Tomato pest recognition using convolutional neural network in Bangladesh

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ABSTRACT

The tomato is one of the most popular and well-liked veggies among Asians. It is interesting to note that in Bangladesh, it is the second most significant vegetable consumed. Moreover, tomato is served not only as a vegetable, but it is also served as sauce, jam, etc., and used in making different types of cuisines. But the fact is due to the pests, thousands of tons of tomatoes are harmed every year in Bangladesh. The production of tomatoes in Bangladesh is harmed by a number of dangerous pests. We develop a solution to recognize pests at an early stage. Five different pest types, including aphids, red spider mites, whiteflies, looper caterpillars, and thrips, have been studied in this research. To identify tomato pests, we curated image datasets from online and offline repositories and processed them using a convolutional neural network (CNN) model. We used features from CNN layers for three machine learning algorithms: Random Forest (RF), support vector machine (SVM), and K-Nearest Neighbors (K-NN). This comprehensive approach allowed a thorough comparison of these algorithms in tomato pest recognition. For recognizing tomato pests, our methods generate excellent results. The accuracy of our experiment is 95.49% which indicates the successful completion of the experiment.

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1. INTRODUCTION

Interestingly, tomatoes are called LOVE APPLE which originated in South America. It's an herbaceous annual plant of the 'Solanaceae' family. Tomato plants can grow 0.7-2 meters high. It produces yellow flowers of 3-12 cymes and is a round fruit of different colors (red, orange, pink, purple, brown, and yellow). The color of this plant differs in various countries. Normally tomatoes grow at 21°-24°C temperature with 5.5.6.8 of soil pH. Tomatoes can have various types of diseases like other plants. Fungal is one of them. Typical symptoms of both fungal infections and light green or yellowish spots on leaves indicate insect infestations, often growing larger and causing discoloration. In humid environments, the lower leaf surfaces can become coated with a gray, velvety growth caused by the spores produced by the fungal infection.

One of the most well-liked and important crops in the world is considered to be the tomato [1]. An estimated 188 million tons of tomatoes were produced globally in 2018. However, because of the substantial increase in consumption, notably in China and India, there is now an even higher need for this adaptable fruit worldwide [2], [3]. Tomatoes' beneficial benefits are complemented by their exceptionally helpful composition, which is explained by their extraordinarily high antioxidant concentration. Lycopene (nearly 80%) is the most abundant antioxidant in tomatoes [4]. The unique organoleptic, nutritional, and compositional qualities of tomatoes make them essential food ingredients of remarkable gourmet and industrial relevance. Different tomato-based products are frequently suspected of containing various types of food adulteration, which has a serious negative impact on the economy and occasionally even health [5].

Tomato crops in home gardens face damage from various pests, including insects, nematodes, and mites. Nematodes, russet mites, and budworms are particularly destructive. Effective pest management strategies are crucial to protect crops throughout growth stages. Aphids, Whiteflies, Thrips, Looper caterpillars, and red spider mites are the most common pests detected in tomatoes. Tomato plants use a defense mechanism, emitting chemicals like methyl jasmonate, which attract pests and alert nearby plants. When they sense these chemicals, they collaborate to produce deterrent compounds, protecting plants from potential harm and agricultural applications. Tomato is a food that is enjoyed all over the world, and the major output of industrial tomato cultivars is its concentrated paste [6]. Maintaining healthy soil, consistent moisture, and proper nutrition is crucial for home-grown tomatoes, enhancing their resilience against pests and diseases [7]. Pest and diseases are both very common factors for gardening though tomatoes grow faster, those things are challenging for growing domatium pest-attack plants. Pest and diseases both are very common factors for gardening though tomato grows faster. Those things are challenging for growing domatium pest attacks plants.

To increase the profit from the yield and growth of plants, plant diseases must be identified. Plant disease monitoring by hand will not consistently produce correct results. Finding subject matter specialists for tracking plant diseases by pests is also very difficult and expensive for farmers. Numerous artificial intelligence strategies are currently being developed to automatically detect and diagnose plant diseases with minimal human effort. Recently developed artificial intelligence methods for computer vision and natural language processing include convolutional neural networks (CNN) [8]. Using efficient image recognition technology may enhance image identification efficiency, minimize costs, and improve recognition accuracy. As a result, specialists and researchers both at home and abroad have conducted extensive studies, with deep learning serving as the primary emphasis. Deep learning technology's emergence provides substantial technological support for picture recognition. The CNN is a widely used deep learning model. The diseases and pests detection approach based on CNN can automatically extract features from the original image, eliminating the subjectivity and limitations of artificial feature extraction in existing methods. In our work, we studied to detect tomatoes early using deep learning algorithms.

According to Vatti [1], the agriculture industry is embracing scouting robots, with major corporations investing in AI-powered solutions to reduce human labor dependency. Researchers used CNN models like VGG16, VGG19, Xception, ResNet50, and Inception V3 to analyze a dataset and evaluate their effectiveness using various metrics. This research aims to reduce the need for human labor in harvesting. A CNN model achieves a maximum classification accuracy of 0.95. Vitalis *et al.* [2] employed both conventional (soluble solid content and consistency) and advanced analytical techniques to identify and predict extremely low levels of adulterants present in tomato paste, including substances like paprika seed and corn starch (at concentrations of 0.5%, 1%, 2%, and 5%), as well as sucrose and salt (at concentrations of 0.5%, 1%, 2%, and 5%). They applied traditional methods to the data obtained through conventional techniques and conducted univariate statistical analysis (ANOVA). In contrast, for the data generated through advanced analytical methods like NIR spectroscopy and e-tongue, they adopted multivariate approaches such as principal component analysis (PCA), linear discriminant analysis (LDA), and partial least squares regression (PLSR) to assess and interpret the results. Simeone *et al.* [3] show a neural network regression model to predict surface fouling quantity. The study found that three different food fouling materials were effectively cleaned using different cleaning methods. The models achieved 98% accuracy in forecasting fouling area and 97% accuracy in fouling volume. This research highlights the practical application of sensors and machine learning techniques in monitoring and optimizing cleaning procedures. Velioğlu *et al.* [4] implemented a SUB-adaptive neuro-fuzzy inference system (MLA-ANFIS) approach that was applied to a dataset of seven tomato images from a farm. Deep stacked sparse auto-encoders (DSSAEs) were used to assess tomato quality, achieving an impressive 95.5% accuracy rate and proving its effectiveness in tomato quality assessment. The DSSAE method surpassed previous techniques in accuracy and originality. N *et al.* [9] study to assist farmers in identifying the illness and preventing it in its early stages. They work with CNN because it extracts a large number of alternatives from picture datasets rather than alternative classification techniques. The trained model has a 97% associate degree accuracy. Liu and Wang [10] investigated how to build a dataset of tomato diseases and pests in a real-world environment, optimize the feature layer of the Yolo V3 model by using an image pyramid to achieve multi-scale feature detection, improve the detection accuracy and speed of the Yolo V3 model, and accurately and quickly detect the location and category of tomato diseases and pests. The above research breaks through the essential technology of tomato pest image identification in natural environments, providing a reference for intelligent recognition and engineering application of plant diseases and pest detection. Yusiong [11] show a CNN-ELM model that automates tomato maturity grading, combining CNN's feature learning and ELM's computational efficiency, achieving 96.67% classification accuracy and 96.67% F1-score. This model is promising for robust and accurate tomato maturity grading in agricultural applications. Aykas *et al.* [12] used a field-deployable portable infrared spectrometer for tomato paste detection. 1843 samples were collected from 2015-2019 in California, USA from four different leading tomato paste processors. A multi-layer architecture was utilized, incorporating the SUB-adaptive neuro-fuzzy inference system (MLA-ANFIS) method, neural networks, regression, and extreme learning machines (ELMs), to compile a dataset of tomato images obtained from a farm. The sensitivity, specificity, g-mean, and accuracy of the DSSAEs technique are 83.2%, 96.50%, 89.40%, and 95.5% [13]. According to Al-Asheh *et al.* [14], the effects of initial solid concentration, voltage, and current on the amount of water removal were studied. The measured experimental data can be used to compute the energy of dewatering. The neural network modeling method used to represent the experimental data accurately and sufficiently describes the data. Xie *et al.* [15] predict tomato freshness and evaluate the practicality of infrared thermal imaging in tomato freshness prediction. A 70% training dataset, 15% validation, and 15% testing dataset were used. The ANN model showed nearly 90% prediction accuracy, indicating infrared thermal imaging's feasibility and effectiveness in quality assessment and agricultural applications. To properly identify and count tomatoes at various growth stages, Fawzia *et al.* [16] proposed a ground-breaking method for accurate tomato counting that combines deep instance segmentation, data synthesis, and color analysis. A mask R-CNN neural network was trained using artificial data, and a color-based thresholding technique was applied to determine each tomato's growth stage. The experiment demonstrated accurate tomato counting at three distinct stages: green, half-ripe, and fully ripe, showcasing its potential for precise tomato analysis and counting across different developmental stages. This paper follows the structural process as follows: section 1 is introduction, section 2 is method, section 3 is results and discussion, and section 4 is conclusion.

2. METHOD

This section of our research focused on the approach we proposed in our study that describes how to recognize tomato pests. The use of high-throughput technology in the field of biology has produced enormous amounts of data. Now, computational biology's main difficulty is turning these enormous volumes of data into knowledge. Deep learning algorithms are currently promoting the use of machine learning in several fields of biology, including plant virology [17]. Production losses from different plant diseases can be prevented by remaining vigilant. Botanists and agriculture professionals must manually monitor plant diseases, which is time-consuming, difficult, and prone to mistakes. Machine vision technology can be very helpful in lowering the risk of illness severity [18]. Data collection is the first step, then preprocessing and data augmentation are done gradually. Then, using CNN, develop a model, and then compare it to supervised machine learning techniques such as K-Nearest Neighbor (K-NN), support vector machine (SVM), and Random Forest (RF). Our data is gathered from both online and offline sources, and it is divided into two categories: training and testing. We have used 80% for the training and 20% of the data for testing. In Figure 1, we have demonstrated the working process that we have followed for our research to reach the goal of our study starting from the data collection to the result of the study.

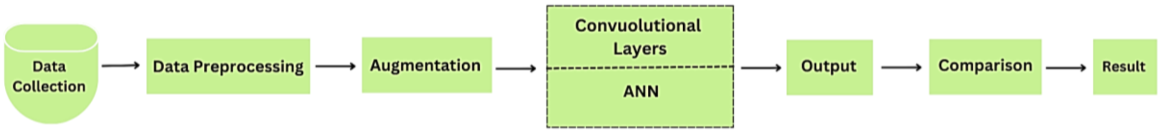


Figure 1. Workflow diagram

2.1. Data preprocessing

Processing is transforming unprocessed data into a format that computer programs and machine learning algorithms can understand and evaluate. Before being used as an input to the CNN, the raw picture data for image classification needs to be preprocessed [19]. The quality of the preprocessed data has a big impact on the final result's quality. Any research study must include the vital process of data cleansing. We removed images that were out of focus, redundant, and irrelevant from our data collection. 60% of our dataset is collected from online platforms and 40% from offline sources.

2.2. Data augmentation

To artificially increase the amount of data, which is necessary for deep learning networks to function well, data augmentation entails creating new data points from the already existing ones [20]. A machine learning model's parameters are adjusted or optimized during training so that it can convert a given input, such as an image, into a certain intended output. We have made augmentation to our dataset by using the flip technique and rotation techniques (such as 45, 90, 180, and 270 degrees). Additionally, we have modified the dataset by enhancing the brightness and darkness of the data. Moreover, images were cropped, sharpened, and blurred. Thus, 11,424 datasets were generated. Data points are prepared for the next processes as a result.

2.3. Implementation process

In our research, we worked with 40x40x3 images featuring five different pests: Aphids, Looper caterpillars, Thrips, Whitefly, and red spider mites. Our proposed model employs a CNN for feature extraction, consisting of the following key layers: an initial convolutional layer with 96 filters and a 3x3 kernel size, followed by a pooling layer. A subsequent convolutional layer with 256 filters, a 3x3 kernel size, and activation functions, followed by another pooling layer. A secondary convolutional layer with 384 filters, utilizing the same padding, a 3x3 kernel size, and ReLU activation, followed by pooling with a 2x2 window. An additional convolutional layer with 522 filters, employing the same padding, a 3x3 kernel size, and ReLU activation, followed by another 2x2 pooling layer. The output layer comprises 5 neurons, using softmax activation, after a flattened layer. Further downstream, a dense layer with 64 neurons, each employing ReLU activation, is included in the architecture. The optimization process uses a sparse categorical cross-entropy loss function and Adam optimizer with a 0.001 learning rate. This model is tailored to efficiently extract features from the input images and make predictions about the five pest classes. Well, our CNN model follows the formula which is:

$$F(i, j) = (I * K)(i, j) = \sum\sum I(i + m, j + n)\, K(m, n)$$

where F denotes the output, K denotes the filter where size id m*n and the operation are denoted by I*K. Moreover, we have used the activated function Relu which can be expressed as $f(x)=\max(0, x)$ to increase the nonlinearity. Our model uses max pooling, a commonly used technique for identifying and retaining the highest value in a specified input area. In this study, we have proposed our CNN model which is presented in Figure 2. Figure 2 shows the layers, filters, kernel size, and parameters with the output.

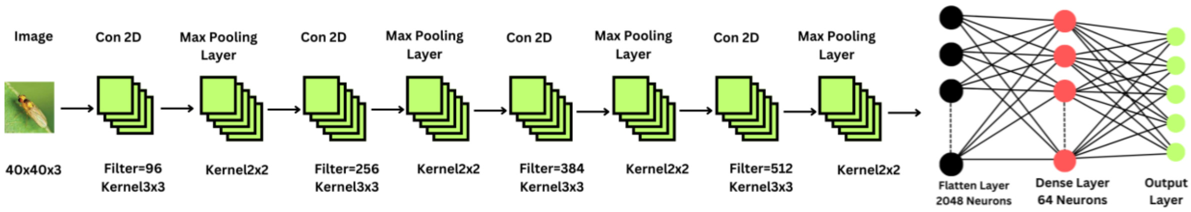


Figure 2. CNN model

2.3.1. The summary of the convolutional neural network model

In Table 1, the layers of the proposed model are presented with output shape and parameters. total parameter 3,010,693, trainable parameter 3,010,693, and non-parameter 0. A summary of the proposed model is shown in Table 1.

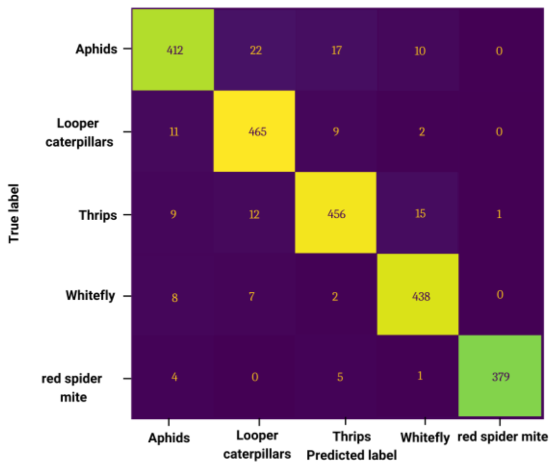
2.3.2. Performance evaluation matrix

To measure the performance matrix as shown in Figure 3 is used where TP denotes true positive, TF true negative, FN for false negative and, FP for false positive. In Figure 3, a confusion matrix is presented where we can see the performance of RF in Figure 3(a) along with SVM in Figure 3(b), K-NN in Figure 3(c), and CNN in Figure 3(d) which is used to evaluate the performance and comparison. Subfigures illustrate the visual representation.

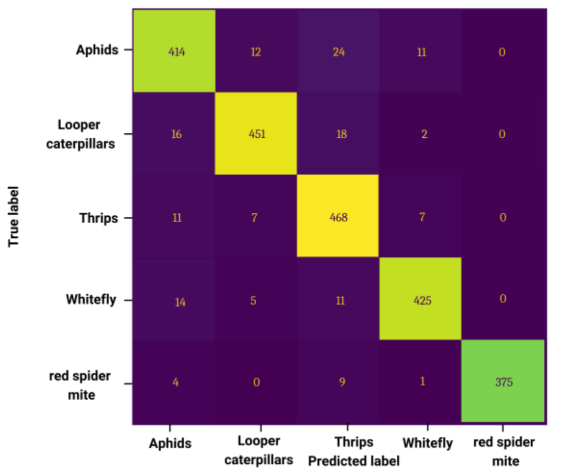
In the method, 80% of the data is trained. On the 20% of the dataset that is yet untested, tests are run. In order to observe the resulting graph and produce the output since it would look to be overfitted otherwise, we then ran 25 epochs. So, it is possible to calculate the likelihood for each class. Comparing K-NN, RF classification, and SVM classifier, we found RF's versatility in handling continuous and categorical variables in regression and classification tasks. SVM can be used to address classification or regression problems. Additionally, regression and classification are both done using RF. While RF achieves 94.09% accuracy, SVM achieves 93.34% accuracy, and K-NN achieves 94.09% accuracy, CNN achieves 95.49 percent accuracy.

Table 1. Layers of the proposed CNN model

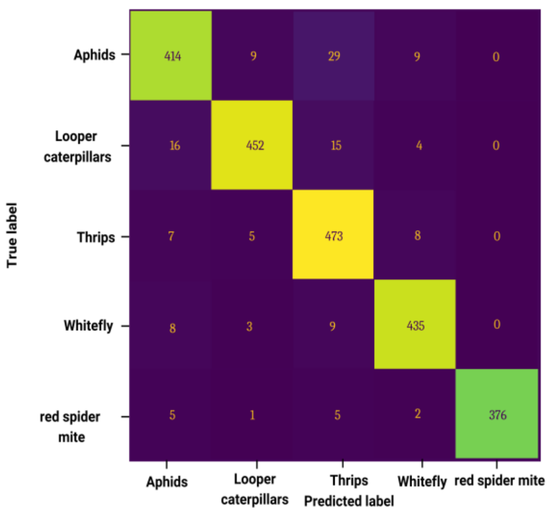
Layer (type)	Output Shape	Parameter
conv2d (Conv 2D)	(None, 38, 38, 96)	2688
max_pooling2d (MaxPolling2D)	(None, 19, 19, 256)	0
conv2d_1 (Conv 2D)	(None, 19, 19, 256)	221440
max_pooling2d_1 (MaxPolling2D)	(None, 9, 9, 256)	0
conv2d_2 (Conv 2D)	(None, 9, 9, 384)	885120
max_pooling2d_2 (MaxPolling2D)	(None, 4, 4, 384)	0
conv2d_3 (Conv 2D)	(None, 2, 2, 512)	1769984
max_pooling2d_3 (MaxPolling2D)	(None, 2, 2, 512)	0
flatten (flatten)	(None, 2048)	0
dense (Dense)	(None, 64)	131136
dense_1 (Dense)	(None, 5)	325



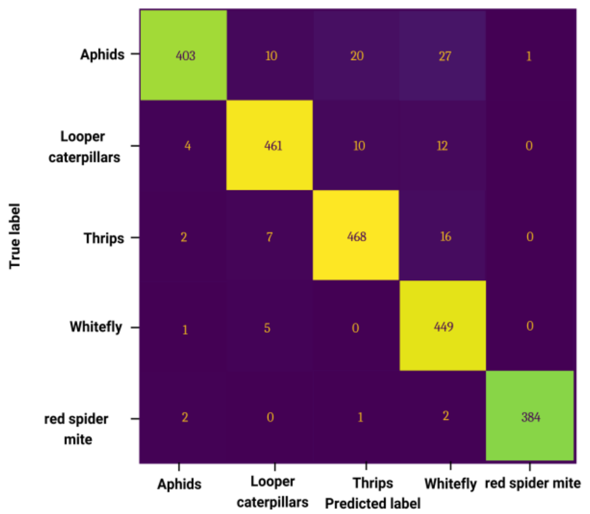
(a)



(b)



(c)



(d)

Figure 3. Comparison of the confusion matrix; (a) RF, (b) SVM, (c) K-NN, and (d) SNN

3. RESULTS AND DISCUSSION

3.1. Result

Images of five tomato pests are used in our study. One of the most effective picture categorization methods is the CNN [21], [22]. We have used CNN to evaluate the performance. In the comparison of results, we also employed the features extracted from the convolutional layer as inputs for SVM, RF, and K-NN. Though they all present good performances, CNN presents the best result. Table 1 shows the results of the performance that is measured. Here, we can see the highest score is presented by CNN compared to other machine learning algorithms. From the Table 2, we can see the difference between the results. Performance is measured using precision, recall, F1-score, and support. Accuracy plays an important role for the performance analysis. In Table 3, classification performance is analyzed, and the comparison between models are presented. Model accuracy is presented in the Figure 4 using a line graph. Figure 4 likely shows how the model's accuracy on the training dataset compares to its test accuracy over the course of 25 epochs.

Table 2. Performance analysis of CNN and other algorithms

Model	Metrics score	Pests				
		Aphids	Looper caterpillars	Thrips	Whitefly	Red spider mite
CNN	Precision	0.98	0.95	0.94	0.89	1.00
	Recall	0.87	0.95	0.95	0.99	0.99
	F1	0.92	0.95	0.94	0.93	0.99
	Support	461	487	493	455	389
Convolution layer + RF	Precision	0.93	0.92	0.93	0.94	1.000
	Recall	0.89	0.92	0.92	0.96	0.97
	F1	0.91	0.94	0.93	0.95	0.99
	Support	461	487	493	455	389
Convolution layer + SVM	Precision	0.90	0.95	0.88	0.95	1.000
	Recall	0.90	0.93	0.95	0.93	0.97
	F1	0.90	0.94	0.91	0.94	0.98
	Support	461	487	493	455	389
Convolution layer + K-NN	Precision	0.92	0.96	0.89	0.95	1.000
	Recall	0.90	0.93	0.96	0.96	0.97
	F1	0.91	0.94	0.92	0.95	0.99
	Support	461	487	493	455	389

Table 3. Classification performance of CNN and other algorithms

	CNN (%)	Convolution layer + RF (%)	Convolution layer + SVM (%)	Convolution layer + K-NN (%)
Accuracy	95.49	94.09	93.34	94.09
Precision (avg)	95.2	94.4	93.6	94.4
Specificity (avg)	95.0	93.8	92.8	93.4
Sensitivity (avg)	95.0	93.7	93.4	94.4
G-mean (avg)	92.1	91.6	92.0	92.0

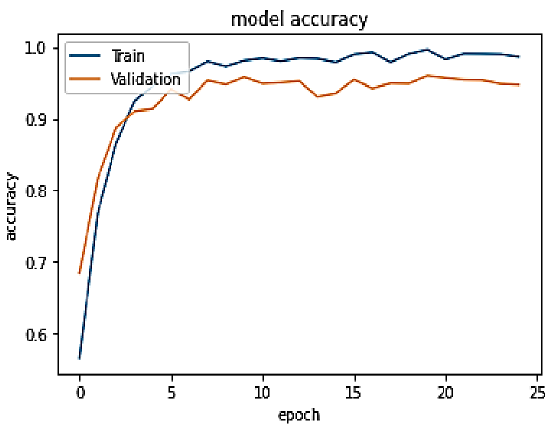


Figure 4. Training accuracy vs validation accuracy

3.2. Discussion

Our proposed model shows excellent performance. According to the evaluation metrics, Table 2 compares the classification performance of CNN and convolution with other machine-learning techniques. Moreover, one would want to be able to identify tomato plants in addition to plot-based comparisons. This would also solve the assignment issue, as each plant could be readily coded by a label at the pot, and tomatoes could be distinguished by how far away from the pot they were on the stem [23]–[25]. The best accuracy is 95.49% for CNN, whereas the corresponding figures for convolution layer + RF, convolution layer + KNN, and convolution layer + SVM are 94.0%, 93.09%, and 93.34%. Additionally, CNN achieves the highest sensitivity, specificity, accuracy, and g-mean of 92.1%, 95.0%, 95.0%, and 95.02%, respectively. In this work, our approach is successful at recognizing pests.

4. CONCLUSION

The development of agriculture contributes to the success of the national economy. Bangladesh is a country that mostly depends on agriculture. One of the important vegetables in Bangladesh is the tomato. The majority of people would consider tomatoes as a sort of vegetable, although some individuals also consider them to be fruits. For the nine years from 2012 to 2021, the average annual rate of tomato consumption increased by 6.8%. The percentage of tomatoes is increasing every year. Almost all types of cuisine require tomatoes. Moreover, Bangladesh exports tomatoes annually to several countries. Pests hampered tomato production, leading farmers to suffer significant losses and affecting the nation's economy. Early detection and treatment of plant diseases dramatically reduce production losses. The use of image-based automatic plant disease identification (APDI) systems in pest management tactics has begun to spread. CNN are used to extract target areas from images, segment objects, and determine the quantity and kind of pests on leaves, fruits, and vegetables. Image recognition is mostly utilized in training neural network models to classify categories. Our proposed approach to solving this issue produces excellent results regarding recognizing pests. In this study, five types of pests are examined by gathering image data sets from both online and offline platforms. We got the desired result using 80% training data and 20% test data set. Comparing CNN to other machine learning algorithms has shown that it can regularly produce impressive results. The study's findings show that our CNN model has a 95.49% accuracy rate for recognizing pests. CNN offers fresh approaches and concepts as well as a solid technological foundation. Mankind would greatly benefit from this approach.

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