A Review of Farmer-Centric Accessibility and Usability in Plant Disease Detection Technologies

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***Abstract*—Over the years, the way plant disease detection has been carried out has changed significantly. In the past, farmers mostly relied on visual inspection and laboratory tests to detect plant diseases. Today, a variety of technologies, including machine learning, deep learning, advanced imaging, spectroscopy, biosensors, the Internet of Things (IoT), unmanned aerial vehicles (UAVs), and edge-based systems, are being employed for this purpose. As a result, disease detection has become more accurate and is now capable of spotting diseases in their early stages. However, there is one important point to bear in mind. A system might perform well in a research setting, but it can still be challenging to put it into practice in real farming situations. This review examines plant disease detection technologies from a practical standpoint, taking into account factors such as cost, availability, ease of use, the resources needed, and their usefulness in the management of diseases. It also discusses the difficulties involved in applying advanced diagnostic methods in actual agricultural fields, where farmers often have limited resources and little technical knowledge. Therefore, focusing solely on detection accuracy is not sufficient. Future plant disease detection systems should not only offer reliable results but also be affordable, easy to operate, and accessible to farmers under real farming conditions.**

***Keywords*—Plant disease detection, deep learning, farmer-centric technology, accessibility, usability, field deployment, precision agriculture, smartphone-based diagnosis, non-destructive detection, edge AI.**

I. INTRODUCTION

Plant diseases are a problem in agriculture because they lower crop yields, reduce the quality of harvested crops, and hurt farmers' financial returns. It is important to detect plant diseases because it can reduce crop losses and allow the right treatments to be applied on time. In the past, farmers and agricultural experts diagnosed plant diseases by looking at the plants or by using laboratory tests. Although these traditional methods are valuable, they require a lot of work, take time, need skilled people, and are impractical for routine use over large farms [1], [2], [14].

Because technology has advanced, many automated methods have been created to detect plant diseases. These methods include machine learning (ML), deep learning (DL), digital imaging, spectroscopy, hyperspectral imaging (HSI), molecular testing, biosensors, the Internet of Things (IoT), unmanned aerial vehicles (UAVs or drones), and edge computing systems [1], [7], [9]–[13], [17], [19]–[25], [30]. Convolutional neural networks (CNNs), a type of deep learning model, have proven effective because they can automatically find important features in images and diagnose plant diseases accurately [2], [4], [15], [27], [28].

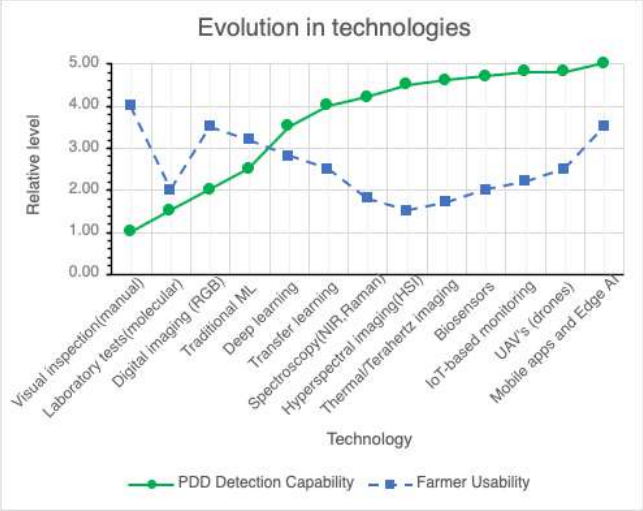
However, high performance in a controlled setting does not always mean usefulness for farmers in real farms. Models that score high on benchmark data often struggle in fields because of changes in light, background noise, disease stage, image quality, and weather conditions [5], [16]–[18], [29]. Moreover, these advanced tools usually bring costs and operational challenges such as expensive equipment, large computing needs, complex data processing, reliable internet, and expert knowledge [8], [9], [10], [12], [13], [30]. Taking pictures with a smartphone or a regular camera is cheap and portable. Hyperspectral imaging and some advanced spectroscopic devices need much more costly and complex hardware [9], [13], [25].

Many review articles have compared plant disease detection methods by looking at the algorithms used, the data sets, the model designs, and the accuracy reported [2], [7], [14], [15], [28], [29]. Although recent studies are often looking at portability, field use, cost, and real deployment, there is still a big gap in the literature about how accessible, affordable, understandable, and easy to use these technologies are for farmers and what real benefit they bring (Rahman et al., 2023).

This review goes beyond accuracy and performance numbers to really look at how ready plant disease detection technologies are for real-world farming. It focuses on how easy it's for farmers to use these tools how much they cost and how accessible they are. The review checks what kind of resources these technologies need, like equipment, internet, or power, and how well they can actually help farmers take action to control diseases. It also compares detection methods, looking at their strengths and weaknesses in real farm settings. A big part of the review is about the challenges farmers face when trying to use these technologies things like not having technical knowledge, dealing with high costs or not getting proper training.

II. EVOLUTION OF PLANT DISEASE DETECTION TECHNOLOGIES

The way we find plant diseases has changed a lot over time. It used to be manual checks and lab tests. Now we have automated, data-based, and field-ready ways. At first, diagnosis mostly relied on farmers or agricultural experts looking at plants with their eyes. They also used lab methods like testing. These older methods can give results, but they usually take a long time. They need expert skills. They require lab setups. They depend on equipment [11], [14], [20].



Graph 1. Evolution of PDD technologies in terms of detection capability and farmer usability

Graph 1. Conceptually summarizes this change and the way detection ability and farmer usability have evolved. As PDD moves toward learning and advanced sensing technologies, diagnostic ability usually goes up. Farmer usability does not always go up the same way. Specialized methods like spectroscopy and HSI may offer earlier diagnostic information. They can also need more equipment, more processing, more money, and more expertise [7], [9], [19], [25]. On the other hand, mobile and edge-based methods can make things easier for farmers by bringing automated diagnosis closer to them [3], [17], [24]. The figure shows a look at trends from the reviewed studies. It is not based on numbers from experiments.

Overall, the change in PDD shows that new technology does not always make things easier for farmers. New tools have made disease detection faster and more accurate. They have also made detection possible in many situations. Using these tools in real farming is still hard. Whether they work for farmers depends on things. These include cost, how easy they're to carry what kind of setup they need how much technical skill is required and how easy they are to use. So, along with making detection, there is also a need to create PDD tools that farmers can actually use in the field [8], [12], [17], [29], [30].

III. TECHNOLOGICAL ADVANCEMENT AND PRACTICAL DEPLOYMENT

Plant disease detection has progressed far, bringing accuracy, automation, and earlier problem spotting. Yet advanced technology does not always translate into practicality on farms. Every method brings trade-offs among strength, cost, computing demand, portability, infrastructure needs, and operational complexity.

Table 1. Technological advantages and practical deployment challenges of major PDD technologies

TECHNOLOGY	MAJOR ADVANTAGE	PRACTICAL DEPLOYMENT CONCERN
Deep learning/CNN	High classification performance	Field generalization, computation
HSI	Early and detailed spectral detection	High cost, data processing
Raman Spectroscopy	Early biochemical detection	Equipment, environmental concern
qPCR	Highly sensitive molecular diagnosis	Laboratory equipment and expertise
Nanobiosensors	Rapid/early detection	Stability, scalability, cost
IoT	Continuous/large-area monitoring	Infrastructure, maintenance, cost
Smartphone/Edge AI	Portable and accessible	Field-image reliability, Device limitations

Plant disease detection uses deep learning methods, such as neural networks (CNNs), giving higher accuracy in disease classification and extracting features automatically. Simpler networks like MobileNet and EfficientNet reduce computing load. Help run on mobile phones or at the network edge [3], [7], [15], [17], [24], [26], [27]. Yet models trained on lab data may work less well in real fields because lighting, background, disease stage, and environmental conditions differ [5], [16], [18], [29].

Plant disease detection can also use tools like hyperspectral imaging (HSI), Raman spectroscopy, molecular tests, and biosensors, adding more ways to diagnose. HSI and Raman can spot biochemical changes tied to disease, which may help find infections before clear visual signs appear [7], [9], [19], [25]. Likewise, quantitative polymerase chain reaction (qPCR) offers sensitive detection of plant pathogens (Alemu, 2014), and nano-enabled biosensors are being built for quick early diagnosis (Chaturvedi et al. 2025). Still, these tools often need sensors, lab setups, calibration steps, data processing power, expert knowledge, or higher costs, which may limit their wide use in the field [10]–[13], [25].

Plant disease detection benefits from the Internet of Things (IoT) and unmanned aerial vehicles (UAVs) by offering watch and monitoring over large fields. UAVs with cameras can quickly scan large farmland, and IoT plus edge computing can deliver real-time monitoring and local data processing [1], [12], [14], [30]. Putting these systems into real use depends on having sensors, communication networks, power supply, regular upkeep, trained staff, and the required money [8], [12], [14], [30].

Plant disease detection via smartphone cameras is cheaper, portable, and widely available [3], [17], [24]. Mobile apps show that disease classification can also include severity checks and give treatment advice (Ramana Reddy et al. 2025).

IV. FROM DISEASE DETECTION TO ACTIONABLE FARMER SUPPORT

The practical value of plant disease detection does not end with naming a disease. For farmers, a prediction becomes useful when it backs a management decision. Many plant disease detection studies mainly concentrate on disease classification, accuracy, precision, recall, and other technical performance measures. The final output is often only a disease label [3], [7], [15], [28]. However, recognizing a disease is not the goal of agricultural disease management; diagnostic information should ultimately help in effective intervention and in reducing crop loss [8], [14]. For plant disease detection, the desired progression can therefore be shown as:

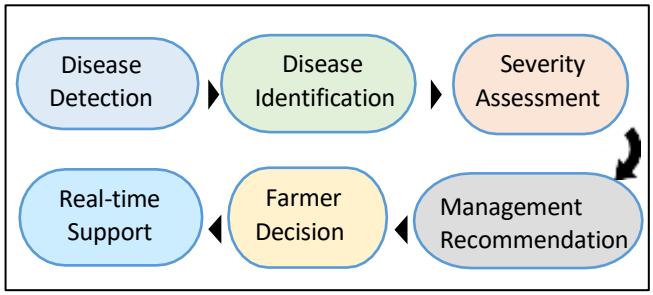


Fig1.From disease detection to actionable farmer support

Fig1. Illustrates the shift from basic disease detection to practical farmer support. Naming a disease may not give enough help for disease management. A farmer-oriented plant disease detection system should also determine disease severity, give management recommendations, and show this information in a way that aids the farmer in making an informed decision and taking proper action [3], [8], [14].

The practical value of plant disease detection does not stop at naming a disease. For farmers, a prediction gains value when it supports a management decision. Many plant disease detection studies concentrate on disease classification, accuracy, precision, recall, and other technical performance measures. They usually return only a disease label [3], [7], [15], [28]. Yet recognizing a disease is not the aim of agricultural disease management; diagnostic information should ultimately aid in effective intervention and in cutting crop loss [8], [14].

Recent systems have begun moving past classification by adding disease severity estimation, disease information, treatment recommendations, and real-time alerts. Mobile applications can give results together with severity data and suggested remedies [3], [17], [24], while IoT, UAV and edge-based approaches can support monitoring and more precise agricultural interventions [1], [12], [14], [30]. These advances show a shift from automated detection toward decision-support systems.

However, recommendations must be clear, relevant to field conditions, and practically doable by the farmer (Rahman et al. 2023). Therefore, future plant disease detection systems should be judged not by "Can the system detect the disease accurately?" but also by "Can the detection result help the farmer decide what to do next?"

V. COMPARATIVE FARMER-CENTRIC ANALYSIS

A farmer-centric evaluation of plant disease detection technologies must look beyond just how accurate they are. Even if a technology can detect disease early or with sensitivity, it may still be hard for farmers to use if it needs expensive tools, special training, complex setup, or lots of data processing. On the other hand, simpler tools that are cheaper, easy to carry, simple to use, and give useful info for managing disease can be more valuable in real farming situations [8], [14], [16], [29], [30].

Among the technologies compared, qPCR and hyperspectral imaging (HSI) are not easily accessible to farmers. qPCR provides sensitive molecular diagnosis. HSI also gives spectral data and can help catch disease early. Both require expensive equipment, something most individual farmers can't afford.

Table2. Part1 Comparative Farmer-Centric Analysis Of PDD Technologies

Technology	Cost	Portability
qPCR	High	Low
HSI	High	Low-Medium
Raman Spectroscopy	Medium-High	Medium-High
Nanobiosensors	Variable	High
UAV-based Detection	High	Medium
IoT Systems	Medium-High	Medium
Smartphone + DL	Low-Medium	High

Table2. Part2 Comparative Farmer-Centric Analysis Of PDD Technologies

Expertise Required	Early Detection	Farmer Accessibility
High	High	Low
High	High	Low
Medium-High	High	Medium
Variable	High	Emerging
High	Medium-High	Low-Medium
Medium-High	Medium	Medium
Low	Low-Medium	High

Table 2 compares plant disease detection (PDD) technologies from a farmer's point of view. It shows that strong diagnostic ability doesn't always mean the tool is easy for farmers to use. qPCR can detect disease before symptoms appear, which's great.. It needs lab equipment, special chemicals, and trained people. All of which limit its use on farms (Alemu, 2014). Hyperspectral imaging (HSI) also has early-detection potential by picking up on subtle spectral changes in stressed plants. Still, the high cost of the equipment, the large amount of data it generates, and the need for processing make it hard for regular farmers to use regularly [9], [25].

Raman spectroscopy gives details and can help spot disease early. New handheld versions make it more portable. It still needs specific equipment, is sensitive to environmental conditions, and requires technical skill to interpret. All of which limit its use by farmers [7], [19]. Nano-biosensors are promising because they are sensitive,

fast, portable, and can detect disease before symptoms show. Their use is still emerging. Costs, stability in the field, scaling up, and practical deployment are still being worked out (Chaturvedi et al. 2025).

UAV-based detection. Like drones. Is good for checking fields. They can carry RGB and hyperspectral sensors. Drones and their sensors are expensive. They also need maintenance, data processing, and someone trained to operate them. These things create barriers for small-scale farmers [12], [14]. IoT-based systems let farmers monitor crops and the environment continuously. They need sensors, internet or communication networks, power, and ongoing maintenance. All this means moderate accessibility for most farmers [1], [8], [30].

In contrast, smartphone-based learning systems are more accessible. Smartphones are cheap and easy to carry. They can take images. Run disease diagnosis apps right in the field [3], [17], [24].

Overall, Table II shows a trade-off: the more advanced or early the detection, the more resources the technology usually needs. Meanwhile, tools that are easier for farmers to use may not be as accurate or sensitive. So developing plant disease detection tools should focus on balance. Not accuracy. It should consider detection performance, how early it can find disease, cost, portability, technical needs, and how easy it is to use on a farm [8], [14], [16].

VI. THE ACCURACY ADOPTION GAP

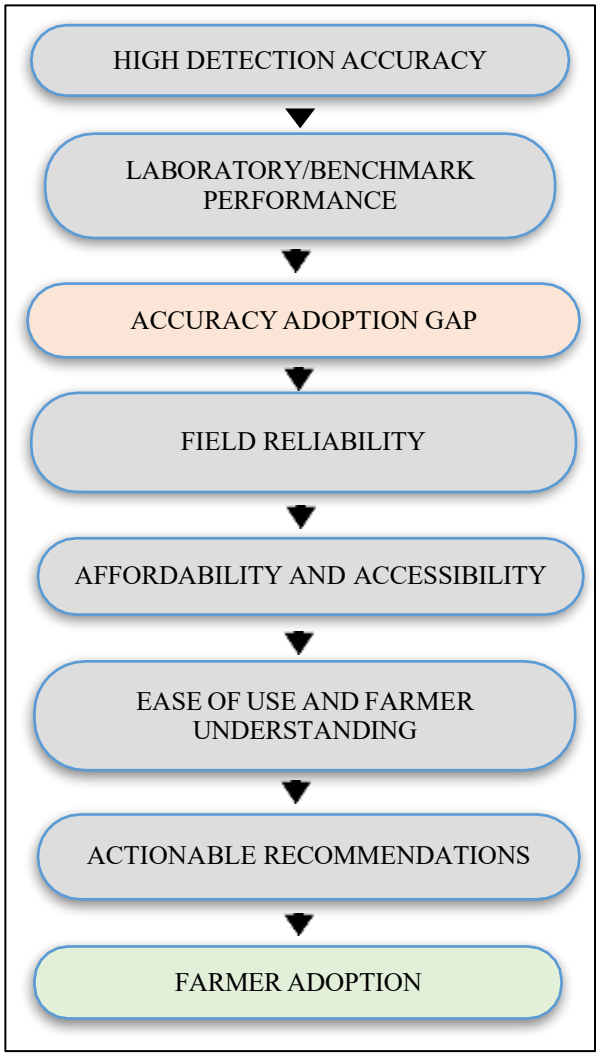


Fig 2. Accuracy adoption gap in PDD technologies

Figure 2 shows the gap between accuracy and adoption in plant disease detection. High detection accuracy and strong benchmark performance alone do not guarantee that farmers will adopt the technology. Turning performance into practical use also relies on reliable field performance, affordability, accessibility, ease of use, farmer understanding, and the presence of actionable recommendations [8], [14], [16], [29]. Therefore, these factors must be considered with detection accuracy when judging the real-world effectiveness of plant disease detection technologies.

The quick progress in plant disease detection has led to models that perform better and better at classification. Still, high diagnostic accuracy does not automatically lead to farmer adoption. Accuracy tells us how well a system can spot a disease under controlled evaluation conditions, while adoption depends on whether the technology is accessible, affordable, understandable, reliable in the field, and helpful for making farming decisions [8], [14], [16].

The gap becomes obvious when systems that perform well on controlled datasets are used in farms. Changes in light, background, crop condition, disease stage, and how images are taken can lower a model's ability to generalize [5], [16], [18]. Additionally, advanced technologies such as HSI, molecular diagnostics, biosensors, IoT and UAV systems can enable detection or better monitoring, yet their use may be limited by the cost of equipment, lack of infrastructure, maintenance needs, connectivity problems, computing demands and the need for technical skill [1], [8]–[13].

Farmer adoption also depends on factors that classification accuracy does not capture. Agricultural ICT research identifies barriers such as technical knowledge, poor training, high device and internet costs, connectivity limits and reliance on others (Rahman et al., 2023). Thus, even an accurate system may have little real impact if farmers cannot access it, use it, understand it, or act on its results on their own [8], [14], [16].

VII. RESEARCH GAP

Despite a lot of progress in identifying plant diseases, there are still some gaps between new technology and what farmers can actually use. Based on what I read, the main gaps are as follows.

Accuracy is the thing people look at: Many studies keep checking plant disease detection systems by using accuracy, precision, recall, F1-score, and other measures of how well the model works. These numbers are important for checking how good the system is at detecting diseases. They don't show if the technology is cheap, easy to understand, or something that farmers can use in real life.

Not enough testing with farmers in mind: More and more studies are creating apps, small networks, small sensors, and systems that work on the edge [1], [3], [17], [24], [26]. Saying a system is mobile, portable, or easy to use doesn't mean farmers can use it by themselves. There is no testing that focuses on whether farmers can use the system easily, how much training they need, how good their digital skills are, how well they can complete tasks, how much they understand, and what they think about the system (Rahman et al., 2023).

The difference between lab conditions and real life: Models trained on data or standard datasets might not work as well when they are used in real fields. This is because of background changes in lighting, different stages of disease, weather, and other problems [5], [16], [18], [29].

Not everyone can use the tools: Some advanced methods like HSI, molecular tests, UAVs, and some sensor systems have big benefits like finding disease early or over large areas. The cost of the equipment they need, strong computers, good infrastructure, internet, maintenance, and technical skills can make it hard to use them, especially in places where resources are limited [8]–[11], [19]–[25], [30].

Finding the disease is not enough: Just knowing a plant has a disease isn't helpful if farmers don't know what to do next. Some new systems include how bad the disease is and what to do about it (Ramana Reddy et al. 2025), but not all systems have ways to show the problem, explain the severity, give easy-to-understand advice, and help farmers take action [1], [3], [14], [17], [24].

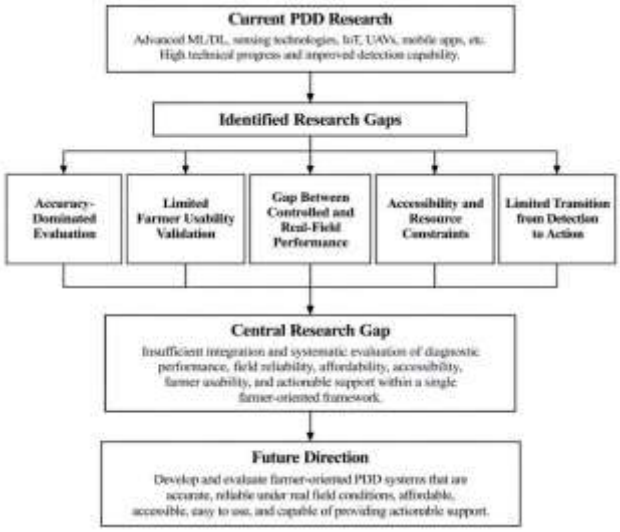


Fig 3. Major research gaps between technical advancement and farmer-level application in plant disease detection

Fig 3. Shows the problems in current PDD tools and shows the need to connect new tech with real, easy-to-use, farmer-friendly tools.

So the main problem is not that we do not have ways to find plant diseases but that we do not link and check in a full way how well the systems work how reliable they are in real fields how much they cost, how easy they are to get, how easy they are for farmers to use, and how helpful they are, for taking action. Future work should go beyond just making detection better and focus on making systems that really work when farmers use them.

VIII. CONCLUSION

Plant disease detection has changed a lot because of technologies. Machine learning, better imaging, spectroscopy, molecular tools, biosensors, the Internet of Things, drones, and mobile and edge computing have all played a part. These tools have helped improve how we find plant diseases. They allow for classification, faster detection, automation, and the ability to monitor crops over large areas [1]–[7], [9]–[15], [17]–[30]. Even with all these advances, the real question is whether these tools are actually useful for farmers.

Some systems can detect diseases early and with high accuracy. They often need expensive equipment, lab setups, stable internet, strong computing power, or technical knowledge. That makes them hard to use in farm settings [8]–[14], [16], [19]–[25], [30]. So just because a method works well in a lab doesn't mean it works well in the field.

Future research in plant disease detection should not aim to build better tools but also make sure the tools work in real farming environments. We need testing in actual field systems that use fewer resources and involve farmers when testing usability. It's also important to connect disease detection with measuring how bad the disease is and giving advice on what to do. A detection system is only truly successful if it helps a farmer understand the disease, make a decision, and take the right steps. In the end, success is not about accuracy. It's about how the system supports the farmer in solving the problem.

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