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Exploration of machine learning approaches for automated crop disease detection

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ABSTRACT

In the era of frequently changing climatic conditions along with ever increasing world population, it becomes imperative to ensure food security. The burden of biotic stresses pose serious threat to crop productivity, therefore, early and accurate detection of plant diseases is essential. Conventional methods exclusively rely on human expertise, and are often labor-intensive, time-consuming, and prone to errors. Recent advancements in machine learning (ML) offer promising alternatives by automating the disease detection processes with high precision and efficiency. We comprehensively analyze various ML techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), Random Forest (RF), and Deep Learning Architectures like ResNet and Inception, among others, highlighting their methodologies, datasets, performance metrics, and real-world applications. This systematic review provides a comprehensive analysis after text mining the most recent literature resources of the last half a decade. The review discusses the proposed models, techniques, accuracy, feature selection, extraction methods, the types of datasets used to perform experiments, and the sources of the datasets. Additionally, this review provides critical analyses of existing models in the context of their limitations and gaps. Our findings suggest that while ML based methods demonstrate substantial potential for enhancing agricultural disease management, there is a urgent need for more robust, scalable, and adaptable solutions to address diverse agricultural conditions and disease complexities. By systematically analyzing the extracted data, this review aspires to provide a valuable resource for researchers and practitioners aiming to develop and implement ML-based systems for crop disease detection, thereby contributing to sustainable agriculture and enhancing food security.

1. Introduction

Agriculture is crucial for providing the basic needs of global population, but frequently changing climate and the unpredictable occurrence of different bacterial, fungal, and viral crop diseases affect the quality and quantity of the crop, which ultimately affects crop production and results in food insecurity [1–3]. Among cereal grains, wheat, rice, and maize constitute 80 % of global cereal production and provide over half of the world's caloric intake and are staple foods in many cultures [4,5]. Wheat is vital in temperate regions, while rice dominates Asian diets, and maize is crucial in the Americas and Africa. The global demand for cereal grains is continually rising due to population growth and dietary shifts. Wheat is the primary food source grown in diverse climates, from temperate to subtropical regions (major producing

Abbreviations: SVM, Support Vector Machines; CNN, Convolutional Neural Networks; RNN, Recurrent Neural Networks; ANN, Artificial Neural Networks; DMD, Dynamic Mode Decomposition; RTSV, Rice Tungro Spherical Virus; TBV, Rice Tungro bacilliform Virus; NSVMBPNN, Novel Support Vector Machine-Based Probabilistic Neural Network; YOLO, You Only Look Once; ResNet, Residual Networks; RF, Random Forest; DT, Decision Trees; SLR, Systematic literature Review SLR; DenseNet, Densely Convolution Neural Network.

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countries- China, India, Russia, and the United States). Different wheat diseases like rust, septoria, powdery mildew and Fusarium head blight are common, which significantly affect the production of wheat [6–8]. Rust caused by pathogenic fungi leads to orange or reddish-brown spots on the leaves, stems, and grains. Crop loss due to wheat rust is estimated at around 45–50 % and this significant loss severely impacts global wheat production, threatening food security and economic stability [9]. Wheat rust spreads rapidly, affecting large areas and leading to reduced yields and lower grain quality. Powdery mildew appears as a white or gray powdery substance on the leaves, and stems, which can reduce photosynthesis, leading to stunted growth and lower yields [10,11]. Fusarium head blight fungus impacting wheat leads to the development of shrivelled grains and a decline in overall grain quality [12]. In rice, Bacterial blight, Leaf blast, Brown spot, and Tungro are the most common diseases [13]. Bacterial blight, initiated by bacterial pathogens, manifests as the development of brown spots on the plant leaves and the eventual death of the affected areas [1]. Rice blast, attributed to the pathogen *Magnaporthe oryzae*, is a fungal disease that affects various plant parts, encompassing stems, leaves and panicles. Its rapid spread substantially threatens crop yield [14]. Brown spot disease is a type of fungal disease caused by the pathogen *Bipolaris oryzae*, characterized by the appearance of dark brown or black spots on the leaves of the plant. High humidity and frequent rainfall can facilitate the rapid growth of this disease [15]. Tungro disease, resulting from the presence of two viruses, namely Rice tungro spherical virus (RTSV) and rice tungro bacilliform virus (RTBV), is characterized by symptoms such as leaf yellowing and stunted growth [16]. Maize, also known as corn, is a globally significant cereal crop that serves as a staple food for many populations and can be used for various purposes, including human consumption, livestock feed, and industrial applications such as the production of maize syrup and biofuels [17]. Many diseases in the maize plant can affect its growth and productivity. In various regions of India, approximately 65 different diseases can be identified [18,19]. Leaf Blight, identified as a highly contagious fungal foliar disease, primarily causes a decrease in yield due to the substantial loss of photosynthetic leaf area [20]. Rust disease can initially be detected by observing small, light yellow dots, typically evident in the middle and upper sections of the leaves. As time progresses, these dots enlarge into round to oblong, yellowish-brown, or brown lesions, resulting in the adjacent epidermis curling upwards [21]. Maize leaf Cercospora leaf spot, also known as Grey leaf spot and maize mildew, represents a more severe disease. During the initial phases of the illness, noticeable light brown spots similar to water stains appear, stretching along the veins and often taking on a rectangular shape [21].

Ensuring sustainable production and addressing challenges like climate change, pests, and diseases are critical for meeting future dietary needs and maintaining food security worldwide. Advanced agricultural practices and innovations are essential to achieve this goal. Conventionaly, crop diseases can be identified through visual inspection, but early detection becomes difficult and can severely impact crop production in terms of quantity and quality [22]. The early detection of diseases is very important to protect the crop, so that artificial intelligence can help in the early and accurate detection of diseases [23]. Algorithms can process large volumes of data and identify patterns that human experts might not easily recognize. While traditional methods rely on manual observation and analysis, which can be subjective and prone to human error, machine learning-based systems provide consistent and reliable results. Machines can be trained by diverse datasets, making them adaptable to various environments and disease conditions. Machine learning (ML) and deep learning (DL) techniques have been used in the field of agriculture over the past decade and are very helpful in crop monitoring, disease detection and various other tasks [22–24]. This systematic review aims to examine different ML/DL models used for crop disease detection and to analyze them for their comparative efficacy and range of applications.

2. Machine learning techniques and models

Machine learning is a pivotal branch of artificial intelligence, focusing on creating and refining algorithms and statistical models. These tools imbue computers with the capacity to accomplish tasks autonomously without explicit programming directives [25]. Instead, the system learns patterns and makes predictions or decisions based on input data. Various types of machine learning aid in efficient model training [26]:

- **Supervised learning** is when the training dataset consists of input-output pairs, where each input is associated with a known output.
- **Unsupervised learning** aims to identify patterns, structures, or relationships within the data without prior guidance.
- **Reinforcement learning** represents a paradigm within artificial intelligence where an agent iteratively learns decision-making skills by interacting with an environment. Through this process, the agent receives feedback through rewards or penalties contingent upon its actions. This feedback mechanism lets the agent acquire optimal strategies through experience and exploration.
- **Semi-supervised learning** combines labelled and unlabelled data for training, which is particularly useful when obtaining labelled data is resource-intensive or expensive.
- **Transfer learning** leveraging knowledge from pre-trained models on one task to enhance performance on a related task is the essence of transfer learning. Pre-trained models are adapted for specific disease detection tasks in wheat, rice, and maize, have shown promising results in cases where labelled data may be limited. For example, when a computer learns something well (let's say, recognizing objects in pictures), it can use that knowledge to be good at something else.
- **Ensemble learning** combines multiple models to improve robustness and accuracy. Ensemble learning techniques, such as AdaBoost, Gradient Boosting, and Bagging, have been utilized to combine multiple models to improve overall prediction accuracy and robustness in disease detection applications.

Deep learning, a specialized branch of machine learning, emphasizes neural networks to mimic the intricate structure and functionality of the human brain [27]. These networks, comprised of layers of interconnected nodes, process and transform input data to generate meaningful outputs. This architectural depth empowers these models to extract progressively abstract and intricate features from the input data autonomously. Deep learning is advantageous for automatically extracting meaningful features from raw data for manual feature engineering [13,28,29]. Both machine and deep learning are applicable across various fields, attaining substantial success.

- **Convolutional Neural Networks (CNNs)**: CNNs are widely used for image classification tasks in plant disease detection. They are effective in learning spatial hierarchies and patterns within images, making them valuable for identifying visual symptoms of diseases in crops [21,30].
- **Recurrent Neural Networks (RNNs):** RNNs are useful for analyzing sequential data and have been applied in crop disease detection to capture temporal dependencies in developing plant diseases over time.
- **Support Vector Machines (SVMs):** SVMs are employed for classification tasks and have been used in crop disease detection to distinguish between healthy and infected plants based on extracted features from image data or other relevant data sources [31].
- **Random Forest (RF) and Decision Trees (DT):** RF and DT algorithms are popular for classification and regression tasks in agriculture. They have been used for disease detection in crops by creating decision rules based on input features derived from various data sources[32].

- **Deep Learning Architectures (e.g., ResNet, Inception, DenseNet):** Various deep learning architectures, such as Residual Networks (ResNet), Inception, and DenseNet, have demonstrated strong performance in crop disease detection tasks, particularly for their ability to handle complex patterns and large datasets [33].
- **Image Segmentation Algorithms:** Various image segmentation algorithms, including U-Net, Mask R-CNN, and FCN, have been used to identify and delineate specific regions or lesions associated with diseases within crop images [24].
- **Bayesian Networks and Probabilistic Graphical Models**: Bayesian and probabilistic graphical models have been applied to model complex relationships between various factors contributing to spreading and manifesting diseases in wheat, rice, and maize.

3. Data extraction, keyword analysis, and problem design

The text mining was done using an advanced search in the SCOPUS database with the help of the keywords "Artificial Intelligence OR Machine learning OR Deep learning AND Plant Disease AND Prediction OR Detection Models OR Mathematical models". In this keyword search, terms such as "Prediction" "Detection models" and "Mathematical models" were used to target the research studies specifically related to the development of predictive and detection models for plant diseases. The literature was retrieved within the time frame limitation of 2019–2023 to obtain the literature data of the last five years. Articles were filtered based on source type (journals, conference papers, and dissertations), document type (Academic articles and reviews), subject area (computer science), and language (English) that resulted in 2008 documents (Fig. 1).

Further, 565 articles were screened for further analyses based on their title and abstracts. The crop disease-related papers were selected for further analysis based on the assessment of the full-text article. Finally, A total of 30 articles were analyzed in this study. The evolution of publications in crop disease detection models is shown in (Fig. 2A). Out of these articles, The analysis also reflected that about 63 %, 26 %, and 10 % of selected articles belonged to rice, corn and wheat, respectively (Fig. 2B). The VOSviewer tool (https://www.vosviewer.com/) was used to construct and visualize bibliometric networks. This tool helps to represent the data through network, overlay and density visualization [34]. The analysis revealed the formation of seven distinct clusters, distinguished by colours such as red, blue, green, purple, sky blue, orange, and yellow. Notably, the central node 'disease' emerged as the most prominent, interconnected node linked to terms like 'plant,' 'crop,' 'detection,' and 'model,' suggesting their significance in the field (Fig. 3). Additionally, the study identified 79 keywords demonstrating significant co-occurrence, each occurring at least thrice, highlighting key concepts' inter-connectedness. This analysis aided us in navigating the complex research domains and underscored the prevalence of artificial intelligence techniques, particularly convolutional neural networks, in disease detection research. Moreover, the prominence of accuracy as a determining factor in model selection was also evident, as reflected by the larger node size in the visualization.

The cluster of techniques employed in the selected papers (Fig. 4) represents the interconnection between the techniques used in the selected articles. The VOS network illustrates the connections between various techniques in selected articles, showcasing four major clusters. Each cluster is identified by a different colour: red, blue, yellow, and green. This visual representation offers insights into the prevalent methodologies researchers utilize in their articles. The network highlights that neural networks emerge as the most frequently employed technique among researchers. Closely followed is the utilization of convolutional neural networks, indicating their significance in the research landscape. The study suggests a prevalent trend towards leveraging neural network-based approaches in the studies surveyed, underscoring their relevance and effectiveness in addressing the research objectives. By visually mapping out the interconnections between different techniques, the VOS diagram provides a comprehensive overview of the methodologies favoured by researchers, offering valuable insights into prevalent trends and areas of focus within the field.

4. Research questions (RQ)

We designed the questions to gather comprehensive insights into the accuracy and efficiency of these machine learning models in crop disease detection (Table 1). By addressing these questions, we aim to gain a complete understanding of how effectively machine learning can identify and manage crop diseases.

RQ 4.1. What are the current state-of-the-artmachine-learning techniques and algorithms used for disease detection in wheat, rice, and maize?

Advanced machine learning techniques and algorithms significantly contributed to the development of robust and efficient disease detection systems in wheat, rice, and maize, aiding in the timely identification and management of crop diseases. Different research studies using different machine learning or deep learning techniques to detect crop diseases are summarised inTable 2. Krishnan et al. [35] focused on a novel hybrid model for detecting fungal diseases in wheat, emphasizing further enhancements for segmentation excellence and noise reduction. A novel support vector machine-based probabilistic neural network (NSVMBPNN) employing sophisticated algorithms and a comprehensive

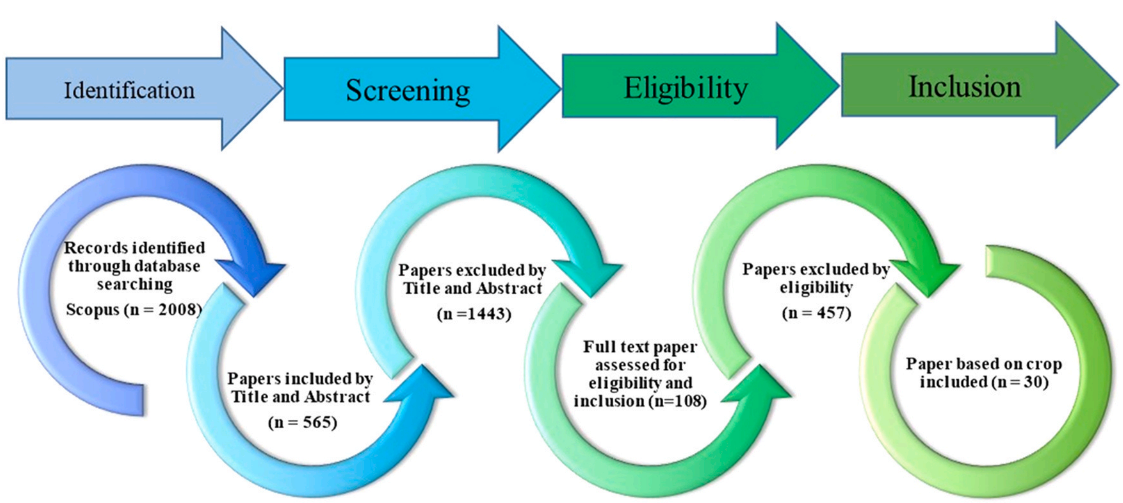
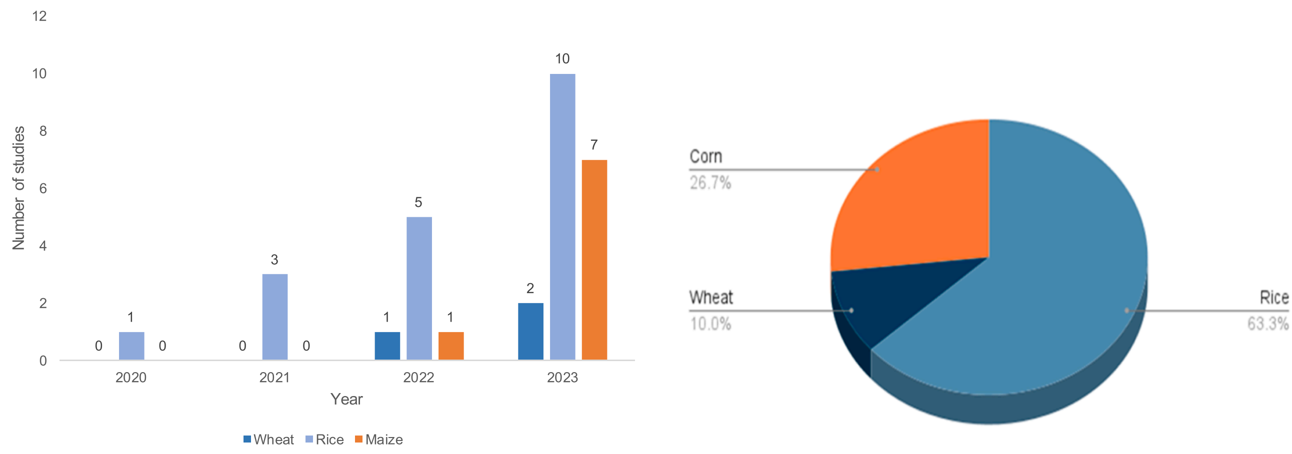


Fig. 1. Flow-Chart represents the data extraction.



A B

Fig. 2. Distribution of studies. A) year-wise distribution of the publications. B) Distribution of crop-specific publications.

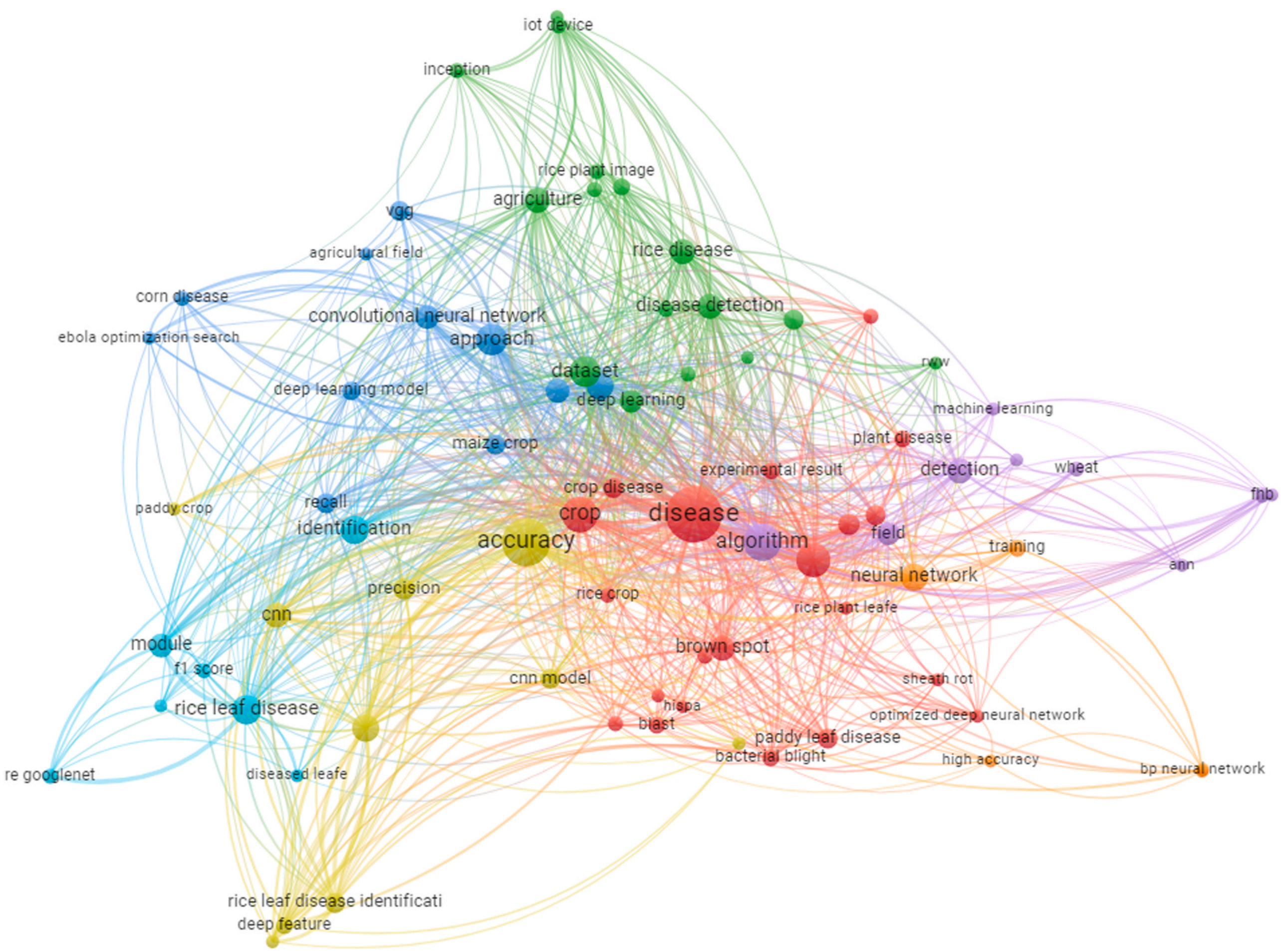


Fig. 3. VOS diagram visualizing the relationships and clusters among keywords extracted from the selected papers, offering insights into the thematic connections.

feature extraction approach to identify the brown spot, bacterial leaf blight, and rice blast in rice crops [1]. Sudhesh et al. [13] further enriched the field by exploring machine learning and deep learning approaches, introducing Dynamic Mode Decomposition, attention-driven preprocessing, and on-field data analysis. Sowmyalakshmi et al. [36] pushed the boundaries of crop disease detection with their FPA-WELM model and histogram segmentation technique for Bacterial Leaf Blight, Brown Spot, and Leaf Smut in rice.

Similarly, a hybrid model was proposed for high-accuracy wheat disease detection, emphasizing improving disease severity quantification and extending to other crops [24]. Jain et al. [15] leveraged the YOLOv4 model for rice disease detection, introducing the user-friendly mobile application docCrop, which helps farmers detect crop disease. A comprehensive approach to Fusarium head blight detection in wheat using hyperspectral imaging, paving the way for selective harvest strategies, was discussed by [12]. Ashwini and Sellam, [37] introduced a

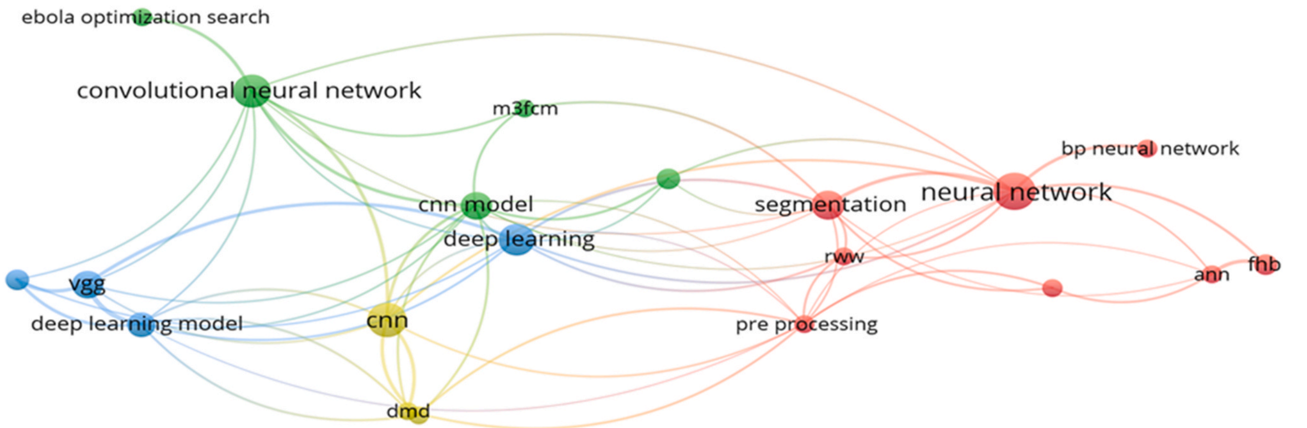


Fig. 4. VOS diagram depicting the relationships and groupings among techniques employed in the selected papers, visually representing the methodological landscape within the reviewed literature.

Table 1
Research Questions.

Sr. No.	Research Questions
1	What are the current state-of-the-art machine-learning techniques and algorithms for disease detection in wheat, rice, and maize?
2	What primary data sources are utilized for disease detection in wheat, rice, and maize?
3	How do the feature selection and extraction methods impact the performance of machine learning models in crop disease detection?
4	How accurate and reliable are machine learning-based disease detection systems compared to traditional agriculture methods?
5	Are there specific machine learning models or techniques more suitable for different types of diseases (e.g., fungal, viral, bacterial) in wheat, rice, and maize?
6	What are the common challenges and limitations of implementing machine-learning techniques for disease detection in these crops?
7	What future directions and potential research areas exist in developing and improving wheat, rice, and maize disease detection models?

3D-Dense Convolutional Neural Network (3D-CNN approach) for maize disease detection, introducing the Ebola Optimization Search algorithm and emphasizing sensitivity in parameter settings, which can reduce the classification errors of the 3D-CNN approach. Chaudhari and Malathi, [38] describe the Inception-ResNet V2 model for accurate disease detection in rice, combining the strength of image segmentation with CNN-SVM hybrid models.

Researchers often combine multiple techniques to make them more specific for crops and disease identification [39]. Additionally, domain-specific knowledge and collaboration with experts in agriculture and plant pathology are crucial for the success of these applications. Integrating advanced algorithms, innovative models, and attention to real-world challenges pave the way for more resilient and accurate agricultural practices, ensuring food security and sustainable crop management. These studies contribute to the current state of knowledge and lay a solid foundation for future research directions in precision agriculture.

RQ 4.2. What primary data sources are utilized for disease detection in wheat, rice, and maize?

Disease detection models use a variety of data sources to detect the diseases accurately. Some data sources are the Kaggle: agricultural pests and insects picture database, UCI: The machine learning repository, agricultural field, the rice pest database, rice leaf disease image samples dataset, smart farming-based IoT cameras, Indian Rice Research Institute (IRRI) website, laboratory images, WheatRust21 dataset (Table 1). Integrating diverse data allows for a more comprehensive understanding of the factors influencing crop health. Combining these data sources allows for a holistic approach to disease detection in agriculture. By leveraging a diverse information set, models can be trained to recognize complex patterns and relationships, leading to more accurate predictions and timely interventions for disease management in wheat, rice, and maize crops [51].

RQ 4.3. How do the feature selection and extraction methods impact the performance of machine learning models in crop disease detection?

Each phase within the typical architecture of an image-based plant disease detection system, including image acquisition, image preprocessing, region of interest identification, feature extraction and selection, and disease classification, holds equal significance, collectively contributing to the accurate identification of diseases based on observable symptoms on plant leaves. The feature selection and extraction methods are particularly influential in shaping machine learning models' performance in crop disease detection [52]. In wheat, rice and maize, different algorithms like Visualization Algorithms, Grey-Level Co-Occurrence Matrix (GLCM), Grab-Cut algorithm, Stochastic Gradient Descent (SGD) Algorithm, bit pattern features (BPF), Histogram Segmentation Technique, Ebola optimization search (EOS) algorithm, Descent Algorithm, SGDM (Stochastic Gradient Descent with Momentum), RMSPropper (Root Mean Square propagation) and Adaptive Moment Estimation (ADAM) and K-means algorithm were used for feature extraction by the different machine learning techniques [1,30,36] (Table 1). These methods directly influence the quality and relevance of the input data, which in turn affects the model's ability to make accurate predictions [53]. By leveraging appropriate feature selection and extraction methods, researchers can optimize the performance of machine learning models in crop disease detection, enabling more accurate and reliable identification of crop diseases and timely implementation of effective mitigation strategies.

RQ 4.4. How accurate and reliable are machine learning-based disease detection systems compared to traditional agriculture methods?

"Accuracy" typically refers to a metric that quantifies the correctness of predictions made by a model. The accuracy analysis of machine learning techniques in crop disease detection is a critical aspect of evaluating the performance and reliability of the models. The model's accuracy mainly depends on the ability of feature segmentation, extraction and verification methods [54,55]. In agricultural applications, accurately identifying crop diseases is essential for timely interventions and effective crop management. All the papers were analyzed based on accuracy; nearly 90 % accuracy was observed in all the articles (Fig. 5). Table 1 provides accuracy information, indicating the level of accuracy achieved by each model. Deep Neural Network Based Model, rE-GoogLeNet (E-Inception module), Vulture-based

Table 2
Different research studies using ML or DL techniques to detect crop diseases.

Paper ID	Crop	Disease	Machine Learning Techniques	Features Extracted	Data set	Data set source	Accuracy	Limitation of models	Proposed Model/ Application Name	Reference
P1	Rice	Tungro, Blast, Brown spot and Bacterial blight	Supervised learning	Feature extraction method not mentioned	3416	Insects picture database Plant Village and Kaggle agricultural pests.	93.87 %	The accuracy is lower than that of contemporary models.	Random Forest + Naive Bayes + SVM	[13]
P2		Bacterial leaf blight, Sheath blight, Leaf blasts, Leaf smut and Brown spots	Supervised learning and Deep learning	Visualization Algorithms	120	UCI Machine Learning Repository	97.30 %	Further development is necessary to combine the proposed approach with other advanced methods, such as clustering techniques and deep learning models, to enhance the system's performance and accuracy in detecting various plant leaf diseases.	Random Forest Classifier and R-CNN with VGG−16	[24]
P3		Hispa, Leaf Blast and Brown spot	Deep Neural Network-Based Model	Grey-Level CoOccurrence Matrix (GLCM)	5447	Kaggle website	99.87 %	Not used for real-time data	You Only Look Once (YOLO) v5	[40]
P4		Hispa, Brown spot, Leaf blast	ResNet34 with a self-attention layer, ResNet50, ResNet34, ResNet18 with self-attention	Feature extraction method not mentioned	3355	Kaggle	98.54 %	There is potential for accuracy improvement through incorporating additional datasets and parameter tuning in the CNN model, and there is a need for future validation of the same classification algorithm for disease identification in different crops.	ResNet34	[41]
P5		Leaf Smut, Brown Spot, Bacterial Leaf Blight	Deep learning	Feature extraction method not mentioned	5000	Kaggle,Google	95 %.	CNN model	CNN with 15-layer architecture	[2]
P6		–	A hybrid CNN (Inception-ResNet)-SVM model	Grab-Cut algorithm		Agricultural field	97 %	More advanced deep-learning techniques should be includedto develop a comprehensive multiple-disease prediction system for rice leaves.	A hybrid CNN (Inception-ResNet)-SVM model	[15]
P7		Red blight, Rice blast, Aphelenchoidesbesseyi, Leaf smut, Bacterial leaf streak, Bacterial leaf blight, Brown spot and Rice sheath blight	GoogLeNet (E-Inception module)	Feature extraction method not mentioned	1122	Jiangxi Agricultural University, Kaggle website and the rice pest database,	99.58 %	Ongoing Optimization Efforts -Limited Performance Comparison -Scope for Overfitting and Generalization Issues	GoogLeNet (E-Inception module)	[42]
P8		Tungro, Brown spot and Bacterial blight	Vulture-based Auto-metric Graph Neural Network (VAGNN) proposed for RLDC		5932	Rice Leaf Disease Image Samples dataset	99.56 %	It does not elaborate on the specific types of hybrid optimization techniques or their potential application in the context of rice leaf disease identification, limiting the depth of understanding regarding their practical implementation and impact.	A vulture-based Automatic Graph Neural Network (VAGNN) was proposed for RLDC.	[43]

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Table 2 (*continued*)

Paper ID	Crop	Disease	Machine Learning Techniques	Features Extracted	Data set	Data set source	Accuracy	Limitation of models	Proposed Model/ Application Name	Reference
[illegible]		[illegible]	[illegible] network (RWW-NN)	[illegible] Otsu Threshold to segment disease spots.	Number not mentioned	[illegible] based IoT cameras	[illegible] %	[illegible] various rice diseases.- Further exploration of standard optimization approaches is essential to assess the relative efficacy of conventional methods and improve the model's overall performance.	[illegible] Decision Tree, Linear Regression	[illegible]
P11		Sheath spot, Grassy stunt virus, Brown spot, Sheath rot, False smut, yellowing motel, Sheath, Leaf scald, Eyespot, Blast, tungro virus, kernel smut, Footrot, Leaf smut, Sheath blight, ragged stunt, Bacterial leaf streak, Crown sheath rot, Flag leaf sheath, Powdery mildew, Bacterial blight, Narrow brown leaf spot, and Pecky rice (kernel spotting)	VGG−16 (Visual Geometry Group) + GoogleNet convolutional neural network (CNN)	Stochastic Gradient Descent (SGD) Algorithm	12,000	Dharwad, India and paddy farmlands situated at the University of Agricultural Sciences (UAS)	92.24 %	There isa need for further improvement by leveraging advanced models like DenseNet, Inception-v4, ResNet, and AlexNet, alongside optimizing training time for CNN models through Matlab code optimization.	VGG−16 and GoogleNet	[30]
P12		Leaf Smut Bacterial Leaf Blight and Brown spot	DenseNet with multilayer perceptron(MLP)	Feature extraction method not mentioned	1500	Kaggle	97.68 %.	The possibility of enhancing detection performance by utilizing hyperparameter tuning techniques for fine-tuning deep learning models is high in the future.	DenseNet169-MLP	[44]
P13		Neck blast, Hispa, Tungro, Bacterial blight, False smut, Blast, Brown spot and Stemborer	RDD_CNN model	Feature extraction method not mentioned	3256+487	Field	98.47 %	The study is limited in scope as it focuses solely on the IIE process for a specific set of diseases.	RDD_CNN model (automated Rice Disease Diagnosis System (RDDS))	[28]
P14		Rice blast, Brown spot and Bacterial leaf blight	Support Vector Machine	A grey-level co-occurrence matrix (GLCM) is used to extract texture features and bit pattern features (BPF), and to extract colour features, a novel intensity-based colour feature extraction (NIBCFE) is used.	109 + 16	Indian Rice Research Institute (IRRI) website and Neduvasal in the Pudukkottai District of Tamil Nadu, India	95.20 %	Environmental factors like fading, blurring, illumination, and variable lighting can affect recognition and accuracy.		[1]
P15		Hispa, Leaf Blast and Brown spot	Deep learning-based object detection framework	Feature extraction method not mentioned	762	On-field images • Laboratory images	97.36 %	There is a need for future resolution of smartphone-related constraints, alongside the system's potential extension to cover more crop diseases and facilitate regional language support for enhanced user accessibility.	E-crop doctor (app) and a user-friendly chatbot (docCrop)	[38]

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Table 2 (*continued*)

Paper ID	Crop	Disease	Machine Learning Techniques	Features Extracted	Data set	Data set source	Accuracy	Limitation of models	Proposed Model/ Application Name	Reference
P16		Leaf smut, Bacterial leaf blight and Brown spot	Inception with ResNet v2 based on Convolutional Neural Network	Histogram Segmentation Technique	115	Kaggle	94.20 %	The model focuses solely on diagnosing diseases in rice plants, with potential expansion to fruit plants yet to be explored.	Optimal Weighted Extreme Learning Machine (CNNIR-OWELM) and Inception with ResNet v2 based on Convolutional Neural Network	[36]
P17		Rice leaf blast, Brown spot and Rice Hispa damage	Depthwise Separable Neural Network with Bayesian optimization (ADSNN-BO)	Gradient Descent	2370	Kaggle	94.65 %	- The study's reliance on a specific dataset different from those used in earlier literature may limit the direct comparison and validation- Neglect other relevant external factors that could influence rice disease detection accuracy, such as socioeconomic factors or regional variations in agricultural practices.- Application on different public datasets is proposed but not executed within the study, leaving room for uncertainty regarding its adaptability and robustness across various datasets and real-world scenarios.	Depthwise separable neural network with Bayesian optimization (ADSNN-BO)	[45]
P18		Sheath Blight	Deep learning	gray level co-occurrence matrix and grayscale stroke statistics	480+120		88 %	The accuracy is lower than that of contemporary models.	Backpropagation (BP) neural network	[46]
P19		Sheath rot, Brown spot, Bacterial blight and Leaf blast	Optimized Deep Neural Network with Jaya Algorithm	Grey-Level CoOccurrence Matrix (GLCM)	650	Rural area of ayikudi and panpoli, Tirunelveli District, Tamil Nadu	98.90 %.	Restrict the ability to determine potential improvements' practical significance and impact in reducing false classifications.	DNN-JOA	[47]
P20	Wheat	Brown rust (Leaf rust), Yellow rust(Stripe rust) and Black rust (Stem rust)	Deep Learning Based Model	Feature extraction method not mentioned	6556	WheatRust21 dataset	99.35 %	Despite EfficientNet B4 demonstrating superior testing accuracy among traditional CNN models, further exploration of B5-B7 architectures is hindered by significant computational demands and limitations in hardware resources. Using a batch size of 32 exacerbates these challenges, particularly due to constraints in GPU memory. As a result, fully leveraging the potential advancements offered by larger model variants remains challenging,	EfficientNet B4	[9]

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Table 2 (*continued*)

Paper ID	Crop	Disease	Machine Learning Techniques	Features Extracted	Data set	Data set source	Accuracy	Limitation of models	Proposed Model/ Application Name	Reference
								impeding the pursuit of even higher performance in various machine-learning tasks.		
P21		Fungal Diseases like Powdery mildew,rust and septoria	A Novel Hybrid Model	Feature extraction method not mentioned	256	Kaggle	98.06 %	The practical implementation of these findings at the entire field level may face significant challenges.	FCM technique called marker and mask-based membership filtering (M3FCM) which is faster and more reliable	[35]
P22		Fusarium head blight	Logistic Regression, Support Vector Machine, Artificial Neural network	Feature extraction method not mentioned	Number not mentioned	Kaggle	95.60 %	Limitations in Disease Quantification -the practical implementation of these findings at the entire field level may face significant challenges.		[12]
P23	Corn	Northern maize leaf blight	Deep Neural Network-Based Model	Feature extraction method not mentioned	9070	NLB dataset	87.50 %	The oversight in assessing the model's resilience in different weather conditions highlights the necessity for future research. Enhancing the model's capability to detect maize leaf blight across diverse environmental settings is crucial. Researchers can improve the model's reliability in real-world agricultural applications by addressing this gap.	CEMLB-YOLO	[48]
P24	Corn	Common rust Blight disease and Gray leaf spot	3D-dense convolutional neural network (3D-DCNN)	Ebola optimization search (EOS) algorithm+ GradientDescent Algorithm	Number not mentioned	Plant doc and Plant village	98 %	-Need for Dataset Expansion -Scope for Bias and Overfitting -Challenges in Real-World Implementation	3D-DCNN-EOS	[37]
P25		Gray Leaf Spot, Blight and Common Rust	AlexNet architecture	Adaptive Moment Estimation, Root Mean Square propagation, Stochastic Gradient Descent with Momentum	4188	Kaggle	98.91 %	-Complexity of Implementation -lack of comprehensive validation strategies for evaluating the effectiveness of these integrated models may hinder the accurate assessment of their performance	AlexNet-Inception	[19]
P26		Gibberella stalk rot, Anthracnose leaf blight, Northern corn leaf spot, Eyespot, Anthracnose stalk rot, Southern rust	Deep learning	Feature extraction method not mentioned	15,960	Plant Village and Kaggle fields are situated in the state of Telangana	97.51 %	NPNet−19	NPNet−19	[49]
P27		Fungal Foliar disease, Northern Leaf Blight/Turcicum Leaf Blight	Attention U-Net segmentation model, Res U-Net, Deep Learning-based U-Net	Feature extraction method not mentioned	1500	Kaggle	98.97 %	-Lack of Real-World Validation -Complexity of Segmentation Approaches	Attention U-Net	[20]

(*continued on next page*)

Table 2 (*continued*)

Paper ID	Crop	Disease	Machine Learning Techniques	Features Extracted	Data set	Data set source	Accuracy	Limitation of models	Proposed Model/ Application Name	Reference
P28		Northern Corn Leaf Blight, Gray Leaf Spot and Common Rust	Deep Learning Techniques (mostly convolutional neural networks	Feature extraction method not mentioned	3852	PlantVillage	99.10 %	-Restricted to images captured on uniform background conditions, limiting its effectiveness in real-world scenarios	Deep convolutional neural network (CNN) model	[17]
P29		Eyespot, Puccinia-sorghi, Southern rust, Healthy Samples, Exserohilumturcicum, PDD DB with Downy mildew, Northern leaf blight, Cercospora-zeae-maydis	Deep learning	Feature extraction method not mentioned	3852 +164	Plant Village and PDD database	96.29 %	Deep Cluster-Based Model	The Deep clustering (RDC) algorithm integrates the efficacy of convolutional autoencoder models with local structure preservation constraints and regularization techniques.	[50]
P30		Rust, Gray spot and Leaf spot	CNN Model	K-means algorithm	900	Crop Disease Recognition of the 2018 Artificial Intelligence Challenger Competition	90.83 %	A more extensive and diverse dataset is neededto improve disease identification, further verify the model's generalization ability, and more efficient optimization methods for image preprocessing in corn leaf disease classification and diagnosis.	CNN model	[21]

Auto-metric Graph Neural Network proposed (VAGNN) for RLDC, Deep Learning Based Model, Deep Learning Techniques (especially convolutional neural networks (CNNs/ConvNets)) showed the accuracy above 99 %. Research has demonstrated that Convolutional Neural Networks (CNNs) exhibit the potential to achieve remarkable accuracy levels when tasked with classifying images depicting plant leaves afflicted by diseases and pests [56].

RQ 4.5. Are there specific machine learning models or techniques more suitable for different types of diseases (e.g., fungal, viral, bacterial) in wheat, rice, and maize?

The choice of model or technique often depends on various factors, such as the nature of the disease, available data, and the desired level of accuracy. For example, convolutional neural networks (CNNs) are commonly used for image-based diseases like leaf spots. In contrast, recurrent neural networks (RNNs) might be employed for time-series data related to viral infections. Support vector machines (SVMs) and decision trees are versatile and can be adapted to different diseases based on their characteristics [5]. The selection of a specific model or technique should be tailored to the specific requirements and characteristics of the disease under consideration. Table 1 provides information regarding the researchers' focus on specific crops and the types of diseases they selected for their studies.

RQ 4.6. What are the common challenges and limitations of implementing machine-learning techniques for disease detection in these crops?

Implementing ML techniques for disease detection in crops has several common challenges and limitations [57] which are;

Data quality, quantity, and biased data - insufficient and biased datasets cause hindrances in the model's efficiency. Researchers should focus on comprehensive data collection, ensuring crop diversity, geographical locations, and diseases. Reducing bias in training data is crucial for model performance [58].

Variability in Symptoms - disease symptoms can vary significantly across different crop varieties, growth stages, and environmental conditions, complicating the detection process and requiring robust models to handle this variability.

Model validation and generalization - overfitting or poor generalization of the model to new and unseen data. Employ rigorous model validation techniques such as cross-validation to assess performance across various subsets of the data. Ensuring the model performs well on diverse datasets is essential for reliable disease detection.

Resource constraints - limited resources, including computational power and infrastructure, can impede the deployment of sophisticated machine-learning models. Optimize models for efficiency and explore edge computing solutions to make them more accessible to farmers with limited resources. Collaboration between researchers, industry, and policymakers can help address these resource constraints.

Interpretability of the output - interpretation of the resulted data of ML algorithms can be difficult for the farmers. Researcher have to take care of the output of an ML algoritm, which can be easily understand by the famers and the agronomist.

Integration with Existing Systems - integrating ML solutions with existing agricultural practices and tools requires compatibility and user-friendly interfaces, which can be challenging to develop.

RQ 4.7. What future directions and potential research areas exist in developing and improving wheat, rice, and maize disease detection models?

Developing and improving disease detection models for crops like wheat, rice, and maize involves a combination of technological advancements, data science, and agriculture. Here are some future directions and potential areas of research in this field:

- Collaboration with agricultural research institutions, extension services, and farmers to collect and share datasets. Establish partnerships to create centralized repositories for agricultural images.

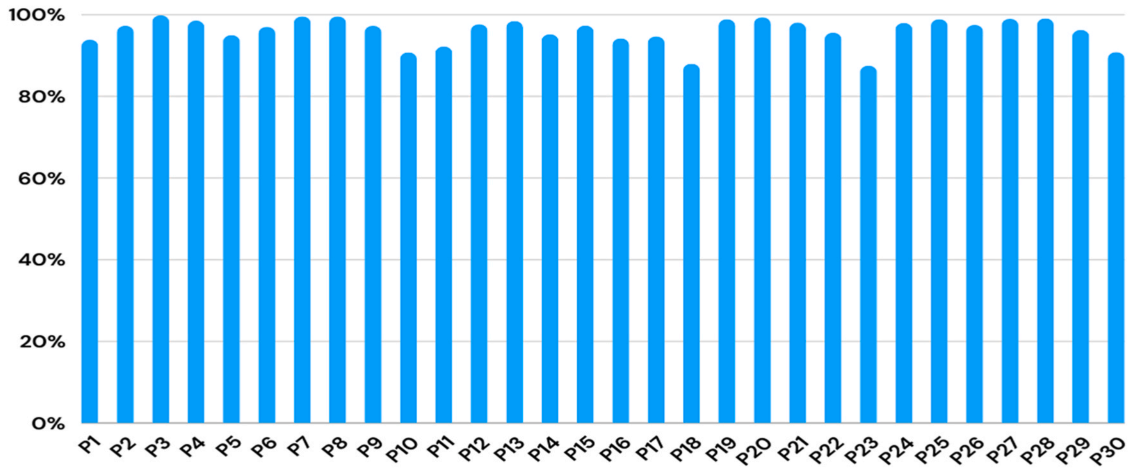

Fig. 5. The performance accuracies of the models outlined in prior studies.

- Increase the datasets with images captured under various conditions to adapt the models for different lighting and environmental factors.
- Work with relevant authorities and collaborate with technology companies that specialize in remote sensing for agriculture.
- Develop offline data collection solutions to process data locally before transferring it. Implement data compression techniques to reduce the size of image datasets for easier transport.
- Plan data collection campaigns in coordination with crop cycles across different growth stages or crops.
- Establish protocols for sensor calibration and maintenance. Train local technicians or farmers to perform routine checks and calibrations. Implement remote monitoring systems for sensor health.
- Models can be designed to recommend eco-friendly disease management strategies, reducing the reliance on chemical pesticides and promoting integrated pest management techniques.

5. Qualitative assessment of the articles

A scoring scale is a systematic set of criteria to evaluate and quantify the quality of a particular subject. The scale often ranges from low to high, with each score representing a specific level of quality. Establishing a clear and well-defined scoring scale is essential to maintain consistency in the assessment process. In the present study, quality assessment was done based on quality assessment questions compiled in Table 3.The numerical range of the quality assessment scale is 0–1; a score of zero indicates the absence of the particular information, while one represents comprehensive detail present in the particular research. This numerical representation provides a clear and precise means of evaluating and quantifying the quality of the subject.

Based on the above questions, each study was evaluated based on scores compiled in Table 4. These papers show different ways to handle challenges in detecting crop diseases, demonstrating creative and innovative strategies. Each paper is evaluated based on five quantitative criteria (QE1-QE5), contributing to a final score. The majority of the papers (22 out of 30) achieved a score of 3 or above, indicating a high level of quality in terms of disease detection by their proposed model. Quality assessment of these articles revealed that the highest scoring article is P6 (Jain et al. [15]), and adopted a hybrid CNN (Inception--ResNet)-SVM model of machine learning. Research articles which scores the 4 were found to be used algorithms like- Supervised learning, Deep Neural Network-Based Model, Vulture-based Auto-metric Graph Neural Network (VAGNN) proposed for RLDC, VGG-16 (Visual Geometry

Table 3
The quality assessment questions (QE).

No.	Question for evaluation of quality
QE1	How accurate are machine learning-based disease detection Models?
QE2	Do the accuracy, F1 score, recall, and precision get measured in the results?
QE3	Do the proposed models detect all types of diseases?
QE4	Is the dataset taken from a real-time environment?
QE5	Has the model been tested in agricultural settings like farms or plantations?

Table 4
The quality evaluation table represents the scores for each study.

Paper ID	Authors	QE1	QE2	QE3	QE4	QE5	Final Score
1	Archana et al. [1]	1	1	1	1	0	4
2	Sudhesh et al. [13]	1	1	1	0	0	3
3	Rezk et al. [22]	1	1	1	1	0	4
4	Sowmyalakshmi et al. [36]	1	1	1	0	0	3
5	Rajpoot et al. [24]	1	1	1	0	0	3
6	Jain et al. [15]	1	1	1	1	1	5
7	Leng et al. [48]	1	0	1	0	0	2
8	Yakkundimath et al. [30]	1	1	1	1	0	4
9	Yu et al. [21]	1	0	1	0	0	2
10	Narmadha et al. [44]	1	1	1	0	0	3
11	Nigam et al. [9]	1	1	1	1	0	4
12	Mishra et al. [40]	1	1	1	0	0	3
13	Krishnan et al. [35]	1	1	1	0	0	3
14	Stephen et al. [41]	1	1	1	0	0	3
15	Chaudhari and Malathi, [38]	1	1	1	1	0	4
16	Almoujahed et al. [12]	1	0	1	0	0	2
17	Ashwini and Sellam, [37]	1	1	1	0	0	3
18	Balasubramanian, [19]	1	1	1	0	0	3
19	Yang et al. [42]	1	1	1	0	0	3
20	Parasa et al. [2]	1	1	1	0	0	1
21	Nagaraju and Chawla, [49]	1	1	1	0	0	3
22	Rai and Pahuja, [20]	1	0	1	0	0	2
23	Rajasekhar et al. [43]	1	1	1	0	0	3
24	Ramesh and Vydeki, [47]	1	1	1	1	0	4
25	Haque et al. [17]	1	0	1	0	0	2
26	Vasantha et al. [28]	1	1	1	1	0	4
27	Wang et al. [45]	1	1	1	0	0	3
28	Daniya and Vigneshwari, [16]	1	1	1	0	0	3
29	Lu et al. [46]	1	0	1	0	0	2
30	Resti et al. [50]	1	0	1	0	0	2

Group) + GoogleNet convolutional neural network (CNN), Deep learning-based object detection framework, 3D-dense convolutional neural network (3D-DCNN).

6. Conclusion and future perspectives

In this comprehensive analysis, we meticulously examined 2008 documents to pinpoint 30 articles that met stringent inclusion and exclusion criteria. Our study focused on ML and DL models for detecting crop diseases in staple crops such as rice, wheat, and maize. Through this systematic review, we analyzed the proposed methodologies, techniques, accuracy rates, feature extraction methods, and the datasets and their respective sources. In this review, we discussed the diverse array of models and techniques employed, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), Random Forest (RF), and Deep Learning Architectures like ResNet and Inception. Transfer Learning, Ensemble Learning, Image Segmentation algorithms, and Bayesian Networks are also featured in the AI tools. These findings not only shed light on the current landscape of AI applications in agriculture but also underscore the potential of these technologies in revolutionizing crop disease detection. By highlighting the strengths and limitations of existing models, this review sets the stage for future research endeavours to enhance the accuracy, efficiency, and scalability of automated systems for timely disease identification in crops.

Looking forward, the integration of AI and ML in agriculture will likely see exponential advancements. The utilization of models such as CNNs, RNNs, and advanced deep learning architectures will become more sophisticated, enabling even more accurate and timely disease detection in staple crops. Future research should focus on overcoming current limitations, improving feature extraction methods, and optimizing datasets. Innovations in transfer learning and ensemble learning will enhance the robustness of these systems, making them more adaptable to diverse agricultural environments. Ultimately, these advancements will contribute significantly to global food security and sustainable agricultural practices.

Declaration of Competing Interest

Authors declare no Conflicts of interest/Competing interests.

Data Availability

No data was used for the research described in the article.

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