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CropNet: A Smart Framing Approach to Soybean Disease

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ABSTRACT

Background: Rapid spread of plant diseases is still one of the serious threats exerted against global crop production, which causes significant economic losses and puts food security at risk. Several studies have investigated deep learning architectures (CNN/R-CNN variants, EfficientNet and hybrid models) that were developed using big datasets *viz* PlantVillage, hyperspectral images and field-collected samples. Promising results have indicated that these approaches would achieve classification accuracies up to 96.52%. Nonetheless, problems including poor diversity of dataset, lack of generalization to real-world situations, computations involved and deployment limitations do exist.

Methods: This article summarizes several recent research works, which examine various deep learning models to detect plant diseases. It also presents evaluations of CNN-based models, region-based detection techniques (R-CNNs), as well as lightweight high-performance architectures that include EfficientNet and hybrid deep learning method variants. The considered models were trained on popular datasets: PlantVillage, hyperspectral image databases and data collected from the field. Moreover, this paper introduces our 16 layers CropNet model trained and tested on a self-collected dataset and then compared to the proposed deep learning architectures. The comparative methodological study considers accuracy, computational efficiency, generalizability and deployment feasibility, leading to a comprehensive evaluation of the proposal in cropnet architecture.

Result: The accuracy of the proposed CropNet model outperforms other networks and achieves performance close to the state-of-the-art with a value of 98.75%. Yet, the findings also point to current limitations due to dataset variety, generalization on realistic field scenarios and computation costs.

Key words: Accuracy, Artificial intelligence, CNN, Deep learning, Disease.

INTRODUCTION

Agriculture is a vital element in the economic stability and food security of an agricultural country. When a country has the ability to sustainably grow, process and supply food without over-reliance on imports or technologies, the country is said to be agriculturally independent. A robust and independent agricultural infrastructure needs to be constructed so that food is always available and the economy is resilient. One of the most important aspects of such independence is the integration of modern technologies that would prevent and cure crops diseases at an early stage. Plant disease detection systems, which are designed and trained on deep learning, play an important role in this objective by allowing the timely diagnosis of plant diseases and improving the overall quality and quantity of agricultural products (Patil and Kumar, 2017).

Despite its central role in world food security, the agriculture sector continues to face numerous. problems, one of the most severe threats being crop diseases. These diseases may drastically lower agricultural. output and productivity and result in colossal economic losses and pose a severe risk to global food supplies. The traditional methods of plant disease detection are mostly manual and therefore labor intensive and subject to error. in addition to being inefficient in identifying plant diseases in large scale farming operations (Patil and Mandlik, 2024). These conventional approaches tend to be knowledge intensive and non-scalable.

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The recent developments in the sphere of Artificial Intelligence (AI) have re-invented the sphere of crop disease detection (Sunil *et al*., 2023). Since it is bound, Deep Learning (DL) models have demonstrated impressive performance in plant disease detection. to study complex leaf image characteristics. These models are capable of completely automating the feature extraction process and have been demonstrated to be much more effective than conventional machine learning techniques. In addition, the object detection methods have increased the chances of detecting more than a single disease in an image, which improves. the diagnostic efficiency and accuracy.

However, there are several problematic issues with the application of DL models to the real agricultural setting.

Most models are trained using benchmark datasets such as PlantVillage, which are not typically as environmentally diverse as the field (Moupojou *et al*., 2023). The variation in light, composition, disease progression and multiplicity of infection may also limit the degree to which a model can be capable of generalizing to acceptable degrees. To address these weaknesses, scholars propose the use of in-situ collected data, high-resolution imaging such as hyperspectral imaging and the application of data augmentation processes to increase the strength and generalisation of the models (Sharmila *et al.*, 2024).

Another significant issue of the DL models is that they are not interpretable. To encourage farmers and agronomists to utilize such techniques that could be interpreted, the models provided by XAI must be included and it will be simpler to know why a model made a decision in favor of or against a disease. Open decision-making will build trust amongst users and establish an informed basis for decision-making in the field.

The objective of this research is to provide a comprehensive assessment of DL algorithms for plant disease detection by comparing multiple CNN architectures and object detection models. In combining the knowledge obtained from different investigations, the present work aims to bridge this gap between theoretical studies and farming practice. Ultimately, this will support the creation of resilient, scalable and real-time disease detection solutions that underpin precision agriculture.

MATERIALS AND METHODS

An extensive review of recent studies was carried out in order to recognize relevant methods and benchmark models for crop disease detection. Mehta *et al*. (2025) provided an extensive review on plant disease recognition and categorization. Table 1 provides a summary of selected literature on different crops, datasets and types of machine/ deep learning methods for disease detection. The table provides the details on the models employed, accuracies obtained and the significant findings, as well as the future directions suggested by individual authors.

The proposed model that we have named as CropNet system is a deep learning based framework for the detection of plant leaf diseases and generally, it works in some main stages (as illustrated in Fig 1), such as data collection; data processing; data augmentation; data splitting CropNet model building and performance analysis.

Data collection

The soybean was chosen as the test crop. Acquisition of an appropriate training set for the soybean leaf disease images is essential and it depends greatly on occurrences and severity of diseases, which are a function influenced by environmental factors, such as location. The dataset was gathered during multiple growing seasons with the objective of collecting diseased leaf images. This took approximately three consecutive years from 2022. The images were captured in the south-west part of Maharashtra state of India (Fig 2) from an EOS 1500D Kit camera with a resolution of 24.1 megapixels. High-resolution images are 1990×1280×3 and preserve the fine-grained details that are crucial to disease recognition.

Data preprocessing and augmentation

The preprocessing is critical to improve image quality and robust training on Convolutional Neural Networks (CNNs). This includes scaling, normalization and noise filtering, which enhance accuracy and speed up the convergence. The normalization typically used is given in equation (1):

$$I_{norm} = \frac{I - \mu}{\sigma} \quad ...(1)$$

Where,
I= The input image,
μ= Mean.
σ= Standard deviation of the dataset.

Data augmentation artificially increases the size of datasets by applying transformations, such as rotation, flipping cropping, to the original images. This helps CNN produce better generalization by feeding in a lot of different versions of the same image, thus reducing its overfitting. Schemes such as random zoom, brightness and affine transformations help the model to be more robust. Equation (2) represents an affine transformation.

$$\begin{bmatrix} A' \\ B' \\ 1 \end{bmatrix} = \begin{bmatrix} p & q & t_A \\ r & s & t_B \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} A \\ B \\ 1 \end{bmatrix} \quad ...(2)$$

Where,
(A, B)= The original coordinates,
(A′, B′)= The transformed coordinates.
The matrix $\begin{bmatrix} p & q \\ r & s \end{bmatrix}$ = Scaling and rotation.
$[t_A, t_B]^T$= Translation.

Preprocessing and augmentation make the data sufficiently varied. They are also used for the normalization of CNNs with respect to changes in lighting, scale and orientation of the images.

Data splitting

Data separation is crucial for training a robust CNN model with good generalization capability to unseen data. It works to prevent overfitting. The dataset is split into a training set (for model training), a validation set (for tuning hyperparameters) and a test set (for unbiased evaluation). Sufficient splitting prevents data leakage, ensures unbiased evaluations and leads to more reliable accuracy.

CorpNet model

Constructing the CNN involves designing a deep learning framework for image classification (Pakruddin *et al*., 2025). The architecture typically includes convolutional layers, activation functions, pooling layers, fully connected layers and an output layer. The proposed 15-layer CropNet model is built using three convolution layers followed by ReLU

Table 1: Comparative study of literature review.

Authors/study	Crop dataset	Techniques/ models used	Accuracy (%)	Highlights/key findings	Future scope/ recommendations
Sujatha *et al.* (2021)	Citrus leaf dataset (5 disease classes)	ML: SVM, RF; SGDDL: Inception-V3, VGG-16, VGG-19	RF: 76.8; SVM: 87.0; VGG-16: 89.5	Demonstrated that DL achieves superior accuracy and feature extraction compared to ML.	Integration with IoT, cloud computing and bioinspired systems for field deployment.
Nalini *et al.* (2021)	Paddy leaves (120 images)	DNN optimized with crow search algorithm (CSA); K-Means clustering for feature extraction	96.96	CSA-DNN outperforms SVM; uses color, texture and shape as key features.	Develop real-time disease monitoring *via* IoT, cloud and mobile app platforms.
Syed-Ab-Rahman *et al.* (2022)	Citrus dataset (Kaggle)	End-to-end CNN with region proposal network (RPN)	94.37	RPN enables lesion localization; robust detection under varying illumination.	Employ field-based validation, enhanced augmentation and real-time monitoring integration.
Pawar *et al.* (2022)	10 plant species (incl. Soybean; 50,000+ images)	Deep CNN with 15 layers	93.0	Multi-crop disease detection suggests pesticides, suppliers and sends SMS alerts.	Expand system for web/ mobile deployment and progressive phase-wise disease tracking.
Ahmad *et al.* (2023)	Review of 70 DL studies	Various DL models across crops	-	Comprehensive survey on AI-driven plant disease diagnosis; Analyzed dataset diversity, robustness and sensor modalities.	Recommend transfer learning, multi-modal sensing and standardized severity metrics.
Amin *et al.* (2022)	Corn leaf dataset	Hybrid CNN combining EfficientNetB0 and DenseNet121	98.56	Feature fusion improves classification beyond ResNet152 and InceptionV3.	Explore hybrid CNNs and larger real-world datasets for robustness
Islam *et al.* (2023)	PlantVillage dataset (10,000 images)	DeepCrop system using CNNs (VGG-16, VGG-19, ResNet-50)	-	Smart web platform for disease detection and treatment recommendations.	Integrate hybrid models and spatial localization for improved detection precision.
Prathik *et al.* (2023)	Soil nutrient dataset	DL-based fertilizer recommendation using nutrient deficiency prediction	-	Supports smart decision-making in precision agriculture.	Integrate with crop disease models and IoT-based soil sensors.
Mohanty *et al.* (2023)	Plant village dataset	CNNs and vision transformers comparison	-	Benchmarked modern CNNs and ViTs for plant diseas e classification.	Use field-collected diverse datasets and multimodal data for generalization.

Activation functions, as shown in Fig 3(a). The details analysis of CropNet concerning the number of parameters at each layer is shown in Fig 3(b).

The forward propagation in a convolutional layer is mathematically expressed by equations (3) and (4) below:

$$Z^{[l]} = W^{[l]} * A^{[l-1]} + b^{[l]} \quad ...(3)$$

$$A^{[l]} = g^{[l]}(Z^{[l]}) \quad ...(4)$$

Where,

*= Convolution operation.

$W^{[l]}$= The learnable filters (kernels) at layer l.

$A^{[l-1]}$= The input activation of the preceding layer.

$b^{[l]}$= Bias vector.

$g^{[l]}$= The ReLU activation function which is defined by equation (5):

$$g(z) = \text{Max}(0, z) \quad ...(5)$$

Following convolution, max-pooling layers are used for downsampling, reducing spatial dimensions and computational complexity. The max-pooling operation for a given pooling window Ri,j is defined in equation (6):

$$p_{i,j,k} = \underset{(m,n) \in R_{i,j}}{\text{Max}} a_{m,n,k} \quad ...(6)$$

Where,

$a_{m,n,k}$= The activation at position (m, n) in the k-th feature map.

The output layer uses a softmax activation function to generate the probability distribution over the C target classes as presented by equation (7):

$$\hat{y}c = \frac{e^{z}c}{\sum_{j=1}^{c} e^{z}j} \text{ for } c = 1, ...,C \quad ...(7)$$

Where,

$\hat{y}$= The predicted probability for class c.

z= The input vector to the output layer.

The model is trained by minimizing the categorical cross-entropy loss function, which measures the discrepancy between the predicted probability distribution $\hat{y}$ and the true label distribution y (typically one-hot encoded):

The model is trained by minimizing the categorical cross-entropy loss function, which measures the discrepancy between the predicted probability distribution(w) and the true label distribution (y), commonly expressed by equation (8):

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{c} y_{i,c} \log(\hat{y}_{i,c}) \quad ...(8)$$

Where,

N= The number of samples in the batch.

C= The number of classes.

Parameter optimization is carried out with the Adam optimizer, which adaptively adjusts the learning rate for every parameter. The corresponding update rules are expressed in equations (9) through (12) as below:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \nabla_\theta L_t \quad ...(9)$$

$$\nu_t = \beta_2 \nu_{t-1} + (1 - \beta_2) (\nabla_\theta L_t)^2 \quad ...(10)$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \hat{\nu}_t = \frac{\nu_t}{1 - \beta_2^t} \quad ...(11)$$

$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{\nu}_t} + \in} \quad ...(12)$$

With hyperparameters set to η=0.001 (learning rate), β1 =0.9, β2 =0.999 and $\in$=10^{-8}.

The research work was carried out in Bharati Vidyapeeth's College of Engineering, Kolhapur, Maharashtra, India, during the years 2022-2025.

RESULTS AND DISCUSSION

This section is subdivided into the training phase and testing phase to provide a comprehensive assessment of the proposed CropNet model.

Training phase

In training, along with the proposed CropNet model, some predefined models, such as CNN and VGG-16 (Patil and More, 2025), are tested for disease detection. Out of 400 soybean leaf images, 320 images were used for training the module using the ADAM solver having learning rate of 0.001. For experimentation, 100 epochs are used with a validation frequency of 50 on a computer having specifications of 16 GB RAM, a 13th Gen Intel(R) Core (TM) i7 2.40 GHz, 64-bit Windows 11 and MATLAB programming language.

In this research, 80% of the images were applied for training, while the remaining 20% was evenly divided, with 10% assigned to validation and 10% to testing. The models underwent a constant training regimen for 100 epochs to ensure optimal performance. Training also included the reduction of cross-entropy loss across both the predicted and actual labels of the images (Dagur *et al*., 2023). The models were evaluated using several metrics, including training accuracy and loss as illustrated in Fig 4, the confusion matrix (depicted in Fig 5) and additional quantitative measures such as precision, recall and F1-score (presented in Fig 6) (Feng *et al*., 2022; Jayamala *et al*., 2024).

Fig 4 shows the performance on training and validation of a CropNet model over 18 epochs. The first plot shows the training and validation accuracy. The training accuracy (blue) quickly ramps up towards one, indicating successful learning and the validation accuracy (orange) also improves, but at a slower pace and to not much more than 0.9. These graphs indicate that the model is not overfitting severely, and training accuracy outpaces validation accuracy with a small gap. The second graph displays the training and validation loss; the training loss (in blue) starts out at a high value, but quickly decreases, reaching to about 0.2 after some epochs. Validation Loss is shown in orange and behaves similarly, but has a higher value than Training Loss throughout the epochs.

The confusion matrix in Fig 5 presents the classification performance of the CropNet model in four different soybean leaf conditions (Healthy, Mosaic Virus, Insect Bite, Southern Blight (SBS).

The four-class confusion matrix, which included Soybean-Healthy, Soybean-Insect Bite, Soybean-Mosaic Virus and Soybean-SBS, confirmed the proposed model's exceptional performance. The model consistently delivered high classification accuracy, demonstrating an unflinching ability to detect Mosaic Virus with 100% success. Healthy and SBS categories were classified with 99% and 98% accuracy, respectively, with errors being minimal (*e.g.*, only one Healthy sample was misclassified as SBS). Similarly, 98% of Insect Bite samples were correctly identified. These findings underscore the model's high robustness against inter-class confusion and its effective generalization across diverse symptomatic soybean leaf conditions, making it a reliable diagnostic tool. The general accuracy is computed as in equation (13):

$$\text{Accuracy} = \frac{TP_{Healthy} + TP_{Mosaic} + TP_{Insect\ bite} + TP_{SBS}}{\text{Total test samples}} = \frac{99 + 98 + 100 + 98}{400} = 98.75 \quad ...(13)$$

Where,

TP= True Positives for each class.

Fig 6 shows a quantitative analysis of CropNet model using precision, recall and F1 score.

Precision, which measures the correctness of positive predictions, is computed using equation (14):

$$\text{Precision}_c = \frac{TP_c}{TP_c + FP_c} \quad ...(14)$$

The precision results demonstrate that the model has performed remarkably well with perfect precision (1.0) for Soybean-Insect Bite, Soybean-Mosaic Virus and Soybean-SBS with almost perfect precision (0.98) for Soybean-Healthy, meaning very robust classification across all classes.

Recall (or Sensitivity), which measures the ability to find all positive samples, is calculated as:

$$\text{Recall}_c = \frac{TP_c}{TP_c + FN_c} \quad ...(15)$$

The recall, which is the ability of Soybean infection detection in different classes, suggests that FWL earns an excellent result-they detected excellently all kinds of soybeans with a high percentage near (1.0) -for Soybean-Mosaic Virus- tends toward perfect and by 98-99% for other

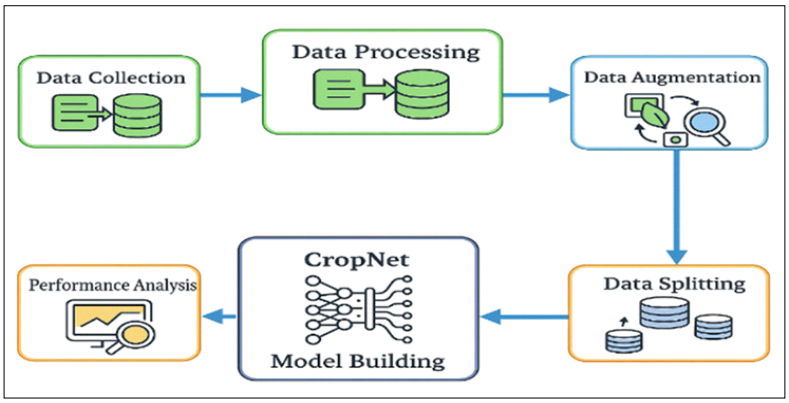


Fig 1: The architecture of the proposed CropNet.

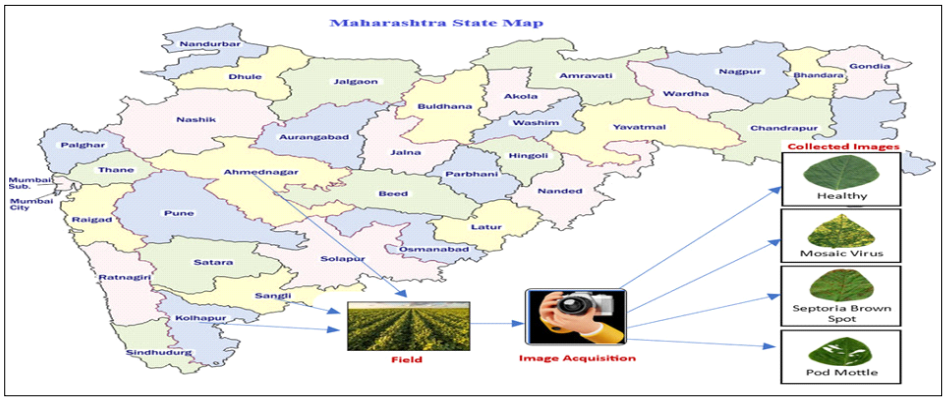
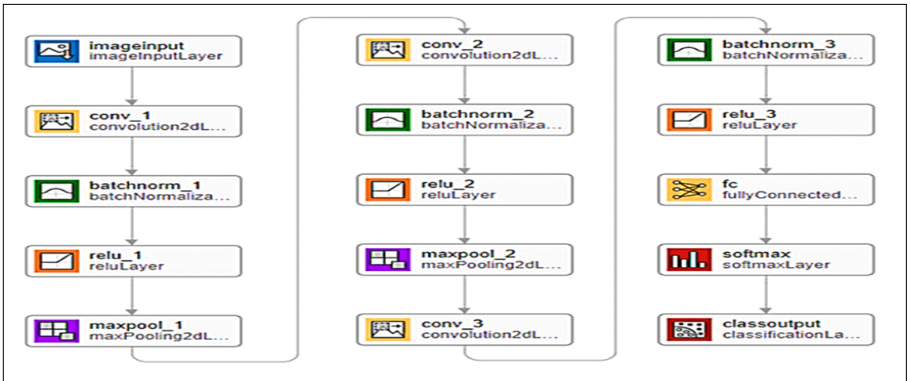


Fig 2: Data collection process.



(a) CropNet architecture

ANALYSIS RESULT

	Name	Type	Activations	Learnable Proper...	States
1	imageinput 224×224×3 images with 'zerocenter' nor...	Image Input	224(S) × 224(S) × 3(C) × 1(B)	-	-
2	conv_1 16 3×3 convolutions with stride [1 1] and...	2-D Convolution	224(S) × 224(S) × 16(C) × 1(B)	Weig... 3 × 3 × 3 ... Bias 1 × 1 × 16	-
3	batchnorm_1 Batch normalization	Batch Normalization	224(S) × 224(S) × 16(C) × 1(B)	Offset 1 × 1 × 16 Scale 1 × 1 × 16	TrainedMean 0 ×... TrainedVari... 0 ×...
4	relu_1 ReLU	ReLU	224(S) × 224(S) × 16(C) × 1(B)	-	-
5	maxpool_1 2×2 max pooling with stride [2 2] and pa...	2-D Max Pooling	112(S) × 112(S) × 16(C) × 1(B)	-	-
6	conv_2 32 3×3 convolutions with stride [1 1] and...	2-D Convolution	112(S) × 112(S) × 32(C) × 1(B)	Weig... 3 × 3 × 16... Bias 1 × 1 × 32	-
7	batchnorm_2 Batch normalization	Batch Normalization	112(S) × 112(S) × 32(C) × 1(B)	Offset 1 × 1 × 32 Scale 1 × 1 × 32	TrainedMean 0 ×... TrainedVari... 0 ×...
8	relu_2 ReLU	ReLU	112(S) × 112(S) × 32(C) × 1(B)	-	-
9	maxpool_2 2×2 max pooling with stride [2 2] and pa...	2-D Max Pooling	56(S) × 56(S) × 32(C) × 1(B)	-	-
10	conv_3 64 3×3 convolutions with stride [1 1] and...	2-D Convolution	56(S) × 56(S) × 64(C) × 1(B)	Weig... 3 × 3 × 32... Bias 1 × 1 × 64	-
11	batchnorm_3 Batch normalization	Batch Normalization	56(S) × 56(S) × 64(C) × 1(B)	Offset 1 × 1 × 64 Scale 1 × 1 × 64	TrainedMean 0 ×... TrainedVari... 0 ×...
12	relu_3 ReLU	ReLU	56(S) × 56(S) × 64(C) × 1(B)	-	-
13	fc 4 fully connected layer	Fully Connected	1(S) × 1(S) × 4(C) × 1(B)	Weights 4 × 200704 Bias 4 × 1	-
14	softmax softmax	Softmax	1(S) × 1(S) × 4(C) × 1(B)	-	-
15	classoutput crossentropyex	Classification Output	1(S) × 1(S) × 4(C) × 1(B)	-	-

(b) Parameter analysis

Fig 3: Details of the CropNet model.

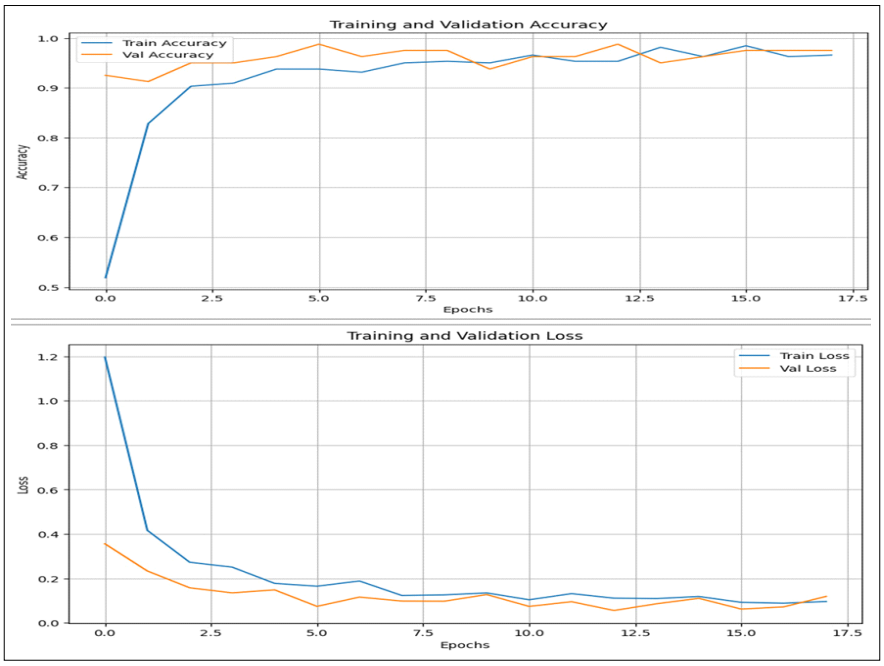


Fig 4: Training accuracy and losses of cropNet model.

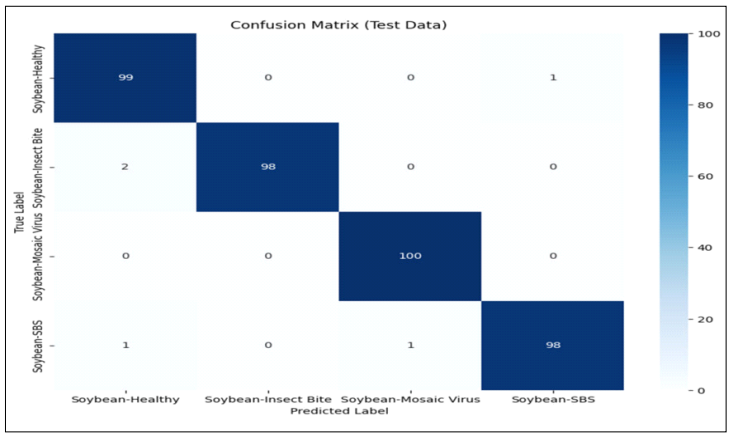
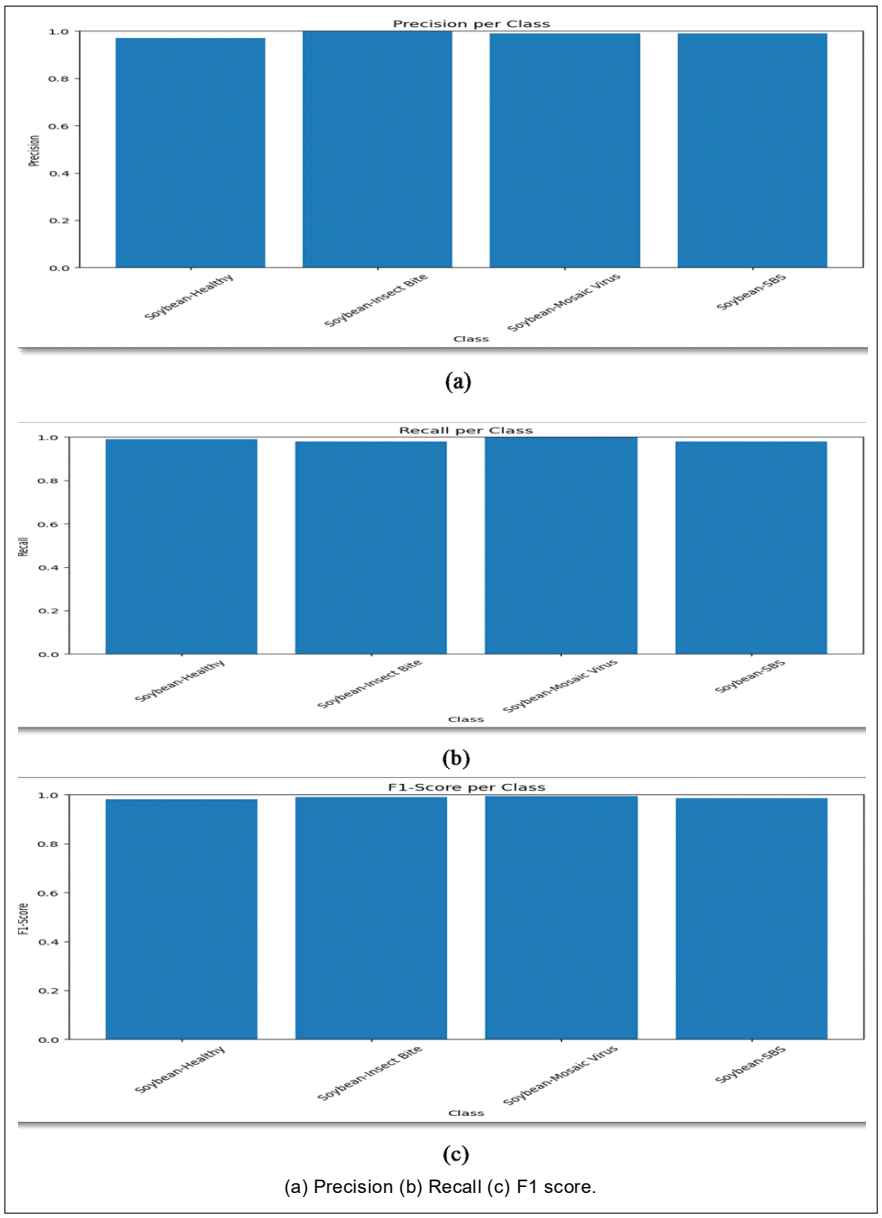


Fig 5: Confusion matrix.



(a) Precision (b) Recall (c) F1 score.

Fig 6: Quantitative analysis of CropNet.

categories such as Soybean-Insect Bite, Soybean-SBS and Soybean-Healthy, this means that is their consistency across kind was excellent. The F1-Score, the harmonic mean of precision and recall, provides a single metric that balances both concerns:

$$F1_c = 2 \times \frac{Precision_c \times Recall_c}{Precision_c + Recall_c} \quad ...(16)$$

The overall F 1-score results show a remarkable balance between precision and recall, where Soybean-Mosaic Virus, Soybean-SBS and Soybean-Insect Bite present almost perfect values of 0.99-1.0, followed by Soybean-Healthy at 0.98 which means very robust and consistent classification for all the categories considered.

The comparative overview of the proposed CropNet model with predefined CNN and VGG-16 models is shown in Fig 7. The best overall accuracy (98.75%) was achieved by the presented CropNet model, which is significantly higher than both VGG-16 (96.52%) and baseline CNN (94.35%). CropNet performs consistently better in all measures. The step-by-step improvement of CNN→VGG-16→ CropNet demonstrates the influence of model depth

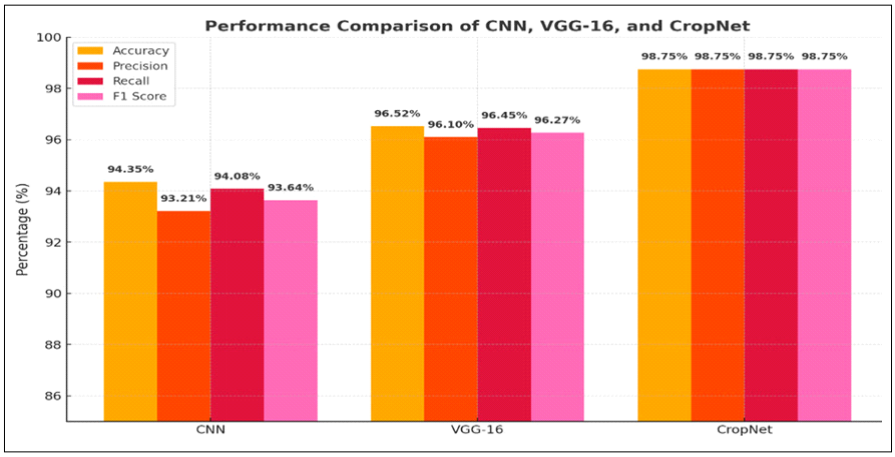


Fig 7: Performance comparison of CNN, VGG-16 and CropNet.

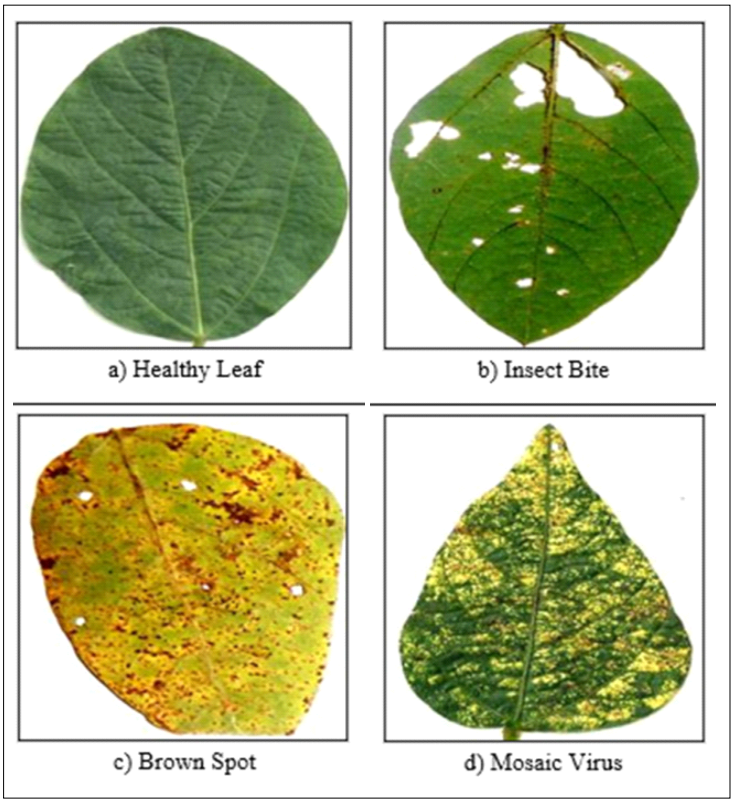


Fig 8: Sample soybean leaf images.

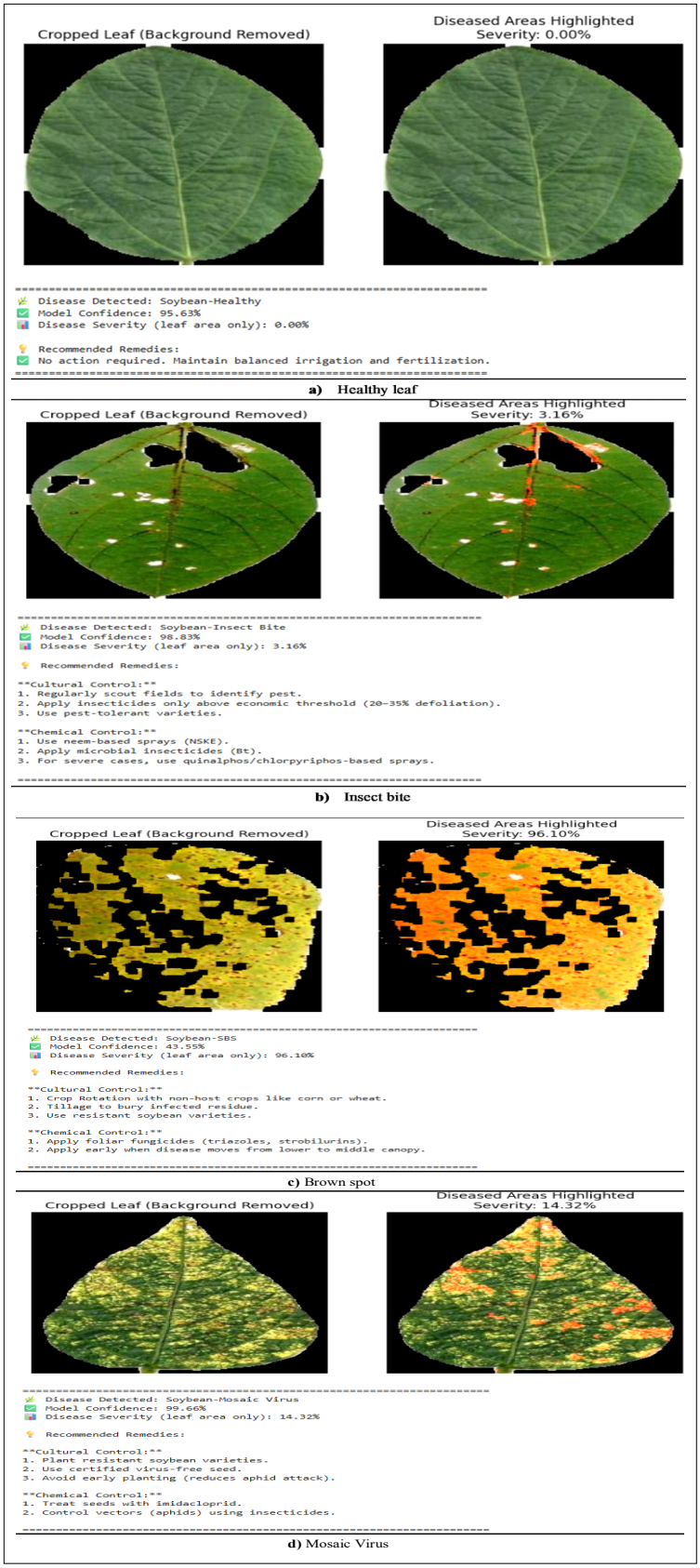


Fig 9: Results of the testing phase for all soybean classes.

increase and domain-specific architectural tuning. The uniform values of precision and recall (98.75%) in CropNet indicate a precise but comprehensive model. CropNet achieves a higher F1 score (98.75%) than VGG-16 (96.27%), which further demonstrates its balance and robustness, a fact that it can play an important role in agricultural applications where both the prediction correctness and coverage matters equally much.

Testing phase

During testing, we feed each crop out superpixels to the trained CropNet model and estimate the category for every image in a hold-out test set to assess its generalization performance. The model could accurately classify all four classes of crops. This is shown in sample input images (Fig 8) and their predicted outputs by the developed CropNet model (Fig 9). This experimental validation demonstrates the effectiveness of this model and its application to actual cases.

CONCLUSION

The proposed CropNet model is more efficient and is the most appropriate model to be applied for critical classification like crop disease detection. Its overall satisfactory performance across all metrics also indicates its potential to provide accurate, dependable and generalizable predictions, which are key to applications of AI in agriculture. The overall accuracy of CropNet model was 98.75%, representing its robust performance for real world classifications. The monotonic increases of accuracy and decrease of the loss show that the learning is working. Additionally, the fast convergence of the model shows that few iterations are needed for it to attain its best results. This is efficient when the training duration and computational budget are limited. It remains evident that the high-performance model can be deployed in practice due to the ease of training, noise and consistent validation results.

The potential directions for future research can allow more diversity dataset, real-world deployment optimization deep learning (DL) models and combining multi-modal sensor data (hyperspectral, thermal and LiDAR images) to improve the accuracy and reliability of plant disease detection.

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Disclaimers

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

REFERENCES

Ahmad, A., Dharmendra, S. and Gamal, A.E. (2023). A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. *Smart Agricultural Technology*. **3:** 100083. pp 1-13. ISSN 2772-3755. https://doi.org/10.1016/j.atech.2022.100083.

Amin, H., Darwish, A., Hassanien. A.E. and Soliman, M. (2022). End-to-end deep learning model for corn leaf disease classification. *IEEE Access*. **10:** 31103-31115. https://doi.org/10.1109/ACCESS.2022.3159678.

Dagur, A., Singh, K., Mehra, P.S. and Shukla, D.K. (2023). Artificial Intelligence, Blockchain, Computing and Security, Proceedings of the International Conference on Artificial Intelligence, Blockchain, Computing and Security (ICABCS 2023), Gr. Noida, UP, India, 24-25 February 2023 (1st ed.). CRC Press. **1:** https://doi.org/10.1201/9781003393580.

Feng, X., Zhao, C., Wang, C., Wu, H., Miao, Y. and Zhang, J. (2022). A vegetable leaf disease identification model based on image-text cross-modal feature fusion. *Front. Plant Sci.* **13:** 918940. https://doi.org/10.3389/fpls.2022.918940.

Islam, M.M., Adil, M.A.A., Talukder, M.A., Ahamed, M.K.U., Uddin, M.A., Hasan, M.K., Sharmin, S., Rahman, M.M., Debnath, S.K. (2023). DeepCrop: Deep learning-based crop disease prediction with web application. *Journal of Agriculture and Food Research*. **14:** 100764. pp 1-12. ISSN 2666-1543. https://doi.org/10.1016/j.jafr.2023.100764.

Jayamala, K.P., Sampada, A.D., Vinay, S.M. and Sachin, B.J. (2024). Comparative study for applicability of color histograms for cbir used for crop leaf disease detection, in machine learning applications: From computer vision to robotics. *IEEE*. pp. 49-68. https://doi.org/10.1002/978139417 3358.ch4.

Mehta, R.A., Kumar, P., Prem, G., Aggarwal, S. and Kumar, R. (2025). AI-powered innovations in agriculture: A systematic review on plant disease detection and classification. *Indian Journal of Agricultural Research*. **59(9):** 1321-1330. doi: 10.18805/IJARe.A-6371.

Mohanty, S.P., Hughes, D.P. and Salathe, M. (2023). Using Deep Learning for Image-Based Plant Disease Detection: A Comparative Study of CNNs and Vision Transformers on the PlantVillage Dataset, in *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Vancouver, BC, Canada, 2023. pp. 838-847. https://doi.org/10.1109/CVPRW59228.2023.00090.

Moupojou, E., Tagne, A., Retraint, F., Tadonkemwa, A., Wilfried, D., Tapamo, H. and Nkenlifack, M. (2023). Field plant: A dataset of field plant images for plant disease detection and classification with deep learning. *IEEE Access.* **11:** 35398-35410. https://doi.org/10.1109/ACCESS.2023.3263042.

Nalini, S.N. Krishnaraj, T., Jayasankar, K., Vinothkumar, F.B.A.S. *et al.* (2021). Paddy leaf disease detection using an optimized deep neural network. *Computers, Materials and Continua*. **68(1):** 1117-1128. https://doi.org/10.32604/cmc.2021.012431.

Pakruddin, B. and Hemavathy, R. (2025). Performance evaluation of deep learning models for multiclass disease detection in pomegranate fruits. *Indian Journal of Agricultural Research.* **59(10):** 1535-1542. doi: 10.18805/IJARe.A-6396.

Patil, G.R. and Ajit, M. (2025). A comparative study and optimization of deep learning models for grape leaf disease identification. *Indian Journal of Agricultural Research.* **59(4):** 654-663. doi: 10.18805/IJARe.A-6242.

Patil, J.K. and Kumar, R. (2017). Analysis of content based image retrieval for plant leaf diseases using color, shape and texture features. *Engineering in Agriculture, Environment and Food.* **10(2):** 69-78. ISSN 1881-8366. https://doi.org/10.1016/j.eaef.2016.11.004.

Patil, J.K. and Mandlik, V.S. (2024). Plant leaf disease detection using integrated color and texture features. *Nature Environment and Pollution Technology.* **23(4).** https://doi.org/10.46488/NEPT.2024.v23i04.016.

Pawar, S., Shedge, S., Panigrahi, N., Jyoti, A.P., Thorave, P. and Sayyad, S. (2022). Leaf Disease Detection of Multiple Plants using Deep Learning, International Conference on Machine Learning, Big Data, Cloud And Parallel Computing (Com-It-Con).

Prathik, K., Madhuri, J. and Bhanushree, J.K. (2023). Deep Learning-Based Fertilizer Recommendation System Using Nutrient Deficiency Prediction. 2023 7th International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), Bangalore, India, pp. 1-6. https://doi.org/10.1109/CSITSS60515.2023.10334122.

Sharmila, V., Kannadhasan, S., Kannan, A.R., Sivakumar, P. and Vennila, V. (2024). Challenges in Information, Communication and Computing Technology, Proceedings of the 2nd International Conference on Challenges in Information, Communication and Computing Technology, Namakkal, Tamil Nadu, India.

Sujatha, R., Chatterjee, J.M., Jhanjhi, N.Z. and Nawaz, B.S. (2021). Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocessors and Microsystems*. **80:** 103615. pp 1-11. ISSN 0141-9331. https://doi.org/10.1016/j.micpro.2020.103615.

Sunil, C.K., Jaidhar, C.D. and Patil, N. (2023). Systematic study on deep learning-based plant disease detection or classification. *Artif. Intell. Rev.* **56:** 14955-15052. https://doi.org/10.1007/s10462-023-10517-0.

Syed-Ab-Rahman, S.F., Hesamian, M.H. and Prasad, M. (2022). Citrus disease detection and classification using end-to-end anchor-based deep learning model. *Appl. Intell.* **52:** 927-938. https://doi.org/10.1007/s10489-021-02452-w.