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A Novel Deep Learning Models for Efficient Insect Pest Detection and Recommending an Organic Pesticide for Smart Farming

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Abstract*:* Plant pests pose a significant threat to agricultural production worldwide, as their outbreaks become increasingly intense and widespread. However, traditional methods of identifying these pests through lesion image segmentation are both inefficient and time-consuming, impeding the ability to generalize and apply their findings. To address this issue, this study introduces an enhanced convolutional neural network with Adaptive Particle Swarm Optimization with Long Short Term Memory (ICNN-APSO-LSTM), which improves the identification of plant pests in natural agricultural environments. The resulting pest identification system classifies harmful pests, enabling farmers to take corrective action. The study begins with an overview of current pest identification techniques, highlighting their pros and cons. Based on the limitations of these methods, the study proposes a new and improved classification technique. The mathematical model is derived using an objective function, combining pest recognition and pesticide recommendation using machine vision and CNN. The model also uses soil NPK sensors to acquire soil nutrient values, analyzing them to prescribe appropriate fertilizers. Choosing the right fertilizer for soil and yield is crucial for farming, and this article describes a powerful technique for estimating soil nutrient content and recommending suitable fertilizers. The study successfully identified five pests - aphids, magnolias, leaves, leaf miners, and sables - with over 99% accuracy. Field results using this technique resulted in recommended pesticide application times within 10 seconds and fertilizer recommendations within 80 seconds.

Keywords: *Deep learning; pest detection; organic pesticide; smart farming*

1. Introduction

The agricultural sector in India has experienced significant growth due to globalization [1]. Additionally, there has been an increase in demand for high-quality food as people become more health-conscious. To achieve higher yields, farmers sometimes use pesticides and fertilizers [2]. However, pesticides can be more toxic than herbicides and fungicides, which are also used to protect crops from pests [3]. The Pesticides Act of 1968 strictly regulates the manufacturing, sale, importation, and proper application of pesticides in India. Also, the Indian government has banned the use of 30 pesticides and refused to license 18 plant protection agents [4]. Some farmers may be unaware of the harmful effects of excessive pesticide use and the need to check soil quality before applying fertilizers. Overuse of pesticides can cause respiratory disease, cancer, venereal syndrome, and even death if consumed directly or indirectly. Pesticides can also pose environmental hazards, such as soil and water pollution, and can harm animals and plants [5]. In India, pesticides are consumed at a rate of approximately 76%, followed by fungicides at 13%, and herbicides at 10%. To address this issue, a recommendation system using the "Pests in Crops and Their Treatment" ontology (PCT-O) was developed to detect pests and suggest relevant treatments [6]. The ontology utilizes datasets of pests, insecticides, and symptoms to classify and handle pesticides effectively [7]. The platform helps farmers optimize their resources, reduce production costs, and increase their profit margins. It promotes integrated pest management strategies, which involve using natural and approved pesticides to protect crops from pests. The platform also provides farmers with up-to-date information on pesticide regulations and useful advice on safely storing, handling, and applying pesticides [8].

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2. Motivation

Our objective in this study is to create a cutting-edge recommendation system that utilizes AI and machine learning algorithms to deliver precise guidance to farmers regarding the ideal fertilizers and irrigation techniques for the optimal growth of their crops. Furthermore, we strive to integrate sensor technology to monitor soil conditions in real-time and provide customized and timely recommendations that cater to each farm's unique requirements. Fertilizers are essential substances that provide necessary nutrients for optimal plant growth. The soil naturally contains vital nutrients such as nitrogen (N), phosphorus (P), and potassium (K). However, without proper knowledge of soil fertility, excessive use of fertilizers can lead to plant deterioration, mineral accumulation, and soil pollution. The automation of agriculture is rapidly increasing, as modern technology offers more efficient and accurate solutions than traditional methods. Recommendation systems, which incorporate artificial intelligence (AI) and machine learning (ML) algorithms, help farmers achieve healthier crops by suggesting appropriate plant protection agents and fertilizers. These systems use sensors to detect various parameters such as temperature, pH, and moisture, which play a crucial role in determining soil suitability. By providing recommendations on fertilization, irrigation, and pH, these systems pave the way for better and more sustainable agricultural practices. Crop recommendations based on seasonal variation, geographic location, and planting time are available through recommender systems. These systems utilize machine learning techniques to address misconceptions and misinformation, enabling the Internet of Things to be utilized as a tool in smart farming. Proper planting and fertilizer advice is provided for optimal production.

3. Survey

With the rapid advancement of computer vision and pattern recognition technologies, machine learning and deep learning have emerged as primary study topics for identifying agricultural pests [9]. For example, k-means cluster segmentation proposed a method for identifying pests, but manually labeling features is time-consuming for large datasets [10]. After extracting the morphological characteristics of the pest using the Prewitt operator and the Canny edge detection algorithm, in insects from cabbage the accuracy is close to 91% [11].

The researchers in [12] created an aphid detection approach based on a genetic algorithm to recognize and count aphids in difficult field situations efficiently. With specified backgrounds, using static matrices to extract lesion shape properties in combination with the ARTMAP neural network technique achieved recognition accuracy of 86%. Unlike manual detection, the soy flour monitoring system built based on digital image processing can automatically recognize and count flour [13]. Conventional machine-learning algorithms for identification work best when the number of plant pests is modest; however, when there are many pest species and limited input circumstances, machine-learning approaches cannot extract crucial functional information. The durability of the model is reduced.

Deep learning uses multi-stage neural networks to allow computers to extract meaningful properties from large amounts of images automatically. Enhanced Convolutional Neural Networks (CNNs) are extremely powerful deep learning networks [14]. CNN forgoes complex preprocessing and feature extraction in favor of a complete architecture that successfully merges global and local data and substantially simplifies the recognition process. As a result, CNN is often used in real-world agricultural situations to identify crop information, and automatic pest identification combined with CNN improves detection accuracy and reduces labor costs [15-19].

The tomato leaf pest classification system was developed with an accuracy of 90%. However, it can only be used for rudimentary ambient pest detection and cannot be integrated into actual applications [20]. The residual network structure was optimized by including a high-resolution convolutional layer and the appropriate amount of channels, and the lesion recognition accuracy was 92%. Integrate pest condition data into CNNs to increase the accuracy of pest detection and identification in complicated contexts [21-24-].

A practical method for optimizing multiscale data from lesion images has been proposed. The existing single image size method cannot detect and recognize small target changes; therefore, the proposed approach incorporates image optimizations of different sizes in the identification model. The proposed CNN approach for fruit fly recognition achieves an accuracy of 96% [25-29].

A Generative Adversarial Network (GAN) was applied to augment the dataset and feed the augmented dataset to a pre-trained CNN model to achieve 92% accuracy in plant disease classification [30-31]. This method achieved an average accuracy of 93.84% for training and testing 10 pest species in a pest detection and diagnosis system designed based on transfer learning [32-34]. The author proposed to fine-tune the VGG-16 network to classify tea pests and found that the classification accuracy is as high as 97.75%.

Recently, attention mechanisms have been widely used in machine translation, generative antagonism, etc., due to their properties that extract distinctive features from regions of interest [35-39]. The researchers used the call attention mechanism to scan the entire image for regions of interest quickly. However, plant pest detection is still in its early stages [40-44]. The proposed CNN method for malware identification combines an attention control mechanism with CNN. In experiments on 16 kinds of field pests, the average accuracy reached 75.46%, significantly improving the accuracy rate [45-47]. The self-service engine was designed and integrated into the CNN framework to achieve an F1 best score of 93.21% against 11 plant pests and diseases and presented a DenseNet-based approach and attention mechanism capable of detecting navel orange and a total of seven pests in the experiment set with 97% of accuracy [48-50].

4. Problem Definition

The detection and identification of plant pests pose a significant challenge in the field of agriculture. Due to the evident variations between pest species, detecting and classifying them is much more complex than detecting ordinary objects. To prevent the invasion of pests, it is necessary to enhance crop productivity and reduce economic losses through early pest diagnosis. Different machine learning algorithms have been introduced to detect various types of pests, but these techniques are not effective on all pest types. A deep learning method is proposed to identify and categorize pests into two groups: harmful insects and beneficial pests. Unfortunately, most farmers in India lack the education and skills to distinguish between beneficial and harmful pests, leading to the killing of both types of pests and damaging long-term yields. Therefore, distinguishing between beneficial and harmful pests is a crucial task.

Previous studies have primarily focused on using various soil properties and data mining techniques to predict crop yield. However, the vital aspect of fertilizer recommendation has often been overlooked. Therefore, it is crucial to develop a comprehensive system that incorporates soil nutrients and crop yield data to accurately predict crop yield and provide fertilizer recommendations for different crops. Unfavorable agricultural practices have led to a decline in soil quality and nutrient availability. The excessive use of chemical fertilizers has exacerbated this issue. To address this, there have been attempts to use artificial intelligence models to forecast nutrient levels, but these models, such as deep learning and machine learning, have limitations in terms of training time and memory usage. As a result, there is still untapped potential to improve the accuracy, time efficiency, and memory consumption of classification models. To address the issues mentioned earlier, this paper employs an optimized neural network to solve the pest detection and recognition problem. Farmers are often unaware of the pests that destroy crops and use inappropriate pesticides, making crops harmful to human health. Farmers are also uninformed about soil fertility and spread manure without permission. Therefore, the excessive use of pesticides in plants should be controlled, and a certain amount of fertilizers should be added to the soil. To avoid these major agricultural difficulties, an intelligent system with pest identification and treatment suggestions, as well as soil testing and NPK fertilization advice, has been developed. These recommendations are provided in accordance with safety standards established by governing bodies.

5. Contribution

Compared to the suggested model, provide a model for identifying useful and harmful pests using a deep learning classifier. The suggested model minimizes the number of hidden layers, reducing time complexity, and increasing accuracy.

This research provides an improved CNN and APSO-LSTM model for identifying plant pests. To achieve unity of the parallelism mechanism, spatial attention, and channel attention are integrated. The ResNet network model deeply incorporates the Parallel Attention module.

The Attention module sets multi-dimensional dependencies for the extracted cropped feature maps, which is lightweight and easy to add to the network. This method has been used to identify crop pests very accurately in complex agricultural environments.

The proposed method consists of four steps: soil analysis, data preprocessing, data analysis, and recommendations. The soil sample is analyzed using an IoT-based device that uses a two-electrode NPK sensor to determine the ratio of NPK to soil nutrients and preprocess the sensor output as a valid dataset.

6. Proposed

The proposed model aims to enhance agricultural productivity by utilizing intelligent technology to suggest effective pesticides and fertilizers for plants and soil. The improved APSO-LSTM CNN can capture images of pests in a short time and recommend pesticides based on scientific criteria. This paper also uses a soil NPK sensor to make intelligent fertilizer recommendations based on soil fertility in just 50 seconds, which is a relatively short time compared to laboratory soil testing methods. The proposed model is expected to help improve the standard of living of farmers and boost economic growth.

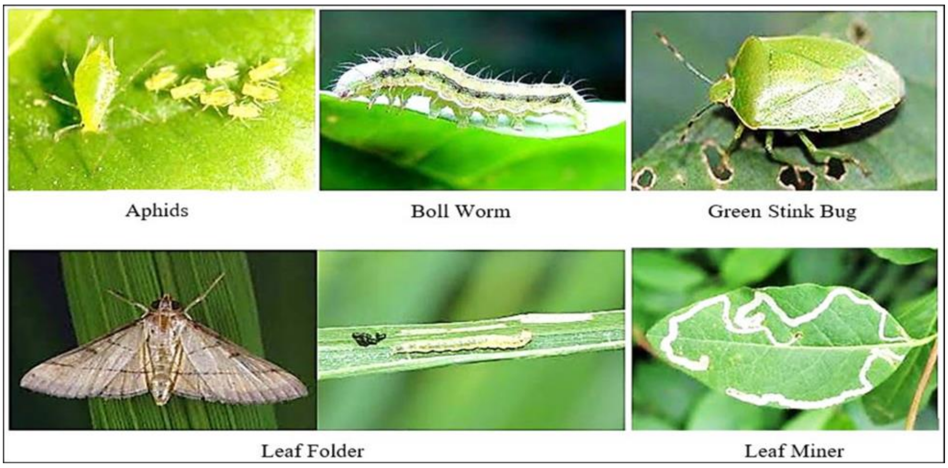

Fig. 1. Images of 5 pest [5]

Crop pests:

Figure 1 shows images of the five pests that were part of this study.

Aphids: They feed on plant sap and are a harmful pest that can cause viral plant diseases in cabbage, mustard greens, peas, peaches, tomatoes, soybeans, cotton, and potatoes.

Bollworms: They cause severe crop damage and cause global economic losses. It is found in grain crops such as cotton, tomatoes, soybeans, corn, sorghum, and chickpeas.

Green Stinkbug: They are in abundance and cause yield-reducing damage to crops, found in soybeans, corn, and cotton.

Leaf Folder: They can be seen in regions with a warm climate, typically areas where rice is the primary crop. This insect is notorious for causing significant losses in rice yields.

Leaf Miner: It is a tiny pest that can damage plant health by feeding on leaves and causing rot. This species is commonly found in plants such as tomatoes, cucumbers, and watermelons, as illustrated in Figure 1.

7. Material and Study

A study was conducted in India to identify two classifications of pests - harmful and beneficial - across multiple crops. The study involved examining 10 different types of pests and 10 instruments. Among the harmful insects discovered were kudzu, aphids, black beans, ladybugs, bed bugs, and caterpillars. Figures 2 and 3 present examples of both detrimental and advantageous changes. However, the images used for this research were sourced from various farms and the internet, which may not provide sufficient data for training deep neural networks. To overcome overfitting issues, it is recommended to expand the image dataset by applying techniques such as rotation, scaling, and database manipulation.

Fig. 2. Beneficial Pest

Fig. 3. Harmful Pest

The data was approached with care because the collected images were noisy and of poor quality. Each image has a size of 50 * 50 pixels. The collection contains approximately 9,500 images from these two categories.

8. Soil Analysis

Near-Infrared Spectroscopy (NIRS) methods are used for identifying soil nutrients. NIRS is a laboratory device that enables testing of additional samples in a shorter time period. It checks and recommends nutrients, such as nitrogen, phosphorus, potassium, sodium, and zinc, as needed. A mobile laboratory device on a chip has been developed for detecting soil nutrients in fields. The plate is employed in capillary electrophoresis where the charge variation adapts to the concentration of nutrients in the soil. The instrument successfully analyzed the ion concentrations of NO3, PO4, K, and NH4.

9. Classification

The gradient descent approach is utilized to update the weight and threshold parameters of the LSTM neural network model. As the number of hidden hierarchies increases, the convergence speed rate decreases, and the weight adjustment may decrease towards the local maximum, affecting the standardization of the LSTM model and the accuracy of the predictions. Therefore, this paper proposes an enhanced LSTM neural network model based on the Adaptive Particle Swarm Optimization algorithm (APSO-LSTM).

9.1. Improved CNN model

The researchers hypothesized about different attention strategies and tested them on conventional CNN learning tasks and significantly increase network performance using modest parameters and processing overhead. The channel attention mechanism and the spatial attention mechanism are the two fundamental components of the attention system.

9.1.1. Spatial Attention Mechanism

A spatial attention model highlights regions of interest from features and quantifies feature importance based on dependencies between different locations within a feature. To improve the representation of key region features, appropriate weight parameters need to be defined. The spatial attention model allows the network to better assess the role of individual resource locations in the categorical resource extraction process, further enhancing the network's modeling capabilities. We perform maximum summation and aggregation operations on the input feature map F, collect information on two different feature maps successively, and apply the convolution layer used to create the spatial conduction map. Then, a 7×7 achieves resource fusion. The convolution process and sigmoid activation function, both contained in the original input feature map, are used to produce the weight map. Finally, the spatial attention model has improved the efficiency of the target pixel area.

9.1.2. Channel Attention Mechanism

Channel attention predicts the correlation of resource maps between different channels, learns the relevance of each resource channel by automatically learning the backpropagation parameter, and provides distinct weighting factors for each channel. The cost function determines the weight of different channels, and the weight factor of each resource channel is calculated automatically. It optimizes effective resource channels and excludes invalid resource channels based on the weighting factor size for each resource channel.

9.1.3. Parallel Attention Mechanism Model

Based on the pest detection, highlight the function of the spatial unit of the lesion area in terms of spatial location, while the function of the channel monitoring unit conveys more meaningful information within the channel. Multi-attention must be combined to achieve improved attention. As a result, in this study, provide a parallel method, PCSA, that effectively integrates the spatial module with the channel module for pest identification as shown in Figure 4.

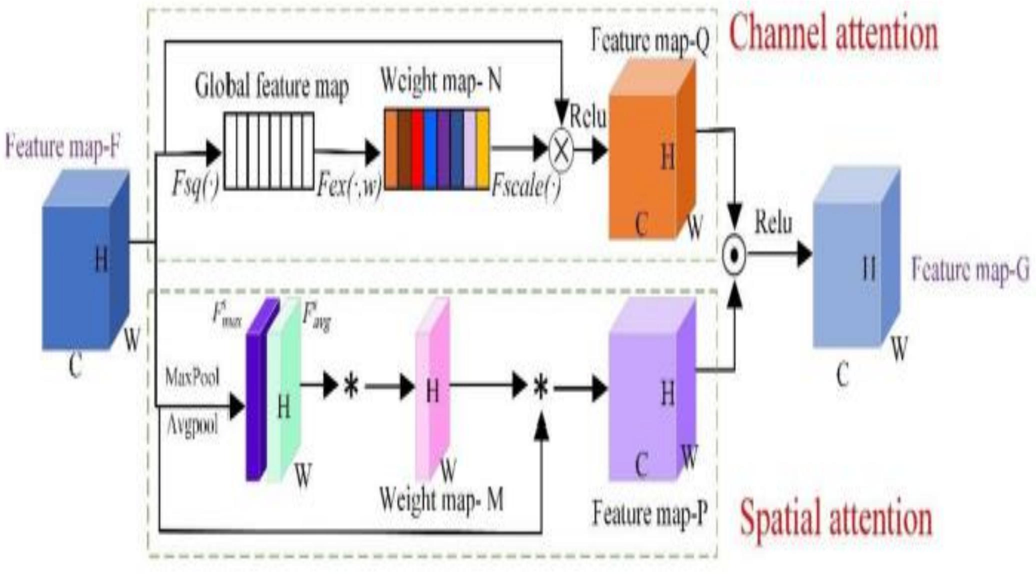

Fig. 4. Improved CNN structure of the parallel attention mechanism

(1) Channel model basically redistributes the channel weights to the resource maps by 1D convolution, which increases the damage-related channel weights while decreasing the remaining channel weights. In the first perform a global mean clustering on the terrain map with input size C × H × W through the compression process (Fsq) to obtain 1 × 1 × C feature vectors that are inserted into two fully connected elevation layers.

(2) Spatial surveillance performs mean and max clustering operations on the F-dimensional channel feature map, creating two single-channel feature maps F_{ang}^{s} and F_{max}^{s}. The F_{ang}^{s} and F_{max}^{s} resource maps are then merged to generate the M weight map, and the F resource map is weighted by the M weight map to create the P resource map. Finally, the pest related locations are given an additional weight in the map resource P.

(3) The feature map Q using the activation function of ReLu and it is a dot product of the feature map P. The G-feature map integrates the weight distribution in the channel dimension.

9.1.4. Activation Function:

ResNet's blocking architecture can effectively minimize network characteristics and computational complexity. The block structure consists of two convolutional layers 1×1 and a convolutional layer 3×3. A 1×1 convolution reduces the input feature vector from 256 dimensions to 64 dimensions, the features are learned using a 3×3 convolution layer, and the feature vector is restored to 256 dimensions using a 1×1 convolution layer. Finally, the ReLU activation function adds mapping and ID output. The improved ResNet network architecture is shown in Figure 5.

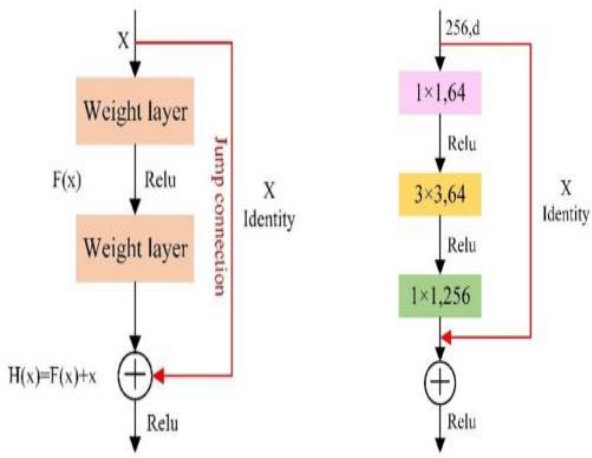

Fig. 5. The residual block (left) and the bottleneck structure (right)

9.2. Adaptive Particle Swarm Optimization (APSO) Algorithm:

Particle swarm optimization (PSO) is an empirical optimization algorithm [8]. The particles are iterated in a logical space to develop viable solutions, replicating the biological process of harvesting algae. Each iteration represents a possible solution to an optimization difficulty.

In most optimization scenarios, the PSO algorithm does not require the use of previous optimal positions to update the particle states. This approach increases training costs, slows down convergence, and enables particle diversity through the use of random number techniques. The APSO algorithm, on the other hand, does not require any modification of the initial velocity of the particles and can be replaced with a random number technique. This simplifies the process, accelerates convergence, and facilitates the discovery of the global optimum.

$$V_{i,j}^{t+1} = wV_{i,j}^{t} + \alpha r + \beta r_{2,i,j}^{t}(\widehat{y_j^t} - x_{i,j}^{t}) \qquad (1)$$

$$x_{i,j}^{t+1} = (1-\beta)x_{i,j}^{t} + \beta\widehat{y_j^t} + \alpha r \;) \qquad (2)$$

Where (1), r is a random number in the range [0,1]. Use random number techniques to replace $\alpha r_{1,i,j}^{t}(\widehat{y_j^t} - x_{i,j}^{t})$ in the equation (1). The Eq. (2), the parameter r makes the particles more mobile. In General α∈[0.1,0.5], β∈[0.2,0.7].

9.3. Improved LSTM

To preserve the reliability of long-range time series information and generate high-precision predictions, only closed modules are used in the LSTM neural network to train and save the sequence data. Figure 1 illustrates the structure of LSTM neurons.

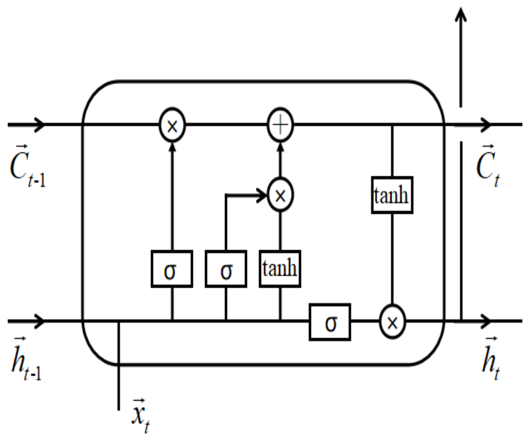

Fig. 6. LSTM neuron structure

As illustrated in Figure 6, an LSTM neuron has an input gate, an output gate, and a forget gate. The inbound gateway primarily handles incoming data. The forgetting gate determines whether past information from current neurons should be retained. The output port is the neuron's output. Given an input sequence $(x_1, x_2, \ldots x_t)$, calculate the formula for each LSTM neuron parameter at time t:

$$i_t = S(W_i * [h_{t-1}, x_t] + b_i) \qquad (3)$$

$$f_t = S(W_f * [h_{t-1}, x_t] + b_f) \qquad (4)$$

$$o_t = S(W_o * [h_{t-1}, x_t] + b_o) \qquad (5)$$

$$c_t = f_t * c_{t-1} + i_t * \tanh(W_c * [h_{t-1}, x_t]) \qquad (6)$$

$$h_t = o_t * tanh(c_t) \qquad (7)$$

At a given instance, x_t serves as the input for an LSTM neuron, while h_{t-1} represents the output state of the hidden hierarchy at the previous time step, $t-1$. The gates, i_t, f_t and o_t receive input from the input gate, forget gate, and output gate respectively, at time$t$. Weight matrices W_i, W_f and W_o are responsible for the input, forget, and output gates of the neuron at time t, while offset vectors b_i, b_f and b_o correspond to each gate. Additionally, there is a weight, W_c, that connects the input and unit cell. The output of the hidden layer at time t is denoted by h_t, and a sigmoid function represented by S is used in the process.

9.4. APSO-LSTM Model

The APSO-LSTM model suggested in this article uses real number encoding. The image illustrates the architecture of an LSTM neural network with three hidden layers as shown in Figure 7.

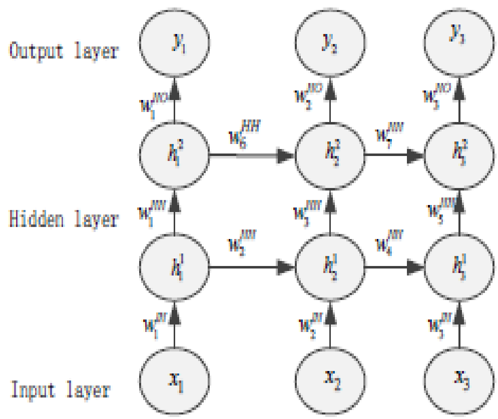

Fig. 7. The structure of LSTM neural network with 2 hidden layers

Fitness Function:

The AGA-LSTM model chromosomes correspond to individuals in the population and constitute weight groupings among the LSTM model nodes. The particle fitness function in the APSO-LSTM model tries to evaluate these particles in a population. The RMSE between the LSTM model output value and the actual value was modeled as a fit function during the model validation step to assess particle importance. The lower the RMSE, the more rational is the change in particle weight of the LSTM model and the more powerful the model.

Working:

In order to determine the initial values for the weights using the APSO algorithm, and create weights between each node for the particular dimensional attributes of the particles during the validation step of the APSO-LSTM model, i.e. the model right after the initial training of the LSTM network, as a neuron represents the resulting set of candidate weights from the entire network as shown in Figure 4.

Procedure:

Here is the corrected version of the text:

(1) Configure the LSTM model and APSO algorithm settings such as the LSTM network structure, node count, APSO cluster count, iteration count, and so on.

(2) Use the test data set to train the LSTM neural network and obtain the fundamental starting weights.

(3) Calculate the APSO population of particles.

(4) Determine the best universal particle. Compare the trapping value of the smallest particle to that of the best particle and select it as the next global best particle.

(5) Update all particle velocities and positions according to equations (3) and (4).

(6) Carry out n+1 iterations and determine whether the current value of n exceeds the maximum number of iterations.

(7) The LSTM network emits globally ideal particles corresponding to the ideal weight distribution.

10. Experimental Results

This paper explores the use of ICNN-APSO-LSTM, Faster-RCNN, and Mask-RCNN neural networks for time series prediction modeling. ICNN-APSO-LSTM, in particular, is an LSTM model that optimizes network weights using the standard APSO algorithm. The deep learning framework used is TensorFlow 1.10.0, and the programming language used is Python 3, all running on Ubuntu 16.4. The simulation parameters include a learning rate of 0.00145, a momentum of 0.8, a weight loss of 0.0001, and a batch size of 1 for Improved CNN-APSO-LSTM, Faster-RCNN, and Mask-RCNN.

10.1. Performance Metrics

The primary metric for evaluating pest detection performance is accuracy, although recall is also crucial. To comprehensively analyze model performance, four criteria are used: accuracy, precision, recovery, and recall. These metrics are calculated based on True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). Accuracy is determined by the proportion of correctly detected pests to total predictions (as shown in equation (8)), Precision is the proportion of TP among detected positives (as shown in equation (9)), and recall is the fraction of TP correctly predicted (as shown in equation (10)).

$$Accuracy = \frac{TP+FN}{TP+FP+TN+FN} \quad (8)$$

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

(a) (b)(c)

Fig. 8. Simulation results of insect pest detection

(a) Faster-RCNN, (b) Mask-RCNN and (c) ICNN-APSO-LSTM model

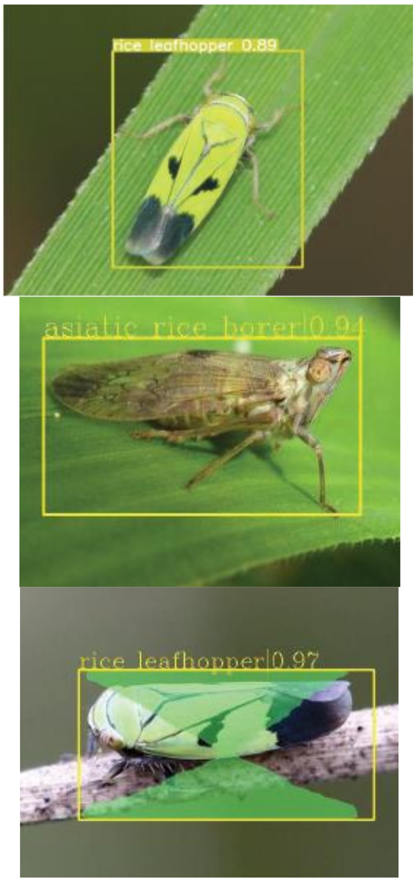

Fig. 9. Simulation results of proposed insect pest detection of ICNN-APSO-LSTM

The simulation results of the proposed insect pest detection of ICNN-APSO-LSTM are shown in Figures 8 and 9. In Table 1, the 3 different algorithms have a good ability to detect insect pests of different sizes with an accuracy of more than 98%, among which the accuracy of the proposed ICNN-APSO-LSTM is the highest 99.53%.

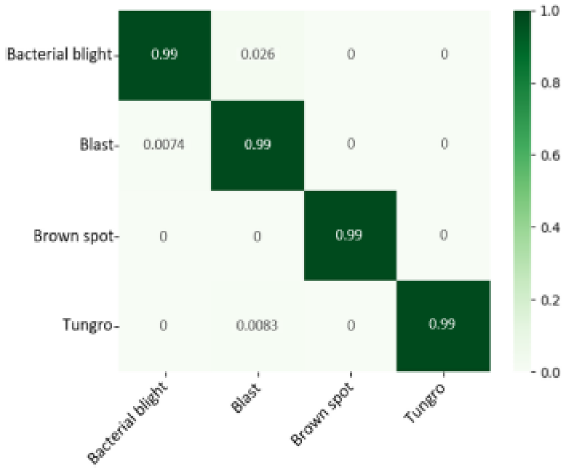

Fig. 10. Confusion matrices for rice leaf pest detection

In Figure 10, the detection results of the confused matrix are shown, and the detection rate of all four rice leaf diseases exceeds 99%. Compared to plant diseases and insect pests, rice foliar diseases' diagnostic accuracy increased by 1.27%. The primary reason for this is that only four forms of foliar diseases exist, while the remaining six are lesser-known illnesses and insect pests. The suggested method has a broader applicability and superior performance than depth-based methods used with publicly available datasets.

Table 1. Performances of Proposed ICNN-APSO-LSTM, Faster-RCNN and Mask-RCNN pest insect detection

Models	Accuracy (%)	Precision (%)	Recall (%)
Faster-RCNN	98.14	99.33	99.36
Mask-RCNN	98.42	99.63	99.82
Proposed ICNN-APSO-LSTM	**99.53**	**99.53**	**99.64**

10.2. Pesticide Recommendation System

Soil Analysis

The feeder detection system comprises an NPK monitor and an Arduino UNO microcontroller. The Arduino UNO is responsible for retrieving data from the NPK monitoring devices. The NPK instrument operates through a soil conductivity measurement procedure that employs two electrodes of the same material, which are submerged several centimeters into the soil to determine the ion current in the soil. One electrode receives an alternating voltage, while the other electrode's voltage gain is adjusted by the Arduino, which amplifies the flow of ions to the ground. The ion flow is proportional to the NPK ratio of the soil, allowing for the collection of NPK rates from the NPK monitors and transmission to the data preparation system.

10.3. Data Preparation

Java programming was used to compute additional soil components, conduct data preprocessing, and transfer the information to the cloud for streamlined data management. The data is preserved in comma-separated value (.csv) format to enable future analysis. The data is garnered through soil analysis of soil samples from diverse agricultural regions, and is stored in both cloud and local databases for subsequent analysis and synthesis. Farmers can enter crop details, as well as other criteria like soil category, location, and current season, into this crop cycle for further scrutiny and study.

Experiment Analysis:

The fertilizer contents FN, FP2O5, and FK2O, measured in kg/HA, are necessary to achieve the target yield T. Meanwhile, the soil nutrient contents SN, SP, and SN, also measured in kg/HA, are considered when taking a soil sample with an 8:9:10 ratios.

The concentration level in parts per million (ppm) will be:

For Nitrogen: Ppm N = 13.1925 * 8 = 106

For Phosphorus: Ppm P = 5.8047 * 9 = 52

For Potassium: Ppm K = 10.949 * 10 = 109

The value of nutrients in kilograms per hectare (kg/HA) will be:

N(kg/HA) = ppm N * 2.5 = 265

P(kg/HA) = ppm P * 2.5 = 130

K(kg/HA) = ppm K * 2.5 = 273

Crop: rice

Season: rabi

Soil: Alluvial

State: Tamil Nadu

Target yield= 70q/HA

FN = 2.3T – 0.32SN = 2.3 * 70 – 0.32 * 265 = 161 – 95.2 = 65.8

FP = 1.91T – 1.9SP = 1.91 * 70 – 1.9 * 130 = 247 – 275 = 0 (as it is a negative value)

FK = 2.27T – 0.27SK = 2.27 * 70 – 0.27 * 273 = 158.9 – 75.6 = 83.3

10.4. Pesticide Recommendation System

To achieve maximum yield in farming, two key factors must be considered: protecting crops from pests and providing the soil with the proper nutrients. Our smart system has implemented two functions to address these concerns. Firstly, we utilize machine vision and convolutional neural networks to identify pests and recommend appropriate pesticides. Furthermore, we utilize a soil NPK sensor to evaluate soil nutrient levels and suggest appropriate fertilizers accordingly. Our innovative system consists of a Raspberry Pi 4, Arduino nano, Soil NPK Sensor, RS485 to TTL Converter, DC-DC Buck Converter, Pi Camera, Cooling Fan, and Batteries. Figure 11 and 12 show an experimental setup of the model's pest identification operation.

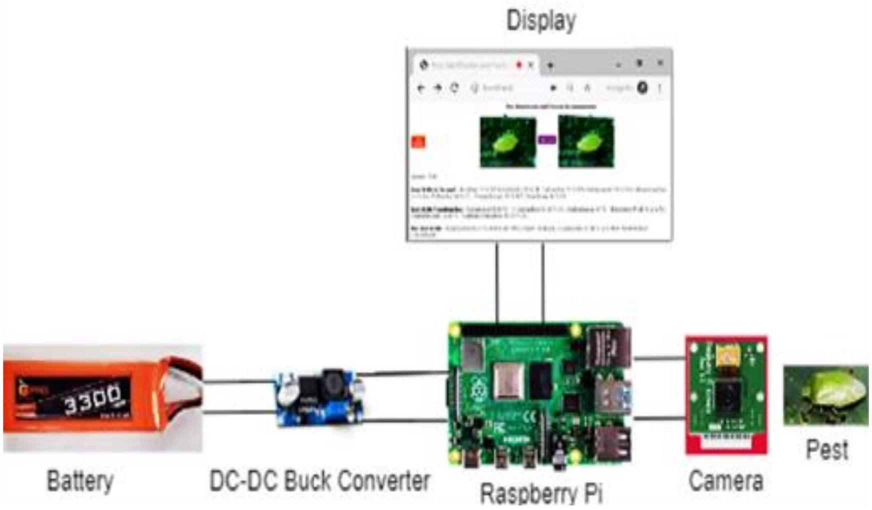

Fig. 11. Experimental Setup of Pest Identification

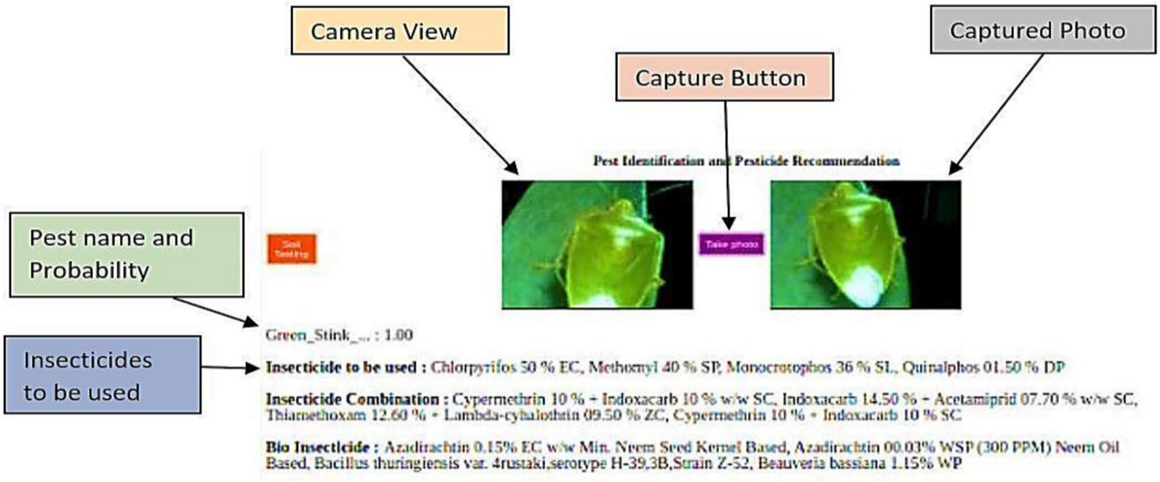

Fig. 12. Simulation Snapshot of Pest Detection

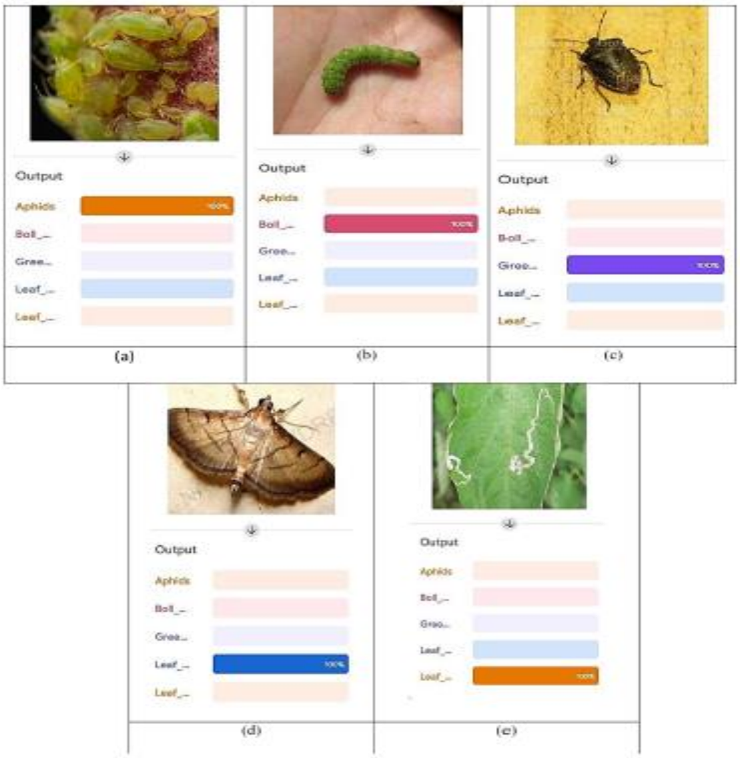

Fig. 13. Simulation Results of Different Pest Identification

To create the pest dataset, in addition to importing Google images, real plant pests were also imported as input for the machine learning module. The operation scheme of the NPK soil nutrient detection and fertilization proposal can be seen in the figure. It consists of a total of 5 parts, as shown in Figure 13. The first part is the front and back of the camera, the second part is the upper part of the body collar, the third part is the LCD touch screen, the fourth part is the key switch, and the fifth part is equipped with a sensor.

To operate the pest detection system, the system must be positioned horizontally with the camera facing the insect and the operator looking at the LCD touch screen. It opens a browser, takes a picture of the pest, and uses the recommended exterminator. The model was only valid for five crops, such as cotton, rice, tomato, banana, pepper, eggplant, sugarcane, cabbage, and potato. Run the files required to run the NPK soil testing system and submerge the NPK soil testing probe into the soil sample. After 50 seconds, a page will open showing the NPK value and the recommended fertilizer dose.

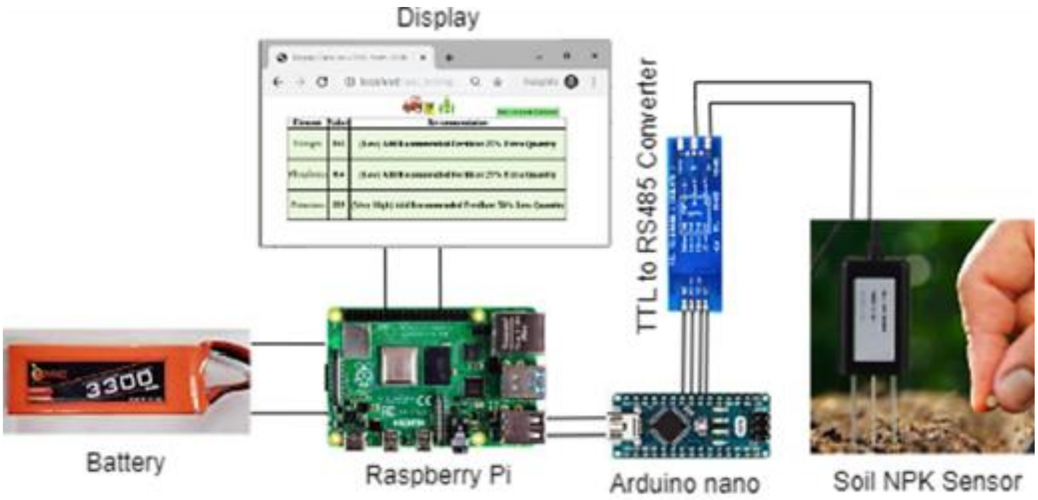

Fig. 14. Experimental Setup of Soil NPK Value Data Collection

Data on fertilizer brands and NPK rates were collected in a survey used to make fertilizer recommendations. The collected data set is then analyzed using appropriate clustering algorithms and parameter settings, depending on the desired results. This is not an automatic process, but rather requires trial-and-error for knowledge discovery or interactive multi-objective optimization. One commonly used algorithm is K-means, which divides the data based on distance to clustering centers. The algorithm selects centers randomly, calculates distances to each center, and assigns data to the closest cluster. After each iteration, the algorithm calculates the average parameters and checks if any data needs to be transferred to another cluster. The algorithm terminates if no data is transferred. Representation involves distinguishing subpopulations based on a training dataset with known class memberships.

An effective method involves utilizing appropriate fertilizers to address the specific soil needs of chosen crops and crystal trees, as determined through soil analysis. By feeding fertilizer nutrient requirements into a decision tree, the optimal fertilizer is determined. Through report calculations, the necessary amount of fertilizer to be applied throughout the crop cycle of the selected crop is recommended. A computation is then performed to determine the precise amount of fertilizer needed for the soil based on the selection made.

$$Amount\ of\ fertilizer = (kg/ha\ nutrient\ /\ \%\ nutrient\ in\ fertilizer) * 100$$

The amount of Fertilizer, to use for the farmer are intimidated by the farmer's understanding GUI. The NPK ratios obtained in the soil analysis step are subjected to a data preprocessing step to calculate individual ppm of NPK.

Crop	State	Season	Variety	District	Soil	N(kg /HA)	P(kg/ HA)	K(kg /HA)	Target yie	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficientt of SK
Rice	Andra pra	kharif	Mashuri	guntur	Black soil(Vertiosols)	330	105	372	55	3.79	0.5	3.19	3.17	1.6	0.19
Rice	Andra pra	kharif	Pothana	Karimnag	Inceptisols (Sandy loam)	364	90	370	60	3.78	0.44	1.96	2.13	2.96	0.36
Rice	Andra pra	kharif	MTU-2067	Maruteru	Alluvial	342	88	428	60	2.3	0.32	1.91	1.9	2.27	0.27
Rice	Andra pra	kharif	MTU-5182	Nandyal	Black Soil	302	41	439	70	3.35	0.32	2.52	4.53	1.24	0.12

Rice	Andr a pra	kha rif	NLR - 9672	Nellore	Alluvial	331	93	375	50	3.47	0.37	2.53	2.12	1.89	0.2
Rice	Andr a pra	kha rif	Tell aha msa	Rajend rar	Light Black Soil (Sandy clay)	346	97	399	55	4.2	0.55	2.7	2.67	2.22	0.21
Rice	Andr a pra	kha rif	Poth ana	Waran gal	Black Soil(vertis ols)	330	39	449	55	4.75	0.75	2.75	4.2	1.99	0.15
Rice	Andr a pra	Rab i	Tell aha msa	Nandya l	Black Soil	419	71	550	55	2.83	0.32	2.29	2.98	1.34	0.17

Fig. 15. Trimming the dataset

Once all necessary calculations have been made, the next step is to analyze the data. Farmers must specify which plants they plan to harvest during the current season. Soil samples are combined using historical data, as illustrated in Figure 15. Crop data sets are then used to determine the amount of nutrients required for the current soil conditions. This quantity is measured in kg/ha. By referencing the fertilizer dataset, appropriate fertilizers are chosen for the soil samples. The final step is to calculate the exact amount of selected fertilizer required to nourish the soil and produce maximum yield during the recommended stage.

Fertilizer N	P	K	Weight
Ammoniu	20.6	0	0 100kg
Ammoniu	25	0	0 100kg
Calcium A	13	0	0 100kg
Calcium N	15.5	0	0 100kg
Urea	46	0	0 100kg
SSP 14%	0	14	0 100kg
SSP 16%	0	16	0 100kg
Rock phos	0	18	0 100kg
Potassium	0	0	60 100kg

Fig.16. Fertilizer dataset

The number is the result of the project, which shows that the necessary fertilizer is potassium chloride, and the appropriate dose is 100 kg as shown in Figure 16.

The soil parameter NPK is shown in a table with each value and fertilization recommendations for each nutrient. Also, check the recommended capacity for each crop by clicking the green button at the top named Recommended, as shown in Figure 17 (a) and (b). The simulation result of fertilizer recommendation of different crops as shown in Figure 17 (c).

Recommendations

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)

Recommendations

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)

```
 Temperature (in degree unit) = 23.0
 atmospheric pressure (in hPa unit) :
 humidity (in percentage) = 88
 description = broken clouds

Suitable Crops and Required Ferilize
1 Rice
         Amonium Sulphate
         Single Superphosphate
2 Jowar
         Amonium Sulphate
3 Corn
         Amonium Sulphate
         Groundrock Phosphate
4 Wheat
         Amonium Sulphate
         Groundrock Phosphate
5 Cowpeas
         Amonium Sulphate
         Groundrock Phosphate
6 Soyabean
         Amonium Sulphate
         Groundrock Phosphate
7 Peanut
         Amonium Sulphate
         Single Superphosphate
8 Sunflower
         Amonium Sulphate
9 Cotton
         Amonium Sulphate
         Groundrock Phosphate
10 Sugarcane
         Amonium Sulphate
         Single Superphosphate
11 Chilli
         Amonium Sulphate
         Single Superphosphate
12 Onion
         Amonium Sulphate
```

(c)

Fig. 17. Fertilizer recommendation (a) soil test sample 1, (b) soil test sample 2 (c) Simulation results of different crops

11. Discussion

The suggested method employs a Multi-layer convolutional neural network, trained on 500 images. When trained on 5 pest types, the model achieves a maximum accuracy of 91%, with 100 epochs, 32 batch sizes, and a learning rate of 0.001. Similarly, for all three injury classes, the computation time is under 5 minutes with 99% accuracy.

The detected pests are used to make pesticide recommendations. Using the ICNN-APSO-LSTM technique, the network attains 99.53% accuracy per period and 29.51% test loss per period. It outperforms other techniques in detecting five pest species and providing corresponding pesticide recommendations, with an accuracy of 99%. NPK soil testing takes approximately 50 seconds, which is faster and more cost-effective than conventional lab approaches that take around 24 hours per sample. The ICNN-APSO-LSTM method is compared to Faster-RCNN and Mask-RCNN, and it displays the highest accuracy.

12. Conclusion and Future Direction of Research

This paper presents a novel deep learning-based algorithm for recognizing plant pests. A manually collected dataset of over 5,000 images was used to train the model to classify ten different pests. The proposed system integrates pesticide and fertilizer recommendations to help maximize crop yields. By enhancing the CNN with an APSO-LSTM attention mechanism, it achieves superior performance compared to other models such as Faster-RCNN and Mask-RCNN. The attention mechanism effectively suppresses complex backgrounds and recovers lesion details at multiple scales, enabling rapid and accurate detection of varied lesions. The proposed method provides pesticide recommendations in less than 10 seconds and fertilizer recommendations in 50 seconds. Future work may include incorporating additional sensors to collect data such as pH, temperature, and humidity for outdoor and indoor growing. The proposed algorithm is implemented in an agricultural inspection robot to complement cropping data in real-world farming environments and improve robotic models' performance.

In the future, it would be possible to expand upon this work by utilizing a vast data set. By incorporating additional parameters, such as calcium, magnesium, sulfur, lime, and carbon, which are related to micro and macro nutrients, the accuracy score could be improved. Furthermore, one could consider adding various distinguishing features, like leaf color and thickness, to achieve more precise outcomes. It may also be possible to broaden the scope of this work by including the following functionalities: developing a mobile application that enables farmers to upload images of their farms; utilizing image processing technology to identify crop diseases and provide pesticide recommendations based on those images; and implementing a smart irrigation system to enhance crop yields.

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