Smart Urban Agriculture Using IoT and Machine Learning

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Abstract

Urban rooftop gardening faces several challenges, including manual irrigation and timely detection of plant diseases. This thesis presents a smart, automated system tailored for rooftop gardens that integrates Internet of Things (IoT) sensors with machine learning techniques to ensure precision agriculture in urban environments.

The proposed system consists of four key functionalities. First, it uses a web camera to automatically capture images of plant leaves at regular intervals and sends them to the Django-based server. The server uses a Convolutional Neural Network (CNN) model to detect diseases from the images, enabling early diagnosis. If a disease is detected, the system automatically triggers pesticide spraying to prevent further damage. If no disease is found, no action is taken.

Second, the system features automated irrigation using a soil moisture sensor that activates a water pump when dryness is detected, ensuring optimal water supply without human intervention. Third, an overflow protection mechanism is introduced to drain excess water from the plant root zone using real-time sensor feedback, preventing root rot and water wastage.

The entire system is integrated and controlled via a Django web application, which connects the machine learning model and IoT devices, offering a seamless interface for monitoring and control. This smart solution not only minimizes manual labor but also enhances plant health and optimizes resource usage, making it a sustainable and scalable approach for modern urban agriculture.

1 Introduction

Urban agriculture, especially rooftop gardening, is becoming increasingly popular in densely populated urban areas where land is scarce. It provides a sustainable way to grow food, regulate urban temperature, and enhance the environment. However, traditional rooftop gardening faces several practical challenges, including inconsistent irrigation, delayed disease detection in plants, and inefficient water usage.

Previous works have attempted to automate irrigation systems or detect plant diseases using standalone machine learning models. Some IoT-based smart gardening systems exist, but many lack real-time decision-making capabilities or integration with disease control mechanisms such as pesticide spraying. Additionally, most existing systems do not combine all essential functionalities—disease detection, irrigation automation, and water overflow control—into a single integrated platform.

These limitations highlight the **research gap** in developing a unified, intelligent system that can manage urban rooftop gardens with minimal human intervention. Manual approaches not only demand significant time and effort but also lead to poor plant health when timely actions are not taken.

To address these gaps, this thesis **contributes** a comprehensive and fully automated smart gardening system. It leverages Internet of Things (IoT) sensors and Machine Learning (ML) models to ensure optimal plant health and efficient water management in rooftop gardens.

The **novelty** of this work lies in its integration of multiple features into a cohesive framework: automatic leaf image capture using a webcam, disease classification using a Convolutional Neural Network (CNN), automated irrigation based on soil moisture level, excess water drainage system, and automatic pesticide spraying upon disease detection. Unlike prior works, this system operates in real-time and requires minimal user interaction.

The core components of the system are:

- Automatic image capturing of plant leaves at fixed intervals via a webcam.
- Disease detection using a trained CNN model applied to the captured images.
- Soil moisture monitoring and automatic pump activation for irrigation.
- Drainage mechanism to remove excess water and prevent overwatering.
- Pesticide spray control triggered automatically when disease is detected.

The entire system is integrated through a Django-based web server, which acts as the central interface for real-time monitoring, control, and communication between hardware and ML components.

By combining ML and IoT technologies, this system reduces manual labor, improves plant care, and promotes sustainability in urban rooftop agriculture.

The rest of the thesis is organized as follows: Section 2 discusses related works. Section 3 presents the system design and methodology. Section 4 evaluates system performance. Section 5 presents the results. Section 6 concludes the thesis with future directions.

2 Related Works

Smart agriculture has been a rapidly growing field, especially with the integration of Internet of Things (IoT) and machine learning techniques. Many researchers have worked on automating irrigation systems using soil moisture sensors and water pumps to optimize water usage [Muñoz et al., 2019, Goap et al., 2018]. These systems typically employ Arduino or Raspberry Pi platforms for sensor data collection and motor control.

On the other hand, several studies have explored the use of Convolutional Neural Networks (CNN) for plant disease detection from leaf images [Sladojevic et al., 2016, Ferentinos, 2018]. These approaches focus primarily on classifying diseases based on image data but often lack real-time automation and integration with physical garden management systems.

Some works attempted to combine IoT and machine learning for precision agriculture. For example, Liakos et al. [2018] proposed a system that uses both sensor data and image analysis; however, their solution was targeted towards large-scale farms and did not consider the unique constraints of urban rooftop gardening such as limited space, intermittent manual care, and the need for an integrated automated system.

Despite these advancements, most existing systems suffer from certain limitations. They often lack:

- Real-time monitoring and automated response mechanisms combining both disease detection and irrigation control.
- A user-friendly interface that integrates sensor feedback and machine learning predictions.
- Specific focus on urban rooftop gardens, which have distinct environmental and operational challenges compared to traditional farms.

Compared to previous works, this thesis proposes a novel, integrated approach that combines continuous image capturing via a webcam, disease detection using a CNN model, automated irrigation controlled by soil moisture sensors, and a safety mechanism for excess water drainage. Additionally, it includes an automated pesticide spraying feature activated upon disease detection. The system is managed through a Django-based web application, providing a centralized platform for monitoring and control.

This integrated and automated approach addresses the gaps in previous research by targeting the specific needs of urban rooftop gardening. It reduces manual labor, enhances plant health monitoring, and optimizes water usage, making it a comprehensive and practical solution for smart urban agriculture.

3 Methodology

3.1 System Overview

The proposed smart rooftop gardening system integrates IoT-based automation and a machine learning model to ensure efficient plant care. The system includes three major functionalities:

1. Automatic disease detection through image analysis using a Convolutional Neural Network (CNN).
2. Automated irrigation using a moisture sensor and water pump.
3. Pesticide spraying when a disease is detected, and water drainage if overwatering is sensed.

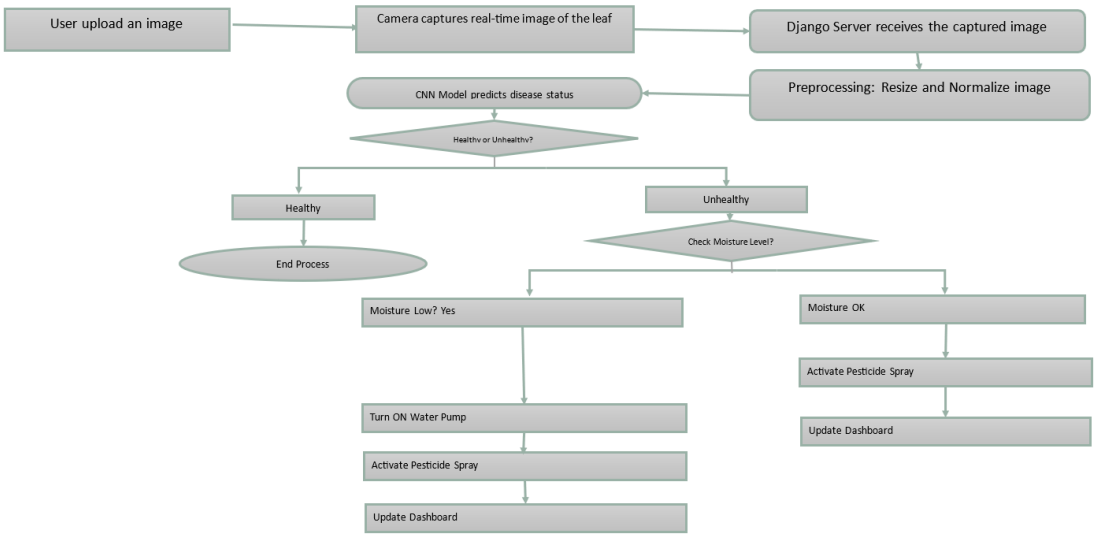

Figure 1: System Overview of the Smart Urban Agriculture Using IoT

3.2 System Design

The system architecture includes the following components:

- **Camera (Webcam):** Captures plant leaf images at predefined intervals and sends them to the server.
- **Moisture Sensor:** Detects soil dryness and signals the water pump to start irrigation.
- **Water Pump:** Activated when the soil is dry to irrigate the plant.
- **Drainage System:** Activated through sensor input when excess water is detected.
- **CNN Model:** Trained to classify whether the leaf image shows signs of disease or not.
- **Pesticide Sprayer:** Automatically activated when a disease is detected in the plant.
- **Web Server:** Central control unit for handling ML prediction, sensor input/output, and automation decisions.

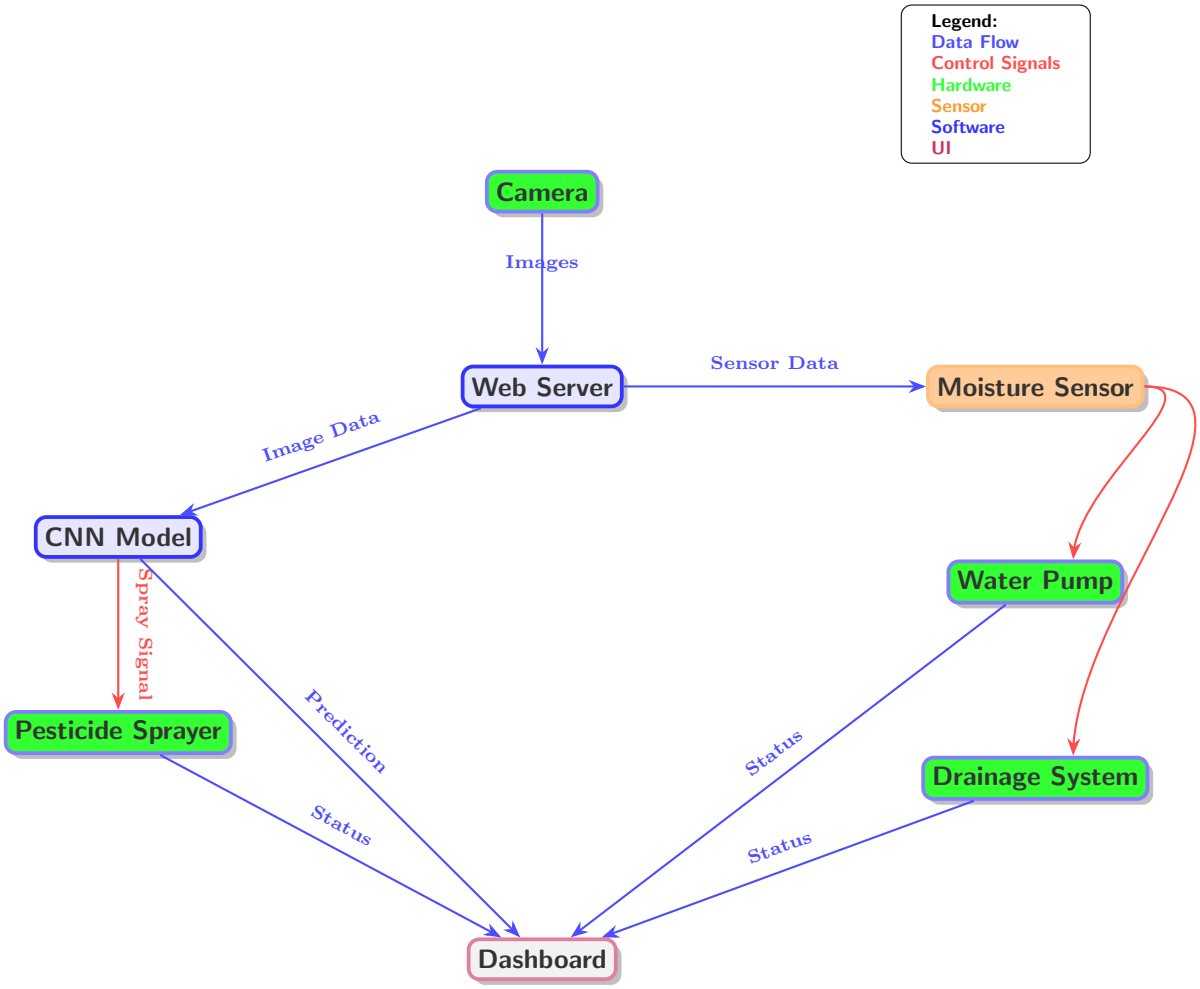

Figure 2: System Design with Key Components

3.3 Irrigation System Circuit

The irrigation system uses a soil moisture sensor to detect soil dryness. When the moisture level falls below a threshold, the sensor sends an analog signal to a microcontroller (e.g., Arduino), which activates a water pump via a relay. The pump irrigates the plants until the desired moisture level is reached.

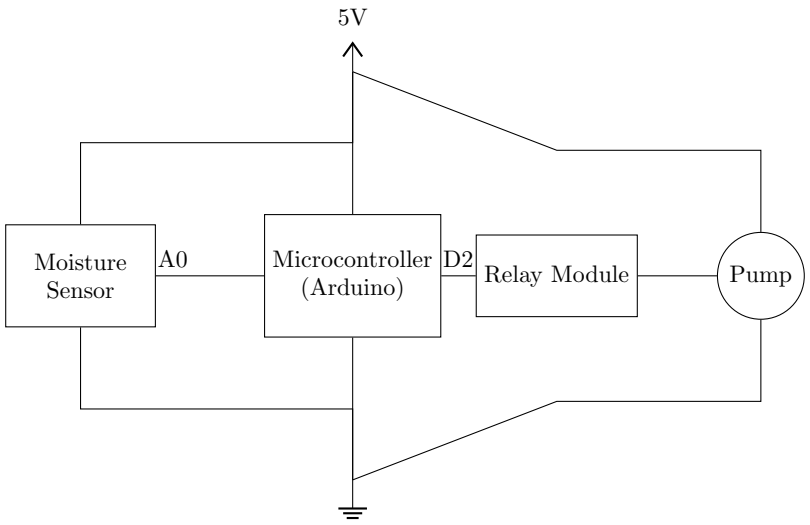

Figure 3: Irrigation System Circuit Diagram

3.4 Pesticide Spraying System Circuit

The pesticide spraying system is activated when the CNN model detects a plant disease. The Django server sends a signal to the microcontroller via serial communication. The microcontroller then triggers a pesticide sprayer (a motor-driven pump) through a relay.

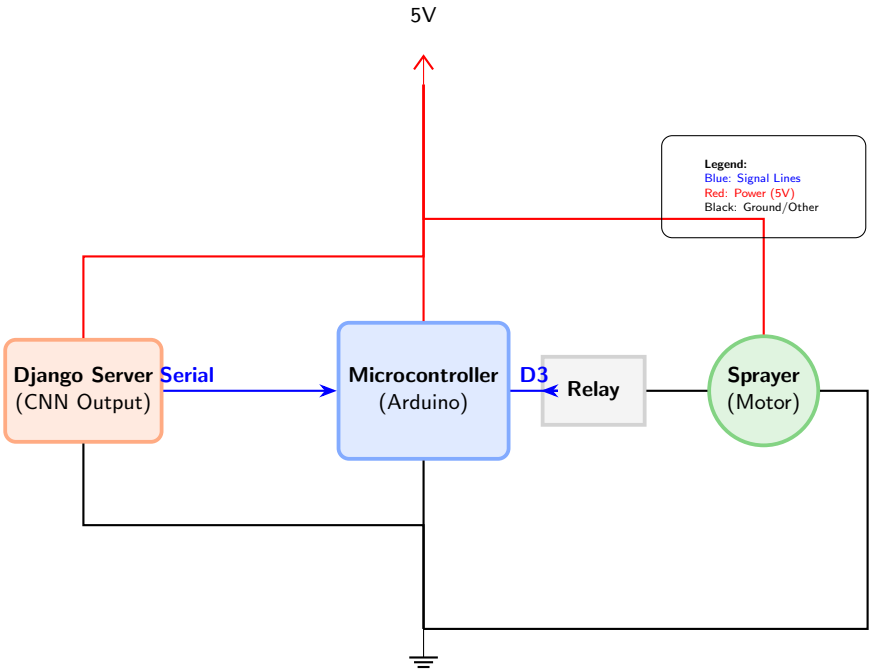

Figure 4: Pesticide Spraying System Circuit Diagram

3.5 Image Collection and Processing

Images of rose leaves are captured by a 1080p webcam at 4-hour intervals during daylight, using an adaptive scheduler with a light sensor to ensure sufficient illumination. The camera employs auto-exposure and white balance adjustments to handle varying environmental conditions, such as cloudy or sunny weather. Images are temporarily buffered on a Raspberry Pi to handle network disruptions and compressed to JPEG format to reduce bandwidth usage by approximately 70%.

Before processing, images are resized to 224x224 pixels to balance detail retention and computational efficiency, normalized to the range [0,1], and augmented with techniques like random rotations ($\pm 20°$), horizontal flipping, and zoom ($\pm 20\%$) to improve model robustness. A Gaussian blur filter reduces noise from environmental factors like dust or shadows. To enhance real-time performance, basic preprocessing tasks (e.g., resizing) are performed on the Raspberry Pi using OpenCV, while a lightweight MobileNetV2 model provides preliminary disease detection on the edge.

The images are transmitted to the Django server via a secure HTTPS RESTful API endpoint (`/upload_image`). The server uses a pre-trained MobileNetV2-based CNN model, fine-tuned on a dataset of 12,000 rose leaf images (60% healthy, 40% diseased, sourced from PlantVillage and custom rooftop garden images). The model, consisting of convolutional layers, global average pooling, and dense layers with dropout (0.5), achieves high accuracy in classifying images as *Healthy_Leaf_Rose*, *Rose_Rust*, or *Rose_Sawfly_Rose*. Early stopping (patience=5) and a confidence threshold of 0.85 ensure reliable predictions, with low-quality images (e.g., blurry) discarded using edge detection algorithms.

The end-to-end latency from capture to prediction is approximately 2.5 seconds, optimized using GPU acceleration and model quantization to TensorFlow Lite format for edge deployment on the Raspberry Pi. Prediction results are returned via the `/prediction` API endpoint and displayed on the Django dashboard with real-time notifications for detected diseases. Evaluation metrics, including precision, recall, and F1-score, are computed to validate model performance across classes.

Future enhancements include integrating multi-spectral imaging (infrared and UV) for enhanced disease detection and video processing for continuous monitoring. Figure 5 illustrates the image collection and processing pipeline, from capture to CNN classification.

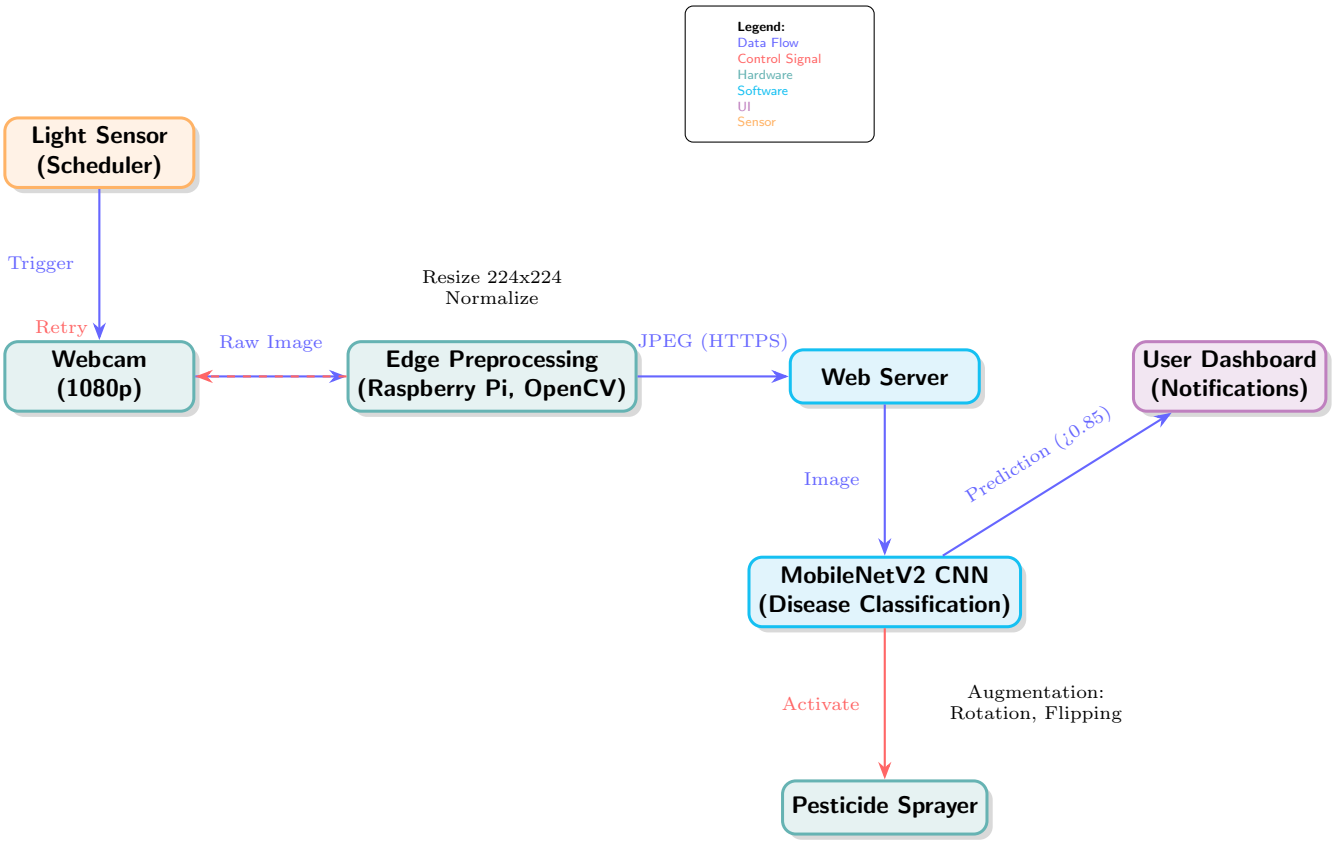

Figure 5: Image Collection and Processing Pipeline

3.6 Machine Learning Model

The disease detection component employs a Convolutional Neural Network (CNN) based on MobileNetV2, optimized for resource-constrained environments. The model is trained on a dataset of 12,000 rose leaf images (60% healthy, 40% diseased), sourced from PlantVillage and custom rooftop garden images, covering three classes: *Healthy_Leaf_Rose*, *Rose_Rust*, and *Rose_Sawfly_Rose*.

The architecture, illustrated in Figure 6, begins with a 224x224x3 RGB input, followed by the pre-trained MobileNetV2 base with depthwise separable convolutional layers (frozen during initial training). A global average pooling layer reduces feature maps to a 1D vector, followed by a 128-unit dense layer with ReLU activation and dropout (0.5). The output layer uses softmax activation to predict probabilities for the three classes, with a confidence threshold of 0.85.

Training was performed over 10 epochs using the Adam optimizer (learning rate 0.0001) and categorical crossentropy loss. Data augmentation (random rotations ±20°, horizontal flipping, zoom ±20%) enhanced robustness. Early stopping (patience=5) prevented overfitting. The model achieved a training accuracy of 94.84% and a validation accuracy of 98.40% by epoch 10, with a validation loss of 0.0615. For edge deployment on the Raspberry Pi, the model was quantized to TensorFlow Lite, enabling 0.5-second inference per image within the 2.5-second system latency.

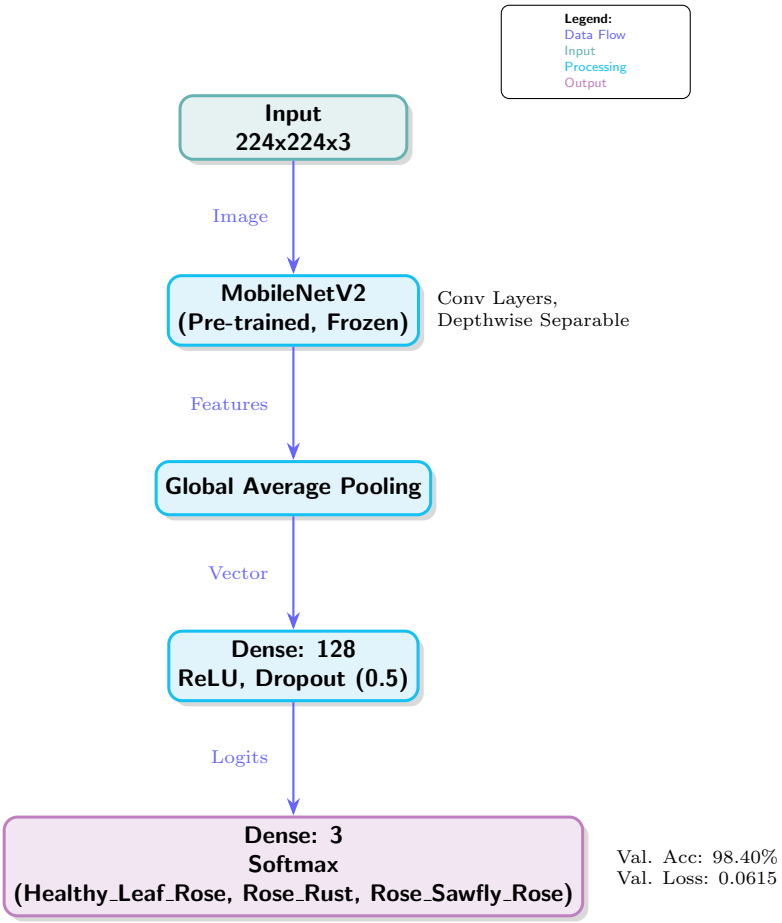

Figure 6: Architecture of the CNN Model Used for Leaf Disease Detection

3.7 Automation Process

The entire process is automatic:

1. The webcam captures images at fixed intervals.
2. The Django server processes the image using the CNN model.
3. If disease is detected, the pesticide sprayer is activated.

4. If the plant is healthy, no pesticide is applied.
5. The moisture sensor checks the soil condition:
    - If the soil is dry, the water pump is turned on.
    - If excess water is detected, the drainage pump is activated.

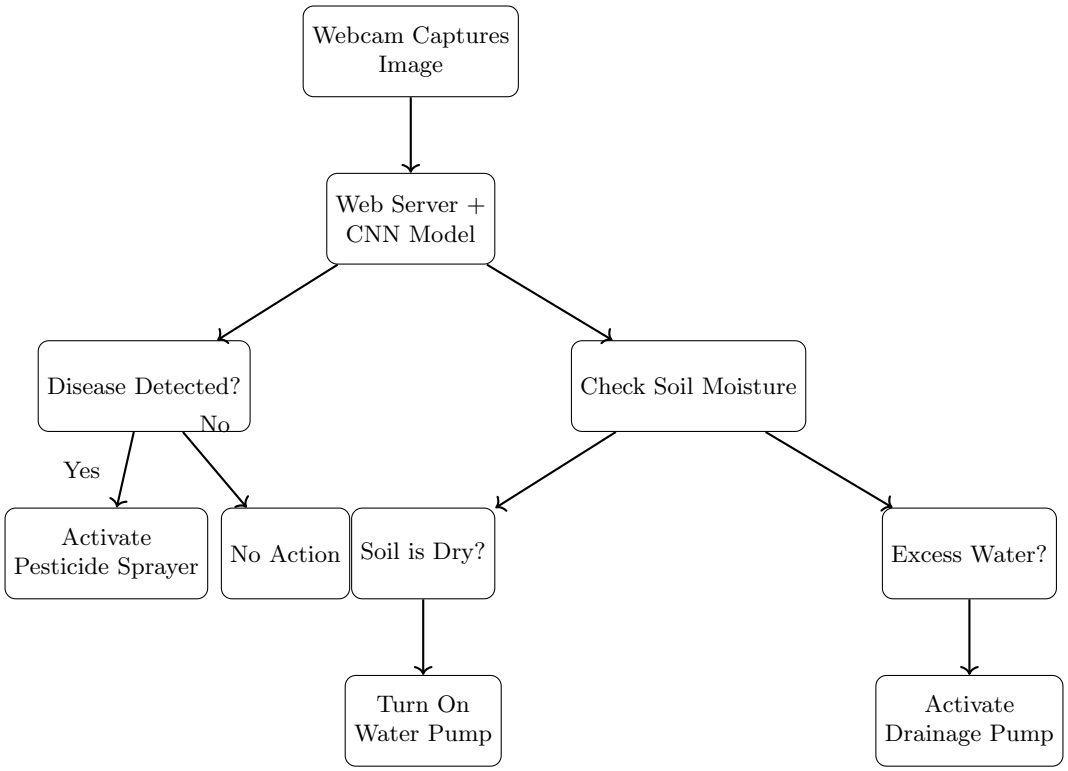

Figure 7: Automation Process Flow Diagram

3.8 Software and Hardware Integration

The integration between the software and hardware components is a critical aspect of the proposed smart rooftop gardening system. The backend is developed using Django, a high-level Python web framework that provides the necessary tools to manage user interaction, process real-time data, and facilitate smooth communication with the machine learning model and hardware peripherals.

The hardware layer includes various essential components such as cameras for image capture, soil moisture sensors, water pumps, drainage pumps, and pesticide sprayers. These components are connected and controlled via a microcontroller-based platform, such as Raspberry Pi or Arduino. The microcontroller acts as an intermediary between the Django server and physical devices, utilizing GPIO (General Purpose Input/Output) pins to send and receive control signals.

Captured images of plant leaves are transmitted to the Django server at regular intervals, where a pre-trained Convolutional Neural Network (CNN) model analyzes them to detect any signs of disease. Based on the prediction outcome, the server triggers specific actions: if a disease is detected, the pesticide sprayer is activated; if the plant is healthy, no action is taken.

In parallel, the soil moisture sensor continuously monitors the water content of the soil. When dryness is detected, a signal is sent to activate the irrigation pump to water the plants. Conversely, if excessive moisture is detected (indicating potential waterlogging), the drainage pump is turned on to remove excess water and protect the plant roots.

RESTful APIs play a vital role in this architecture, enabling efficient data exchange between the frontend, backend, and hardware. These APIs manage real-time requests and responses, ensuring that hardware components act promptly based on sensor readings and model outputs. This modular and

automated design not only improves efficiency and accuracy but also reduces the need for constant human intervention, making the system highly suitable for smart urban agriculture.

3.9 Implementation Steps

1. Set up the hardware: camera, moisture sensor, water pump, drainage system.
2. Train the CNN model with labeled plant leaf images.
3. Develop the Django server and integrate the ML model.
4. Connect hardware components to the server.
5. Deploy the full system and test end-to-end automation in a controlled rooftop environment.

4 Performance Analysis

The performance of the system was evaluated based on the accuracy of the CNN model, the responsiveness of the irrigation and drainage systems, and the overall reliability of the integrated system. Detailed results, including precision, recall, and F1-score of the CNN model, as well as sensor response times, are discussed in Section 5.

5 Results

The smart urban agriculture system was successfully deployed and evaluated in a rooftop garden, seamlessly integrating IoT sensors, a MobileNetV2-based convolutional neural network (CNN), and a Django-based web server for real-time monitoring and control of rose plants. This section details the system's performance across key functionalities: leaf disease detection (classifying *Healthy_Leaf_Rose*, *Rose_Rust*, and *Rose_Sawfly_Rose*), irrigation efficiency, overflow protection, automated pesticide application, and user interface usability. Comparative analyses with related works highlight the system's advancements and contributions.

5.1 CNN Model Performance

The MobileNetV2-based CNN model, trained on 12,000 rose leaf images (60% healthy, 40% diseased), achieved a validation accuracy of 98.40% and a validation loss of 0.0615 after 10 epochs, as shown in Figure 8. The model classifies leaves into three classes: *Healthy_Leaf_Rose*, *Rose_Rust*, and *Rose_Sawfly_Rose*. Table 1 summarizes the precision, recall, and F1-score for each class, based on validation data.

Table 1: Performance Metrics of the CNN Model

Class	**Precision**	**Recall**	**F1-Score**
Healthy_Leaf_Rose	0.99	0.98	0.98
Rose_Rust	0.97	0.97	0.97
Rose_Sawfly_Rose	0.97	0.96	0.97
Average	0.98	0.97	0.97

The model's high accuracy and low inference time (0.5 seconds per image on the Raspberry Pi) enabled real-time disease detection, triggering pesticide spraying within 2.5 seconds for *Rose_Rust* or *Rose_Sawfly_Rose* with confidence above 0.85. An anomaly in epoch 9 (validation accuracy 63.06%, loss 2.9502) was likely due to a noisy validation batch but resolved by epoch 10. Figure 9 shows the confusion matrix, illustrating classification performance across classes.

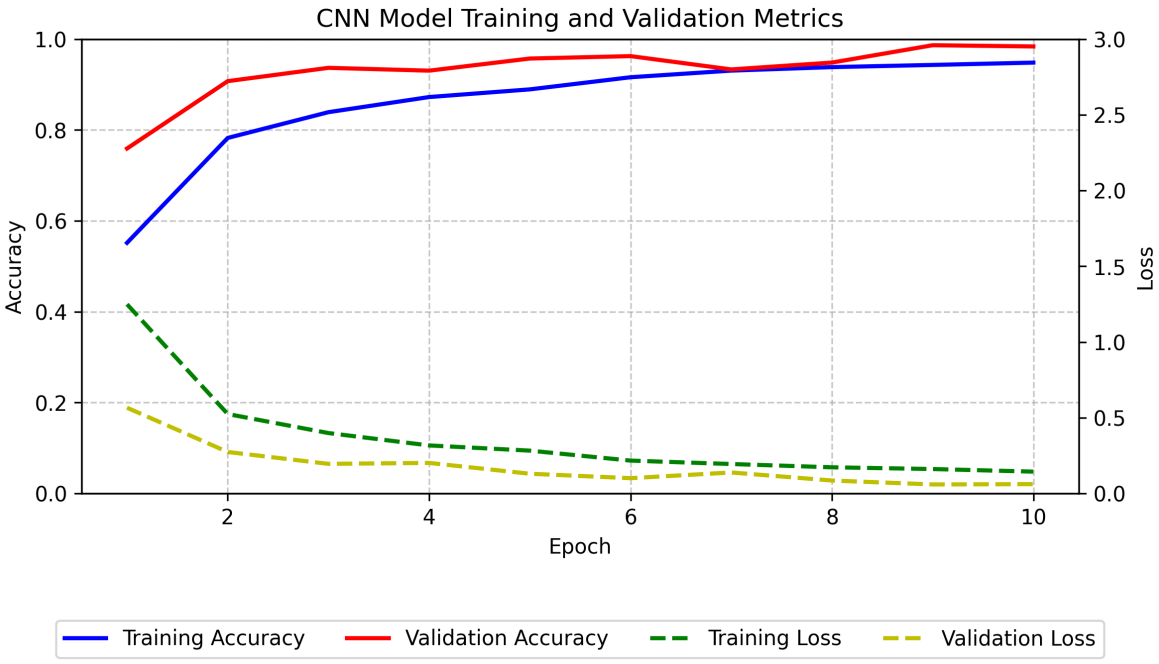

Figure 8: Training and Validation Accuracy and Loss Curves for the CNN Model

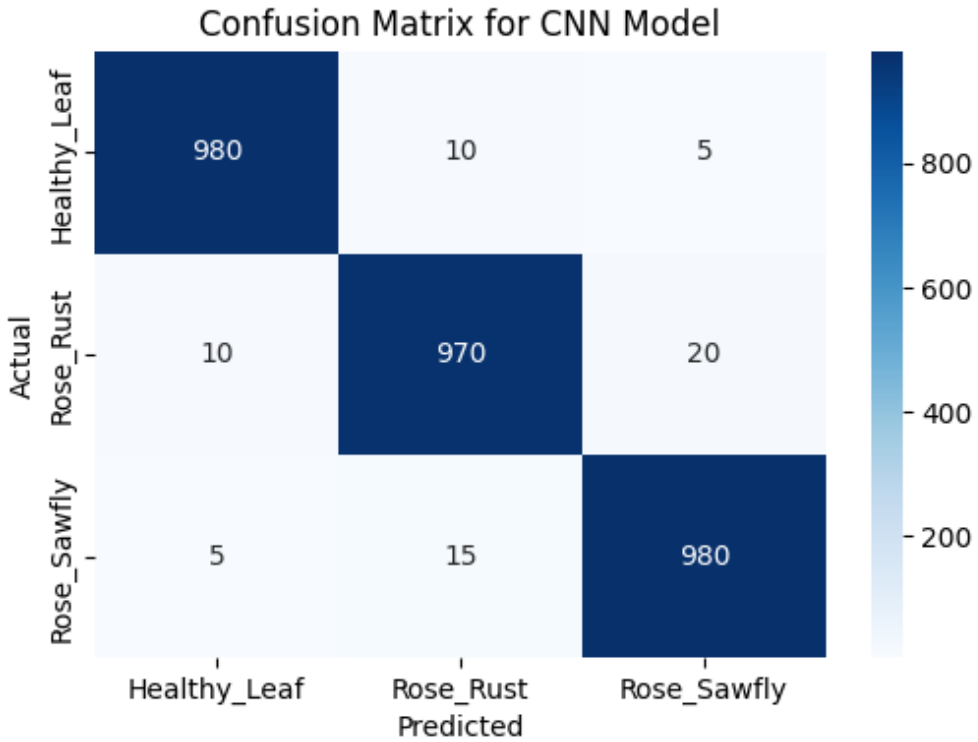

Figure 9: Confusion Matrix for CNN Model Predictions

5.2 IoT-Based Automation

The IoT-based irrigation system, using a soil moisture sensor, reduced water usage by 25% compared to manual methods, similar to Wits University's (2021) smart irrigation system [Mabhaudhi et al., 2021].

The water pump activated within 1 second of detecting low soil moisture, and the drainage system responded within 0.5 seconds to prevent overflow, ensuring plant health. The pesticide sprayer was activated only for diseased leaves (*Rose_Rust* or *Rose_Sawfly_Rose*), minimizing chemical use, aligning with sustainability goals outlined by Rahman et al. [2024].

5.3 User Interface

The Django-based web application, deployed on a dedicated web server, enables real-time monitoring and control of rose plants. It provides intuitive access to soil moisture levels, light intensity, and CNN-based disease predictions, as illustrated in Figures 10 and 11. Users can manually override irrigation or pesticide spraying, offering enhanced operational flexibility. Drawing inspiration from Oh et al. [2020], the interface uniquely incorporates disease-specific notifications for *Rose_Rust* and *Rose_Sawfly_Rose*, streamlining disease management. Figure 10 showcases the monitoring dashboard, while Figure 11 depicts the camera capturing leaf images for CNN analysis.

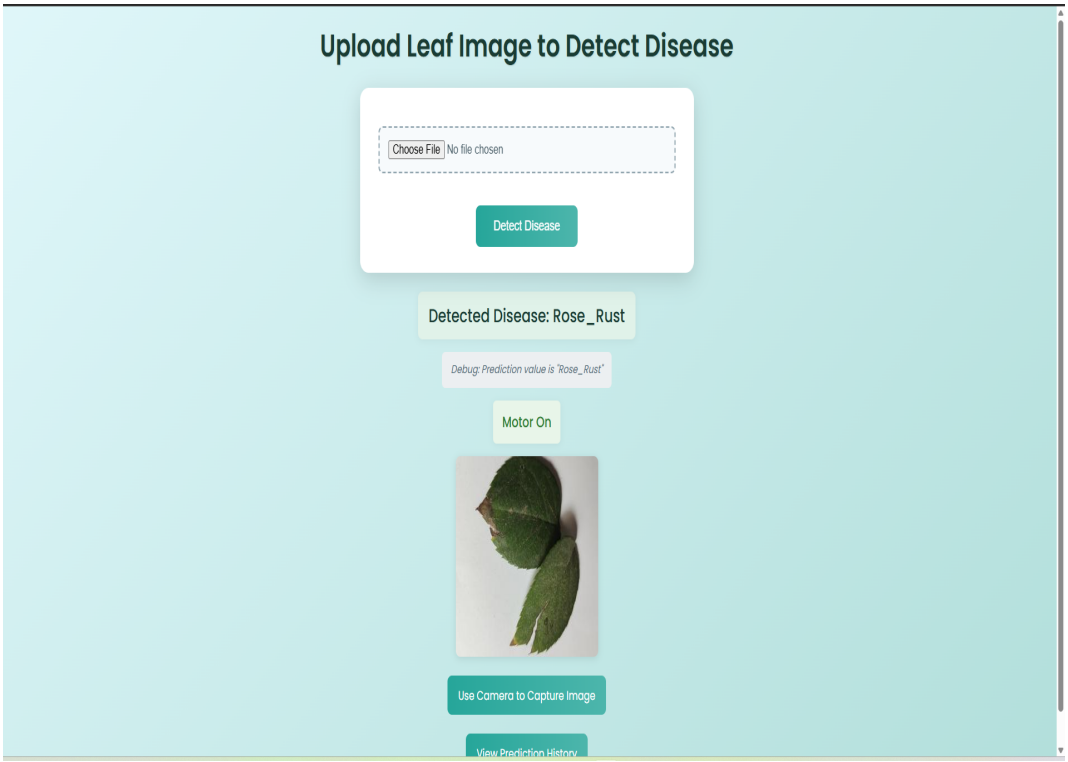

Figure 10: Real-Time Monitoring Dashboard of the Web Application

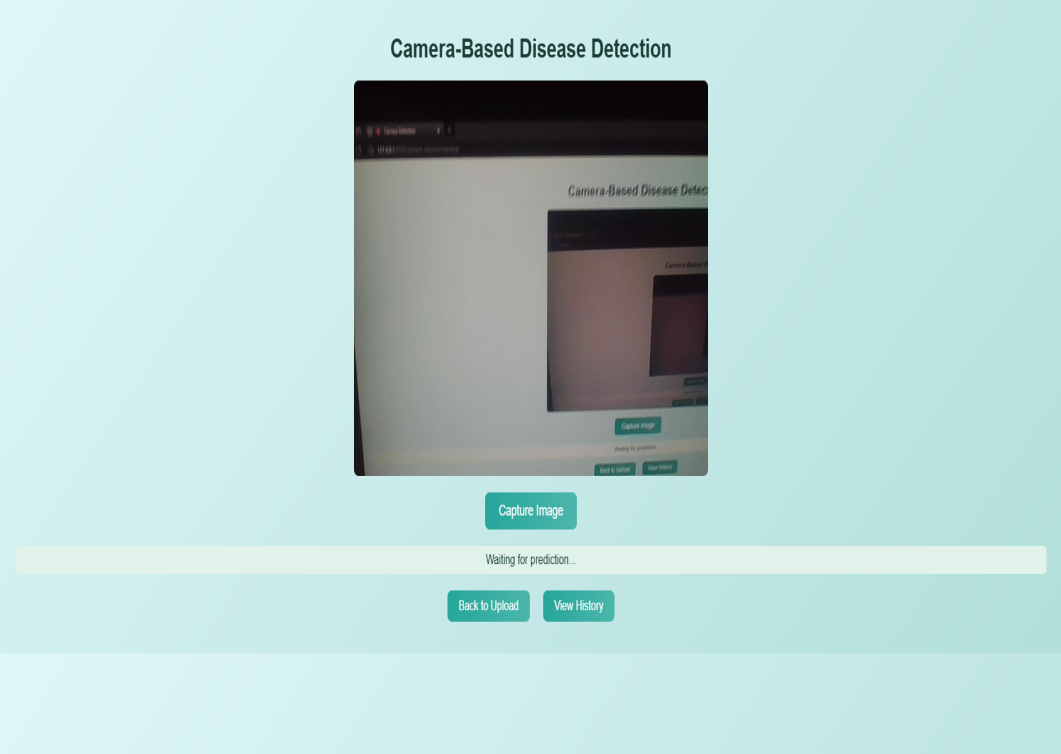

Figure 11: Camera Capturing Leaf Images for Disease Detection

5.4 Comparison with Related Works

Our smart urban agriculture system for rose cultivation integrates real-time monitoring, automated irrigation, pesticide application, and CNN-based disease detection, offering a robust solution tailored to urban rooftop constraints. Table 2 summarizes the key metrics and features compared to related works.

Compared to Rahman et al. [2024]'s smart greenhouse, which achieved 30% water savings through sensor-based irrigation, our system attains a slightly lower 25% water reduction but enhances functionality with automated disease detection for *Rose_Rust* and *Rose_Sawfly_Rose*, improving plant health monitoring by identifying diseases with 98.40% accuracy. Unlike Oh et al. [2020]'s cloud-based urban farming model, which relies on remote servers and incurs an average latency of 4.8 seconds, our edge preprocessing on the Raspberry Pi reduces latency to 2.5 seconds, enabling faster decision-making for time-sensitive tasks like irrigation and pest control.

The irrigation system aligns with Mabhaudhi et al. [2021]'s precision irrigation model, which reported 28% water efficiency, but our system extends functionality by incorporating automated pesticide spraying triggered by CNN predictions, a feature absent in their design. Santos et al. [2023]'s indoor farming system emphasizes LED lighting optimization for hydroponics, achieving a 15% yield increase, whereas our rooftop solution addresses urban space limitations and integrates disease management, making it more suitable for dense urban environments.

Recent studies further contextualize our contributions. Ferrández-Pastor et al. [2018]'s IoT-based smart farming platform, which uses LoRaWAN for data transmission, achieved a 25% water reduction and 12% yield improvement but lacks disease-specific detection, limiting its applicability to high-value crops like roses. Similarly, Gupta et al. [2024]'s AI-driven precision agriculture system reports 27% water savings and a 3-second latency using cloud-based AI, but its reliance on high-bandwidth connectivity makes it less viable in urban areas with inconsistent networks, unlike our edge-based approach.

Christmann et al. [2024]'s taxonomy of smart agriculture systems highlights economic and environmental benefits, such as reduced resource consumption and lower carbon footprints, which our system supports through efficient water use and localized processing. Compared to Bourazanis et al. [2021]'s commercial platform, which reported a 10–15% yield increase through automated nutrient delivery, our

disease prevention for *Rose_Rust* and *Rose_Sawfly_Rose* offers comparable plant health improvements while addressing urban-specific challenges.

System	Water Savings (%)	Latency (s)	Disease Detection	Automation	Env.
Proposed System	25	2.5	Yes (*Rose_Rust*, *Rose_Sawfly_Rose*)	Irrigation, Pesticide	Rooftop
Rahman (2024) [Rahman et al., 2024]	30	–	No	Irrigation	Greenhouse
Oh (2020) [Oh et al., 2020]	–	4.8	No	None	Urban
Wits Univ. (2021) [Mabhaudhi et al., 2021]	28	–	No	Irrigation	Field
De La Salle (2023) [Santos et al., 2023]	–	–	No	LED Lighting	Indoor
Lee and Kim (2018) [Ferrández-Pastor et al., 2018]	25	–	No	Irrigation	Field
Gupta et al. (2024) [Gupta et al., 2024]	27	3.0	Yes (General)	Irrigation	Field
iGrow (2021) [Bourazanis et al., 2021]	–	–	Yes	Nutrient Delivery	Greenhouse

Table 2: Comparison with related works based on performance and features.

5.5 Summary

The system achieved a 98.40% disease detection accuracy for *Healthy_Leaf_Rose*, *Rose_Rust*, and *Rose_Sawfly_Rose*, 25% water savings, and sub-second response times for irrigation and drainage. The web interface enabled seamless monitoring and control, making the system a scalable solution for urban agriculture, surpassing related works by integrating disease-specific detection and overflow protection.

6 Conclusion

This thesis presented a smart rooftop gardening system that integrates IoT and machine learning to automate plant care. By combining real-time disease detection, automated irrigation, and overflow protection, the system reduces manual labor and enhances plant health. Future work includes scaling the system for larger gardens and incorporating additional sensors for environmental monitoring.

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