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Classification and Prediction of Crop Diseases: A Review

Abstract: *Agriculture is the foundation of civilization which faces several problems in the 21st century. Crop diseases threaten global food security by reducing yields. Visual inspection to detect diseases can be time-consuming, subjective, and error-prone. Recent advances in various machine learning (ML) and deep learning (DL) techniques have led to ease in the identification of crop diseases. ML and DL demonstrate their versatility in image recognition, segmentation, and anomaly detection. In this paper, some of the recent works based on crop-disease detection using various ML and DL techniques are reviewed. It includes early illness detection and appropriate interventions to reduce yield loss. The review emphasizes the relevance of crop disease detection for food security and sustainable agriculture. ML and DL techniques can help farmers monitor crop health and optimize resource allocation.*

Keywords—Crop, Disease Prediction, Machine Learning, Artificial Intelligence, Agriculture

I. Introduction

Agriculture plays a pivotal role in sustaining human life. It ensures food security, provides raw materials for various industries, and contributes significantly to the global economy. However, crop diseases pose a constant threat to agricultural productivity and can lead to significant losses in yield and quality. Early and accurate detection of crop diseases is crucial for timely intervention and minimizing damage. In this context, machine learning (ML) and deep learning (DL) techniques offer a powerful and promising solution for revolutionizing crop disease management.[1]

Traditional methods of disease detection rely on visual inspection by farmers or trained personnel. These methods are labor-intensive, time-consuming, and prone to human error, especially in the initial stages of disease development. Moreover, they require expertise in plant pathology, which may not be readily available in many rural areas. Additionally, traditional methods often struggle to distinguish between diseases with similar symptoms, leading to misdiagnosis and ineffective treatment.[2]

ML and DL offer a paradigm shift in crop disease diagnosis with their ability to automate the process, analyze large datasets of images, and identify subtle patterns that may be imperceptible to the human eye. These techniques can extract meaningful features from diseased leaves, such as colour changes, texture variations, and lesion shapes, and use them for training models that can accurately classify diseases. This

automation not only reduces the reliance on expert knowledge but also enables real-time monitoring and early detection, which are critical for mitigating crop losses.

The field of ML- and DL-based crop disease detection has witnessed significant advancements in recent years. Researchers have explored various techniques, including supervised learning algorithms such as SVM and Random Forest and unsupervised learning approaches like K-means clustering.

CNNs have emerged as the leading DL architecture for this task due to their ability to learn complex features from images automatically. Several pre-trained CNN models, like VGG and ResNet, have been successfully adapted for crop disease classification with remarkable accuracy.[3]

The benefits of using ML/DL for crop disease detection extend beyond mere classification. These techniques can be further utilized to:

- Predict disease severity: By analyzing the extent and characteristics of lesions on leaves, ML/DL models can estimate the severity of the disease, allowing farmers to tailor their treatment strategies accordingly.
- Identify the specific disease type: By analyzing additional features, such as the spatial distribution

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of lesions and the presence of other disease symptoms, ML/DL models can identify the specific type of disease affecting the crop, enabling targeted treatment application.

- Estimate potential yield loss: By integrating disease severity and crop growth stage information, ML/DL models can predict the potential yield loss due to the disease, aiding farmers in making informed decisions about resource allocation and harvesting.
- Develop intelligent decision support systems: By combining disease detection models with weather data, soil analysis, and other relevant information, intelligent decision support systems can be developed to provide farmers with personalized recommendations for disease prevention and management.

Despite the promising advancements, there are still several challenges that need to be addressed to fully realize the potential of ML/DL in crop disease management. These include: [4]

- Data availability and quality: Developing robust and reliable ML/DL models requires access to large datasets of high-quality images of diseased leaves, which can be difficult to acquire, especially for diverse crops and geographically dispersed regions.
- Model interpretability and explainability: The complex nature of ML/DL models often makes it difficult to understand how they arrive at their predictions, which can hinder their adoption by farmers who need to trust the technology.
- Computational resources: Training and deploying ML/DL models can be computationally expensive, especially for resource-constrained environments.
- Limited field testing and validation: Many ML/DL models have shown promising results in controlled laboratory settings, but their performance needs further validation in real-world field conditions.

Addressing these challenges through collaborative efforts between researchers, technologists, and agricultural stakeholders is crucial to ensure the successful integration of ML/DL into mainstream crop disease management practices. By overcoming these hurdles, we can unlock the full potential of these transformative technologies to revolutionize crop health monitoring, disease diagnosis, and, ultimately, agricultural productivity and sustainability [5]

In the next section, we will be looking at some of the recent works done in the detection of crop Disease using various ML and DL techniques, followed by discussing some of the common techniques that are being used, and finally concluding the reviews of the papers, followed by discussing the open challenges and future scopes as discussed in the review.

II. Literature review

V. Tanwar et al. employ CNN models to detect and categorize sugarcane Red Stripe disease. As sugarcane is essential for sugar and ethanol production, early disease prediction is necessary. The study predicts Red Stripe Sugarcane Disease well, helping farmers manage it.[6]

V. Tanwar et al. propose utilizing CNN to predict and categorize sugarcane grassy shoot disease, addressing existing disease prediction method shortcomings. The study predicts disease well.[7]

Anitha B. et al. examine insect attacks and infectious diseases on coconut plantations and present a DenseNet-121-based early disease recognition method. It was to improve coconut leaf health and farmer productivity through automated disease identification. The suggested method addresses vanishing gradients and improves feature propagation to outperform previous methods in accuracy. An automated, cost-effective illness identification method is the goal.[8]

R. Tyagi et al. suggest experimental disease detection in plant leaves using ML algorithms like LR, KNN, Random Forest, Naive Bayes, and SVM. The Random Forest method is most accurate on the dataset of crops.[9]

A. Bajpai et al. suggest early and accurate ML/DL illness identification. Three DL architectures—VGGNet16, ResNet101, and AlexNet—are implemented for four leaf categories. AlexNet has the best training and testing accuracy, promising to reduce crop losses.[10]

S. Harika et al. discover ailments in the Indian economy-critical Black gramme crop. We examine four Black gramme illnesses. Determining Black Gramme Crop Disease uses ML (decision tree, random forest, KNN) and DL (ANN, CNN) on the BPLD dataset. This investigation shows that the CNN model is better at diagnosing Black gramme crop diseases.[11]

Mayalekshmi K. M. et al. address the difficulty of detecting chili leaf illnesses in the field, where images are complex due to unstructured surroundings and mixed disease areas on young leaves. A chili field was photographed with an RGB camera and the YOLOv5 DL object identification model. The model's mean average precision (mAP) of 0.461 showed promise for chili crop disease diagnosis in real-world situations despite a tiny dataset.[12]

Narayana P. et al. created an ML model to help farmers choose crops. For crop, fertilizer, and disease detection, it considers soil (nitrogen, phosphorus, potassium, pH), weather (temperature, humidity), and tomato leaf images. CNN and ResNet architecture ML models trained on leaf pictures predict illness. The software helps farmers, especially newcomers, make better crop production decisions by offering real-time weather data, fertilizer recommendations, and disease predictions. The web app uses Flask.[13]

P. K. Lakineni et al. developed an upgraded CNN with wrapping filter pre-processing and Logistic Decision Regression feature selection. The LDR feature selection finds the finest plant disease diagnostic characteristics. The study emphasizes leaves in medicinal plant identification, and automated disease detection systems use foliar disease states. CNN models are noted for picture classification and recognition accuracy.[14]

S. Prasher et al. wants to automate and efficiently detect diseases during blossoming to boost potato crop yield. To discover key dataset features, the proposed model sequentially uses a pre-trained DL model using RMSProp, Adam, and SGD optimizers.[15]

S. R. J. Reddy et al. suggest a CNN model to detect cotton splint disease early, improving plant growth monitoring. The model considers Alternaria, Red spot, Cercosporin, white spot, and unheroic spot cotton leaf diseases.[16]

R. R. Patil et al. explores using a plant disease forecasting model to predict and manage illnesses before applying herbicides. Comparison of ML vs DL accuracy. ANN outperforms them.[17]

A. S. Ahmed et al. present an AI model for early plant disease identification. The model improves plant disease prediction using KNN classifier and k-efficient clustering (k-medoids and k-means). The paper compares k-NN before and after clustering for soybean disease prediction using k-medoids, k-mean, and k-efficient. K-NN with k-efficient surpasses other methods in inter-class, intra-class, normal mutual information, accuracy, precision, recall, F-measure, and running time.[18]

H. Tabassum et al. examine how plant leaf diseases affect agriculture, given that many Indians depend on farming. ML algorithms for plant leaf disease detection include SVM, Naive-Bayes, LR, KNN, ANN, CNN, Back Propagation, Genetic algorithm, and PNN. The publication presents a complete introduction of image processing techniques and compares leaf disease detection approaches to help identify diseased plants.[19]

A. Chug et al. offer a Hybrid DL system for early plant disease detection using pre-trained EfficientNet topologies and ML classifiers. Real-time tomato datasets gave HDL models higher accuracy than PlantVillage datasets. Farmers can detect and control crop diseases using the Optuna framework-optimized technique.[20]

R. Verma studies ML for crop classification, disease detection, and weed infestation. It uses five main models—KNN, SVC, Random Forest, Decision Tree, and Gradient Boosting—to predict optimal crop yields under different weather and soil conditions.[21]

Y. Liu et al. propose a modified, lightweight convolutional neural network for fine-grained crop disease classification. To extract lesion features accurately, it uses multi-scale convolution kernels and coordinate attention.[22]

V. K. Vishnoi et al. developed a CNN model for apple crop disease identification. Augmentation approaches improve the training set without adding photos, reducing computing complexity.[23]

D.N.V.S.L.S. Indira et al. focuses on enhancing agricultural productivity in India, a vital sector comprising 54% of the country's land. Employing ML, the study develops advanced models for crop estimation, fertilizer recommendations, and plant disease identification, aiming to address challenges like soil infertility and promote sustainable farming practices for increased yield.[24]

H. K. Mehedi et al. address the significant issue of crop diseases in agriculture and propose a detection framework using transfer learning with pre-trained models (EfficientNetV2L, MobileNetV2, ResNet152V2). The study covers 38 leaf diseases in 14 plant species, showcasing EfficientNetV2L with the highest accuracy. Additionally, Explainable AI via LIME is applied to enhance model interpretability and provide clear explanations for predictions, increasing reliability.[25]

D. Dhabliya focuses on enhancing rice crop yield by identifying and classifying diseases using image processing and AI. It addresses four common rice plant diseases, employing K-means for leaf segmentation and extracting features like variety and texture. Utilizing classifiers including ANN, DNN, KNN, and an advanced DNN with Jaya optimization, the model performs well in detecting diseases in greenhouse conditions, outperforming traditional agricultural settings. The study evaluates various performance metrics for each classifier, comparing them with existing algorithms.[26]

S. Nandhini et al. developed a detection system for plant disease detection using Tensorflow, Keras, and OpenCV. The system was executed in a cloud computing environment for a large, automated farm, employing three convolution layers and ten nodes. With a substantial dataset, the model achieves high accuracy in disease identification. The focus on Indian plants and the dataset size makes this model distinctive and valuable for enhancing food safety in the Indian agriculture system.[27]

S. Toomula et al., reviews existing studies on crop disease identification and detection, emphasizing computer vision and image processing. Concluding that research leans towards ML and DL, with DL algorithms consistently outperforming ML counterparts in crop disease detection.[28]

R. Qasrawi et al. focus on the detection and classification of tomato plant diseases using ML in the Palestinian agriculture sector. Utilizing 3000 smartphone images of five diseases across three West Bank districts, the study employs image embedding, hierarchical clustering, and various ML models (neural network, random forest, naive Bayes, SVM, decision tree, logistic regression). The proposed approach achieves satisfactory accuracy rates in disease clustering, detection, and classification, indicating its potential for helping Palestinian farmers manage and control tomato diseases effectively.[29]

R. Sujatha et al. emphasize the importance of identifying plant diseases that can significantly impact crop production. Various ML and DL methods are compared for citrus plant disease detection. The study evaluates the performance of ML algorithms (SVM, Random Forest, Stochastic Gradient Descent) and DL models (Inception-v3, VGG-16, VGG-19). Results indicate that DL methods outperform ML methods, with VGG-16 yielding the highest disease classification accuracy.[30]

A. Lakshmanarao et al. propose "Convnets," ML and DL methods for plant disease detection and classification. We use the PlantVillage dataset of 15 potato, pepper, and tomato leaf classes.[31]

M. Agarwal et al. offer a tomato crop disease diagnosis model for prompt treatment. A simple CNN model with eight hidden layers outperforms pre-trained models and ML techniques. The suggested model with picture pre-processing and augmentation uses the PlantVillage dataset and is highly accurate.[32]

Gokulnath B. V. et al. stress the need to analyze Indian agricultural data on rice, wheat, pulses, and spices. The growing population increases agricultural product demand. Predicting crop yield, soil quality, plant diseases, and weather effects on productivity are covered in the article. To reduce disease, insect, weed, and animal losses, crop protection is essential. The survey uses ML methods, including Random Forest, Bayesian Network, Decision Tree, and SVM, to detect plant diseases automatically and improve early diagnosis and prevention for agricultural productivity.[33]

R. Dhaya et al. found that Fusarium wilt (FW), a widespread fungal disease that affects tomato, sweet potato, and tobacco crops, is difficult to manage. This hybrid algorithm detects Fusarium oxysporum illness in tomato leaves. The suggested technique uses 87k pictures to identify diseases with good accuracy using a two-step classification approach.[34]

G. Fenu et al. use Big Data Analytics and ML to predict potato late blight disease in Sardinia. Using DSS LANDS, the study uses Feed-forward NN and SVM Classification. Regional meteorological variables predict illness risk with excellent accuracy in the models.[35]

Below is a comparison table that shows all the reviewed papers year-wise, along with the year it was published, the crop(s) on which the models were trained, the models or the technologies used, and the accuracy of each work.

Table 1. Comparing all related work, crops used, model and technologies employed for the task, and their accuracy.

Citation	Year	Crop	Model/Technology Used	Accuracy
[6]	2023	Sugarcane	Proposed Method, SVM, KNN	98.5%, 93%, 91%
[7]	2023	Sugarcane	Proposed, SVM, KNN	96%, 92%, 90%
[8]	2023	Coconut	DenseNet-121	99.00%
[9]	2023	Tomato, Potato, Apple, Corn, Grapes	LR, KNN, RF, NB, SVM	90%, 92%, 95%, 86%, 77%
[10]	2023	paddy	AlexNet	99.76%
[11]	2023	Black Gram	CNN	89%
[12]	2023	Chilli	YOLOv5	75.64%
[13]	2023	Tomato	Decision Tree, SVM, LR, Random Forest, Naive Bayes,	60%, 99.71%, 72.40%, 96.37%, 99.80%
[14]	2023	Apple, Blueberry, Cherry, Corn, Grapes, Orange, Peeper, Raspberry, Potato,	CNN, LTSM, PLSR	95%, 90%, 83%

		Peach, Soybean, Squash, Strawberry, Tomato		
[15]	2023	Potato	CNN with (RMSProp, Adam, and SGD optimizers)	97.6%, 96%, 94.3%
[16]	2023	Cotton	CNN	89%
[17]	2022	-	CNN, RNN, ANN, SVM, KNN	88.85%, 88.48%, 99.79%, 86.22%, 84.21%
[18]	2022	Soyabean	k-NN, k-NN with K-Means, k-NN with K-Medoids, k-NN with K-Efficient Clustering	81.2%, 91.5%, 94.7%, 100%
[19]	2022	NA	NA	NA
[20]	2022	tomato	EfNet-B3 with (LR, KNN, RF, SGB, ADB)	100%
[21]	2022	apples, chickpea, coconut, coffee, mango, rice	KNN, SVC, Random Forest, Decision Tree, and Gradient Boosting.	97.8%, 94.3%, 97.9%, 99.4%.
[22]	2022	apples	SqueezeNext (Mod-0), SqueezeNext + Inception, SqueezeNext + Inception + CA (Mod-1)	88.92% 89.53% 91.94%
[23]	2022	Apple	CNN	98%
[24]	2022	NA	XGBOOST, RANDOM FOREST, Mobile Net	99%, 95.7%, 92%
[25]	2022	Apple, Blueberry, cherry, corn, grapes, orange, peeper, raspberry, potato, peach, soybean, squash, strawberry, tomato	EfficientNetV2L, MobileNetV2, and ResNet152V2	99.63%, 98.86%, 98.44%
[26]	2021	Rice	A model made by combining ANN, DNN, KNN and A-DNN along with Jaya Optimization	97%
[27]	2021	Tomato	CNN	-
[28]	2021	NA	NA	NA
[29]	2021	Tomato	Decision Tree, SVM Random Forest, NN, Naïve Bayes, LR	66.6%, 90.9%, 79.9%, 92.3%, 81.5%, 93.1%
[30]	2021	Citrus	Stochastic Gradient Descent, Random Forest, SVM, Vgg-19, Inception V3, VGG-16	76.8%, 86.5%, 87%, 87.4%, 89%, 89.5%.
[31]	2021	peeper, potato, tomato,	ConvNet	98.50%
[32]	2020	Tomato	Proposed CNN Model combining K-NN and VGG-16	98.40%
[33]	2020	NA	NA	NA
[34]	2020	tomato, sweet potatoes, tobacco, legumes, cucurbits	modified Naive Bayes with Image processing	96%

[35]	2019	Potato	ANN, SVM	96%, 98%.

III. METHODOLOGY

SVM finds a hyperplane that best separates classes in high-dimensional space, maximizing the margin for optimal classification [6]. LR models the probability of an event using a linear relationship between features and a logit function, suitable for binary classification [9]. RF combines multiple decision trees, each trained on a random subset of features, for improved robustness and accuracy in classification and regression. NB classifies data based on Bayes' theorem, assuming independence between features and efficient for text classification and spam filtering [13]. DT splits data into subsets based on features, creating a tree-like structure for classification and regression, interpretable but prone to overfitting. GB is A general technique for combining weak learners sequentially, where each learner focuses on improving the errors of the previous one, which is powerful for regression and ranking [21]. SGB builds an ensemble of weak decision trees sequentially, improving predictions with each iteration, powerful for regression and ranking [20]. SGD optimizes a loss function iteratively by updating model parameters based on the gradient used in various learning algorithms like LR and SVM. ADB is like SGB, but focuses on boosting misclassified instances, effective for imbalanced data classification [20]. SVC is an extension of SVM for multi-class classification problems, using one-vs-rest or other strategies. K-NN classifies data points based on the k nearest points in the training set, which is simple but effective for high-dimensional data. LTSM is a specific type of RNN that excels at learning long-term dependencies in sequential data and is widely used for language processing and time series forecasting [14]. PLSR is a statistical method for analyzing relationships between sets of variables, particularly useful for high-dimensional data with collinearity. XGBoost is a powerful ensemble learning method based on gradient boosting, combining weak decision trees for improved accuracy and robustness in various tasks [24].

NN is a network of interconnected nodes (neurons) inspired by the human brain, capable of learning complex patterns and relationships from data. ANN is a specific type of NN, often referring to feedforward networks where information flows from input to output layers [27]. CNN is a specialized NN architecture for image and video recognition, extracting features through filters and convolutional layers [36]. DNN is an NN with multiple hidden layers, enabling complex function approximation and learning powerful representations from data. RNN is an NN architecture designed for sequential data like text and time series, capable of capturing temporal dependencies.

DenseNet connects each layer to all other layers in the network, promoting feature reuse and improving information flow. AlexNet is a pioneering CNN architecture with five convolutional and three fully connected layers, achieving significant performance in image classification tasks. Yolov5 is an efficient and powerful object detection model known for its speed and accuracy. Squeezenet emphasizes parameter efficiency using 1x1 convolutional filters and fire modules for dimensionality reduction. Inception introduces Inception modules with parallel convolutional paths for capturing diverse features and improving efficiency. MobileNet optimizes for mobile deployment, utilizing depth-wise separable convolutions to reduce computational cost while maintaining accuracy. EfficientNet scales up CNN architectures for better accuracy and efficiency, utilizing compound scaling and novel activation functions. ResNet introduces skip connections directly connecting earlier and later layers, mitigating the vanishing gradient problem and improving performance. VGG is a series of CNN architectures with increasing depth and complexity, demonstrating the power of deeper networks for image classification.

Some of the Optimization algorithms include RMSProp helps to adaptively adjust learning rates for individual parameters based on squared gradients, effective for non-stationary data, ADAM [15] combines features of RMSProp and AdaGrad, addressing their limitations and achieving efficient learning with momentum, Jaya[27] is a nature-inspired optimizer based on the foraging behaviour of jays, demonstrating robustness and performance across various tasks.

IV. CONCLUSION

The reviewed research papers underscore the diverse applications of ML and DL in crop disease management. Covering various crops and diseases, studies showcase the efficacy of CNNs, hybrid models, and advanced classifiers. The holistic approaches integrate environmental factors, aiding farmers in informed decision-making. Comparative analyses in a year-wise table highlight the evolving landscape of methodologies. Collectively, these advancements signal a transformative era in agriculture, offering precision and scalability for resilient crop management and global food security.

V. CHALLENGES & FUTURE SCOPE

Accurate agricultural plant disease forecasting models require data from host, pathogen, weather, soil, and genetic sources. However, challenges like macro-scale data gathering, interdisciplinary collaboration, and agricultural ecosystem complexity hinder progress. Future research should focus on real-time implementation, IoT integration, and model expansion to include new diseases and environmental variables. Challenges include dataset imbalances, model robustness, climate change, and data security. Real-time monitoring systems face challenges like small datasets, class imbalances, and ethics. Agricultural IoT issues include model adaptability, scalability, and data privacy. The viability of proposed approaches depends on overcoming data and infrastructure constraints, efficient pre-processing, and expanding datasets to diverse agricultural environments.

IoT, machine intelligence, satellite photography, and global collaboration will improve plant disease prediction and management. Optimizing algorithms, adapting models to crops, and supporting multiple agricultural approaches are difficult. Research goals include real-time implementation, adding more diseases to models, and integrating dynamic environmental elements for practical usage. Technology, precision agriculture, and community participation are needed for sustainable success. Expanding datasets, real-time monitoring, and innovative architectures increase disease diagnosis and control, boosting farm efficiency and resilience.

VI. ABBREVIATIONS

SVM-Suppoer Vector Machine, LR- Logistic Regression, RF- Random Forest, NB- Naïve Bayes, DT- Decision Tree, GB- Gradient Boosting, SGB- Stochastic Gradient Boosting, SGD- Stochastic Gradient Descent, ADB- Adaptive Boosting, KNN- K-Nearest Neighbours, LSTM- Long-Short Term Memory, PLSR- Partial Least Squares Regression, NN- Neural Network, ANN- Artificial NN, CNN- Convolutional NN, DNN- Deep NN, RNN- Recurrent NN, VGG- Visual Geometry Group.

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