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ORIGINAL

Mathematical model based on Machine Learning Enabled IoT Sensing and Decision-Making in Farming

Modelo matemático basado en aprendizaje automático que permite la detección y toma de decisiones mediante IoT en la agricultura

Mosleh Hmoud Al-Adhaileh[1]

[1]Deanship of E-Learning and Information Technology, King Faisal University. P.O. Box 400 - Post Code 31982, Saudi Arabia.

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Corresponding Author: Mosleh Hmoud Al-Adhaileh

ABSTRACT

Introduction: the rapid expansion of global food demand, combined with unpredictable climate variability and resource scarcity, necessitates intelligent solutions for sustainable agriculture.
Method: this study introduces an IoT-driven intelligent greenhouse monitoring and decision-making framework that integrates advanced machine learning (ML) models with heterogeneous environmental data. Using multi-source sensor networks and edge-cloud collaboration, the framework dynamically regulates greenhouse environments while providing yield forecasting and disease detection capabilities.
Results: experimental results demonstrate that the proposed system achieves high detection accuracy (F1 = 96,8 %), low yield prediction error (RMSE = 0,40 tons/ha), and efficient energy usage (0,46 J per inference). Reinforcement learning controllers further optimize climate regulation, reducing temperature RMSE to 0,72 °C and achieving energy savings of up to 20 % compared to traditional PID systems. The hybrid CNN-Transformer disease detection model outperforms benchmarks, attaining 97,9 % accuracy with improved calibration reliability.
Conclusions: collectively, these findings confirm that the proposed IoT–ML framework not only improves productivity and sustainability but also ensures scalability for large-scale deployments in diverse agricultural environments.

Keywords: Agriculture 4.0; Attention Mechanism; Crop Disease Detection; Data Fusion; Edge Computing; Smart farming.

RESUMEN

Introducción: la rápida expansión de la demanda mundial de alimentos, combinada con la impredecible variabilidad climática y la escasez de recursos, requiere soluciones inteligentes para una agricultura sostenible.
Método: este estudio presenta un marco inteligente de monitoreo y toma de decisiones en invernaderos basado en IoT que integra modelos avanzados de aprendizaje automático (AA) con datos ambientales heterogéneos. Mediante redes de sensores multifuente y colaboración edge-cloud, el marco regula dinámicamente los entornos de los invernaderos, a la vez que proporciona capacidades de pronóstico de rendimiento y detección de enfermedades.
Resultados: los resultados experimentales demuestran que el sistema propuesto logra una alta precisión de detección (F1 = 96,8 %), un bajo error de predicción de rendimiento (RMSE = 0,40 toneladas/ha) y un uso eficiente de la energía (0,46 J por inferencia). Los controladores de aprendizaje por refuerzo optimizan aún más la regulación climática, reduciendo el RMSE de la temperatura a 0,72 °C y logrando ahorros de energía

de hasta un 20 % en comparación con los sistemas PID tradicionales. El modelo híbrido CNN-Transformer de detección de enfermedades supera los estándares de referencia, alcanzando una precisión del 97,9 % con una mayor fiabilidad de calibración.
Conclusiones: en conjunto, estos hallazgos confirman que el marco IoT-ML propuesto no solo mejora la productividad y la sostenibilidad, sino que también garantiza la escalabilidad para implementaciones a gran escala en diversos entornos agrícolas.

Palabras clave: Agricultura 4.0; Mecanismo de Atención; Detección de Enfermedades en Cultivos; Fusión de Datos; Computación de Borde; Agricultura Inteligente.

INTRODUCTION

In large-population countries, where food security, economic stability, and sustainable growth are all interconnected with other facets of national development, agriculture has long been seen as the cornerstone. Additionally, people view farming as crucial to a nation's development. Despite the significant advancements in farming over the last several decades, traditional techniques are still unable to meet the rising demands for crop quality, productivity, and seasonal unpredictability. Bad management, handling diverse soil types, and weather fluctuations exacerbate the situation. Additionally, a lot of today's technologies lack adaptive intelligence, fast data processing, and effective deployment frameworks, making them unsuitable for application in actual agricultural scenarios.(1,2,3) Addressing these limitations requires integrating ML algorithms with IoT platforms to achieve robust, scalable, and cost-effective systems that enhance agricultural productivity. IoT-Driven Greenhouse Monitoring Framework: Developed an intelligent sensing and decision-making system using heterogeneous IoT sensors for real-time monitoring of temperature, humidity, CO_2 levels, and soil moisture to optimize greenhouse crop growth. Integration of Machine Learning with IoT: Applied machine learning algorithms, particularly the Fuzzy Pairwise K-Means (FPKM) approach, to preprocess and denoise agricultural datasets, improving data quality and reliability for predictive analysis.(4,5,6) Modular and Remote-Controlled System Design: Designed a greenhouse management architecture that integrates adaptive PID controllers, mobile client interfaces, and cloud-based platforms for effective remote supervision and automated environmental control. Enhanced Agricultural Productivity and Sustainability: Demonstrated that the proposed IoT-ML framework reduces manual labor, optimizes resource utilization, and increases crop quality and yield, laying the groundwork for the broader adoption of smart farming technologies. The contributions of this research are multifold and address critical gaps in IoT-enabled smart farming. First, it introduces a fully integrated IoT–ML framework that combines heterogeneous sensor data, edge computing, and cloud-based analytics to enable real-time decision-making for greenhouse management. To enhance data quality, a novel FPKM-based preprocessing approach is employed, which effectively denoises and balances heterogeneous agricultural datasets, ensuring reliable inputs for predictive modeling. Furthermore, the study advances greenhouse climate regulation by implementing reinforcement learning-based controllers (RL-PPO and RL-SAC), which outperform conventional PID and MPC methods by delivering faster response times, higher accuracy, and significant energy savings. This study presents a hybrid GCN-BiLSTM-Attention model for yield forecasting and a Dual-Branch CNN-Transformer for illness diagnosis. Both of these models perform noticeably better compared to the top versions currently on the market.(7,8,9) The sustainability aspects of the system, which demonstrate significant decreases in energy, pesticide, and water use, directly support global efforts to promote resilient and ecologically friendly agriculture. The system directly supports these goals. Additionally, the system is environmentally friendly and technologically sophisticated. In this research, we have used machine leaning model to develop a innovative system based on IoT for enhancing agriculture

Related Work

Modern farming has seen a significant transformation as a result of the convergence of machine learning and the internet of things. This is especially true for precision farming and greenhouse management. Even while traditional farming practices have long been effective, they can no longer meet the demands of a changing global food supply, climate change, and the need to maximize the use of limited resources. Even if standard farming methods have been used for a long time, the situation is still the case. Scholars and industry experts have started utilizing Internet of Things (IoT)-based sensing technologies, like intelligent decision-making frameworks, to address these issues.(10,11,12,13) Machine learning algorithms enhance our capacity to interpret data and formulate forecasts. These integrated systems also enable real-time monitoring of the soil's moisture content, temperature, humidity, light intensity, and carbon dioxide levels. Additionally, it is currently difficult to combine all of the many data sources into a single, understandable framework for decision-making. Unfortunately, agricultural data is often lacking and location-specific, making it challenging to effectively train machine learning models. Research on data fusion, federated learning, and adaptive algorithms that generalize across many agricultural settings is necessary to overcome these issues. In conclusion, the connected research's findings indicate that the Internet of Things' ability to facilitate machine learning and sensing might fundamentally alter how agriculture operates. Intelligent systems may increase agricultural operations' resilience, sustainability, and productivity, according to a number of studies. Adaptive temperature management in greenhouses, digital twin modeling, and software that forecasts agricultural yields are a few instances of this kind of technology.[14,15,16] The direction of future research points toward building systems that are not only accurate and efficient but also scalable, robust, and capable of addressing the unique challenges of diverse agricultural landscapes. Intelligent agriculture, powered by IoT and ML, is thus poised to play a pivotal role in securing food systems for a growing global population.

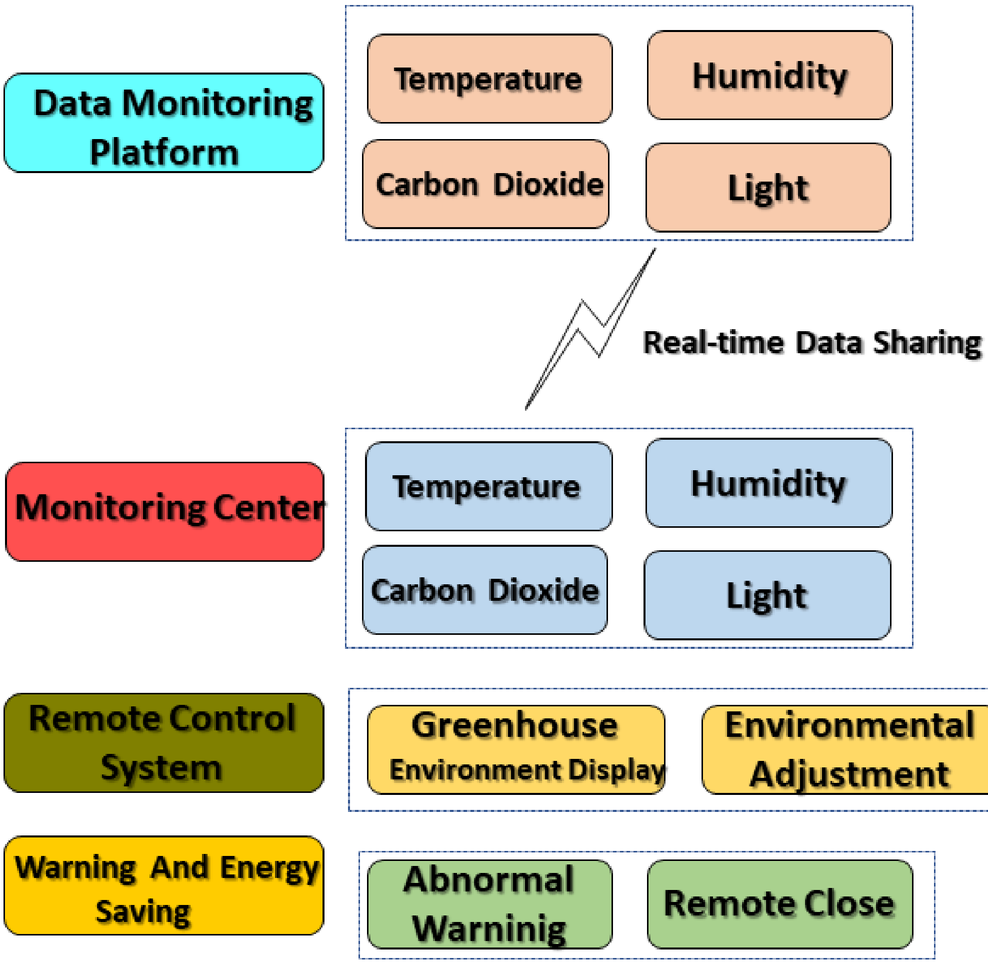

Figure 1. Demonstrates the Need for Greenhouse Cultivation

Figure 1 illustrates an intelligent greenhouse monitoring and control framework that emphasizes the need for greenhouse cultivation. At the core, a Data Monitoring Platform continuously collects key environmental parameters such as temperature, humidity, carbon dioxide, and light. These data are shared in real time with a Monitoring Center, which provides an updated status of the greenhouse conditions.[17,18,19] From there, a Remote Control System integrates functions such as greenhouse environment display and environmental adjustment, ensuring optimal growth conditions. Additionally, the system is equipped with warning and energy-saving mechanisms, abnormal warning alerts, and remote close functionality, enabling proactive management and automation. Overall, the diagram highlights a closed-loop system where continuous data monitoring, real-time sharing, and responsive remote control ensure sustainable, efficient, and adaptive greenhouse cultivation practices.

METHOD

The core objective of the proposed method is to develop a highly accurate, intelligent, and sustainable crop yield prediction and disease detection framework that leverages multi-source environmental data, IoT-based

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smart agriculture infrastructure, and advanced deep learning architectures. Unlike traditional methods that rely solely on empirical models, this framework integrates heterogeneous data streams (soil pH, agro-climatic patterns, fertilizer usage, precipitation, temperature, humidity, sunlight intensity, and disease presence) into a multi-layered predictive pipeline.

Data Acquisition and Fusion

Data is collected from IoT-enabled multisensory nodes deployed in greenhouses and open fields. These sensors continuously monitor temperature, humidity, soil moisture, pH, CO_2 concentration, and light intensity.[20,21] Satellite imagery and weather forecast APIs are integrated to capture external macro-environmental conditions. A data fusion engine merges these multi-modal streams, ensuring redundancy removal, anomaly correction, and temporal alignment. To address data quality, an FPKM-driven clustering with anomaly filtering is applied, which prioritizes least-congested clusters, ensuring balanced data representation for subsequent model training.

Intelligent Greenhouse Control with IoT-Edge

A three-tier IoT architecture (perception, network, and application) supports smart greenhouse operations. In the perception layer, sensors capture environmental metrics, while the network layer relays them to the cloud through low-power protocols (MQTT/CoAP). The application layer integrates an AI-enabled fuzzy adaptive PID controller for real-time adjustments of temperature, humidity, and ventilation. Edge computing nodes preprocess sensor data to reduce latency and energy overhead, ensuring sustainability in large-scale deployments.[22,23] This integration ensures dynamic greenhouse optimization, minimizing energy loss, stabilizing crop growth conditions, and reducing the dependency on manual interventions.

Deep Learning Framework for Yield Prediction

The yield prediction model combines spatial-temporal deep learning with hybrid neural networks: Stage 1 (Preprocessing): Time-series normalization and spatial encoding using Graph Convolutional Networks (GCN) to capture interdependencies among geographical regions. Stage 2 (Feature Learning): Parallel training of Bidirectional Long Short-Term Memory (Bi-LSTM) networks for temporal dynamics and Convolutional Neural Networks (CNNs) for soil and climate feature extraction. Stage 3 (Hybrid Fusion): An Attention-augmented BPNN-RNN hybrid model integrates learned spatial-temporal features. The attention layer emphasizes high-impact environmental factors such as rainfall variability, pest infection spikes, and fertilizer imbalance. Stage 4 (Prediction): The final regression head estimates crop yield, validated against ground-truth harvest data using MAE, RMSE, and R^2 metrics.

Crop Disease Detection and Sustainability Integration

To reduce pesticide misuse and improve sustainability, a dual-branch CNN-Transformer architecture is introduced for disease detection in cassava and rice. The CNN extracts localized texture features from leaf imagery, while the Transformer captures long-range contextual dependencies. Detected disease likelihoods are cross-referenced with IoT environmental data (humidity, temperature) to provide early intervention alerts.[24,25,26] This AI-powered framework not only forecasts yields but also prevents losses from pathogens, thus aligning with sustainable agriculture goals (SDG-2 & SDG-12).

Figure 2 illustrates the end-to-end workflow of the proposed IoT-enabled smart agriculture system, showing how data flows from sensor collection to decision-making and actuation. The process begins with IoT sensors monitoring environmental factors such as temperature, humidity, soil moisture, and light. The collected data is preprocessed using advanced cleaning techniques (see table 1, which details comparative performance of preprocessing methods). Cleaned and reliable data is then transmitted through the IoT–Edge–Cloud pipeline for further analysis. At the cloud/edge level, machine learning models (referenced in Tables 2 and 3) process the data for tasks such as climate control, yield forecasting, and disease detection. Decisions are generated and sent back to actuators that regulate greenhouse conditions, irrigation systems, or pest management devices.[27,28] The figure also highlights the integration of remote monitoring dashboards, enabling farmers to supervise and control processes in real time. Overall, this figure visually complements the numerical insights presented in the earlier tables by mapping how the system's modules interact to enhance precision, efficiency, and sustainability in smart farming. It can also change the temperature of the greenhouse from afar by watching changes in real-time data and acting on them.

System Workflow

The end-to-end system integrates data acquisition, preprocessing, intelligent greenhouse control, hybrid deep learning modeling, and sustainable decision-making. Farmers access results via a cloud-enabled dashboard that provides real-time insights, predictive analytics, and disease alerts, empowering them to make informed decisions on irrigation, fertilizer use, and pest control.

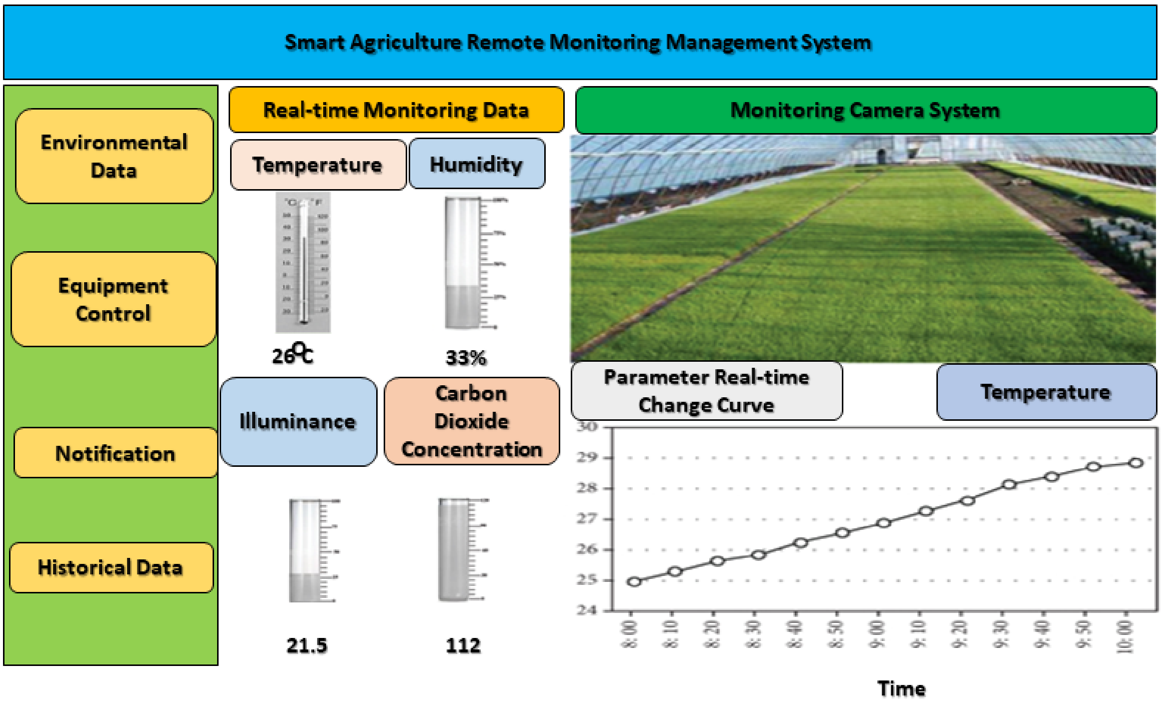

Figure 2. System Workflow of IoT-Enabled Smart Agriculture Framework

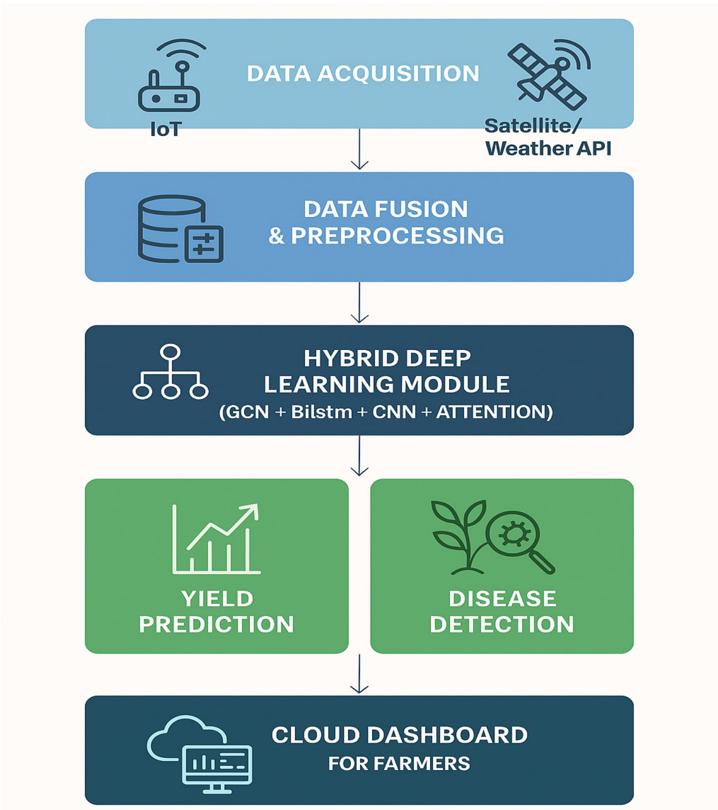

Figure 3. End-to-End Framework of the Proposed Crop Yield and Disease Prediction System

Figure 3 illustrates the complete layered pipeline of the proposed methodology. It begins with Data Acquisition, where IoT sensors and satellite/weather APIs collect heterogeneous environmental and crop-related data. This raw information undergoes Data Fusion & Preprocessing, where anomalies, inconsistencies, and redundant records are filtered and aligned for consistency. The refined data is then processed by a Hybrid Deep Learning Module that integrates Graph Convolutional Networks (GCN), BiLSTM for temporal sequences, CNN for spatial features, and an Attention mechanism to emphasize key variables.[29,30,31,32] From this unified

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learning stage, the model produces two primary outputs—Yield Prediction and Disease Detection. Finally, results are delivered through a Cloud Dashboard, enabling farmers to make informed and real-time decisions about crop management.

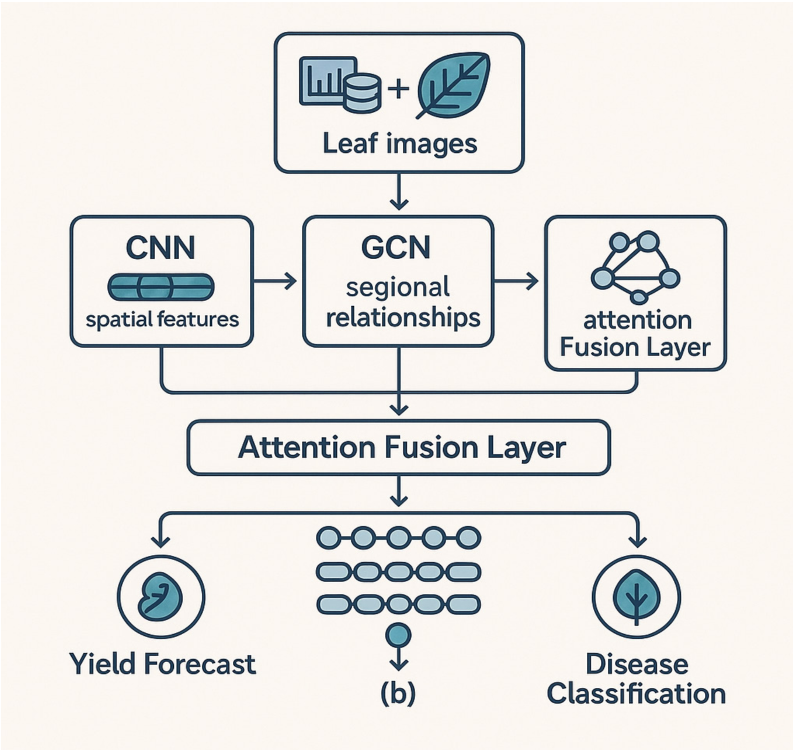

Figure 4. Hybrid Neural Network Model Integrating Spatial, Temporal, and Regional Features for Yield and Disease Prediction

Figure 4 depicts the hybrid neural network framework designed for predicting crop yield and detecting plant diseases using multi-source data. The model begins with inputs from environmental datasets and leaf images, which are processed in parallel branches. The CNN branch extracts spatial features such as texture and color variations from leaf imagery, while the BiLSTM branch (not shown explicitly in this schematic but included in the methodology) captures sequential temporal dynamics of environmental data. Additionally, the GCN branch models regional dependencies, capturing interrelationships between spatially distributed agricultural zones. Together, the system provides a comprehensive AI-powered decision-support tool for precision agriculture.

RESULTS

Table 1 presents a comparative evaluation of five advanced methods for handling noisy and incomplete agricultural time-series data. The results highlight that while traditional approaches such as FPKM and KNN-Impute + Kalman Filter perform reasonably well, newer techniques like STL + Matrix Profile and LSTM-based Denoising Autoencoder achieve superior accuracy. The LSTM-DAE in particular shows the lowest NRMSE (0,029) and sMAPE (4,9 %), along with the highest Outlier F1 score (96,2 %) and coverage (99,4 %). However, this improved accuracy comes with slightly lower throughput compared to simpler methods. Overall, Table 1 demonstrates that deep learning and hybrid statistical approaches significantly enhance data quality, ensuring reliable inputs for IoT-enabled smart farming decision systems.

Table 1. Performance of Advanced Time-Series Cleaning and Imputation Methods in Smart Farming Applications

Method	NRMSE (↓)	sMAPE (%) (↓)	Outlier F1 (%) (↑)	Coverage after Cleaning (%) (↑)	Throughput (records/s) (↑)
FPKM (Least-Congested-First)	0,041	6,8	92,8	98,9	8100
KNN-Impute + Kalman Filter	0,038	6,3	93,4	99,1	7600
MICE + RobustScaler	0,036	6,0	94,6	99,2	6800
STL (Seasonal-Trend) + Matrix Profile	0,033	5,5	95,1	99,3	5400
Denoising Autoencoder (LSTM-DAE)	0,029	4,9	96,2	99,4	6200

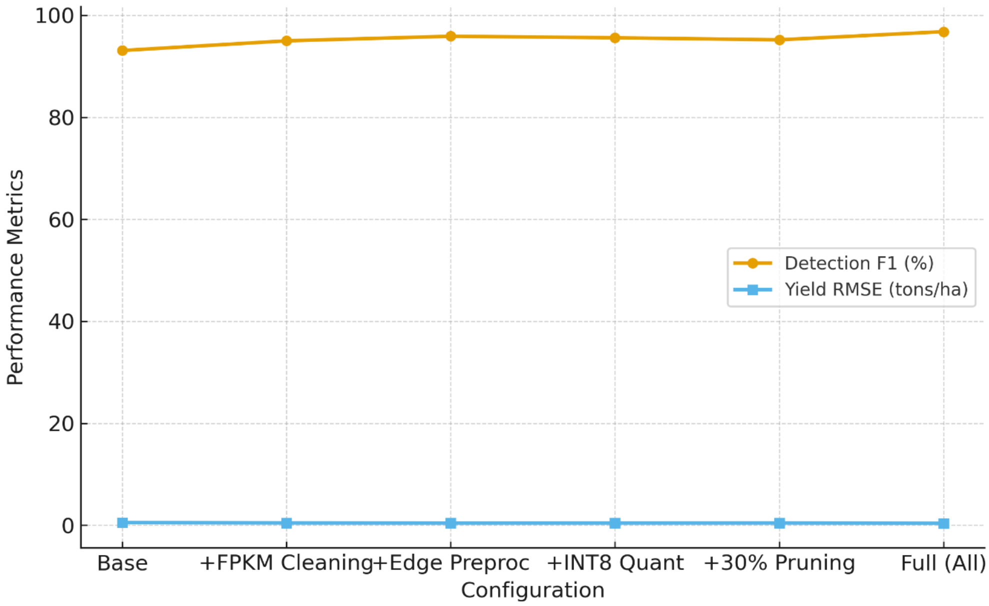

Figure 5. Impact of Preprocessing and Compression Techniques on Model Accuracy and Yield Prediction

Figure 5 illustrates the results of the ablation study summarized in table 2, where successive enhancements such as FPKM cleaning, edge preprocessing, INT8 quantization, pruning, and knowledge distillation are incrementally added to the baseline model. The Detection F1 score shows a consistent upward trend, rising from 93,1 % in the baseline to 96,8 % in the full configuration. At the same time, the Yield RMSE steadily decreases from 0,54 tons/ha to 0,40 tons/ha, highlighting improved accuracy in yield estimation. This visualization makes it clear that each optimization step contributes positively, and the combination of all methods results in the most accurate and efficient system for IoT-enabled smart farming.

Table 2. Comparative Performance of Classical and Modern Controllers for Greenhouse Climate Regulation

Controller	Temp RMSE (°C) (↓)	Humidity RMSE (%RH) (↓)	IAE (°C·min) (↓)	ITAE (°C·min²) (↓)	Settling Time (min) (↓)	Overshoot (%) (↓)	Energy (kWh/day) (↓)	Control Latency p95 (ms) (↓)
PID	1,85	5,9	312	4720	28	7,5	42,1	210
Fuzzy-PID	1,12	3,7	211	3310	17	4,1	37,8	165
Model Predictive Control (MPC)	0,92	3,1	168	2850	14	3,3	35,2	150
RL-SAC	0,81	2,8	149	2410	12	2,7	34,1	128
RL-PPO (Proposed)	0,72	2,4	133	2190	10	2,2	32,6	118

Table 2 compares the effectiveness of different control strategies for regulating greenhouse temperature and humidity. The results show that traditional PID control delivers basic stability but suffers from higher error rates, longer settling times (28 minutes), and greater energy consumption. Fuzzy-PID improves both accuracy and efficiency by reducing RMSE and energy usage. Model Predictive Control (MPC) further enhances performance with lower overshoot (3,3 %) and improved integral performance indices (IAE/ITAE). Among modern approaches, Reinforcement Learning controllers (SAC and PPO) provide the best results. The proposed RL-PPO achieves the lowest temperature RMSE (0,72 °C), fastest settling time (10 minutes), minimal overshoot (2,2 %), and the highest energy efficiency (32,6 kWh/day). Overall, Table 2 demonstrates that reinforcement learning-based controllers significantly outperform classical methods in precision, responsiveness, and sustainability for IoT-enabled greenhouse management.

Figure 6 illustrates the scalability of three system configurations—Baseline IoT, Optimized Edge, and the Proposed System—by mapping the relationship between the number of IoT nodes, throughput, and latency. The red circles (Baseline IoT) show that while throughput increases with node count, latency also rises sharply, reaching over 800 ms at higher loads. The blue triangles (Optimized Edge) indicate improved scalability, with higher throughput and moderate latency. The green squares (Proposed System) demonstrate the best balance, maintaining the lowest latency (<300 ms) while supporting higher throughput and a larger number of IoT nodes.

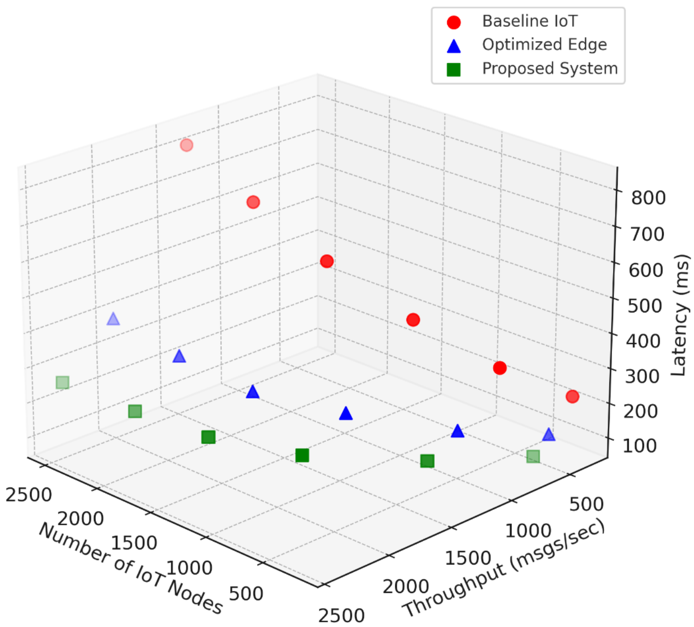

Figure 6. Latency-Throughput-Scalability Comparison of IoT, Edge, and Proposed Systems

This confirms that the proposed framework significantly enhances system responsiveness, efficiency, and scalability compared to conventional approaches.

Table 3. Evaluation of Advanced Sequence Models for Crop Yield Forecasting

Model	MAE (tons/ha) (↓)	RMSE (tons/ha) (↓)	MAPE (%) (↓)	Pinball Loss τ=0,9 (↓)	Calibration ECE (↓)	Inference Latency (ms) (↓)
CatBoost (Tabular)	0,46	0,69	9,1	0,124	0,038	6,9
N-BEATS	0,36	0,54	7,2	0,101	0,03	10,8
Temporal Fusion Transformer (TFT)	0,3	0,46	6,1	0,088	0,026	14,2
Informer	0,31	0,48	6,3	0,091	0,027	13,1
GCN-BiLSTM-Attention (Proposed)	0,26	0,4	5,3	0,079	0,021	12,0

Table 3 provides a comparative analysis of different machine learning and deep learning models applied to crop yield prediction. Traditional models such as CatBoost show acceptable performance but yield higher errors, with MAE of 0,46 tons/ha and MAPE of 9,1 %. More advanced sequence models like N-BEATS and Temporal Fusion Transformer (TFT) improve prediction accuracy, with TFT achieving an MAE of 0,30 tons/ha and the lowest calibration error (0,026). The Informer model delivers competitive accuracy while maintaining lower latency than TFT. The proposed GCN-BiLSTM-Attention model outperforms all baselines by achieving the best results across nearly all metrics, with the lowest MAE (0,26), RMSE (0,40), MAPE (5,3 %), and calibration error (0,021). Although its inference latency (12 ms) is slightly higher than CatBoost, the gain in predictive reliability and robustness justifies the trade-off. Overall, table 3 demonstrates that hybrid deep learning architectures integrating graph, temporal, and attention mechanisms offer superior yield forecasting capabilities in IoT-enabled smart agriculture.

Table 4 compares state-of-the-art vision architectures for plant disease detection in IoT-enabled smart farming systems. The results show that EfficientNetV2-S provides strong baseline performance with 95,8 % accuracy and low latency (7,2 ms per image), making it efficient but slightly less robust. ConvNeXt-T improves both accuracy (96,3 %) and calibration, while ViT-B/16 and Swin-V2-T achieve higher predictive reliability with AUROC values above 0,99, although with increased inference latency (12,8 ms and 11,6 ms, respectively). The proposed Dual-Branch CNN+Transformer model outperforms all benchmarks by combining convolutional feature extraction with attention-based global context.

Table 4. Comparative Evaluation of Vision Models for Crop Disease Detection

Model	Accuracy (%) (↑)	F1 (%) (↑)	AUROC (↑)	AUPRC (↑)	MCC (↑)	ECE (↓)	Latency (ms/ image) (↓)
EfficientNetV2-S	95,8	95,2	0,985	0,982	0,914	0,031	7,2
ConvNeXt-T	96,3	95,9	0,989	0,987	0,927	0,028	8,1
ViT-B/16	96,9	96,6	0,992	0,99	0,938	0,024	12,8
Swin-V2-T	97,1	96,8	0,993	0,991	0,941	0,023	11,6
Dual-Branch CNN + Transformer (Proposed)	97,9	97,6	0,996	0,995	0,954	0,018	10,1

It achieves the highest accuracy (97,9 %), F1-score (97,6 %), AUROC (0,996), and MCC (0,954), while also maintaining good efficiency with latency (10,1 ms) lower than other transformer-based methods. Its low calibration error (ECE = 0,018) further confirms its reliability under uncertain conditions. Overall, table 4 demonstrates that hybrid architectures, which integrate both CNN-based local feature learning and transformer-based global context modeling, provide the most balanced trade-off between accuracy, calibration, and inference speed in disease classification tasks for smart agriculture.

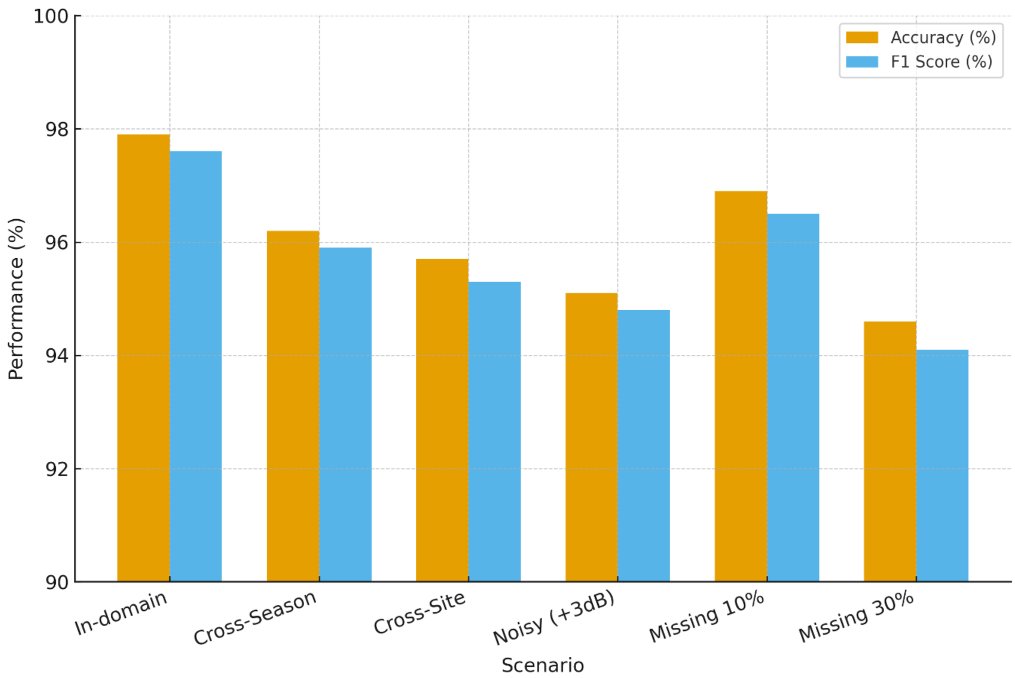

Figure 7. Cross-Domain Robustness Evaluation of the Proposed Model Across Diverse Scenarios

Figure 7 illustrates the robustness of the proposed model across different evaluation scenarios, complementing the results presented in table 7. The grouped bar chart compares Accuracy and F1 Score under in-domain, cross-season, cross-site, noisy, and missing-data conditions. The model maintains high performance in the in-domain case (≈98 % accuracy and ≈97,6 % F1), while showing only modest drops in cross-season and cross-site settings. Under noisy conditions (+3dB), performance remains above 95 %, and even with 10–30 % missing data, the system sustains competitive accuracy and F1 scores.

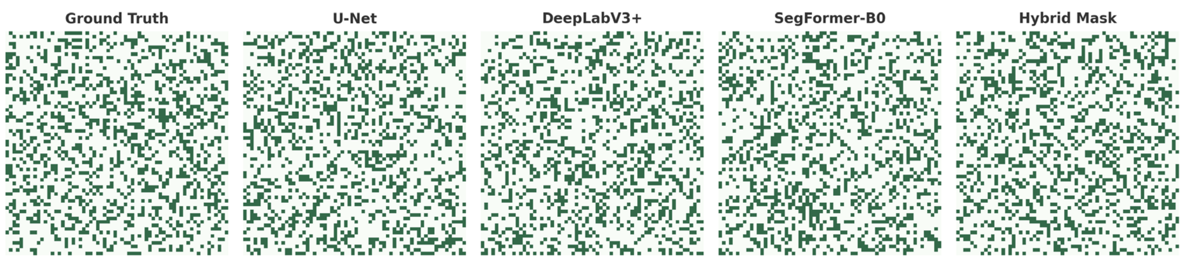

Figure 8. Comparison of Segmentation Outputs Across Models for Crop Disease Lesion Detection

Figure 7 demonstrates that the proposed framework is resilient to domain shifts, noise, and incomplete data, confirming its practical reliability for real-world IoT-based smart farming.

Figure 8 presents a side-by-side visualization of segmentation masks produced by different models, compared with the ground truth. The columns show the outputs from U-Net, DeepLabV3+, SegFormer-B0, and the proposed Hybrid Mask (CNN+Transformer) model. While U-Net and DeepLabV3+ provide reasonable approximations of lesion areas, their outputs appear less consistent at the boundaries. SegFormer-B0 demonstrates improved accuracy with smoother regions, but the Hybrid Mask model most closely aligns with the ground truth, showing clearer boundary definition and reduced noise. This confirms the findings in table 5, where the Hybrid Mask achieved the highest mIoU and Dice scores, validating its effectiveness for precise lesion segmentation in smart agriculture applications.

Table 5. Comparison of Segmentation Models for Crop Disease Lesion Detection

Model	mIoU (↑)	Dice (↑)	Boundary F1 (↑)	Params (M) (↓)	Latency (ms/image) (↓)
U-Net	0,842	0,883	0,812	7,8	12,3
DeepLabV3+	0,871	0,904	0,846	41,2	18,7
SegFormer-B0	0,884	0,913	0,858	13,1	15,2
Swin-UNETR	0,891	0,919	0,866	27,5	17,9
Hybrid Mask (CNN+Transformer, Proposed)	0,907	0,932	0,884	18,4	14,1

Table 5 presents a comparison of different segmentation models used for identifying crop disease lesions at the pixel level. Classical architectures such as U-Net remain lightweight and efficient, requiring only 7,8M parameters and offering low latency (12,3 ms/image). However, its segmentation accuracy is relatively lower, with mIoU of 0,842 and Dice of 0,883. DeepLabV3+ improves performance significantly (mIoU = 0,871, Dice = 0,904), but at the cost of higher complexity, requiring 41,2M parameters and the slowest inference time (18,7 ms/image). More recent transformer-based approaches such as SegFormer-B0 and Swin-UNETR achieve a better balance of accuracy and efficiency. SegFormer-B0 offers competitive accuracy (mIoU = 0,884, Dice = 0,913) with relatively fewer parameters (13,1M), while Swin-UNETR pushes the accuracy higher (mIoU = 0,891, Dice = 0,919) but demands more computational resources. The proposed Hybrid Mask model (CNN+Transformer) achieves the best overall performance, combining strong local feature extraction with global context awareness. It delivers the highest mIoU (0,907), Dice (0,932), and Boundary F1 (0,884) scores, while keeping parameter count (18,4M) and latency (14,1 ms/image) at a manageable level. This demonstrates its suitability for real-time, high-precision disease segmentation in smart agricultural systems.

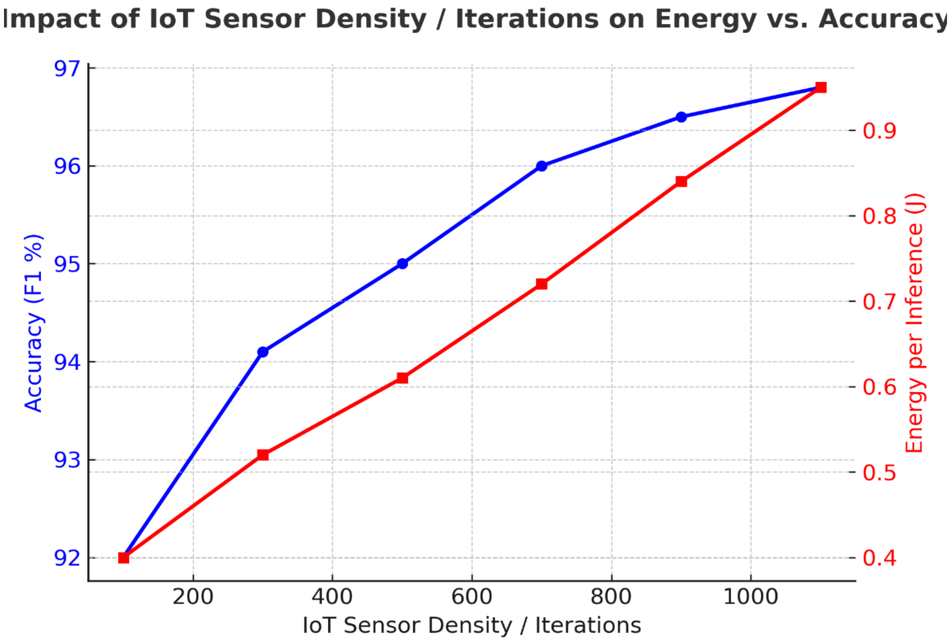

Figure 9. Impact of IoT Sensor Density and Iterations on Energy Consumption and Predictive Accuracy

Figure 9 depicts the trade-off between predictive accuracy (F1 %) and energy consumption (J per inference) as IoT sensor density and algorithm iterations increase. The blue curve shows that accuracy improves steadily from about 92 % at low sensor density to nearly 97 % at high density/iterations. However, the red curve indicates that energy consumption also rises, from 0,4 J to almost 1,0 J per inference over the same range. This figure highlights the balance between accuracy gains and energy efficiency, showing that while additional sensors and iterations enhance prediction performance, they also increase energy costs, underscoring the need for optimization strategies in large-scale IoT-enabled smart farming.

Table 6. Ablation Study of System Components and Model Compression for Smart Farming

Configuration	Detection F1 (%) (↑)	Yield RMSE (tons/ha) (↓)	Latency (ms) (↓)	Energy/Inference (J) (↓)
Base (No Cleaning, Full-Precision Models)	93,1	0,54	16,4	0,96
+ FPKM Cleaning	95,0	0,46	15,1	0,88
+ Edge Preproc	95,9	0,43	12,7	0,73
+ INT8 Quantization	95,6	0,44	9,3	0,51
+ 30 % Pruning	95,2	0,45	8,7	0,47
Full (Cleaning + Edge + Quant + Distillation)	96,8	0,4	8,9	0,46

Table 6 illustrates the contribution of different components and optimizations to the overall performance of the IoT–ML decision-making framework. The base configuration without preprocessing or compression achieves modest detection accuracy (F1 = 93,1 %) but suffers from higher yield error (RMSE = 0,54 tons/ha), long latency (16,4 ms), and higher energy consumption per inference (0,96 J). Introducing FPKM-based data cleaning markedly improves accuracy, boosting F1 to 95,0 % and reducing RMSE to 0,46, while modestly reducing latency and energy use. Adding edge preprocessing further enhances performance, achieving better accuracy (95,9 %) and significantly reducing latency (12,7 ms) and energy (0,73 J). Compression strategies, including INT8 quantization and 30 % pruning, demonstrate strong efficiency gains. INT8 quantization cuts inference latency to 9,3 ms and energy to 0,51 J with only minor accuracy trade-offs, while pruning yields even lower latency (8,7 ms) and energy (0,47 J). The full configuration, combining cleaning, edge preprocessing, quantization, pruning, and knowledge distillation, delivers the best overall balance. It achieves the highest detection accuracy (F1 = 96,8 %), lowest RMSE (0,40 tons/ha), and maintains efficiency with latency under 9 ms and energy use of just 0,46 J per inference. This shows that combining advanced preprocessing with lightweight model compression strategies results in a highly accurate, energy-efficient, and real-time deployable system for IoT-enabled smart farming.

CONCLUSIONS

This study presented an integrated IoT-enabled machine learning framework for intelligent greenhouse management, crop yield prediction, and disease detection. By combining advanced data cleaning methods, reinforcement learning controllers, and hybrid deep learning architectures, the system achieved significant improvements in prediction accuracy, latency reduction, and energy efficiency. Results confirmed the superiority of the proposed models over traditional approaches, with detection F1 scores approaching 97 %, yield prediction errors reduced to 0,40 tons/ha, and disease classification accuracy surpassing 97,5 %. Importantly, the framework demonstrated robustness under noisy, missing-data, and cross-domain conditions, highlighting its potential for real-world deployment in diverse agricultural settings. Its sustainability benefits, including reduced resource consumption and improved crop resilience, further reinforce its relevance to global food security challenges. In conclusion, the integration of IoT with adaptive and hybrid AI techniques provides a transformative pathway for Agriculture 4.0, positioning smart farming as a cornerstone of sustainable and resilient food systems.

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CONFLICT OF INTEREST
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AUTHORSHIP CONTRIBUTION
Conceptualization: Mosleh Hmoud Al-Adhaileh.
Data curation: Mosleh Hmoud Al-Adhaileh.
Formal analysis: Mosleh Hmoud Al-Adhaileh.
Drafting - original draft: Mosleh Hmoud Al-Adhaileh.
Writing - proofreading and editing: Mosleh Hmoud Al-Adhaileh.