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Optimized convolution neural network with ant colony algorithm for accurate plant disease detection

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ABSTRACT

In India, agriculture is the primary source of income for half the people. Even in situations of fast population growth, agriculture supplies nourishment for all people. To provide food for the entire population, it is advised to detect plant diseases at an early stage. Plant leaf diseases are recognized using images of the affected leaves. Deep learning (DL) research seems to offer several opportunities for increased accuracy. Ant colony optimization with convolution-neural-network (ACO-CNN), a new deep learning technique for identifying and categorizing diseases, is presented in this article. Ant colony optimization (ACO) was used to examine the efficacy of disease diagnostics in plant leaves. The convolution neural network (CNN) classifier is used to remove texture, color, and leaf arrangement geometry from the input images. The ACO-CNN model outperformed the support vector machine (SVM) and CNN models in terms of precision, recall, and accuracy. CNN's rate is 81.6% as compared to SVM's 80% accuracy level. In the “ACO-CNN” approach, the F1-score, recall, and precision have higher rates as compared to other models, and the “F1-score” has the highest rate compared with other models since the ACO-CNN model has an accuracy rate of 91.00%.

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1. INTRODUCTION

In India, the agriculture industry employed 50% of the workforce and made up 19.9% of the country's gross domestic product (GDP) in 2020–2021. The most recent technical developments must be used to promote the efficient crop cultivation. Due to plant diseases and pest damage, crops experience significant losses. Because of pest damage and plant diseases, crops experience significant losses. By 2050, there will be 9.2 billion population on the planet, and to fulfill their food requirements, food production will need to rise by almost 70% utilized in [1]. Food crops experience significant losses as a result of unfavorable weather, strong winds, drought, fungi, viruses, and bacteria. 70-80% of agricultural losses worldwide are due to plant diseases. The development of technologies has made it possible to produce enough food to meet societal needs. However, the security and safety of the food and the crop were never attained. Farmers experience challenges because of things like climate change, a decline in pollinators, plant diseases, and other problems [2]. To grow healthy food, it is essential to protect the plants against diseases. Pollinator decline, climate change, plant diseases, and water quality significantly impact food security. According to the Food and Agriculture Organization (FAO), pests, and diseases destroy up to 40% of food crops annually, highlighting the importance of managing plant diseases to improve yield quality. Diseased leaves show symptoms like deformation, discoloration, curling, and decay. Quick, accurate detection and identification of these diseases are essential. Traditional manual methods are costly, time-consuming, error-prone, and require expertise. Deep learning offers higher accuracy in disease detection, addressing limitations of conventional methods. Plant diseases can reduce lifespan, affect reproduction, degrade soil quality, and ruin crops by persisting in the soil for years. Modern AI technologies, including support vector machine (SVM), k-nearest neighbors (KNN), and convolution neural network (CNN), can help prevent crop loss. This research uses datasets to train these algorithms, showing that many plant diseases are caused by temperature changes and bacterial infections.

2. LITERATURE REVIEW

Plant diseases are the biggest obstacles to producing agricultural products. This disease identification technique has decent potential because it can immediately spot plant leaf issues. Speed and accuracy are the two key aspects of crop disease diagnosis in “machine learning systems”. According to [3], plant diseases can be found using the histogram matching method. The definition of this histogram is based on the detection of edges and the frequency of occurrence of each color. Layers are represented by red, green, and blue pixels in the sample photographs using the layer segregation approach. Additionally, the procedure will involve contour identification. According to [4] software tools can automatically recognize and classify plant leaf diseases. Here, a visualization technique is used to quickly identify the disorders. “K-means clustering, gray-level co-occurrence matrix (GLCM) is a statistical texture analysis technique used in image processing to extract features from images), and backpropagation neural network (BPNN)” are three effective approaches and key techniques that can be utilized to identify crop diseases with greater accuracy and in less time. Software tools can automatically recognize and classify plant leaf diseases. Here, a visualization technique is used to quickly identify the disorders. “K-means clustering, GLCM, and BPNN” are three effective approaches and key techniques that can be utilized to identify crop diseases with greater accuracy and in less time. More than 30,000 photos from the [5] model were divided into many classifications, including “tomato, grape, maize, apple, and sugarcane diseases” [6]. The “CNN model” was developed using an “application programming interface (API)” that was compatible with “Python's neural network applications”. To get over the vanishing gradient's drawbacks, [7] introduced the “CNN and AlexNet architectures” for building a classifier. The AlexNet design has a higher accuracy rate of 98.33%. More correct outcomes can be achieved by utilizing the “AlexNet architecture” to identify sick leaves [8]. The accuracy of the “CNN” many pre-trained architectures, including “visual geometry group network (VGGNet), residual network (ResNet), and GoogLeNet”, are compared. A network was proposed by [9] so that AlexNet may be contrasted with the conventional “SVM”. Both “SVM and AlexNet” performed well, with SVM having an accuracy of 91%. According to [10], the “neural network ensemble (NNE)”, which was employed in the model to identify healthy leaves with an accuracy of 87.5%, can identify mango leaf illnesses.

Using inception-visual geometry group network (INC-VGGN), the identification of illnesses in rice plants. VGGNet is a built-in component of ImageNet and has a sizable collection of categorized datasets rather than having to be created from scratch and given values [11]. It was the most efficient method of obtaining correct findings for the finding of crop diseases, with a precision of 91.83%, which was significantly higher than that of other approaches, even in the face of significant obstructions. The performance of numerous pre-trained neural networks was summarized by [12], and the transfer learning model's pre-trained weights, which comprises of VGG16, Mobile-Net, InceptionV3, ResNet50, Inception-ResNet-V2, and pre-trained networks, were provided by built-in Keras apps. The authors of [13], [14] describe using CNN to identify tomato plant leaves. They accomplished this using an imported ResNet-50 model and the transfer learning theory. They divided a dataset of 2,006 pictures in half “80% and 20%” for validation and training of the model. The model can identify the ailment in the shortest amount of time due to their high level of accuracy (97%). [15] As opposed to where a dataset of over 7,000 images was used to create the “CNN-based Alex-Net model” and compare it against the “VGG16 and Lenet5 models”. They applied certain fundamental machine learning algorithms, such as SVM and KNN, and were able to attain an accuracy of 96.7% however, their performance lagged behind that of VGG-16 and LeNet-5.

Local-binary-patterns (LBP) and histogram of oriented gradients (HOG) are utilised to distinguish different aspects from Otsu's technique in [16] to segment some of the diseases. The data was classified using an SVM technique, and a polynomial kernel was utilized to get an accuracy of 94.6%. Therefore, early identification of crop disease will stop the crop's output from declining. The “K-means clustering” technique is used by [17] to identify infected leaves with accuracy; it finds the leaf's dead or diseased areas [18].

Additionally, the precision of the SVM and KNN algorithms were compared. The accuracy of the SVM algorithm was 95%, while the accuracy of the KNN approach was 85%. Table 1 shows the performance of various crops.

The document has been organized in the manner as follows. The techniques for pre-processing the image dataset, such as image acquisition, image augmentation, and image dataset construction, are introduced in section 3. The Ant colony optimization with convolution-neural-network (ACO-CNN) methodology utilized for this investigation is discussed in section 4. The segmentation outcomes of the suggested model are examined in section 5. Finally, our conclusion is presented.

Table 1. Performance of various crops

Crop Type	Dataset	Performance	Framework	References	Year
Apple	26,377	Accuracy increased	DBNet	[19]	2023
Tea	4,000	Better accuracy	YOLOv7	[20]	2023
Apple, Corn, Potato, Tomato, and Rice	37,315	Greater precision and adequate detection speed	AlexNet, MobileNet	[21]	2022
38 Classes	54,305	Better accuracy	DenseNet-121, ResNet-50	[22]	2022
Apple	1,200	Better accuracy	Mask RCNN	[23]	2021
Papaya	2,000	Introduce the usage of YOLO variants that are lighter, more effective, and have a rapid detection rate.	YOLO	[24]	2021
Citrus	392	Higher precision	YOLOv4	[25]	2020
Grape	4,449	Greater precision and sufficient response time	Faster DR-IACNN	[26]	2020
Cassava	2,415	Evaluate the model's performance on mobile-captured images and videos post-deployment in an app.	SSD	[27]	2019

3. MATERIALS AND METHODS

Finding areas that are infected with plant diseases and identifying where they are in difficult natural conditions is essential for proper categorization and identification of crop illnesses as well as the evaluation of crop disease severity. Computer vision technology is used in plant disease detection to achieve this. Early-stage phytopathology analytics employed a sliding window approach to choose candidate regions, extract candidate region attributes, and then classify them using a classifier to determine area of interest. This technique iteratively moves across the image while utilizing various sizes and widths. Even though this technique doesn't miss any infected zone targets, the duplicate candidate regions that appear need a lot of processing work and take a while to traverse the disease picture again, which leads to poor real-time detection. Various methods for computational imaging and the use of the picture categorization system are based on artificial vision due to the quick growth of artificial intelligence technology. The five steps of the methodology suggested by Reference to identify the cogollero worm damage in maize fields are image collection, preprocessing, segmentation, feature extraction, and classification.

3.1. Steps for plant leaf disease identification

3.1.1. Image acquisition

The datasets for rice, pepper, and potatoes are used in this study. For both the potato, pepper, and rice datasets, the data are split into 80:20 ratio, where 80% of the pictures are used for learning and 20% of images are used for evaluation. The total of 5,932 images in the Rice dataset depicts four distinct categories of rice crop infection, comprising "blast, bacterial blight, tungro, and brown spot". 3,785 photos were used for training with an "80:20" test train split, and 947 various images were used for testing. Figure 1 displays representative photos from the rice dataset. The study makes use of a dataset of 1,500 photos of potato leaves. 300 photos were utilized for testing, while 1,200 pictures were used for training and evaluation. Healthy potato leaves, Early blight, and late blight are represented in the collection in different ways. In Figure 2, a sample of potato leaves is displayed. The total number of training and test pictures in the datasets is shown in Table 1.

3.1.2. Pre-processing

Pre-processing happens once the picture has been chosen as the foundation for the diagnosis of leaf disease. The median filter has been used to improve the crop photos by reducing noise and removing undesirable elements. The "median filter, a non-linear, well-structured digital filtering method", is frequently used to minimize the noise in pictures. The outcome of the median filter formula as in (1).

$$\hat{g}(a,b) = median(x,y) \in Tab\ \{f(x,y)\} \tag{1}$$

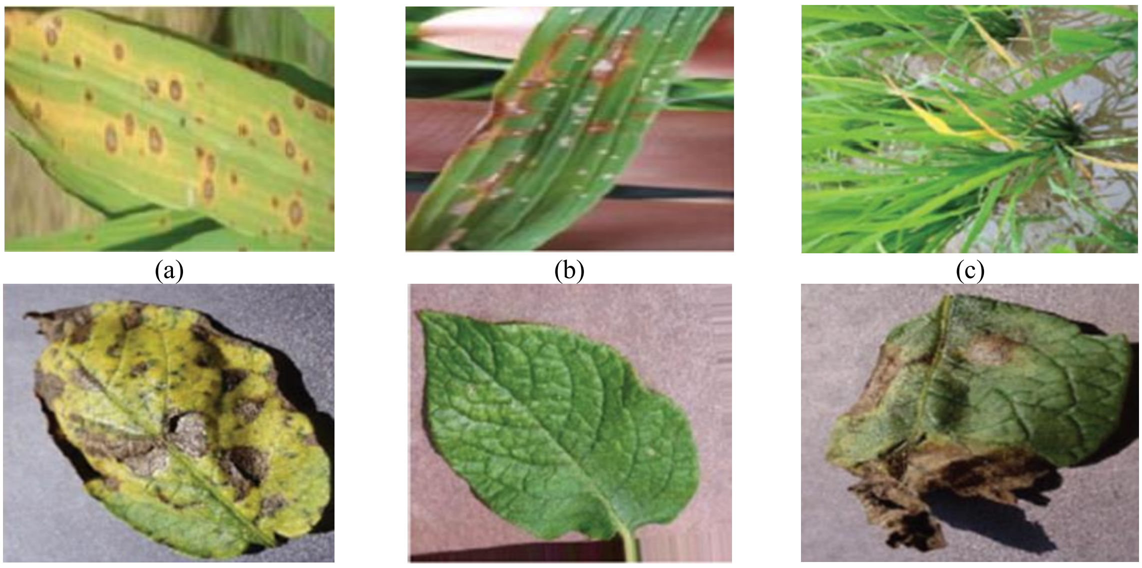
3.1.3. Segmentation

Based on predefined parameters, segmentation breaks up plant leaf images for easy manipulation. The suggested separation method divides the crop leaf into its components. The similarity and volatility of pixel concentration make segmentation difficult. Similarities are found using "color-based thresholding". Equation defines segmentation.

$$|h(r,q)| = \begin{cases} 0, g(r,q) < r \\ 1, g(r,q) > r \end{cases} \tag{2}$$

3.1.4. Feature extraction

The process of feature extraction during image identification is essential. Figure 1(a) shows the maize leaf blight, Figure 1(b) shows the wheat leaf spot, Figure 1(c) shows the wheat yellow leaf, Figure 1(d) shows the soybean brown spot, Figure 1(e) shows the potato mild leaf curl, and Figure 1(f) shows the potato dark brown spot. The figures show the sample images of the diseased dataset that are used in the research work. For feature extraction and classification, ACO and CNN are utilised, respectively. It is used to identify the infected area utilising unique ant communication behavior and categorize the diseased crop leaf for the goal of upcoming prevention. Additionally, the ACO method has emerged as a novel approach to approximate optimization. To find the fastest path to their food source, ants' major way of communicating is through indirect means. This ant has a special characteristic that is used in ACO. The ACO is utilized to differentiate between healthy and sick plant leaves in this instance. The pheromone rate is a critical database attribute that must be modified initially. With G as the number of unique feature vectors in its rows and columns, a matrix (h) of dimensions G*G comprises the feature analysis data. Following modification of the ACO the main computation using experimental technique F is carried out. Select the best materials and subgroups for the upcoming iteration. The initial and very important phase in applying the ACO algorithm is the initialization of its factors. Additionally, the "ACO algorithm" includes a separate calculation procedure and excellent resilience. When dealing with complex optimization problems, ACO excels and is readily interchangeable with other methods. Ants employ mathematical techniques to find objects in the search space whereas ACO utilise the updated pheromone. Local and global searches serve as the basis of ACO.



(a) (b) (c)

(d) (e) (f)

Figure 1. Sample images of the diseased dataset of (a) maize leaf blight, (b) wheat leaf spot, (c) wheat yellow leaf, (d) Soybean brown spot, (e) potato mild leaf curl, and (f) potato dark brown spot

3.2. Classification

The leaf is then sorted in a neural network using different categorization techniques. Figure 2 shows the CNN architecture for image classification. Different algorithms are compared using their performance metrics after being loaded into the suggested "neural network model" for classifying photos. To identify and categorize the grape and mango infection-affected plant leaf, visualization methods and mapping functions are ultimately utilized for file delivery and naming.

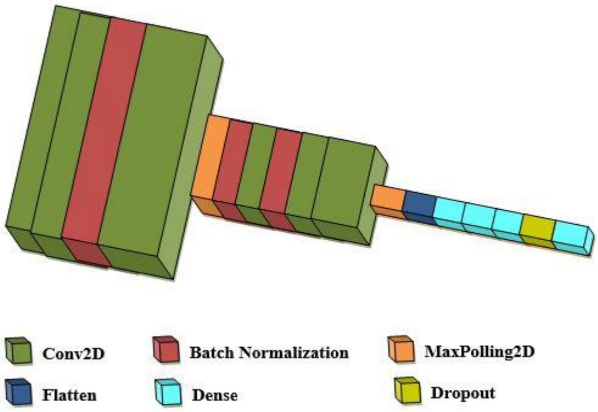


Figure 2. CNN architecture for image classification

3.2.1. Convolutional neural network

Each form of leaf infection is distinguished using CNN classifiers. It evaluates graphical representations effectively and eliminates extraneous elements thanks to its hierarchical architecture. Its multi-layered architecture lets it effectively assess visual representations and cut out extraneous components. Four layers comprise the CNN classifier: output, fully connected, max pooling, and convolutional. Before training a CNN, spectra of pixel intensities in the dataset of plant leaf images. The CNN model performs quite well all during training. The pictures offered for input should all be the same size. Each picture in the training set underwent the following normalization as (3).

$$p(a,b) = \frac{O(a,b)-\mu}{\sigma} \tag{3}$$

- Convolution layer: using different layers to evaluate the complexity of every image, the convolution layer evaluates a restricted number of input images. It directly corresponds with the features of the images.

$$f_i^m = x(\sum_{j\in N_i} f_j^{m-1} * p_{ji}^m + a_i^m) \tag{4}$$

  N_i refers to an input option. An additive bias *b* was thereby generated. After applying the kernel to map *i*, it determined if map *j* and map *k* added up to map *i*.
- Max pooling layer: in order to decrease fitting and the size of the neurons used in the down-sampling layer, this layer is deployed. While reducing the computational rate, feature map dimensions, training length, and number of parameters, the pooling layer mitigates overfitting. Half of the training data and all of the test data must be considered overfitting.
- Fully connected layer: images have been classified using the fully-connected layer. Before every convolutional layer, there exist the fully linked layers. The mapping between the input and output representations is made easier by the fully connected layer. At the very top of the network, you'll find fully connected layers. The fully connected layer takes its input from the max pooling layer.
- SoftMax layer: a normalized probability distribution is created from the scores by means of the SoftMax layer. The output is fed into the classifier. In the SoftMax layer, plant diseases are categorized using the well-known softmax classifier.

$$\sigma(\vec{x})_n = \frac{e^{x_n}}{\Sigma_{i=1}^{m} e^{x_i}} \tag{5}$$

A CNN model identifies patterns in images using filters and convolution layers, with the processed data passed through ReLU to eliminate negative values. The pooling layer then reduces the input size and accelerates processing using hyperparameters like filter size, stride, and pooling type (max or average). A CNN can have multiple pooling-layers and multiple convolution layers, ending in fully connected layers for classification. The dropout layer prevents overfitting, while the softmax function outputs probabilities for classes. The proposed 16-layer CNN model includes five convolution layers, three batch normalization layers, two max-pooling layers, and five fully connected layers, designed to detect plant leaf diseases. Algorithm 1 shows the ACO-CNN.

Algorithm 1. ACO-CNN
1. Load dataset (leaf images)
   L= {L1, L2, L3, …}
2. Preprocessing Images
   $L_{pp=L-k}$
3. Feature extraction
   Set the infected portion's beginning point to zero
   If (Ant moves on to the next position.)
      Gather the subset
      Using (1), locate the area of the leaf that is affected.
   Else
      Using (2), identify the next component
      Continue until the stopping condition is satisfied.
   Endif
4. Return
   Output: Healthy and unhealthy leaf classification

4. RESULTS AND DISCUSSION

We implemented the suggested approach using Python 3.7.10 and assess it against other well-known, state-of- the-art machine-learning image classifiers for plant disease prediction. Different datasets for rice and potatoes were used to train these models, and the model performance parameters were then compared. In comparison to existing classifiers, the suggested CNN model outperformed the datasets for rice and potatoes. Figure 3 display the CNN model architectures and hyper-parameter setups is shown in Table 2. In deep neural network, valuable elements from the input image are extracted to produce precise predictions. The application of filters to the input image at each layer of the CNN model produces activation maps or feature maps.

Table 2. Parameters for CNN model training

Parameters	Value
Size od batch	32
Activation function	SoftMax, ReLU
Metrics	Accuracy
Loss	Sparse_categorical_crossentropy
Optimizer	Adam and learning rate (lr) =0.0001

Feature extraction retrieved for a particular picture can be gained by analyzing the output activation maps of each layer. To understand the model's inner workings for a given input at a certain layer, one can look at the activation map or the filter. Each model layer gathers the characteristics maps for a specific input image of potatoes, as shown in Figure 3. As can be observed in Figure 3, the first layer keeps practically all of the details or information from the original inputted image, including the complete shape of the leaf. Features like single borders, corners, and angles are extracted from deeper layers. This means that in order to classify images, deeper layers can access more relevant data. Testing and training have been completed on the suggested CNN model. Applying the "sparse_categorical_crossentropy" loss function and using accuracy as the metric, the Adam Keras optimizer is utilized with a learning rate of 0.0001.

The proposed method has been evaluated utilizing images of the gathered leaf samples. To differentiate between healthy and unhealthy leaves, the proposed technique uses ACO-CNN. Four widely used evaluation measures categorization recall, precision, accuracy, and F1 score are examined in the study. The supplied leaf images are accurately reproduced by precision. Precision is a measure of how well a classifier performs. Precision is increased when there are fewer positive signals from the plant leaf, while precision is decreased when there are more positive signals. The recall rates the performance of the classifier. The increase of positive samples found corresponds with the recall.

$$Accuracy = \frac{TN+TP}{FN+FP+TN+TP} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$Recall = \frac{TP}{FN+TP} \quad (8)$$

Regarding recall, precision, and accuracy, the ACO-CNN model performed better than the SVM and CNN models. CNN's rate is 81.6% as opposed to SVM's 80% accuracy rate. With an accuracy rate of 91.00%, the ACO-CNN model has the highest F1-score value, and the methodology as a whole outperforms competing models in terms of recall, precision, and accuracy. Figure 4 shows the model performance, Figure 4(a) shows the performance metrics and Figure 4(b) shows the confusion matrix, validates these findings. The best accuracy of 95% is provided by the proposed algorithm for potato early blight is 95%, while the accuracy for rice bacterial blight, and pepper leaf spot is 91% and 89%, respectively.

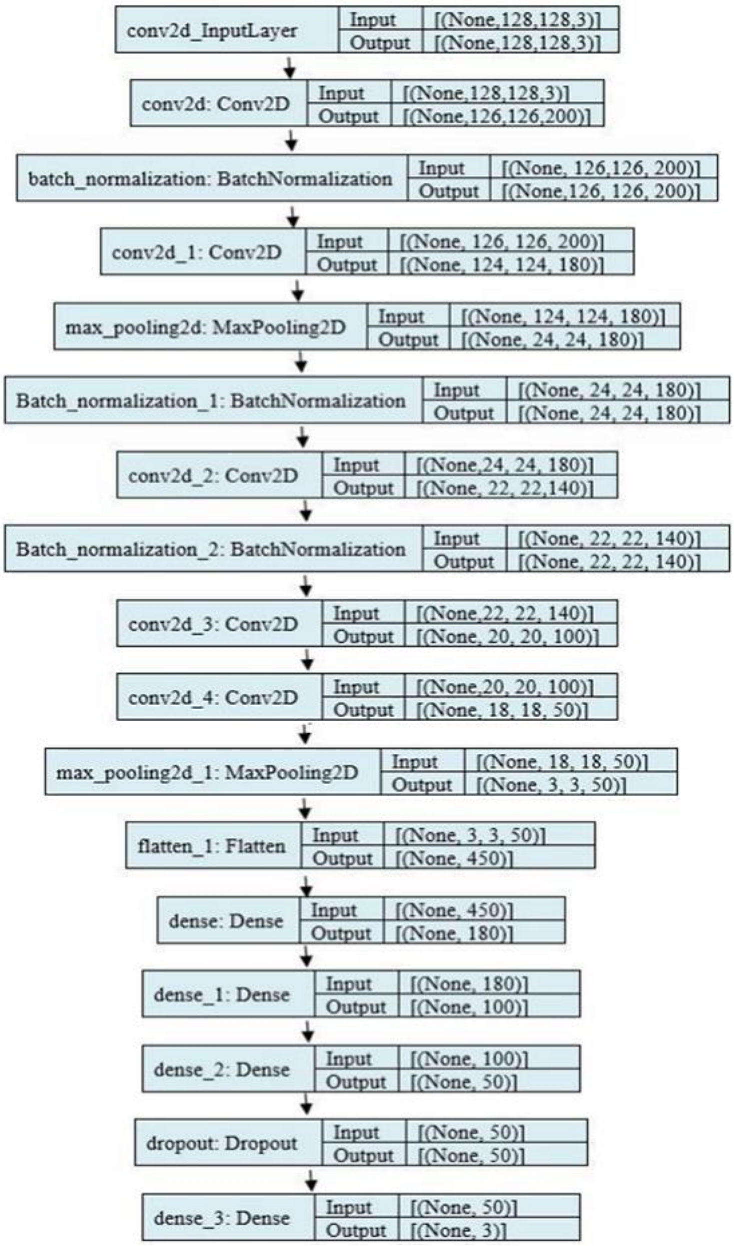
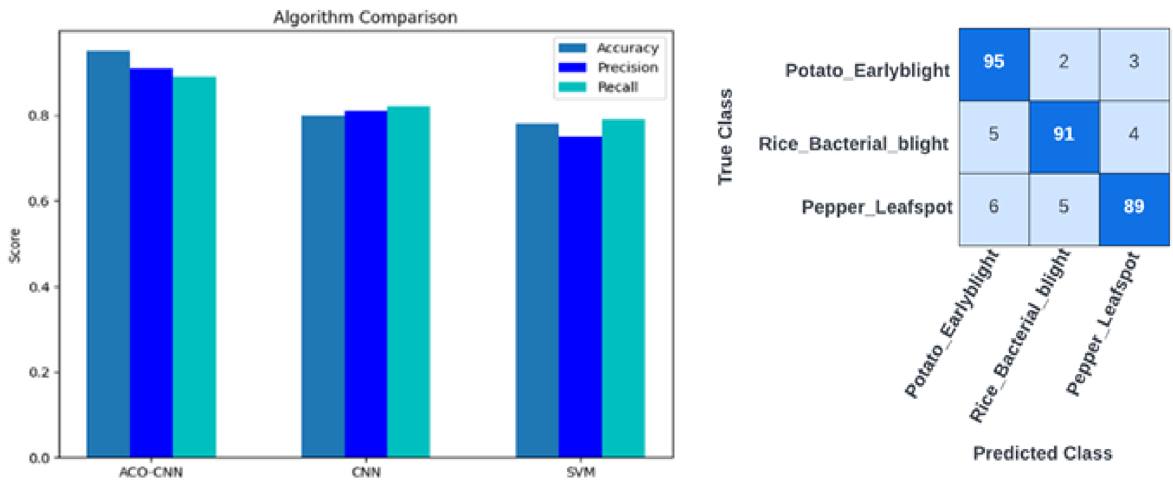


Figure 3. CNN model diagram



(a) (b)

Figure 4. Model performance of (a) performance metrics and (b) confusion matrix

5. CONCLUSION

This paper detected diseases in plant leaves using an ACO-CNN model. Datasets for potatoes, peppers, and rice were used in this investigation. For potato leaf disease, our model reached a detection accuracy of 95.00%. A total of 5,932 rice photographs and 1,500 images of diseased and healthy pepper, potato, and rice leaves were used in this investigation. When compared to existing top-tier machine learning picture classifiers like SVM and CNN, the proposed model demonstrated significantly higher accuracy. CNN classifier was utilized for the organization, whereas ACO was employed for feature extraction. The suggested method is used to distinguish between infected and healthy leaves using optimization and search algorithms inspired by nature, hyperparameters of the proposed CNN model, including batch size, number of epochs, quantity of convolutional layers, activation functions for convolutional layers, number of fully connected layers, number of neurons per layer, and filter dimensions, may be tuned in future studies. The performance of the model may be further improved by careful choice of these hyper-parameters.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY

The data that support the findings of this study are open available in Kaggle at https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset.

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