Chapter

Recognition and Early Stage Detection of Phytophthora in a Crop Farm Using IoT

Pooja Vajpayee and Kuldeep Kr. Yogi

Abstract

Detection of agricultural plant pests is seen as one of the farmers' problems. Automated Pest Detection Machine enables early detection of crop insects with advanced computer vision and image recognition. Innovative research in the field of agriculture has demonstrated a new direction by Internet of Things (IoT). IoT needs to be widely experienced at the early stage, so that it is widely used in different farming applications. It allows farmers increase their crop yield with reduced time and greater precision. For the past decade, climate change and precipitation have been unpredictable. Due to this, many Indian farmers are adopting smart methods for environment known as intelligent farming. Smart farming is an automated and IOT-based information technology (Internet of Things). In all wireless environments IOT is developing quickly and widely. The Internet of Things helps to monitor agricultural crops and thus quickly and effectively increase farmers' income. This paper presents a literature review on IoT devices for recognizing and detecting insects in crop fields. Different types of framework/models are present which are explaining the procedure of insect detection.

Keywords: Internet of things (IoT), smart agriculture, pest detection, deep learning

1. Introduction

The livelihoods of Indians are mainly from agriculture. It has been noted in the last decade that there has not been much agricultural crop development. As crop prices decrease, food prices are constantly increasing. Since 2010 more than 40 million people have been driven into poverty [1]. This may be due to water wastes, low soil fertility, abuse of fertiliser, climate change and diseases, etc. There are numerous factors responsible Effective farm intervention is very important and IOT is the solution for integration with wireless sensor networks. It is capable of changing the way agriculture develops and contributes greatly to making smart agriculture. There is a three-tier system in the internet. It contains the layer, network layer and application layer of perception. Sensor motes include perception layer. Devices enabled by ICT, sensor motes are the building blocks of sensor technology. It comprises cameras, RFID tags, sensors and network sensors for object recognition and real-time information collection. The network layer is a universal service IOT infrastructure. The combination of the layer of perception and the application layer is directed. The layer of application is a layer that combines the IOT with specific industry technology.

The internet has almost been applicable in all industries, including intelligent agriculture, smart parking, environmental monitoring for intelligent buildings, health transport and much more.

1.1 Internet of Things (IOT)

The Internet of Things (IOT) is the easiest and most powerful way to solving problems. IOT is established from different assemblies, with tonners of recorders, software, pieces of axes. It also makes details more detailed. Without human interference IOT permits the sharing of data over a network. We will mirror things naturally on the internet as everyday people like a sensor, a car driver etc. An IP address is given so that data can be transmitted across a network. In 2016, the number of connected devices grew 30% relative to 2015 according to the report produced by Garner. He adds that this number is set to grow by 26 billion by 2020 [2].

For the following factors, IOT technology is more efficient:

- Faster Access
- Efficient Communication
- Time Efficiency
- Global Connectivity through any devices
- Minimum human efforts

2. A model for smart agriculture using IoT

In 2016, Patil and Kale [3] reviewed climate change and rainfall over the past decade as annoying. As a result, many Indian farmers are implementing climate-intelligent practices in recent times called intelligent agriculture. Smart farming is an integrated and IOT-driven information technology (Internet of Things). In all wireless settings IOT evolves easily and broadly. Within this article, the introduction of sensor systems and wireless communications to the implementation of IOT technologies and the systems in current agriculture are analyzed and evaluated, in conjunction with the current conditions of the agricultural system Remote Management System (RMS) is proposed to incorporate an approach with internet and cellular communications. Main aim is to capture real-time farming production data offering easy access to farming equipment such as fast massage service warnings and guidance on weather conditions, crops etc (**Figure 1**).

3. Design and realization of a real-time detection device for insect pests of field crops

Mercedes, S., Bo, G. And Yuxia, H., in 2011 [4] investigated the vast species and huge quantity of insect parasites of field crops. Hundreds of common insect pests in farmland are caught by lamps. After the Black Light was trapped, the insect pests were manually recognized and numbered. And the process of predicting was used primarily for a long time in China. It was closely linked to the overall quality of the forecast person's impact, accuracy and efficacy, and was ultimately determined by greater subjective factors.

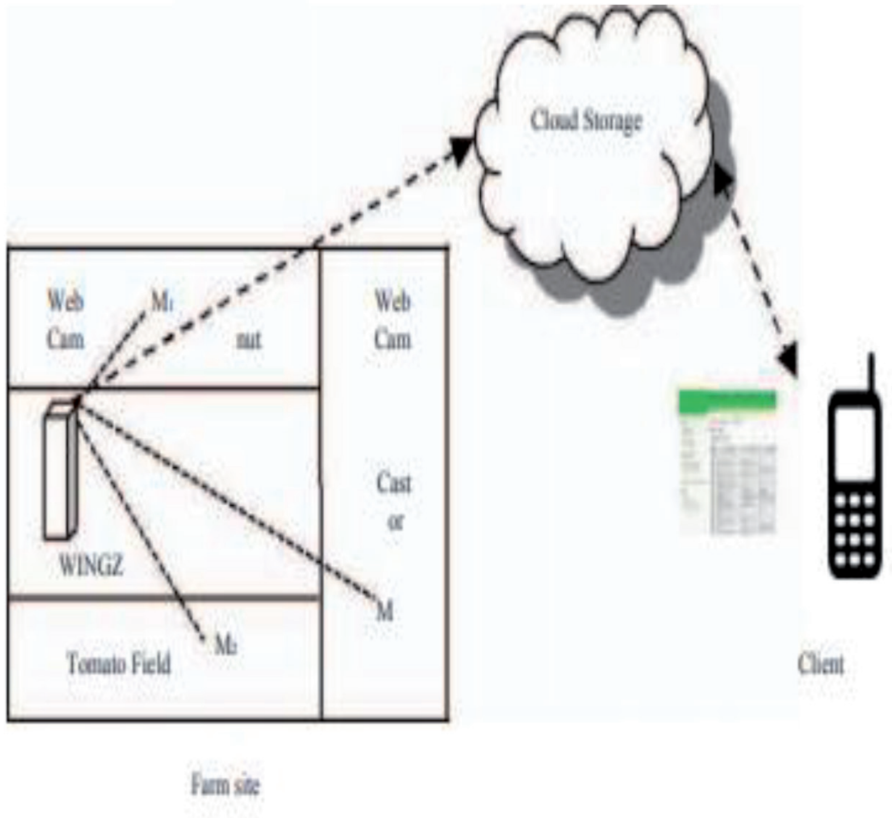


Figure 1.
SAIoT model.

Students studied the picture identification on field plants of insect pests in detail. The static digital camera pictures were categorized of 40 species (25 families, 8 orders) of nightmarish insect pests [5]. With gray-scale images, the 30-five typical plagues (Lepidoptera) manually put were recognized [6]. The auto trapped, killed, and placed into laboratory for further study the eight species of insect pests in cotton fields [7].

3.1 Hardware and software system

With the hardware and software framework the second-generation insect pest detection device was developed. Hardware provided trapping, astonishment and buffering, a uniform lighting, a dispersion-transporter and a vision machine. The software framework has improved image, segmented images, chosen functionality and known insect pests. The unit carried out the entire automation from the collection of insect pests to the identification.

3.2 Hardware design of the detection system

See **Figure 2**.

3.3 Software design of the detection system

Owing to the vast number of details and high efficiency in real time, the cost of the image processing equipment has been raised. Windows 2003 used the framework and the Visual C++ 6.0 language for visual development. MFC-based application software was developed using an OK C30S acquisition graphics card with API functions.

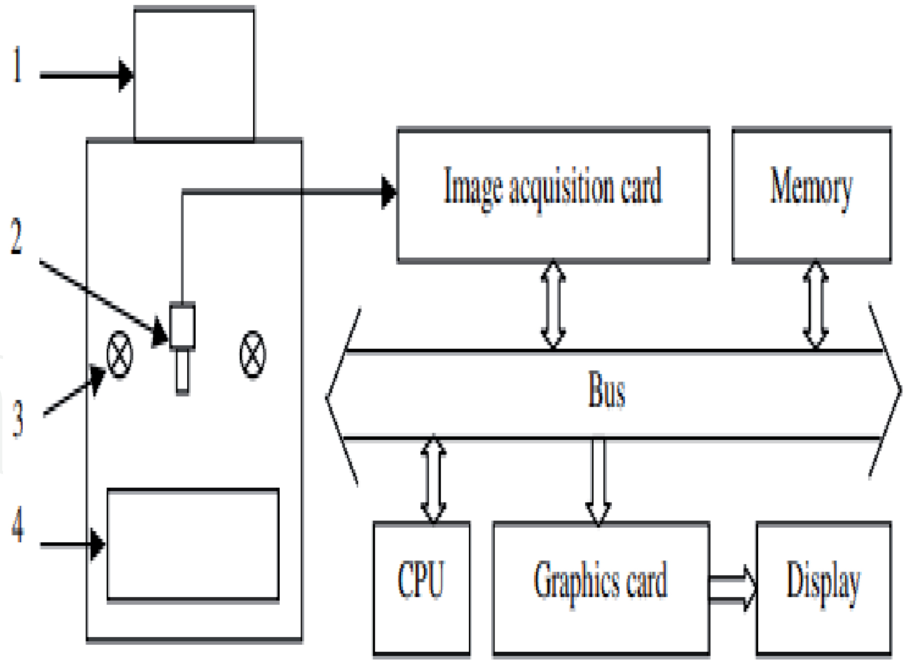


Figure 2.
Hardware components for real time monitoring system for insect pests on field crops. (1) "Trapping, stunning and buffering unit, (2) CCD (3) Illumination unit and (4) Scattering and transporting unit".

3.4 Inference

Real-time detection device for field plagues of second generation has been developed. It performed all automation, from the capture, dispersion, transport, collecting of images, picture analysis to pest recognition. It reduced the duration of detecting pests and increased the degree of automation. The right identification ratio of nine species of pests surpassed 86%. The study further focused on enhancing pest species and improving the detection efficiency.

4. Internet of Things application to monitoring plant disease and insect pests

Shi, Y., Z., Wang, X. Shi, Y. And Zhang, S.in 2015 [8] studied the efficient way of enhancing agricultural low-tech culture quality by using information and communication technology to establish a plant disease and long-term insect pest control system as the farm expert was unable to use the farm for farm management and insecticide disease control. The article introduces internet-based information perception technology (IOT) as well as the role of IOT technology for agricultural disorders and for the control of insect pests, including farming disabilities and the insect pest control system, the collection of sensor nodes, data processing and exploitation of insect pest information, etc. An IOT-based disease and insect pest control system consisting of three levels and three systems were proposed. A new way of accessing agricultural information on the farm is provided by the system.

5. Agricultural crop monitoring using IoT

"Sreekantha, D.K. and Kavya, A.M", in 2017 [9] investigated the reorganisation of the IOT for agriculture, helping farmers to deal with problems in the region with a broad variety of technology including accuracy and sustainable agriculture. IOT technology helps to gather information on conditions such as weather, precipitation, soil temperatures and fertility, field tracking online allows weed identification, water level, pest detection and interference of livestock, crops growth and farming. IOT moves farmers from everywhere and at any time to link to their farm. Farms are monitored using wireless sensor networks, and microcontrollers for the control and automation of agricultural processes. Wireless cameras have been used to view the environments remotely in the form of pictures and images. A smart telephone enables farmers, at every time and anywhere in the world to keep up to date with the current conditions of their agriculture. IOT technology can cut costs and increase conventional agriculture's productivity.

5.1 Inference

The Internet of things helps agricultural crop tracking to increase crop production and thus the farmers' income quickly and effectively. A wireless sensor network and sensors of all kinds are used for the collection of crop conditions and environmental change and are transmitted to farmers/devices via a network to cause corrective action. Farmers are in connection with the circumstances of the agriculture sector around the globe at any moment and wherever. Few connectivity drawbacks have to be addressed by encouraging the technologies to conserve resources and also by facilitating the user experience.

6. Remote insects trap monitoring system using deep learning framework and IoT

"Ramalingam, B., Mohan, R.E., Pookkuttath, S., Gómez, B.F., Sairam Borusu, C.S.C., Wee Teng, T. and Tamilselvam, Y.K in 2020" [10] researched that early insect identification and control (human physical conditions as an example houses, hospitals hotels, parks, camps, flooring, industries related to food etc) and agricultural farms were important for developed environments. These pest control steps are currently labor-dependent manual, repetitive, unpredictable and time-consuming activities. Latest advances in Internet of Things (IOT) and Artificial Intelligence (AI) and the can automate a range of maintenance operations, improving efficiency and safety dramatically. This document includes the implementation of Deep Learning (DL) and IOT monitoring system of insect traps in real-time as well as the detection of insects. *"The system architecture for remote trap monitoring is developed with IOT and the unified target detection framework of faster RCNN (Region-based convolution neural networks) Residual neural Networks 50 (ResNet50). The object detection system for Faster RCNN (ResNet 50) was trained and deployed in IOT using designed environmental insects and farm insect imagery"*. The proposed device was tested with four-layer IOT and the picture of constructed ecosystem insects caught by sticky trap sheets in real time. In addition, insects from farms have been examined by a different database of photographs of insects (**Figure 3**).

6.1 Inference

In this article, the IOT and deep learning system was proposed for the remote insect tracking and the automated process of insect detection. The Faster version of RCNN ResNet object identification mechanism was accustomed to automately classifies the parasite type, using the Four-Layer IOT system to built the remote trap insect tracking mechanism. Included is an ecosystem insect data base and farm field insect archive that has been checked for offline and on-line reliability in

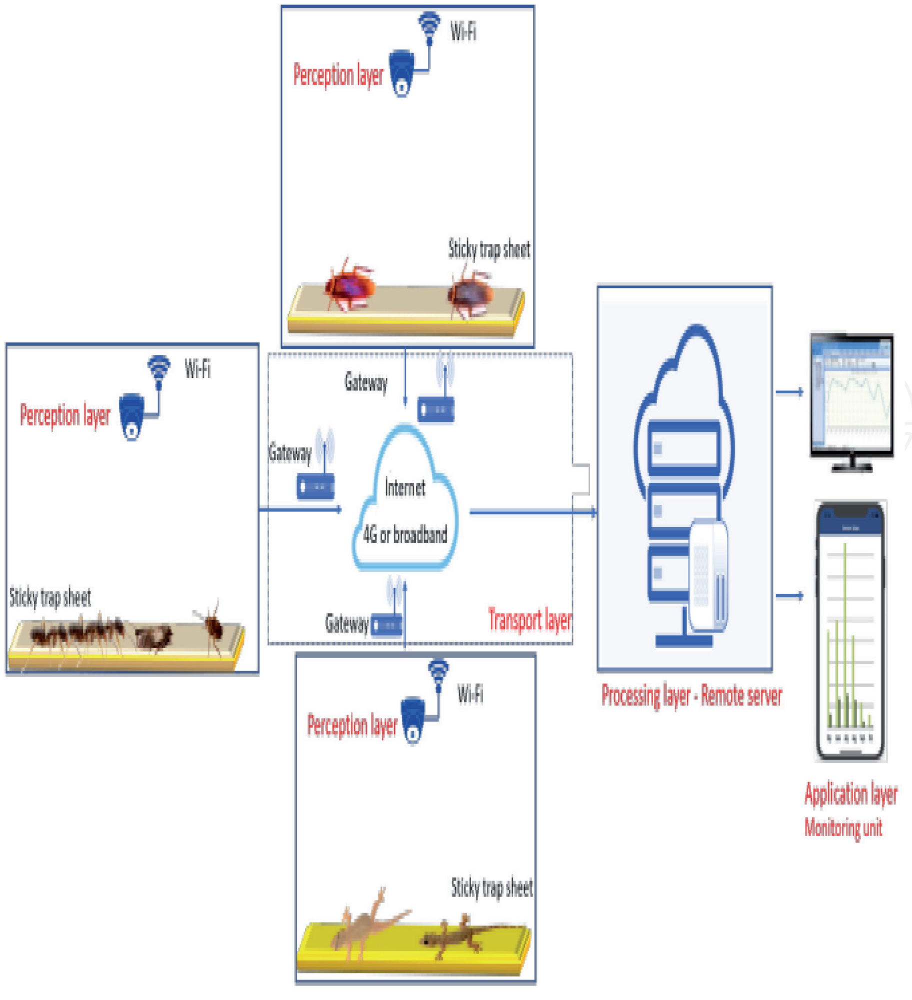


Figure 3.
System for remote trap control and insect detection based on IOT and DL.

the detection of intensely learning insects. According to other object recognition mechanisms such as SSD and Yolo, the accepted device provided optimal insect detection efficiency. The research has shown that 96 percent of insects identified with built-in environmental insects were obtained by the qualified model, 94 percent were identified with farmland insects, and 0.2 s were needed on average for processing the one image. This case study has demonstrated the automation of remote identification through IOT and a DL-based insect monitoring system using a qualified CNN framework and overcomes insect control systems failure.

7. Automated remote insect surveillance at a global scale and the Internet of Things

"Potamitis, I., Eliopoulos, P. and Rigakis, I" in 2017 [11] In many of our records, a large number of extreme insect plagues of agricultural and health importance were studied in a broad spatial scale as the principle of remote insect control. The trap is used to make the trap, the timeline, the GPS tag and where necessary, the inbound insect species from the wing beat safe to inject. Standard low-cost pest traps for certain insect species augment the insects. Both large crop insects are tracked in order to decide if a treatment strategy can be undertaken before a significant infestation takes place. Monitoring processes are based on specially designed mosquito traps. Conventional insect monitoring is used in the spectrum of such tracking. It takes physical labour, consumes money and also needs an expert to be accurate enough, often with the potential for raising human security concerns. It is limited on its own expenses.

These drawbacks decrease the amount of manual insect surveillance and thus its precision, which eventually contributes to considerable cultivation losses due to pest damage. You intend to monitor the existence, the stamping period, the detection of species and the population density of target plaguicides with 'supervision' to unmatched data extraction levels. Insect counts are wirelessly transmitted to the central supervisory agency, and predictive tools for the control of insect pests and environmental factors related to population growth are visualized and streamed through. The work illustrates how traps can be organized in networks that report collectively on local, state, world, continental and international data using the new Internet of Things technologies (IOT).

This research is undoubtedly cross-disciplinary, lies at the intersection of entomology, optoelectronic engineering and computer and crop-science and involves the production and introduction by many of the most important agricultural pests of low-cost low-energy technologies to minimize the amount of quantitative and qualitative crop failure. They claims that clever traps interacting through IOT will have a huge effect on the crops security decision-making process in real time and would undermine current manual practices directly from the field to a manually managed entity in the very near future. In this article three instances of Rhynchophorus ferrugineus are investigated: track the use of (a) picusan, (b) lindgren and (c) monitoring various stored grain beetle pests using sored grain pitfall trap for Rhynchophorus ferruginus (Olivier) (Coleoptera: curculionidae). There is a very detailed approach to the industry that delivers accuracy per cent on automated quantity when as opposed to the actual defined number of insects in each type of trap.

8. IoT monitoring system for early detection of agricultural pests and diseases

"Materne, N. and Inoue, M. in 2018" [12] examined the advancement in sensor technology has driven the technological revolution in agriculture. In these days, however the opportunity to use digital technologies relating to the Internet of Things (IOT) increase sharply; the growth of the roles system of farming continues in its early stages. The current threats of less preferred climate conditions thrive on the increased risk of cross-border plant pesticides and diseases that damage crops, as well as on the danger to the food security and on some major losses for the farmers, provided that agricultural sector is still suffering from climate changes. In this study, they merged Wireless Sensor Network (WSN) sensor devices to establish an agricultural field monitoring framework that simultaneously tracks eight primary environmental parameters that are known as highly interconnectioned to booming pests and plant diseases. The overall system configuration provided for real-time tracking and regular collection of the huge volume of data. This is why they have investigated the knowledge obtained using machine learning approaches using "KNN, Random Forest, Logistic Recovery and Linear Regression algorithms". The purpose of this article is to perform an experiment on the advantage of using the IOT systems in agricultural lands to gather and analyze data to determine a prediction model that could be used to help forecast the outbreaks of plantation diseases.

8.1 Inference

They suggested an IOT framework with functionalities for day-to-day tracking of farmland environmental parameters. They also developed a predictive model for the provision by applying machine learning algorithms to avoid the outbreaks of pest and diseases in planting. The study merged IOT and machine learning technologies to improve agriculture and agriculture to draw on new concepts and developments in technology in order to sustain, increase yields and increase agricultural efficiency. The work represents only eight sensed parameters; the number of sensors, like meteorological information, may be added for potential production purposes. In addition, it is important to enhance the work of cloud providers so long as the behaviour and features of each type of pest and disease are taken into account.

9. Research on insect pest image detection and recognition based on bio-inspired methods

"Deng, L., Wang, Y., Han, Z. and Yu, R" in 2018 [13] performed a study entitled "Research on insect pest image detection and recognition based on bio-inspired methods". In this study, methods inspired by human visual systems were suggested to easily identify and identify insect pests. SUN was used for the generation of saliency and area of interest maps and identification in pest images using a Natural Statistics Model (NGM) to inspire human visual focus. In order to exclude invariant characteristics, the bio- influenced Hierarchic Model and X (HMAX) model were used to reflect a plague presence. Scale Invariant Function Transform (SIFT) in the HMAX model was integrated to improve rotational changes invariance. In the meanwhile, Coarse non-negative encoding (NNSC) simulates clear cell replies. Furthermore an Invariant Texture Properties has been removed using the Local Pattern (LCP) algorithm. Finally, the extracted characteristics were provided for recognition by Support Vector Machines (SVM). Experimental studies have shown a gain from the proposed approach relative to the approaches "HMAX, Sparse Coding and Normal Input Memory (NIMBLE), which is similar to the Deep Convolution Network" (**Figure 4**).

9.1 Framework

See **Figure 5**.

9.2 Result

With an identification rate of 85.5%, the proposed approach obtained a successful outcome and could efficiently identify insect pests in diverse ecosystems. The suggested solution offered a new approach to the identification and recognition of insect pests.

"P. Tirelli, N.A. Borghese" [14] found that surveillance of the population of pesticides in the plant sector is currently a concern. At present, the device is based on dispersed images, which can be automatically collected and transmitted images of stuck areas to a remote station by means of a wireless sensor network. The station tests the density of the production of insects at various farm sites and alerts when the threshold of the insect is surpassed. The client nodes are spread in the fields that serve as monitoring stations. The main node co-ordinates the network and retrieves images from client nodes. During the four week monitoring cycle, the network periodically operates, and the viability is assessed, forecasts the population curve of the pest insects compared with everyday assessment.

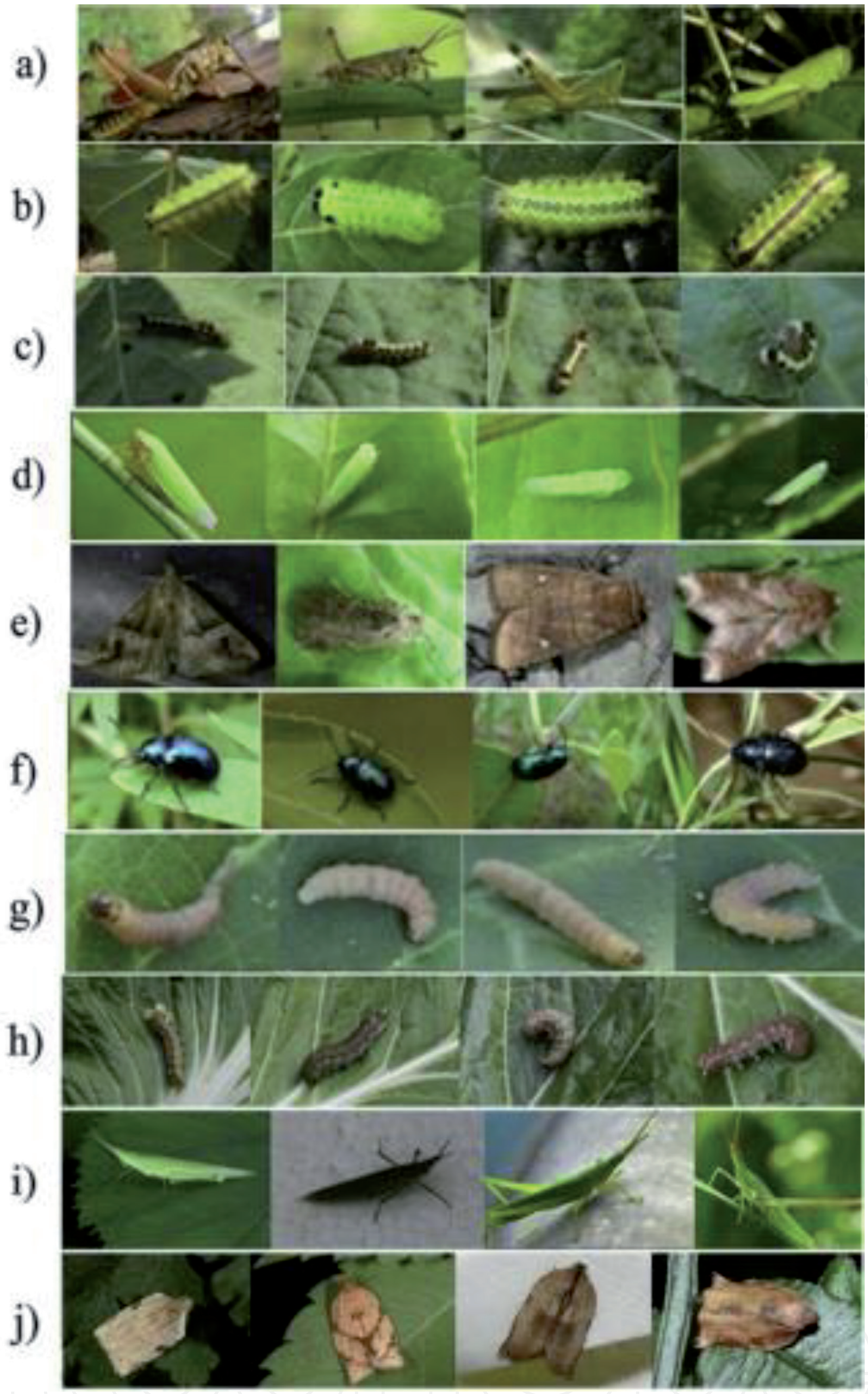


Figure 4.
Sample images taken in natural conditions. (a) Locusta migratoria, (b) Parasa lepida, (c) Gypsy moth larva, (d) Empoasca flavescens, (e) Spodoptera exigua, (f) Chrysochus chinensis, (g) Laspeyresia pomonella larva, (h) Spodoptera exigua larva, (i) Atractomorpha sinensis, (j) Laspeyresia pomonella.

10. Insect pest image detection and recognition based on bio-inspired methods

"Nanni, L., Maguolo, G. and Pancino, F" in 2020 [15] performed a study entitled "Insect pest image detection and recognition based on bio-inspired methods". Identification of insect pests is important for crop safety in many areas of the world. They introduce in this article an artificial classification based on the combination of saliency and neural networks. SALIENCY techniques are widespread image processing algorithms that identify the most important image pixels. In this paper you are using three different salience approaches as preprocessing of images and make three distinct images for each form of saliency. For each original image they generate new photographs to train various neural convolution networks, they create 3*3 = 9 new pictures (**Figure 6**).

10.1 Result

They evaluate each execution of each preprocessing/network pair as well as they examine the performance of their grouping. You assess your solution on the major IP102 and a tiny dataset. Its best ensembles achieve the maximum degree of

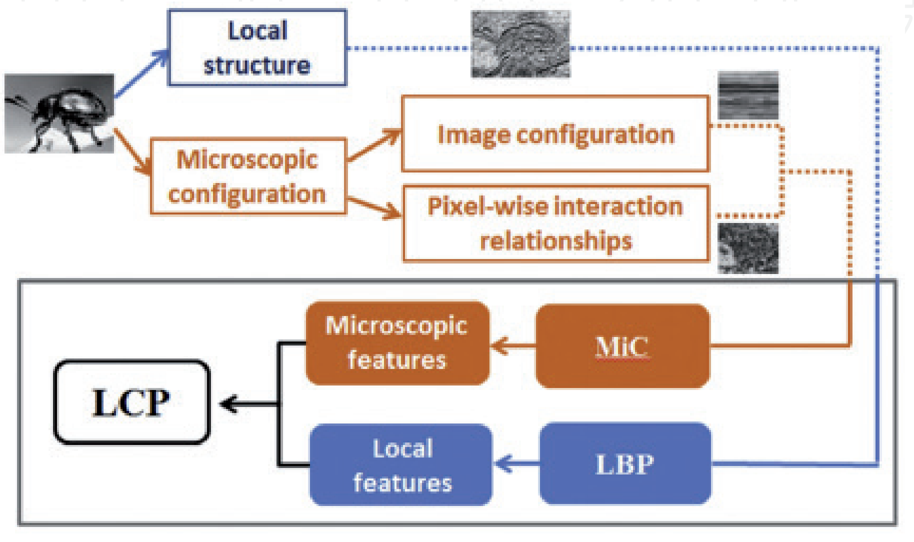


Figure 5.
Feature extraction framework of LCP.

Figure 6.
Image samples from IP102.

Species	Number of Samples
Locusta migratoria	72
Parasa lepida	59
Gypsy moth larva	40
Empoasca flavescens	41
Spodoptera exigua	68
Chrysocus chinensis	50
Laspeyresia pomonella larva	50
Spodoptera exigua larva	56
Atractomorpha sinensis	62
Laspeyresia pomonella	65

Table 1.
Composition of dataset.

technical precision, with both the smaller (92.43%) and the IP102 (61.93%), matching the efficiency of smaller human experts (**Table 1**).

11. Automatic detection and monitoring of insect pests-A review

Cardim et al. in 2020 [16] studied that certain insect pest species can be automatically identified and tracked. In order to develop integrated pesticide management (IPM) for precision agriculture, several systems were developed. For many essential pests, automatic detection traps were developed. This emerging methods and strategies are very promising to identify hostile and quarantine pests early on and to monitor them. The paper attempts to evaluate technological and scientific state-of-the-art sensor technologies in order to track and automatically identify insect pests (**Figure 7**).

"In the article the methods are discussed for the identification, the applications are introduced, as well as recent progress, comprising machine learning and the Internet of Things, infrared monitors for pests, audio sensors and classification through images".

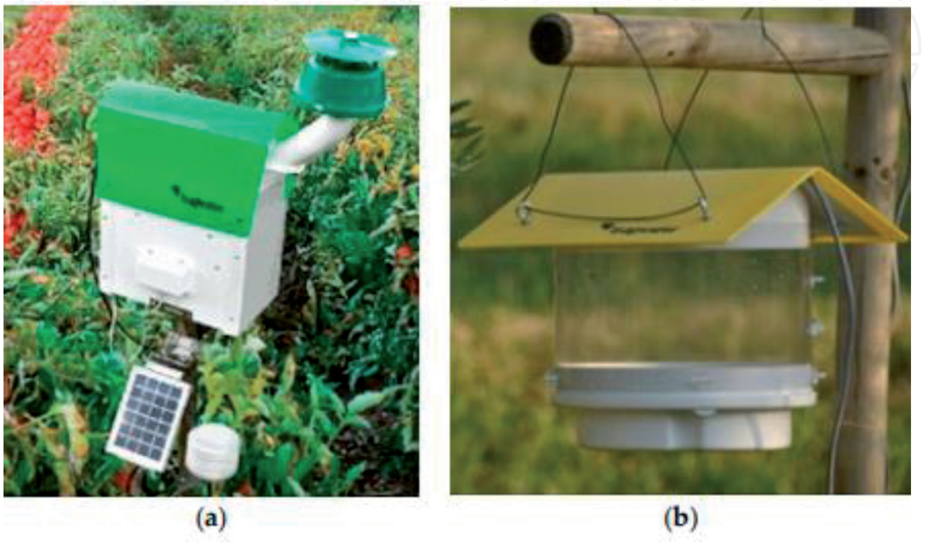


Figure 7.
Automatic trap for moth species tracking (a) and fruit flies (b) EFOS, Trapview, Slovenia.

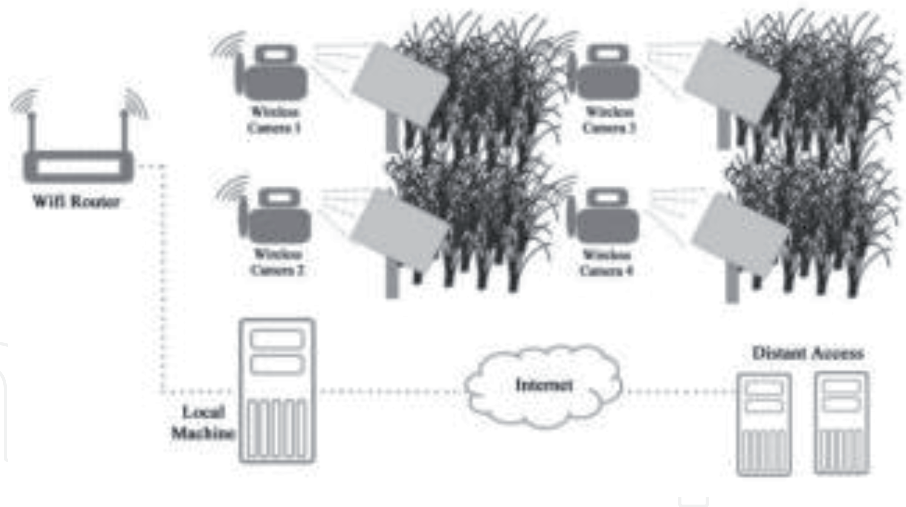


Figure 8.
Global architectural design.

12. Pest detection and extraction using image processing techniques

"Miranda, J.L., Gerardo, B.D. and Tanguilig III, B.T" in 2014 [17] performed a study entitled "Pest Detection and Extraction Using Image Processing Techniques". Detecting pests in paddy fields is an important problem in agriculture, so effective steps to tackle infestation and reduce the use of pesticides should be created. Imaging techniques are commonly used in agriculture to offer optimum protection for crops, thereby leading to greater crop management and production. The surveillance of pests depends on workers but electronic control is developing to mitigate the efforts and mistakes of human beings (**Figure 8**).

This study broadens the application of various imaging procedures for the identification and extraction of insect pests through the establishment of an integrated paddy field detection and extraction device for estimating plague densities. Experimental review shows the proposed approach to detect pests in rice fields to provide a quick, reliable and simple solution.

13. Insect detection and classification based on an improved convolutional neural network

"Xia, D., Chen, P., Wang, B., Zhang, J. and Xie, C" in 2018 [18], to solve the issue of multi-classification of insects in the field, evaluated a prototype of a neural network. The model will use the benefits of the neural network such that multifaceted insect traits are completely extracted. In the regional proposal process, rather than a standard, selection technique, the regional proposal network is implemented in order to produce fewer proposal windows, which are particularly valuable for improving the accuracy of forecasts and accelerating calculations. Experimental studies indicate that the proposed approach is better than the current conventional insect classification algorithms and is higher reliably (**Figure 9**).

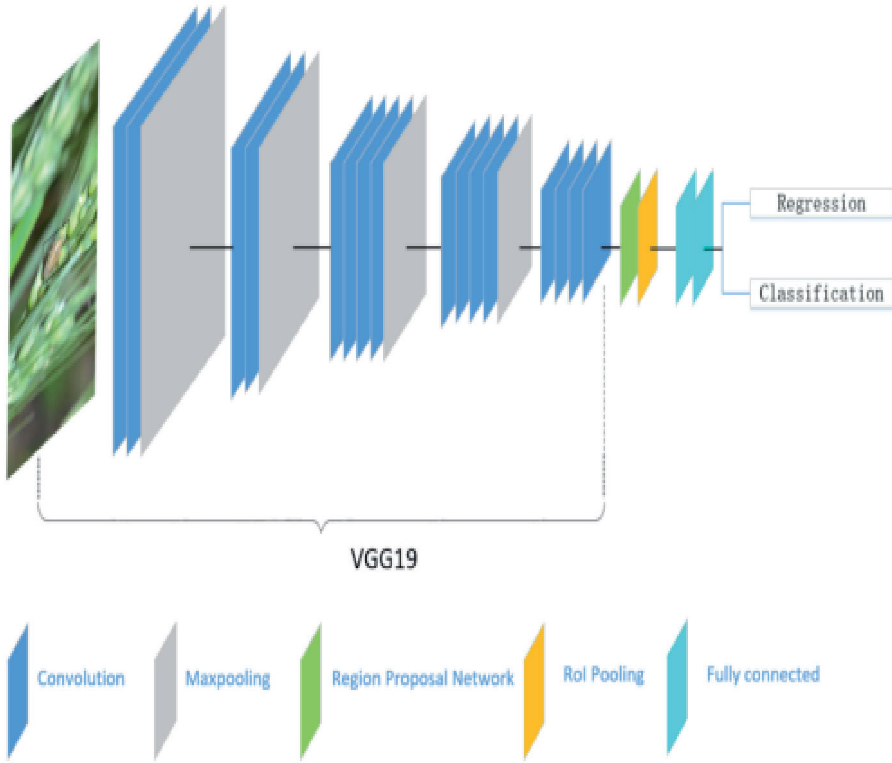


Figure 9.
The proposed detection model using VGG19 having schematic structure.

14. Image processing techniques for insect shape detection in field crops

Thenmozhi, K. and Reddy, U.S., 2017 [19] performed a study entitiled "Image Processing Techniques for Insect Shape Detection in Field Crops". In farming, the identification of crop pest is considered one of the farmers' challenges. An integrated machine vision and picture analysis device for insect detection enables improved identification of early-stage plant insects with a lower time and greater precision that will improve crop yield. Digital image processing methods were used in the current work to detect the insect forms in the sugar cane crop with photographs of crop insects for pre-processing, segmentation and extraction. Sobel edge detecting is introduced to distal media. In the extraction of the feature nine geometrical features can be defined in the structure of the insect. This recognition of insect shape performs well and achieves high precision for round (circular), oval, triangular and rectangular sugarcane field insects. The study was carried out using the Image Processing Toolbox in MATLAB 2015b (**Figure 10**).

15. IOT-based drone for improvement of crop quality in agricultural field

"Saha, A.K., Saha, J., Ray, R., Sircar, S., Dutta, S., Chattopadhyay, S.P. and Saha, H.N.", in 2018 [20] researched that the need for increased population and agriculture is becoming increasingly frequent with unmanned air vehicles. Drones with suitable cameras, sensors and modules can help to make agriculture simpler, more effective and more accurate. The solutions proposed relating to these drones will help to expand the potential of further improvement if combined with various machine learning and the Internet of Things concepts. The relevant work in

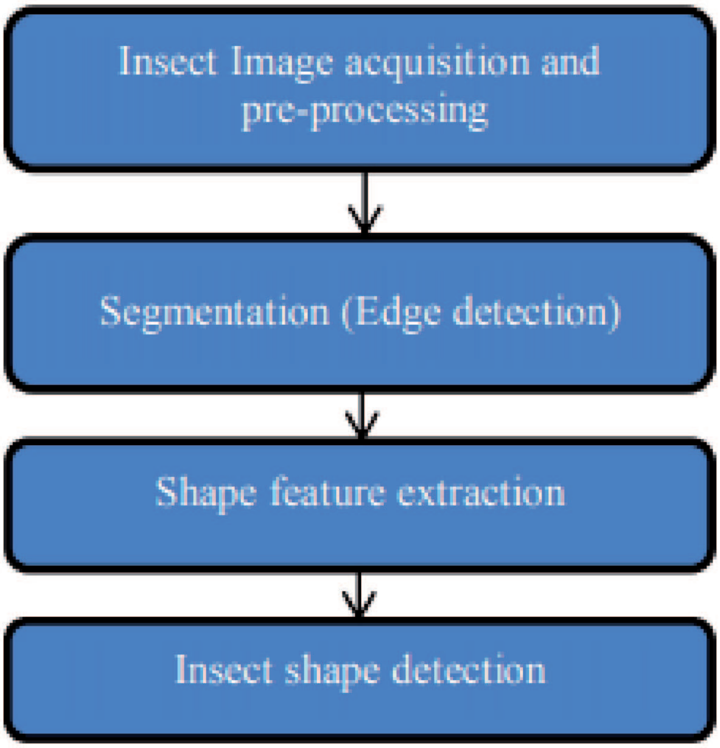


Figure 10.
Flow chart for detecting crop insects form.

this field and the solutions which could be incorporated into the drone using the Raspberry Pi 3 B module were highlighted in this paper.

15.1 Inference

They conclude that drones or UAVs would be of tremendous help in agriculture as they are crucial at the start of a crop cycle with an increasing population. Not only will it minimize time, but it will also generate better cultivation based on analyzed data. The systematic monitoring will make crop management more effective. With the next developments, with less electricity usage, the output rate will increase rapidly. Drones are used in the planting of plant nutrients in the soil not just in soil and field analysis but also in planting seeds. The use of drones could also eliminate the crop monitoring obstacles that had previously been faced. Drones are not stopped here because they are integrated into hyper-spectral, thermal, or multi-spectral sensors and drones may detect which parts of the soil are dry. Furthermore, drones will also be used for scanning with near-infrared and visible light in order to determine crop health. Drones therefore act as an ideal aeroplane for the accuracy data collection.

16. In intelligent agriculture, a vision-based flying insects counting and recognition system

"Zhong, Y., Gao, J., Lei, Q. and Zhou, Y" in 2018 [21] studied that a Design and implementation of flying insects counting and classification system based on vision. The system is built as follows: firstly, in the surveillance area a yellow sticky trap is installed to catch flying insects, and the camera is mounted to capture images on the spot. Then the process of detection and

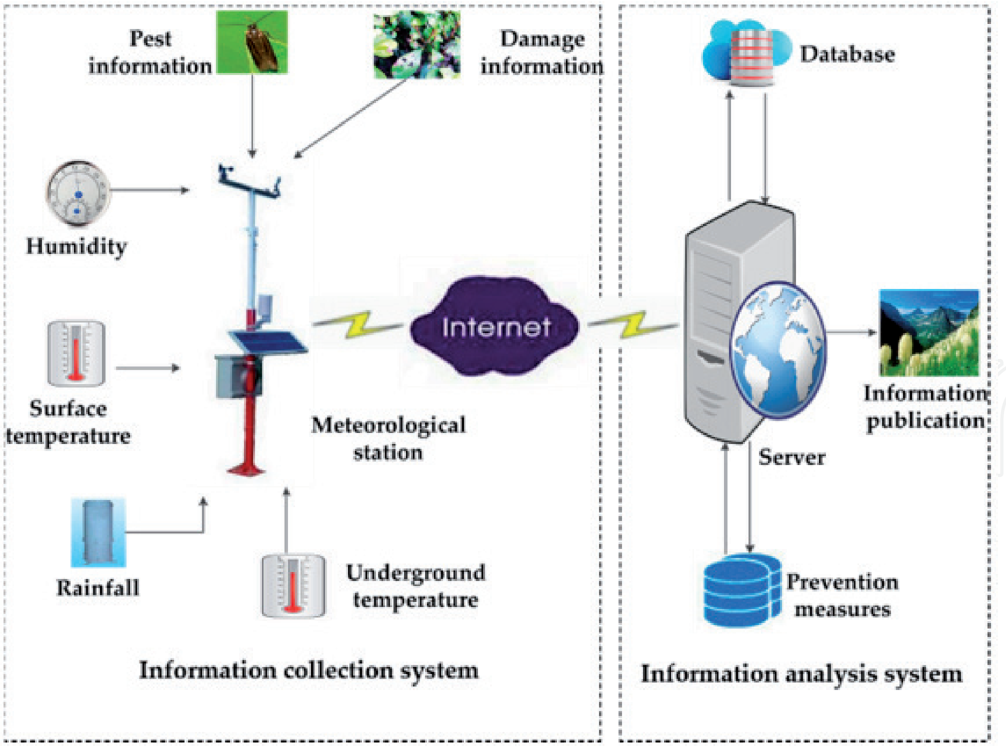


Figure 11.
The components of agricultural monitoring service platform.

coarse counting on the basis of the detection and classification of objects by You Only Look Once (YOLO), using global functionalities is designed. Six insect species including fly, fruit fly, bee, mouth, moth, and chaff have been chosen to evaluate the efficacy of the system. The Raspberry PI insect counting and recognition system is implemented. The results of the tests show promising performance compared to conventional methods. On Raspberry PI the average counting accuracy is 92.5% and average classification accuracy is 90.18 percent. The system proposed is simple to use and provides fast and reliable identification data; it can therefore be applied for smart farming applications (**Figure 11**).

17. Pest24: a large-scale very small object data set of agricultural pests for multi-target detection

"Wang, Q.J., Zhang, S.Y., Dong, S.F., Zhang, G.C., Yang, J., Li, R. and Wang, H.Q.", in 2020 [22] studied that Accurate agriculture poses new challenges for on-site pest monitoring in real time based on the new AI technology generation. This paper establishes a large-scale standardised data collection of agricultural pests, called Pest24 to provide a large data resource for the training of profound learning models for the detection of pests. In particular, the current data set consists of 25.378 images from our automatic plague trap and imaging system annotated with pests. 24 typical pest categories, which are mainly responsible for destroying field crops in China every year, are involved in Pest24. They use various cutting-edge methods of detection, such as RCNN Faster, SSD, YOLOv3 and Cascade R-CNN, to detect pests in the data set and to generate promising findings for in real time field pests monitoring. In the exploration of factors that impact on pest detection accuracy, the data set are analysed into a range of aspects and the three factors that mainly affect the performance of the pest detection, i.e. relative scale, number of instances and adhesion of objects. Overall, Pest24 usually features large-scale multi-pest image data, small object sizes, high object resemblance and dense pesticide distribution.

Numbers of images and instances of each pest category in Pest24

Index	Pest name	Images	Instances
1	Rice planthopper	316	1511
2	Rice Leaf Roller	944	1240
3	Chilo suppressalis	454	1285
5	Armyworm	3828	8880
6	Bollworm	9049	28,014
7	Meadow borer	5526	16,516
8	Athetis lepigone	7520	30,339
10	Spodoptera litura	1588	1951
11	Spodoptera exigua	3614	7263
12	Stem borer	1357	1804
13	Little Gecko	2503	4279
14	Plutella xylostella	531	953
15	Spodoptera cabbage	1707	2302
16	Scotogramma trifolii Rottemberg	3223	4679
24	Yellow tiger	1388	1686
25	Land tiger	369	475
28	Eight-character tiger	154	168
29	Holotrichia oblita	90	108
31	Holotrichia parallela	3111	11,675
32	Anomala corpulenta	5228	53,347
34	Gryllotalpa orientalis	3629	6528
35	Nematode trench	118	167
36	Agriotes fuscicollis Miwa	1814	6484
37	Melahotus	239	768

18. Internet of things for smart agriculture: technologies, practices and future direction

"Ray, P.P" in 2017 [23] studied that innovative science in agriculture has taken a new path with the introduction of the Internet of Things (IoT). IoT must be widely experimented to be applied in different agricultural applications at the emerging stage. In this paper, they review many possible IoT applications and the particular questions and challenges relating to improved agricultural IoT deployment. The devices and wireless communication technologies linked to IoT are evaluated extensively to meet the unique requirements of agricultural and agriculture applications. Research has been carried out on those IoT sensor systems which deliver intelligent and intelligent services to smart farming. Various case studies are provided to analyse the IoT-based solutions implemented according to their implementation parameters by different organisations and individuals and categories. The related issues in these solutions are also illustrated, while defining progress factors and potential IoT work maps.

19. Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks

"Jiang, P., Chen, Y., Liu, B., He, D. and Liang, C.", in 2019 [24] examined that The Alternarial leaf spot, the brown spot, the mosaic, the grey spot and Rust are five common types of apple leaf conditions. However, the detection of apple diseases in current research is not reliable and easy to ensure that the apple industry is growing healthy. This paper provides a deeper learning approach aimed at the detection in real time of enhanced neural networks (CNNs). This article is the first use of the Apple Leaf Disease Data Set (ALDD) data augmentation and annotation technology which consists of laboratory pictures and complex images in real life. Based on this proposal a new apple leaf detection model that uses deep-CNN is proposed by integrating the GoogLeNet Inception and Rainbow concatenation system. Finally, five common Aple Leaf diseases using a dataset of 26,377 image of diseased Apple leaves are trained by the proposed INAR-SSD (SSD with Initiation and Reinbow Concatenation Module) model. The experimental results show that a high rate of 23.13 FPS 78.80 per cent of mAP is used for the INAR-SSD model in the ALDD. The results show that an early diagnosis approach to apple leaf disease has been established by the new INAR-SSD model, which detects these diseases in real time with greater precision and rapidity than before.

20. A review of advanced machine learning methods for the detection of biotic stress in precision crop protection

"Behmann, J., Mahlein, A.K., Rumpf, T., Römer, C. and Plümer, L.", 2015 [25] studied that the early and accurate biotic stress detection is needed for effective crop protection. Important results have been obtained in recent years on the early identification of weeds, herbal diseases and insect pesticides in crops. The findings relate both to the development of optical sensors that are non-invasive high resolution and methods for data processing that can manage signals from the resolution, size and complexity of these sensors. Several machinery learning methods, such as vector machines and neural classification (supervised learning) networks, have been used for precision agriculture (unsupervised learning). These methods can measure both linear and non-linear models and require few statistics. Early detection of plant diseases by the use of supervised or unattended learning methods, and weed detection by the use of formal descriptors, is effective applications. A brief introduction to machine learning that an analysis of its potential to protect precision crops and an overview of instructive examples from several areas.

21. A novel cloud computing based smart farming system for early detection of borer insects in tomatoes

"Rupanagudi, S.R., Ranjani, B.S., Nagaraj, P., Bhat, V.G. and Thippeswamy, G.", 2015 [26], examined that farmers suffer tremendous losses every year as a result of plague infestations and that affects their livelihoods. In this article we will address a new solution to this problem by continuous video processing, cloud computing and robotics monitoring of crops. The paper describes the methods for pesticide detection in one of the most popular tomato fruits in the world. "An insight into how in this project even the notion of the Internet of Things can be conceptualized".

22. Wireless sensor network based automated irrigation and crop field monitoring system

"Nisha, G. and Megala, J." in 2014 [27] studied that wireless Sensor Automatic irrigation system based on a network to maximise agricultural water use. A network of wireless sensors and temperature sensors distributed with solid moisture in the field is the unit. The Zigbee Protocol is used for the management of sensor information and for the control by means of an algorithm with sensor threshold values to a microcontroller irrigation system. A solar panel and a mobile Internet guide are used for the unit. A wireless camera in the field with image processing techniques monitors the area of the disease. The device is low costs and benefits power independence in water-limited geographically isolated areas.

23. A review of recent sensing technologies to detect invertebrates on crops

This study is performed by "Liu, H., Lee, S.H. and Chahl, J.S." in 2017 [28]. In order to detect pesticides more effectively, researchers have developed different technologies. The existing sensing technology, however, is still limited to effective field applications. This review paper is designed for exploring relative technologies and finding a method for the sensing and detection of crop invertebrates such as butterflies, sauté, snails and slugs. Two main areas for the identification and detection of invertebrates were identified: acoustic sensing and vision system (MVS). The acoustic sensor is suitable for detection and identification of soil pests, stored grains and wood, whereas acoustic sensors must usually be fitted to inspection samples causing difficulties for efficient inland applications. MVS has the potential to detect and identify invertebrates in crops in a more efficient and flexible manner. The invertebrate identification technologies have recently been studied in detail with MVS, but the detection of infertile fields is relatively weak. This study summarizes current research deficiencies and discusses possible research directions.

24. IOT based strawberry disease prediction system for smart farming

This study performed by "Kim, S., Lee, M. and Shin, C.", 2018 [29]. In this study cloud-based technology was built to manage information

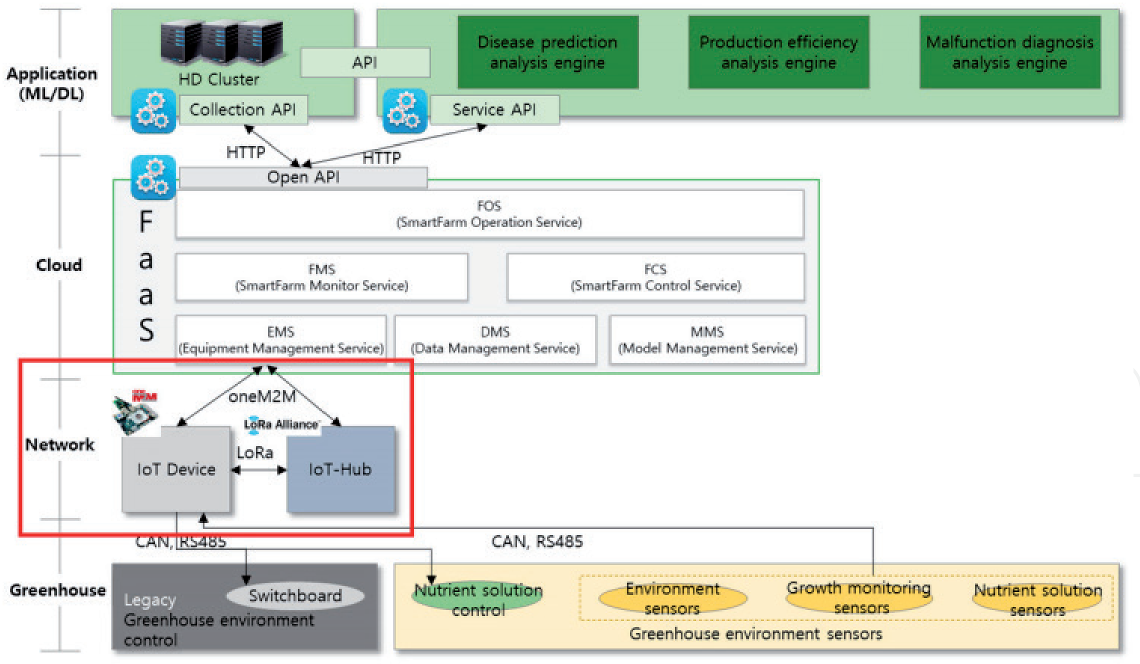


Figure 12.
The Internet of Things (IoT)-Hub is used in this network model. FaaS: Farm as a Service; api: application programming interface; LoRa: Long Range.

gathering, analysis and prediction in a shared framework. The proposed integrated system Farm as a Service (FaaS) assists high-level applications support through farms activity and observing and associated equipment, data and models management. Such a system records, connects and manages IoT devices and analyses information about the environment and growth. Furthermore, this study consisted of the IoT-Hub network model. Effective data transmission for every IoT device and communication for non-standard items is supported by this model and is highly reliable in communication in most difficult circumstances. IoT-Hub thus make sure the steadiness of agricultural environment-specific technology. Specific systems are implemented at different levels in an integrated agricultural specialist FaaS system. A strawberry infection prediction system has been designed and analysed, and this system has been compared with other infection models (**Figure 12**).

25. A multispectral 3-D vision system for invertebrate detection on crops

"Liu, H., Lee, S.H. and Chahl, J.S.", in 2017 [30] examined that the benefits of multi-spectral and hyperspectral vision systems have been demonstrated to detect such invertebrate pests efficiently and accurately. However, the identification of certain camouflaged pests on host plants has been restricted by only use of spectral details. Three-dimensional (3-D) representations are widely studied for multifaceted object recognition and scene perception in many fields. However, because of a lack of appropriate data collection methods and efficient algorithms, 3-D technologies have no invertebrate detection applications. "They created a multi-spectral vision system that enables the development of denser plant and pest clouds with multi-spectral images of UV, blue, green, red, and near-infraround". An algorithm was designed to differentiate wide leafs from relatively large pests in nuclei at the noisy stage. The vision can be used as an automated pesticide sprayer sensor, or to support advanced pesticide monitoring systems.

26. Design of intelligent agriculture management information system based on IoT

Yan-e, D., in 2011 [31] studied that Agricultural IT (AIT) has been the most productive means and instruments for improving agriculture productivity and making maximum use of agricultural resources and has been widely used on all aspects of agricultural. The use of information technology from agricultural production as an important sub technology of AIT measures the level of agricultural computerization and the efficacy of decision-making on farm production. In this paper the methods for MIS intelligent agriculture design and architecture is discussed based on the implementation of the concept of management of agricultural knowledge and analysis of agricultural data characteristics (**Figure 13**).

Early detection of Phytophthora spp using IOT and machine learning architecture

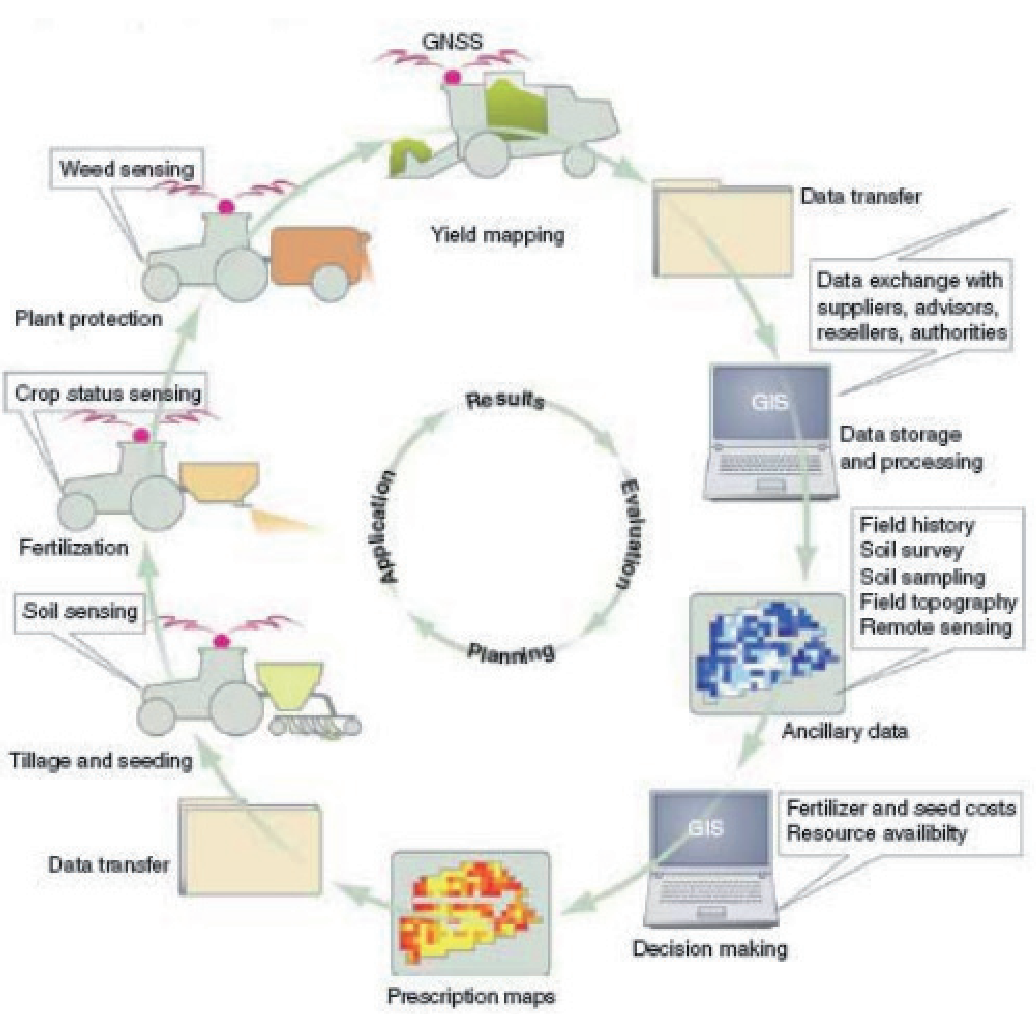


Figure 13.
Investigation in Crop Production of Agriculture Information Management Flow.

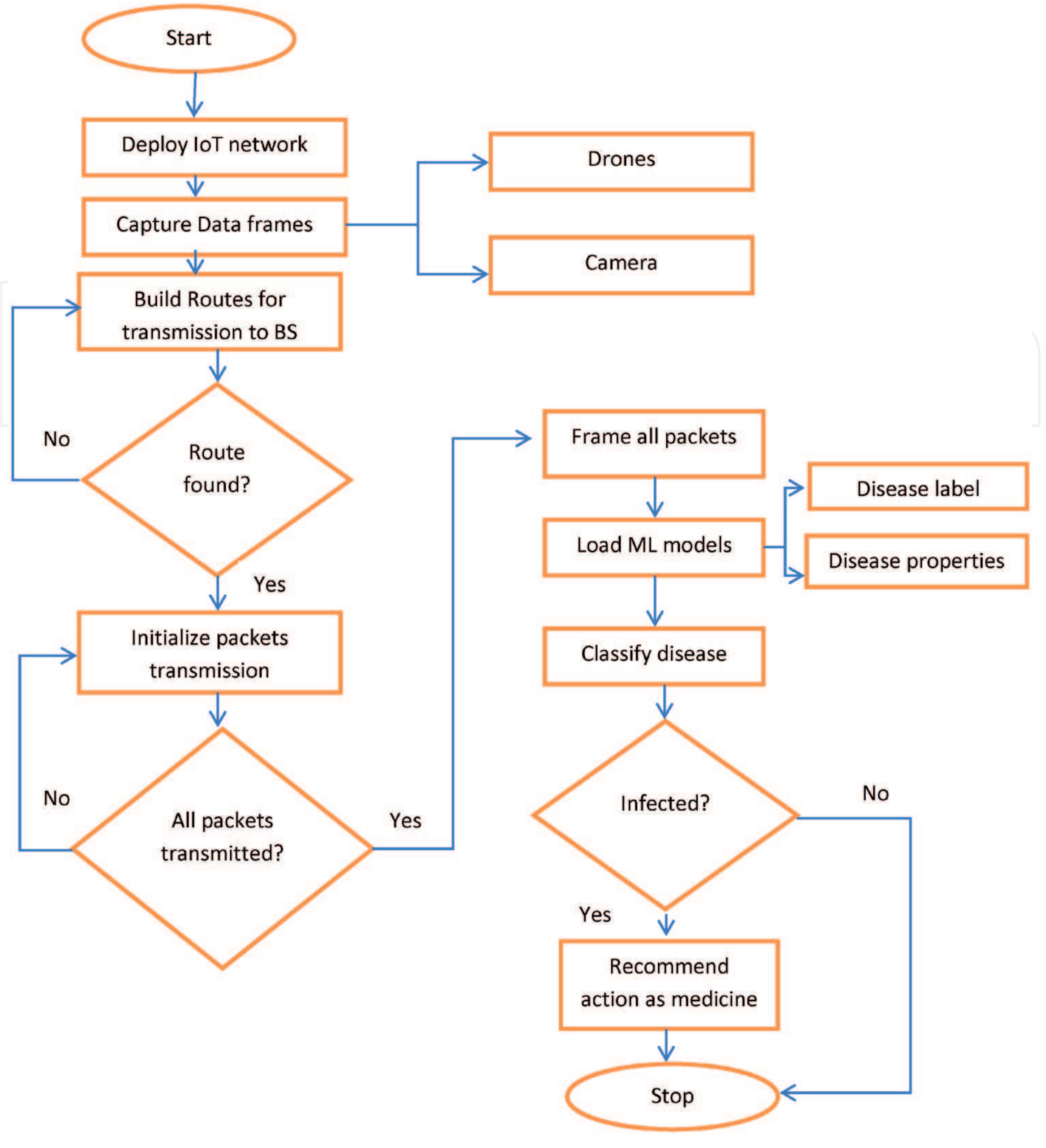
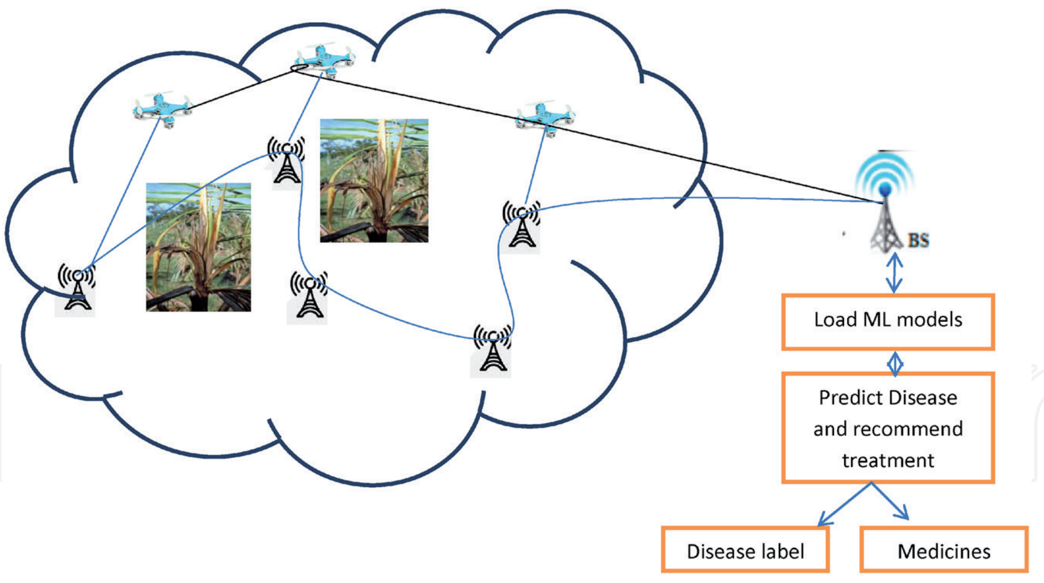


Figure 14.
IoT architecture for Phytophthora spp. detection.

See **Figure 14**.

The above flow is a combination of IoT networks and machine learning models to predict and recommend the Phytophthora spp. from crops. Here the initial steps to form the architecture are network deployment and configure with initial node parameters. This phase have various sub-modules where the network nodes placed on field, sensing areas formations etc. Once the nodes deployed in the field, network node regularly sense data in the form of captured frames and send it to the base station. The base station having various detection and recommendation models to analyse the data frames.

All transmitted frames from the field to the base station formed in the actual format and load in the ML models. ML models in the network base station are already trained models for various crops disease properties and labels. These are able to classify the captured properties and recommend the disease and various possible treatments. After classification, if the model predicts infection then it suggests the medicines and track for future updates.



S. No	Author name	Paper description	Publication year
1	Patil and Kale	In all wireless settings IOT evolves easily and broadly. Within this article, the introduction of sensor systems and wireless communications to the implementation of IOT technologies and the systems in current agriculture are analyzed and evaluated, in conjunction with the current conditions of the agricultural system Remote Management System (RMS) is proposed to incorporate an approach with internet and cellular communications.	2016
2	Mercedes, S., Bo, G. And Yuxia, H	Real-time detection device for field plagues of second generation has been developed. It performed all automation, from the capture, dispersion, transport, collecting of images, picture analysis to pest recognition. It reduced the duration of detecting pests and increased the degree of automation.	2011
3	Shi, Y., Z., Wang, X. Shi, Y. And Zhang, S	An IOT-based disease and insect pest control system consisting of three levels and three systems were proposed. A new way of accessing agricultural information on the farm is provided by the system.	2015
4	Sreekantha, D.K. and Kavya, A.M	A smart telephone enables farmers, at every time and anywhere in the world to keep up to date with the current conditions of their agriculture. IOT technology can cut costs and increase conventional agriculture's productivity.	2017
5	Ramalingam, B., Mohan, R.E., Pookkuttath, S., Gómez, B.F., Sairam Borusu, C.S.C., Wee Teng, T. and Tamilselvam, Y.K	Latest advances in Internet of Things (IOT) and Artificial Intelligence (AI) can automate a range of maintenance operations, improving efficiency and safety dramatically. This document includes the implementation of Deep Learning (DL) and IOT prototype for the tracking of insect traps in real-time and the identification of insects.	2020
6	Potamitis, I., Eliopoulos, P. and Rigakis, I	Conventional insect monitoring is used in the spectrum of such tracking. It takes physical labour, consumes money and also needs an expert to be accurate enough, often with the potential for raising human security concerns. It is limited on its own expenses.	2017

S. No	Author name	Paper description	Publication year
7	Materne, N. and Inoue, M.	IOT framework with functionalities for day-to-day tracking of farmland environmental parameters. They also developed a predictive model for the provision by applying machine learning algorithms to avoid the outbreaks of pest and diseases in planting.	2018
8	Deng, L., Wang, Y., Han, Z. and Yu, R	To exclude invariant characteristics, the bio-influenced Hierarchic Model and X (HMAX) model were used to reflect a plague presence. Scale Invariant Function Transform (SIFT) in the HMAX model was integrated to improve rotational changes invariance. In the meanwhile, Coarse non-negative encoding (NNSC) simulates clear cell replies. Furthermore an Invariant Texture Properties has been removed using the Local Pattern (LCP) algorithm.	2018
9	P. Tirelli, N.A. Borghese	The device is based on dispersed images, which can be automatically collected and transmitted images of stuck areas to a remote station by means of a wireless sensor network. The station tests the density of the production of insects at various farm sites and alerts when the threshold of the insect is surpassed.	2011
10	Nanni, L., Maguolo, G. and Pancino, F	SALIENCY techniques are widespread image processing algorithms that identify the most important image pixels. In this paper you are using three different salience approaches as an image preprocessing and create three different images for each form of saliency.	2020
11	Cardim et al	For many essential pests, automatic detection traps were developed. This emerging methods and strategies are very promising to identify hostile and quarantine pests early on and to monitor them.	2020
12	Miranda, J.L., Gerardo, B.D. and Tanguilig III, B.T	Imaging techniques are commonly used in agriculture to offer optimum protection for crops, thereby leading to greater crop management and production. The surveillance of pests depends on workers but electronic control is developing to mitigate the efforts and mistakes of human beings.	2014
13	Xia, D., Chen, P., Wang, B., Zhang, J. and Xie, C	Experimental studies indicate that the proposed approach is better than the current conventional insect classification algorithms and is higher reliably.	2018
14	Thenmozhi, K. and Reddy, U.S.	An integrated machine vision and picture analysis device for insect detection enables improved identification of early-stage plant insects with a lower time and greater precision that will improve crop yield. Digital image processing methods were used in the current work to detect the insect forms in the sugar cane crop with photographs of crop insects for pre-processing, segmentation and extraction.	2017
15	Saha, A.K., Saha, J., Ray, R., Sircar, S., Dutta, S., Chattopadhyay, S.P. and Saha, H.N.	Drones with suitable cameras, sensors and modules can help to make agriculture simpler, more effective and more accurate. The solutions proposed relating to these drones will help to expand the potential of further improvement if combined with various machine learning and the Internet of Things concepts.	2018

S. No	Author name	Paper description	Publication year
16	Zhong, Y., Gao, J., Lei, Q. and Zhou, Y	The detection and coarse counting method on the basis of the detection and classification of objects by You Only Look Once (YOLO), using global functionalities is designed. Six insect species including fly, fruit fly, bee, mouth, moth, and chaff have been chosen to evaluate the efficacy of the system.	2018
17	Wang, Q.J., Zhang, S.Y., Dong, S.F., Zhang, G.C., Yang, J., Li, R. and Wang, H.Q	24 typical pest categories, which are mainly responsible for destroying field crops in China every year, are involved in Pest24. They use various cutting-edge methods of detection, such as RCNN Faster, SSD, YOLOv3 and Cascade R-CNN, to detect pests in the data set and to generate promising findings for in real time field pests monitoring.	2020
18	Ray, P.P	The devices and wireless communication technologies linked to IoT are evaluated extensively to meet the unique requirements of agricultural and agriculture applications. Research has been carried out on those IoT sensor systems which deliver intelligent and intelligent services to smart farming. Various case studies are provided to analyse the IoT-based solutions implemented according to their implementation parameters by different organisations and individuals and categories.	2017
19	Jiang, P., Chen, Y., Liu, B., He, D. and Liang, C.	This article is the first use of the Apple Leaf Disease Data Set (ALDD) data augmentation and annotation technology which consists of laboratory pictures and complex images in real life. Based on this proposal a new apple leaf detection model that uses deep-CNN is proposed by integrating the GoogLeNet Inception and Rainbow concatenation system.	2019
20	Behmann, J., Mahlein, A.K., Rumpf, T., Römer, C. and Plümer, L.	The findings relate both to the development of optical sensors that are non-invasive high resolution and methods for data processing that can manage signals from the resolution, size and complexity of these sensors. Several machinery learning methods, such as vector machines and neural classification (supervised learning) networks, have been used for precision agriculture (unsupervised learning).	2015
21	Rupanagudi, S.R., Ranjani, B.S., Nagaraj, P., Bhat, V.G. and Thippeswamy, G	The paper describes the methods for pesticide detection in one of the most popular tomato fruits in the world. "An insight into how in this project even the notion of the Internet of Things can be conceptualized".	2015
22	Nisha, G. and Megala, J.	A network of wireless sensors and temperature sensors distributed with solid moisture in the field is the unit. The Zigbee Protocol is used for the management of sensor information and for the control by means of an algorithm with sensor threshold values to a microcontroller irrigation system.	2014
23	Liu, H., Lee, S.H. and Chahl, J.S.	This paper is designed for exploring relative technologies and finding a method for the sensing and detection of crop invertebrates such as butterflies, sauté, snails and slugs. Two main areas for the identification and detection of invertebrates were identified: acoustic sensing and vision system (MVS).	2017

S. No	Author name	Paper description	Publication year
24	Kim, S., Lee, M. and Shin, C.	Cloud-based technology was built to manage information gathering, analysis and prediction in a shared framework. The proposed integrated system Farm as a Service (FaaS) assists high-level applications assistance through farms activity and observing the associated equipment, data and models management.	2018
25	Liu, H., Lee, S.H. and Chahl, J.S.	"They created a multi-spectral vision system that enables the development of denser plant and pest clouds with multi-spectral images of UV, blue, green, red, and near-infraround". An algorithm was designed to differentiate wide leafs from relatively large pests in nuclei at the noisy stage.	2017
26	Yan-e, D.	In this paper the methods for MIS intelligent agriculture design and architecture is discussed based on the implementation of the concept of management of agricultural knowledge and analysis of agricultural data characteristics.	2011

27. Conclusion

A literature review on IoT devices to identify and track insects in crop fields is discussed in this article. Each solution has been seen to have its possibilities and limitations. The species of pests must be increased and the identification must be improved. Detailed knowledge on the real-time and historical context is required to ensure effective control and allocation of capital. The Internet of Things allowed the rapid and efficient tracking of agricultural crops so as to increase the crop production and hence the farmer's revenues. In order to gather information on crop conditions and environmental changes, the wireless sensors network and sensors of various kinds were used.

This information is transmitted to the equipment network which initiates corrective action. For remote insect control and automatic insect identification, IoT and deep learning technologies are used. The Faster RCNN ResNet IoT Target Recognition Platform can be used to automatically identify the insect type with a four-layer IOT for remote trap insect monitoring.

Author details

Pooja Vajpayee[1*] and Kuldeep Kr. Yogi[2]

1 Department of Computer Science and Engineering, RKGIT, Ghaziabad, India

2 Department of Computer Science and Engineering, Banasthali Vidyapith, Jaipur, India

*Address all correspondence to: poojafcs@rkgit.edu.in

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