S.No	Introduction	Model Used	Result	Limitations
1.	Feng et al. (2024) - introduced a comparative study on soil texture classification, evaluating traditional geostatistical interpolation methods and artificial neural networks (ANN).	Inverse Distance Weighting (IDW), Kriging, Co-kriging, Artificial Neural Network (ANN).	High accuracy in soil texture classification: ANN (45%-50% correlation), Co-kriging (30%-40%), Kriging (25%-35%), IDW (Lowest precision).	Low correlation in ANN predictions (<50%), reduced accuracy in IDW interpolation, and dependence on high-quality auxiliary variables in co-kriging.
2.	Giakoumoglou et al. (2024) - introduced a deep learning approach for the early detection of Botrytis cinerea symptoms in cucumber plants using multi-spectral imaging. The study aims to improve disease detection accuracy and assist in early intervention for better crop protection.	U-Net++, DeepLabV3, DeepLabV3+ with ResNet-34, ResNet-50, and MobileViT-S encoders.	High accuracy in disease detection: U-Net++ with MobileViT-S achieved 90.1% accuracy.	Model performance varies across different disease stages, with lower precision in early infection detection. The dataset's complexity and similarity between abiotic stress and disease symptoms can lead to misclassification
3.	Mahadevan et al. (2024) - introduced an automatic Rice Plant leaf disease detection system using deep learning. The study aims to enhance accuracy and efficiency in diagnosing plant diseases through advanced neural network techniques, reducing yield loss and	Deep Spectral Generative Adversarial Neural Network (DSGAN2), Improved Threshold Neural Network (ITNN), Segment Multiscale Neural Slicing (SMNS), Social Spider	High accuracy in disease classification: DSGAN2 achieved 97% accuracy, outperforming ACPSOSVM-DCCNN (78%), AlexNet (82%), and CNN (91%). The proposed method also reduced the false rate to 40.8% compared to existing systems (APS-DCCNN: 55.2%,	Performance is affected by dataset quality and complexity, requiring large-scale labeled data for better generalization. Early-stage disease detection remains a

	improving agricultural productivity.	Optimization (S2O-FCW)	AlexNet: 50.4%, CNN: 49.5%).	challenge due to subtle visual difference s.
4.	Sofuoglu & Birant (2024) introduced a deep learning-based approach for detecting potato plant leaf diseases. The study aims to enhance automated disease classification using convolutional neural networks (CNN) to improve agricultural yield and sustainability.	Convolutional Neural Network (CNN).	High accuracy in disease classification: CNN achieved 98.28% accuracy, outperforming existing state-of-the-art models (average 89.67%). The proposed model also recorded precision (0.9794), recall (0.9784), and f-score (0.9783), demonstrating robust performance.	Model performance is limited to labeled diseases in the dataset. The system requires diverse and well-structured datasets for broader disease detection. Future improvements could include mobile-based detection for real-time application s.
5.	Liu et al. (2024) - introduced a machine-learning-based approach for estimating rice yield using multi-temporal remote sensing data. The study aims to enhance accuracy and efficiency in rice yield prediction by integrating vegetation indices with advanced regression models.	Partial Least Squares Regression (PLSR), Support Vector Regression (SVR), Random Forest Regression (RFR), Back Propagation Neural Network (BPNN).	High accuracy in rice yield estimation: RFR achieved an R^2 of 0.65, RMSE of 388.79 kg/ha, and rRMSE of 4.48%, outperforming PLSR (R^2 = 0.34), SVR (R^2 = 0.34), and BPNN (R^2 = 0.21).	Model performance depends on dataset quality and spatial heterogeneity. The accuracy of early-season yield prediction is affected by limited training data and the complexity of crop growth variation s.

6.	Tussupov et al. (2024) - introduced a machine-learning-based approach for verifying pests and diseases in crops using spectral brightness coefficients (SBC). The study aims to optimize agricultural productivity by leveraging remote sensing and advanced classification techniques.	Logistic Regression, eXtreme Gradient Boosting (XGBoost), Vanilla Convolutional Neural Network (CNN).	High accuracy in pest and disease verification: XGBoost achieved 90.32% accuracy, outperforming Vanilla CNN (83.87%) and Logistic Regression (80%).	Model accuracy depends on dataset quality, and early-stage pest detection remains challenging due to spectral similarities between diseased and healthy cro ps.
7.	slam et al. (2021) - introduced a machine learning-based approach for early weed detection in an Australian chilli farm using UAV images. The study aims to improve agricultural productivity by identifying weeds early to prevent crop yield loss.	Random Forest (RF), Support Vector Machine (SVM), k-Nearest Neighbors (KNN).	RF achieved the highest accuracy (96%), followed by SVM (94%) and KNN (63%). RF and SVM proved more efficient for weed detection from UAV images.	The performance of KNN was lower due to false detections. Environmental conditions and image quality can impact detection accur acy.
8.	Crane-Droesch (2018) - introduced a semiparametric deep learning approach for crop yield prediction and climate change impact assessment. The study integrates machine learning with statistical models to improve the accuracy of agricultural forecasts under varying climate conditions.	Semiparametric Neural Network (SNN), Ordinary Least Squares (OLS), Fully Nonparametric Neural Network.	SNN achieved the highest accuracy in crop yield prediction, outperforming both OLS and fully nonparametric neural networks.	The model's performance depends on the availability of high-quality weather and yield data. Uncertainties in climate projections and adaptation responses also affect prediction reliab ility.
9.	Yang et al. (2024) - introduced a machine learning-based approach for wheat yield prediction using UAV remote sensing	Random Forest (RF), Partial Least Squares (PLS), Ridge Regression (RR), k-Nearest	High accuracy in wheat yield prediction: XGBoost achieved R^2 = 0.660 and RMSE = 0.754, while the simple	Model performance is influenced by dataset quality and

	data. The study focuses on integrating multi-sensor data fusion to enhance prediction accuracy and support precision agriculture.	Neighbor (KNN), Extreme Gradient Boosting (XGBoost).	average ensemble method improved prediction performance to $R^2 = 0.733$ and RMSE = 0.668 t/ha.	environmental conditions. Multi-sensor fusion improves accuracy but increases computational c omplexity.
10.	Kumar et al. (2024) - introduced a machine learning-based approach for detecting rice leaf diseases using image classification techniques. The study focuses on automating disease identification to improve agricultural efficiency and reduce yield loss.	Convolutional Neural Network (CNN), Support Vector Machine (SVM), Random Forest (RF).	High accuracy in disease detection: CNN achieved 96.5% accuracy, outperforming SVM (89.2%) and RF (85.6%).	Model performance is affected by dataset quality, environmental variations, and similar visual symptoms among different diseases, leading to potential misclassification s.
11.	Muruganantham et al. (2022) - reviewed deep learning applications in crop yield prediction using remote sensing data. The study explores different methodologies, remote sensing technologies, and key features influencing yield prediction.	Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Deep Neural Network (DNN), Bayesian Neural Network (BNN), 3D-CNN, CNN-LSTM, Residual Network (ResNet).	LSTM and CNN were the most effective deep learning models for crop yield prediction, with high accuracy when combined with vegetation indices and remote sensing data.	Challenges include data quality dependence, black-box nature of deep learning models, and the need for large datasets to improve accurac y.
12.	Dhaliwal & Williams (2024) - introduced a machine learning approach for predicting sweet corn yield using field-level data. The study leverages historical crop management, weather, and soil data to enhance yield estimation accuracy.	Random Forest (RF), Principal Component Regression (PCR), Partial Least Squares Regression (PLSR), Multiple Linear Regression (MLR),	Random Forest achieved the highest accuracy with RMSE = 3.29 Mt/ha and Pearson's correlation coefficient r = 0.77.	Model performance is affected by the quality and granularity of input data. Overfitting and limited generalization remain

		Regularized Regression, Multivariate Adaptive Regression Splines (MARS).		challenges, especially when predicting across diverse regions.
13.	El-Kenawy et al. (2024) - introduced a machine learning and deep learning-based approach for predicting potato crop yield. The study integrates multiple models to improve yield forecasting accuracy and support sustainable agricultural practices.	K-Nearest Neighbors (KNN), Gradient Boosting, XGBoost, Multilayer Perceptron (MLP), Graph Neural Networks (GNNs), Gated Recurrent Units (GRUs), Long Short-Term Memory Networks (LSTMs).	GNNs achieved the highest accuracy with MSE = 0.02363 and R^2 = 0.51719, outperforming Gradient Boosting (MSE = 0.03438, R^2 = 0.49168) and XGBoost (MSE = 0.03583, R^2 = 0.35106).	Model performance depends on data quality, environmental variability, and the availability of historical yield records. Deep learning models require high computational resources and large datasets for effective trainin g.
14.	Mathieu et al. (2024) - introduced SeptoSympto, a deep learning-based image analysis tool for detecting and quantifying Septoria tritici blotch (STB) disease symptoms in wheat. The study aims to improve disease assessment accuracy and facilitate large-scale phenotyping.	U-Net, YOLOv5 (You Only Look Once v5).	High accuracy in STB symptom quantification: U-Net achieved an F1-score of 0.90 for necrosis detection, while YOLOv5 achieved an F1-score of 0.34 for pycnidia detection.	Model performance depends on image quality and dataset diversity. Pycnidia detection remains challenging due to variations in symptom appearance and environmental c onditions.
15.	Roopashree et al. (2024) - introduced a machine learning approach to map soil suitability for medicinal plant	Extra Trees Classifier (EXTC), Random Forest (RF), Bagging Classifier,	EXTC achieved the highest accuracy for both soil classification (99.01%) and subregion classification (98.76%),	The model does not account for climatic conditions affecting plant

	cultivation. The study integrates GIS-based spatial analysis and supervised learning models to enhance the conservation and productivity of endangered medicinal plants.	Extreme Gradient Boosting (XGBoost), k-Nearest Neighbors (KNN).	outperforming other models.	growth. Data accuracy depends on GIS and soil datasets, which may introduce errors in mappin g.
16.	Lu et al. (2024) - introduced a deep learning framework for soybean yield estimation at the county level in the United States. The study integrates multi-source remote sensing data with an advanced CNN-BiGRU-Attention model optimized using the Grasshopper Optimization Algorithm (GOA) to improve prediction accuracy.	CNN-BiGRU-Attention (GCBA), Random Forest Regression (RFR), Support Vector Regression (SVR), Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), CNN-GRU.	High accuracy in soybean yield prediction: GCBA achieved R^2 = 0.7057 and RMSE = 4.4612 bushels/acre in 2020, outperforming CNN-GRU (R^2 = 0.6671, RMSE = 4.7926) and other models.	Model performance depends on the quality of multi-source data, and extreme weather events can reduce predictive accuracy. The computational complexity of the deep learning framework requires high processing pow er.
17.	Mupangwa et al. (2020) - introduced a machine learning-based approach to predict maize yield under conservation agriculture (CA) in Eastern and Southern Africa. The study evaluates the performance of different ML algorithms in highland and lowland cropping systems.	Logistic Regression (LR), Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Classification and Regression Trees (CART), Naïve Bayes (NB), Support Vector Machine (SVM).	LDA achieved the highest accuracy (61%), followed by NB (59%) and LR (58%), while SVM had the lowest accuracy (42%).	Model performance varies across different agro-ecologies. SVM showed poor prediction accuracy, and data availability remains a challenge in smallholder farming systems .

18.	Caldeira et al. (2021) - introduced a deep learning-based approach to identify lesions on cotton leaves using image processing. The study aims to enhance precision agriculture by automating plant health monitoring and optimizing pesticide application.	GoogleNet, ResNet50, Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Neuro-Fuzzy Classifier (NFC).	ResNet50 achieved the highest accuracy (89.2%), followed by GoogleNet (86.6%). CNN models outperformed traditional classifiers like SVM and KNN by up to 25%.	Model performance depends on image quality and environmental variations. Lesion detection in early disease stages remains challenging due to symptom similar ities.
19	Harinath et al. (2024) - introduced a machine learning-based approach for predicting agricultural yields to enhance smart farming practices. The study leverages AI, IoT, and data-driven techniques to improve food security and optimize crop production.	Random Forest, Decision Tree, XGBoost, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM).	Random Forest achieved the highest accuracy (98.96%) for crop yield prediction, outperforming Decision Tree (89.78%) and XGBoost (86.46%). CNN performed better than LSTM with a lower test loss (0.00060 vs. 0.00063).	Model accuracy depends on historical data quality and climate variability. More deep learning models and remote sensing integration are needed for further improve ments
20.	García-Vera et al. (2024) - reviewed the integration of hyperspectral imaging and machine learning for crop disease detection. The study highlights how these technologies enhance precision agriculture by enabling early disease identification and improving crop monitoring.	Support Vector Machines (SVM), Random Forest (RF), Convolutional Neural Networks (CNN), Principal Component Analysis (PCA), Partial Least Squares Regression (PLSR).	Hyperspectral imaging combined with machine learning improves disease detection accuracy, with SVM and CNN achieving the highest classification performance for various crop diseases.	Model performance depends on dataset quality, spectral range selection, and environmental variability. High costs and computational complexity of hyperspectral imaging limit large-scale adoption.

21.	Pavan et al. (2025) - introduced a deep learning-based system for detecting areca nut diseases. The study addresses challenges in manual inspection and dataset limitations by utilizing image processing techniques for automated classification.	ResNet-50 (Pre-trained Convolutional Neural Network).	High accuracy in disease classification, effectively distinguishing between Mahali Koleroga, Yellow Leaf Disease, and Stem Bleeding.	Model performance is affected by dataset size (only 181 images), image quality variations, and complex disease symptoms leading to classification ch allenges.
22	Howlader et al. (2025) - introduced a high-resolution image dataset for eggplant leaf disease detection. The dataset supports machine learning and computer vision applications in precision agriculture, aiming to improve early disease identification.	Convolutional Neural Network (CNN), Support Vector Machines (SVM), MobileNet.	The dataset enables high-accuracy disease classification, supporting CNN-based models for automated detection of six eggplant leaf diseases, including Leaf Spot, Mosaic Virus, and White Mold.	Data collection is limited to specific regions in Bangladesh, and class imbalance may affect model generalization. The dataset lacks temporal progression data, restricting early-stage disease detection capabi lities.
23	Shoib et al. (2025) - introduced a high-resolution image dataset for black gram leaf disease detection. The dataset aims to enhance machine learning-based classification of common leaf diseases, supporting precision agriculture and early disease identification.	Convolutional Neural Network (CNN), VGG16 (Pretrained Model).	The dataset supports high-accuracy classification of five black gram leaf diseases: Cercospora Leaf Spot, Leaf Crinkle, Yellow Mosaic, Insect Damage, and Healthy Leaves.	Data collection is limited to specific regions in Bangladesh, which may affect generalization. The dataset lacks real-time progression tracking, limiting its effectiveness for early disease detection.

24	Balasundaram et al. (2025) - introduced a machine learning approach for detecting tea leaf diseases using the Segment Anything Model (SAM) and a custom Convolutional Neural Network (CNN). The study aims to improve early detection of tea leaf diseases, ensuring better crop yield and reduced economic losses for farmers.	Segment Anything Model (SAM), Convolutional Neural Network (CNN), Multilayer Perceptron (MLP), Support Vector Machine (SVM), Decision Tree (DT).	The CNN+MLP model achieved the highest accuracy of 95.06%, outperforming other models. The SAM model effectively segmented diseased portions but had slightly lower accuracy (92%) compared to the CNN model alone.	SAM's zero-shot segmentationBalasundaram et al. (2025) introduced a machine learning approach for detecting tea leaf diseases using the Segment Anything Model (SAM) and a custom Convolutional Neural Network (CNN). The study aims to improve early detection of tea leaf diseases, ensuring better crop yield and reduced economic losses for farmers.
25	Shoib et al. (2025) - introduced a high-resolution image dataset for black gram leaf disease detection. The dataset aims to enhance machine learning-based classification of common leaf diseases, supporting precision agriculture and early disease identification.	Convolutional Neural Network (CNN), VGG16 (Pretrained Model).	The dataset supports high-accuracy classification of five black gram leaf diseases: Cercospora Leaf Spot, Leaf Crinkle, Yellow Mosaic, Insect Damage, and Healthy Leaves.	Data collection is limited to specific regions in Bangladesh, which may affect generalization. The dataset lacks real-time progression tracking, limiting its effectiveness for early disease detection.

26	Arwa Alzughaibi (2025) - introduced a pest detection system using a fusion of the Modified Artificial Hummingbird Algorithm with Deep Learning (MAHADL-PDC) for efficient pest detection and classification. The system aims to improve pest recognition accuracy in agriculture by enhancing image quality and employing deep learning models.	Modified Artificial Hummingbird Algorithm (MAHA), EfficientNet-B4, Deep Belief Networks (DBNs).	The MAHADL-PDC model achieved high accuracy, with 99.18% accuracy, 97.16% precision, and 97.18% recall using an 80:20 dataset split, demonstrating superior performance over traditional models.	The model's performance may vary with complex environmental conditions and image noise. Further improvements are required for real-time pest detection in diverse agricultural setti ngs.
27	Temitope Dada et al. (2025) - proposed an IoT-enabled system for plant growth prediction and health monitoring using sensor fusion and machine learning techniques. The system addresses the challenge of inaccurate manual observations in traditional farming practices.	Random Forest Classifier for plant growth prediction and Support Vector Machine (SVM) for detecting potential health problems.	The system achieved approximately 92.5% accuracy for plant growth prediction and 95.2% accuracy for detecting plant health issues. The system effectively optimizes crop yields while reducing resource consumption and environmental impact.	The system requires a larger dataset with diverse plant types and environmental conditions for improved accuracy. Additional field trials and improved sensor calibration are necessary for practical deploy ment.
28	Kumar et al. (2024) - introduced a deep learning framework for crop disease identification using hyperspectral imaging data. The framework enhances early detection of crop infections, supporting precision agriculture.	Convolutional Neural Network (CNN), ResNet50.	Achieved 92% accuracy in classifying common crop diseases, including rust, blight, and mildew.	The model’s performance decreases in low-light conditions, and requires high computational resources for real- time analysis.

29	Rao et al. (2023) - introduced a machine learning framework for soil texture classification using multispectral satellite data. The framework enhances soil texture prediction accuracy in agricultural regions by combining spectral and spatial features.	Random Forest, Support Vector Machine (SVM).	Achieved 91% accuracy in distinguishing sandy, loamy, and clayey soils across diverse terrains.	Model performance is sensitive to cloud cover interference in satellite data, reducing prediction reliability in heavily overcast conditi ons.
30	Wang et al. (2025) - introduced a deep learning-based approach for detecting leaf diseases in Hemerocallis fulva. The study focuses on improving detection accuracy using multi-scale feature extraction and dynamic sampling to enhance precision in complex environments.	Hemerocallis fulva Multi-Scale and Enhanced Network (HF-MSENet), YOLOv8 (Baseline), Channel–Spatial Multi-Scale Module (CSMSM), C3_EMSCP Module, DySample Module.	HF-MSENet achieved mAP@50 = 94.9% and mAP@50–95 = 80.3%, outperforming the baseline YOLOv8 by 1.8% and 6.5%, respectively.	Performance may vary in highly complex backgrounds, and computational efficiency improvements are needed for real-time application s
31	Yin et al. (2025) - introduced a deep learning-based approach using hyperspectral imaging for the rapid identification of rice seed blast. The study aims to enhance accuracy and efficiency in detecting infected seeds to support rice germplasm management.	UeAMNet (Unsupervised Extraction Attention-Based Mixed CNN), 2DCNN, 3DCNN, A2DCNN, A3DCNN, Ue2DCNN, Ue3DCNN, UeA2DCNN, UeA3DCNN, MNet, AMNet, UeMNet.	UeAMNet achieved 100% accuracy with sufficient training data and 96.85% accuracy with only 5% of the training data, outperforming all comparison models.	Model performance depends on data quality and environmental conditions. Handling small datasets remains a challenge, and computational complexity can limit real-time application s

32	Hati & Singh (2023) - introduced a deep learning-based plant phenotyping model for analyzing plant traits in a hydroponic system. The study leverages AI and computer vision to improve plant monitoring and optimize growth in a soilless farming environment.	Deep Neural Network (DNN) based on YOLOv3 (You Only Look Once Version 3).	The model achieved above 95% detection accuracy for Calendula plants and demonstrated superior performance in identifying species, growth stages, and health conditions.	Performance depends on image quality and lighting conditions. The model struggles with detecting stressed plants and differentiating them from dead plants due to visual similaritie
33	Kanade et al. (2025) - introduced a deep learning-based approach for detecting Mungbean Yellow Mosaic Virus (MYMV) in soybean crops. The study leverages YOLOv8 object detection models to improve disease identification and support sustainable agricultural practices.	YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, YOLOv8x.	YOLOv8x achieved the highest precision (98.1%), while YOLOv8s demonstrated the best recall (78.6%), mAP@0.5 (85.3%), and F1-score (86.9%). YOLOv8n had the fastest inference time (3.6 ms).	Model performance depends on image quality and environmental conditions. Real-world implementation is constrained by the need for large datasets and computational r esources.
34	Wang et al. (2025) - introduced a deep learning-based model, Maize-Rust, for identifying common and southern maize rust diseases. The study aims to enhance accuracy and efficiency in detecting maize rust to improve crop management.	Maize-Rust (based on YOLOv8s), Faster-RCNN, SSD.	Maize-Rust achieved an accuracy of 94.6%, an average accuracy of 91.6%, a recall rate of 85.4%, and an F1-score of 0.823. It outperformed Faster-RCNN and SSD by 16.35% and 12.49%, respectively, and detected a single rust image at 16.18 frames per second.	Performance is affected by complex field environments and subtle phenotypic changes in early rust stages. The model struggles with distinguishing between early rust symptoms and healthy leav es.

35	Choong & Hong (2025) - introduced an improved convolutional neural network (CNN) for detecting and diagnosing plant diseases across multiple crop species. The study aims to enhance accuracy while being lightweight enough to function on mobile devices.	Custom Convolutional Neural Network (CNN), VGG16, MobileNetV2.	The proposed CNN achieved an accuracy of 96.87% after 100 training epochs, outperforming standard architectures like VGG16 and MobileNetV2.	The model's performance is limited by external factors such as noise in the dataset and environmental conditions. High-resolution datasets are required to avoid overfitting .
36	Saha et al. (2025) - introduced a lightweight Convolutional Neural Network (CNN) for detecting potato leaf diseases, including Early Blight, Late Blight, and Healthy leaves. The study aims to enhance accuracy while reducing computational complexity.	Custom Convolutional Neural Network (CNN), VGG16, Inception V3, ResNet50.	The proposed CNN model achieved an accuracy of 99.3% on the PlantVillage dataset and 99.23% on the PLD dataset, outperforming other models.	The model's performance is influenced by the quality of the datasets and the variability of symptoms across regions and clim ates.
37	Das et al. (2025) - introduced XLTLDisNet, a novel and lightweight deep learning model for detecting tomato leaf diseases. The study aims to improve classification accuracy while enhancing transparency through explainable AI techniques.	XLTLDisNet (Custom CNN), AlexNet, XceptionNet, VGG16, VGG19, DenseNet121	XLTLDisNet achieved an overall accuracy of 97.24%, with precision of 97.20%, recall of 96.70%, and an F1-score of 97.10%. It outperformed other models while maintaining fewer trainable parameters (4.6 million).	Class imbalance in the dataset affected performance, especially for less represented classes like Mosaic Virus. Additionally, shadows and background noise in images led to occasional misclassification s.

38	Chen & Liu (2025) - introduced CBSNet, a deep learning-based method for classifying potato leaf diseases. The study aims to improve recognition accuracy by handling tiny spots, blurred edges, and noise interference in images.	Channel Reconstruction Multi-Scale Convolution (CRMC), Spatial Triple Attention (STA), Bat–Lion Algorithm (BLA).	CBSNet achieved an average accuracy of 92.04% and a precision of 91.58% on a self-built potato disease dataset, effectively extracting subtle spots and blurry edges.	Model performance is affected by noise and variations in image acquisition environments. The generalization ability for different crop diseases needs further verificati on.
39	Aboelenin et al. (2025) - introduced a hybrid deep learning framework that combines Convolutional Neural Networks (CNNs) and Vision Transformers (ViT) for plant leaf disease detection and classification. The goal is to leverage CNNs for feature extraction and ViT for enhanced accuracy in multi-class disease classification.	VGG16, Inception-V3, DenseNet201 (CNN models), and Vision Transformer (ViT	The hybrid model achieved 99.24% accuracy on the apple leaf dataset and 98% on the corn leaf dataset, outperforming individual CNN models and other state-of-the-art approaches.	The model requires high computational power and large datasets for training. Additionally, the high similarity between disease patterns and the emergence of new diseases due to climate change pose challenges.
40	The study proposes a hybrid deep learning approach for crop disease classification. It leverages a Dirichlet weighted ensemble technique, transfer learning-based CNN models, and SHAP-based interpretability to enhance accuracy and transparency.	InceptionV3, Xception, NASNetMobile (combined through a Dirichlet weighted ensemble and stacking meta-ensemble with CatBoost).	The best-performing ensemble model achieved a weighted F1-Score, Precision, and Recall of 99.52% and an overall ROC AUC of 1.000.	Model performance is influenced by class imbalance and the need for high-quality, diverse datasets from both real-world field conditions and controlled envir onments.

1. **Precision diagnosis of tomato diseases for sustainable agriculture through deep learning approach with hybrid data augmentation**

The precise diagnosis of tomato illnesses by hybrid data augmentation and deep learning is the main emphasis of this study. By using the PlantDoc dataset and YOLOv8n, the study overcomes the shortcomings of conventional disease identification techniques and the lack of real-world data. To improve the dataset, a hybrid data augmentation technique was implemented, which greatly increased the accuracy and resilience of the model. The efficacy of the YOLOv8n model in identifying seven distinct tomato illnesses and healthy plant leaves was demonstrated by its 96.5% mAP, 97% precision, 93.8% recall, and 95% F1 score. The study emphasizes how AI-powered precision farming may contribute to sustainable agriculture.

Future work can focuses on, Extension to Other Crops: To further investigate the YOLOv8n model's adaptability and enable its use in a variety of agricultural contexts, it should be trained on datasets pertaining to other crops.

Development of Cloud-Based Platforms: Establishing a cloud-based platform that enables farmers to submit crop photos for examination and obtain real-time disease diagnosis and management advice.

2. **TomConv: An Improved CNN Model for Diagnosis of Diseases in Tomato Plant Leaves**

This paper introduces "TomConv," a novel Convolutional Neural Network (CNN) model designed for the diagnosis of diseases in tomato plant leaves. The study utilizes the PlantVillage dataset, comprising over 16,000 images of both healthy and diseased tomato leaves, categorized into 10 distinct classes. The proposed TomConv model is a relatively simple architecture, consisting of four convolutional layers followed by max pooling, and achieves an accuracy of 98.19% after training for 105 epochs. The authors emphasize the model's simplicity compared to existing state-of-the-art models and demonstrate its performance against other approaches, highlighting its effectiveness in classifying tomato leaf diseases.

Future work can focuses on, Testing in an Uncontrolled Environment: The model was trained and evaluated in a controlled setting. Future research should concentrate on evaluating and enhancing the model's functionality in uncontrolled, real-world settings with different backgrounds, lighting conditions, and image quality. Extension to Other Plant Parts: Only leaf diseases are the subject of the current model. The model's ability to identify illnesses in the tomato plant's roots, stems, and blooms may be extended in future studies. Integration of

Explainable AI (XAI): utilizing XAI approaches to increase farmers' trust and usability by offering insights into the model's decision-making process.

3. Enhancing paddy leaf disease diagnosis -a hybrid CNN model using simulated thermal imaging

This research introduces a groundbreaking hybrid deep learning model designed to revolutionize rice leaf disease diagnosis. By ingeniously integrating simulated thermal imaging with a hybridized Convolutional Neural Network (CNN), specifically a Darknet53 backbone enhanced with a Support Vector Machine (SVM) classifier, the model achieves unprecedented accuracy in early disease detection. Traditional methods often rely on visible symptoms, leading to delayed intervention and significant yield losses. However, this innovative approach leverages thermal imaging to capture subtle temperature variations indicative of stress, effectively detecting diseases before they become visually apparent. The rigorous evaluation of eighteen CNN models, followed by statistical validation using Duncan’s Multiple Range Test (DMRT), confirmed Darknet53 as the superior performer, achieving 95.79% accuracy. Further hybridization with SVM significantly boosted performance, reaching an impressive 99.43% accuracy, 99.43% sensitivity, 99.81% specificity, and an F1 score of 0.99. This model's exceptional capabilities pave the way for real-time agricultural applications, offering an efficient and reliable solution for small-scale farmers and highlighting the transformative potential of combining thermal imaging with advanced deep learning techniques in sustainable crop disease management.

4. An ensemble of deep learning architectures for accurate plant disease classification

In order to improve the classification accuracy of plant leaf diseases, this study presents an ensemble of deep learning architectures (DenseNet201, EfficientNetB0, InceptionResNetV2, and EfficientNetB3). In order to solve the imbalanced dataset, the researchers also used a class-weighted data balancing method and suggested a novel image-processing strategy that combined CLAHE with an adaptive median filter. The PlantVillage dataset, which consists of over 87,000 RGB photos in 38 classifications, was used to train and evaluate the models. With an accuracy of 99.89%, the ensemble model outperformed both individual models and cutting-edge techniques. Transfer learning, ensemble learning, and a thorough performance evaluation utilizing metrics like as accuracy, precision, recall, and F1-score were all part of the process.

Future work can focuses on, Development of user-friendly interfaces: Making the diagnostic instruments easy to use for farmers through the creation of intuitive interfaces. Additional research on the interpretability of the model: using methods to comprehend and see the characteristics that the model classifies.

5. **Towards high throughput in-field detection and quantification of wheat foliar diseases using deep learning**

The paper presents a deep learning-based method for detecting and quantifying wheat foliar diseases, specifically Septoria tritici blotch (STB) and leaf rust, in field conditions. The authors created a dataset (Eschikon Foliar Disease - EFD) of high-resolution images of wheat leaves with detailed annotations for leaves, lesions, insect damage, pycnidia, and rust pustules. They then trained deep learning models (SegFormer for semantic segmentation and YOLOv8-pose for keypoint detection) to automate the detection and quantification of these disease symptoms.

6. **A comprehensive review on detection of plant disease using machine learning and deep learning approaches**

A thorough analysis of plant disease detection utilizing machine learning and deep learning techniques is presented in this research. The study highlights how crucial early and precise disease detection is to sustainable farming practices and higher crop yields. In addition to deep learning approaches like CNN, Inception-V4, and VGG variations, the authors cover a variety of machine learning techniques, such as Naive Bayes, KNN, Decision Tree, SVM, Random Forest, and MLP. A comparison of different methods is shown in the article, emphasizing how well deep learning models identify plant diseases from photographed data.

Future work can focuses on, Multi-modal Data Fusion: Investigate combining data from several sources, including weather, sensor, and picture data, to increase the precision and resilience of disease detection models.

Research on New Diseases and Pathogens: To help build efficient management strategies, apply deep learning to detect and categorize novel or emerging plant diseases and pathogens.

7. **DeepCrop: Deep learning-based crop disease prediction with web application**

The goal of this project is to create DeepCrop, a deep learning-based crop disease prediction system that also includes a web application to help farmers detect and control crop illnesses. The study uses a 10,000-image plant-village dataset to assess the effectiveness of CNN, VGG-16, VGG-19, and ResNet-50 models. With a 98.98% accuracy rate, ResNet-50 performs better than other models and is selected for web application development. By giving farmers an easy-to-use tool for early disease identification and initial treatment recommendations, the DeepCrop online application hopes to support resource conservation and financial stability in the agriculture industry.

Future work can focuses on, Extension to other crops and diseases: The DeepCrop system can be extended to encompass a greater variety of crops and diseases, increasing its adaptability and suitability for a range of agricultural environments.

Real-time disease monitoring and detection: By incorporating real-time image analysis capabilities, crop diseases can be immediately detected in the field and continuously monitored.

Multi Modal Fusion : In order to increase the precision and resilience of disease prediction, multi-modal data fusion involves combining information from multiple sources, including weather data, soil sensors, and drone footage.

8. Identification of soybean planting gaps using machine learning

This study explores the effectiveness of machine learning in identifying soybean planting gaps using UAV imagery, a crucial aspect of precision agriculture. Traditionally, manual scouting for these gaps is inefficient and imprecise. This research compares three machine learning algorithms: Decision Trees, Support Vector Machines (SVM), and Multilayer Perceptron (MLP) Neural Networks, to automate and improve this process during the V4 growth stage of soybeans.

The results highlight the superior performance of Neural Networks and SVM over Decision Trees. The Neural Network model achieved an AUC of 0.984 and an accuracy of 94.5%, demonstrating its ability to accurately classify planting gaps. Similarly, the SVM model with a Polynomial kernel showed even better results, with an AUC of 0.989 and an accuracy of 95.5%. In contrast, the Decision Tree model performed significantly lower, with an AUC of 0.805 and an accuracy of 79%.

These findings demonstrate the potential of advanced machine learning techniques to enhance crop management. By accurately identifying planting gaps, farmers can make more informed decisions regarding replanting or adjusting input applications, ultimately optimizing crop yield. The study also underscores the importance of parameter optimization in machine learning, as the careful tuning of each algorithm significantly impacted its performance. Overall, this research contributes to the advancement of precision agriculture by providing a more efficient and reliable method for identifying planting gaps in soybean fields.

9. Machine Learning Approaches for Detecting Vine Diseases: A Comparative Analysis

In this study effectively establishes the critical context for automated vine leaf disease detection by highlighting the significant challenges posed by diseases like Grapevine Red Blotch Virus (GRBV) and powdery mildew. Traditional diagnostic methods, reliant on expert observation, are shown to be inadequate for large-scale, timely interventions, prompting the exploration of advanced technological solutions. The survey underscores the emergence of innovative techniques such as LAMP and CRISPR Cas12a probes for rapid GRBV detection, as well as multispectral imaging for early powdery mildew identification, illustrating the growing potential of technology in agricultural diagnostics. Furthermore, it emphasizes the economic and quality-related impacts of these diseases on grape production, reinforcing the necessity for accurate and efficient detection to maintain yield and quality. By advocating for sustainable agricultural practices through the development of disease-resistant varieties and precision agriculture, the survey effectively justifies the study's focus on Convolutional Neural Networks (CNNs) as a promising tool for automated and efficient vine leaf disease classification.

10. Efficient model for cotton plant health monitoring via YOLO- based disease prediction

This paper focuses on developing an efficient model for cotton plant health monitoring using deep learning, specifically the YOLO object detection algorithm and EfficientNet architectures. The authors highlight the importance of early disease detection in cotton plants to prevent yield loss and ensure food security. They discuss the evolution of agriculture, from traditional methods to the integration of AI and smart devices in Agriculture 4.0, emphasizing the role of technology in addressing challenges like plant diseases and climate change. This covers various aspects of plant disease detection using machine learning and deep learning techniques. It examines previous studies on tomato and rice disease identification, highlighting the challenges of applying lab-developed models to real-world images and the need for accurate disease severity assessment. The authors also discuss the advantages of deep learning in feature extraction and complex problem-solving, as well as its application in object segmentation and analysis. The research also mentions previous research reaching accuracies of 96.4% using CNNs on cotton leaf disease, and other research using other architectures reaching accuracies of 98.7% and 99%. The paper then goes on to show that their model reaches 100% accuracy for healthy leaf and powdery mildew classes using EfficientNetB4, and achieves precision, recall and mAP scores of 96%, 98.3%, and 99.2% respectively, using YOLOv4.

The paper identifies gaps and challenges in current deep learning models for cotton disease prediction, such as limited access to large and diverse datasets, model interpretability, and the need for transparency to encourage adoption by farmers. It emphasizes the importance of addressing these challenges to improve the accuracy, efficiency, and practicality of deep learning models for real-world agricultural applications.

11. Automated System for Detecting, Identifying, and Preventing Cotton Leaf and Boll Diseases Using Deep Learning

This study aims to create an automated system that detects, identifies, and prevents diseases in cotton leaves and bolls through deep learning and IoT integration. The research overcomes the shortcomings of earlier studies that mainly concentrated on leaf diseases by including boll diseases in the evaluation. A tailored dataset of 7289 images, featuring both healthy and unhealthy leaves and bolls, was developed. Deep learning models (VGG16, InceptionV3, and a custom model) were utilized to assess the accuracy of disease identification and the detection of infection levels. The customized model attained high precision, similar to pre-trained models. The suggested decision system, which integrates IoT and relies on perception, facilitates early disease identification and applies preventive strategies, with the goal of enhancing crop productivity and reducing financial losses.

12. Empowering Agricultural Insights: RiceLeafBD - A Novel Dataset and Optimal Model Selection for Rice Leaf Disease Diagnosis through Transfer Learning Technique

The study addresses the critical issue of rice yield reduction due to diseases, especially in agricultural countries like Bangladesh. It highlights the limitations of existing datasets and proposes a new dataset, RiceLeafBD, collected from Bangladeshi fields. The paper then evaluates the performance of a light CNN model and pre-trained models (InceptionNet-V2, EfficientNet-V2, and MobileNet-V2) using this dataset. EfficientNet-V2 achieved the highest accuracy of 91.5%. The study emphasizes the significance of the RiceLeafBD dataset for future research in this area.This study sets itself apart by developing a new dataset that is locally sourced, tackling a critical limitation found in earlier research.

In contrast to the other papers, this one strongly focuses on the dataset and its significance.

Similar to the other papers, this study also employs CNNs and transfer learning.

13. **A Multi-Scale Feature Extraction and Fusion Deep Learning Method for Classification of Wheat Diseases**

The research suggests a technique that merges multi-scale feature extraction with superior image segmentation methods to enhance the precision of wheat disease classification. The authors employ deep learning frameworks (Xception, Inception V3, and ResNet 50) along with ensemble machine vision classifiers (voting and stacking) on a substantial wheat disease classification dataset (LWDCD2020). The suggested technique reached an impressive accuracy of 99.75%, with the Xception model showing the highest effectiveness. This research stands out by integrating deep learning with conventional machine vision methods while employing a multi-scale feature extraction strategy.

This study additionally employs a substantial dataset.

This study, by employing feature extraction and fusion, attained a remarkably high accuracy relative to the other studies.

14. **Title: A Multi-Scale Feature Extraction and Fusion Deep Learning Method for Classification of Wheat Diseases**

This paper presents a deep learning-based approach for classifying wheat diseases using multi-scale feature extraction and fusion techniques. A convolutional neural network (CNN) is employed for feature extraction, and a fusion strategy is introduced to combine multi-scale features, enhancing the model's ability to capture detailed patterns. The model outperforms traditional CNN models in terms of classification accuracy, demonstrating significant improvements in precision and recall.

Future work could focus on extending the model to classify a broader range of crop diseases and improving real-time performance for practical field deployment. Enhancing the feature fusion strategy and increasing the model’s generalization capability could further improve accuracy and adaptability.

15. **Title: Enhanced Detection of Bean Leaf Diseases Using a Stacked CNN Ensemble with Transfer Learning**

The paper proposes a stacked CNN ensemble combined with transfer learning to improve the detection of bean leaf diseases. The ensemble approach leverages the strengths of multiple CNN models to enhance feature extraction and classification accuracy. Transfer learning allows the model to benefit from pre-trained networks, reducing training time and improving performance on smaller datasets. The results show that the proposed model outperforms traditional CNN-based approaches, achieving higher accuracy and better generalization.

Future work can focus on expanding the dataset to include more disease variants and testing the model's real-time efficiency in field conditions. Further optimization of the ensemble strategy and integrating additional preprocessing steps could enhance model robustness and adaptability.

16. Title: A Model for Detecting Xanthomonas campestris Using Machine Learning Techniques Enhanced by Optimization Algorithms

This paper presents a machine learning-based model for detecting Xanthomonas campestris, a plant pathogen. The model uses supervised learning algorithms like Support Vector Machines (SVM) and Decision Trees, enhanced by optimization algorithms to improve accuracy. The optimization strategies help in selecting the most relevant features and fine-tuning the model parameters. The results demonstrate that the optimized model achieves higher classification accuracy and reduced false positives compared to traditional machine learning approaches.

Future work can explore real-time implementation and scalability to detect a wider range of plant diseases. Improving the computational efficiency of the optimization algorithms and incorporating additional environmental factors could further enhance performance.

17. Title: Research on a Potato Leaf Disease Diagnosis System Based on Deep Learning

This paper presents a deep learning-based system for diagnosing potato leaf diseases. The model uses a convolutional neural network (CNN) architecture trained on a dataset of potato leaf images. The system employs data augmentation techniques to increase the dataset size and improve model generalization. The proposed model achieves high accuracy and robustness in identifying different types of potato leaf diseases, outperforming traditional machine learning methods. The system also features a user-friendly interface for practical deployment.

Future work could involve extending the model to other crops and improving real-time diagnosis capabilities. Further refinement of the CNN architecture and incorporating multispectral imaging data could enhance classification accuracy and disease differentiation.

18. Title: Smart Agriculture Applications Using Deep Learning Technologies: A Survey

This paper surveys various deep learning applications in smart agriculture, focusing on crop health monitoring, yield prediction, and disease diagnosis. It highlights the use of CNNs, RNNs, and transfer learning models for image classification and sequence prediction tasks. The paper compares the performance of different deep learning techniques, showing that CNN-based models are particularly effective for plant disease recognition and RNNs excel in yield forecasting. The survey also discusses the limitations and challenges in deploying deep learning models in agricultural settings.

Future work can focus on developing lightweight models suitable for edge devices and improving the interpretability of predictions. Enhancing data collection methods and integrating satellite imagery and environmental data could further boost model accuracy and applicability.

19. **Title: The Lightweight Deep Learning Model in Sunflower Disease Identification: A Comparative Study**

This paper explores the development of a lightweight deep learning model for identifying sunflower diseases. The proposed model is based on a simplified CNN architecture that reduces computational complexity while maintaining high classification accuracy. The study compares the performance of the lightweight model with standard CNN models, demonstrating that the lightweight version achieves comparable accuracy with reduced training time and memory usage. The model is designed for deployment on edge devices, making it suitable for real-time agricultural applications.

Future research can focus on enhancing model robustness against environmental variations and extending the approach to other crop diseases. Integrating advanced data augmentation techniques and expanding the dataset could further improve accuracy and generalization.

20. **Title: Automated Tomato Disease Detection and Classification Using Image Processing and Machine Learning for Precision Agriculture**

This paper presents an automated system for detecting and classifying tomato diseases using image processing and machine learning techniques. The model combines feature extraction through image processing with classification using machine learning algorithms like Support Vector Machines (SVM) and Random Forest. The system achieved high accuracy in identifying different tomato diseases and demonstrated improved performance over traditional image classification methods. The paper also highlights the importance of using high-quality image data for better model performance.

Future work could focus on improving the system's ability to handle complex environmental conditions and introducing real-time detection capabilities. Enhancing the model’s adaptability to different tomato species and expanding the dataset could further improve accuracy and generalization.

21. Title: Efficient Deployment of Peanut Leaf Disease Detection Models on Edge AI Devices

This paper focuses on deploying peanut leaf disease detection models on edge AI devices. The model uses a lightweight CNN architecture optimized for low-power edge devices, enabling real-time disease detection. The authors employ model pruning and quantization techniques to reduce the model size and improve inference speed without compromising accuracy. The results demonstrate that the optimized model maintains high classification accuracy while significantly reducing latency and power consumption.

Future research could explore expanding the model to support other crop types and improve robustness under varying lighting and environmental conditions. Incorporating federated learning techniques could also enhance model adaptability and data privacy.

22. Title: Comprehensive Analysis of a YOLO-based Deep Learning Model for Cotton Plant Leaf Disease Detection

This paper presents a YOLO-based deep learning model for detecting cotton plant leaf diseases. The YOLO (You Only Look Once) model is designed for real-time object detection and classification, making it suitable for agricultural applications. The study shows that the YOLO-based model outperforms traditional CNN models in terms of speed and accuracy. The model's ability to detect multiple diseases simultaneously enhances its practical usability in field conditions.

Future work could focus on improving the model's adaptability to different lighting and environmental conditions. Expanding the dataset and incorporating multispectral imaging could further enhance detection accuracy and generalization.

23. Title: An Improved ShuffleNetV2 Method for Soybean Leaf Disease Detection

This paper presents an improved ShuffleNetV2-based deep learning model for detecting soybean leaf diseases. ShuffleNetV2 is a lightweight model optimized for fast and efficient inference, particularly suited for mobile and edge devices. The authors enhance the original

ShuffleNetV2 architecture by introducing additional feature extraction layers and attention mechanisms, leading to improved classification accuracy. The proposed model achieves high accuracy with low computational costs, making it suitable for real-time deployment in agricultural settings.

Future work could involve expanding the model to handle more complex environmental conditions and increasing the dataset size for better generalization. Integrating multispectral and hyperspectral imaging could also improve classification performance and disease differentiation.

24. Title: Advancing Precision Agriculture with Transformer-Based Models for Crop Disease Classification

This paper introduces a transformer-based deep learning model for crop disease classification. Transformers, originally used in natural language processing, are adapted to process crop image data through self-attention mechanisms. The model can capture complex spatial relationships within the images, leading to improved classification accuracy and robustness. The study demonstrates that the transformer-based model outperforms traditional CNNs, particularly in handling large datasets with diverse disease patterns.

Future work could focus on optimizing the transformer architecture for edge deployment and improving data augmentation techniques. Incorporating multimodal data, such as environmental and weather data, could enhance model performance and adaptability in real-world scenarios.

25. Title: Enhancing Plant Disease Detection Using a Hybrid CNN-Transformer Model

This paper proposes a hybrid CNN-Transformer model for plant disease detection. The CNN component extracts local features from crop images, while the transformer component captures long-range dependencies and contextual relationships. The combination of CNN and transformer mechanisms allows the model to handle complex image patterns and improve classification accuracy. Experimental results show that the hybrid model outperforms standalone CNN and transformer models, particularly in distinguishing visually similar diseases.

Future work could involve enhancing model scalability for large datasets and optimizing the architecture for real-time deployment on edge devices. Integrating environmental and soil data could further improve model robustness and prediction accuracy.

26. **Title: Plant Disease Detection Using Deep Learning**

This paper presents a deep learning-based model for detecting plant diseases using CNNs. The model is trained on a dataset of plant leaf images, where CNN layers extract complex features and classify different disease types. The study demonstrates that the CNN model achieves high accuracy and faster inference times compared to traditional machine learning models. The model also shows strong generalization capability across different plant species and environmental conditions.

Future work could focus on expanding the dataset to include more plant varieties and improving model adaptability to varying lighting conditions. Enhancing the model's edge compatibility for real-time detection in agricultural fields could further increase its practical usability.

27. **Title: A Smart Camera With Integrated Deep Learning Processing for Disease Detection in Open Field Crops**

This paper introduces a smart camera system integrated with deep learning models for detecting diseases in grape, apple, and carrot crops. The system uses a CNN-based model optimized for edge processing, allowing real-time disease detection directly in the field. The smart camera processes high-resolution images and classifies diseases with high accuracy. The results show that the system achieves over 90% accuracy in identifying diseases, demonstrating the potential of combining deep learning and smart sensor technology for precision agriculture.

Future work could explore expanding the system to other crop types and improving its ability to operate under varying environmental conditions. Enhancing the camera's resolution and incorporating multispectral data could further improve disease classification accuracy.

28. **Title: Plant Disease Detection using Deep Learning**

This paper discusses the use of deep learning to detect plant diseases like downy mildew, apple scab, and Alternaria leaf blight in grapes, apples, and carrots. A smart camera integrated with a YOLOv5 model is used for real-time disease detection. The system is part of an Integrated Pest Management (IPM) setup, aiming to reduce pesticide use. The model was tested in both lab (closed-set) and field (open-set) environments, showing better accuracy under controlled lab conditions.

Future work could focus on improving real-time performance on commercial farms and enhancing the model's adaptability to different environmental conditions. Expanding the dataset, using multispectral imaging, and developing a user-friendly interface for farmers could further improve the system's effectiveness.

29. Title: Plant Disease Detection using Deep Learning (IRJET)

This paper presents a deep learning-based system for detecting plant diseases using the ResNet-34 model. The model is trained on the PlantVillage dataset and achieves 96.21% accuracy. A web app is developed for real-time diagnostics, helping farmers quickly identify diseases and improve crop yield. The system's high accuracy and fast response make it suitable for practical agricultural use.

Future work could involve creating a mobile app for field use and using drones for large-scale crop monitoring. Expanding the dataset, offering automated treatment recommendations, and improving model efficiency for faster deployment could enhance the system's effectiveness. Integrating the model with smart farming systems and ensuring multilingual support would increase accessibility and impact.

30. Title: Multi-Modal Deep Learning for Robust Tomato Leaf Disease Detection

This paper discusses a multi-modal deep learning model for detecting tomato leaf diseases such as Early Blight, Late Blight, and Tomato Mosaic Virus. The model combines CNNs, LSTMs, and SCNNs to analyze RGB images, achieving high classification accuracy. A user-friendly app is developed for real-time disease prediction, helping farmers monitor and manage crop health more effectively.

Future work could involve expanding the dataset to include more disease types and using multispectral imaging for better accuracy. Developing a mobile app, improving real-time performance, and integrating the model with IoT for automated monitoring could increase its practical value. Predicting disease progression using LSTMs and enhancing adaptability to different environmental conditions would further improve the system.

31. Title: LeafDNet: Transforming Leaf Disease Diagnosis Through Deep Transfer Learning

This paper introduces LeafDNet, a deep transfer learning model designed to detect diseases in roses, mangoes, and tomatoes. The model is based on the Xception architecture and improves accuracy through additional convolutional layers and regularization techniques. It achieves 98% accuracy, significantly outperforming traditional methods, and enables early disease detection, making it suitable for practical agricultural use.

Future work could focus on expanding the dataset to improve generalization across different plant species and environmental conditions. Integrating IoT and edge computing for real-time disease detection, optimizing the model for low-power devices, and ensuring fairness through Responsible AI (RAI) practices could enhance the system's effectiveness and accessibility.

32. Title: Image-Based Crop Disease Detection Using Machine Learning

This paper explores the use of machine learning (ML) for crop disease detection through image-based analysis. CNNs and transformer-based models are applied to identify diseases across various crops. Advanced imaging platforms such as UAVs, satellite sensors, and smartphones are used for data collection, improving the accuracy of disease identification. The system enhances early disease detection, supporting precision agriculture and improving food security.

Future work could focus on expanding the dataset to include more crop types and environmental variations. Enhancing real-time performance using IoT and edge computing, developing lightweight models for resource-limited areas, and improving interpretability with Explainable AI (XAI) would increase the system's efficiency and farmer trust.

33. Title: Plant Disease Detection and Classification by Deep Learning

This paper reviews the role of deep learning in detecting and classifying plant diseases. It highlights the advantages of deep learning over traditional image processing methods, such as automating feature extraction and improving accuracy. Techniques like CNNs, transfer learning, and hyperspectral imaging are discussed, showing how deep learning enhances efficiency in disease identification.

Future work could involve expanding datasets beyond lab-based images like PlantVillage and improving model robustness for real-world scenarios. Enhancing early detection using hyperspectral imaging and Explainable AI (XAI) and optimizing lightweight models for real-time deployment could make the system more practical for farmers.

34. Title: Plant Disease Detection Using Vision Transformers

This paper explores the use of vision transformers (ViTs) for plant disease detection. ViTs use self-attention mechanisms to capture detailed patterns in plant images, leading to accurate disease classification. The model was trained on a balanced dataset with 55 plant disease classes and achieved high accuracy, showing its potential for precision agriculture and sustainable farming.

Future work could focus on increasing dataset diversity to include more plant species and environmental conditions. Optimizing ViTs for faster processing and lower computational cost, integrating real-time detection using IoT, and developing hybrid models that combine CNNs and ViTs could further improve model performance and usability.

35. Title: Diagnosis of Anthracnose of Chili Pepper Using Convolutional Neural Networks-Based Deep Learning Models

This paper applies CNN models—MobileNet, ResNet50v2, and Xception—for diagnosing anthracnose in chili peppers. The dataset includes 4,455 images, and the study analyzes how dataset size affects model performance. MobileNet shows strong generalization even with fewer samples, highlighting the importance of transfer learning in improving classification accuracy.

Future work could involve expanding datasets to improve model robustness across different environmental conditions. Optimizing CNN architectures for better accuracy with limited data, integrating IoT and mobile apps for real-time detection, and using Explainable AI (XAI) to make predictions more transparent and trustworthy could further enhance the system's impact.

36. Title: Early Detection of Sugar Beet Cercospora Leaf Spot Disease Using Machine Learning-Assisted Thermal Image Processing Method

This paper applies machine learning-assisted thermal imaging to detect Cercospora Leaf Spot (CLS) disease in sugar beets. UAV-based thermal and multispectral imaging are used to analyze leaf temperature variations, enabling early disease detection before visible symptoms appear. KNN and SVM models are used, with multispectral imaging achieving higher accuracy than thermal imaging.

Future work could involve improving model accuracy by combining hyperspectral imaging and deep learning. Adjusting the model for varying climate conditions, developing real-time monitoring systems, and extending the method to other crops could broaden the model's agricultural impact.

37. Title: Development of a Handheld GPU-Assisted DSC-TransNet Model for the Real-Time Classification of Plant Leaf Disease Using Deep Learning Approach

This paper introduces DSC-TransNet, a hybrid deep learning model that combines VGG19 and transformer encoder blocks for real-time plant disease classification. The model is trained on grape, bell pepper, and tomato leaf datasets, achieving 99.97% accuracy. By using depthwise separable convolutions, the model improves computational efficiency while maintaining high accuracy, making it suitable for deployment on handheld GPU devices.

Future work could focus on increasing dataset diversity to cover more crop types and environmental conditions. Optimizing the model for low-power edge devices, integrating IoT for real-time monitoring, and using Explainable AI (XAI) to enhance transparency and farmer trust could further improve the model's impact.

38. Title: Optimized Sequential Model for Superior Classification of Plant Disease

This paper presents a sequential CNN model for plant disease classification, focusing on improving early detection and classification accuracy. The model is trained on mango and groundnut leaf datasets, achieving 96% accuracy. Through image preprocessing and augmentation, the model enhances feature extraction and outperforms conventional machine learning techniques.

Future work could involve expanding datasets to cover more plant species and environments. Optimizing CNN models for real-time deployment on mobile and IoT platforms, improving model interpretability using Explainable AI (XAI), and incorporating multimodal imaging like hyperspectral and thermal imaging could further enhance the model's performance.

39. Title: Enhanced Multiscale Plant Disease Detection with the PYOLO Model Innovations

This paper introduces PYOLO, a plant disease detection model based on YOLOv8n. It integrates advanced feature fusion techniques like BiFPN for multiscale feature fusion, EC2f for efficient feature extraction, and MHC2f for improved background perception. PYOLO outperforms YOLOv8n by 4.1% in mAP (mean Average Precision), demonstrating superior performance in plant disease detection.

Future work could focus on expanding datasets to improve model robustness across diverse crops and environmental conditions. Optimizing computational efficiency for low-power deployment, integrating IoT and cloud computing for real-time monitoring, and using Explainable AI (XAI) for better farmer trust and adoption could enhance the system's effectiveness.

40. Title: A Hybrid Deep Learning Approach for Cotton Plant Disease Detection Using BERT-ResNet-PSO

This paper introduces a hybrid deep learning model combining BERT for image segmentation, ResNet for feature extraction, and Particle Swarm Optimization (PSO) for parameter tuning. The model is trained on a PlantVillage extension dataset, achieving 98.5% accuracy. By combining transfer learning and optimization techniques, the model improves early disease detection and classification accuracy.

Future work could focus on expanding datasets to cover more environmental conditions and crop types. Optimizing the model for real-time deployment on edge devices, integrating multimodal data (e.g., hyperspectral and thermal imaging), and using Explainable AI (XAI) to enhance transparency and farmer trust could improve the system's practical impact.