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Early Leaf Disease Detection of Soybean Plants using Convolution Neural Network Algorithm

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ABSTRACT

Background: Agricultural specialists usually examine leaves closely to check for plant diseases, that process takes a long time and can have errors. To overcome these problems, nowadays, machine learning methods, specifically sequential convolution neural networks (CNN) are widely used, because of their extensive potential to extract features and patterns from the image dataset.

Methods: This study introduces a complete methodology for detecting diseases in soybean plants by employing Convolutional Neural Networks (CNNs). A dataset sourced from the Mendeley database, containing images of soybean legume crops affected by caterpillars, Diabrotica Speciosa diseases and undamaged (healthy) foliage is used., The research explores the efficacy of the CNN Model in accurately classifying these diseases. The CNN algorithm is trained in such a way that it can handle the complex nature of soybean leaf imaging by utilizing convolutional layers for extracting features, pooling layers for reducing dimensionality and softmax layers for classification.

Result: The training and validation results exhibit remarkable accuracy rates (97.64% accuracy) after 150 epochs. The evaluation metrics, such as precision, recall and F1-score, demonstrate the model's performance across different leaf diseases of soybean, suggesting its ability to accurately identify instances inside each category. The classification matrices provide complete knowledge of the accuracy of the prediction of different diseases. The overall accuracy of the proposed model is 94.05%. This study can be utilized as a reference to increase the progress of agricultural disease detection, in turn, can enable enhance the reduction of crop losses and ensure food security.

Key words: Convolutional neural networks (CNNS), Diabrotica speciosa, Food security, Machine learning, Soybean leaf disease.

INTRODUCTION

Among other essential crops, soybean [*Glycine max* (L.) Merril] is the most significant seed legume globally. It contributes about 25% of the world's edible oil production, serves as the primary source of protein concentrate for animal feed and is necessary for the making of chicken and fish feeds. Soybeans are also a significant supplier of raw materials for the food, pharmaceutical and other industries. India ranks fifth in soybean output volume and fourth in cultivation area worldwide, based on estimates from the FAO and AMIS. During the 2020-21 growing season, soybeans in India were cultivated on 12.06 million hectares, producing 13.58 million tonnes at a productivity rate of 1,126 kg/ha. In contrast, the global average soybean productivity is approximately 2,900 kg/ha, with the highest yields (>3,000 kg/ha) recorded in the United States and Brazil (FAO, 2020). However, soybean plants are exposed to a range of leaf diseases caused by pathogens including fungus, bacteria and viruses. If these diseases are not immediately recognised and controlled, they may have a significant negative effect on crop output and quality. Timely identification of leaf diseases is essential for implementing timely solutions that might reduce economic losses and promote sustainable farming practices. Traditional disease identification techniques often depend on agricultural experts visually examining the plants, a process that is time-consuming and susceptible to human mistakes. Consequently, there is an increasing need to use advanced methods like machine learning and computer vision to automate and improve disease detection procedures.

Computational methods such as convolutional neural networks (CNN), support vector machine (SVM), random forest (RF) *etc*. are widely recognized for their exceptional ability to address computer vision tasks (Saleem *et al.,* 2022). CNN has gained widespread recognition for its proficiency in interpreting image data, particularly in applications such as image classification, segmentation and detection. The remarkable effectiveness of the CNN architecture in these tasks might be attributed to its capability to handle raw data without any previous

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knowledge (Senan *et al.,* 2020). Several researchers have contributed to improving the performance of CNNs. According to the research, enhancing the performance of the convolutional neural networks (CNNs) model requires adjusting architectural parameters and weights (Gonzalez, 2007). Improving the performance of the model generally can be achieved by increasing the size of the training dataset, implementing transformations on the training data and fine-tuning different parameters (Zhang *et al.,* 2020; Semara *et al.,* 2024; Maltare *et al.,* 2023; Bagga *et al.,* 2024).

Various machine learning techniques have found applications in agricultural research (Rumpf *et al.,* 2010). Traditionally, image classification tasks relied on handcrafted features like SIFT (van Dokkum *et al.,* 2000), HoG (Zhang *et al.,* 2012), SURF, followed by the utilization of learning algorithms within these feature spaces (Bay *et al.,* 2008). However, the effectiveness of such approaches heavily depended on predefined features (Ma *et al.,* 2021). Utilizing learned representations, which are more successful and efficient, has been more popular in recent years. With the use of representation learning, algorithms can automatically analyse large image collections and identify characteristics that help classify images with the least amount of mistakes (Taye, 2023). Sequential neural network techniques have become an effective tool for classifying images and recognizing objects. It is a kind of deep neural network (DNN) made especially for processing images and it draws inspiration from the human visual system. For object recognition, a number of CNN architectures have been put out; baseline models for these tasks are AlexNet (Mall *et al.,* 2023) and LeNet (Alzubaidi *et al.,* 2021).

This study introduces the benefits of the CNN model to identify soybean disease from leaf images captured in uncontrolled environments. The models are structured according to the sequential architect and the image dataset is sourced from the Mendeley database. The dataset images are preprocessed before sending for training. The overall performance of the proposed model is evaluated in terms of classification matrices such as accuracy, precision, recall, F1-Score and confusion matrix.

Related work

Farming used to be about feeding more people, but now it's a really important part of economies worldwide. However, plant diseases are a big problem, causing a lot of losses in crops and money for agriculture and forestry. One example is soybean rust, a fungal disease that has caused substantial financial damage to soybean crops. Eliminating just 20% of the infection has the potential to generate farmers a profit of almost $11 million (Singh *et al.,* 2020). Hence, prompt intervention is vital for the early detection and identification of plant diseases. Multiple techniques are available for identifying plant diseases. Certain diseases may not pre sent any observable symptoms or only become apparent when it is already too late to take action. For such situations, intricate examinations are required, frequently utilizing high-powered microscopes. Furthermore, some indications may solely be discernible in segments of the electromagnetic spectrum that are imperceptible to the human visual system (Liu and Wang, 2021). This section explores the current trends in utilizing deep learning and CNNs architectures in the field of agriculture. Before deep learning became popular, image processing and machine learning methods were used to classify different plant diseases (Tugrul *et al.,* 2022). Usually, these systems would go through a series of steps: first, digital images were taken using a digital camera and then image processing techniques like enhancement, segmentation, color space conversion and filtering were applied to prepare the images for further analysis. Subsequently, the images were subjected to feature extraction, resulting in the identification of important characteristics. These features were then employed as input for the classification process. The total accuracy of categorization was highly dependent on the techniques used for image processing and feature extraction (da Silva and Mendonca, 2004). Nevertheless, recent research has shown that networks trained using generic data can achieve state-of-the-art performance.

Artificial Intelligent based algorithms have consistently shown exceptional performance in almost all-important classification tasks (Salvi *et al.,* 2021). The same architecture allows for both feature extraction and classification to be performed. Convolutional Neural Networks (CNNs), a distinct category of artificial neural networks, have been extensively utilized in several domains of pattern identification, including computer vision and speech recognition. Patil and Rane (2021) employed three architectural concepts to guarantee a certain level of invariance to shifts, scales and distortions: local receptive fields, shared weights and spatial or temporal sub-sampling. Several CNN architectures, like as LeNet, AlexNet and GoogLeNet, have been suggested for object recognition (Shamsaldin *et al.,* 2019; Wasik and Pattinson, 2024; Cho, 2024; Porwal *et al.,* 2024; AlZubi, 2023; Hai and Duong, 2024).

The LeNet architecture, pioneered by Boulent *et al.* (2019), was the inaugural convolutional neural network specifically engineered for identifying handwritten numerals. The model consists of an array of convolutional and sub-sampling layers, which are then followed by dense layers connected MLP (Boulent *et al.,* 2019).

Researchers have proposed the use of convolutional neural networks (CNNs) for plant disease classification and leaf identification. By examining leaf pictures, Atabay (2017) created a convolutional neural network (CNN) structure for plant recognition. According to Atabay (2017), the model's classification accuracy was 97.24% for the Flavia leaf dataset and 99.11% for the Swedish leaf dataset. Using 1.8 million images from the ILSVRC 2012 dataset, Wallelign *et al.* (2018) trained a convolutional neural network (CNN) using a deep learning technique. For the task of plant

identification, they obtained an average precision of 0.486 (Wallelign *et al.,* 2018). Plant diseases were categorised by Mohanty *et al.* (2016) using well-known deep convolutional neural network (CNN) models as AlexNet and GoogLeNet. With a publicly accessible dataset of 54,306 images, they attained an astounding accuracy of 99.35%. However, when tested on images taken in a different environment, the model's accuracy dropped to 31.4%. Still, these results highlight how well deep convolutional neural networks (CNNs) classify plant illnesses (Mohanty *et al.,* 2016).

MATERIALS AND METHODS

The realm of machine learning, particularly deep learning, employs complex neural networks to interpret a large dataset. Various data types, spanning text, audio, video, images, time series, sensor data and even Internet of Things streams, find application in deep learning frameworks. Notably, convolutional neural networks (CNN) excel in processing image data, making them pivotal in tasks like distinguishing between diseased and healthy soybean leaves with remarkable precision. This process typically uses four key stages. The base is first established via data collecting and then the model is developed. Afterward, priority is given to data training, leading to the final stage of model testing.

Datasets

For image recognition throughout the process, from training to performance evaluation, a precise dataset is essential to empower the algorithms. In this study, the training dataset was sourced from the Mendeley database (Mignoni *et al.,* 2022), encompassing three distinct categories of soybean leaf: Caterpillar, Diabrotica Speciosa and Healthy. These images depict soybean leaves affected by caterpillars, Diabrotica Speciosa disease and undamaged (healthy) foliage (Fig 1).

Altogether, the dataset comprises 6,410 images, distributed across the three categories as follows: Caterpillar (3,309 images), Diabrotica Speciosa (2,205 images) and Healthy (896 images).

Pre-processing and tagging

Before feeding the raw images into the CNN classification algorithm for analysis, they were preprocessed to enhance their quality or adjust their attributes. Images sourced from various origins may exhibit diverse sizes, necessitating resizing and rescaling to ensure uniformity. This standardization is crucial for maintaining consistency and expediting the training process, as larger images entail higher processing overheads. To ensure uniformity, the images were resized to dimensions of 256×256×3 and then converted to grayscale. Subsequently, the resized soybean leaf images were categorized by type, with each image labeled according to its corresponding health status acronym. This categorization process identified three classes: healthy, caterpillar and Diabrotica Speciosa within both the training and test datasets.

Training dataset

In developing a CNN model for detecting diseases in soybean plants, several sequential steps are involved. Initially, the process begins with importing the necessary libraries and compiling a dataset containing images of soybean leaf diseases, as depicted in Fig 2.

Subsequently, the dataset is divided into three categories-training, validation and testing using an 8:1:1 ratio. Following this division, the dataset undergoes pre-processing and augmentation to enhance its quality and increase its diversity. During the training phase, the model is fed with tensor images from the training set, allowing it to learn and associate inputs with their corresponding labels. Finally, the model's accuracy is evaluated by fine-tuning its learning outputs against the tensor labels, enabling an assessment of its performance.

Architecture of convolutional neural network (CNN) model

Three main building blocks are used in Convolutional Neural Networks (CNNs): convolutional layers, pooling layers and activation functions (usually Rectified Linear



Fig 1: Categorizing images of soybean plants as healthy, infected with caterpillars and diabrotica speciosa.

Units; ReLUs). The configuration of layers, their arrangement and the incorporation of additional processing units differ across architectures, thereby influencing their specificity and performance.

The convolution layer is a fundamental component of CNN architecture, positioned after the input layer and comprises a set of convolution kernels (neurons) (Boulent *et al.,* 2019). Each kernel (neuron) corresponds to a small region, termed a receptive field, within the input image. The performance and training speed of CNNs are directly influenced by hyperparameters such as kernel size, number of kernels, stride length and pooling size. The hyper parameters of the CNN model are represented in Table 1.

The input image is divided into smaller segments, or receptive fields and convolved with a predetermined collection of weights by the layer. The convolution layer of CNN operates in the following manner (Alajrami *et al.,* 2019).

$$Z^{l} = h^{l-l} * W^{l}$$

Following the operation of convolution, the max pooling layer is added in CNN architecture. This layer conducts down sampling (Loussaief and Abdelkrim, 2018), aiming to reduce the dimensionality of the information gathered from the convolution layer while retaining essential features. Simultaneously, the pooling layer considers the following notations as input (Alajrami *et al.,* 2019).

$$h^{1}_{XY} = \max_{i=o..s, j=0..s} \; h^{l-l}(X+i)(Y+j)$$

Fully connected layers constitute a crucial component of convolutional neural networks (CNNs), demonstrating significant effectiveness in image classification (Alyami *et al.,* 2020). These layers take a finite number of neurons as input and classify them into relevant classes (Ali *et al.,* 2019). Below are mathematical representations of the fully connected layer.

Taking into account the Jth node of a convolutional or pooling layer with the dimensions.

$$Z_j = W_j * h_{j-l}$$

The output of a dimensional convolution or pooling process could be the input

$$(h_j^{[l-l]}, h_{Wj}^{[l-l]}, h_j^{[l-l]})$$

To input into a fully connected layer, the tensor needs to be flattened into a 1D vector with the dimension:

$$(h_j^{[l-l]}, h_j^{[l-l]}, h_j^{[l-l]})$$

The feature map obtained from the last maximum pooling layer is combined and transformed into a one-dimensional array, which is then passed to the fully connected layers (ReLu, Softmax). The mathematical expression for connected layers (ReLu, Softmax) is mentioned below (Alajrami *et al.,* 2019):

$$\text{Relu}(z_i) = \max(0, z_i)$$

$$\text{softmax}(z_i) = e^{zi} / \sum_j e^{zj}$$

Following multiple iterations of forward and backward propagation, the model has been trained and is now capable of making predictions. Fig 3 represents the complete architecture of the proposed CCN model.

After training, the model's performance is evaluated using test data to assess its ability to generalize to new

Table 1: Hyper-parameter of CNN model.

Parameter	Description
Convolution layer	Six
Max pooling layer	Six
Dropout rate	1/2
Network weight assigned	Uniform
Activation function	ReLU
Flatten	(32, 2048)
Epoch	150
Batch size	32
Learning rate	10-6

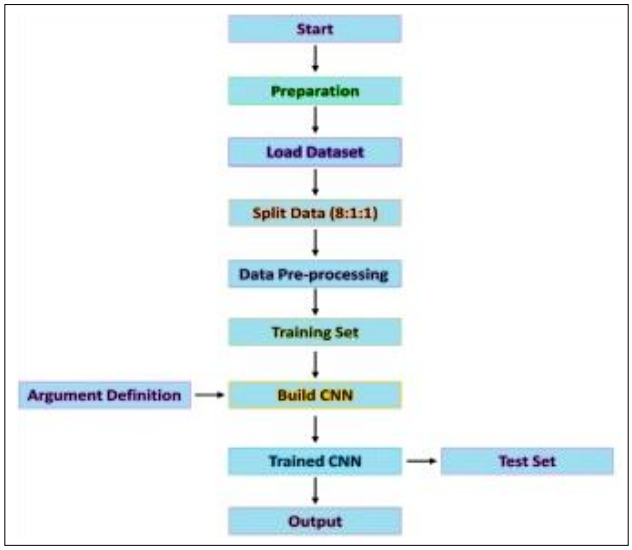


Fig 2: Flow chart of CNN model for the customized dataset.

data. Metrics such as overall accuracy, recall, precision and F1 score are computed from the classification report and confusion matrix to gauge the model's effectiveness.

Evaluation parameters

A widely used algorithm for tackling classification problems, encompassing both binary and multiclass scenarios, is the confusion matrix. This matrix comprises four variables: True positive (TP), False positive (FP), False negative (FN) and True negative (TN) (Genemo, 2023). Utilizing the provided parameters (TP, FP, TN and FN), we calculated the accuracy rate, precision, recall, F1-score and specificity to evaluate the model's performance. The formulas for assessing these metrics are provided below:

$$\text{Accuracy rate} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 - score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{specificity} = \frac{TN}{TN + FP}$$

Accuracy quantifies a model's overall performance and its ability to correctly predict labels. Precision assesses prediction accuracy by comparing the total number of predicted images in a soybean leaf disease category with the accurately predicted images in that category, as per the following equation. Recall evaluates the proportion of correctly predicted images in a soybean disease category compared to all actual observations. Finally, the F1 score combines recall and precision into a single metric for performance evaluation.

Results and Discussion

In this work, we report the outcomes acquired from the training and validation processes utilizing the entire dataset. This analysis primarily examines the results obtained from training with the enhanced dataset, as it acknowledges the capacity of convolutional networks to efficiently acquire features when exposed to larger datasets. Fig 4 (a) and 4 (b) illustrate the comparison of accuracy and loss throughout both the training and validation periods. The training phase reached an accuracy rate of 97.64% after 150 epochs. This implies that additional rounds have the potential to improve the accuracy of the data using the study methodology. Significantly, as the time of training grows, the number of epochs correspondingly increases. In addition, each class was subjected to an individual assessment to determine the efficacy and confidence rating of the trained model. Fig 5 exhibits a collection of photos illustrating both real and predicted diseases. The results show a high level of confidence and accuracy in the predictions.

The confusion matrix represents the relationship between predicted classes and actual classes. The columns represent the predicted classes, while the rows represent the actual classes. It provides a visual depiction of the expected classification results. True positives are located on the diagonal of the matrix, whereas false negatives occupy the rest of the matrix. The confusion matrix in Fig 6 illustrates the classification of soybean leaf diseases into the categories of Caterpillar, Diabrotica Speciosa and Healthy.

The categorization report includes three classifications, namely Caterpillar, Diabrotica Speciosa and Healthy, which are used to assess the machine learning model's performance. The model demonstrates good predictive

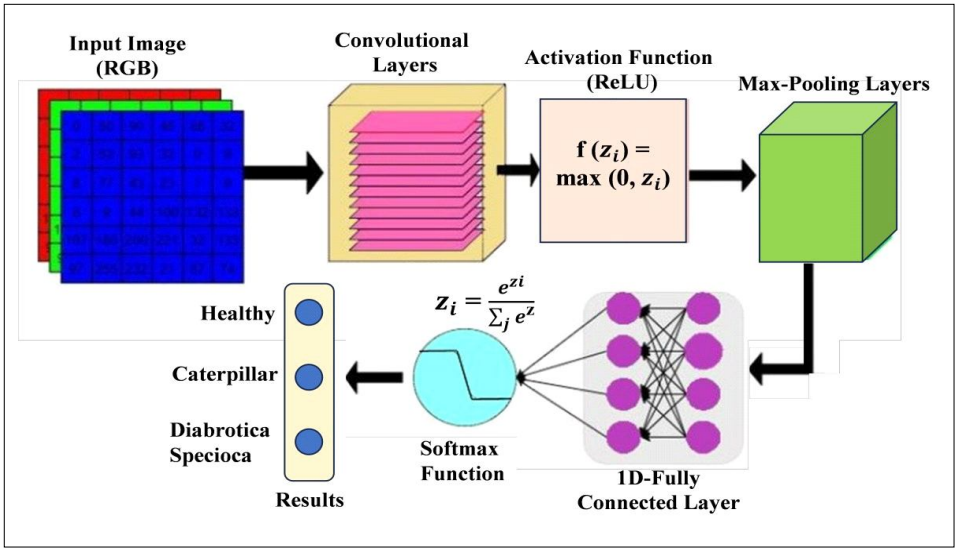


Fig 3: Architecture of the CNN model with convolution and pooling layer specifications.

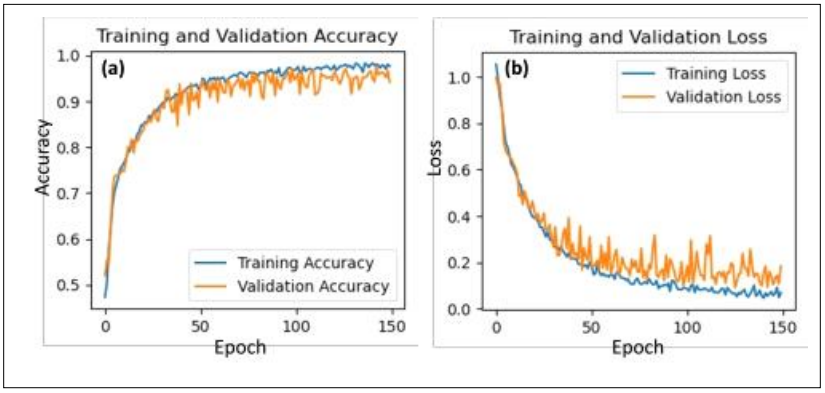


Fig 4: Training and validation (a) accuracy and (b) loss after 150 epochs.



Fig 5: The disease type and the level of confidence in recognizing the image within the dataset.

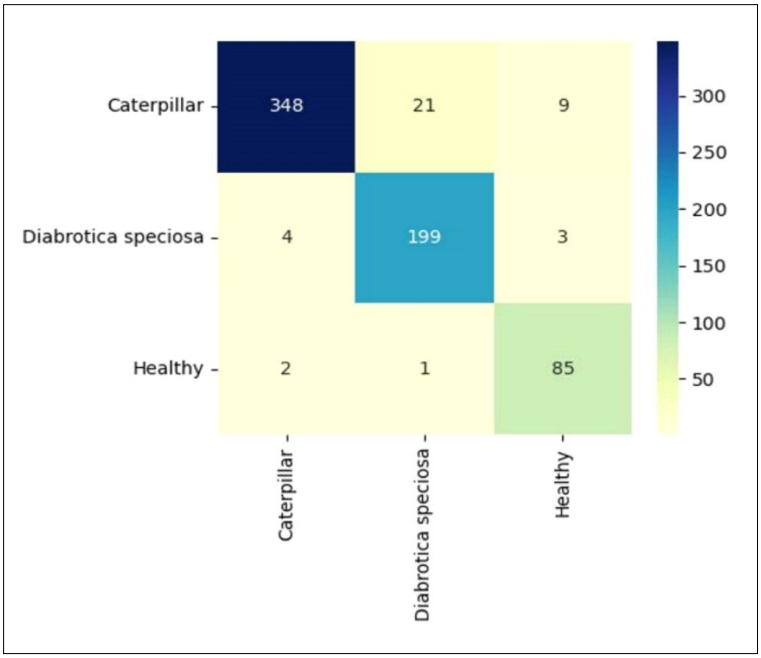


Fig 6: Confusion matrix of soybean leaf disease.

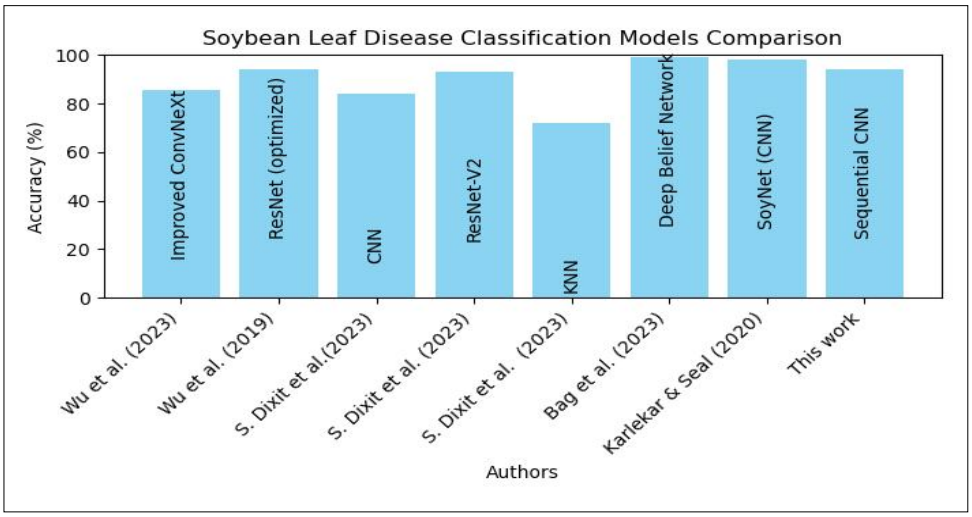


Fig 7: Comparison of presented work with existing literature.

Table 2. classification accuracies, precision, F1-score and support.

Classification	Precision	Recall	F1-score	Support
Caterpillar	0.98	0.92	0.95	378
Diabrotica speciosa	0.90	0.96	0.93	206
Healthy	0.87	0.96	0.91	88
Accuracy			0.94	672
Macro avg.	0.91	0.95	0.93	672
Weighted avg.	0.94	0.94	0.94	672

power, as seen by high precision scores ranging from 0.87 to 0.98. These numbers accurately reflect the model's accuracy in making positive predictions for each class. In addition, the model routinely achieves high recall values, ranging from 0.92 to 0.96, which demonstrates its effective ability to accurately identify real positive events. The F1-Scores, which balance precision and recall, are particularly noteworthy. They vary from 0.91 to 0.95 across courses, as seen in Table 2.

The overall total accuracy rate of the model is 94.04%, that indicates its significant precision in identifying situations. Furthermore, the model's efficacy is strengthened by the macro and weighted average metrics, which exhibit equitable performance across classes while taking into account possible class imbalances.

We have compared several studies that examined deep learning models to help categorise diseases in soybean leaves Fig 7. Wu *et al.* (2023) introduced the Enhanced ConvNeXt model and it had an accuracy rate of 85.42%. Conversely, Wu *et al.* (2019) enhanced ResNet's performance and attained a higher accuracy rate of 94.29%. Dixit *et al.* (2023) evaluated the performance levels of several models in their investigation, including CNN (83.9%), ResNet-V2 (93.01%) and KNN (71.98%). Bag *et al.* (2023) developed a Deep Belief Network that demonstrated its extraordinary capacity for identifying diseases by achieving an amazing detection rate of 99%. Karlekar and Seal (2020) achieved an excellent accuracy rate of 98.14% by successfully deploying a Convolutional Neural Network (CNN) called SoyNet. This result highlights the network's excellent ability to diagnose diseases properly. In contrast, this work demonstrated good performance in comparison to the other models studied, achieving a 94% accuracy rate with the application of a Sequential CNN approach. Hence, the Sequential CNN turns out to be a strong tool for real-world use, allowing fast and precise identification of soybean leaf diseases that are important for good farming management.

LIMITATIONS AND FUTURE WORKS

Considering the encouraging outcomes, this study is subject to various constraints. The performance of the CNN model may be affected by the quality and variety of the dataset. This suggests that a wider and more diverse dataset is required to improve the model's ability to generalize. Furthermore, the study exclusively examined soybean leaf diseases, hence restricting its relevance to other crop species and types of illnesses. In addition, the computational resources needed to train CNN models might be limiting, especially for researchers who have limited access to high-performance computing infrastructure.

To overcome these constraints and propel the area of agricultural disease detection, potential avenues for future study could involve: (1) Gathering a broader and more diversified dataset that encompasses different crop species and types of diseases, in order to strengthen the resilience

and applicability of the models. (2) Investigating sophisticated convolutional neural network (CNN) structures and methodologies, such as transfer learning and ensemble approaches, to enhance the effectiveness and efficiency of the model. (3) Exploring the fusion of remote sensing data and IoT technology to enable immediate monitoring and early identification of crop diseases. (4) Performing field trials and validation studies to evaluate the practical feasibility and scalability of convolutional neural network (CNN)-based disease detection systems in agriculture. By focusing on these specific areas, future research efforts can make valuable contributions to the advancement of more efficient and scalable strategies for managing agricultural diseases and protecting crops.

CONCLUSION

This study emphasized the effectiveness of Convolutional Neural Networks (CNNs) in precisely identifying soybean plant diseases. This study provides significant knowledge for the management of agricultural diseases and the protection of crops. The CNN model achieved remarkable accuracy in classifying soybean leaf photos of caterpillar-infested, Diabrotica Speciosa-affected and healthy foliage classes by carefully preprocessing and enhancing a varied dataset obtained from the Mendeley database. The CNN architecture successfully extracted features reduced dimensionality and enabled accurate classification with an attained accuracy rate of 94.04% after 150 epochs. The evaluation criteria, such as precision, recall and F1-score, confirmed that the model is good in all categories, demonstrating its effectiveness in detecting diseases. These discoveries have important implications for those involved in agriculture, allowing them to take preventive measures to reduce crop losses and assure food security. Future studies may investigate the scalability and generalizability of CNN models across many crop species and disease kinds, thereby promoting the development of comprehensive disease detection systems in agriculture.

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Author contributions

The authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Data availability statement

Not applicable

Declarations

Author(s) declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that they have no conflict of interest.

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