Labuan Bulletin of International Business &Finance

Volume 22 Issue 2 eISSN 2600- 7894

ARTIFICIAL INTELLIGENCE AND PRECISION AGRICULTURE: OPTIMIZING CROP MANAGEMENT AND YIELD_ A NARRATIVE REVIEW

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ABSTRACT

The integration of Artificial Intelligence (AI) in precision agriculture represents a transformative advancement in optimizing crop management and yield. This narrative article examines the role of AI technologies in enhancing agricultural practices by analyzing recent developments in AI-driven tools and methods. The review synthesizes findings from various studies to highlight the impact of AI on crop monitoring, predictive analytics, and decision-making processes. Key AI applications such as artificial intelligence, precision agriculture, crop management, yield optimisation are explored to understand their effectiveness in improving crop management strategies. The article identifies emerging trends and future research directions, emphasizing the potential of AI to address challenges in precision agriculture and promote sustainable farming practices

JEL classification:*O1, Q1*
Keywords: *artificial intelligence; precision agriculture; crop Management; yield optimisation*

Received: October 20, 2024
Revised: November 19, 2024
Accepted: December 17, 2024

1. INTRODUCTION

The integration of artificial intelligence (AI) into precision agriculture represents a transformative shift in agricultural practices, enabling enhanced crop management and increased yields (Kirkaya, 2020; Lee et al., 2020). As the global population continues to rise, the demand for food production intensifies, necessitating innovative approaches to farming (Zha, 2020a; Zhang et al., 2021). Precision agriculture, characterized by the use of technology to monitor and manage field variability, is increasingly reliant on AI to optimize agricultural outputs. This synergy between AI and precision agriculture not only improves efficiency but also addresses the challenges posed by climate change and resource scarcity (Chen et al., 2021; Nitin, 2023)

Artificial intelligence facilitates data-driven decision-making in crop management by processing vast amounts of information collected from various sources, including sensors and drones (Dayioğlu & Türker, 2021). These technologies enable farmers to monitor soil conditions, weather patterns, and crop health in real time, allowing for timely interventions that can significantly enhance (Domingues et al., 2022; Qazi et al., 2022; Vrochidou et al., 2022). For instance, AI algorithms can analyze data to predict pest infestations or disease outbreaks, enabling proactive measures that protect crops and maximize yields (Linaza et al., 2021; Robin Sharma, 2021). This capability is crucial in an era where traditional farming methods are increasingly inadequate to meet the demands of modern agriculture. Moreover, the application of AI in precision agriculture extends beyond mere data analysis (Kakani et al., 2020); it encompasses automation and robotics (Ampatzidis et al., 2020), which streamline farming operations (Naresh et al., 2020). Autonomous machinery equipped with AI can perform tasks such as planting, watering, and harvesting with minimal human intervention, thereby reducing labor costs and increasing operational efficiency (Chen et al., 2021; Raouhi et al., 2023; Ünal, 2020). These advancements not only improve crop management practices but also contribute to sustainable farming by minimizing waste and optimizing resource use, thus ensuring environmental conservation (Krul et al., 2021; Nitin, 2023; Sishodia et al., 2020).

Artificial intelligence (AI) has started to play a significant role in precision agriculture, though much of its potential remains underutilized due to gaps in current research. AI applications have been introduced across several agricultural areas, but the exact processes by which they improve crop management and yield optimization lack thorough documentation. This limits the ability to fully utilize AI to address critical agricultural challenges, such as resource scarcity, climate impacts, and food security. Current studies often examine AI applications in isolation, without considering the integration needed for a comprehensive crop management approach (Javaid et al., 2023; Zha, 2020a, 2020b). Although advancements in machine learning and data analytics assist with tasks like pest control and yield forecasting, a unified framework incorporating the full agricultural ecosystem is still missing. Additionally, limited empirical research has explored the long-term sustainability and economic outcomes of AI in farming, despite its growing adoption. Examining the cost-effectiveness and environmental impacts of AI would offer stakeholders deeper insights for promoting sustainable practices. Ethical concerns, including data privacy, algorithmic fairness, and access disparities between technologically advanced and conventional farming, also need attention to ensure fair and effective AI use in

agriculture. Addressing these research gaps could enable more holistic applications of AI, ultimately improving crop management and food systems.
This paper provides a conceptual explanation for one of the central social issues of artificial intelligence and precision agriculture, which is the potential adaptation strategies towards a betterment of agriculture practice. The paper also highlights potential adaptation strategies that are pertinent to their needs, abilities, and interests. Set against this backdrop, this paper provides an explanation.

2. METHODOLOGY

The initial step in the development of an adaptation strategy was the analysis of pertinent papers to establish and articulate the connections between precision agriculture and artificial intelligence, as well as their impact on crop management and yield. Relevant articles were collected from search engines like Scopus (http://www.scopus.com) and ScienceDirect (http://www.sciencedirect.com) during this procedure. Keywords such as "artificial intelligence," "precision agriculture," "crop management," "yield optimisation," and "smart farming," "the impact of artificial intelligence on agriculture practice," "the adaptation of artificial intelligence by farmers on crop management," and "the benefits of artificial intelligence on yield" were employed in this process. These endeavours led to the identification of 253 articles; however, only 64 articles remained after the second stage of the vetting process. Five distinct scopes have been assigned to each of the articles: 13% pertains to crop monitoring with AI technologies, 24% to yield prediction and optimisation, 26% to irrigation and fertilisation, 25% to agricultural operations, and 12% to economic benefits.

Following the introduction, and the scope of the article that has been segmented. There are five relevant themes presented in the following sections which cover: AI-driven innovation for sustainable agriculture, precision and smart technologies in food security and disease detection, robotics and automation in agricultural tasks, AI in climate-smart and sustainable agriculture, industry 4.0 and smart agriculture technologies and AI and smart systems in aquaculture and food production. By adapting these recommendations, farmers can enhance sustainability, boost productivity, improve food quality and security, reduce environmental impact, and increase resilience to climate change, all of which lead to greater efficiency and profitability.

3. DISCUSSION

3.1 AI-Driven innovation for sustainable agriculture

Artificial intelligence (AI) has quickly become an essential resource in climate-smart agriculture (CSA) (Fountas et al., 2015), offering creative solutions that help agricultural systems adjust to climate change while maintaining productivity and minimising environmental effects (Modi et al., 2023). Utilising AI's data analysis, predictive modelling, and real-time monitoring abilities, CSA practices can be customised to address the challenges posed by a shifting climate, providing considerable advantages for sustainability and resilience. AI plays a significant role in CSA through precision agriculture, employing data-driven methods for efficient crop monitoring and management (Vasileiou et al., 2024). AI algorithms examine satellite and sensor data to identify shifts in crop health and soil conditions, enabling prompt actions that minimise resource consumption and enhance productivity (Partel et al., 2019). Techniques powered by AI, such as soil moisture monitoring and variable-rate irrigation, contribute to lowering water usage and improving crop resilience in the face of unpredictable weather conditions. Furthermore, AI applications facilitate the early detection of disease outbreaks and pest infestations, enabling preventive actions that reduce chemical usage and foster ecological balance.

AI plays a crucial role in yield forecasting, which is vital for planning and maintaining food security. AI models leverage historical weather patterns, soil data, and crop growth metrics to deliver precise yield predictions, facilitating effective resource allocation (Gutiérrez et al., 2008). These predictive models allow stakeholders to make informed decisions regarding crop selection and resource investment, ensuring that production goals are in harmony with expected yields (S.S. et al., 2024). Models for yield prediction that utilise machine learning improve productivity by tailoring recommendations to suit local conditions and anticipated climate changes. In sustainable land management, AI aids in monitoring land usage and executing soil conservation practices vital for enduring productivity (Conde et al., 2024). The challenges posed by climate change require practices such as crop rotation and soil preservation, while AI-driven systems track indicators like soil erosion and nutrient levels to suggest the best strategies for sustaining soil health (Akiva et al., 2022). The ability of AI to recognise patterns facilitates a thorough identification of vulnerable regions, aiding in the prevention of nutrient depletion and erosion, thereby protecting soil structure and fertility (Deng et al., 2024; Jimenez et al., 2020).

Data integration platforms powered by AI gather information from various sources, such as satellite imagery, weather forecasts, and soil data, to create a thorough basis for informed decision-making (Saqib et al., 2023). These platforms facilitate adaptive management strategies that respond to climate changes, strengthening agricultural resilience (Mahlein et al., 2024). Additionally, AI applications in predictive modelling encompass early warning systems for extreme weather events, providing timely alerts for droughts, floods, or temperature fluctuations, which aids in the implementation of adaptive measures to safeguard crops and livestock from unfavourable conditions (Kapetas et al., 2024). Barriers to implementing AI in CSA encompass issues related to data accessibility, the expenses associated with technology, and the need for specialised expertise. AI applications frequently depend on comprehensive, high-quality datasets to guarantee precision, which can be challenging to acquire, especially in resource-constrained areas. The expense associated with AI solutions may restrict accessibility, particularly for smaller farms. Addressing these challenges may necessitate cooperation among governments, technology providers, and agricultural stakeholders to foster fair access to AI resources and training opportunities.

3.2 Precision and smart technologies in food security and disease detection

Artificial intelligence (AI) has swiftly emerged as a vital element in enhancing precision agriculture and disease detection technologies, offering significant assistance for food security and sustainability throughout agricultural sectors (Denarda et al., 2024). Through the integration of AI-driven tools like machine learning, remote sensing, and predictive analytics, conventional agricultural methods are transforming to allow for accurate resource management, immediate disease identification, and improved supply chain effectiveness. These technologies improve crop health monitoring, promote efficient resource use, and strengthen food safety measures, leading to resilient and sustainable food production (Storm et al., 2024). In precision agriculture, AI algorithms analyse extensive real-time data gathered from sensors, drones, and satellite imagery to assess crop health, soil quality, and environmental conditions. This approach, grounded in data, enables precise interventions in irrigation, fertilisation, and pest management, contributing to the reduction of resource waste and an increase in productivity. Technologies in precision agriculture driven by AI enhance adaptability to climate variations, catering to specific crop requirements and promoting more resilient food production systems (López-Martínez et al., 2024; Molin et al., 2020; Yousefi D.B. et al., 2021).

The influence of AI is profound in the realm of disease detection, a vital field where sophisticated AI models, such as convolutional neural networks (CNNs) and ensemble learning techniques, provide remarkable precision in recognising early-stage diseases via image analysis (Russo et al., 2024). In crop farming, these models are capable of identifying pathogens from images captured by drones or field cameras, allowing for timely interventions that reduce disease transmission and limit yield lossesv(Kanwal et al., 2023). Applications in aquaculture and livestock farming have demonstrated effectiveness in early identification of health abnormalities and potential infections, leading to reduced economic losses and enhanced food quality through automated disease monitoring and early detectionv(Md-Tahir et al., 2024). The use of AI significantly bolsters food security in agricultural supply chains by improving forecasting abilities and logistical management. Predictive analytics powered by AI evaluate past and present data regarding weather, crop yields, and market demands to forecast production requirements and enhance distribution strategies, thereby reducing post-harvest losses and ensuring food distribution meets market needs. Furthermore, AI-driven systems guarantee food quality by monitoring product conditions, quickly detecting contaminants, and contributing to the preservation of consumer safety and trustv(Gupta & Tripathi, 2024; Heidari et al., 2022).

3.3 Robotics and automation in agricultural tasks

The combination of artificial intelligence (AI) with robotics and automation is transforming agricultural practices by tackling significant challenges in productivity, labour efficiency, and sustainability (Taseer & Han, 2024). Through the use of AI-driven robotic systems, agriculture has evolved into a model where repetitive, labour-intensive tasks are handled autonomously, thereby improving efficiency across various farming operations (Chindasombatcharoen et al., 2024). This development has laid the groundwork for more flexible and efficient agricultural systems, where precision management, harvesting accuracy, and enhanced livestock monitoring are standard practices. In crop management, robotics powered by AI are essential, enhancing various tasks that traditionally demanded significant labour. Cutting-edge sensor technologies enable robots to traverse fields, evaluate plant health, and accurately administer inputs such as fertilisers and pesticides (Anbazhagan & Mugelan, 2024). Autonomous tractors, sprayers, and seeders utilise AI algorithms to enhance their routes and modify application rates according to real-time data, thereby decreasing resource waste and lessening environmental impact while maintaining consistent crop quality. Automated weeding robots employ computer vision and machine learning to differentiate between crops and weeds, deliver precise treatments, and minimise herbicide application, thereby fostering ecological sustainability (Ma et al., 2024).

In the field of harvesting, robotics powered by AI significantly boost productivity, especially for labour-intensive crops that need meticulous handling to preserve quality. Harvesters powered by AI and equipped with computer vision are capable of evaluating fruit ripeness and optimal harvesting conditions, allowing for precise picking with reduced human involvement(Gautron et al., 2022; Ma et al., 2024). These systems utilise algorithms to differentiate between fruits, leaves, and stems, enhancing harvest precision and minimising crop damage. Specialised robots in horticulture guarantee that fruits and vegetables are harvested at their peak maturity, leading to enhanced yields and superior-quality produce prepared for market distribution(Chojnacka & Chojnacki, 2024). AI-based robotics play a significant role in enhancing operational efficiency and promoting animal welfare in livestock management. AI-enabled robotic systems assess health indicators, track feeding behaviours, and identify possible health concerns, facilitating timely interventions. Through the ongoing monitoring of livestock conditions, these robotic systems deliver essential information regarding animal health, enabling early disease identification and minimising reliance on antibiotics. Furthermore, automated milking systems, driven by AI, enhance milking schedules, increase output, and ensure consistent quality, thereby further elevating the efficiency of livestock management(Thamarai et al., 2024).

AI-enhanced robotics significantly improve post-harvest handling and processing in the agricultural supply chain (Feng et al., 2024). Robotic systems that utilise AI assess crop quality and categorise produce according to size, ripeness, and various quality metrics, enhancing the efficiency of sorting and packaging processes. Automated quality control in post-harvest handling minimises food waste while improving storage practices, thereby bolstering market readiness and ensuring food safety. Although the advantages of AI-driven robotics in agriculture are significant, there are still challenges to overcome regarding their adoption. The significant initial expenses, the necessity for specialised infrastructure, and the requirement for skilled personnel to manage and maintain these systems hinder their broad adoption. The digital divide impacts the availability of advanced tools, especially for small-scale farmers, making adoption even more challenging. Cooperation between governments, technology providers, and various stakeholders could enhance the accessibility and affordability of AI-driven solutions by implementing training programs and providing financial assistance.

3.4 AI in climate-smart and sustainable agriculture

The incorporation of artificial intelligence (AI) into climate-smart and sustainable agriculture has become an essential element in tackling the intricate challenges presented by climate change and food security (Mienye et al., 2024). By utilising advanced data analysis, predictive modelling, and real-time monitoring, AI promotes farming practices that are both resilient and environmentally sustainable, adapting to changing climate conditions while improving productivity (Jakobsen et al., 2023). The use of AI technologies in agriculture allows for improved resource efficiency, accurate crop management, and contributes to sustainable ecological health over time. An important use of AI in sustainable agriculture is precision farming, which employs data-driven methods for thorough monitoring of crops and effective resource management. AI-driven systems analyse data from various sources, such as satellite imagery, drones, and sensors, to assess crop health, soil conditions, and moisture levels. This analysis facilitates focused actions in irrigation, fertilisation, and pest management, leading to a reduction in resource waste and a decrease in environmental impact. Precision agriculture, supported by AI, proves to be particularly beneficial in regions facing water scarcity or erratic weather, where the efficient use of resources is crucial. Furthermore, AI models that evaluate historical and real-time data offer precise predictions regarding crop yields and disease risks, facilitating proactive measures against potential challenges (Alka et al., 2024; Morchid et al., 2024).

AI plays a crucial role in sustainable land management, especially in addressing climate-induced pressures on land resources. AI systems monitor soil health indicators, including nutrient levels and erosion potential, and suggest conservation strategies. The combination of remote sensing and geospatial analytics enables AI to pinpoint vulnerable areas and recommend soil-preserving practices such as crop rotation or cover cropping, aimed at improving soil fertility and preventing degradation. The ability to track soil health over time guarantees that land resources stay productive and resilient, supporting sustainable land use practices (Yang et al., 2024). In climate adaptation, AI plays a crucial role in predictive modelling, offering essential early warnings about adverse weather conditions. Alerts powered by AI provide information on potential droughts, floods, or significant temperature changes, allowing for proactive measures to safeguard crops and livestock from harm. Predictive models that combine data on weather, crop development, and soil conditions improve the adaptability of agricultural systems, strengthening their resilience to climate variability(Konfo et al., 2024).

AI technologies contribute to biodiversity conservation in agricultural landscapes, aiding in the preservation of ecological balance(Shah et al., 2024). Through the monitoring of biodiversity metrics, AI-driven systems direct sustainable practices that safeguard vital species such as pollinators and beneficial insects, crucial for the health of crops and the functioning of ecosystems. These tools assist in creating practices that enhance ecological resilience, guaranteeing that agricultural systems stay productive while supporting biodiversity conservation objectives. Even with these advantages, various obstacles impede the widespread adoption of AI in climate-smart agriculture. The restricted availability of high-quality data, especially in developing areas, limits the precision of AI models. Moreover, the elevated expenses linked to AI technology can discourage small-scale farmers, and the need for technical know-how in managing AI systems presents additional challenges (Thapa et al., 2024). Cooperation between governments, technology providers, and agricultural institutions will be crucial in tackling these challenges, fostering affordable and accessible AI solutions across various agricultural environments (Ludwig-Ohm et al., 2023).

3.5 Industry 4.0 and smart agriculture technologies

The integration of artificial intelligence (AI) within Industry 4.0 and smart agriculture technologies has become a transformative force in modern agriculture, enhancing productivity, precision, and sustainability (Rohit Sharma et al., 2024). Leveraging advanced technologies such as the Internet of Things (IoT), machine learning, and robotics, AI creates a connected ecosystem where data-driven insights optimize decision-making and resource efficiency. This interconnected system enables precision farming, automation, and real-time analysis, equipping agriculture to meet challenges posed by climate variability, resource scarcity, and rising food demands (Paul et al., 2023; Uctu et al., 2024). AI's role in precision agriculture involves comprehensive monitoring and resource management. By utilizing data from sensors, satellite imagery, and drones, AI-driven systems analyze real-time soil conditions, crop health, and weather patterns to support precise interventions in irrigation, fertilization, and pest control. These applications minimize resource waste, boost crop yield, and reduce environmental impacts. Additionally, AI models can leverage historical data to predict crop yields, providing valuable insights for planning and resource allocation (Chehri et al., 2020; Debauche et al., 2022).

Automation, powered by AI, is a critical component of Industry 4.0 agriculture, driving labor efficiency and consistency. Robotic systems equipped with AI algorithms autonomously perform tasks such as planting, harvesting, and weeding, reducing the need for manual labor in repetitive activities (Sridhar et al., 2023). Autonomous tractors, drones, and robotic harvesters navigate fields accurately, optimizing paths and adapting actions based on real-time data. This automation of labor-intensive activities enhances operational efficiency, particularly benefiting large-scale agricultural enterprises and regions facing labor shortages (Kuppusamy et al., 2024). AI's synergy with IoT further strengthens smart agriculture by creating a network of interconnected sensors and devices that continuously gather and transmit data. IoT-enabled sensors measure parameters such as temperature, humidity, soil moisture, and nutrient levels, while AI algorithms analyze this data to provide actionable insights. This interconnected system fosters responsive decision-making, supporting an adaptive approach to changing conditions and contributing to agricultural resilience (Abiri et al., 2023; Kaur et al., 2023).

In addition, AI enhances supply chain management by ensuring that food production aligns with market demands and reduces waste (Magazzino et al., 2024). Predictive analytics applications use historical and real-time data on crop yields, weather patterns, and market trends to anticipate production needs, enabling better planning for harvesting, storage, and distribution. This predictive approach minimizes post-harvest losses, optimizes logistics, and ensures a stable flow within the supply chain, which is essential for meeting consumer demands and minimizing food waste (Jerhamre et al., 2022).

AI also supports sustainable agricultural practices by monitoring environmental impacts and fostering biodiversity (Abegaz et al., 2024). Through data analysis on ecosystem health and crop diversity, AI systems provide guidance on sustainable land use, reducing chemical input reliance and encouraging practices like crop rotation. These insights align agricultural practices with sustainability goals that emphasize long-term resource health and ecological balance. Despite the extensive advantages, challenges remain in adopting AI within Industry 4.0 agriculture. High initial costs, particularly for small-scale farms, present financial barriers, and data quality or accessibility issues can impact model accuracy. Additionally, specialized technical skills are often required to operate AI systems effectively, posing further obstacles. Collaborative efforts from governments, technology providers, and agricultural institutions will be essential to expand access, lower costs, and provide training for broader adoption (Hasan et al., 2024; Mandal et al., 2024).

3.6 AI and smart systems in aquaculture and food production

Artificial intelligence (AI) has become a pivotal element in the evolution of intelligent systems for aquaculture and food production, leading to remarkable improvements in efficiency, productivity, and sustainability (Kabir & Ekici, 2024; Li et al., 2024). Through the integration of real-time monitoring, predictive analytics, and data-driven decision-making, AI improves resource management, disease detection, and food quality, enabling the sector to respond effectively to global challenges like climate variability, increasing demand, and resource constraints. In aquaculture, artificial intelligence enhances critical elements of aquatic farming, such as water quality and feeding schedules (Boursianis et al., 2022). AI-driven systems assess data from sensors that track factors like temperature, pH, and oxygen levels, allowing for immediate adjustments that ensure a consistent environment for aquatic life. These insights enable accurate resource management, reducing water and feed waste while fostering sustainable practices. Furthermore, AI algorithms examine fish behaviour to create effective feeding routines, guaranteeing optimal feed distribution that minimises costs and promotes healthy fish growth (Jutagate et al., 2024; Mahanty et al., 2024).

The application of AI in aquaculture has significantly enhanced disease detection and prevention, resulting in better animal welfare and production outcomes (Amiri et al., 2024). Machine learning algorithms analyse image and behavioural data to identify early indicators of disease or stress in fish populations, facilitating prompt interventions that reduce disease transmission and decrease mortality rates. The use of AI for automated health monitoring minimises the reliance on antibiotics and improves food safety, fostering more sustainable practices in the industry. AI enhances various stages in food production, including processing, quality control, and packaging. AI-driven automation systems detect product inconsistencies, guaranteeing that only top-quality items move forward in the production process. Through the analysis of data gathered from cameras and sensors, these systems categorise products based on attributes like size, colour, ripeness, and texture, enhancing the sorting process and improving quality control (Akkem et al., 2024; Kong et al., 2024; Mahato & Neethirajan, 2024). Furthermore, AI-driven predictive maintenance oversees machinery performance, averting downtime and reducing disruptions in production.

The efficiency of supply chain management in food production has been enhanced by the use of AI applications (Grahmann et al., 2024). Predictive analytics utilises data regarding demand patterns, seasonal trends, and logistics to anticipate supply requirements and enhance storage and distribution strategies (Harfouche et al., 2019; Petrović et al., 2024; Sow et al., 2024). This predictive strategy effectively reduces post-harvest losses, synchronises supply with demand, minimises food waste, and improves food availability. Additionally, AI-powered traceability in supply chains monitors products from their source to distribution, enhancing transparency and ensuring food safety. The combination of AI and the Internet of Things (IoT) has significantly enhanced the functionalities of smart aquaculture and food production systems. IoT devices consistently collect data regarding environmental and operational conditions, which AI algorithms assess to provide actionable insights.

This interconnected system of AI and IoT promotes adaptive management strategies, enhancing resource efficiency, operational precision, and resilience to environmental changes (Gebresenbet et al., 2023; Mühl & de Oliveira, 2022).

Nonetheless, obstacles to the integration of AI in aquaculture and food production remain. The significant initial investment costs, necessary data infrastructure, and the requirement for technical expertise restrict accessibility, especially for smaller producers (Chandio et al., 2023; Koutridi & Christopoulou, 2023). Concerns like data privacy and quality significantly impact the accuracy of AI models, and it is essential to tackle these issues to guarantee ethical and dependable applications. Cooperation among industry stakeholders, governments, and technology providers will be crucial for enhancing the accessibility of AI solutions and ensuring the availability of training and resources necessary for successful implementation.

4. CONCLUSION

Artificial intelligence plays a transformative role in advancing sustainable and resilient agricultural systems across climate-smart agriculture, smart aquaculture, and food production. By facilitating precision farming, yield forecasting, adaptive land management, and disease detection, AI contributes significantly to food security and environmental sustainability, particularly in an era of climate change. Integrating AI with Industry 4.0 technologies, such as IoT and robotics, enhances efficiency and operational precision, addressing challenges like resource scarcity and fluctuating environmental conditions. While barriers remain in data accessibility, costs, and technical requirements, collaborative efforts across sectors can expand access to AI solutions. As innovations continue, AI is poised to support agriculture's adaptability and efficiency, building a foundation for sustainable food systems that meet future global demands.

ACKNOWLEDGEMENT

We express our sincere gratitude for the financial assistance provided by the University Technology Sarawak to fund this project.

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