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PLANT DISEASE DETECTION USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING – A SURVEY

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ABSTRACT

The routine process of plant disease testing, which usually requires trained professionals, is time-consuming, labor-intensive, and prone to bias. This article explores the use of artificial intelligence (AI) and machine learning (ML) technologies to treat plant diseases, providing faster, more accurate, and large-scale problem solving. We provide an overview of recent developments, discuss widely used data and machine learning models, and address the challenges and limitations in improving plant genetics and variability. Education, art, healthy crops.

Keywords: Plant Disease Detection, Machine Learning, Deep Learning, Image Processing, Crop Health.

I. INTRODUCTION

Agriculture is the foundation of global food production, and keeping plants healthy is essential for crop management and food security. Plant diseases caused by diseases such as fungi, bacteria, and viruses threaten agricultural crops, causing serious losses worldwide. Early detection and accurate diagnosis of plant diseases are important to reduce crop damage, but traditional methods are used by experts and are limited by human skills, time constraints, and training. Advances in artificial intelligence and machine learning have opened up new avenues for automated, targeted, and high-speed disease detection using image-based methods for disease diagnosis. AI-based disease diagnosis, especially those using deep learning (DL), holds promise for identifying specific diseases based on features such as color, shape, and texture of bacteria on leaves. This article aims to review existing scientific methods for plant disease detection, evaluate their results, and discuss ways to improve them for export. The following sections present new data, methods, challenges, and opportunities for using AI as a solution for plant disease diagnosis.

II. LITERATURE REVIEW

1. Ghosal et al. (2018) in SVM vs. CNN found that while SVMs performed well with smaller datasets, CNNs consistently outperformed SVMs in accuracy and scalability with larger datasets.
2. Liu et al. (2020) in Random Forest vs. CNN indicated that while Random Forest models were robust for feature extraction, CNNs provided superior classification accuracy, especially in complex datasets with high variability.
3. Picon et al. (2019) implemented deep learning techniques to classify apple diseases, reaching an accuracy of 90.4%. This research addresses the challenges posed by real-world conditions like varying lighting and disease symptom similarity.
4. Amara et al. (2017) focused on using LeNet CNN architecture for detecting banana leaf diseases, achieving an accuracy of 96.5%. The study points out that even simple CNN architectures can be effective for specific crop-disease combinations.
5. Pawar et al. (2019) implemented an AlexNet-based deep learning model to classify leaf blight and other fungal infections in potato crops, achieving 94% accuracy. This study underscores the effectiveness of pretrained models like AlexNet in agricultural applications.
6. Ramcharan et al. (2017) developed a mobile application using TensorFlow for cassava disease detection, achieving an accuracy of 92%. This application emphasizes the practicality of deploying AI models on mobile platforms, making plant disease detection accessible to farmers in remote areas.

III. METHODOLOGY

System architecture: A plant disease study consists of several stages: data collection, prioritization, model training, and disease classification. Leaf images are first collected, then pre-processed to normalize their quality, and then fed into a machine learning model trained to classify different diseases.

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Data collection and preparation: Good image data is essential for accurate classification. Most of the time, vegetation images are captured in a controlled environment or on a farm. Use data preprocessing techniques such as resizing, color normalization, and more to ensure consistent images across all files. This step reduces noise and highlights relevant features, making images suitable for input into machine learning models.

Algorithm selection: CNNs are widely used to detect plant diseases because they are well-suited to image processing. Different models such as ResNet, VGGNet, and DenseNet have good features. For example, ResNet's cross-linking helps solve the lossy problem by allowing deep sampling, which is necessary to capture complex patterns. In addition, heavyweight models like MobileNet are often used for emergency applications on mobile devices or low-power devices, allowing farmers to use the skills in the field where needed.

Training and validation: During the training process, the dataset is usually split into training, validation, and testing to optimize the model and avoid overloading. Data enhancement techniques like rotation, scaling, and translation are often used to increase data diversity and help improve models. Adaptive learning is another method where a pre-trained model is optimized on disease-specific data to achieve faster and more accurate integration with less data.

Measurements: Model performance is often measured using metrics such as accuracy, precision, recall, and F1 score. These metrics provide information about the effectiveness of the model in identifying infected plants while minimizing false positives and negatives. Cross-validation is often used to test the stability and consistency of a model, especially when dealing with inconsistent data.

IV. SYSTEM ARCHITECTURE

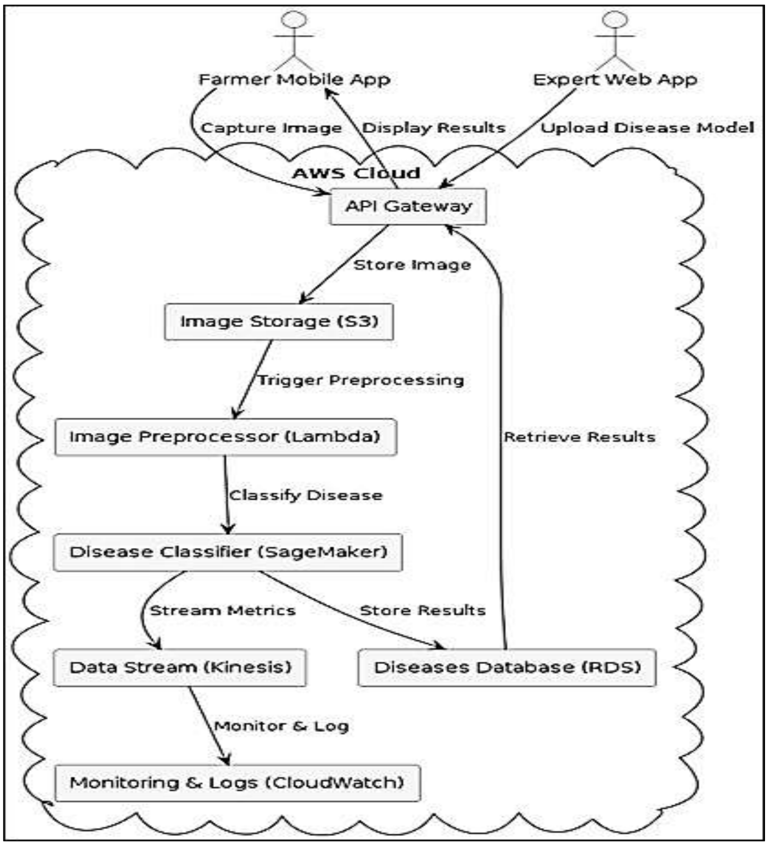

Fig 1: Proposed System Architecture

User Interface: Farmers Mobile Application: Farmers use this application to capture crop images and send them to the disease detection system. Diagnosis was made after treatment.

AWS Cloud Components:

API Gateway: Provides primary access to data for mobile and web applications. Manages incoming requests, stores images, and reports on services.

Image Storage (S3): Amazon S3 (Simple Storage Service) is used to store images uploaded by farmers. These images will be stored until they are pre-processed and scanned for viruses.

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Image preprocessor (Lambda): AWS Lambda is used to preprocess images stored in S3. These preliminary steps may include resizing, filtering, or normalizing the image data in preparation for analysis

Disease Classifier (SageMaker): Amazon SageMaker hosts machine learning models to classify crop diseases. Once processed, images are sent to SageMaker, where the model predicts diseases affecting crops.

Disease Database (RDS): Amazon RDS (Related Database Service) stores disease identification and diagnostic information. The Farmer mobile app can query this data to display results

Streaming data (Kinesis): Amazon Kinesis collects and processes streaming data in real time, enabling further integration and analysis of metrics related to disease distribution and physical activity.

Monitoring and logging (CloudWatch): Amazon CloudWatch is used to monitor tasks, tasks, and logs. It provides insights into health and performance by monitoring data streams and metrics from other AWS services

V. CONCLUSION

This article provides an overview of the current state of plant disease diagnosis using AI and machine learning, highlighting the potential of this technology to transform agriculture. AI-based models, particularly deep learning, hold great promise for accurately detecting diseases and enabling farmers to manage healthy crops again. While challenges remain, particularly in terms of model robustness across environments, continuing to use AI provides a path forward. Continued research and development in this area can provide easier and more immediate solutions, ultimately improving food security and promoting global culture.

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