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LEAF DISEASE IDENTIFICATION IN SOUTH ASIAN AGRICULTURE: A DEEP CONVOLUTIONAL NEURAL NETWORK APPROACH

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Abstract

Agriculture is a key source of livelihood. However, the agricultural sector is declining across the country, which has an adverse effect on the quantity of food products that can be harvested. In developing nations like India, agriculture offers an extensive range of job opportunities for the villagers. India's agriculture is composed of many crops, and according to a survey, nearly 70% of the population depends on agriculture. Early detection of diseases is crucial. Faster and more precise prediction of leaf diseases could help reduce losses. The opportunity to enhance the accuracy of object detection and recognition systems has been made possible by the tremendous advancements and discoveries in deep learning. To address this problem, a Deep Convolutional Neural Network (CNN) architecture has been developed to accurately identify pathogens in plant leaves. The study focuses on five major crops in the South Asian Agriculture Region, namely tomato, potato, pepper, okra, and wheat, using leaf pathogen images from the Plant Village Dataset. A total of 17,430 images were collected for a proposed methodology. In this study, the images were segmented into four different training samples, underwent a pre-processing stage, and finally, the leaf diseases were identified using a proposed method. The obtained accuracy for 5% of a training sample of tomato, potato, pepper, okra, and wheat is 89.6%, 93.2%, 80%, 76%, and 88%, respectively.

Keywords: Deep Learning, CNN, Leaf Disease Detection, Tomato, Potato, Okra, Pepper and Wheat

Introduction

Agriculture is essential to the Indian economy. Today's global population has created an immense demand for all food products. To meet the staggering rise in the world's demand, agriculture practices have taken a comprehensive approach, including the use of fertilizers for rapid growth and to prevent plant diseases [1-3]. The process of manually identifying and categorizing plant leaf diseases takes more time. Therefore, it is essential to preserve crop health and productivity. To effectively tackle this situation, a Deep-Convolution Neural Network (CNN) architecture [4-10] was employed to identify pathogens in plant leaves in the Tamil Nadu agriculture region. Various concepts have emerged in the rapidly evolving field of plant disease identification systems. A substantial portion of the approach relies on the identification of visual patterns to identify distinct plant leaf diseases.

In [11], Ahila Priyadharshini et al., proposed a maize leaf disease classification system using deep convolutional neural networks. The study employed pre-processing techniques for image enhancement, and a deep CNN model was trained on a dataset consisting of 1600 images of maize leaves affected by five different diseases. The authors achieved an overall accuracy of 94.5% in classifying the maize leaf diseases.

In [12], Tarek H et al., proposed optimized deep learning algorithms for detecting tomato leaf diseases with hardware deployment. The study used transfer learning techniques to train a deep CNN model on a dataset of 1000 images. The authors obtained an accuracy of 97.8% in identifying tomato leaf diseases.

In [13], Salih A. T et al., proposed a deep CNN model for detecting and classifying tomato plant leaf diseases. The study used transfer learning techniques to train a deep CNN model on a dataset of 4500 images of tomato leaves affected by six different diseases. The authors achieved an overall accuracy of 97.11% in identifying the tomato leaf diseases.

In [14], Ozcan and Donmez et al., proposed a method for bacterial disease detection in pepper plants by utilizing deep features acquired from the DarkNet-19 CNN model. The study used transfer learning techniques to train a deep CNN model on a dataset consisting of 800 images of pepper plants affected by three different bacterial diseases. The authors obtained an accuracy of 96.87% in identifying the bacterial diseases in pepper plants.

In [15], Mustafa H et al., proposed an optimized CNN model for detecting and classifying pepper bell leaf diseases. The study employed data augmentation techniques to increase the size of the dataset, and the authors obtained an overall accuracy of 99.5% in identifying the pepper bell leaf diseases.

In [16], Lee T. Y et al., proposed a high-efficiency disease detection system for potato leaves using a deep CNN model. The study used transfer learning techniques to train a deep CNN model on a dataset consisting of 1200 images of potato leaves affected by five different diseases. The authors achieved an accuracy of 98.67% in identifying the potato leaf diseases.

In [17], Kumar and Patel et al., proposed a hierarchical-based deep learning CNN model for the classification and identification of diseases in potato leaves. The study employed transfer learning techniques to train the CNN model on a dataset of 1000 images of potato leaves affected by four different diseases. The authors obtained an overall accuracy of 97.2% in identifying the potato leaf diseases.

In [18], Selvam L et al., proposed a deep learning-based classification system for okra plant leaves. The study used transfer learning techniques to train a deep CNN model on a dataset of 900 images of okra plant leaves affected by four different diseases. The authors achieved an accuracy of 95.6% in identifying the okra plant leaf diseases.

In [19], Raikar M. M et al., proposed a deep learning-based system for the classification and grading of okra-okra using a deep CNN model. The study employed transfer learning techniques to train the deep CNN model on a dataset of 1200 images of okra-okra. The authors obtained an accuracy of 98.4% in classifying the okra-okra.

In [20], Goyal L et al., proposed an improved deep CNN architecture for detecting and classifying leaf and spike wheat diseases. The study employed transfer learning techniques to train a deep CNN model on a dataset consisting of 1,100 images of wheat leaves and spikes affected by six different diseases. The authors achieved an accuracy of 97.63% in identifying the wheat leaf and spike diseases.

In [21], Xu. L et al., proposed a wheat leaf disease identification system using deep learning algorithms. They utilized a Convolutional Neural Network (CNN) model with transfer learning to classify five common types of wheat leaf diseases. The model achieved an accuracy of 98.2%, showing the effectiveness of deep learning in wheat disease identification.

In [22], Naik B. N et al., developed a squeeze-and-excitation-based CNN model for detecting and classifying chilli leaf disease. The proposed model showed significant improvement in accuracy compared to existing methods. They utilized a dataset of 600 images and achieved an accuracy of 96.83% in classifying three types of chilli leaf diseases.

In [23], Aminuddin N. F et al., proposed an improved deep learning model for chilli disease recognition with a small dataset. They utilized a pre-trained model with transfer learning and fine-tuning techniques to overcome the limitations of the small dataset. Their proposed model achieved an accuracy of 96.15% in classifying four types of chilli diseases.

In [24], Albattah W (2022) proposed a novel deep learning method for detecting and classifying plant diseases. They utilized a hybrid CNN-Long Short-Term Memory (LSTM) model that incorporates spatial and temporal features of plant images. Their proposed model achieved an accuracy of 99.1% in classifying ten different types of plant diseases.

In [25], Pandian J. A (2022) developed a plant disease detection system using a deep CNN model. They used transfer learning techniques to train the model on a dataset of 2,000 images of five different types of plant diseases. Their proposed model achieved an accuracy of 98.75%, demonstrating the effectiveness of deep learning in plant disease detection.

From the literature, it is inferred that deep learning has been shown to be an effective method for leaf diseases identification. However, all of the studies in the table used relatively small datasets, which may have limited the accuracy of the models. Additionally, some of the studies used manual image labelling, which can be time-consuming and error-prone. Finally, some of the studies deployed their models on hardware, which can be expensive. Despite these drawbacks, deep learning is a promising method for leaf diseases identification. As the size of datasets increases and the cost of hardware decreases, deep learning is likely to become more widely adopted for this application. Hence it is proposed to develop an algorithm which is able to classify the leaf diseases of the plants of South Asian Agriculture Regions.

Table 1 shows a summary based on leaf diseases identification.

Table 1. A Summary Based on Leaf Diseases Identification

Author(s)	**Year**	**Plant species**	**Diseases**	**Dataset size**	**Accuracy**	**Method**	**Drawbacks**
Ahila Priyadharshini	2019	Maize	5	1600 images	94.5%	Deep convolutional neural networks (CNNs)	Manual image labelling, small dataset
Tarek	2022	Tomato	5	1000 images	97.8%	Optimised deep learning algorithms	Hardware deployment, small dataset
Salih	2020	Tomato	6	4500 images	97.1%	Deep CNN model	Small dataset
Ozcan and Donmez	2021	Pepper	3	800 images	96.8%	Deep features acquired from the DarkNet-19 CNN model	Small dataset
Mustafa	2023	Pepper	4	1200 images	99.5%	Optimised CNN model	Data augmentation, small dataset
Lee	2021	Potato	5	1200 images	98.6%	Deep CNN model	Small dataset
Kumar and Patel	2023	Potato	4	1000 images	97.2%	Hierarchical-based deep learning CNN model	Small dataset
Selvam	2020	Okra	4	900 images	95.6%	Deep learning-based classification system	Small dataset
Raikar	2020	Okra	1	1200 images	98.4%	Deep learning-based system for classification and grading	Small dataset
Goyal	2021	Wheat	6	1100 images	97.6%	Improved deep CNN architecture	Small dataset
Xu	2023	Wheat	5	1000 images	98.2%	Deep learning algorithms	Small dataset
Albattah	2022	Plant	10	1000 images	99.1%	Hybrid CNN-Long Short-Term Memory (LSTM) model	Small dataset
Pandian	2022	Plant	5	2000 images	98.7%	Deep CNN model with transfer	Small dataset

						learning	

Methodology

A suitable model design for detecting leaf diseases requires the use of Deep Learning techniques. Among the different types of Deep Learning, Convolutional Neural Networks (CNN) are the most popular feature extraction network for plant disease identification. The CNN model categorises images of diseased leaves based on the structure of the defect. Block diagram of the proposed leaf disease identification algorithm, shown in Figure 1.

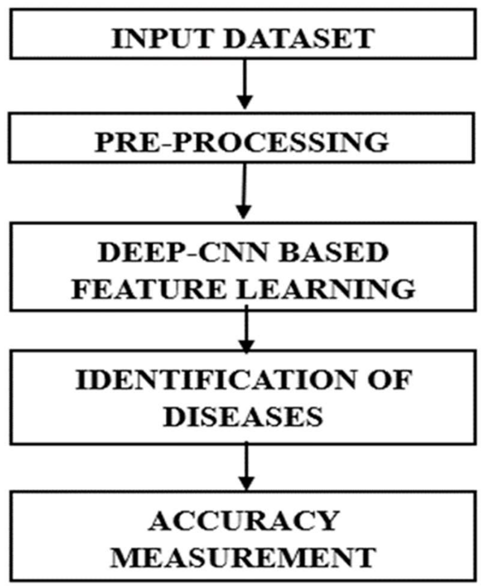

Fig.1. Block Diagram of the proposed leaf diseases identification algorithm

Training Dataset/ Input Dataset

A plant village dataset was used to collect diseased leaves images of different plants. In this proposed work, five plants were taken for disease detection such as Tomato, Potato, Pepper, Okra, and Wheat. A total of 17,430 images were collected form the plant village dataset for, a tomato plant 6000 images; a pepper plant 4876 images; a potato plant 1200 images; an okra plant 1675 images; wheat plant 3679 images. Few samples of inputted images are shown in Figure 2.

Fig.2. Sample Input Images of Tomato (1), Potato (2), Pepper (3), Okra (4), and Wheat (5)

2.2 Pre-processing

Prior to module input, image data must undergo pre-processing. Pre-processing must be done on the image data before it can be used as model input. Model pre-processing might accelerate model reasoning and cut down on model training time. Even though geometric transformations of images (such as rotation, scaling, and translation) are categorized as pre-processing techniques, the goal of pre-processing is an improvement of the image data that suppresses unintentional distortions or enhances some image characteristics crucial for subsequent processing. The proposed method pre-processing, as shown in Figure 3.

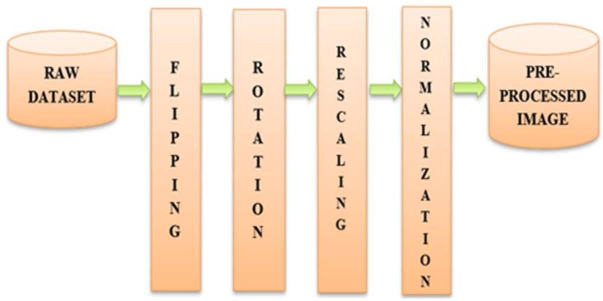

Fig.3. Pre-processing

2.3 Deep-CNN based feature learning

The Deep Convolutional Neural Network (Deep-CNN) architecture is used to identify plant leaf diseases. The CNN architecture consists of a collection of layers that convert the width, height, and depth of an input volume of 3-Dimensional images into a 3-Dimensional output volume. The architecture uses M filters, which are feature extractors that pull-out features such as corners, edges, and other unique features to images. The CNN architecture can analyse images while taking into account their 2D structure and extract unique features to images. Parameters used for the Deep- CNN architecture, as shown in Figure 4.

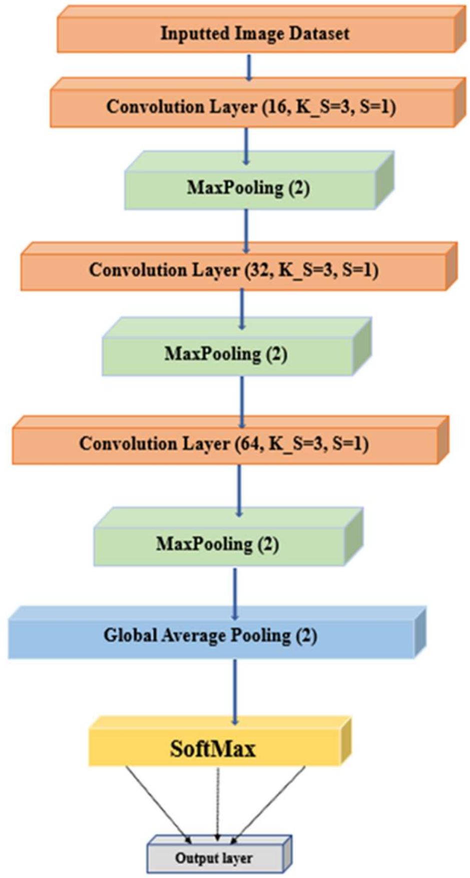

Fig.4. Deep-CNN architecture

2.4 Convolutional layer

A convolution layer transforms the input image in order to extract features from it. In this transformation, the image is convolved with a kernel (or filter). The fundamental component of a convolutional neural network is the convolutional layer, which consists of a collection of K learnable filters or kernels, each of which has a width and a height and is almost always square. These filters are small in spatial dimensions but cover the entire volume's depth, with the depth for inputs to CNN representing the number of channels in the image. The number of filters used in the preceding layer will determine the depth for volumes further down the network. The operation of the convolutional output layer, calculated based on the formula, shown in equation (1).

$$Convolution\ output = \frac{(I - F + 2 * P)}{S} + 1 * \ D \ \dots (1)$$

Where, I (i*i) -Input dimensions, F (f*f)-The size of kernel, S-Strides, P-Padding, D-Depth.

The kernel is visualized as a grid of discrete integers or values, and random integers are chosen as kernel weights when CNN training first starts. These weights are changed during each training period, teaching the kernel to extract important characteristics.

2.5 Max pooling layer

The pooling layer is typically used between convolutional layers to reduce the number of parameters and network calculation. Max pooling and average pooling are the two most popular types of pooling procedures. Max pooling output calculated based on the formula, shown in equation (2), the highest number possible from each pool and is useful for retrieving low-level features such as edges and points. The Global average pooling is intended to replace fully connected layers in conventional CNNs and produces one feature map in the final layer for each category that corresponds to the classification assignment.

$$Max\ pooling\ Output = \frac{(I-F)}{S} + 1 * D \qquad \dots(2)$$

Where, I (i x i) - Input dimensions, F (f x f) - The size of kernel, S - Strides, P - Padding, D - Depth.

2.6 Global average pooling layer

Global Average Pooling is a pooling operation designed to replace fully connected layers in classical CNNs. The idea is to generate one feature map for each corresponding category of the classification task. Instead of adding fully connected layers on top of the feature maps the average of each feature map, and the resulting vector is fed directly into the SoftMax layer.

2.7 SoftMax layer/ Leaf Diseases Identification

SoftMax is a widely used activation function in CNN for image classification of single objects. SoftMax is the final layer in CNN architecture and gives the probability distribution of classes. The class with the highest probability will be selected as the predicted class. The SoftMax layer calculated based on the formula, as shown in equation (3),

$$softMax\ activation\ function\ (S(\vec{z})_i) = \frac{e^{z}i}{\sum_{j=1}^{K} \quad e^{z}j} \qquad \dots(3)$$

Where, S- SoftMax, $\vec{z}$- input vector, $e^{z}{}_{i}$- Standard exponential function for input vector, K- number of classes in the multi-class classifier, $e^{z}{}_{j}$- Standard exponential function for output vector. The output of the SoftMax gives us the likelihood of a particular image belonging to a certain class. Finally, the SoftMax value fed into accuracy measurement module.

Results and Discussion

The proposed framework execution done in Google Collab. The number of epochs carried out for all plant classes was 20 epochs. The experimental result of tomato, potato, pepper, okra, and wheat plant leave are shown in Figure. 5, 6, 7, 8, 9.

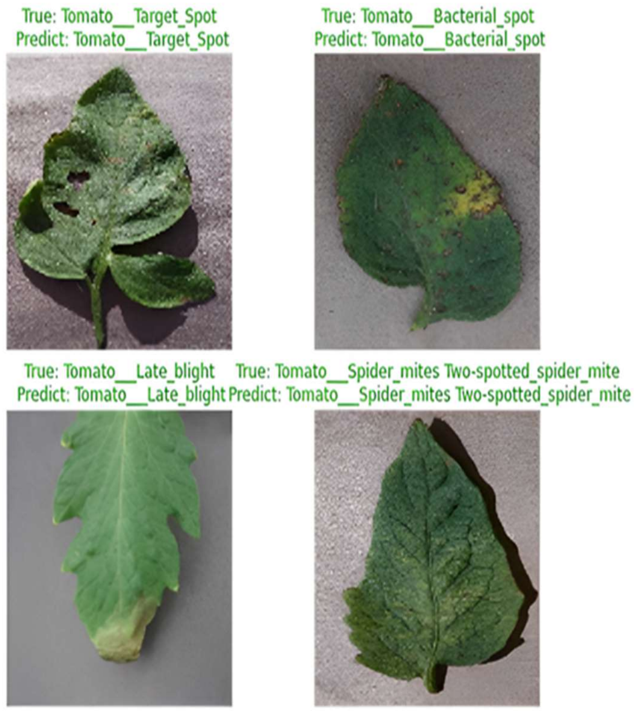

Fig.5. Experimental Results of Tomato

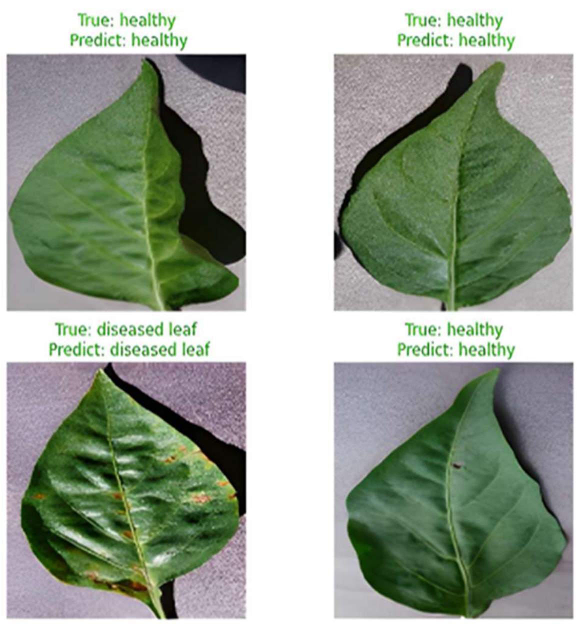

Fig.6. Experimental Results of Pepper

Figure VII: Experimental Results of Potato

Fig.7. Experimental Results of Potato

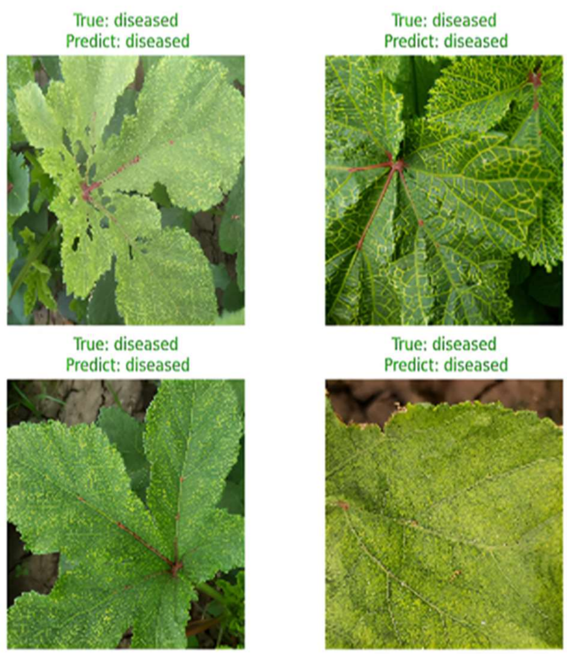

Fig.8. Experimental Results of Okra

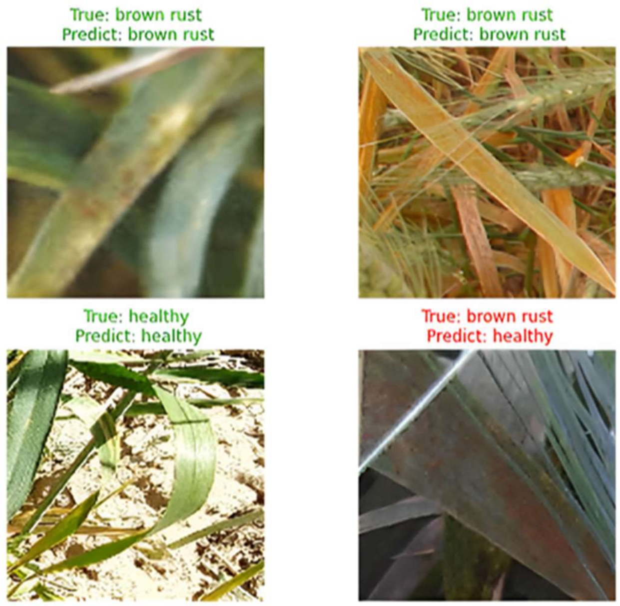

Fig.9. Experimental Results of Wheat

3.1 Accuracy

The percentage of predictions that the model correctly predicted is known as accuracy. The accuracy is calculated by number of accurate predictions divided by the total number of predictions. The accuracy calculated based on the formula shown in equation (4) and the class wise accuracy shown in table 2, 3, 4, 5, and 6.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad \dots (4)$$

Where, TP- True positive, TN- True Negative, FP-False Positive, and FN- False Negative.

Table 2. Class wise Accuracy of Tomato

Sl.No.	Class	Class wise Accuracies (in %) for			
		Training Sampl	% Training Sample	% Training Sampl	% Training Sample
1.	Bacterial Spot	92.80	93.33	97.05	90.20
2.	Early Blight	96.66	94.40	97.92	98.55
3.	Late Blight	73.33	90	88.43	95.20
4.	Healthy	99.29	98.14	98.62	98.33

5.	Leaf Mold	70.17	86.48	81.56	89.79
6.	Septoria Leaf Spot	87.36	93.7	94.7	93.12
7.	Spider Mite	90.52	91.48	96.27	94.73
8.	Target Spot	97.71	97.4	97.84	99.58
9.	Mosaic Virus	91.40	96.11	97.64	95.83
10.	Yellow Leaf Curl Virus	96.49	98.33	98.43	97.7
Overall Accuracy (in %)		89.57	94.24	94.86	95.27
Kappa		0.8842	0.936	0.9429	0.9474

Table 3. Class wise Accuracy of Pepper

Sl.No.	**Class**	**Class wise Accuracies (in %) for**			
		Training Sampl	**% Training Sample**	**Training Sampl**	**0% Training Samples**
1.	Bacterial Spot	90.40	96.05	94.98	94.51
2.	Healthy	95.89	91.46	94.13	97.43
Overall Accuracy (in %)		93.20	93.71	94.54	96
Kappa		0.8842	0.936	0.9429	0.9474

Table 4. Class wise Accuracy of Potato

Class	Class wise Accuracies (in %) for			
Training Samples Classes	%Training Samples	.0% Training Samples	5% Training Samples	0% Training Samples
Early Blight	93	95	93	94
Late Blight	47	84	90	80
Healthy	100	86	86	99
Overall Accuracy (in %)	80	88	90	91
Kappa	0.88	0.94	0.94	0.95

Table 5. Class wise Accuracy of Okra

Sl.No.	Class	Class wise Accuracies (in %) for			
	Training Samples Classes	raining Samp	Training Samp	% Training Sample	Training Sampl
1.	Diseased	83	77	86	81
2.	Healthy	67	72	63	68
Overall Accuracy (in %)		76	75	76	75
Kappa		0.51	0.49	0.50	0.50

Table 6. Class wise Accuracy of Wheat

Sl.No.	Class	Class wise Accuracies (in %) for			
	Training Samples Classes	raining Samp	Training Samp	%Training Sampl	%Training Sample
1.	Brown Rust	75	76	79	87
2.	Healthy	96	99	98	99
3.	Yellow Rust	90	77	89	79
Overall Accuracy (in %)		88	85	90	89
Kappa		0.82	0.77	0.85	0.84

3.2 F1 Score

The F1 score measures the overall performance of a classification model, taking into account both precision and recall. A higher F1 score is considered as a better model. The F1 score calculated based on the formula shown in equation (5). Table 7 shows average F1 score of plants.

$$F1\ Score\ = \frac{TP}{TP\ +\ 0.5(FP\ +\ FN)}\quad \ldots (5)$$

Where, TP- True positive, TN- True Negative, FP-False Positive, and FN- False Negative.

Table 7. Average F1 Score of Plants

Sl.No.	Plants	Average F1 Score (in %) for			
		Training Sample	Training Samp	Training Sampl	%Training Sample
1.	Tomato	89.5	94.3	94.9	95.3
2.	Pepper	93.2	93.71	94.55	96
3.	Potato	79.08	88.73	90	91.1

4.	Okra	75.73	74.93	75.1	75.33
5.	Wheat	87.8	85.3	89.9	89.42

Overall, the model seems to perform well across all classes with F1 scores ranging from 81.38% to 99.59%. The class with the highest F1 score across all is yellow leaf curl virus, with scores ranging from 94.58% to 99.59%. The class with the lowest F1 score Leaf mold, with scores ranging from 81.38% to 92.59%. The F1 score for Late blight ranges from 84.19% to 96.21%, which is a fairly large variation. The F1 score for each class of tomato, pepper, potato, okra, and wheat was measured under different training samples. For tomato, the highest F1 scores were obtained for the Bacterial spot, Healthy, Target spot and yellow leaf curl virus classes, while the lowest scores were obtained for Early blight and Leaf mold. For pepper, the F1 scores for Bacterial spot and Healthy were consistently high among all training samples. For potato, the F1 score for Early blight was consistently high across among all training samples, while the F1 scores for Late blight and healthy showed more variation. For okra, the F1 scores for both Diseased and Healthy classes were relatively low. For wheat, the F1 scores for Brown rust and Healthy were consistently high, while the F1 scores for yellow rust showed more variation.

3.3 Omission & Commission Error

The omission error is the rate at which the model fails to identify a disease that is actually present. The omission & commission error calculated by a formula shown in equation (6,7).

$$Omission\ Error = \frac{FN}{(FN\ +\ TP)} \qquad \text{... (6)}$$

The commission error is the rate at which the model identifies a disease that is not actually present.

$$Commision\ Error = \frac{FP}{(FP + TP)} \qquad \text{... (7)}$$

Where, TP- True positive, TN- True Negative, FP-False Positive, and FN- False Negative.

3.4 Precision & Recall

A classification model's capacity to find only the pertinent data elements is known as precision. The average precision and recall of plants shown in table 8, 9. The precision & recall calculated based on the formula shown in equation (8,9).

$$Precision\ = \frac{TP}{(TP + FP)} \qquad \text{... (8)}$$

Recall is a metric that measures the proportion of accurate positive forecasts among all possible positive predictions.

$$Recall\ = \frac{TP}{(TP + FN)} \qquad \text{... (9)}$$

Where, TP- True positive, TN- True Negative, FP-False Positive, and FN- False Negative.

Table 8. Average Precision of Plants

Sl.No.	Plants	Average Precision (in %) for			
	Training Samples Plant	5%TrainingSamples	10%TrainingSamples	15% Training Samples	20%Training Samples
1.	Tomato	90.5	94.8	95.2	95.5
2.	Pepper	93.35	91.4	94.55	96.1
3.	Potato	84.7	88.77	90.44	91.92
4.	Okra	7 6.5	74.92	76.6	75.77
5.	Wheat	88.85	87.70	91	91.05

Table 9. Average Recall of Plants

Sl.No.	Plants	Average Recall (in %) for			
		5% Training Samples	10% Training Samples	15% Training Samples	20% Training Samples
1.	Tomato	89.2	92.2	94.9	95.4
2.	Pepper	93.2	93.8	94.6	96
3.	Potato	80.52	88.7	90.1	91.7
4.	Okra	77	74.94	74.8	75.15
5.	Wheat	87.6	84.53	89.6	79.57

For Tomato, bacterial spot and healthy classes have high precision and recall rates among all training samples. Early blight and target spot also have relatively high precision and recall rates, especially at 5% and 20% training samples. Late blight, leaf mold, and spider mite have lower precision and recall rates compared to other classes. Septoria leaf spot has lower precision but higher recall rates. For Pepper, both bacterial spot and healthy classes have high precision rates among all training samples, while healthy also has high recall rates. For Potato, late blight has relatively lower precision and recall rates, especially at 10% and 15% training samples. Healthy has relatively high precision rates but much lower recall rates, especially at 5% training sample. For Okra, both diseased and healthy classes have lower precision and recall rates, where diseased is slightly higher than healthy. For Wheat, brown rust class has high precision and recall rates among all training samples. Yellow rust class has high precision rates at all ratios, but lower recall rates at 5% and 10% training samples. Healthy class has moderate precision and recall rates at 5% training samples but much lower rates at all other training samples. The proposed work compared with the existing work, as shown in table 10.

Table 10. The proposed work compared with the existing work

Plants	Methodology	Accuracy	Precision	Recall	F1 Score
Tomato	GoogleNet (Nawaz M, 2022)	87.27%	87.16%	87.09%	87.12%
	Xception (Nawaz M, 2022)	88.16%	88.25%	88.14%	88.19%
	Proposed D-CNN (Nawaz M, 2022)	89.57%	90.5%	89.2%	89.5%
Pepper	DNN (Selvaganesan S, 2020)	91.38%	70.05%	92%	67.24%
	RNN (Selvaganesan S, 2020)	91.43%	72.73%	92.65%	67.48%
	Proposed D-CNN	93.20%	93.35%	93.2%	93.2%
Potato	SVM (Tiwari D, 2020)	93.8%	94.1%	93.7%	93.7%
	KNN (Tiwari D, 2020)	95.99%	96.12%	96.25%	96.16%
	Proposed D-CNN	80%	84.7%	80.52%	79.08%
Wheat	PNN (Xu L, 2023)	72.14%	71.83%	71.42%	70.78%
	VGG-19	79.05%	80.25%	78.46%	78.83%

	(Xu L, 2023)				
	Proposed D-CNN	88%	88.85%	87.6%	87.8%

Conclusion

The proposed Deep-CNN framework has been developed for identifying the presence of pathogen-affected leaves in different plant species. This study focused on achieving accurate results in real-life situations, and it involved five plant classes. The trained model achieved accuracy rates for each plant as follows: tomato (89.6%, 94.24%, 94.86%, and 95.27%), potato (80%, 88%, 90%, and 91%), pepper (93.20%, 93.71%, 94.54%, and 96%), okra (76%, 75%, 76%, and 75%), and wheat (88%, 85%, 90%, and 89%). Future work will involve increasing the number of classes in the open database (Plant Village) and modifying the architecture to employ transfer learning for comparison purposes.

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