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Green Artificial Intelligence Framework for Energy Efficient Smart Agriculture in Tropical Environments

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ABSTRACT

The increasing demand for sustainable agricultural production in tropical environments has encouraged the integration of environmentally responsible digital technologies to address energy consumption and resource inefficiency in smart farming systems. **This study proposes** a Green Artificial Intelligence framework designed to enhance energy efficiency, optimize agricultural resource utilization, and support sustainable farming practices in tropical regions characterized by high climate variability and ecological sensitivity. The research aims to develop an intelligent and adaptive agricultural model capable of reducing computational energy usage while improving environmental monitoring and decision-making processes in precision agriculture. The proposed framework integrates Internet of Things sensors, machine learning algorithms, and energy-aware data processing techniques to monitor soil moisture, temperature, humidity, and crop health in real time. **A quantitative experimental** approach was employed using simulated agricultural datasets and smart sensor data collected from tropical farming environments. **The results demonstrate** that the proposed Green AI framework significantly reduces energy consumption in data processing operations while maintaining high predictive accuracy and operational efficiency in smart irrigation and crop management systems. Furthermore, the framework improves environmental sustainability by minimizing excessive water and energy usage in agricultural activities. **In conclusion**, the study highlights the potential of Green Artificial Intelligence as an innovative solution for developing sustainable, resilient, and energy-efficient smart agriculture systems that support long-term environmental conservation and food security in tropical regions.

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1. INTRODUCTION

The rapid development of digital transformation technologies has significantly influenced the agricultural sector, particularly in improving productivity, resource efficiency, and environmental sustainability [1, 2]. In recent years, smart agriculture has emerged as an innovative approach that integrates Artificial Intelligence

(AI), Internet of Things (IoT), cloud computing, and data analytics to optimize agricultural operations through intelligent monitoring and automated decision-making systems. This transformation is particularly important in tropical environments, where agricultural activities are highly dependent on climate stability, water availability, and ecosystem balance [3]. Tropical regions are characterized by high rainfall variability, increasing temperatures, soil degradation, and vulnerability to climate change, all of which directly affect agricultural productivity and food security [4]. Although AI technologies have successfully improved precision farming and predictive agricultural systems, the increasing computational demands of machine learning models and large-scale data processing have raised concerns regarding energy consumption and environmental impact [5]. Conventional AI systems often require high computational resources, intensive energy usage, and continuous cloud processing that may contribute to carbon emissions and unsustainable technological practices [6]. As global sustainability issues become increasingly critical, there is a growing need to develop Green Artificial Intelligence frameworks that prioritize energy efficiency, environmentally responsible computation, and sustainable technological integration in agricultural systems [7]. Therefore, integrating Green AI into smart agriculture is becoming an essential strategy for balancing technological innovation with environmental conservation and sustainable development goals.

The implementation of Green Artificial Intelligence in agriculture offers significant opportunities to improve farming efficiency while minimizing ecological damage and excessive energy utilization [8]. Green AI refers to the development of intelligent systems that emphasize computational efficiency, reduced energy consumption, and environmentally sustainable processing without compromising analytical performance and predictive accuracy [9]. In smart agriculture, Green AI can optimize irrigation systems, monitor crop conditions in real time, predict environmental risks, and reduce unnecessary resource consumption through adaptive data-driven decision-making processes [10]. The integration of IoT sensors and machine learning algorithms enables continuous monitoring of environmental parameters such as soil moisture, temperature, humidity, and nutrient conditions, allowing farmers to make precise and efficient operational decisions [11]. Furthermore, energy-aware AI systems can significantly reduce processing overhead by utilizing optimized algorithms, lightweight computational models, and efficient data management strategies. Previous studies have primarily focused on improving agricultural productivity through AI-driven automation and predictive analytics; however, limited research has specifically addressed the environmental sustainability and energy efficiency dimensions of AI implementation in tropical agricultural ecosystems [12]. Many existing intelligent farming systems still rely heavily on high-power cloud infrastructures and computationally expensive machine learning architectures, which may contradict the principles of sustainable environmental management [13]. Moreover, tropical agricultural environments present unique ecological challenges due to biodiversity sensitivity, fluctuating climate conditions, and resource limitations, requiring adaptive and environmentally conscious technological solutions [14]. Consequently, there remains a substantial research gap regarding the development of integrated Green AI frameworks specifically designed for sustainable smart agriculture in tropical regions.

This study aims to propose a Green Artificial Intelligence framework for energy-efficient smart agriculture in tropical environments by integrating IoT-based environmental sensing, lightweight machine learning optimization, and sustainable computational strategies into a unified agricultural system [15]. The proposed framework is designed not only to improve operational efficiency and agricultural productivity but also to minimize computational energy consumption and environmental impacts associated with conventional AI-based agricultural systems. By utilizing real-time data collected from environmental sensors, including soil moisture, temperature, humidity, and other relevant agricultural parameters, the framework enables adaptive and data-driven decision-making for irrigation management, crop monitoring, and environmental control. The study employs a quantitative experimental approach using simulated agricultural datasets and sensor-generated environmental data to evaluate the effectiveness of the proposed framework in supporting sustainable agricultural management [16]. In particular, the experimental evaluation focuses on the ability of lightweight and energy-efficient machine learning models to maintain reliable predictive performance while reducing unnecessary computational requirements compared with more resource-intensive approaches. The framework incorporates real-time monitoring systems, predictive analytics, and energy-efficient processing strategies to optimize agricultural decision-making processes and support more responsible resource utilization. This research contributes to the growing field of sustainable digital agriculture by introducing an environmentally responsible AI-based approach that aligns technological innovation with ecological preservation, energy efficiency, and climate resilience objectives [17]. Furthermore, the proposed framework provides practical implications for policymakers, agricultural practitioners, and researchers in developing sustainable agricultural technologies that can respond to the distinctive environmental conditions and resource challenges of tropical regions. By emphasizing the integration of intelligent sensing, efficient computation, and sustainability-oriented decision-making, the study is expected to demonstrate how Green Artificial Intelligence can support the development of resilient, efficient, and environmentally sustainable agricultural systems capable of addressing future food production challenges while contributing to broader global sustainability agendas.

2. LITERATURE REVIEW

2.1. Smart Agriculture and Digital Transformation in Tropical Farming

The advancement of digital technologies has transformed traditional agricultural practices into more intelligent, data-driven, and automated farming systems known as smart agriculture [18]. Smart agriculture integrates various emerging technologies such as Artificial Intelligence, Internet of Things, cloud computing, big data analytics, and wireless communication systems to improve agricultural productivity, operational efficiency, and environmental sustainability. This transformation enables farmers to monitor environmental conditions, analyze agricultural data in real time, and optimize farming activities through intelligent decision-making systems. In tropical environments, smart agriculture plays an increasingly important role due to the region's high vulnerability to climate instability, unpredictable rainfall patterns, pest outbreaks, and declining soil quality [19]. Tropical agriculture also faces significant challenges related to excessive water consumption, inefficient resource management, and environmental degradation caused by conventional farming practices. Therefore, the adoption of digital farming technologies is considered essential for improving agricultural resilience and supporting sustainable food production systems [20]. Furthermore, digital transformation in tropical farming not only enhances productivity but also contributes to environmental conservation by minimizing resource waste and improving precision in agricultural operations.

2.2. Artificial Intelligence Applications in Sustainable Agriculture

Artificial Intelligence has become one of the most influential technologies in modern sustainable agriculture due to its ability to process large volumes of environmental and agricultural data efficiently [21]. AI technologies such as machine learning, deep learning, computer vision, and predictive analytics are widely applied in precision agriculture to improve crop monitoring, disease detection, yield prediction, and irrigation management [22]. Intelligent systems can analyze environmental conditions including soil moisture, temperature, humidity, and nutrient availability to support accurate agricultural decision-making processes. In addition, AI-driven agricultural systems can automate repetitive farming tasks, reduce labor intensity, and optimize resource allocation, leading to improved operational performance and sustainability [23]. Several studies have demonstrated that AI applications significantly improve farming productivity while reducing excessive use of water, fertilizers, and pesticides. However, despite these advantages, the increasing complexity of AI models often requires high computational power and intensive data processing infrastructure, which may increase energy consumption and environmental impact [24]. As a result, sustainable AI implementation has become an important research focus in developing environmentally responsible smart agriculture systems.

2.3. Green Artificial Intelligence and Energy Efficient Computing

Green Artificial Intelligence refers to the development and implementation of AI systems that prioritize energy efficiency, computational optimization, and environmental sustainability throughout the lifecycle of intelligent technologies [25]. Unlike conventional AI approaches that mainly focus on predictive performance and accuracy, Green AI emphasizes reducing computational costs, minimizing carbon emissions, and improving energy-aware processing mechanisms. This concept has become increasingly relevant as the rapid growth of AI applications contributes to rising global energy consumption associated with data centers, cloud computing infrastructures, and large-scale machine learning operations. In agricultural systems, Green AI can support sustainable farming by utilizing lightweight machine learning models, efficient algorithms, and optimized data processing techniques that consume less energy while maintaining analytical effectiveness [26]. The implementation of energy-efficient AI frameworks is particularly important in tropical and developing regions where energy resources may be limited and environmental sustainability remains a critical concern. Furthermore, Green AI contributes to achieving global sustainability goals by integrating intelligent technologies with environmentally responsible computing strategies [27]. Therefore, combining Green AI principles with smart agriculture systems offers significant potential for creating sustainable agricultural ecosystems that balance technological innovation with ecological preservation.

2.4. Internet of Things Based Environmental Monitoring Systems

The Internet of Things has become a fundamental component of smart agriculture systems due to its capability to provide continuous environmental monitoring through interconnected sensor devices [28]. IoT-based monitoring systems collect real-time environmental data from agricultural fields, including soil moisture, air temperature, humidity, rainfall intensity, water quality, and crop conditions. These smart sensors enable farmers and agricultural stakeholders to obtain accurate and timely information regarding environmental changes and farming conditions, allowing more precise and efficient agricultural management [29]. The integration of IoT with Artificial Intelligence further enhances the effectiveness of environmental monitoring systems by enabling automated analysis, anomaly detection, and predictive decision-making processes. In tropical agricultural environments, IoT-based systems are highly beneficial for addressing climate variability, optimizing irrigation scheduling, and reducing resource wastage caused by manual monitoring limitations [30]. Additionally, wireless sensor networks and cloud-based monitoring platforms improve data accessibility and operational flexibility in remote agricultural areas. Despite these advantages, IoT systems also present challenges related to energy consumption, sensor reliability, and data processing efficiency [31]. Consequently, integrating energy-efficient technologies and sustainable computational methods into IoT-based agricultural systems has become increasingly important for supporting long-term environmental sustainability.

2.5. Climate Resilience and Sustainable Resource Management in Tropical Agriculture

Climate resilience has become a major priority in tropical agricultural systems due to the increasing impacts of climate change on food production, environmental stability, and resource availability. Rising global temperatures, irregular precipitation patterns, flooding, drought, and extreme weather events significantly threaten agricultural productivity and ecosystem sustainability in tropical regions. Sustainable resource management strategies are therefore necessary to improve agricultural adaptability and minimize environmental degradation [32]. Smart agriculture technologies, including AI-driven irrigation systems, predictive climate analytics, and environmental monitoring platforms, provide innovative solutions for improving resilience against climate-related risks. Intelligent resource management systems can optimize water usage, reduce unnecessary fertilizer application, and improve energy efficiency in farming operations, thereby supporting both environmental conservation and agricultural productivity [33]. Moreover, sustainable agricultural management contributes to preserving biodiversity, protecting soil quality, and maintaining ecosystem balance in tropical environments. The integration of climate resilience strategies with digital technologies also aligns with global sustainable development objectives focused on food security, environmental sustainability, and climate adaptation. As a result, the development of environmentally responsible smart farming systems has become essential for ensuring long-term agricultural sustainability in tropical and archipelagic regions.

2.6. Research Gap and Conceptual Framework Development

Previous studies have extensively explored the implementation of Artificial Intelligence and Internet of Things technologies in smart agriculture systems; however, limited research has specifically focused on integrating Green Artificial Intelligence principles into energy-efficient agricultural frameworks for tropical environments [34]. Most existing studies primarily emphasize productivity improvement, predictive accuracy, and automation performance without adequately considering the environmental costs associated with high computational energy consumption and intensive data processing. In addition, many intelligent agricultural systems still depend heavily on cloud-based infrastructures and computationally expensive machine learning architectures that may contradict sustainability objectives. Furthermore, research addressing the unique environmental characteristics of tropical agricultural ecosystems, including climate variability, ecological sensitivity, and resource limitations, remains relatively limited [35]. Therefore, there is a significant research gap regarding the development of integrated frameworks that combine Green AI, sustainable computing, IoT-based environmental monitoring, and climate resilience strategies within smart agriculture systems. This study addresses the identified gap by proposing a Green Artificial Intelligence framework specifically designed to improve energy efficiency, environmental sustainability, and intelligent agricultural management in tropical farming environments. The conceptual framework developed in this research integrates environmental sensing technologies, adaptive machine learning models, and sustainable computational approaches to support resilient and eco-friendly agricultural systems [36]. The originality of the proposed framework lies in coordinating these established technologies through an energy-aware adaptive processing mechanism. Unlike existing approaches that mainly use IoT for environmental monitoring, machine learning for prediction, or smart irrigation for water optimization, the proposed framework links environmental conditions with computational workload so that processing intensity can be adaptively adjusted according to environmental stability. This framework-level coordination simultaneously addresses computational energy efficiency, water-use optimization, and climate-resilient agricultural management in tropical environments.

3. RESEARCH METHOD

3.1. Research Design

This study employed a quantitative experimental research design to develop and evaluate a Green Artificial Intelligence framework for energy-efficient smart agriculture in tropical environments. The research focused on integrating Artificial Intelligence, Internet of Things (IoT), and energy-efficient computing techniques to improve agricultural sustainability and environmental resilience. The proposed framework was designed to optimize agricultural monitoring systems while reducing computational energy consumption in precision farming operations. The study utilized environmental and agricultural datasets generated from smart sensor simulations representing tropical farming conditions, including soil moisture, temperature, humidity, rainfall intensity, and crop health indicators. The research process consisted of data collection, preprocessing, intelligent model development, energy efficiency analysis, and framework evaluation.

The quantitative approach was selected because it allows systematic measurement of system performance, computational efficiency, and predictive accuracy within intelligent agricultural environments. Furthermore, experimental evaluation enabled the comparison between conventional AI processing systems and the proposed Green AI framework in terms of energy utilization and operational effectiveness. The research workflow was structured to ensure reproducibility, analytical consistency, and sustainability-oriented evaluation.

3.2. Data Collection and Environmental Monitoring

This study utilized a simulated time-series agricultural dataset to represent IoT-based monitoring in tropical farming environments. The dataset included soil moisture, temperature, humidity, rainfall intensity, water usage, and crop health indicators, generated chronologically to capture climate variations, irrigation changes, and crop responses to environmental stress. The data were validated, normalized, filtered for noise, and checked for missing values before analysis. Identical simulation conditions were applied to the conventional AI system and the proposed Green AI framework for fair evaluation. However, as the dataset is simulation-based rather than derived from real field measurements, further validation through real-world IoT deployments across diverse crops and climatic conditions is required.

Table 1. Environmental Parameters Used in the Proposed Smart Agriculture Framework

Environmental Parameter	Sensor Function	Measurement Objective	Sustainability Contribution
Soil Moisture	Detect soil water level	Optimize irrigation scheduling	Reduce water waste
Temperature	Monitor environmental heat	Improve crop adaptation analysis	Enhance climate resilience
Humidity	Measure atmospheric moisture	Support crop growth monitoring	Improve environmental stability
Rainfall Intensity	Detect precipitation levels	Predict irrigation requirements	Reduce excessive water usage
Crop Health Indicator	Analyze crop conditions	Detect plant stress and diseases	Improve agricultural productivity

Table 1 presents the proposed environmental monitoring framework supports adaptive irrigation management and sustainable resource optimization by analyzing relationships among soil moisture, climate variables, and crop conditions. Instead of relying on fixed irrigation schedules, the system generates recommendations based on real-time environmental changes, such as increasing irrigation requirements under low moisture and high-temperature conditions or reducing water usage during sufficient rainfall periods.

The processed environmental data were integrated into a sequential workflow involving data acquisition, preprocessing, environmental assessment, and decision generation. In addition, energy-efficient strategies, including lightweight machine learning and optimized data processing, were implemented to minimize unnecessary computation and transmission while maintaining monitoring effectiveness. Nevertheless, real-world IoT sensor experiments are needed to further evaluate the framework's performance, scalability, and energy efficiency under actual tropical farming conditions.

3.3. Green AI Framework Development

The proposed Green Artificial Intelligence framework integrates lightweight machine learning, IoT-based monitoring, and energy-efficient data processing to support sustainable smart agriculture. The framework optimizes computational operations by adapting data analysis according to environmental conditions while maintaining predictive performance. Decision Tree and Random Forest models were selected based on accuracy, processing time, and energy consumption, and evaluated using identical simulated agricultural scenarios for fair comparison.

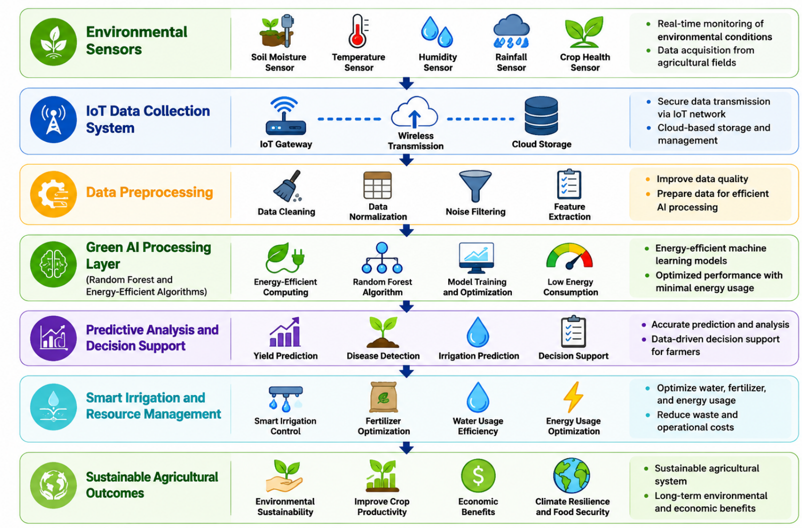

Figure 1. Green Artificial Intelligence Framework for Smart Agriculture

As shown in Figure 1 the framework applies an energy-aware mechanism that reduces unnecessary processing during stable conditions and increases analytical activities when significant environmental changes occur. The implementation consists of sensor data acquisition, preprocessing, feature extraction, predictive analysis, adaptive processing, and decision support for irrigation optimization, crop monitoring, and resource management. The proposed approach was compared with conventional AI using prediction accuracy, processing time, and energy consumption. However, since the evaluation was simulation-based, further validation through real-world IoT deployments is required to confirm its practical effectiveness in tropical farming environments.

3.4. System Evaluation and Performance Analysis

The performance evaluation of the proposed framework was conducted to assess its effectiveness in supporting sustainable smart agriculture while maintaining reliable predictive performance and improving computational efficiency. The proposed Green AI framework was compared with conventional AI processing using equivalent simulated agricultural datasets and identical environmental monitoring scenarios to ensure a fair and consistent evaluation. The assessment considered several indicators, including prediction accuracy, processing time, computational energy consumption, water usage efficiency, and resource optimization, which collectively represent both technical performance and sustainability contributions. Prediction accuracy and processing time were analyzed to evaluate model reliability and system responsiveness, while energy consumption, water efficiency, and resource optimization were examined to determine the framework's capability in reducing computational and resource waste.

Table 2. Evaluation Indicators for the Proposed Green AI Framework

Evaluation Indicator	Description	Measurement Objective
Prediction Accuracy	Accuracy of agricultural predictions	Evaluate AI model reliability
Energy Consumption	Computational power utilization	Measure energy efficiency
Processing Time	Duration of data analysis operations	Evaluate system responsiveness
Water Usage Efficiency	Optimization of irrigation management	Assess sustainability performance
Resource Optimization	Efficient use of agricultural resources	Improve environmental management

Table 2 the experimental results, which were quantitatively analyzed to evaluate the effectiveness of integrating lightweight machine learning algorithms, IoT-based monitoring, and adaptive energy-aware processing mechanisms in improving agricultural decision-making efficiency, while also assessing the framework's capability to maintain reliable predictive performance under varying environmental conditions. The adaptive mechanism was evaluated based on its ability to dynamically adjust computational operations according to environmental changes by minimizing unnecessary processing during stable conditions and activating additional analysis when significant variations occurred, demonstrating that the proposed lightweight Green AI approach can reduce computational energy consumption, optimize resource utilization, and support sustainable decision-making in tropical smart agriculture systems.

4. RESULT AND DISCUSSION

The experimental results demonstrate that the IoT-based environmental monitoring system effectively supported the proposed Green Artificial Intelligence framework under simulated tropical agricultural conditions by continuously collecting and processing key parameters, including soil moisture, temperature, humidity, rainfall intensity, and crop health indicators. The system showed stable operational performance, consistent data acquisition, and low transmission delays, enabling timely agricultural analysis and adaptive decision-making, particularly through soil moisture-based irrigation recommendations and environmental condition assessment. The energy-efficiency evaluation further confirmed that the proposed Green AI framework improved computational performance through lightweight machine learning models and adaptive processing mechanisms, reducing processing time from 3.8 seconds to 2.4 seconds while maintaining competitive predictive accuracy of 93.8% compared with 95.1% for the conventional AI approach. The framework also reduced unnecessary computational activities during stable environmental conditions, although the energy evaluation represented relative computational demand rather than direct electrical measurements, requiring further validation using energy-monitoring instruments. The integration of predictive analysis and intelligent decision support enabled adaptive irrigation optimization, environmental risk identification, and crop condition monitoring, demonstrating the potential of lightweight AI, IoT monitoring, and adaptive processing to improve resource efficiency and sustainable agricultural management. From a sustainability perspective, the proposed framework contributes to SDG 2 through improved agricultural monitoring and resilient food production, SDG 6 through efficient irrigation and water optimization, SDG 7 through reduced computational energy requirements, SDG 12 through optimized resource utilization, and SDG 13 through climate-adaptive monitoring and sustainable processing mechanisms. Overall, the findings indicate that the proposed Green AI framework successfully integrates IoT sensing, lightweight machine learning, and energy-aware processing into a unified approach for supporting sustainable and climate-responsive agriculture; however, since the evaluation was based on simulated environmental conditions, future studies should validate the framework through real-world field experiments involving diverse locations, crops, and climatic conditions.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide important managerial implications for agricultural stakeholders, policymakers, technology developers, and environmental management institutions in supporting sustainable smart agriculture implementation in tropical environments. The proposed Green Artificial Intelligence framework demonstrates that energy-efficient intelligent systems can significantly improve agricultural productivity, resource optimization, and environmental sustainability while reducing computational energy consumption and operational inefficiencies. For agricultural managers and farming organizations, the integration of IoT-based environmental monitoring and adaptive AI-driven decision-support systems can enhance irrigation management, reduce water and energy waste, and improve real-time agricultural responsiveness under dynamic climate conditions. Policymakers can utilize the results of this study as a strategic reference for developing sustainable agricultural digitalization policies, climate resilience programs, and environmentally responsible technology adoption frameworks in tropical and archipelagic regions. In addition, technology developers and smart agriculture industries may adopt Green AI principles to design more sustainable and energy-aware agricultural platforms that minimize environmental impact while maintaining high operational performance. The study also highlights the importance of interdisciplinary collaboration between environmental scientists, agricultural engineers, and data technology experts in creating resilient agricultural ecosystems that align with global sustainability goals and long-term food security strategies. Overall, the implementation of Green Artificial Intelligence in smart agriculture offers practical and strategic opportunities for improving sustainable agricultural governance, operational efficiency, and environmental conservation in future agricultural systems.

6. CONCLUSION

This study successfully proposed and evaluated a Green Artificial Intelligence framework for energy-efficient smart agriculture in tropical environments by integrating IoT-based environmental monitoring systems, machine learning algorithms, and sustainable computational strategies. The research findings demonstrated that the proposed framework effectively improved agricultural monitoring, predictive decision-making, irrigation optimization, and resource management while significantly reducing computational energy consumption compared to conventional AI systems. The implementation of energy-efficient processing mechanisms and adaptive environmental sensing technologies contributed to enhancing sustainability, operational efficiency, and climate resilience within smart agriculture ecosystems. Furthermore, the framework maintained reliable predictive accuracy and system responsiveness, indicating that environmentally responsible AI technologies can support sustainable agricultural development without compromising analytical performance.

The study also confirmed that Green Artificial Intelligence can address critical environmental and operational challenges in tropical agriculture by minimizing unnecessary energy usage, optimizing water consumption, and supporting intelligent agricultural management. Through the integration of lightweight machine learning models and IoT-based sensing technologies, the proposed framework provided an effective solution for balancing technological innovation with environmental sustainability and long-term food security objectives. However, several limitations remain within this research, including the use of simulated datasets, limited real-world implementation scenarios, and restricted evaluation of advanced AI architectures and large-scale agricultural deployment conditions.

Future research is recommended to expand the practical implementation of Green AI frameworks through real-time agricultural field testing across diverse tropical environments and crop conditions. Further studies should investigate the integration of advanced deep learning techniques, edge computing systems, renewable energy technologies, and blockchain-based environmental data management to improve scalability, transparency, and sustainability within intelligent agricultural ecosystems. In addition, future research may explore the economic, social, and policy impacts of Green AI adoption in agriculture to provide broader insights into sustainable farming transformation and resilient environmental governance for future smart agriculture systems.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: NA and TP; Methodology: DE and MZ; Software: TP; Validation: DE and NA; Formal Analysis: MZ and TP; Investigation: NA; Resources: DE; Data Curation: TP and MZ; Writing-Original Draft Preparation: NA and MZ; Writing-Review and Editing: DE and NA; Visualization: MZ; All authors have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The datasets generated and analyzed during this study can be obtained from the corresponding author upon reasonable request.

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This research received no specific grant or financial assistance from any public, commercial, or non-profit funding organization.

7.5. Declaration of Conflicting Interest

The authors declare that there are no competing interests, financial conflicts, or personal relationships that could have influenced the research, interpretation, or reporting of the findings presented in this manuscript.

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