

Crop Disease Diagnosis Using Deep Learning: A Review of Current Trends and Methods

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ABSTRACT

In agriculture, crop diseases can lead to significant financial losses for farmers. Hence, early disease diagnosis is very critical to maintain crop health and increase agricultural production. Recent advancements in artificial intelligence (AI) and deep learning (DL) techniques have made the detection of crop diseases faster and more accurate. Traditionally, identifying diseases in crops has relied on personal expertise, which is labor-intensive, time-consuming, and expensive especially for big farms. This was susceptible to errors and often led to delays in disease detection with reduced crop yield and quality. Hence, there is a need of automated system to detect plant disease automatically at an early stage with more accuracy. Deep learning excels at identifying complex features in large datasets, which makes it a valuable and reliable approach for accurate crop disease diagnosis. Automatic plant leaf disease detection approaches using Deep Learning techniques help farmers to detect diseases at the early stage without or with less human interference. This review explores various deep learning approaches for plant leaf disease detection such as CNN, GAN, AlexNet, LeNet, Inception, DenseNet and SVM. This review also highlights the challenges and presents future directions for further developing more efficient and robust plant leaf disease detection system.

Keywords: crop disease detection, deep learning, CNN, GAN, SVM

1. INTRODUCTION

Agriculture plays a significant role in India due to rapid population growth and increased food demands. Hence, there is a need to enhance the crop yield. However, plant diseases create serious losses in crop production. Hence, early and accurate detection is very crucial in order to prevent and spread of plant diseases. In recent years, advances in deep learning and data processing technologies have opened new perspectives for the detection of plant diseases. The article presents diverse deep learning techniques implemented to detect and classify plant diseases.

2. LITERATURE SURVEY

M. Xin et al. [1] proposed Enhanced GAN Model based on the Wasserstein GAN loss function for plant leaf disease efficiently resolves the over-fitting problem in the small sample training set. The model is capable of generating sufficient images of maize leaf diseases, making it a feasible solution for data augmentation of plant disease images and achieved an accuracy of 98.4% in the ResNet18 network. Maria Tariq et al. [2] proposed the model VGG16 to deal with the images used to detect the disease of corn leaves. Sethy et al. (2020) al. [3] successfully identified four rice leaf diseases by combining deep convolutional neural networks and SVM. The deep feature of ResNet50 plus SVM performs better with F1 score of 0.9838. Srdjan Sladojevic et al. [4] developed an approach of plant disease recognition model, based on leaf image classification using deep convolutional networks, the model achieved precision between 91% and 98%. X.E. Pantazi et al. [5] presented an approach that demonstrates an automated way of crop disease identification on various leaf sample images corresponding to different crop species. The approach used Local Binary Patterns (LBPs) for feature extraction and a dedicated One Class Classifier for classification and achieved a 95% success rate across all 46 plant and condition combinations. S. Coulibaly et al. [6] proposed a method that used transfer learning to analyze images of millet crops and achieved 95% accuracy, with a precision of 90.5%, recall of 94.5%, and an F1-score of 91.75%. S. Ramesh et al. [7] developed a deep learning approach for detecting diseases in paddy leaves. The suggested approach used an optimized deep neural network model enhanced by the Jaya algorithm (DNN_JOA). The model demonstrated an accuracy of 98.9% for the blast affected, 95.78% for the bacterial blight, 92% for the sheath rot, 94% for the brown spot and 90.57% for the normal leaf image. Thenmozhi et al. [8] designed a deep convolutional neural network (CNN) combined with transfer learning for classifying crop pests and achieved accuracy of 96.75, 97.47, and 95.97% for NBAIR, Xie1 and Xie2 insect datasets

respectively. In another study, T. Fan and J. Xu [9] introduced a deep learning approach integrated with a fuzzy system for classifying images of crop diseases and pests. The experimental results indicated strong robustness, generalization capability, and improved accuracy in segmenting disease and pest regions. Additionally, J. Yang et al. [10] proposed a data-driven method for pest identification using edge distance and entropy features aimed at supporting sustainable agriculture. Their experiments showed that the method could achieve full recognition performance using only about 60% of the data, outperforming other data evaluation techniques and achieving state-of-the-art results. Priyanka Kulkarni [11] proposed an innovative CNN model for identifying rice leaf diseases and achieved an accuracy of 95%. Similarly, Shreya Ghosal et al. [12] recommended combining CNNs with transfer learning to classify rice leaf diseases successfully identifying 92.46% of the test images. K. P. Ferentinos et al. [13] developed a rice plant disease detection model using AlexNet and LeNet-5 CNN architectures. Their findings showed that using stochastic pooling enhanced the model's generalization ability and helped prevent overfitting. The final model achieved an impressive 99.53% accuracy on a test set of 17,548 previously unseen images. Similarly, P. Jiang et al. [14] introduced a deep learning technique for real-time detection of apple leaf diseases, leveraging the GoogleNet Inception framework enhanced with Rainbow concatenation, reaching an average precision of 78.80%. X. Zhang et al. [15] used GoogleNet and Cifar10 models to recognize maize leaf diseases. In identifying eight different maize diseases, the GoogleNet model achieved a top-1 average accuracy of 98.9%, while the Cifar10 model closely followed with 98.8%. Munaf Mudheher et al. [16] introduced a method combining Convolutional Neural Networks (CNNs) and MobileNet architectures with Explainable Artificial Intelligence (XAI) to enable early and accurate detection of plant diseases. The suggested approach achieved an accuracy of 89%, with a precision and recall of 96%, and an F1-score of 96%. In comparison, the MobileNet model performed even better, reaching an accuracy of 96%. In another study, Mushkan Bothra et al. [17] developed a system that uses convolutional neural networks along with TensorFlow to extract features from PlantVillage leaf images and achieved a classification accuracy of 95.80%. Tej Bahadur Shahi et al. [18] introduced a taxonomy for crop disease detection using UAV-based remote sensing, incorporating both machine learning and deep learning techniques. Their work systematically categorized existing research efforts that utilize UAV imagery for detecting crop diseases. Meanwhile, Amreen Abbas et al. [19] presented a deep learning approach for identifying tomato plant diseases, employing Conditional GANs (C-GAN) for data augmentation. They trained a DenseNet121 model on both real and synthetic tomato leaf images, the model achieved an accuracy of 99.51% in a five-class classification task. K. Lakshmi Narayanan et al. [20] developed a hybrid model for classifying banana plant diseases by combining a Convolutional Neural Network (CNN) with a Support Vector Machine (SVM). In their approach, features extracted from the CNN were used as input for a binary SVM classifier. The model achieved an overall accuracy of 99%. Similarly, Punam Bedi et al. [21] proposed a hybrid method that integrates a Convolutional Autoencoder (CAE) with a CNN to detect diseases in peach plants. Their model reached a testing accuracy of 98.38% and stood out for requiring fewer training parameters than many existing methods, which significantly reduced both the training time and the time needed to identify plant diseases.

Table 1: Summary of Literature Review for crop Disease Detection using Deep Learning Techniques

Sr. no.	Author(s)	Approach	Crop	Dataset	Accuracy
1.	M. Xin et al.(2023)	Enhanced GAN Model	maize leaf diseases	PlantVillage dataset	98.4%.
2.	Maria Tariq et al.(2024)	VGG16 empowered by explainable AI,	Corn leaf disease	Kaggle repository	99.92%
3.	Sethy et al. (2020)	resnet50 and SVM classification	Rice Leaf Diseases	agricultural site of Sambalpur and Bargarh district, Odisha, India.	F1 score of 0.9838
4.	Srdjan Sladojevic et al.(2016)	deep CNN	diseased leaves	Internet	96.3%.
5.	X.E. Pantazi et al.(2019)	dedicated One Class Classifier	Various crops	Images were taken on field	95%

				conditions.	
6.	S. Coulibaly, et al., (2019)	CNN model VGG16 with transfer learning	millet crop	ImageNet	
7.	S. Ramesh et. al. (2019)	DNN_JOA	paddy leaf diseases	Images from farm field	98.9%
8.	Thenmozhi et al. (2019)	DCNN & transfer learning	Crop pest dataset	NBAIR pest dataset	96.75
9.	T. Fan, J. Xu (2019)	DL and Fuzzy	Leaf and pest diseases	IDADP dataset	97.17%
10.	J. Yang, S. et al. (2022)	edge distance-entropy	Crop pest diseases	crop pest dataset called CP-10	100%
11.	Priyanka Kulkarni (2024)	CNN model	Rice Leaf Diseases Detection	Kaggle	95%
12.	Shreya Ghosal et al. (2020)	CNN With Transfer Learning	Rice Leaf Diseases Classification	Own dataset collected from rice field	92.46%.
13.	K. P. Ferentinos et al. (2018)	Alex Net and LeNet-5 CNN models	rice plants	Openly available database of 87,848 images	99.53%
14.	P. Jiang et al (2019).	GoogLeNet Inception and Rainbow concatenation	apple leaf disease	apple leaf disease dataset (ALDD)	average precision of 78.80%
15.	X. Zhang et. al (2018)	GoogLeNet and Cifar10 models	maize leaf diseases	Plant Village and Google websites	98.9%,
16.	Munaf Mudheher et al. (2024)	CNNs and MobileNet,XAI	Diseased leaf images	Kaggle	96%.
17.	Mushkan Bothra et al. (2023)	CNN with Tensorflow technology	Bell Pepper, Tomato and Potato.	PlantVillage	95.80%
18.	Tej Bahadur Shahi et al. (2023)	Multimodal Deep Learning Techniques	Crop diseases	UAV images	97%
19.	Amreen Abbas et. al. (2021)	C-GAN ,DenseNet121	Tomato leaf disease	PlantVillage	99.51%
20.	K. Lakshmi Narayanan et al., (2022)	Hybrid approach using CNN and SVM	Banana leaf disease	Manually from the fields of South India	99%
21	Punam Bedi et al. (2021)	CAE and CNN	peach plants	PlantVillage	98.38%

3. METHODOLOGY

The methodology for detecting plant diseases using artificial intelligence (AI) and deep learning (DL) as shown in Fig.3.1 involves five systematic steps:



Figure 3. 1 Steps in Crop Disease Identification

Data Acquisition

The initial process is to collect a diverse set of images of healthy and diseased plants. Images can be sourced from agricultural databases, field photography.

Data Preprocessing

Pre-processing techniques are applied to enhance the quality of the images through techniques such as noise reduction, contrast adjustment, and color correction, resizing, normalization (Standardizing image data), and augmentation (e.g., rotation, flipping, cropping) to improve model training.

Model Development

This step involves three phases, first is selecting an appropriate deep learning model for image recognition tasks, and the second to design the neural network architecture, including the number of layers, types of layers (convolutional, pooling, fully connected), and activation functions, and the third to optimize hyperparameters (Hyperparameter Tuning) such as learning rate, batch size, and number of epochs to improve model performance.

Training

It involves training the model using the training dataset, adjusting weights and biases through backpropagation and gradient descent and validate the model on the validation dataset to monitor its performance and prevent overfitting.

Evaluation

Final step is to evaluate the trained model on the test dataset to assess its accuracy, precision, recall, and F1 score.

4. CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional Neural Networks (CNNs) are best for crop disease detection [11] due to their ability to automatically extract spatial features from images. It consists of multiple layers, each containing several interconnected neurons. As illustrated in Fig 4.1. the output of one layer serves as the input for the next, enabling hierarchical feature extraction. The core building blocks of a Convolutional Neural Network (CNN) are convolutional layers, activation functions, and pooling layers. Convolutional layers use filters (also called kernels) to scan the input data and capture important features such as edges, shapes, textures, and other distinctive patterns. Pooling layers help by reducing the size of the feature map, shrinking the height and width. So, the network becomes more efficient reducing the amount of computing power required to process the data while preserving the key information needed for accurate predictions.

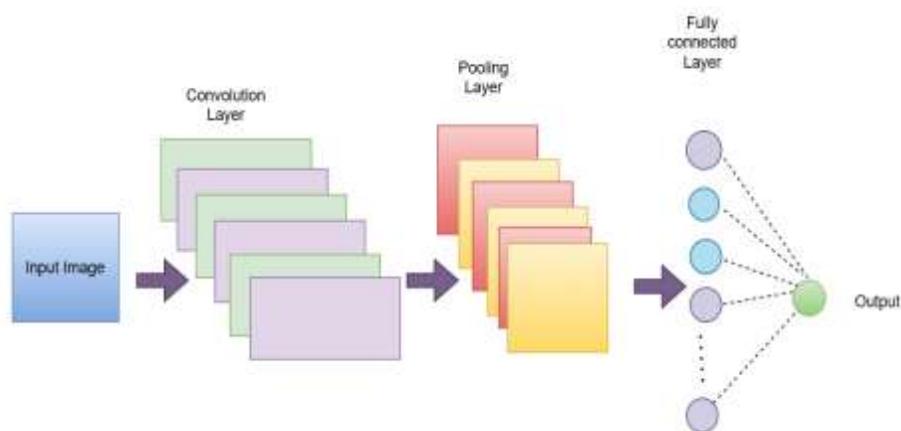


Fig 4.1 Convolutional Neural Network (CNN) Architecture

Data Augmentation

Data augmentation method is used to artificially expand a dataset by applying various transformations to existing images such as rotation, flipping, scaling, brightness adjustment, thus overcomes the issue of limited dataset [1]. Thus, Data augmentation helps to improve model generalization, reduce overfitting, and handles variability in real-world conditions (e.g., different lighting, angles, and background noise)

5. SUPPORT VECTOR MACHINE (SVM)

Support Vector Machine is a supervised learning algorithm used for classification [3] [20], regression, and outlier detection. It is particularly effective in plant disease identification due to its ability to find the optimal decision boundary between healthy and diseased samples. SVM works by mapping data points into an n-dimensional feature space, where n represents the number of features extracted from the data. It finds the optimal hyperplane that best separates the data into distinct classes (e.g., healthy vs. diseased leaves) while maximizing the margin (distance) between the hyperplane and the nearest data points of each class. A wider margin enhances the model's ability to generalize, leading to improved classification performance. As shown in Fig. 5.1, the data points closest to the hyperplane are referred to as support vectors, as they define the classification boundary.

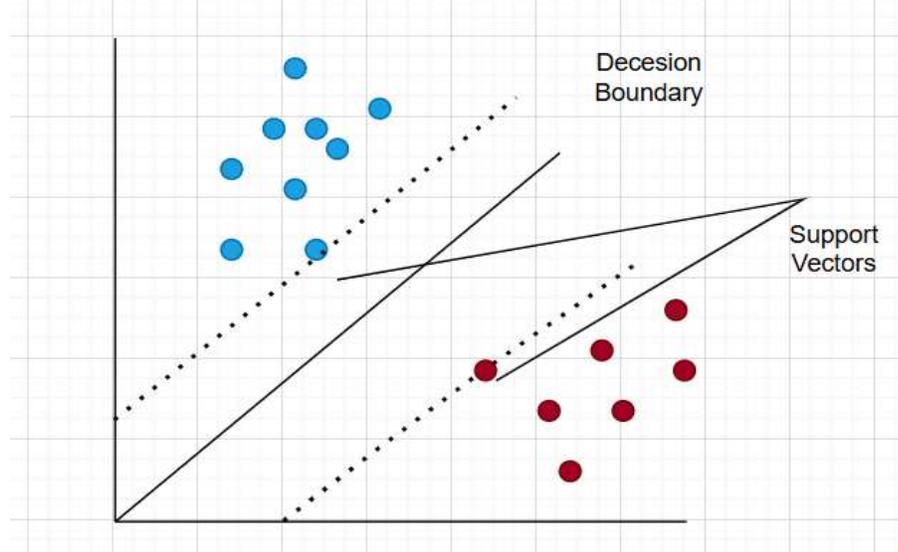


Fig. 5.1 Support Vector Machine (SVM)

6. CHALLENGES

Limited availability of data on diseased and defective crops hampers efforts to understand the extent of the problem and develop effective solutions, thus presents a significant challenge for researchers. However, collecting the real time data from the field is also a big challenge. Another major challenge is the limited robustness and poor generalization ability of many trained models. Although many deep learning models exhibit strong performance on their training datasets, they often struggle to maintain this performance when applied to different datasets.

7. FUTURE SCOPE

By creating more diverse training data, deep learning models can be trained to recognize a wider variety of conditions and scenarios. Conducting extensive field trials and real-world testing of trained models can help to identify and address practical challenges. Enhancing the interpretability and explainability of deep learning models can build trust and acceptance among farmers and end-users.

8. CONCLUSION

This paper has reviewed various deep learning approaches that has been applied in agriculture sector specifically for identifying crop leaf diseases. Deep learning methods are capable of learning complex patterns from large datasets,

making them highly effective for detecting plant diseases. The analysis demonstrates that deep learning can significantly enhance productivity and economy of our nation by identifying the crop diseases at early stage and more accurately, which can have significant impacts on the agricultural industry.

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