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IDENTIFICATION OF ARMYWORM-INFECTED LEAVES IN CORN BY IMAGE PROCESSING AND DEEP LEARNING

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Corn is rich in fibre, vitamins, and minerals, and it is a nutritious source of carbohydrates. The area under corn cultivation is very large because, in addition to providing food for humans and animals, it is also used for raw materials for industrial products. Corn cultivation is exposed to the damage of various pests such as armyworm. A regional monitoring of pests is intended to actively track the population of this pest in a specific geography; one of the ways of monitoring is using the image processing technology. Therefore, the aim of this research was to identify healthy and armyworm-infected leaves using image processing and deep neural network in the form of 4 structures named AlexNet, DenseNet, EfficientNet, and GoogleNet. A total of 4500 images, including healthy and infected leaves, were collected. Next, models were trained by train data. Then, test data were evaluated using the evaluation criteria such as accuracy, precision, and F score. Results indicated all the classifiers obtained the precision above 98%, but the EfficientNet-based classifier was more successful in classification with the precision of 100%, accuracy of 99.70%, and F-score of 99.68%.

Keywords: EfficientNet; classification; image; convolutional neural networks

Corn, also known as *Zea mays*, is one of the most popular grains in the world that is a plant from the grass family and native to Central America. But it grows in countless varieties all over the world. Corn is one of the most widely consumed foods which has many health benefits. Corn kernels are rich in fibre, vitamins, and minerals. Since they are a nutritious source of carbohydrates, they can be used instead of rice, bread, potatoes, or other sources of carbohydrates. Especially for celiac patients who are sensitive to gluten, it is an excellent solution to replace wheat and barley with corn. Also, these grains are used to feed livestock and poultry, and countries that are very rich in terms of animal husbandry should be very rich in terms of the amount of corn. Therefore, the amount of cultivation considered for corn is very high because this grain is not only used to supply livestock food, but also used for the raw materials of industrial products.

Diagnosing pests is very helpful in increasing the quality of food and it also helps to increase the country's economy. Also, a rapid invasion of pests and insects may cause serious problems in agricultural performance (Prasath et al., 2023). Invasive pests are among those that cause a significant reduction in yield and product quality, and in addition to economic, ecological and social effects, they have a great impact on the livelihood of smallholders (Pratt et al., 2017). The reduction of yield due to pests causes the loss of income and increase of famine and hunger. Also, smallholders often lack knowledge, tools, technology, and management

methods or financial resources to identify and sustainably respond to new pest species (Day et al., 2017).

Corn cultivation is exposed to various pests such as armyworm (Sun et al., 2021). The armyworm is one of the most damaging quarantine pests, which originated in South America, but in the last two years, it has become an epidemic and in less than two years, it has affected more than 23 African countries and some German farms (Goergen et al., 2016). Considering the speed of its spread, the presence of this pest in Iran should be expected. This pest can feed on more than 90 host plants representing at least 30 different families and causes severe economic losses most of the time (Abdullah et al., 2019), but among all the products that can be to harm them, it usually prefers corn (Longkumer et al., 2023; Overton et al., 2021). The larvae of this worm can damage all the growth stages of corn plants (Brévault et al., 2018). Although the armyworm is a generalist herbivore that is likely to be more influenced by common or non-specific stimuli for host selection, females are attracted to maize-specific volatiles and prefer to oviposit on plants that are not damaged by herbivores (Signoretto et al., 2012). Moreover, armyworm babies are attracted to the damaged tissue of corn leaves (Stuhl et al., 2008).

The regional monitoring of armyworm pests is intended to actively track the presence, population, and movement of this pest in a certain geography, which is done by an agricultural expert (Prasanna et al., 2022). According to Li et al. (2022), the usage of image processing technology

or hyperspectral imaging is one of the ways of disease monitoring.

The autumn armyworm pest has posed significant threats to Chinese agriculture since it was first reported in 2019; but it is still not clear how the size and distribution of threats differ between Chinese provinces. In a study conducted by Wu et al. (2021), total potential cost was calculated for each of the 31 provinces of China and the provinces with the greatest threat were identified. The general conclusions indicated that larger agricultural producers may be more at risk and may suffer greater absolute losses from the threat of fall armyworm. Underdeveloped provinces may be relatively more vulnerable to armyworm and are likely to be the main source of armyworm. Zhao et al. (2022) proposed a deep learning-based automatic detection system with DPeNet structure. The results show that DPeNet achieved an average accuracy (AP) of 0.932, outperforming benchmark methods including faster R-CNN, SSD, and Yolov3.

Wang et al. (2022) declared that commonly used models for classification of pest images require a wide range of labelled training images, which usually require intensive work to obtain them in real applications. To overcome this limitation, many existing studies rely on unsupervised deep metric learning (UDML) to take full advantage of the similarity of unlabelled pest images. However, they still have two limitations:

1. Clustering using image methods has performance bottlenecks and there is no semantic similarity in the learned metric space.
2. The classification structure of pests has not been fully discovered yet. To address these issues, they proposed a new UDML-based pest image classification method called unsupervised deep metric learning guided pseudo-multimodal information (MmPI) for agricultural pest images, in which the labels are extracted from unlabelled images.

In a study by De Groote et al. (2020), crop losses due to armyworm were calculated in 2017 and 2018 across all maize producing regions of Kenya. These information and statistics were collected during the months of June and July 2018 through 121 group discussions with 1439 farmers (697 men and 742 women), by randomly selecting the main corn

growing areas. The results showed armyworm suddenly became the major pest in Kenya and caused the loss of about a third of the annual corn production. This amount is estimated to be around 1 million tonnes.

In Prasath et al. (2023), images are collected from IoT sensors to detect and classify pests. First, the input images were collected and entered into an optimized Yolov3 model. Deep feature extraction was done with the help of Residual Network50 (ResNet50) and Visual Geometry Group16 (VGG16) models. Then, classification was done using the weight-optimised deep neural network (WO-DNN) model. In the whole analysis, the accuracy and F1 score of the designed method reached 96% and 84%.

Pest monitoring is a prerequisite for accurate decision-making to support integrated pest management (IPM) in smart agriculture. Therefore, the aim of this research was to identify healthy and armyworm infected leaves using image processing and deep neural network.

Material and methods

Data collection

The total number of 4507 images (including 2127 healthy and 2380 infected leaves) of corn were collected from different regions of Iran – Darab (28.6170° N, 54.8731° E); Fasa (29.0° N, 53.7° E); Estahban (29.1267° N, 54.0394° E); Larestan (27.8097° N, 54.3467° E), and Gerash (27.6640° N, 54.1482° E). The degree of damage of leaves was around 30% to 50% depending on region. Figure 1 gives the examples of healthy and infected leaves. The fall armyworm is a species in the order *Lepidoptera* and one of the species of the fall armyworm moths distinguished by their larval life stage. The term “armyworm” can refer to several species, often describing the large-scale invasive behaviour of the species’ larval stage. Fall armyworm (FAW) larvae can damage corn at various stages of development by feeding on leaf or ear tissues.

The platform of Python (3.10.12) was used as a programming language, and Pytorch (2.1.0) was used as a deep learning framework to build and train neural network for image classification. Libraries included os,



Fig. 1 Examples of healthy and infected leaves of corn

zipfile, numpy, pandas, matplotlib, sklearn, torch, and torchvision. Google colab was used as the interactive development environment to write and execute the Python code. Four convolutional neural networks (CNN), namely AlexNet, DenseNet, EfficientNet, and GoogleNet for image classification using Pytorch, were implemented. A dataset of labelled images split into training (70%), validation (15%), and test (15%) sets. The neural network is trained using backpropagation and gradient descent to minimise the loss function. After training, the model's accuracy was evaluated on the validation set.

Structures of proposed convolutional neural networks

AlexNet

The input to AlexNet is an RGB image of size 256×256 . This means all images in the training set and all test images need to be of size 256×256 . If the input image is not 256×256 , it needs to be converted to 256×256 before using it for training the network (Pourdarbani et al., 2023; Dahham et al., 2023). AlexNet is a complex model with many parameters, making it computationally expensive and time-consuming to train. It is susceptible to overfitting, especially when trained on smaller datasets.

DenseNet

DenseNet is densely connected-convolutional networks. In classic CNNs, each layer only has access to the characteristics of the layer immediately before it. The architecture DenseNet is composed of transition layers and dense blocks. Each convolutional layer inside a dense block is linked to every other layer within the block (Pourdarbani et al., 2023).

EfficientNet

EfficientNet is a convolutional neural network architecture and scaling method that uniformly scales all the dimensions of depth/width/resolution using a compound coefficient. Unlike conventional practice that arbitrary scales these factors, the EfficientNet scaling method uniformly scales network width, depth, and resolution with a set of fixed scaling coefficients (Tan and Quoc, 2019).

GoogleNet

GoogleNet is a type of convolutional neural network based on the inception architecture. It utilises inception modules, which allow the network to choose between multiple convolutional filter sizes in each block (Tang et al., 2017).

The criteria for evaluating the performance of classifiers

The criteria for evaluating the performance of classifiers were in the form of confusion matrix and receiver operating curve (ROC). The confusion matrix is the matrix that relates the real and predicted samples by the classifier. This is a square matrix, and it has dimensions equal to the number of classes (Table1). For example, if there are two floors, the confusion matrix is 2×2 . By using this matrix, various criteria can be defined and applied, and some of these criteria will be reviewed in the following (Sabzi et al., 2020):

The ROC plots are drawn within a coordinate system with three axes, the horizontal axis being the FP rate, the vertical axis being the TP rate, and a bisector. The graph is drawn according to the number of classes that exist. As much as the lower level of the chart is higher than its upper level, it indicates the high performance of the classification system. Therefore, the more the graph resembles the vertical state, the higher the performance of the classification system will be (Madrid-Guijarro et al., 2013). One of the criteria that evaluates the performance of classifiers based on the ROC diagram is the area under the diagram (AUC).

Results and discussion

AlexNet-based classifier

The accuracy and loss graph of the AlexNet model reached an accuracy value above 98% in epoch 15 and later, but the model fluctuates and did not converge with the number of 30 epochs (Fig. 2). It was not possible to continue training the model due to hardware limitations. Because in epoch 28, the model simultaneously achieved the lowest error value and the highest accuracy (98%), the result was acceptable.

Table 2 gives the confusion matrix of the samples in the AlexNet based classifier. According to the figure, the number of samples that are correctly labeled as healthy and infected

Table 1 The criteria for evaluating the performance of classifiers

Description	Equation	No.
How many percent of correct samples have been correctly diagnosed	$recall = \frac{TP}{TP + FN} \cdot 100$	1
Total percentage of correct answers of the system	$accuracy = \frac{TP + TN}{TP + FN + FP + TN} \cdot 100$	2
What percentage of correctly detected outputs are actually true	$precision = \frac{TP}{TP + FP} \cdot 100$	3
Harmonic weighted average of recall and precision	$F\_measure = \frac{2 \cdot recall \cdot precision}{recall + precision}$	4

TP – the number of samples of each class that are correctly classified; TN – equal to the number of samples on the main diagonal of the confusion matrix minus the number of samples that are correctly classified in the desired class; FN – defined as the sum of horizontal samples of the studied class minus the number of samples that are correctly classified in the desired class; FP – the sum of the vertical samples of the examined class minus the number of samples that are correctly classified in the desired class

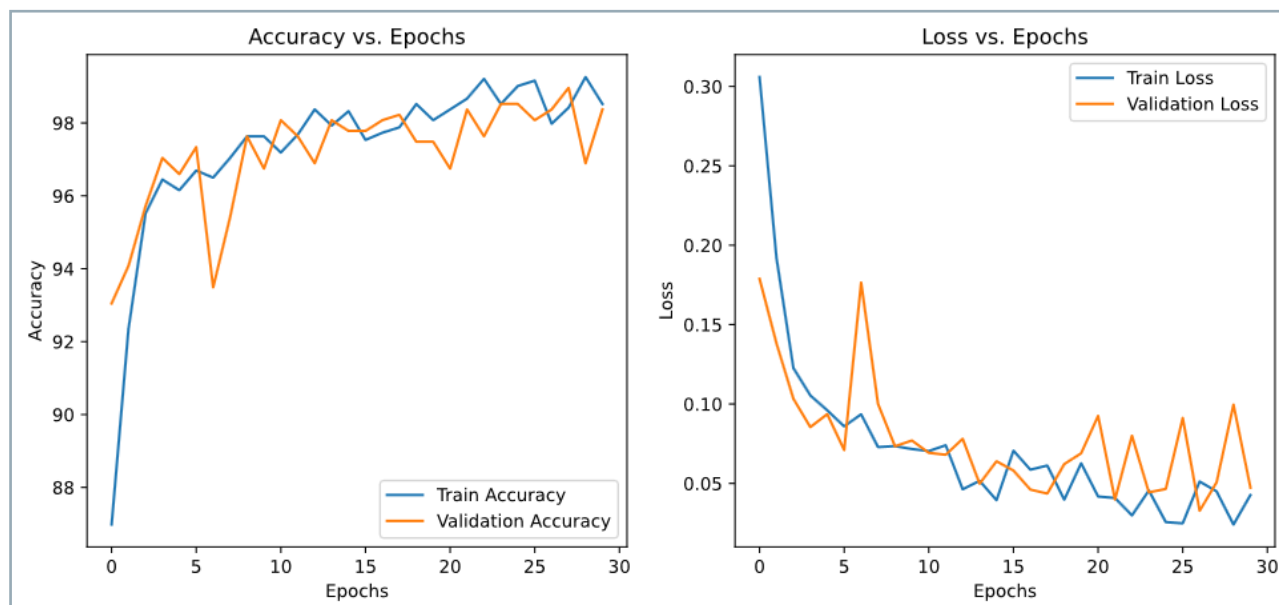


Fig. 2 Accuracy and error graph for each epoch in AlexNet-based classifier

are 310 and 353, respectively. And the number of samples that were falsely labeled as healthy and infected are 4 and 9 samples, respectively. Therefore, according to equation 3, the overall accuracy of the method is equal to 98.07%.

Table 2 Prediction results of the AlexNet-based classifier in the form of confusion matrix

	Healthy leaves	Infected leaves
Healthy leaves	310	9
Infected leaves	4	353

According to Fig. 3, from summarising the results of the accuracy-recall curve and the ROC curve in the AlexNet-based classifier and their value being one, it can be concluded that the AlexNet model is able to maintain a proportional balance between the predictions of healthy

and infected classes. In general, the number of incorrect predictions has been insignificant.

DenseNet-based classifier

The accuracy and loss plot of the DenseNet model states that the model reached an accuracy value of over 98% from Epoch 4 onwards. Despite the fluctuations of the model, from epoch 26 onwards, the model consistently achieved the lowest error value and the highest accuracy (Fig. 4).

Table 3 Prediction results of the DenseNet-based classifier in the form of confusion matrix

	Healthy leaves	Infected leaves
Healthy leaves	316	3
Infected leaves	0	357

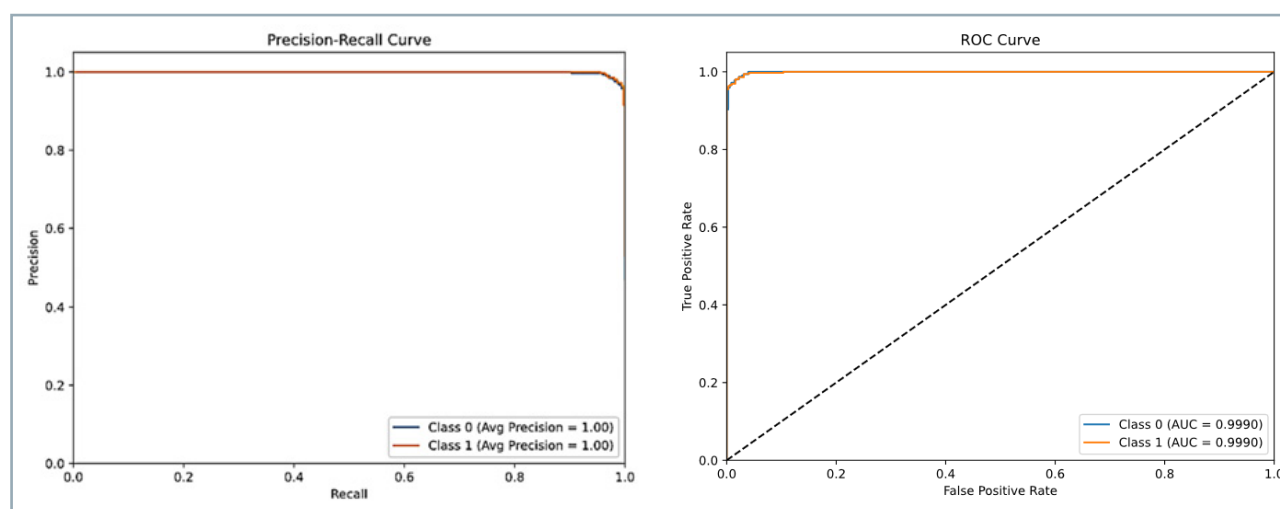


Fig. 3 Accuracy-recall coefficient and ROC curve in the AlexNet method

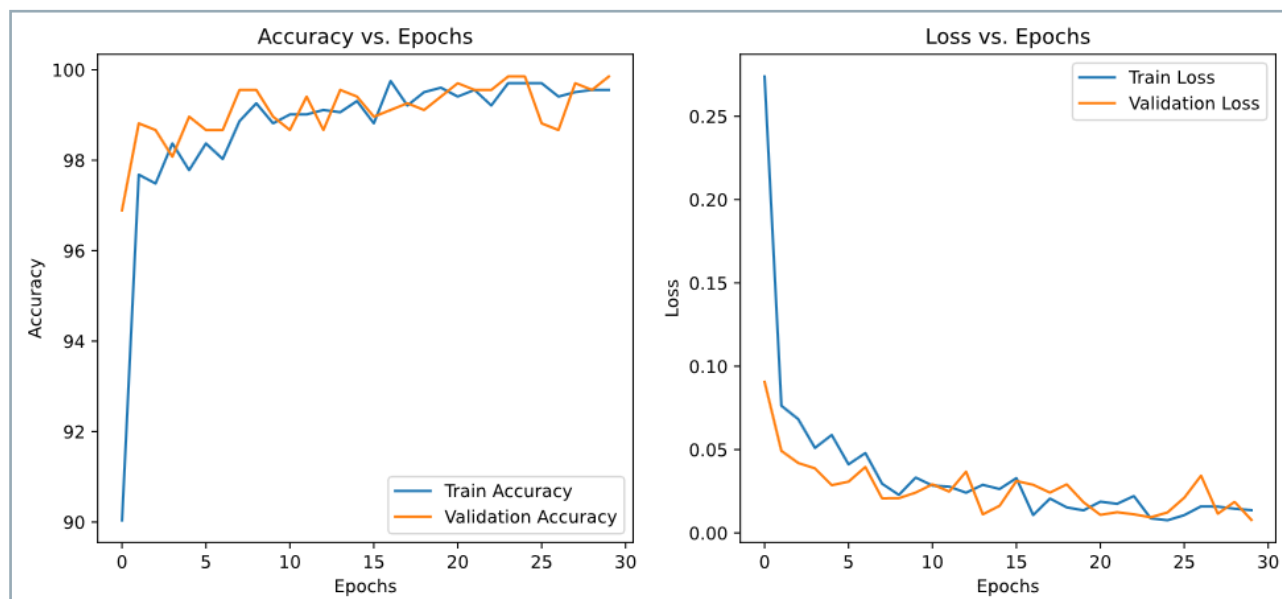


Fig. 4 Accuracy and error graph for each epoch in the DenseNet-based classifier

According to Table 3 of the confusion matrix of the samples in the DenseNet method, the number of samples that are correctly labelled as healthy and infected are 316 and 357, respectively. The number of samples that were wrongly labelled as healthy and infected is 3 and 0 samples, respectively. Therefore, according to Eq. 3, the overall accuracy of the method is equal to 99.70%.

The value of accuracy-recall curve and ROC curve in the DenseNet method is 1, and the presence of the curve indicates the ability of the DenseNet model in predicting healthy and infected classes (Fig. 5).

EfficientNet-based classifier

The accuracy and loss diagram of the EfficientNet model states that the model achieves an accuracy value of over 98% and the lowest error value from epoch 21 onwards. Compared to the previous two methods, this method has very few fluctuations, which shows the ability of this model

(Fig. 6). The number of samples that are correctly labelled as healthy and infected are 319 and 355, respectively. The number of samples that are falsely labelled as healthy and infected is 0 and 2 samples, respectively. Therefore, the overall accuracy of the method is equal to 99.70% (Table 4). The accuracy-recall curve and the ROC curve of the model are also the same. According to the presence of the curve, the ability of the model in predicting healthy and infected classes is confirmed (Fig. 7).

Table 4 Prediction results of the EfficientNet-based classifier in the form of confusion matrix

	Healthy leaves	Infected leaves
Healthy leaves	319	0
Infected leaves	2	355

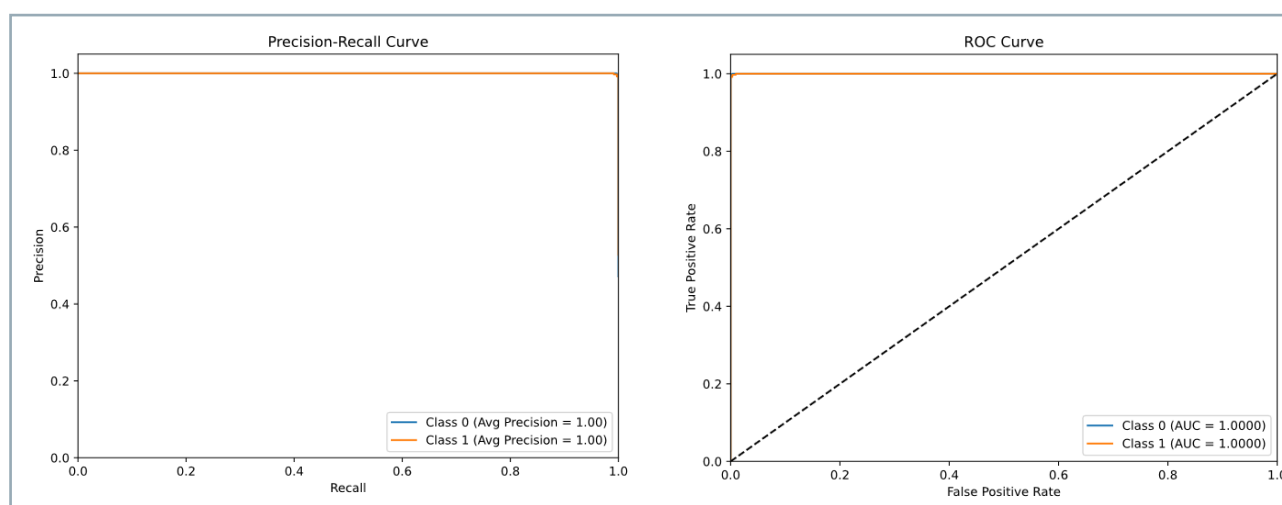


Fig. 5 Accuracy-recall coefficient and ROC curve in the DenseNet method

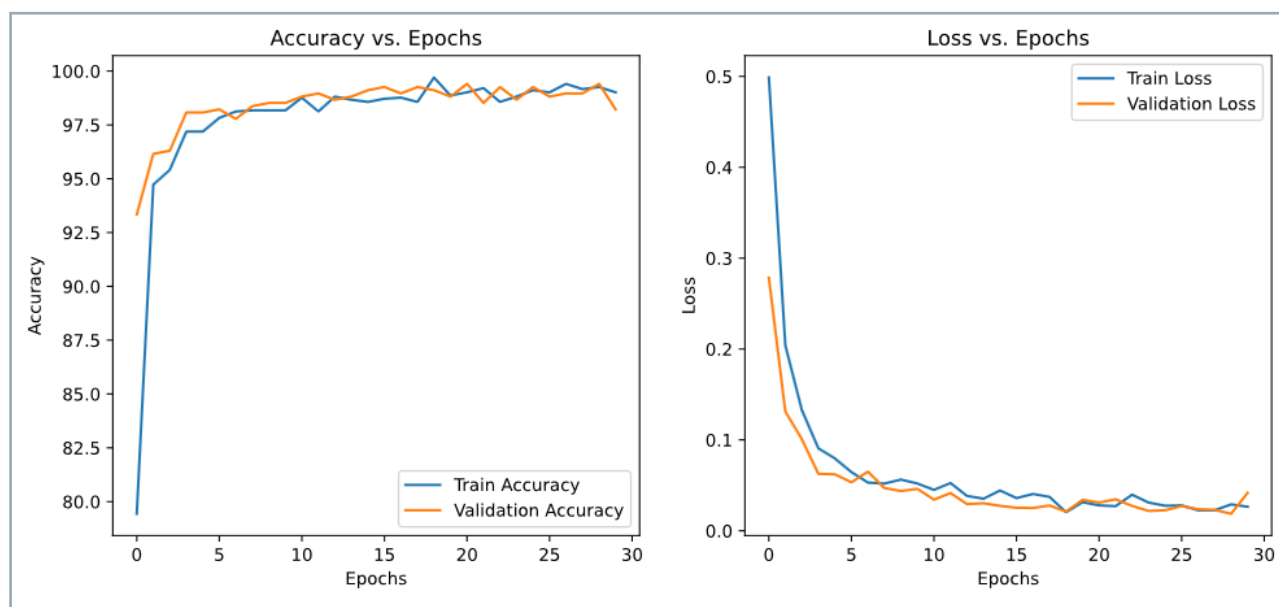


Fig. 6 Accuracy and error graph for each epoch in the EfficientNet-based classifier

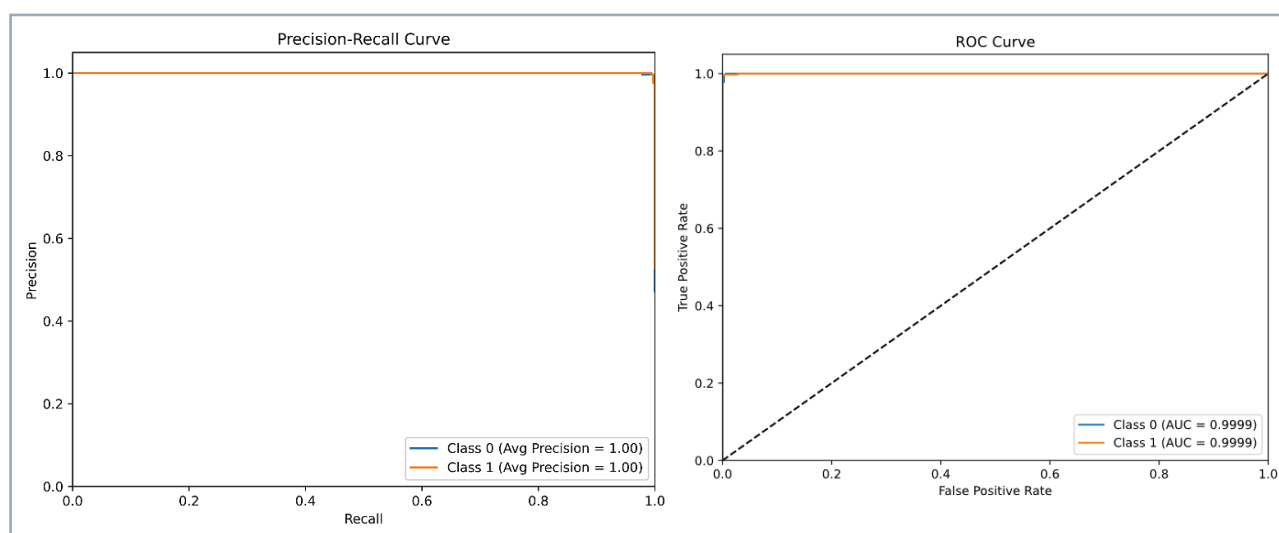


Fig. 7 Accuracy-recall coefficient and ROC curve in the EfficientNet method

GoogleNet-based classifier

The accuracy and loss diagram of the GoogleNet model states that the model from epoch 15 has very low fluctuations, high accuracies of 98%, and the lowest amount of error. According to the correct prediction rate of healthy and infected classes (Table 5), the overall accuracy of the method is equal to 99.70% (Fig. 8). The accuracy-recall curve and the ROC curve of the model are also the same. Due to the presence of the curve, the ability of the model in predicting healthy and contaminated classes is confirmed (Fig. 9).

Table 5 Prediction results of the GoogleNet-based classifier in the form of confusion matrix

	Healthy leaves	Infected leaves
Healthy leaves	317	2
Infected leaves	2	355

Criteria of evaluating the classifiers

Table 6 shows the evaluation results of classifications in the form of 4 criteria of precision, accuracy, recall, and *F*-score. Accuracy actually describes the ability of a measuring instrument to detect an accurate value. In other words, the closeness of the measured value to the actual and standard value is called measurement accuracy. To understand the accuracy of the measurement, the measurement must be repeated many times. If the average of these measurements is closer to the real value, it means that the measurement is very accurate, whereas the closeness of two or more measurement results to each other is called precision. For example, if an image is analysed several times, and the same result is recorded by the output every time, the measurement is very precise but not necessarily accurate. The precision of the measurement is always independent of the accuracy of the measurement.

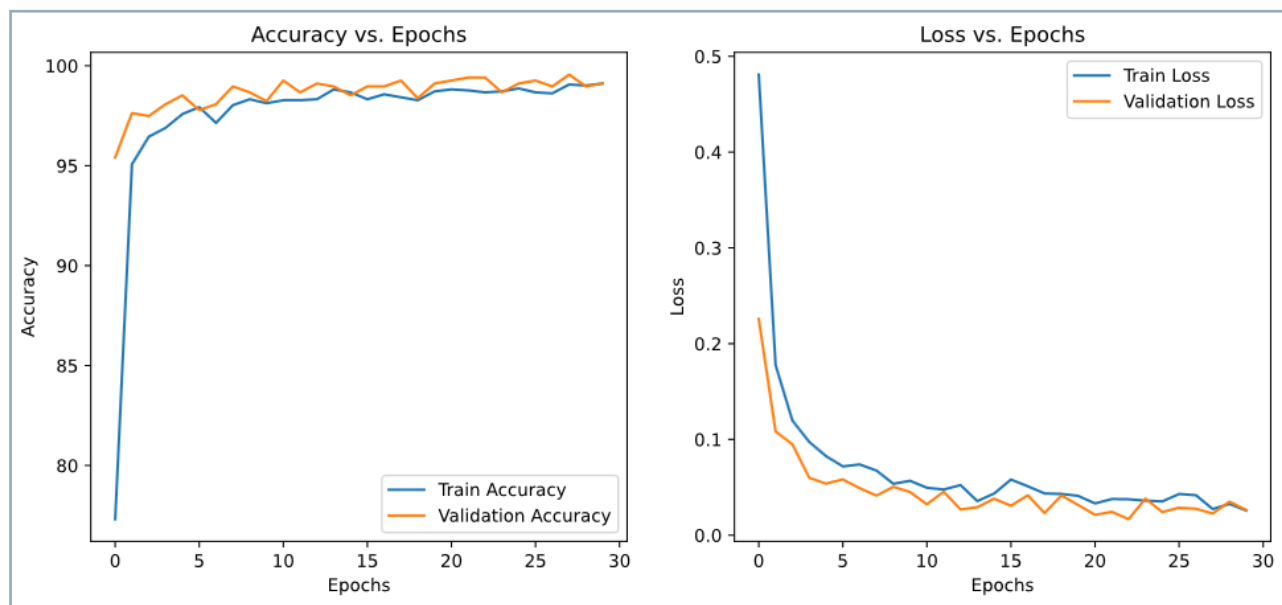


Fig. 8 Accuracy and error graph for each epoch in the GoogleNet-based classifier

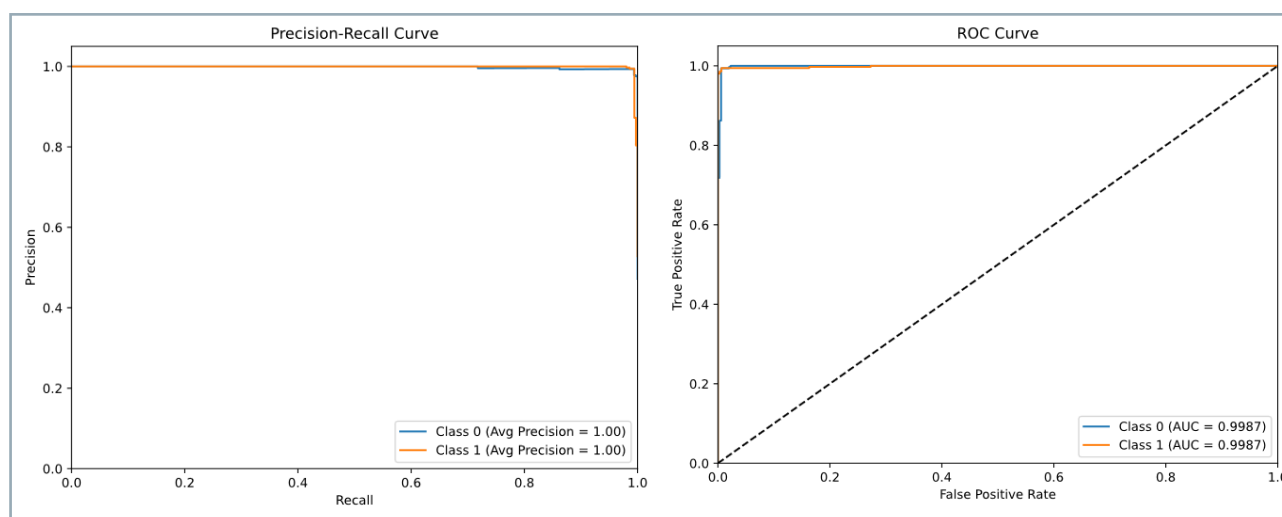


Fig. 9 Accuracy-recall coefficient and ROC curve in the GoogleNet method

In other words, for example, related to the matrix confusion of the EfficientNet-based classifier, among total 676 samples of the test set, 674 leaves were correctly detected (Eq. 3) and precision was equal to 100%. But this criterion has a weakness that it cannot differentiate between false negative (FN) and false positive (FP). In fact, this criterion considers all errors equally. Thus, if the number of FN and FP were reversed, the result would be different. To overcome this problem, the correctness criterion has been introduced,

which includes positive and negative false according to Eq. 2. Therefore, the accuracy of the EfficientNet-based classifier was 99.7%. In some issues, the recall is more important than the accuracy. For example, in the present paper, if the algorithm mistakenly detects a healthy leaf as infected, the wrong pest control should be applied, and there will be little loss. But suppose that the leaf is really infected, and it is wrongly diagnosed as healthy, it can cause a lot of damage to the agricultural community. The F1 criterion, which is

Table 6 The evaluating criteria of classifiers in terms of precision, accuracy, recall, and *F*-score

	Precision	Accuracy	Recall	<i>F</i> -score
AlexNet	0.987	0.980	0.971	0.979
DenseNet	0.990	0.995	1	0.995
EfficientNet	1	0.997	0.993	0.996
GoogleNet	0.993	0.994	0.993	0.993

Table 7 Comparison of proposed methods with literature

Author	Type of research	Proposed method	Precision (%)
Present paper	detection of armyworm in corn	AlexNet	98.7
		DenseNet	99
		EfficientNet	100
		GoogleNet	99.3
Kasinathan and Uyyala (2023)	detection of armyworm in crops	R-CCN	94.21
Vakilian and Massah (2013)	detection of armyworm in beet	ANN	89
Sena et al. (2003)	detection of armyworm in corn	Image segmentation	94.72

actually a balanced combination between precision and recall, can be used in cases where the cost of FP and FN is different. Also, if the research data is unevenly distributed in the classes, it is better to use precision, recall, and F1 criteria.

Comparison of proposed methods with literature

Table 7 compares the correct classification of proposed classifiers with other research. As it is obvious, the results are compromising. As can be seen in Table 6, the correct classification rate of all the four proposed methods was higher than the results of previous similar research, especially that the proposed methods based on deep learning are far more popular and successful than the old common neural network and image segmentation.

Conclusion

Corn is one of the most widely consumed food all over the world, which has many properties for human and animal health. Since the detection of pests is very helpful in increasing the quality of food, it helps increase the country's economy as well. The armyworm pest has posed significant threats to agriculture since it was first reported in 2019, so the present paper aimed to identify this threatening pest using image processing and deep learning-based models with 4 proposed structures, namely AlexNet, DenseNet, EfficientNet, and GoogleNet.

The results show that the accuracy values of all the proposed models were above 98%. Also, the EfficientNet method had the highest values of precision and accuracy, so the F1 score of this model is also higher than others, with a value of 0.9968.

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