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A Review on Sensing Technologies for High-Throughput Plant Phenotyping

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ABSTRACT The current epidemic, population growth, and decreasing arable lands lead to a severe food crisis, which calls for productive and efficient agricultural methods to ensure a sustainable food supply for mankind. Crop monitoring is considered to be a potential solution for the improvement of food production. Current crop monitoring combines agriculture methodologies with other advanced technologies, including sensing technology, geographical information systems (GIS), Internet of Things (IoT), information and communication technology (ICT), robotics, and drone techniques to increase production with low labor cost. The high-throughput plant phenotyping is crucial for crop monitoring on the data acquisition of large-scale crop characteristics. The high-throughput plant phenotyping studies aim to achieve fast and precise large-scale crop monitoring techniques with minimum environmental impact by applying special plant phenotyping platforms. The phenotyping platforms are integrated with various sensors and data communication systems, which can help to achieve automatic data acquisition and transmission. This paper reviews the current high-throughput plant phenotyping development in crop monitoring, including sensors, communication protocols, data management, and plant phenotyping platforms. State-of-art challenges are reviewed and discussed. Also, the paper provides discussions on the current situation, upcoming challenges, and possible future trends for researchers in this field.

INDEX TERMS High-throughput, plant phenotyping platforms, crop monitoring, sensing technology, communication protocols.

I. INTRODUCTION

AGRICULTURE has played a vital role in the development of the socio-economic condition and human civilization [1]. With the ever-increasing population, rapid urbanization, and the unexpected outburst of the pandemic, the supply chain of the food has been adversely affected [2], [3]. A recent report stated that by the year 2060, the world population would reach around 9.3 billion [4]. This crisis indicates that additional efforts and techniques are required to multiply the food production to feed the world's population [5]. Therefore, food production needs to be increased under the limited space condition to mitigate future food supply issues. One method is to employ crop monitoring practices with effective and efficient technologies to help overcome the food supply problems [6].

Crop monitoring is an effective agriculture method. It combines agriculture methodologies with advanced technologies, which include sensing technologies, geographical information systems (GIS), Internet of Things (IoT), information and communication technology (ICT), robotics, and drones techniques to increase the yield with relatively low labor cost [7]–[10].

The crop characteristics are influenced by various factors such as soil condition, temperature, crop moisture content, plant disease, etc. Even the same type of crop plants planted in a different field will have other characteristics.

In traditional farming practice, the farmers need to visit the agriculture fields frequently to monitor crop conditions. However, this monitoring process is laborious and can consume up to 70% of farmer's time [11], [12]. Hence, advanced technologies such as sensor networks, ubiquitous computing [13], [14], and grid computing with satellite navigation services can improve the monitoring process and help make beneficial decisions for farmers.

Various sensors and their networks can constantly monitor the crop phenotyping with high accuracy, while the sensing data can be transferred to a secured platform through suitable communication protocols. Besides, robotic, unmanned ground vehicles (UGV) and unmanned aerial vehicles (UAV) are applied as a platform where sensors are installed to collect plant characteristics data. These data can be used to design decision-making platforms for the farmers [11]. To acquire and deal with large-scale plant characteristics data, studies regarding high-throughput plant phenotyping are essential [15]. Through high-throughput plant phenotyping, detailed and non-invasive large-scale plant information is enabled to be acquired throughout the plant life cycle for agricultural decision making and production increase [16]–[19].

This paper aims to aid the researchers in acquiring the knowledge of the sensing technologies for high-throughput plant phenotyping, the current challenges, and advancing the state-of-the-art. The paper summarizes the plant phenotyping parameters, communication protocols, and data management analyzes the current plant phenotyping sensors, and highlights the features of various sensor types, communication protocols, and data management methods. Furthermore, the paper reviews the up-to-date plant phenotyping platforms available for high-throughput plant phenotyping. This paper aims to provide an insight for the researchers to resolve the current challenges in high-throughput plant phenotyping. Compared with existing review papers, this study includes more comprehensive information on high-throughput plant phenotyping. It covers all the relevant details on high-throughput plant phenotyping, from basic plant phenotyping parameters and plant phenotyping sensors to sensing platforms, communication protocols, and data management.

The paper is organized as follows. Section II introduces the concept of plant phenotyping, the essential parameters, and communication protocols for plant phenotyping. Section III reviews the sensors used for high-throughput plant phenotyping. Section IV describes the up-to-date plant phenotyping platforms for plant phenotyping. Section V summarizes this paper and highlights the current challenges that need to be addressed and potential solutions.

II. OVERVIEW OF HIGH-THROUGHPUT PLANT PHENOTYPING

A. HIGH-THROUGHPUT PLANT PHENOTYPING

The term plant phenotyping refers to the plant appearance and performance, which can be written as $P = G \times E$, where P indicates the plant appearance and performance, G indicates the plant genotype, E indicates the environmental variables. In other words, plant phenotyping is the result of genotype and environmental variables on the plant [20]. Plant phenotyping is related to the quantitative and qualitative plant traits, which is essential for studying plant response to environmental conditions. Hence, it does not only include the plant itself but also includes the response of plants in a specific environment, such as a specially controlled environment (greenhouse, etc.) or the natural environment [21]. The target of plant phenotyping is to provide an analysis of plant traits to acquire its influence factors, which can help the plants to have a better yield in limited growing environments [20]. With the rapid development of electrical, computer science, and sensor technologies, high-throughput plant phenotyping has been a trendy field of study [22]. High-throughput plant phenotyping means automatic, non-invasive phenotyping systems, which have the ability for automated data acquisition, processing, analysis, and visualization [21]. Currently, the requirements for high-throughput plant phenotyping research are increasing because it plays a crucial role in crop monitoring [20], [23]. Fig. 1 illustrates the process of high-throughput plant phenotyping.

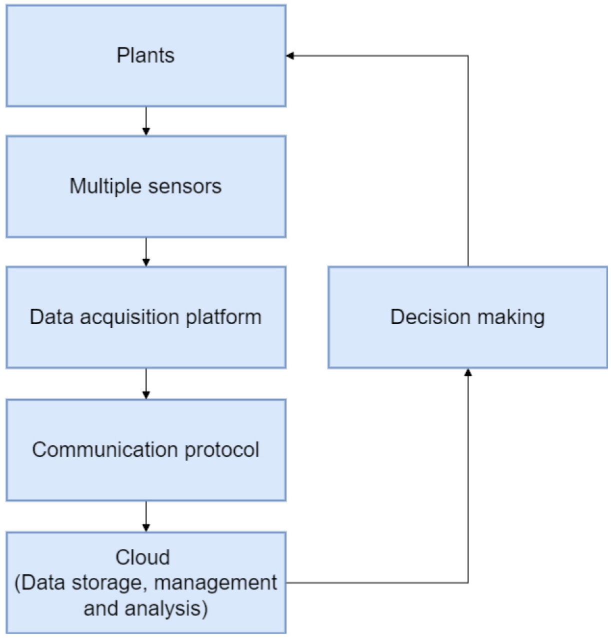


FIGURE 1. The process of high-throughput plant phenotyping.

B. SENSING PARAMETERS FOR HIGH-THROUGHPUT PLANT PHENOTYPING

The plant phenotyping parameter is an essential part for high-throughput phenotyping studies. Recent studies show that the phenotyping parameters of economic crops (including barley [24], wheat [25], sorghum [26], maize [27], tomato [28], bean [29] and cotton [30]) are taken into account. These plant phenotyping parameters can be grouped into two categories: morphometric and physiological [22]. Fig. 2 presents some

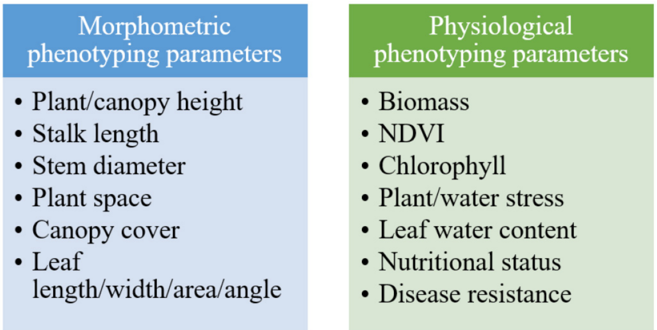


FIGURE 2. Plant phenotyping parameters.

of important plant phenotyping parameters in morphometric and physiological phenotyping.

Morphometric phenotyping is a mathematical description of biological forms based on the geometric definition of an object's size and shape [31]. Detailed morphometric information can help understand the effect of plant genes and the environmental condition on plant development. In morphometric phenotyping parameters, the plant height, stalk length, stem diameter, and leaf morphology (leaf length/width/area/angle) are crucial parameters because they are directly related to the plant growth [22]. The limitation of morphometric phenotyping parameters is that these parameters only stay on the external plant phenotyping, which is not enough to fully represent plant conditions like water or nutrient content [21].

Physiological phenotyping is about all the internal activities of plants, such as photosynthesis, plant nutrition, environmental stress, etc. Although many high-throughput plant phenotyping kinds of research still focus on morphometric phenotyping, the measurement of physiological phenotyping has been expected as an essential part of studying plant gene and plant performance relationships. In a physiological view, many abiotic (water, light, radiation, temperature, humidity, and soil condition) and biotic (human influence, pathogens, and disease) factors will affect plant cellular responses, ultimately determining plant performance. The physiological phenotyping parameters contain high dimensional data such as biomass, NDVI, chlorophyll, plant/water stress, leaf water content, disease resistance, and plant nutritional status. The limitation of physiological phenotyping is that the detection processes are relatively more sophisticated and expensive than morphometric phenotyping [21], [32].

C. COMMUNICATION PROTOCOLS FOR HIGH-THROUGHPUT PLANT PHENOTYPING

Data communication is another essential part of high-throughput plant phenotyping because it enables sensing data transmission. Through communication protocols, sensors can exchange the plant phenotyping data over the network. Different protocols have various frequency bands, data rates, transmission ranges, energy consumption, and costs [33]. Therefore, the choice of communication protocols depends on actual applications. The commonly used communication protocols include IEEE 802.11 (WiFi), WiMax, BlueTooth, Cellular, LoRaWAN, and NB-IoT. The following contents briefly describe these communication protocols. Table 1 presents the comparison of these communication protocols.

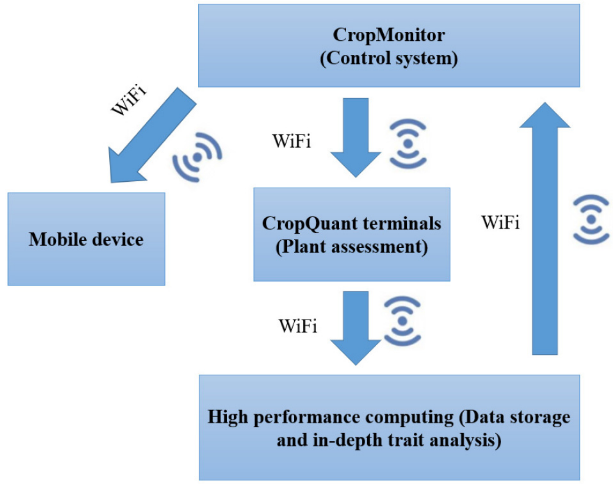


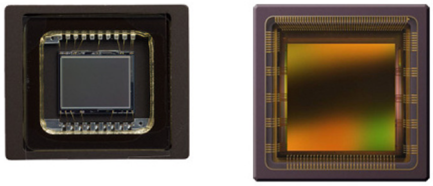
FIGURE 3. CropQuant system. (Concept adapted from [37]).

1) **IEEE 802.11 (WiFi)** is a series of the Wireless Local Area Network (WLAN) communication standards, including the IEEE 802.11, 802.11a, 802.11b, 802.11g, 802.11n, 802.11ac, 802.11ax standards. The state of art standard is 802.11ax (also called WiFi 6), which was developed in May 2014 to improve the throughput-per-area in high-density scenarios [34]. Different standards have various technical parameters; the frequency band of WiFi varies from 5 to 60 GHz, while the rated speed varies from 0.25 Mb/s to 6.75 Gb/s. The latest standard reaches a significant rate speed of 6.75 Gb/s, with 2.4GHz and 5GHz frequencies. Besides, the current range of WiFi covers from 20 m to 100 m [33], [34]. With relatively stable and high data rates, WiFi has become a universal solution for many applications, including crop monitoring [35]. The study [36] applied WiFi to do the data transmission in their system, which is an imaging technology and cloud technology-based system. Their system can achieve real-time crop detection and crop growth status recording. The result of this work shows that this system can complete real-time detection and data transmission in the field of crop monitoring [36]. Zhou *et al.* [37] introduced a large-scale automatic field phenotyping platform, CropQuant, which is a low-cost Internet of Things (IoT) powered system. By using high-resolution time-lapse photography, in-field evaluation, and a WiFi-based data exchange system, this platform can achieve continuous crop monitoring [37]. Fig. 3 shows the principle of the CropQuant system.

TABLE 1. Comparison of communication protocols.

Protocol Name	Frequency Band	Data Rate	Transmission Range	Energy Consumption	Cost	References
IEEE 802.11-WiFi	5 GHz – 60 GHz	0.25 Mb/s – 6.75 Gb/s	20 m – 100 m	High	High	[33, 34]
IEEE 802.16-WiMax	2 GHz – 66 GHz	Mobile: 100 Mb/s, Fixed: 1 Gb/s	50 km	Medium	High	[33]
Bluetooth	2.4 GHz	1 Mb/s – 24 Mb/s	8 – 10 m	Very Low	Low	[33, 41]
Cellular	865 MHz, 2.4 GHz, 5G (5.8 GHz, 60 GHz)	3G: 200 kbps, 4G: 5 – 16 Mbps, 5G: 100 Mbps – 1 Gbps	Whole Cellular Area	Medium	Medium	[33, 39, 43, 44]
LoRaWAN	868/915 MHz, 2.4 GHz	4 kbps	30 km	Very Low	High	[39, 49]
NB-IoT	800/900/1800 MHz (EU)	29 kbps	10 km	Low	High	[39, 46, 50]

2) **WiMAX (Worldwide Interoperability for Microwave Access)** is a high-speed wireless data communication protocol based on IEEE 802.16 standard [38]. It provides a data rate from 1.5 Mb/s to 1 Gb/s. The new standard version 802.16m can reach the data rate of 100 Mb/s through mobile stations and up to 1 Gb/s through fixed stations [33]. The WiMAX frequency band varies from 2 to 66 GHz, while the covering range can reach a maximum of 50 km. However, these features are also accompanied by relatively high cost and medium energy consumption [39]. The study [40] applied Wimax-based technology to develop an agriculture monitoring system, which can integrate the wireless sensor network and send the data to the central server [40].
3) **Bluetooth** is a kind of low energy consumption and low-cost wireless data communication protocol based on the IEEE 802.15.1 standard. The Bluetooth standard can build a communication link between portable devices, such as laptops, over 8 to 10 m. It provides a personal area network (PAN) communication on the 2.4 GHz band. The data rate ranges from 1 Mb/s to 24 Mb/s in different standard versions [33], [41]. Kuhlgert *et al.* [42] designed a device called MultispeQ to collect large-scale, high-quality field data. The MultispeQ can provide useful plant phenotyping such as chlorophyll and pigment information. These plant phenotyping data can be transmitted from the MultispeQ to mobile phones or laptops and be saved to their data management platform. The communication method between the MultispeQ and other devices is Bluetooth or micro-USB. Their study shows that this system can measure, send, store and analyze the plant phenotyping data [42].
4) **Cellular**, also called mobile communication, is suitable for portable devices which have the requirement of high data transmission rate. There are four generations of cellular standards, which include second generation (2G including GSM and CDMA), third generation (3G including UMTS ad CDMA2000), fourth generation (4G including LTE), fifth-generation (5G NR) [33], [43]. Based on this kind of communication protocol, portable devices can communicate over cellular networks. Data rate of cellular range from 9.6 Kb/s (2G) to 1 Gbps (5G) [33], [44]. The study [45] developed a multi-billion pixel ("gigapixel") image sensor system, which can detect the high-throughput phenotyping in field settings and transmit the images to a remote server by cellular connection. The authors state that the data rate of 4G is enough for gigapixel images uploading in their system [45].
5) **LoRaWAN** is a new communication protocol for long-distance data communication. It has the advantage of long-range data transmission. The LoRaWAN network applies a new technique to achieve multiple messages received through various channels during data transmission. By using the new design, LoRaWAN can increase the data communication range and network size while keeping a long battery life [46]. To sum up, LoRaWAN has a high capacity and low energy consumption with limited data rates. Its data rates can reach the requirements of standard agriculture sensors [39]. Singh *et al.* [47] developed a LoRaWAN-based sensor network to monitor tomato crops in the greenhouse. The LoRaWAN will transmit the raw sensor data to the LoRaWAN gateway and forward it to a working network. Then a data parser will subscribe to the data from the working network and use the data for visualization and store [47].
6) **NB-IoT** is the Low Power Wide Area Network (LPWAN) radio technology standardized by 3GPP. It focuses on indoor, low energy consumption, low expense, and high connection density communication work. Although it applies the subset of LTE (Long Terminal Evolution) standard, it removes some features of LTE to reduce the energy consumption and cost [39], [46]. The study [48] stated an intelligent plant temperature control system based on NB-IoT low-rate narrow bandwidth network. The system can do the data transmission within an indoor distance and achieve automatic regulation of plant growth temperature. The result of this study shows that the



(a) CCD sensor (b) CMOS sensor

FIGURE 4. **CCD and CMOS sensors [73].**

system can stably regulate a beneficial condition for plant growth [48].

D. DATA MANAGEMENT FOR HIGH-THROUGHPUT PLANT PHENOTYPING

The massive data generated from the high-throughput plant phenotyping process must be managed. The managed data will be used for processing and analysis to obtain the plant phenotyping results. The database management system (DBMS) needs to be applied to maintain and control access to plant phenotyping data [51]. The database management systems can be divided into relational and non-relational. A relational database is a set of tables that store and provide data access. The row in the table is a unique ID, and corresponding columns contain attributes of the data. The non-relational database does not apply tables as a data storage structure. It provides a solution for large-scale data storage requirements of the Internet. According to the difference in structure and application scene, the non-relational database can be divided into key-value stores, document stores, and XML databases [52]. The frequently-used relational database management systems include MySQL, PostgreSQL, Microsoft SQL Server, Oracle, and Microsoft Access. The frequently-used non-relational database management systems include MongoDB, Redis, and CouchDB. Most real-time plant phenotyping data can use relational databases since they are suitable for the representation of tables [53]. Schmidt *et al.* [54] developed a distributed information system called Phenomics to manage massive plant phenotyping data. In the developed system, a relational database management system PostgreSQL was applied to save plants' treatments and measurements data. The plant data are divided into various parts in database tables (like experiments, plants, locations) [54]. Reynolds *et al.* [55] developed a distributed plant phenotyping management system called CropSight. In the developed system, a relational database management system, MySQL, was applied for storing various data, including images, weather data, and experimental settings [55].

With the enormous development of cloud storage, various organizations have started to upload their data to cloud storage since it can provide a low-cost and convenient method for large-scale data storage. Through the Internet, users can access the stored crop data anytime and anywhere [56]. The current commercial cloud storage systems include Amazon S3, Microsoft Azure, Alibaba Cloud, etc. [56].

III. SENSORS FOR HIGH-THROUGHPUT PLANT PHENOTYPING

Currently, many sensors have become essential elements for plant phenotyping parameters measurement as it could provide fast and noninvasive information of plants [20]. Many advanced technologies have been integrated with sensors to perform the plant phenotyping work, such as image techniques [57], machine learning [58] and communication techniques [59]. Studies show that the traditional and even new sensors are integrated for plant phenotyping parameters measurement, which includes visiable spectrum image sensor [60], thermal image sensor [61], NIR image sensor [24], multi-spectral image sensor [62], hyperspectral image sensor [63], Light detection and ranging (LiDAR) [64], ultrasonic sensor [65], fluorescence sensor [66], depth image sensor [67] and etc. The following subsections discusses different types of sensors that are being widely used for plant phenotyping.

A. VISIBLE SPECTRUM IMAGE SENSOR

The visible spectrum is the segment of the electromagnetic spectrum that human eyes can view-typically, visible spectrum wavelengths about 400 to about 780 nm [68]. A visible spectrum image sensor can collect visible light and create images based on red, green, and blue wavelengths (RGB) for accurate color representation [69]. The visible spectrum image sensor mostly consists of charge-coupled device (CCD) silicon sensors and active-pixel sensors (CMOS) [69]. Photons fall on the sensor surface and generate a charge, which can be transferred into a visible copy on the device. Therefore, a visible spectrum image sensor can obtain visible radiation of an object to form an RGB image, which can be used to present a plant's physical information (morphological and texture features), biotic stress, and plant status [22]. Afterimage processing and analysis, various plant phenotyping parameters (including plant height, stalk height, stem diameter, leaf length/width/area/angle and biomass) could be acquired [60]. Visible spectrum image sensors are low-cost, simple, and ubiquitous. Moreover, the technical parameters of visible spectrum image sensors such as light sensitivity, image resolution, and ability to focus have been significantly improved every year [70]. Besides, with the rapid development of computer vision, implementing computer vision technology to extract helpful information from RGB images has become a key method for plant phenotyping studies. It can automate the data acquisition of the plant phenotyping parameters. This can help save time and cost for the farmers because they do not have to go to the fields for plant monitoring and measurement. In addition, the applications of deep learning and convolutional neural networks in plant image analysis have greatly improved the high-throughput plant phenotyping work efficiency [71]. Furthermore, high-throughput platforms have been greatly developed and can provide a controlled environment to study the plant responses to the environment [72]. Therefore, visible spectrum image sensors in high-throughput plant phenotyping studies are gaining popularity. Fig. 4 presents the CCD and CMOS

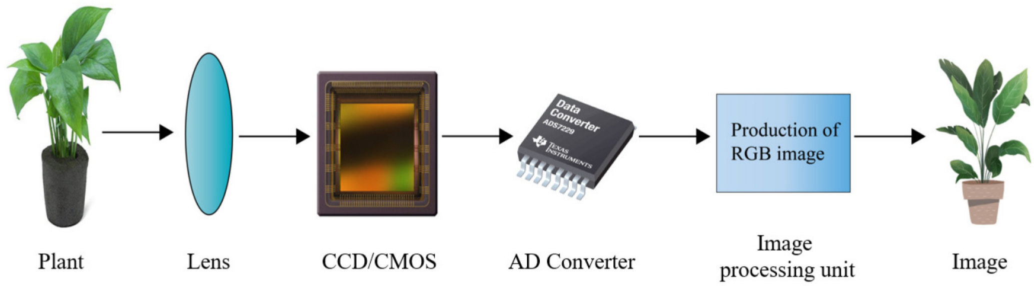


FIGURE 5. Visible spectrum image sensor principle.

sensor. Fig. 5 shows the visible spectrum image sensor principle. When the visible spectrum image sensor starts to work, then the light of the plant will enter through the lens. Then, photons fall on the CCD/CMOS sensor surface and generate a charge. That charge will be converted to a voltage, amplified, and processed by an analog to digital Converter (AD converter). After that, the image processing unit will process the digital signal and generate a digital image.

One methodology for applying visible spectrum image sensors in high-throughput platforms is using multiple image sensors to take many images of plants from different views. This can help to acquire consistent and accurate phenotyping parameters. The research [74] applied the visible spectrum image sensors based on LemnaTec 3D Scanalyzer (LemnaTec, GmbH, Wuerselen, Germany) high-throughput platform to take RGB images of barley plants in three different views (one top view image and two side-view images with a 90-degree horizontal rotation). These RGB images were used to predict barley growth and estimate the biomass. The result of this research shows that there is a high correlation between visible spectrum image-based biomass estimation and actual plant biomass. This indicates that the visible spectrum image sensor-based phenotyping system had good performance on high-throughput plant phenotyping estimation [74]. Similarly, [24] developed an integrated framework for high-throughput plant phenotyping data analysis. This new framework can extract plant phenotyping parameters from noninvasive images regularly. The multiple image sensors were also used to take three different views of RGB images to measure the status and biomass of the plant for the barley plants and store the data. This study shows that the framework data are precious to the plant development and biomass variation. It also helps to quantify further plant growth and performance features [24]. The study [66] also used the LemnaTec 3D Scanalyzer system (LemnaTec GmbH, Aachen, Germany) to take three different views of RGB images of two different salinity tolerance rice cultivars for plant assessment. The RGB images were used for plant height; the images were also applied to estimate approximation biomass. The result from this study shows that the projected shoot area obtained by RGB image analysis has a strong positive correlation with biomass on older plants [66]. Similar study methods are also applied to the sorghum [75] and wheat plants [76].

Combining the digital image sensor and UAV is another popular methodology in plant phenotyping studies. The study [77] built a high-throughput plant phenotyping platform based on UAV for soybean yield estimation and crop maturity prediction. The designed system applied a fast and inexpensive method for plant evaluation and improved crop breeding efficiency. The result of this study shows that the traditional yield estimation method could be greatly improved, and high accuracy (93%) has been achieved in soybean maturity classification [77].

The studies above did not mention the relationship between plant phenotypes and genomics. Therefore, the study [78] developed a high-throughput rice phenotyping facility (HRPF) and collaborated it with genome-wide association studies (GWAS). A visible spectrum image sensor-based high-throughput platform can obtain morphology parameters (including plant height, green leaf area, plant compactness) and rice biomass. Plant compactness is a new trait that traditional plant phenotyping methods cannot be defined and obtain among these morphology parameters. Their novel work shows that the new high-throughput plant phenotyping method performs better than the conventional plant phenotyping method. It can provide valuable plant gene identification information. Besides, the use of multiple phenotyping tools includes in-depth information and insight into the relationship between plant phenotyping and genetic architecture [78].

One big challenge of the visible spectrum image sensor-based plant phenotyping is the difficulty of object distinction between plant and background with similar plant colors such as grapevine and field. A study conducted by [79] used a normally visible spectrum image sensor to compute grapevine leaf surface areas and fruit-to-leaf ratios. They segmented RGB images into four classes (leaf, stem, grape, and background) by depth reconstruction, color classifier, and edge detector. The segmented images help to acquire the leaf surface areas and fruit-to-leaf ratio. The study result shows a good determination coefficient and minor error compared with the traditional method. This research found a possible way to solve the challenge of object distinction in plant phenotyping. This advance may improve the development of high-throughput plant platforms and image acquisition [79].

Although significant progress has been made so far for applying visible spectrum image sensors on plant

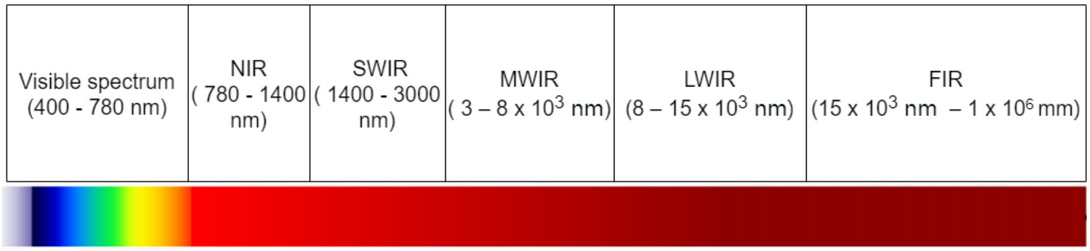


FIGURE 6. Infrared spectrum principle.

phenotyping, such as the visible spectrum image sensor-based high-throughput platform and image analysis, the limitation of digital image sensors still needs to be considered. Firstly, the visible spectrum image sensor is limited to visual spectral bands [80], which means it may lose some spectrum information such as infrared spectrum. Various spectra can provide different details about the plant phenotyping, such as plant water content and plant temperature [72]. This will lead the high-throughput platforms to apply more sensors for efficient plant information. Secondly, the performance of the visible spectrum image sensor is easily affected by the varying light conditions [22]. The study [81] explored a method to use the visible spectrum image sensor scene mode to measure nitrogen nutrition of corn without additional artificial illumination. Therefore, the development of visual spectrum image sensor scene mode may be a potential solution to the problem of light effect.

B. INFRARED SPECTRUM IMAGE SENSOR

The wavelength of the infrared spectrum is about 780 nm - 1000 μm. The light wavelength is just outside the visible range of the human eyes, and it can offer unique details about plants [82]. Based on the wavelength, the infrared spectrum can be divided into five parts: near-infrared (NIR), short-wave infrared (SWIR), mid-wave infrared (MWIR), long-wave infrared (TIR/LWIR), and far-infrared (FIR). Fig. 6 shows the infrared spectrum principle. Some properties of the plant are related to infrared light, which could be potentially helpful for plant phenotyping analysis [72].

Near-infrared (NIR) image sensor contains Indium Gallium Arsenide (InGaAs) sensors. Because of its spectral sensitivity, the NIR image sensor can detect near-infrared and short-wave infrared spectrum, which is useful for measuring leaf water content [72]. Compared with visible light, NIR and SWIR lights could be greatly reflected by plant tissue, and the reflection is influenced by leaf thickness, which is related to leaf water content. Many studies have applied the NIR image sensor in leaf water content measurement and plant drought response. Fig. 7 presents the reflectance under different leaf water content. When the leaves have a regular water content (healthy), the reflection of near-infrared light is larger than blue, green, and red light. When the water content of leaves decreases (stressed), the reflection of near-infrared light will gradually reduce. After the leafs withered (dead), the near-infrared reflection will be almost the same

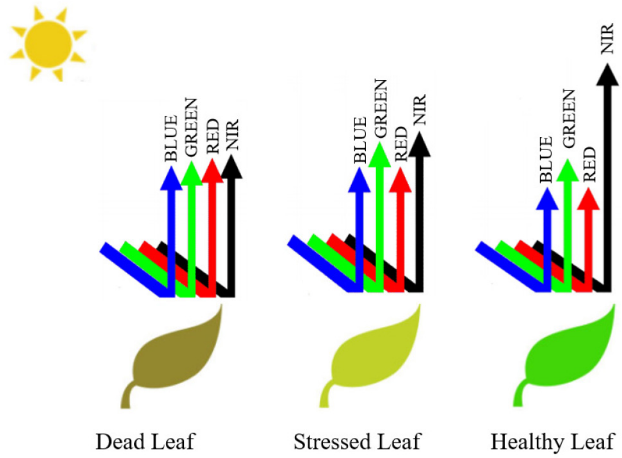
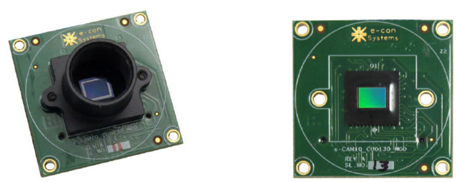


FIGURE 7. An illustration of leaf reflectance [83].

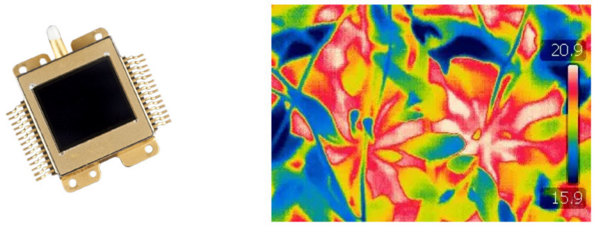


(a) (b)

FIGURE 8. NIR image sensor [84].

as blue, green, and red light. Fig. 8 shows the image of the NIR sensor.

The research [85] used a NIR image sensor to detect plant water content. Their study is based on a standard plant feature that leaf dehydration will decrease NIR light's absorption. The result of the study shows that some wavelengths (970/1200 nm) have lower sensitivity due to small absorption troughs, while some wavelengths (1450/1930/2500 nm) have much higher sensitivities of leaf water indices to leaf water content [85]. The research [24] applied multiple image sensors to extract phenotyping parameters of barley by non-invasive imaging constantly. In this system, the NIR image sensor was used to obtain the plant water content [24]. The study [86] introduced that the morphometric and plant drought response of grapevines can be acquired through RGB and NIR image analysis. The result of this study shows that NIR is related to the levels of plant drought and enhances



(a) Thermal infrared sensor (b) Thermal infrared image

FIGURE 9. Thermal infrared image sensor [89].

(a) Multi-spectral sensor (b) Multi-spectral camera

FIGURE 10. Multi-spectral sensor [93], [94].

the role of the NIR image sensor in plant drought response study [86].

NIR image sensor also has similar limitations as digital image sensor. It is limited to specific bands, and the other wavelength information will be lost in the NIR image. The potential solution is to apply multiple image sensors together or use the hyperspectral image sensors instead of NIR image sensors [72].

Thermal infrared (TIR) image sensor can detect the long-wave infrared (LWIR) spectrum. Thermal infrared imaging is a remote, non-invasive technology that can provide temperature mapping of an object. Thermal infrared imaging has been widely applied in many areas such as aerospace, automotive industry, medicine, and security. All the objects above 0 °C will emit infrared rays, which can be represented as surface temperature. The higher temperature of the surface will have a greater infrared radiation intensity.

Therefore, thermal infrared imaging technology can convert the radiation into temperature data. The main advantages of thermal imaging are it can be operated remotely. It is non-invasive, easy to handle, and has higher accuracy than other sensors. Besides, thermal infrared imaging can acquire a temperature map of the captured region with a fast response, not the simple spot temperature data. In addition, unlike other imaging systems, thermal infrared imaging does not have a strict requirement for illumination, which means it can effectively work in a dark environment. The thermal infrared image sensor is comprised of infrared detectors' signal processing parts. The infrared detectors can detect the intensity of radiation and convert it into an electrical signal, which will be translated into a thermal image in the signal processing part [87]. Thermal infrared images can be used to represent plant temperature, plant water stress, and plant quality [72], [88]. Fig. 9 presents the thermal infrared sensor and a thermal infrared image.

Matos *et al.* [90] used thermal infrared image sensors to study the influence of environment temperature and light changes on the plants. They used different temperature and light environment conditions to test the plant's growth rate. This study shows that temperature might primarily influence plant growth rate. In addition, the temperature variation did not affect the size of the leaf cell length [90]. Crusiol *et al.* [91] applied the thermal infrared image to evaluate the temperature of soybean plants and their water status. A thermal infrared image sensor was integrated with an unmanned aerial vehicle (UAV) to capture the thermal infrared image of plants. This work shows the relationship between plant thermal infrared behavior and soil water availability. The lower soil moisture conditions will lead to higher plant temperatures. Besides, this work shows the value of applying UAV and thermal infrared image sensors for plant water monitoring and crop management [91].

The thermal infrared image sensor plays a vital role in the temperature mapping of the plant. Due to its powerful advantages, various thermal infrared image sensors have already been applied in plant phenotyping. However, the thermal infrared image sensor is easily affected by environmental conditions, and it is hard to detect the difference in minor temperature variations [80]. The study [87] introduces that the thermal infrared image sensor can be divided into the uncooled and cooling device. The uncooled device can be operated at room temperature, and most studies used it. Although these uncooled devices are inexpensive, their resolution and image quality is lower than the cooling device. The cooled thermal infrared imaging devices have high resolution and can detect a difference of slight temperature variations (0.1 °C). However, the cooled thermal infrared imaging devices are expensive and need to be maintained under 0 °C. With the development of new materials, the cooled thermal infrared imaging devices may solve the current problems of the thermal infrared image sensor and become the typical sensor for plant phenotyping measurement [87].

C. MULTI-SPECTRAL IMAGE SENSOR

Multi-spectral imaging is primarily developed for space-based imaging. It has been successfully applied in many fields, such as environment, national defense, and agriculture. The multi-spectral image sensor can detect light with a few discrete wide spectral bands (generally 3 to 10). Therefore, it can provide more detailed spectral information. In the agricultural field, multi-spectral image sensors are usually used to detect the information of visible spectrum and near-infrared spectrum, which can be used to measure some specific plant phenotyping such as plant stress, water stress, disease detection and normalized difference vegetation index (NDVI) [80], [92]. Fig. 10 presents the images of the multi-spectral sensor and camera. Fig. 11 presents the multi-spectral principle.

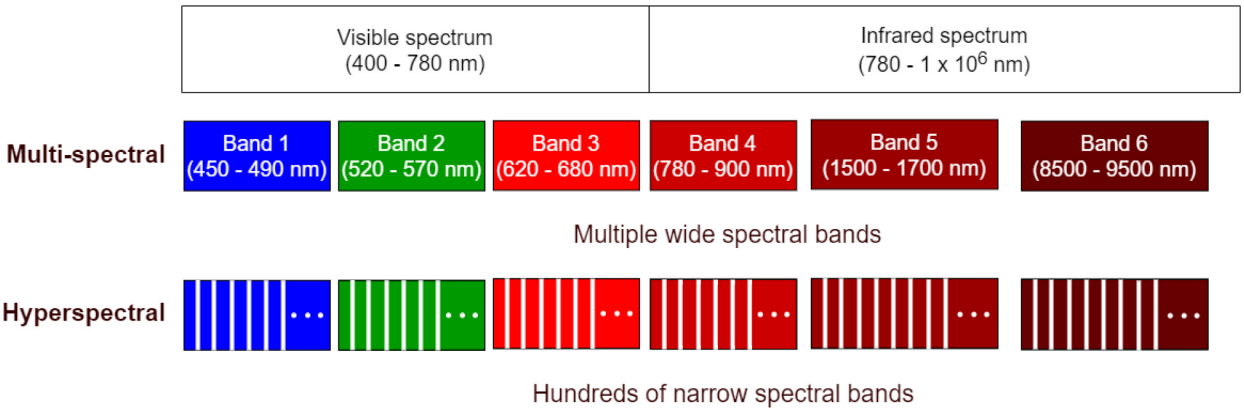


FIGURE 11. Multi-spectral and hyperspectral principle.

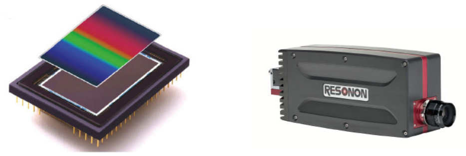
Andrade-Sanchez *et al.* [95] used a multi-spectral crop canopy image sensor to measure the cotton canopy reflectance. The multi-spectral image sensor has three channels for detecting the visible and NIR spectrum. The canopy reflectance data in the infrared spectrum regions were implemented to calculate the normalized difference vegetation index (NDVI) [95]. Zaman-Allah *et al.* [96] used an unmanned aerial platform (UAP) equipped with sensors to get multi-spectral images of maize's performance under low nitrogen stress. The study results show that the study indicates that UAP based platform can effectively assess crop performance under low nitrogen stress. The NDVI data from multi-spectral images have a strong correlation with ground-measured data [96]. Patrick *et al.* [97] applied multi-spectral image sensor for tomato spot wilt disease resistance in peanuts research. Their study used a quadcopter with a multi-spectral image sensor to get multi-spectral images for high-throughput plant phenotyping of tomato spot wilt disease resistance among twenty different genotypes of peanuts. The multi-spectral images were analyzed and processed into several vegetation indices (each plot has a further distribution of pixel intensities), which can be applied to develop a model for plant disease assessment by working with manually acquired data. The result of the study shows it can save time and provide more reliable results than human visual work [97]. Kumar *et al.* [98] used a multi-spectral image sensor mounted on an unmanned aerial vehicle (UAV) to get the near-infrared, green, and red band images, which were applied to achieve the vegetative index for maize crop health monitoring. The study results show that this method successfully detects the water-stressed area. The irrigation process and crop health monitoring have been optimized through this study [98]. Mardanisamani *et al.* [99] applied a multi-spectral image sensor with five spectral channels (red, blue, green, near the infrared, and red edge) on a quadcopter to get the images of wheat and canola from two breeding field trials. A deep convolutional neural network was used on these images to build a detection model for plant lodging. The result of this study shows that the model can achieve real-time plant lodging classification and reduce the work cost [99].

The limitation of the multi-spectral image sensor is that it is limited to a few spectral bands. Few spectral bands may not be enough for some applications. A hyperspectral image sensor that provides hyperspectral details might solve this problem because the hyperspectral images have more measured wavelength bands than multi-spectral images [80]. Besides, employing a combination of image sensors could also be a potential solution for this limitation.

D. HYPERSPECTRAL IMAGE SENSOR

Hyperspectral images have hundreds of narrow spectral bands, which means they can provide enough spectral information for object analysis. The main difference between the multi-spectral and the hyperspectral image sensor is the number of wavebands and bandwidth being detected. Hyperspectral image sensor provides a potential method for more accurate and detailed plant phenotyping information than any other type of sensor. With the development of hyperspectral image sensors, it has become one of the most powerful sensors in the field of remote sensing [100]. Therefore, the hyperspectral image sensor is turning into a gradually popular method for high-throughput plant phenotyping as it can provide valuable insights into the plant conditions such as water content, plant stress, and chlorophyll [101]. In high-throughput plant phenotyping studies, the hyperspectral image sensor is usually applied to plant stress, plant quantitative assessment, and plant condition monitoring [102]. Fig. 11 presents the hyperspectral principle. Fig. 12 presents the images of the hyperspectral image sensor and camera.

Seiffert *et al.* [105] applied the hyperspectral image sensors to do the quantitative assessment of various genetically different tobacco varieties under different growing environments. The artificial neural networks were used to analyze the hyperspectral images in their study. This study shows that the different genotypes and growing conditions will lead to the difference in plant spectrum [105].



(a) Hyperspectral image sensor (b) Hyperspectral camera

FIGURE 12. **Hyperspectral sensor [103], [104].**

As the plant condition monitoring area, [106] stated a method to classify the nutrition state of the crop through hyperspectral imaging. In their research, artificial neural networks were used to predict a plant's nutrition condition based on leaf age or intra-leaf pixel position. The result shows that their method can boost classification performance, where leaf age had a more substantial impact. Besides, the result also indicates that different spectral bands have different weights on plant nutrition condition prediction [106].

Römer *et al.* [107] applied unsupervised learning on the hyperspectral images, which are acquired by a hyperspectral image sensor SOC-700. Their work model can compare the plant spectrum with observed typical spectra to measure if the plant is suffering from stress. The result of this study tests the plant drought stress detection in cereals and provides a method to visualize the plant stress [107]. Mahlein *et al.* [108] developed specific spectral disease indices (SDIs) for the detection of sugar beet diseases. They tried to test all possible combinations of light wavelength to get the best-weighted variety on the hyperspectral imaging data set. The result of this study shows that the spectral disease indices can improve disease detection and crop monitoring in agriculture practice [108]. Asaari *et al.* [109] did the detection of plant responses to drought by hyperspectral images for drought-tolerant maize selection. Their study used the standard normal variate (SNV) method to reduce illumination effects due to hyperspectral images being easily affected by illumination. The different plant spectra were compared to assume the plant trait's variation. The result of this study successfully detects the drought stress responses of maize and plant recovery effects after re-watering [109]. Yang *et al.* [110] developed a convolutional neural network (CNN) model to analyze the hyperspectral images for estimating the cold damage of corn seedlings. This study shows that the spectral analysis result based on CNN modeling correlates with the chemical method result. The study provides a reference for plant cold damage study [110].

Although the hyperspectral image sensor is very promising for plant phenotyping applications, the limitations of hyperspectral image sensors still need to be considered. Currently, significant problems are the challenge of image processing, image analysis, and the heavy price of sensors [72], [80]. Many advanced methods like unsupervised learning [107], image fusion, artificial neural networks [105], [106] and convolutional neural network [110] may become potential solutions for the image processing and analysis problems.

FIGURE 13. **Depth Image Sensor [114].**

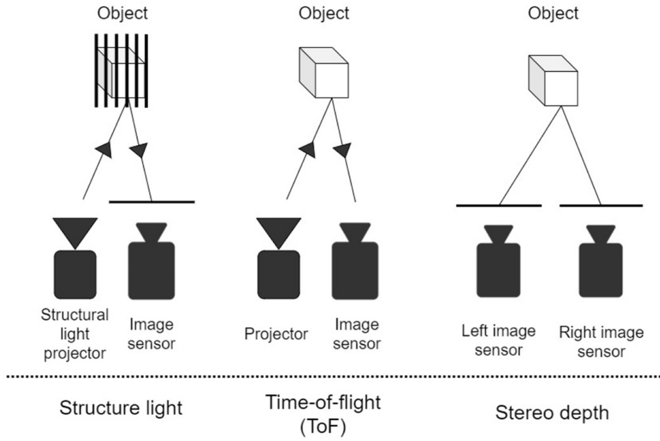
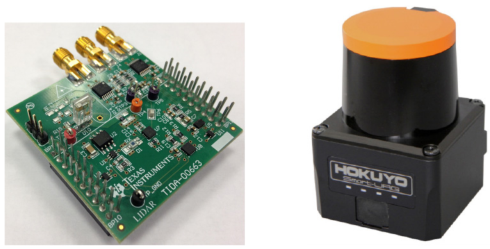


FIGURE 14. **Depth image sensor principle.**

E. DEPTH IMAGE SENSOR

A depth image sensor can provide images with real-time depth information. The current principle of depth camera can be divided into three parts: structure light, time-of-flight (ToF), and stereo depth. Fig. 14 presents the three depth image sensor principles. In the structure light method, the structural projector will emit patterned light on the object. Since the projected light pattern is known, the image sensor could provide depth information based on the deformation of pattern [111]. In the time-of-flight (ToF) method, the projector will emit light to the object. Because the speed of light is known, the time that light flight to an object and is reflected the image sensor will provide depth information [112]. Two image sensors (spaced a small distance apart) will be applied to take two images in the stereo depth method. Because the distance between the two image sensors is known, the comparison of two images will provide depth information [113]. Based on these principles, depth image sensors can produce an image showing the distance between the object and the image sensor [22]. The popular depth image sensor is currently an RGB-D image sensor equipped with a digital image, depth, and infrared emitters. Since RGB-D image sensor can simultaneously provide RGB and depth images of an object, it has been widely integrated into various applications such as 3D reconstruction, object recognition, and remote control [67]. Fig. 13 presents the image of depth image sensor.



(a) LiDAR pulsed time of flight reference design (b) Hokuyo LiDAR

FIGURE 15. LiDAR [120], [121].

In the high-throughput plant phenotyping field, the RGB-D image sensor has shown its impressive ability for 3D plant phenotyping and automation of agricultural applications [115]. Seiffert *et al.* [67] applied Kinect RGB-D image sensor to capture RGB and depth images of plants for the segmentation of plant leaves. This study shows the success of 3D segmentation of individual plant leaves, which could be used for plant stress and disease resistance. Paulus *et al.* [115] proved the reliability of a low-cost RGB-D image sensor for plant traits (height, width, volume, surface, and compactness) measurement from the 3-D reconstruction of the plant. Bahman *et al.* [116] applied Intel RealSense D435 depth image sensor for non-invasive and automated plant height measurement. In this study, the depth image sensor was set up on the top of the plants. Image segmentation was applied to reduce the background impacts in plant height measurement. The plant height are calculated by using the distance of the depth camera from the ground subtracting the shortest length of the depth camera from the plant and the height of the pot. The result of this study shows high correlations and accuracy between depth image sensor measured plant height and actual plant height [116].

The limitations of depth image sensors are low resolution, short sensing distance, and sensitivity to optical interference [117].

F. LIDAR

Light detection and ranging (LiDAR) (also called laser scanner) is a popular remote sensing technique in many fields such as robotics, smartphones, transport, agriculture, etc. LiDAR can measure the distance by illuminating the object with laser light and measuring the reflection [118]. Differences in laser return time can be used to make digital 3-D representations of the thing. After computer processing, the 3-D data from LiDAR can provide an accurate estimated model of object [57]. In high-throughput plant phenotyping research, LiDAR is usually used for 3-D reconstruction of plants and estimation of plant's traits [64], [119]. Fig. 15 presents the image of LiDAR and pulsed time of flight reference design. Fig. 16 presents the LiDAR principle.

Eitel *et al.* [122] applied LiDAR for biomass and crop nitrogen estimation on wheat. The plant biomass and nitrogen concentration show a strong relationship with

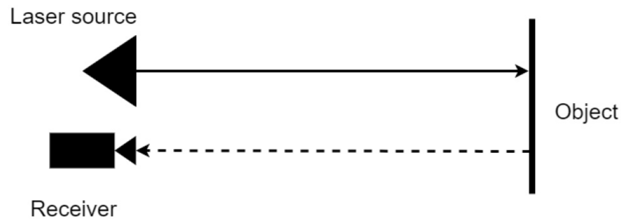


FIGURE 16. LiDAR principle.

LiDAR-derived results; this proves the ability of LiDAR to improve crop nitrogen management in the wheat-growing section [122]. Jimenez-Berni *et al.* [123] mounted a LiDAR on a ground-based platform to estimate canopy height, ground cover, and above-ground biomass of maize. In their study, red reflectance image and canopy height were applied for the ground cover estimation, while the 3D voxel index (3DVI) and 3D profile index were used to estimate biomass. This study shows that all the estimated parameters have a strong relationship with LiDAR. Their work provides a more efficient and reliable method for plant phenotyping measurement [123].

Sun *et al.* [124] did a cotton plant growth analysis by using LiDAR. The LiDAR was implemented to measure plant height, canopy area, and plant volume. The result represents a strong relationship between manual measurements and LiDAR measurements [124]. Besides, [125] utilized the LiDAR data for corn plant. The leaf area, leaf distribution, and 3D model were automatically extracted from LiDAR point clouds by Difference of Normal (DoN). The result of this study shows overall 94.10% of the accuracy assessment [125]. In addition, [126] used LiDAR and other sensors to do a tree induction classification for the identification of post-harvest growth [126]. Sirault *et al.* [127] applied LiDAR to capture the structural dynamic of plant growth [127].

Although LiDAR provides a method to measure some plant traits accurately, some limitations need to be addressed. The end of LiDAR is that it has a high sensitivity to slight variations in path length [80]. Besides, high accurate LiDAR is very expensive [22]. According to [128], multiple LiDAR sensors might be a potential solution for the sensitivity problem because of their features of long-range and high resolution. Besides, the MEMS LiDAR sensors could be a good choice. About the high-cost problem, with the development of LiDAR manufacturing, high accurate LiDAR will gradually become affordable [128].

G. FLUORESCENCE SENSOR

Fluorescence sensors can measure chlorophyll by detecting fluorescence. Generally, a fluorescence sensor uses a charge-coupled device (CCD) sensitive to fluorescence signals. Since the plant chlorophyll will use the external light to excite the photosynthesis, the FLUO images can be captured by giving an external light excitation such as visible or UV (ultraviolet) light. The plant's metabolism will change when photosynthesis is affected by environmental conditions.

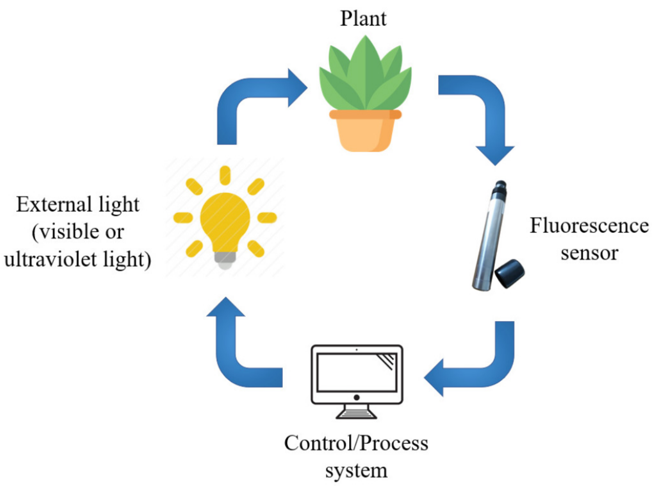


FIGURE 17. Fluorescence sensor principle.

FIGURE 18. Fluorescence sensor [130].

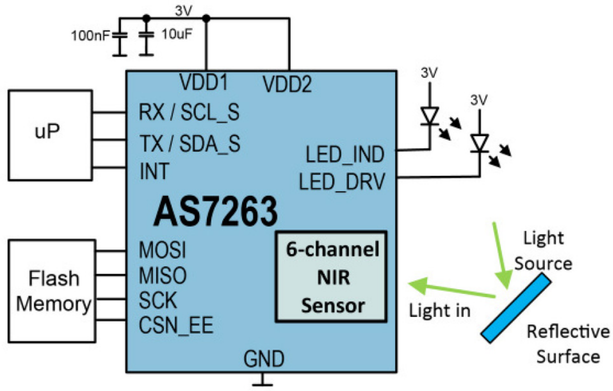


FIGURE 19. AS7263 spectral sensor principle [132].

Therefore, the fluorescence sensor can be used for plant stress and plant disease detection [57], [129]. Fig. 17 presents the fluorescence sensor principle. The control system sends the instruction to an external light emitter, which will emit visible or ultraviolet light to the surrounding environment. The plant will use external light to excite its photosynthesis. At the same time, the fluorescence sensor will measure chlorophyll data and send data to the process system to acquire the plant condition. Fig. 18 shows the image of the fluorescence sensor.

In [66] work, they applied a fluorescence sensor on the LemnaTec 3D Scanalyzer system. A fluorescence sensor captured the FLUO images through constant blue light excitation. These images could be applied for the detection of plant diseases like senescence, necrosis, and chlorosis [66]. Chen *et al.* [24] also used fluorescence sensor on the LemnaTec system. The FLUO images were applied to detect signals of chlorophyll fluorescence. The chlorophyll fluorescence excited by constant blue light can be used to describe the plant's health condition in a drought environment [24].

A fluorescence sensor is a powerful tool for plant phenotyping because it can measure the chlorophyll related to the plant's metabolism. However, the limitations of the fluorescence sensor are the requirement for intensive illumination and the view limitation [22]. Besides, most FLUO images are limited to single leaves or the seedling level of model crops. The research [57] suggested that a more robust data analysis software might be a potential solution for large-scale plant phenotyping. In addition, a standard procedure needs to be developed for fluorescence image processing to achieve large-scale plant phenotyping task [57].

H. LOW COST PLANT PHENOTYPING SENSORS

1) AS7263 SPECTRAL SENSOR

The "ams multi-spectral sensor" product includes low-cost spectral sensors that can detect multiple channels in the visible and near-infrared spectrum. In these spectral sensors, the AS7263 near-infrared (NIR) spectral sensor is a low-cost plant phenotyping sensor based on the near-infrared spectrum principle. The AS7263 spectral sensor has six near the infrared channel, which can detect 610, 680, 730, 760, 810, and 860 nm wavelengths. Fig. 19 shows the AS7263 spectral sensor principle. Since the NIR lights could be greatly reflected by plant tissue, the AS7263 spectral sensor can be applied to detect the quality. Sripaurya *et al.* [131] implemented an AS7263 spectral sensor to do the banana quality measurement by attaching the sensor to the banana peel. The AS7263 spectral sensor will emit light to banana tissue by its LED driver. Then, the reflected light from banana tissue will pass through the sensor's six near the infrared channel. The reflected light intensity results are related to banana properties and maturity stages [131]. The study shows that low-cost multiple channels near-infrared (NIR) spectral sensor can be applied to estimate the quality parameters of banana fruits.

2) LOW-COST CHLOROPHYLL METER

Chlorophyll is important for the determination of health condition [133]. However, the current commercial chlorophyll meters (SPAD-502 chlorophyll meter, CL-01 chlorophyll meter, and MC-100 chlorophyll meter) are relatively expensive. There is a demand for a low-cost chlorophyll meter. Evan Hutomo *et al.* [134] developed a low-cost chlorophyll meter (LCCM) based on the light reflectance mechanism. The chlorophyll meter includes one near-infrared LED, and

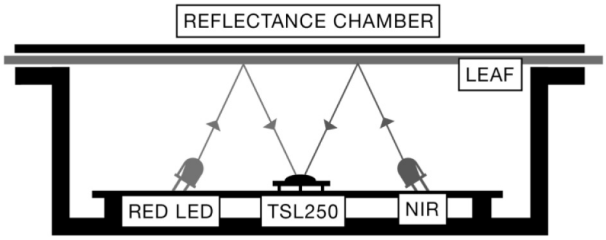


FIGURE 20. Low-cost chlorophyll meter (LCCM) principle [134].

one red LED as resources of light. One TSL250 photodiode was used to convert light intensity to the output voltage. Fig. 20 shows the low-cost chlorophyll meter (LCCM) principle. The result of this study shows that the low-cost chlorophyll meter can measure the chlorophyll with a high coefficient of determination in correlation with the SPAD-502 chlorophyll meter's result [134].

3) FLIR LEPTON

The FLIR Lepton is a low-cost long-wave infrared image sensor for thermal image generation. The current FLIR Lepton has two versions (Lepton 3.5 : 160 × 120 pixels and Lepton 2.5 : 80 × 60 pixels) and can easily integrate into multiple platforms [135]. Acorsi *et al.* [136] assessed the performance of the FLIR Lepton 3.5 in both ground and aerial situations based on the result from the commercial infrared thermometer. Their study shows that FLIR Lepton has comparable measurement performance to more expensive in-ground and aerial models. Besides, the study demonstrates that FLIR Lepton accuracy decreased towards increasing flight altitudes. Additional calibration can be the solution for measurement accuracy problems at high flight altitudes [136]. Bruno *et al.* [137] applied FLIR Lepton 3.5 integrated with a Raspberry Pi to generate thermal images of crops. The evaluation of yield thermal images can predict crop water stress. The study shows that FLIR Lepton 3.5 can work as a low-cost and non-invasive infrared image sensor for determining the status of crops.

4) RASPBERRY PI SERIES CAMERAS AND SENSORS

The Raspberry Pi series cameras are a series of low-cost cameras, which includes one Raspberry Pi Camera Module 2 and one Raspberry Pi Camera Module 2 with no infrared filter (NoIR). The module 2 camera has a Sony IMX219 8-megapixel image sensor and can be used to take RGB images. The module 2 NoIR camera includes the same Sony IMX219 8-megapixel image sensor but excludes an infrared filter. Therefore, the module 2 NoIR camera is suitable for capturing infrared images. Sangjan *et al.* [138] applied Raspberry Pi Module 2 and Module 2 NoIR cameras-based sensor system for automated in-field spring wheat plant phenotyping measurement. The study used low-cost sensor systems with dual cameras to capture RGB images and NoIR images and extract information. The image analysis calculated the plant height, vegetation index, and NDVI data. The proposed sensors system provides a low-cost method for high-throughput plant phenotyping [138].

Table 2 presents the summary of the plant phenotyping sensors. Table 3 presents sensors related parameters.

IV. SENSING PLATFORMS FOR HIGH-THROUGHPUT PLANT PHENOTYPING

With the development of sensor technology, automatic control technology, aeronautics, and computer engineering, plant phenotyping platforms have significantly been applied to do plant phenotyping research. A plant phenotyping platform can facilitate high-throughput plant phenotyping study by providing an automatic measurement solution for multiple plant phenotyping parameters. Many research institutions have introduced or developed different plant phenotyping platforms to integrate various sensors. The current plant phenotyping platforms can be divided into two parts: ground-based phenotyping platform and aerial-based phenotyping platform [22], [57]. The following subsections will discuss different types of plant phenotyping platforms.

A. GROUND BASED PLANT PHENOTYPING PLATFORMS

Ground-based phenotyping platforms include conveyors, vehicles, or robotics with sensing sensors. Various sensors are installed on different positions and heights for measuring multiple plant phenotyping. Besides, the power system, microcontroller, GPS receiver, encoder, and other accessories will be installed on the platform to help the whole system work successfully [144]. The ground-based plant phenotyping platforms can reduce human labor and improve work efficiency. It plays an essential role in high-throughput plant phenotyping application [22].

The ground-based plant phenotyping platforms are suitable for sensor deployment. Various sensors can be applied on platforms and achieve multiple plant phenotyping measurements. Besides, ground-based plant phenotyping platforms are ideal for GPS/GIS tagging, which can help the platform's position check and automatic work. Moreover, ground-based phenotyping platforms can capture plant data at the plot level, which makes the data in high spatial resolution with relatively simple post-processing [57].

The ground-based plant phenotyping platforms also have some limitations. It generally takes a long time to cover a field. Therefore, large-scale plant phenotyping measurements of plants in a short time are impossible with ground-based phenotyping platforms [57].

Companies or universities have developed many ground-based plant phenotyping platforms. The ground-based plant phenotyping platforms are summarized in Table 4.

1) LEMNATEC 3D SCANALYZER

LemnaTec designs LemnaTec 3D Scanalyzer platform for the quantitative, non-invasive analysis of large scale plants. Each plant can be continuously imaged by various image sensors, employing different spectra to get additional plant phenotyping information. The large-scale significant plant data will

TABLE 2. Summary of the plant phenotyping sensors.

Sensor Type	Operation Principle	Advantages	Applications	Limitations	Potential Solutions
Visible spectrum image sensor	Detect visible spectrum (400 to 780 nm) to form the RGB image [22]	Low cost [70], Easy to handle [72], Ubiquitous [72]	Morphometric parameters [74], Plant growth [74], Biomass [78]	Limited to visual spectral bands [80], Easily affected by the light condition [22]	Apply multiple image sensors platform, Digital image sensor scene mode [81]
Infrared spectrum image sensor	Detect infrared spectrum (780 nm - 1000 μm) information [87]	Easy to handle [87] Reflectance is related to water content (NIR) [72] Accurate plant temperature measurement (TIR) [87]	Leaf water content (NIR) [24], Drought response (NIR) [86], Plant temperature (TIR) [90], Plant water stress (TIR) [91]	Limited to specific bands [72], Easily affected by environment condition [80], Hard to detect the difference of small temperature (TIR) [80]	Apply multiple image sensors platform, Apply cooled device (TIR) [87]
Multi-spectral image sensor	Detect the light with few discrete wide spectral bands [80]	Provide multi-spectral information [80]	Plant stress [96, 99], Disease resistance [97], NDVI [95]	Limited to few spectral bands [80]	Hyperspectral image sensor [80]
Hyperspectral image sensor	Detect the light with hundreds of narrow spectral bands [101]	Provides hyperspectral information [101]	Plant stress [107] [110], Plant assessment [105], Condition monitor [108, 109]	Image processing [72], Image analysis [72], High cost [80]	Image fusion [105], Machine learning [106, 110]
Depth image sensor	Provides image with depth information [22]	Relative low cost [115], Provides depth information [115]	3-D reconstruction of plant to estimate plant traits [115], Plant stress [67]	Low resolution [117], Short sensing distance [117], Sensitive to optical interference [117]	Apply multi-depth image sensors [117], Apply image segmentation [116]
LiDAR	Generates digital 3-D representations of the plant [64]	High resolution [57], Highly accurate [57]	3-D reconstruction of plant to estimate plant traits [64, 119]	Hard to sense small variations [80], High cost [22]	Improve algorithm, Working with other sensors [126]
Fluorescence sensor	Measures the chlorophyll by fluorescence [129]	Acquire plant metabolic information [129]	Plant stress [24], Disease resistance [66]	Require intensive illumination [22], View limitation [22], Does not work for large scale plants [57]	Powerful data analysis software [57], Formulate standard procedure [57]

play an essential role in plant analysis. All plant data is available in the database within minutes of imaging for plant development. These comprehensive data will be helpful for physiological and genetic plant modeling, which can provide deep insights into plant phenomics and plant breeding [24], [66], [74], [86].

2) HIGH-THROUGHPUT RICE PHENOTYPING FACILITY

High-throughput rice phenotyping facility works on the rice traits. Group G1 will be transported to the conveyor from the greenhouse by an automatic guided vehicle on this platform. Then the G1 plants will be transported to the inspection unit, where the G1 plants are constantly measured by X-ray devices and image sensors. After that, another group, G2, will be swapped with G1 and measured by the inspection unit. The inspection unit applies a control software LabVIEW 8.6 (National Instruments, USA) for image capturing, image processing, and data communication [78].

3) PHENOVISION

PHENOVISION is a greenhouse system for high-throughput plant phenotyping of crops. Plant Pots are transported through a conveyor belt system. The imaging cabins can apply up to three image sensor systems including visual spectrum image sensors, thermal infrared image sensor and state-of-the-art hyperspectral imaging system in a light-controlled conditions to get the plant phenotyping data [145].

4) LEEAGRA 3434 DL

The LeeAgra 3434 DL is a kind of ground vehicle. It has a height of 1.93 m and provides minimal impact to the ground plants. A boom is attached in the front of the tractor, where various sensors and instrument components are installed for plant phenotyping measurement [95].

5) LEICA SCANSTATION 2

Leica ScanStation 2 is a laser instrument. The LiDAR scanner (TLS) uses a 532 nm pulsed green laser. In the range of 0–50 m, the LiDAR scanner can work with a 4 mm beam diameter, sample density of 1 mm, and 50 kHz rate [122].

6) PHENOMOBILE LITE

Phenomobile Lite is an advanced phenotyping buggy with the advantages of being adaptable and easy to handle for

TABLE 3. Sensors attributes.

Sensor Type	Plant Parameters	Resolution/Range	Sensitivity	Cost (USD)
Visible spectrum image sensor	Plant height Leaf length/width/area/angle Canopy cover Biomass Plant stress	2056 × 2454 pixels [74] 4056 × 3040 pixels [139]	60 mm per pixel [74]	≈ 1000
Infrared spectrum image sensor	Plant/Water stress Leaf water content	14-bit radiometric resolution (TIR) [91], 1280 × 1024 pixels (NIR) [140]	0.5 °C (TIR) [91], 35 mm per pixel (NIR) [140]	≈ 375 (TIR) ≈ 500 (NIR)
Multi-spectral image sensor	Plant/Water stress Leaf water content Disease detection NDVI Biomass	2048 × 1536 pixels [96] 1260 × 960 pixels [98]	60 mm per pixel [96] 35 mm per pixel [98]	≈ 2000
Hyperspectral image sensor	Plant height Plant/Water stress Leaf water content Disease detection Chlorophyll NDVI Biomass	510 × 328 pixels [109] 640 × 640 pixels [107] 510 × 328 pixels [109]	Spectral resolution of 4 nm [107] Spectral resolution of 2.8 nm [108] Spectral resolution of 3.1 nm [109]	≈ 2000
Depth image sensor	Plant height Leaf length/width/area/angle Canopy cover Biomass Plant stress	1280 × 720 pixels [141] 1280 × 800 pixels [142]	Error <2% at 2 m [141] Error <2% at 4 m [114]	≈ 200
LiDAR	Plant height Leaf length/width/area/angle Canopy cover Plant stress Biomass	100 m [143] 50 m [122] 80 m [124]	3 cm [143] 4 – 6 mm [122]	≈ 1800
Fluorescence sensor	Chlorophyll	0.01mg/L [130]	±0.2% FS [130]	≈ 500

field plant phenotyping applications. It has a flexible space for different sensor equipment. This ground platform can provide a non-destructive high-throughput plant phenotyping solution by rapidly scanning field crops [146].

7) SPIDER DL

The Spider DL is a tractor platform for plant phenotyping work. It has large tires, which can provide minimal plant disturbance. Its lightweight (3300 lb) can reduce the damage to the field and make transportation easier [124].

8) TEXAS A&M GROUND PHENOTYPING VEHICLE

The Texas A&M Ground Phenotyping Vehicle is a ground vehicle for plant phenotyping. It can carry various sensors for multiple plant phenotyping data. The three meters height and high stability can essentially reduce the disturbance to the crops when working for corn, sorghum, and other row crops plant phenotyping measurement [65].

B. AERIAL BASED PLANT PHENOTYPING PLATFORMS

Aerial-based plant phenotyping platforms gradually increase since they can overcome some ground-based plant phenotyping platforms' limitations. It has been considered an essential component of plant phenotyping [147]. Aerial-based plant phenotyping platforms can enable the measurement of plant parameters from several plots within minutes. Typical aerial platforms can be divided into manned aerial vehicles (MAVs), unmanned aerial vehicles (UAVs), and satellites. Currently, the more popular platform is UAVs since the satellites have the limitation of image resolution, and the MAVs need more manual operations. Unmanned aerial vehicles (UAVs), also known as a drone, is an aircraft that can do flight work without any humans on board. The flight of UAVs can be operated by a human operator or autopilot system. UAVs are excellent aerial-based platforms for taking high-quality and vast amounts of sensing data. Sensors such as visual spectrum image sensors, infrared image sensors, hyperspectral image sensors, multi-spectral image sensors, depth image sensors, and LiDAR systems can be mounted on UAVs for multiple plant phenotyping parameters measurements [80], [148]. Besides, with the rapid development of control technology, various drones can be applied by farmers who were trained in a short time.

The aerial-based platforms have a larger measuring area and better efficiency than ground-based platforms. Aerial-based plant phenotyping platforms can measure large-scale plants quickly, which is impossible on ground-based platforms. Therefore, the plant data collected by aerial-based media can represent large-scale plant conditions without any time delay [57].

However, aerial-based plant phenotyping platforms have a limitation of load. The payload of a UAV varies from 0.8 to 10 kg, which means it can not bring too many sensors on the platforms for multiple plant phenotyping measurements [80].

TABLE 4. Ground based plant phenotyping platforms.

Platform Name	Image Sensors	Measured Phenotyping Parameters	References
LemnaTec 3D Scanalyzer	Visible spectrum image sensor, NIR image sensor	Plant height, Plant space, Biomass, Plant stress	[24, 66, 74, 86]
High-throughput rice phenotyping facility	Visible spectrum image sensor	Plant height, Leaf area, Plant compactness, Biomass	[78]
PHENOVISION	VNIR-HS image sensor	Plant stress	[109]
LeeAgra 3434 DL	Sonar proximity sensor, Apogee SI-121 infrared radiometer (IRT) sensors, Crop Circle ACS-470 multi-spectral crop canopy sensor	Plant height,Temperature, Canopy reflectance-NDVI	[95]
Leica ScanStation 2	Time-of-flight, terrestrial LiDAR	Biomass, Crop nutritional status	[122]
Phenomobile Lite	LiDAR (SICK LMS 400-2000, SICK AG, Waldkirch, Germany), NDVI sensor (GreenSeeker, Trimble, USA), Visible spectrum image sensor (Canon 6D, Canon Inc., Tokio, Japan)	Plant height, Canopy cover, Biomass	[123]
Spider DL	LiDAR (LMS 511 PRO SR, SICK AG, Waldkrich, Germany)	Plant height, Projected canopy area (PCA), Plant volume (PV)	[124]
Texas A&M Ground Phenotyping Vehicle	Senix 15S-485 Ultrasonic sensors, Crop Circle ACS-430 spectral sensors, Apogee SI-131 IRT sensors, Micro Epsilon CTF-CF15 IRT sensors	Canopy height, NDVI, Canopy temperature	[65]

TABLE 5. Aerial based plant phenotyping platforms.

Platform Name	Image Sensors	Measured Phenotyping Parameters	References
X8 Octocopter	Two Canon S110 point-and-shoot, Visual spectrum image sensors	Canopy area, Plot row length	[77]
Tarot Iron Man 1000 octocopter	DIY-Thermocam	Canopy temperature, Water status	[91]
Airelectronics fixed-wing	Tetracam image sensor	NDVI, Plant stress	[96]
DJI Phantom 3 quadcopter	MicaSense RedEdge multi-spectral image sensor	Plant disease detection	[97]
DJI Inspire-1 Pro UAV	Digital Zenmuse X5 image sensor, MicaSense RedEdge image sensor	Plant/Water stress	[98]
Draganfly X4P quad-copter	MicaSense RedEdge image sensor	Plant stress	[99]
DJI M600	Sony alpha 7R, Velodyne VLP-16 Puck HI-RES LiDAR	Plant height, Canopy cover	[143]
UAVs	Headwall Photonics Nano-Hyperspec pushbroom scanner, Velodyne VLP-16 3D LiDAR sensor	Plant height, Canopy cover, Biomass	[152]

Besides, speed and altitude will influence the resolution of aerial-based platform sensors, which may lead to image loss [22].

Companies or universities have developed many aerial-based plant phenotyping platforms. The aerial-based plant phenotyping platforms are summarized in Table 5.

1) X8 OCTOCOPTER

X8 is an autonomously flying octocopter, which can carry a 1 kg payload with 15 minutes flight duration. The flight system uses GPS and onboard data to allow two control modes: full autopilot mode and manual mode [77].

2) TAROT IRON MAN 1000 OCTOCOPTER

The Tarot Iron Man 1000 octocopter is composed of carbon fibers. It has brushless 600 W power T-Motors for holding fiber propellers. Its payload capacity is 4 kg and the flight time is about 20 minutes [91].

3) AIRELECTRONICS FIXED-WING

Airelectronics fixed-wing is a UAV-based remote aerial sensor platform. It is a fixed-wing platform that can be controlled through an autopilot system. It also has the ability of waypoint navigation and altitude control. Its payload capacity is 1.5 kg and flight time is about 30 minutes [96].

4) DJI PHANTOM 3 QUADCOPTER

DJI Phantom 3 quadcopter system has a microcontroller, 10 DOF sensors, 3D printed supporting stand, and vibration dampeners. This system can calculate the angle of the image sensor through built-in accelerometers and gyroscopes. Besides, the altitude can be determined by the built-in barometer. When the mounted image sensor is stable and at the target height, the plant images will be captured [97].

5) DJI INSPIRE-1 PRO UAV

DJI Inspire-1 Pro UAV has a payload capacity of 3.5 kg, and its flight duration measured approximately 15 minutes.

It has various intelligent flight modes, including waypoint, home lock, point of interest, and course lock. These modes will be beneficial for getting better plant phenotyping data [98], [149].

6) DRAGANFLY X4P QUAD-COPTER

Draganfly X4P quadcopter is designed for line-of-sight flying. It has the ability of automatic take-off and intelligent flight navigation. Users can use normal flight mode or build-in software to control the quadcopter [99], [150].

7) DJI M600

The DJI Matrice 600 (M600) is an aerial platform designed for aerial photography and multiple industrial applications. It integrates various powerful DJI technologies, including intelligent flight control and battery management systems. Its payload capacity is 5.5 kg and flight time is about 15 minutes [143], [151].

V. SUMMARY AND FUTURE PERSPECTIVES

As discussed in this review paper, crop monitoring could be a potential solution to the problems of food shortage for growing world's population since it can provide up-to-date information regarding crops for farmers in support of increasing food production. High-throughput plant phenotyping is believed to be a crucial part of crop monitoring on the data acquisition of the large-scale crop characteristics. The related advanced technologies and sensors can facilitate the development of high-throughput phenotyping for crop monitoring. It is believed that with the development of new technologies, crop monitoring with high-throughput phenotyping will gradually become the central part of agriculture. Below is the summary of the significant challenges of high-throughput plant phenotyping and future perspectives:

- High accuracy and low-cost sensor solution for plant phenotyping measurement.
- The challenge of crop image processing and image analysis. Integration of advanced technologies like machine learning and image fusion may become the potential solution.
- The relationship between plant phenotyping and genomics needs to be further studied to understand higher-level breeding requirements and application potential.
- High speed, wide range, low energy consumption, and low-cost communication protocol need to be developed for the high-quality crop monitoring system.
- Currently available plant phenotyping system can be broadly divided into two categories:
  (a) Plant phenotyping system;
  (b) Plant phenotyping system + IoT based plant growth environment monitoring system;
- The development of integrated plant phenotyping systems for plant growth environment monitoring, plant phenotyping measurement, data transmission, data management, and data visualization will be a future research trend.

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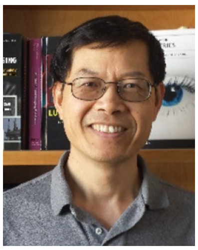

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