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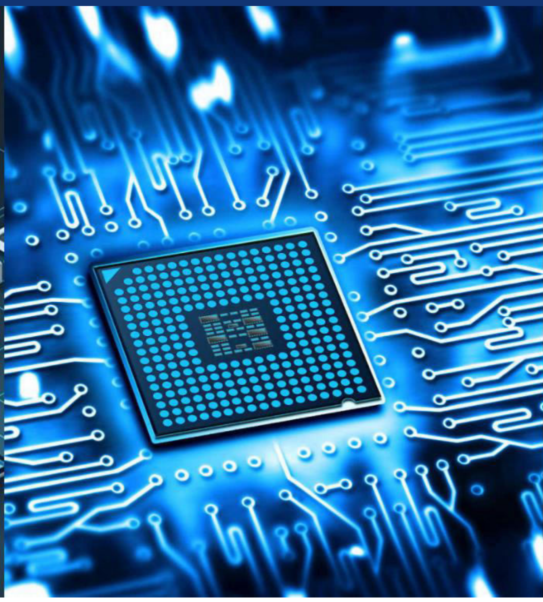


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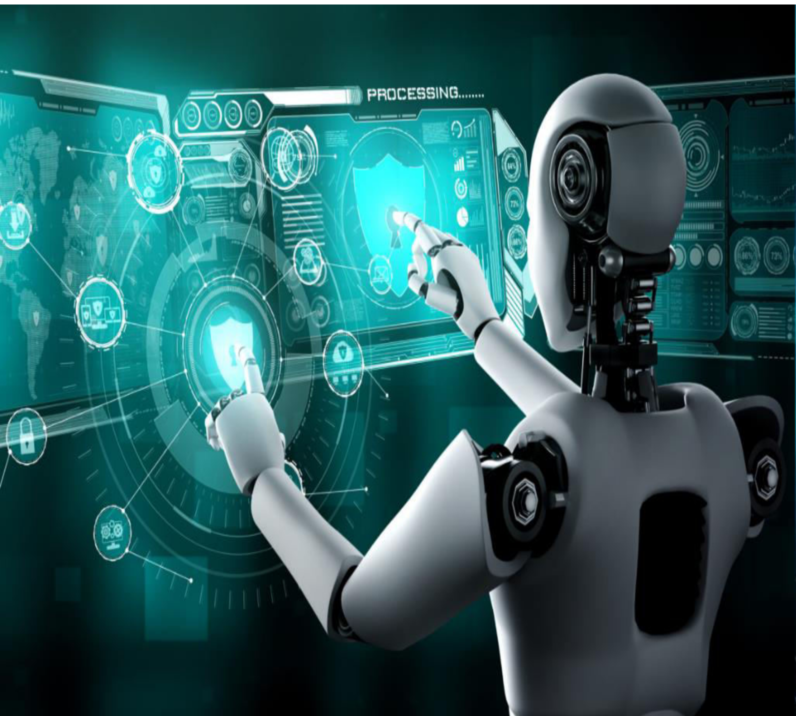

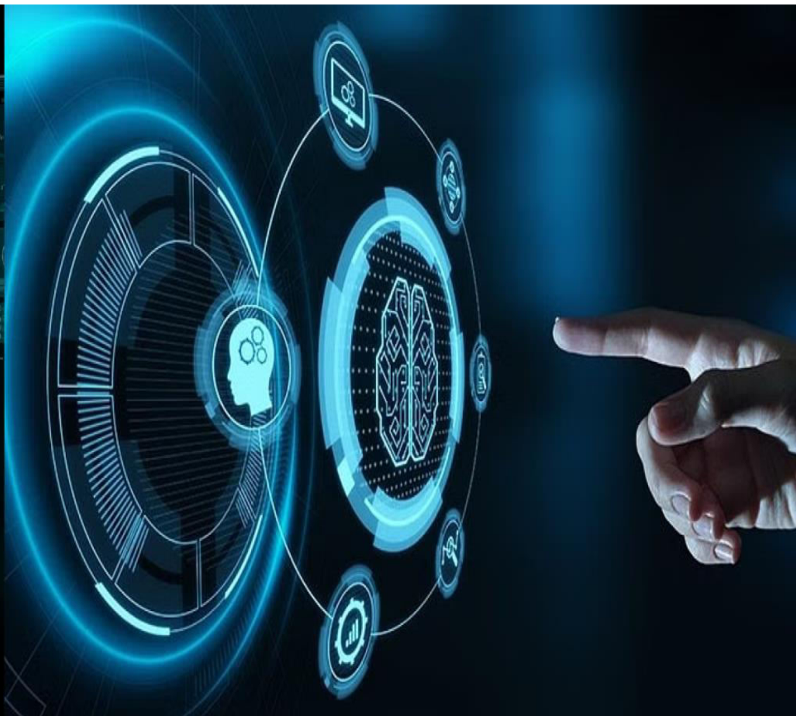

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Multiple Crop Leaf Disease Detection and Classification Using Deep Learning

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ABSTRACT: Crop diseases have a major negative impact on global food security and agricultural output. Effective crop management and economic loss control rely on the accurate and timely identification of plants illnesses. Traditional methods for identifying diseases, which are typically resource-intensive, subjective, and unfeasible for wide coverage, mostly rely on the human inspection of agricultural experts. In this research, we introduce an approach based on Deep learning (DL) framework for that identification and categorization of different crop leaf diseases. In order to automatically excerpt discriminating, include from the leaf photos and classify them into classes of healthy or unhealthy in various crop species, it uses a CNN, or Convolutional Neural Network architecture. The proposed approach combines feature extraction, data enrichment, picture pre-processing and model training to improve classification performance and generalization. According to the experimental findings, developed model demonstrate a remarkable performance with classification accuracy is 93.80 % in multi-crop data sets, proving its potential to detect Apple, Tomato, Potato, Grapes and Sugarcane leaf diseases efficiently. Moreover, the proposed model possesses excellent generalization ability, rendering it applicable for practical scenarios. It may help farmers detect crop diseases at an early stage.

KEYWORDS: Crop disease detection, Deep Learning (DL), Convolutional neural Network (CNN), Image classification.

I. INTRODUCTION

One of the most crucial industries for the production of food and the advancement of the world economy is still agriculture. Crop diseases, however, continue to be a major threat to agricultural output, frequently leading to large yield losses and lower crop quality. If not identified early, plant illnesses brought on by bacteria, viruses, fungus, and environmental factors can spread quickly. For efficient disease control and to ensure sustainable agricultural practices, crop diseases must be promptly identified and properly diagnosed. Traditionally, farmers or scientists in agriculture have employed eye inspection to identify plant illnesses. This procedure can be difficult, prone to human error, and takes a great deal of knowledge and experience. Early disease diagnosis is challenging in many rural and large-scale farming situations due to the lack of availability to plant pathology specialists. Because of this, farmers can use the wrong treatments or put off taking preventative action, which could worsen crop damage. Automated plant disease detection systems have received a lot of attention lately due to the quick development of this article suggests using deep learning and computer vision techniques. CNNs, a type of DL, possesses shown impressive results in the tasks involving pattern recognition and picture categorization. A deep learning-based methods for identify and categorize various crop leaf diseases in this paper. The technology determines if a leaf is healthy or afflicted with a certain illness by analyzing photos of leaves from various crop kinds. The recommended strategy aims to employ CNN-based image classification algorithms to provide accurate and efficient disease diagnosis. These automated tools are able to reduce crop losses and boost agricultural output overall.

The suggested strategy advances precision agriculture and helps create intelligent agricultural technologies. This work's primary contributions include: [1] creation of a CNN-based classification model for multiple crop leaf diseases [2] implementation of an image based automatic detection [3] performance evolution applying common criteria like f1 score, precision, accuracy, and recall.

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II. RELATED WORK

The prevalence of plant diseases is one of the main issues affecting agricultural productivity and global food security. To reduce crop loss and guarantee sustainable farming methods, it is essential to identify these disorders early and accurately. Using photos of leaves, plant diseases can be automatically recognized and classified researchers have recently investigated a variety of computer vision and DL methods. Because CNNs can autonomous study discriminating characteristics from huge set of data, they have demonstrated notable success in image classification tasks. T. B. Shahi et al. [1] looked into using deep learning to find crop diseases with UAVs in this study. Their work shows how large-scale monitoring can improve the accuracy of precision agriculture. In this research, W. Shafik et al. [2] introduced a transfer learning-based framework for the identification of plant diseases. The method enhances classification efficacy and promotes sustainable agricultural practices. . In their review, J. Yao et al. [3] examined machine learning methodologies, datasets, and applications for the categorization of leaf diseases. Its research elucidates present difficulties and prospective trajectories.

B. Yang et al. [4] presented LDI-NET for determining the type, degree, and disease of a plant in this study. The model makes it easier to extract features and makes classification more accurate. M. H. Ashmafee et al. [5] put forward a transfer learning-based method for classifying diseases in apple leaves. Their method makes things more efficient and less complicated to learn. In this research, K. Indira et al. [6] concentrated on CNN-based DL methodologies or the recognition of illness of plant. The research shows that using image-based classification makes things more accurate.

R. Polly et al. [7] used deep learning and semantic segmentation to find diseases in this study. This method improves how well pixels can be classified and detected. S. M. Alhammad et al. [8] combined explainable AI with deep learning to categorize potato illnesses in this study. Their method makes the model easier to understand and see through K. Chenni et al. [9] suggested high-resolution deep learning methods for keeping an eye on farms in this study. The model enhances detection precision for intricate disease patterns.

III. PROPOSED ARCHITECTURE

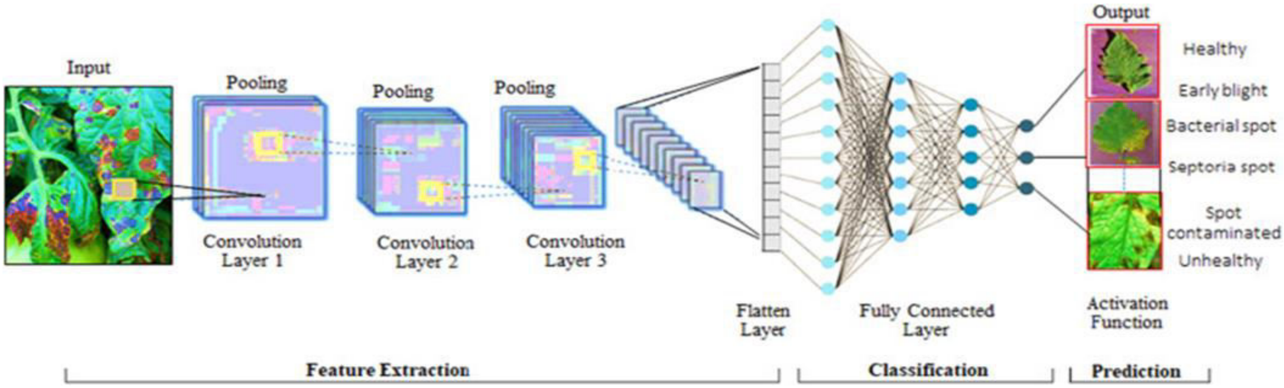

Fig. 1 Proposed Architecture of the CNN.

Fig. 1 shows how the suggested approach makes use of CNN for plant leaf illness detection. CNN is a profound learning model this automatically takes pertinent features out of pictures and performs classification with high accuracy. The suggested CNN model's structure is made up of multiple layers including the input layer, convolution layers, activation functions, collecting, outcome, fully linked, and flattened layers. The entire procedure is separated into three primary phases: prediction, categorization and extraction of features.

Input layer: A digital picture of a plant leaf is accepted by the input layer. The picture is shown as a quantitative matrix that is that represents the level of sensitivity of each pixel RGB channel values. For instance, a 224 × leaf image 224 × 3 has three channels, 224 pixels in height, and 224 pixels in width. For blue, green, and red. For instance, a picture of a healthy tomato leaf is transformed into a matrix of numbers, with three values (R, G, and B) for each pixel. Its power of color. The CNN receives this matrix.

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Convolution Layer: Important visual characteristics are extracted from the input image by the convolution layers. Kernels, which are tiny filters, move over the picture and execute to create feature maps, use convolution operations. These maps of features draw attention to patterns such as disease spots, veins, edges, and textures. The convolution operation's mathematical expression is as follows:

y=f (Wx+b)

Where:

- The input feature map is denoted by x.
- Weight matrix analyzer is W
- prejudice phrase id b
- f () stimulation equation

For instance, a 3x3 kernel that recognizes vertical edges will generate high values anywhere there are disease lines or vertical veins in the leaf image, and low values in other places. The initial convolution layer could identify basic edges, whereas intricate details like brown spots are detected by deeper layers brought on by bacterial infections.

Activation Function:

f(x) = max (0, x) For instance, ReLU converts if the convolution output contains negative values them to zero. This enables the network to concentrate solely on characteristics that favorably aid in locating disease hotspots. As an example, ReLU will draw attention to fungal spots' bright areas while disregarding unrelated dark areas.

Layer of Pooling:

The feature's spatial aspects are decreased using the pooling layer. The maps generated by the convolution layers. This decrease aids in lowering computational complexity and preventing overfitting while retaining the most significant features. Frequently utilized pooling Max Pooling is the method which selects the highest amount from a little area within the functionality map. This operation preserves important information while reducing the size of the feature representation. Pooling layers also improve the model's capacity to identify characteristics of individuals of small spatial variations in the input image.

Extraction of Feature:

Important patterns from leaf images, such as color, texture, and shape, are automatically identified by the feature extraction layer. Usually, it learns these features automatically using CNNs are examples of DL models. To assist in distinguishing between healthy and sick leaves, this layer transforms raw image data into meaningful representations. By concentrating on disease-specific traits across various crop types, it also increases accuracy. Robust and scalable disease classification depends on efficient feature extraction.

Flatten Layer:

After feature extraction the combination layer's result is a set of maps of features with several dimensions. The flatten layer converts these multidimensional arrays into a vector in a single dimension, getting ready the information for levels that are completely connected layers. Example: A feature map of size 32 × 7 × 7 is flattened into a 1568 × 1 vector, where each element represents a specific feature learned by the network. This single-sequence representation enables the fully connected layer to process all features simultaneously.

Completely Integrated Layer:

A multi-crop leaf disease detection model's completely connected layer maps the high-level features that CNN extract to particular disease classes. Global interpretation of features throughout the entire image is made possible by the connections between every neuron and every activation from the preceding layer. It learns intricate decision boundaries between various crop diseases by performing a weighted summation and then a non-linear activation. In order to accurately classify leaf diseases, a softmax Function is finally used to generate probability scores for each class.

Output Layer

The final prediction probabilities for every class are generated by the output layer. Usually, raw scores are transformed into probabilities using a Softmax activation function:

P(y=i) = e^zi /Σje^zj, where jjj iterates over all possible classes and ziz_izi is the input to the Softmax neuron corresponding to class iii. For instance, the Softmax output for a tomato leaf image might be Healthy → 0.05, Early

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Blight → 0.88, Bacterial Spot → 0.04, and Septoria Spot → 0.03.Early Blight has the highest probability, so the model predicts it. This probabilistic output facilitates downstream decision-making and enables confident classification.

IV. EXPERIMENTATION

Hardware and software Used for Proposed Technique:
The tests were done on a computer with an Intel Core i7 processor, 16 GB of RAM, and 500 GB of storage. The system has an NVIDIA RTX 2060 GPU that speeds up calculations. The Windows 10 operating system makes up the software environment. The implementation was done in Python, and the development was done in Visual Studio Code.

V. RESULTS AND DISCUSSION

Training of model:

TABLE 1: DETAILED TRAINING APPROACH

Model	Dataset Name	Train Images (Total Value)	Test Images (Total Value)	Optimizer	Learning Rate (LR)	Batch Size	Epochs
CNN	Plant Village dataset	30,066	5,007	Adam	0.001	32	30

The suggested CNN model's training parameters are shown in Table 1. The PlantVillage Dataset has 30,066 training images and 5,007 testing images that are used to train the CNN model. For quick weight updates, the model uses the Adam Optimizer with a learning rate of 0.001. There are 30 epochs of training with batch size is 32 .

- TABLE 2: TRAINING RESULTS ON CPU + GPU

Paper / Model	Dataset	Epochs	Accuracy (%)	Recall (%)	Specificity (%)	F1 Score (%)
ToT-Net [12]	PlantVillage dataset, and VisDrone2019 dataset	36	94.6	89.9	95	90.5
CNN(Federated Learning)[14]	Farm data	20	94	93	95	93
ESA-ResNet34 [15]	AI Challenger 2018 (pest & disease)	20	87.09	86.91	87.65	85.91
Our Model	**PlantVillage Dataset**	**30**	**96**	**95**	**97**	**95**

Table 2 shows the training results on CPU + GPU. The suggested model's performance was contrasted with that of other methods as ToT-Net, CNN with Federated Learning, and ESA-ResNet34. With 96% accuracy, 95% recall, 97% specificity, and 95% F1-score, the suggested model outperformed the other approaches in the majority of evaluation criteria.

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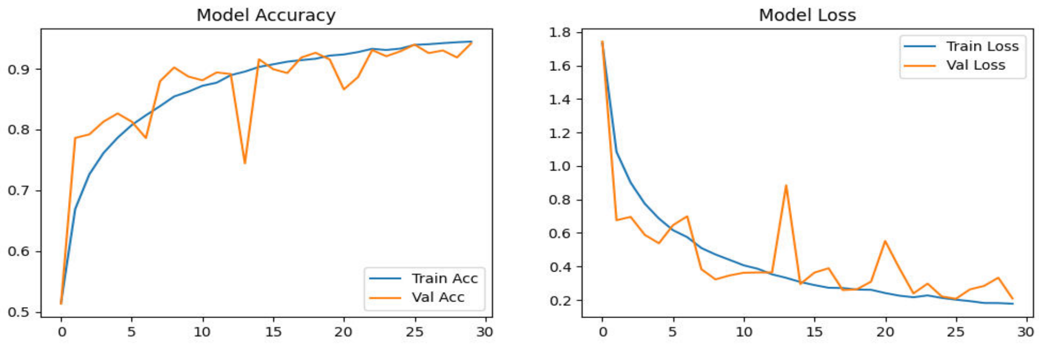

Fig.2 Training Performance proposed model's graph

Figure 2 shows the CNN model training and validation outcomes for multi-crop leaf disease. The graph is composed of accuracy and loss graphs.

Testing result of proposed model:

TABLE 3: TESTING DATASET RESULTS ON CPU

Model	Dataset	Accuracy (%)	Recall (%)	Specificity (%)	F1Score (%)
YOLOv7[19]	Detecting Diseases Dataset	91.05	89.40	90.45	89.60
ToT-Net[12]	PlantVillage dataset and VisDrone2019 dataset	93.54	92	94	92
YOLOv8[20]	Detecting Diseases Dataset	86.3	82.3	84.45	83.3
Our Model	**Plant Village Dataset**	**93.80**	**94**	**95**	**93.80**

Table 3 summarizes the testing results of the suggested CNN architecture on the PlantVillage dataset with existing model. The proposed model was contrasted with current methods for plant disease detection, including YOLO-v7, ToT-Net, and YOLO-v8. The suggested approach outperformed the majority of current models overall, with 93.80% accuracy, 94% recall, 95% specificity, and 93.80% F1-score.

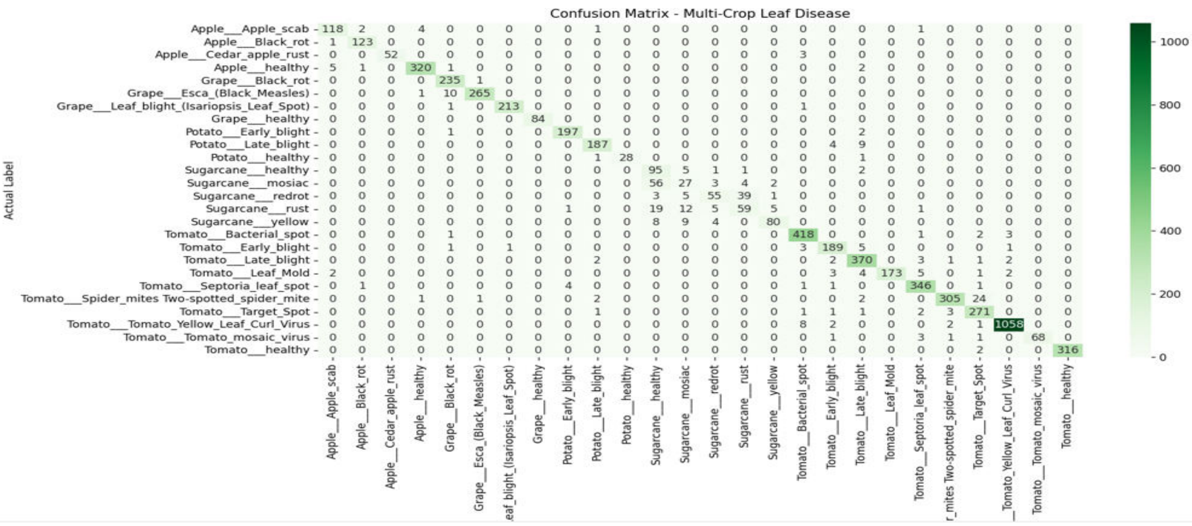

Fig 3. Confusion Matrix of Multi-crop Leaf Disease

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Disease detection of proposed model:

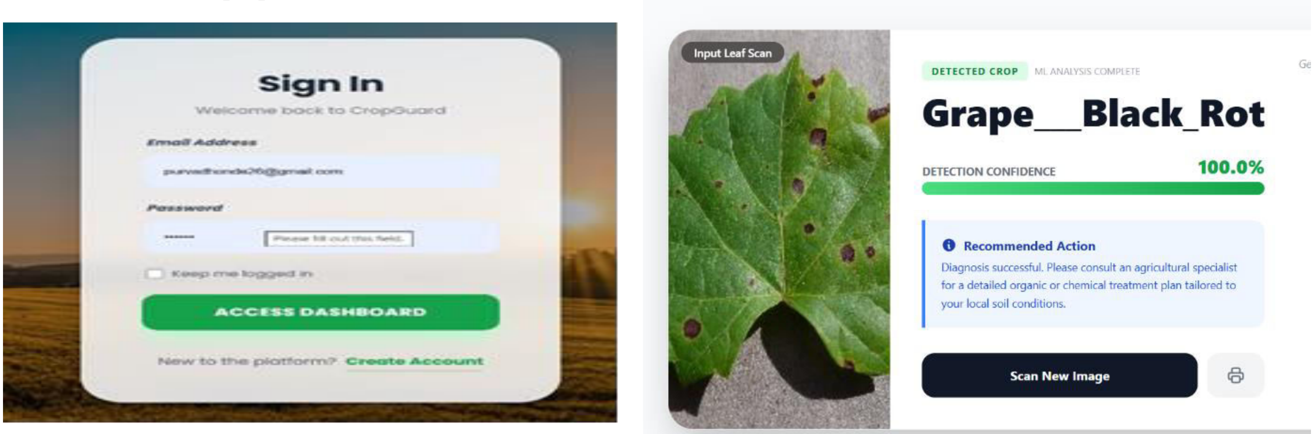

Fig-4: Leaf Disease Detection Output

The CropGuard system login page, depicted in figure 3, allows users to safely access the platform by inputting their password and email address. Crop disease detection services can be managed and analyzed by registered users thanks to features like "Keep me logged in," "Access Dashboard," and "Create Account.".

The plant disease detection output is shown in figure 4, where the system 100% confidently detects Black Rot in a grape leaf. In order to assist farmers in taking the proper disease control measures, it also offers suggested treatment activities, such as chemical treatment plan tailored to local soil condition.

VI. CONCLUSION AND FUTURE WORK

This project provides evidence that CNN machine learning methods are a viable option to classify images of crops on leaves for the purpose of identifying diseases on multiple crops. A leaf image is analyzed by the deep learning algorithm, identifying specific patterns associated with a disease, including changes in color, spots or discolorations, and texture differences. Early detection by the present system of disease on crops will result in lower levels of crop losses and thus contribute to increasing the productivity of crops. By using CNN-based data comparative to the traditional way of manually inspecting crops for disease, the present system would lead to more rapid and accurate determinations of plant disease. The present system also provides users with a web based platform to upload images of leaves and receive classification from CNN algorithms. This will enable farmers to practice smarter agricultural methods and manage crop productivity more effectively. The experimental findings from the implementation of the suggested system show that it

provides high accuracy is 93.80% in identifying the presence of various diseases among different types of crops. Pesticide recommendations for efficient disease treatment can be added in future studies. Additionally, the system can be connected with other smart agricultural modules and expanded to cover other crops.

REFERENCES

[1] T. B. Shahi, C.-Y. Xu, A. Neupane and W. Guo, “Recent Ad. Vances in Crop Disease Detection Using UAV and Deep Learning Tech niques,” Remote Sens., vol. 15, no. 9, art. 2450, 2023. DOI: 10.3390/rs15092450.
[2] W. Shafik, A. Tufail, C. D. S. Liyanage et al., “Using transfer learning-based plant disease classification and detection for sustainable agriculture,” BMC Plant Biol., vol. 24, Art. No. 136, 2024. DOI: 10.1186/s12870-024-04825
[3] J. Yao, S. N. Tran, S. Sawyer and S. Garg, “Machine learning for leaf disease classification: data, techniques and applications,” Artif. Intell. Rev., vol. 56, pp. 3571–3616, 2023. DOI: 10.1007/s10462-023-10610-4.
[4] B. Yang, X. (other authors), “A novel plant type, leaf disease and severity identification network (LDI-NET),” Sci. Rep., 2024. DOI: 10.1038/s41598-024-62452-x.
[5] M. Hamjajul Ashmafee, T. Ahmed, S. Ahmed et al., “An Efficient Transfer Learning-based Approach for Apple Leaf Disease Classification,” J. (preprint / open access), 2023.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[6] K. Indira, "Classification of Plant Leaf Disease Using Deep Learning," Journal of Engineering and Innovation (JIE), 2024. DOI: 10.1007/s40031-024-00993-5.
[7] R. Polly, "Semantic segmentation for plant leaf disease classification using advanced deep learning," Comput. Electron. Agricult, 2024. DOI: 10.1016/j.compag.2024.107891.
[8] S. M. Alhammad, et al., "Deep learning and explainable AI for classification of potato leaf diseases," Frontiers in Artificial Intelligence, vol. 7, 2024. DOI: 10.3389/frai.2024.1449329.
[9] K. Chenni, "High-resolution leaf disease classification using deep learning — advancing agricultural monitoring," Proc. SPIE, 2025. DOI: 10.1117/12.3055893.
[10] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., Stefanovic, D., 2016. Deep neural networks based recognition of plant diseases by leaf image classification. Comput. Intell. Neurosci. 2016
[11]Mohit Agarwal, Abhishek Singh, Siddhartha Arjaria, Amit Sinha, Suneet Gupta. ToLeD: Tomato Leaf Disease Detection using Convolutional Neural Network. Elsevier 2020.
[12]J. Tong, L. Zhang, J. Tian, Q. Yu, and C. Lang, "ToT-Net: A generalized and real-time crop disease detection framework via task-level meta-learning and lightweight multi-scale transformer," Smart Agricultural Technology, vol. 12, p. 101249, Dec. 2025, doi: 10.1016/j.atech.2025.101249.
[13]B. Patel, D. Rathod, D. Rathod, and S. Patel, "Detection of disease using machine learning," Neural Networks, Machine Learning, and Image Processing, pp. 157–166, Nov. 2022, doi: 10.1201/9781003303053-14.
[14]S. Behera, N. Padhy, R. Panigrahi, and S. Kumar Kuanar, "Crop Disease Prediction Using Deep Learning in a Federated Learning Environment: Ensuring Data Privacy and Agricultural Sustainability," Procedia Computer Science, vol. 254, pp. 137–146, 2025, doi: 10.1016/j.procs.2025.02.072.
[15] Ananda S. Paymode, Vandana B. Malode. Transfer Larning for Multi-Crop Leaf Disease Image Classification using Convolutional Neural Network VGG. Elsevier, December 2021.
[16] Arun Pandian, J., Geetharamani, G., Annette, B., 2019. Data augmentation on plant leaf disease image dataset using image manipulation and deep learning techniques. Proceedings of the 2019 IEEE 9th International Conference on Advanced Computing, IACC 2019, pp. 199–204 https://doi.org/10.1109/IACC48062.2019.8971580.
[17] Chen, J., Chen, J., Zhang, D., Sun, Y., Nanehkaran, Y.A., 2020. Using deep transfer learning for image-based plant disease identification. Comput. Elects. Agricult. 173 (November2019) 105393.
[18] Chen, C.J., Huang, Y.Y., Li, Y.S., Chen, Y.C., Chang, C.Y., Huang, Y.M., 2021. Identification of fruit tree pests with deep learning on embedded drone to achieve accurate pesticide spraying. IEEE Access 9, 21986–21997.
[19] Alencastre-Miranda, M., Johnson, R.M., Krebs, H.I., 2021. Convolutional neural networksand transfer learning for quality inspection of different sugarcane varieties. IEEETrans. Indust. Inform. 17 (2), 787–794.
[20]Ai, Y., Sun, C., Tie, J., Cai, X., 2020. Research on recognition model of crop diseases and insectpests based on deep learning in hars environments. IEEE Access 8, 171686–171693.https://doi.org/10.1109/access.2020.3025325
[21] Sujatha R, Chatterjee JM, Jhanjhi NZ, Brohi SN. Performance of deep learning vs machine learning in plant leaf disease detection. Microprocess Microsystem. Feb. 2021; 80:1–11. Doi: 10.1016/j.micpro.2020.103615.