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A UMV Framework for a Rose Plant and Flower Disease Identification System

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Abstract:

In order to properly diagnose rose leaf illnesses, this study offers a hybrid detection and classification framework that combines cutting-edge machine learning (ML) algorithms with Internet of Things (IoT) sensing technologies. This research employs Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and ensemble techniques to produce a scalable, real-time system that focuses on early mildew detection and broader illness categorization, building on and refining the methods from two foundational studies. The goal is to increase rose crop output and reduce losses by bridging the gap between computational disease recognition accuracy and real-world agricultural sensor deployment.

Introduction

The global floriculture sector depends heavily on the production of healthy roses, which is continuously challenged by a number of illnesses, particularly mildew. The emergence of artificial intelligence and precision agriculture has created opportunities to lessen these risks. One study uses Internet of Things (IoT) sensors to identify mildew in real time, while the other uses deep learning-powered image-based smart diagnostic systems to classify various rose leaf illnesses. These two research offer different but complimentary approaches. This study offers a thorough strategy that combines the two methods to provide a reliable hybrid solution.

LITERATURE REVIEW

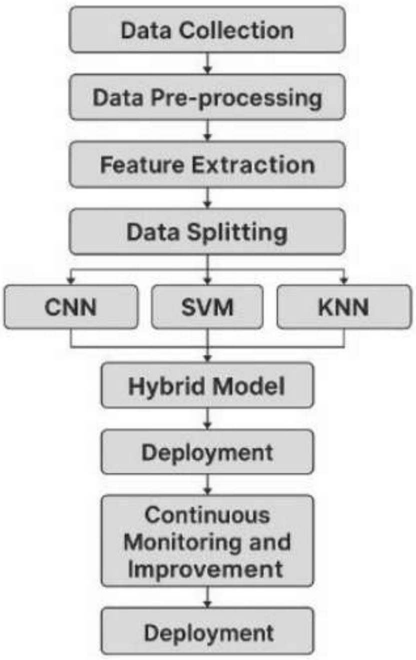
In order to forecast the development of powdery mildew, the Internet of Things-based project uses feed-forward neural networks to install temperature and humidity sensors in greenhouses. In contrast, a CNN-based image classification pipeline is developed in the second study and trained on a labeled dataset of sick rose leaves. It emphasizes how well CNNs perform in comparison to more conventional ML classifiers like Random Forest and k-NN.

Important drawbacks of both include:

The reliance of IoT models on constrained environmental characteristics. The dependence of image-based models on optimal imaging circumstances. Therefore, integrating visual and real-time sensor data fills in these gaps and strengthens illness detection systems.

Methodology

Though their scopes and technological integrations vary, both research stress methodical processes for illness identification.



2.1 IoT-Enabled System: This system consists of sensor nodes that have ESP32 microcontrollers that send environmental data over Wi-Fi, a light sensor (TSL2561), and temperature and humidity sensors (DHT22). This arrangement keeps an eye on factors that can lead to the development of downy mildew, especially persistently high relative humidity (>85%). Additionally, a web-based interface enables the uploading of images that are classified using CNNs.

2.2 Hybrid Machine Learning System: The hybrid model uses sophisticated preprocessing techniques like segmentation, augmentation, and noise reduction. Both manually developed techniques (such LBP and edge detection) and pre-trained CNN architectures (like VGG16 and ResNet50) are used to extract features.

These characteristics are fed into SVM and KNN classifiers, whose outputs are aggregated using ensemble methods such as weighted averaging and majority voting to increase accuracy.

Data acquisition and preprocessing

The significance of high-quality datasets is emphasized in both studies. 200 photos of both healthy and diseased leaves were taken in both controlled and outdoor settings for the IoT study. Multiple illness types were included in the hybrid approach's datasets, which were annotated by specialists to guarantee validity. The key to increasing model resilience was image preprocessing, which included background segmentation, noise removal, scaling, and normalizing.

Feature Extraction and model traning:

Because CNNs can automatically learn spatial hierarchies from visual data, they are essential to both feature extraction and model training. Using picture datasets, the IoT-based system trained four CNN variations, obtaining an overall accuracy of 64% with ShallowNet and 68% with MiniVGGNet. The hybrid system employed CNNs as feature extractors and combined their outputs with SVM and KNN classifiers. SVM showed superior precision (0.75), while CNN achieved perfect recall (1.00) on diseased samples, emphasizing its ability to minimize false negatives.

System Architechture and Deployment:

The IoT system has a strong architecture that includes:

- Sensor nodes for gathering data in real time
- A central application server that makes use of Flask and ASP.NET
- Sensor data and picture categorization results are stored in a SQL Server database.

- A user interface with dashboard, alert, and report modules

Meanwhile, the hybrid model is deployed via:

- A Flask API backend for real-time predictions.
- A cloud-hosted (AWS) model inference layer.
- A mobile and web interface for user accessibility.

Performance Evaluation:

Accuracy, precision, recall, F1-score, and confusion matrices were all used by each system as comprehensive evaluation measures.

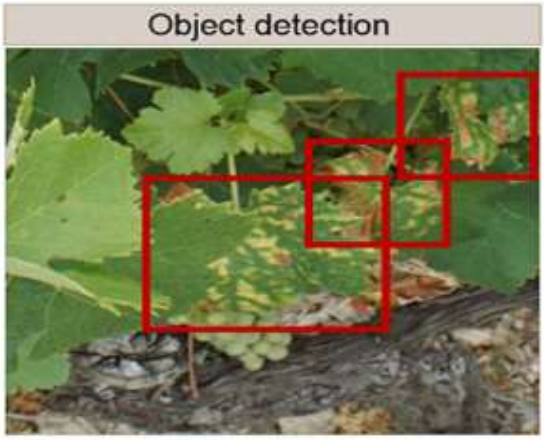
IoT System Results:

MiniVGGNet: 68% Accuracy, 0.75 Precision, and 0.55 Recall.The best model demonstrated validation accuracy of 59% and training accuracy of >89%. It has been established that one important environmental determinant for the emergence of downy mildew is relative humidity.

Hybrid System Results:

CNN: Recall 1.00, Accuracy 60% (for ill class)

SVM: 60% Accuracy, 0.75 Precision
KNN: F1-score 0.62, accuracy 50%
Consistency across class boundaries was enhanced by ensemble approaches.



Observations:

Both approaches highlight AI's benefits and drawbacks in managing diseases in floriculture. By establishing a correlation between environmental factors and the occurrence of disease, the CNN-based Internet of Things method proved to be useful in actual greenhouse environments. But it was only able to classify things into two categories: healthy and downy mildew. The hybrid model, on the other hand, did not have real-time environmental connection but dealt with multiclass classification with a wider range of diseases.

Combining the two approaches is a potential path. A more complete and scalable solution can be achieved by combining the high-resolution disease categorization of the hybrid model with the ambient sensing of the IoT system. In order to maximize resource usage and reduce plant loss, environmental abnormalities (such as increases in humidity) may, for instance, prompt intense picture analysis or early alerts.

Conclusion

For the diagnosis of rose leaf disease, this synthesis shows a potent synergy of IoT, image processing, and machine learning. While SVMs provide greater precision and KNN provides interpretability, CNNs are good at identifying subtle illness features. Contextual information from IoT data is essential for enhancing image-based predictions. Future Scope:

Increase the number of rose kinds and geographic conditions in datasets. For adaptable models, combine active learning and transfer learning. Use federated learning to use data in a way that protects privacy. Improve mobile integration to empower farmers and provide on-site diagnosis. When combined, these tactics have the potential to revolutionize disease surveillance in ornamental horticulture andsupport the accuracy, efficiency, and sustainability objectives of precision agriculture.

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