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Review Article

# Technological Interventions for Sustainable Agriculture: Scope and Impact Assessment

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## Abstract

Technological interventions in conventional agriculture practices have become inevitable in recent times. Conventional agriculture practices cannot meet the projected future global food demand. Moreover, the recent changes in environmental conditions, in the form of global warming and climate change, etc., have also changed the agriculture scenario. It is advisable to seek technology interventions in solving such potential challenges. Many emerging technologies can assist conventional agriculture practice for its improvisation. The present paper attempts to summarize some relevant technologies such as the Internet of Things (IoT), thermal imaging, hyperspectral imaging, and fluorescence imaging that are useful and relevant to agriculture. The influence and impact assessments of these technological interventions are also included in this report.

**Keywords:** *Infrared Thermography, Thermal Imaging, Hyperspectral imaging, Fluorescence Imaging, Mechatronics, Robotics, Drone, Artificial Intelligence, Machine Learning.*

## Introduction

The application of scientific knowledge into practical implications for human benefits in various sectors encapsulates technological interventions in our life. The advancement of modern technology has brought a great deal of progress in innumerable spheres of life. Technological innovations have successfully managed to mark their footprints in agriculture. In the beginning, most of the agricultural activities were accomplished manually, but farmers were encouraged to implement different ideas that would make the process simpler and faster (Upendra, *et al*., 2020). Technologically advanced farming involves incorporating technologies into machinery, equipment, and sensors for use in better production systems. Agricultural practices have progressively hastened to meet the increasing population and their demands. In order to sustain the changing lifestyles and climatic patterns, efficient agriculture is required to employ new technologies and new opportunities to update the existing agricultural practices and widen the scope for better productivity in the field (Raza, *et al*., 2019). Conventional agriculture practices cannot meet the projected future global demand. Moreover, the recent changes in environmental conditions in global warming and climate change have also challenged the agriculture scenario (Singh, *et al*., 2017). Consequently, technology has helped to solve the potential challenges.

Significant innovation advancements in the area have primarily centered around indoor vertical cultivating, mechanization and mechanical technology, present-day nursery rehearses, exact farming and artificial consciousness, and square chain (Kalantari, *et*

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*al.*, 2017). Due to the impact of the pandemic, the world may have a slowdown in its rapid progress but has not stopped from achieving new trends towards a brighter future. Ag-Tech sector has experienced massive growth over the last decades, and it continues to flourish every passing year and only accelerated in these challenging times (Vyas, *et al.*, 2021). Numerous technological innovations may assist conventional agriculture practice for its improvisation. Crop (field and horticulture) contributes 60.2% to the total agricultural GDP and 9.63 % of the National GDP. Keeping in view the fact that during 2017-18 contribution of the agriculture sector (15.4%) is much higher than world's average (6.4%), similarly, the contribution of industry and services sector is lower than world's average 27 % for industry sector and 58% for the services sector. Under the current Indian agriculture scenario, ways and means for the agriculture sector contribute to making India a $5.0 trillion economy in the quickest possible time (Singh, *et al.*, 2020).

Experts have made considerable efforts to enhance the inclusion of technological advancements in agriculture production. At present, the techniques employed in agricultural practices include non-destructible and non-contact techniques (Mesery, *et al.*, 2019). In the recent past, drones have been used to spray the pesticide/weedicide and deliver accurate crop health information. Technologies involved in distant learning are similar to those for remote work and include virtual reality and artificial-intelligence-enabled devices for better field governance (Ayed, *et al.*, 2021). Core technologies such as Big Data, cloud computing, Internet-of-Things ("IoT") (Ghosh, *et al.*, 2018), and blockchain are building a more resilient management system for the future by enhancing the accuracy of data and encouraging data sharing among the cultivators and experts (Gill, *et al.*, 2017). A scientifically advanced technological beginning such as different imaging techniques i.e., hyperspectral imaging (Lu, *et al.*, 2020) and thermal imaging (Ishimwe, *et al.*, 2014) is essential, providing a prospect to quickly analyze the significant factors to control crop yield and management.

This review focuses on current scopes of technological innovations amalgamated with agricultural practices, mainly on irrigation scheduling and early pathogen detections in crops (Buja, *et al.*, 2021 ; Yazar, *et al.*, 1996) Internet of Things, thermal imaging, fluorescence imaging, hyperspectral imaging, electronic nose, drones, artificial intelligence, and robotics are the few advancements in the agriculture sector briefly summarized on existing knowledge. This review comprises working principles and applications of the above mentioned technologies. It has also discussed the factors that govern and limit the real-life applications of these agriculture techniques and compared their advantages and disadvantages. To conclude, the review considers the potential prospects in this area for rapid development.

## Applied Technologies in Agriculture

### Internet of Things

The Internet of Things (IoT) is a network of interconnected devices. They work together to collect and transfer data or information over a wireless network without any human involvement. IoT system contains devices that give sensing, actuation, control, and monitoring activities and contains several interfaces for communication to other devices, both wired and wireless (Patel, *et al.*, 2016).. The semantic meaning of the Internet of Things is "an Internet application sharing the thing's information in the whole world" (Huang, *et al.*, 2010) IoT has been used in many areas as it allows establishing a global connection between any electronic devices, with fewer human efforts, and provides faster accessibility with good communication between the devices. IoT contains different divisions, including several sensors, software for communication and analysis, and electronics devices. IoT establishes communication from one end to another with the wireless network without human intervention (Ahmad, *et al.*, 2019).

IoT is widely used in the agricultural sector, which has helped farmers adopt a smarter farming technique with improved output and minimum input. The framework of this conceptual technology is a four-layer structure comprised of an integrated layer, an information management layer, a network management layer, and an information collection layer (Fig. 1). The first layer acts as a user interface layer, which includes personal devices such as cell phones, which allow the farmer to protect his crops and local monitoring of the agricultural land. The second layer is used to classify data, help decision-making, and conduct monitoring practices related to agriculture-related applications. Communication technologies such as gateways, RFID, GSM, wi-fi, 3G, and ZigBee exist in the third layer of the Internet of Things. The last layer is the information collection layer, composed of various sensors and cameras to collect information on farmland and crop health. Some of the wireless sensors are listed in Table 1 (Mekala, *et al.*, 2017).

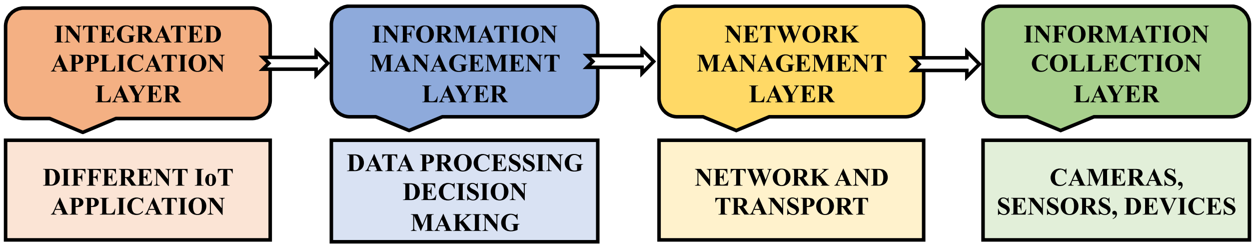

**Fig 1:** Layers of IoT structure

**Table 1:** IoT platforms and wireless technologies (Mekala, *et al.*, 2017)

| Wireless technologies | Standard | Transmission rate | Data rate | Commonly used IoT platforms | Real-time data capture |
|---|---|---|---|---|---|
| LI-FI | IEEE 802.15.7 | 10m above | 224Gb/s | Ubidots/ Thing Speak | Yes |
| WI-FI | IEEE 802.11 A/B/C | 20-100m | 1mb/s-6.75gb/s | Ubidots/ Thing Speak | Yes |
| WIMAX | IEEE 820.16 | <50km | 1mb/s-1gb/s | Ubidots/ Thing Speak | Yes |
| LR-WPAN | IEEE 802.15.4 | 10-20m | 40-250kb/s | Ubidots/ Thing Speak | Yes |
| BLUETOOTH | IEEE 802.15.1 | 8-10m | 1.24 mb/s | Ubidots/ Thing Speak | Yes |
| LORA | LORA WAN R1.0 | <30km | 0.3-50kb/s | Ubidots/ Thing Speak | Yes |

The Internet of Things has a wide range of applications in various fields of agriculture. Improper water management, such as leaky irrigation systems, inefficient application techniques, and cultivating water-intensive crops in areas with sparse rainfall, has declined the planting yields. In today's time, water use is smartly managed in agriculture by monitoring water volume, place, and duration of flow with the help of IoT. IoT also governs the efficient use of fertilizers and pesticides. As a result, the Internet of Things improves the best performance of the agricultural sector and makes it easy for farmers to understand the potential of new technologies (Mekala, *et al.*, 2017; Koksal, *et al.*, 2017).

### Irrigation Scheduling

Irrigation scheduling is a method of watering at the right time and maintaining the right frequency to promote the growth of plants and crops. The irrigation scheduling helps determine the amount of water applied and its interval to obtain a good yield (Gu, *et al.*, 2020). Irrigation scheduling is planned based on weather conditions of the field, the plant's growing state, and field specifications.

Repeated drought conditions have increased the population, and climate change has hugely impacted agricultural activities in different regions (Kercheva, *et al*., 2010). These challenges are gradually overcome by integrating modern and efficient methods, such as using recycled water in certain areas, drip irrigation, an autonomous network of sensors, and various predictive methods to detect water deficiency in crops.

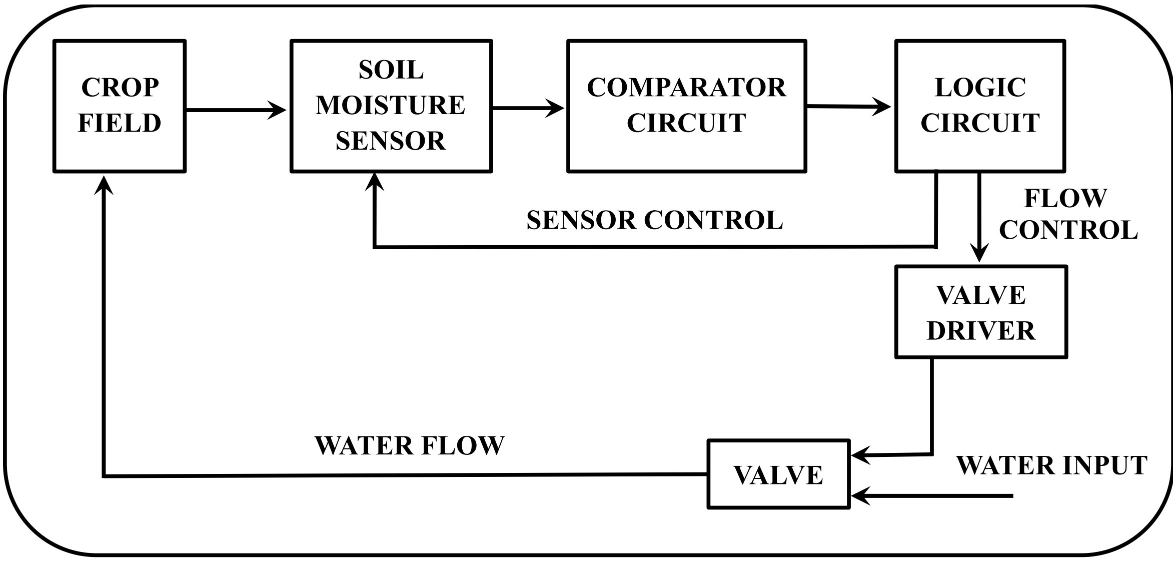

**Fig 2:** Irrigation scheduling with valve controlling system

Hence, IOT-framework comes into the picture, which allows the cultivators to monitor the environmental problems and govern the use of required technologies to design an autonomous network of sensors that can collect data about various parameters, such as soil, water, sunlight, air, and nutrient quantities of the plant (Severino, *et al*., 2018). Wireless sensor networks are part of the Internet of Things. WSN helps solve different applications, including agricultural monitoring (Mat, *et al*., 2016). The wireless sensor network is used for irrigation scheduling based on different agriculture applications. A crop monitoring system, automatic drip irrigation system, control irrigation valve creates an agriculture infrastructure using a wireless sensor network (Fig. 2) (Garcia, *et al*., 2020).

**Nursery Monitoring Using Sensors and IoT**

Nurseries need to effectively control various parameters that affect agricultural yields, such as temperature, humidity, light, and water, in order to obtain high-quality crops, and plants are needed for maintaining crop growth (Leakey, 2017). By using advanced systems such as the Internet of Things, these parameters can be monitored more intelligently. The system is fully automatic and usually contains a microcontroller to turn the appliances on and off. The Internet of Things system uses wireless communication modules such as Bluetooth, wi-fi, and ZigBee modules to communicate between the system and users and track information about the impact of climate change in the nursery (Naik, *et al*., 2020).

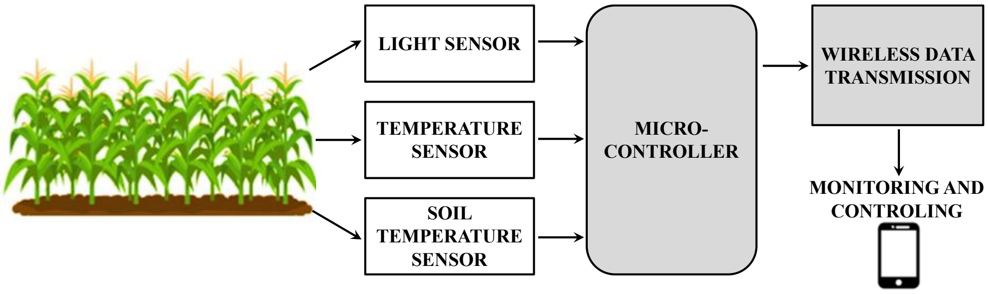

**Fig 3:** Nursery monitoring system using IoT

Different types of sensors (Fig. 3) are used to monitor the nursery, as, like a temperature sensor is used to measure temperature changes in a nursery when the temperature exceeds a critical value, it turns on the fan and directs a message to the operator. Light intensity is the main factor, and if the light intensity is low, it automatically turns on artificial light. Soil moisture content can also be monitored by sensor value, which will govern the frequency of watering the crops (Samshiri, *et al*., 2021). All sensors are connected to IoT and wi-fi modules to monitor the field according to parameter alterations. This system is controlled with the help of a mobile phone, which gets information from the IoT cloud. In this way, different types of intelligent systems based on the Internet of Things can monitor and control the nursery (Singh, *et al*., 2020).

### Thermal Imaging

Thermal imaging is a technique that uses infrared radiation emitted by an object in the form of thermal energy to provide information about its existence. This energy released is referred to as the object's heat signature, and the quantity of radiation emitted is proportional to the total heat content in the object. This technology produces thermal images instead of visual images, which are electronically processed to collect information about various parameters (Sosnowski, *et al*., 2017). The basic principle of thermal imaging technology is that any material emits infrared radiation at a temperature above 0K (Sarawade, *et al*., 2018). This radiation lies in the electromagnetic spectrum in the wavelength range of 0.75 to 100 µm. The infrared region includes a near-infrared region (0.75 to 2.5 µm), short-infrared region (1.4-3 µm), mid-infrared region (13 to 8 µm), long-wave infrared region (above 8 µm), and far-infrared region (15 to 100 µm). The thermal imaging technique can detect short and long-wave infrared radiation (Meola, *et al*., 2004). Thermal imaging works on the principle of Planck's distribution law. The law states that the radiation energy is distributed according to the wavelength at a different temperature (Yongqing, *et al*., 2017). Thermal imaging technology uses thermal imaging cameras or infrared [IR] cameras with passive sensors that contain spectral sensitivity in the 7µm to 14µm band. This will help detect ailments in plants that often go unnoticed by human vision or are captured by normally visible images. It is a safe and non-invasive method for remote sensing of temperature distribution patterns on the surface of the body. Thermal imaging works on the principle of Planck's distribution law. The law states that the radiation energy is distributed according to the wavelength at a different temperature (Yongqing, *et al*., 2017). Infrared thermal imaging cameras provide higher sensitivity with infrared resolution and the highest and lowest temperature values. The thermal imaging setup is illustrated in Fig. 4.

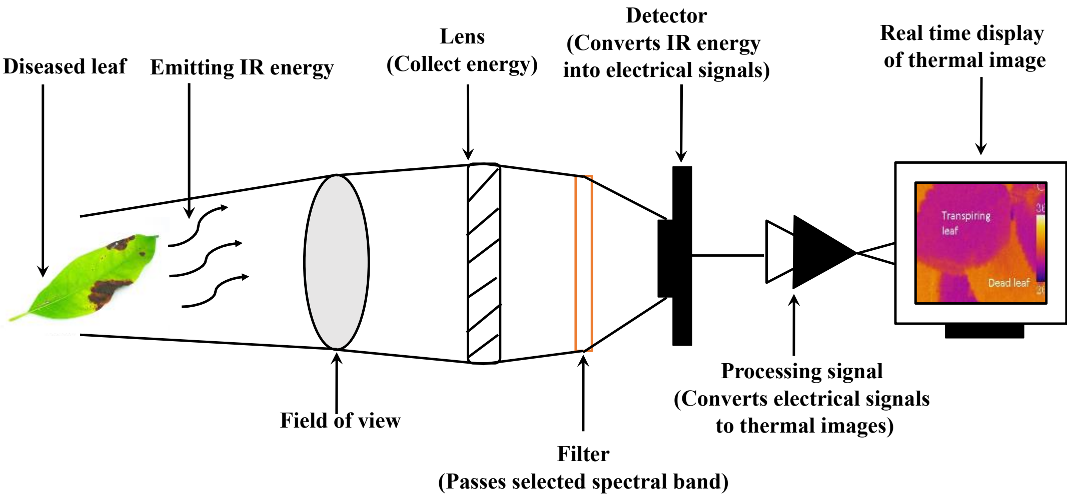

**Fig 4:** Thermal imaging setup

For example, FLIR company produced T420 infrared thermal imager thermal sensitivity <0.04oc, infrared solution of 320x240 pixels, an isothermal curve, visible light images, and a multi-position temperature display (Yongqing, *et al*., 2017). This thermal imaging technology is an unconventional method that helps crop health monitoring and disease detection methods in agricultural applications. This technology has a wide range of applications in the agricultural field. For example, it helps to detect infections and diseases early and sends signals of changes in heat near the point of infection (Cui, *et al*., 2013). Infrared thermal imaging helps to observe and analyze the soil composition of cultivated land, especially the moisture content and is used to monitor crop growth, water planning, and crop yield prediction. Thermal imaging, like a sensor technology for agricultural accuracy, has high sensitivity and considerable potential in the future. However, it is suggested that enhancements in these techniques are required to identify plant diseases accurately in in-situ investigations. Thermal imaging technology plays a significant role in the temperature mapping of essential processes and products in many industries and is gaining momentum in agriculture (Aryalekshmi, *et al*., 2019).

The non-contact, non-destructive properties and rapid online availability of thermal imaging are the main reasons for the rapid increase in demand for this technology in the agricultural field. Due to its many advantages, researchers are exploring the potential of using thermal imaging in various agricultural processes. Many aspects of crop management have already benefited from remote sensing and other technologies. The future brings a tremendous prospectus for integrating the spatially and temporally rich information provided through these innovative technologies (Quattrochi, *et al*., 2004).

### Irrigation Scheduling Using Thermal Imaging

Every plant has specific requirements for physical factors, such as light, water, temperature, air, etc., optimal for proper growth and development. Any deviation from this optimal condition of any factor essential for the growth will lead to an aberrant change in physiologic processes, and this will cause tension in the plant body, which is referred to as plant under stress. Therefore, it is essential to monitor changes in crop pressure to maintain crop health (Lakhiar, *et al*., 2018). One of the most prominent stress conditions experienced by plants is water stress, lack of water due to insufficient irrigation, or flooding. Water stress, gas exchange rate, evapotranspiration rate, stomatal conductance, and closing of stomata are the critical features to govern the irrigation method and duration. In a water stress situation, stomata will close, and due to this plant heating up, cease to transpire, the temperature of the canopy will rise (Rahman, *et al*., 2012). Thermal remote sensing helps to monitor plant temperature, stomatal conductance, and evapotranspiration rate by evaluating stomatal responses. The images formed by this technique are thermal imaging, which helps to differentiate between different components like sunlit versus covered plant portions and wet against dry soil surfaces. This is used to maintain a sound irrigation system and keep good water stress and radiation emission. Smart agriculture with thermal imaging can help to utilize energy efficiently (Fig. 5) (Roopaie, *et al*., 2017).

**Fig 5:** Information from thermal imaging (Roopaie, *et al*., 2017)

## Disease Detection Using Thermal Imaging

Early detection of pathogen attacks can help reduce agricultural losses facilitated by thermal imaging technology. These early detections are carried out by infrared thermal imaging cameras, which measure the temperature of local areas to analyze the physical changes in the parts affected by pathogen infection (Hashim, *et al*., 2020). Changes in photosynthesis rate, transpiration, stomatal conductance, accumulation of salicylic acid (SA), reduction in water volume due to reduced stomatal openings, and even cell death are the main changes in plants affected by pathogens (Delaney, *et al*., 1994). Thermal remote sensing helps monitor the various stages of disease development and establish temporal and spatial trends. The thermal imaging system includes an infrared thermal imager, a color image capture card, and a computer. The radiation is emitted from the surface of the object. These are the images collected by the thermal imaging camera. Infrared thermal imaging cameras use the far-infrared range of 7~12μm to study plant leaves (Xu, *et al*., 2006).

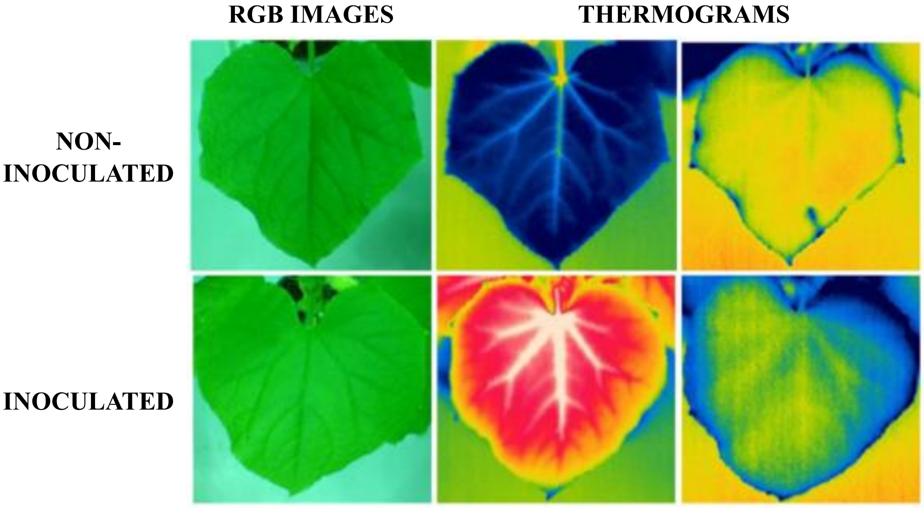

**Fig 6:** Thermal images of diseased leaves (Wang, *et al*., 2021)

Initially, plants were visually analyzed to detect any signs and symptoms of pathogen attack. Spectral imaging techniques based on various physiological factors have further replaced these signs and symptoms in many fields. The difference in foliage temperature of plant leaves between affected and unaffected plants was considered one of the significant physiological factors for study (Fig. 6) (Wang, *et al*., 2021). The temperature difference was correlated to water stress in the plant, where it was observed that well-irrigated plants show a rise in temperature at the point of infection, whereas the water-stressed plants show a particular decline in the temperature of the affected part. Infrared thermography has been found as a valuable tool for detecting pathogen attacks on plants/ crops, even before visible symptoms. This is due to the difference in local temperature of plant parts that get attacked (Plotnikova, *et al*., 2007).

Disease detection of the plant using thermal imaging can be done using different water statuses of the plant. Leaf temperature is monitored using thermal imaging, under different irrigation treatments as control, irrigated to field capacity and non-inoculated plants, irrigated to field capacity and inoculated plants, non-irrigated and non-inoculated plants, and non-irrigated and inoculated plant. Different types of thermal imagers (such as TH7102MX, Flir) can obtain thermal images. The analysis of these thermal images gives the intensity of disease development which has caused the rise in leaf temperature under water stress. The maximum temperature variations in the healthy and infected leaves are studied using their thermal images recorded a few days after inoculation. Usually, the maximum temperature variation in infected leaves is significantly more than that of non-inoculated plants (Vadivambal, *et al*., 2011).

Chaerle L. studied the plant–virus interaction between resistant tobacco and tobacco mosaic virus (TMV) and its first symptoms by using the thermal imaging technique. This technique detected a local rise in temperature due to pathogenic infections or defense mechanisms for the interaction of tobacco plant viruses. The chlorophyll fluorescence imaging (Chl-FI) monitored a local increase in fluorescence intensity. The same technique can detect leaf spots in sugar beet early before damage occurs. The research was carried out in a plant growth chamber with the help of a portable thermal imaging camera (Chaerle, *et al*., 2004).

Stoll, *et al*., studied the potential of the infrared thermal technique in plant pathogen detection on the grapevine. Two conditions were considered for the study, i.e., sufficient irrigation or non-irrigated condition. This was conducted in a greenhouse set up, where the difference in leaf temperature between the irrigated and non-irrigated plants was monitored. It was observed that in irrigated grapevines, there was an increase in the temperature of the leaf, while non-irrigated grapevines showed a lower temperature at the inoculation spots/ the region where the pathogen has attacked. The local pathogen attack was detected before the appearance of any visual symptoms with the help of portable thermal cameras (Stoll, *et al*., 2008).

Oerke, *et al*., studied phytopathogenic fungi affecting both the cuticular and the stomatal conductance of apple plant tissue resulting in significant modifications of its leaf temperature. *Venturia inaequalis* is made to colonize the cuticle of the leaves that cause apple scabs. Subcuticular growth of the pathogen caused localized decreases in leaf temperature before visible symptoms led to a significant increase in the maximum temperature difference (MTD) of leaves. MTD increases with the development of scabs and is related to the size of the infection site and the overall severity of the disease. The efficiency of digital infrared thermography technique, for early detection and quantification of apple scab disease, by investigating the effects of V. inaequalis on the water balance of apple leaves about the disease stage and the severity of scab. This study was set up in a greenhouse and monitored using a portable thermal camera (Oerke, *et al*., 2011).

### Nursery Monitoring Using Thermal Imaging

Thermal imaging is used in the nursery for monitoring and quality assessment. When any biological and environmental factor varies, these factors affect plant growth. Conventional methods fail to detect early if any variation happens in plant growth (Ryu, *et al*., 2000). To inspect various nursery products and nurseries, thermal imaging is used. There is a variation between radiation emitted by diseased tissue and good tissue. Both plant tissue images are captured in a thermal imager to find the difference. The system includes a thermal imaging camera and analysis system in nursery monitoring.

The thermal imager continuously captures the nursery plants. The temperature changes quickly because the thermal imager has a high acquisition speed and it provides an online monitoring system without any contact with the plant (Fig. 7).

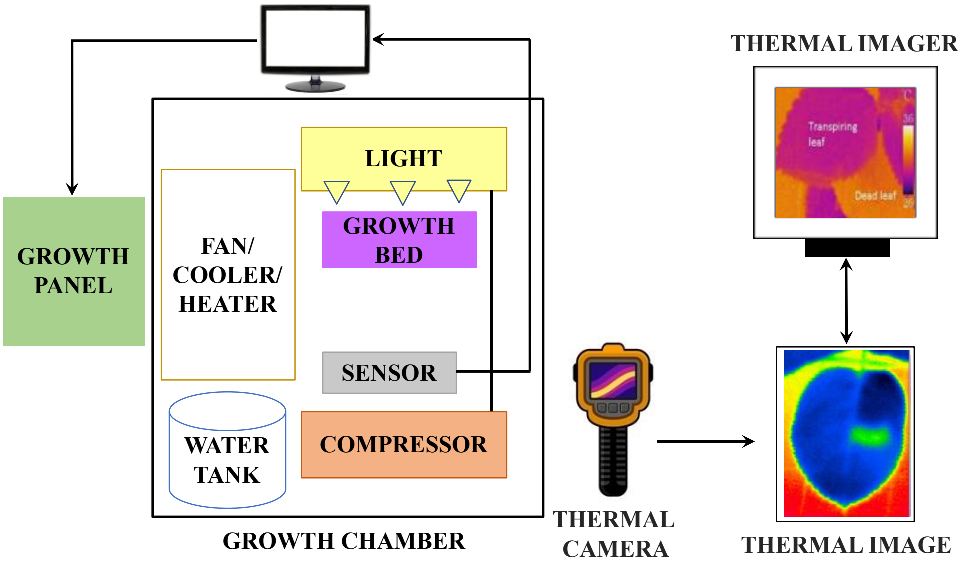

**Fig 7:** Thermal imaging for nursery monitoring

Ryu, K. H. explained that twenty-day-old lettuce and cucumber plants were taken at the nursery chamber to study thermal behavior and based on thermal characteristics, and needful things were provided to plants in the nursery (Ryu, *et al*., 2000). At 25 °C and 60% RH, plants were placed in the growth chamber. Experiments were made to identify deficiency and excess temperatures in plants. Variations in the temperature of the leaves were monitored in 2-min sample intervals with the thermal imaging system. Images were captured with the help of a thermal camera, and results were considered in the computer for analysis and Fig. 7 shows the schematic diagram of the thermal imaging system.

**Fluorescence Imaging**

Fluorescence imaging works with images taken by a camera. In this technology, fluorescence excitation of the object is done by using ultraviolet (UV) light then the wavelength of the object is recorded in the camera (Marshel, *et al*., 2017). Here fluoresce parameters are used to analyze the problems of the object, and a change in fluorescence parameter based on electron reactions that happened with the UV light incidence is observed (Fang, *et al*., 2015). Fluorescence Imaging is a process that happens when some molecules called fluorophores, fluorochromes, or fluorescent dyes absorb the incident light. The absorption of light from the molecules increases their energy level to an excited state from their ground state. At these excited states, molecules emit fluorescent light at a different wavelength, and this wavelength of the object is captured in the camera.

The critical elements of fluorescence imaging systems are excitation sources, light delivery optics, light collection optics, filtration of the emitted light, detection, amplification, and digitization (Yadav, *et al*., 2017) Fig. 8 shows the experimental setup of the fluorescence imaging method. The factors that affect fluorescence images are the excitation and detection wavelength, the intensity of the excitation light, the fluorophore's quantum efficiency, the fluorophore's saturation, the resonance energy transfer partner, and the oxidizing or reducing agent in the medium (Christensen , *et al*., 2006). When a plant absorbs light, it undergoes Two quantum transformations: fluorescence and heat dissipation. Ultraviolet radiation induces the fluorescence emission spectrum to capture the emission wavelength, and the maximum fluorescence emission light is blue (F440nm), green (F520nm), red (F690nm), and far-red (F740) spectral regions (Fig. 8). The fluorescence system uses a fluorescence spectrometer, which is used to analyze the fluorescence spectrum characteristics (Buschmann, *et al.*, 1998).

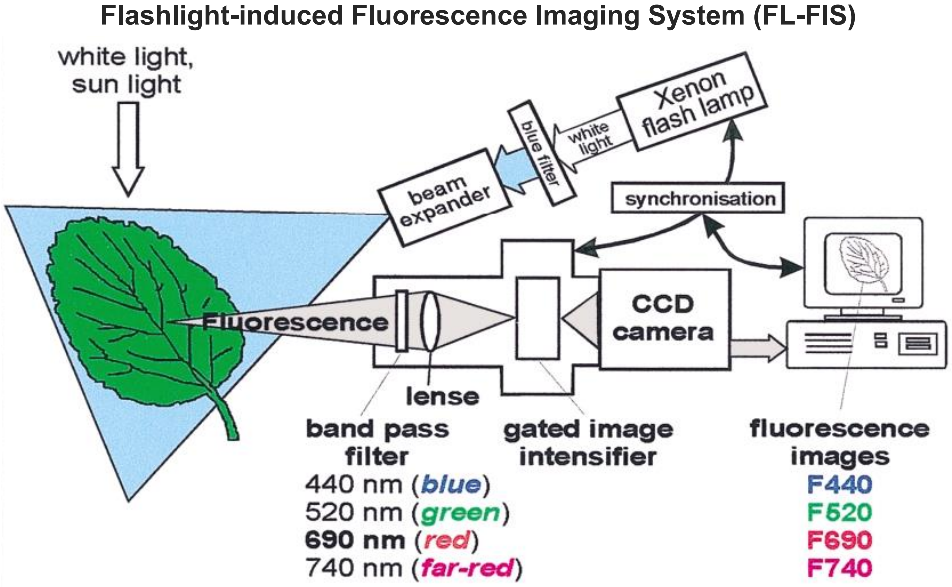

**Fig 8:** Fluorescence imaging system

If the plant is under any stress conditions, it cannot be fully used for carbon fixation, and the unused light energy will be re-emitted at a longer wavelength, called chlorophyll fluorescence. The system is used to capture these emitted fluorescence wavelengths in images. Hence, fluorescence imaging technology can detect crop diseases, research, or monitor crop health parameters, and we will explain fluorescence imaging interventions in the agricultural field later. If the disease is affected, these images will find the disease (Pérez-Buen, *et al.*, 2016).

### Fluorescence Imaging to Detect Plant Disease

Fluorescence imaging is an indirect method to identify the disease of plants. When light is incident on a plant, a dynamic change in chlorophyll fluorescence intensity occurs, and intensity level will vary depending on the plant's health (Takayama, *et al.*, 2014). Recording the dynamic light intensity changes is called the chlorophyll fluorescence induction phenomenon. In this method, chlorophyll fluorescence is done by blue light, which is passed through a short pass filter, and after detecting by CCD camera, is passed through a long-pass filter. The output of two filters is combined to prevent the blue excitation light from reflecting the image. Images of chlorophyll fluorescence were recorded at different resolutions using a computer and were captured before and after the light irradiation treatment (Takayama, *et al.*, 2014). The fluorescence spectrometer can be used to distinguish between healthy and infected seedlings.

### Hyperspectral Imaging

Hyperspectral imaging is an electronics-based technology; that uses a broader range of wavelengths for each pixel of an object. Output image of this technology contains a set of pixels' values at each spectra wavelength (Bajwa, *et al.*, 2015). Initially, hyperspectral imaging is implemented on satellite and airborne platforms for remote sensing applications. A hyperspectral image takes different types of electromagnetic spectrum bands of an image like narrow, contiguous spectral bands through visible, near-infrared, and thermal infrared portions (Khan, *et al.*, 2018). Hyperspectral images are defined by their spatial and spectral resolution. The spatial resolution talks about the geometric relationship of the image pixels to each other, and the spectral resolution defines the variations within image pixels as a function of wavelength (Kim, *et al*., 2001).

The hyperspectral imaging system is composed of hardware and software, and the structure varies from object to object. The system contains (Fig. 9) a light source provider, a detector that obtains both spectral and spatial information, respectively, a hyper spectrograph to scatter the wavelength towards the photosensitive surface of the detector, an objective lens to adjust the range of the light acquisition. The hyperspectral image detection system includes a camera, which can be any camera, such as a CCD (charge-coupled device) or a complementary metal-oxide-semiconductor (CMOS) camera (Huang, *et al*., 2014).

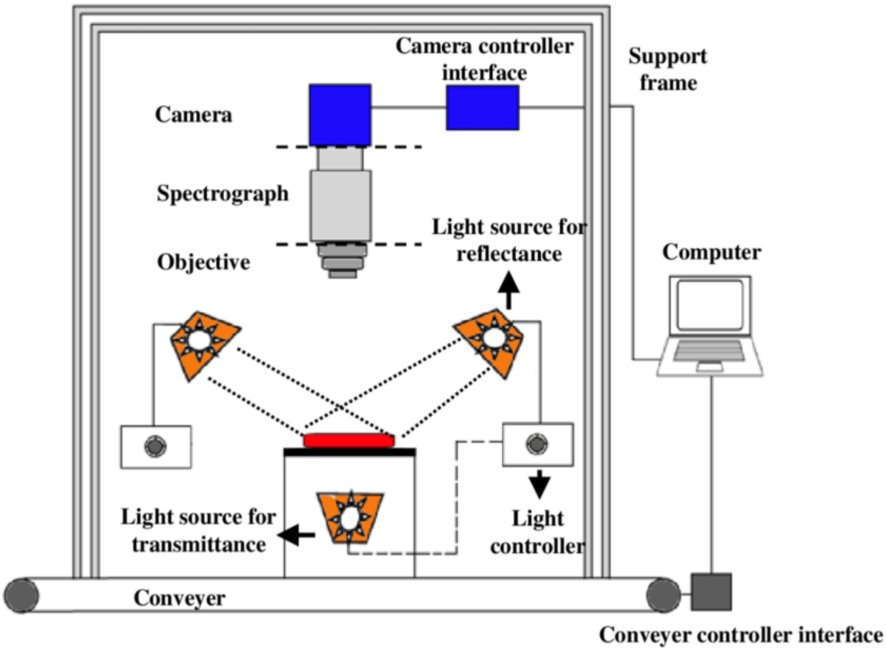

**Fig 9:** Hyperspectral imaging setup (Huang, *et al*., 2014)

The hyperspectral imaging system can acquire reflectance images of leaf/fruit samples to diagnose its health. The overall hyperspectral data analysis starts with considering raw hyperspectral images collected using the system, and before analysis, the relative reflectance of the hyperspectral image cube is calculated by doing a flat field correction. A correlation analysis between the peel conditions and the reflectance wavelength is performed to obtain a multispectral image cube with only four bands. A linear discriminant classifier and artificial neural network are developed to detect image disease (Huang, *et al*., 2014).

### Hyperspectral Imaging to Detect Plant Disease

Plant disease detection, characterization, classification, and modeling can be done with hyperspectral imaging (Singh, *et al*., 2020). This can be used to measure the reflected light of hundreds of narrow-band pants as a hypercube. According to leaf biochemical compounds and leaf anatomy, plants interact with different parts of the electromagnetic spectrum. When plants are infected with any disease and under various stress conditions, they react to their biophysical and biochemical changes, such as the degradation of chlorophyll content or changes in leaf cell structure. To detect these subtle changes in the spectral reflectance of plants, hyperspectral imaging is used (Govender, *et al*., 2007).

This technology is used to obtain reflection images of various plant samples. The system includes a push-broom, line-scanning electron-multiplying charge-coupled device camera with a resolution of 1004x1002 pixels, thermoelectrically cooled by a Peltier device. An imaging spectrograph and c-mount zoom lens were attached to the camera to acquire the hyperspectral reflectance image. An image processing method is applied to hyperspectral plant/crop samples images. Different type of software is used to analyze the hyperspectral image. After analyzing each sample, it can be concluded whether the plant is affected by disease or not (Moghadam, *et al*., 2007). The hyperspectral imaging system includes two push-broom hyperspectral cameras from the VNIR A series and the SWIR M-series. The VNIR has a spectral range of 400-1000nm with 324 spectral bands and a spectral resolution of 1004 pixels. The SWIR ranges 900-2500nm with 384 pixels (Blaaberg, *et al*., 2014). The cameras are attached to a frame with a linear motion stage whose axis of motion is perpendicular to the spatial axis of the two cameras. Six 20W halogen lights are used for illuminating the leaf samples.

**Electronic Nose**

An electronic nose is a copy of the human smell sensing system. An array of sensors works based on aromas in a plant. The electronic nose is used to find crop diseases, identify insect infestations and monitor food quality. An electronic nose is effective for volatile organic compounds (VOC) produced by plants/fruits with diseased conditions (Gardner, *et al*., 2000). An electronic nose contains a multisensory array, an information-processing unit such as an artificial neural network (ANN), software with digital pattern – recognition algorithms. The array of sensors sends its output to a data processing unit. The output of each sensor is combined to produce a distinct digital pattern that is used to study and characterize the combined output of sensors (Li, *et al*., 2010).

The electronic nose contains two main components: the first is the sensing system, and the second is the pattern recognition system. The sensing system contains an array of several sensing elements, the air sample is considered at the electronic sensor array, and during this interval, the sensor's responses are recorded and passed to the signal processing unit. The sensor responds to the physical and/or chemical changes by such processes, and sensor outputs are measured as an electrical signal. Sensors used in the electronic system are conductivity sensors, piezoelectric sensors, surface acoustic wave sensors, quartz crystal microbalance sensors, optical sensors, and MOSFET sensors (Wilson, *et al*., 2009). The Electronic Nose works the same as the mammalian sensing system. Below Table 2 compares the electronic nose system with the mammalian sensing system (Siyang, *et al*., 2013), and Fig. 10 shows the experimental system on the electronic system. After the automatic input image is segmented, a grid is detected in the image, the grid objects are removed, and a grid mask is generated that ends with making a grid mask for each leaf segment. Cluster analysis is used to find the unique position of each classification spectrum and generate a 2d leaf mask. All these steps help find the plant diseases affected by the leaf part (Govender, *et al*., 2007).

**Table 2:** Comparison between mammalian nose and electronic system (Siyang, *et al*., 2013)

| Mammalian System | Electronic System |
|---|---|
| Odor molecules | Odor molecules |
| Nostril | Sampler |
| Primary Neurons | Sensor array |
| Secondary Neurons | Signal and data processing |
| Brain | Pattern Recognition |

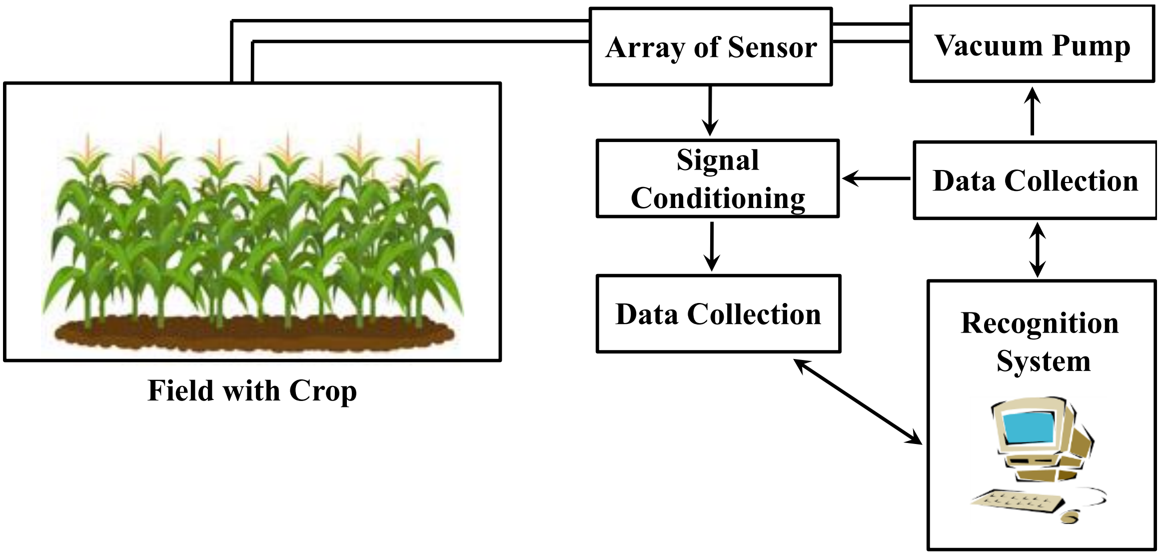

**Fig 10:** Experimental setup of an electronic nose

In order to find spectral measurement, grid removal is used, and a particular matched filter approach is used to find and remove the grid. This uses a high-pass filter to find the whitened image, based on which a specially matched filter is created, and it will be convoluted with whitened image, and the absolute value of the output is found. To obtain the horizontal position of each grid line, a 1d vector is used, and to find the location of the grid mask; continuous waves peaks are created by using wavelength transform. The wavelength value of the extracted image can be used to measure the vegetation index and the normalized difference vegetation index. Machine learning techniques can compare these values with trained values and determine the affected disease (Siyang, *et al*., 2013).

### Disease Detection Using Electronics Nose

An electronic nose is a device to monitor the health of the plant and helps to detect diseases and pests of the plants (Turner, *et al*., 2004). The plant emits volatile organic compounds (VOCs) when attacked by pests or disease. VOCs emitted by the plant are specific to the type of attack to combat the threat, and VOCs, which a plant emits, are spread from one plant to others and infect another plant (Hu, 2006). The electronic nose system mainly includes a detection part and a processing part. The compound detection unit contains an array of non-specific chemical sensors that react with various chemical compounds in a gaseous phase, such as atoms, molecules, ions, etc. If any changes occur on sensors, they are converted into electronic signals, and based on the concentration of specific particles strength of the signal is related.

The electric nose is used to identify the most common diseases in plants, such as powdery mildew and spider mites. This method is suitable for a limited number of plants. Different sensors are placed around the plant. These signals are monitored and then compared with a good plant, and software is used to analyze whether the plant is infected with the disease based on the sensor value (Hu, 2006). As explained, the electronic unit is explained by studying the tomato plant. The system contains 13 gas sensors with a sampling process consisting of four, which is explained as follows:

Baseline: Clean air was pumped into the sampling, and baseline resistance of the sensor value was recorded.

Absorption: this gas sample was pumped into the chamber. In this stage again, the resistance of sensors was recorded.

Desorption: The clean air inlet was open again while the sample inlet was kept shut. The resistances ideally returned to the baseline as the volatiles left the sensor surface.

Fish: This was the extension of the desorption phase. In this experiment set up, tomato plants were grown in a controlled chamber for six weeks then moved into three glass boxes. The box has a unique irrigation and ventilation system.

**Drones**

The Unmanned Aerial Vehicle (UAV), also known as a drone, is one invention and an additional technology revolution to help people in various aspects of life. A drone is an impactful invention of science, which can be used in scientific research, agricultural fields, photography, film production, sports, thermography, domestic policing, inspection and survey, military performances, etc. (Kardasz, *et al.*, 2016). Nowadays, drones are used extensively in agriculture and cultivation processes to increase the products' output. Drones help to monitor the crop, analyze data in less time, and take necessary action on the problem detected in the plants (Zhang, *et al.*, 2011). Drones have proved to be one of the most reliable technological developments in the 21st century as they are developed with many engineering disciplines such as aerodynamics, electronics, materials structure, computer programming, economy, and quickly analyzing software (Kurkute, *et al.*, 2013).

The drone is made of lightweight composite materials to reduce weight and have a more vital ability to change position. UAVs are equipped with different types of navigation systems and recording equipment, such as RGB cameras, thermal imaging cameras, etc. (Cramer, *et al.*, 2017). In Fig. 11, the drone's block diagram and its components are explained. Depending on the application, they can fly at various altitudes and can travel where ships and cars cannot move. Drones can help provide real-time status of affected areas. UAVs are made of sensors, microcontrollers, and communication systems. Communication happens between a ground station and a drone, with the help of GPS. The technology used in drones helps control and navigate drones like pilots (Liuzza, *et al.*, 2018).

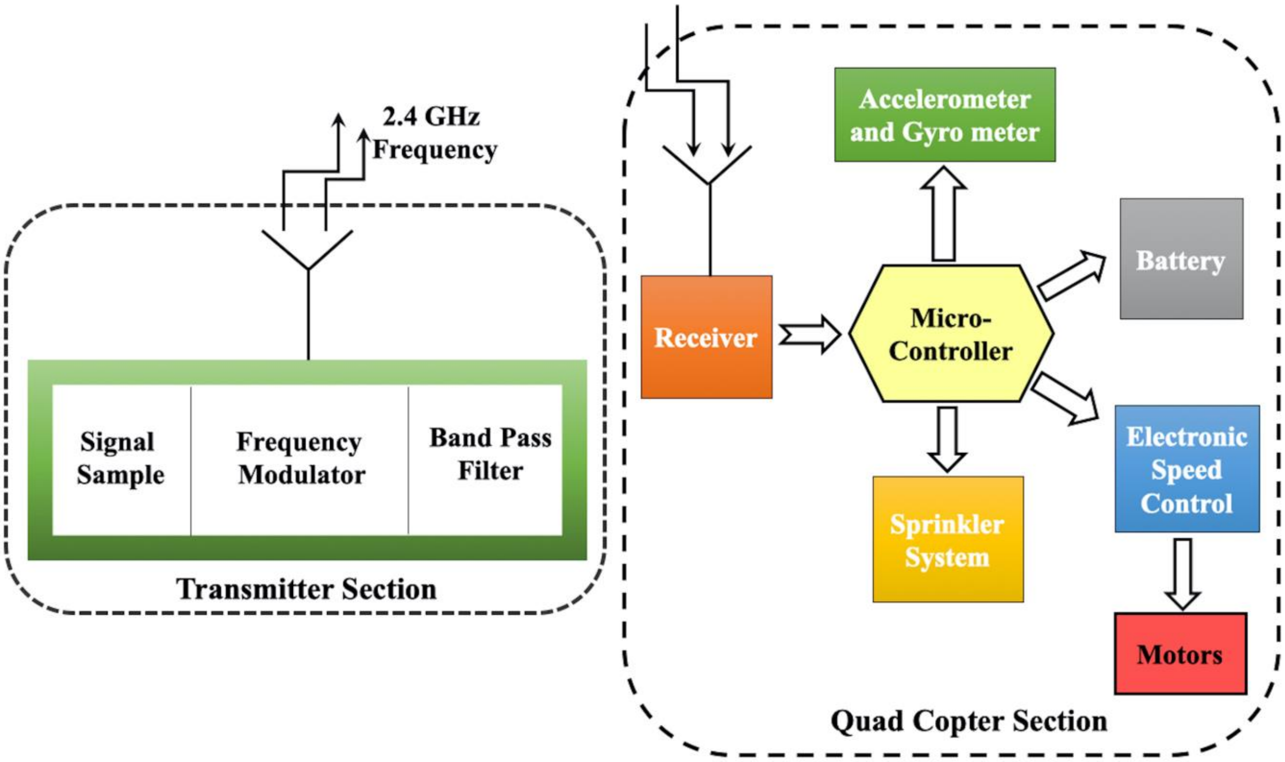

**Fig 11:** Drone block diagram

With such images, farmers can get information related to crops as follows: it gives patterns of irrigation or soil, and fungal infections which are not visible to the naked eyes and drones images are the combination of multispectral images, infrared or visible. It gives plant or field images that are needed for observation. These images reveal problem areas or improve crop management opportunities (Kurkute, *et al.*, 2018).

## Disease Detection of Crop Using Drone and Image Analysis

Lately, drones have been playing a crucial part in precision agriculture. In order to find problematic crop areas infected by diseases, drones are used for quick detection and efficient treatment. The drone's primary purpose is to capture images of plants affected by pests and pathogens. The drone is designed at an affordable price and can capture ground data images of its geographic location, helping users to obtain detailed picture information on the ground and agricultural fields. Drones with multispectral cameras are advantageous in getting an image of the near-infrared part of the electromagnetic spectrum over the crops, which helps to provide the crop's health parameters.

UAVs may compose commercial cameras, thermal imaging cameras, hyperspectral cameras, or a camera that captures fluorescent images based on the requirement of the field. The drone is also equipped with multiple sensors, microcontrollers, and multispectral cameras. The system includes GPS to provide location information in the area. With these main things in the drone, it is possible to obtain positioning estimates. The data of each stream is captured, stored, and sent to the base station using a cloud server (Murgan, *et al.*, 2016) The use of drones can provide information (Fig. 12) to the farmers if any parasites attack the crop. It also provides information on sudden climate changes that severely affect the quality of agricultural products (Tripicchio, *et al.*, 2015). To find disease on a crop field, most drones use the distributed algorithm, which is done to coordinate messages between the systems. Each drone is attached with a memory to store previously visited areas, which helps update the information in the new area and eliminate information that is no longer valid (Bafila, *et al.*, 2020).

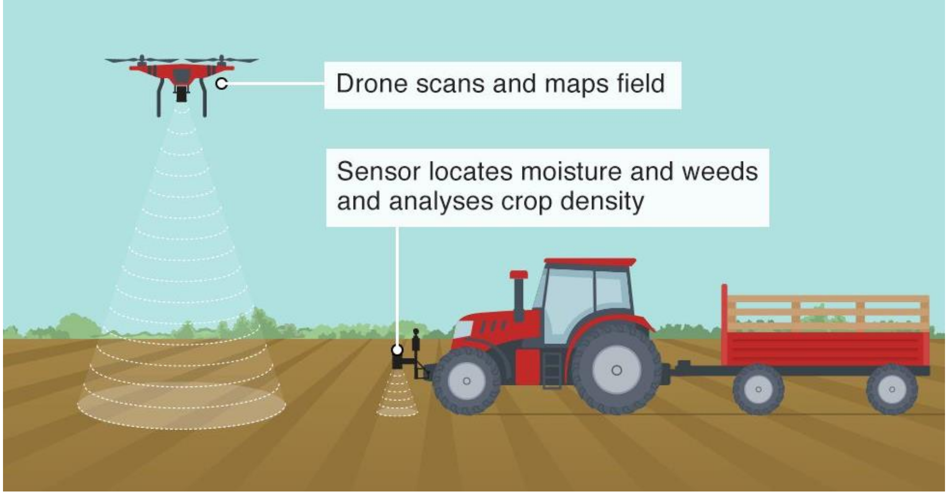

**Fig 12:** Drone used in agriculture field

Whenever drones are used to find plant diseases, aerial images are taken by cameras fixed on drones. In order to analyze the captured images, different frames are used. Disease detection of a plant using a drone system contains three steps: sensing stage, processing, and actuation stage. Sensing stages collect the images of field and crop/plant. The processing stage is to analyze the captured images. To identify the health of a plant, environmental indices can be calculated from the image. The commonly used indices are normalized difference index (NDVI), normalized difference water index (NDWI), and soil adjust vegetation index, which can be calculated from the pixel value of the image (Wijitdechakul, *et al.*, 2016). The value of these indices can range from -1.0 to

1.0, which helps to analyze plant health, photosynthetic activity, and environmental objects to find agricultural area and disease affected to crop (Wijitdechakul, *et al.*, 2016). The start-up step of the system interprets the image's meaning through disease detection and analysis. In order to discover plant diseases, the system uses the data set values of environmental indicators to explain. Different environmental index equations are used to find the value of the captured image and then compare it with the environmental index value of healthy plants. Based on the compared result, the system can tell whether the plant is affected by disease or not (Wijitdechakul, *et al.*, 2016).

### Robotics in Digital Farming

In agricultural production and management, robotics has emerged to play an essential role by providing an autonomous and time-saving technology for agriculture to obtain efficient farm management. Robots are used for harvesting, chemical spraying, picking fruits, scouting, weeding, and harvesting are also made with robots. Robots are designed with different sensors, which can identify parameters influencing the crop/plants. Some robots are designed with cameras to efficiently give crop nutrient status, multispectral responses, visible images, weed species, and weed density (Shamshiri, *et al.*, 2018). The schematic working of robotic in the agriculture sector is elucidated in Fig. 13.

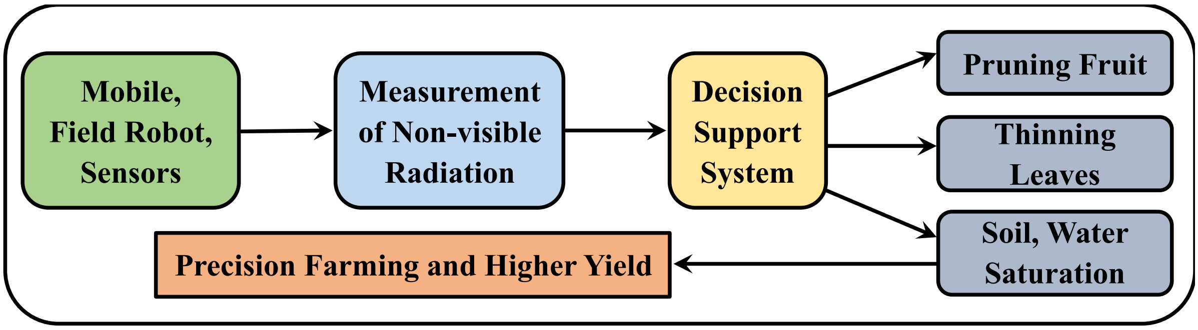

**Fig 13:** Robotics in digital farming

### Remote Sensing Methods

Remote sensing technology uses the phenomena of emission and reflection of radiation from a distance ground to monitor the status of an area by studying its physical characteristics. This is carried out by analyzing the remotely sensed images by this technique which allows to sense the condition on the ground and helps formulate its maintenance. Its ability to sense data and store them for analysis has paved the path for the potential growth of this technique in agriculture. The basic principles of remote sensing are similar to phenomena of visual observations with the assistance of satellites and aircraft (Ajmi, *et al.*, 2009). Numerous factors influence the working application of remote sensing, including radiometric resolution, spectral resolution, spatial resolution, and temporal resolution. The brief remote sensing process includes: (i) emission of electromagnetic energy from the sun to plants and a portion of this electromagnetic energy is transmitted through the leaves, (ii) the satellite detects the reflected energy with its sensor, and data is then transmitted to the respective ground station that is analyzed and presented on field maps (Fig. 14). In the remote sensing method, different types of components are used. Some remote sensing methods collect data from satellite data, and some systems contain cameras like a hyperspectral, multispectral, or thermal camera to capture images from a long distance, and the captured image data is collected.

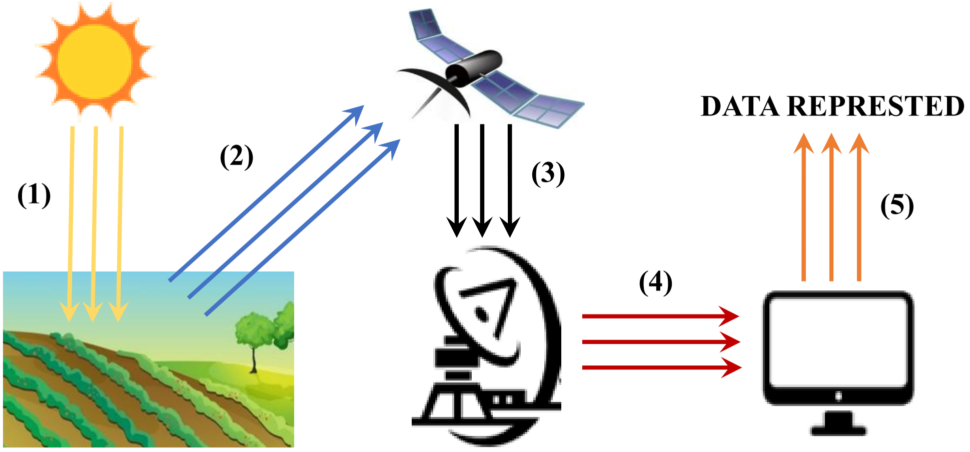

**Fig 14:** Remote sensing technology

**Disease Detection of Crop Using Remote Sensing Method**

Control of disease and pest of plant/crop could be easier if the disease in the field can be found on time and treatment for the disease is done efficiently by gathering the information of disease affected in the field as early as possible. For a large area, finding disease may be tricky, which can be managed by remote sensing method giving spatial distribution information of diseases over an extended area at a lesser cost. Disease or pest-infected plant /crop causes changes in pigment, chemical concentrations, cell structure, nutrient and water uptake, and gas exchange. These changes give variations in color and temperature of the canopy and change canopy reflectance characteristics, which can be identified using remote sensing (Raikes, *et al*., 1998). Remote sensing provides a rapid, harmless, and cost-effective on finding and checking crop stress from variations in the spectral characteristics of canopy surface affected by abiotic and biotic stress factors.

Remote sensing helps identify diseases like yellow rust, aphid, and some other fungal diseases, using electromagnetic radiation methods to identify the health level of plants. Variation of a wavelength of radiation occurs when a plant undergoes the interaction of electromagnetic radiation, depending on the health level of the plant. The occurrence and effect of the disease can be monitored according to the variations of spectral characteristics between healthy and disease plants/crops (Huang, *et al*., 2009). Some remote sensing methods include high spectral resolution spectrometers. Pro spectrometers are equipped with many optical fields of view to measure the spectral reflectance of the canopy. All canopy spectrum measurements are taken from a certain height above the ground. All measurements are recorded at the optimized integration time. The data recorded by remote sensing covers all crop growth stages, such as stem elongation, booting, flowering, and milk development (Huang, *et al*., 2009).

In a few remote sensing methods (Fig. 15), images of crops are taken from standard cameras with the help of drones or robots. The camera is fitted in drones or robots, which can be controlled remotely, and from this system, collects remote sensing data. The captured images are recorded in the storage file. This method starts with training images for both samples, such as healthy and infected leaf images. It is then compared with images collected by remote sensing that are taken periodically. RGB values are extracted and then compared with threshold values of images. Edge detection technology is used to find specific crop diseases. Histogram analysis is also used to find variation in diseased plants/crops (Shanmugam, *et al*., 2017).

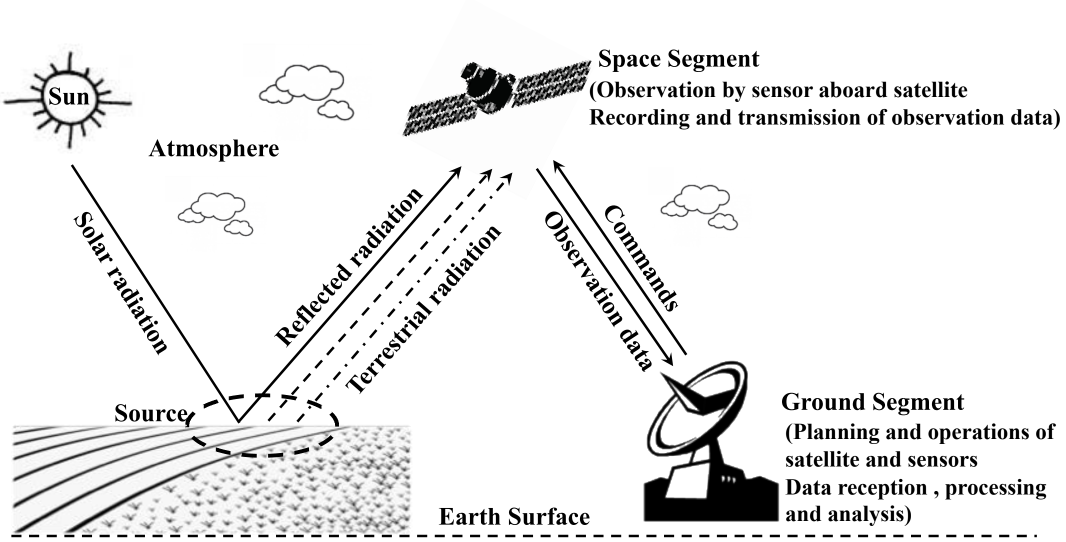

**Fig 15:** Remote sensing data-based system

## Artificial Intelligence (AI)/ Machine Learning (ML) in Agriculture

Artificial Intelligence (AI) provides a branch of learning with a practical approach and provides an accurate yield prediction based on numerous factors, and this is called machine learning (ML). This methodology allows determining a correlation and a pattern and extracts knowledge from various data sets (Mokaya, *et al*., 2019). Agriculture has lately seen an all-embracing of Artificial Intelligence (AI) and Machine Learning (ML) in agricultural products and various cultivation techniques. Machine learning for cognitive study has become the emerging technology asset in agriculture practices as it helps the cultivators to understand, study, and plan according to different situations to improve output and efficiency. The latest service like a chatbot or other conversational platform provides solutions to all the farmers that might help them keep pace with rapid technological advancements and apply the same in their farming practices to yield the benefits of this development. Artificial Neural Network (ANN) is an example of a tool working on artificial intelligence/ machine learning (Fig. 16) (Kujawa, *et al*., 2021).

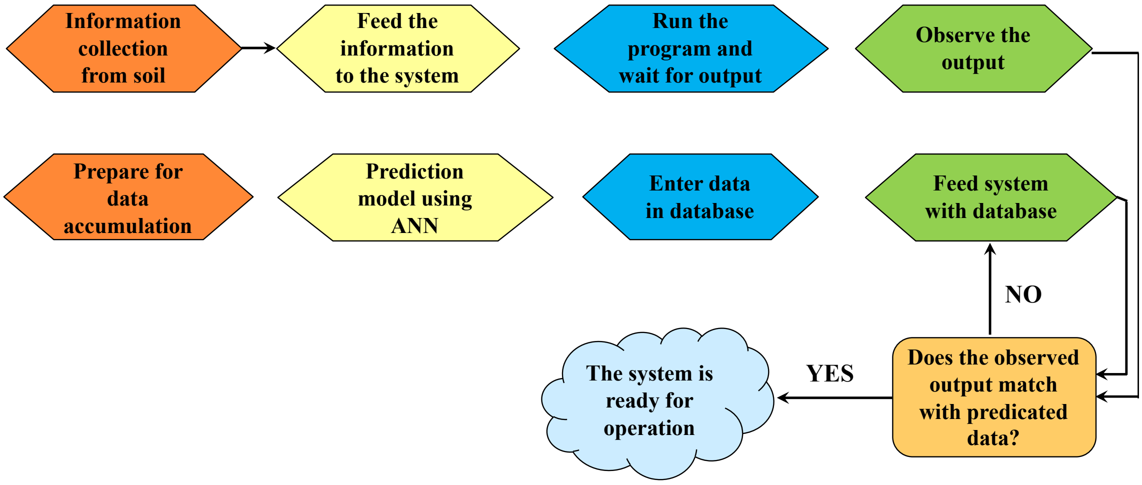

**Fig 16:** Flowchart of ANN-based crop predictor using smartphones

Artificial intelligence helps in formulating a computational model such as Artificial Neural Networks. This structure is homologous to the human neural network, which helps in prediction, classification, decision-making, etc. This acts as an advanced method of data analysis in agricultural activities, which is inspired by artificial intelligence. This method helps in precision farming and acts as a support tool for higher yield and better-quality production. This system is an alternative for a mathematical model for decision-making and provides a broad spectrum of applications (Jha, *et al.*, 2019).

### Yield Estimation of Crop Using AI/ML

Crop yield estimation is an essential task in crop/plant management. The current manual sampling-based yield estimation is time-consuming, labor-intensive, and inaccurate (Sagar, *et al.*, 2018). The agriculture crop production of principal crops in the country is usually estimated as a product of the area under the crop and the average yield per unit area of the crop. The crop acreage at a district level is estimated through complete account, whereas the average yield is obtained through general crop estimation surveys based on crop cutting experiments (Venugopal, *et al.*, 2021). This new-age technology is effectively creating a network for smart farming. An amalgamation of this technological progress empowers farmers to achieve higher yields and smarter price control. Artificial Intelligence in agriculture manages to help the cultivators systematize their farming procedure and provides the scope to shift conventional cultivation for higher crop yield and better quality, using fewer resources.

### Yield Estimation Using Data Analytics

Variations in the climatic conditions, crop production, have become challenging tasks in agriculture. Parameters like climate, geographical conditions, economic and political conditions play an essential role in crop production. Crop yield estimation is one of the crucial factors in agriculture. To get enhanced crop yields, farmers need information related to crop yield before sowing seeds in their fields. Data analytics is one way to inform farmers about crop management and monitoring crop health and yield estimation. Data analysis is related to crop yield prediction, crop health monitoring, and related activities (Sagar, *et al.*, 2018). Data mining is one of the methods to do data analysis for yield estimation. Data mining is a method of analyzing large amounts of data, identifying patterns, and estimating the desired results. For yield estimation, data sets are used in certain situations, such as soil data sets, rainfall data sets, and yield data sets (Venugopal, *et al.*, 2021).

Climatic factors play an essential role in crop growth, and to get a good yield, evaluation and study of climatic factors are important. The use of historical values requires a set of data for analysis. To create yield models, the data set should have climatological variables and agroclimatology indices. Based on the correlation coefficient, create statistics, estimate the standard error and the relative deviation of the previous year's data set. Various agroclimatic indexes at different growth stages are collected (Bazgeer, *et al.*, 2014). Yield estimation is carried using the data analytics process, depicted in Fig. 17.

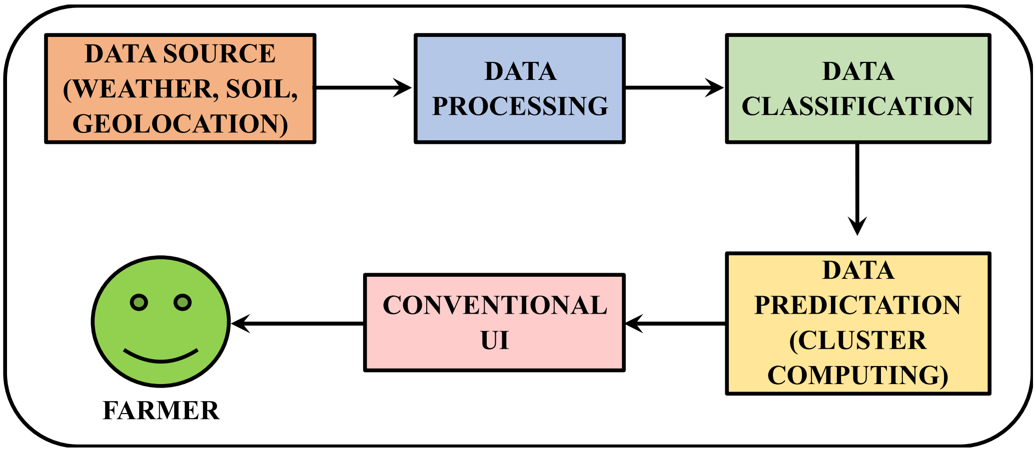

**Fig 17:** Yield estimation system

Yield estimation can also be made using satellite data. Satellite data contains high-resolution images, which are easy to find individual farmers' fields. These images help to calculate field-level NDVI. Sometimes along with satellite data, secondary data is also collected. Secondary data is the data on geomorphological units, water shade, drainage lines, water bodies and communication systems, and other shapes files of land. Also, a table of social and climatic data was available through the National Remote Sensing Agency of India. These secondary data are used to compare with satellite data. Data collected from images and secondary data were entered into a spreadsheet. All data is coded and standardized. Nominal and categorical data were normalized into ratio data. Before the data analysis, all data are tested for normality to find a good distribution for analyzing the data. After this, data is analyzed statistically. The statistical analysis starts with establishing the relationship between NDVIs and yield data at the field level. Later, land and management parameters are compared with yields and Nevis. Then through multiple regression, the comparative data is further tested, the output prediction model is established, and the output is predicted and estimated (Bhosale, *et al.*, 2018).

## Limitations

Today, technological advancements such as drones, artificial intelligence, various imaging techniques are utilized for crop monitoring and data processing. The significant agricultural challenges faced by Indian farming sectors are: (a) inadequate infrastructural and suitable facilities concerning farming practices, (b) insufficient ability to deliver specific services for farmers, (c) lack of awareness about sustainable agricultural practices among the farmers, and (d) issues regarding ownership of the data generated on analysis of collection from various sources. To overcome these shortcomings, technological progress has paved a wider path for a new future considering the latest requirements. A region's socioeconomic and techno-economic advancements play a determining factor in the development and implication of various technologies in developing countries (Singh, *et al.*, 2019).

However, while agricultural advancements have gained their rapidity and offer a lot in theory, there are considerable challenges in the field applications. The wireless equipment implanted in farms is exposed to vandalization, and changes in weather conditions may cause loss of signal, which will hinder the working of the wireless setups. Various imaging techniques can fail to provide efficient results due to instrumental error and invasion of new pathogens, whose symptoms are unknown to the cultivators. The low rate of symptom appearance in crops prevents the detection of abnormality through thermal, infra-red, and hyper-spectral cameras. Drones and artificial intelligence systems use GPS systems, but their accurate working and location detection cannot be trusted entirely due to the presence of inaccessible areas that are difficult to trace under the radar. At such locations, the signal bounces back, and it is challenging to locate the exact location with certainty. The initial setup of farm-based technological applications costs higher than any conventional techniques, requiring regular maintenance (Nedumaram, *et al.*, 2020). Installation of cheap equipment fails to provide an accurate result with efficiency. A farmer with a moderate source of income fails to bear the initial expense of integrated automated robotics into conventional practices. Hence, the financial budget governs establishing and adapting the technologies mentioned above in a small or moderate farm-based setup. Cultivators should be privileged to benefit from training programs and interact with experts for efficient and professional guidance, which still acts as a barrier due to lesser awareness and reach to the interiors of the country.

## Conclusion and Future Perspectives

This review article summarizes the current state of the art and the possible usage of technological intervention in agricultural practices. Technology and its recent advancements are heightened as potential means for a sustainable future. Identifying early plant diseases, irrigation scheduling, monitoring different aspects of the field area, and the control setup are few such applications in the agricultural field. The recent advances in the Internet of Things (IoT), infrared thermography (Thermal Imaging), mechatronics (Drones), and extensive data analytics have positively influenced the principles of agriculture. However, the techniques discussed in this review article still have some limitations, majorly because of limited available infrastructure and lack of awareness and its application by farmers in remote areas of developing countries. Thus, to fully exploit usage of technology in the agricultural sector, we must first understand the judicial implications of these techniques with consideration to the socioeconomic background of the nation, the gravity of knowledge among the users, and the potential challenges faced in the process of implementation. Thus, great efforts are required for understanding and overcoming the issues with a sustainable approach.

The gradual improvement of digital farming is limited penetration of mechanization tools, and frequent natural calamities, like droughts, floods, and excessive monsoon rains, have negatively impacted the deployment of digital solutions in the sector. Thus, a customized approach could be implemented on a smaller and larger scale. Following measures could be implemented to make digital agriculture a success:

Affordable technology: This low income of a developing nation's farmer explains the ambiguous financial circumstances in which a typical farmer operates. Thus, lowering the cost of technology will help.

Portable equipment: Small farms can use portable hardware as a better opportunity for farmers to lease land and move from one plot to another every season. Hence, advancing in portable equipment can be better for farmers.

Academic backing: Agricultural organizations and institutes can provide regular interactive sessions with farmers through various programs and government initiatives. Training facilities and awareness about technology usage will improve digital adoption among farmers.

Overall, the discussed techniques can detect crop diseases and classify them with accuracy and successful applications. IoT and thermal imaging techniques are efficient in scheduling irrigation patterns based on different field characters and the crop's health. The researchers are exploring the potential of using thermal and hyperspectral imaging in various processes in agriculture due to its numerous advantages. Integrated crop management has already benefited from remote sensing and other technologies. The future brings a tremendous possibility for integrating the spatially and temporally rich information provided through these innovative technologies to assist conventional agriculture. Moreover, these emerging technologies can also provide useful solutions to the present and future challenges in agriculture.

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