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Convolutional Neural Network-Based Phytopathological Diagnostic Framework for Precise Plant Disease Identification and Classification.

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Abstract

Plant leaf diseases have a major impact on agricultural productivity worldwide and threaten food security. To address this challenge, this paper presents a deep learning-driven technique for the automatic Identifying and categorizing plant leaf diseases using CNN-based models. The proposed model is trained on a diverse dataset comprising images of both healthy and diseased leaves. with Image normalization and augmentation strategies employed To optimize accuracy, robustness As well as generalization. The CNN automatically extracts discriminative features from input images, enabling accurate disease identification without the need for manual intervention. Results indicate that the proposed model successfully reaches a high level of accuracy is 98.71% and outperforms conventional approaches, while maintaining efficiency under varying environmental even under varying Under lighting and background noise variations.. Furthermore, The system is lightweight along with optimized for use On mobile and edge computing devices, enabling in real-time disease monitoring directly On site. This makes the approach practical and scalable,Enabling farmers to identify diseases promptly, thereby reducing crop losses. and promote more sustainable agricultural practices.

Introduction

Agriculture lays the foundation of food security across all nations, and to maintain yield and quality; it is essential to keep crops healthy. Plant leaf diseases, which spread quickly, are detrimental to productivity and farmer's income. Manual inspection has been a major and traditional way for farmers to detect these diseases; however, it is a slow process and often requires labor time, such that The state of the leaf can go unnoticed in big fields. Hence, delayed or practically undetected leaf diseases ultimately impact crop quality, causing economic losses and threats to food supply.

The last decade has seen a surge in advancement of artificial intelligence, which fosters quicker and more reliable ways of detecting diseases. Deep learning approaches such as CNN estimates have done wonders in analyzing images for various purposes as well as automatically learning disease patterns without manual feature design. In this study, we introduce a convolutional neural network (CNN)-based system for identifying plant leaf diseases, trained and tested using the PlantVillage open-source dataset, which contains Thousands of leaf images, both healthy and diseased, collected from different plant species. The prepared dataset is pre-processed and augmented for enhanced generalization of the model, enabling the system to deal with variations of illumination, background, and leaf isotropism.

A device that is light and easy to move around so that the farmer can find the disease right away in the field. This reduces crop loss and enhances sustainable productivity through early and appropriate interventions to identify and manage the disease with accuracy and speed.

Literature Review

Sujatha et al. [1]Combining machine learning with deep learning methods significantly improves the accuracy of disease detection in plant leaves.Their approach demonstrated that hybrid methods can perform better in extracting features and classifying as compared to classical methods.

Rahman et al. [2] developed a real-time monitoring framework using deep learning that possessed the utmost confidence level in detecting plant leaf diseases inside the field. This early diagnosis was made even more practical in terms of real agricultural applications.

Bouacida et al. [3] proposed a general deep learning framework capable of cross-crop plant disease detection that can detect unhealthy leaves from different species without specific retraining to the crop. Their model was less sensitive to noise and hence very robust and far exceeded the limitations of early CNN models that were restricted to single-crop datasets.

Kaur et al. [4] Developed a hybrid CNN-based model approach that improved both automation, precision in classifying leaf diseases. By combining multiple layers of feature extraction and classification, their method achieved improved accuracy over conventional CNN architectures

Arshad et al. [5] developed PLDPNet, A hybrid deep learning architecture created to accurate prediction to potato leaf diseases.Their model outperformed traditional approaches by achieving higher classification accuracy and demonstrating robustness in disease detection.

De Silva and Brown [6] conducted a detailed review of deep CNN architectures implemented in plant disease identification. They highlighted the strength of CNNs in automatically extracting features from raw leaf images and confirmed their effectiveness in improving detection accuracy, thereby advancing precision agriculture practices.

Md. Chowdhury et al. [7] put forward a methodology based on deep learning-based approaches to detect and classify diseases associated with the leaves of plants. The study indicates that the CNN models are competent enough to segregate leaves as healthy or diseased reflecting the efficacy of deep learning in the management of agricultural diseases in a real-world scenario.

In their research, Harakannanavar et al. [8] studied detection of diseases and classification of leaves using computer vision integrated with machine learning. They emphasized preprocessing, feature extraction, and classifications as important for improving accuracy and also raised issues concerning variability of datasets and applicability in real time.

Thakur et al. [9] This paper introduces PlantViT, a Vision Transformer model designed specifically for plant disease identification.that captures fine-grained features from leaf images. Their method outperformed traditional CNN approaches, achieving higher accuracy in classification tasks.

Murk C. et al. [10] Introduced a CNN-based framework designed to classify diseases affecting plant leaves using the PlantVillage dataset with image augmentation, achieving ~98% accuracy, though evaluation was limited to curated data. Earlier works and surveys confirm CNNs outperform traditional methods but highlight challenges such as dataset bias, poor cross-domain generalization, and limited real-world validation

S. D. M. [11] developed PomeNetV1, a CNN-based model for detecting bacterial blight in pomegranate leaves. The method achieved 99.8% accuracy, demonstrating CNN's high effectiveness for plant disease detection from images.

Proposed Methodology

The validation process for the proposed system for plant leaf disease detection includes the following steps.

Input Image Acquisition – Images of leaf samples were obtained from the PlantVillage open-source database, which contains many healthy and diseased samples across different species of crops.

Image Preprocessing –The process begins with resizing,Preparing and enhancing raw images to achieve consistency in quality and prepare them for accurate feature extraction. CUDA light: To render our model resilient to differences in lighting on backgrounds . and orientation, we must employ data augmentation strategies.

Feature Extraction: The convolutional layers of CNN themselves suffice for the automatic extraction of significant visual features, that includes color pattern, texture pattern, and shape pattern, which are quite useful for classification purposes later on without manual feature design.

Classification Using CNN- After the feature extraction, the input of the CNN is going through fully connected layers, in which the classification is happened, that is healthy or disease specific classes.

Leaf Disease Detection –The final stage classifies leaves as healthy or diseased and further identifies the specific type of disease present and gives accurate and reliable results that could be employed in the early intervention

A.Dataset

Images of plant leaf used for assessing model performance were obtained from the PlantVillage dataset, an open-access collection available on the PlantVillage website (www.plantvillage.org) [4]. The dataset contains 51,806 images belonging to 38 different categories, including 12 for healthy leaf and 26 for diseased leaf.The diseases encompassed in the database include major biotic stresses: bacterial, viral, and fungal pathogens, as well as abiotic stresses such as cold and heat stress, nutrient deficiencies, limited water availability, and moisture stress.

All datasets were gathered in a regulated laboratory setting with a pristine backdrop at a resolution of 256 × 256 pixels. The images used in the experiment were split into training and testing datasets in an 80:20 ratio. The distribution characteristics for each class are listed in Table 2, while sample images depicting both healthy and diseased leaves are shown in Figure 1.

High integrity data acquisition is one of the cornerstones of real-life agricultural applications. Any fault in the gathered data may degrade the final model performance or trustworthiness. Therefore, it is fundamental to define and apply a carefully-drafted data acquisition protocol beforehand, to guarantee sound and reproducible research outcomes.

Table 2: Number of plant leaf disease data set samples.

Dataset class name	Train sample size	Test sample size
Blueberry_Healthy	1202	300
Apple_Cedar_apple_rust	220	55
Apple_scab	504	126
Apple_Black_rot	497	124
Cherry_Powdery_mildew	842	210
Orange_Haunglongbing_(Citrus_greening)	4406	1101
Corn Cercospora_leaf_spotGray_leaf_spot	411	102
Corn_Common_rust	954	238
Corn_Northern_Leaf_Blight	788	197
Corn_healthy	930	232
Peach_Bacterial_spot	1838	459
Peach_Healthy	288	72
Grape_Leaf_blight_(Isariopsis_Leaf_Spot)	861	215
Grape_Black_rot	944	236
Grape_Esca_(Black_Measles)	1107	276
Grape_Healthy	339	84
Pepper_Bacterial_spot	798	199
Pepper_Healthy	1183	295
Potato_Early_blight	800	200
Potato_Late_blight	800	200
Potato_Healthy	122	30
Raspberry_Healthy	297	74
Soybean_Healthy	4072	1018
Squash_Powdery_mildew	1468	367
Strawberry_Leaf_scorch	888	221
Strawberry_Healthy	365	91
Tomato Septoria_leaf_spot	1417	354
Tomato_Bacterial_spot	1702	425
Tomato_Early_blight	800	200
Tomato_Target_Spot	1124	280
Tomato_Late_blight	1528	381
Tomato_mosaic_virus	299	74
Tomato_Leaf_Mold	762	190
Tomato_Yellow_Leaf_Curl_Virus	4286	1071
Spider_mites Two-spotted_spider_mite	1341	335
Tomato_Healthy	1273	318
Total	41,456	10,350

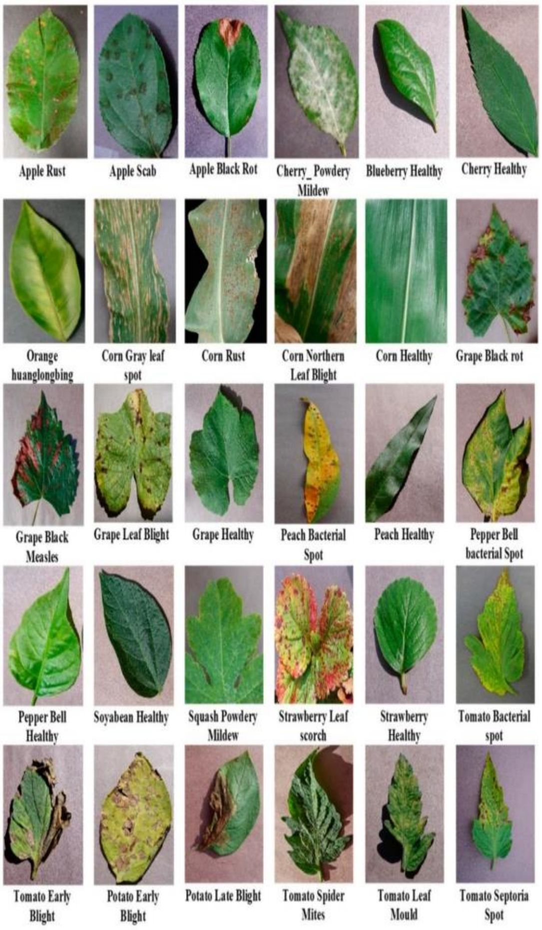


Figure 1: Sample input images of plant leaf disease

B. Image Preprocessing

The initial process starts with the original leaf images. This is scaled to a standard size for feeding into the model.. To augment the data for improved accuracy and resilience for the model, augmenting data forms multiple copies of the same leaf image through several techniques- scaling, rotation, flip, or brightness changes- before scaling.

Analysis

After all preprocessing stages, three-phase analysis of the image takes place, which includes:

1.Crop Classification:

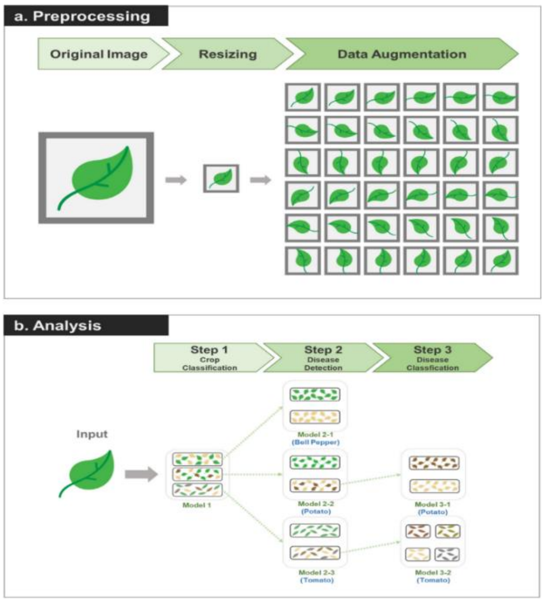
The system first determines the crop to which the leaf belongs (bell pepper, potato, or tomato, for example).

2.Disease Detection:

After confirming the crop identity, it checks whether the leaf is healthy or diseased.

3.Disease Classification:

If there happens to exist a disease, then classification is carried out. A second network comes into play when working on chili peppers, detecting and classifying diseases related to it.



C. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNN) [10] They are commonly employed for detecting plant leaf diseases because of their superior performance on image-based tasks compared to conventional artificial neural networks (ANNs). CNN uses the repeated patterns in images to successfully learn discriminative features. . Two primary operations in CNN are convolution, which extracts features including edges and patterns,, followed by pooling layer, which reduces the spatial dimensions while retaining essential information. Common CNN architectures applied to plant leaf disease detection include: (i) Simple CNN, (ii) VGG, and (iii) InceptionV3. Model training was conducted using Jupter Notebook and the using the The Keras API of TensorFlow serves as a high-level interface for building and training deep learning models.

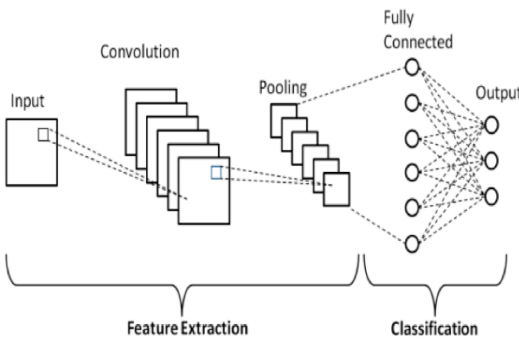


Figure 2: Schematic Diagram of a Basic CNN Architecture

Convolutional layers: These are concrete parts that make up a Deep CNN. They learn different features from the data during training and convert low-level information into higher-level patterns for classification. Pooling layers reduce the data size, making it quick and efficient.[7]

Pooling layers: pool The spatial size of feature maps is reduced, thereby decreasing the number of parameters and computational complexity.This process helps prevent overfitting and enhances computational efficiency. Pooling scans the image using a small window and compresses features—commonly such as Max pooling selects the highest value from a region, while average pooling computes the average value. In this process, pooling helps reduce the spatial dimensions of feature maps.the model, 2×2 max pooling was used, giving better precision. [7]

The Fully Connected layer: The Fully Connected (FC) layer is applied subsequent to convolution, pooling layers for transforming extracted features into a vector. [7] It does the actual classification, where all neurons are connected and create an N-dimensional feature vector. The last dense/FC layer outputs the image class. The model is trained using the training dataset and assessed on the test dataset based on key performance indicators.

Data from CNN models for detecting plant leaf diseases

ref #	*Species*	*Data source*	*Model*	*Accuracy*	*Year*
[8]	Tomato	Self	CNN	99.6%	2022
[5]	Potato	Self	CNN	98.66 %	2023
[4]	Multiple	Plant village Dataset	CNN	98.72 %	2023
[7]	multiple	Online Dataset	CNN	85.31 %	2023
[2]	Peach	Self	VGG16	100%	2025
[1]	Potato	Self	VGG19	97.2%	2025
[3]	Multiple	Plant village Dataset	CNN	97.13 %	2025

D. Evaluation of Leaf Disease Detection Performance:

Parameters such as Precision, Recall, and F-measure [8] for the proposed model were calculated and are presented in the following equations, where a, b, and c represent.

Precision Measure (%)

$$= \frac{\text{True Positives}}{\text{True Positives + False Positive}} \text{ X100 } \ldots\ldots\ldots\ldots\text{a}$$

$$\text{Recall Measure (\%)} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}} \text{ X100 } \ldots\ldots\ldots\ldots\text{b}$$

$$\text{F} - \text{measure(\%)} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision + Recall}} \text{ X100 } \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{c}$$

Result And Conclusion

Results

The proposed CNN-based model was trained and tested on the PlantVillage dataset. containing diverse healthy as well as diseased leaf images. After preprocessing and augmentation, the model effectively distinguished between classes by learning discriminative features automatically. Experimental results showed a classification accuracy of 98.71%, along with high precision and recall, outperforming conventional machine learning methods. The lightweight design enabled efficient execution on mobile and edge devices, while robustness was maintained under varying lighting, background, and leaf orientations, confirming suitability for real-world applications.

Conclusion

A CNN-based system is proposed for the detection of plant leaf diseases was developed, achieving an accuracy of 98.71% on the PlantVillage dataset. The model is capable of running on mobile and edge devices supports real-time field deployment, enabling early detection and timely interventions.

The results confirm that CNN-based architectures offer Provide a practical and scalable approach to monitoring crop health, helping reduce crop losses and improve sustainable agriculture. Future work will focus on expanding to real-world datasets and integrating IoT-based solutions for precision farming.

Reference

[1] R. Sujatha, S.Krishnan, J. Chatterjee & A.Gandomi "Advancing plant leaf disease detection integrating machine learning and deep learning" (2025) 15:11552https://doi.org/10.1038/s41598-024-72197-2

[2] K. Rahman, S. Banik, R. Islam, A. Fahim A real time monitoring system for accurate plant leaves disease detection using deep learning" February 2025, 100092 https://doi.org/10.1016/j.cropd.2024.100092

[3] I.Bouacidaa, B.Faroua, L.Djakhdjakhaa, H.Seridia, M.Kurulay "Innovative deep learning approachforcross-crop plantdisease detection: A generalized methodforidentifying unhealthy leaves" Information Processing in Agriculture Volume 12, Issue 1, March 2025, Pages 54-67. https://doi.org/10.1016/j.inpa.2024.03.002

[4] P. Kaur, A. Mishra, N. Goyal, S. Gupta, A. Shankar, W. Viriyasitavat "A novel hybrid CNN methodology for automated leaf disease detection and classification" (feb 2024) John Wiley & Sons Ltd. Pp.1:18 **https://doi.org/10.1111/exsy.13543**

[5] Arshad F, Mateen M, Hayat S, Wardah M, Al-Huda Z, Gu YH, Al-antari MA (2023) PLDPNet: "end-to-end deep learning framework for potato leaf disease prediction". Alexandria Eng J 78:406–418. https://doi.org/10.1016/j.aej.2023.07.076

[6] De Silva M, Brown D (2023) "Multispectral plant Disease Detection with Vision transformer–convolutional neural network hybrid approaches". Sensors 23(20):8531. https://doi.org/10.3390/s23208531

[7] Md.Chowdhury, Z. Mou, R. Afrin & S. Kibria "Plant Leaf Disease Detection and Classification Using Deep Learning" International Journal of Science and Business, Volume: 28, Issue: 1 Page: 193-204 2023 DOI: 10.58970/IJSB.2214

[8]S. Harakannanavar, J. Rudagi, V. Puranikmath, A. Siddiqua, R Pramodhini "Plant leaf disease detection using computer vision and machine learning algorithms" Global Transitions Proceedings 3 (2022) 305–310https://doi.org/10.1016/j.gltp.2022.03.016

[9] Thakur PS, Khanna P, Sheorey T, Ojha A (2021), "December Vision Transformer for Plant Disease Detection": PlantViT. In International Conference on Computer Vision and Image Processing (pp. 501–511). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-11346-8_43

[10] Murk.C, Adil.K, Rozina.C, Saif.K, Muhammad.M "Plant Disease Detection using Deep Learning" International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878 (Online), Volume-9 Issue-1, May 2020. p.909-914. DOI:10.35940/ijrte.A2139.059120

[11] S. D.M., Akhilesh, S. A. Kumar, R. M.G., and P. C. "Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight" (2019). **DOI:** 10.1109/ICCSP.2019.8698007

[12]Pravin Tajane "Compact Size of Multiband Planar Monopole Antenna for Portable Device Applications" Progress In Electromagnetics Research C, Vol. 156, 207–216, 2025.(SCI)

[13]Pravin Tajane "Transforming healthcare: Harnessing the power of IoT in the healthcare system"AIP Conference Proceedings 3214(1) and 2024.(SCOPUS)

[14]Pravin Tajane "Size reduction in multiband planar antenna for wireless applications using current distribution technique" Lecture Notes in Bioengineering pp. 151-160 and 2021.(SCOPUS)

[15]Pratiksha Girsaware, Kushal Masarkar, Suraj Mahajan (March 2025)Review On Real Time Monitoring System for Medical Treatment using smart Syringe pump, www.isteonline.in vol 48,special issue no 2.PP.323-326.

[16] Pragati Patil, Ritesh Banpurkar, Suraj Mahajan Technological Innovations & Applications in Industry 4.0,27 January 2025,eBook ISBN9781003567653 T&F.

[17]Pravin Tajane "Design and implementation of multiband planar antenna with DGS for wireless applications" Lecture Notes in Electrical Engineering 546, pp. 503-512 and 2020.(SCOPUS)

[18]Pravin Tajane "Design of Multiband Planar Antenna by using Mirror Image of F Shaped with Inverted U Shaped and Modified Ground Plane" IEEE International Conference on Electrical Computer and Communication Technologies ICECCT 2019.(SCOPUS)

[19]Pravin Tajane and P.L.Zade "Design of multiband antenna with U shaped strip and L shaped strips for WLAN/BLUETOOTH/WIMAX/HYPERLAN "international conference on trends in electronics and informatics(ICEI 2017),11 may 2017,Tirunevely,india.(Scopus)

[20]Lu,J.; Tan, L.; Jiang, H. Review on convolutional neural network (CNN) applied to plant leaf disease classification.Agriculture2021,11,707. https://doi.org/10.3390/agriculture11080707

[21] Al-Hiary, H.Bani-Ahmad, S.Reyalat, M.Braik, M and ALRahamneh, Z. "Fast and Accurate Detection and Classification of Plant Diseases" (2011).DOI:10.5120/2183-2754

[22] Nagaraju, M.; Chawla, P. Systematic review of deep learning techniques in plant disease detection. Int. J. Syst. Assur. Eng. Manag. 2020, 11, 547–560. https://doi.org/10.1007/s13198-020-00972-1

[23] Altieri, M.A. Agroecology: The Science of Sustainable Agriculture; CRC Press: Boca Raton, FL, USA, 2018. DOI: 10.1126/science.1183899

[24] Gebbers, R.; Adamchuk, V.I. Precision agriculture and food security. Science 2010, 327, DOI: 10.1126/science.1183899

[25] Carvalho, F.P. Agriculture, pesticides, food security and food safety. Environ. Sci. Policy 2006, 9, 685–692. https://doi.org/10.1016/j.envsci.2006.08.002

[26] Kamilaris, A.; Prenafeta-Boldú, F.X. Deep learning in agriculture: A survey. Comput.

Electron. Agric. 2018, 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016
[27] Lu,J.; Tan, L.; Jiang, H. Review on convolutional neural network (CNN) applied to plant leaf disease classification. Agriculture 2021,
11,707. https://doi.org/10.3390/agriculture11080707
[28] V.S.Dhaka, S.V.Meena, G.Rani, D.Sinwar; M.F.Ijaz, M.Wo´zniak, A survey of deep convolutional neural networks applied for prediction of plant leaf diseases. Sensors 2021, 21, 4749. https://doi.org/10.3390/s21144749
[29] Strange, R.N.; Scott, P.R. Plant disease: A threat to global food security. Annu. Rev. Phytopathol. 2005, 43, 83–116. https://doi.org/10.1146/annurev.phyto.43.113004.133839
[30]Oerke, E.-C. Crop losses to pests. J. Agric. Sci. 2006, 144, 31-43. https://doi.org/10.1017/S0021859605005708