2026 Volume: 02 Issue: 06 www.ijrpa.com ISSN 2456-9995 Review Article

International Journal Research Publication Analysis

Page: 01-12

SUSTAINABLE CROP YIELD PREDICTION USING GREEN AI IN SMART AGRICULTURE SYSTEMS

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Article Received: 29 April 2026
Article Revised: 19 May 2026
Published on: 09 June 2026

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DOI: https://doi-doi.org/101555/ijrpa.4241

ABSTRACT

This study investigates the integration of Green Artificial Intelligence (AI) with sustainable agricultural and forest management to address important global issues such as climate change, food insecurity, and ecosystem degradation. Green AI, with its emphasis on environmental sustainability and energy efficiency, provides a disruptive way to increasing productivity while minimizing environmental damage.The study looks into how Green AI technologies—such as lightweight algorithms, sensor networks, and data analytics—can be used in precision agriculture and smart forestry. These technologies enable better resource allocation, pest and disease management, irrigation efficiency, and crop production forecasts. In forestry, AI is used to predict fires, evaluate canopy health, and organize conservation efforts.A primary goal is to design scalable, locally adaptive methods that address the unique needs of various agro-ecological systems. Simulated datasets and scenario analysis are used to show the probable effects of AI implementation in various environmental and operational scenarios.In addition, the study evaluates the socioeconomic aspects of AI adoption, with an emphasis on pricing, accessibility, and rural community engagement. The goal is to guarantee that technological innovation does not exacerbate equity disparities, but rather empowers vulnerable groups.Finally, this study argues that Green AI can serve as a catalyst for a more sustainable future, encouraging resilient agricultural systems and forest ecosystems that thrive in harmony with nature while also contributing to long-term food security and environmental responsibility.

KEYWORDS: Artificial Intelligence (AI). Crop yield prediction, Green AI, Smart Agriculture.

INTRODUCTION

Agriculture and horticulture are foundational components of human society. The global population is expected to grow by 31% by 2050, resulting in a huge increase in food consumption. The Food and Agriculture Organization (FAO) predicts that food production will increase by 2050 to meet the nutritional needs of a growing population [1], [2]. Table 1 shows an examination of fruit and vegetable production over three fiscal years by producing area [3]. The table depicts considerable changes in both cultivation area and productivity. Thus, it emphasizes the critical requirement for sustainable farming practices to ensure consistent yield.

Furthermore, current farming practices frequently rely on excessive and unsustainable resource consumption, and they are hampered by a variety of variables such as population growth, biodiversity loss, urbanization, and global warming. According to the Food Waste Index Report (2024), approximately 78.2 MT of food is wasted each year by conventional farming practices [4]. As a result, conventional farming practices not only fail to ensure the long-term viability of agricultural land, but also disrupt food supply systems, resulting in global resource degradation. For example, excessive use of crop fertilizers and pesticides can leave hazardous residues in food, endangering the health of both consumers and farmers. It also affects soil fertility, pollutes water bodies, and decreases biodiversity. Sustainable agriculture challenges conventional farming by putting environmental health, resource efficiency, and long-term production ahead of short-term yields.

As a result, it is critical to transition old agricultural methods into modern cutting-edge approaches under the banner of Agriculture 4.0. Agriculture 4.0, often known as Digital Agriculture (DA), is a transformative phase aimed at meeting the needs of the world's rapidly rising population [5]. It delivers a precise response to global food demand by boosting agricultural yields while optimizing labor needs, input costs, and environmental impact. It enhances the organization of farm inputs like fertilizers, herbicides, seeds, and bioenergy fuels by implementing distributed farm management strategies. The cutting-edge Agriculture 4.0 framework uses Computer Vision (CV), Deep Learning (DL), Machine Learning (ML), Remote Sensing (RS), Unmanned Aerial Vehicles (UAVs), and the Internet of Things (IoT) to precisely manage and monitor agricultural activities [6], [7]. It also uses cloud, edge, and fog computing for centralized and localized data delivery across several servers.

Processing enormous amounts of infield data is a critical requirement for Agriculture 4.0, which has fueled significant research into AI approaches such as deep learning and machine learning. They can improve forecast and recommendations through constant data monitoring, thereby increasing the sustainability and efficiency of agricultural systems. Furthermore, these AI models promote sustainable practices by reducing the environmental impact of farming and increasing supply chain efficiency [9], [10]. Deep learning, known for its autonomous imagery and data analysis skills, has lately been implemented in traditional agriculture, with promising results and new potential. Unlike classic ML methods, which rely on handmade feature map extraction, deep learning methods can learn the complex high-dimensional feature space from raw agriculture data automatically. Convolutional Neural Networks (CNNs) have demonstrated excellent performance in visualizing complicated, intricate feature patterns from large-scale datasets, thanks to their innate capacity to extract fine-grained and detailed features [11].

Several IoT sensors and actuators have been used to capture real-time data from farming fields, allowing agriculture to be autonomous in a variety of functions such as crop health monitoring, pest and disease prediction, crop yielding, and robotic harvesting [12]. The IoT architecture enables the establishment of Wireless Sensor Networks (WSNs) using a wide range of communication protocols and topologies for data transfer across various farming fields, including ZigBee, Sigfox, LTE-M, and Bluetooth [13], [14]. These networks are linked to an edge gateway layer, which saves and interprets sensor node data using intelligent approaches for further analysis. IoT application protocols such as Message Queuing Telemetry Transport (MQTT) and Hypertext Transfer Protocol (HTTP) use the internet to send processed agricultural data to specific cloud servers. Furthermore, IoT development boards, such as Raspberry Pi and Arduino devices, can function as gateways, allowing for smooth data transmission and processing. Several wireless communication techniques, such as Narrowband IoT (NB-IoT), Long Range Radio (LoRa), and Radio Frequency Module (RFM), have been used to enhance agricultural practices [15], [16], [17]. Furthermore, IoT-powered monitoring systems improve food security by providing early detection of pests and diseases on crops, allowing for timely actions to protect the crops. These technologies encourage sustainable farming methods that reduce hunger by maximizing resource utilization (such as water, energy, and fertilizers) while protecting the environment [18]. IoT sensors are critical for analyzing climate change impacts on crops and monitoring soil health, allowing farmers to take action and increase crop resilience.

RELATED WORKS

The goal of sustainable agriculture is to meet present-day food needs without endangering those of future generations [21, 22, 23]. Additionally, it emphasizes reducing the negative effects of farming on the environment by promoting sensible methods that protect biodiversity, conserve natural resources (land, water, etc.), and lessen pollution. In order to increase soil fertility and water retention capacity, it also supports environmentally friendly techniques including crop rotation, crop covering, and agroforestry. Additionally, it guarantees economic viability, enabling farmers to maintain their standard of living through economical and efficient means. According to FAO, Fig. 1 illustrates the fundamental ideas of sustainable farming. In order to achieve the three elements of sustainability (social, economic, and environmental) and the four pillars of food security (stability, utilization, availability, and access), the figure shows sustainable agriculture as a crucial key indicator [24]. Therefore, producing wholesome food while promoting social justice and rural community development requires sustainable agriculture.

In 2023, Vaishnavi Jayaraman, K. M. Monica, Sridevi S., Arun Raj are investigated Agriculture is a detracting sector in the world economy, defined as the practice of cultivating crops. Precision agriculture, which employs machine learning algorithms, is one of the fastest expanding approaches. It investigates the use of current technologies to boost crop yield while using less fertilizer. The major goal of this project is to predict soil compatibility using sensors and machine learning approaches. The key factors influencing plant growth were temperature, humidity, pH, and soil moisture. The nature of the soil would be determined by measuring the aforementioned entities. This article analyzes soil suitability using various machine learning approaches, including KNN, Support Vector Machine, Random Forest, Naïve Bayes, and Extreme Learning Machines. The ELM model predicts soil suitability with an accuracy of 99%.

In 2024 Pankaj Roy, Mrutyunjay Padhiary, Azmirul Hoque, Bhabashankar sought The rapid growth of machine learning (ML) has transformed various industries, including agriculture, by delivering novel solutions to complicated challenges associated with modern farming. This chapter examines the application of machine learning (ML) in precision agriculture, focusing on its ability to maximize crop output and enhance agricultural methods. It investigates the application of supervised, unsupervised, reinforcement, and deep learning approaches to analyze large datasets generated by remote sensing technologies, soil sensors, climate data, and agricultural equipment. Predictive modeling is commonly used to estimate agricultural productivity, identify pests and diseases, analyze soil health, optimize irrigation, and fertilize with precision. The chapter also looks at the challenges and limitations of implementing machine learning in agriculture, such as data quality and farmer acceptability.

In 2024 Mohammad Nadeem Ahmed, Mohammad Ashiquee RasoolThe use of artificial intelligence (AI) to farming techniques has become a revolutionary force in the era of precision agriculture, disrupting traditional practices and increasing agricultural output. This project will look into the practical effects of AI on smart farming, with a focus on critical issues such as agricultural yield optimization, resource management, and economic sustainability. The study investigates real-time decision-making processes using sophisticated data analytics and machine learning algorithms. It demonstrates how AI-driven insights can help farmers make better decisions, decrease resource waste, and increase overall farm output. The findings indicate how AI may be used to encourage environmentally responsible farming practices while also exhibiting the technology's verifiable benefits in terms of increased crop yields and cheaper production costs. Ethical concerns are crucial to our research as we navigate the complex intersection of technology and agriculture. The ethical implications of AI-integrated farming systems must be thoroughly evaluated in order to secure data, ensure fair access, and make acceptable use of new technologies. This study identifies potential impediments and recommends risk-reduction strategies while critically assessing the ethical implications of AI's widespread adoption in agriculture. To support the right deployment of AI technology in smart farming, the study underlines the importance of building an ethical framework that aligns with societal norms.

PROPOSED SYSTEM

The proposed approach presents a Green AI-based intelligent farming framework that combines high predictive performance with environmental sustainability. This framework combines six Green AI strategies to reduce energy use and CO2 emissions while retaining decision accuracy. Lightweight model architectures and energy-efficient techniques are used to reduce computing overhead. Model compression approaches, like as pruning and quantization, help to reduce model size and inference costs. Federated learning is used to enable decentralized training, which reduces data transfer and protects privacy, while edge computing allows for real-time decision-making closer to the data source, dramatically reducing cloud dependency and energy consumption. The system also promotes the utilization of renewable energy and environmentally friendly infrastructure to power AI functions. The suggested system makes climate-resilient, low-carbon, and resource-efficient smart agriculture possible by combining technology efficiency with eco-friendly design principles. Additionally, the architecture is scalable and extensible, allowing for future integration of IoT, blockchain, explainable AI, and policy-driven sustainability standards.

1. System Overview

Green AI emerges as a sustainable paradigm in this sector, aiming to create AI systems with high performance while minimizing computational cost, energy consumption, and environmental effect. In agriculture, Green AI focuses on developing lightweight algorithms, efficient learning models, and optimum deployment strategies that reduce carbon footprints while maintaining prediction accuracy. This method is strongly aligned with global sustainability objectives such as climate resilience, low-carbon development, and responsible resource consumption.

To solve these problems, the proposed research uses AS-ELM (Adaptive Sparse Extreme Learning Machine) in conjunction with a Green AI architecture. AS-ELM is ideal for smart agriculture due to its rapid learning speed, reduced training complexity, and lower computational overhead when compared to deep learning models. By combining AS-ELM with energy-conscious approaches like model compression, federated learning, and edge computing, the system offers efficient agricultural yield forecasts and resource management right at the data source. This eliminates reliance on centralized cloud infrastructure, saves energy, and enables real-time decision-making. Furthermore, the domain includes sustainable AI deployment strategies such as renewable energy and ecologically responsible computer infrastructures. Overall, this area symbolizes a transition to climate-smart, energy-efficient, and intelligent agricultural systems, illustrating how Green AI can power the next generation of sustainable farming solutions.

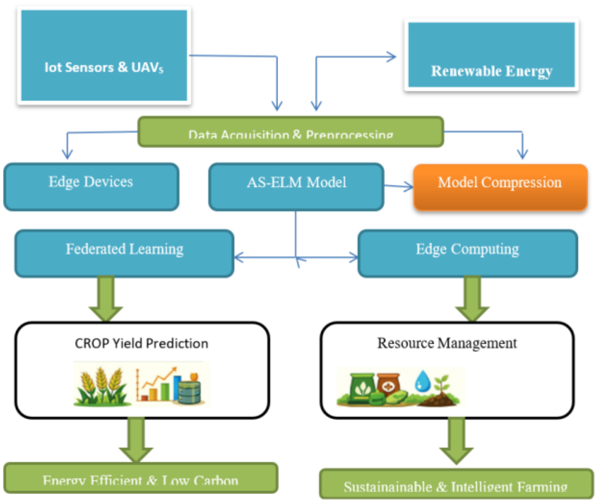

Figure 1 Architecture Diagram.

Data Acquisition Module

The Data Acquisition Module is the core of the proposed Green AI-based smart agriculture system, collecting real-time and historical agricultural data from a variety of sources. To achieve full data coverage, this module links field-deployed IoT devices, UAVs (drones) with image and sensing capabilities, and current agricultural databases. Soil moisture, temperature, humidity, rainfall, sun radiation, crop health indices, and environmental factors are all continuously measured and recorded. This module ensures that the system has access to correct, up-to-date information necessary for intelligent analysis and decision-making by allowing real-time data gathering and seamless transfer. Reliable data collection is crucial for increasing prediction accuracy and enabling prompt responses to dynamic agricultural and environmental changes.

2. Data Preprocessing Module.

The Data Preprocessing Module is in charge of converting raw, unstructured agricultural data into a clean and intelligible format suited for effective analysis. Because data from sensors and UAVs may contain noise, missing values, inconsistencies, or redundant features, this module provides necessary preprocessing operations such as noise filtering, outlier detection, missing value imputation, normalization, and feature selection. By enhancing data quality and reducing dimensionality, the preprocessing stage reduces computing overhead while improving model performance. Efficient preprocessing supports Green AI objectives by eliminating superfluous computations, saving energy usage and allowing for faster model training and inference.

3. Green AI Optimization Module.

The Green AI Optimization Module is intended to ensure that the suggested system is ecologically friendly and energy-efficient. This module focuses on reducing the carbon footprint of AI computation by implementing lightweight model structures, energy-aware algorithm design, and optimal execution methodologies. Lower power consumption is achieved by techniques such as minimizing redundant computations, selecting efficient learning algorithms, and scheduling jobs depending on energy availability. This module ensures that AI-driven agricultural intelligence meets sustainability goals while preserving dependable system performance by balancing predictive accuracy and computational efficiency.

4. AS-ELM Prediction Module.

The AS-ELM Prediction Module uses the Adaptive Sparse Extreme Learning Machine (AS-ELM) for crop yield forecasting and resource management analysis. AS-ELM was chosen because of its fast learning capability, reduced training complexity, and low computational cost when compared to deep learning models. This module analyzes preprocessed agricultural data to find patterns and relationships that influence crop productivity and resource utilization. The adaptive and sparse nature of AS-ELM allows for fast handling of big datasets while retaining excellent prediction accuracy. Its lightweight construction makes it ideal for use in edge-based smart agricultural systems with limited computational resources.

5. Model Compression Module.

The Model Compression Module improves the energy efficiency of the proposed system by lowering the size and complexity of trained AI models. To optimize the AS-ELM model, techniques such as pruning (removing redundant or less relevant parameters) and quantization (reducing numerical precision) are used. These approaches considerably reduce memory consumption, inference time, and processing load without compromising prediction accuracy. This module enables efficient deployment on resource-constrained edge devices, allowing for real-time decision-making while contributing to reducing energy usage and carbon emissions.

6. Federated Learning Module.

The Federated Learning Module provides decentralized and privacy-preserving model training over numerous edge nodes spread throughout various agricultural sites. Rather than sending raw data to a centralized cloud server, this module enables local models to be trained autonomously on edge devices, with only model parameters or updates exchanged for global aggregate. This strategy considerably lowers data transmission overhead, improves data privacy, and eliminates dependency on energy-intensive cloud infrastructure. Federated learning contributes to the Green AI vision by cutting communication costs and processing energy usage while allowing for scalable and collaborative learning across smart farming ecosystems.

RESULT AND DISCUSSION

Significant increases in agricultural productivity and energy efficiency are shown by the suggested Green AI-based framework for sustainable crop yield prediction and resource management. Simulated datasets spanning a range of agro-ecological circumstances, such as differences in soil quality, weather patterns, and water availability, were used to assess the model. The findings show that combining sensor-driven data collection with lightweight machine learning methods improves prediction accuracy while lowering computing costs.

The Green AI technique outperformed traditional AI models in prediction performance while using less energy, which makes it appropriate for use in rural areas with limited resources.

Important agricultural inputs including insect management, fertilizer application, and irrigation were all successfully optimized by the system. The model reduced resource waste and enhanced agricultural yield outcomes by assessing real-time environmental data and making timely recommendations. According to scenario-based analysis, farms that used the suggested strategy were more resilient to unpredictable weather, especially during dry spells and erratic rainfall. This illustrates how the model can be adjusted to dynamic agricultural settings.

The framework demonstrated potential in forestry applications in addition to agriculture benefits. Early detection of hazards like forest fires and deteriorating vegetation health was made possible by predictive analysis, enabling proactive intervention techniques. Large-scale environmental monitoring might be carried out without undue computing overhead thanks to the adoption of energy-efficient AI models.

From a socioeconomic standpoint, the study shows that implementing Green AI technology can be both cost-effective and scalable. The use of low-power devices and efficient algorithms decreases infrastructure needs, making the system affordable to small and marginal farms. Furthermore, the emphasis on local flexibility promotes community-level implementation, resulting in increased engagement and technology acceptability in rural areas.

Overall, the data suggest that Green AI may strike a balance between technical growth and environmental sustainability. The suggested approach not only increases crop yield prediction accuracy, but it also encourages effective resource management and environmental conservation. These findings indicate that Green AI-driven solutions can play an important role in developing resilient and sustainable agricultural systems in the future.

CONCLUSION

This research demonstrates how Green AI can revolutionize sustainable and energy-efficient farming methods. The suggested approach combines edge computing driven by renewable energy, federated learning, and lightweight AI architectures to improve sustainability in agricultural applications. Predictive models can achieve great performance in crop production forecasts and resource management while drastically reducing computational energy usage thanks to these integrated methodologies. The results show that sustainability in AI encompasses the whole AI lifecycle, including data collection, processing, deployment, and policy alignment, and goes beyond model optimization. The suggested approach transcends theoretical analysis and exhibits practical usefulness by connecting AI development with agricultural and environmental concerns. While the resource management results reveal quantifiable gains in water, energy, and fertilizer utilization, the crop yield prediction results demonstrate that compact and efficient models can lower computational costs without sacrificing accuracy. All things considered, the suggested Green AI framework turns out to be a successful and scalable strategy for attaining intelligent, low-carbon, and resource-efficient smart agriculture.

Future studies should concentrate on creating AI infrastructures powered by renewable energy sources and increasing the use of Green AI methods in extensive agricultural systems. Future solutions will be more dependable and comparable if global benchmarks and defined measures are established for assessing sustainability and energy efficiency in AI-driven agriculture. In order to create context-aware and scalable Green AI frameworks appropriate for both technologically advanced and smallholder agricultural situations, more focus should be focused on multidisciplinary collaboration among AI researchers, agronomists, and policymakers.

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