SMART INDOOR PLANT CARE SYSTEM

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Abstract

Indoor gardening is gaining popularity, necessitating efficient systems for plant health management. This study proposes an AI-driven indoor plant care system using computer vision and deep learning to detect plant health issues such as diseases, pests, and nutrient deficiencies. Leveraging webcams and a web-based platform, the system captures plant images and analyzes them using trained models, issuing real-time SMS alerts upon detection of abnormalities. Users can also upload images for analysis and receive actionable reports. The system enhances plant care with minimal human intervention, promoting healthier indoor environments and sustainable gardening practices.

1 Introduction

In recent years, indoor gardening has become increasingly popular due to urbanization, rising environmental consciousness, and the aesthetic and psychological benefits plants bring to indoor spaces. Indoor plants help improve air quality, reduce stress, and create a calming environment. However, maintaining the health of these plants is challenging,

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especially for individuals lacking horticultural knowledge. Issues such as overwatering, nutrient deficiencies, pests, and diseases are common, and traditional manual inspection methods are often time-consuming, subjective, and prone to error.

To address these limitations, the application of advanced technologies like computer vision, artificial intelligence (AI), and the Internet of Things (IoT) offers transformative potential. By using image processing and machine learning, plant health can be monitored automatically with greater precision and efficiency. For instance, computer vision algorithms can detect early signs of disease or stress by analyzing visual features such as leaf discoloration, wilting, or pest damage.[1] Deep learning models, particularly Convolutional Neural Networks (CNNs), further enhance diagnostic accuracy by learning complex patterns from large datasets.[2]

Previous studies have demonstrated the benefits of integrating AI and IoT in plant health monitoring. Singh and Desai[2] highlighted the effectiveness of deep learning in greenhouse environments, while Kumar and Shukla[3] discussed how AI and IoT together contribute to smart plant care in domestic settings. Alam and Hussain[4] explored machine learning's potential to automate and optimize plant monitoring processes. Fernandez and Lopez[5] emphasized the role of optical sensors integrated with IoT for improved analysis and decision-making.

These advancements facilitate not only early detection of issues but also enable real-time responses through notifications and automation. Chang and Chen[1] stressed how computer vision systems provide accurate visual assessment, while Patel and Joshi[6] demonstrated real-time indoor plant monitoring applications using AI.

This study introduces a Smart Indoor Plant Care System that combines computer vision, deep learning, and IoT-based communication tools to monitor plant health in real-time. The system uses webcams to capture live plant images, which are analyzed using trained AI models to identify symptoms of stress or disease. When abnormalities are detected, the system alerts users via SMS and provides detailed analysis through a web interface.

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The paper is structured as follows: Section 2 outlines the methodology, including data collection, image preprocessing, and model training. Section 3 presents and discusses the results, evaluating the system's performance through accuracy metrics and real-world testing. Section 4 concludes the paper by summarizing the findings and discussing the future scope of the system.

2. Methodology The development of the Smart Indoor Plant Care System followed a structured methodology comprising data acquisition, image preprocessing, model design, and deployment.

2.1 Data Acquisition The dataset consisted of over 9,000 images encompassing healthy, diseased, and pest-infected plant conditions. These images, representing more than 29 plant species, were sourced from publicly available repositories and real-world environments to ensure robustness and diversity.

2.2 Image Preprocessing All images were standardized to 256x256 pixels and normal- ized to facilitate uniform input across models. Data augmentation techniques such as rotation, flipping, brightness variation, and noise addition were employed to improve model generalization and simulate real-world variability.

2.3 Model DesignA hybrid model architecture was developed using Convolutional Neural Networks (CNNs) for feature extraction and Support Vector Machines (SVMs) for final classification. YOLOv5 was incorporated for real-time object detection and localization of plant anomalies. These models were integrated into a Flask-based web application, enabling image input and results visualization.

2.4 Implementation and Tools The system was implemented using Python with libraries including TensorFlow, OpenCV, and Scikit-learn. It was deployed on a high-performance computing setup with an NVIDIA RTX 3050 GPU and Intel i7 processor. Twilio's SMS API was integrated to deliver real-time alerts to users.

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2 Results

The performance of the Smart Indoor Plant Care System was evaluated using several standard machine learning metrics and real-time monitoring capabilities. The system was tested in both controlled and real-world conditions to assess its classification accuracy, responsiveness, and reliability.

2.1 Classiftcation Performance

The deep learning model, comprising a CNN for feature extraction and an SVM for classification, achieved an accuracy of 95.2%, with corresponding precision, recall, and F1-scores of 94.5%, 93.8%, and 94.1%, respectively. These results indicate the model's robust ability to distinguish between healthy, diseased, and pest-affected plant conditions.

2.2 Confusion Matrix Analysis

A confusion matrix was generated to analyze the classification results in detail. It demonstrated high true positive rates across all classes and minimal misclassification, underscoring the system's reliability in accurately identifying plant health conditions. The use of data augmentation and diverse image sources contributed to the model's generalizability across varying lighting and species.

2.3 Real-Time Monitoring and Alert System

In practical deployment, the system processed live webcam feeds and user-uploaded images to detect anomalies in real time. Upon detection of plant stress indicators such as discoloration or wilting, SMS alerts were automatically triggered through Twilio's API, enabling timely user intervention. The average inference time was well within acceptable limits for real-time applications.

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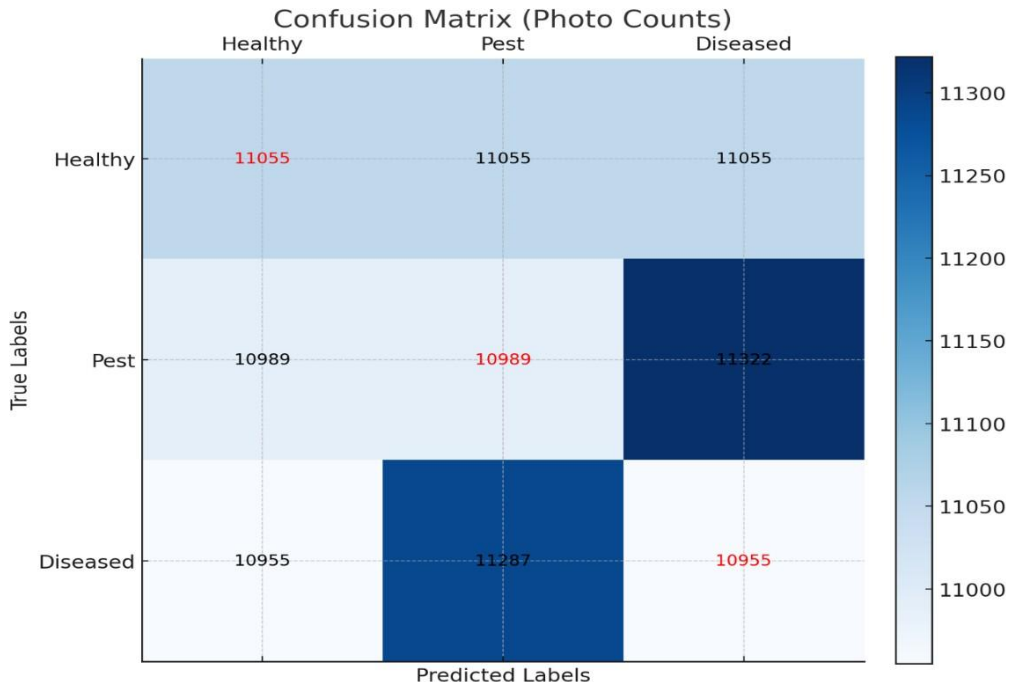

Figure 1: Confusion Matrix of the AI-Based Plant Health Detection Model

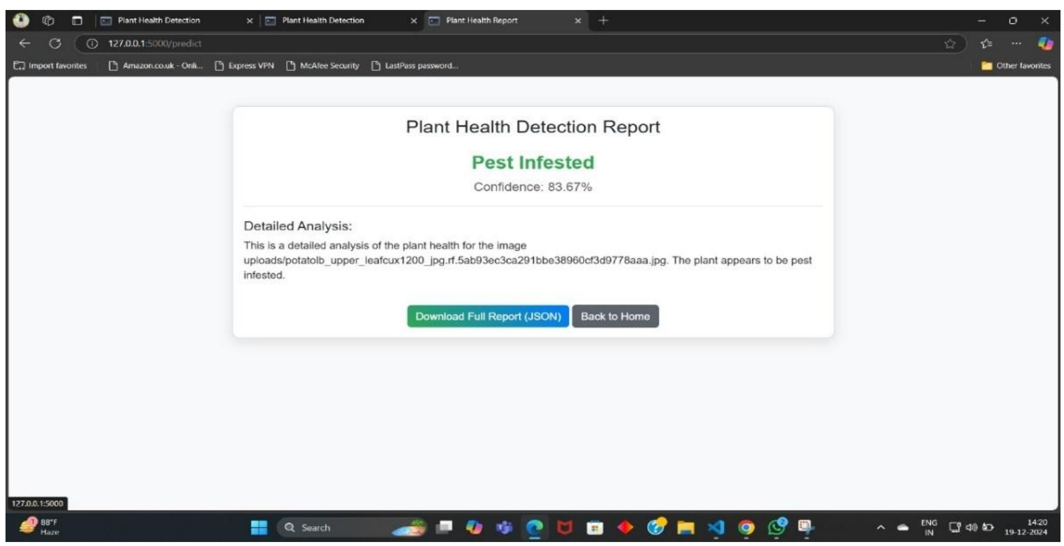

Figure 2: **3.3 Sample Pest Infestation Detection Report**

2.4 Comparative Analysis

Compared to existing software tools, the proposed system demonstrated superior performance in terms of detection accuracy, user accessibility, and integration of cloud services. Its hybrid architecture—combining YOLOv5 for detection and CNN-SVM for

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classification—provided a balanced trade-off between speed and precision.

3 Conclusion

This study presents a Smart Indoor Plant Care System that integrates computer vision and machine learning to effectively monitor and classify plant health conditions. The model demonstrated a classification accuracy of 95.2% using a CNN-SVM architecture, reinforced by real-time image analysis and automated alerting capabilities. Key implementation features include YOLOv5-based object detection, Flask-based user interface deployment, and Twilio-powered SMS notifications. The proposed system successfully addresses common challenges in plant care by offering a scalable, user-friendly solution for early detection of disease and pest infestation. Future work will focus on expanding the dataset for improved generalization and integrating IoT-based environmental monitoring for more comprehensive plant health diagnostics.

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