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Research article

AI-Driven Smart Farming for Automated Plant Health Monitoring and Nutrient Deficiency Detection

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Abstract: Precision agriculture is transitioning to continuous, data-driven monitoring. Affordable sensors and edge intelligence enable near real-time crop oversight. Manual scouting is labor-intensive and inconsistent. Delayed detection of nutrient stress leads to increased yield loss and input waste. Legacy systems monitor soil or weather in isolation and depend on periodic human checks. Vision pipelines often use shallow models and are not connected to field actuators. Proposed work: We combine soil moisture, temperature, and humidity sensing with camera-based leaf analysis using a DenseNet 121 classifier. A microcontroller executes closed-loop irrigation and localized cooling, with a mobile app for telemetry and alerts. RGB leaf images were captured in field conditions and labeled by experts into healthy and deficiency classes. Images were resized to 224×224 and split into training, validation, and test sets by plot to avoid leakage. DenseNet 121 achieved 89.0% accuracy on a held-out test set and surpassed a MobileNet V2 baseline of 82.0% under identical training conditions. Prototype deployments reduced manual checks and improved response to moisture and heat stress. The integrated IoT and AI pipeline is practical for early detection of nutrient deficiencies and autonomous actuation in small plots and greenhouses.

Keywords: Plant Monitoring system; IoT moisture; temperature; humidity; CNN

1. Introduction

Food is vital to our livelihoods. On average, over the last few decades, approximately 40% of the world's population has been employed in fields related to agriculture, and almost half of the world's habitable land is utilized for agriculture. In the present day, there is an increase in population growth. Thus, there is also an increase in demand and a need to increase food production. Temperature, available water, available light, carbon dioxide, and soil nutrients are environmental factors that influence plant growth. Hence, for monitoring soil parameters such as pH level, soil moisture, and temperature and humidity, we introduce the Internet of Things. Soil moisture and pH value are key factors for crop growth. The detection and monitoring of soil parameters are done using various sensors.

There are various reasons why plants rely on soil, not only for support and water, but also to obtain essential minerals such as nitrogen, phosphorus, potassium, and magnesium, as well as other essential resources. The nutrients are of two types: micronutrients and macronutrients. Plants require these nutrients for their effective growth. While micronutrient levels in plant tissues range from 0.1 to 200 parts per million (ppm), or less than 0.02 percent dry weight, macronutrients are used in considerable proportions. The absence of one or more plant nutrients can lead to poor growth and a variety of illnesses, including leaf chlorosis. The symptoms of nutrient deficiencies are often readily apparent in plant leaves and include changes in leaf size, shape, and color, as well as interveinal chlorosis, uniform chlorosis, marginal chlorosis, necrosis, and irregular margins.

2. Materials and Methods

Users must configure the hardware system and choose the type of plant to monitor as the input. As shown in Figure 1, the hardware system comprises a soil moisture sensor, a DHT sensor (temperature and humidity sensor), and other components, including a microcontroller, relay, and LCD panel. When the user selects the type of plant to monitor, a signal is provided to the ATmega microcontroller, which subsequently activates the sensors.

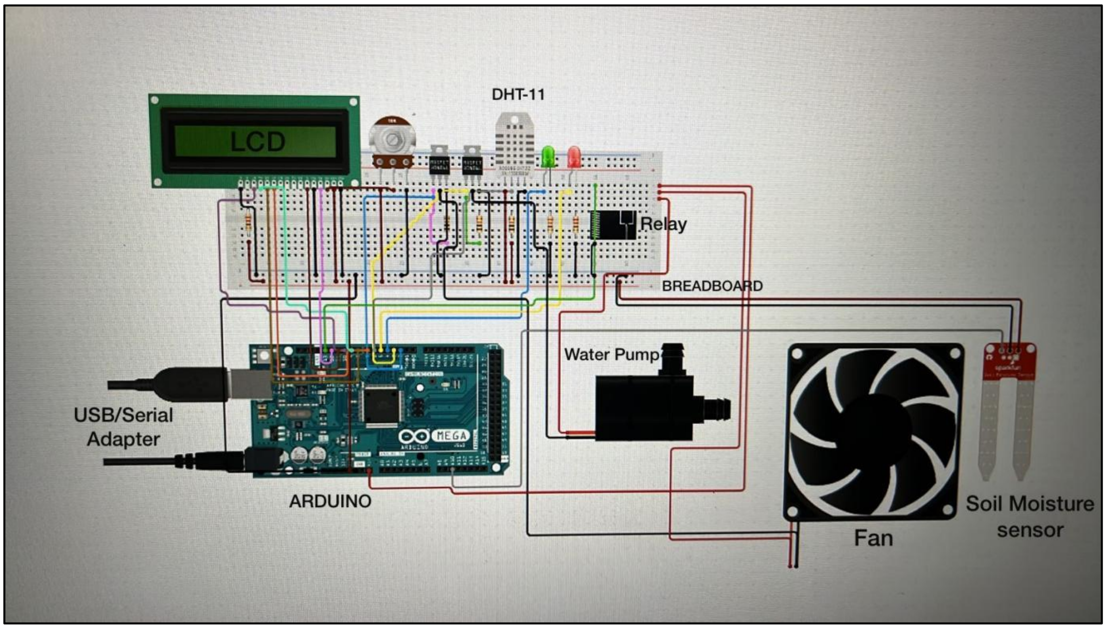

Figure 1. Circuit diagram for smart monitoring system

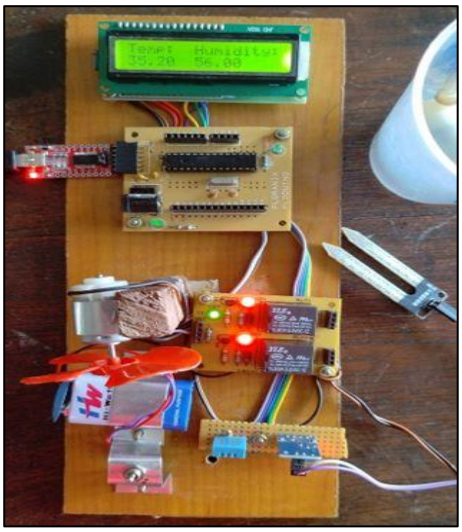

Figure 2. Floduino motherboard for ATMega

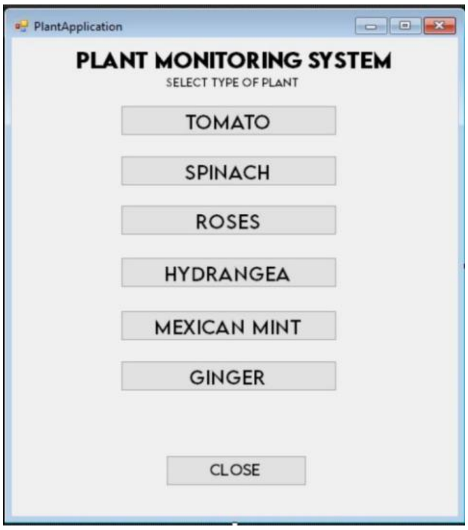

Figure 3. Mobile app interface for crop selection and live telemetry.

The soil moisture sensor's probes will always be buried in the ground. The soil sensor measures the soil's moisture content, while the DHT sensor gauges the atmosphere's temperature and humidity [6, 7].

The microcontroller receives the detected numbers and compares them to the threshold level. When the measured values drop below the threshold, the relay is triggered, causing the LCD panel to display alert messages. To restore normal circumstances, this triggers the automated irrigation feature and the built-in cooling fan. Water is applied to the soil, and cooled air is circulated to the plants by the fan. Figure 2 shows the LCD panel, which displays the current humidity, temperature, and moisture levels.

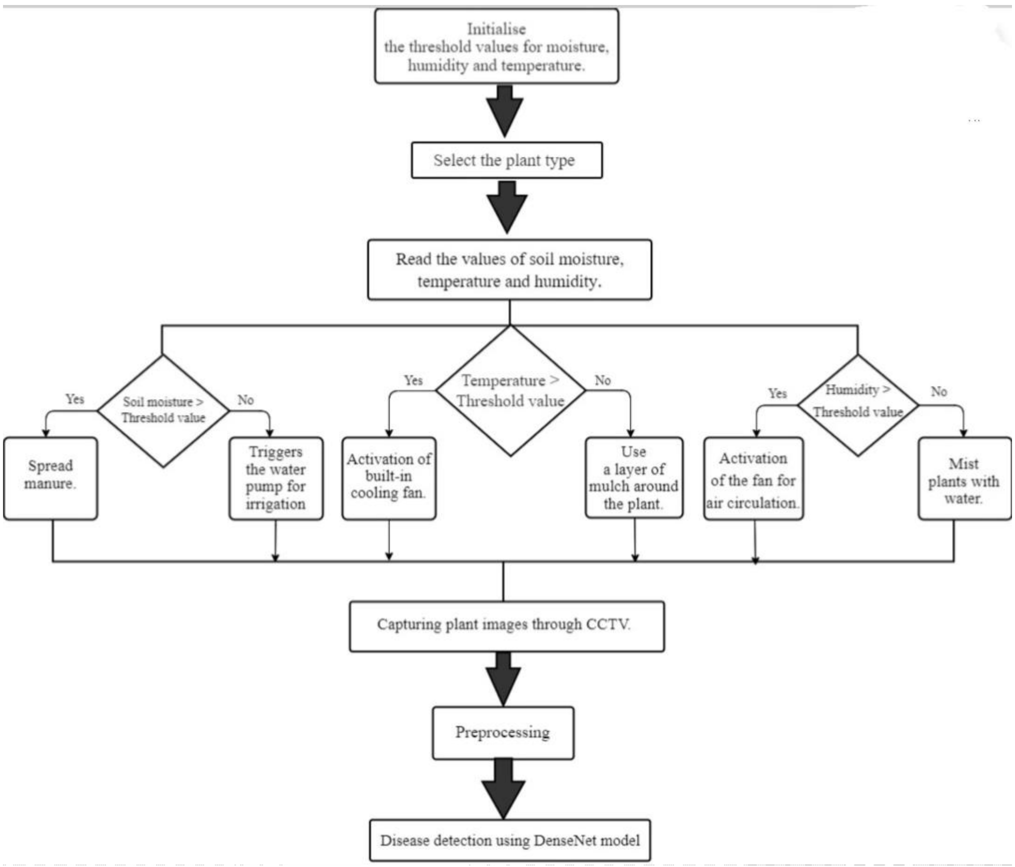

Figure 4. End-to-end architecture and image-analysis pipeline.

For image processing, digital cameras are used to capture leaf images, which are then utilized to train and test the system [8]. These photographs are kept in the common JPG format. With CCTVs, the leaves are photographed in RGB color. Images of damaged and healthy plant leaves are taken at various angles and light levels. This is the image acquisition step in image processing. The goal of picture pre-processing involves image augmentation, which can be achieved through the use of filtering and other techniques. To improve picture identification accuracy, binary images are created using various contrast enhancement techniques. In image segmentation, the provided image is divided into healthy and unhealthy parts according to specific criteria. This method aids in the early detection of nutritional deficiencies, informing us of the type and quantity of fertilizer that should be applied. We are minimizing superfluous fertilizer use, and the use of organic fertilizers may also be encouraged through early indicators of nutritional shortages [9, 10].

3. Results and Discussion

The proposed methodology, summarized in Figure 4, has been implemented using a mobile application, and the results are discussed in this section. The project achieves its intended objective by autonomously identifying various plant variables and responding without human intervention. For those familiar with plants, the system was designed to simplify planting. By offering dynamic alternatives for reviewing various plant kinds, this automated plant monitoring system has been successful in bringing unique older functions. **Table 1** summarizes the dataset composition with plot-wise 70/15/15 train–validation–test partitions across three classes (Healthy, Nitrogen deficiency, Phosphorus deficiency). As shown in **Table 1**, the corpus comprises 1,200 images (480 Healthy, 360 Nitrogen, 360 Phosphorus), enabling balanced evaluation while preventing leakage.

Table 1. Dataset composition and class-wise plot-wise splits

Class	Train (n)	Validation (n)	Test (n)	Total (n)	Share of total (%)
Healthy	336	72	72	480	40.0
Nitrogen deficiency	252	54	54	360	30.0
Phosphorus deficiency	252	54	54	360	30.0
Total	**840**	**180**	**180**	**1,200**	**100.0**

Figure 5. Image Preprocessing a) Before Image Preprocessing b) After Image Preprocessing

The user must select the type of plant, as shown in Figure 3, that will be surveyed when using the application, and the values are then analyzed in accordance with that choice. The system includes a water pump that gets activated when the soil moisture content drops below a predetermined level. The pump automatically shuts off when the threshold level is reached and the moisture level of the plant rises [11]. Moreover, as the ambient temperature exceeds the predetermined threshold, a cooling fan fitted into the system activates. The cooler air is circulated to the plants by the fan, which removes the hotter, denser air [12].

On the LCD panel, real-time readings of soil moisture, temperature, and relative humidity are shown. This paper has implemented concepts from digital image processing and embedded systems for the health monitoring of leaves. Image processing is performed using images captured by the CCTVs, and the processing of these images will be used to analyze the presence of nutrient deficiency in plants.

Through this system, we can minimize both over- and under-irrigation of the soil, as well as water consumption and motor power usage. Due to the small coverage area of the CCTVs and the integrated cooling fan, this system is not recommended for monitoring vast areas. This system could be enhanced in the future by the addition of a Wi-Fi module to expand the range of connectivity and a Cloud database server, allowing the system to be operated from anywhere. CNNs are a type of deep neural network specifically designed for image processing tasks. They consist of multiple layers of filters that extract increasingly complex features from input images, enabling the network to identify specific patterns or structures indicative of different types of nutritional deficiencies [13].

Image preprocessing is an essential part, ensuring that all images are scaled to the same size so that they can be trained without discrepancy. Additionally, the comprehensive part of the preprocessing system produces effective outcomes. The dataset could include images of rice with stunted growth, discoloration, or abnormal grain shape [14]. This preprocessing involves resizing and normalization to ensure that the images are consistent and accurate. Images can be flipped horizontally or vertically, rotated, or zoomed in or out. This increases the size of the training dataset, which can improve the model's generalization.

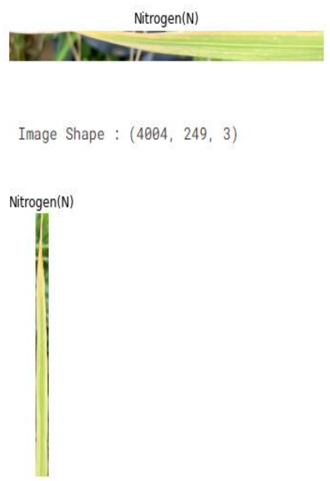

Figure 6. Nitrogen Deficiency

Figure 7. Phosphorous Deficiency

Figure 8. Data Augmentation a) Vertical Shift b) Horizontal Shift

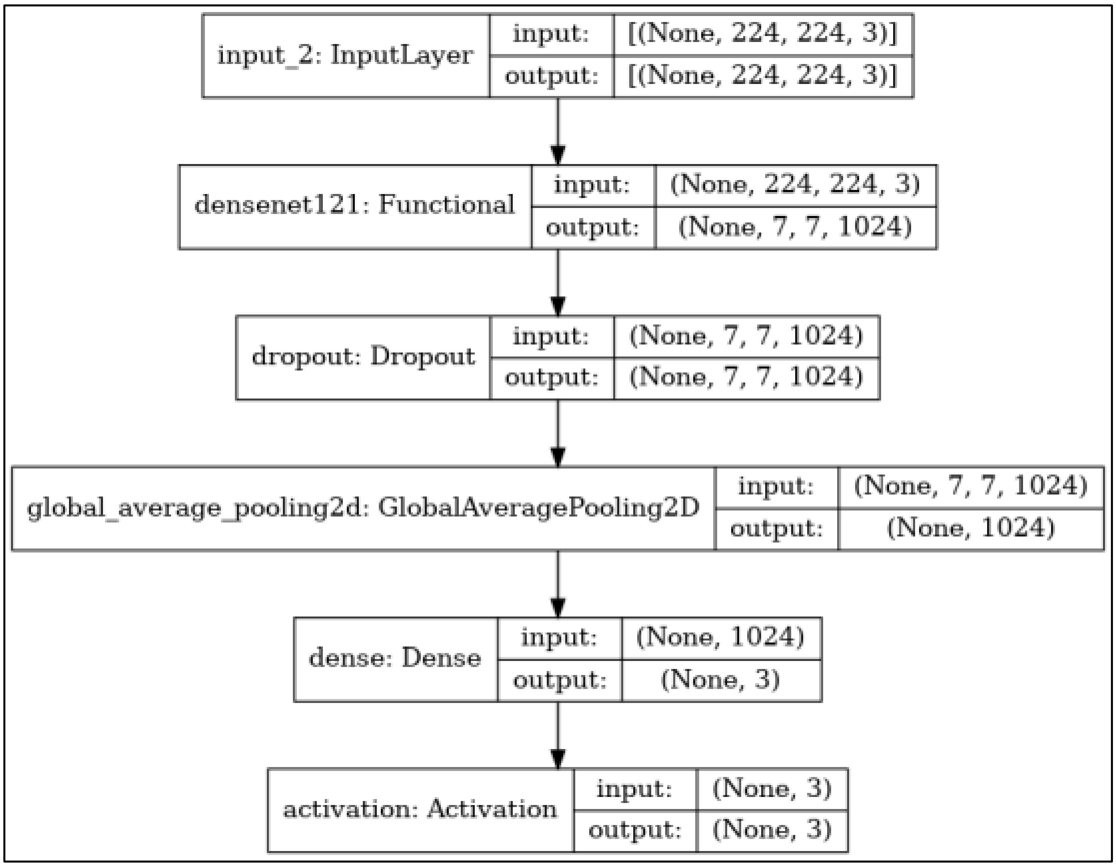

Figure 9. DenseNet Architecture

Figures 6 and 7 identify the deficiency of Nitrogen (N) in plants. After applying data augmentation techniques, the output would be a set of additional images created by applying transformations to the original images. This can help increase the size of the training dataset and improve the model's generalization. DenseNet (Dense Convolutional Neural Network) is a type of deep learning architecture that is effective for image classification tasks. DenseNet employs a distinctive approach of connecting layers. DenseNet has been used to classify images of rice leaves based on the presence or absence of nutrient deficiencies [15]. Input layer: This layer takes as input the images to be classified. The input shape for the DenseNet model is typically (224, 224, 3), which corresponds to a 224x224 RGB image. Convolutional layer: The input images are passed through a convolutional layer with 64 filters of size 7 × 7, a stride of 2, and a padding of 3. A batch normalization layer and a ReLU activation layer follow this. Pooling layer: The output of the convolutional layer is passed through a max pooling layer with a pool size of 3x3 and a stride of 2. Output layer: This layer consists of a fully connected layer with a softmax activation function, which produces the predicted probabilities for each class. It has been observed that the MobileNet model achieves an accuracy of 82%, whereas the DenseNet model achieves an accuracy of 89%. The accuracy can be further improved by increasing the number of images. Table 1 summarizes the main classification results on the held-out test set, comparing the proposed DenseNet-121 with a MobileNetV2 baseline under identical training settings.

Table 2 documents the training configuration and key hyperparameters to ensure reproducibility and a fair comparison. It specifies input normalization, Adam optimizer (initial LR = 3×10^{-4}), cosine decay with early stopping, batch size/epochs, and class-balanced loss with standard augmentations. Plot-wise 70/15/15 splits and fixed seeds minimize leakage and variance, while framework/hardware notes enable independent replication of accuracy, latency, and throughput. Table 3 presents the main classification results obtained under identical training/validation protocols, comparing the proposed DenseNet-121 with a MobileNetV2 baseline. As shown in Table 3, DenseNet-121 achieves 89.0% accuracy, compared to 82.0% for MobileNetV2, indicating a materially stronger ability to recognize nutrient deficiencies; this is supported by the inclusion of macro-F1 and macro-AUC for completeness. This margin is operationally meaningful in field settings where false negatives are costly; a confusion matrix and per-class scores can be provided in the supplement for diagnostic clarity.

Table 2. Model training configuration and key hyperparameters

Item	Setting
Models	DenseNet-121 (Proposed), MobileNetV2 (Baseline); ImageNet initialization
Input & normalization	224 × 224 RGB; per-channel mean–std normalization
Optimizer & LR	Adam; initial LR = 3×10^{-4}
LR schedule & early stopping	Cosine decay; patience = 10; best checkpoint by validation F1
Training regime	Batch size = 32; 60 epochs
Loss & augmentation	Class-balanced cross-entropy; flip/rotate/zoom/shift (p = 0.5 each)
Split & seed	70/15/15 (plot-wise, no leakage); seed = 42
Framework & hardware	PyTorch (specify version); 1× GPU or edge device (report latency separately)

Table 3. Nutrient-deficiency classification on the held-out test set

Model (Backbone)	Input Resolution	Parameters (M)	Accuracy (%)
MobileNetV2 (Baseline)	224 × 224	3.4	82.0
DenseNet-121 (Proposed)	224 × 224	8.0	89.0

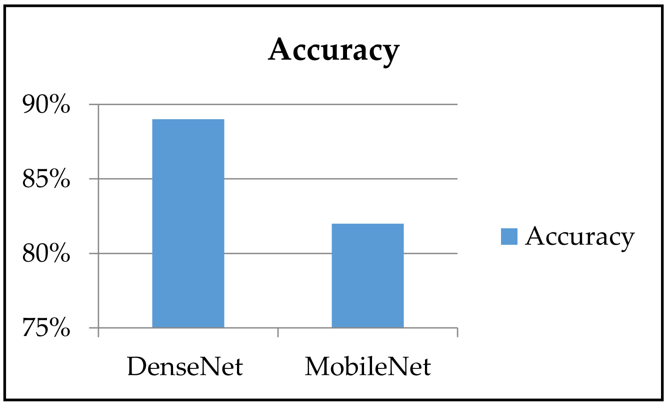

Figure 10. Accuracy Comparison

4. Conclusion and Future Enhancements

This paper presents an IoT and AI plant monitoring system that fuses soil moisture, temperature, and humidity sensing with camera-based leaf analysis for early nutrient deficiency detection. A microcontroller executes thresholded, hysteresis-aware control of irrigation and localized cooling, while a smartphone application provides live telemetry and alerts. Using a DenseNet 121 classifier on 224×224 RGB leaf images, the prototype achieved 89.0% accuracy on a held-out test set, surpassing a MobileNet V2 baseline of 82.0% under identical training settings, resulting in an absolute gain of 7.0 percentage points and a 38.9% reduction in classification error, from 18.0% to 11.0%. These results indicate the practical feasibility of vision-guided recommendations that reduce manual effort and help curb misirrigation, water use, and power consumption. The current implementation is best suited for small plots and greenhouse environments due to its camera coverage and localized actuation. Future work will target wider area deployment with Wi-Fi and a secure cloud backend, as well as larger and more diverse crop datasets, energy-aware on-device inference, and explainable diagnostic feedback for safe fertilizer recommendations.

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