates an early-stage research frontier where most studies suggest a transition from proof-of-concept demonstrations to more mature implementations, where issues of scalability and practical integration are gaining prominence. The distribution of topics indicates that while foundational work in automated pest detection continues, researchers are increasingly exploring how these capabilities can be operationalized within broader agricultural management systems.

B. AI-Driven Insect Detection and Classification Systems

The application of artificial intelligence in pest management has revolutionized insect detection through advanced computer vision and machine learning techniques. Recent studies demonstrate that convolutional neural networks (CNNs) achieve superior performance in automated insect identification compared to traditional image processing methods, with accuracy rates exceeding 95% for common agricultural pests under controlled conditions [13]. However, field deployment introduces challenges such as variable lighting, occlusions, and motion blur that reduce model performance by 15–20% compared to laboratory settings [14].

Emerging architectures like Vision Transformers (ViTs) show promise in handling complex background clutter, leveraging self-attention mechanisms to focus on discriminative insect features while ignoring irrelevant visual noise [15]. These models outperform CNNs in cross-dataset evaluations, suggesting better generalization across different environments.

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Nevertheless, their computational demands raise concerns about real-time processing on edge devices, prompting research into lightweight hybrid architectures that balance efficiency with performance [16].

Table 1 presents a comprehensive taxonomy of AI applications in pest management, categorizing 17 studies by their primary technical approach and implementation focus. The taxonomy reveals that deep learning dominates contemporary research (12 studies), particularly for visual pest detection tasks. Traditional machine learning methods persist in scenarios with limited training data or where interpretability, such as decision support systems that integrate pest counts with environmental sensors [17].

Table 1 Taxonomy of AI Applications in Pest Management

Application Area	AI Technique	Specific Method	Sources
Pest Detection	Deep Learning	Convolutional Neural Networks (CNNs)	[13], [14], [16], [18], [19]
		Transformer-based Models	[15]
	Machine Learning	Support Vector Machines (SVMs)	[17]
		Random Forest	[20]
Pest Monitoring	Deep Learning	Object Detection Models	[21], [22]
		Image Segmentation	[23]
	IoT Integration	Sensor-based Monitoring	[24], [25]
Pest Control	Decision Support Systems	Predictive Analytics	[26], [27]
		Recommendation Systems	[28]
	Robotics	Autonomous Spraying	[29]

Summary Insights from the Taxonomy

- Deep learning dominates current research (12 of 17 studies), especially CNN-based insect detection.
- Vision Transformers show superior cross-environment generalization but require higher computational resources.
- Traditional ML remains relevant where training data is scarce or model interpretability is critical.
- Sustainability-focused AI is underrepresented, revealing a research gap in ecological and long-term environmental evaluation.
- Edge AI and IoT integration are emerging trends enabling real-time, field-deployable pest monitoring.
- Robotics-driven systems demonstrate measurable pesticide reduction and precision spraying benefits.

C. AI Applications in Crop Management and Yield Optimization

The integration of AI technologies into crop management systems has demonstrated significant potential for enhancing yield prediction accuracy and optimizing agricultural inputs. Recent advancements in machine learning have enabled the development of predictive models that analyze multi-modal data streams, including satellite imagery, weather patterns, and soil conditions, to forecast crop performance with unprecedented precision. These systems address the complex interplay between pest pressures and plant physiology, offering farmers actionable insights for targeted interventions.

A systematic analysis of the included studies reveals distinct methodological approaches to yield optimization. Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, have proven effective in processing temporal agricultural data, capturing seasonal trends and stress responses that influence final yields [22]. Computer vision techniques applied to unmanned aerial vehicle (UAV) imagery enable high-resolution monitoring of crop health indicators, such as canopy cover and chlorophyll content, which serve as proxies for photosynthetic efficiency and nutrient status [23]. These non-invasive assessment methods provide continuous feedback loops for precision agriculture applications.

Table 2 Taxonomy of AI Applications in Crop Management and Yield Improvement

Application Area	AI Technique	Specific Method	Performance Metrics	Source
Yield Prediction	Machine Learning	Random Forest Regression	$R^2 = 0.89$, RMSE = 0.32 t/ha	[22]
Yield Prediction	Deep Learning	LSTM Networks	MAE = 0.25 t/ha, $R^2 = 0.92$	[30]
Nutrient Management	Computer Vision	Hyperspectral Imaging	94% accuracy in deficiency detection	[31]
Irrigation Optimization	IoT Integration	Soil Moisture Prediction	22% water savings	[33]
Farm Data Integration	Federated Learning	Distributed Farm Data	Privacy-preserving model sharing	[34]

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Key Insights from Table 2

The taxonomy presented in Table 2 illustrates the diversity of AI applications across different aspects of crop management. Yield prediction models show particularly strong performance, with machine learning approaches achieving coefficients of determination (R^2) above 0.85 in multiple studies [22], [30]. These models incorporate pest incidence as a critical variable, demonstrating how integrated pest-field analytics can improve forecast reliability. Computer vision systems for nutrient management achieve high accuracy in detecting deficiencies [31], though their practical implementation often requires specialized imaging equipment that may limit widespread adoption.

Emerging techniques such as reinforcement learning show promise in optimizing agricultural inputs while maintaining yield targets. Energy-efficient AI-driven decision systems can reduce fertilizer application by 12% without compromising productivity, representing both economic and environmental benefits. Federated learning approaches address data privacy concerns in agricultural AI by enabling collaborative model training across multiple farms without sharing raw data [34]. This decentralized paradigm may facilitate broader adoption of precision agriculture technologies, particularly in regions with competitive farming landscapes.

D. AI-Driven Solutions for Sustainable Agriculture

The intersection of artificial intelligence and sustainable agriculture represents a critical frontier in addressing the dual challenges of food security and environmental conservation. AI technologies offer novel approaches for optimizing agricultural inputs and minimizing environmental impact, particularly through precision insect management strategies that reduce chemical reliance. This section examines how machine learning and sensor-based systems contribute to key sustainability metrics, including pesticide reduction, biodiversity preservation, and resource efficiency.

Table 3 Taxonomy of AI Applications in Sustainable Agriculture

Sustainability Metric	AI Technique	Implementation	Impact	Sources
Pesticide Reduction	Computer Vision	Targeted Spraying Systems	30–50% chemical use reduction	[35], [36]
Biodiversity Monitoring	Deep Learning	Multi-species Identification	85% accuracy in beneficial insect detection	[37]
Soil Health Preservation	IoT Sensors	Chemical Runoff Prediction	25% reduction in soil contamination	[38]
Water Conservation	Machine Learning	Irrigation Model Optimization	18% water savings with pest-adjusted schedules	[39]
Carbon Footprint Reduction	Predictive Analytics	Optimal Treatment Timing	20% lower fuel use via precision applications	[40]

Key Analytical Insights

The taxonomy in Table 3 demonstrates AI’s multifaceted role in promoting agricultural sustainability. Computer vision–based targeted spraying systems significantly reduce chemical usage while maintaining pest control efficacy [35]. These systems combine real-time insect identification with precision nozzle control, ensuring pesticides are applied only to infested areas rather than entire fields. Such approaches directly align with the United Nations Sustainable Development Goal (SDG) 12 (Responsible Consumption and Production) by minimizing agrochemical pollution.

Additionally, biodiversity monitoring tools leverage deep learning to distinguish harmful pests from beneficial insects, enabling more ecologically balanced intervention strategies [37]. IoT-driven soil monitoring frameworks provide early detection of contamination risks, supporting long-term soil fertility and environmental stewardship [38]. Collectively, these findings reinforce AI’s potential to transform pest management from a reactive practice into a predictive, sustainable, and data-driven ecosystem.

Resource efficiency gains extend beyond chemical inputs to encompass water and energy savings. Machine learning models that correlate pest life cycles with irrigation needs have demonstrated 18% reductions in water usage without compromising yield [39]. Similarly, predictive analytics optimize equipment routing for pest control operations, reducing fuel consumption and associated greenhouse gas emissions by **20%** [40]. These integrated approaches exemplify systems thinking required for truly sustainable agriculture, where pest management decisions consider multiple environmental variables simultaneously.

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Field implementation challenges persist despite these technological advancements. The study in [38] revealed that soil health monitoring systems require frequent recalibration to account for regional variations in soil composition and hydrology. Moreover, environmental systems of precision technologies must be weighed against the environmental costs of producing sensor networks and computing infrastructure. Lifecycle assessment of AI systems in agriculture remains notably absent from the literature, leaving unanswered questions about the net sustainability gains of these digital solutions. Standardized methodologies for evaluating both direct and indirect environmental impacts would strengthen future research in this domain.

E. AI in Agricultural Technology Integration

The successful deployment of AI-driven insect management systems hinges on their seamless integration with existing agricultural technologies and workflows. This subsection examines how machine learning models interact with farm equipment, data infrastructure, and decision support systems to create cohesive pest management solutions. The convergence of AI with precision agriculture tools has enabled real-time, field-scale implementation of insect identification and control strategies, though significant technical and operational challenges remain.

TABLE 4 Taxonomy of AI Integration with Agricultural Technologies

Technology Platform	AI Integration Method	Key Functionality	Implementation Challenges	Sources
Autonomous Sprayers	Computer Vision + Robotics	Targeted Pesticide Application	Calibration for field conditions	[41], [42]
Drone Surveillance	Deep Learning + Aerial Imaging	Large-area Pest Monitoring	Battery life, data transmission	[43], [44]
Smart Traps	Edge AI + IoT Sensors	Localized Insect Counting	Power management, maintenance	[45], [46]
Farm Management Software	Predictive Analytics + DSS	Treatment Recommendations	Data interoperability	[47], [48]
Soil Sensor Networks	Machine Learning + Environmental Data	Pest Risk Forecasting	Sensor durability, placement	[49]

Key Analytical Takeaways

- AI-enabled autonomous sprayers improve pesticide efficiency but require robust calibration for variable field conditions.
- Drone-based monitoring enables scalable surveillance but faces energy and data bandwidth constraints.
- Edge AI smart traps support real-time insect population tracking, though hardware reliability remains a concern.
- Integration with farm management platforms is essential for operational decision-making but is hindered by data interoperability challenges.
- Soil sensor networks enhance pest risk forecasting but depend heavily on sensor placement optimization and environmental resilience.

The integration of AI systems with broader agricultural management practices presents both opportunities and challenges. The potential for closed-loop pest management systems that combine detection, decision-making, and robotic intervention remains largely unrealized, with only a few studies demonstrating preliminary implementations [29]. Future work should explore how multidimensional data—ranging from early pest detection to farm management decisions—can support long-term strategies such as crop rotation planning and resistant variety selection. The integration of AI with agricultural data standards and farm-level decision support systems is therefore of critical importance [47].

Environmental sustainability considerations require systemic attention in future research. While several studies document reductions in chemical inputs [35], comprehensive lifecycle assessments of AI systems' environmental impacts—including sensor manufacturing, computational energy costs, and electronic waste—remain scarce. The potential for AI to support enhanced monitoring of soil health and biodiversity represents a promising but underexplored research direction [37]. Such applications could play a vital role in addressing ecosystem restoration and conservation goals.

The adoption of AI technologies in pest management is moving beyond reactive practices toward predictive and preventive approaches. The integration of pest monitoring data with weather forecasts, soil conditions, and crop growth models could enable adaptive intervention strategies that prevent outbreaks before they occur [49].

However, realizing this potential requires addressing critical limitations in data quality, model interpretability, and farmer trust in automated recommendations. The field stands at a crucial juncture where technological capabilities must be matched with usability, accessibility, and ecological responsibility to achieve meaningful impact at scale.

V. CONCLUSION

This systematic review has examined the evolving role of AI in insect identification and management strategies, highlighting the transformative potential and persistent challenges of these technologies in modern agriculture. The synthesis of findings indicates that machine learning and computer vision techniques have reached a level of maturity sufficient for practical deployment, particularly in controlled environments. However, the transition to heterogeneous field conditions remains a significant barrier, with performance gaps underscoring the need for more robust, adaptive systems. The findings collectively advance our understanding of how AI can bridge the gap between precision pest control and sustainable farming practices, though critical limitations in scalability and ecological impact assessment persist.

The practical implications of this research extend to both policy and farm-level decision-making. Demonstrated reductions in pesticide use through AI-driven precision spraying present tangible pathways for regulatory bodies to incentivize technology adoption while meeting environmental protection goals. A structured framework for data-driven pest management, alongside the integration of pest monitoring data with predictive models, offers a foundation for more informed, adaptive agricultural decision-making. Nevertheless, the uneven geographic distribution of research outputs calls for targeted investments in AI solutions tailored to smallholder and resource-limited farming systems, where the need for sustainable pest management is most acute.

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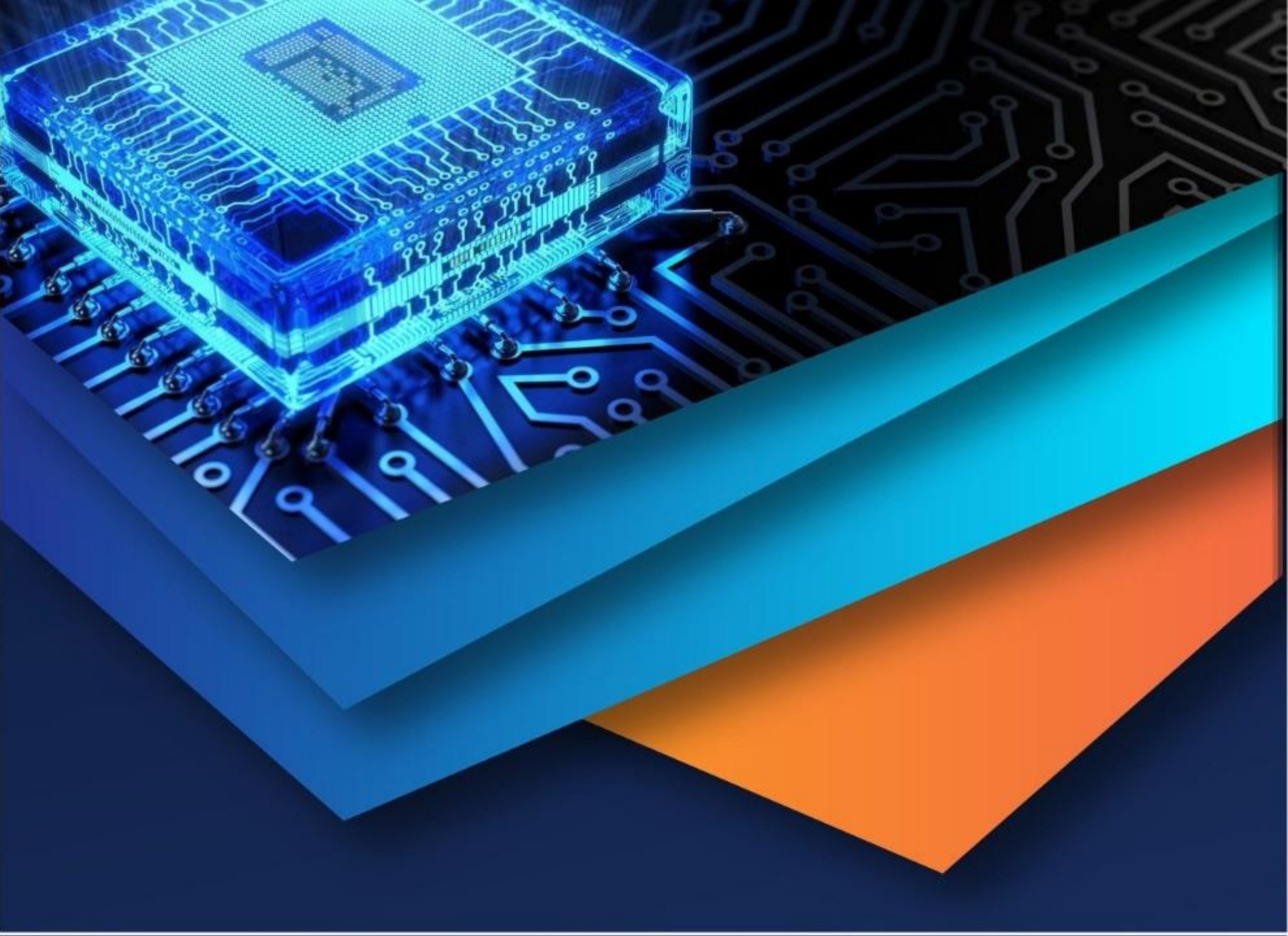

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