AI-Driven Automated System for Paddy Disease Detection Using Sensor Networks and Drone-Based Image Analysis

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ABSTRACT

Paddy cultivation is vital for Sri Lanka's food security, but increasing plant diseases due to adverse climate, declining soil health, irregular water availability, and unpredictable weather have caused a continuous drop in yield, highlighting the need for effective disease detection. This study presents an integrated paddy disease detection system that combines Internet of Things based environmental sensing with drone-based remotesensing imagery and artificial intelligence techniques. The proposed system employs an ESP32 microcontroller interfaced with more accurate sensors to monitor soil, water, and agro-climatic parameters in real time. Machine learning models are applied to analyze the collected sensor data and predict potential paddy diseases based on environmental conditions. In parallel, a drone imaging system captures high-resolution images of paddy fields, which are processed using deep learning models developed with Keras and TensorFlow to detect and classify disease symptoms. A Flask-based web application is developed to visualize sensor data, display disease predictions, and provide actionable recommendations for farmers and agricultural officers. Experimental results demonstrate that the proposed system achieves an overall disease detection accuracy of 98%, with additional evaluation using precision, recall, F1-score, and confusion matrix analysis confirming its robustness and reliability. The practicality of the proposed system is enhanced by its low cost, portability, and modular design, enabling easy deployment in small and large paddy fields and allowing scalability to regional and national agricultural monitoring systems.

Keywords: Sensor-based paddy disease detection system, Machine learning, Remote-sensing drone imaging, ESP32, Internet of things

INTRODUCTION

Paddy farming remains essential for food security in Sri Lanka, serving as the primary staple food and supporting the livelihoods of a large proportion of rural farming communities. However, the productivity of paddy fields is affected by a range of biotic and abiotic stresses, with diseases of the crops posing a major threat to productivity [1-3]. The epidemiology of diseases in paddy crops is usually determined by a combination of weather, soil health, irrigation, and management practices. Recently, there has been a noticeable reduction in paddy yields, mostly because of the higher incidence of fungal, bacterial and viral diseases, unreliable weather, and poor soil [3]. These challenges create an urgent need to monitor the health of the crops in a timely and precise manner and prevent losses in a quick and economical way.

Recent studies on paddy disease detection have mainly based on either images captured using mobile phones or on soil conditions monitoring alone [4]. While image-based approaches are effective in identifying visible disease symptoms, they face practical limitations in large-scale paddy fields [5]. A sufficient number of images are acquired manually in such fields is both time-consuming and labor-intensive [6]. Systems that based on soil monitoring such as measuring moisture levels and pH in soil, provide only partial insights, as they cannot capture visual symptoms or account for climatic and environmental factors that contribute to disease development [4]. These limitations highlight that single-source detection methods are often inadequate for achieving comprehensive, accurate, and timely disease management.

The proposed system in this study addresses these above mentioned limitations by integrating two types of data. Remote-sensing drone imaging allows efficient and high-resolution capture of field-level visuals across large areas. And critical parameters including soil conditions, water quality, and climatic factors are monitored by using environmental sensors. By combining these complementary data sources and applying machine learning algorithms, the system can achieve higher accuracy and provide real-time disease detection. Therefore, the main aim of the implemented system here is to provide real-time detection of paddy diseases and deliver actionable recommendations through a web-based application to enhance crop health and improve productivity in largescale paddy cultivation. The system combines low cost, portability, and durability, providing an effective and scalable solution for real-time paddy disease monitoring, suitable for both small farms and large regional or national deployments.

SYSTEM DESIGN AND METHODOLOGY

System Overview

The experimental system was carried out through three primary processes. First, the sensor-based setup measured key environmental parameters of the paddy field, including soil moisture, pH, temperature, and humidity. Second, a remote-sensing drone equipped with an RGB camera captured aerial images of the crops. Finally, the collected sensor data and drone images were uploaded to a Flask-based web application, where integrated machine learning algorithms analyzed the combined inputs to detect and classify paddy diseases.

Sensor-Based Environmental Data Acquisition

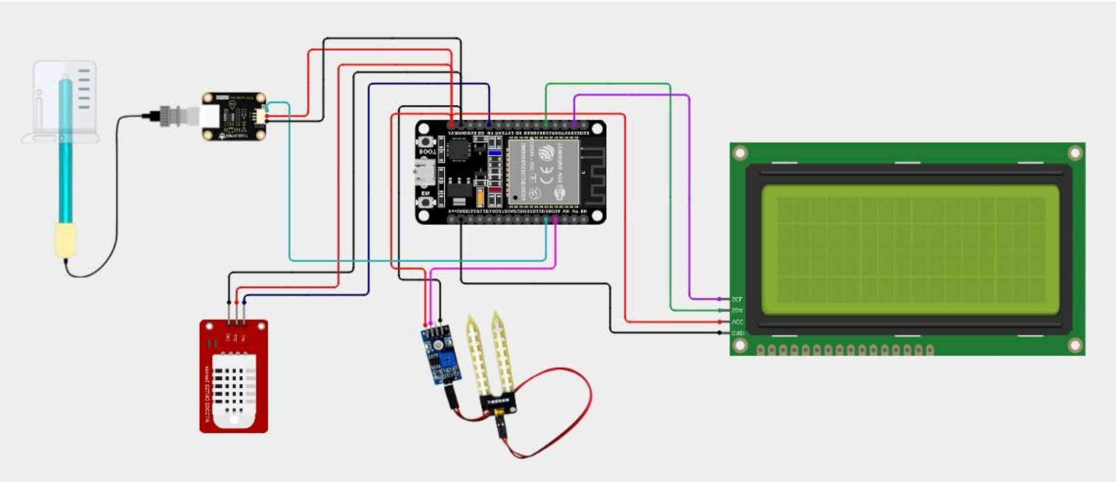

Figure 1. Circuit schematic of the sensor-based system detailing pin connections between ESP32, OLED display and sensors.

The hardware architecture of the proposed sensor-based paddy disease detection system is illustrated in Figure 1. The system monitors soil moisture, pH, temperature, and humidity using dedicated sensors interfaced with the ESP32 microcontroller. Specifically, the soil moisture sensor measures the water content in the soil, while the liquid pH sensor determines the acidity or alkalinity of the irrigation water. Atmospheric temperature and relative humidity are recorded using the DHT22 sensor. All sensor data are transmitted wirelessly to a Flask-based web server via the ESP32, which is programmed using PlatformIO in Visual Studio Code.

A 20×4 LCD module is incorporated to sequentially display soil moisture, pH, temperature, and humidity readings in real time. Careful pin mapping on the ESP32 ensures seamless operation of all peripherals across different interfaces. The ESP32 manages the sensors through I2C and GPIO buses, while the LCD is connected through standard digital pins. Power is supplied via a regulated 5V rail. The sensor-based system allows individual components to be replaced or upgraded without disrupting the overall system.

By using standard buffer solutions at pH 4.01 and pH 6.86, the pH sensor was calibrated to ensure accurate measurements, establishing the offset and slope required to convert sensor voltage into true pH values. The third buffer at pH 9.18 was used to confirm the calibration accuracy. The soil moisture sensor was calibrated using three representative soil samples taken from the paddy field. The DHT22 sensor did not require calibration. After calibration, the sensors provided reliable data, which were transmitted via the ESP32 to a web based application for storage and preprocessing, forming the foundation for subsequent disease detection using machine learning.

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Drone-Based Image Collection

The remote sensing drone equipped with a high resolution RGB camera was utilized to capture the aerial images of the paddy fields affected by diseases. The acquisition of drone images were carried out in the Horana area (latitude=6.743625, longitude=80.085426 and altitude=1.0m). To minimize the effects of shadows and glare, the flights were scheduled in the morning hours between 7.00 a.m. to 9.00 a.m., thereby maintaining a standard lighting condition. All captured images were geo-tagged to align with the sensor data obtained from the corresponding field region. As shown in Figure 2, a remote sensing drone was used to capture aerial images for paddy disease detection.

Figure 2. Remote-sensing drone equipped with an RGB camera capturing high-resolution aerial images of paddy fields.

Machine Learning Based Disease Detection

Both structured sensor data (soil moisture, pH, temperature, and humidity) and unstructured drone images were integrated to enhance the accuracy of paddy disease detection. The drone images were preprocessed for training and validation of the machine learning model using TensorFlow's image_dataset_from_directory function, with each image resized to 128×128 pixels and converted to RGB format. The dataset was divided into training (70%), validation (15%), and testing (15%) sets.

The sensor dataset, comprising measurements of soil moisture, pH, temperature, and humidity, was also preprocessed prior to model training. To ensure that all sensor features contributed equally, the training and testing data were normalized using a Min-Max scaler, rescaling values to a standard range between 0 and 1. This preprocessing enabled the machine learning algorithm to efficiently learn patterns from the sensor data and accurately predict paddy diseases.

As shown in Table 1, a sample of the collected dataset is provided.

Table 1. Sampled data of the dataset used

pH	Temperature (°C)	Humidity (%)	Moisture	Disease
5.8	30.4	67.9	724	hispa
6.4	23.0	70.3	844	normal
6.4	24.3	79.7	913	Bacterial leaf streak
4.9	33.1	74.4	750	tungro

Upon detection of a disease, the system provides tailored recommendations, guiding farmers and agricultural officers on the appropriate measures to effectively manage and treat the affected crops. The schematic overview of the proposed paddy disease detection system is presented in Figure 3.

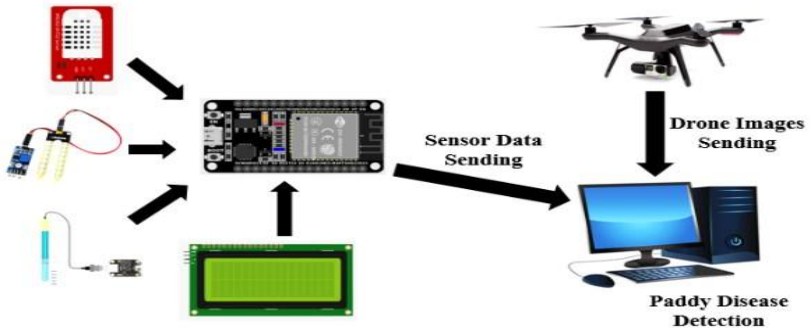

Figure 3. Schematic overview of the proposed sensor and drone based disease detection system Deep Learning Architecture for Image-Based Disease Detection

The image-based disease classification model was implemented using a Convolutional Neural Network developed with TensorFlow and Keras. The architecture consists of five convolutional layers with 32, 64,128, 256 and 512 filters respectively, each followed by ReLU activation and max-pooling layers to reduce spatial dimensionality. A flattening layer converts extracted feature maps into a one-dimensional vector, which is then passed through two fully connected dense layers with ReLU activation. A Softmax layer at the output provides multi-class disease classification.

Sensor and Image Data Fusion Strategy

The proposed system adopts a decision-level data fusion strategy to combine predictions from sensor-based machine learning models and image-based deep learning models. Sensor data contribute environmental risk assessment, while drone images enable visual disease identification. The final classification is obtained using a weighted decision rule that prioritizes image-based predictions when visible symptoms are present, thereby improving detection accuracy and reducing false positives.

Testing of the System

The paddy disease detection system was tested using five common paddy diseases across five distinct locations. Both environmental sensor data (soil moisture, pH, temperature, and humidity) and remote-sensing drone images of the paddy crops were collected and fed into the system. Then the machine learning model analyzed the combined inputs to identify the disease present in each location. The system also provides corresponding recommendations alongside the detected disease.

RESULTS AND DISCUSSION

The final design of the proposed system was constructed as illustrated in Figure 4. And it was evaluated in five distinct phases across five different locations, corresponding to its design and implementation. The results obtained from each phase and location are presented and analyzed below.

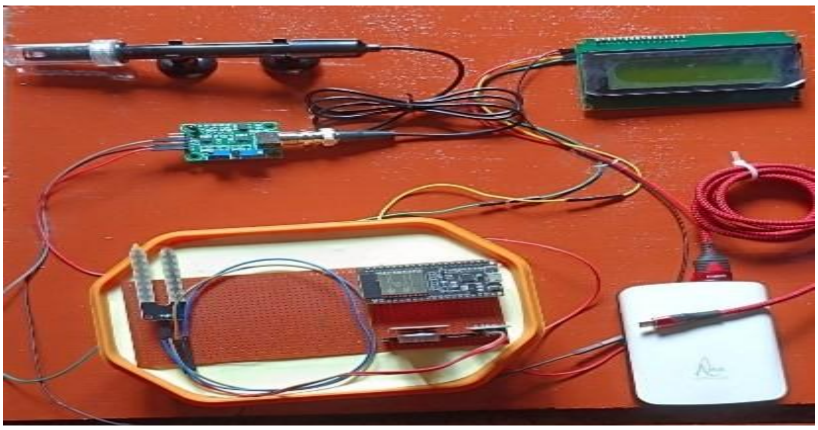

Figure 4. Prototype of the sensor based circuit Environmental Sensing Results

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In the first phase, the sensor-based circuit was employed to monitor environmental parameters affecting for the paddy diseases. The soil moisture sensor was inserted into the soil, the liquid pH sensor was immersed in water, and the DHT22 sensor was used to measure humidity and temperature. The sensor measurements were recorded across five distinct locations. The acquired sensor values were simultaneously displayed on the 20×4 LCD module and transmitted to the server.

As illustrated in Figure 5, the system continuously records environmental parameters through the connected sensors.

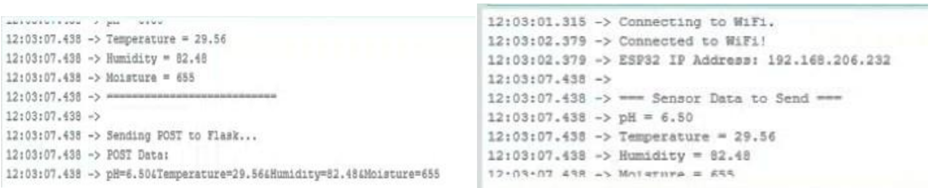

Figure 5. Sensor data reading

Drone-Based Image Analysis

In the second phase, the aerial images captured by a remote-sensing drone were processed to identify visual symptoms of paddy diseases. By using machine learning algorithms which are trained on a labeled dataset of paddy diseases, the images were analyzed. Aerial images of the paddy fields captured by the drone at two different locations are presented in Figure 6 and Figure 07.

Figure 6. Drone images capture at Location 01.

Figure 7. Drone images capture at Location 02

Integrated Disease Detection

In the third phase, sensor data and drone images were fused to generate a comprehensive disease prediction. By integrating soil moisture, pH, temperature, and humidity data with visual cues from the drone, the system provided a more accurate assessment of disease risk. The integrated system successfully identified presence in all tested scenarios. When the sensor values were automatically entered into the corresponding fields, the detected diseases and their recommendations were displayed correctly as shown in Table 2. The developed Flaskbased web application interface is shown in Figure 8.

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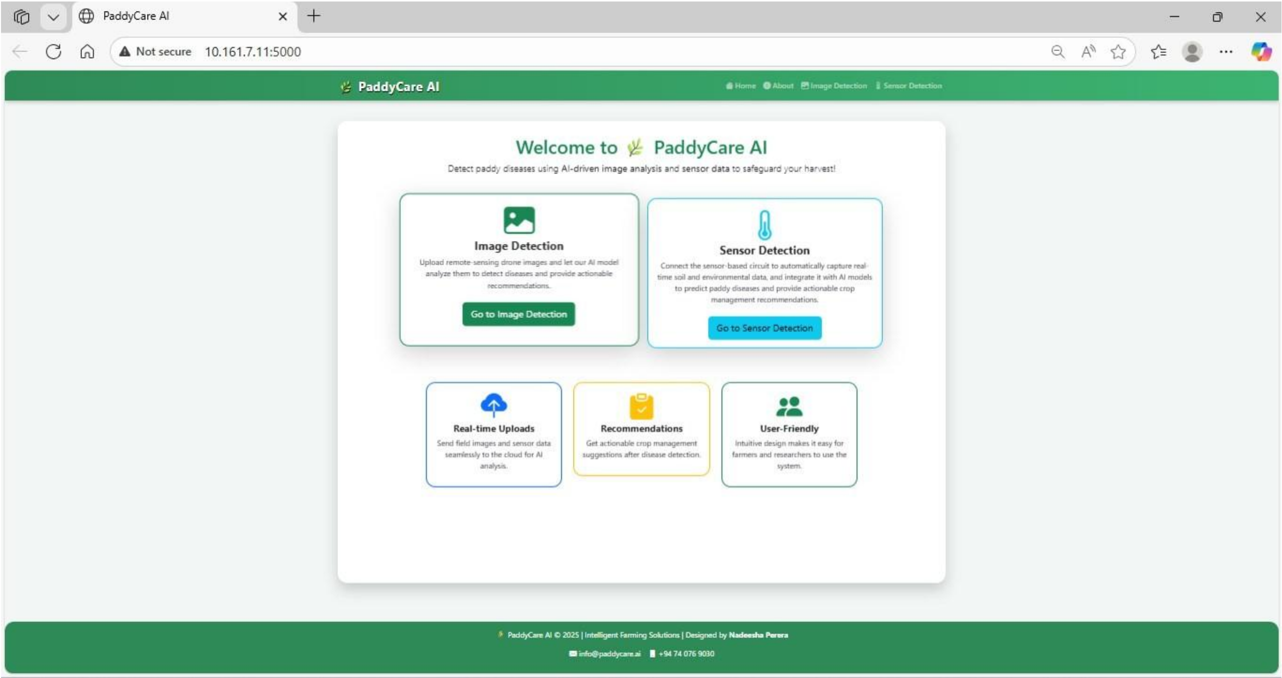

Figure 8. User interface of the web application.

The detection of blast disease at Location 01 using both sensor data and drone images is presented in Figure 9 and Figure 10 respectively.

Figure 9. Detection of blast at the Location 01 using sensor data analysis

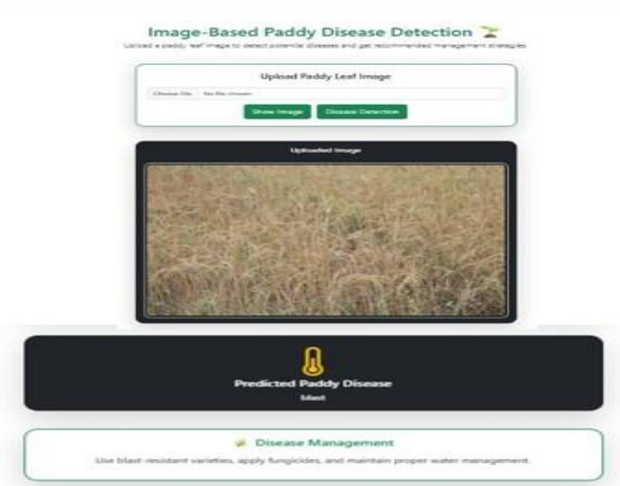

Figure 10. Detection of blast at the Location 01 using (b) drone image

Table 2. Acquired sensor data and detected paddy diseases across five locations

Paddy Field	pH	Temperature (ºC)	Humidity (%)	Moisture	Detected Disease
Location 01	7.40	25.6	81.6	843	Blast
Location 02	7.70	33.6	87.3	1023	Brown Spot
Location 03	6.50	28.3	73.9	848	Normal (Healthy)
Location 04	5.20	29.1	74.9	729	Tungro
Location 05	7.20	32.3	90.1	959	Bacterial Leaf Blight

Performance Evaluation of the Proposed Model and Feature Correlation Analysis

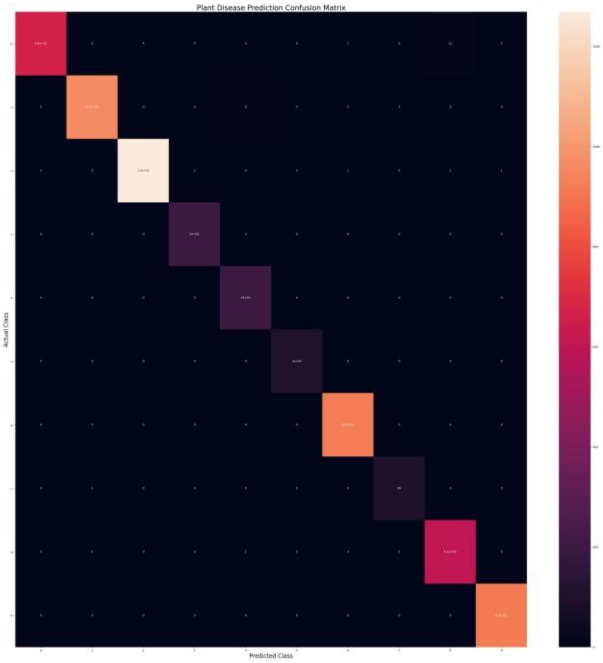

Figure 11. Confusion matrix illustrating the performance of the image-based paddy plant disease prediction model, showing the distribution of actual versus predicted classes.

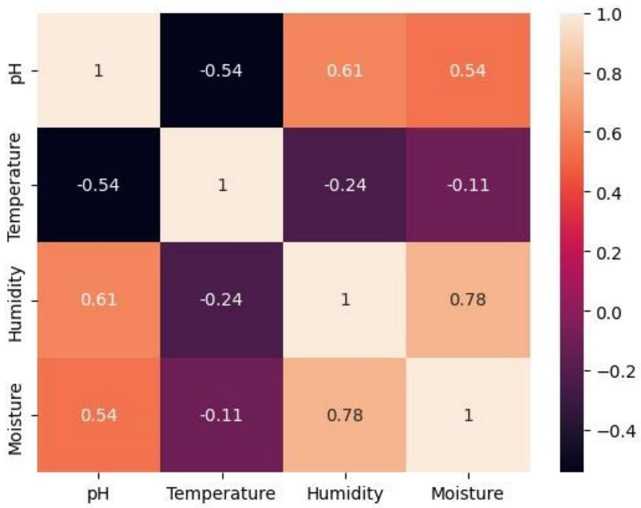

Figure 12: Correlation heatmap showing the relationships among numerical features in the paddy disease weather dataset, with color intensity indicating the strength and direction of feature correlations.

The performance of the proposed image-based paddy plant disease prediction model was evaluated using a confusion matrix, as illustrated in Figure 11. The matrix provides a detailed comparison between the actual disease classes and the predicted outputs generated by the model. A strong concentration of values along the diagonal indicates a high number of correctly classified samples, demonstrating the effectiveness of the model in learning discriminative visual patterns from paddy leaf images.

In addition to overall accuracy, the performance of the proposed model was evaluated using precision, recall, and F1-score to provide a more comprehensive assessment, particularly for imbalanced disease classes. The confusion matrix demonstrates strong diagonal dominance, indicating high classification reliability across multiple disease categories.

The relationships among numerical features in the paddy disease weather dataset were analyzed using a correlation heatmap, as shown in Figure 12. The heatmap illustrates both the strength and direction of correlations between environmental parameters such as temperature, humidity, soil moisture, and pH. Strong positive correlations indicate that certain climatic and soil-related factors tend to vary together, potentially influencing disease development, while weaker or negative correlations suggest relatively independent feature behavior.

Together, these results indicate that integrating image-based disease detection with key environmental features provides a reliable and effective approach for accurate paddy disease prediction, supporting precision agriculture and early intervention strategies.

CONCLUSION

This study accomplished the development of a paddy disease detection system using sensors for environmental monitoring, drone imaging, and machine learning for detection of paddy diseases with greater accuracy and timely intervention. It enabled sensors to obtain data on soil moisture levels, pH of water, and weather conditions like humidity and temperature. Drones were also incorporated to take images of the paddy fields which were later on fused with the gathered sensor data to enhance disease detection accuracy. The system was implemented in actual paddy fields and validated to be working as intended. It was capable of diagnosing a range of common paddy diseases such as paddy bacterial panicle blight, tungro, shea, false, downy mildew, blast, dead heart, bacterial leaf streak, brown spot, hispa, and bacterial leaf blight. The implemented system was tested in five differing paddy fields and validated to be working as intended. This proposed system accurately identifies various paddy diseases with an overall accuracy of 98%, supported by standardized performance metrics, demonstrating its effectiveness for real-time, scalable paddy disease monitoring. The overall system addresses the needs of farmers and agricultural officers in Sri Lanka and supports decision making on disease prevention and enhance crop productivity.

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