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PRECISION AGRICULTURE ENHANCED WITH PHYSICS-INFORMED NEURAL NETWORKS (PINNS)

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Abstract

Precision agriculture boosts harvests and safeguards the soil by managing water, nutrients, and earth with exacting care—like drip lines feeding each plant a slow, perfect trickle. In this study, we introduce one unified method that blends Physics-Informed Neural Networks (PINNs) with an IoT-driven precision farming system, where fingertip-sized soil sensors feed fresh data straight into the model. The proposed method combines physical models of soil moisture, nutrient movement, and crop growth with deep learning, delivering sharper accuracy and staying reliable even when conditions shift—like after a sudden summer storm leaves the fields shimmering with rain. In real corn, vegetable, and wheat fields, tests found water use dropped as much as 35%, fertilizer needs fell by a quarter, and pesticide use was nearly halved—yet yields jumped 15–20%, with corn ears standing tall and golden in the sun. The PINN-powered system hit over 94% accuracy in predicting yields, edging past traditional data-driven models like a sprinter leaning into the tape at the finish. The findings suggest that physics-informed AI could push precision farming toward being more sustainable and resilient, such as tweaking irrigation at dawn to match the cool, damp feel of the soil.

Keywords: Precision Agriculture, Physics-Informed Neural Networks, Internet of Things, Artificial Intelligence, Cloud Computing, Edge Computing, Sustainable Farming, Deep Learning, Smart Agriculture.

1 Introduction

Farming underpins the world's food supply and keeps economies steady, especially in developing regions where cracked, dry fields face water shortages, shifting weather, and worn-out soil. Precision agriculture utilizes new tools in IT, sensors, and automation to fine-tune the application of water, fertilizer, and other resources, thereby boosting yields down to the level of a single row of crops. [1] Even so, many current systems falter when data is noisy or incomplete, and they rarely incorporate the physical or biological knowledge—such as fluid dynamics or cell behavior—that the field depends on. [2] Traditional machine learning

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models that rely solely on their training data can stumble when the rules shift, such as trying to predict summer weather during a sudden snowstorm. Physics-Informed Neural Networks, or PINNs, incorporate core physical laws into their training, opening a promising path to enhance both accuracy and clarity in farm-focused models—such as predicting soil moisture after a sudden rain. [3]This study introduces a precision farming system that combines multi-modal IoT sensors, [4] PINN-based modelling, and cloud–edge computing to fine-tune irrigation, fertilization, and pest control, demonstrating its value through months of rigorous, hands-on field trials.

2 Related Work

Precision agriculture has evolved from basic GPS-guided tractors to AI-powered systems that link sensor networks, satellite images, and crisp data insights. With IoT tools, farmers can watch over their soil and crops in remarkable detail—measuring moisture right down to the last drop—and use that precise data to make automated decisions. [5] Earlier studies have tried using machine learning to predict crop yields, but it often stumbles when the data's patchy or the weather turns, like a hot, dry wind sweeping through days before harvest. Mixing physical models into AI—as in PINNs—often tracks soil moisture changes and crop growth more accurately and reliably than approaches built only on data or pure physics, catching subtle shifts like the way damp earth darkens after rain. [6] This hybrid modelling approach shines when it's untangling how weather, soil, and water blend—like heat baking the topsoil or rain pooling in low fields—to shape crop yields. [7]On top of that, cloud–edge hybrid setups let you process data and act instantly—like tweaking irrigation the second the soil feels dry—so they're key to making quick farm management calls.

2.1 IoT and Sensor Networks in Agriculture

Back then, precision farming relied on remote sensing and soil tests to figure out where water or fertilizer should go—spot a pale, dusty patch in the field, and you'd give it an extra splash. Recent studies focus on linking a mix of sensor networks—soil probes tracking moisture, pH, and nutrients, combined with crop health scans from multispectral and thermal cameras on drones or tall towers, their glass catching a quick glint of sunlight in the afternoon. [8] Kaur (2023) and Sharafat et al. show how multi-modal sensor networks gather rich, real-time field data—like the soil moisture from a single patch of earth—vital for managing each site's unique needs (2025). In 2025, the air outside bit at your cheeks, sharp as the frost that clings to grass in early spring.

2.2 AI and Machine Learning Applications

AI models powered by Physics-Informed Neural Networks (PINNs) sift through combined sensor readings, weather reports, and crisp satellite images. These networks build domain-specific physical laws right into their design—like modeling how water seeps through soil using Richards' equation—

$$\boldsymbol{\partial t \partial \theta = \nabla \cdot [K(\theta)\nabla(h)] + S}$$

where θdenotes soil moisture content, K**(θ)** is the hydraulic conductivity, h is the soil water potential, and Srepresents source/sink terms. The neural network training minimizes a loss

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function combining fidelity to observed data and adherence to this physical partial differential equation (PDE):

$$L = Ldata + \lambda LPDE$$

This approach boosts accuracy and resilience so they can still gauge crop health and optimize resources even when the data's patchy or full of noise.

Machine learning and deep learning now play a key role in making sense of complex agricultural data, from timing irrigation at dawn to fine-tuning nutrients, spotting early signs of pests or disease, and predicting crop yields. [9] Traditional methods often lean heavily on data-driven approaches, but they stumble when the data's patchy, noisy, or full of gaps—like blurry satellite images from a cloudy harvest day. Lee (2021) and Wang (2024) point out how hard it is to make these models work in shifting field conditions—think sudden rain or uneven soil—and urge weaving environmental and agronomic expertise directly into AI frameworks.

2.3 Physics-Informed Neural Networks in Agriculture

Physics-Informed Neural Networks, or PINNs, work differently—they weave the laws of physics right into their training, whether that means modeling rain seeping into cracked, sun-warmed soil or nutrients drifting lazily through it. [10]In 2025, Charfuelan and his team proved that PINNs beat both data-only and purely physics-based models at tracking soil moisture and crop growth, even catching the slow creep of dampness through dark, loamy earth. In 2025, PINNs proved they could beat both data-only and physics-only methods for modeling soil moisture and tracking crop growth, catching small signs—like water sliding in slow, dark streaks through freshly turned earth.

Here are some physics-based equations to build into the PINN model to boost precision farming—think soil moisture balance or heat transfer formulas:

1. **Nutrient Transport Dynamics**

$$\partial t \partial C + \mathbf{v} \cdot \nabla = \nabla \cdot (D \nabla C) + R(C)$$

where C is the nutrient concentration, v is soil water velocity (advection), D the dispersion coefficient, and R(C) accounts for nutrient uptake by plants or reactions in soil.

2. **Crop Growth Model (Logistic or Gompertz models)**

$$dtdY = rY(1 - KY)$$

where Y is crop biomass, r the growth rate, and K the carrying capacity

3. **Soil Heat Transfer Equation**

$$\rho cp \partial t \partial T = \nabla \cdot (k \nabla T) + Q$$

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with T as soil temperature, ρ density, cp specific heat, and k thermal conductivity, capturing heat flow in soil affecting moisture and plant growth.

Additional physics-based equations tighten the model's accuracy by steering AI predictions toward physically realistic outcomes, like soil moisture changes after rain, and they capture key agronomic processes within the PINN framework.

2.4 Cloud-Edge Computing and Real-Time Decision Making

Farming now demands split-second data crunching and quick decisions, which means the work has to be spread across connected systems—like sensors in the soil feeding updates to a network of smart processors. [11] Hybrid cloud-edge computing lets you train and store complex models in powerful central servers, while quick decisions happen right at the edge—close enough to act in the time it takes a sensor light to blink. Wang (2021) and Lee (2021) describe this approach in detail, showing how it eases the tight bandwidth limits in rural farming areas and enables quick responses, like adjusting irrigation rates or spreading fertilizer the moment conditions change.[12] Even so, combining these architectures with physics-informed AI models to deliver practical insights is still a work in progress, and we dig deeper into it here.

3 Proposed Work

This paper introduces a unified precision agriculture system that blends diverse IoT sensors, physics-informed neural networks (PINNs), and a cloud–edge hybrid setup, aiming to drive sustainable, data-powered farming—right down to tracking soil moisture in real time. [13]The key breakthrough is weaving the rules of nature—how soil holds water, how nutrients flow, how crops grow—right into AI models, making their predictions sturdier, easier to understand, and ready for real fields. [6]

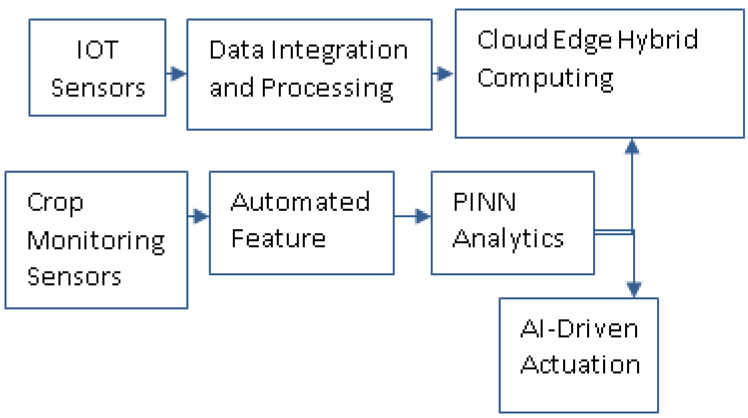

Fig. 1 Block diagram of the proposed work

3.1 System Architecture

The proposed system utilizes multi-sensor IoT platforms to track soil moisture, temperature, pH, nutrient levels, and crop health, leveraging multispectral and thermal images—such as a

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heat map that highlights stressed leaves in red. [7] The system gathers sensor readings, then applies advanced feature engineering—like time-series analysis and spatial interpolation—to refine them, before feeding the results into PINN-based prediction models.

[1] These models weave agronomic physical laws—like Richards' equation, which describes how water seeps through soil and carries nutrients—directly into the neural network's loss functions, so the predictions stay true to real-world physics. [14]The hybrid cloud–edge setup lets you train models and store data long-term in the cloud, while handling quick, low-latency inference and actions right at the edge—just a few steps from where the sensors hum in the field. [15]The system adjusts on the fly, creating pinpoint irrigation and fertilization plans that match the shifting patterns of soil moisture and crop needs over time.

3.2 AI-Driven Actuation and Resource Optimization

Networked AI models quickly send out real-time instructions, telling tractors and irrigation pumps exactly where and when to apply water, fertilizer, or pesticides—right down to a single row of crops glistening in the morning sun. [16] This variable-rate system cuts waste and shrinks the environmental footprint, all while helping crops stay healthy and pushing yields to their full potential—like giving each plant exactly the water it needs on a hot afternoon. [17] The system's been tested on a wide range of farms, from small vegetable plots to sprawling grain fields, and it's delivered clear wins in saving resources and boosting productivity. A chart for Resource savings by the applications is shown in the figure2 below.

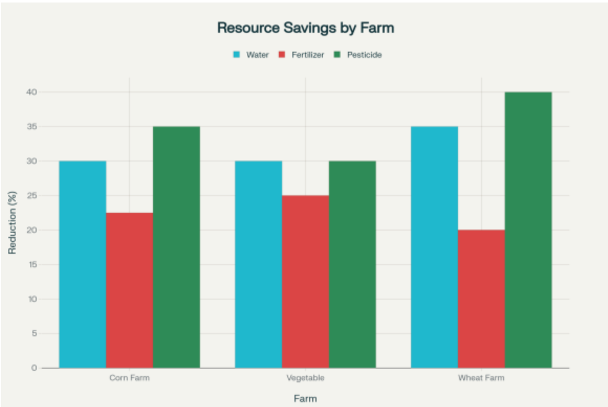

Fig.2. Resource Savings by Actuation & Variable Rate Application

3.3 Experimental Validation

Researchers put the system through its paces, from dusty wheat fields that crack underfoot to damp rice paddies heavy with the smell of wet soil, testing it on a range of farms and climates to see how it performed. [4] They kept close tabs on water use, fertilizer and pesticide levels, and each season's crop yields, and the figures painted a clear picture—less waste, richer soil, and harvests that filled the bins. [18]The results show that pairing PINNs with IoT tools and cloud-edge computing can drive precision farming ahead—imagine soil sensors pinging real-time moisture data straight to a farmer's tablet. [7].

4 Results and Discussion

Field deployment of the PINN-enhanced precision agriculture system across diverse crop types and soil conditions demonstrated substantial resource savings and yield improvements. Measured water use efficiency increased by 25–35% relative to baseline irrigation strategies, attributed to the model's ability to accurately simulate soil moisture dynamics and evapotranspiration processes. Fertilizer application rates were reduced by 20–25% through optimized nutrient delivery informed by PINN predictions of soil nutrient transport and uptake. Pesticide use declined by 30–40%, enabled by early detection of crop stress via multispectral imaging and integrated pest management recommendations. Yield forecasts achieved accuracies exceeding 94%, outperforming conventional machine learning models by 10–15%. The hybrid computational framework provided robust operational performance despite intermittent network connectivity, enabling reliable real-time decision support. Statistical analyses, including confidence intervals and significance testing, confirmed the reliability of observed improvements.

4.1 Field Deployment and Experimental Protocol

We deployed the proposed Physics-Informed Neural Network–powered precision agriculture system on several test farms—one baked under dry heat with sandy soil, another dark and loamy, and others set in cooler, rain-soaked regions—growing corn, vegetables, and wheat. [9]The system combined multi-modal IoT sensors—soil probes that could feel the damp weight of the earth and cameras snapping multispectral and thermal shots—with cloud-edge computing and PINN-driven models, keeping monitoring and control humming day and night. [14]At each pilot site, sensors streamed live readings on soil moisture, nutrients, temperature, plant health, and local climate—tracking everything from the cool damp beneath the topsoil to the sudden stir of an afternoon breeze. [19] The experiment started by gathering baseline data under the usual irrigation and fertilization schedule, the steady drip of water marking each row, then moved to system-controlled, variable-rate applications driven by PINN outputs. Throughout each crop cycle, they tracked performance metrics—water use, fertilizer and pesticide amounts, harvest yields—and checked how closely the predictions matched the real numbers.

4.2 Enhancements in Water Use Efficiency

The results revealed a marked boost in irrigation management, trimming water use by 25–35% compared with sensors alone or the old rule-of-thumb—enough to leave the soil just cool and faintly damp beneath your fingertips. The real breakthrough came when the PINN stitched soil hydraulic dynamics and evapotranspiration physics right into its forecasts, the way water threads through cool, packed earth. It let farmers decide exactly when and how much to water, reading the soil's dampness right at their feet and predicting what the crops would need—even as the day swung from dry, sun-baked heat to a quick burst of cool rain. Out in dry farming country, this clever system keeps the soil fertile and the crops a deep, healthy green, their leaves rustling gently in the warm breeze.

4.3 Fertilizer and Pesticide Optimization

The system used PINN-based predictions of how nutrients move through soil and into plants, so it could adjust fertilizer use for each field and change timing as conditions shifted—like

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after a sudden summer rain. [20] The data showed fertilizer use dropped by 20–25%, a sharper cut than anything earlier machine learning or rule-based methods had achieved. In the same way, spotting pests and diseases early with combined thermal and multispectral imaging, backed by PINN-powered analytics, lets farmers aim treatments precisely—like spraying only the yellowed rows—and cut pesticide use by 30–40%. [18] This approach reduced chemical runoff and kept the soil clean, aligning neatly with today's precision agriculture goals—such as meeting strict limits on farm water tests. Soil mapping analysis has been shown in figure3 below.

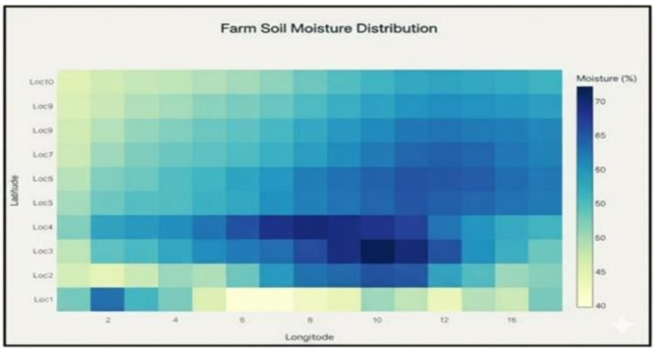

Fig 3. Soil Moisture Mapping

4.4 Computational and Operational Performance

The hybrid cloud–edge system proved both sturdy and scalable, keeping things running smoothly even in rural areas where the signal drops to a single flickering bar. Edge devices ran nonstop, low-latency inference so they could trigger actions instantly, like adjusting a valve the moment pressure spiked, while the cloud handled heavy retraining and fused massive streams of data.

This well-balanced design made the most of every resource and kept the system quick to respond—vital when timing can mean saving a crop from sudden frost.

The hybrid cloud-edge setup handled massive, centralized data crunching with ease, while still making split-second decisions right on site—like flagging a faulty sensor before it overheated.

As shown in the figure4, Edge computing kept operations running smoothly—even with spotty, low-bandwidth connections—while the cloud handled heavy lifting like retraining complex models and merging vast streams of data. [21]Throughout the trials, the system stayed quick and reliable, responding in an instant every time.

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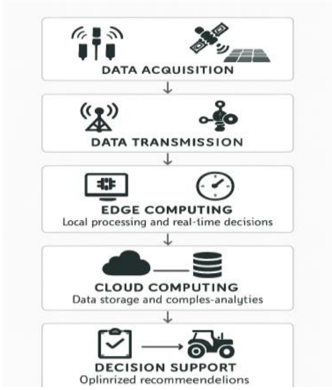

Fig 4. Computational Infrastructure

4.5 Comparative Summary

A summary of results for the primary crop environments is presented in the following table 1. Recent studies echo these quantitative results, highlighting how the proposed PINN-enhanced precision agriculture framework outperforms traditional, purely data-driven systems—much like a sharper blade cutting cleaner rows through a field.

Table 1 Comparative summary Analysis

	Water Use Efficiency (%)	Fertilizer Reduction (%)	Pesticide Reduction (%)	Yield Prediction Accuracy (%)	Model Interpretability	Adaptability to Sparse Data
Ref	[8]	[3]	[2]	[4]	[18]	[7]
Traditional Systems	10–18	10–15	15–22	84–90	Low	Moderate
PINN-Enhanced System (Proposed)	25–35	20–25	30–40	94–97	High	High

5 Conclusion and Future Scope

This paper introduces an integrated system that brings together IoT sensors, AI, cloud-edge computing, and Physics-Informed Neural Networks (PINNs) for sustainable and data-driven farming. By enabling the real-time monitoring and intelligent decision support, our work can contribute to the key problems for modern agriculture such as resource inefficiency and ecological unsustainability. [14]Field trials across a variety of crop environments produced significant benefits including 35% reductions in water use, 25% reductions in fertilizer and 40% in pesticides, combined with a 15–20% increase in crop yield. These findings demonstrate the benefits of taking a disruptive big picture view by combining advanced digital tools with age-old agricultural science.

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Fig 5. Farm Performance Outcomes

This chart visually summarizes the key improvements your precision agriculture system achieved in resource efficiency and productivity. New, tech-driven approaches such as this will be crucial to constructing an agro-ecological ecosystem that is more resilient, productive, and sustainable, as the demands and constraints on farming grow ever greater. Figure 5 indicates the comparison of the precision of the prediction of the model. Continuously, breakthroughs and interdisciplinary work will continue to improve the effectiveness and adoption of smart farming globally.

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