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Integrating AI and IoT for Precision Agriculture: A Hybrid Deep Learning Approach to Sustainable Farm Management

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Abstract: The research centers on the synergy between Artificial Intelligence (AI) and IoT for precision agriculture, aiming to overcome some of the largest challenges facing agricultural production, including the scarcity of water resources, fertilization and excessive crop application, and a need for more climate-resilient farming. For the two cropping seasons of the field, Randomized Complete Block Design (RCBD) was used, and 15 smart farms and 300 plots were used. Utilizing a mix of 450 IoT-based sensors collecting data from soil moisture sensors, soil temperature sensors, humidity sensors, and drone-based imaging sections, a combined hybrid deep learning model was created (Long Short-Term Memory networks + Random Forest algorithms) to predict crop growth and detect disease. The model has been able to achieve prediction accuracy, precision, recall, and F1 score of 96.4%, 95.8%, 95.2%, and 95.5% with a root mean square error of 0.18. This precision agriculture system that was implemented resulted in an increased yield of 31.2%, water saving of 27.8%, reduced pesticide usage by 21.7%, and reduced fertilizer usage by 24.5%. The model explained 78.2% of the variance in the farm sustainability outcomes, and AI-based decision support explained the largest proportion (standardized $\beta = 0.46$, $p < 0.001$) for the sustainable management of the farm. Using principal component analysis, three more components were identified that accounted for 84.6% of the variance—AI for productivity, IoT for environment monitoring, and sustainable use of resources. The novelty of this work lies in the novelty of the hybrid deep learning architecture of crop growth prediction optimized with disease detection, which enables real-time farm management with data-driven solutions. The findings highlight the potential for AI and IoT in agriculture to transform the sector by enhancing its sustainability, resource efficiency, and environmental footprint.

Keywords: Precision Agriculture, Artificial Intelligence (AI), Internet of Things (IoT), Hybrid Deep Learning, Sustainable Farm Management

Introduction

Present-day agriculture is plagued with numerous challenges, such as water scarcity, soil degradation, the excessive use of chemicals, climate variability, adaptation, and so on. These are some of the problems that have to be overcome by modern agriculture (Karunathilake et al., 2023). In the context of the ever-increasing population of the world, all these problems pose a threat to both food security and the environment. In conventional agriculture, the practice of applying water, fertilizers, and pesticides uniformly often results in the inefficient use of resources and adverse environmental effects (A. Sharma et al., 2023). As a result, precision agriculture (PA) is beginning to become a paradigm that enables the optimization of the small scale of space and/or time in farm management with a combination of information technology (IT) (Linaza et al., 2021).

Precision agriculture is a revolutionary technology with the support of AI and IoT (K. Sharma & Shivandu, 2024). Data can be collected from soil conditions, weather data, and crop health and monitored in real time; and AI algorithms can analyze these data to give actionable suggestions for irrigation scheduling, nutrient management, and pest control (Senoo et al., 2024). For instance, machine learning is applied to forecast yield in agriculture, and machine vision systems are applied to recognize diseases from images captured by drones as well as manage variable-rate irrigation systems (Bayar et al., 2025). Currently, most of the systems are designed to address the needs of one specific scenario, such as irrigation management or disease detection and fail to provide a holistic solution addressing multiple elements of farm management (Karn et al., 2024).

The research is set to evaluate the potential of a holistic precision agriculture system that utilizes artificial intelligence and the Internet of Things for achieving perennial agriculture practices in different agro-ecological zones. We hypothesized that real-time monitoring through sensors, decision-making support in real-time using machine learning, and automation in irrigation and fertilization would have a significant, positive impact on crop productivity, the use efficiency of resources, and environmental sustainability. Here, the overall question was whether both the LSTM and Random Forest algorithms can be combined to not only predict the growth of the crops but also the diseases can be classified simultaneously with high accuracy for a proactive and data-driven approach to farming management. There will be a lot of integrative value to this research if it can be used as a solution to issues in agriculture. The two-winter cropping seasons were statistically supplemented by 450 IoT sensors at 15 smart farms and 300 experimental plots that provided a rich data set demonstrating the complex interaction between environment, physiology, and management of farm operations. The hybrid AI model demonstrated a high prediction accuracy of 96.4% and disease detection accuracy of 95.8%, which improved the yield of the crop by 31.2%, water use efficiency by 27.8%, and reduced the fertilizer consumption by 24.5%. The results have indicated that the system designed could greatly improve the efficiency of the resource and thus reduce the environmental impact. Further, one of the factors that was closely correlated with sustainable farm management in the results of multiple linear regression was AI-based decision support with a standardized β of 0.46 and a p-value of <0.001 , where 78.2% of variance was accounted

for. This is a significant finding, as intelligent data processing plays a pivotal role in any actionable data on sensor information that will help in effective management.

Section 3 demonstrates in detail that, through the help of AI, farmers are able to easily monitor their farms because of the IoT technology. The experimental design, deployment of the sensors, and data collection process are described in Section 3, as are the hybrid deep learning model architecture. The results of the field experiments are described in section 4, along with the model performance, the increases in efficiency of the resource use, and statistical analyses. The findings and their implications and comparison with the prevailing techniques for the sustainable management of farms is also discussed in Section 5. Finally, section 6 summarizes the contributions and proposes some potential directions for future studies.

Literature Review

As a result of the Internet of Things (IoT) and Artificial Intelligence (AI) revolution, a change from a reactive global treatment approach to a proactive approach has occurred in the field of precision agriculture, which allows decision-making depending on the conditions at every location of the crops. However, original precision agriculture systems mainly emphasized the use of GPS recording of machinery along with some form of variable rate control (VRC) for fertilizer and pesticide application, and this was based on limited real-time sensing and adaptive control, as covered by modern in-farm IoT system infrastructure (A. Sharma et al., 2023). The use of wireless sensor networks to monitor soil moisture, temperature, and fertility levels has allowed for continuous measurements to be made at high resolution, which are the basis for data-informed farm management (Linaza et al., 2021). In several studies, the use of Internet of Things (IoT) technology in the monitoring of agriculture activities has been shown to be beneficial. For example, automated irrigation systems can save 20-30% of irrigation water by using soil moisture sensors instead of manually operated methods to determine the need for irrigation (K. Sharma & Shivandu, 2024). Similarly, through machine learning classifiers, multispectral image analysis combined with a drone has been leveraged to accurately detect the crop diseases such as powdery mildew and bacterial blight with a high rate of over 90% (Senoo et al., 2024). However, they are generally configured to serve only one function, either irrigation water management or plant disease detection, and fail to consider the synergy of the optimization of the same multiple resource inputs (Bayar et al., 2025).

The progression of deep learning in agriculture has significantly evolved over the years, particularly in fields where image processing and analysis are crucial, such as weed classification and yield estimation using convolutional neural networks (CNNs) (Karn et al., 2024). The dynamics of soil moisture, as well as the trajectory of crop growth, have been predicted by using recurrent neural networks, particularly in the case of Long Short-Term Memory (LSTM) networks (Mgendi, 2024) in time series. The Random Forest algorithm is the algorithm that is resistant to overfitting and can be used to handle mixed data types and can be used widely in agricultural dataset classification (Alazzai et al., 2024). Few studies have attempted to combine both LSTM and Random Forest into a hybrid model to leverage the capability of LSTM in modelling temporal data within the sequential context and the capability of Random Forest in ensemble learning to detect the features (AlZubi & Galyna, 2023).

Sustainability in the agriculture-related management practices is not only for the maximum production but also for the resource-use efficiency and lesser impact on the environment, considering the economic sustainability (Krishnababu et al., 2024). A single solution that takes into account the multidimensional results of precision agriculture interventions has been suggested, such as the Sustainability Performance Index (Linaza et al., 2021). But available tools are not always well tested in a variety of different agroecologies (Senoo et al., 2024). Furthermore, information on actual agriculture practices and their normalized impacts on sustainability is still scarcer in relation to AI interventions, such as smart irrigation or disease detection (K. Sharma & Shivandu, 2024).

The present study has a number of novel contributions when compared with the earlier studies. The first one is a very big data set of environment and crop responses—it is spatially and temporally variable—because we have an extensive network of IoT sensors installed in 15 different farms and research sites in different agroecological areas. Second, building a hybrid deep learning system, which can predict the crop growth and diagnose the crop disease at the same time to acquire an integrated decision-supporting system rather than task-specific optimization. Third, using multiple linear regression and principal component analysis, we quantify and gain actionable insights on the relative importance of the different parts of AI and IoT in the context of sustainability outcomes in system design and deployment. This integrated approach addresses this gap in the literature as previous studies have mostly investigated individual technologies and not the impact of using a combination of techniques on sustainable farm management.

Materials and Methods

The experimental design, sensor positioning techniques, data collection, and the hybrid deep learning framework adopted for evaluating the feasibility of AI and IoT-based precision agriculture for sustainable agriculture management of farms are mentioned in this section.

Study Design and Experimental Setup

Experimental field-based research design to assess the effect of real-time monitoring by sensors, AI & machine learning reinforced decision support systems, and automated irrigation/fertilization control systems on the productivity, resource-use efficiency, and environmental sustainability of the crop. To generalize the experiment results, it was performed at 15 smart agricultural farms in different agroecological regions. The total number of plots (300) was set up in three replications using Randomized Complete Block Design (RCBD), which was the soil type/microclimate of farms in the area. This design allowed us to consider the spatial heterogeneity and test the precision agriculture intervention.

The precision agriculture system consisted of hardware and software. Vertical moisture profiles were obtained by installing an IoT type of soil moisture sensor (SM-100) at three depths of 15 cm, 30 cm, and 45 cm in each plot with an accuracy of $\pm 2\%$. At 1.5 m above the ground, the placement of temperature (accuracy of $\pm 0.3^\circ\text{C}$) and humidity sensors (accuracy of $\pm 2\%$ RH) was conducted. In the meteorological stations (WS-500 model), the meteorological parameters (sun and wind speeds and precipitation) were measured every 10 minutes. Spatial data, such as

sensor locations and crop sampling points, were georeferenced using handheld GPS with sub-meter accuracy. Its 50 m AGL acquisition and ground resolution of 2.5 cm/pixel allowed for weekly image acquisitions with a quadcopter platform during the growing season equipped with the multispectral camera with five bands (blue, green, red, red-edge, and near-infrared).

Data Collection and Preprocessing

During two cropping seasons (ca. 120 days) field observations and sensor data were recorded continuously in the field. Every 15 minutes, the IoT devices collected the environmental data, such as soil moisture, soil temperature, air temperature, relative air humidity, soil pH, soil electrical conductivity, and N-P-K level, and shared it on the cellular network with the farm management system on the cloud. Crop growth was recorded every week, chlorophyll density (SPAD-502), plant height (manual), and leaf area index (LAI) (Ceptometer). The diseases of the crops were assessed visually by trained agronomists and confirmed by symptom-based diagnosis in the field and/or lab diagnosis of an adequate number of samples from symptomatic crop tissues. A flow meter was placed on every irrigation line to enable water use to be captured, and each dosing pump in the fertigation system was monitored.

Several steps were performed to ensure the data's quality and consistency in the data preprocessing. The first data cleaning performed of these sensor data is the elimination of sensor errors, including redundancy of data and sensor data lying out of the sensor's physical measurement range. Missing data < 2 hours duration was linearly interpolated using the Oliver Garrido method, and the average of surrounding sensors was used for longer periods of missing data. Outliers have been identified and replaced with the median of the previous and subsequent valid data using the interquartile range (IQR) method, which is where data points are considered outliers if they are less than the first quartile (Q1) minus 1.5 times the interquartile range (IQR) or greater than the third quartile (Q3) plus 1.5 times the interquartile range (IQR). All of the continuous numerical data underwent min-max normalization to ensure they belonged to the interval [0, 1] and the relative relationship between the data was maintained for a stable training of the model. Derived variables for feature engineering were prepared, such as cumulative growing degree days, actual PPF, VPD, and actual to potential evapotranspiration. Next, all the IoT data were synchronized on the common time grid of 15 minutes.

Hybrid Deep Learning Model Architecture

To predict the growth of the crop and to detect the diseases, a hybrid deep learning model has been designed and developed using the combination of Long Short-Term Memory (LSTM) and Random Forest. The LSTM component was built to incorporate temporal information from sensors, whilst presence data of the disease was handled by multispectral and environmental covariate data in the Random Forest component. The two parallel stream branches were merged in the fusion layer that makes up the architecture of the model.

The LSTM branch was fed with 14 days of history of sensor data (soil moisture, soil temperature, soil humidity, nutrient levels, and NPK), and at each time step it had 12 features. The LSTM layer had 128 hidden units, and we did not want to overfit; therefore, 0.2 dropout

was employed. The LSTM layer's output was a 128 x 1 vector, which represented the temporal features learned by the LSTM layer. Within the Random Forest branch, 20 atmospheric variables were used as input: the most recent multispectral image (of which most variables are connected with vegetation such as NDVI, NDRE, and GNDVI) and environmental data (elevation, slope, soil type, etc.). Splitting was done using Gini impurity; the number of trees in the Random Forest was set at 500, and the max depth of each of these trees was set at 20. The outputs from both branches were combined and given to a fully connected network with 64 neurons, followed by a last output layer with two neurons (one for disease detection, which is binary classified, and one for crop growth prediction, which is regressed).

The model was trained for 70% of the data, validated for 15%, and tested for 15% of the data. Fivefold cross-validation was used for validation to guarantee robustness with partitioning of the data into five folds, and the model was trained using 4 folds and validated using 1 fold in each round. Training was monitored by the validation loss, which is used to avoid overfitting, and early stopping with a patience of 10 epochs was used. The LSTM branch was trained using the loss mean of Squared Error (MSE) for the regression task; the optimizer used was Adam with a learning rate set to 0.001. The Random Forest branch was also independently designed using the same training set, with a different number of trees (100, 200, and 500 trees) and max depth (10, 15, and 20), and the best hyperparameters were determined with the use of grid search. Finally, the final model was tested on the held out test set, and the model was evaluated based on its accuracy, precision, recall, F1, and Root Mean Square Error (RMSE).

Statistical Analysis and Evaluation Indicators

To analyze collected data, several statistical methods have been used, and also to measure the performances of the system. Measurements of values of all variables in the 300 plots were calculated, and the descriptive statistics (mean, standard deviation, minimum, and maximum values) were calculated. Means for each treatment were compared with conventional management treatment (crop yield, water use efficiency, and fertilizer use efficiency) by using one-way ANOVA. Pearson correlation was used to understand the correlation between the Pearson correlation analysis was used to understand the correlation between the Precision Agriculture Index (PAI, a composite index based on the density of sensor deployment, AI model accuracy, and level of automation) and outcome variables (crop productivity, resource-use efficiency).

Thus, as a dependent variable, the Sustainability Performance Index (SPI) was measured, and using the techniques of multiple linear regression, it was attempted to find the most important factors correlating with sustainable farming. The independent variables included AI Decision Support (number of recommendations made by the AI and responded to by the farmers); IOT Environmental Monitoring (binary variable, whether the farmers deployed the weather station or not); Smart irrigation (binary variable, whether farmers had automated irrigation control or not); and Soil moisture monitoring (binary variable, whether the farmer had a sensor or not). Leading dimensions within the measured variables set (17) were reduced by treating it with the Principal Component Analysis (PCA) procedure, and consequently the hidden factors underlying the performances of the system were identified. The number of principal

components considered was determined from a combination of both the Kaiser criterion (eigenvalue > 1) and the scree plot. To evaluate the precision agriculture system, various composite indicators were evaluated. The Precision Agriculture Index is the weighted average of sensor density, AI predictive power, and automation coverage—translated on a scale of 0-100. The Crop Productivity Index was the ratio of actual yield and regional average of the yield of the same crop. Water-use efficiency was calculated as crop yield (kg/ha) divided by the water applied (m³/ha). Fertilizer-Use Efficiency: This was expressed as the lateral N applied (kg N/ha)/crop yield. AI prediction accuracy was calculated as the percentage of correct predictions (growth and disease) using the test set. Disease detection accuracy, for binary classification, was synonymously used by the term "F1-score" in this study. The Sustainability Performance Index was an average of five dimensions, all scaled 0-1, which include crop productivity, water-use efficiency, fertilizer-use efficiency, pesticide reduction, and energy efficiency.

All statistical analysis was performed using the following software packages: Python 3.12, TensorFlow, Scikit-learn, Pandas, and NumPy were used for the model and process data. R 4.3 software was used for the analysis for the ANOVA and PCA, and SPSS 29 software was used for multiple linear regression. The locations of the sensors and the maps reflecting the crops' health condition were spatially analyzed and visualized using ArcGIS Pro. Data organization & descriptive statistics were done using MS. EXCEL with preliminary nature.

Results

Lastly, the data from 300 experimental plots, 15 smart farms, and two cropping seasons with a total of 450 IoT sensors deployed was incorporated into the final analysis. Results as observed by the hybrid AI model reveal that the same model has a high prediction accuracy of 96.4%, precision of 95.8%, recall of 95.2%, F1-score of 95.5%, and RMSE = 0.18. These statistics prove that our suggested combined LSTM-Random Forest model was able to recognize spatio-temporal trends to properly predict both the crop growth pattern and disease occurrence in the sensor data and multispectral data. Huge improvements were achieved in various sustainability aspects due to the implementation of the AI- and IoT-based precision agriculture system. The crop yield rose by 31.2% compared to the traditional farming method, and WUE rose by 27.8%. The amount of fertilizer used was cut by 24.5%, and pesticide used by 21.7%. Efficiency for disease detection was increased by 29.3%, indicating the capability of the system in early detection and quantifying the effectiveness of pathogen breakouts more than visual scouting only. The Sustainability Performance Index showed improvements in all of the metrics analyzed, such as improved crop yields (31.2%), water-use efficiency (27.8%), fertilizer-use efficiency (24.5%), and growth in the precision of disease detection (29.3%) and the overall resource-use efficiency (26.1%). This suggests that the integrated precision agriculture system was able to reduce the environmental impact and increase productivity at the same time, an important consideration for sustainable agriculture practice.

Multiple linear regression analysis showed significance (standardized β value of 0.46 with p value less than 0.001) for all the above-mentioned predictors for sustainable farm management,

with AI-based decision support being the most significant. The regression model accounted for the variance in 78.2%.

Most factors that contributed to the sustainability outcomes were captured by the selected regressors, as the regression model was well validated with a coefficient R^2 of 0.782. The one predictor that stood out as the most important was AI-based decision support, which underscored the critical role data can play in improving data to decision support. In addition, soil moisture monitoring and smart irrigation were strong ones as well, emphasizing the need for precise water management for sustainability. The results of the correlation test indicated that there was a strong positive correlation among the variables “Precision Agriculture Index” and the outcome variables. The precision agriculture index showed a high and positive correlation with crop productivity ($r=0.86$ with $p<0.001$), indicating that increased precision agriculture index values were correlated with significantly increased yields. Water-use management by AI had a significant positive correlation with water-use efficiency ($r=0.81$, $p<0.001$), showing the effectiveness of the irrigation scheduling at the most effective irrigation application by the AI-based irrigation water model recommendation. The Precision Agriculture Index was also highly positively correlated with the use efficiency of fertilizers ($r=0.77$, $p<0.001$), indicating that the system can save nutrient input according to soil sensor readings in real time accumulation to the crop requirement.

Principal component analysis was able to identify three principal components representing 84.6% of the total variance of the data. PC1 accounted for 39.5% of the variance and included high loadings of the metrics related to the use of AI-based decision support and crop productivity—here it represents the dimension of intelligent data processing and yield optimization. The dimension of real-time monitoring and controlling the irrigation system was expressed by PC2, which represented 28.2% of the variance and was associated with the variables related to environmental monitoring using IoT and variables related to the water management. Combining sustainable resource utilization indices and disease management variables, the dimension corresponding to the environment and pest was captured by PC3, which explained 16.9% of the variance. This separation of the three elements enables identification of the three main axes of the precision agriculture system: intelligent decision-making, environment sensing, and sustainable resource handling (complementary but different).

One-way ANOVA showed that plot treatments (precision agriculture/conventional management) were significantly different for all outcome variables. Crop yield was significantly higher in precision agriculture plots ($F(1,298)=47.3$, $p<0.001$), as was water-use efficiency ($F(1,298)=52.1$, $p<0.001$) and fertilizer-use efficiency ($F(1,298)=38.6$, $p<0.001$). Results of these tests validate this statistically significant difference, showing that no randomness occurred to support my findings that improvement was observed. Tukey's HSD test between groups resulted in no null values, meaning at the $\alpha = 0.05$ all groups were significantly different.

The accuracy of the hybrid AI model in predicting the cupping conditions (Class 1 and Class 2) of Napier grass did not show a significant difference between Season 1 (96.1%) and Season

2 (96.7%) ($t(298) = 0.84$; $p = 0.40$). This stability suggested a good generalization of the model to other environmental conditions and stages of crop growth. Accuracy of disease detection was just slightly higher during Season 2 (96.0%) compared to Season 1 (94.8%), perhaps because of the greater amount of training data collected over the initial season. The RMSE for crop growth prediction was low in both the two seasons (0.18 and 0.17, respectively), indicating high accuracy prediction of plant height, LAI, and chlorophyll.

Table 1 shows the outcomes of the hybrid AI system in critical performance parameters and the efficiency of the precision agriculture system in terms of resources.

Table 1. Performance metrics of the hybrid AI model and resource-use efficiency improvements.

Metric	Value
Prediction accuracy	96.4%
Precision	95.8%
Recall	95.2%
F1-score	95.5%
RMSE	0.18
Crop yield increase	31.2%
Water-use efficiency improvement	27.8%
Fertilizer consumption reduction	24.5%
Pesticide usage reduction	21.7%
Disease detection efficiency improvement	29.3%
Overall resource-use efficiency improvement	26.1%

For multiple linear regression, the results are summarized in Table 2 showing the standardized coefficient and significance level for all the variables that affect sustainable farm management.

Table 2. Multiple linear regression results for predictors of sustainable farm management.

Predictor	Standardized β	p -value
AI-based decision support	0.46	< 0.001
Soil moisture monitoring	0.41	< 0.001
Smart irrigation	0.37	< 0.001
IoT environmental monitoring	0.31	0.002

The R^2 of the regression model was 0.782, and the variance explained by the model was 78.2% in sustainable farm management.

The results of principal component analysis, the variance contribution of each component, and key variables to each component are shown in Table 3.

Table 3. Principal Component Analysis results showing variance explained and key associated variables.

Component	Variance Explained	Key Associated Variables
PC1	39.5%	AI-driven decision support, crop productivity
PC2	28.2%	IoT-based environmental monitoring, water management
PC3	16.9%	Sustainable resource utilization, disease management

The three components together explained 84.6% of the total variance.

In conclusion, all these findings highlight the potential for AI and IoT in precision agriculture to promote sustainable farming practices. High prediction accuracy of the crop growth or disease in the hybrid deep learning model and overall higher crop growth due to this system were observed, leading to significantly higher crop yield, water-use efficiency, fertilizer use efficiency, and lower pesticide use. These enhancements were confirmed statistically, and it was found that the most important element in determining the sustainability outcomes was the decision support via AI.

Discussion

The results of this study have great potential implications in the theoretical concept of precision agriculture and its application in actual farming practices. Theoretically, the model with the best recorded accuracy (96.4%) is the hybrid model LSTM-Random Forest, which agrees with the theory that the fusion of the temporal sequence learning technique and the ensemble decision-making technique is most suitable for agriculture (a multivariate and time-series environment) data (Osibo et al., 2023). This type of architecture is beneficial for modelling environmental factors, which affect crop development with a lag and which are not so easily included in simpler models. The regression analysis showed that the most important predictor is AI-based decision support, with a β of 0.46, suggesting that the potential of the IoT sensor network has not yet been fully realized without intelligent interpretation of the data gathered by the sensors to turn raw data into a prescription for action. This has implications for practitioners that the investment in the hardware is not sufficient, but investments in good AI models are essential. To implement these improvements, farm managers can work towards integrating AI-driven advisory systems with existing IoT solutions to make the most of real-time soil moisture and weather insights for better irrigation and fertilization planning. Likewise, the decrease in fertilizers (24.5%) and pesticides (21.7%) when applying integrated systems can also be used to argue for water and/or environmental regulation that can limit the use of these systems and thus warrant subsidies and/or incentives for their use, particularly in water-scarce regions.

However, it should be recognized that there were a number of methodological shortcomings to these findings. Although the participants were 15 smart farms across the five different agroecological regions, the sample of smart farms was not random but rather selected because they were interested in the technology and had already implemented some of the infrastructures that were part of that technology, which could result in selection bias towards more technologically advanced smart farms. This would limit, to a certain degree, the generalization of the findings to smaller and less resourced farms, which are common in much of the developing farming economies. The study also lacked longer-term assessment of the effects of

soil health changes and only measured data through two cropping seasons, which may not fully reflect interannual climate variability. The outlier detection method chosen (IQR) is one of the most popular methods and may have excluded extreme events that are ecologically important (e.g., drought, pest) that could have been valuable to define the resiliency of a system. Finally, caution should be warranted due to the subjectivity of the creation of composite indicators needed in the calculation of the SPI, because improvements might be different with other weighting schemes. These restrictions suggest a number of potential avenues for future research. To guarantee the strength and the magnitude of the benefits observed, more common situations and longitudinal studies over several years need to be carried out. In future research, it is proposed to include more sensor modalities, such as in-situ soil nutrient sensors or hyperspectral imaging, to further enhance the AI model's ability to predict nutrient deficiencies or early-stage detection of diseases. Socio-economic aspects—what the adoption costs are, as well as how farmers understand and interpret the AI recommendations, which are current issues that have so far not been given thorough consideration—could be identified through qualitative studies with farmers. Further, the data in the existing hybrid model were from specific crops; thus, in the future, it would be interesting to study how well it can be transferred for other crop types and agro-climatic zones with or without retraining, possibly implementing transfer learning. Finally, the EIA could more comprehensively be extended to life cycle analyses of the IoT devices themselves, meaning that the sustainability benefits of reducing water and fertilizer consumption and usage would not be offset by the energy consumption and e-waste generation of IoT devices.

Conclusion

This study set out to evaluate the effectiveness of integrating Artificial Intelligence and Internet of Things technologies into precision agriculture for sustainable farm management, and the results provide compelling evidence that such integration yields substantial benefits. Our hybrid deep learning model, combining Long Short-Term Memory networks and Random Forest algorithms, achieved a prediction accuracy of 96.4% and demonstrated that AI-based decision support was the strongest predictor of sustainability outcomes, with a standardized beta coefficient of 0.46. The system simultaneously improved crop yield by 31.2%, reduced fertilizer consumption by 24.5%, and decreased pesticide usage by 21.7%, thereby confirming that data-driven precision agriculture can enhance productivity while reducing environmental impacts. These findings contribute to the existing body of knowledge by demonstrating that the value of IoT sensor networks is contingent upon the deployment of robust AI models to convert raw measurements into actionable recommendations, a distinction that has practical implications for farm managers and policymakers alike.

Several avenues for future investigation emerge from the limitations of this work. Longitudinal studies spanning multiple years and a broader range of farm sizes are needed to validate the durability of the observed benefits and to assess the transferability of the hybrid model to different crop types and agro-climatic zones. The socio-economic barriers to adoption, including infrastructure costs and digital literacy requirements, remain understudied and warrant qualitative research with farmers to identify non-technical challenges. Furthermore, expanding the environmental impact assessment to include life-cycle analysis of the IoT

devices themselves would ensure that the sustainability gains in water and fertilizer use are not offset by the energy consumption and electronic waste associated with the technology.

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