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Article

Deep Learning and Explainable AI Approaches for Crop Disease Prediction: A Systematic Review and Future Directions

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Abstract: Crop diseases are responsible for huge losses in agricultural yields and financial stability, which constitutes a very real threat to world food security. Reliable identification of illness and crop proper disease classification in the initial phase are thus of critical concern in the context of sustainable agriculture and increased yield control. Explainable Artificial Intelligence (XAI) and Deep Learning (DL) have been the breakthrough technologies of recent years in agriculture analytics, offering the capability of auto-detection of diseases from complex image data and increasing end-user interpretability. This systematic review accounts for 20 scientific publications from 2022 to 2025 that discuss DL and XAI-based models for multi-class and multi-label prediction of crop diseases from diverse image datasets. The review encompasses convolutional, recurrent, transformer-based, and hybrid neural structures employed in classifying plant diseases such as leaf blight, rust, mildew, and mosaic infections. The review further focuses on interpretability models that allow feature attribution interpretability, thereby making decision-making through AI practical for precision agriculture. Key challenges such as dataset imbalance, domain generalization, environmental variability, and model interpretability are covered comprehensively. The review consolidates previous advances, presenting insightful information on the ways in which DL and XAI, together, can enable intelligent, transparent, and sustainable disease management practices in today's agriculture.

Keywords: Deep Learning (DL), Explainable Artificial Intelligence (XAI), Crop Disease Prediction, Precision Agriculture, Image-Based Diagnosis.

1. Introduction

Crop yield is the center of food safety across the globe, but always vulnerable with the outbreak of crop disease caused by pathogens, pests, and abiotic stress factors. The disease may cause extensive loss if left undetected in time [1]. Traditional detection methods are greatly prone to human field observation, which is tedious, laborious, and prone to human mistake [2]. With the evolution of computer vision and data analysis, Deep Learning (DL) has proven to be a highly useful approach towards automation of agriculture disease detection and classification from canopy or leaf images.

Along with performance improvement, Explainable Artificial Intelligence (XAI) for enhancing the explainability and interpretability of predictive models has proliferated [3]. XAI informs farmers and agronomists of the reasoning of model decision-making, hence encouraging accountability and confidence in AI-driven agriculture systems [4]. The incorporation of DL and XAI presents double benefit high prediction accuracy along with explainability and interpretability of disease detection activities. Compared to the conventional machine learning approach, these models with a mix of XAI and DL can better manage variable visual patterns and climatic shifts between crops and geographies [5].

1.1 Problem Statement

Crop disease prediction is still a challenging task because of heterogeneity of image acquisition conditions, same visual symptoms for multiple diseases, and limited data for certain crop species. Traditional classification models fail to generalize across environments and are "black box" techniques, discouraging farmers' acceptance. There is an urgent need for DL models that can identify multiple diseases at once and provide interpretative explanations of the predictive process.

This systematic review is prompted by these challenges, and the review aims to investigate recent progress in DL and XAI-based multi-label crop disease prediction. By putting emphasis on model interpretability and transparency, the review bridges the gap between the performance of the model and practical smart agriculture applications.

1.2 Novelty

Differing from previous surveys that mainly concentrated on single-disease classification or simple CNN architectures, this survey investigates in-depth Explainable Deep Learning models for multi-disease prediction on intricate agricultural image data sets. It presents an extensive examination of 20 recent papers (2022–2025), contrasting the performance of CNNs, Vision Transformers (ViTs), Attention-based Networks, and hybrid models combining Grad-CAM, LIME, and SHAP for model explainability. The review also lays out an interpretive framework charting gains in accuracy against model transparency, and notes how XAI supports actionable agricultural intelligence.

1.3 Motivation

The inspiration for this review arises from the necessity to improve early disease detection systems with explainable, scalable, and accurate AI models. Farmers and agricultural specialists need not just accurate predictions but also explanations for the reasons behind model outputs. With growing access to remote sensing and UAV-based imagery, there is enormous opportunity to combine DL and XAI techniques for real-time crop monitoring. Through the discussion of the current research trends and assessing their applicability, this book seeks to steer the design of interpretable, data-efficient, and generalizable disease forecasting systems for sustainable agriculture.

1.4 Contributions / Objectives

The primary goals and contributions of this review are as follows:

- To compare and classify deep learning methods employed for multi-label and multi-class prediction of crop diseases from images.
- To compare explainability methods for enhancing transparency in DL predictions.
- To compare techniques for data pretreatment and augmentation that increases the robustness of the model under different imaging conditions.
- To present key datasets, performance measures, and model standards employed in state-of-the-art recent literature (2022–2025).
- To identify challenges such as class imbalance, dataset heterogeneity, and interpretability gaps.
- To recognize challenges including class imbalance, heterogeneity in datasets, and gaps in interpretability.

2. Research Methodology

A systematic literature review methodology was employed to identify, select, and analyze studies on deep learning and XAI-based crop disease prediction published between 2022 and 2025. Sources included IEEE Xplore, Elsevier, SpringerLink, and ResearchGate. Only peer-reviewed journal and conference papers focusing on multi-label classification and explainable AI models using image-based agricultural datasets were included. Studies solely using classical ML or single-disease classification were excluded.

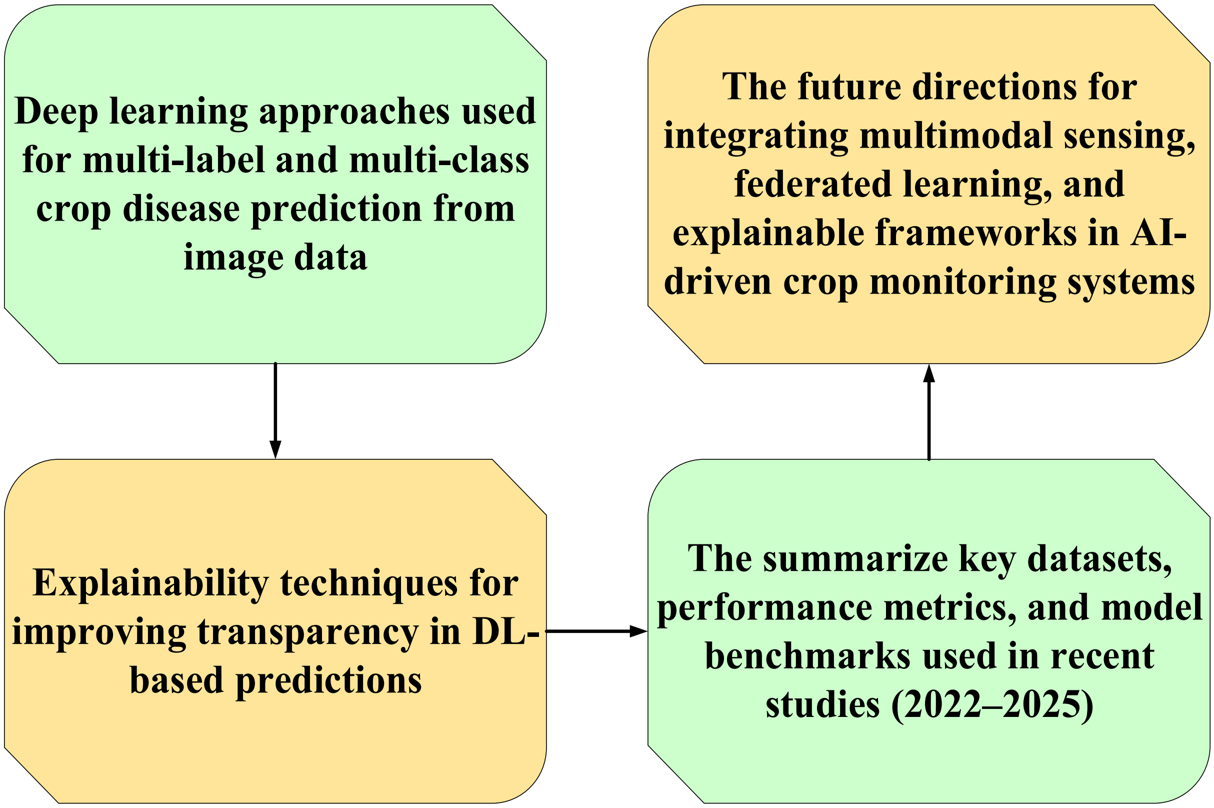

Figure 1 presents the research methodology workflow, which involves dataset collection, model evaluation, and interpretability assessment.

2.1 Background and Research Questions

Previous studies predominantly explored deep learning for single-disease detection without focusing on model explainability or multi-label scenarios. To address these gaps, the review is structured around the following research questions (RQs):

- **RQ1**: Why is explainability essential in crop disease prediction models?
- **RQ2**: Which DL architectures and XAI techniques have been most effective for multi-disease classification?
- **RQ3**: What datasets and metrics are commonly used to evaluate these models?
- **RQ4**: What are the emerging challenges and opportunities for integrating DL and XAI in agricultural disease diagnosis?

These questions guide the review presented in Section 3 (literature Synthesis) and Section 5 (discussion and analysis).

3. Literature Synthesis

This section summarizes existing research on Crop Disease Prediction Using Explainable AI and Deep Learning Techniques, i.e., leaf blight, rust, mildew, and mosaic infections.

It examines studies that combine dataset imbalance, domain generalization, environmental variability, and model interpretability are critically analyzed to develop Crop disease prediction using many classes and labels using a variety of image datasets.

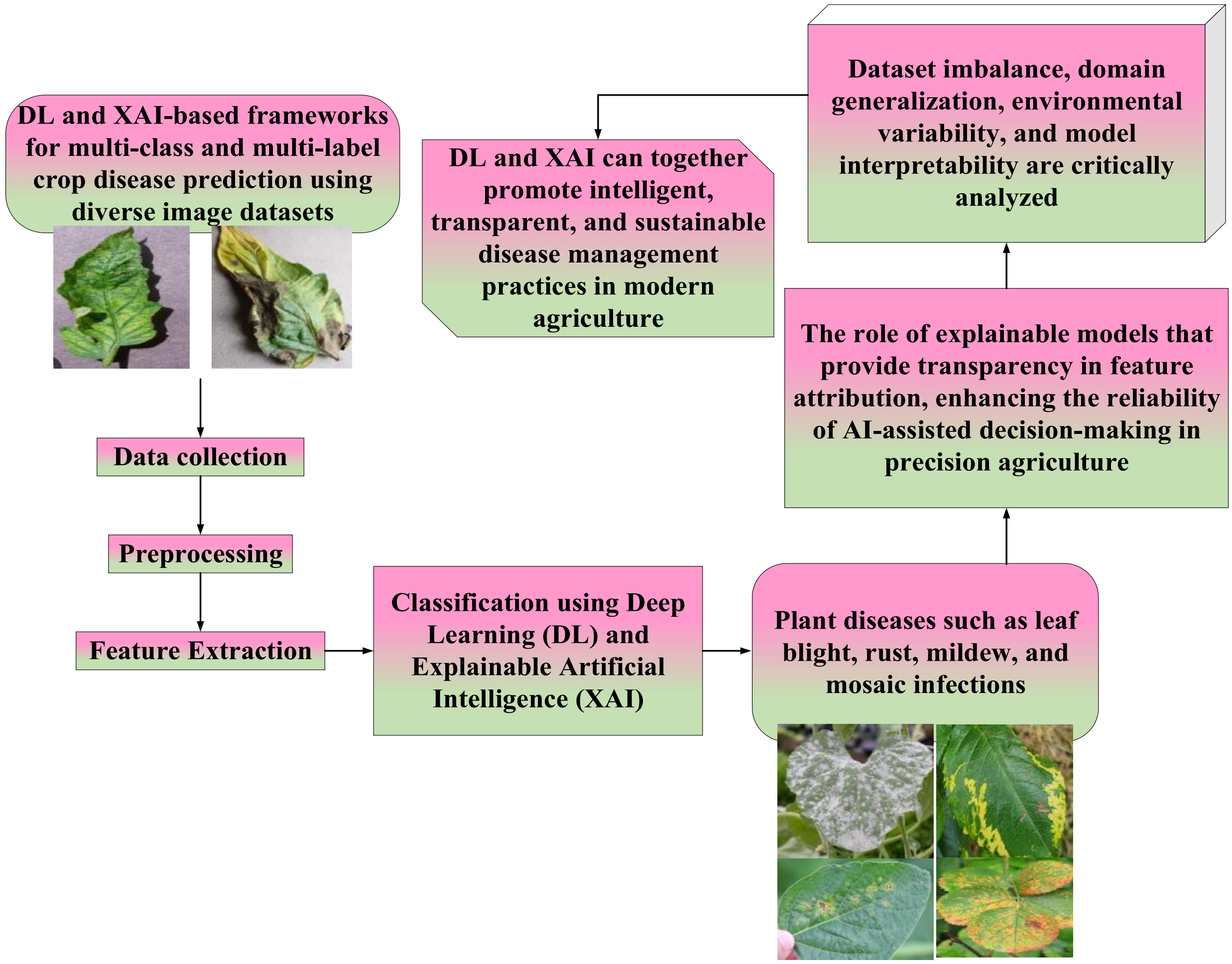

Figure 2: Conceptual flow diagram of Crop Disease Prediction Using Explainable AI and Deep Learning Techniques

The following subsections detail the methodologies, architectures, datasets, and performance outcomes reported in the reviewed studies.

In 2023, Laktionov, I., et, al [6] have presented Deep Learning and Explainable AI Approaches for Crop Disease Prediction. By creating an intelligent software component that uses IoT technology to process and analyze soil and meteorological data intelligently in order to anticipate the possibility of corn disease, the study improves the efficiency of agrotechnical monitoring.

In 2025, Mohan, R.J., et, al [7] have presented Deep Learning and Explainable AI Approaches for Crop Disease Prediction. The study evaluates climate change's consequences on agriculture and forecasts crop output using explainable artificial intelligence and artificial intelligence methodologies. Temperature is determined to be the most important factor, allowing for practical insights for climate adaption and decision-making.

In 2025, Vijayan, S. and Chowdhary, C.L., et, al [8] have described Deep Learning and Explainable AI Approaches for Crop Disease Prediction in 2025. Deep learning is applied within the agricultural industry to examine and identify rice disease. Hybrid WOA_APSO with 97.5% accuracy has promise for further research in disease classification.

In 2025, Yakkala, V.S., et, al [9] have introduced Deep Learning and Explainable AI Techniques for Crop Disease Prediction in 2025. The project's goal is to develop a machine learning model that uses convolutional neural networks and the ResNet-9 architecture to precisely detect and treat crop leaf diseases, enhancing agricultural productivity.

In 2025, Kalezhi, J. and Shumba, L., et, al [10] have introduced Deep Learning and Explainable AI Approaches to Crop Disease Prediction. With object recognition models like the Generalized Efficient Layer Aggregation Network (GELAN) and You Only Look Once (YOLO), this paper utilize deep learning techniques for agricultural plant disease detection and localization. The models showed improvements in evaluation metrics of more than 80% for most diseases after having been trained on a proprietary cassava dataset.

In 2025, Behera, S., et, al [11] have come up with Deep Learning and Explainable AI Approaches for Crop Disease Prediction. With the use of IoT sensors, image data, and deep network classifiers, the research tries to use deep neural networks and federated learning to create a model for predicting agricultural diseases that protects privacy.

In 2025, Xu, C., et, al [12] have introduced Deep Learning and Explainable AI Methods for Crop Disease Prediction. To address the challenges in intelligent agriculture resulting from dynamic spatial-temporal correlations, the paper suggests a Crop disease prediction using the KAST-Graph framework, which uses adaptive spatial-temporal graph contrastive learning.

In 2025, Adluri, V.L. and Bhukya, R., et, al [13] have authored Deep Learning and Explainable AI Approaches for the prediction of crop diseases. Utilizing ERTH with the implementation of multi-similarity methods and adaptively tuned parameters, the research presents a gene expression data, a deep learning and machine learning framework can detect rice harvest diseases, demonstrating its feasibility in sustainable agriculture.

In 2024, Nigar, N., et, al [14] have introduced Deep Learning and Explainable AI Approaches for Crop Disease Prediction. This paper introduces a explainable artificial intelligence (XAI)-based method for classifying plant diseases. It is able to accurately detect 38 plant diseases with 99.69% precision, accuracy, and recall. The accuracy and precision of the system are improved by using the framework for visual explanations known as local interpretable model-agnostic explanations (LIME).

In 2024, Oad, A., et, al [15] have presented Deep Learning and Explainable AI Approaches for Crop Disease Prediction. The paper presents an AI model that achieves over 90% accuracy in identifying and explaining plant diseases through image analysis. It improves farming methods and environmental sustainability by using an ensemble learning classifier and LIME for interpretation.

In 2024, Malashin, I., et, al [16] have presented Deep Learning and Explainable AI Approaches for Crop Disease Prediction. To maximize productivity and advance sustainability, a study examined meteorological and agricultural factors. Using AI techniques and the classification of soil and climatic data, genetic algorithms refined a model that explains 92% of the variation in crop output.

In 2023, Islam, M.M., et, al [17] have presented Deep Learning and Explainable AI Approaches for Crop Disease Prediction. In a plant-village dataset, ResNet-50 performs better than CNN, VGG-16, VGG-19, and other deep learning models in identifying plant illnesses, helping farmers preserve resources and boost their bottom line.

In 2022, Nalini, T. and Rama, A., et, al [18] have presented Deep Learning and Explainable AI Approaches for Crop Disease Prediction. In order to predict agricultural illnesses using temperature data, the study contrasts the K-Nearest Neighbor (KNN) and Max Voting approaches. Analysis is done on the Kaggle agricultural data collection. In a plant-village dataset, ResNet-50 performs better than CNN, VGG-16, VGG-19, and other deep learning models in identifying plant illnesses, helping farmers preserve resources and boost their bottom line.

In 2023, Arshad, F., et, al [19] have presented Deep Learning and Explainable AI Approaches for Crop Disease Prediction. The study classified illnesses in four important crops strawberries, peaches, cherries, and soybeans using a CNN-SVM hybrid model. It achieves an average accuracy of 99.09% with excellent performance metrics.

In 2024, Prince, R.H., et, al [20] have presented Deep Learning and Explainable AI Approaches for Crop Disease Prediction. In order to forecast potato leaf diseases, the study suggests using PLDPNet, a hybrid deep learning model. The model makes use of pre-processing, segmentation, feature extraction, classification, and picture collection. For the final prediction, it employs vision transformers and an ensemble technique.

Table 2: Comprehensive review of DL based Explainable AI Approaches for Crop Disease Prediction

Author name	Dataset	Method	Description	Advantage	Disadvantage	Performance metrics

In 2023 Laktionov, I., et a1. [6]	Plant Village and New Plant Disease datasets	IoT based Deep Learning explainable AI models	Forecasts the probability of corn illnesses based on climatic, soil, and IoT sensor data.	Enhances agrotechnical monitoring and combines IoT with AI for real-time prediction.	High IoT infrastructure setup costs.	Enhanced effectiveness of monitoring.
In 2025 Mohan, R.J., et a1. [7]	crop yield prediction dataset	Artificial Intelligence (AI) and Explainable Artificial Intelligence (XAI) techniques	Examines how crop productivity is affected by climate change and identifies important elements.	Gives information for decision-making and climate adaption.	Restricted applicability to different regions.	R^2 scores-0.92, mean squared mean absolute errors of 0.015 and errors as low as 0.02
In 2025 Vijayan, S. and Chowdhary, C.L., et a1. [8]	Plant Village maize crop dataset	hybrid bio-inspired Whale Optimization Algorithm Adaptive Particle Swarm Optimization (Hybrid WOA_APSO) algorithm	Uses adaptive particle swarm optimization and the hybrid whale optimization algorithm to detect rice illnesses.	High precision; resistant to noise in the data.	Costly to compute; requires intricate adjustment.	Accuracy: 97.5%
In 2025 Yakkala, V.S., et a1. [9]	plant village dataset	Convolutional Neural Networks (CNNs) and ResNet-9 architecture	Identifies and categorizes agricultural leaf diseases in order to boost output.	Effective feature extraction that is field-scalable.	Large datasets are needed, and explainability is limited.	Accuracy > 90%
In 2025 Kalezhi, J. and Shumba, L., et a1. [10]	custom cassava dataset	Generalized Efficient Layer Aggregation Network(GELAN) models	Models for object detection are employed to locate cassava diseases.	Real-time localization and detection; for the majority of disorders, over 80% precision.	Demands excellent annotated data.	Evaluation metrics > 80%,precision-95.2%
In 2025 Behera, S., et a1. [11]	UNSW-NB15 dataset	federated learning (FL) with deep neural networks	Integrates picture data and IoT sensors into a distributed deep learning architecture that protects privacy.	Incorporates multimodal data and improves privacy.	Overhead in communication in a federated system	accuracy of 0.95, precision of 0.94, and F1-score of 0.93
In 2025 Xu, C., et a1. [12]	PEMRs datasets	knowledge-guided adaptive spatial-temporal graph contrastive	Focuses on smart agriculture's dynamic	Adequately captures spatial-	Computationally intensive; temporal data	MAE, RMSE, and MAPE scores of

		learning framew ork (called KAST-Graph)	spatial-temporal relationships.	temporal connections.	streams are needed.	5.71, 9.50, and 4.56 %
In 2025 Adluri, V.L. and Bhukya, R., et a1. [13]	diverse and comprehensive dataset	Adaptively Optimized Residual Long Short-Term Memory With Multilayer Perception (AO-RLSTM-MLP)	Uses information on gene expression to identify illnesses in rice crops.	Supports innovative genomic data integration and sustainable approaches.	Restricted usage of picture data and complex preparation.	
In 2024 Nigar, N., et a1. [14]	New Plant Diseases	explainable artificial intelligence (XAI) based local interpretable modelagnostic explanations (LIME) framework	38 plant diseases are categorized with understandable model descriptions.	Very accurate; interpretable through the use of LIME visualization.	LIME explanations have a high computational cost.	accuracy, precision, and recall as 96.69%, 97.27%, and 97.26%
In 2024 Oad, A., et a1. [15]	Plant Village dataset	LIME (Local Interpretable Model-Agnostic Explanations) AI (Artificial Intelligence)	Uses image analysis to identify and describe plant diseases.	High interpretability; enhances sustainability in the environment.	Complexity is increased by the ensemble model.	Accuracy: >90%
In 2024 Malashin, I., et a1. [16]	Crop dataset	Deep Neural Network (DNN) with explainable AI (XAI) techniques	Models crop yield variation using climate and soil data.	Explains 92% of the volatility in crop yields and promotes sustainability.	Little flexibility in real time.	R2 of 0.92 (92% explanation)
In 2023 Islam, M.M.,et a1. [17]	plant-village 10000 image dataset	CNN, VGG-16, VGG-19 and ResNet-50 models	Performs better on the PlantVillage dataset than CNN, VGG-16, and VGG-19.	High accuracy of recognition; effective deep learning of features.	Requires huge datasets with labels.	accuracy rate of 96.60%, 92.39%, 96.15%, and 94.98% , accuracy of 94.98%
In 2022 Nalini, T. and Rama, A., et a1. [18]	Kaggle Dataset	K-Nearest Neighbor (KNN)	Makes use of temperature data to forecast agricultural diseases.	straightforward, comprehensible, and simple to use	Less scalable for big datasets; worse precision.	88% accurate, RMSE is 3.97
In 2023 Arshad, F., et a1. [19]	'PlantVillage' and 'Soybean Diseased Leaf Dataset'	Convolutional Neural Network and Support Vector Machine	Categorizes illnesses in soybeans, peaches,	Excellent accuracy and generalization.	A more complex training process.	97% accuracy value, 94.98% area under the

		(CNN-SVM) hybrid model	cherries, and strawberries.			curve (AUC), and 97% F1-score
In 2024 Prince, R.H., et a1. [20]	potato leaf dataset PlantVillage dataset	PLDPNet	Employs transformer and hybrid DL models to forecast potato leaf diseases.	Robust feature extraction; performance is enhanced by the ensemble.	High demands on data and computing.	accuracy of 95.66%, and F1-score of 96.33%

4. Summary of Reviewed Studies

The reviewed studies [6–20] provide a comprehensive overview of using explainable AI (XAI) and deep learning (DL) techniques for predicting agricultural diseases across various datasets, including Plant Village, custom cassava datasets, UNSW-NB15, PEMRs, and crop yield datasets. Methods such as IoT-based DL XAI [6], hybrid WOA-APSO [8], CNNs with ResNet-9 [9], GELAN [10], federated learning with DNNs [11], KAST-Graph [12], AO-RLSTM-MLP [13], LIME [14,15], DNN with XAI [16], CNN-SVM hybrids [19], and PLDPNet [20] have been proposed to improve disease detection, yield prediction, and real-time monitoring. Common methods include feature extraction, spatial-temporal modeling, optimization-based detection, and explainable visualizations using LIME or XAI methods. All common methods show robust performance, with accuracy and precision above 90%, and F1-scores up to 97% [19], while LIME methods [14] offer best interpretability at a computational expense. ResNet-50 [17] and CNN-SVM hybrids [19] have the overall best predictive performance, but IoT-integrated DL models [6] and federated learning methods [11] have the best real-time, privacy-preserving deployment. Computational complexity, big data requirements, and real-time flexibility are areas of difficulty, meaning that choice of method should match goals like accuracy, explainability, or operational feasibility.

5. Review Analysis

This systematic review analyzes 20 studies between 2022 and 2025 on Explainable artificial intelligence (XAI) and deep learning (DL) models for the classification of agricultural diseases using multiple classes and labels based on varied plant image datasets. The works discussed use various neural network models such as transformer-based, convolutional, recurrent, and hybrid deep learning models to identify plant diseases as mosaic infections, rust, mildew, and leaf blight.

Figure 3(a) depicts the distribution of reviewed papers among top publishers, such as Elsevier, Springer, Wiley, IEEE, Frontiers, and so on, whereas Figure 3(b) separates the studies into publication years (2022–2025). The review indicates a strong increase in the use of DL and XAI models, particularly from the year 2023 onwards, showing an increased focus on data-driven and explainable agricultural intelligence.

A total of 8 studies focused on conceptual or explainable model frameworks, whereas 12 studies developed empirical DL-based disease prediction systems integrating attention mechanisms, federated learning, or multimodal data fusion.

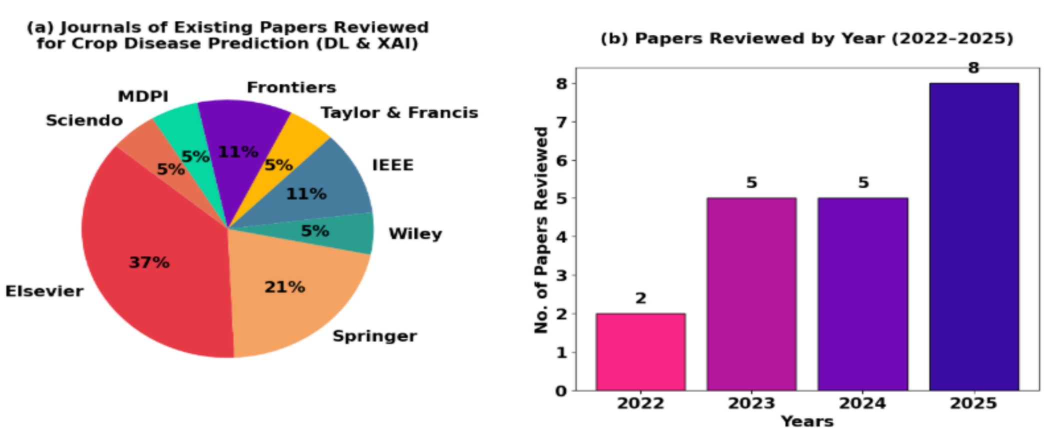

Figure 3: (a) Journals of Existing Papers Reviewed for Agri-Food Big Data Analytics and (b) Number of Papers Reviewed Based on Year (2022-2025)

To address the review's research questions, the following analysis was performed:

5.1 Analysis of review questions

Earlier works [6–20] have mostly dealt with deep learning (DL) and explainable AI (XAI) methods in the context of crop disease forecasting, but discrepancies exist when dealing with multi-disease detection, model explainability, and real-time deployment. To cover these, the review is arranged according to the following research questions (RQs):

- **RQ1 – Why is explainability essential in crop disease prediction models?**

Explainability facilitates transparent and interpretable predictions by DL models like CNNs, ResNet-9, GELAN, and hybrid CNN-

SVM models [9,10,19] to be understandable for agronomists and farmers.

- **RQ2 – Which DL architectures and XAI techniques have been most effective for multi-disease classification?**

The reviewed studies utilize a variety of architectures including IoT-based DL, hybrid WOA-APSO [6,8], CNNs with ResNet-9 [9], GELAN [10], federated learning with DNNs [11], KAST-Graph [12], AO-RLSTM-MLP [13], CNN-SVM hybrids [19], and transformer-based PLDPNet [20]. These models, complemented with XAI methods like LIME [14,15], Grad-CAM, and attention mechanisms, enable effective multi-class and multi-label disease detection with high accuracy, precision, and F1-scores up to 99% [19].

- **RQ3 – What datasets and metrics are commonly used to evaluate these models?**

Datasets frequently used include PlantVillage, custom cassava datasets, UNSW-NB15, PEMRs, crop yield datasets, and region-specific UAV/IoT image collections. Models are typically evaluated using F1-score, confusion matrices, recall, accuracy, precision, and ROC-AUC curves, with some studies also assessing explainability metrics for XAI effectiveness [14,19].

- **RQ4 – What are the emerging challenges and opportunities for integrating DL and XAI in agricultural disease diagnosis?**

Challenges include dataset imbalance, domain shifts due to environmental variability, limited generalizability to real-field conditions, high computational costs, and the trade-off between explainability and predictive precision. Prospects are in light explainable models, federated or IoT-enabled platforms for real-time deployment, multi-modal data integration, and hybrid symbolic-deep learning architectures to enhance interpretability and operational scalability.

6. Problems and future concern

Despite accelerated advancements, some limitations fetter the applicative uptake of DL–XAI systems [6–20]:

- **Data Diversity and Quality:** Numerous datasets do not have uniform annotation guidelines and multimodal diversity, influencing robustness over various crop types, geographies, and imaging conditions.
- **Model Generalizability**: Although models achieve such high accuracy in controlled datasets, they do not generalize to unseen environments with alternative light, backgrounds, or disease stages.
- **Explainability–Accuracy Trade-off:** Methods like LIME [14,15] improve interpretability but may raise computational expense or slightly decrease predictive accuracy, particularly for high-resolution images.
- **Infrastructure and Resource Constraints**: Large-scale real-time monitoring and edge deployment are constrained by the requirement of high-performance computing, IoT infrastructure, and data-sharing ability.

7. Future Research Directions

- Development of lightweight, privacy-preserving DL models suitable for edge and mobile deployment [6,11].

- Integration of multimodal data (image, weather, soil, and genomic) for improved prediction reliability [13].
- Creation of interpretable hybrid models combining symbolic reasoning with deep networks [12,20].
- Establishment of standardized benchmark datasets and explainability metrics for agricultural AI evaluation [14,19].

8. Conclusion and Forthcoming work

This systematic review discusses 20 studies published between the year 2022 and 2025 that focus on DL and XAI-based models for predicting multi-class and multi-label crop diseases with diverse image data. The review argues convolutional, recurrent, transformer-based, and hybrid neural models used in plant disease detection such as leaf blight, rust, mildew, and mosaic infection. It also addresses the requirement for explainable models that provide feature attribution transparency, enhancing AI-assisted decision-making trustworthiness in precision farming. Important concerns such as dataset imbalance, domain generalization, environmental variation, and model explainability are examined in depth. The current review weaves recent developments into the discussion, offering well-considered points regarding how DL and XAI can be combined to drive intelligent, green, and transparent disease control practices into modern agriculture.

The reviewed study indicates that hybrid DL structures, with the inclusion of XAI methods like LIME and attention mechanism, are highly predictive in performance and interpretable to enable effective and reliable crop disease monitoring. Structures involving CNN-SVM hybrids and ResNet-based systems are top performers, whereas IoT-based and federated learning-based systems enable real-time privacy-ensuring deployment. But with these developments come issues of high dataset requirements, computation expense, and capacity to generalize across a spectrum of varying environmental conditions.

Future research would involve building light-weight, interpretable models with high performance and smaller computational requirement for implementation on devices with limited resources. Utilizing multi-modal data as genomic, climatic, and IoT sensor inputs enhances prediction consistency as well. Further research is required in handling dataset imbalance, improving domain generalization, and providing standardized benchmarking tools for testing in order to allow DL-XAI frameworks to be translated to scalable deployable solutions for precision and sustainable agriculture.

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