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# IOT based Smart Traps and Sensors in Pest Surveillance

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***Abstract***

The majority of animal species on Earth are insects, which can be found in every type of terrestrial habitat. Among the whole insect species, significant groups are recorded as crop pests affecting the agriculture production globally causing enormous economic losses. To the existing pest group, many new species are added through host shift, migration or invasion from the neighboring habitat. Identification and monitoring of local and invasive pest species is a challenging task. Most of the methods employed at present for pest monitoring are traditional, time consuming and ineffective. However, as digital technology advances, new solutions to this worldwide issue may soon be provided via sensors and the Internet of Things (IoT). The multifunctional technology IOT has the potential to significantly improve peoples' lives in a number of ways. Unmanned aerial vehicles and IoT-enabled devices are helpful in precisely monitoring pest attacks and related diseases in agricultural vegetation. In particular, IoT has been used in agriculture to increase its ecological sustainability. This chapter illustrates the uses, advantages and present challenges as well as future directions for IoT in smart pest surveillance.

***Keywords*** Devices, Internet of things, Pest monitoring, Sustainability

## 1. Introduction

Agriculture is an essential source of sustenance. Moreover, modern technologies have been used in horticulture, forestry and agriculture to improve disease detection, pest population control and plant growth monitoring. Here, timely pest management greatly aids in raising food supply and quality, which in turn boosts the nation's economy. Furthermore, diseases and insect pests can spread quickly, which could seriously affect agricultural productivity. It is regrettable that there is so little knowledge available regarding insects, despite the fact that they comprise the great bulk of all animal species.

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Sustainable farming requires extensive monitoring coverage to support farmers in maintaining plentiful crops while reducing and optimizing the usage of pesticides. In the present world, artificial intelligence (AI) is one such technology that is developing fast. AI is currently widely used across a number of industries, from environmental monitoring to robots development (Guo *et al.*, 2022). A range of intelligent sensors that process data more accurately in real time is used by AI. Because of this, artificial intelligence (AI) has multiplied the performance of every gadget while improving its sensitivity and accuracy. IoT is a cutting-edge technology that was developed as a result of AI and intelligent sensors. The IoT serves as a central hub for wireless systems and AI processes data instantly to produce relevant results (Malley *et al.*, 2020). Artificial Intelligence and Internet of Things have many expanding applications in agriculture, including soil quality, weather monitoring, pest identification, harvesting schedule estimation and more as shown in figure 1 (Kaloxylos *et al.*, 2013).

The IoT comprises physical items that have sensors installed in them that gather and share data with other systems and objects across the network. Many researchers have tried to investigate how IoT devices may be used to create smart farming. These tools have the capacity to collect enormous amounts of data to help farmers identify pests (Prasath and Akila, 2023). Intelligent insect traps and electronic monitoring systems that identify and monitor pests are made possible by IoT technology in the field of pest surveillance. Business, agriculture, surveillance and almost every other aspect of life have changed due to the rapid rise of IoT-based products. Through the Internet of Things, farmers may efficiently employ technology to remotely monitor their crops at all times.

The Internet of Things-based smart sensors can measure environmental parameters like temperature, humidity and wetness with high precision. Certain sensors can evaluate the water content and nitrate levels in soil to determine even soil quality. A high-resolution camera with a General Packet Radio Service (GPRS) system can be used to detect crop diseases and insect pests. Surveillance using unmanned aerial vehicles (UAVs) aids in tracking crop growth and farm field topography. Crop productivity can be determined using automated mass flow sensors (Rajak *et al.*, 2023).

The fields of IOT, remote sensing and data analytics have come to save crop management. Using remote sensing, UAVs can locate, identify and control pests. Unmanned Aerial Vehicles (UAVs) provide the capability to operate in challenging and rough environments, providing high-definition imagery that aids in both pest detection and control. Many crop protection challenges that cannot be resolved by traditional pest management techniques can be resolved by UAVs equipped with cameras. Using UAVs, automated pest damage in cultivated areas has been achieved (Maslekar *et al.*, 2020). Real-time agricultural meteorology and pest identification systems on mobile applications are evaluated based on environmental IoT data and intelligent pest identification. Precise positioning reduces pesticide damage to soil and

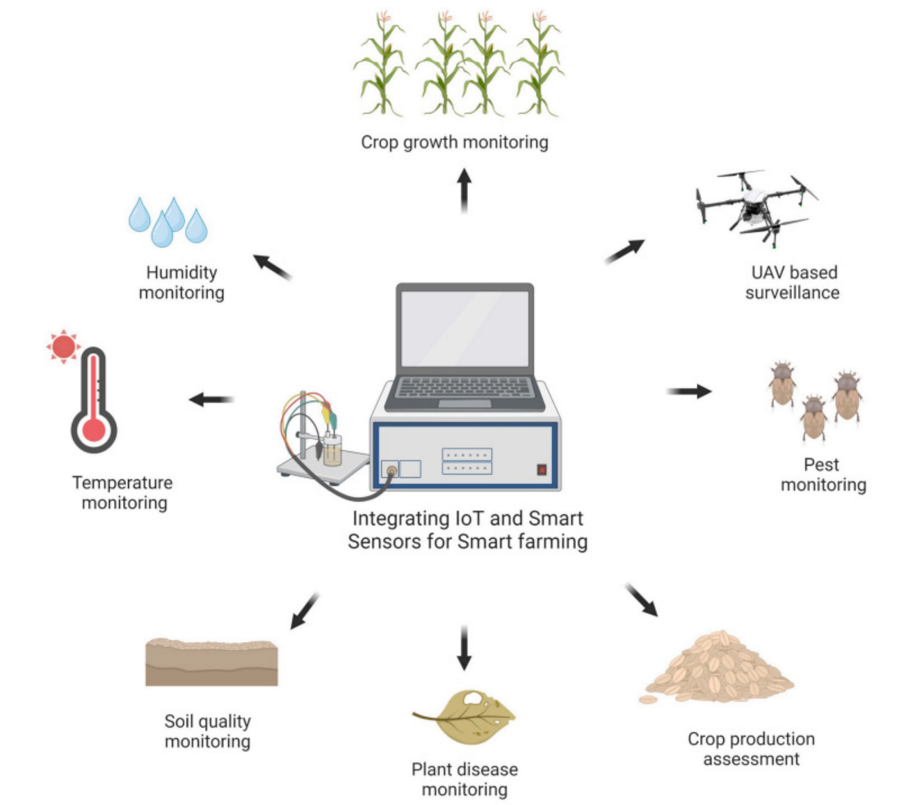


**Figure 1:** Pictorial representation of applications of integrated IoT and smart sensors for precision farming (Adapted from Rajak *et al.*, 2023)

reduces the amount of insecticides used (Chen *et al.*, 2020). Through online interaction and data exchange, the IOT aims to bridge the gap between the real and virtual worlds.

## 2. Why IoT Pest Control is so Exciting?

IOT-based pest control solutions are still in their infancy, but they have already shown benefits for both homes and field professionals.

• *Efficiency and Effectiveness*: By automating the tracking and identification of pests, IoT devices free up technicians to work on other projects.

• *Reduced Costs*: Regular inspections and treatments are less necessary with IoT technologies. Additionally, they stop costly damage to crops and property by spotting insect activity early.

• *Environmental Impact*: By allowing technicians to target treatments more precisely, real-time and all day, all night data on insect activity helps to minimize chemical waste.

• A central system receives the data collected by IoT devices where AI may analyze and make decisions based on the data, which is another important way that IoT contributes to the application of AI in pest management.

## 3. How IoT Pest Control Works?

Typically, Internet of Things pest control solutions install a network of sensors and traps in a cropping ecosystem. The sensors gather information about pest activity and environmental conditions. The central hub receives this information and uses it to detect and locate pests. The device has the ability to automatically set off traps or notify technicians when it finds a bug (Christopher, 2024). The significant advancement in on-field pest management has resulted from the application of IoT in the agriculture sector. These days, using a variety of sensors, a farmer may keep an eye on the development of pests and take extra measures to eradicate them. The assortment of sensors that are being used to detect and monitor insect growth is provided below.

### *3.1. IoT-based Crop Monitoring*

The implementation of IoT for microclimate, soil and crop sensing has caused a paradigm shift in crop monitoring, moving it from an experience-based qualitative effort to a quantitative and data-driven endeavor. Farmers can precisely monitor crop growth and health using IoT-based technology. Additionally, it helps to evaluate plant diseases and pest attacks in real time (Kaloxylos *et al.*, 2013). It's interesting to note that unmanned aerial systems (UAS) can be paired with laptops, smart watches and phones to gather visual and environmental data more effectively. IoT-based devices are utilized to accurately perform data collecting, monitoring and field surveillance for multipoint assessment systems. IoT technologies help regulated supervision and computerized data processing in green house setups, which has improved the digital system's usefulness in managing pests and diseases. IoT-enabled tools help farmers quickly and effectively take appropriate preventive action by enabling them to track pests in real time (Singh *et al.*, 2021).

### *3.2. Application of IoT on Weather Sensing*

Weather plays an important role in supporting pest population. With congenial weather condition, pest population increases rapidly thus, causing huge economic loss within short period of time. For instance, high temperature coupled with low rainfall and humidity increases the population of thrips and leafhoppers in cotton ecosystem (Zhang and Kovacs, 2012). Similarly, high humidity in the paddy ecosystem results in rapid buildup of brown plant hopper resulting in hopper burnt symptoms (Zhang, 2014). Hence, monitoring the weather parameters along with pest helps in effective pest management. The IoT has gained popularity in sensing meteorological characteristics such as soil humidity, moisture and temperature. When vital environmental parameters alter beyond the threshold level, IoT-connected sensors immediately notify the administrator, enabling them to take appropriate action to prevent impending challenges. Additionally, the smart system offers real-time monitoring of temperature, humidity, brightness and $CO_2$ concentration for crop growth (Windsperger *et al.*, 2019).

### 3.3. Monitoring of Soil Properties

Soil properties such as moisture, physicochemical properties not only aid crop growth but also influence insect pest population. Low moisture in the soil may lead to poor crop growth making it vulnerable to pest attack. IoT is able to detect temperature, nutrient levels and moisture in soil. Farmers can remotely access and adjust the data to take prompt action against pests and diseases. Consequently, farmers may find it beneficial to practice smart farming (Navulur and Prasad, 2017).

### 3.4. Remote Sensing using Smart Sensors

Field scouts often use expensive, time-consuming sites checks to monitor insect infestations, which leads to low temporal and spatial resolution. Due to developments in electronics, informatics and remote sensing, remote monitoring is now feasible. Using camera-equipped traps can maximize the efficacy and cost of monitoring. Algorithms for picture analysis can find and count insect pests that are caught in traps automatically with very little assistance from humans.

### 3.5. Sensors for Smart Farming

The use of many sensors in smart farming is becoming more prevalent. Some of them are listed below.

#### *3.5.1. Acoustic based Sensors*

Plant quality can be effectively ensured by using vibrations to detect pests and rodents. An acoustic sensor is a type of electronic device that detects changes in sound frequencies. These sensors are able to pick up vibrations that are reflected off of moving objects. During normal feeding, movement and mating activities, a variety of insects produce sounds. An increased concentration of bugs is indicated by areas with high sound waves. These instruments allow for the exact identification of the feeding sound of stem bores in field crops and plantations, such as coffee, mango, *etc.* A variety of acoustic instruments, including microphone systems and portable accelerometers, can identify these sounds (Mankin *et al.*, 2021).

The information acquired by the acoustic devices is uploaded to international databases, where it can be examined by experts from all around the world to help build automated acoustic sensors that will enable more precise pest detection at the species level. Acoustic sensors may become covered in soil particles and dust during agricultural operations, but this does not affect the sensor's efficacy and they continue to yield more precise information on the target pests. The main advantages of using acoustic sensors are their enhanced sensitivity, reduced maintenance costs and increased accuracy. In agricultural fields, acoustic-based sensors are commonly employed for the purpose of identifying and tracking diverse pest populations (Hoye *et* *al.*, 2021).

*3.5.2. Electrochemical Sensors*

The most portable and lightweight, environmental friendly sensors for use in agricultural areas are electrochemical ones. These sensors are effective at tracking diseases, plant development and pollution in the environment more precisely in real time (Singh *et al.*, 2021).

*3.5.3. Radars and Light Detection and Ranging (LiDAR)*

Use of LiDAR and radar in entomological field is a novel attempt. Insect pest population movements, such as migration, can be efficiently detected and monitored using radars, especially polar metric systems. Radars can also be used to track insects' high-altitude migration routes. Doppler weather radars can identify and localize sources of population density. They are also able to detect dense concentrations of flying insects. LiDAR technology uses light to estimate the distance between a target object and a sensor. Due to the constant speed of light, LiDAR is able to determine the precise distance between the object that the light-emitting sensor collides with and the sensor. LiDAR creates a map of the surrounding area by regularly emitting light pulses and detecting a series of collisions. The advanced LiDAR system has fewer pulses, which increases the equipment's effectiveness (Reger *et al.*, 2022).

Consequently, data on density of pest infestation and population life cycle is provided by radars and LiDARs. Entomologists will be able to forecast the migration of insect pests by combining the climatic conditions with the aforementioned data. During the day or night, the portable harmonic radar system is a helpful instrument for efficiently detecting pests. An additional helpful instrument for tracking terrestrial insects is the harmonic radar system. A LiDAR system can find even the smallest insects. LiDARs, as opposed to radars, can be used up close to investigate insects, including their ecology and ethology (Dwivedi *et al.*, 2020).

*3.5.4. Vertical Looking Radar (VLR)*

An important advancement in insect radar technology is the vertical-looking radar (VLR), which can identify biological characteristics and the migratory behavior of insects. To gather data on insect movement, VLR, also known as insect monitoring radar, or IMR, was created. This combines rotational polarization with a narrow-angle conical scan, allowing one to identify the alignment and direction of travel of an insect transiting the beam. Long-term monitoring of migrating insect populations is made possible by this method, which routinely pulls information from individual targets on size, shape, alignment and displacement vectors. The capacity of VLRs to identify insect species and detect biological and behavioral aspects has led to their widespread nowadays. VLRs use the zenith-pointing linear-polarized conical-scan design. It also offers an automated, cost-effective long-term monitoring capability for insect migration research (Wolf *et al.*, 1993).

*Radar Equipment*: Using a mechanically turned upward-pointing wave-guide feed, the VLR constantly rotates the plane of linear polarization to produce a vertically looking, circularly symmetric beam. Moreover, the beam slightly oscillates due to the feed's little angle offset (0.18°) around the vertical axis. This results in nutation, a conical-scan motion that slows down and resembles the wobbling of a spinning top (Figure 2). The targets passing through the beam are automatically detected within 15 altitude bands (range gates), which are situated between 150 and 1166 meters above the radar. Each range gate is 45 meters deep, with non-sampling intervals of 26 meters between them (Figure 3). When an insect or other target passes across the radar beam, the receiver detects the signal that is bounced back. Almost continuous coverage is provided by the recording of signals within the 15 range gates, which occurs once every 15 minutes, for five minutes period at a time. The modulation of the returning signal is contingent upon the target's shape, size, position and speed. Signals are automatically analyzed using a novel iterative process based on their complex Fourier transformations throughout the 10-minute interval that follows each sample period (Smith *et al.*, 1993).

The confirmation of the identification of targets identified by VLR throughout the night, which were presumed to be migrating DBMs, was achieved by contrasting their temporal frequency with the actual DBM catches in light-trapping networks located on the ground. Radar cross-sectional data from the returning signals was combined with body mass information to identify the targets (Chapman *et al.*, 2002a).

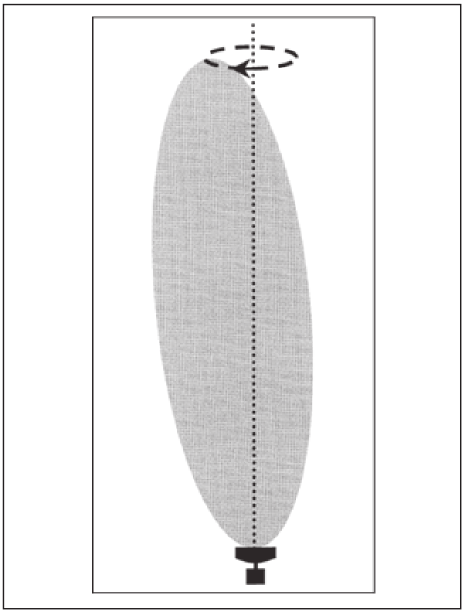

**Figure 2:** Schematic elevation view of the vertical-looking radar beam (Wolf *et al.*, 1993)

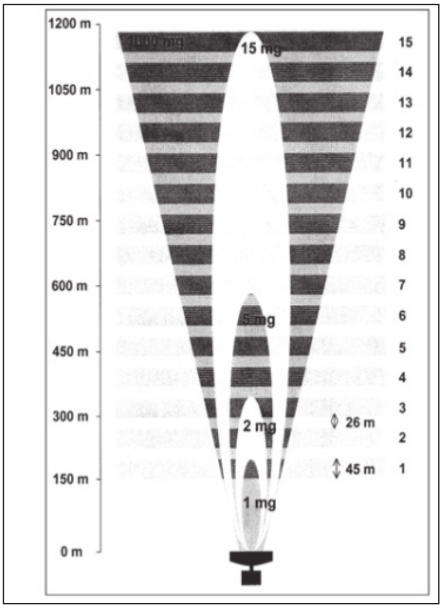


**Figure 3:** Vertical-looking radar's sampling regime (VLR) (Wolf *et al.*, 1993)

### *3.5.5. Hormonic Radar*

In entomological studies, a harmonic radar device is presented for tracking flying insect movements. Predicting the system's range performance given realistic antenna dimensions, transmit power and receiver performance is the goal. The receiver is described, along with the computations for signal level and noise. It is demonstrated that a maximum range of 251 m is feasible with reasonable assumptions. Tracking insects that fly across flat terrain and at low altitudes is a useful application of harmonic radars. Thus far, they have been applied in a wide range of fields, including short-range dispersal analysis, odor-mediated anemotaxis, classical pollinator ecology and bee neuroethology. The study of several other insects, such as beetles, carabids, caterpillar moths, butterflies and honeybees, might also be done with the help of this entomological tracking radar (Colpitts *et al.*, 2000).

### *3.5.6. Optical Sensors*

Potential applications for a wide spectrum of optical sensors include agriculture. The basis for these sensors is their capacity to identify different wavelengths of light. A light source emits light with a particular wavelength in order to collide with the target item. With the use of optical sensing technologies, data on the distribution of weeds in agricultural lands has been successfully acquired. According to a study that employed a tolerance threshold, an optical sensor in conjunction with spectroscopy proved to be highly accurate in recognising cells infected with green weed. A total of 90.9% of the reported percentage agreement was equivalent to the 90.5% and 91.2% of the two reference methods that were applied (Barroso *et al.*, 2017).

Insect traps are outfitted with electronic sensors (*i.e.*, acoustic, optical and image) to facilitate automated detection and monitoring for precise and effective observation. Smart traps are made possible by connecting the traps via a communication network, which enables remote pest monitoring without the need for regular field trips.

## **4. Pest Monitoring in Smart Farming**

Numerous pests in agricultural fields can be repelled by certain gadgets that generate ultrasonic sound waves. Tiwari *et al.* (2016), for example, developed an electronic insect repellent that emits powerful ultrasonic sound waves. Pests such as mosquitoes and rats are repelled by these waves. As a result, these tools are a good substitute for chemical pesticides, which have a lot of negative effects on beneficial organisms. Electronic insect repellents are inexpensive, safe for the environment and have no negative effects on people. These devices primarily work to repel pests by appealing to their auditory receptors. Pest detection can be greatly aided by specific image processing algorithms. UAVs can be used to collect high-resolution macro and micro photos of the farmland using spectral camera technology (Rajak *et al.*, 2023). Analyzing such photos can help identify insect infestation and the onset of related crop diseases (Gao *et al.*, 2020).

Automated traps with cameras can be used to manage the number of pests. In order to control the apple codling moth *Cydia pomonella* L. in orchards, Guarnieri *et al.* (2011) transformed a commercial trap into an automated trap with the ability to collect and process data. A delta-shaped trap equipped with a GPRS, solar panel, battery, charging unit and high-definition camera was developed by Unlu *et al.* (2019). Shaked *et al.* (2017) developed the sticky delta trap to track the Mediterranean fruit fly, *Ceratitis capitata*. Fruit flies *Bactrocera oleae* were captured using bucket traps combined with an electronic McPhail trap that was camera-based. Fruit flies that were trapped were automatically photographed in real time and uploaded to a server for archiving. With the help of the taken pictures, entomologists were able to recognize the fruit flies with more than 80 per cent accuracy. Bark beetles and forest longhorn beetles can be remotely monitored with an integrated multi-funnel trap and camera system. More precise identification and characterization of agricultural pests may be facilitated by studying insect behavior through the use of multiple wireless sensors (Singh *et al.*, 2022).

The sensor node can be used to measure the temperature, humidity and light intensity in a greenhouse in addition to taking pictures of sticky paper traps. Using an image processing technique, insect pests on an insect sticky trap may be automatically detected and counted with an average temporal detection accuracy of 93% when compared to manual counting. Further analysis was done on the temporal and spatial distribution of insect pest concentrations in relation to environmental parameters. The normalized hourly increase in the number of insect pests appears to be related to changes in temperature, relative humidity and light intensity, according to analyses of experimental data. The suggested system makes it possible to avoid tedious manual counting and to quickly examine insect pest and environmental data. Additionally, the system provides a useful tool for practical applications in integrated pest control as well as long-term observations of insect pest behavior (Rustiaa *et al.*, 2019).

### *4.1. Low-Power Cameras and Sensors*

Farmers use image-capturing sensors for pest monitoring because they are affordable, have a high return on investment (ROI) and are mobile and highly scalable. They equip traps with an inexpensive image sensor that takes pictures of pests and wirelessly transmits them to a central platform. Farmers identify the area of insect infestations and begin management measures to eradicate them from fields based on the insect population found in the traps.

### *4.2. High-Power Thermal Sensors*

Low-power image sensors usually take random pictures of insects that are visible to the unaided eye. On the other hand, diverse crop diseases in the fields are also caused by different pathogens that measure in millimeters. The thermograph is a technique for measuring the quantity of light reflected by a surface using infrared and thermal sensors. Every surface has a unique spectral signature, or amount of light energy that it reflects.

Spectrophotometers are devices that record the unique spectral spectrum of plants and soil. Should a disease cover the leaf surface, the plant's spectrum will shift, signaling a pest invasion. This technique works very well for identifying the insects and stage of their life cycle. Nevertheless, this approach is costly and subject to alteration.

### *4.3. Fluorescence Image Sensing*

Using this method, chlorophyll content a plant is determined by observing changes in its fluorescence characteristics. Images of plant leaves are captured by an optical camera, which then compares the results with stock photos of a leaf in good condition. The presence of pests or pathogens is indicated by changes in chlorophyll patterns. Although this approach finds pests in a crop, its scalability problems severely restrict its field applicability. Furthermore, only crops containing chlorophyll can be employed with this technique.

### *4.4. Gas Sensors*

Under stress, several volatile chemical compounds are produced by plants. These substances vary according to the amount of stress they experience. For example, the compounds released as a result of environmental changes will differ from those released as a result of pest infestation. Therefore, before these substances can be utilized to identify attacks caused by rodents or bugs, more research must be done on them. A gas sensor can be used to determine the type and nature of the infection or the pest attack after these substances have been investigated. These techniques' lone flaw is the sampling needed to gather volatile chemicals for data analysis.

## 5. Image Recognition

The expansion of artificial intelligence in image processing models has led to an increase in the use of picture recognition. To reduce agricultural pest damage and boost crop yield, image recognition technology has been utilized in recent years to help in pest identification (Mary *et al.*, 2019).

### *5.1. Machine Learning to Recognize and Categorize Pictures of Pests*

#### *5.1.1. Supervised Learning*

Labeled data must be given to machines during the machine training process. For instance, we could show a machine a test image and ask it to identify if it contains apples or oranges after the machine has seen 1,000 labelled photographs of the fruit.

#### *5.1.2. Unsupervised Learning*

The data does not need to be pre-labeled and during learning, the machine is unable to determine whether or not the outcome of its classification is accurate. To categorize on its own, the computer has to extract the rules from each of the input samples.

In conclusion, supervised learning employs regression analysis techniques to produce the expected outcomes by appending fictitious labels to the input data. With the use of algorithms, unsupervised learning automatically classifies vast amounts of data by identifying relevant patterns.

### *5.2. Deep Learning to Identify and Classify Pest Images*

Since the foundation of deep learning is the machine learning framework, unsupervised learning is used during the training phase to group the training data set and determine the type of data that will be classified. Then, supervised learning is used to identify the expected output value of each entry by using the feature vectors in the training data set as input and the expected classification as output. Lastly, the standard deviation between the expected and actual outputs is computed using the loss function. When it comes to deep learning, there are two common approaches for classifying and identifying pests: (i) Miranda *et al.* (2014) detected 24 different pest species from crop photos using the VGG19 technique for image feature extraction and recognition; (ii) Gondal and Khan (2015) used a variety of CNN techniques to identify and categorize 12 distinct pests. They then compared the classification outcomes with those of other machine learning techniques, including SVM and Fisher. The CNN approach had a classification accuracy rate of 95%, whereas the machine learning method had an accuracy rate of 80%.

### *5.3. Using Image Augmentation to Increase the Pests Training Sample Database*

Geometric transformation and photometric transformation are the two broad categories into which data augmentation techniques can be separated. Ding and Taylor (2016) investigated how various data augmentation techniques affected the accuracy of picture recognition. Three brightness adjustments (colour jittering, edge enhancement and fancy principal component analysis) and three geometric transformations (flipping, rotating and cropping) are applied. The CNN model is trained using both the original and amplified image samples as training data.

## 6. Monitoring Insect Pests using Camera-Equipped Traps: Advantages and Disadvantages

The traditional method of tracking on insect pests involves setting up a number of traps in individual infected areas and periodically having human operators inspect them. The labour costs associated with this method are considerable and the spatial and temporal resolution obtainable by a single operator is inadequate. Using image sensors to track insect pests can have a number of useful benefits. To automatically identify and/or count insect species from images, image recognition methods and software can be used. With the high image resolution that can be obtained and the potential to use wireless technology to take advantage of data transfer systems, it is feasible to control insect catches remotely, which would reduce the need for field trips. With the development of online and real-time pest monitoring technologies, it is now possible to measure the dynamics of insect populations continuously and simultaneously in a large number of traps with a low labor demand from humans. The real drawbacks are the exorbitant price, the prototypes' poor image quality, low battery autonomy and low cost; also, completely automated pest identification still requires work.

## 7. IoT-based Pest Control Systems: Advantages

Farmers are using these sensors to help them pinpoint areas of their fields where viruses and insects are present. Instantaneous wireless communication of the data gathered by these sensors to a centralized platform occurs. Through the use of this platform, a farmer may keep an eye on the condition of their crop from a distance and defend it against pests and rodents. In terms of pest control, the agricultural industry can benefit from IoT in the following ways:

### *7.1. Monitoring Pest Infestation and Crop Health*

- An agriculturalist can readily gather data regarding the existence of rodents and insects by using remote monitoring. Pest or disease infestation is detected by sensors positioned in various fields and relayed to a dashboard. A farmer can monitor crop health and establish instant communication with his fields using this dashboard.

- Random site visits and manual inspection have been significantly reduced by remote pest monitoring. Farmers can now spray insecticides solely on the necessary regions and concentrate their efforts on places where pests are present. By significantly lowering the needless application of pesticides, this lowers the risk of crop poisoning and environmental damage. The breed and number of the insects in the impacted crop zones can also be determined using the data gathered.

### *7.2. Weather Monitoring and Analytics*

Appropriately recorded and analyzed, the data collected from pest detection devices can forecast when pests will attack. An additional tool for determining the threat level of insect populations is monitoring weather and breeding trends. The likelihood of infestations is very high during the breeding seasons. Additionally, before going into hibernation, rats consume crops to gain fat. These kinds of data are used by predictive analytics to identify patterns and trends that indicate potential pest outbreaks and swarm activities. The analytics component can also provide advice for full treatment as well as future prevention measures based on the type of insect infestation and population.

### *7.3. Automated Crop Health Surveillance*

The practice of integrated pest management, or IPM, is one that promotes the positive ecological, social and economic effects of pest management. IoT integration with the IPM system can automate labor-intensive processes like manual data point inspection and measurement. As a result of automation, the process is more precise, economical and helps farmers respond quickly to sensor readings. Additionally, pesticide usage will be optimized, potentially reducing environmental contamination and crop health risks.

## 8. Challenges and Future Possibilities

Different challenges faced in the implementation of Internet of Things-based intelligent sensors and auxiliary equipment for completely automated agriculture (Figure 4).

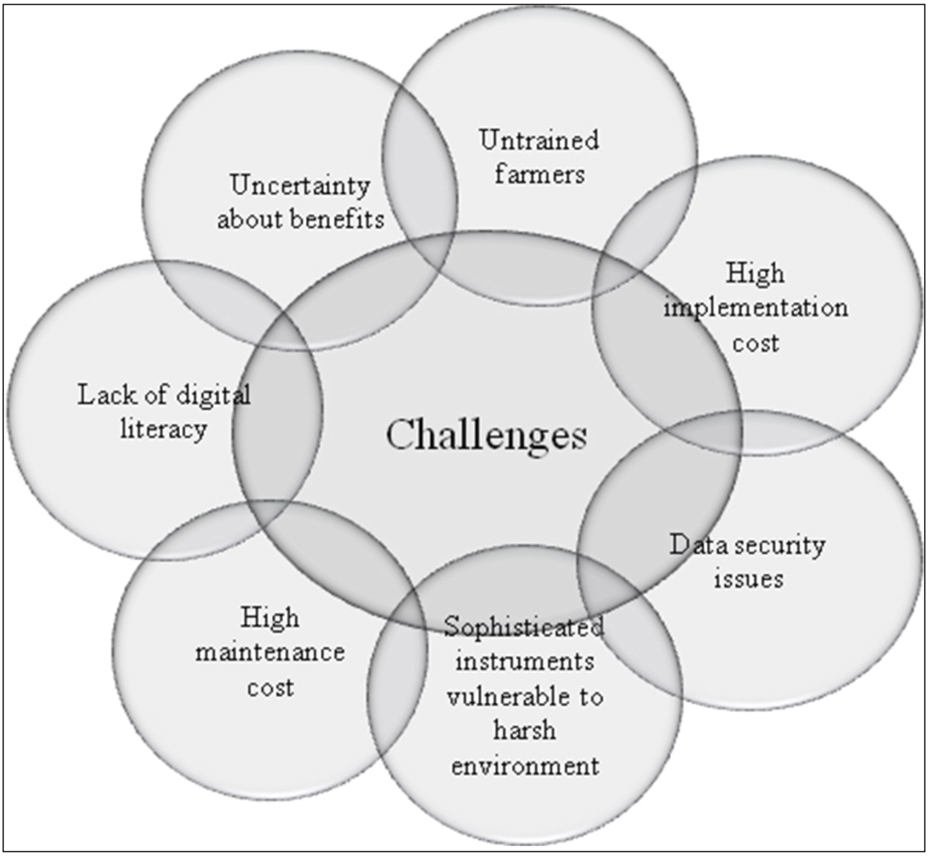


**Figure 4:** Challenges and future possibilities IOT based smart surveillance

- The financial burden associated with the deployment and installation of IoT-tagged sensors and accessories across a big acreage of agricultural land is one of the main obstacles.
- The ambiguity around the relationship between implementation costs and profit margins.
- To ensure that the Internet of Things is deployed internationally, there needs to be a major global drive to increase farmers' technology literacy. Low knowledge and literacy about the uses, promotion strategies and implementation of Internet of Things (IoT) technologies in farming may be the cause of underutilization of smart systems in the agricultural sector.
- Economic strategies must be developed by government policy makers to

enable farmers to successfully and more productively use IoT on their farms.

- Another issue that could seriously hinder the widespread adoption of IoT and smart systems is data security and privacy.
- Smart farming requires trustworthy encryption to protect digital systems and important data from global cybercriminals. Strong keys combined with cryptography may help thwart cyber attacks targeting cloud services.
- Installing IoT devices outdoors exposes them to inclement weather, wind, dust, heavy precipitation and other environmental factors. This is one of the main issues with IoT devices. Such unfavorable climatic circumstances could cause the complex electronics to unexpectedly malfunction mechanically. Therefore, in order to extend the lifespan of complex equipment with more consistent output, makers of IoT devices for smart farming should utilize raw materials that can endure such harsh climatic variables.

## 9. Conclusion

To ensure the crop health, farmers must control and eradicate pests from their fields. An agriculturalist may now remotely monitor and manage pest infestation with the advent of IoT. The remote real-time detection using smart sensor trap is a significant advancement over the current manual delta traps, especially for biosecurity monitoring applications. Predicting which traps to inspect based on recorded activity, independent of the species that set it, will cut down on maintenance costs and carbon emissions associated with semiochemical trap-based monitoring networks. The possibility to extend to additional species and/or a larger surveillance area for existing programs could be made possible by the notable decrease in the cost of physical labour. The likelihood of effectively eliminating insects before they establish themselves should rise when intrusions can be identified early on through the use of smart sensor traps. In conclusion, the potential to get substantial datasets through intelligent sensor traps in the future will enhance machine learning models and raise the accuracy of species identification. Thus, these datasets may develop into novel tools for diagnoses as well as surveillance. An IoT-powered pest management system can be integrated by a farmer with a one-time expenditure, allowing for the accurate detection of pests and rodents without the need for manual inspection. But the full potential of IoT in agriculture depends on how its agri-based applications are used in tandem. Along with crop management, weather monitoring and livestock management, remote pest control is making it possible for the agriculture sector to develop a variety of contemporary farming techniques that were previously unheard of.

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