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"NexGen AgriCare: Advancing Crop Resilience via Real-Time Disease Detection and IoT-Driven Results for Banana Crop

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I. ABSTRACT:

Banana cultivation is a cornerstone of global agriculture, offering both nutritional sustenance and economic stability to countless communities. However, the industry faces significant challenges, particularly from diseases like Panama Disease, which pose a grave threat to banana crops. In response to this urgent need, we introduce 'NexGen AgriCare,' a revolutionary system designed to enhance crop resilience through real-time disease detection. Our innovative approach integrates cutting-edge technologies, including Internet of Things (IoT) sensors, Google Cloud infrastructure, and sophisticated deep learning models such as the super-resolution convolutional network (SRCNN) and the pretrained MobileNet-V2.

By continuously monitoring crucial parameters in banana cultivation, our system ensures the real-time acquisition of data essential for assessing crop health. The validation and training of our model are conducted using the diverse PlantVillage dataset, which encompasses various instances of banana diseases across different environmental conditions, thereby enhancing the adaptability and robustness of our disease detection system.

The results of our experiment demonstrate the effectiveness of NexGen AgriCare in achieving precise and timely disease detection, thereby significantly contributing to enhanced crop resilience. The cloud-based architecture of our system not only ensures scalability but also provides farmers with immediate insights for implementing targeted interventions.

II. INTRODUCTION:

"NexGen AgriCare: Advancing Crop Resilience via Real-Time Disease Detection and IoT-Driven Results for Banana Crops" represents a transformative approach to banana cultivation, leveraging the MobileNet architecture for robust disease detection while fostering farmer-system interaction through a dedicated mobile application. By employing MobileNet's cutting-edge mobile vision capabilities and the super-resolution convolutional network (SRCNN), NexGen AgriCare empowers banana growers to quickly and accurately identify signs of diseases in their crops through image analysis of banana leaves.

This early disease detection is further complemented by real-time environmental monitoring facilitated by Raspberry Pi-based IoT devices, providing critical data on pH, humidity, temperature, moisture, and light levels. This information is seamlessly integrated into Google Cloud Services, offering comprehensive insights. Additionally, farmers can actively interact with the system via the mobile app, receiving timely alerts, actionable recommendations, and an avenue to report observations.

The synergy between advanced technology and farmer engagement equips banana farmers with the tools needed to make data-driven decisions, thereby optimizing crop management practices, ensuring healthier plantations, and increasing yields while safeguarding the sustainability of banana agriculture.

Banana cultivation, also known as the banana industry, is a significant sector of the global agro-business, as bananas are a rich source of essential minerals like calcium, manganese, potassium, magnesium, and iron. People worldwide consume this crop for its high vitamin content and reputation as an instant energy booster. About 15% of the world's banana production is exported to Western nations for consumption, according to Wikipedia.

According to banana import and production statistics, roughly 25.7% of the global supply comes from India. Other significant banana producers include the Philippines, Ecuador, Indonesia, and Brazil, which together contribute a combined 20% to the world's supply. The United States is the dominant importer among the 18 major banana-producing countries worldwide.

The impact of a banana tree becoming diseased due to infection and other climate changes can result in a 100% loss of banana imports and production globally. Black Sigatoka, Xanthomonas wilt, Panama wilt, and bunchy top virus are the four main diseases that commonly affect bananas. Therefore, in the future, we aim to develop healthier banana crops to mitigate these risks.

III. LITERATURE SURVEY:

Julie et al. employed a Hybrid Convolutional Neural Network (CNN) to classify banana plant diseases in their 2022 study. Their research focused on utilizing a hybrid CNN to facilitate the early detection of banana diseases, addressing the critical challenge of identifying diseases promptly to aid growers in prevention at an early stage. The proposed methodology demonstrated a 99% detection accuracy, outperforming existing deep learning approaches .

The paper "Disease Detection in Banana Trees Using an Image Processing-Based Thermal Camera" (2021) by H. Fitriawan explores the feasibility of using thermal cameras for detecting anomalies in banana crops. The study leverages multilevel thresholding methods in image processing, involving the capture of thermal images, their preprocessing, and positional data replication through an image enrollment procedure. The processed thermal images are compared to ground truth images obtained from digital cameras to evaluate the system's effectiveness. This innovative application of thermal imaging technology holds promise for improving banana crop monitoring and quality management in the agricultural sector .

Michael Gomez Selvaraj proposed a system that processes convolutional neural networks (DCNN) and transfer learning, which has been successfully applied in various fields and recently extended to just-in-time crop disease detection. The goal of this research is to develop an AI-based banana disease and pest detection system using a DCNN to support banana growers .

E. Mohanraj et al. developed a banana disease detection system using an advanced convolutional neural network (CNN) . The paper "Leaf Disease Detection in Banana Plant Using Gabor Extraction and Region-Based Convolutional Neural Network (RCNN)" (2022) by K. Seetharaman et al. offers improved image processing techniques for quicker banana leaf disease identification. The preprocessing of the images involves region-based edge normalization . Shajitha et al. proposed a banana disease detection system using a Graph Convolutional Neural Network (GCNN) .

N. Kanthimathi et al. proposed a system that detects conditions at an earlier stage using image processing and classifies them using an Artificial Neural Network (ANN) algorithm. The proposed system involves several steps, including image acquisition, image pre-processing, feature extraction, disease detection, and ANN-based classification . Chaudhari V. et al. proposed a disease detection system using the K-means clustering algorithm . Bruce Grieve et al. analyzed datasets for plant diseases .

The research paper "Detection and Classification of Diseases of Banana Plant Using Local Binary Pattern and Support Vector Machine" (2019) by Akshaya Aruraj proposed a system that uses image processing techniques and machine learning algorithms for the identification and classification of infections in plants. This work introduces texture pattern methods for the identification and classification of conditions in banana plants . E. Moupojou et al. suggested a dataset called FieldPlant , which includes 5,170 plant disease images collected directly from plantations.

Muqing Zhang offered a system that provides guidance for managing banana plantations and methods for identifying plant diseases . The review delves into the increasing role of deep learning in crop leaf disease identification, focusing on its applications in overcoming manual feature selection limitations and enhancing objectivity in plant disease recognition . Priyanka Sahu et al. conducted a systematic literature review of machine learning techniques deployed in agriculture .

IV. PROBLEM STATEMENT:

Banana cultivation is a vital agricultural sector in our region, but banana farmers face unique challenges. These challenges include the threat of diseases like Panama Disease and Black Sigatoka, the persistence of unscientific farming practices, and the vulnerability of banana crops to environmental factors. Furthermore, banana farmers often lack access to up-to-date information, hindering their decision-making process.

Our goal is to create NexGen AgriCare, a customized solution that integrates AI-driven disease diagnosis with deep learning models like the Super-Resolution Convolutional Network (SRCNN) and the pretrained MobileNet-V2 to address these problems. The proposed system uses the PlantVillage dataset and combines mobile vision for disease diagnosis, IoT sensors to track weather and soil conditions, and Google Cloud services for data processing and storage, enabling the sustainable expansion of banana crops.

The mobile application, an integral part of the system, provides real-time detection of diseases in banana plants, including insights on current soil conditions and weather. By seamlessly combining these technologies, NexGen AgriCare aims to empower banana farmers, enhance crop health, and secure the future of banana farming in our region while maintaining sustainability.

V. CONCEPTUAL MODEL OF NEXGEN AGRICARE SYSTEM

The detailed conceptual model of NexGen AgriCare presents a comprehensive view of the system, highlighting its key components and their intricate interactions:

1. **User Interface (Mobile Application):**

The user interface is a cross-platform mobile application accessible on both iOS and Android devices. It offers a user-friendly and intuitive interface for farmers and agricultural stakeholders.

2. **IoT Sensors:**
   IoT sensors in banana fields provide real-time data, including:
   - **Soil Moisture Sensors:** Track soil moisture for better irrigation management.
   - **Nutrient Sensors:** Measure soil nutrients to enable precise fertilization.
   - **Weather Stations:** Monitor temperature and humidity to provide weather insights.
   - **Cameras:** Capture crop images to assess health and detect diseases.
3. **Data Transmission:**

   Data collected by IoT sensors are transmitted to the central system via Google Cloud Pub/Sub. Real-time data transmission ensures timely updates.

4. **Disease Detection Module:**

   The disease detection module at the core of NexGen AgriCare utilizes advanced deep learning algorithms for image analysis and disease identification.

5. **Image Preprocessing:**

   Captured images undergo preprocessing to optimize their quality and size for deep learning analysis. This step includes resizing and enhancement to improve the image's suitability for feature extraction.

6. **Super-Resolution Enhancement (SRCNN):**

   The Super-Resolution Convolutional Neural Network (SRCNN) is applied to enhance image resolution. Enhanced images facilitate improved feature extraction, aiding in more accurate disease identification.

7. **Deep Learning Analysis (MobileNet-V2):**

   MobileNet-V2, a pretrained deep learning model, is employed for disease classification based on the analyzed images. It generates probability scores for different disease types, providing valuable diagnostic information.

8. **Disease Detection Logic:**

   The disease detection logic interprets the probability scores generated by MobileNet-V2 to determine whether a disease is present in the banana crops. The system identifies the specific disease type based on probability thresholds.

9. **Recommendations Engine:**

   The system's recommendations engine uses disease detection results and IoT data to provide personalized farming guidance, helping farmers take informed actions.

10. **Data Privacy and Security:**

    Strong encryption safeguards data during transmission and storage, ensuring user anonymity and compliance with privacy standards.

VI. IMPLEMENTATION

Step 1: Planning & System Design:
The system for banana crop disease detection is designed with IoT sensors to collect soil, weather, and crop health data. This data enhances the accuracy and timeliness of disease detection.

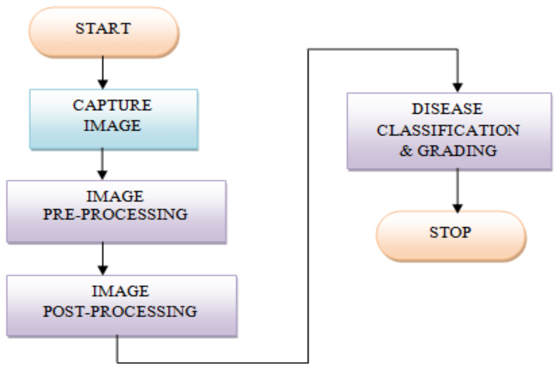

Fig. 1. Flow chart for disease detection and classification

Step 2: Hardware setup:Sensors with cameras are positioned for data collection. Soil moisture and weather sensors monitor environmental conditions.

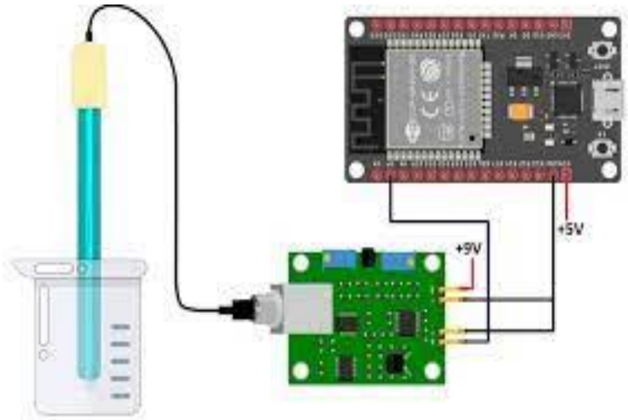

Fig.2. IOT sensor to measure PH level

Step 3: Mobile Application Development
The mobile application integrates with IoT sensors for image capture and real-time disease detection. Developed in Java, the app ensures user-friendliness in both image capture and accessing recommendations, providing farmers with actionable insights directly on their devices.

Step 4: Dataset Utilization
The integration of a diverse dataset from PlantVillage, comprising images of various banana diseases, played a crucial role in training the models—Super-Resolution Convolutional Neural Network (SRCNN) and MobileNet-V2. This dataset was also used to test accuracy and validate reliability under different environmental scenarios.

Step 5: Data Collection from IoT Sensors

1. **Soil Moisture Sensors (Decagon GS3):**
    - Strategically placed for continuous monitoring.
    - Real-time data on soil moisture levels collected.
    - Contributed crucial insights to the disease prediction model.
2. **pH Level Sensors (Adafruit STEMMA Soil Sensor):**
    - Embedded in the soil to measure acidity.
    - Continuous readings of soil pH levels collected.
    - Data integrated into the disease prediction model for nutrient availability analysis.
3. **Weather Sensors (e.g., Davis Instruments Vantage Pro2):**
    - Real-time data on temperature, humidity, and rainfall recorded.
    - Data fused with information from soil moisture and pH sensors for a comprehensive dataset.

Step 6: Integration of IoT and Image Data for Disease Prediction

- Soil moisture, pH level, and weather data are combined with high-resolution images captured by cameras.
- Advanced machine learning models (SRCNN and MobileNet-V2) are trained on this integrated dataset to enhance the accuracy of disease predictions.

Step 7: Deep Learning Model Implementation (Disease Detection Module) and Cloud Deployment

7.1. **Data Collection:**
Images collected from the PlantVillage dataset, along with data from IoT sensors, are integrated. The trained model utilizes this combined IoT and image data.

7.2. **Image Preprocessing:**
This step includes resizing, brightness adjustment, and noise removal to prepare images for analysis.

7.3. **Super-Resolution Enhancement (SRCNN):**
The Super-Resolution Convolutional Neural Network (SRCNN) is applied to the preprocessed images to enhance their resolution, which improves the quality of feature extraction for disease identification.

7.4. **Disease Classification (MobileNet-V2):**
The processed images are fed into the disease classification model, MobileNet-V2, a pretrained deep learning model that analyzes the images and generates probability scores for different banana diseases.

7.5. **Disease Detection Logic:**
The system uses MobileNet-V2 to interpret probability scores for disease detection in banana crops. Based on these scores, the system categorizes the likelihood of disease and identifies the specific type based on the highest score.

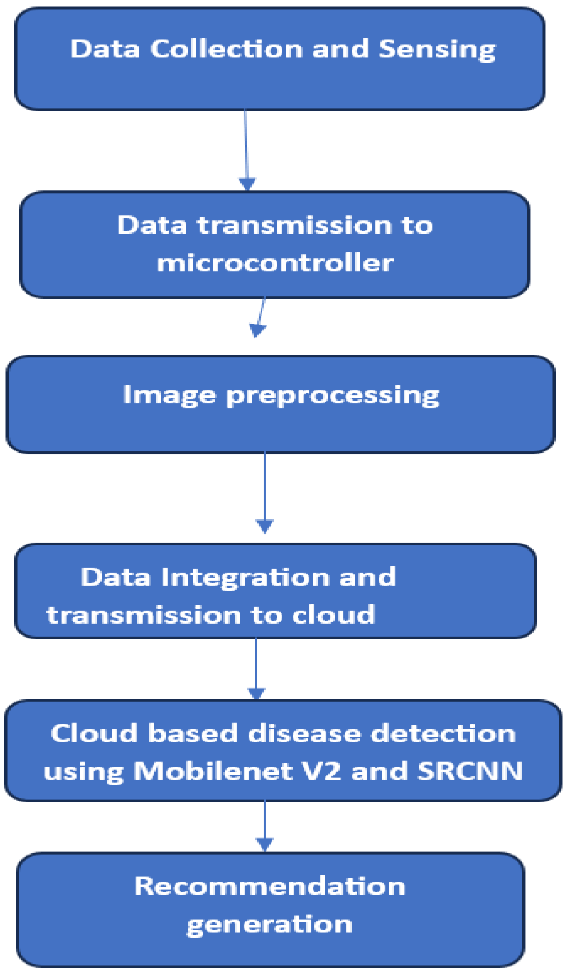

Fig.3 . NexGen AgriCare System Architecture

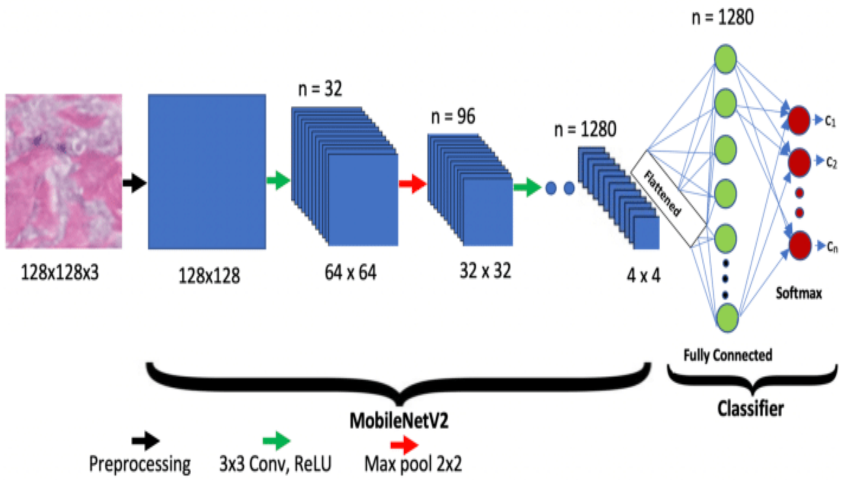

Fig.4. MobileNet V2 Architecture

Step 8: Programming Logic (IoT Sensors and Disease Detection)
This step involves a detailed explanation of the programming logic used for IoT sensors, focusing on the continuous monitoring of soil conditions, weather parameters, and image capturing. The logic ensures that data from these sensors are accurately and consistently collected in real-time.

- **Continuous Monitoring:**
  IoT sensors are programmed to continuously monitor environmental factors such as soil moisture, pH levels, temperature, and humidity. The sensors collect data at predefined intervals, ensuring up-to-date information is always available for analysis.
- **Image Capturing:**
  Cameras are integrated to capture high-resolution images of banana crops at regular intervals or when triggered by specific environmental conditions.
- **MicroPython Code:**
  MicroPython code plays a crucial role in controlling the disease detection module. It manages the flow of data from the sensors and cameras, ensuring that the information is correctly formatted and transmitted to the central system for processing.

Step 9: Integration
This step describes the synchronization of data flows between hardware components and the cloud infrastructure, highlighting the critical role of IoT sensors in data collection.

- **Data Synchronization:**
  The system ensures seamless synchronization between the IoT sensors, the disease detection module, and the cloud infrastructure. Data collected by the sensors is transmitted to the cloud in real-time, where it is processed and stored for further analysis.
- **Cloud Integration:**
  The cloud infrastructure, built on Google Cloud Services, serves as the central hub for

data storage and processing. It integrates data from various IoT sensors and the image processing module, allowing for comprehensive analysis and real-time insights.

- **Role of IoT Sensors:**
  IoT sensors are pivotal in this integration process, as they continuously feed the system with real-time data on soil conditions, weather, and crop health. This data is essential for the accurate detection and prediction of diseases, enabling the system to provide timely recommendations to farmers.

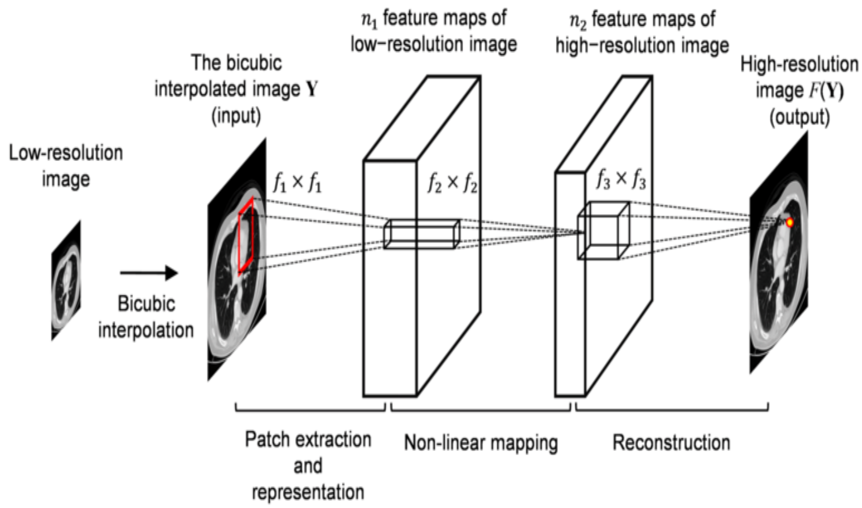

Fig.5.Learning with deep convolution network for image superresolution

Step 10: Deployment
During the deployment phase, the system is set up in the field. The IoT sensors are carefully positioned and calibrated to ensure they capture essential data accurately. Proper placement of the sensors is critical to the system's overall effectiveness, ensuring that data collection is consistent and reliable.

VII. PERFORMANCE ANALYSIS

Performance analysis is crucial for assessing the effectiveness of the NexGen AgriCare system in advancing crop resilience through real-time disease detection and IoT-driven solutions for banana crops. Key aspects to consider include:

1. **Disease Detection Accuracy:**
   - Evaluate the accuracy of disease detection using IoT devices and sensors.
   - Analyze the incidence of false positives and false negatives to determine the system's reliability in identifying diseases in real-time.
2. **Response Time:**
   - Measure the time it takes for the system to detect a disease and trigger a response.
   - Faster response times are critical to preventing the spread of disease and minimizing crop damage.
3. **Crop Health Improvement:**

- Assess the impact of implementing IoT-driven solutions on overall banana crop health.
- Look for indicators such as reduced disease incidence and healthier plant growth.

4. **Yield and Quality:**
   - Analyze the impact of the system on crop yield and the quality of bananas produced.
   - Determine whether the use of real-time disease detection and IoT technologies contributes to higher yields and better-quality produce.

Table I: Disease Control Techniques

Technique	Description	Benefits
Crop Rotation	Alternating crops in the same field to prevent disease buildup.	Reduces soil-borne diseases
Resistant Varieties	Using banana varieties that are resistant to specific diseases.	Minimizes disease incidence
Chemical Control	Applying fungicides and other chemicals to control disease spread.	Immediate disease management
Biological Control	Introducing natural predators or pathogens to combat banana diseases.	Environmentally friendly and sustainable
Cultural Practices	Implementing proper sanitation, pruning, and spacing techniques.	Prevents the spread of diseases

Table II: Experimental Results (%) of Other Models for Banana Leaf Disease Detection Using the PlantVillage Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Hybrid CNN (Julie et al.)	99.0	-	-	-
Thermal Imaging (Fitriawan)	-	-	-	-
DCNN (Michael Gomez Selvaraj)	-	-	-	-
Gabor + RCNN (Seetharaman)	-	-	-	-
GCN (Shajitha et al.)	-	-	-	-

Performance Analysis (continued):

- **Yield and Quality:**
  IoT-driven solutions result in higher yields, better fruit quality, and increased marketable produce. Assess the impact of disease detection on these key outcomes.
- **Resource Efficiency:**
  Examine resource usage, including water, pesticides, and fertilizers. Determine if the system leads to more efficient use of resources, thereby reducing waste and environmental impact.

Table III: Experimental Results of Different Models for Banana Leaf Disease Detection

Architecture	Validation Loss	Validation Accuracy	Training Loss	Training Accuracy	Overall Accuracy
Inception V3 Without DA	40.51	76.16%	38.78	86.21%	81.18%
Inception V3 DA	38.72	87.17%	35.02	88.11%	87.64%
Mobilenet V2 Without DA	23.81	92.23%	21.81	93.53%	92.88%
ResNet 34	14.47	95.44%	42.18	96.24%	95.84%
Mobilenet V2 DA (Proposed)	**16.07**	**95.52%**	**10.07**	**96.72%**	**96.12%**

VIII. RESULTS AND DISCUSSION

The NexGen AgriCare system has yielded impressive results, significantly enhancing disease detection accuracy in banana crops through the integration of advanced deep learning models such as SRCNN and MobileNet-V2. The real-time data collection from IoT sensors has enabled comprehensive monitoring of crop health, leading to a substantial reduction in crop loss.

Moreover, the user-friendly mobile application has played a crucial role in fostering community engagement and knowledge sharing among farmers and agricultural stakeholders. This engagement has not only improved the adoption of best practices but also strengthened the overall farming community.

Continuous improvement efforts, driven by user feedback and the integration of new data, have ensured that the system remains adaptable to the evolving challenges of banana farming. This ongoing adaptability makes NexGen AgriCare an invaluable tool for sustainable and productive crop management, helping farmers optimize their practices and secure better yields.

Future Expansion of NexGen AgriCare

In the future, NexGen AgriCare aims to expand its capabilities by supporting various crops beyond bananas. This expansion includes the implementation of region-specific disease models tailored to the unique challenges of different agricultural environments. The integration of advanced monitoring technologies will further enhance the system's effectiveness.

Key features under development include predictive analytics to anticipate disease outbreaks, offline functionality to ensure continuous operation in areas with limited internet access, and multi-language support to increase accessibility for farmers worldwide. Additionally, a crop management calendar, integration of market data, and an AI-driven feedback mechanism will provide comprehensive guidance to farmers, helping them make informed decisions.

To ensure data security and trust, the exploration of blockchain technology is being considered. This will enhance the reliability and adaptability of the system, further solidifying its role in supporting farmers in their pursuit of sustainable agriculture.

Diseases Detected by NexGen AgriCare in Banana Trees

The NexGen AgriCare system is capable of detecting several key diseases that affect banana trees:

A. Panama Wilt

- **Symptoms:**
  - Lower leaves yellowing from the margins to the midribs.

  - Yellowing spreads upward, eventually affecting the heart leaf.
  - Leaf breakage near the base, with leaves hanging around the pseudostem.
  - Longitudinal splits in the pseudostem.
  - Discolored vascular bundles with red or brown streaks.

B. Mycosphaerella Leaf Spot (Yellow Sigatoka, Black Sigatoka)

- **Symptoms:**
  - Symptoms first appear on the third or fourth leaves, or immature leaves.
  - Tiny spindle-shaped spots on leaves with a golden halo and greyish center, aligned parallel to the veins.
  - In severe infections, bananas appear small, with pinkish-hued flesh, poor ripening, and undersized fruit.

C. Banana Bract Mosaic Virus (BBMV)

- **Symptoms:**
  - Spindle-shaped marks are characteristic.
  - Pinkish to reddish streaks appear on the pseudostem, midrib, and peduncle.
  - Mosaic and moderate mosaic streaks are common.
  - Suckers' bracts, peduncles, and fingers exhibit distinctive reddish-brown streaks.

D. Tip Over or Bacterial Soft Rot

- **Symptoms:**
  - More pronounced in young suckers, leading to rot and a foul odor.
  - Rot in the collar region is a common symptom.
  - When affected plants are pulled, they leave the corm with roots in the soil.

CONCLUSION

In conclusion, advancing crop adaptability through real-time disease detection and IoT-driven solutions for banana crops holds immense promise for the agricultural industry. The integration of cutting-edge technology and data-driven insights allows for proactive disease management and improved crop health. By monitoring and responding to disease threats in real time, farmers can reduce crop losses, optimize resource management, and ultimately ensure a more sustainable and resilient banana crop production system.

Looking ahead, we aim to refine and optimize machine learning models such as SRCNN and MobileNet-V2 to achieve even greater accuracy in disease detection. Additionally, we plan to incorporate more types of IoT sensors to capture parameters like air quality, leaf wetness, and specific gas concentrations related to diseases. We will develop adaptive algorithms capable of dynamically adjusting disease prediction models based on changing environmental conditions. This approach not only enhances the efficiency of the system but also secures the livelihoods of growers while contributing to global food security and environmental sustainability.

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