Proceedings of the International Conference on Sustainable Computing and Smart Systems (ICSCSS 2023)
IEEE Xplore Part Number: CFP23DJ3-ART; ISBN: 979-8-3503-3360-2

Crop Disease Prediction using Machine Learning and Deep Learning: An Exploratory Study

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2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS) | 979-8-3503-3360-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICSCSS57650.2023.10169612

***Abstract*—Crop diseases are caused by pests, insects, and pathogens, and if not promptly handled, they significantly reduce the yield. Farmers are losing money because of different crop diseases. When the cultivated area is large (in acres), it becomes tiresome for the cultivators to examine the crops regularly. The farming business needs an automatic crop disease identification and analysis. It may be used to diminish the loss of money and other resources, reduce yield losses, and enhance the effectiveness of treatment leading to healthier crop output. Many industries today have benefited from the development of new technologies, particularly artificial intelligence, Machine Learning (ML) and Deep Learning (DL). This study examined the significant advancements and issues, such as reduction in harvest yield, lower quality of produce and crop damage, using ML and DL approaches for crop disease detection and prediction in the recent studies.**

Keywords— Crop disease, Agriculture, Machine learning, Deep learning

I. Introduction

In India, arable land occupies more than half of the country's total land area . In terms of volume, it is one of the leading producers of rice, wheat, cotton, fruits, vegetables, and dairy products in the world. As the population increases, the demand for agricultural products increases at a very high alarming rate [1]. The body gets all the vitamins, minerals, and nutrients from a nutritious diet which are needed for the proper functioning of the body.

Crop diseases and infections can occur due to several reasons such as environmental and age-related, for instance, lack of high-quality land manures, choice of inappropriate crops, alterations in the weather, rodents, etc. Around 30–33% of India's total output loss is attributable to pest illnesses alone [2]. Fungi, viruses, and bacteria etc. are the primary sources of plant infections. These infections have a large impact on the overall productivity and crop quality, therefore, in order to prevent these, farmers face many challenges when changing from one infection control approach to another.

Crop diseases can differ in size, color, and form. Some diseases may have varying colours but may share the same shape, while others may differ in shape but have the same color. The models are created by capturing images of the damaged leaves and identifying the disease patterns, which are helpful in preventing crop loss caused by the spread or escalation of multiple leaf diseases [3]. In these models, the captured images are continuously transferred to a system that can identify core crop leaf disease for analysis. Also, information regarding crop leaf disease is generated by the system as output.

Despite having access to sophisticated tools to identify any illness that may be present in a plant at any point of time, agriculturalists continue to use traditional and old-fashioned ways to recognize crop diseases and thoroughly examine the crops to make their assessments. According to the farmer's observations, the conventional method of crop observation and analysis by the naked eye has a variety of drawbacks and disadvantages.

Farmers have practiced the fundamental steps in farming to prevent crop loss and maintain crop quality. These steps include diagnosing infections and choosing efficient medications. Yet, a sharp increase in many crop diseases may occur due to climatic changes worldwide [4]. To identify and manage these crop diseases, farmers find it challenging as there is a need of more knowledge about them. Furthermore, a farmer cannot physically or economically oversee a large-scale production.

Due to the intense visual resemblance of diseases, which require distinct care and treatment, disease detection from plant photos is considered as a critical research area. It utilizes a variety of techniques like image processing, ML, and computer vision to highlight the disease in plant leaves. It has demonstrated good results and has great potential to be effectively applied in a variety of agricultural sub-domains, including crop disease identification, harvest prediction, soil analysis, etc. [5].

This study provides an overview of the recently used ML and DL techniques used for agricultural disease diagnosis. This work highlights the significance of these methods, to resolve agricultural issues. The application of the above mentioned techniques in agriculture is relatively new, progressing, and steadily gaining favour in the recent publications.

The related work of various crop disease diagnosis is briefly discussed in Section II, while the datasets used for the implementation are discussed in section III along with a brief discussion on the open challenges covered in Section IV. The work is then concluded in Section V with the future scope of the work.

II. LITERATURE SURVEY

The existing literature on the methods and procedures for identifying and predicting crop disease in vivid variety of crops is discussed in this section. Numerous techniques for predicting diseases have been utilized and published in the recent years. Table I summarizes the existing work related to crop disease detection and prediction. It provides the summary, techniques used, categories of crop disease, advantages, disadvantages and performance measures of the existing work.

Fig. 1 graphically represents the classification of the considered studies based on the years in which they were published along with their count.

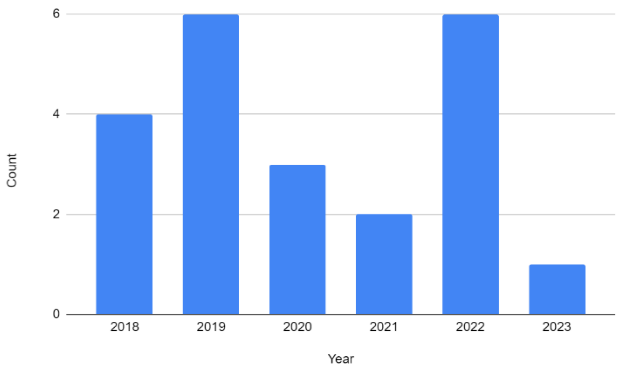

Fig. 1 Year-wise published articles.

Similarly, Fig. 2 diagrammatically represents various kinds of crops in the existing work considered for this study to predict and detect diseases in crops.

III. DATASET USED

Table II presents the datasets used in the existing work related to crop disease detection and prediction. It gives the accessibility of the datasets (public/own create), the year of availability of these datasets and their characteristics.

IV. OPEN CHALLENGES

This section focusses on the unresolved problems or the open challenges discovered after summarizing the most recent ML and DL methods for the crop disease identification and prediction.

To create a more dynamic and real time dataset, field data can be gathered from all around the world specially from the areas which are highly prone to such diseases and areas which are prime producing areas, since they significantly contribute to a country's economy and food reserves of the country as the dataset utilized in [11][12][15][17][26][28]. Further, new features and factors should be incorporated to improve and help in early crop disease detection. Though ML and DL techniques are used for the identification and prediction, further, they can be integrated with the mobile applications and Internet of Things frameworks for the development of recommendation systems as proposed in [6][8][12][13][16][19][29]. It can help farmers in correct usage of pesticides and timely treatment to prevent or at least minimize the damage which can be caused to the crops. The overall performance of the models can be improved by using a hybrid approach and more feature-oriented data. Hyper parameter tuning may also be used to increase the efficiency of the results. Moreover, nature inspired algorithms and other advanced techniques such as soft computing may be considered.

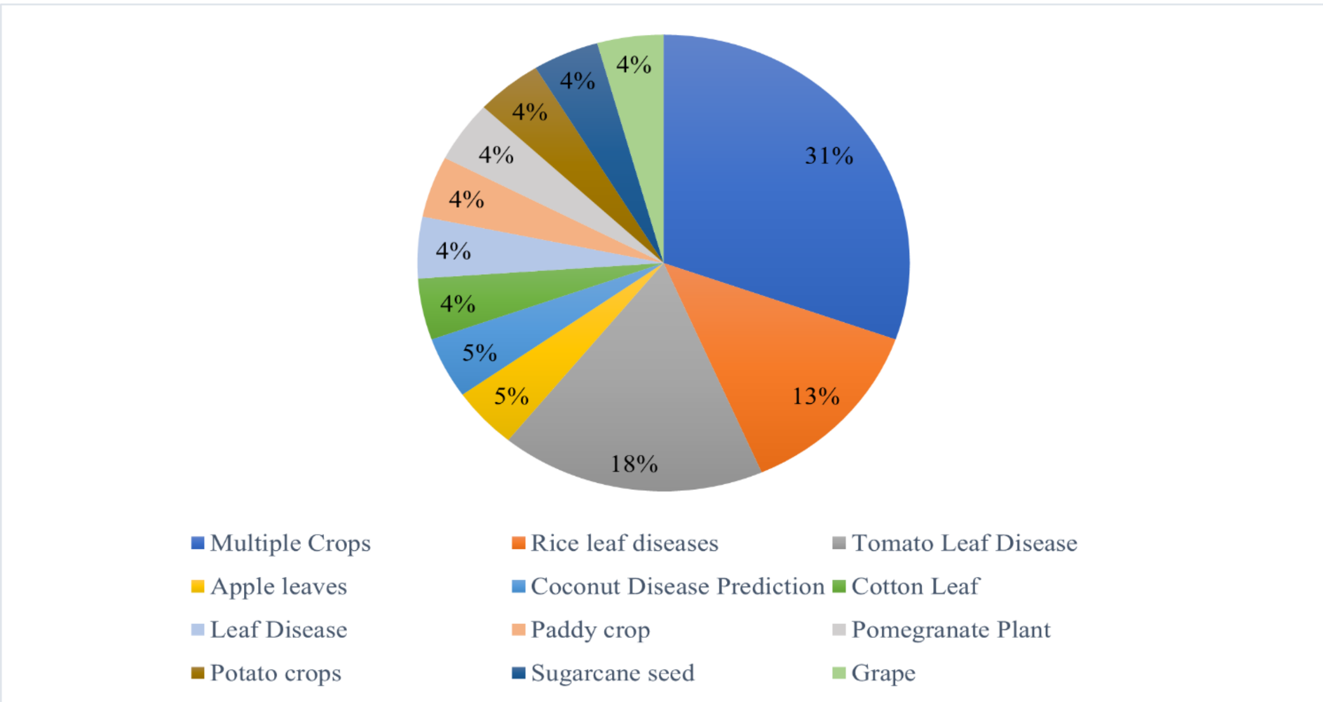

Fig. 2 Identified crops.

TABLE I. EXISTING WORK RELATED TO CROP DISEASE DIAGNOSIS.

Article	Year	Summary	Algorithm Used	Crop Disease Categories	Merits	Demerits	Performance Measure
[6]	2018	Developed (CNN) models that can distinguish between healthy and diseased plant leaves.	VGG, CNNs.	Multiple Crops	High Accuracy.	-	Success rate:99.53%
[7]	2018	SVM classifier was used to identify sugarcane seeds that were affected by sugarcane borer disease.	SVM, RBF kernel function	Sugarcane	Reduced the blind area and improved the detection precision.	Gathering of multiple images at different angles may require additional time and resources.	Accuracy: 96% for diseased sugarcane and 95.83% for disease-free sugarcane.
[8]	2018	DL approach was used for tomato leaves disease detection for which a smartphone application was developed.	CNN, ConvNet	Tomato	High detection accuracy and can be used in several areas, including recommender systems.	-	Full-colour accuracy of 99.84%, Gray-Scale accuracy of 95.54%.
[9]	2018	ML methods and multispectral remote sensing images were used to identify the severity of late blight infection in potato crops.	CNNs, SRs	Potato	Improved disease detection and prediction in agriculture by providing more accurate and timely information.	Large amount of high-quality data required for training, which was a challenge due to the variability in environmental conditions.	MAE: 11.72% RMSE: 17.1%
[10]	2019	Real-time detection method for five of the most prevalent apple leaf diseases using CNN approach.	INAR-SSD, CNN	Apple	Advanced method for early detection of apple leaf diseases that offered better accuracy and quick real-time detection.	CNN frequently experienced the overfitting problem during the training phase.	mAP: 78.80
[11]	2019	It used ML methods to categorize diseases in rice plants based on colour features as the sole parameter.	SVM	Rice	Aided farmers to make well-informed decisions and choose the right pesticides at the correct time.	Approach relied solely on colour features, which is always not sufficient to distinguish between different types of diseases.	Accuracy: 94.68%
[12]	2019	Transfer learning and deep feature extraction were the 2 methods used for identifying the plant diseases.	SVM, ELM, KNN	Multiple Crops	Performed feature extraction without applying segmented methods.	Due to the inflexibility of the model, it is difficult to transfer them to new environments.	Accuracy: 97.86%.
[13]	2019	The developed system replaced manual disease identification techniques and provided the optimal suggestions for the use of pesticides and their dosages, as suggested by agricultural experts.	GMM	Pomegranate	Degree of infection was determined, and preventive measures, such as biological and chemical solutions, were advised.	Unable to detect all types of diseases for different fruits. It provided inaccurate and incomplete results in terms of early-stage disease detection.	High accuracy for different infection levels.
[14]	2019	The significance of early detection of crop diseases and the integration of technology in the agriculture sector were examined.	KNN, SRG	Cotton	Image pre-processing technique examined each pixel in the image, and affected regions were successfully eliminated from three different disease-affected leaf disease.	-	Region with diseased portion 98.025% accuracy and segmented region have 0.964%
[15]	2019	It explored several types of diseases that affect plant leaves. Reviewed and evaluated various methods for identifying such diseases.	KNN, PCA, SVM,	Multiple plants	Early-stage detection, reduced the spread of diseases, and improved crop yields.	Not applicable to other types of diseases or pests that affect agricultural production.	Accuracy: 98.56%

[16]	2020	Comparison between the effectiveness of various methods for identifying plant diseases was done using deep feature extraction techniques and transfer learning.	CNNs	Rice plant	Techniques were efficient, automated, quick, and exact.	-	Accuracy of multiple diseases: 98.63%. Public dataset accuracy: 94.07%.
[17]	2020	Coconut-related disease detection using ML-DL approach. It provided an advanced agricultural guide for farmers to identify nutrient deficiency and pest attack diseases.	SVM, CNN, PNN	Coconut	Early automatic detection method of diseases in coconut plants.	Accuracy is highly dependent on the input. It may suffer if the images are of poor quality.	SVM accuracy: 93.54% CNN accuracy: 93.72%
[18]	2020	The efficiency of DL approaches compared to ML methods for spotting diseases in citrus plants was assessed.	SGD, SVM, RF, ANN, Inception-v3, VGG-16, VGG-19	Multiple Crops	Feasible in choosing the best suited pesticide.	--	Accuracy:RF-76.8% SGD-86.5%, SVM-87%, VGG-19–87.4%, Inception-v3–89%, VGG-16–89.5%
[19]	2021	A model that distinguishes ten distinct kinds of paddy crop diseases was developed..	DCNN	Paddy crop	High accuracy among the existing work in paddy crop type.	-	Accuracy: 95.012%
[20]	2021	A (DCNN) named InceptionResNetV2 was used to examine three major diseases that impact rice plants such as leaf blast, bacterial blight, and brown spot.	DCNN	Rice	DL outperformed ML techniques in processing large amounts of data efficiently, automatically learning input features, and producing results based on predetermined principles.	-	Accuracy: 95.67%
[21]	2022	A model that can recognize 25 type of diseases in 16 different variety of crops was created.	CNN	Multiple crops disease	High accuracy.	A physical examination or lab test may be necessary for an accurate diagnosis.	Accuracy: 99.35%
[22]	2022	A framework was presented that integrates the advantages of both ML and DL. It included 40 different Hybrid DL models that contain the combination of eight different variants of pre-trained DL architecture.	KNN,RF, LR,AdaBoost ,SGB	Tomato plants	Early detection of diseases.	Images with numerous leaves or groups of leaves were not appropriate for the study.Limited dataset and slow computation speed were another issues.	SGB: Accuracy: 92.73%
[23]	2022	A CNN-based DL method was introduced for identifying and categorizing crop diseases in tomato crop.	CNN, ResNet15, VGG19, InceptionV3	Tomato Crop	Quick identification of disease, improved the yields of tomatoes in both quality and quantity.	CNNs are computationally expensive, especially when dealing with large datasets.	Training accuracy: 98% Testing accuracy:88.17%
[24]	2022	An intelligent classification method for leaf diseases using AI and CV techniques was created.	CNN, HoG	Apple, corn, potato, tomato, rice.	Total number of trainable parameters were smaller than that of the frequently used canonical designs.	Availability of labelled datasets for some plant diseases may be limited, which could affect the model performance.	Accuracy: 96.1%
[25]	2022	A lightweight (CNN) model was built on the ResNet architecture that detected plant diseases.	CNN, CBAM	Tomato	Outperformed the current generic models, performed more accurately and effectively.	Success rates were significantly lower (about 33%) in real conditions.	Best (average accuracy: 99.69%)
[26]	2022	A deep transfer learning-based model for grape plant leaf lesions detection was developed.	CNN, Hy-CNN.	Grape	Significant improvement over the existing results.	Selecting the most relevant features was not defined.	Accuracy: 98.7%

[27]	2023	A novel method was developed using DL models for diagnosing plant diseases without expanding the dataset.	CNNs, GAN, HOG	Tomato, orange, grape, corn, apple	Accurate disease detection.	Poor recall value.	Accuarcay: 88% and very low recall: 46%

VGG: Visual Geometry Group, CNN: Convolutional Neural Networks, SVM: Support Vector Machine, SRS: Spectral Ratios, INAR-SSD: Integrated Narrow-Aspect Ratio Single Shot Detector, ELM: Extreme Learning Machine, KNN:K Nearest Neighbor, GMM; Gaussian Mixture Model, SRG; Seed Region Growing, PCA; Principal Component Analysis, PNN; Probabilistic Neural Network, SGD: Stochastic Gradient Descent, RF; Random Forest, DCNN; Deep Convolutional Neural Network, LR; Logistic Regression,VGG19; Visual Geometry Group 19, HOG: Histogram Of Oriented Gradient, CBAM: Convolutional Block Attention Module, HY-CNN: Hybrid : Convolutional Neural Networks NN: Neural Network, GAN-Generative Adversarial Networks

TABLE II: DATASET RELATED USED IN THE EXISTING WORK RELATED TO CROP DISEASE DIAGNOSIS.

Article	Dataset	Description	Accessibility Public/Own Create	Public Year
[6]	Multiple plant disease dataset	87,848 images	Public	2015
[7]	Sugarcane borer diseases dataset	309 images of sugarcane seeds without any diseases and 147 images of sugarcane seeds with 49 different diseases were used.	Own Created	2017
[8]	Tomato leaves diseases dataset	9,000 images on Tomato leaves for five types of Tomato diseases.	Public	
[9]	Potato crops diseases dataset	A farm in Vent Quemada, Boyacá, Colombia, was used to grow 14 different potato genotypes.	Own Created	2018
[10]	Apple leaf diseases	In Baishui County, Shaanxi Province, China, the Apple Experiment Station of Northwest A&F University provided a dataset of 2029 images of diseased apple leaves.	Public	2019
[11]	Rice plant disease dataset	Total of 619 different images showing sick rice plants collected from the agricultural areas at the IGAU in Raipur, Chhattisgarh, India.	Own Created	2019
[12]	Plant disease and pest detection dataset	1965 image dataset with eight different plant diseases in Turkey's Malatya, Bingöl, and Elazg areas were chosen.	Own Created	2019
[13]	Pomegranate plant disease dataset	Multiple infected images of 400 samples.	Own Created	2019
[14]	Leaf blight disease dataset	NARO images and the Arkansas plant diseases database.	Public	2019
[15]	Plant leaf disease	A collection of 75 plant leaves, of which 55 served as training data and the remaining 20 as testing data.	Own Created	2019
[16]	Rice plant diseases	The Fujian Institute of Subtropical Botany's experimental area at the Agricultural Scientific Innovation Base, Xiamen, China, was used to capture about 500 images of rice plant diseases.	Public	2020
[17]	Coconut disease prediction	Captured images using devices.	Own Created	2020
[18]	Plant leaf disease	With the help of experts and the Citrus Research Centre under the Government of Punjab, 690 images were manually gathered.	Public	2020
[19]	Paddy crop disease	Total of 3549 images.	Public	2018
[20]	Rice leaf diseases	It contains three categories of diseases in 5200 images.	Own Created	2021
[21]	Crop disease prediction	64412 images, representing 16 harvests and 25 diseases.	Public	
[22]	Plant disease detection	910 images, known as IARI-Tom EBD, were collected from IARI. For the same reason, a second collection of 2475 images known as Plant village-BBLS was also acquired.	Public	2015
[23]	Tomato crop disease	The Plant Village dataset from Kaggle served as the source consisting of 300 images divided into 10 different classes.	Public	2021
[24]	Detection in plant leaf	A dataset of 37,315 images, including 7,771 images of apples, 7,316 images of maize, 3,763 images of potatoes, 18,345 images of tomatoes, and 120 images of rice, was used.	Public	2015
[25]	Tomato leaf disease	At Gyeongsang National University in South Korea, a greenhouse was used to capture pictures of Fusarium wilt diseased plants. A total of 19,510 images from 10 distinct disease classes and one class of healthy images were used to create dataset.	Public	2015
[26]	Detecting grape plant leaf lesions	The collection of photos used in this dataset was acquired from Plant Village, which has a total of 4,875 photos, including 2,115 photos of healthy plants and 2,360 photos of plants with illnesses.	Public	2015
[27]	Multiple leaf disease identification	Three datasets: Plant Village, IPM, and Bing datasets resulting in total of 1400 images.	Public	2016

V. CONCLUSION

In this study, recent advancements in the ML and DL techniques for the prediction and detection of diseases in various varieties of crops is explained. It concluded that these techniques are effective at predicting the diseases in crops at an early stage, preventing huge losses in terms of produce and other resources. In addition, summary, techniques used, categories of crops, merits, demerits and performance measures of the existing work are shown in tabular form. Additionally, description of used datasets is also provided. It will aid the scientists and farmers working in the agricultural domain involving the diagnosis, automatic detection, prediction, and proper management of the crop.

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