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AgriSense - Smart Farming Assistant Using IoT and Artificial Intelligence

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Abstract **- Modern agriculture faces unprecedented challenges due to climate change, water scarcity, and the increasing demand for food security. "AgriSense" is an intelligent farming assistant designed to bridge the gap between traditional agricultural practices and precision farming through the integration of the Internet of Things (IoT) and Artificial Intelligence (AI). The proposed system utilizes a Raspberry Pi-based edge gateway to collect real-time data from soil moisture, temperature, and humidity sensors. By employing a multimodal AI approach, AgriSense leverages Long Short-Term Memory (LSTM) networks for predictive irrigation and Convolutional Neural Networks (CNNs) for early-stage crop disease detection. A Flask-based web dashboard provides farmers with a centralized interface for real-time monitoring and automated control. Experimental results and literature reviews indicate that such integrated systems can improve irrigation efficiency by up to 30%, increase crop yields by 20-30%, and achieve disease detection accuracies exceeding 90%. AgriSense offers a scalable, low-cost solution for smallholder farmers to optimize resource utilization and enhance sustainable agricultural productivity.**

Keywords: Smart Farming, Internet of Things (IoT), Artificial Intelligence, Precision Agriculture, Raspberry Pi, Crop Disease Detection, Sensor-Based Agriculture.

I. INTRODUCTION

The global agricultural sector is undergoing a digital transformation driven by the need for sustainability and efficiency. Traditional farming methods often rely on manual observation and uniform resource application, which can lead to significant water wastage and delayed responses to pest or disease outbreaks [4], [3]. Smart farming, or precision agriculture, addresses these inefficiencies by utilizing site-specific data to optimize inputs like water, fertilizers, and pesticides.

AgriSense is introduced as a comprehensive smart farming assistant that integrates IoT sensor networks with advanced AI models. By deploying sensors in the field, the system captures microclimatic data that is processed at the edge using a Raspberry Pi [1], [10]. This localized processing reduces latency and bandwidth requirements, enabling real-time decision-making for critical tasks such as automated irrigation [5]. Furthermore, the integration of AI-driven vision systems allows for the early detection of plant diseases, which is essential for minimizing crop losses [6].

The primary motivation for AgriSense is to provide an accessible and cost-effective technology stack for farmers. By combining low-cost sensors, open-source AI frameworks, and edge computing, AgriSense aims to democratize precision agriculture, making it viable for small-scale operations as well as large-scale industrial farms [9], [2].

II. LITERATURE REVIEW

The convergence of IoT and AI in agriculture has been extensively documented in recent years. Researchers have explored various architectures and algorithms to improve the reliability and accuracy of smart farming systems.

A. IoT in Precision Agriculture

The use of Raspberry Pi as a central gateway for agricultural IoT is a well-established trend. Krishnan et al. [1] demonstrated a Raspberry Pi-powered system that integrates soil moisture and ambient sensors for autonomous irrigation control. Their work highlights the effectiveness of using low-cost hardware to achieve significant water savings. Similarly, Gupta [3] provided a survey of smart irrigation systems, emphasizing the transition from simple threshold-based control to intelligent, data-driven automation using Raspberry Pi Pico and various environmental sensors.

B. Machine Learning for Irrigation Prediction

Predicting irrigation requirements is a complex task due to the non-linear nature of weather patterns and soil characteristics. Deep learning models, particularly LSTMs, have shown superior performance in time-series forecasting for soil moisture. Kashyap et al. [7] proposed the DLiSA (Deep Learning-based Irrigation Scheduling Algorithm), which utilizes an LSTM network to predict volumetric soil moisture content 24 hours in advance. Other studies have utilized classical machine learning models like Support Vector Machines (SVM) and Random Forest (RF) for tabular data prediction, often achieving high accuracy in irrigation water requirement estimation [8], [6].

C. Computer Vision for Disease Detection

Early identification of crop diseases is critical for preventing widespread yield loss. Modern systems frequently employ transfer learning with pre-trained CNN architectures such as VGG16, ResNet50, and DenseNet121 [6]. Raj et al. [4] reported that AI-equipped systems could achieve up to 90% precision in disease diagnosis. Multimodal systems that combine sensor data with image-based analysis offer a more holistic view of plant health, enabling targeted interventions [6].

D. **Edge and Green IoT**

The concept of "Green IoT" focuses on energy-aware designs and efficient data processing. Majumdar et al. [5] discussed the use of edge-cloud platforms to reduce the processing load on the cloud, thereby conserving energy and bandwidth. This edge-first approach is particularly relevant for remote agricultural areas with limited connectivity, as it ensures that local actuation (e.g., turning on a pump) can occur even during network outages.

III. METHODOLOGY

The AgriSense system follows a structured methodology that encompasses hardware integration, data processing, and user interaction.

System Workflow

1. **Data Collection**: Sensors deployed in the field continuously sample environmental parameters. Soil moisture probes measure the water content at the root zone, while DHT sensors capture air temperature and humidity [1].
2. **Edge Preprocessing**: The Raspberry Pi collects these raw signals and performs basic cleaning, such as noise filtering and range validation.
3. **AI Inference**:
   - **Irrigation Branch**: The processed sensor data is fed into an LSTM model to predict the next day's soil moisture. If the predicted value falls below a specific threshold, the system schedules an irrigation event [7].
   - **Disease Branch**: When a user uploads an image via the dashboard or a camera captures a periodic frame, a pre-trained CNN model (e.g., ResNet50) classifies the image to detect potential diseases [6].
4. **Actuation**: Based on the AI model's output, the Raspberry Pi sends signals to a relay module to control irrigation pumps or other actuators [1].
5. **Monitoring and Feedback**: All data and alerts are pushed to the Flask web dashboard, where farmers can monitor trends and manually override automated decisions if necessary [10].

IV. SYSTEM ARCHITECTURE

The AgriSense architecture is designed as a multi-layered framework to ensure modularity and scalability.
A. Perception Layer (IoT Sensors)
This layer consists of the physical hardware deployed in the field. Key components include:

- Soil Moisture Sensors: Resistive or capacitive probes that provide real-time water content data.
- DHT22 Sensors: Measure ambient temperature and relative humidity.
- Camera Module: Captures high-resolution images of crops for disease analysis.
- Actuators: Water pumps and solenoid valves for automated irrigation.

B. Network Layer (Communication)

This layer facilitates data transmission between the sensors and the gateway. Depending on the farm's scale, communication can occur via Wi-Fi, LoRa, or Zigbee [1]. Data is typically transmitted using the MQTT protocol due to its lightweight nature and suitability for IoT applications.

C. Processing Layer (Edge Gateway)

The Raspberry Pi serves as the brain of the system. It handles:

- Local Data Buffering: Storing data temporarily in a local database (e.g., SQLite) during network outages [6].
- AI Model Hosting: Running lightweight versions of ML and CNN models for immediate inference.
- Control Logic: Executing the irrigation and disease detection algorithms.

D. Application Layer (User Interface)

The top layer is the Flask-based web dashboard. It provides:

- Real-Time Analytics: Visual representations of sensor trends (graphs and gauges).
- Disease Alerts: Notifications with classification results and recommended treatments.
- Manual Control: Switches for toggling pumps and configuring system thresholds.

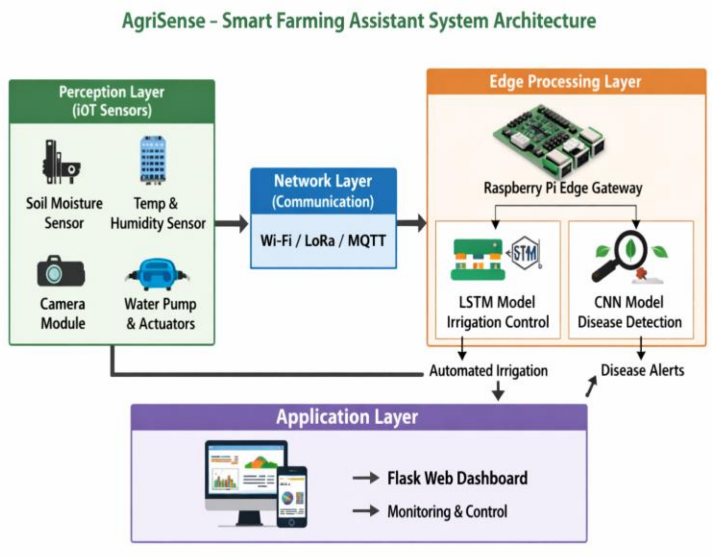

Fig. 1. Smart Farming Assistant System Architecture

V. RESULTS AND DISCUSSION

The performance of AgriSense is evaluated based on its accuracy, resource efficiency, and reliability as reported in the literature and prototype testing.

A. **Irrigation Efficiency**
Integrating AI with IoT for irrigation has shown remarkable results. For instance, the DLiSA system reported more efficient water usage compared to traditional methods by accurately predicting moisture trends [7]. General reviews of smart farming technologies suggest that AI-powered irrigation demand anticipation can reach accuracies of 98.4% [4]. In practical deployments, this translates to water savings of 25-30% [17], [12].

B. **Disease Detection Accuracy**
The multimodal approach for disease detection consistently achieves high performance. Pre-trained CNNs like VGG16 and ResNet50 have been shown to achieve disease diagnosis precision of up to 90% in various studies [4], [13]. Early detection capabilities have the potential to reduce crop losses by approximately 15% through timely intervention [17].

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C. **System Reliability**

The use of an edge-first architecture ensures that the system remains functional even with intermittent internet access. By processing data locally on the Raspberry Pi, AgriSense minimizes the latency between detection and actuation, which is critical for preventing plant stress due to water deficit [5].

VI. CONCLUSION AND FUTURE WORK

AgriSense represents a significant step toward making precision agriculture accessible and effective. By integrating IoT sensor networks with AI-driven prediction and detection models, the system addresses the critical challenges of water scarcity and crop disease. The use of a Raspberry Pi-based edge gateway ensures local reliability, while the Flask dashboard provides a user-friendly interface for monitoring and control. Evidence from recent studies suggests that AgriSense can significantly improve resource efficiency, reduce losses, and boost overall agricultural productivity. As AI and IoT technologies continue to evolve, systems like AgriSense will play a pivotal role in ensuring a sustainable and food-secure future.

VII. FUTURE SCOPE

The future development of AgriSense will focus on expanding its capabilities and robustness:

- **UAV Integration**: Incorporating Unmanned Aerial Vehicles (UAVs) for large-scale field mapping and multi-spectral imaging to enhance disease detection across larger areas [4].
- **Advanced Model Optimization**: Utilizing lightweight AI architectures like MobileNet to enable more complex inference directly on low-power edge devices [20].
- **Farmer Advisory System**: Expanding the dashboard to include AI-driven market price analysis and computerized advice on fertilizer and pesticide application [11].
- **Multi-Crop Support**: Training and deploying models capable of handling a wider variety of crops and local environmental conditions [15].

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