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Crop Disease Detection and Automatic Removal Using Deep Learning and IoT-Based Smart Spraying System

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Abstract: Agriculture plays a crucial role in global food security and economic sustainability. However, plant diseases significantly affect crop productivity and quality, leading to substantial economic losses. Early detection and timely treatment of crop diseases are essential for sustainable farming practices. This research proposes an intelligent crop disease detection and automatic spraying system using Deep Learning and Internet of Things (IoT) technologies.

The proposed system utilizes a Convolutional Neural Network (CNN) model to identify diseases from crop leaf images captured through a camera module. Once a disease is detected, a Raspberry Pi-based controller activates a smart spraying mechanism that applies pesticides only to infected regions. This precision spraying approach minimizes pesticide consumption and reduces environmental impact.

Experimental evaluation using the PlantVillage dataset demonstrated a disease classification accuracy of 94.8%. Furthermore, the proposed system reduced pesticide usage by approximately 35% compared to traditional manual spraying methods. The system contributes to smart agriculture by improving disease monitoring, reducing labor dependency, and enhancing crop productivity.

Keywords: Crop Disease Detection, Deep Learning, Convolutional Neural Networks, IoT, Smart Agriculture, Precision Spraying

I. INTRODUCTION

Agriculture is the backbone of many economies and plays a crucial role in ensuring global food security. A large percentage of the world's population depends directly or indirectly on agriculture for livelihood and economic stability. However, crop production is severely affected by various plant diseases caused by fungi, bacteria, viruses, and environmental conditions. These diseases reduce crop quality, decrease agricultural productivity, and result in significant economic losses for farmers every year. Therefore, early detection and effective treatment of crop diseases are essential for improving crop yield and ensuring sustainable agricultural development.

Traditionally, crop disease identification is performed through manual observation by farmers or agricultural experts. Although this method is widely used, it has several limitations. Manual inspection is time-consuming, labor-intensive, and highly dependent on expert knowledge. In large agricultural fields, continuous monitoring becomes difficult and often leads to delayed disease detection. Furthermore, excessive and uncontrolled use of pesticides during manual treatment increases production costs and causes harmful environmental effects such as soil degradation and water pollution.

Recent advancements in Artificial Intelligence (AI), Deep Learning (DL), and the Internet of Things (IoT) have introduced new opportunities for modernizing agricultural practices. Among various deep learning techniques, Convolutional Neural Networks (CNNs) have shown remarkable performance in image classification and object recognition tasks. CNN-based models can automatically learn important visual features from leaf images and accurately identify plant diseases without the need for manual feature extraction. At the same time, IoT technologies enable real-time monitoring, automation, and smart control of agricultural equipment.

This research proposes a smart agriculture system for Crop Disease Detection and Automatic Removal using Deep Learning and IoT-based precision spraying technology. The proposed system captures crop leaf images using a camera module and processes them using a CNN-based disease classification model. Once a disease is detected, a Raspberry Pi-based microcontroller automatically activates a smart spraying mechanism to apply pesticides only to infected areas. This targeted spraying approach reduces unnecessary pesticide usage, minimizes environmental impact, and lowers labor costs.

The proposed system combines image processing, deep learning, embedded systems, and IoT technologies to create an efficient and automated disease management solution for modern agriculture. The system aims to improve disease detection accuracy, enhance crop monitoring efficiency, and promote sustainable farming practices. Experimental evaluation using the PlantVillage dataset demonstrates that the proposed CNN model achieves high classification accuracy while significantly reducing pesticide consumption compared to traditional spraying methods.

1.1 Population and Sample

Population

In this research, the population consists of all crop leaf images belonging to healthy and diseased plant categories used for crop disease identification. The study mainly focuses on crop species such as:

1.Tomato
2.Potato
3.Corn

The population includes images of leaves affected by different plant diseases caused by fungi, bacteria, and viruses, along with healthy leaf samples collected from the PlantVillage dataset and real-time field conditions.

Sample

The sample used in this study was selected from the PlantVillage dataset, which contains more than 20,000 labeled crop leaf images. From this dataset, a subset of images was used for training and testing the CNN model.

Sample Distribution

Dataset Category	Percentage
Training Sample	70%
Validation Sample	15%
Testing Sample	15%

The selected sample includes:

i)Healthy leaf images
ii)Diseased leaf images
iii)Multiple crop varieties
iv)Different disease categories

The sampling technique used in this research is random sampling, ensuring that images from all disease classes are included to improve model generalization and classification accuracy.

1.2 Data and Sources of Data

Data Used in the Research

The research utilizes image-based agricultural data for crop disease detection and automated smart spraying. The primary data consists of digital images of healthy and diseased crop leaves collected for training, validation, and testing of the Convolutional Neural Network (CNN) model.

The dataset contains images from multiple crop categories, including:

1.Tomato

2.Potato
3.Corn

The images include various plant disease classes such as:

i)Early Blight
ii)Late Blight
iii)Leaf Mold
iv)Bacterial Spot
v)Healthy Leaves

The collected data was used to train the deep learning model to accurately identify crop diseases and trigger the automated pesticide spraying mechanism.

Sources of Data

i. Primary Data Source

Primary data refers to real-time data collected directly from the agricultural environment using hardware devices integrated into the proposed system.

Primary Data Includes:

- Live crop leaf images captured using the Pi Camera Module
- Sensor readings from IoT devices
- Real-time disease detection outputs
- Smart spraying activation records

The real-time images were captured through the camera connected to the Raspberry Pi module during field testing and system implementation.

ii. Secondary Data Source

Secondary data was collected from publicly available agricultural datasets and research resources.

2. Theoretical framework

Theoretical Framework

The theoretical framework of this research is based on the integration of **Deep Learning**, **Computer Vision**, and **Internet of Things (IoT)** technologies for intelligent crop disease detection and automated pesticide spraying. The framework explains the relationship between image processing, disease classification, and automated treatment mechanisms used in the proposed smart agriculture system.

1. Conceptual Basis of the Study

The study is founded on the idea that crop diseases can be identified through visual symptoms present on plant leaves. Deep learning algorithms, especially Convolutional Neural Networks (CNNs), can automatically learn disease-related patterns from leaf images and classify them accurately.

Once the disease is detected, IoT-enabled hardware components can automatically activate a smart spraying mechanism to apply pesticides only to infected areas.

The framework combines:

- Artificial Intelligence (AI)
- Deep Learning (CNN)
- Image Processing
- IoT-Based Automation
- Precision Agriculture

3.Equations Used in the Proposed System

3.1. Convolution Operation

The convolution operation is the core mathematical function used in Convolutional Neural Networks (CNNs) for feature extraction from crop leaf images.

$$S(i,j) = (I * K)(i,j) = \sum_{m} \sum_{n} I(m,n) \cdot K(i-m, j-n)$$

Where:

- I= Input image
- K= Kernel / Filter
- $S(i,j)$= Output feature map

This equation helps detect important disease features such as spots, discoloration, and texture changes on leaves.

3.2. ReLU Activation Function

The Rectified Linear Unit (ReLU) introduces non-linearity into the CNN model.

$$f(x) = \max(0, x)$$

Explanation:

- If $x > 0$, output = x
- If $x \leq 0$, output = 0

ReLU improves training speed and prevents vanishing gradient problems.

3.3. Max Pooling Operation

Max pooling reduces image dimensions while preserving important features.

$$M = \max(x_1, x_2, x_3, \ldots, x_n)$$

Where:

- M= Maximum value selected from pooling region

This reduces computational complexity and overfitting.

3.4. Softmax Function

The Softmax function converts CNN outputs into probability values for disease classification.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Where:

- $P(y_i)$= Probability of class i
- z_i= Output score of class i
- n= Number of classes

The class with the highest probability is selected as the predicted disease category.

3.5. Categorical Cross-Entropy Loss Function

Used to measure prediction error during CNN training.

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)$$

Where:

- L= Loss value
- y_i= Actual class label
- $\hat{y}_i$= Predicted probability

Lower loss values indicate better model performance.

4.RESEARCH METHODOLOGY

The research methodology describes the systematic procedures and techniques used to develop the proposed Crop Disease Detection and Automatic Removal System using Deep Learning and IoT technology. The methodology includes data collection, preprocessing, model development, hardware integration, testing, and performance evaluation.

4.1. Research Design

The study follows an experimental and implementation-based research design. The research focuses on developing a smart agriculture system capable of:

- Detecting crop diseases using deep learning techniques
- Automatically activating a smart pesticide spraying mechanism
- Monitoring crop health using IoT technology

The system integrates software and hardware components to achieve automated disease management.

4.2. Data Collection

The dataset used in this research was collected from both primary and secondary sources.

4.2.1 Primary Data

Primary data includes:

- Real-time crop leaf images captured using a Pi Camera Module
- Sensor readings from IoT devices
- Automated spraying response data

4.2.2 Secondary Data

Secondary data was obtained from:

- PlantVillage Dataset
- Research journals and scientific publications
- TensorFlow and OpenCV documentation

The PlantVillage dataset contains more than 20,000 labeled crop leaf images from different crop categories and disease classes.

4.3. Population and Sample

Population

The population consists of all healthy and diseased crop leaf images related to tomato, potato, corn, and other agricultural crops.

Sample

A sample of 20,000+ labeled images was selected from the PlantVillage dataset.

Dataset Distribution

Dataset Type	Percentage
Training Data	70%
Validation Data	15%
Testing Data	15%

Random sampling was used to ensure equal representation of all disease categories.

4.4. Data Preprocessing

Before training the CNN model, the images underwent preprocessing to improve classification accuracy.

Preprocessing Techniques

- Image resizing to 128 × 128 pixels
- Image normalization
- Data augmentation:
  - Rotation
  - Horizontal flipping
  - Zooming

These techniques improve model generalization and reduce overfitting.

4.5. Deep Learning Model Development

The proposed system uses a Convolutional Neural Network (CNN) for crop disease classification.

CNN Architecture

The CNN model includes:

- Convolutional layers
- ReLU activation function
- Max pooling layers
- Fully connected layers
- Softmax output layer

Training Parameters

Parameter	Value
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Epochs	25
Batch Size	32
Learning Rate	0.001

4.6. Hardware Implementation

The hardware system was developed using IoT devices and smart spraying components.

Hardware Components

Component	Function
Raspberry Pi 4	Main controller
Pi Camera Module	Image capturing
Relay Module	Pump control
Water Pump	Pesticide spraying
Nozzle Sprayer	Precision spraying
Pesticide Tank	Chemical storage

The Raspberry Pi processes the CNN model output and activates the smart spraying system when disease is detected.

4.7. Software Tools and Technologies

The following software tools were used:

Software	Purpose
Python	Programming
TensorFlow/Keras	CNN model training
OpenCV	Image processing
Flask	Web dashboard development

4.8. System Workflow

The working process of the proposed system follows these steps:

1. Crop leaf images are captured using the camera module.
2. Images are preprocessed through resizing and normalization.
3. The CNN model analyzes the image.
4. The system classifies the leaf as healthy or diseased.
5. If disease is detected:
    - Raspberry Pi activates the relay module
    - Smart sprayer applies pesticide only to infected regions
6. Results are stored in the cloud monitoring dashboard.

4.9. Performance Evaluation

The performance of the CNN model was evaluated using standard classification metrics.

Evaluation Metrics

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

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5. RESULTS AND DISCUSSION

The proposed CNN model achieved the following results:

Metric	**Value**
Accuracy	94.8%
Precision	93.5%
Recall	92.7%
F1-Score	93.1%

The automated spraying mechanism also reduced pesticide usage by approximately 35% compared to traditional spraying methods.

Comparative Analysis

The proposed CNN model was compared with traditional machine learning approaches.

Method	*Accuracy*
K-Nearest Neighbor (KNN)	*82%*
Support Vector Machine (SVM)	*85%*
Traditional CNN	*91%*
Proposed CNN Model	*94.8%*

The proposed CNN architecture outperformed conventional machine learning methods due to its automatic feature extraction capability and improved image classification performance.

7. Smart Spraying System Performance

The IoT-based smart spraying mechanism successfully applied pesticides only to infected crop regions.

Spraying Efficiency

Method	*Pesticide Usage*
Traditional Manual Spraying	*100%*
Proposed Smart Spraying System	*65%*

Pesticide Reduction Calculation

$$Pesticide\ Reduction = \frac{100 - 65}{100} \times 100$$
$$= 35\%$$

The experimental results demonstrate that the proposed system reduced pesticide consumption by approximately 35%.

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8. Discussion

The obtained results confirm that deep learning techniques are highly effective for crop disease classification. The CNN model accurately extracted disease-related features such as:

- *Leaf discoloration*
- *Spots and lesions*
- *Texture variations*
- *Shape abnormalities*

The integration of IoT-based automation improved the practical applicability of the system by enabling automatic pesticide spraying without human intervention.

The proposed system offers several advantages:

- *High disease detection accuracy*
- *Reduced labor requirements*
- *Lower pesticide consumption*
- *Real-time crop monitoring*
- *Environmentally sustainable farming practices*

The precision spraying mechanism also minimizes chemical wastage and reduces environmental pollution caused by excessive pesticide application.

However, certain limitations were observed during experimentation:

- *Performance depends on image quality and lighting conditions*
- *Field conditions may vary significantly from laboratory datasets*
- *Initial hardware setup cost is relatively high*

Despite these limitations, the proposed system demonstrates strong potential for large-scale smart agriculture applications.

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