Journal of
Image Processing & Pattern Recognition Progress

ISSN: 2394-1995
Volume 13, Issue 1, 2026
January–April
DOI (Journal): 10.37591/JoIPPRP

https://journals.stmjournals.com/joipprp

Review JoIPPRP

A Review of Automated Pomegranate Disease Detection and Classification Using Machine Learning

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Abstract

The abstract outlines a research study focused on developing an automated system for detecting and classifying diseases that affect pomegranate fruits. Pomegranates, like many other crops, are vulnerable to several types of diseases that appear as visible colored spots on the fruit's surface. These visible symptoms, such as lesions or discoloration, can significantly impact the fruit's quality, market value, and yield. Therefore, timely and accurate identification of such diseases is crucial, especially during the fruit's growth and harvesting stages. The study aims to address this issue by designing a system capable of identifying the most common pomegranate diseases, including bacterial blight, Cercospora fruit spot, fruit rot, and Alternaria fruit spot. These diseases not only reduce the marketability of the produce but can also spread rapidly if not controlled. Traditional disease identification methods are often manual, time-consuming, and prone to human error. To overcome these limitations, the proposed approach leverages machine learning techniques to automate the process of disease detection and classification. The system uses image processing and a machine learning approach to analyze the affected areas on fruit images, extract relevant features, and classify the severity of the disease. The abstract also highlights some key challenges, such as variability in image conditions, overlapping disease symptoms, and the need for accurate training data. Overall, this study proposes a technological solution aimed at improving disease monitoring efficiency, ensuring early intervention, and reducing crop losses in pomegranate farming.

Keywords: Disease detection, bacterial blight, *Cercospora* fruit spot, fruit rot, *Alternaria* fruit spot, pomegranate, machine learning

INTRODUCTION

India is one of the most important countries in the world for agriculture. It produces a large variety of fruits and is the largest fruit producer globally. India alone contributes approximately 10% of the world's fruit production, which means millions of tons of fruit are grown every year. This includes popular fruits, such as bananas, grapes, mangoes, guavas, and pomegranates. Among these, pomegranates hold a special place, both in terms of their economic value and health benefits. It is grown mainly in the states of Maharashtra and Karnataka, where the climate and soil conditions are ideal for cultivation. These regions have the right combination of warm temperatures, dry air, and well-drained soil for pomegranate trees to grow well and produce high-quality fruits.

Pomegranate is an important fruit crop not only because it is widely consumed in India, but also because it is exported to other countries, which

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Received Date: May 23, 2025
Accepted Date: July 13, 2025
Published Date: November 07, 2025

Citation: Vidya Shejwal, K.J. Karande, Anjali C. Pise. A Review of Automated Pomegranate Disease Detection and Classification Using Machine Learning. Journal of Image Processing & Pattern Recognition Progress. 2026; 13(1): 1–13p.

brings income to Indian farmers and contributes to the economy. This fruit is well known for its nutritional and medicinal properties. It is rich in antioxidants, vitamins (e.g., vitamins C and K), and minerals. These nutrients make pomegranates popular in the health-food industry. They are used in juices, skincare products, and dietary supplements, which increases their demand both within and outside India.

However, pomegranate farming faces serious challenges such as crop diseases. Just as humans become sick, plants can also become infected by bacteria, fungi, or viruses. These diseases can affect the stems, leaves, flowers, and fruits of plants. When pomegranates become infected, they develop dark spots, rot, and become inedible. Consequently, farmers are unable to sell them in the market, leading to huge financial losses. This is especially problematic for small-scale farmers, who rely on the sale of fruits for their livelihood.

Pomegranate fruits are affected by several common diseases that significantly affect crop quality and yield. Fungal and bacterial infections were most prevalent. *Cercospora* fruit spots, for instance, cause black or brown circular lesions on the leaves and fruits. It thrives under humid conditions and spreads rapidly, leading to noticeable damage if not controlled in time. Another fungal infection, Fruit Rot or Anthracnose, results in softening and rotting of fruits, making them unsuitable for consumption or sale. Bacterial blight, on the other hand, is caused by bacteria and manifests as fruit cracks, leaf wilting, and overall poor fruit development. Alternaria fruit spots are another serious concern; they present as dark brown or black patches that often spread from infected leaves to fruits, affecting both their appearance and taste.

These diseases typically begin in the leaves or stems, and eventually reach the fruit, making early detection crucial. Unfortunately, by the time visual symptoms appear, the damage may have already been extensive. Traditionally, farmers have relied on manual inspection to identify such diseases. They examine plants for signs such as discoloration, spots, or deformities, and then decide on a course of action, such as applying pesticides or consulting agricultural officers. Although this approach is commonly used, it has notable limitations. Manual inspection is labor-intensive and time-consuming, particularly in large orchards. It also requires expert knowledge to distinguish between diseases that may appear similar, and misdiagnosis can lead to improper treatment. Furthermore, reliance on human observation increases the chance of missing early signs, allowing infections to spread unchecked.

To address these challenges, researchers have explored advanced techniques for the detection of plant diseases. These modern methods offer accurate, timely, and scalable solutions. Spectroscopic methods analyze how plants reflect or absorb light to detect chemical changes before visible symptoms emerge. Molecular analysis examines the plant's DNA or RNA to identify signs of infection at the genetic level. The profiling of plant volatile organic compounds (VOCs) allows the detection of stress-related gases released by plants under attack. The most practical and widely used approach is digital imaging, in which images of leaves and fruits are analyzed using computer software to identify disease symptoms based on color, texture, or pattern variations. These modern tools have the potential to transform plant disease detection, enabling early intervention and helping farmers protect their crops more effectively.

These methods are more accurate and faster than manual inspection. However, many of them require expensive laboratory equipment or trained scientists to carry out the tests. This makes it difficult to use them in regular farming situations, especially in rural areas.

The most promising developments in recent years have been the use of artificial intelligence (AI) and machine learning (ML). These technologies are being applied in many areas of farming, including crop prediction, yield estimation, soil analysis, and disease detection. AI and ML can analyze large amounts of data, such as images, much more efficiently than humans can. Using thousands of images of healthy and diseased pomegranate plants, ML models can be trained to recognize patterns that indicate the presence of a disease.

ISSN: 2394-1995

In the case of pomegranate disease detection, ML involves a few simple steps. First, many pictures of both healthy and diseased pomegranates were collected. These images were labeled based on the type of disease or whether the fruit was healthy or not. The images are then fed into an ML model, often using image processing techniques. The model learns the differences between healthy and infected fruits by identifying features such as the color, shape, size, and texture of spots. Once trained, the model can be used to analyze new images and predict the type of disease or its severity.

This study proposes a machine learning-based system to automatically detect and classify common pomegranate diseases. The system uses images of the affected leaves and fruits as inputs and processes them using image analysis and classification algorithms. The main advantage of this approach is that it can provide fast, accurate, and consistent results without requiring expert knowledge of the farmer. Once implemented, this system can be made available as a mobile application that farmers can use by simply taking a picture of the affected fruit or leaf using their smartphones.

Such a system has many benefits. First, it helps in early detection so that farmers can take action before the disease spreads too far. Second, it reduces the chances of misdiagnosis, which often leads to incorrect use of pesticides or fungicides. Third, it saves time and labor because farmers no longer need to inspect every plant manually. Fourth, it helps reduce costs because targeted treatment can be applied instead of spraying chemicals over the entire field. Finally, it supports sustainable farming by reducing the overuse of pesticides and protecting the environment.

The implementation of such a system is challenging. An ML model requires a large amount of training data to perform well. Gathering good-quality images of different diseases under different lighting and background conditions is difficult. However, technical challenges also exist. For example, ensuring that the model works on mobile devices with limited processing power or ensuring that it provides accurate results under different environmental conditions. Additionally, many farmers in rural areas may not be familiar with smartphones or AI tools; therefore, there is a need for training and awareness programs.

Despite these challenges, the potential impact of AI and ML in agriculture is enormous. Governments, agricultural universities, and private tech companies are working together to bring these technologies to the field. Several pilot projects have shown that AI-based disease detection tools can help farmers improve crop health and productivity.

This study focuses on the development of a machine learning-based system for the detection and classification of pomegranate diseases. The aim is to provide a smart solution that helps farmers quickly and accurately identify diseases based on simple images. The ultimate goal is to reduce crop loss, improve fruit quality, and make pomegranate farming more profitable and sustainable. Applying modern technology to traditional agriculture can solve long-standing problems and improve the lives of farmers worldwide.

LITERATURE REVIEW

With the increasing adoption of AI in agriculture, numerous studies have been conducted on plant disease detection using ML and deep learning (DL). While much of the literature focuses on general plant diseases, specific applications of pomegranate remain comparatively limited but are growing.

Advanced Deep Learning Approaches

A dual-stream DL model developed by Zahra et al. [1] combines standard red, green and blue (RGB) image features with disease-specific information to improve detection performance. This method, designed for general fruit disease identification, achieves approximately 96% accuracy by effectively merging different types of features, demonstrating the benefits of using multiple data streams.

A novel approach called unsupervised salient map approach with bag-of-features (USMA-BOF) was presented by Vijh et al. [2], which enhances plant disease classification by focusing on important areas in the image and using engineered features. Although this study did not focus on pomegranates, it shows how non-DL methods can still be highly effective, especially when data are limited.

Comprehensive review of DL techniques for fruit detection and classification. Their analysis of models such as YOLO, Faster R-convolutional neural networks (CNN), and U-Net revealed that deep architecture such as CNN and ResNet significantly outperformed traditional ML models when large datasets were available. This model is offered by Ukwuoma et al. [3], a customized CNN model for identifying banana plant diseases, and reached 95% accuracy. Despite being applied to different crops, this study highlights the potential of tailored DL models for fruit disease detection based on specific visual patterns proposed by Narayanan et al. [4].

Feature Optimization and ML Models

Ali Ibrahim et al. [5] proposed a sophisticated method for selecting the most relevant image features using rough set theory combined with Binary Honey Badger Optimization proposed by Ali Ibrahim, R. et al. [5]. Although not focused on pomegranates, their technique can improve ML performance by eliminating unnecessary data.

Sharath et al. [6] implemented a basic CNN-based system for detecting plant diseases, achieving solid results with approximately 92% accuracy. This early work provides a fundamental reference for using DL in agricultural image analysis.

Vasumathi and Kamarasan [7] designed a CNN-LSTM hybrid model specifically for identifying diseases in pomegranates. Their network captured both spatial and sequence-based patterns, resulting in a high accuracy of approximately 93.7%. This makes it one of the most advanced approaches for the detection of pomegranate disease.

Pomegranate-Specific Applications

Khatawkar et al. [8] conducted a focused study on the detection of diseases in pomegranate fruits using classic ML techniques. Their method, which includes steps such as image pre-processing and segmentation, delivered promising results (approximately 90% accuracy) using relatively simple tools.

Chakali et al. [9] explored disease detection in pomegranate leaves by using a lightweight CNN model. Despite being a short study, it achieved more than 90% accuracy and is one of the few studies that address leaf-level disease classification for pomegranates.

Gaikwad et al. [10] were among the first to explore pomegranate disease detection using image processing. They extracted basic visual features, such as color and shape, and used traditional classification methods to assess disease severity. This study laid the groundwork for further research in this field.

Plant leaf disease detection has become an important research area, particularly with the advancement of computer vision and ML technologies. Harakannanavar et al. [11] explored various computer vision and ML algorithms to effectively detect plant leaf diseases. Their work focused on extracting meaningful features from leaf images and applying traditional ML classifiers to identify diseases, showing promising results in terms of accuracy and speed.

Bhargava et al. [12] expanded this by providing a comprehensive review of state-of-the-art AI and computer vision methods for plant leaf disease detection, classification, and diagnosis. They highlighted the increasing use of DL models, such as CNNs, that automatically learn disease features, which have significantly improved classification accuracy compared to traditional approaches. The review emphasized the challenges of dataset quality, variability in disease symptoms, and the need for large, annotated datasets.

Roy and Bhaduri [13] introduced a deep learning-enabled multiclass model for plant disease detection that utilizes computer vision techniques to handle diverse disease classes in leaves. Their model demonstrated improved generalization across multiple crops, validating the power of DL for handling complex visual patterns caused by diseases.

Ouhami et al. [14] surveyed the integration of computer vision with Internet of Things (IoT)technologies and data fusion techniques to detect crop diseases. Their study emphasized that combining image-based disease detection with real-time sensor data can enhance disease monitoring in smart agriculture, enabling timely intervention and reducing crop loss.

Habib et al. [15] reviewed machine vision techniques for fruit and vegetable disease recognition and underscored the importance of image processing and ML algorithms for early and accurate disease detection. Firouz and Sardari [16] focused on defect detection in fruits and vegetables using machine vision and showed that automated image analysis can assist in quality control in agricultural supply chains.

Recent developments include the use of vision transformers (ViTs) and other transformer-based models for disease classification, as highlighted by D. Na [17]. These models leverage self-attention mechanisms to capture spatial dependencies in images better, often outperforming traditional CNNs. Palei et al. [18] provided a systematic review of citrus disease perception and grading, demonstrating how machine vision can support automated fruit quality assessments.

Several studies have also addressed specific crops, such as potatoes. Sinshaw et al. [19] systematically reviewed computer vision applications for automatic disease detection in potato plants. The trend towards precision agriculture and the use of machine vision for stress and disease detection was summarized by Shin et al. [20], who emphasized the practical deployment of these technologies in the field.

In a broader context, Salvi et al. [21] reviewed the impact of image pre-processing on DL frameworks, which is crucial for improving model robustness and accuracy in digital pathology and plant disease image analysis. Rosca [22] compared traditional image processing with AI-based object classification, highlighting the superiority of AI models in complex classification tasks such as plant disease detection.

Xiao et al. [23] reviewed object detection and recognition methods based on digital image processing and traditional ML for robotic harvesting of fruits and vegetables. This work detailed the challenges in automated harvesting, such as occlusion and varying illumination, and surveyed solutions that combined classical vision techniques with ML to improve robot perception.

Wang et al. [24] analyzed the performance differences between traditional machine learning classifiers and DL architectures on image classification tasks and concluded that DL, especially CNNs, significantly outperforms classical ML models by automatically extracting hierarchical features, reducing the need for manual feature engineering.

Marias [25] discussed the evolution of medical image processing from traditional techniques to advanced imaging biomarkers and radiomics, highlighting the increasing role of DL in oncology for improved diagnosis and prognosis. This evolution reflects broader trends in image processing, where data-driven models dominate the handcrafted features.

Karypidis et al. [26] presented a comparative study that focused on both traditional ML and DL for data and image classification. Their findings emphasized that, while traditional ML can still be useful for smaller or simpler datasets, DL models provide superior accuracy and generalization on large, complex image datasets, particularly when computational resources are sufficient.

Iqbal et al. [27] reviewed analyses of medical images using both traditional ML and CNNs, underlining how CNNs have revolutionized medical image analysis by effectively learning spatial features and patterns in data, outperforming conventional methods that rely heavily on manual feature extraction.

El-Shafai et al. [28] explored traditional and deep learning-based denoising techniques for medical images and concluded that DL methods offer better noise reduction while preserving crucial image details, which is critical for accurate diagnosis and downstream tasks such as segmentation or classification.

Sreedhar et al. [29] compared melanoma skin cancer detection approaches using traditional image processing techniques and current DL methods. Their study highlighted how DL methods achieve higher detection accuracy and robustness than earlier traditional approaches, suggesting a paradigm shift in image-based disease detection.

Vision transformers (ViTs) have introduced new possibilities for image classification and computer vision. Parvaiz et al. [30] provided a contemplative review of the applications of ViTs in medical computer vision, noting how self-attention mechanisms enable these models to capture the global context effectively, surpassing CNNs in several benchmarks.

Al-Hammuri et al. [31] offered a detailed tutorial and survey of ViT architectures in digital health applications, demonstrating how transformers can enhance performance in medical image tasks, such as classification, segmentation, and diagnosis.

Khan et al. [32] broadly surveyed transformer models, summarizing the advancements and challenges associated with adapting transformers, originally developed for natural language processing, to visual data.

Papa et al. [33] reviewed efficient vision transformers, focusing on algorithmic improvements, performance benchmarks, and practical deployment, addressing the challenges of high computational costs in vanilla ViTs.

Jamil et al. [34] provided a comprehensive survey of transformers for computer vision, covering their architecture, applications, and emerging variants and highlighting their growing role in diverse vision tasks, including plant disease classification, medical imaging, and autonomous systems.

Yu et al. [35] proposed an inception convolutional vision transformer model that effectively captures multiscale features for plant disease classification, demonstrating improved performance over standard CNNs by utilizing self-attention mechanisms that better model spatial dependencies.

Thakur et al. [36] introduced hybrid architectures combining CNNs and vision transformers, such as the PlantViT model, to classify plant diseases more robustly. These models harness convolutional layers for local feature extraction and transformers for global context understanding, thereby enabling accurate classification across diverse disease types.

Borhani et al. [37] developed a fully transformer-based DL approach for automated plant disease classification, achieving state-of-the-art results by exploiting the transformer's ability to learn complex visual patterns without relying heavily on extensive pre-processing.

Parez et al. [38] surveyed the use of efficient vision transformers in precision agriculture, emphasizing how these models contribute to real-time disease detection in crops and support early intervention to reduce yield loss.

A complementary research direction focuses on semantic segmentation to localize and quantify disease symptoms in plant leaves. Li et al. [39] proposed methods for the automatic localization of image semantic patches relevant to crop disease recognition, enabling the precise identification of infected regions.

Taghanaki et al. [40] provided a comprehensive review of deep semantic segmentation methods for natural and medical images, highlighting architectures applicable to plant disease detection. Khanna et al. [41] further explored DL frameworks for semantic segmentation to estimate the severity of foliar symptoms, which is critical for assessing crop health.

Liu et al. [42] demonstrated deep semantic segmentation approaches for quantifying grape foliar diseases directly in vineyards, demonstrating the practical benefits of in-field disease monitoring. Mzoughi and Yahiaoui [43] confirmed the efficacy of segmentation-based DL models for precise disease identification in agricultural contexts.

Leaf image localization, as studied by Kurmi and Gangwar [44] and Nawaz et al. [45], provides algorithms for robust leaf detection and disease classification, even under complex background conditions. This enhances the reliability of automated diagnostic systems in real-world environments.

Segmentation models have also been applied to detect pine wilt disease in aerial images captured by drones [46] and potato foliage diseases in complex backgrounds [47], indicating the scalability of these techniques for diverse crops and imaging conditions.

To address the computational demands of transformer-based models, researchers such as Zhang et al. [48] proposed efficient variants such as Cas-ViT, which combines convolutional and additive self-attention mechanisms for mobile and edge devices. Nag et al. [49] developed ViTA, a vision transformer inference accelerator designed for edge applications that facilitates deployment in resource-constrained agricultural settings.

Edge computing plays a vital role in smart farming, enabling real-time processing close to data sources and reducing the latency. Zhang et al. [50] discussed edge server placement strategies for service offloading in smart farming applications and optimized the computational resources for large-scale deployments.

Oteyo et al. [51] surveyed mobile applications for smart agriculture and revealed the increasing adoption of mobile software to aid farmers in crop monitoring and management. Sathya et al. [52] reviewed the revolution brought about by edge computing combined with intelligent robots and drones for precision agriculture, highlighting the potential to transform traditional farming into a data-driven, automated process.

Godase et al. [53] proposed a secure Industrial Internet of Things (IIoT) environment framework by integrating MapReduce and Kalman Filter algorithms within a Hadoop ecosystem. Their work focused on enhancing data security and processing efficiency for IIoT applications, ensuring reliable sensor data aggregation and analysis in distributed environments.

Gadade et al. [54] developed an IoT-based smart school bus-tracking system aimed at improving student safety and real-time monitoring. Their system utilizes GPS and IoT technologies to provide accurate location tracking, enabling parents and school authorities to monitor school bus movements efficiently.

Dhanawadel, Mulani, and Pise [55] introduced a smart farming solution leveraging IoT and agricultural robots for automated agricultural practices. Their system aimed to improve farming efficiency through remote monitoring and control of environmental conditions, facilitating precision agriculture, and reducing manual labor.

Mulani and Mane [56] focused on digital watermarking using discrete wavelet transform (DWT) techniques to develop a robust and invisible watermarking method. This approach enhances image security by embedding imperceptible watermarks that are resistant to various attacks, aiding copyright protection.

Ghodke et al. [57] presented the design and development of a cost-effective surveillance quadcopter built using Arduino hardware. Their work emphasized affordability and efficiency, enabling the deployment of security monitoring with wireless communication capabilities.

In another study, Ghodke et al. [58] designed a wireless-controlled robot using Bluetooth. Robot architecture supports remote operation with low latency, highlighting applications in automation and remote surveillance.

Swami and Mulani [59] proposed an efficient field-programmable gate array (FPGA) implementation of the DWT for image compression. Their design optimized resource utilization and processing speed on FPGA platforms, making them suitable for real-time image processing applications.

Mane and Mulani [60] developed a high-speed, area-efficient FPGA implementation for the advanced encryption standard (AES) algorithm. This work contributes to embedded security by balancing throughput and hardware resource usage, thereby enabling encryption for resource-constrained devices.

Mulani and Mane [61] explored FPGA-based invisible watermarking for image authentication. Their method delivers high-speed processing with area efficiency on FPGA hardware, providing a practical solution for digital image authentication and copyright enforcement.

These studies collectively show a rapid evolution from traditional ML methods to sophisticated DL and transformer-based models, integrated with IoT and edge computing for real-time agricultural monitoring. Advances have made it possible to detect, classify, and diagnose plant diseases more accurately and efficiently, which is critical for improving crop yield and sustainable agriculture.

COMPARATIVE ANALYSIS

A comparative analysis of the selected research papers is presented below, highlighting their key approaches, methodologies, and contributions in relation to the current study (Table 1).

CONCLUSION

Recent research in the field of plant disease detection has shown a major shift from traditional image processing techniques to more advanced DL methods. Previously, basic image processing methods were used to identify diseases; however, DL models are now becoming more popular because they offer much higher accuracy. While most studies have focused on common crops such as wheat, rice, or tomatoes, research on pomegranate disease detection is also gaining attention.

Several DL models developed specifically for identifying diseases in pomegranates have shown promising results. These models can accurately detect and classify diseases based on leaf images. However, several challenges remain. Most existing research has been conducted using small or limited datasets, which may not work well in real-world conditions where image quality and disease appearance can vary.

Table 1. Comparative analysis of some papers.

S.N.	Author (year)	Focus	Dataset	Technique	Model/method	Strengths	Limitations
1	Zahra et al. (2023) [1]	Fruit disease recognition	Fruits 360 + Custom	Two-stream DL	ResNet + EfficientNet Fusion	High accuracy via info fusion	High complexity, needs computation
2	Vijh et al. (2023) [2]	Infected plant leaf images	Public dataset	Bag-of-Features	USMA-BOF + SVM	Lightweight, interpretable	May not handle real-time scenarios well
3	Khatawkar et al. (2023) [8]	Pomegranate fruit	Real field data	ML classifiers	SVM, KNN, RF	Realistic images, simple ML	No deep learning, limited generalization
4	Ukwuoma et al. (2022) [3]	Fruit detection and classification	Multiple datasets	Literature Review	CNN, YOLO, etc.	Broad DL comparison	No experimental work
5	Elaziz et al. (2022) [5]	Feature selection	Benchmark	Optimizatio n	Rough Set + Binary HBB	Efficient feature reduction	Not plant-specific
6	Narayanan et al. (2022) [4]	Banana disease classification	Banana leaf dataset	Hybrid DL	CNN (DenseNet + Inception)	Boosted accuracy via hybrid	Higher model complexity
7	Vasumathi and Kamarasan (2021) [7]	Pomegranate fruit	Custom	DL	CNN + LSTM	Spatio-temporal learning	Small dataset
8	Sharath et al. (2020) [6]	General plant disease	Leaf dataset	DL	Basic CNN	Easy to implement	No hybrid/advanced features
9	Chakali (2020) [9]	Pomegranate leaf	Leaf dataset	DL	CNN	Domain-specific, DL-based	Lacks performance details
10	Gaikwad and Karande (2016) [10]	Pomegranate grading	Review	Image Processing	Color, Shape, Texture	Early foundational work	lacks ML
11	Gaikwad et al. (2016) [62]	Pomegranate detection	Field images	Traditional methods	Thresholding, Segmentation	Simple techniques	less robust

To improve the reliability and usefulness of these systems, researchers must develop larger and more diverse datasets that cover different disease stages and environmental conditions. Additionally, practical solutions should be tested in real farming situations. Overall, although DL has improved disease detection in pomegranates, more focused research is needed to make these solutions usable and accessible to farmers in real-world agriculture.

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