

Novel Biomimicry Techniques for Detecting Plant Diseases

Adeshina Fadeyibi^{1*} and Mary Fadeyibi²

¹*Department of Food and Agricultural Engineering, Faculty of Engineering
and Technology, Kwara State University, Ilorin, Kwara State, Nigeria*

²*Department of Biological Science, Faculty of Science, Augustine University,
Ilara-Epe, Lagos State, Nigeria*

Abstract

Biomimicry techniques (BmT) can be regarded as crop management concepts deployed for detecting, measuring, and responding to diseases during agricultural production. In this paper, various approaches of the BmT for the efficient management of unhealthy plants during preharvest and postharvest operations were reviewed. The remote sensors, machine vision, and robotics BmT approaches are mostly applied during preharvest operations for detecting plant diseases. Certain diseases, such as white-soft, gray-mold, and Sclerotium rots, may attack vegetables after harvest, thus requiring a high resolution BmT, like neural network and support vector machine to manage. To the best of our knowledge, this technology is mostly applied for protecting tropical and temperate fruits and vegetables but have not been tested for cereal and legume plants disease management. Also, the resulting image from the BmT can sometimes be misleading due to bad weather and other factors related to equipment performance. Thus, this study will help provide meaningful insights for the advancement of the technology on plant management practice during preharvest and postharvest processing and storage.

Keywords: Plant disease, detection, preharvest and postharvest management, biomimicry techniques

*Corresponding author: deshina.fadeyibi@kwasu.edu.ng

Inamuddin, Tariq Altalhi and Ashjan Alrogi (eds.) *Biomimicry Materials and Applications*, (199–214)
© 2023 Scrivener Publishing LLC

9.1 Introduction

Plant physiology can be influenced by environmental factors such as temperature, rainfall, and soil condition [1]. It can also be affected by diseases from bacteria, yeast, fungi, and other pathogens [2–5]. Sometimes, ectoparasites, like insects, mites, vertebrate, and other pests, can affect plant health by eating its tissue. The physical damage imposed by these agents can be so enormous if adequate preventive measures are not taken before harvest and during processing or storage [6, 7]. Thus, the control of the plant diseases is crucial to the production of food that can meet the population need, and provide a significant solution to the agricultural land, and water uses [8]. However, most crops can have *in vitro* ability for the disease control without involving any external agent [9, 10]. The plants can be genetically engineered to possess high resistance abilities to protect themselves against external agents that can cause diseases [11, 12]. Thus, continuous advances in the science of plant pathology are essential to improve disease control [13, 14], and ensure healthy food products availability during preharvest and postharvest operations [15–18]. Structurally, this category of the plant contains layers of stomata guard, cuticle, and cell wall that can act on the pathogens and render them inactive by creating a strong intercellular barrier against the pathogens [5, 19, 20].

A physical observation or visual monitoring of the plant on and off the farm may not effectively identify the disease or prevent it. There is a need therefore for an improved and effective technology that can provide in-depth feasibility of the nature of the disease and facilitate plant protection during processing and storage [7, 21]. Many different techniques have been described for detecting plant diseases before and after harvest operations in agricultural production [22, 23]. The remote sensing, machine vision and robotics are among the most applied BmT for the detection of the physiological changes in the plant occurring due to the disease infestation. Certain diseases, like white-soft, gray-mold and Sclerotium rots, may attack vegetables after harvest, thus requiring a high resolution BmT, like neural network and support vector machine to manage. However, these require high level of technical know-how to operate and are expensive thereby making them less attractive to the farmers. Also, it is mostly applied for protecting tropical and temperate fruits and vegetables that are used either as spices or for medicinal purposes. This review provides detailed information on how these techniques can effectively act on the plant to detect the diseases and provide protection. We also proposed the use of the BmTs for protecting cereal and legume plants during preharvest and postharvest processing and storage.

9.2 Preharvest Biomimicry Detection Techniques

9.2.1 Remote Sensing Technique Approach

This technique permits the detection and protection of the physical behavior or characteristics of the plant by measuring the way it reflects and emits radiation at a distance or before harvest [24–26]. The remote sensor (RS) can also enable a quantitative and qualitative assessment of the plant growth indices such leaf area, stem size, root penetration, and son on, thus revealing the health status of the plant [1, 27–29], as shown in Figure 9.1 (a) and (b) for single and multiphase RS imaging, respectively. According to Zhang *et al.* [30], the RS is a useful technique for monitoring diseases at every growth cycle stage of the plant system. In another related study, Feng *et al.* [31] proposed the use of unmanned aerial vehicle RS technique to monitor the plant growth and physiology on the farm especially the influence of genotypes and environment on plant growth. Also, Borges *et al.* [32] designed a pocket RS for controlling and quantifying the color of plant leave. The technique was able to sense the nutritional and physiological status of the plant. The RS tool has also been successfully applied for the detection of diseases in banana plant, classifying color changes due to the disease infestation [33] and for rapid screening of a death syndrome diseases in soybeans [29]. A high success rate was reported for detecting the banana bunchy top and *Xanthomonas* Wilt of Banana diseases. In precision

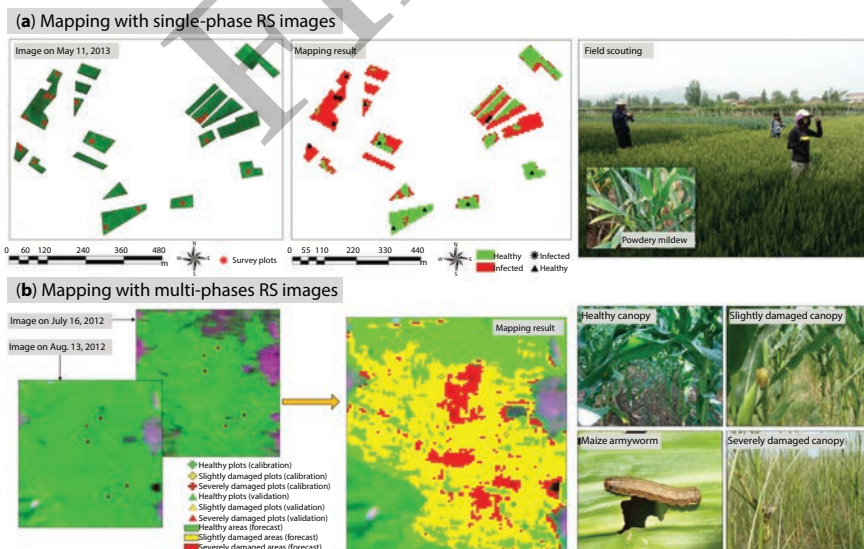


Figure 9.1 A typical map of plant diseases with a remote sensing technique [30].

agriculture, the RS has also found practical application [34]. Thanks to the high throughput of this practice, a site-specific fungicide may be applied to infested areas if the disease is stable, although the traditional uniform application is more suitable for diseases that can spread quickly through the field. Although a wide range of practical applications of the RS for plant disease monitoring and control have been reported, the commercial application of this technology is not yet exploited. Also, the RS tool requires a high-level technical ability to operate, thus the uneducated farmers may not be able to handle it effectively. Sometimes the image obtained may not reflect the plant disease scenario due to bad weather and other factors that can affect the equipment performance. There is, therefore, the need to simplify this technology to make it less technical and accommodate different weather variables for wider preharvest plant disease detection applications.

9.2.2 Machine Vision and Fuzzy Logic Approaches

Machine vision (MV) and fuzzy logic (FL) are novel biomimicry techniques applied for detecting plant diseases during preharvest processing. The MV is an enabling new automated process in agriculture, which promotes greater efficiency [35–37], while the fuzzy logic (FL) can capture the required knowledge of the agriculture domain and detect or control, for example, the plant diseases during preharvest operations. These two techniques can be integrated into the precision agriculture technology process to ensure an effective automation of the agricultural processes including the detection, monitoring, and control of the various degree of the plant that may occur during its growth cycle [38–40]. A novel MV was proposed for the identification and classification of the plant leaf diseases by Dhingra *et al.* [41]. The quality of the leaf defines the degree of excellence or a state of being free from defects, deficits, or variations [42]. According to Iqbal *et al.* [43], who reviewed the potentials of the image processing technology for detecting diseases in citrus plant, the MV is an excellent tool for detecting citrus plant diseases, such as canker, blackspot, scab, melanose, greening, and anthracnose defects. A typical citrus plant diseases detected using the MV technique is shown in Figure 9.2. If not corrected, this can pose serious threats to the economic and production status of the plant [44]. Thus, the MV process can help decrease the over dependence on human labor for protection offered to the growing plant [43, 45–47]. Hence, the planning activities on the farm, which includes routine fertilizer application and irrigation, will be encouraged. Meanwhile, the application of FL tool in plant disease detection is relatively new. So far, it has only been applied for the automatic detection of the black measles diseases [48] in



Figure 9.2 Typical citrus plant diseases detected using the MV technique [43].

grapes and for wolfberry pickling [49]. To best of our knowledge, the MV and FL technique has not been applied for detecting preharvest diseases in cereal and legume plants. Thus, these present a new frontier for future research.

9.2.3 Robotics Approach

Robotics (RO) is an artificial intelligent system designed to perform human tasks with greater accuracy and efficiency [50, 51]. In agriculture, the RO is used to automate slow, dull, and repeating tasks on the field, thus allowing the farmers to focus more on the improvement of plant yields [52, 53]. A typical robotic system for automatic in-field leaf disease detection is shown in Figure 9.3. A pneumatic controlled robotic system, which was developed by Gao *et al.* [54] for harvesting or picking cherry tomatoes fruits on the farm, can be modified to assist in detecting the disease of the product before and during the harvest operations. To archive this, certain detection accessories like the hyperspectral MV must be attached to the robot, especially around the picking device. An experimental electric robotic platform, mainly destined for spraying operations, was developed by Loukatos *et al.* [55] to improve its functions and to host a high-quality optical camera for detecting and capturing areas of defects on the plant parts. Also, Chen *et al.* [52] designed an automated robotic system for in-field measurement of maize leaf diseases as shown in Figure 9.3. The technology uses hyperspectral imaging system to sense and detect areas of defects around the leaf and send responses to the farmer who will in turn provide timely treatment for



Figure 9.3 A robotic system for automatic in-field leaf disease detection [52].

the defective plant. However, the RO technology is highly technical to operate and costly, in terms of equipment and energy costs. Thus, it is less attractive, and many peasant farmers may not be able to afford it. Hence, research is needed to build a less technical and more affordable RO system for use in the detection of the plant diseases on the farm.

9.3 Postharvest Biomimicry Detection Techniques

9.3.1 Neural Network Approach

Neural network (NN) provides a mapping between the image of the disease plant (input) to the crop disease pair (output) [56, 57], as shown in Figure 9.4. This involves creating a network structure that can effectively connect the nodes, edge-weights, input, and output variables together [58, 59]. The network parameters can be turned to ensure adequate training of the input data, as characterized in Table 9.1. To develop accurate algorithm for the purpose of the plant disease diagnosis, images of diseased plants were normally compared with those of the healthy plants [60–63]. The application of the NN for detecting various diseases in various plant parts has been widely studied and reported in the literature [64–69]. Certain diseases, like white-soft, gray-mold and Sclerotium rots, may attack vegetables after harvest, thus requiring a high resolution BmT, like the SVM to manage. For example, Zhang *et al.* [70] developed the NN tool for the smart disease detection in apple using an Internet of Things (IoT) device to extract the color and texture features of the food product. This NN could combine the features that are extracted by color and texture analysis

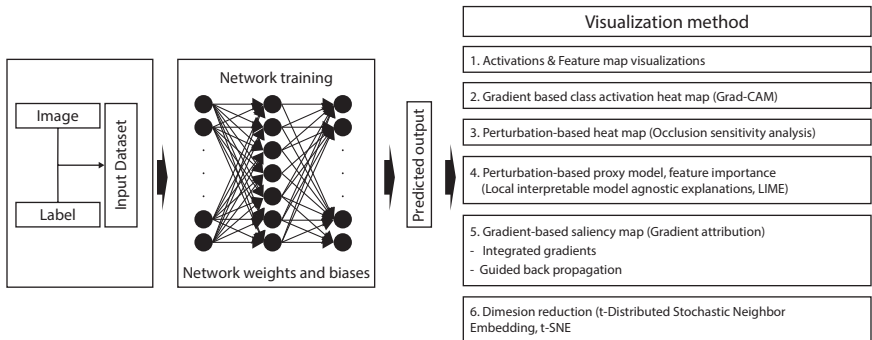


Figure 9.4 Plant disease classification procedure using NN biomimicry technique [73].

Table 9.1 Characteristics of NN biomimicry procedure.

Layer name	Number of layers in each network				
	Network 1	Network 2	Network 3	Network 4	Network 5
Image input	1				
Convolution	106				
Group convolution	7				
Batch normalization	105	102			100
Instance normalization	1	4			6
Group normalization	7				
Re LU	-	-	20	-	-
Leaky	-	20	-	-	-
Swish	108	88	88	88	87
Elu	-	-	-	20	-
Clipped Re LU	-	-	-	-	21
Avg Pooling	13				

(Continued)

Table 9.1 Characteristics of NN biomimicry procedure. (*Continued*)

Layer name	Number of layers in each network				
	Network 1	Network 2	Network 3	Network 4	Network 5
Max pooling	3				
Space to Depth	5				
Addition	7				
Depth concatenation	9				
Dropout	5				
Fully connected	1				
Soft max	1				
Class output	1				

Source: Islam *et al.* [73].

subnets, thereby improving the resulting disease image expression of the infected apple. The NN has also been applied as a smart device for the provision of automatic diagnosis of corn diseases and prevent severe losses in silos and bins [71, 72]. This technology was also effective for detecting corn leaf disease with an accuracy of 88.46%. Also, Islam *et al.* [73] and Agarwal *et al.* [74] visualized the tomato leaf disease by combining several convolutional NN approaches and predicted the performance of each NN protocol in response to their abilities to recognize the plant diseases, as shown in Figure 9.4. Regardless of the type of approach used, the authors concluded that the NN provided overall training, learning, and detection accuracy through the ability to visualize disease symptoms on the target tomato leaf. However, as promising as the NN technique may sound, it can encounter greater computational problem and is highly dependent on the hardware system. The network may malfunction unexpectedly thus making prediction unreliable at times. Therefore, further research is needed to address these challenges.

9.3.2 Support Vector Machine Approach

Support vector machine (SVM) is a supervised learning model that can analyze data for classification and recognition purpose [75, 76]. Recently,

the SVM has been applied in agriculture, alone or in combination with other techniques, to detect and classify different types of plant leaf diseases. For example, a combination of RS and SVM technologies was reported by Griffel *et al.* [77] and Mokhtar *et al.* [78] for detecting and differentiating the diseases as they occur during postharvest processing of potato and tomato crops. This technique to detect viral diseases in potato (Figure 9.5), leading to an improvement in the quality of the product needed to maximize yields. Rumpf *et al.* [79] reported a procedure for early detection and classification of diseases in sugar beet based on the application of the SVM and spectral vegetation indices. The technique was able to differentiate and identify the various diseases, including cercospora leaf spot, powdery mildew diseases, before their symptoms are revealed. Also, Leena and Saju [80] reported another SVM technology was effective for classifying the micro-nutrient-deficient parts of a harvested maize crop. The potential of radial basis SVM and NN approaches were compared by Omrani *et al.* [81] for detecting apple diseases. The authors concluded that the SVM was a better tool especially for identifying and classifying apple black spot, *Alternaria*, and apple leaf miner diseases of the harvested apple fruit. To the best of our knowledge, there is not enough information on the commercial applications of SVM technique for detecting and classifying diseases of cereals and legume plants. Thus, this presents a new area for future studies.



Figure 9.5 Potato plant (a) appearing healthy before harvest (b) exhibiting strong visual symptoms of potato virus disease with stunted growth after harvest as detected using the SVM technique [77].

9.4 Prospects and Conclusion

A visual control and monitoring of the plant growth during preharvest and postharvest processing and storage may not effectively identify diseases or provide protection for future use. In this paper, several novel procedures for plant disease detection including the RS, NN, MV, RO, and SVM, which are noted for their unique identification abilities were reviewed. Although a wide range of practical applications of the RS for plant disease monitoring and control have been reported, the commercial application of this technology is not yet exploited. It also requires a high-level technical ability to operate, thus the uneducated farmers may not be able to handle it effectively. Recent studies have shown that the MV technique can lower the over dependence on human labor for plant protection. It was used to detect and quantify the level of nutritional properties in the plant at every stage of its growth cycle. However, the application the FL tool in plant disease detection is relatively new. So far, it has only been applied for the automatic detection of the black measles diseases in grapes and for wolfberry pickling. The RO technology is highly technical to operate and costly, in terms of equipment and energy costs. Thus, it is less attractive, and many peasant farmers may not be able to afford it. Hence, research is needed to build a less technical and more affordable RO system for use in the detection of the plant diseases on the farm. Also, to best of our knowledge, the MV and FL technique has not been applied for detecting diseases in cereals and legumes plants. In general, the image obtained from these tools may sometimes not reflects the actual plant disease scenario due to bad weather and other factors related to equipment performance. There is therefore the need to simplify these technologies to make them less technical and accommodate different weather variables for wider applications. These present new frontiers for future research.

References

1. Ali, M.M., Bachik, N.A., Muhadi, N.A., Tuan Yusof, T.N., Gomes, C., Non-destructive techniques of detecting plant diseases: A review. *Physiol. Mol. Plant Pathol.*, 108, 1–10, 2019.
2. Zhang, J., Huang, Y., Pu, R., Gonzalez-Moreno, P., Yuan, L., Wu, K., Huang, W., Monitoring plant diseases and pests through remote sensing technology: A review. *Comput. Electron. Agric.*, 165, 104943, 2019.

3. Bischoff, V., Farias, K., Menzen, J.P., Pessin, G., Technological support for detection and prediction of plant diseases: A systematic mapping study. *Comput. Electron. Agric.*, 181, 105922, 2021.
4. Sanghavi, K., Sanghavi, M., Rajurkar, A.M., Early stage detection of downey and powdery mildew grape disease using atmospheric parameters through sensor nodes. *Artif. Intell. Agric.*, 5, 223–232, 2021.
5. Amarasingam, N., Ashan Salgadoe, A.S., Powell, K., Gonzalez, L.F., Natarajan, S., A review of UAV platforms, sensors, and applications for monitoring of sugarcane crops. *Remote Sens. Appl.: Soc. Environ.*, 26, 100712, 2022.
6. Fadeyibi, A., Osunde, Z., Applied, M.Y., Effects of period and temperature on quality and shelf-life of cucumber and garden-eggs packaged using cassava starch-zinc nanocomposite film. *J. Appl. Packag. Res.*, 12, 1, 1–10, 2020.
7. Fadeyibi, A., Lamidi, W., Ademola, S., Engineering and proximate properties of miracle berry fruit (*Synsepalum dulcificum* L.) essential for its processing equipment design. *Agric. Eng. Int.: CIGR J.*, 23, 4, 227–235, 2021.
8. Mohammad-Razdari, A., Rousseau, D., Bakhshipour, A., Taylor, S., Poveda, J., Kiani, H., Recent advances in E-monitoring of plant diseases. *Biosens. Bioelectron.*, 201, 113953, 2022.
9. Yousfi, S., Marín, J., Parra, L., Lloret, J., Mauri, P.V., Remote sensing devices as key methods in the advanced turfgrass phenotyping under different water regimes. *Agric. Water Manage.*, 266, 107581, 2022.
10. Jafarbiglu, H. and Pourreza, A., A comprehensive review of remote sensing platforms, sensors, and applications in nut crops. *Comput. Electron. Agric.*, 197, 106844, 2022.
11. Zhou, Y., Flynn, K.C., Gowda, P.H., Wagle, P., Ma, S., Kakani, V.G., Steiner, J.L., The potential of active and passive remote sensing to detect frequent harvesting of alfalfa. *Int. J. Appl. Earth Obs. Geoinf.*, 104, 102539, 2021.
12. He, Y., Chen, G., Potter, C., Meentemeyer, R.K., Integrating multi-sensor remote sensing and species distribution modeling to map the spread of emerging forest disease and tree mortality. *Remote Sens. Environ.*, 231, 111238, 2019.
13. Jiao, W., Wang, L., McCabe, M.F., Multi-sensor remote sensing for drought characterization: Current status, opportunities and a roadmap for the future. *Remote Sens. Environ.*, 256, 112313, 2021.
14. Cardoso, R.M., Pereira, T.S., Facure, M.H.M., dos Santos, D.M., Mercante, L.A., Mattoso, L.H.C., Correa, D.S., Current progress in plant pathogen detection enabled by nanomaterials-based (bio)sensors. *Sens. Actuators Rep.*, 4, 100068, 2022.
15. Fadeyibi, A., Osunde, Z.D., Yisa, M.G., Okunola, A.A., Investigation into properties of starch-based nanocomposite materials for fruits and vegetables packaging-A review. *FUTA J. Eng. Technol.*, 11, 1, 12–16, 2017.
16. Alabi, K., Olalusi, A., Olaniyan, A., Fadeyibi, A., Gabriel, L., Effects of osmotic dehydration pretreatment on freezing characteristics and quality of frozen fruits and vegetables. *J. Food Process Eng.*, 48, 8, 14037, 2022.

17. Fadeyibi, A., Osunde, Z.D., Yisa, M.G., Prediction of some physical attributes of cassava starch–zinc nanocomposite film for food-packaging applications. *J. Package Technol. Res.*, 3, 1, 35–41, 2019.
18. Wang, T., Mei, X., Alex Thomasson, J., Yang, C., Han, X., Yadav, P.K., Shi, Y., GIS-based volunteer cotton habitat prediction and plant-level detection with UAV remote sensing. *Comput. Electron. Agric.*, 193, 106629, 2022.
19. Lassalle, G., Monitoring natural and anthropogenic plant stressors by hyperspectral remote sensing: Recommendations and guidelines based on a meta-review. *Sci. Total Environ.*, 788, 147758, 2021.
20. Xie, C. and Yang, C., A review on plant high-throughput phenotyping traits using UAV-based sensors. *Comput. Electron. Agric.*, 178, 105731, 2020.
21. Fadeyibi, A., Modeling rheological behavior of beef based on time-dependent deformation and packaging. *Gazi Univ. J. Sci.*, 35, 3, 997–1008, 2022.
22. Fadeyibi, A., Osunde, Z.D., Yisa, M.G., Optimization of processing parameters of nanocomposite film for fresh sliced okra packaging. *J. Appl. Packag. Res.*, 11, 2, 1–10, 2019.
23. Fadeyibi, A., Osunde, Z.D., Egwim, E.C., Idah, P.A., Performance evaluation of cassava starch-zinc nanocomposite film for tomatoes packaging. *J. Agric. Eng.*, 48, 3, 137–146, 2017.
24. Lin, C., Labzovskii, L.D., Mak, H.W.L., Fung, J.C.H., Lau, A.K.H., Kenea, S.T., Bilal, M., vande Hey, J.D., Lu, X., Ma, J., Observation of PM2.5 using a combination of satellite remote sensing and low-cost sensor network in Siberian urban areas with limited reference monitoring. *Atmos. Environ.*, 227, 117410, 2020.
25. Žibrat, U., Širca, S., Susič, N., Knapič, M., Gerič Stare, B., Urek, G., Noninvasive detection of plant parasitic nematodes using hyperspectral and other remote sensing systems, in: *Hyperspec Rem Sen: Theory and Applications*, pp. 357–375, 2020.
26. Kattenborn, T., Leitloff, J., Schiefer, F., Hinz, S., Review on convolutional neural networks (CNN) in vegetation remote sensing. *ISPRS J. Photogramm. Remote Sens.*, 173, 24–49, 2021.
27. Kabisch, N., Selsam, P., Kirsten, T., Lausch, A., Bumberger, J., A multi-sensor and multi-temporal remote sensing approach to detect land cover change dynamics in heterogeneous urban landscapes. *Ecol. Indic.*, 99, 273–282, 2019.
28. Lin, F., Weng, Y., Chen, H., Zhuang, P., Intelligent greenhouse system based on remote sensing images and machine learning promotes the efficiency of agricultural economic growth. *Environ. Technol. Innov.*, 24, 101758, 2021.
29. Hatton, N., Sharda, A., Schapaugh, W., van der Merwe, D., Remote thermal infrared imaging for rapid screening of sudden death syndrome in soybean. *Comput. Electron. Agric.*, 178, 1–10, 2020.
30. Zhang, J., Huang, Y., Pu, R., Gonzalez-Moreno, P., Yuan, L., Wu, K., Huang, W., Monitoring plant diseases and pests through remote sensing technology: A review. *Comput. Electron. Agric.*, 165, 104943, 2019.

31. Feng, L., Chen, S., Zhang, C., Zhang, Y., He, Y., A comprehensive review on recent applications of unmanned aerial vehicle remote sensing with various sensors for high-throughput plant phenotyping. *Comput. Electron. Agric.*, 182, 106033, 2021.
32. Borges, C.S., Vega R, R.A., Chakraborty, S., Weindorf, D.C., Lopes, G., Guimarães Guilherme, L.R., Curi, N., Li, B., Ribeiro, B.T., Pocket-sized sensor for controlled, quantitative and instantaneous color acquisition of plant leaves. *J. Plant Physiol.*, 272, 153686, 2022.
33. Gomez Selvaraj, M., Vergara, A., Montenegro, F., Alonso Ruiz, H., Safari, N., Raymaekers, D., Ocimati, W., Ntamwira, J., Tits, L., Omondi, A.B., Blomme, G., Detection of banana plants and their major diseases through aerial images and machine learning methods: A case study in DR Congo and Republic of Benin. *ISPRS J. Photogramm. Remote Sens.*, 169, 110–124, 2020.
34. Yang, C., Remote sensing and precision agriculture technologies for crop disease detection and management with a practical application example. *Eng.*, 6, 5, 528–532, 2020.
35. Singh, V. and Misra, A.K., Detection of plant leaf diseases using image segmentation and soft computing techniques. *Inf. Process. Agric.*, 4, 1, 41–49, 2017.
36. Sowmya, B.J., Shetty, C., Seema, S., Srinivasa, K.G., Utility system for premature plant disease detection using machine learning, in: *Hybrid Comput Intel*, pp. 149–172, 2020.
37. Jafari, M., Minaei, S., Safaie, N., Detection of pre-symptomatic rose powdery-mildew and gray-mold diseases based on thermal vision. *Infrared Phys. Technol.*, 85, 170–183, 2017.
38. Pane, C., Manganiello, G., Nicastro, N., Ortenzi, L., Pallottino, F., Cardi, T., Costa, C., Machine learning applied to canopy hyperspectral image data to support biological control of soil-borne fungal diseases in baby leaf vegetables. *Biol. Control*, 164, 104784, 2021.
39. Gladju, J., Kamalam, B.S., Kanagaraj, A., Applications of data mining and machine learning framework in aquaculture and fisheries: A review. *Smart Agric. Technol.*, 2, 100061, 2022.
40. Nturambirwe, J.F.I. and Opara, U.L., Machine learning applications to non-destructive defect detection in horticultural products. *Biosyst. Eng.*, 189, 60–83, 2020.
41. Dhingra, G., Kumar, V., Joshi, H.D., A novel computer vision based neutrosophic approach for leaf disease identification and classification. *Meas.: J. Int. Meas. Confed.*, 135, 782–794, 2019.
42. Xue, J., Zhang, L., Grift, T.E., Variable field-of-view machine vision based row guidance of an agricultural robot. *Comput. Electron. Agric.*, 84, 85–91, 2012.
43. Iqbal, Z., Khan, M.A., Sharif, M., Shah, J.H., ur Rehman, M.H., Javed, K., An automated detection and classification of citrus plant diseases using image processing techniques: A review. *Comput. Electron. Agric.*, 153, 12–32, 2018.

44. Kaur, N. and Devendran, V., Novel plant leaf disease detection based on optimize segmentation and law mask feature extraction with SVM classifier. *Mater Today: Proc.*, 2020.
45. Tian, Z., Ma, W., Yang, Q., Duan, F., Application status and challenges of machine vision in plant factory—A review. *Inf. Process. Agric.*, 9, 2, 195–211, 2021.
46. Sujatha, R., Chatterjee, J.M., Jhanjhi, N.Z., Brohi, S.N., Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocess. Microsyst.*, 80, 103615, 2021.
47. Barbedo, J.G.A., Detection of nutrition deficiencies in plants using proximal images and machine learning: A review. *Comput. Electron. Agric.*, 162, 482–492, 2019.
48. Ji, M. and Wu, Z., Automatic detection and severity analysis of grape black measles disease based on deep learning and fuzzy logic. *Comput. Electron. Agric.*, 193, 106718, 2022.
49. Ma, Y., Zhang, W., Qureshi, W.S., Gao, C., Zhang, C., Li, W., Autonomous navigation for a wolfberry picking robot using visual cues and fuzzy control. *Inf. Process. Agric.*, 8, 1, 15–26, 2021.
50. Hejazipoor, H., Massah, J., Soryani, M., Asefpour Vakilian, K., Chegini, G., An intelligent spraying robot based on plant bulk volume. *Comput. Electron. Agric.*, 180, 105859, 2021.
51. Yoganandhan, A., Rajesh Kanna, G., Subhash, S.D., Hebinson Jothi, J., Retrospective and prospective application of robots and artificial intelligence in global pandemic and epidemic diseases. *Vacunas*, 22, 2, 98–105, 2021.
52. Chen, Z., Wang, J., Wang, T., Song, Z., Li, Y., Huang, Y., Wang, L., Jin, J., Automated in-field leaf-level hyperspectral imaging of corn plants using a Cartesian robotic platform. *Comput. Electron. Agric.*, 183, 105996, 2021.
53. Montoya-Cavero, L.E., Díaz de León Torres, R., Gómez-Espinosa, A., Escobedo Cabello, J.A., Vision systems for harvesting robots: Produce detection and localization. *Comput. Electron. Agric.*, 192, 106562, 2022.
54. Gao, J., Zhang, F., Zhang, J., Yuan, T., Yin, J., Guo, H., Yang, C., Development and evaluation of a pneumatic finger-like end-effector for cherry tomato harvesting robot in greenhouse. *Comput. Electron. Agric.*, 197, 106879, 2022.
55. Loukatos, D., Templalexis, C., Lentzou, D., Xanthopoulos, G., Arvanitis, K.G., Enhancing a flexible robotic spraying platform for distant plant inspection via high-quality thermal imagery data. *Comput. Electron. Agric.*, 190, 106462, 2021.
56. Ibrahim, M.H., Wba-Dnn: A hybrid weight bat algorithm with deep neural network for classification of poisonous and harmful wild plants. *Comput. Electron. Agric.*, 190, 1–10, 2021.
57. Golhani, K., Balasundram, S.K., Vadamalai, G., Pradhan, B., A review of neural networks in plant disease detection using hyperspectral data. *Inf. Process. Agric.*, 5, 3, 354–371, 2018.

58. de Vita, F., Nocera, G., Bruneo, D., Tomaselli, V., Giacalone, D., Das, S.K., Porting deep neural networks on the edge via dynamic K-means compression: A case study of plant disease detection. *Pervasive Mob. Comput.*, 75, 101437, 2021.
59. Tiwari, V., Joshi, R.C., Dutta, M.K., Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images. *Ecol. Inform.*, 63, 101289, 2021.
60. Yogeshwari, M. and Thailambal, G., Automatic feature extraction and detection of plant leaf disease using GLCM features and convolutional neural networks. *Mater. Today: Proc.*, 2021.
61. Sathiya, V., Josephine, M.S., Jeyabalaraja, V., An automatic classification and early disease detection technique for herbs plant. *Comput. Electron. Agric.*, 100, 108026, 2022.
62. Ashwinkumar, S., Rajagopal, S., Manimaran, V., Jegajothi, B., Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks. *Mater. Today: Proc.*, 51, 480–487, 2021.
63. Al-windi, B.K.M.A. and Abbas, A.H., Eucalyptuses leaf disease detection using multiple analyses systems and backpropagation neural network. *Mater. Today: Proc.*, 2021.
64. Wang, Y., Wang, H., Peng, Z., Rice diseases detection and classification using attention based neural network and bayesian optimization. *Expert Syst. Appl.*, 178, 114770, 2021.
65. Paymode, A.S. and Malode, V.B., Transfer learning for multi-crop leaf disease image classification using convolutional neural network VGG. *Artif. Intell. Agric.*, 6, 23–33, 2022.
66. Picon, A., Seitz, M., Alvarez-Gila, A., Mohnke, P., Ortiz-Barredo, A., Echazarra, J., Crop conditional convolutional neural networks for massive multi-crop plant disease classification over cell phone acquired images taken on real field conditions. *Comput. Electron. Agric.*, 167, 105093, 2019.
67. He, C., Li, X., Liu, Y., Yang, B., Wu, Z., Tan, S., Ye, D., Weng, H., Combining multicolor fluorescence imaging with multispectral reflectance imaging for rapid citrus Huanglongbing detection based on lightweight convolutional neural network using a handheld device. *Comput. Electron. Agric.*, 194, 106808, 2022.
68. Afonso, M., Blok, P.M., Polder, G., van der Wolf, J.M., Kamp, J., Blackleg detection in potato plants using convolutional neural networks. *IFAC-PapersOnLine*, 52, 30, 6–11, 2019.
69. Zhang, Y., Yu, J., Chen, Y., Yang, W., Zhang, W., He, Y., Real-time strawberry detection using deep neural networks on embedded system (rtsd-net): An edge AI application. *Comput. Electron. Agric.*, 192, 106586, 2022.
70. Zhang, W., Zhou, G., Chen, A., Hu, Y., Deep multi-scale dual-channel convolutional neural network for Internet of Things apple disease detection. *Comput. Electron. Agric.*, 194, 106749, 2022.

71. Mishra, S., Sachan, R., Rajpal, D., Deep convolutional neural network based detection system for real-time corn plant disease recognition. *Proc. Comput. Sci.*, 167, 2003–2010, 2020.
72. Yisa, M., Fadeyibi, A., Adisa, O., Finite element simulation of temperature variation in grain metal silo. *Res. Agric. Eng.*, 10, 3, 8–17, 2018.
73. Islam, M.P., Hatou, K., Aihara, T., Seno, S., Kirino, S., Okamoto, S., Performance prediction of tomato leaf disease by a series of parallel convolutional neural networks. *Smart Agric. Technol.*, 2, 100054, 2022.
74. Agarwal, M., Singh, A., Arjaria, S., Sinha, A., Gupta, S., ToLeD: Tomato leaf disease detection using convolution neural network. *Proc. Comput. Sci.*, 167, 293–301, 2020.
75. Hussein, M.A. and Abbas, A.H., Plant leaf disease detection using support vector machine. *Al-Mustansiriyah J. Sci.*, 30, 1, 105–110, 2019.
76. Rumpf, T., Mahlein, A.K., Steiner, U., Oerke, E.C., Dehne, H.W., Plümer, L., Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. *Comput. Electron. Agric.*, 74, 1, 91–99, 2010.
77. Griffel, L.M., Delparte, D., Edwards, J., Using support vector machines classification to differentiate spectral signatures of potato plants infected with potato virus Y. *Comput. Electron. Agric.*, 153, 318–324, 2018.
78. Mokhtar, U., El-Bendary, N., Hassenian, A.E., Emary, E., Mahmoud, M.A., Hefny, H., Tolba, M.F., Mokhtar, U., Hassenian, A.E., Emary, E., Mahmoud, M.A., SVM-based detection of tomato leaves diseases. *Adv. Intell. Syst. Comput.*, 323, 641–652, 2015.
79. Rumpf, T., Mahlein, A.K., Steiner, U., Oerke, E.C., Dehne, H.W., Plümer, L., Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. *Comput. Electron. Agric.*, 74, 1, 91–99, 2010.
80. Leena, N. and Saju, K.K., Classification of macronutrient deficiencies in maize plants using optimized multi class support vector machines. *Eng. Agric. Environ. Food*, 12, 1, 126–139, 2019.
81. Omrani, E., Khoshnevisan, B., Shamshirband, S., Saboohi, H., Anuar, N.B., Nasir, M.H.N.M., Potential of radial basis function-based support vector regression for apple disease detection. *Meas.: J. Int. Meas. Confed.*, 55, 512–519, 2014.