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Intelligent insecticide and fertilizer recommendation system based on TPF-CNN for smart farming

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ABSTRACT

Nowadays, artificial intelligence and sensor technology play a vital role in the agriculture field. The use of excess insecticides and fertilizers in farming poses a risk to human health. It is necessary to control them to ensure healthy crop production. Many techniques are used to identify the pest, suggest medications, and do soil nutrient analysis techniques separately. This paper applies the dual operator, Transition Probability Function (TPF), and Convolution Neural Network (CNN) to process the pest's image discretely and continuously for applying the recommended insecticide. The mathematical model with the objective function is derived in this paper. The proposed system combines two major aspects in farming: pest identification and insecticide recommendation using machine vision and CNN. Secondly, the soil nutrient analysis uses a soil NPK sensor with the recommendation of fertilizers according to the obtained nutrient values. On-spot results are obtained, and the time required for insecticide recommendation is within 10 s, and for fertilizer recommendation, it is within 80 s. Successful identification of five pests, namely aphids, bollworms, leaf folder, leaf miner, and green stink bug, was done with more than 90% accuracy. The proposed approach is also compared with the other intelligent approaches, such as Artificial Neural Network (ANN), K-Nearest Neighbour (KNN), and Support Vector Machine (SVM), and it is observed that the proposed TPF-CNN approach gives higher accuracy in the shortest time.

1. Introduction

The agriculture sector in India is advancing due to globalization [1]. As people become more health-conscious, producing quality crops is needed for today's world. Farmers spray pesticides and add fertilizers to the soil to obtain maximum production. Pesticides are toxic substances used to kill pests, weeds, fungus, etc., including herbicides, fungicides, insecticides, etc. [2]. Insecticides are substances that prevent pest attacks on crops and are more toxic than herbicides and fungicides [3]. The production, sales, and import of pesticides are regulated under "The insecticide act, 1968″, including rules for the safe and proper use of pesticides. These rules and regulations ensure pesticide industries operate within limits under supervision. The government of India has also banned the use of 30 pesticides, and 18 pesticides have declined registration [4]. Some farmers are unaware of the ill effects of spraying an excess quantity of insecticides on plants and adding the excess quantity of fertilizers to the soil without testing the quality of the soil. Excess spraying of insecticides can lead to human as well as environmental damage. Direct or indirect consumption of these insecticides can cause respiratory issues, cancer, and genital syndrome and can even cause death. Environmental damages include soil pollution, water pollution, and toxic produce [5]. Insecticides have the highest consumption rate in India at about 76%, followed by fungicides at 13% and herbicides at 10% [6]. A recommendation system has been developed that identifies pests and recommends suitable treatment, using the "Pest in Crops and their Treatment" ontology (PCT-O). The ontology uses various data sets for pests, pesticides, and symptoms which helps classify the insect and suitable treatment [7]. Using a cloud-based system that will help the farmers to use pesticides in an optimal manner to ensure the safety of traceable vegetables. The platform guides the users about pesticide information like use, purchase, evaluation, and harvest. This provides an undue advantage to our farmers by reducing banned pesticide use and improving the quality of vegetables [8]. Developing a knowledge-based system that identifies watermelon disease was introduced. The knowledge-based system consists of working memory, inference engine, general and domain knowledge, and a user interface. This system accurately identifies the disease on watermelon and suggests the disease treatment method [9]. Implementation of the

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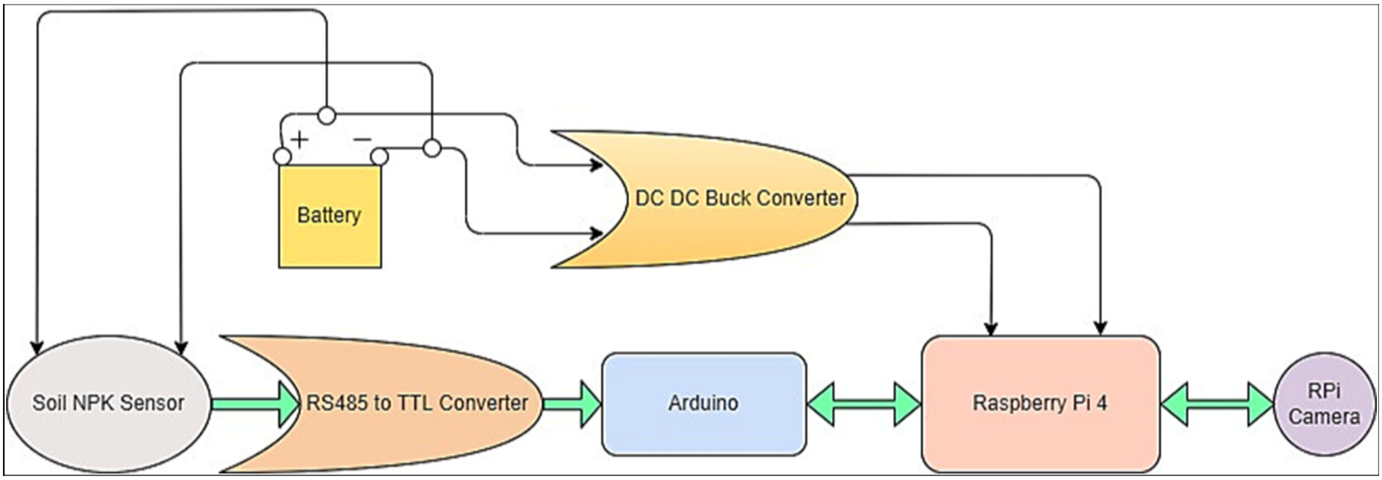


Fig. 1. Flowchart of the system.

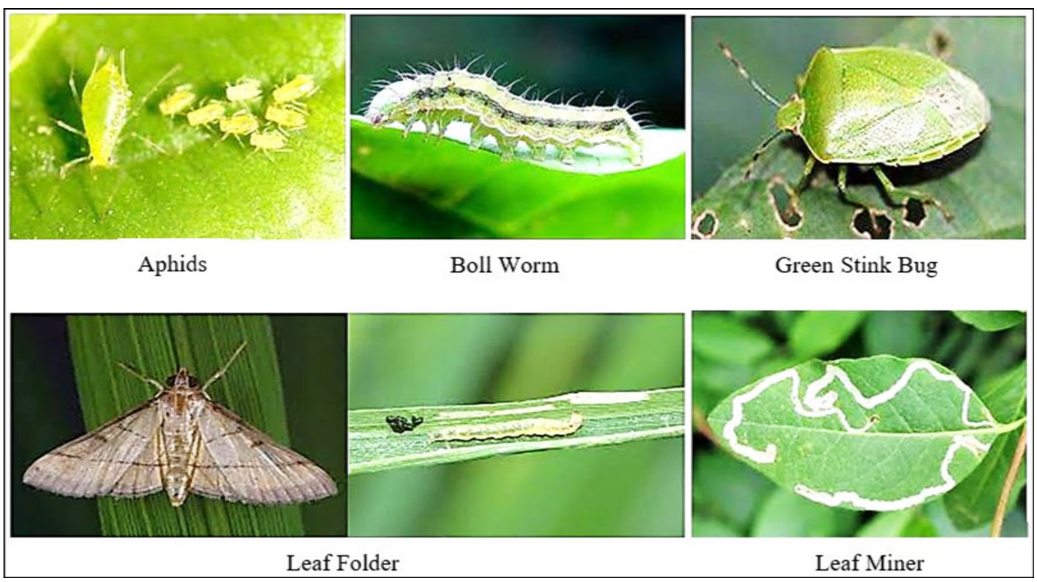


Fig. 2. Images of 5 pest classes, namely aphids, bollworms, green stink bug, leaf folder, and leaf miner.

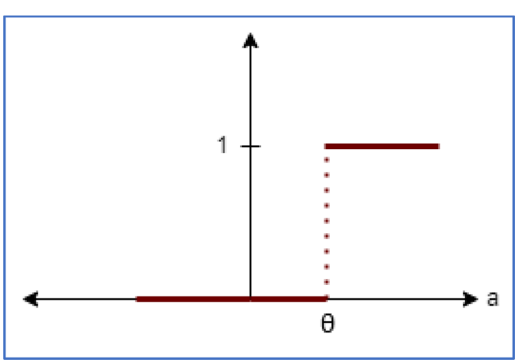


Fig. 3. Activation output threshold relation.

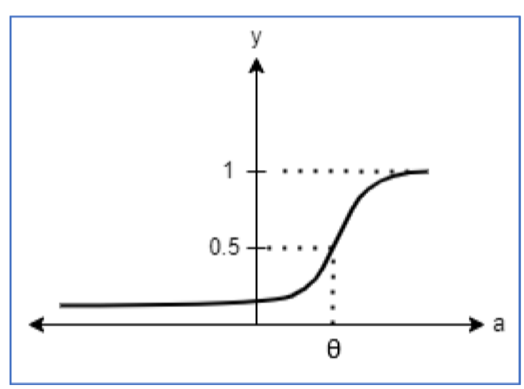


Fig. 4. The sigmoid function.

convolutional neural network (CNN) in machine learning is used to identify the disease on leaves and recommend pesticides for the disease. Using CNN, the accuracy achieved is 99.32% [10]. The application of machine learning techniques provides high accuracy. A google cloud auto-machine learning was used to train the model to detect aphid pests. Data set of 400 was found to have an accuracy of 96% [11]. The use of AI techniques for optimizing irrigation and pesticide application in farming was discussed. The use of AI was verified for applications such as weeding, irrigation, and spraying. The use of robots and drones for spraying pesticides ensures equal spray on plants with the required

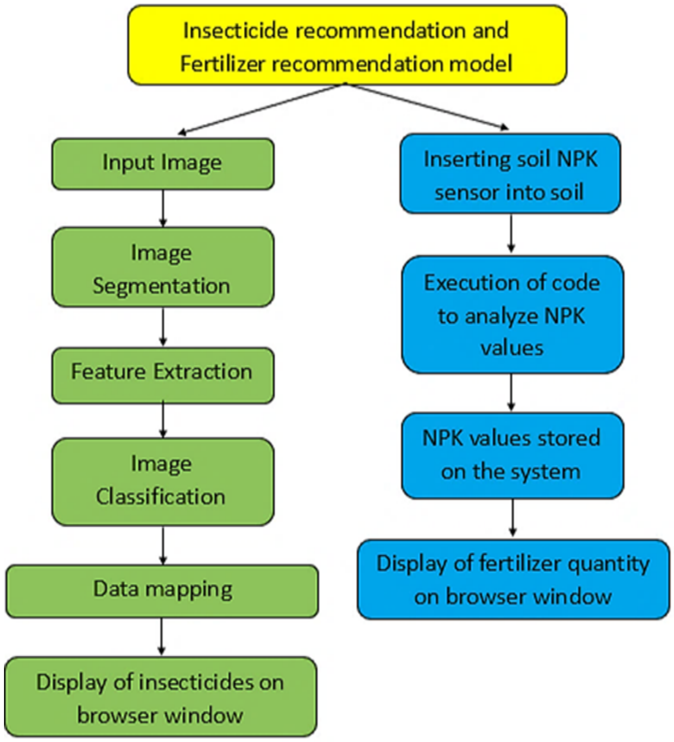


Fig. 5. Brief flowchart of the model algorithm.

Table 1
Component specifications.

Component	Specifications
Raspberry Pi 4	4GB SDRAM, 40 pin GPIO, 2.4 GHz and 5.0 GHz IEEE 802.11ac wireless, Bluetooth 5.0, BLEGigabit Ethernet2 USB 3.0 ports; 2 USB 2.0 ports, 5 V DC, 3A.
Arduino Nano	5 V, 40 mA, 19 mA power consumption, 22 Digital output pins.
Soil NPK sensor	9 V, output signal RS485, resolution 1 mg/kg, 0–1999 mg/kg measuring range.
Pi Camera	v1.3, 5MP, 1080p.
RS485 to TTL converter	5 V, RX, TX, 128 nodes identification.
DC-DC Buck Converter	92% conversion efficiency, input 4–35 V, output 1–26 V, response speed 200µs.
Battery	11.1 V, 2000mAh.

quantity only using wireless sensors, accelerometer, and gyroscope [12]. Due to unattended diseases, the crops are affected at a large scale which hampers production. To detect the disease segmentation, feature extraction and classification must be done. In order to identify the diseases, BP-NN, CNN, and SVM algorithms have been compared with an adaptive learning algorithm. The image processing is done, followed by ML algorithm and mapping. The accuracy of 99.2% is achieved for the prediction of rice crop disease [13].

Fertilizers are substances that provide nutrition to plants which are essential for their healthy growth. Soil contains nutrients such as nitrogen (N), phosphorus (P), and potassium (K) which are the major nutrients, followed by minor nutrients such as boron, iron, chlorine, copper, manganese, zinc, and nickel [14]. Farmers are unaware of the fertility of the soil and add fertilizers by assumption. The overdose of fertilizers in soil may degrade the plants and cause soil pollution as minerals accumulate in the soil. This causes the emission of oxides of nitrogen and sulfur, and consumption of heavy nitrogen-based leafy vegetables can cause an adverse effect on human beings [15,16]. Automation in farming is increasing as the results obtained by using sensors and processors compared to traditional farming are more. There is a need to develop a recommendation system to help farmers obtain healthy and maximum yield by recommending proper insecticides and fertilizers. The recommendation systems include artificial intelligence (AI) and machine learning (ML) algorithms, also the use of sensors to sense different parameters [17]. A crop recommendation system has been developed which uses ML models, which uses data on season change, geographic location, and sowing season. Assisting the ranchers with the quality of soil by examining different locations of a farm. Also, misguiding or false information is overcome using ML. [18–20]. The use of IoT as a tool in smart farming eases the process, and the recommendation of proper seed sowing and the use of fertilizers produce maximum yield [21,22]. Further, ML models combined with IoT have been implemented for crop disease prediction and harvest prediction. This system was deployed in real-time, with data acquisition from sensors [23]. Sensors play a major role in detecting the suitability of a soil as it senses temperature, pH, moisture, and nutrients present in the soil. When combined with IoT and AI, recommendations can be made for fertilizers, water supply, and pH value [24–26]. The near-infrared spectroscopy (NIRS) techniques are used to determine the nutrients in the soil. The NIRS is a laboratory technique and can be used to test more samples in less time. Nutrients such as nitrogen, phosphorus, potassium, sodium, and zinc were identified and recommended as per need [27]. A mobile lab-on-a-chip device was developed to detect soil nutrients on-site. The chip works on capillary electrophoresis, and the change in charge is calibrated with the concentration of soil nutrients. This device successfully analyzed NO_3, PO_4, K, and NH_4 ion concentrations [28]. A

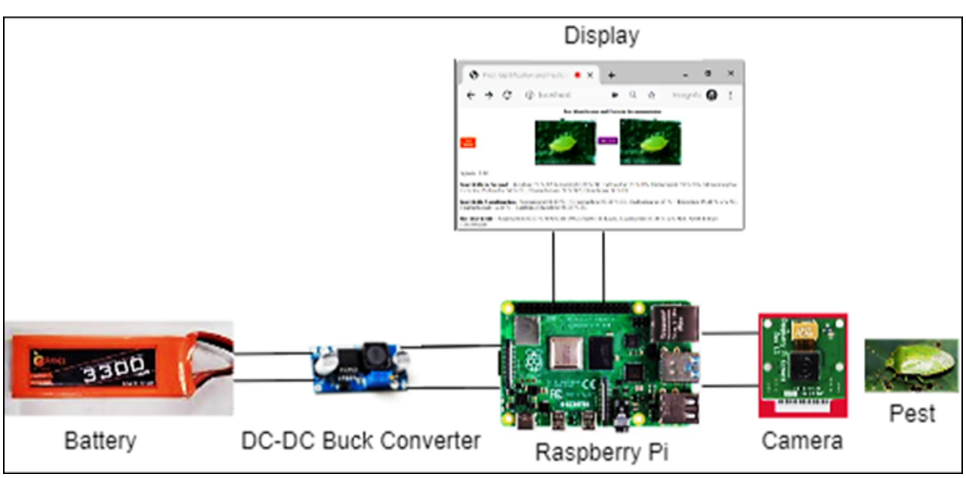


Fig. 6. Outline of pest identification and insecticide recommendation.

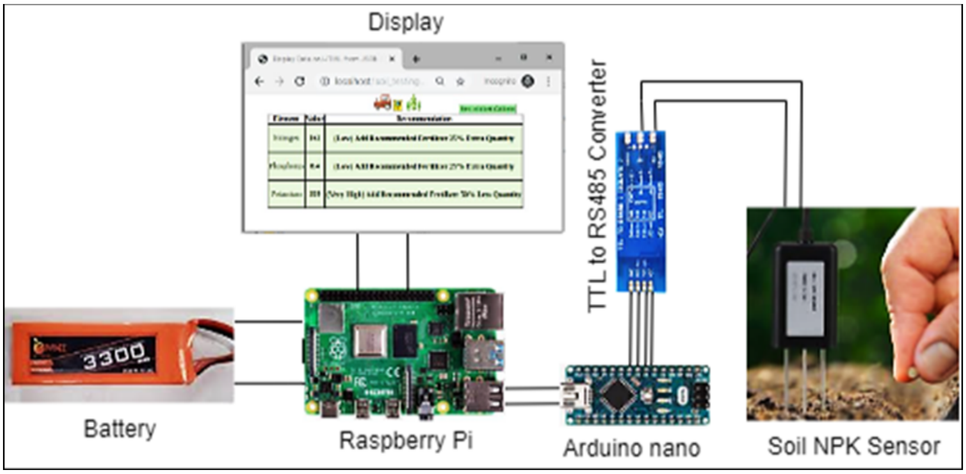


Fig. 7. Outline of Soil NPK value identification and fertilizers recommendation.

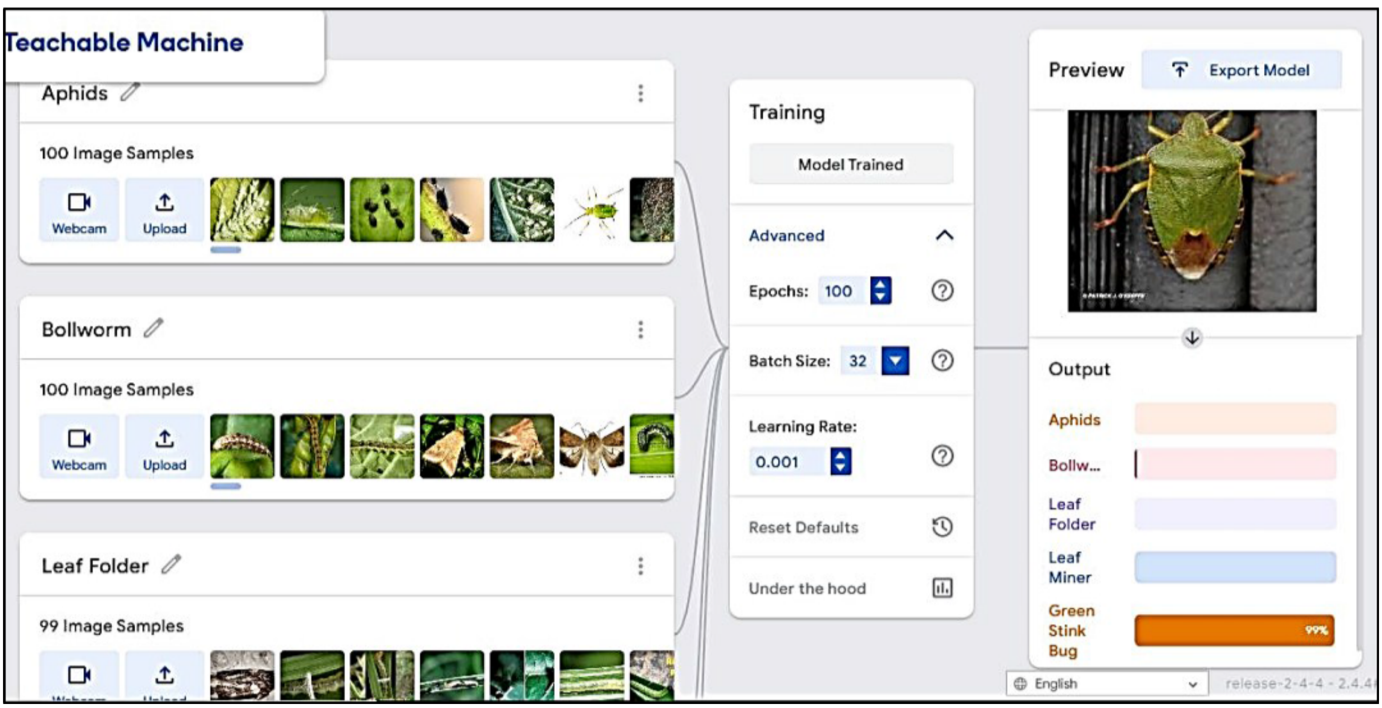


Fig. 8. Machine training model.

soil toxicity prediction and recommendation system were developed using data mining techniques. A decision tree algorithm has been implemented for classification. The system recommends toxicity of the soil, fertility of the soil, and crops [29].

Farmers are unaware of the pest that destroy the crops and use excessive insecticides, which makes the crop toxic to human health. Also, farmers are unaware of the fertility of the soil and add fertilizers according to their will. Hence, there is a need to control the excessive use of insecticide on crops and the addition of particular fertilizer quantities to the soil. To overcome these main problems in farming, an intelligent system is developed, which includes pest identification and insecticide recommendation along with soil NPK monitoring and fertilizer recommendation. These recommendations are given as per safety standards decided by the governing body. A TPF-CNN approach was applied to identify pests, as it is fast and accurate compared to other techniques such as ANN, SVM, and KNN. ANN is hardware dependent and cannot determine proper network structure. SVM has difficulty choosing the kernel with a long training time. KNN requires ample storage space and cannot handle complex dependencies. Thus, TPF-CNN duality optimizes operation concerning time and quantity. These efficient and compact advantages are achieved by transitioning the frequency distribution of images from continuous to discrete over probability.

The main objective of the proposed work is to enhance agricultural production and productivity by offering smart technology which will recommend insecticides and fertilizers for crops and soil respectively. The developed TPF-CNN approach captures the image of pests and recommends insecticides as per the scientific standards in a short time. This paper also offers intelligent fertilizer recommendations based on the fertility of soil using a soil NPK sensor and it takes 60 s for doing this which is comparatively very low as compared to laboratory methods of soil inspection. This will help in raising the living standard of farmers and will boost their economic growth. The farmers can use this technology anytime and anywhere.

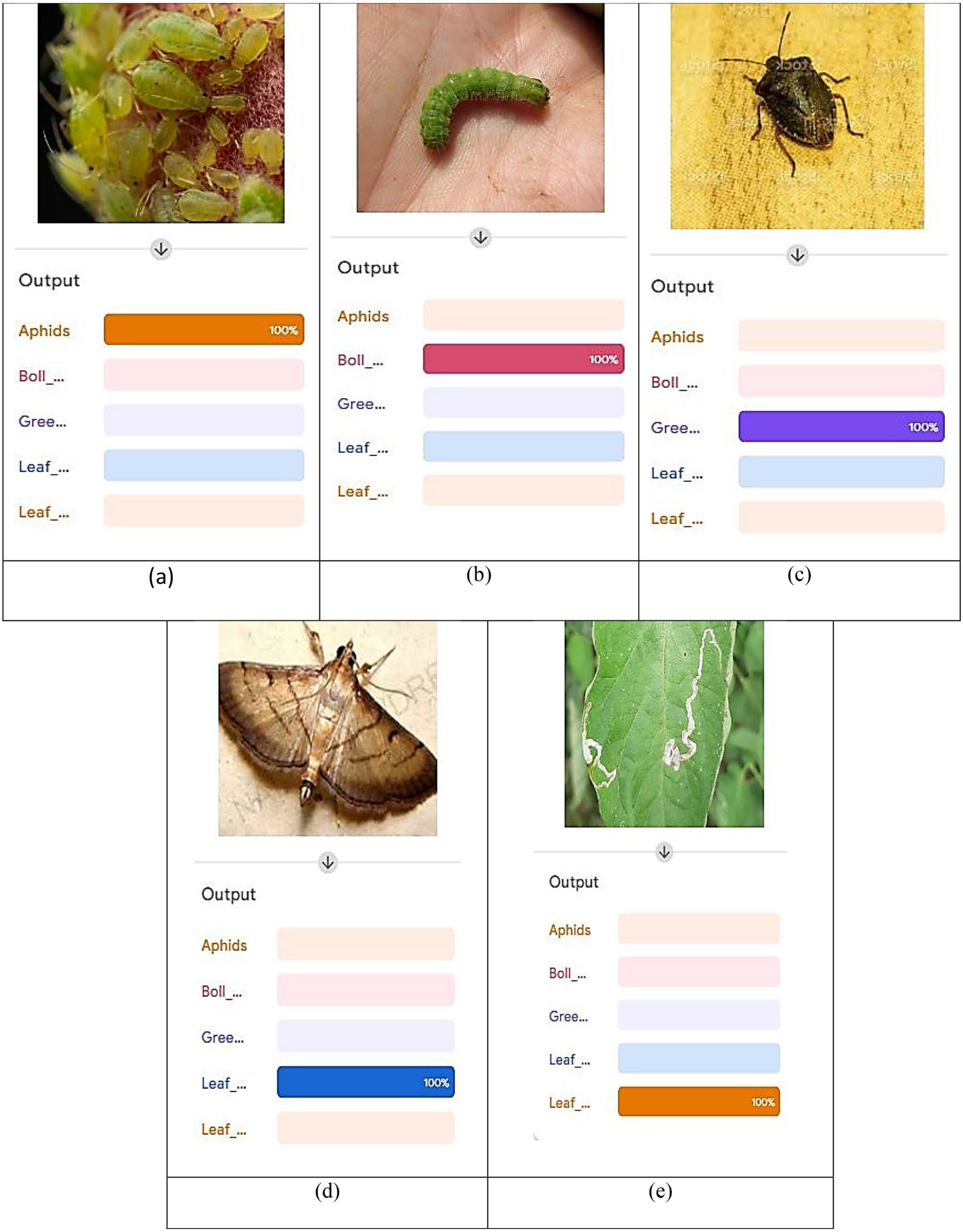


Fig. 9. Accuracy of detecting various pests. (a) Aphids, (b) Boll Worm, (c) Green Stink Bug, (d) Leaf Folder, (e) Leaf Miner.

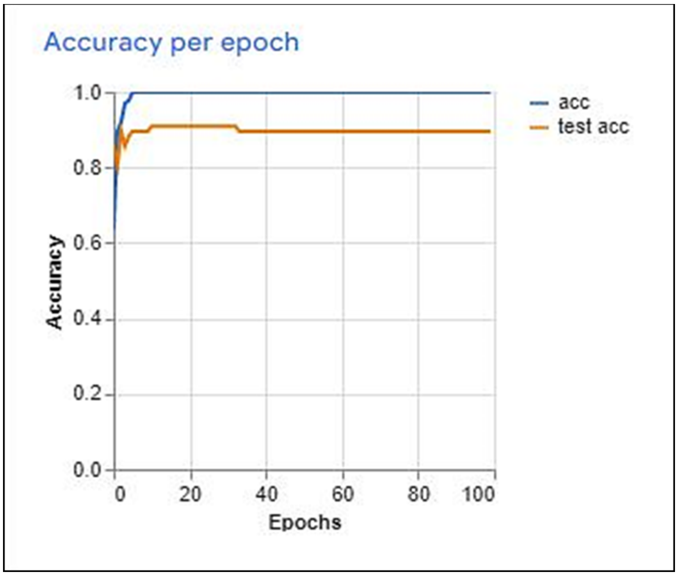


Fig. 10. Accuracy per epoch.

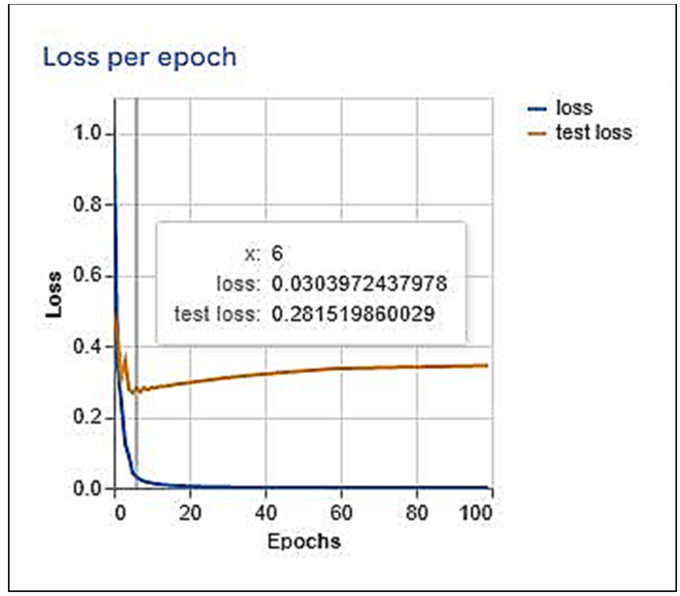


Fig. 11. Loss per epoch.

Table 2
Accuracy per class.

Class	Accuracy	Samples
Aphids	0.87	15
Bollworm	0.87	15
Leaf Folder	0.93	15
Leaf Miner	1.00	17
Green Stink Bug	0.80	15

Table 3
Confusion matrix.

Class	Aphids	13	1	0	0	1
	Bollworm	1	13	1	0	0
	Leaf Folder	0	1	14	0	0
	Leaf Miner	0	0	0	17	0
	Green Stink Bug	3	0	0	0	12
		Aphids	Bollworm	Leaf Folder	Leaf Miner	Green Stink Bug
	Prediction					

2. Proposed TPF-CNN model

The flowchart of the system can be seen in Fig. 1. The study includes five types of pests, namely aphids, bollworms, green stink bugs, leaf folder, and leaf miner, as shown in Fig. 2, commonly found on various crops. The description of each pest is as follows-

2.1. Crop pests

- **Aphids**: They are a damaging pest that consumes the sap of the plant and can cause viral plant diseases found on cabbage, mustard, pea, peach, tomato, soybean, cotton, and potato [30].
- **Bollworms**: They cause great harm to crops and are responsible for global economic loss. They can be found on cotton, tomato, soybean, and grain crops such as corn, sorghum, chickpea, and other pulses [31].
- **Green Stinkbug**: They are abundant in population and cause harm to crops reducing their production, and can be found on soybean, corn, and cotton [32].
- **Leaf Folder**: They are found in warm climate areas, majorly where rice crop is grown. They result in a loss in the yield of rice [33].
- **Leaf Miner**: They are small pests in larva state that eat leaves while mining in them, which causes decay of plant. They are found on tomatoes, cucumbers, and melon leaves [34].

2.2. TPF-CNN based image processing

The proposed system contains the data set of pests. The images hold discrete and distinct characters from physical and insecticide points of view. Each image is unique to the computational approach. There may be two challenges: first, analyze each image discretely and correlate their characteristics. Secondly, analyze the cluster of images and generate the classified set of images. There exist finite parameters for the classification of images. The characteristics of each parameter comprise the insecticide. There is a possibility of a mutually disjoint set of images and their contradiction. The insecticide application will be generalized correspondingly. The images are classified by the probability function over the transition of the images. Thus, there exists the TPF. The CNN is the nonlinear insecticide operator for the TPF of the pests. The TPF-CNN mechanism is presented as follows:

The input state of the image is (i), and the output state of the image is (j). The variation in images is denoted by the transition function (X) with respect to the finite time interval (t) and the set of classified images (each image is an element (s) of the classified set of images). The classified image element (s) will become the activation input for applying the insecticide and fertilizer. The process of image classification is represented by the following transition probabilistic function:

$$P_{ij}(t) = P\{X(t+s) = j | X(s) = i\}$$

A neural network sequences the set of classified images. Each image is referred to as the element of the classified set of images. The transition of the classified set of images corresponds with the set of nodes,$x_1, x_2, x_3, \ldots, x_n$and its deviation will be measured by the corresponding discrete weight probabilities,$w_1, w_2, w_3, \ldots, w_n$.The continuous images exist as the identity characteristic as an image node and an inverse characteristic of image weight. Thus the convolution of both the characteristics by CNN is represented as follows:$w_1x_1, w_2x_2, w_3x_3, \ldots, w_nx_n$.Its continuous activation is denoted by

$$\alpha = w_1x_1 + w_2x_2 + w_3x_3 + \ldots + w_nx_n.$$

TPF-CNN requires the activator to transform the continuous activa-

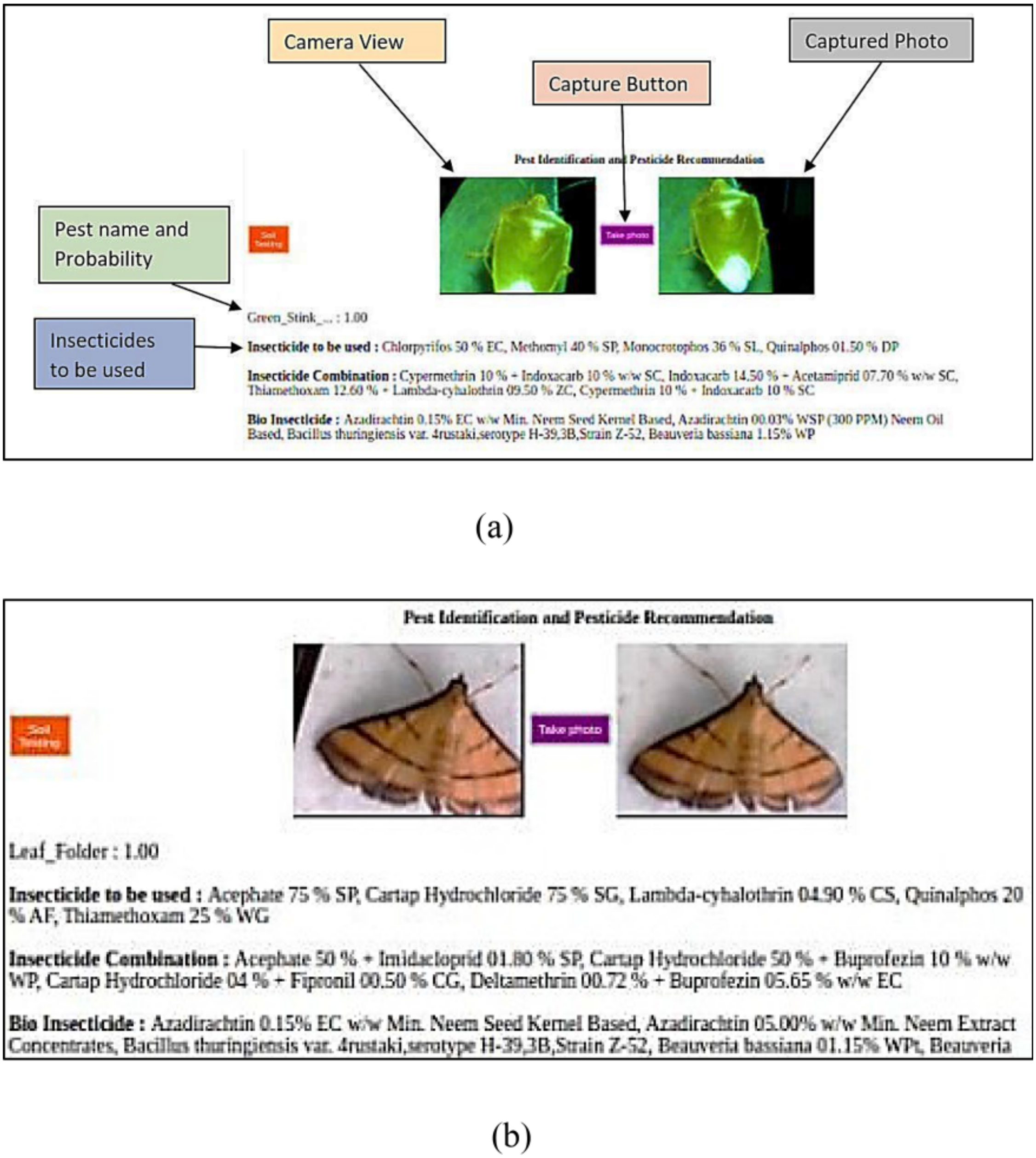


Fig. 12. (a). Insecticide recommendation on browser window for green stink bug. (b). Insecticide recommendation on browser window for leaf folder.

tion into discrete activation. Each image has an individual weight, and its continuous distribution is required for operating the insecticide with respect to the bounded operation. The insecticide operation is programmed in the system, and its distribution follows the discrete distribution of the weight activator represented by,

$$\alpha = \sum_{i=1}^{n} w_i x_i$$

The above activator function classifies images, but the insecticides have to be classified correspondingly. Thus, there exists the threshold distribution function. Each image carries the threshold character, so its discrete probability distribution is required. Optimizing the insecticide operation depends on the objective function of the homogeneous pest images. The insecticide operation on the TPF-CNN activated continuous images requires error-free nodes; thus, its threshold relation is defined by the threshold function, and its graph is shown in Fig. 3 as follows:

$$y = \begin{cases} 1, \text{ a } \leq \theta \\ 0, \; a < \theta \end{cases}$$

The above threshold distribution may occur the error by the piecewise interval domain. Thus, it is required to transform the threshold image characteristic from continuous to discrete. There exist absolute and relative errors in the image activator function. To minimize the error, there will be an inverse threshold activation function for finding the identity operation. If there exists the large error (a), then it will be minimized by the following sigmoid function and its graph shown in Fig. 4 with the least count identity (σ = 1):

$$y = \sigma(a) = \frac{1}{1 + e^{-(a-\theta)/\sigma}}$$

The inverse TPF-CNN activation will be defined on the continuous classified images of pests by the continuous insecticide set correspondingly. The standard information of pests installed in the proposed system is represented as the discrete distribution, $p_1, p_2, p, \ldots, p_n$. The recom-

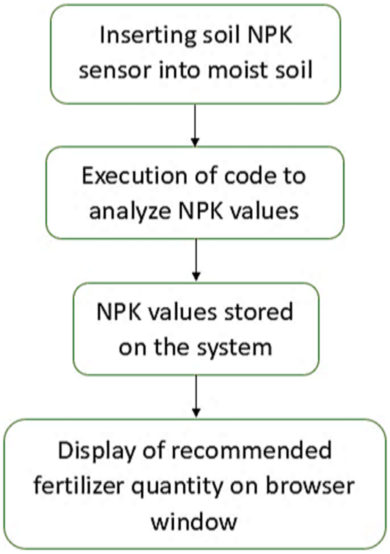


Fig. 13. Flowchart of soil NPK analysis and fertilizer recommendation.

Table 4
Comparison of soil NPK values.

Sample No.	Time for detection	NPK values obtained by soil NPK sensor	NPK values obtained by lab test
1	60 s	162 – 8.4 – 359	168.53 – 8.93 – 385.64
2	60 s	151 – 7 – 325	156– 7.5 – 329.2

mended discrete-time of prevention by the inverse TPF-CNN insecticide activation is represented by, $t_1, t_2, t_3, \ldots, t_n$. The correspondence between the classified image set by the proposed system and the installed recommended image set in the proposed system is indefinite. Thus there exists the discrete probability distribution function defined as follows:$P_1(t_1), P_2(t_2), P_3(t_3), \ldots, P_n(t_n)$.

The inverse insecticide activator is applied to the classified image set defined on the finite time interval [t_1, t_2] for obtaining the sequence represented by the following,

$$P_{ij}t_1 = P\{X(t_1 + s_1) = j | X(s_1) = i_l$$

$$P_{ij}t_n = P\{X(t_n + s_n) = j | X(s_n) = i_n.$$

The sequence of images is as follows:$i_1 < i_2 < i_3 < \ldots < i_n$. Its optimization lies with the minimization of the error. Thus, each image of the sequence is defined by the magnitude,$w_1, w_2, w_3, \ldots, w_n$.

The minimized activator is defined by,

$$\alpha = w_1 i_1 + w_2 i_2 + w_3 i_3 + \ldots + w_n i_n$$

The absolute error over TPF-CNN is computed discretely as follows:

$$|\alpha_1| = \left| P_{11}\left(\frac{w_1 i_1}{t_1}\right) + \ldots + P_{1n}\left(\frac{w_n i_n}{t_n}\right) \right|$$

$$|\alpha_n| = \left| P_{m1}\left(\frac{w_1 i_1}{t_1}\right) + \ldots + P_{mn}\left(\frac{w_n i_n}{t_n}\right) \right|$$

Similarly, the relative error over TPF-CNN defined discretely as follows:

$$\alpha_1 = P_{11}\left[\frac{w_1 i_1 + w_2 i_2 + w_3 i_3 + \ldots + w_n i_n}{t_1 + t_2 + t_3 + \ldots + t_n}\right]$$
$$\cdots \quad \cdots \quad \cdots$$
$$\alpha_n = P_{mn}\left[\frac{w_1 i_1 + w_2 i_2 + w_3 i_3 + \ldots + w_n i_n}{t_1 + t_2 + t_3 + \ldots + t_n}\right]$$

Next, the objective function is defined.
Decision Variables: Finite category of insecticides: $i_1, \ldots, i_n$.
The corresponding magnitudes: $w_1, \ldots, w_n$.
The corresponding time: $t_1, \ldots, t_n$.
The rate of processing: $\frac{w_1}{t_1}, \ldots, \frac{w_n}{t_n}$.
Hence, the objective function: $\min Z = \frac{w_1}{t_1} + \ldots + \frac{w_n}{t_n}$.
Subject to the constraint, $P_{11}\frac{w_1}{t_1} + \ldots + P_{1n}\frac{w_n}{t_n} = \alpha_1$.

$$P_{m1}\frac{w_1}{t_1} + \ldots + P_{mn}\frac{w_n}{t_n} = \alpha_n.$$

and $\frac{w_1}{t_1}, \ldots, \frac{w_n}{t_n} \geq 0$.
The proposed system is presented in Section 3.

3. Insecticides and fertilizers recommendation system

Farming requires two major things to obtain maximum yield: the protection of crops from pests and providing proper fertilizers to the soil. To ensure adequate insecticide and fertilizers are used in farming, two features implemented in the smart system are discussed below. First, the pest identification and insecticide recommendation using machine vision and a convolutional neural network. Secondly, the soil nutrient analysis using a soil NPK sensor and recommendation of fertilizers according to the obtained nutrient values. To develop this model, Raspberry pi 4, Arduino nano, Soil NPK sensor, RS485 to TTL converter, DC-DC buck converter, Pi camera, Cooling fan, and Battery were used. The brief flowchart of the model working is shown in Fig. 5.

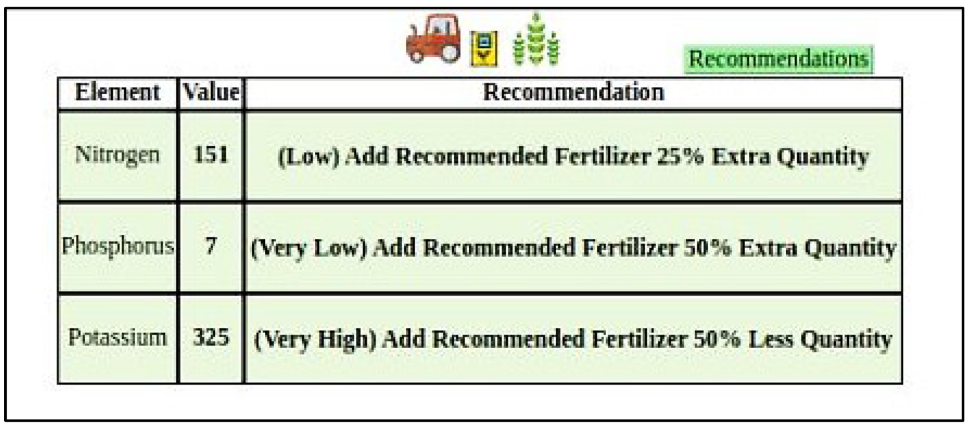
The details of the components have been listed in Table 1. The data set for insecticides and fertilizers were prepared by visiting official government websites [35,36] and conducting surveys in pesticide shops, and discussing with farmers. To generate the data set for pests, images were taken from google as well as real-life pests on crops were taken and fed to the machine learning module. The working diagram for pest identification and insecticides recommendation with actual parts is shown in Fig. 5, while the working diagram for soil NPK nutrient detection and fertilizers recommendation with actual parts is shown in Fig. 6, which consists of five parts. The first part is the camera front and back casing, the second part is the upper body which is in white color, the third part consists of touch screen LCD mounting, the fourth part consists of on-off buttons, and the fifth part consists of the soil NPK sensor mounting. To operate the system for pest identification, the system is held horizontal as the camera points toward the pest, and the operator sees the touch screen LCD. The browser is opened, and a pest picture is taken, which results in the captured image of the pest along with recommended insecticides. This model operates for only five pests that are commonly found on crops like cotton, rice, tomato, banana, chili, brinjal, sugarcane, cabbage, and potato. To operate the system for soil NPK testing, the required file is run, and then the probes of the soil NPK sensor are dipped into the soil sample. After 60 s, the webpage is opened, which shows the NPK values along with the recommended dose of fertilizers.

3.1. Pest identification and insecticide recommendation

Classification of insects is done by training the model using a google teachable machine. The google teachable machine uses a 28-layer convolutional neural network as a machine learning algorithm. The images and names of insects need to be uploaded, and the data set was prepared by using images from google and capturing on-site pest images from the farm; further, the training model needs to be set for epochs, batch size, and learning rate. After doing the required steps, the model must be trained and verified. If proper accuracy is not achieved, there is a need to change the number of images uploaded as more images may over-train the model, and fewer images may undertrain the model. Also, changes in epochs, batch size, and learning rate must be done. Maximum accuracy was observed for 100 images uploaded per insect with epochs at 100,

Element	Value	Recommendation
Nitrogen	162	(Low) Add Recommended Fertilizer 25% Extra Quantity
Phosphorus	8.4	(Low) Add Recommended Fertilizer 25% Extra Quantity
Potassium	359	(Very High) Add Recommended Fertilizer 50% Less Quantity

(a)



Element	Value	Recommendation
Nitrogen	151	(Low) Add Recommended Fertilizer 25% Extra Quantity
Phosphorus	7	(Very Low) Add Recommended Fertilizer 50% Extra Quantity
Potassium	325	(Very High) Add Recommended Fertilizer 50% Less Quantity

(b)

Fig. 14. (a). Fertilizer recommendation for soil sample 1 on the browser window. (b). Fertilizer recommendation for soil sample 2 on the browser window.

batch size at 32, and learning rate at 0.001, as shown in Fig. 7.

The accuracy of each pest detection is shown in Fig. 8. When the required accuracy is reached, the model can be exported via tensorflow, tensorflow.js, and tensor flow lite. The model was exported via the tensorflow.js onto raspberry pi 4, and to display the required solution, localhost was created and a webpage to display it on the browser window. The accuracy per epoch is shown in Fig. 9, and the test loss is shown in Fig. 10. The accuracy per class is shown in Table 2, where the highest accuracy is obtained for leaf miner, followed by leaf folder, aphid, bollworm, and green stink bug. The confusion matrix for the model is shown in Table 3, and the confusion state is shown as an overlap of two insects, where the number indicates the total images leading to confusion. To validate the outcome of the device for pest identification and insecticide recommendation, the image of the pest is captured, as seen in Fig. 11(a) and 11(b), which show us the pest identification and insecticide recommendation browser window. The camera captures the image, and the image can be seen in the box. The recommendations are displayed below the images with the pest name, the probability of the insect, and the recommended insecticides.

3.2. Soil NPK analysis and fertilizers recommendation

Soil NPK analysis was done by using a soil NPK sensor. The output of this sensor was given to Arduino nano via TTL to RS485 converter, which converts the analog signal to digital form, and it was given to Raspberry pi 4. A soil sample was tested in a laboratory, and from those values, the output was calibrated according to the error. The data set for the recommended dose is mapped along with the NPK values in the python code. The flowchart for soil NPK nutrient analysis and fertilizer recommendation is shown in Fig. 12. To analyze the soil NPK values, the soil sensor is inserted into moist soil. Then the code is executed to analyze the NPK nutrient values in the soil. After 60 s, the values stabilize and are stored in the system file. These values can be viewed on the browser window. The webpage of insecticide recommendation consists of a soil sensor link that opens a new browser window for fertilizer recommendation, as shown in Fig. 12(a) and 12(b). The soil parameters NPK are displayed in the table with their respective values and the recommendation of fertilizer dose for each nutrient. Further, the recommended dose for each crop can be seen when the green color button named recommendation is clicked on top, which is shown in Fig. 13. Table 4 shows the comparison of soil NPK values which were tested in laboratory and with the sensor. The values show less deviation and fall in the exact range specified by the norms (Figs. 14, 16).

4. Result and discussion

The proposed technique uses a 28-layer convolutional neural network. The model was trained for 500 images. While training the model for 5 classes of pests, maximum accuracy was observed as 91%, with epochs at 100, batch size at 32, and learning rate at 0.001.

Crop Name	Crop Image	N (Kg/ha)	P(Kg/ha)	K(Kg/ha)
Tomato		300	150	150
Potato		100	60	120
Onion		100	50	50
Brinjal		100	50	50
Cucumber		100	50	50
Green Chilies		50	50	50
Cabbage		80	80	80
Cauliflower		75	75	75
Sugarcane		250	115	115

Fig. 15. NPK value recommendations for particular crops.

Similarly, for 3 classes of pests 94% accuracy is obtained with a computation time of less than 5 min for both classes. The recommendation of insecticide is made as per the pest detected. The accuracy per epoch generated by the TPF-CNN technique was 91%, and the test loss per epoch was observed at 28.15%. The TPF-CNN network has maximum accuracy (91%) in detecting 5 classes of pests and recommends insecticides accordingly. The soil NPK sensor has an error of ±5% compared to the laboratory test, but the values lie in the prescribed range as per norms. Further, the farmers will be aware of the particular pest and use government-approved insecticides. The time required for soil NPK recommendation is around 60 s which is faster than the laboratory technique, which takes around 24 h for one sample. Also, the cost of testing soil NPK values is reduced. The performance analysis of proposed TPF-CNN was compared with other techniques. To obtain the comparative results, an experiment was conducted for 3 classes of pests and 5 classes of pests in which various machine learning techniques were used, such as artificial neural networks (ANN), and k-nearest neighbors (KNN), support vector machine (SVM), and TPF-CNN model. The TPF-CNN showed the highest accuracy among these techniques, as shown in Fig. 15. The ANN technique shows74% and 62% accuracy, SVM shows 78% and 71% accuracy, and KNN shows 75% and 71% accuracy for 3 and 5 classes of pests, respectively.

5. Conclusion

The TPF-CNN dual operator approach makes the insecticide recommendation operation efficient and compact. The proposed system consists of combined insecticide and fertilizer recommendation systems, which will help farmers gain maximum farm yield. Also, the soil nutrients would be managed efficiently, resulting in nutrient-rich soil. The cost incurred for laboratory testing of soil nutrients will reduce. The proposed approach gives the recommendation of insecticides in a short time of 10 s and fertilizer recommendation in 60 s only. Compared to other approaches such as KNN, SVM, and ANN, it gives nearly 20% higher performance. This system can be used anywhere as it is standalone and does not require an internet connection. In the future, the system can be integrated with more sensors such as pH, temperature, humidity, and moisture sensors for open and indoor farming. Also, this system can be used in online and offline modes. This system can be recommended for farmers, soil testing laboratories, and seed hybridizing companies. The limitations of this model are it does not save any data on the system or cloud database.

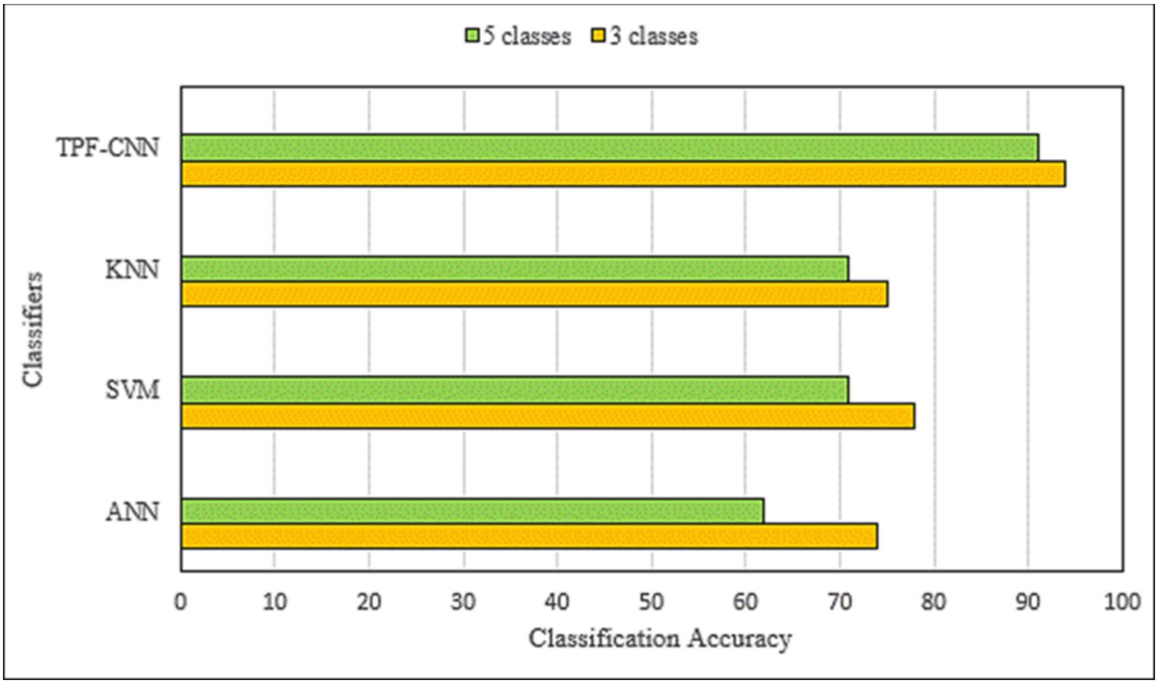


Fig. 16. Classification accuracy of machine learning algorithms.

Declaration of Competing Interest

None.

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