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How AI is helping farmers detect diseases in tomatoes

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Abstract
Tomato diseases pose a significant challenge to agricultural productivity, as delayed identification and incorrect diagnosis can lead to crop losses, increased treatment costs, and reduced fruit quality. Traditional disease detection methods often depend on farmers' experience and the availability of agricultural experts, which may not always be accessible in rural areas. This paper examines the role of Artificial Intelligence (AI), particularly machine learning and deep learning, in detecting diseases in tomato plants through image-based analysis. It discusses the use of Convolutional Neural Networks (CNNs), transfer learning, smartphone cameras, drones, and sensors for identifying disease symptoms and supporting early diagnosis. The paper also explores how AI-based applications can help farmers reduce unnecessary pesticide use, improve crop management, and protect agricultural productivity. However, challenges such as limited real-world training data, varying environmental conditions, internet accessibility, and similarities between disease symptoms can affect the accuracy and reliability of these systems. The paper highlights the importance of training AI models using images collected from actual agricultural fields and combining technological assistance with expert agricultural knowledge. It concludes that AI can serve as a practical decision-support tool for tomato farmers, particularly when developed to meet the needs of small-scale farmers and local agricultural conditions.

Keywords: Artificial Intelligence, Tomato Diseases, Deep Learning, Machine Learning, Convolutional Neural Networks, Agriculture, Disease Detection

1. Introduction

Tomato cultivation plays an important role in agricultural production, food supply, and the economic activities of farming communities. Tomatoes are widely consumed and commercially cultivated because of their nutritional value, versatility, and demand in domestic and international markets. However, tomato plants are vulnerable to various diseases that can affect their growth, productivity, fruit quality, and commercial value. The appearance of disease symptoms may initially be limited to a few leaves, but under favourable environmental conditions, infections can spread rapidly and cause substantial damage. Early identification and appropriate management are therefore essential for maintaining crop health and reducing agricultural losses.

Tomato diseases frequently present diagnostic difficulties because different infections may produce similar visible symptoms. Yellowing leaves, dark spots, curling, wilting, and discoloration may indicate a particular disease, but these symptoms can also result from nutrient deficiencies, water-related stress, environmental conditions, or pest activity.

Consequently, farmers may experience difficulties distinguishing between diseases and other plant health problems through visual observation alone. Incorrect diagnosis can lead to inappropriate treatment, unnecessary pesticide application, increased expenditure, and continued disease development. Accurate identification is therefore an important requirement for effective tomato disease management.

Traditional disease identification generally depends on farmers' experience, visual inspection, and consultation with agricultural experts. Although these methods remain valuable, their effectiveness may be limited when professional assistance is unavailable, particularly in rural areas where agricultural services may be difficult to access. Furthermore, identifying diseases at an early stage requires continuous observation and familiarity with the symptoms associated with different plant conditions. Delays in diagnosis can reduce the effectiveness of treatment and increase the possibility of disease transmission within cultivated areas.

Artificial Intelligence has introduced new possibilities for addressing these limitations by enabling computer systems to analyse plant images and identify patterns associated with different diseases. Machine learning and deep learning techniques can be trained using labelled images of healthy and diseased plants to recognise characteristics such as colour variations, spots, leaf structures, and visible damage. These technologies can support the identification of disease symptoms and provide farmers with preliminary information about the health of their crops. Mohanty *et al.* (2016) [1] demonstrated the potential of deep learning for image-based plant disease detection, establishing an important foundation for further research in agricultural image analysis.

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The application of AI in agriculture is particularly relevant because smartphones, digital cameras, and agricultural monitoring systems can provide images for disease assessment. Farmers may capture photographs of affected leaves and submit them to AI-based applications, which analyse the images and generate possible disease classifications. More advanced systems can incorporate information from environmental sensors and agricultural monitoring technologies to provide a broader understanding of crop conditions. However, the usefulness of these systems depends on the quality of their training data, their ability to operate under field conditions, and the reliability of their predictions.

This paper examines how AI technologies can support tomato disease detection and agricultural decision-making. It discusses the major tomato diseases and their visible symptoms, the limitations of traditional diagnostic approaches, the development and operation of AI-based disease detection models, and the practical applications of these technologies in agricultural settings. It also evaluates the benefits, limitations, and future possibilities of AI-assisted disease management, with particular attention to the requirements of farmers operating under different environmental and technological conditions.

2. Artificial Intelligence and Its Application in Agriculture

Artificial Intelligence refers to computational technologies designed to perform tasks that ordinarily require human cognitive abilities, including pattern recognition, classification, prediction, and decision-making. In agriculture, AI can be applied to analyse crop images, monitor environmental conditions, identify potential plant health problems, and support agricultural planning. Its application is particularly useful in situations where large quantities of visual information must be examined consistently and efficiently.

Machine learning is a branch of AI that enables computer systems to identify patterns from examples rather than relying entirely on manually programmed rules. A machine learning model can be trained using agricultural images that have been classified according to plant health conditions. Through training, the model learns relationships between the characteristics of an image and the corresponding disease category. When presented with a new image, the trained system uses the patterns it has learned to generate a prediction.

Deep learning represents a more advanced approach within machine learning that uses multiple layers of computational processing to identify complex patterns in data. It has become particularly relevant to agricultural image analysis because plant diseases frequently produce visual characteristics that can be identified through image-based learning. Deep learning models can examine different features of an image, including edges, textures, colour variations, and spatial relationships, to distinguish between healthy and diseased plant material.

Convolutional Neural Networks are among the most widely used deep learning architectures for image classification. CNNs process images through convolutional operations that identify visual patterns at different levels of complexity. During training, the model learns to recognise relevant features associated with particular disease categories. These capabilities make CNNs suitable for examining tomato leaves and identifying visible symptoms associated with common plant diseases. However, their performance depends on the availability of representative training images and appropriate validation procedures.

AI-based agricultural systems should therefore be understood as decision-support technologies rather than independent replacements for agricultural expertise. Their primary contribution lies in assisting farmers with preliminary identification, improving the consistency of observations, and supporting timely decisions. The effectiveness of such systems depends on their integration with reliable agricultural information and their ability to account for the environmental conditions in which crops are cultivated.

3. Major tomato diseases and their identification

Tomato plants are susceptible to several diseases that can affect their leaves, stems, fruits, and overall development. The identification of these diseases is important because their symptoms may differ in appearance, severity, and progression. AIbased systems can assist in recognising visible characteristics, but accurate classification requires sufficient information about the disease and the conditions affecting the plant.

Early blight is commonly associated with dark lesions that may develop concentric ring-like patterns, particularly on older leaves. As the disease progresses, affected leaves may become yellow and deteriorate, reducing the plant's ability to maintain healthy growth. The recognition of these characteristic patterns can assist in identifying possible early blight infections.

Late blight can produce water-soaked or darkened lesions on leaves and other plant parts. Under favourable environmental conditions, the disease may spread rapidly and cause extensive damage. Its symptoms can sometimes resemble those of other infections, making careful examination necessary. AI-based image analysis may assist in identifying visible characteristics associated with late blight, although additional information may be required to distinguish it from similar conditions.

Tomato leaf curl disease is generally associated with leaf curling, yellowing, reduced plant growth, and changes in the overall appearance of the plant. The disease is commonly transmitted by whiteflies. Since leaf curling and yellowing can also result from environmental stress or nutritional deficiencies, identifying the underlying cause requires more than observing a single symptom.

Septoria leaf spot is characterised by the appearance of numerous small, circular lesions that may develop greyish centres and darker margins. These lesions can become increasingly visible as the infection progresses. Image-based systems may assist in recognising the size, shape, distribution, and colour characteristics of these spots.

Bacterial spot can produce small, dark lesions on leaves and fruits, sometimes accompanied by raised or irregular surfaces. The symptoms may overlap with those associated with other diseases, particularly during the early stages of infection.

Consequently, disease identification should consider the overall pattern of symptoms rather than relying exclusively on individual spots.

Tomato disease symptoms may appear on different parts of the plant. Leaves may exhibit spots, yellow patches, curling, holes, or powdery growth. Stems may develop dark streaks, cracks, or areas of decay. Fruits may display sunken lesions, discoloration, cracking, or signs of rotting. General symptoms may include wilting, reduced growth, and a decline in flowering or fruit development.

The similarity between disease symptoms presents an important challenge for AIbased diagnosis. A model trained to identify visible patterns may incorrectly classify a plant when the symptoms resemble those of another disease or arise from non-infectious conditions. Therefore, disease identification should incorporate representative images, reliable disease labels, and appropriate agricultural knowledge. AI predictions should be treated as preliminary assessments, particularly when the symptoms are unclear or the consequences of an incorrect diagnosis are significant.

4. Limitations of traditional tomato disease detection

Traditional tomato disease detection primarily involves visual inspection by farmers, agricultural workers, and plant health specialists. Farmers often rely on their experience to identify changes in leaf colour, plant structure, and fruit appearance. This approach can be effective when the symptoms are familiar and the observer has sufficient knowledge of local agricultural conditions. However, the accuracy of visual diagnosis may vary according to experience, the severity of the disease, and the availability of relevant information.

One important limitation is the accessibility of agricultural experts. Farmers in remote areas may face difficulties obtaining timely professional assistance. When expert consultation is delayed, disease symp

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toms may become more severe before appropriate treatment is initiated. The lack of accessible diagnostic support can therefore contribute to agricultural losses and increase the difficulty of disease management.

Another limitation concerns the similarity between symptoms associated with different plant conditions. Yellowing, wilting, leaf curling, and discoloration may result from infections, pests, nutrient deficiencies, or environmental stress. Farmers may incorrectly identify the cause and apply unsuitable treatments. Such decisions can increase costs and potentially contribute to unnecessary pesticide use.

Traditional inspection also requires continuous monitoring of cultivated plants. In large agricultural areas, examining every plant individually may be difficult and timeconsuming. Early symptoms may remain unnoticed, particularly when they occur on lower leaves, inside dense plant growth, or in areas that are difficult to access.

AI-based systems can help address some of these limitations by providing rapid imagebased assessments and supporting the identification of visible disease patterns. Nevertheless, their effectiveness depends on the quality of the available images, the representativeness of the training data, and the ability of the model to distinguish between diseases and other plant health conditions. AI should therefore complement traditional diagnostic methods rather than replace them entirely.

5. Development of AI-based tomato disease detection models

The development of an AI-based tomato disease detection model begins with the collection of images representing healthy plants and different disease categories. These images provide the examples from which the model learns to identify diseaserelated characteristics. A dataset may include photographs of leaves, fruits, and other plant parts showing different stages of disease development.

The quality and diversity of the dataset are essential for developing a reliable model. Images should represent different tomato varieties, environmental conditions, lighting situations, camera angles, and symptom severity. A dataset containing only clean images captured under controlled conditions may not adequately represent the difficulties encountered in agricultural fields. Consequently, models trained exclusively on laboratory images may perform poorly when presented with photographs containing shadows, dust, overlapping leaves, or complex backgrounds.

Image annotation is another important stage in model development. Each image must be assigned an appropriate label identifying the plant condition represented in the photograph. These labels may include healthy plants and specific disease categories such as early blight, late blight, or leaf curl disease. Accurate annotation is necessary because the model learns from the information provided during training. Incorrect labels can introduce errors and reduce the reliability of the resulting predictions.

Following dataset preparation, the images are used to train the model. During training, the CNN identifies patterns associated with the different categories and adjusts its internal parameters to improve classification performance. The model learns to recognise characteristics such as colour differences, lesion shapes, textures, and patterns of damage. Repeated training allows the system to improve its ability to distinguish between the categories represented in the dataset.

Model evaluation is necessary to determine whether the trained system can identify diseases in images that were not used during training. A separate testing dataset can be used to assess the model's ability to classify unfamiliar images. Evaluation should include images collected under different conditions to determine whether the system performs reliably beyond the controlled environment in which it was developed.

Transfer learning can further support the development of agricultural image classification systems. This approach involves using a model that has already learned general visual features from a large dataset and adapting it to recognise tomato diseases. Transfer learning may reduce the amount of training data and computational resources required compared with developing a model entirely from the beginning. However, the adapted model must still be evaluated using representative agricultural images.

The development process should therefore include dataset collection, annotation, model training, testing, and validation. The reliability of the final system depends not only on the architecture of the model but also on the quality of the agricultural information used to train and evaluate it.

6. Technologies used in AI-based tomato disease detection

Smartphone cameras provide an accessible method for collecting images of tomato plants. Farmers can photograph affected leaves and upload the images to applications designed for plant disease identification. Smartphone-based systems may reduce the need for specialised equipment and allow preliminary diagnosis to be performed directly in agricultural fields. However, image quality, camera limitations, lighting conditions, and the user's ability to capture clear photographs can influence the accuracy of the resulting classification.

Convolutional Neural Networks provide the principal image-processing capability in many AI-based disease detection systems. They identify visual patterns that may correspond to particular disease symptoms and classify images according to the categories represented in the training dataset. CNN-based models can support the identification of visible lesions, discoloration, and other characteristics associated with plant diseases. Their performance nevertheless depends on the availability of suitable training data and appropriate model validation.

Transfer learning offers another approach for improving agricultural image classification. Instead of training a model entirely from scratch, researchers can adapt an existing deep learning model to the specific task of tomato disease detection. This approach may be particularly useful when agricultural datasets are relatively small. However, the resulting model must still be trained and evaluated using images that accurately represent the target agricultural conditions.

Object detection technologies can provide more detailed information than image classification alone. Rather than assigning a single disease category to an entire photograph, object detection systems may identify and locate regions containing visible symptoms. This can help users understand which parts of the plant appear affected. The effectiveness of such systems depends on the quality of image annotations and the ability to distinguish disease-related regions from normal plant structures.

Drones and agricultural cameras can support crop monitoring over larger cultivated areas. These technologies may collect images of plants that can be analysed using AI-based systems. In agricultural environments where manual inspection is difficult, automated image collection can help identify areas requiring further examination. However, the practical usefulness of drone-based disease detection depends on image resolution, environmental conditions, operational costs, and the suitability of the detection model for the cultivated crop.

Agricultural sensors can provide additional information about environmental conditions, including temperature, humidity, and soil moisture. Such information may help farmers understand conditions that influence plant health and disease development. When combined with image-based observations, environmental data can contribute to a more comprehensive assessment of crop conditions. However, environmental measurements should not be treated as direct confirmation of a particular disease. They are most useful when interpreted alongside visible symptoms and agricultural expertise.

7. Working mechanism of AI-based tomato disease detection

An AI-based tomato disease detection system generally begins with the collection of an image of the affected plant. The image may be captured using a smartphone camera, a digital camera, or an agricul

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tural monitoring system. The quality of the photograph is important because the model must be able to identify the visual characteristics associated with the plant's condition.

The captured image is then processed by the AI application. Depending on the system, image processing may involve resizing, normalising, or preparing the photograph for analysis. These operations help ensure that the image is presented in a format suitable for the trained model.

The trained model examines the image and identifies patterns associated with the disease categories represented in its dataset. It may analyse the colour, texture, shape, and distribution of visible symptoms. Based on these characteristics, the system generates a classification or prediction indicating the plant condition that most closely matches the patterns it has learned.

The application may then display the predicted disease category and, where supported, provide general information about the identified condition. Such information can help farmers understand the possible cause of the symptoms and determine whether further examination is required. However, the prediction should not automatically be considered a confirmed diagnosis.

More advanced agricultural systems may combine image analysis with environmental monitoring. Cameras can collect images of plants, while sensors record information about temperature, humidity, and soil moisture. These observations may help identify areas requiring additional attention and support decisions regarding crop monitoring.

The overall process demonstrates how AI can improve the speed and accessibility of preliminary disease assessment.

Nevertheless, the reliability of the system depends on the quality of the image, the suitability of the model, and the extent to which the observed plant conditions are represented in its training data.

8. Research and existing applications

Research on AI-based plant disease detection has demonstrated the potential of deep learning for identifying disease-related patterns in agricultural images. Mohanty *et al.* (2016) [1] examined the application of deep learning to image-based plant disease detection and demonstrated how computational models can classify plant conditions using visual information. Their research provides an important foundation for understanding the role of deep learning in agricultural disease identification.

PlantVillage has contributed to agricultural image analysis through the availability of plant disease image datasets used in research and model development. Such datasets allow researchers to train and evaluate image classification systems using labelled photographs of healthy and diseased plants. However, the conditions under which images are collected can influence the performance of trained models. Models developed using controlled images may not achieve similar results when applied to photographs collected directly from agricultural fields.

Jelali (2024) [2] reviewed research on deep learning-based tomato disease and pest detection, with particular attention to studies using real-field datasets. The review highlights the importance of examining the performance of disease detection models under conditions that reflect actual agricultural environments. Real-field datasets are valuable because they incorporate variations in lighting, backgrounds, plant growth, and disease appearance that may not be adequately represented in controlled image collections.

The difference between controlled and field based evaluation is particularly important when interpreting reported model accuracy. A model may perform well when images contain clearly visible symptoms and limited background interference. However, agricultural photographs may include overlapping leaves, shadows, soil, insects, and multiple symptoms. These conditions can make disease classification more difficult and may reduce the reliability of predictions.

Plantix is an example of an agricultural application that provides crop diagnosis and treatment-related information. Such applications illustrate the potential of digital technologies to make agricultural information more accessible to farmers. However, the effectiveness of any disease diagnosis application depends on the accuracy of its identification process, the relevance of its recommendations, and the conditions under which it is used.

The available research indicates that AI based disease detection is a developing area with practical potential. Nevertheless, reported performance should be interpreted in relation to the datasets, evaluation methods, and environmental conditions used in individual studies. Further research involving representative field images and practical agricultural testing is necessary to establish the reliability of these systems across different farming environments.

9. Benefits of AI-Based Tomato

Disease Detection

One of the principal benefits of AI-based tomato disease detection is the possibility of identifying visible symptoms at an early stage. Early identification may help farmers recognise plant health problems before they spread across cultivated areas. By providing rapid preliminary assessments, AI applications can support timely decisions regarding further inspection and disease management.

AI-based systems may also improve the accessibility of agricultural diagnostic information. Farmers who have access to smartphones and suitable applications can obtain preliminary information about plant diseases without immediately requiring direct consultation with an agricultural expert. This may be particularly valuable in areas where agricultural extension services are difficult to access.

Another potential benefit is the reduction of unnecessary pesticide application. When farmers have better information about the possible cause of plant symptoms, they may be able to avoid treatments that are inappropriate for the identified condition. However, AI-based identification alone cannot guarantee a reduction in pesticide use. Such improvements depend on the accuracy of diagnosis, the suitability of treatment recommendations, and the farmer's ability to implement appropriate management practices.

AI can also support agricultural monitoring by analysing images collected from different parts of a cultivated area. Automated image analysis may help identify locations where plant health conditions require further attention. This can reduce the time required for preliminary observation and support more targeted field inspections.

The use of AI may contribute to improved crop management by providing farmers with information that supports decision-making. When integrated with agricultural expertise, disease detection systems can help farmers understand potential problems and consider appropriate responses. Their contribution is therefore not limited to classification but also includes supporting the broader process of agricultural observation and management.

The benefits of AI-based disease detection should nevertheless be evaluated in relation to its practical limitations. Accessibility, affordability, data quality, and diagnostic reliability remain important factors affecting its usefulness. A system that performs well in research settings may not provide the same benefits when used by farmers under different environmental and technological conditions.

10. Challenges and limitations

The accuracy of AI-based tomato disease detection depends significantly on the quality and diversity of the training dataset. Models trained using images collected under controlled conditions may struggle to identify diseases when photographs contain shadows, dust, overlapping leaves, or complex backgrounds. This limitation can reduce the reliability of predictions in actual agricultural environments.

Another important challenge is the similarity between symptoms associated with different diseases. Several infections may produce yellowing, spots, wilting, or discoloration. Non-infectious conditions, including nutrient deficiencies and environmental stress, may produce similar visual characteristics. Consequently, an image classification model may incorrectly identify the cause of a plant's condition when the available photograph does not contain sufficient diagnostic information.

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Environmental variability also affects model performance. Tomato varieties, climatic conditions, soil characteristics, cultivation practices, and disease prevalence may differ across regions. A model developed using images from one agricultural environment may not perform equally well in another. Therefore, training datasets should include images representing the conditions under which the system is expected to operate.

The availability of smartphones, internet connectivity, and digital infrastructure presents additional challenges. Some farmers may not have access to reliable internet services or devices capable of running advanced applications. The accessibility of AI-based agricultural technologies may therefore vary according to location, income, and technological resources.

Language accessibility is another important consideration. Applications developed primarily in English may be difficult to use for farmers who prefer regional languages. Providing understandable information and accessible interfaces can improve the practical usefulness of disease detection systems.

The reliability of treatment recommendations also requires careful consideration. A disease classification does not necessarily establish the most appropriate treatment for a particular plant. Incorrect recommendations may result in unnecessary expenditure, unsuitable pesticide use, or further crop damage. AI applications should therefore provide appropriate limitations and encourage expert consultation when the diagnosis is uncertain.

These challenges demonstrate that AI-based disease detection cannot be evaluated solely through laboratory accuracy. Its effectiveness must also be assessed through field testing, accessibility, practical usefulness, and the ability to provide reliable information under varying agricultural conditions.

11. Practical recommendations for using AI-based disease detection applications

The usefulness of an AI-based disease detection application depends partly on the quality of the images submitted for analysis. Farmers should capture photographs in adequate natural light and ensure that the affected area is clearly visible. Blurred images, shadows, and photographs containing multiple unrelated objects may reduce the model's ability to identify relevant symptoms.

Photographs of individual affected leaves can provide useful information about visible disease characteristics. Images showing the entire leaf and the surrounding plant may also help provide context. Where several plants exhibit similar symptoms, examining multiple photographs can assist in understanding whether the problem is isolated or more widely distributed.

Farmers should avoid making treatment decisions solely on the basis of a single AI generated prediction. When the symptoms are unclear or the suggested diagnosis does not correspond with the observed plant condition, consultation with an agricultural expert is advisable. This is particularly important when diseases have similar symptoms or when the recommended treatment could have significant consequences.

Maintaining records of plant health observations may also support agricultural management. Information about the date of observation, visible symptoms, environmental conditions, and treatments applied can help farmers understand changes in crop health over time. Such records may also contribute to more informed discussions with agricultural experts.

Preventive agricultural practices remain important regardless of the availability of AI-based diagnostic systems. Appropriate plant spacing, healthy planting material, crop rotation, sanitation, and suitable cultivation practices can contribute to reducing disease risks. AI should therefore be used alongside established agricultural management methods rather than as a substitute for prevention.

The responsible use of AI applications requires farmers to understand that predictions are based on the information available to the model. A system may provide useful preliminary information, but the final management decision should consider the broader agricultural context and the possibility of alternative explanations for the observed symptoms.

12. Role of agricultural institutions, researchers, and farmers

The successful development of AI-based tomato disease detection requires collaboration between agricultural institutions, technology developers, researchers, and farmers. Agricultural universities can contribute by collecting disease images, identifying plant conditions, and developing datasets that represent local agricultural environments. Their involvement is important because reliable disease classification requires accurate agricultural knowledge.

Technology developers can use these datasets to create models and applications that are accessible to farmers. The development of affordable systems, simple interfaces, and regional language support can improve the practical usefulness of AI based agricultural technologies. Applications should be designed with consideration for the technological resources and requirements of their intended users.

Government institutions and agricultural extension services can support the adoption of AI by providing training, information, and access to appropriate digital resources. Improving internet connectivity and promoting agricultural technology awareness may help reduce barriers to adoption in rural areas.

Farmers also play an important role in improving disease detection systems. Their observations can provide information about the symptoms encountered in actual agricultural fields. Images collected under different conditions may help researchers identify limitations in existing datasets and improve the ability of models to recognise disease symptoms outside controlled environments.

Collaboration between these stakeholders can support the development of AI systems that are more reliable, accessible, and relevant to agricultural needs. Such cooperation is particularly important when developing technologies for small-scale farmers, whose requirements may differ from those of large commercial agricultural operations.

13. Future scope of Artificial Intelligence in tomato disease management

The future development of AI-based tomato disease detection is likely to involve improvements in image classification, field monitoring, and the integration of agricultural information. Researchers may develop models capable of identifying multiple disease categories and distinguishing between different types of plant health problems. Such improvements could support more comprehensive agricultural diagnosis.

The development of lightweight AI models may also improve accessibility. Models that can operate on smartphones or other affordable devices without requiring continuous internet connectivity may be particularly useful in areas with limited digital infrastructure. However, their performance must be evaluated to ensure that reduced computational requirements do not compromise diagnostic reliability.

The integration of image analysis with environmental information represents another important research direction. Temperature, humidity, soil moisture, and other observations may provide additional context for interpreting plant health conditions. Combining these sources of information may help improve agricultural monitoring, although further research is required to determine how reliably they contribute to disease identification.

Future research should also prioritise the development of datasets collected under actual field conditions. Such datasets can include variations in plant varieties, environmental conditions, disease severity, and image quality. Testing models using independent field datasets can provide a more realistic assessment of their performance and help identify areas requiring improvement.

The development of accessible agricultural applications may further increase the practical value of AI. Regional language interfaces, simple image capture procedures, and understandable diagnostic information can make these systems easier to use. However, accessibility

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should be accompanied by clear explanations of the limitations of AI predictions and the importance of expert consultation.

AI-based disease detection may ultimately contribute to more informed agricultural decisions by improving the availability of preliminary diagnostic information. Its long term effectiveness will depend on continued research, reliable datasets, practical validation, and the integration of technology with agricultural expertise.

14. Conclusion

Tomato diseases remain an important challenge for agricultural productivity, crop quality, and farmers' economic security. Traditional disease identification methods provide valuable agricultural knowledge but may be limited by the availability of experts, the difficulty of recognising early symptoms, and the time required for field inspection. Artificial Intelligence offers a promising approach to addressing these challenges through image-based disease classification, automated monitoring, and accessible agricultural applications.

Machine learning and deep learning technologies, particularly Convolutional Neural Networks, can identify visual patterns associated with tomato diseases and support preliminary diagnosis. Smartphone cameras, agricultural monitoring systems, drones, and sensors may further contribute to the collection and analysis of plant health information. These technologies can help farmers recognise possible disease symptoms and make more informed decisions regarding crop management.

However, the effectiveness of AI-based disease detection depends on the quality of training data, the representativeness of field images, and the ability of models to operate under varying environmental conditions. Similar disease symptoms, non-infectious plant conditions, limited internet connectivity, and technological accessibility remain important challenges. High performance under controlled conditions does not necessarily establish reliability in actual agricultural environments.

The development of locally relevant datasets, practical field validation, accessible applications, and collaboration between agricultural researchers, technology developers, and farmers is therefore essential. AI should be considered a decision-support tool that complements agricultural expertise rather than replacing professional diagnosis or established preventive practices.

In conclusion, AI has the potential to improve tomato disease detection by making preliminary identification faster, supporting agricultural monitoring, and providing farmers with accessible diagnostic information. Its contribution to sustainable and effective disease management will depend on the development of reliable models, responsible application, and integration with practical agricultural knowledge.

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