# Implementation of Crop Pest Recognition and Classification Using Deep Learning Techniques

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**Abstract –Effective pest management techniques are becoming more and more necessary as a result of agriculture's quick development to meet the world's rising food demand. Conventional manual techniques for classifying and identifying pests take a lot of time and are frequently prone to mistakes. This research proposes the use of image processing techniques to develop a reliable and automated system for crop pest recognition and classification in order to address these issues. Using image analysis, the suggested system will automatically identify and categorize agricultural pests. Targeted pesticide sprays will then be applied using IoT-enabled devices. In order to reduce environmental impact and maximize resource utilization, the suggested system focuses on automating the processes of insect recognition, classification, and targeted pesticide spraying. Using photos taken in the field, the system's initial module employs image processing algorithms to precisely identify and categorize agricultural pests. Using a variety of pest picture datasets, Convolutional Neural Networks (CNNs) are trained to produce a reliable pest classification model. This technique allows for accurate pest identification by differentiating between different pest species and healthy crops. The second module focuses on integrating machines and IoT devices to facilitate targeted and effective pesticide application. Real-time data on crop health, pest populations, and environmental variables is collected via IoT sensors positioned across the field. In order to minimize total pesticide usage and lessen environmental harm, automated pesticide sprayers with precision spraying mechanisms are used to apply pesticides selectively to regions where pest infestations exist.**

**Keywords: Deep Learning, Pest Detection, Disease Classification, Image Processing, Convolutional Neural Network (CNN), Generative Adversarial Networks (GANs).**

## . INTRODUCTION

Crop pest management is a long-standing issue in agriculture that dates back to the early days of human settlement. The constant threat that pests pose to the world's food security calls for the creation of reliable and effective techniques for identifying and managing them. The emergence of contemporary technology, namely in the domains of computer vision and artificial intelligence (AI), presents a wonderful prospect to transform pest identification in agriculture.

Crop pest recognition is essentially the process of identifying and categorizing different organisms that destroy or negatively impact agricultural crops. This role has historically mostly relied on manual inspection by farmers and agricultural specialists, which frequently causes delays in pest detection and response times as well as the possibility of mis-identification. However, the ubiquitous availability of high-resolution imaging technologies and current AI developments provide a paradigm shift in the way we approach pest recognition.

Image-based pest recognition using machine learning methods, especially deep learning, is one of the most promising directions in this respect. Historically, manual observation and action have been the mainstays of pest detection and management, whichled to numerous inefficiencies and a delay in responding. But with the introduction of cutting- edge technologies like the Internet of Things (IoT) and Deep Learning (DL), our understanding of and approach to managing agricultural pests is undergoing a radical change. Deep Learning is a branch of artificial intelligence (AI) that simulates the neural networks found in the human brain. It has become a potent tool for pattern analysis, picture identification, and categorization.

Researchers and developers may accurately identify a variety of crop pests and diseases by using Deep Learning techniques to train models to recognize complex patterns in visual data. Furthermore, real-time data collecting from agricultural areas is made easier by the integration of deep learning with IoT technologies through linked sensors and equipment.

Fig 1: Pest in Crop

The combination of deep learning and IoT has the potential to completely transform agricultural pest management techniques. It is impossible to overestimate the importance of crop pest identification utilizing Deep Learning and IoT. Periodic visual inspections are a common component of traditional pest monitoring techniques, but they are labor- intensive, time-consuming, and prone to human mistake. On the other hand, early illness and pest identification is made possible by deep learning-powered image recognition systems which can quickly and accurately evaluate enormous volumes of visual data.

These systems offer continuous monitoring capabilities when combined with Internet of Things (IoT) devices like drones, cameras, and sensors placed throughout farmlands. This gives farmers timely information into pest infestations and environmental conditions. The resilience of Deep Learning algorithms and the caliber of input data are critical to successful pest identification. To achieve good generalization and precise pest identification in a range of environmental settings, deep learning models need to undergo substantial training on a variety of datasets. As such, cooperation amongst scientists, farmers, and technology suppliers is necessary in order to compile extensive databases that cover various crop varieties, pest species, and geographical areas. In order to improve deep learning algorithms' accuracy, scalability, and efficiency in actual agricultural settings, they also need to be continuously improved and optimized. Deep learning - powered systems can provide insightful information on pest behavior, lifecycle stages, and spatial distribution patterns in addition to pest identification. These technologies enable proactive pest control tactics by forecasting and predicting potential pest outbreaks through the analysis of previous pest data gathered over time. Furthermore, with the integration of meteorological data and several environmental characteristics, deep learning-IoT platforms may offer customized advice to farmers about the best times to use pesticides, crop varieties resistant to pests, and cultural practices.

## II. RELATED WORKS

Ching Presents an intelligent pest recognition system to tackle this pest problem by utilizing novel applications of edge intelligence. In order to detect T. papillosa in the orchard and ascertain the pests' location in realtime, we utilized a detecting drone to take pictures of the pest and a Tiny-YOLOv3 neural network model based on an embedded system NVIDIA Jetson TX2.

The agricultural drone's ideal pesticide spraying route is then planned based on the locations of the pests. In addition to scheduling the drone to spray pesticide in an efficient manner, the TX2 embedded platform sends the location and production of pests to the cloud so that a computer or mobile device can record and evaluate the growth of longan [1].

Chen[2] describes For pest identification, environmental sensors, the Internet of Things (IoT), and picture recognition technologies are coupled. Based on environmental Internet of things data and intelligent pest identification, real-time agricultural meteorology and pest identification systems on mobile applications are assessed. We integrated deep learning with the state-of-the-art IoT technology to create smart agriculture. In order to locate Tessaratoma papillosa, we employed deep learning YOLOv3 for picture recognition. We next used Long Short-Term Memory (LSTM) to assess meteorological data and forecast the presence of pests. Accurate placement helps minimize soil damage from pesticides and help cut down on their usage. The goal of smart agriculture is achieved as a result of the present study, which gives farmers the location and extent of pests so they can apply pesticides accurately, at the right time and place, and so reduce the number of agricultural workers needed for timely pest management. The suggested method alerts farmers to the existence of several pests before they begin to proliferate widely [2].

Wenjie Liu proposed handling the problem of recognizing insect pests with a feature fusion residual block. We fused a feature from an earlier layer between two 11-convolution layers in a residual signal branch, which was based on the original residual block, in order to boost the block's capacity. We also looked into how each residual group affected the functionality of the model.

It has been found that adding residual blocks from earlier residual groups significantly improves model performance, which in turn boosts the model's capacity for generalization. By stacking the feature fusion residual block, we constructed the Deep Feature Fusion Residual Network (DFF-ResNet). The experimental results show that our models outperform baseline models in terms of test error. Next, we employed our algorithms to detect pest insects and validated them with the IP102 reference dataset. Based on the experimental data, our models outperform the original ResNet and other state-of-the-art methods [3].

Fuji proposed a new, straightforward structure called the "feature reuse residual block," which mixes features from the input signal of a residual block with the residual signal itself. Learning half and reusing half of the features improves the representational capacity in each feature reuse residual block. We created the feature reuse residual network (FR-ResNet) by stacking the feature reuse residual block, and we used the IP102 benchmark dataset to assess performance. The testing findings demonstrated that FR-ResNet can significantly increase performance when it comes to classifying insect pests. In addition, we examined the approach's adaptability on a number of benchmark datasets, such as CIFAR-10, CIFAR-100, and SVHN, and applied it to other types of residual networks, such as ResNet, Pre-ResNet, and WRN. The outcomes of the experiment demonstrated that performance might be clearly enhanced over the original networks [4].

Li Rui Pests are always the main source of field damage in agriculture, leading to large losses in crop productivity. Currently, the process of manually classifying and counting pests takes a long time, and the accuracy of the population enumeration might be influenced by a variety of subjective factors. Furthermore, because to the many scales and attitudes of pests, current Convolutional Neural Network (CNN)-based techniques for pest location and recognition are insufficient for effective field- based pest prevention. This research proposes an efficient data augmentation mechanism for CNN-based method to tackle these issues. During the training phase, we use data augmentation, which involves clipping photographs into multiple grids after rotating them to different degrees. By doing this, we could gather a substantial amount of additional multi-scale instances, which we could then use to train a multi-scale pest identification model. During the testing phase, we apply the test time augmentation (TTA) approach, which uses the trained multi-scale model to independently infer input images with different resolutions.

In order to arrive at the final result, we finally fuse these detection findings from various picture scales using non-maximum suppression (NMS) [5].

Radhamadhab Dalai One of the main goals of this effort is to demonstrate the need for biological pest and disease control utilizing computer and internet technology, rather than pesticides, in order to safeguard crops. The primary goal of agricultural research is to boost food quality and productivity while lowering costs and increasing profits. In the agricultural industry, the use of vision-based technologies for pest monitoring has grown significantly in relevance recently. In many nations today, there is a significant demand for non-chemical methods of controlling illnesses or pests. Unfortunately, there are currently no automated techniques that can accurately and consistently identify plant pests. In actuality, workers in greenhouses periodically monitor plants and look for pests under production settings. This manual approach takes a long time and is ineffective. We have explored and tried deploying deep learning based pest detection in actual farming fields. To achieve this, a Deep Learning-based segmentation and RCNN-based detection technique has been tested. According to the trial, the RCNN-based technique outperforms common pest detection mechanisms by a large margin [6].

Wang Yang suggests a discriminative approach based on low-rank representation and sparsity for pest identification on leaves in order to increase the detection accuracy. Our method breaks down the original image into a low-rank image and a sparse noise image that contain all of the pests on the leaf. It does this by using the low-rank qualities of natural photos, the sparsity of the noise image, and the previous knowledge of color information of the crop pest images. After that, it will be possible to distinguish the agricultural pests with leaves from the backdrop and accurately count them.

The outcomes of the experiment demonstrate how easily our technology can identify pests on leaves. This will have a significant impact on future decisions about and control of pests [7].

## III. PROPOSED METHODOLOGY

Using deep learning methods combined with Internet of Things (IoT) devices, including Arduino microcontrollers, drivers, pump motors, and wireless transceivers, the suggested system applies a revolutionary method for agricultural pest identification. By addressing the critical issue of timely insect detection in agricultural areas, the system seeks to increase crop yield and decrease losses. Using image processing and the Internet of Things (IoT), crop pests can be identified and pesticides can be applied. This technique involves a combination of hardware and software components to automate and optimize pest management. The suggested solution uses IoT and deep learning to identify and control agricultural pests. In particular, a CNN-based model is created for the purpose of automatically identifying pests from photos taken by Internet of Things devices that are placed in the field. The Internet of Things system consists of Arduino microcontrollers that have wireless transceivers for data transmission, pump motors, drivers, and sensors installed. The first step in the workflow is the placement of IoT devices in strategic locations across the agricultural area.

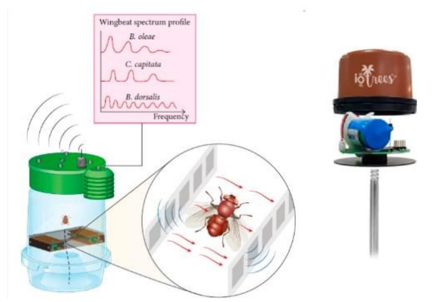


Fig 2: Pest Control work flow

These gadgets use wireless transmission to send high-resolution photos of crops to a central processing unit. After being pre-trained on a sizable dataset of annotated pest photos, the CNN model is used to examine the incoming photographs and detect the presence of any illnesses or pests. The Microcontroller determines whether spraying pesticides is required after identifying the pests. To choose the best course of action, it takes into account variables including crop stage, insect type, and pest density.

In the event that the Microcontroller determines that spraying pesticides is required, it will turn on the pump motor and gear motor. The microcontroller handles data processing, drives motors and actuators, and coordinates with all other hardware elements. The pump that sprays pesticides are managed by the pump motor driver. To adjust the pesticide's flow rate, the driver receives control signals from the microcontroller. The gear motor is managed by the L293D driver. It controls the voltage and current given to the motor for exact movement control after receiving directions from the microcontroller.

To effectively cover the entire crop area, the gear motor moves the spraying device (such as the nozzle or sprayer arm). With the use of the proper commands, the microcontroller regulates the direction and rotation of the gear motor. Communication between an IoT device (microcontroller) and a user interface or central control system is made possible by the wireless transceiver module. By allowing for prompt and focused pest management treatments, this real-time feedback loop minimizes crop loss and maximizes resource use. The suggested method has a number of benefits, such as increased pest detection efficiency and accuracy, less dependency on human monitoring, and increased sustainability due to lower pesticide use. Moreover, the use of IoT facilitates remote observation and management, endowing farmers with practical information to make anticipatory pest management choices. Several essential elements are included in the suggested deep learning and Internet of Things crop pest identification system. First, use Internet of Things (IoT) sensors and devices to gather data on temperature, humidity, and soil moisture in the agricultural field. Examples of these include Arduino microcontrollers, drivers, pump motors, and wireless transceivers.

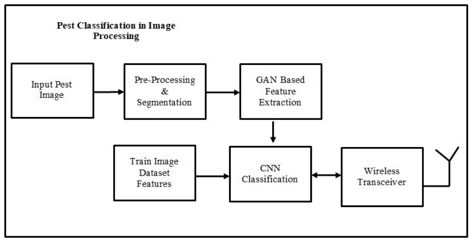


Fig 3: Block Diagram for Transmitter Module

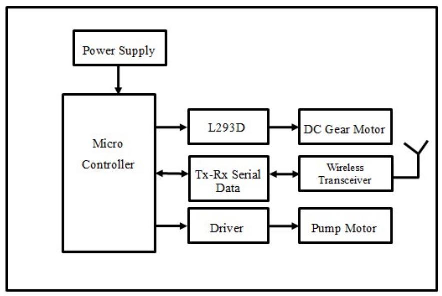


Fig 4 : Receiver Module Block diagram

The data from these Internet of Things sensors will be transmitted to a central hub, where deep learning algorithms particularly trained for pest recognition will process and evaluate the data. A wide range of datasets including photos of pest-affected and healthy crops can be used to train the deep learning model. Once installed, the system uses cameras or sensors to take pictures of the area and analyzes them for indications of pest infestation. The system notifies farmers via wireless transceivers or activates pump motors to administer pesticides upon detection of a possible pest, allowing for prompt response to minimize crop damage. Additionally, by allowing farmers to submit updates on insect observations, the system may continuously improve its accuracy. This allows the deep learning model to adapt and increase its identification capabilities over time. With the help of this integrated system, crop pests may be monitored and managed in real time, increasing output and lowering.

## Dataset

The crop pest images are collected and used to training and testing. This dataset is available on the open source websites.

## processing and Segmentation

Preprocessing is the term used in image processing to describe a range of techniques used to enhance an image's quality before further examination.This may entail modifications such as noise reduction, contrast enhancement, and picture normalization. On the other hand, segmentation is the process of breaking an image up into items or areas that have significance. Among the segmentation approaches are thresholding, edge detection, and clustering. Preprocessing typically occurs before segmentation in order to improve the accuracy and efficiency of segmentation algorithms.

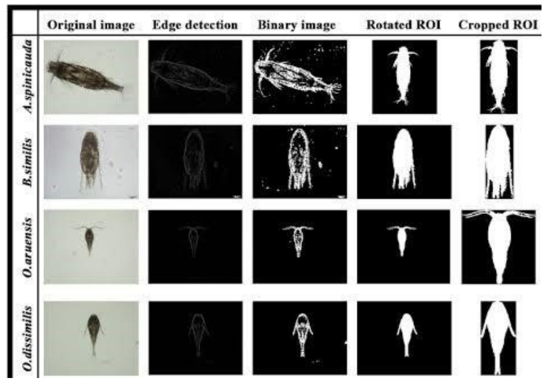


Fig 4:Pre-processing and Segmentation

## Genrative Adversial Network (GAN)

For a generative adversarial network, use GAN. This is a particular kind of Machine Learning framework in which a game-like situation pits two neural networks, the discriminator and the generator, against one another. The generator network creates new instances of data, like pictures, based on inputs such as random noise. Generating data with a realistic appearance and a plausible distribution, similar to the training data, is its aim.

The discriminator network is responsible for differentiating between instances of actual data from the training set and pseudo data produced by the generator. It picks up the ability to distinguish between phoniness and real instances.

The generator and discriminator communicate back and forth continuously during the training process. As the discriminator gains more proficiency in differentiating between actual and phony data, the generator strives to produce more realistic data. Until both networks achieve a state of equilibrium where the generator generates realistic data that the discriminator finds it difficult to differentiate from genuine data, this adversarial process will continue.

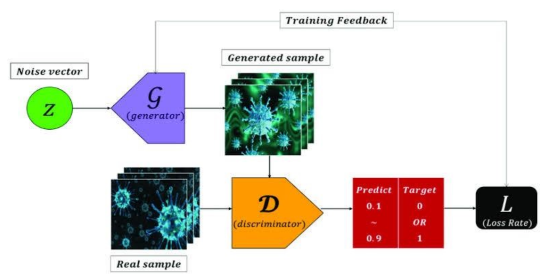


Fig 5: Generative Adversarial Network

## Convolutional Neural Network (CNN)

Convolutional Neural Networks are analogous to the complex insect sensory systems.CNNs replicate the process of feature detection by extracting features from images using layers if filters, much way insects see their surroundings with compound eyes. Similar to how insects are hierarchical processing to effectively navigate their environment, CNNs use multiple layers gradually acquire more abstract representations of the incoming

data. Furthermore, CNNs do astonishingly fast and accurate tasks like object detection and image categorization, just like insects can swiftly recognize patterns that are essential to their survival.

Convolutional neural networks (CNNs) are sophisticated and efficient image processing tools, as demonstrated by the comparison between CNNs and insect sensory process.

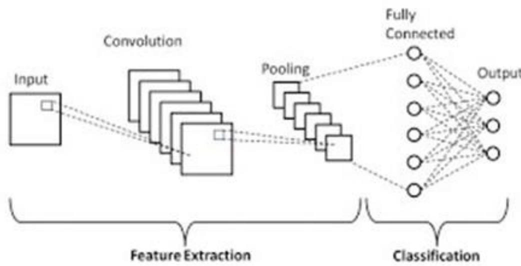


Fig 6 Convolutional Neural Network

## L293D

A motor driver IC is an integrated circuit chip which is usually used to control motors in autonomous robots. Motor driver IC's act as an interface between microprocessors in robots and the motors in the robot. The most commonly used motor driver IC's are from the L293 series such as L293D, L293NE, etc. These IC's are designed to control 2 DC motors simultaneously. L293D consist of two H-bridge. H-bridge is the simplest circuit for
controlling a low current rated motor. For this tutorial we will be referring the motor driver IC as L293D only

Motor Driver IC's are primarily used in autonomous robotics only. Also most microprocessors operate at low voltages and require a small amount of current to operate while the motors require a relatively higher voltages and current.

Thus current cannot be supplied to the motors from the microprocessor.

## TX-RX Serial Data

TX (Transmit) and RX (Receive) serial data communication is a method of transmitting data between devices sequentially over a single wire or pair of wires. In this scheme, the transmitting device sends data by toggling the TX line to represent each bit, while the receiving device listens to the RX line to receive the transmitted data. Each bit is typically sent one after the other, synchronized with a clock signal or baud rate. Both transmitting and receiving devices usually have both TX and RX lines, allowing bidirectional communication. This method is commonly employed in serial interfaces like UART, RS-232, and RS-485, facilitating data exchange in various applications from simple microcontroller projects to complex communication systems between computers and peripherals.

## Pump Motor

A pump is a mechanical device, that is used to pick up water from low-pressure level to high-pressure level. Basically, the pump changes the energy flow from mechanical to the fluid. This can be used in process operations which needs a high hydraulic force. This process can be observed within heavy duty equipment. This equipment needs low suction and high discharge pressure. Because of low force at suction part of the pump, the liquid will pick up from certain deepness, while at expulsion side of the pump with high force, it will drive liquid to pick up until reach preferred height. The pump has since developed into a continuous range of forms, sizes, & applications. This article discusses an overview of what is a pump, working principle, types, specifications and difference between pump & motor.

## DC Gear Motor

A gear motor is an electric motor and a power reducer combined into a single unit that reduces the number of revolutions but increases the torque of the operating shaft. Such gears for electric motors are often used in modern machines and mechanisms; it is universal for many types of equipment. Some hybrid models combine practicality and durability. The housing is made of plastic and the gears are made of metal. This design gives a minimum noise level during the operation of the devices; the voltage can be from 12 to 24 V.

### Wireless Transceivers

A wireless transceiver consists of a transmitter and a receiver. In the transmitter, a process known as modulation converts electrical digital signals inside a computer into either RF or light, which are analog signals. Amplifiers then increase the magnitude of the signals prior to departing an antenna. At the destination, a receiver detects the relatively weak signals and demodulates them into data types applicable to the destination computer. The transceiver is generally composed of hardware that is part of the wireless NIC.

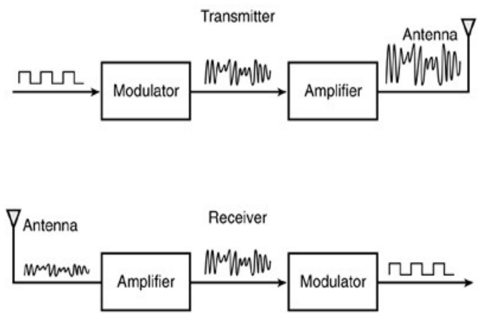


Fig 7 Wireless transmitter Diagram

In a transceiver, the listener won't hear the signals when the emitter sends them. The transmitter and receiver can be linked to the same antenna with the help of an electric switch. This keeps the emitter's signal from hurting the receiver.

The transceiver generates a signal, which could be electrical optical, or radiofrequency, depending on the medium of communication. The signal is then subjected to modulation. The modulated signal is then sent out through an antenna or through a cable. At the receiving end, another transceiver is waiting to capture the incoming signal. Then finally the signal gets subjected to demodulation and transmitted data gets recovered and the data gets provided to system for further processing or display.

## IV RESULTS AND DISCUSSION

In terms of crop pest identification, the combination of deep learning and IoT technology produced encouraging results.

The deep learning model distinguished between several pest species and non-pest objects in the photos with a high degree of accuracy. The system performed admirably in identifying pests in a variety of environmental settings, including varied illumination and weather. Extensive field testing in agricultural environments confirmed that the system is capable of quickly detecting and addressing insect infestations. The effective use of the crop pest identification system will impact pest control techniques and agricultural practices in a number of ways. First off, automated and precise pest identification is made possible by deep learning algorithms, which eliminates the need for labor- and

time-intensive human inspection techniques. Furthermore, proactive pest control is made possible by the real-time monitoring capabilities offered by IoT devices, which empower farmers to take prompt action to reduce crop losses and alleviate pest damage. Furthermore, the incorporation of Internet of Things elements enables farmers to remotely monitor and control pest recognition systems, allowing them to efficiently manage their crops from any location through the use of web-based or mobile applications.

Particularly for large- scale agricultural enterprises, this remote accessibility improves pest management operation's flexibility and ease. The four main performance indicators in crop pest recognition are F1-score, accuracy, precision, and recall.

These measures evaluate how well the model can identify pests and crops in photos. When tested on a variety of datasets, a well-trained CNN model ought to produce high values for these measures.

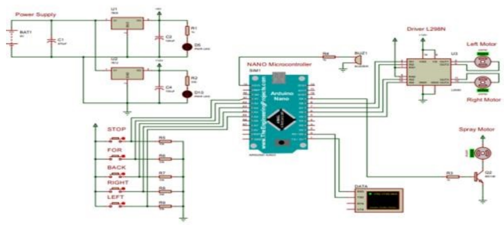


Fig 8: Experimental Setup

Accuracy: The percentage of accurately identified instances among all instances is known as accuracy. Accuracy in the context of crop pest identification denotes the model's general capacity for accurate pest identification. A high accuracy score indicates that the model can effectively discriminate between things in the crops that are pests and those that are not.

Precision and Recall: Recall calculates the percentage of actual positives among all true positive predictions, whereas precision calculates the percentage of true positive predictions across all positive predictions. Recall shows the model's capacity to identify pests while they are present, while precision shows the model's ability to prevent misclassifying non-pest objects as pests. In order to guarantee that the model correctly detects pests without producing an excessive number of false alarms, precision and recall must be balanced.

F1 Score: The F1 score offers a metric tossess a model's performance; it is the harmonic mean of precision and recall. Because it takes into account both false positives and false negatives, it is a reliable metric for evaluating classification performance, particularly in unbalanced datasets where the proportion of pest and non-pest cases may vary greatly.

Confusion Matrix: A comprehensive analysis of the model's predictions is given by a confusion matrix, which displays the quantity of true positives, true negatives, false positives, and false negatives.

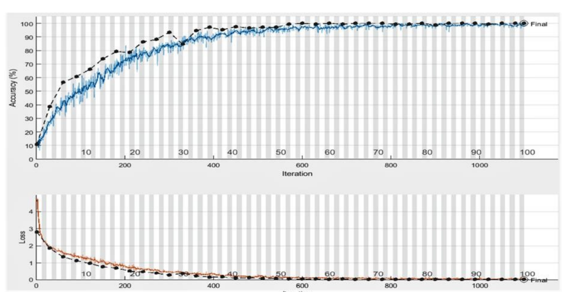


Fig. 9 Training accuracy and loss of proposed model

A fuller understanding of the model's advantages and disadvantages, such as its propensity to incorrectly categorize some pest categories or non-pest objects, can be gained by analyzing the confusion matrix.

In order to evaluate the training performance of the proposed method, we have shown accuracy and loss in Fig. 3, explaining that, following epoch "55," accuracy and loss essentially stay the same (roughly equal to 100%), indicating that we can still achieve good results at lower classification epochs. By achieving the optimal values for accuracy, precision, recall, specificity, and F1-score, the suggested method proved to be successful in classifying pest photos into many classes.

## V. CONCLUSION

A promising method for crop pest identification and control is the combination of deep learning, more especially Convolutional Neural Networks (CNN), with Internet of Things (IoT) devices including wireless transceivers, Arduino microcontrollers, drivers, and pump motors. Farmers and agriculturalists may accurately and efficiently identify and categorize a variety of crop-damaging pests by using CNNs, which are skilled at extracting complex patterns from large datasets. Quick identification of pests allows for the prompt application of intervention methods, reducing crop damage and output losses. Furthermore, the system gains a layer of automation and real-time monitoring from the addition of IoT components.

The core of the system is made up of Arduino microcontrollers, which provide smooth coordination and communication between various components. Based on the CNN's identification results, drivers and pump motors enable the automated deployment of pest management measures, such as targeted pesticide administration or pest deterrent devices. Remote monitoring is made possible by wireless transceivers, which enable farmers to stay in one place and get updates and alerts on pest activity straight to their computers or mobile devices.

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