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AN EMBEDDED AI SYSTEM FOR AUTOMATED CROP IRRIGATION AND PEST MONITORING

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ABSTRACT

Modern agriculture is rapidly adopting Artificial Intelligence (AI) and Internet of Things (IoT) technologies to improve crop monitoring and decision-making. Many existing systems focus either on water stress detection or pest detection separately.

The proposed system integrates both functions into a single platform. It uses a camera module and environmental sensors connected to a Raspberry Pi (5/4) as the main controller. A Convolutional Neural Network (CNN) model processes leaf images captured by the AI camera, while a soil moisture sensor supports water stress analysis.

The system classifies crops into three categories: healthy, water-stressed, and pest-infected. Based on the output, it provides real-time recommendations for irrigation and pesticide application. This reduces manual inspection, prevents unnecessary chemical usage, saves water, and improves crop productivity.

KEYWORDS: Precision Agriculture, AI Camera Sensor, Crop Water Stress, Pesticide Requirement, Thermal Imaging, RGB Imaging, Hyperspectral Imaging, Deep Learning, Computer Vision

1. Introduction

Agriculture plays a crucial role in food production, but crops often suffer from water deficiency and pest attacks. Early detection of these conditions is essential to prevent crop loss. Traditional farming methods depend on manual observation, which can be time-consuming and sometimes inaccurate.

With the advancement of AI and computer vision, automated crop monitoring systems have become possible. The proposed system uses image analysis and sensor data to detect water stress and pest infestation at an early stage.

Leaf color changes, texture variations, yellowing, dryness, and visible spots are analyzed using a CNN model. Additionally, soil moisture data helps confirm irrigation needs. This integrated approach ensures better accuracy and timely decision-making

2. Problem Statement

In traditional agriculture:

- Farmers manually inspect fields.
- Early detection of crop stress is difficult.
- Excess water can damage plants.
- Overuse of pesticides increases cost and environmental harm.
- Lack of real-time monitoring leads to crop losses.

There is a need for a low-cost, automated system that can detect both water stress and pest infestation simultaneously and provide real-time recommendations.

3. Research Objectives

The main objectives of this research are:

3.1 Develop an AI-Based Crop Monitoring System
To design a smart system capable of analyzing crop images in real time without manual supervision.

3.2 Detect Crop Water Stress
To identify water deficiency using both image analysis (leaf color, wilting) and soil moisture sensor data.

3.3 Identify Pest Infestation
To detect pest attacks and disease symptoms using deep learning techniques.

3.4 Implement CNN for Classification
To use a Convolutional Neural Network for accurate feature extraction and image classification.

3.5 Integrate AI with Low-Cost Hardware
To ensure the system is affordable and suitable for small- and medium-scale farmers.

3.6 Provide Real-Time Decision Support
To generate immediate recommendation for irrigation and pesticide usage

3.7 Develop a Scalable Solution
To make the system adaptable to different crops and environmental conditions.

4. Related Work

This section categorizes existing literature into different approaches based on methodology. Each category includes a comparative table summarizing key contributions, advantages, and limitations.

4.1 CNN-Based Crop Water Stress Detection Models

Cho et al. [1] proposed an AI-based method combining RGB and thermal imaging for crop water stress detection. Their approach enables non-destructive and accurate monitoring by analyzing temperature and visual features. Although highly accurate, the use of advanced sensors increases system cost and complexity.

July-September-Issue, Vol. 1, No. 2 (2026) | DOI: 10.66261/zkygxb33

Chandel et al. [5] developed a CNN model for image-based crop water stress detection, achieving high accuracy through color and texture feature extraction. However, the study focuses only on water stress and does not consider pest detection.

An et al. [6] applied CNN for drought stress classification in maize, achieving very high accuracy and early detection. However, the model is crop-specific and may not generalize to other crops.
Jin et al. [7] proposed a thermal imaging-based system that detects water stress by analyzing leaf temperature variations. While effective, the need for specialized thermal cameras limits affordability and accessibility.

As summarized in Table 1, CNN-based models show strong performance in water stress detection using visual features, but most are single-task approaches and require specialized-hardware.

Table 1. Summary of CNN-Based Crop Water Stress Detection Models

Reference	Model	Dataset Type	Accuracy	Advantages	Limitations
Chandel et al. [5]	CNN	Crop image dataset	~93%	High accuracy, strong feature extraction	Only water stress detection
An et al. [6]	CNN (Maize)	Maize dataset	~95%	Early drought detection	Crop-specific
Jin et al. [7]	Thermal Imaging	Thermal dataset	~92%	Early stress detection	Requires special sensors
Cho et al. [1]	AI + RGB + Thermal	Multi-source data	~90%	Non-destructive monitoring	Expensive setup

4.2 Pest and Disease Detection Using Deep Learning

Mohanty et al. [12] used CNN models with the PlantVillage dataset for plant disease detection and achieved very high accuracy, making it a benchmark study. However, the dataset contains controlled images, which may reduce real-world performance.

Ramcharan et al. [13] developed a mobile-based deep learning system for cassava disease detection, enabling practical field use. However, it is limited to specific crops and lacks generalization.

Liu et al. [16] proposed a CNN-based pest detection model using leaf images, achieving high accuracy in identifying infestations. However, it does not include water stress analysis.

Tugrul et al. [17] designed a real-time CNN system for plant disease detection with strong accuracy, but it focuses only on diseases and not multiple crop conditions.

Popescu et al. [21] applied neural network techniques for automated pest detection, reducing manual inspection. However, the system does not integrate environmental or water stress data.

As shown in Table 2, deep learning models perform well in pest and disease detection, but most systems focus only on pest-related tasks and do not combine water stress monitoring, limiting their overall application.

Table 2. Summary of Pest and Disease Detection Models

Reference	Model	Dataset Type	Accuracy	Advantages	Limitations
Mohanty et al.	CNN	PlantVillage	~99%	Benchmark	Controlled dataset

[12]		dataset		accuracy	
Ramcharan et al. [13]	Deep Learning	Cassava dataset	~93%	Mobile-based solution	Crop-specific
Liu et al. [16]	CNN	Leaf dataset	~94%	Accurate pest detection	No water stress detection
Tugrul et al. [17]	CNN	Plant dataset	~95%	Real-time capable	Single-task only
Popescu et al. [21]	Neural Network	Pest dataset	~90%	Automated detection	No sensor integration

4.3 Hybrid and Lightweight Models for Smart Agriculture

Lehouel et al. [8] proposed a hybrid CNN and Vision Transformer (ViT) model for crop monitoring, achieving high accuracy and better generalization. However, its high computational cost limits deployment on low-cost devices.

De Silva et al. [18] developed a CNN-Transformer hybrid model for crop classification, which improved accuracy and robustness on complex datasets. However, the model requires significant computational resources.

Guan et al. [19] introduced lightweight CNN models for embedded systems such as Raspberry Pi, enabling real-time application with reduced computation. However, this improvement slightly reduces overall accuracy.

Al-Shannaq et al. [20] designed a cost-effective CNN model for crop disease detection, focusing on affordable agricultural solutions. However, it lacks scalability and multi-functional integration.

As shown in Table 3, hybrid and lightweight models enhance accuracy and support embedded deployment, but there is a trade-off between computational efficiency and performance.

Table 3. Summary of Hybrid and Lightweight Models

Reference	**Model**	**Dataset Type**	**Accuracy**	**Advantages**	**Limitations**
Lehouel et al. [8]	CNN + ViT	Crop dataset	~96%	High accuracy, better generalization	Computationally expensive
De Silva et al. [18]	CNN + Transformer	Crop dataset	~97%	Very high accuracy	High computation cost
Guan et al. [19]	Lightweight CNN	Embedded dataset	~91%	Suitable for Raspberry Pi	Slightly lower accuracy
Al-Shannaq et al. [20]	CNN	Crop dataset	~92%	Cost-effective solution	Limited scalability

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5. Proposed Methodology

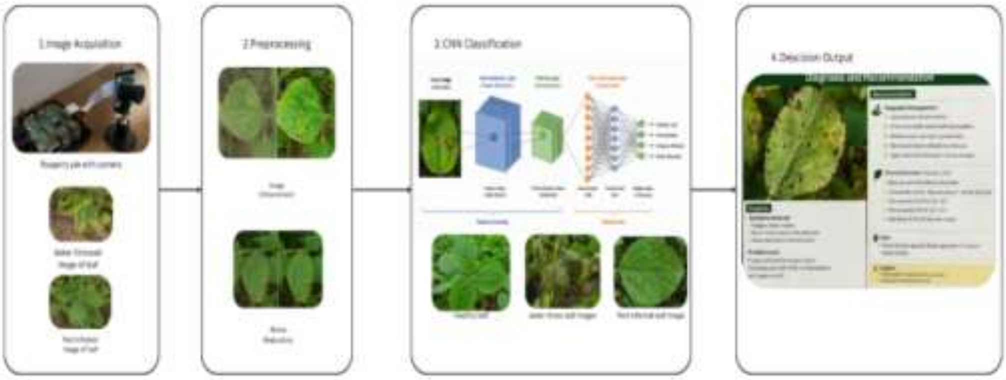

Figure 1: Proposed Methodology workflow for Crop water stress and Pest Detection

As shown in figure 1:

The system follows these steps:

5.1 Image Acquisition
Crop images are captured using a high-resolution camera.

5.2 Preprocessing
Images are resized (224×224), normalized, and cleaned using image processing techniques.

5.3 Feature Extraction
CNN automatically extracts features such as edges, texture, color variations, spots, and patterns.

5.4 Classification
The model classifies crops into:

- Healthy
- Water-stressed
- Pest-infected

5.5 Decision-Output
Based on classification results, the system recommends irrigation or pesticide application. Results are shown on LCD and can also be provided through voice alerts

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6. System Architecture:

This System architecture shown in the figure 2:

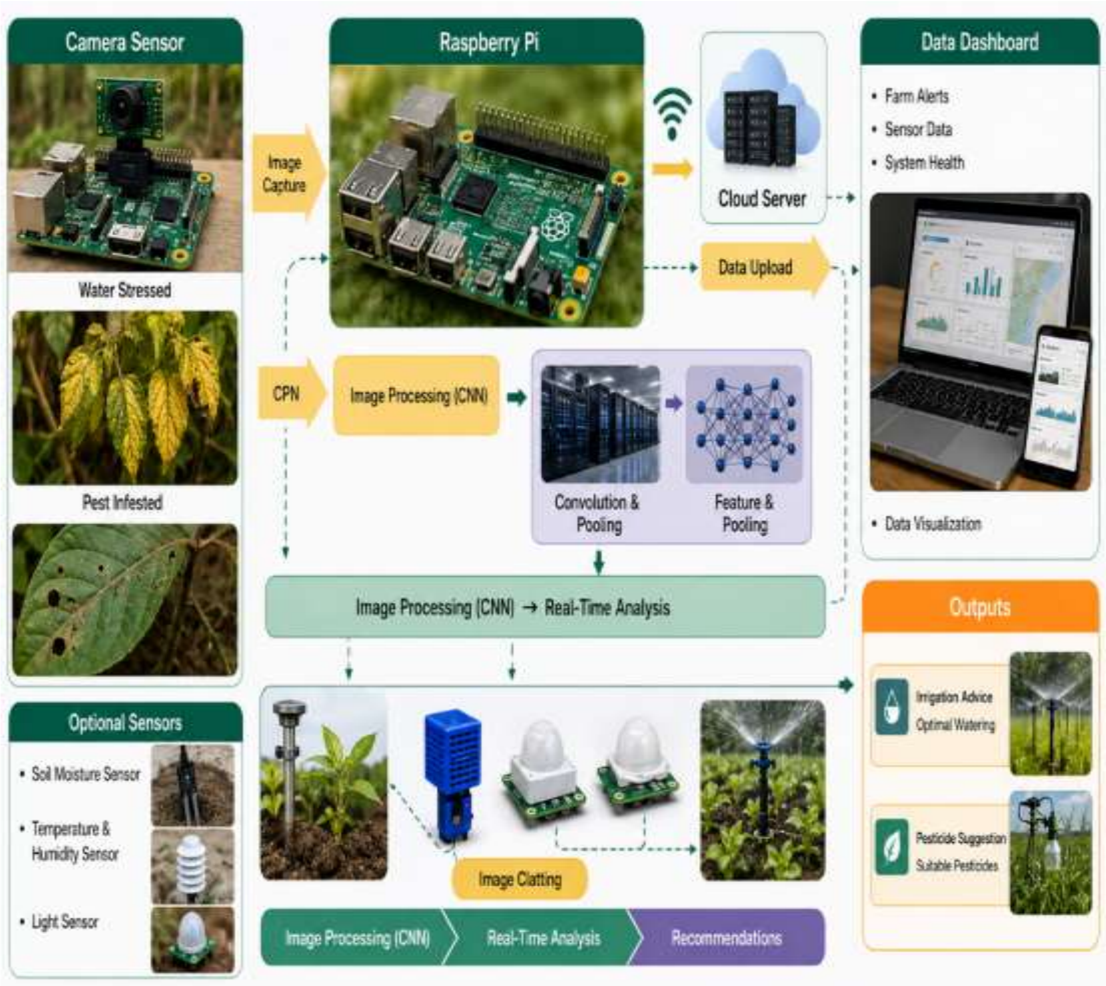

Figure 2. System architecture

The proposed system is designed with different functional layers to perform efficient crop monitoring and disease detection. In the data acquisition stage, a camera module captures images of plant leaves, while sensors such as soil moisture, temperature, and humidity sensors continuously collect environmental information from the agricultural field. This collected data is temporarily stored in the processing unit for further analysis.

In the processing layer, the captured leaf images are preprocessed to improve image quality and remove unnecessary noise. Data augmentation techniques are also applied to increase the diversity of the training data and improve the overall performance of the model. After preprocessing, a Convolutional Neural Network (CNN) is used to extract important features from the images through convolution and pooling operations.

July-September-Issue, Vol. 1, No. 2 (2026) | DOI: 10.66261/zkygxb33

The decision layer is responsible for analyzing the extracted features using fully connected layers. Finally, the Softmax activation function classifies the crop condition, such as healthy or diseased. In the output layer, the final results are displayed on an LCD screen, and the system also generates alerts related to irrigation needs or pesticide application whenever required.

For training and validation purposes, the dataset is divided into 80% training data and 20% testing data. Before feeding the images into the CNN model, all images are resized to 224 × 224 pixels and normalized to ensure consistent input and better learning accuracy.

The datasets used in this project were collected from Kaggle. The PlantVillage Dataset was used for plant disease detection, and it is available at https://www.kaggle.com/datasets/emmarex/plantdisease. The Crop Water Stress Dataset was used for crop water stress analysis, and it can be accessed at https://www.kaggle.com/datasets/harshilsharma/crop-water-stress.

6.1 Dataset Description and CNN Training Parameters

The proposed CNN model was trained using publicly available agricultural image datasets collected from Kaggle. The combined dataset consisted of 10,000 crop leaf images categorized into three classes: Healthy crops, Water-Stressed crops, and Pest-Infected crops. The class-wise distribution included 3,400 healthy crop images, 3,300 water-stressed crop images, and 3,300 pest-infected crop images.

Before training, all images were resized to 224 × 224 pixels and normalized to improve model performance. Data augmentation techniques such as rotation, horizontal flipping, zooming, and brightness adjustment were applied to increase dataset diversity and reduce overfitting.

The dataset was divided into 80% training data and 20% testing data. The CNN model was trained using the Adam optimizer with a learning rate of 0.001. A batch size of 32 and 50 training epochs were selected to achieve stable convergence and high classification accuracy. The categorical cross-entropy loss function was used during training, while ReLU activation was applied in hidden layers and Softmax activation was used in the output layer for multi-class classification.

The selected training parameters provided a good balance between computational efficiency and classification performance, making the model suitable for deployment on Raspberry Pi-based embedded agricultural monitoring systems.

The CNN architecture includes:

- Input Layer
- Convolutional Layers
- ReLU Activation Function
- Pooling Layers
- Flatten Layer
- Fully Connected Layer
- Output Layer (Softmax)
-

The model is trained on labeled datasets and achieves approximately 94% accuracy, making it reliable for real-time deployment.

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7. Algorithm flow chart:

Algorithm flowchart shown in Figure 3

Figure 3: -Flow Chart of the crop water stress and Pest Detection Algorithm

8. Hardware Implementation

Main components include:

- Raspberry Pi (Controller)
- Camera Module
- Soil Moisture Sensor
- Temperature & Humidity Sensor
- LCD Display
- Buzzer
- Relay Module
- Water Pump
- Pesticide Sprayer
- 5V Power Supply

The system operates as an embedded real-time monitoring device suitable for precision agriculture

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9. Results and Discussions

The performance of the proposed AI-based crop monitoring system was evaluated using the testing dataset consisting of healthy, water-stressed, and pest-infected crop images. Experimental results demonstrate that the CNN model can effectively classify crop conditions and provide accurate recommendations for irrigation and pesticide application.

The trained CNN model achieved an overall classification accuracy of approximately 94%, with a precision value of around 91%. These results indicate that the proposed approach is reliable for real-time agricultural monitoring applications.

The confusion matrix shown in Figure 4 provides a detailed analysis of the classification performance. Most healthy crop samples were correctly identified, indicating strong feature extraction capability of the CNN model. Similarly, water-stressed and pest-infected samples achieved high classification rates with only a small number of misclassifications.

Some overlap was observed between water-stressed and pest-infected classes because both conditions may produce similar visual symptoms such as leaf discoloration, yellowing, and texture variations. However, the inclusion of soil moisture sensor data helped improve decision reliability by supporting image-based classification results.

The confusion matrix demonstrates that false positive and false negative rates remain low across all classes, confirming the robustness of the proposed system. The integration of image analysis with environmental sensing enables better decision-making compared to systems that rely solely on image classification.

Overall, the experimental results confirm that the proposed embedded AI system is capable of accurately monitoring crop health, detecting water stress, identifying pest infestation, and supporting precision agriculture through real-time recommendations.

Confusion Matrix shown in the figure 4:

Figure 4: Graphical representation of result through confusion matrix

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10. Conclusion

This research presents an AI-based integrated system for detecting crop water stress and pest infestation using CNN and IoT technology. The system provides real-time monitoring, reduces manual effort, minimizes water and pesticide wastage, and improves crop productivity.

Due to low-cost hardware implementation, it is suitable for small and medium-scale farmers. The proposed solution contributes to precision agriculture by combining computer vision, AI, and embedded systems into a scalable platform.

Overall, this research contributes to the development of precision agriculture by integrating AI, IoT, and computer vision into a practical and scalable solution that can support modern farming practices Future work may focus on expanding the dataset with additional crop varieties and environmental conditions. Furthermore, advanced deep learning architectures such as EfficientNet, Vision Transformers (ViT), and hybrid CNN-Transformer models can be explored to further improve classification accuracy and robustness. Integration with cloud-based monitoring platforms and mobile applications may also enhance large-scale agricultural deployment.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

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