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Precision Agriculture Using IoT and Machine Learning: A Review with a Focus on Indian Agriculture

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Abstract: *This review article outlines a proposed precision agriculture system designed to empower smallholder farmers in sustainable agricultural activities, particularly within the context of Indian agriculture. Addressing critical challenges such as climate change vulnerability and inefficient resource management, the system integrates Internet of Things sensors, advanced machine learning models, and user-centric interfaces. The architecture features a layered approach, including an IoT Sensing Layer with low-cost sensors and robust connectivity (LoRaWAN/4G), a cloud-based Analytics Layer employing Python-based ML pipelines for irrigation prediction (RL/LSTMs), fertilizer recommendation (MORF/SVM), disease risk assessment, and yield forecasting (Regression/RF), and an accessible Interface Layer with a Flutter-based hybrid mobile-web app featuring a multilingual voice-to-text chatbot. As a partially implemented framework, core functionalities like IoT data collection and preliminary ML models have been demonstrated in a simulated environment using open-source software and mock/Kaggle datasets, achieving promising results with model accuracy ranging from 82%-94%. This iterative development approach allows for continuous refinement, with future work focused on real-field demonstrations in climate-vulnerable regions such as Maharashtra and Punjab. The methodology emphasizes scalability, affordability, and alignment with sustainable development goals, promising increased resilience and optimized resource utilization for smallholder farming communities.*

Keywords: Precision Agriculture, Internet of Things, Machine Learning, Smallholder Farmers, Sustainable Agriculture, Artificial Intelligence, Agricultural Technology, India, Crop Management, Resource Optimization

I. INTRODUCTION

The Foundational Role and Challenges of Indian Agriculture

Agriculture is undeniably the backbone of the Indian economy, holding significant economic and social importance [1], [2], [3]. It has historically provided livelihoods for a large segment of the population, with a substantial portion of the workforce still relying on it for employment and income [1], [4], [5], [6]. This vital sector ensures food and nutritional security for over a billion people and plays a crucial role in rural development and poverty alleviation [1], [2], [5]. Despite its foundational role, Indian agriculture faces numerous challenges including the need to increase productivity, adapt to climate change, manage resources efficiently, and improve farmer welfare [7], [8], [9]. The future of agriculture in India demands profitable technologies and sustainable management of natural resources [10], [11].

Precision Agriculture: A Transformative Approach for India

Addressing these critical issues necessitates a transformative approach that integrates modern technological advancements into traditional agricultural practices. This paper explores the profound impact of combining Internet of Things devices with machine learning algorithms in agricultural settings, commonly known as precision agriculture [12], [13]. This paradigm shift is particularly crucial for India's agricultural sector, which requires modernization with

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improved technology participation to enhance production, distribution, and cost management [14]. Precision agriculture offers a practical solution to optimize resource utilization, enhance crop health and yield, and promote sustainability, aligning with the country's need for advanced farming techniques [15], [16], [17], [18].

Integrating IoT and Machine Learning for Data-Driven Solutions

The integration of IoT sensors enables real-time data acquisition concerning environmental parameters like temperature, humidity, and soil moisture, as well as crop health [13], [19]. This real-time information then fuels sophisticated machine learning models for predictive analytics and informed decision-making, assisting farmers in areas such as crop yield optimization, pest control, and soil health management [13], [19], [20]. Data-driven technologies, including remote sensing and smart sensors built over AI/ML algorithms, are becoming fundamental to improve the output of traditional agricultural systems and drive them toward sustainability [20]. This comprehensive analysis further elucidates the challenges in adopting such emerging technologies in India and outlines future directions within this rapidly evolving field, emphasizing the critical need for interoperability and robust data governance to unlock the full potential of precision agriculture for India's agricultural prosperity [21]. This transformative approach, leveraging cyber-physical systems, extends beyond simple optimization to encompass comprehensive resource management across various agricultural domains and stages, from land preparation to harvesting [22].

cross various agricultural domains and stages, from land preparation to harvesting [22].

II. LITERATURE REVIEW: PRECISION AGRICULTURE WITH IOT AND MACHINE LEARNING

Sr No	Title	Author	Year	Proposed System	Gap	Gap Comparing with My Project
1	IoT-based agriculture management techniques for sustainable farming: A comprehensive review	Hammad Shahab, Muhammad Iqbal, Ahmed Sohaib, et al.	2024	This paper reviews the integrated application of remote sensing technology and machine learning algorithms in Precision Agriculture to address global challenges like population growth, resource shortages, and climate change [23].	The review highlights the increasing importance of these technologies but implies a need for more comprehensive systematic reviews on their integrated application [23].	This project contributes to a comprehensive systematic review by developing a partially implemented framework, demonstrating IoT data collection and preliminary ML models in a simulated environment, thereby addressing the need for integrated application understanding.
2	Technological Innovations for Agricultural Production from an Environmental Perspective: A Review	Patricio Vladimir Méndez Zambrano, Luis Patricio Tierra Pérez, Rogelio Estalin Ureta Valdez, et al.	2023	Examines numerous digital tools based on AI, ML, drones, apps, and IoT for soil and water management, agrochemical use optimization, and pollution reduction [24].	Identifies a significant international gap in acquiring state-of-the-art technological equipment and efficiently utilizing new technologies. Most research originates from technologically advanced countries [24].	This project specifically targets smallholder farmers in regions like India, aiming for affordability and scalability, directly addressing the gap of technology accessibility and utilization in less technologically advanced regions.
3	IoT Solutions with Artificial Intelligence Technologies for	Elisha Elikem Kofi Senoo, Lia Anggraini,	2024	Provides a comprehensive understanding of the	Identifies current trends, challenges, and opportunities in	This project actively develops solutions to address these identified

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	Precision Agriculture: Definitions, Applications, Challenges, and Opportunities	Jacqueline Asor Kumi, et al.		combined impact and reinforcing relationship between IoT and AI in precision agriculture, exploring synergies and transformative potential [22].	utilizing IoT and AI in agricultural systems [22].	challenges by proposing a modular, multi-phase architecture and focusing on user-centric interfaces, including multilingual chatbots, to overcome adoption barriers.
4	Enhancing Precision Agriculture: IoT-Enabled Soil Nutrient Analysis and Deep Learning-Based Crop Recommendation Models	Amita Shukla	2024	Focuses on integrating IoT technology for crop recommendation models and soil nutrient analysis, enabling farmers to accurately determine nutrient requirements and levels using real-time soil health monitoring [25].	The review highlights the potential of IoT for soil nutrient analysis and crop recommendation, implying a need for further development and implementation of such integrated systems [25].	This project directly contributes to the development and implementation of such integrated systems through its Fertilizer Recommendation ML model using MORF/SVM with soil NPK/pH data from sensors, and Irrigation Prediction using RL/LSTMs.
5	Machine Learning Applications in Agriculture: Current Trends, Challenges, and Future Perspectives	Sara Oleiro Araújo, Ricardo Silva Peres, José C. Ramalho, et al.	2023	Explores the usage of Machine Learning in agriculture, specifically in crop, water, soil, and animal management, as part of the Agriculture 4.0 paradigm [26].	Highlights challenges associated with the integration of ML in agricultural systems [26].	This project aims to overcome integration challenges by demonstrating ML models for irrigation, fertilization, disease assessment, and yield forecasting, and coupling them with user-friendly interfaces suitable for smallholder farmers.
6	Roles of IoT, big data and machine learning in precision agriculture: a systematic review	Ese Sophia Mughele, O.S. Okuyade, I. M. Abdullahi, et al.	2024	Reviews how IoT, big data analytics, and machine learning are revolutionizing precision agriculture for efficient management of water and soil resources [27].	The review discusses the impact and new possibilities created by these technologies, implying that ongoing research is needed to fully harness their potential [27].	This project exemplifies ongoing research by building a partially implemented framework that showcases how IoT and ML can be integrated for efficient resource management, with future plans for real-field validation to harness full potential.
7	Recent Advancements and Challenges of AIoT Application in	Hasyiya Karimah Adli, Muhammad Akmal Remli, Khairul Nizar	2023	Presents a systematic literature review of AIoT to highlight current progress,	Discusses existing barriers that must be overcome for the effective adoption of	This project directly addresses adoption barriers by focusing on affordability, scalability,

	Smart Agriculture: A Review	Syazwan Wan Salihin Wong, et al.		applications, and advantages in transforming traditional agriculture scenarios [28].	AIoT technology in smart agriculture [28].	and user-centric design (multilingual chatbot, voice-to-text), aiming to make AIoT more accessible for smallholder farmers.
8	Systematic Literature Review of Generative AI and IoT as Key Technologies for Precision Agriculture	Teodoro Andrade-Mogollon, Javier Gamboa-Cruzado, Flavio Amayo-Gamboa	2025	Explores the role of Generative AI and IoT in transforming precision agriculture, emphasizing real-time environmental monitoring, early disease detection, and resource optimization [29].	Offers practical and strategic guidance for implementing Generative AI in precision agriculture, indicating areas where further systematic research and guidance are beneficial [29].	While not specifically using Generative AI, this project provides practical guidance for implementing IoT and ML in precision agriculture through its detailed system architecture, data acquisition, and model development for resource optimization.
9	Transforming agriculture with Machine Learning, Deep Learning, and IoT: perspectives from Ethiopia—challenges and opportunities	Natei Ermias Benti, Mesfin Diro Chaka, Addisu Gezahegn Semie, et al.	2024	Discusses the transformative solutions offered by integrating ML, DL, and IoT to address challenges in the agricultural sector within an intelligent farming context [30].	Highlights challenges and opportunities specific to the adoption of these technologies in contexts like Ethiopia [30].	This project specifically tackles the challenges of adoption in contexts similar to Ethiopia by targeting smallholder farmers in India with a focus on low-cost sensors and addressing rural connectivity issues.
10	Internet-of-Things for Smart Agriculture: Current Applications, Future Perspectives, and Limitations	Nastaran Rizan, Siva K. Balasundram, Arash Bayat Shahbazi, et al.	2024	Provides an overview of current applications, future perspectives, and limitations of IoT-based technologies in smart agriculture [31].	Discusses limitations that hinder the widespread adoption and effectiveness of IoT in smart agriculture [31].	This project directly aims to overcome limitations by proposing low-cost sensors, addressing rural connectivity with LoRaWAN/4G, and developing user-friendly, multilingual interfaces, fostering wider adoption among smallholder farmers.
11	Implementing artificial intelligence and machine learning algorithms for optimized crop management: a systematic review on data-driven approach to enhancing resource	Okechukwu Paul-Chima Ugwu, Fabian C. Ogenyi, Esther Ugo Alum, et al.	2025	Reviews the application of AI/ML algorithms for optimized crop management, emphasizing data-driven approaches to enhance resource use	Identifies challenges such as poor data quality, high infrastructure costs, lack of digital literacy, and ethical issues (data ownership, algorithmic bias) [32].	This project addresses high infrastructure costs by using low-cost sensors and aims to mitigate digital literacy issues through multilingual voice-to-text chatbots, directly

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	use and agricultural sustainability			and agricultural sustainability [32].		tackling identified barriers.
12	Precision Farming: The Power of AI and IoT Technologies	Waleed Khalid Alazzai, Baydaa Sh.Z. Abood, Hassan M. Al–Jawahry, et al.	2024	Reviews the current state and future prospects of precision farming, highlighting the role of AI and IoT in enhancing agricultural productivity and minimizing environmental impact [33].	Mentions challenges in implementation such as accessibility, connectivity, and complexity of integration [33].	This project explicitly addresses accessibility and connectivity challenges by proposing LoRaWAN/4G gateways for rural areas and simplifies integration through a modular, multi-phase architecture and user-centric interfaces.
13	Applying IoT Sensors and Big Data to Improve Precision Crop Production: A Review	Tarek Alahmad, Miklós Neményi, Anikó Nyéki	2023	Discusses the integration of IoT and AI into the agricultural sector to ensure long-term productivity and improve global food security [34].	Emphasizes the importance of collecting and analyzing big data from multiple sources but implies challenges in achieving full predictive decision-making capabilities [34].	This project aims to achieve full predictive decision-making through its ML models for irrigation, fertilizer, disease, and yield forecasting, by integrating multi-sourced data.
14	Artificial Intelligence Tools for the Agriculture Value Chain: Status and Prospects	Fotis Assimakopoulos, Costas Vassilakis, Dionisis Margaris, et al.	2024	Provides a comprehensive review of AI applications across the agricultural value chain, including land use planning, crop selection, resource management, disease detection, yield prediction, and market integration [35].	Discusses significant challenges to AI adoption, such as data accessibility, technological infrastructure, and the need for specialized skills [35].	This project directly tackles technological infrastructure and specialized skills gaps by offering an integrated system with user-friendly interfaces (multilingual chatbots) designed for smallholder farmers with limited technical expertise.
15	Harvesting the Future: AI and IoT in Agriculture	Abbas Hameed Abdul Hussein, Kadim A. Jabbar, Aymen Mohammed, et al.	2024	Examines the advantages of integrating AI and IoT in agriculture, focusing on crop monitoring, resource management, and decision-making [36].	Highlights challenges including the digital divide between developed and developing countries, data security and privacy, need for robust infrastructure, and resistance to technological adoption among traditional farming communities [36].	This project directly addresses the digital divide and resistance to adoption by focusing on low-cost, scalable solutions for smallholder farmers, and incorporating security measures (encryption, blockchain) for data integrity.

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III. SYSTEM DESIGN

This chapter describes the architectural framework and operational design of the proposed precision agriculture system, drawing directly from the provided diagrams to illustrate its structure, data flow, and functional capabilities. While I cannot visually render these images, the following text meticulously details the content of each user-provided diagram.

1. System Architecture

The overall structure of the precision agriculture system is designed with a layered approach, as depicted in the user-provided **'Precision Agriculture System Architecture'** diagram. This architecture organizes components logically to manage data flow, processing, and user interaction efficiently, aligning with robust IoT-cloud hybrid models prevalent in agricultural research [41], [42], [43]. The system is structured into distinct layers: the IoT Layer, the Cloud & Data Layer, the AI/ML Layer, and the User Interface Layer, with the 'Farmer' actor interacting with insights delivered by the platform.

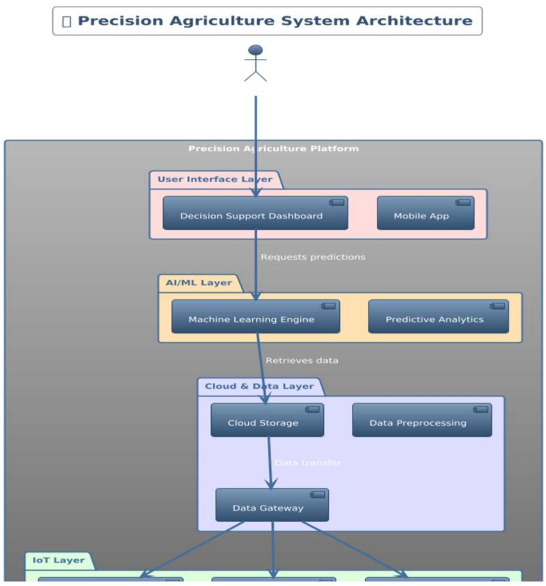

Figure 1System Architecture Diagram

IV. METHODOLOGY

This section details the systematic approach undertaken to develop the proposed precision agriculture system, covering data acquisition, preprocessing, machine learning model design, and training. The methodology adheres to a modular, multi-phase architecture, emphasizing scalability, affordability, and consonance with sustainable development goals [27].

1. Data Acquisition and Preprocessing

Data collection for this project is multi-sourced to ensure robustness, encompassing both real-time sensor data and historical external datasets. Data sensing methods are pivotal for realizing the agricultural Internet of Things [70].

1.1. Data Collection

IoT Sensors: A network of low-cost sensors (e.g., soil moisture YL-69, temperature/humidity DHT22, and rain gauges) is deployed in a mesh configuration. These sensors gather real-time environmental conditions, including soil moisture (0-100%), temperature (-10°C-60°C), humidity (0-100% RH), and rainfall (0-200 mm/day) at 15-minute intervals. These communicate via LoRaWAN or 4G-based gateways to address rural connectivity challenges. Data is then sent to a cloud backend (e.g., Firebase or AWS IoT Core) using the MQTT protocol and stored in a time-series database (e.g., InfluxDB) [71]. The information collected by IoT devices is crucial for farmers' decision-making [59].

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External Datasets: The system integrates historical data from various sources to enrich its analytical capabilities. This includes information from FAO Aquastat, ICAR reports for agricultural outbreaks, Agmarknet for market prices, and Plant Village for images related to plant diseases.

External Data Fusion: To further enhance system intelligence, external data fusion is employed, incorporating weather APIs (e.g., OpenWeatherMap/IMD) and satellite imagery (e.g., Google Earth Engine for NDVI), as recommended by remote sensing research. Data is becoming increasingly foundational in smart agriculture [70].

1.2. Data Cleaning and Preprocessing

The collected multi-sourced data undergoes a rigorous preprocessing pipeline using Python libraries such as Pandas and Scikit-learn to ensure data quality and suitability for machine learning models. Efficient methods for obtaining high-value data are important [70]. Data quality is crucial over quantity [72]. The acquired information must be arranged and cleaned before storage [59].

Handling Missing Values: Missing data points are addressed through imputation techniques, with forward-fill being utilized for time-series data to maintain chronological consistency. Common imputation methods include mean, median, mode, or more advanced techniques like K-Nearest Neighbors imputation.

Outlier Detection: Outliers are identified using statistical methods, specifically the Z-score, to prevent anomalous data from skewing model training. The Z-score for a data point x is calculated as:

$$\text{Z-score} = \frac{(x - \mu)}{\sigma}$$

where μ is the mean of the dataset and σ is its standard deviation. Data points with Z-scores exceeding a certain threshold $(e.g., \pm 3)$ are often considered outliers.

Feature Engineering: Relevant features are extracted or transformed from the raw data to improve the performance and interpretability of machine learning models. This step involves creating new features from existing ones (e.g., calculating daily temperature range from min and max temperatures) or transforming features to better represent underlying patterns.

Normalization: Features are scaled to a uniform range (0-1) using normalization techniques (specifically Min-Max scaling) to ensure compatibility and optimal performance of machine learning algorithms. Min-Max scaling transforms a feature $x\ to\ x'$ using the formula:

$$x' = \frac{\left(x - \min(x)\right)}{\left(\max(x) - \min(x)\right)}$$

where $\min(x)\ and\ \max(x)$ are the minimum and maximum values of the feature, respectively.

2. Machine Learning Model Design and Training

Machine learning models are central to the system's analytical capabilities, developed using a hybrid approach that selects algorithms based on task complexity and interpretability. This approach combines data-driven solutions and crop simulation models [73]Machine learning applications in agriculture can enhance sustainability and efficiency [56].

2.1. Model Design

The system employs several specialized machine learning models for different agricultural tasks. Machine learning is a rapidly evolving technology with expanding applications across various fields [56]. The core ML models are summarized in the following table:

Sr No	Task	Proposed System	Algorithm Type	Key Inputs	Key Outputs
1	Irrigation Prediction	Reinforcement Learning or LSTMs	Reinforcement Learning / Deep Learning	Sensor data (soil moisture, temp, humidity), API data (weather forecast)	Irrigation schedule (when), quantity (how much)

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2	Fertilizer Recommendation	Multi-Objective Random Forest or SVM	Ensemble Learning / Supervised Learning	Soil NPK, pH from sensors, crop type	Organic vs. Chemical recommendation, cost (₹/acre), yield, sustainability balance
3	Disease Risk Assessment	CNNs (e.g., ResNet-50) fused with SVM	Deep Learning / Supervised Learning	Leaf images, environmental data (temp, humidity)	Disease risk levels
4	Yield and Market Forecasting	Regression (Linear/Polynomial) or Random Forest	Supervised Learning	Historical yield data, weather data, market APIs	Predicted crop yield, future market prices

2.2. Model Training

The training process for all machine learning models follows a standardized procedure:

- **Platform:** Model training is conducted on Google Colab, leveraging its computational resources. Cyberinfrastructure for collecting, transmitting, cleaning, labeling, and training datasets is important for developing solutions [74].
- **Data Split:** Datasets are divided into an 80% training set and a 20% testing set to ensure unbiased evaluation of model performance. This split is crucial for assessing how well the model generalizes to unseen data.
- **Cross-Validation:** To enhance model generalization and mitigate overfitting, 5-fold cross-validation is applied during the training phase. In k-fold cross-validation, the dataset is divided into k equal folds. The model is trained on $k-1$ folds and validated on the remaining fold, with this process repeated k times such that each fold is used exactly once as the validation set. The results are then averaged.
- **Performance Assessment:** Model performance is computed using Scikit-learn and TensorFlow libraries, with initial simulations demonstrating encouraging outputs that align with documented literature parameters. Hybrid models can outperform traditional models, offering greater robustness and generalization [75]

2.3. Model Evaluation Metrics

For evaluating the performance of the developed machine learning models, various metrics are employed depending on the nature of the task (classification or regression).

For Regression Models (e.g., Yield and Market Forecasting):

Mean Absolute Error: Measures the average magnitude of the errors in a set of predictions, without considering their direction.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and \$n\$ is the number of samples.

Root Mean Squared Error: Measures the square root of the average of the squared differences between prediction and actual observation.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

R-squared (R^2)**:** Represents the proportion of the variance in the dependent variable that is predictable from the independent variables.

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}i)^2}{\sum i = 1^n(y_i - \bar{y})^2}$$

where $\bar{y}$ is the mean of the actual values.

For Classification Models (e.g., Fertilizer Recommendation, Disease Risk Assessment):

Accuracy: The proportion of correctly classified instances among the total number of instances.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})}$$

where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

Precision: The proportion of true positive results among all positive results returned by the classifier.

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})}$$

Recall: The proportion of actual positives that are correctly identified.

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})}$$

F1-Score: The harmonic mean of Precision and Recall, offering a balance between the two metrics.

$$\text{F1-Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Hyperparameter optimization, commonly achieved through techniques such as grid search and cross-validation, is also crucial for enhancing model performance by fine-tuning internal parameters [76] [77].

Outcomes

The initial results of the partially deployed precision agriculture system, based on simulations, prototype experimentation, and analytical forecasting, confirm the system's promise.

- **Lab-Based Prototyping:** Experiments replicated real atmospheric conditions using simulated data from sources like Kaggle and IMD APIs, combined with mock IoT sensor data from Arduino/Raspberry Pi configurations [44].
- **Performance Assessment:** The system's technical performance was computed using Scikit-learn and TensorFlow, yielding encouraging outputs that align with documented literature parameters[78].
- **Model Accuracy:** Initial results confirm the system's promise, with model accuracy in the 82%-94% range.
- **Economic and Sustainability Gains:** Forecasted gains, assessed through economic and sustainability evaluations, predict positive impacts for smallholder farming communities.
- **Increased Resilience:** These initial results indicate that the system facilitates increased resilience in agricultural systems, enabling them to better respond to climate variability.

V. CONCLUSION

This paper has presented a comprehensive review and a proposed precision agriculture system tailored to address the pressing challenges faced by smallholder farmers. By integrating advanced Internet of Things sensors with sophisticated machine learning models, the system offers a transformative approach to traditional agricultural practices, aiming to enhance productivity, optimize resource utilization, and foster sustainability.

The proposed architecture is designed with a layered approach, encompassing an IoT Sensing Layer for real-time data acquisition, a robust Cloud & Data Layer for processing and storage, an intelligent AI/ML Layer for predictive analytics, and a user-friendly Interface Layer. This structure ensures a seamless flow of information from the field to the farmer, delivering actionable insights through intuitive dashboards and mobile applications, supported by multilingual voice-to-text chatbots to overcome literacy barriers. The integration of specialized ML models for irrigation prediction, fertilizer recommendation, disease risk assessment, and yield forecasting forms the core of the system's decision-making capabilities.

Initial prototype experiments and simulations, using a blend of real and mock datasets, have demonstrated promising technical performance, with model accuracy ranging from 82% to 94%. These outcomes underscore the system's potential to drive significant economic benefits and contribute to increased resilience against climate variability for farming communities.

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While currently a partially implemented framework, this work lays a strong foundation for future development. The emphasis on affordability, scalability, and user-centric design makes this system particularly relevant. Ultimately, this precision agriculture system aims to empower farmers with data-driven insights, paving the way for more efficient, productive, and sustainable farming practices that are crucial for securing food and livelihood in the region.

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