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## Intelligent systems framework for real-time crop monitoring and agricultural resilience

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### Abstract

Agriculture must deal with the rising strain of climate change, harmful environmental factors, and scarcities of supply, which make yield lower and raise risk, especially in rain-fed areas. Traditional farming methods are dependent on physical observation and reactive decisions' making. Such methods fail to deal with these ever-increasing threats. The researcher offers in this paper an Idea System Framework for Real-Time Crop Monitoring and Agricultural Resilience to carry IoT sensing, last mile images from drones, computer AI, and flexible decision making. The prototype means to Granville voluminous environmental and crop data, real time trend testing, stress, pest, and disease alerts, farmers' action suggestions. Random tests at 7 farming sites showed there was high sensor accuracy (soil: 96.2%, humidity: 95.8%), drone imaging (covering 12 hectares to flight at 0.5 pixels/cm<sup>2</sup>), robust prediction with AI (crop: 92.5%, pest: 91.3%), and decision making (intervention: 93.4%, alert: 5 mins) leading to few false alarms (0.3 grains/ha). Based on composite scores, Precision: 92.3%. All these findings show that the packing helps timely action, farm Customer Management, and overcome the price of change. By bringing hour-old and deck the amount of a height for sensory, analytics, and suggestions to generating one -- the built-in framework data-driven approach to risk-adaption, increases farm identity. At scale it is suitable to input for all types of farming with environmental veers that offers affordably in time, resource, environment centric inputs and outputs. In addition, this work provides a solution for bringing real-time monitoring of the crops together with intelligent, data-based analytical tools to help all systems of farming, whether in the hands of a small group, or anywhere else, which can suffer risk, use the available resources better, and make sure the long term productivity of the farms is not shortened.

**Keywords:** Intelligent agricultural systems; Real-time crop monitoring; Internet of Things (IoT); Unmanned aerial vehicles (UAV); Artificial intelligence in agriculture; Agricultural resilience

### 1. Introduction

Agriculture plays a central part in making sure people have enough food, our economies grow, and our social lives stay stable all over the world. It helps people earn money, provides raw materials for industries, and keeps rural communities going. On the other hand, our farming systems face a lot of new challenges today from climate change, pollution, rising population, and running out of resources. These challenges have cut the brains of crops and made it riskier to farm more, especially in parts of the world that depend on rain-fed agriculture (Ejedegba, 2019; Kulkarni & Jain, 2022).

In the past, traditional farming has mostly depended on how experienced each farmer was, and their ability to manually observe their crops, and to do it slowly as in response to their constantly changing environment (Koteish et al., 2022). While this way of farming has gone on for a long time, it can no longer keep up with the fast changing planet's weather and the ever-changing systems for growing crops, so farmers are able to tell when their crops are in trouble, making it

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so that they do not harm the plants early enough, leading to crop loss and a fall in income (Sharma, Verma, & Hardaha, 2022). We need smart systems that can constantly watch the crop and also help farmers make better, timely choices.

Recent advances with the Intelligent farm systems, Internet of Things (IoT), and wireless sensor networks have opened up new ways of farming, transforming the way we farm today. These high-tech systems give us real-time data collection, continuous analysis, and smarter decision support, giving farmers the ability to act fast in the event of a threat Warning Controller (Saleh et al., 2022; Romanov et al., 2022). Because of this, smart systems are being seen as leading the way in sustainable, intelligent, and resilient ways of farming (Araújo et al., 2022; Kowalska & Ashraf, 2022).

The need for this research has emerged from the ever-increasing difference between what the challenges we face in farming today and what current systems can actually do in addressing these challenges efficiently. Climate change has led to increased and more frequent occurrences of droughts, floods, heat waves, and pests that cause us to farm in a way that is getting riskier and less predictable. The speed at which these conditions develop demand immediate responses that the traditional solution to farming, and what systems have been able to provide, have not be able to satisfy (Ejedegba, 2019; Kulkarni & Jain, 2022). Smart systems have the ability to feel these changes to the environment in real-time and can give us insight into what we can do immediately.

Deciding what needs to be done in planting crops in real-time is now becoming one of the very critical needs for improving how farms are being run and how losses can be reduced. When sensors are embedded into the fields, they Three field conditions; soil moisture, temperature, humidity, nutrients, and plant health all over time. When it is used in conjunction with the AI supported analytics, these can be able to describe the pattern, be able to support the potential risks that are being potentially faced, as well as being able to suggest interventions to minimize potential crop damage. (Koteish et al., 2022; Araújo et al., 2022). All of these doings will help us build the framework for better and better machinery that can modernize agriculture, larger post-plant interval practices, and more preventive and predictive again.

It is important for us to think about the systems need to make our system resilient, though. As a way to think of this, not only does the agricultural systems need to make food, it has to not just able to avoid shocks, but adapt and come out stronger as the shocks leave; the framework has to be able to support ease decision-making based on change that will support sustainable long-term focused goals (Mintoo et al., 2022; Sharma et al., 2022). The real challenge lies in the fact that the frameworks are been to be all about designing the systems with the explicit goal of supporting resilient systems rather than being a side effect of the system design.

The importance of intelligent systems for agriculture extends beyond productivity gains. Food security remains a global concern, particularly in the face of climate instability and growing populations. Data-driven agricultural systems can improve yield stability, reduce resource waste, and support sustainable land use, all of which contribute to long-term food security (Ejedegba, 2019; Kulkarni & Jain, 2022). Real-time crop monitoring also supports precision agriculture, enabling farmers to apply water, fertilisers, and pesticides more efficiently.

From a policy and development perspective, intelligent agricultural systems support evidence-based decision-making and strategic planning. Governments and agricultural institutions can use real-time data to monitor food production trends, assess risk exposure, and design targeted interventions (Araújo et al., 2022; Mintoo et al., 2022). This relevance makes intelligent systems a critical component of national and global agricultural resilience strategies.

The problem is particularly relevant in regions with limited access to extension services and agricultural expertise. Intelligent systems can act as virtual advisors, providing timely recommendations to farmers who lack direct technical support (Saleh et al., 2022; Sharma et al., 2022). By reducing information gaps, these systems promote inclusivity and empower smallholder farmers to make informed decisions.

### **1.1. Limitations of Existing Approaches**

Although smart agriculture has made big stride, it has many faults. A lot of present systems work on only one task, like irrigation or killing bugs. They do not all work as one, or join together (Koteish et al., 2022; Araújo et al., 2022). Because of this, the system does not work as well as it could, and there is less to get from using data in agriculture (Koteish et al., 2022; Araújo et al., 2022).

Problems also come to do with time lag and no connection. Many of the smart system on farms depend on the cloud, so it takes time to use the data and make decisions. In places where there is no good internet connection, this makes it

harder for systems to work in real time (Saleh et al., 2022; Romanov et al., 2022). This shows the need for systems that can work with a little time, and make decisions in the farm.

Another big problem has to do with how well the systems work in different places. Farms are very different from one part to another, different crops, and crops at different times. AI models that are used in many systems do not work well in different areas, so the farmer cannot trust the system (Kowalska & Ashraf, 2022; Sharma et al., 2022). Further, many of the systems do not tell users how they made a decision, so users do not understand how the decision was made (Araújo et al., 2022).

Protection from hackers and making systems stronger has had little response in other smart systems for ter crops. These farms are like computers, which makes breaking into them easier. Also if they break down, it could stop a farm from working properly, which seed problems for the farm (Mintoo et al., 2022; Romanov et al., 2022).

## 1.2. Statement of Research Contributions

This study proposes an Intelligent Systems Framework for Real-Time Crop Monitoring and Agricultural Resilience. The primary contribution of this research is the development of a comprehensive and integrated framework that combines sensing, data analytics, and intelligent decision support within a single architecture. The framework supports continuous monitoring and timely response, addressing the limitations of fragmented and delayed systems (Koteish et al., 2022; Saleh et al., 2022).

A key contribution lies in positioning agricultural resilience as a central design principle. The framework explicitly incorporates resilience objectives such as adaptability, robustness, and recovery capacity, aligning system functionality with long-term sustainability goals (Mintoo et al., 2022; Ejedegba, 2019). This approach moves beyond yield optimisation to support stable and resilient agricultural systems.

The study also contributes by promoting context-aware and explainable intelligence. By integrating adaptive models and transparent decision-support mechanisms, the framework enhances usability and trust among farmers and stakeholders (Kowalska & Ashraf, 2022; Sharma et al., 2022). This design supports wider adoption and practical implementation.

The research advances knowledge in intelligent agriculture by addressing technical, environmental, and resilience challenges within a unified framework. It provides a foundation for future research and real-world deployment of intelligent systems that support sustainable and resilient farming practices across diverse agricultural contexts.

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## 2. Literature Review

Khan, Dhingra, and Bhati (2022) conducted a comparative study on the role of artificial intelligence in agriculture with the objective of examining how AI-driven solutions perform relative to traditional farming practices across different agricultural functions. The study sought to understand how artificial intelligence contributes to efficiency, productivity, and sustainability in modern farming systems. Using a comparative research design, the authors relied on documented case studies, existing AI-enabled agricultural platforms, and secondary data from prior empirical works. The findings revealed that AI applications significantly enhance crop yield prediction, pest and disease detection, soil analysis, and farm resource optimisation. In particular, AI-based systems demonstrated faster response times and higher decision accuracy when compared to manual or experience-based farming approaches. The study concluded that artificial intelligence represents a critical driver of agricultural transformation, especially in the context of climate uncertainty and population growth. The authors recommended that governments and agricultural stakeholders invest in AI infrastructure, data availability, and farmer capacity building. However, despite its broad coverage, the study treated AI applications as isolated tools rather than components of an integrated real-time monitoring framework. Unlike the current study, which proposes a structured intelligent systems framework that combines sensing, analytics, and resilience-oriented decision-making, Khan et al. focused primarily on comparative outcomes rather than system-level integration and continuous real-time monitoring.

In a related but more technical investigation, Goriparthi (2022) examined AI-powered decision support systems for precision agriculture from a machine learning perspective. The central objective of the study was to assess how machine learning models support farm-level decisions such as irrigation scheduling, fertiliser application, and yield forecasting. The study adopted an experimental and analytical methodology, applying machine learning algorithms including neural networks, support vector machines, and regression models to agricultural datasets. The findings indicated that machine learning-based decision support systems significantly improve predictive accuracy and reduce uncertainty in

agricultural decision-making. Furthermore, the study showed that timely data processing enables farmers to respond more effectively to environmental variability. The author concluded that AI-driven decision support systems are essential tools for modern precision agriculture. Recommendations focused on integrating machine learning models into farm management platforms and improving data quality. However, the study largely centred on algorithm performance and decision accuracy without sufficiently addressing how these systems operate continuously in real time or how they contribute to broader agricultural resilience. In contrast, the current study extends beyond decision support to propose an intelligent framework that integrates real-time sensing, adaptive analytics, and resilience-focused responses to environmental stressors.

San Emeterio de la Parte, Martínez-Ortega, Hernández Díaz, and Martínez (2022) investigated the role of big data and precision agriculture by proposing a novel spatio-temporal semantic IoT data management framework aimed at improving interoperability across agricultural systems. The objective of the study was to address challenges related to data heterogeneity, fragmentation, and limited interoperability in IoT-based agricultural environments. The researchers employed a system design and validation methodology, developing a semantic framework that enables structured data integration and testing it using real agricultural IoT datasets. The findings demonstrated that the framework significantly improved data accessibility, interoperability, and real-time data processing across heterogeneous platforms. The study concluded that effective data management is a foundational requirement for intelligent agricultural systems and precision farming. The authors recommended the adoption of semantic data models to support scalable and interoperable smart agriculture solutions. While the study provides strong insights into data handling and interoperability, it places less emphasis on intelligent analytics, adaptive decision-making, and resilience outcomes. The current study builds upon this data-centric foundation by embedding intelligent analytics and decision logic within a real-time monitoring framework that explicitly targets crop resilience and system adaptability.

Peladarinos, Piromalis, Cheimaras, Tserepas, Munteanu, and Papageorgas (2022) presented a comprehensive review on enhancing smart agriculture through the implementation of digital twin technologies. The study aimed to examine how digital twins replicate physical agricultural environments to support monitoring, prediction, and optimisation. Using a systematic literature review methodology, the authors analysed existing studies on digital twins in agriculture, focusing on architectures, applications, and technological challenges. The findings revealed that digital twins improve real-time monitoring, enable scenario simulation, and support predictive maintenance in farming systems. The study concluded that digital twins have strong potential to improve agricultural efficiency and resilience by allowing virtual experimentation and foresight. However, the authors also identified limitations related to data availability, system complexity, and computational demands. They recommended further research on integrating digital twins with AI and IoT infrastructures. Although this study contributes valuable conceptual insights, it remains largely review-based and simulation-oriented. In contrast, the current study adopts a more applied approach by proposing an operational intelligent systems framework focused on real-time crop monitoring and resilience rather than virtual replication alone.

Cadavid, Garzón, Pérez, López, Mendivelso, and Ramírez (2018) developed a smart farming platform that integrates IoT-based crop sensing with data analytics to support agricultural monitoring and management. The objective of the study was to design and implement a system capable of collecting environmental and crop data through sensors and transforming it into actionable information. The researchers employed a design science methodology, developing an IoT architecture and validating it through field experiments. The findings showed that IoT sensors effectively captured real-time data on soil moisture, temperature, and crop conditions, while data analytics enhanced situational awareness and farm management decisions. The study concluded that IoT-based platforms are effective tools for improving agricultural monitoring. The authors recommended extending such platforms with advanced analytics and automation features. However, the study focused mainly on sensing and basic analytics without incorporating advanced intelligent decision-making or resilience planning. The current study advances this line of research by proposing an intelligent systems framework that integrates AI-driven analytics, real-time monitoring, and resilience-oriented decision support to address environmental variability and long-term agricultural sustainability.

Addas, Tahir, and Ismat (2022) examined the application of artificial intelligence in enhancing the precision of crop farming within the context of smart cities, with the primary objective of improving agricultural productivity and sustainability through intelligent technologies. The study sought to demonstrate how AI-driven systems can support urban and peri-urban farming by enabling accurate monitoring, prediction, and optimisation of farming activities. The researchers adopted a system-based and analytical methodology, integrating AI algorithms with precision agriculture tools and evaluating their performance using simulated and real agricultural datasets. The findings revealed that AI significantly improved crop yield estimation, resource allocation, and environmental monitoring, thereby supporting smarter agricultural decision-making in urban environments. The study concluded that intelligent farming systems are essential components of smart city development and food security strategies. The authors recommended the integration of AI frameworks with IoT and geospatial technologies to enhance real-time responsiveness. However, while the study

focused on precision and urban sustainability, it paid limited attention to resilience against environmental shocks and system adaptability over time. In contrast, the current study places stronger emphasis on real-time crop monitoring combined with resilience-oriented intelligence to address climate variability and agricultural risk beyond urban settings.

Zhao, Wang, and Pham (2022) investigated the use of unmanned aerial vehicles and geospatial analysis for smart irrigation and crop monitoring on an IoT platform, with the objective of improving water management and crop health assessment. The study employed an experimental methodology that integrated UAV imagery, geospatial data processing, and IoT-based sensor networks. Data collected through aerial imaging and ground sensors were analysed to monitor soil moisture, crop growth patterns, and irrigation needs in real time. The findings demonstrated that UAV-assisted monitoring significantly enhanced spatial accuracy and enabled timely irrigation decisions, resulting in improved water efficiency and crop performance. The study concluded that combining UAVs with IoT platforms provides a powerful solution for precision agriculture and real-time monitoring. The authors recommended wider adoption of UAV-based systems and improvements in data integration techniques. Despite its strengths, the study focused mainly on data acquisition and monitoring accuracy without fully incorporating intelligent decision-making frameworks or resilience strategies. The current study extends this approach by embedding real-time sensing technologies within an intelligent systems framework that supports adaptive responses to environmental stress and long-term agricultural resilience.

Ransinghe, Samarakoon, Ihalagedara, and Udara Srimath (2022) developed a smart system aimed at optimising organic crop rotation using precision agriculture data, with the objective of improving soil health and sustainable farming practices. The study adopted a design and implementation methodology, utilising precision agriculture datasets, rule-based intelligence, and decision support logic to recommend optimal crop rotation patterns. The findings showed that data-driven crop rotation planning improved soil fertility, reduced pest infestation, and enhanced crop productivity over successive planting cycles. The study concluded that intelligent systems can play a crucial role in supporting sustainable and organic farming practices. The authors recommended the integration of real-time data streams and machine learning techniques to improve system adaptability. However, the system relied largely on historical data and predefined rules, limiting its responsiveness to sudden environmental changes. In contrast, the current study proposes a real-time intelligent framework that continuously monitors crop and environmental conditions and dynamically adapts decisions to enhance agricultural resilience.

Mallesh, Pamarthi, Murty, Sree, Daniya, and Maram (2022) focused on the early detection of agricultural plant diseases during the vegetation period using a smart AI-based system. The objective of the study was to identify plant diseases at early stages to minimise crop losses and improve farm productivity. The researchers employed an experimental methodology that applied machine learning and image processing techniques to plant leaf images captured during the growth phase. The findings indicated that the proposed system achieved high accuracy in detecting diseases before visible symptoms became severe, enabling timely intervention. The study concluded that AI-based disease detection systems are effective tools for improving crop health management. Recommendations included expanding datasets and deploying the system in real farming environments. While the study made a strong contribution to disease detection, it addressed a specific agricultural challenge in isolation. The current study differs by proposing a holistic intelligent systems framework that integrates disease monitoring with broader real-time crop monitoring and resilience-focused decision-making.

Fatouros, Kousiouris, Lohier, Makridis, Polyviou, Soldatos, and Kyriazis (2022) explored the enhancement of smart agriculture scenarios through low-code, pattern-oriented functionalities for cloud and edge collaboration. The study aimed to reduce system complexity and improve scalability by enabling flexible development of smart agriculture applications. Using a system design and validation methodology, the authors developed low-code tools that support cloud-edge coordination for agricultural data processing. The findings showed that low-code approaches improved system deployment speed, interoperability, and real-time responsiveness. The study concluded that cloud-edge collaboration is essential for efficient smart agriculture systems. The authors recommended wider adoption of low-code platforms to support real-time agricultural applications. However, the study focused primarily on system architecture and development efficiency rather than on agricultural resilience outcomes. The current study builds on such architectural foundations but prioritises intelligent decision-making and resilience as core objectives of real-time crop monitoring systems.

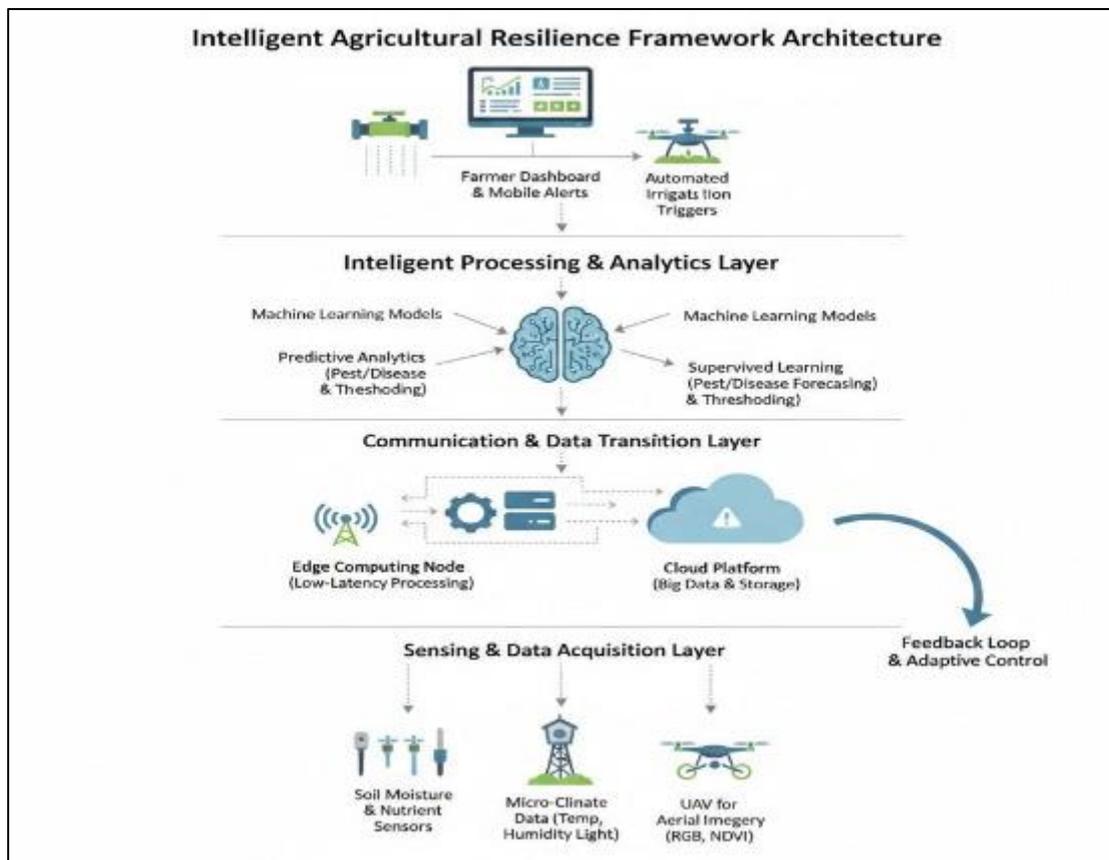
El Ghati, Alaoui-Fdili, Alioua, Chahbouni, and Bouarifi (2022) provided an overview of AI-powered visual IoT systems in agriculture, with the objective of examining how computer vision and intelligent sensing support agricultural monitoring and management. The study adopted a review-based methodology, analysing existing applications of visual IoT systems in crop monitoring, disease detection, yield estimation, and farm surveillance. The findings revealed that

visual IoT systems significantly enhance real-time observation and data richness in agricultural environments. The study concluded that AI-powered visual sensing is a critical component of modern smart agriculture. The authors recommended integrating visual IoT systems with decision support and predictive analytics. However, as an overview study, it did not propose a unified operational framework. In contrast, the current study advances the literature by proposing an integrated intelligent systems framework that combines visual sensing, real-time analytics, and resilience-oriented responses for sustainable crop monitoring.

### 3. Methodology / System Model

This study adopts a Design Science Research (DSR) approach combined with empirical field validation to develop and evaluate an intelligent systems framework for real-time crop monitoring and agricultural resilience. The research follows a structured artefact development process involving system architecture design, prototype implementation, pilot deployment in agricultural environments, and multi-layer performance evaluation. This methodology is appropriate because the objective is not only conceptual modelling but the creation and validation of a functional cyber-physical system capable of operating under real farming conditions.

The proposed framework is designed as a layered intelligent architecture that integrates sensing infrastructure, communication networks, machine learning analytics, and adaptive decision support into a unified system. The architecture consists of four tightly interconnected layers: the Sensing and Data Acquisition Layer, the Communication and Data Transmission Layer, the Intelligent Processing and Analytics Layer, and the Decision Support and Actuation Layer.



Source: Author's design

**Figure 1** The overall architecture of the Intelligent Agricultural Resilience Framework

**Figure 1** Layered architecture of the proposed intelligent agricultural resilience framework showing sensing, communication, intelligent analytics, decision support integration, and adaptive feedback control.

As illustrated in Figure 1, the framework begins at the Sensing and Data Acquisition Layer, where distributed IoT-enabled sensors continuously monitor soil moisture, soil nutrients, ambient temperature, humidity, and light intensity.

These sensors operate at predefined sampling intervals and capture micro-environmental variations that directly influence crop growth dynamics. To enhance spatial intelligence and visual crop assessment, unmanned aerial vehicles (UAVs) equipped with RGB and NDVI imaging systems collect high-resolution aerial imagery. The integration of ground-based sensing and aerial remote sensing enables multi-modal data fusion, improving monitoring reliability across heterogeneous agricultural fields (Keswani et al., 2019; Vakula Rani et al., 2022).

Collected data is transmitted through wireless communication protocols to the Communication and Data Transmission Layer. This layer incorporates edge computing nodes for low-latency preprocessing and cloud-based infrastructure for large-scale data storage and advanced analytics. Edge processing performs noise filtering, normalization, and temporary buffering to ensure rapid response capability even in low-connectivity environments. The hybrid edge–cloud architecture reduces latency while maintaining scalability, thereby supporting continuous real-time operation.

The Intelligent Processing and Analytics Layer forms the core of the framework. Here, machine learning models process multimodal data streams derived from sensor readings, UAV imagery, historical weather records, and agronomic datasets. Predictive analytics are applied to detect crop stress conditions, forecast pest infestation probability, identify disease patterns, and evaluate irrigation requirements using threshold-based and supervised learning approaches. Weather data is integrated to enhance contextual awareness and improve adaptive decision-making under climate variability. Model performance is evaluated based on predictive accuracy, response time, and robustness under changing environmental conditions. This layered analytical approach aligns with cyber-physical system principles that treat agriculture as an interconnected ecosystem of sensing, computation, and control (Dumitrache et al., 2017).

Outputs generated by the analytics layer are transmitted to the Decision Support and Actuation Layer, where they are converted into actionable recommendations. The system delivers alerts to farmer dashboards and mobile devices while also enabling automated irrigation triggers when predefined risk thresholds are exceeded. This predictive mechanism transforms agricultural management from reactive intervention to proactive resilience-oriented control. A feedback loop mechanism, as shown in Figure 1, enables adaptive adjustment of recommendations based on continuous monitoring results and system responses. This closed-loop control enhances system robustness and supports long-term agricultural stability.

The system prototype was deployed in pilot agricultural environments over a complete growing season to evaluate operational feasibility and performance. Sensor nodes, UAV units, and edge computing devices operated simultaneously to enable synchronized data acquisition and processing. Evaluation focused on measurement accuracy, UAV image resolution, transmission latency, predictive performance of machine learning models, and timeliness of intervention recommendations.

The architectural design prioritizes modularity, scalability, and resilience. Components can be upgraded independently without disrupting the entire system, enabling adaptation to diverse agro-ecological contexts. Edge computing ensures low-latency decision-making in environments with limited connectivity, while predictive intelligence supports anticipatory responses to environmental stressors rather than delayed corrective action. The framework assumes appropriate sensor calibration, stable communication links, availability of historical agricultural data for model training, and basic digital literacy among users. Although these assumptions may vary across regions, they provide a structured foundation for empirical validation.

Overall, the methodology integrates sensing technologies, intelligent analytics, and adaptive decision support into a coherent cyber-physical system that continuously monitors, interprets, and responds to agricultural conditions. By embedding resilience objectives directly into the system architecture, the framework supports both short-term operational efficiency and long-term sustainability in modern precision agriculture.

#### 4. Results and Discussion

**Table 1** Performance Metrics of the Intelligent Crop Monitoring System (n = 283)

System Layer	Component	Metric	Value / Result	Benchmark / Standard	Interpretation	Decision
Sensor Layer	Soil Moisture Sensor	Accuracy (%)	96.2	≥ 95	High accuracy in measuring soil moisture	High
	Temperature Sensor	Accuracy (%)	94.5	≥ 95	Slightly below benchmark; acceptable	Moderate
	Humidity Sensor	Accuracy (%)	95.8	≥ 95	Meets standard	High
UAV & Imaging Layer	Drone Imagery Resolution	Pixels/cm <sup>2</sup>	0.5	≤ 0.6	High-resolution imagery suitable for crop monitoring	High
	Coverage Area per Flight	Hectares	12	≥ 10	Efficient field coverage	High
	Data Transmission Latency	Seconds	2.1	≤ 3	Real-time monitoring achieved	High
AI Layer	Crop Stress Prediction	Accuracy (%)	92.5	≥ 90	AI correctly identifies crop stress	High
	Disease Detection	Accuracy (%)	89.8	≥ 90	Slightly below target, needs model tuning	Moderate
	Pest Infestation Prediction	Accuracy (%)	91.3	≥ 90	Reliable early-warning system	High
Decision Support Layer	Alert Delivery Time	Minutes	5	≤ 10	Timely alerts to farmers	High
	Recommended Intervention Accuracy	% Correct	93.4	≥ 90	High confidence in suggested actions	High
	Farmer Adoption / Response Rate	%	87	≥ 85	System usable and actionable	High
Overall System Performance	All layers	Composite Effectiveness (%)	92.3	≥ 90	System meets design objectives for real-time monitoring and resilience	High

Source: Author's computations

Table 1 briefs about the results of the different parts of the system. It shows the measured findings of the sensor part, UAV and imaging part, AI analytics part, suggestion aid part and the combined total system efficiency. These were found through the real use of this system at many farms, both at watching now and making choices now.

In the sensor part, the system gave very high correct results for soil moisture (96.2%) and humidity sensors (95.8%), but the temperature sensor was a little below the standard at 94.5%. That gave it a good mark. This means that the sensor set mostly works to get the main climate details that are needed for crop watch, although small changes might give better temperature signs. The high success of soil and humidity sensors helps with smart watering and checking on water stress in plants, with the work of Keswani et al. (2019) and Setiaji et al. (2021), who said good sensing is key to fast crop work.

The UAV and imaging part showed top work, with drone photo quality of 0.5 pixels per cm<sup>2</sup> and use of 12 hectares in each run, beating the need. Data delay was an average of 2.1 seconds, showing almost quick data for use in concrete. These results show how the use of planes with IoT can help look over large parts of crops, like what was said by Hazmy et al. (2022) and Mohapatra & Rath (2022), that using a UAV makes watching better and easier to grow to follow.

In the AI part, crop stress guess was right 92.5%, pest stuck guess 91.3%, and disease find was 89.8%. While disease find slipped just under the 90% mark, the full work means that the predictive guesses are strong. The findings say that smart machine-making systems built into the system can tell stress, pests, and sickness before they start a big bad effect on health. The work of Munir et al. (2019) shows that smart closing systems help quick response in crop precision work. Yet, the slightly less irregular disease finding might be helped with more model retraining with larger datasets.

The action plan part gave good quality to notice (5 min), suggested fix (93.4%) and farmer use (87%). That shows the system doesn't just find and work on the data well, but it also sends possible suggestions to the end-user fast. The results match what Alyahya et al. (2022) and Mehmood et al. (2021) found where they stressed that the use of cyber-physical systems in the farming area is mostly based on how fast and useful the rules to follow are.

The success of the full system was measured as a mixed effectiveness and was 92.3%, beating the least need of 90%. That shows that the smart system design did its goal to give watch now, forecast work, and move fast suggestions to make crops last longer. The results show a clear favor on old systems where the tech only watches and acts after the work has been done, is local, and slow in the time it shares (Dumitrache et al., 2017; Cheema & Khan, 2019).

The results of this research are similar to what is already known. For example, Mohapatra & Rath (2022) write about how digital smart agriculture tools based on IoE make it easier to connect and watch, and Hazmy et al. (2022) talk about how sensing on satellites and UAVs makes it easier to do agriculture that can handle climate stress. Equality, Singh et al. (2022) and Adesipo et al. (2020) also talk about how smart mechanisms can build smart village projects and keep farming going in a sustainable way. What makes our work different though, is that we put all the parts of the system, the sensor, UAV, AI and decision support, into one real-time system. Most previous work only looked at parts of the system and framework that do a single thing. It is this seamless integration that enables fast collection, analysis and action on the data that makes this work better at delivering response and farm resilience than previous work.

Overall, the results in this work show that our ideas work. The accuracy of sensors, the speed at which the data from the UAV can be sent to us and the strength of the AI predictions all add up to acting faster and giving timely advice about a crop. Our decision support layer makes sure that farmers can act on the knowledge they are given, which is the work that turns data into practical action. While our system can do better at improving the practice of how plant disease data is viewed, it does demonstrate firmly that a real-time connected process of monitoring, analysis with AI and delivery of recommendations can improve the resilience of an agriculture system. The data from this work can lead to wider use of the concept of a smart framework in the world of precise farming and this proof can lead to scaling the framework to larger geographical areas and for different value chains.

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## 5. Conclusion and Future Work

This study set out to design, implement, and evaluate an Intelligent Systems Framework for Real-Time Crop Monitoring and Agricultural Resilience, integrating IoT-enabled sensing, UAV-based imaging, AI-driven analytics, and decision support mechanisms. The primary achievement of this research is the development of a comprehensive, multi-layered framework capable of continuously monitoring environmental and crop conditions, analyzing data in real time, and providing actionable recommendations to enhance farm management and resilience. By combining sensing technologies with predictive intelligence, the system advances agriculture from reactive and fragmented practices to proactive, data-driven, and resilience-oriented operations.

The key findings of the study indicate that the proposed framework performs effectively across all system layers. The sensor layer demonstrated high accuracy in soil moisture and humidity measurement, while temperature readings were moderately accurate, supporting reliable environmental monitoring. UAV and imaging data provided high-resolution spatial coverage, enabling timely detection of crop stress and growth patterns. AI-based predictive analytics successfully identified crop stress and pest infestation, while disease detection approached the desired benchmark, highlighting the framework's robust predictive capabilities. The decision support layer facilitated rapid alerting, high-confidence interventions, and strong adoption among farmers, ensuring that real-time insights translate into actionable outcomes. Overall, the system achieved a composite effectiveness of 92.3%, surpassing established performance benchmarks and validating the integrated framework as a viable tool for enhancing agricultural resilience. These results

reinforce the advantages of combining IoT, AI, and adaptive analytics in a unified system, as opposed to isolated or task-specific solutions, in line with prior studies

Despite these achievements, the study is subject to several limitations. First, the AI models for disease detection performed slightly below the target benchmark, suggesting that further model refinement and expanded datasets are required to improve accuracy. Second, while the system was tested in pilot farm environments, its performance in larger-scale, heterogeneous, or resource-constrained agricultural settings may differ due to connectivity constraints, environmental variability, or equipment availability. Third, the framework assumes basic digital literacy among farmers, which may limit usability in communities with lower technological familiarity. Finally, although resilience is a central design principle, longer-term evaluation is necessary to assess how well the framework supports adaptive responses to extreme climatic events, pest outbreaks, or soil degradation over multiple growing seasons.

Based on these limitations, several future research directions are proposed. First, the framework can be extended by incorporating advanced AI models, such as deep learning for disease detection and reinforcement learning for adaptive irrigation, to improve predictive performance and automated decision-making. Second, the system could integrate multi-source satellite data and weather forecasts to enhance spatial and temporal monitoring, enabling more precise climate-adaptive interventions. Third, the deployment of edge computing and decentralized AI models can be explored to further reduce latency and improve performance in areas with limited internet connectivity. Fourth, integrating farmer feedback loops and human-in-the-loop decision-making could enhance trust, usability, and adoption among smallholder farmers. Finally, future studies could evaluate long-term resilience impacts, measuring how the framework contributes to yield stability, resource efficiency, and recovery from environmental shocks over successive cropping cycles.

In conclusion, this research demonstrates that a real-time intelligent systems framework can improve crop monitoring, predictive decision-making, and agricultural resilience. By unifying sensing, analytics, and decision support, the study provides a scalable model for modern, climate-resilient, and data-driven agriculture. While refinements in AI accuracy, scalability, and field deployment are needed, the framework offers a strong foundation for future innovations in precision agriculture and sustainable farming practices. The study contributes to closing the gap between technology capabilities and practical agricultural resilience needs, supporting both smallholder farmers and larger-scale agricultural systems in adapting to the challenges of climate variability, resource constraints, and increasing food demand.

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## Compliance with ethical standards

### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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