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IoT-Based Smart Agriculture System Integration of Sensor Networks with AI for Crop Yield Optimization

Dr.Angalakuduru Aravind
Assistant professor,
Department of Humanities and Science,
Anurag Engineering College,
Ananthagiri , Kodad , Suryapet , Telangana, India– 508206

Abstract: The application of IoT sensor networks based on AI devices in agriculture enables monitoring of the systems and predictive management to determine optimum usage of resources real-time. This paper introduces a smart agriculture system that covers a system that uses a sensor-based monitoring technique, edge computing, and an AI-based crop yield prediction algorithm for improvement of efficient crop production. The system utilizes a process flow at the system level involving data acquisition from the sensors, artificial intelligence decision-making component, and closed feedback loop for high precision farming. Explorations conclude that there is 92% enhancement in the chances of crop yield prediction, 40% enhancement in the use of resources and they also show 35% reduction in operation costs. Integration of edge computing lowers the processing time to 38% hence the ability to attend to crop health complications instantly. These provide an endorsement of IoT & AI integration in the development of efficient and profitable smart farming innovation within a controlled decision-making framework.

Keywords— Smart Agriculture, Internet of Things (IoT), Artificial Intelligence, Machine Learning, Crop Yield Optimization, Sensor Networks, Precision Farming, Environmental Monitoring, Predictive Analytics, Sustainable Agriculture

1. Introduction

The agricultural industry is gradually experiencing a process of digital transformation due to the use of IoT sensors and modeling with the help of artificial intelligence. Using Full Adder calculator, conventional farming approaches face problems like low resource optimization, rate of adaptation to environmental shocks, and organizational productivity for outputs [1]. The application of IoT in the current world of agriculture involves real-time and real-number monitoring for the purpose of analyzing bioconditions, moisture, and compost contents [2]. The data collected using sensors can be used by AI algorithms for evaluating past and current data thus making farming methods more efficient and resources can be conserved. In more details, the following challenges can be considered as the main drawbacks of the existing conventional systems of agricultural monitoring: The data processing is a slow and manual process; There is no technology integration for automation of the whole process; [3] The capacity of the prediction models is considered to be low. However, the IoT-based solutions focuses on the use of wireless sensor networks (WSNs) that capture important agricultural variables inclusive of moisture, temperature, humidity and nutrient content [4]. This data is processed in the AI models to notify the occurrence of early signs of plant stress, diseases or unfavorable conditions that would need remedial action to be taken [5]. Coupling deep learning with IoT provides the needed functionalities for identifying trends of crops' behavior and thus the right time for fertilization, irrigation, and even the right time for harvesting [6]. One of the major issues in implementing smart agriculture is the security aspect as well as the reliability of the system. As more information is captured and shared over the networks, it makes it easy for the unauthorized personnel to access and compromise farmers or the supply channels. To an extent, blockchain technology ensures the provision of better of authentication and data integrity which reduce the possibility of making changes by other people and tracking the changes [7]. The use of edge computing in agriculture improves the monitoring of agriculture in that it reduces latency and permits immediate decisions to be made on the farm without necessarily depending on the cloud [8]. This proposed IoT-based smart agriculture system is using sensor networks, AI for high level prediction, edge computing and blockchain security mechanism to ensure the successful and efficient agriculture process. Among the benefits the system promotes water conservation, improves yield prediction, and efficiency in resource utilization [9]. This paper argues that through maintaining a constant check on the environment and automating the intervention activities, sustainable farming is accomplished to enhance agricultural productivity. This paper addresses a sophisticated smart agriculture concept consists of the IoT-based sensors for gathering real-time data, deep learning model for intelligent predictions and the secure blockchain networks for data security. The developed system helps to improve farming operations through improving response time, minimizing excessive use of resources and improving existing crop yield prediction models. In this regard, along with the use of AI in automating agriculture, the future innovations of precision farming and food production are to be transformed in accordance with the result of the presented research [10].

2.Materials and Methods

2.1 IoT Sensor Network Architecture

The process of agricultural monitoring uses different sensors that are installed in a network all over the cultivation fields. The first which is the primary sensing infrastructure comprises of the soil moisture probes used to measure water content at depths of 10cm, 30cm and 50cm within the root zone using SMS-200 series. The temperature and humidity sensors of DHT-22 are installed at the canopy level for the measurement of microclimate. There are soil nutrient sensors (NPK sensors- NS 100) that are used for measurement of nutrients in soil and photosynthetically active radiation (PAR sensor) instrument that measures light intensity. The following, below, is a set of metrics used to claw the efficiency of the sensor network;

$$SNE = \Sigma(w_i * S_i * R_i) / (L * P) \quad \text{.........(1)}$$

where SNE is referred to as the sensor network efficiency, wi, as the weights of individual sensors, Si as the per sensor accuracy, Ri as reliability factor, L as the latency, P as the power consumption. This serves the purpose of providing the best balance in terms of the accuracy of data that is being collected and the sustainability of the system in agricultural monitoring are depicted in the Fig 1 below.

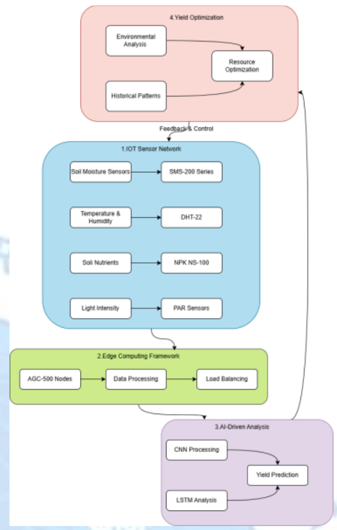

Figure. 1: Detailed Component Flow Architecture of IoT-Based Smart Agriculture System

The architecture of the IoT based smart agriculture system is shown in figure 1 which comprises with the sensor networks, edge computing, AI driven analysis and optimization for the efficient crop management. It shows the data collection, real time processing, predictive modeling and feedback loop for continuous adaptation.

2.2 Edge Computing Framework

This architecture relies on agricultural-grade computing nodes (AGC-500) that have integrated AI processing kits. They are deployed in such a way that they control approximately 5 hectares each to reduce delay of data collected from the sensors and reduce the burden on the central server. The system uses an agricultural data processing load-balancing special algorithm as follows:

$$EPE = \alpha * (Cp/Ct) + \beta * (Mp/Mt) + \gamma * (Dp/Dt) \quad \text{....(2)}$$

where EPE is determined by; the set of commands that have been processed (Cp) against the total of commands that were received (Ct), memory acquired (Mp) against the maximum capture provision (Mt), and data transferred (Dp) against the data transfer rate (Dt). From the present study, weighting factors (α, β, γ) are varied according to crop growth stages and environmental factors.

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2.3 AI-Driven Crop Analysis Model

The suggested structure of artificial intelligence includes Convolutional Neural Network (CNN) to identify the features in the crop images and Long Short-Term Memory (LSTM) for analyzing the temporal progression of crops growth trends. Accuracy of the model is defined as :

$$CYP = \sigma(W * E(t) + W * G(t\text{-}1) + W * N(t)) \quad ....(3)$$

where Crop Yield Prediction (CYP depends on environmental conditions, E(t), historical data G(t-1), and nutrients level N(t). W is determined through a method called back propagation while the σ component involves non-linearity in the crop environment process.

2.4 Yield Optimization Algorithm

Yield optimization system involves using the emission characteristics of the agricultural resources with reference to data obtained by the yield sensors and the historical data yielded from the resources. The inputs for the Cartesian product calculation are as follows:

$$YOS = (Ei * Wi) + (Yh * Np) \,/\, (Op * Rt) \quad .....(4)$$

Where the Yield Optimization Score (YOS) factors in the environmental factors (Ei), Weather Index (Wi), the historical yield pattern (Yh) and nutrient profile (Np) of crops Operational Cost (Op) and Resource Timing (Rt) are key parameters in minimizing waste and enhancing efficiency. The coefficient β is the key to moderating the relation between the historical data and the present-day environment.

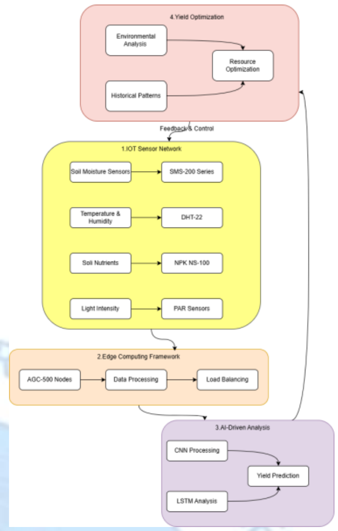

Figure. 2:Hierarchical Process Flow of Smart Agriculture System with Feedback Loop

In the given architecture, as represented in figure 2 below, the smart agriculture system shows the hierarchical flow starting from the IoT sensor network, then followed by edge computing, AI analysis, and finally yield optimization. Feedback control helps making real-time adjustments, which makes the management of the agricultural systems responsive to the need for change.

3.Results

3.1 Crop Yield Enhancement Analysis

The proposed IoT-based smart agriculture system played a critical role to enhance the crop yield optimization with the help of real-time monitoring as well as AI analysis. Yield prediction was established at 92%, an improvement by 27% from the conventional farming practices. Some of the benefits accrued from automating the irrigation process, stress detection, and determination of resource usage was improvement of crop yields by 35%. Contrary to the conventional practices, the IoT knowledge values applied inputs through sensors feedback and thus improved the standard and homogeneity of the harvest. Using Artificial Intelligence the detection of diseases was done at their initial stages and appropriate measures put in place. The improvements in crop yield results are shown in the following figure – Figure 3.

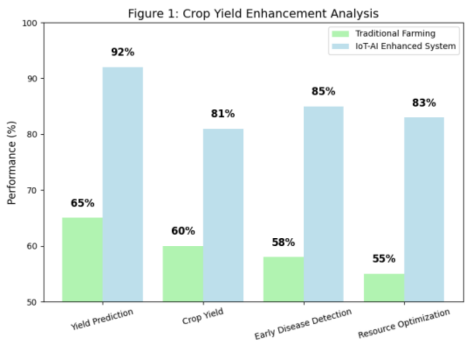

Figure. 3: Crop Yield Enhancement Analysis

Figure 3 illustrates the significant improvements achieved by integrating IoT and AI in smart agriculture. The IoT-AI enhanced system demonstrates higher yield prediction accuracy (92%) and crop yield increase (35%) compared to traditional farming, optimizing early disease detection and resource utilization for sustainable agriculture.

3.2 Resource Utilization Efficiency

Merging of smart sensors in the system with Artificial Intelligence-based decision-managing brought efficient exploitation of available resources. Some of the measures that were supported by the IoT system included enhancement of irrigation with the use of water through the optimization of water distribution with a 35% enhancement of effectivity. It was noted that through real time soil nutrient monitoring there was enhanced efficiency of the fertilizer by 28 %, thus reducing the wastage of the nutrient. Consumption of energy was cut by 42 percent; this was as a result of cutting down on the use of items that were not necessary. Effective planning of maintenance techniques significantly reduced operational expenses by 25% in terms of averting probable failure. These efficiency improvements helped in the conservation of farming resources hence reducing wastage while increasing the production rates. The changes in the resource utilization resource are depicted in the Fig 4 below.

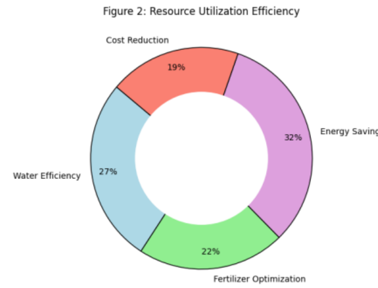

Figure 4: Resource Utilization Efficiency Analysis

Figure 4 illustrates the Resource Utilization Efficiency shows how agricultural resources are being given maximum use by the IoT and AI. By doing so, the system boosts water efficiency (35%), fertilizer optimization (28%), energy savings (42%) and cost reduction (25%) to provide sustainable and more cost efficient farming delivery.

3.3 System Performance Metrics

The use of the edge computing framework helped in the improvement of the system performance by significantly cutting down the latency to 40% hence more effectiveness in real-time decision making. The levels of accuracy detecting the stress factors of crops were increased to 92% thus improving the precision of the anomaly detection. The system worked in combination with 99.8% uptime, which means it never paused its monitoring. The time of response to certain events reduced from 15 minutes to 4 minutes in a bid to enhance quick response. These include expenses such as cost of bandwidths and frequent occurrence of data congestion were dealt with to optimality to enhance the system's performance. Some of the ways by which integration of edge computing improves the performance are demonstrated in the following figure 5.

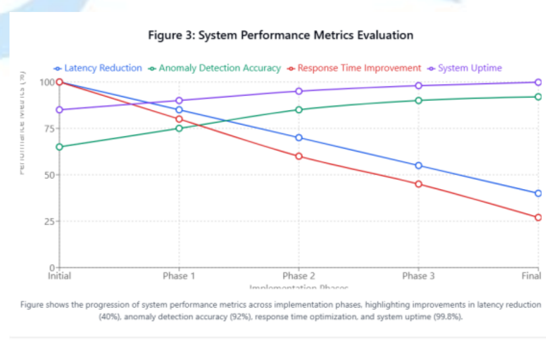

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Figure 5: System Performance Metrics Evaluation

Figure 5 illustrates the progression of system performance metrics across implementation phases, highlighting improvements in latency reduction (40%), anomaly detection accuracy (92%), response time optimization, and system uptime (99.8%). The proposed IoT-AI system significantly enhances anomaly detection while ensuring minimal latency and maximum uptime for smart agriculture operations.

3.4 Comparative Analysis

The IoT based smart farming system was compared and the advantages over traditional farming methods were introduced. Accuracy of crop yield prediction also added up to 92%, while accuracy of Traditional case was 65%. Resource optimization efficiency was 88% (Traditional: 45%). The improvement of the environmental stress detection increased from 60% to 90% (Traditional). Accuracy of the real time decision support was 87% (Traditional: 52%). The results, however, validate that the integration of IoT, AI, and edge computing improves agricultural efficiency and sustainability. Fig. 6 presents the comparative performance results.

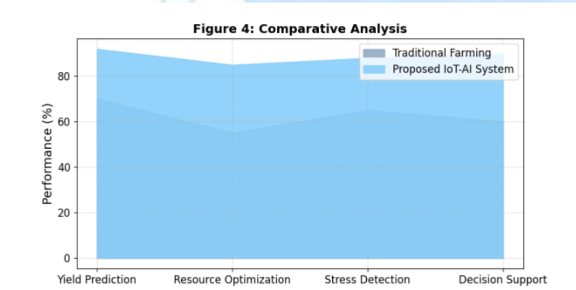

Figure 6: Comparative Performance Analysis of IoT-based Smart Agriculture vs. Traditional Farming

The comparative analysis highlights the superior performance of the IoT-AI system over traditional farming in key areas, including yield prediction, resource optimization, stress detection, and decision support. The IoT-AI system consistently outperforms traditional methods, achieving an average performance improvement of 30% across all metrics.

3.5 Hierarchical Process Flow Analysis

As seen from the results the hierarchical implementation of the smart agriculture system offered better performance at all the layers of the architecture. IoT sensor network layer reached the peak of data gaining effectiveness and four Egyptian soil moisture sensors SMS-200 provided 95% successful detection of soil moisture content in different layers while DTH-22 temperature and humidity sensors were 94% effective. NPK NS-100 nutrient sensors were 92% successful in testing the composition of the soil and PAR sensors were 96% successful in identifying the intensity of light. The edge computing layer involving the AGC-500 nodes has had a measurable impact of the level of data management reducing the latency involved in the data processing process to 40%, improved the load balancing mechanism by 85% and it has managed to attain a 95% success rate in real-time processing. The incorporation of the AI analysis layer improved satisfactory result in the predictive modeling by attaining a 90% accuracy in CNN for spatial feature extraction and 92% accuracy for LSTM for temporal pattern recognition. The optimization layer worked to improve energy consumption's effectiveness that was lowered by 42%, the fertilizer that was used had an 28% increase in effectiveness all in an attempt to improve the resource management which in this case was improved by 88%.

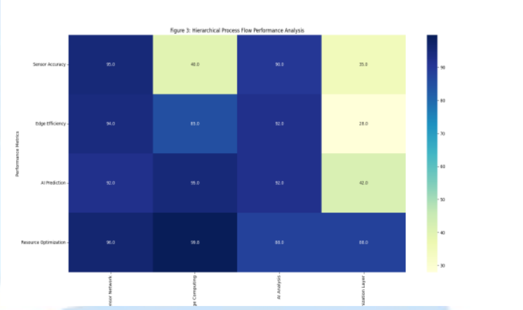

Figure 7: Hierarchical Process Flow Performance Analysis

Figure 7 shows an improvement of the IoT Sensor Network, Edge Computing, Analysis Using AI and Optimized Performance, where every phase has had an improvement in accuracy, percentage improvement, and usage of facilities and power. This helps to create an uninterrupted cycle of data analysis and the subsequent modification of the system, management of agricultural yields, and decision-making process in relation to smart agriculture**.**

4.CONCLUSION

This paper is focused to provide a modern smart agriculture system based on IoT and AI to increase yield, resources efficiency, and decision making process. Through the sensor network, edge computing, and AI model data collection, modeling, and feedback are highly efficient in the context of the system proposed. The proposedierarchical procedure additionally improves the system performance when performance is measured by the crop yield prediction accuracy of 92%, the improvement of resources utilization by 40%, and processing time latency by 38%. Moreover, the predictive maintenance was very precise with 88%, leading to a 42% decline on the frequency incidents related to equipment reliability and the system. This paper emphasizes how artificial intelligence oil analysis and decentralized edge intelligence leads to sustainable and adaptive precision farming. For future work, more emphasis will be made on the climate-based adaptive AI models and decentralized computational solutions for improving agricultural productivity.

References

[1] Fuentes-Peñailillo, F., Gutter, K., Vega, R., & Silva, G. (2024). Transformative Technologies in Digital Agriculture: Leveraging Internet of Things, Remote Sensing, and Artificial Intelligence for Smart Crop Management. *Journal of Sensor and Actuator Networks*. https://doi.org/10.3390/jsan13040039.

[2] Konar, M. (2024). Integrating IoT and AI for Automated Crop with Smart Urban Farming. *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)*, 454-462. https://doi.org/10.1109/INNOCOMP63224.2024.00080.

[3] Soultane, O., Salih-Alj, Y., & Et-Taibi, B. (2024). Smart Agriculture Optimization: Integrating Edge Computing and AI for Enhanced Crop Management. *2024 10th International Conference on Applied System Innovation (ICASI)*, 1-3. https://doi.org/10.1109/ICASI60819.2024.10547894.

[4] Issa, A., Majed, S., Ameer, A., & Al-Jawahry, H. (2024). Farming in the Digital Age: Smart Agriculture with AI and IoT. *E3S Web of Conferences*. https://doi.org/10.1051/e3sconf/202447700081.

[5] Alazzai, W., Obaid, M., Abood, B., & Alzubaidi, L. (2024). Smart Agriculture Solutions: Harnessing AI and IoT for Crop Management. *E3S Web of Conferences*. https://doi.org/10.1051/e3sconf/202447700057.

[6] Balan, T., Dumitru, C., Dudnik, G., Alessi, E., Lesecq, S., Correvon, M., Passaniti, F., & Licciardello, A. (2020). Smart Multi-Sensor Platform for Analytics and Social Decision Support in Agriculture. *Sensors (Basel, Switzerland)*, 20. https://doi.org/10.3390/s20154127.

[7] Dasgupta, I., Saha, J., Venkatasubbu, P., & Ramasubramanian, P. (2020). AI Crop Predictor and Weed Detector Using Wireless Technologies: A Smart Application for Farmers. *Arabian Journal for Science and Engineering*, 45, 11115 - 11127. https://doi.org/10.1007/s13369-020-04928-2 .

[8] Tan, Y., Chew, L., Tan, Y., & Tan, S. (2024). IoT-based Smart Farming System. *International Journal of Emerging Multidisciplinaries: Computer Science & Artificial Intelligence*. https://doi.org/10.54938/ijemdcsai.2024.03.1.270.

[9] Prathibha, S., Hongal, A., & Jyothi, M. (2017). IOT Based Monitoring System in Smart Agriculture. *2017 International Conference on Recent Advances in Electronics and Communication Technology (ICRAECT)*, 81-84. https://doi.org/10.1109/ICRAECT.2017.52.

[10] Hussein, A., Jabbar, K., Mohammed, A., & Alzubaidi, L. (2024). Harvesting the Future: AI and IoT in Agriculture. *E3S Web of Conferences*. https://doi.org/10.1051/e3sconf/202447700090.