International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Crop Monitoring & Disease Detection

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Abstract— Pest proliferation, population growth, and climate change are all still having an adverse effect on agricultural productivity. Both sustainable farming practices and food security depend on careful crop monitoring and early disease detection. This paper summarizes the literature that illustrates how modern technology and methods, like remote sensing, image processing, and machine learning, are used in the field of crop monitoring and disease diagnostics. We examine the advantages, disadvantages, and application of these methods in the modern world. We also talk about upcoming trends and offer a versatile, AI-assisted strategy to advance precision farming. This paper provides a comprehensive overview of contemporary techniques and systems for crop monitoring and disease detection. It explores satellite imaging, unmanned aerial vehicles (UAVs), sensor networks, and deep learning algorithms that collectively enable precision agriculture. Challenges, limitations, and future directions are also discussed. With the objective of highlighting the potential of federated learning in crop disease classification, among the CNN models tested, ResNet50 performed better in several experiments than the other models, and proved to be an optimal choice, but also the most suitable for a federated learning scenario.

Keywords —Crop monitoring, disease detection, remote sensing, machine learning, precision agriculture Deep Learning, IoT, UAV, Smart Farming

I.INTRODUCTION

Crop disease detection and management is an area where data science can provide valuable decision tools to improve productivity, reduce costs, and support development of more environmentally friendly crop treatment methods[1,2]. Precision agriculture, which relies on modern technologies to improve productivity, has revolutionized the way farmers manage their crops. One of the main goals of precision agriculture is to optimize crop yields while ensuring crop quality and environmental preservation[3]. This includes reducing the negative impact of pesticides and other plant protection products. To achieve this, it is essential to use appropriate technological solutions capable of automatically detecting leaf diseases[4], which are often responsible for significant economic losses and reduced crop quality and yield.

Many systems have been developed for automatic detection and management of crop disease, making use of modern technologies such as artificial intelligence, big data, image processing, and machine learning algorithms. Advances in these technologies in the field of agriculture have opened up promising opportunities for early detection and diagnosis of crop abnormalities[5]. Deep neural networks, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), as well as modern approaches based on attention mechanisms (e.g., Vision Transformers)[6,7], are widely used, and have demonstrated outstanding performance in crop anomaly detection and diagnosis[8,9,10].

The various machine learning algorithms used require collecting data, which is then stored on a central server for model training. However, collecting consistent data in large quantities is difficult, time-consuming, expensive, and impractical for producers. In addition, the centralized approach used to train these models presents several limitations, including privacy and data security issues for producers who must release their private data, limited availability of data for model training, regulatory constraints on data protection (such as GDPR : General Data Protection Regulation), prohibitive transfer costs in a context of exploding data volumes to be processed

In this paper, we evaluated and studied convolutional network models and models based on attention mechanisms (in particular Vision Transformers, ViT) using federated learning for disease detection. We have used four open source image datasets from the “Plant Village” platform for our experiments. Our goal is to highlight the strengths of federated learning in crop disease classification, particularly with respect to user data security and enforcement of confidentiality of sensitive data.

II. CROP MONITORING TECHNOLOGIES

A. Remote Sensing

Remote sensing is the process of using satellites, aircraft, or drones to gather data about the condition of crops. Multispectral and hyperspectral imaging provide data on vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), which can provide information on biomass, plant health, and water stress in plants. Satellite-based remote sensing provides multi-spectral and hyper-spectral imagery which can be analysed to determine vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and others. These indices help in identifying plant health, chlorophyll content, water stress, and biomass estimation. High temporal resolution data from satellites such as Sentinel-2, Landsat-8, and MODIS allow for continuous monitoring throughout the crop lifecycle. UAVs, equipped with RGB, multispectral, or thermal cameras, offer higher spatial resolution and flexibility in data acquisition compared to satellites. UAV-based monitoring is particularly useful for small to medium-sized farms, enabling detailed field-level analysis, early disease detection, and precision agriculture applications.

B. IoT-Based Monitoring

With the use of ground-based sensors that assess soil moisture, temperature, humidity, and nutrient levels, the Internet of Things (IoT) makes real-time monitoring possible. These sensors make it possible to gather detailed information that may be combined for extensive analysis and decision-making.
IoT devices typically include wireless sensor nodes, microcontrollers, and communication modules (e.g., LoRa, Zigbee, Wi-Fi, or cellular networks), which transmit data to cloud-based platforms for analysis. These platforms use data analytics and machine learning algorithms to detect anomalies, predict crop performance, and suggest timely interventions.
One of the key advantages of IoT-based monitoring is its ability to provide site-specific insights, enabling farmers to implement variable rate irrigation, fertilization, and pesticide application. This precision reduces resource wastage, lowers environmental impact, and enhances crop yields.
In addition, IoT systems can be integrated with automated actuators such as irrigation valves and drones, facilitating closed-loop systems that respond autonomously to real-time field conditions. Mobile applications and dashboards allow stakeholders to remotely monitor crop conditions and receive alerts, making farm management more efficient and data-driven.

C. Unmanned Aerial Vehicles (UAVs)

Unmanned aerial vehicles, commonly referred to as UAVS or drones, are being used more and more for field observation. Equipped with thermal, multispectral, or high-resolution RGB cameras, they can offer flexible, high-frequency monitoring and identify changes in the amount of chlorophyll and canopy structure that take place before obvious disease signs show up. Equipped with RGB, multispectral, hyperspectral, thermal, and LiDAR sensors, UAVs capture detailed imagery that supports plant health assessment, canopy cover estimation, disease and pest detection, and nutrient deficiency analysis. Multispectral imagery, for instance, is often used to compute vegetation indices such as NDVI, which help detect early signs of crop stress not visible to the naked eye. The ability of UAVs to fly at low altitudes and customizable paths allows for fine-grained monitoring of individual fields, enabling precision agriculture practices. They are particularly beneficial in areas with frequent cloud cover, where satellite imagery is often limited or unavailable.
In addition to data collection, UAVs are increasingly being used for active tasks such as variable rate spraying of fertilizers and pesticides. Integration with AI-based analytics platforms further enhances the utility of UAV-collected data, allowing for real-time interpretation and actionable insights.

III. DISEASE DETECTION METHODS

A. Image-Based Detection

Using characteristics like colour, texture, and shape, digital image processing makes it possible to identify sick plants. Traditional algorithms divide the areas of infection and classify diseases (e.g., k-mean clustering, histogram analysis). The acquired images undergo preprocessing steps such as noise reduction, contrast enhancement, and segmentation to isolate regions of interest. Feature extraction techniques are then applied to analyse colour, texture, shape, and edge patterns, which are indicative of specific plant diseases. These features serve as input to classification models, such as support vector machines (SVM), convolutional neural networks (CNNs), and other deep learning architectures.

CNN-based models, in particular, have shown high accuracy in detecting and classifying multiple diseases, even in complex backgrounds or under varying lighting conditions. Datasets such as Plant Village have played a crucial role in training robust models for different crops and disease types.

Image-based detection systems can be integrated into mobile applications, allowing farmers and agronomists to perform on-field disease diagnostics in real time. The scalability and cost-effectiveness of this method make it a practical solution, especially in regions with limited access to agricultural experts.

B. Machine Learning and Deep Learning

Plant disease classification using leaf photos has demonstrated a substantial degree of accuracy thanks to machine learning approaches, particularly convolutional neural networks (CNNs). Large datasets, like Plant Village, have trained models to identify many diseases, including bacterial, viral, and fungal illnesses. Traditional ML algorithms such as Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Decision Trees, and Random Forests have been employed to classify plant diseases based on manually extracted features from image or sensor data. These methods are relatively efficient for simpler datasets but often require expert-driven feature engineering.

Deep Learning, particularly Convolutional Neural Networks (CNNs), has significantly outperformed traditional ML in image-based disease detection due to its ability to automatically learn hierarchical features directly from raw image data. CNN architectures such as AlexNet, VGGNet, ResNet, and Inception have been successfully applied to classify plant diseases across various crops. These models can detect subtle visual differences between healthy and diseased plant tissue, even in noisy or variable environments.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are also utilized when temporal data is involved, such as sequential changes in plant health over time captured through IoT sensors or drone footage.

C. Multispectral and Hyperspectral Analysis

Delicate biochemical changes linked to disease development are drawn to spectral imaging outside of the visible spectrum. To distinguish between plant tissue that is healthy and that which is sick, appropriate techniques like Principal Component Analysis (PCA) and Spectral Angle Mapper (SAM) are employed. Multispectral imaging typically captures data in a limited number of discrete bands, such as red, green, blue, near-infrared (NIR), and red-edge. It is widely used for computing vegetation indices like the Normalized Difference Vegetation Index (NDVI) and the Disease Water Stress Index (DWSI), which help identify areas of crop stress caused by pathogens or pests.

Hyperspectral imaging, on the other hand, captures data across hundreds of contiguous spectral bands, providing a much more detailed spectral signature of plant tissues.

The resulting high-dimensional spectral data is processed using advanced analytical techniques, including dimensionality reduction (e.g., PCA), spectral unmixing, and classification algorithms such as SVM, random forest, and deep neural networks.

Multispectral and hyperspectral analysis is particularly effective in distinguishing between different types and severities of diseases, even in heterogeneous field environments. These methods support precision agriculture by enabling targeted interventions and reducing unnecessary use of chemicals.

IV. RESULTS AND CASE STUDIES

To evaluate the effectiveness of the proposed crop monitoring and disease detection approaches, several case studies and experimental results are examined across different agricultural scenarios. These include both field deployments and controlled experiments involving remote sensing, IoT, and machine learning-based detection methods.

A. Case Study 1: UAV-Based Crop Monitoring in Maize Fields

A UAV equipped with multispectral and RGB cameras was deployed over a 10-hectare maize field to monitor crop health and detect early signs of stress. NDVI and Red Edge NDVI indices were computed from the captured data. Analysis revealed early-stage nitrogen deficiency in certain zones, which was later confirmed through soil sampling. Targeted nutrient application based on UAV data improved overall yield by 12% compared to a control plot.

B. Case Study 2: IoT Sensor Deployment in Tomato Greenhouses

An IoT-based monitoring system was implemented in a greenhouse cultivating tomatoes. Soil moisture, temperature, humidity, and leaf wetness were continuously monitored using low-power wireless sensor nodes. The data was fed into a predictive model that issued alerts when environmental conditions were favourable for fungal infections such as *Phytophthora infestans*. Early warnings enabled preemptive fungicide applications, reducing disease incidence by 30%.

V. DISCUSSION

Despite the promise of current technology, problems with scalability, crop-type generalization, and real-time deployment remain. Overfitting and data imbalance are frequent issues for machine learning models, especially when field circumstances vary.

Strengths and Advantages

1. **Timeliness and Accuracy**: The ability to detect diseases at early stages, before visible symptoms appear, is one of the key advantages of advanced crop monitoring technologies. UAV-based multispectral and hyperspectral imaging, for example, provides timely and accurate data on crop health, enabling early intervention and mitigating yield loss. Similarly, IoT sensor networks offer real-time environmental monitoring, enhancing disease prevention and management through predictive alerts.

2. **Scalability and Efficiency**: Remote sensing technologies, particularly satellite and UAV-based systems, allow for large-scale monitoring of agricultural fields, reducing the need for labor-intensive field inspections. These systems can cover large areas in short periods, providing consistent and reliable data, thus enabling more efficient farm management and resource allocation.

3. **Precision Agriculture**: Machine learning and deep learning algorithms offer the ability to analyze vast amounts of data and make precise predictions about crop health. This level of precision supports targeted interventions, such as variable rate irrigation, fertilization, and pesticide application, reducing resource wastage and minimizing environmental impact. This shift towards precision agriculture enhances sustainability and economic viability for farmers.

4. **Cost-Effectiveness**: While initial setup costs for UAVs, hyperspectral sensors, and IoT devices may be high, the long-term benefits in terms of increased yield, reduced crop loss, and optimized resource usage make these technologies increasingly cost-effective. Additionally, the use of open-source machine learning models and cloud-based processing platforms has made these technologies more accessible to a broader range of users.

B. Limitations and Challenges

1. **Data Quality and Variability**: One of the major challenges in image-based disease detection is the variability in environmental conditions, such as lighting, soil background, and plant growth stages. These factors can significantly affect the quality and interpretability of the images. For instance, low-resolution images or poor

lighting can result in incorrect disease identification. Similarly, hyperspectral and multispectral data require careful calibration to minimize environmental effects and sensor noise.

2. **Model Generalization**: While machine learning and deep learning models have demonstrated high accuracy in controlled environments, their performance may degrade when applied to new, unseen datasets, especially in diverse or complex field conditions. Training models that generalize well across different crops, disease types, and environmental factors remains an ongoing challenge.

3. **Cost and Accessibility**: Despite the decreasing cost of UAVs and sensor technologies, the initial investment and maintenance costs can still be prohibitive for smallholder farmers, particularly in developing regions. Moreover, the technical expertise required to operate and interpret the data from these advanced systems may limit their adoption in some areas.

4. **Regulatory and Privacy Concerns**: The widespread use of UAVs in agriculture raises concerns regarding airspace regulations and privacy. In some regions, UAVs require specific permissions for flight operations, and there may be concerns about unauthorized surveillance. Establishing clear regulations and ensuring compliance with privacy standards will be crucial for broader adoption.

C. Future Directions

1. **Integration of Multimodal Data**: The future of crop disease detection lies in the integration of multiple data sources. Combining image-based data with environmental parameters from IoT sensors, weather forecasts, and soil health metrics will enable more comprehensive and accurate disease detection. Multimodal data fusion can improve model performance by providing more context and helping to differentiate between disease symptoms and environmental stress.

2. **Real-Time, Autonomous Systems**: Advances in AI and edge computing will enable more autonomous systems capable of real-time decision-making. For example, UAVs equipped with AI algorithms could not only detect disease but also autonomously apply treatments such as pesticides or fertilizers. This would further reduce labor costs and improve the efficiency of precision agriculture.

3. **Machine Learning Advancements**: As machine learning algorithms continue to evolve, the focus will be on improving model robustness, particularly through techniques such as transfer learning and domain adaptation. These approaches can help overcome the challenges posed by limited labeled datasets and improve model performance in real-world, diverse environments.

4. **Lower-Cost and Portable Solutions**: Future research should focus on developing low-cost, portable, and user-friendly systems for smallholder farmers. Mobile applications leveraging smartphone cameras and low-cost sensors can bring disease detection to the hands of farmers, enabling them to make informed decisions without requiring significant technical expertise or expensive equipment.

5. **Sustainability and Environmental Impact**: There is growing interest in sustainable agriculture, and technologies for disease detection and crop monitoring must be aligned with environmental conservation goals. By reducing the use of pesticides and optimizing resource usage, these technologies can help minimize the environmental impact of farming, contributing to more sustainable agricultural practices.

VI. FUTURE DIRECTIONS

As agricultural technologies continue to evolve, the future of crop monitoring and disease detection lies in the integration of innovative solutions and the enhancement of existing systems. Advancements in AI, sensor technologies, and data analytics are expected to drive the next generation of tools that can improve productivity, sustainability, and resilience in agriculture. This section explores the potential future directions for crop monitoring and disease detection.

A. Integration of Multimodal Data for Enhanced Accuracy

One of the key advancements in the near future will be the integration of multimodal data, combining visual (e.g., image, multispectral, hyperspectral), environmental (e.g., soil moisture, temperature), and biological (e.g., plant health, genetic data) inputs. By fusing these different types of data, machine learning algorithms can offer more comprehensive insights into crop health, providing more accurate and earlier disease detection.

For example, combining UAV-captured multispectral images with real-time soil sensor data and environmental weather data could enable more precise predictions of disease outbreaks.

B. Real-Time, Autonomous Disease Management Systems

The demand for real-time monitoring and autonomous response systems will grow as precision agriculture technologies become more sophisticated. Future systems could be designed to not only detect diseases but also autonomously react to them. UAVs, for instance, could use onboard AI algorithms to detect disease and then trigger automated pesticide spraying or other targeted interventions based on real-time data. Additionally, IoT systems integrated with autonomous irrigation and nutrient management systems will help in mitigating crop stress before it leads to disease development. These systems will further reduce the need for human intervention and optimize resource use, thus making agriculture more efficient and environmentally friendly.

C. Machine Learning for Continuous Improvement and Generalization

Current machine learning models, while effective, often require large labeled datasets and may struggle to generalize across different environmental conditions or crop varieties. Future advancements in machine learning will focus on improving the adaptability of these models, enabling them to work in diverse agricultural settings with minimal manual data labeling. Techniques such as transfer learning and few-shot learning will be critical in adapting pre-trained models to new regions, crops, and diseases with limited data.

VII. CONCLUSION

In this paper, we have explored the diverse range of technologies used in crop monitoring and disease detection, emphasizing the growing role of remote sensing, IoT, UAVs, and machine learning. These technologies have significantly advanced precision agriculture by enabling early disease detection, real-time monitoring, and efficient management practices, ultimately leading to increased yield and sustainable farming.

The integration of remote sensing through satellite and UAV-based imaging, coupled with advanced machine learning techniques, allows for timely and accurate disease detection even in the early stages. The application of IoT sensors further enhances the ability to monitor environmental conditions and plant health, offering predictive capabilities that reduce the need for reactive disease control measures. Multispectral and hyperspectral imaging provide a high level of detail for crop health analysis, helping farmers detect diseases before visible symptoms appear.

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