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Artificial intelligence (AI) and pesticides for pest control

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Abstract
The increase in global food demand has led to the development of pest control strategies, and pesticides have been widely used for pest control. However, the overuse of pesticides has caused environmental pollution, pesticide resistance, and negative impacts on human health. Integrated Pest Management (IPM) represents a more sustainable approach, but its implementation is often hampered by a lack of trained personnel and high costs. The application of artificial intelligence (AI) has the potential to transform IPM practices by improving pest management and reducing reliance on pesticides. This study investigates the potential of AI, particularly in the analysis of data from various sources, including imaging, acoustic sensors, and weather data. AI systems have the capacity to identify pests, predict diseases, and suggest management strategies, thus reducing reliance on pesticides. Integration of AI into IPM can address the shortage of professional personnel and the high cost of traditional IPM methods. This new approach has the potential to transform the pesticide industry and make food production more sustainable and environmentally friendly.

Keywords: Artificial intelligence, integrated pest management, pesticides, pest control, sustainable agriculture

Introduction

The term "pest" is used to describe diseases that affect human resources or threaten human health. These can include insects, mites, ticks, nematodes, mollusks, vertebrates, microorganisms, and plants. However, labeling them as pests simply because they compete with humans is not environmentally friendly. This is affected by particle density. Pest control can be used to deter pests. Accurate identification of pests is crucial for pest control. Bacteria considered pests can disrupt ecosystems and cause new pest problems. Understanding the feeding habits of pests and their relationships with natural enemies is important. The impact of major pests on resource yield is significant if appropriate pest management measures are not implemented. Sometimes, pests that cause damage are different from those that have the potential to become pests when changes are made. Migratory diseases often devastate crops and cause serious damage. It is important to remember that insects can be harmless and beneficial to the ecosystem. This includes entomopathogens and the use of selective insecticides, Insect pheromones, genetic manipulation, and computer modeling are used to determine what causes disease. Implementing integrated management systems requires collaboration among many groups, including agricultural engineers, ecosystem management experts, and pest experts. Use IPM strategies when necessary, as they require personnel and resources. The aim is to maintain ecosystem balance and assess financial losses before taking action. IPM considers the entire ecosystem, including human factors, and involves a deep understanding of plant biology, identification of key pests, and assessment of environmental factors that may affect pest control. This approach anticipates the unexpected, reflects the diversity of ecosystems, and is effective. Adhering to IPM principles enables managers to use resources effectively, efficiently, and ethically. It has the potential to transform agriculture and close the digital divide in rural communities, thus contributing to the Fourth Industrial Revolution. There are many benefits to using smart technology in agriculture; these include the ability to manage and farm more efficiently. It assists in water management, crop production, pest management, nutrient management, and crop rotation strategies. By analyzing data on conditions such as rainfall, temperature, wind speed, and solar radiation, artificial intelligence (AI) can improve crop management, solve problems like weeds and pests, and increase the profitability of agricultural businesses. AI is also used in the development of unmanned tractors, agricultural robots, pesticides, and crop and soil monitoring systems. It is constantly evolving. The Internet of Things (IoT) reduces resource use by helping to instantly monitor critical factors such as humidity, temperature, and soil health. It also supports precision agriculture, smart greenhouse management, data analytics, agricultural drones (UAVs), and animal tracking. IoT identifies patterns and relationships between pesticide and toxicity levels. This method can be used to predict pest toxicity and assess human health risks. In other words, machine learning algorithms analyze data collected by AI against large datasets, allowing AI to detect pests and suggest remediation plans.

Pest control strategies

It is estimated that current agricultural profits will decrease by 60% if effective protection is not provided. For example, the loss of rice, an important part of human nutrition, is directly related to the increase in world hunger. This section examines various pest control methods currently in use and discusses the impact of technology on the success of these methods. Various types of pest control are used in insect breeding (Table 1).The classification of these methods shows the existence of six different groups: cultural measures, physical control and control, chemical control, biotechnological control, and genetic control. Among these methods, chemical control (pesticides) is the most popular pest control method due to its rapid effect, low cost, high efficiency, and ease of use. Therefore, intensive use of these chemicals can pose a significant risk to non-target organisms and humans. Furthermore, excessive and inappropriate use of these chemicals can cause many ecological problems and environmental damage (Benke and Tomkins, 2017) [1].

Table 1: Pest control methods

1. Biological Control
2. Biotechnological Control
3. Chemical Control
4. Cultural Practices
5. Genetic Control
6. Physical and mechanical control

In addition, incorrect application time and the use of chemical combinations can also lead to pesticide presence in crops. However, carelessness in pesticide use, lack of information and training can cause serious losses to farmers. Given the problematic effect of pesticides on non-target organisms, the use of multiple selective management strategies is strongly preferred. These should primarily be used as part of your overall planting plan for healthy growth and pest resistance. The use of biotechnological tools and the control of body or chemical resistance is another approach to consider. The above methods, such as biotechnology and biological control, are used to control pests below the financial loss threshold. Significant progress has been made in pest control in recent years with the emergence of biotechnological methods. These methods include disrupting interactions with pheromones, releasing pathogens, and creating plant mutations (Flint and Van den Bosch, 2012) [2].

Integrated pest management

In the 1970s, a new pest management approach called IPM was developed. IPM is an ecological pest management system that relies on natural factors such as natural enemies and weather conditions.

It relies on natural factors to control pests. The aim is to identify management strategies that affect these factors as little as possible. IPM uses pesticides only when pest management and protection are indicated to be necessary. The best pest control plans include all aspects of pest control, including passive ones, and take into account the various managerial, cultural, climatic, and other impacts on the pests and crops to be protected. Integrated Pest Management (IPM) allows for the use of technologies that are very different from traditional pest control methods. These include natural enemies, cultural practices, plant and animal protection, microbial control, seed genetics, chemical messengers (including sexual attractants), and pesticides. These techniques can be used in combination with each other, not together or even backward, as is often the case in pesticide control. The IPM program has six components: (1) employees; (2) producers; (3) managers; (4) knowledge and expertise; (5) biological and ecological knowledge necessary to develop the program; (6) relevant resources and their effects on the physical and biological environment, which vary seasonally and must be monitored and evaluated. A key point is the integration manager or consultant. It is the manager's or consultant's responsibility to continuously monitor the situation, identify pests based on experience and knowledge, and select and monitor appropriate equipment and personnel. Most importantly, pest managers must always understand the ecological and biological impacts of their actions. This knowledge should be extended not only to pests but also to natural and non-harmful enemies (Corallo *et al*., 2018) [3]. Agricultural entomologists have played a significant role in the development of pest management. Taking into account the specific challenges posed by pests, the group of entomologists first defined the level of work and intervention, as well asthe content of self-management.

1. Pest detection and monitoring systems

In the field of remote sensing, the detection of plant pests has been supported in recent years by the use of wireless sensors and some motion/vibration sensors. Currently, acoustic sensors can record specific frequencies produced by pests. However, even when using these sensors, it is still difficult to detect pest populations over large areas. At least, they can indicate that there are some defects in the area. In addition, image processing and optical equipment combined with pheromone technology can directly detect pests. Accurate pest identification is critical when implementing anIPM strategy (Table 2). Specialized acoustic, ultrasonic, and optical sensor technologies are now available to detect, identify, and pinpoint pests (Corallo *et al*., 2018) [3].

Table 2: Basic steps for plant disease detection and classification

1. Image acquisition
2. Image pre-processing
3. Image segmentation
4. Feature extraction in image
5. Detection and classification of plant disease

1.1 Acoustic sensors

Acoustic technology has been used since the twentieth century to detect pests in soil, trees, and plants. The technology has advanced to the point where it can detect defects that would otherwise go unnoticed. The advent of modern computer technology has led to the development of signal processing techniques that help separate sound segments from background noise, and has encouraged research into new acoustic instrument designs to detect and track underground infestation lines. Recently, acoustic technology is being used to detect insects in their feeding areas. Insect identification is generally performed using low-frequency sounds (0,5–150 kHz) produced by insects during activities such as flying, feeding, and talking (Chokkareddy *et al*., 2019) [4].

1.2 Ultrasonic sensors

Insects hiding in seeds, trees, and other plant materials can be detected by emitting ultrasonic signals while feeding. An ultrasonic testing machine consists of several components, including an ultrasonic generator, low-band amplifier, cold signal, and output device. In a system containing this product, the ultrasonic signal emitted by the sensor returns after hitting the line and is sent to a machine that can process the digital signal. Therefore, the direction of movement of the line and the accuracy of the area can be instantly estimated. However, this system has not yet demonstrated consistent performance in different environments. The system works well in areas with background noise, and its ability to detect multiple lines is unknown. Further research and development are needed to develop a smart, portable ultrasonic device for monitoring field pests. No new research has been conducted since the 1990s to confirm this result (Chokkareddy *et al*., 2019) [4].

1.3 Optical sensors

This system uses sensors that utilize infrared light at the device's entrance. The trap is combined with an attractant, which can be a pheromone, light, or bait, and records the time the pest enters the trap. The optical sensor emits light at the entrance of the trap, and when the target insect enters the trap where the attractant is located, the light is blocked. This action causes a change in the voltage in the system controlling the sensor, which is the signal that the pest has entered the trap. Determining the date the pest was first caught in the trap and the population density, plays an important role in integrated pest management (IPM). To be clear, specific preferences should be used for each species (Figure 1). Optical sensors generally have the advantage of counting pests. However, this approach has two important limitations. First, it is not possible to detect the presence of a pest in a trap without species-specific features. Second, it does not work well when used in low light. From the studies, it is clear that more research is needed to more precisely identify species ((Corallo *et al*., 2018; (Chokkareddy *et al*., 2019) [3, 4].

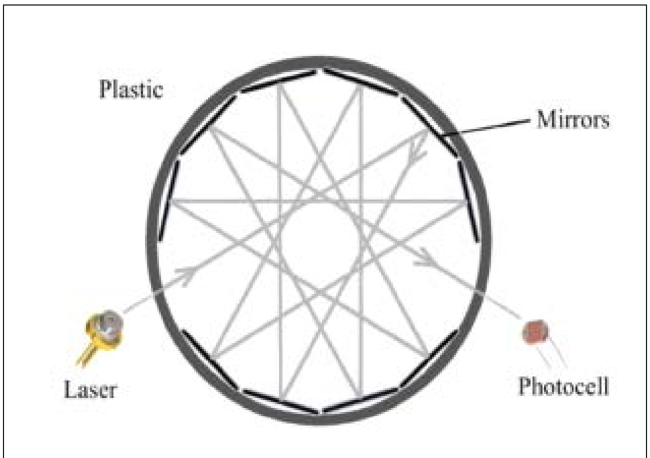

Fig 1: Design of laser scanning application

1.4 Remote monitoring of climate data

Weather data such as wind direction, wind speed, temperature, humidity, precipitation, leaf moisture, solar radiation, and humidity are important for these models. Since agricultural pests are cold-blooded organisms, their biological activityis based on the climate data of their environment. For pests living on fruits,the development of the pests will directly affect the climate data of their environment.Most importantly, the technology is located at the human core of the system, i.e., the decision-makers.An integration manager or consultant is key to this efficient operation. They must constantly “read” the situation, evaluate pests based on their experience and knowledge, and produce and select appropriate products and agents according to the situation. Pest management specialists must always be aware of the ecological and biological impact of their actions not only on pests but also on natural enemies and non-pest diseases. The lack of integrated pest control personnel or consultants poses a major challenge in the implementation of the program. On the other hand, IPM is a commercial enterprise, but if the energy, materials and/or labor required to produce the resource can be reduced, the materials, power and labor will be available to meet the needs of other communities (Devi and Kumari, 2013) [5].

Integrated pest management and artificial intelligence

The technology and techniques used in integrated pest management help determine the optimal time for remote weather monitoring, remote pheromone monitoring, and DD (Degree Day) models. Degree Day (DD) can be calculated as daily average temperatures (including daily maximum and minimum temperatures).However, even for farms or large enterprises using traditional production methods, this technology requires significant energy and labor costs. In this case, advanced system management requires the use of intelligent algorithms that utilize the information obtained from this technology. The system should be able to identify the biological diseases of the pest (using information such as color, pattern, width, length, and drawing tools for diagnosis).The system should be able to continuously monitor pests using the same operating system. The system should be able to collect important information about the weather conditions (temperature, humidity) affecting the pests from the environment where the pests live with high accuracy. The system should be equipped with a mathematical model that can evaluate weather data in real time. The system should be able to process information from images and sensors and instantly evaluate pests. The system should be able to communicate with professionals or companies via online messaging. Depending on the application, the system should be accessible from a smartphone or tablet with Android or iOS operating systems. The software should be able to recommend appropriate licensed (pesticide and/or biotechnology) products based on the latest information according to the critical time of the pest (Devi and Kumari, 2013) [5].

1. Artificial intelligence in integrated pest management

The following areas have been identified as areas requiring further research and analysis. Developing tools to reduce chemical residues in food and environmental pollution requires further research. Occupational safety among farmers requires further research. Obviously, the above information has been obtained from various studies and practical applications. Although there are many studies on Integrated Pest Management (IPM), processing, analyzing, and using this data requires input from IPM experts. The most significant challenge is the limited number of experts who can provide information to farmers. The following article addresses the integration of IPM and expertise, focusing specifically on the application of expertise within the context of IPM. Further research and development is needed in this area.

For entrepreneurs, the process should be as follows:

1. Select the necessary agricultural branch for the business.
2. Determine the growth rate of this branch (minimum: 6,4°C, maximum: 40,2°C).
3. Gather information in the field.
4. Create DD models for specific pests.
5. Monitor the work. Software development (such as image processing algorithms)
6. Create an intelligent algorithm to interpret all this information and make the correct decision.
7. System Validation

8. Continue research and development activities by adding new farming lines to the system (Benke and Tomkins, 2017; De Clercq *et al*., 2018; Aubert *et al*., 2012) [1, 6, 7].

2. Deep learning

Three different types of learning are used in machine learning: supervised learning, semi-supervised learning, and unsupervised learning. Supervised machine learning is provided with appropriate training data, while unsupervised machine learning can learn independently without receiving training data. Semi-supervised learning systems include some or all of the necessary training materials, and less training material is properly documented. Special neural network techniques are used to provide solutions in these courses (Corallo *et al*., 2018) [8]. A selection of the most commonly used neural network architectures in deep learning is shown below.

2.1 Deep neural networks

A deep neural network (DNN) is a special type of training. An artificial neural network is a type of artificial neural network that has many layers and uses mathematical operations to simplify the connection between the input process and the output process. The network moves from one layer to another by calculating the probability of each event. Deep neural networks can be trained to include other topics by gathering information about any given topic and calculating the probability of its occurrence based on network training data. This is done by researching the relevant product, analyzing its properties in depth, and making assumptions that can be used to distinguish the product from many similar products. To illustrate this, a deep neural network trained to recognize cassava stalks can be used as follows: Given an image, the network will make a comparison by comparing the image to the previously obtained cassava stalk characteristics. As a result, the network decides that the image is most likely a potato stalk. A result of 1 means that the network has decided that the image is a cassava stalk. A probability of 4 out of 5 means that the system thinks the image most closely resembles a potato stalk. Instead, a probability of zero provides clear evidence that the image is not actually a cassava plant. The goal of these networks is to identify problems at the atomic level. At this stage, partial attention is paid to artificial objects and their connections. These values or weights are responsible for producing the result as the network runs.

2.2 Recurrent neural network

Recurrent neural networks (RNNs) represent a type of neural network design that can process data in any direction. An RNN consists of a network of neuron-like nodes; each node connects to the next node in a unidirectional manner, and all nodes are connected to each other through successive layers. Each node has the ability to carry data and can receive data from the external network, generate data, or modify data as it is transferred from input to output. Two different types of cross-connection have been identified. These are classified as infinite-pulse or finite-pulse cyclic networks.

The characteristic of finite-pulse recurrent neural networks is a map with undirected cycles that can be expanded. In contrast, infinite-cycle networks have graphs with cycles that cannot be expanded. Both types of recurrent neural Networks Networks have stored states controlled by the neural network. These stored states form the long-range memory network (LSTM) of recurrent neural networks (RNNs). RNNs can process variable-length input data because they can use their internal memory to process the data. Therefore, these RNNs are often used for language modeling and speech recognition. These are multilayer perceptrons where all neurons in one layer are connected to all neurons in other layers and all neurons in all layers. This architecture is often used in image processing. Convolutional neural networks (CNNs) can classify images without requiring experience or special human effort. The network learns the features of the images and then processes them to obtain the desired result. CNNs can capture all spatial and temporal features present in images by applying filters. A CNN consists of input and output layers and multiple hidden layers. Each input neuron is associated with a set of weights. The output is obtained by applying the arithmetic mean to all weighted elements. Minimize the number of measurements as much as possible, and the weights can be reused. This helps the network to understand complex images (Figure 2).

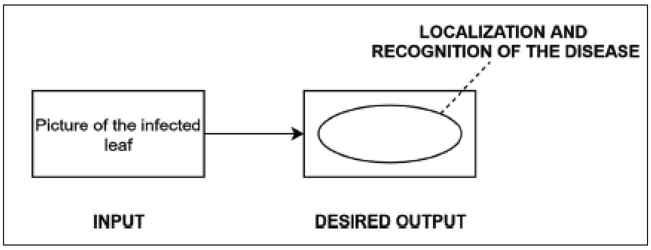

Fig 2: The general process of the disease detection algorithm

In CNN, after receiving the input image, the system creates a 3D map and divides the image into layers and product layers. Then, the image is further divided into layers of different types, and local connections are created from all the neuron volumes that make up the image. Finally, the input quantity is converted into the output quantity. There are various CNN architectures, including VGG, RESNET, DENSENET, Inception, and SQUEEZENET. One of these can measure the efficiency of the dataset and the suitability of the management platform (El-Sawy *et al*., 2016) [9].

3. Crop monitoring using deep learning

Plant diseases pose a major threat to global food security and have a negative impact on small-scale farmers whose livelihoods depend on the growth of all crops. In this new global context, it is estimated that small-scale farmers produce approximately 80% of all agricultural products. It should be noted that this number will increase even further, especially due to food shortages worldwide. It has been revealed that more than 50% of all income is lost each year. The same study found that pests and diseases are responsible for more than 50% of crop losses. It is clear that this statistic should concern all parties. These heavy losses not only cause significant harm to farmers but also affect the limited global food supply. Therefore, a solution must be found. Agricultural engineers have not yet found any cure or treatment for these diseases. However, these drugs are disease-specific, as they are designed to treat specific diseases. Farmers may not understand the specific diseases affecting their crops or the chemicals needed to treat them. Therefore, another solution must be found. Using Deep learning is making agriculture more efficient. The term "precision agriculture" is also used synonymously with the term "satellite agriculture". The concept of precision agriculture involves monitoring, measuring, and responding to different types of crops using decision-making systems (DSS). This approach focuses on improving agricultural resource use while also increasing agricultural yield. By using one of the existing sensors in a GPS device, you can identify specific agricultural products and help create maps showing various conditions, including details of organic matter and moisture. This is an example of how precision agriculture works. Such sensor arrays not only produce these kinds of maps but also measure things like chlorophyll levels and the condition of aquatic plants. When combined with satellite imagery, these measurements are beneficial for plants, sprays, and crops. Equipment collectively known as Variable Rate Technology, uses data from precision agriculture to improve resource allocation and data transfer without requiring any human intervention. Precision agriculture facilitates the identification of crop diseases, pesticide discovery, and fruit counting. It can also directly identify crops, including determining which variety will yield the best results. Mobile cameras are frequently used to collect data, from deep learning to crop monitoring. This image shows a mobile camera collecting and transmitting data. This mobile camera could be an IoT camera. Also, autonomous spraying robots, autonomous painting robots, mobile cameras, and smartphones are good data collection tools. In the following sections, we will show how deep learning can be used to solve the above problems.

4. Plant disease and pest identification

Crops are often affected by a variety of diseases and pests, which together pose a major threat to global food security. It is common for farmers to be unaware of the presence of pests and diseases until it is too late to take control measures. Sometimes farmers may notice that some of their crops are exhibiting unusual characteristics, such as an extra green color or a rough appearance. They may not attribute these changes to an underlying disease, instead assuming that the plant is going through a normal growth cycle. This disease can spread throughout the farm before it is detected, reducing the benefits of the growth cycle. Farmers, especially those without advanced agricultural training, need to have the knowledge to detect diseases early and manage them effectively. In the past, support for identifying plant diseases was provided by agricultural associations and other organizations such as local plant clinics. Most diseases are visible across the spectrum, so observation by a professional is a crucial part of disease identification. However, this approach can be ineffective due to low-quality intelligence analysis. It is important to remember that human potential is limitless. Stress, eye problems, etc., can cause visual impairment, leading to inaccuracies in visual inspection. To overcome these problems and facilitate virus identification, image-based deep learning algorithms can be used. However, this requires the identification and documentation of behaviors and characteristics associated with each disease. The following list shows the characteristics of pests and diseases that can be used for diagnosis:

4.1 Infection

Life cycles that can be used in the identification process. It is important to identify and correct specific patterns found in plants in association with particular diseases. This process should be carried out at all stages to determine whether the emergence of a disease affects the course of the disease. The pattern indicates that the plant is in a specific stage of the disease. An algorithmic approach can make it easy to create a table containing the names of the organisms and their associated images and colors. This will allow for the identification of bacteria based on shape and color.

4.2 Infection area

The infection area is not limited to leaf area; different diseases affect plants in different places. By finding the disease on your plants, you can more easily diagnose the disease and choose the appropriate treatment.

4.3 Fungal species

An easy way to understand different fungal species is to identify and understand the related fungal species. To determine the type of fungus affecting the plants, it is necessary to determine the characteristics of each fungus, the color and shape they leave on the affected plant, and the location of the plants they affect. Changes may be seen in the leaves depending on the disease. If it is determined that the disease leaves a strange mark on the leaves of the affected plant, it will be easy to determine whether the plant is affected by the disease. Although some of these characteristics can be determined visually, this method is unreliable and misleading. However, deep learning allows the integration of the above and other interactions into the network. The network will then acquire more images for analysis. These images will include many plants, including good and bad models. These features will be loaded into the relevant system, and the network will be able to learn and process all the data. Figure 3 shows the best way to solve the above problems, namely the identification and localization of disease in the leaves.

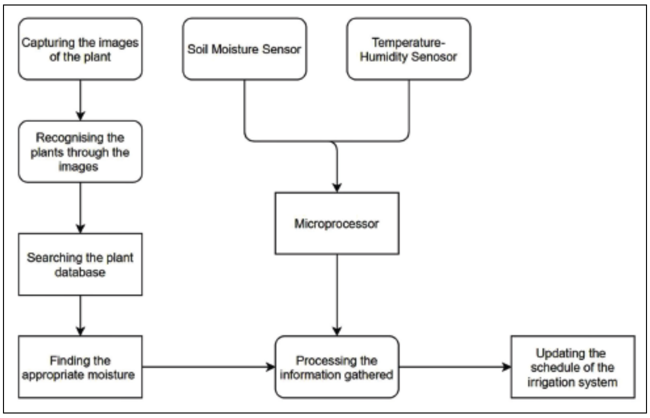

Fig 3: The general process of smart IoT (Internet of Things) based irrigation system

The neural network provides a map from input (image of infected plant) to output (identification of disease).Each part of the neural network represents a mathematical operation, and internal connections are used to collect the input and output of the code as external connections. The most common one is the deep learning tools used in this context are CNNs, which can model similarities and identify patterns in images. The CNN architecture described above has been trained and tested using different datasets containing images of healthy and diseased plants. After capturing a leaf image, the deep learning system analyzes and identifies the disease using the above features. It also detects the disease or pest infecting the plant and presents the user with an appropriate treatment plan (Azfar *et al*., 2015) [10].

5. Solving integrated pest management problems with the help of artificial Intelligence

The foundation of IPM is an IPM specialist who is responsible not only for the development of the system but also for routine procedures such as monitoring and selection of the appropriate procedure. No matter how new pesticide products are developed, decision-makers still play a crucial role in selecting appropriate controls. Changes in plant phenology and population size, along with climate data, are important for predicting disease growth using numerical models. The biggest problem is the lack of specialists who can transfer information to farmers. Therefore, existing and emerging data can be processed in Integrated Pest Management (IPM) and then analyzed using technology output to provide best recommendations to agricultural producers. These methods increase management efficiency and facilitate IPM by increasing productivity and reducing costs (Table 3) (Azfar *et al*., 2015) [10].

Table 3: Comparison of pest control methods (+ Low, ++ Medium, +++ High) WSN: Wireless Sensor Networks, IPM: Integrated Pest Management, AI: Artificial Intelligence

Pest control methods	Cost	Environment friendly	Human health	Product quality	Labor saving	Effectiveness
Chemical	+	+	+	+	+	+++
Biological	++	+++	+++	++	++	++
Genetic	++	+++	+++	++	++	++
IPM system	+++	++	++	+++	+++	+++
WSN (IPM with AI)	++	+++	+++	+++	++	+++

Conclusion

The next section demonstrates the application of deep learning in agriculture. Deep learning is widely used in many areas of agriculture, and this section will show how it can contribute to the success of a particular agricultural practice. Activities include plant disease detection, plant and pest identification, fruit counting, yield estimation, fruit harvesting, and crop evaluation. While deep learning has garnered significant interest in many fields such as healthcare, the analysis shows that the response to deep learning in agriculture is quite different, yet still limited. The main reason for this is that most research results remain limited to theoretical discussions rather than being translated into business applications. However, with time and willingness With the participation of industry stakeholders, these discoveries have the potential to revolutionize agriculture. In addition to deep learning, other types of image processing also have the potential to improve agriculture. However, deep learning has proven to perform better compared to other traditional image processing techniques. The use of this technology has the potential to reduce the number of workers required for agriculture, thus lowering costs. In addition, deep learning not only makes the agricultural process more efficient but also increases the overall profitability of the business. Therefore, the use of deep learning applications will help to obtain more food products to meet the food needs of the growing world population. It will also eliminate existing pest and disease reductions, improve resource utilization, and speed up the entire process. This will undoubtedly increase production, income, and food availability.

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