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# Research Advances in Maize Crop Disease Detection Using Machine Learning and Deep Learning Approaches

**Thangavel Murugan [1,*], Nasurudeen Ahamed Noor Mohamed Badusha [1], Nura Shifa Musa [2], Eiman Mubarak Masoud Alahbabi [1], Ruqayyah Ali Ahmed Alyammahi [1], Abebe Belay Adege [3], Afedi Abdi [4] and Zemzem Mohammed Megersa [4]**

1 College of Information Technology, United Arab Emirates University, Al Ain P.O. Box 15551, United Arab Emirates; nasurudeenahamed@uaeu.ac.ae (N.A.N.M.B.); 201804822@uaeu.ac.ae (E.M.M.A.); 201805038@uaeu.ac.ae (R.A.A.A.)
2 College of Engineering, Al Ain University, Al Ain P.O. Box 64141, United Arab Emirates; nura.shifa@aau.ac.ae
3 Department of Soil, Water, and Ecosystem, University of Florida, Gainesville, FL 33031, USA; abbblybelay@gmail.com
4 Department of Computer Science, Haramaya University, Haramaya P.O. Box 138, Ethiopia; afe2003@gmail.com (A.A.); zemzemmohammed@gmail.com (Z.M.M.)
* Correspondence: thangavelm@uaeu.ac.ae

**Abstract**

Recent developments in machine learning (ML) and deep learning (DL) algorithms have introduced a new approach to the automatic detection of plant diseases. However, existing reviews of this field tend to be broader than maize-focused and do not offer a comprehensive synthesis of how ML and DL methods have been applied to image-based detection of maize leaf disease. Following the PRISMA guidelines, this systematic review of 102 peer-reviewed papers published between 2017 and 2025 examined methods and approaches used to classify leaf images for detecting disease in maize plants. The 102 papers were categorized by disease type, dataset, task, learning approach, architecture, and metrics used to evaluate performance. The analysis results indicate that traditional ML methods, when combined with effective feature engineering, can achieve classification accuracies of approximately 79–100%, while DL, especially CNNs, provide consistent, superior classification performance on controlled benchmark datasets (up to 99.9%). Yet in "real field" conditions, many of these improvements typically decrease or disappear due to dataset bias, environmental factors, and limited evaluation. The review provides a comprehensive overview of emerging trends, performance trade-offs, and ongoing gaps in developing field-ready, explainable, reliable, and scalable maize leaf disease detection systems.

**Keywords:** maize crop; diseases; northern leaf blight; common rust; gray leaf spot; machine learning; deep learning; disease detection; field robustness

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## 1. Introduction

Agriculture remains a fundamental pillar of global economic development and food security, particularly as the growing population intensifies pressure on agricultural productivity and sustainability. Among cereal crops, maize ranks as the third most important staple worldwide after rice and wheat, serving as a primary source of food, animal feed, and industrial raw material across diverse agroecological regions [1]. However, maize production is increasingly challenged by climate change, emerging pests, and plant diseases, collectively threatening crop yields, quality, and farmers' livelihoods [2–4]. Maize cultivation is severely affected by a wide range of diseases and pests, including Northern

Leaf Blight (NLB), Gray Leaf Spot (GLS), common rust, maize streak virus, and stem borers, which cause significant pre- and post-harvest losses worldwide [5,6]. These diseases reduce photosynthetic efficiency, weaken plant structure, and impair nutrient uptake, leading to substantial yield reductions and economic losses [7]. In many maize-producing regions, particularly in sub-Saharan Africa and parts of Asia, disease outbreaks pose persistent risks to food security and the stability of the agricultural supply chain [5,8]. As climate variability increases, the frequency and severity of crop diseases are expected to rise further, amplifying the need for efficient disease monitoring and management strategies [9,10].

Traditional maize disease detection methods primarily rely on manual field inspections and expert visual assessments, which are labor-intensive, time-consuming, and inherently subjective [11]. Such approaches are impractical for large-scale farming operations and often fail to detect diseases at early stages, when intervention is most effective. Delayed or inaccurate diagnosis frequently results in excessive pesticide application, increased production costs, environmental degradation, and risks to human health [12]. These limitations highlight the urgent need for automated, accurate, and scalable disease-detection systems that support modern maize production.

In recent years, machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for crop disease identification and classification, offering high accuracy and rapid processing of large image datasets [13–15]. Vision-based ML and DL approaches have been applied to a variety of crops, including rice, wheat, grapes, tomatoes, and maize, demonstrating promising results in disease detection using techniques such as Support Vector Machines, Random Forests, Artificial Neural Networks, and Convolutional Neural Networks [16–18]. Advances in feature extraction, image segmentation, and deep neural architectures have significantly improved the performance of automated plant disease diagnosis systems [19,20].

Despite the growing body of literature on ML- and DL-based plant disease detection, existing review studies predominantly adopt a generalized, multi-crop perspective [16–19,21,22]. While these studies provide valuable overviews of algorithmic developments, they offer limited maize-specific insights into disease types, dataset characteristics, model performance trends, and real-world applicability. Moreover, the rapid evolution of deep learning architectures, the increasing availability of publicly accessible and field-collected datasets, and the growing emphasis on deployment-oriented solutions necessitate an updated and focused synthesis of recent research. To date, there remains no comprehensive, maize-specific systematic review that critically compares ML and DL approaches, datasets, and performance metrics reported in global studies published between 2017 and 2025. Motivated by the global importance of maize, its high disease burden, and the absence of a consolidated crop-specific review, this study provides a focused, up-to-date synthesis of ML- and DL-based research on maize disease detection.

By systematically analyzing recent studies, the study aims to identify dominant methodologies, evaluate reported performance outcomes, examine dataset limitations, and highlight unresolved challenges. The insights presented are intended to support researchers, agronomists, and system developers in designing robust, scalable, and field-deployable disease detection solutions that contribute to sustainable maize production and improved food security. Despite the rapid growth of research on machine learning techniques, including deep learning approaches for plant disease detection, several critical gaps remain, particularly in maize crop disease identification. Existing studies largely emphasize algorithm development and accuracy evaluation using controlled experimental datasets, while paying limited attention to systematic comparisons across models, datasets, and operational conditions relevant to maize agriculture. Moreover, reported performance metrics vary substantially across studies, making it difficult to determine the relative suitability of traditional machine learning methods versus deep learning architectures for specific maize disease types. A further limitation is the heavy reliance on publicly available datasets collected under ideal imaging conditions, which often lack environmental diversity and do not reflect real-world variability. Consequently, many high-performing models demonstrate reduced robustness and generalization when deployed in practical agricultural settings. Additionally, issues related to scalability, computational complexity, interpretability, and field-level deployment remain underexplored. These limitations highlight the need for a focused, maize-specific synthesis that critically evaluates existing approaches and identifies unresolved challenges to guide future research. Despite the rapid growth of artificial intelligence-based plant disease detection, there remains a lack of a consolidated, maize-specific systematic review that critically compares machine learning and deep learning approaches, datasets, and performance metrics across recent studies. Most existing surveys focus on multiple crops or general plant disease detection, which limits their applicability to maize-specific challenges such as disease diversity, dataset imbalance, and field variability. This review extends the existing literature on accuracy alone by adding sections on Field Robustness, Explainability, Deployment Imbalances, and Data Set Imbalances, linking the laboratory effectiveness of this technology to its performance in real-world settings. A summary and comparative overview of the existing research studies is presented in Table 1.

**Table 1.** Comparative analysis of existing review studies on crop disease detection.

| Ref | Crop | Region | Paper Count | Period Covered | Dataset | Proposed Model | Results | Summarize | Best Model | Research Gap | Year |
|---|---|---|---|---|---|---|---|---|---|---|---|
| [19] | Major Plants (Including Maize Crop) | Global Issues | 45 | 2004 to 2019 | ◉ | ○ | ○ | • | • | • | 2019 |
| [23] | Banana Crop | 10 regions—major producers of bananas in the World | 60 | 2009 to 2021 | • | • | • | • | • | • | 2022 |
| [24] | Potato Plant | Global Issues | 105 | 2005 to 2022 | • | • | • | • | • | ○ | 2022 |
| [16] | Major Plants (Including Maize Crop) | Global Issues | 76 | 2005 to 2022 | • | • | • | • | • | ○ | 2022 |
| [17] | Major Plants (Including Maize Crop) | Global Issues | 256 | 2006 to 2022 | • | • | • | • | • | • | 2023 |
| [21] | Major Plants (Including Maize Crop) | Global Issues | 55 | 2006 to 2022 | • | • | • | • | • | • | 2023 |
| [18] | Major Plants (Including Maize Crop) | Global Issues | 176 | 2010 to 2022 | • | • | • | • | • | ○ | 2023 |
| [22] | Major Plants (Including Maize Crop) | Global Issues | 57 | 2014 to 2024 | • | • | • | • | • | ○ | 2024 |
| [25] | Rice Crop | Global Issues | 166 | 2011 to 2024 | • | • | • | • | • | • | 2024 |
| [26] | Rice Crop | Global Issues | 127 | 1999 to 2022 | • | • | • | • | • | ○ | 2025 |
| Our Work | Maize Crop | Global Issues (India, Tanzania-Majority) | 102 | 2017 to 2025 | • | • | • | • | • | • | 2025 |

Note: • Explicitly Reported; ○ Not Reported; ◉ Partially Reported.

This review makes the following contributions: (i) it provides a maize-focused systematic literature review covering 102 high-quality studies published between 2017 and 2025; (ii) it categorizes and analyzes machine learning techniques, including deep learning approaches applied to maize disease detection; (iii) it examines publicly available and field-collected datasets used in existing studies; (iv) it compares reported performance metrics and methodological trends; and (v) it identifies research gaps and future directions for robust, real-world maize disease detection.

*Foundational Definitions—ML (Machine Learning) and DL (Deep Learning)*

Machine Learning (ML) is a general term for methods in computational science that produce models or decision mechanisms from data rather than through specific programming based on predetermined rules. Deep Learning (DL) is a subcategory of ML that uses network architectures with several interconnected layers of processing units, each of which learns hierarchically from data to complete the entire process through a single continuous mechanism. Compared with more traditional ML methods, which depend on artificial and surface feature constructions and use a model to generate predictions, the DL approach employs both the input data and the underlying model to generate predictive representations. According to established definitions in the literature, ML and DL are related through a set-theoretic inclusion rather than a hierarchical progression.

Machine Learning (ML) encompasses multiple methodological paradigms for identifying patterns and developing decision functions from training data. Two of these paradigms, according to established definitions, are Traditional, feature-based methods and a more recent methodological paradigm within machine learning, referred to as deep learning (DL). The primary difference between Traditional ML and DL, according to established definitions, is how each transforms input data into feature sets: DL uses a multi-layer neural network to create features, while Traditional ML relies on explicit feature engineering and shallow (fewer-layer) models for classification. Both paradigms can exist separately within the ML framework. As such, DL is simply another method, distinct from but not superseding or replacing Traditional ML, according to established definitions, as it shares many of the same learning methods and structures. Furthermore, although Feedforward Neural Networks represent one type of DL model, they do not define or limit DL as a whole; many other types and structures constitute the broader classification of DL, including, but not limited to, Convolutional Neural Networks, Recurrent Neural Networks, Graph Neural Networks, Generative Adversarial Networks, Self-Supervised Learning, and Attention Networks.

The definitions of machine learning and deep learning used throughout this review are those commonly accepted in the relevant literature on these topics (i.e., the ‘foundational literature’). Therefore, the categories and taxonomies provided herein have been developed using a task- and dataset-based approach rather than as a comprehensive classification of the entirety of machine learning or deep learning. Thus, none of the classifications or taxonomies listed in this review should be interpreted as exhaustive; rather, they reflect what has been reported about the methodologies used in studies examining the detection of disease in maize.

## 2. Research Methodology

The systematic review was developed and reported in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (2020). This study adopts a structured and transparent review methodology to identify, screen, and synthesize existing research on maize disease detection using machine learning (ML) and deep learning (DL) techniques. The review process was designed to ensure methodological consistency, analytical rigor, and reproducibility across all stages, including literature retrieval, study selection, quality evaluation, and data synthesis. A comprehensive literature search was conducted using established bibliographic databases and digital libraries, including IEEE Xplore, the ACM Digital Library, PubMed, and multidisciplinary indexing platforms such as Scopus. Through these databases, peer-reviewed journal articles and conference proceedings published by major scientific publishers—such as IEEE, Springer, Elsevier, MDPI, Wiley, Taylor and Francis, and Scientific Reports—were systematically retrieved, ensuring a clear distinction between search databases and publication venues. The search targeted studies published between 2017 and 2025 and was finalized in January 2025.

A systematic search strategy was used in this review to provide complete transparency of the search strategies employed and to achieve full reproducibility. Each database search was conducted with a clearly defined Boolean string tailored to that database. The search terms included those related to maize and its associated diseases, the vision task (i.e., image classification, object detection, segmentation), and machine learning/deep learning. Specifically, for the IEEE Xplore database, the search string was as follows: ("corn" OR "maize") AND ("Northern Leaf Blight" OR "Gray Leaf Spot" OR "Common Rust" OR "Maize Streak Virus") AND ("Image Classification" OR "Object Detection" OR "Image Segmentation") AND ("Machine Learning" OR "Deep Learning"). This Boolean search logic was also used for the ACM Digital Library, Scopus, and PubMed databases. By using a systematic search strategy, this review has covered disease-specific, task-specific, and crop-specific articles, thus satisfying PRISMA requirements for full transparency and reproducibility.

The review outlines the process of diagnosing maize diseases, focusing on the tasks performed (image classification, object detection, and image segmentation) and presenting them as separate sections (as individual computer vision problems). It provides examples (such as YOLO, faster R-CNN, and U-Net) for each task type rather than an exhaustive list of all models implemented for that task. The omission of certain model types from this review does not imply that they cannot be used with deep learning; Accordingly, the review emphasizes models that are most frequently reported in maize-specific studies rather than attempting exhaustive architectural coverage.

To enhance the thoroughness and reliability of the literature review, additional models representing different categories of architectural design have been identified through an extended literature search on Maize Diseases (agricultural diseases affecting maize crops). By exploring crop-specific search terms (e.g., maize disease, corn disease) alongside those at the model and architectural levels (e.g., CNN, YOLO, Faster R-CNN, both localized and non-localized), researchers have created search strings that emphasize studies that are either classification- or localization-based. Using this approach, this search strategy yielded a broad set of recent, methodologically relevant frameworks for maize disease detection. After searching for studies using these methods, we screened the list for those that met strict eligibility criteria, including being maize-specific, peer-reviewed, methodologically sound, and replicable. Thus, while our final set of references contains approximately 102 studies, the selection process was designed to ensure that the studies were high-quality, technically relevant, and specific to the maize domain, rather than to include large numbers.

The initial search yielded 167 records; duplicate entries across databases were then removed. A two-stage screening process was then applied, consisting of title–abstract screening followed by full-text assessment. Explicit inclusion and exclusion criteria were used to ensure relevance and consistency. Studies were included if they focused specifically on maize, employed ML or DL techniques for disease detection or diagnosis, reported quantitative experimental performance metrics, and were published in peer-reviewed journals or conference proceedings. Studies were excluded if they addressed general agriculture or multiple crops without maize-specific analysis, relied exclusively on traditional image-processing techniques, constituted review or opinion papers, or lacked empirical validation and quantitative evaluation. Following this screening process, 65 studies were excluded, leaving a final set of 102 articles for detailed analysis.

To enhance methodological rigor and minimize potential bias, the retained studies underwent a qualitative quality assessment protocol. This assessment considered dataset characteristics (including dataset size, environmental diversity, class balance, and data source), clarity of experimental design, transparency of preprocessing and model training procedures, reproducibility of the proposed methods, and the completeness of performance evaluation using standard metrics such as accuracy, precision, recall, and F1-score. Only studies meeting acceptable quality standards across these dimensions were included in the comparative synthesis. For each selected article, relevant information—such as publication year, dataset source and scale, maize disease classes, feature extraction techniques for ML-based studies, learning architectures, evaluation strategies, and reported performance—was systematically extracted and organized to support consistent cross-study comparison and thematic analysis. Based on this structured extraction, the final corpus of 102 studies was categorized by learning paradigm: 33 machine-learning–based and 69 deep-learning–based. This categorization enabled a structured comparison of methodological trends, dataset dependencies, and commonly reported limitations across ML and DL approaches.

To improve clarity and readability in the presentation of maize disease types and datasets, disease descriptions were summarized in the main text. In contrast, extensive visual examples and detailed descriptions were relocated to the Appendix. In addition, a dedicated dataset comparison table was introduced to synthesize key dataset attributes, including dataset size, number of disease classes, image acquisition conditions (laboratory or field), environmental diversity, and class balance, thereby facilitating more meaningful interpretation of reported model performance. An overview of the identification, screening, exclusion, and classification workflow in Figure 1 is illustrated, while the temporal distribution of publications and publisher-level trends are presented in Figures 2–5.

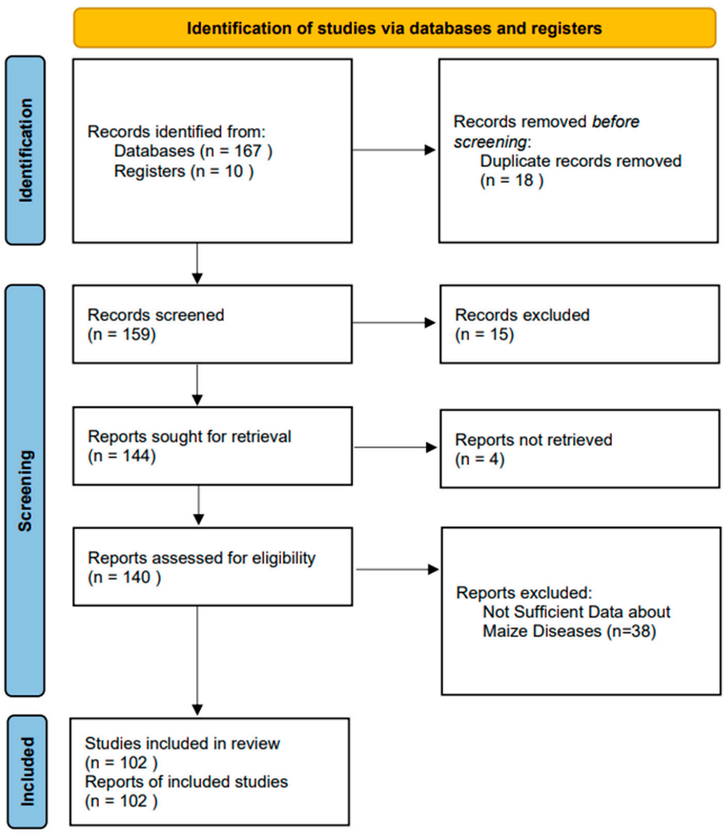



**Figure 1.** Research Articles selection process.

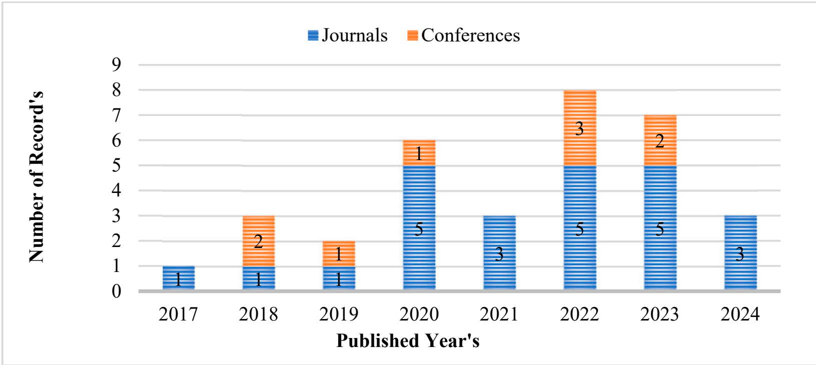



**Figure 2.** Year-wise articles count—Machine Learning.

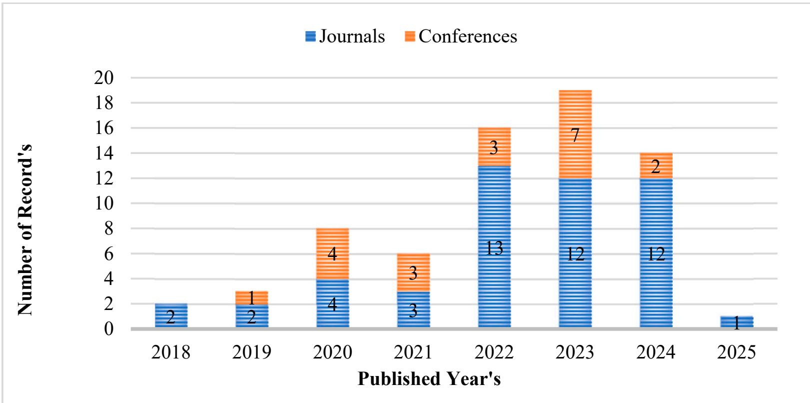



**Figure 3.** Year-wise articles count—Deep Learning.

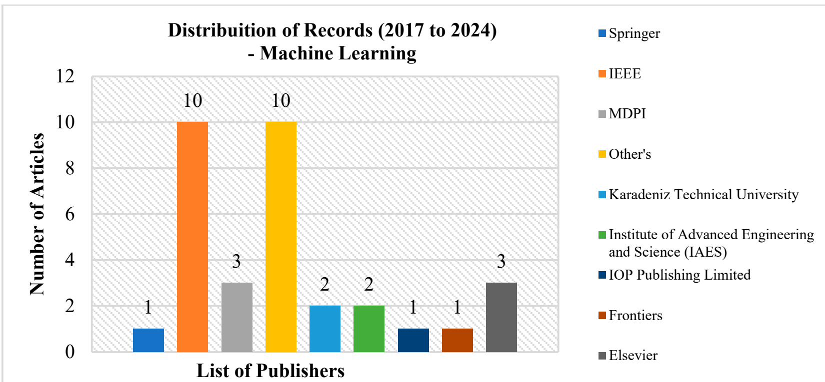



**Figure 4.** Article publishers count based on Machine Learning.

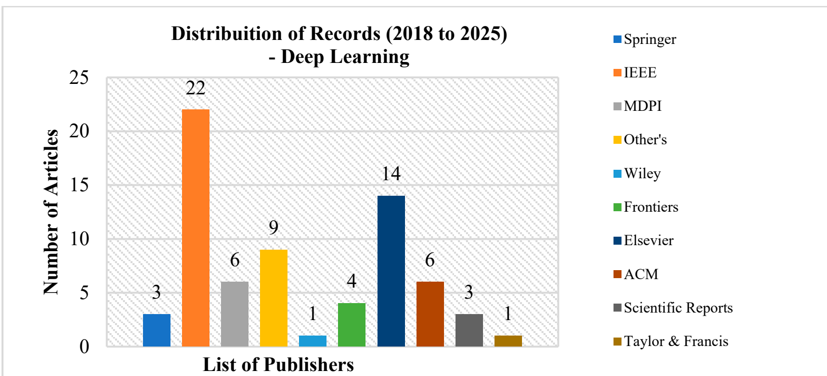



**Figure 5.** Article publishers count based on Deep Learning.

### 2.1. Risk of Bias and Evaluation of Study Quality

To assess the validity of the synthesized results, a qualitative risk-of-bias assessment was conducted for all studies that met the inclusion criteria, evaluating the transparency of the datasets, the clarity of the data preprocessing methods, the validation strategy, and the completeness of the performance metrics reported for each study. Studies that included field evaluation, class-imbalance analysis, and a detailed report of performance metrics per class were classified as low risk. Studies with limited datasets, single-split validation, and accuracy-only reports were classified as moderate to high risk. The results of the risk-of-bias assessment demonstrate substantial variability in study methods and highlight the need to standardize evaluation and reporting methods for maize disease detection studies. The study of maize plant disease detection has primarily focused on semantic segmentation, which assigns pixel-level disease labels, and on instance segmentation, which emphasizes single diseased areas. Panoptic segmentation has very few reports available and is thus not emphasized in this review.

In addition to complying with the PRISMA standards, the current study synthesizes task-focused technical information by comparing model performance with the task formulation and the chosen architecture and deployment environment. CNN-based image classification has performed best in controlled laboratory settings; however, YOLO-based object detection models perform better in field conditions because they are robust to changes in background and lighting conditions. There is currently limited potential for large-scale or device deployment of segmentation models (e.g., U-Net and DeepLab) due to their high computational requirements. These results indicate that the task type, model architecture, and environment will always interact when detecting maize diseases. Table 2 shows the Risk of Bias Assessment Standards.

**Table 2.** Risk of bias assessment standards for included research studies.

| Criteria | Description |
|---|---|
| Transparency in Datasets | Sources, size, class distribution, preprocessing, and any ambiguous or insufficient description of the dataset should all be clearly disclosed. |
| Validation of Robustness | Single train-test split or robust validation (cross-validation or independent test set). |
| Metric Completeness | Only accuracy was presented, along with other metrics (precision, recall, F1-score, and confusion matrix). |
| Field Validation | Evaluation of images taken in real life (Field) or photos taken only in a laboratory. |
| Class Imbalance Handling | Explicitly comment on the use of (Resampling/Weighting/Augmentation) or Not mentioned. |

### 2.2. Examining Literature and Determining Eligibility

To reduce bias in study selection, multiple reviewers independently conducted an initial title and abstract screening and then determined full-text eligibility. Agreement on eligible studies among the reviewers was established through open discussion as needed, and when required, a third reviewer was used to resolve differences. Overall agreement among the reviewers was very high, with over 90% of the studies selected for inclusion agreed upon at each round of screening and data extraction. Hence, the absence of an inter-rater reliability statistic, e.g., Cohen's kappa, is a methodological limitation of the study selection and data extraction process. The temporal distribution of the selected studies is summarized in Figures 2 and 3, which present year-wise publication counts for machine-learning–and deep–learning–based maize disease detection studies, respectively. These figures document the evolution of research activity over the review period (2017–2025) and provide contextual insight into the relative adoption timelines of ML and DL approaches within the maize disease detection literature (Figures 4 and 5).

There were substantial differences among the studies included in the formal meta-analysis, including discrepancies in the datasets used, the environments in which the data were collected, the evaluation metrics used, and the experimental protocols; therefore, it was not possible to conduct a formal meta-analysis. Additionally, the studies used both controlled benchmark datasets and heterogeneous field-collected data. As a result, there was substantial variability in both the distributions of the data and the reported metrics across studies (i.e., accuracy, F1-score, recall, mAP). Therefore, the average classification performance ranged from 72% to 99%, with higher and more consistent performance on controlled datasets (median performance 92–95%) than on field data, which showed greater variability. This variability is also illustrated for the F1-score and recall. All of this variability is a direct result of the imbalance of datasets and the differing methodologies employed in the studies, as reflected in Table 3.

**Table 3.** Performance metric summary statistics from reviewed research.

| Metric | Minimum (%) | Median (%) | Maximum (%) |
|---|---|---|---|
| Accuracy | 72 (approx.) | 92–95 | 99.9 (approx.) |
| Precision | 70 (approx.) | 90–93 | 99 (approx.) |
| Recall | 68 (approx.) | 89–92 | 99 (approx.) |
| F1-Score | 69 (approx.) | 90–93 | 99 (approx.) |

Following this descriptive characterization, the extracted studies were categorized based on the learning paradigm employed, machine learning or deep learning, to enable structured analysis in the subsequent sections. The following sections, therefore, focus on methodological trends, dataset characteristics, and reported performance outcomes within each category. The extracted studies were subsequently categorized by the learning approach employed, namely, machine learning and deep learning. The following sections provide a detailed analysis of these categories, focusing on methodological trends, dataset characteristics, and reported performance outcomes.

### 2.3. Conceptual Structure for DL and ML-Based Maize Disease Identification

This review uses a structured taxonomy to eliminate conceptual ambiguity regarding the scope of learning, task formulation, and model implementation methods. Machine Learning (ML) represents a broad class of data-driven computational methodologies. At the same time, Deep Learning (DL) represents a specific subclass of ML characterized by multi-layer representation learning. Tasks represent the goals of the system being developed (classification, detection, and segmentation). At the same time, Model Architectures indicate how those tasks will be accomplished (e.g., Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Transformer). Attention, feature fusion, and transfer learning were treated as part of the model's architecture rather than as separate paradigms, enabling a more cohesive, logical synthesis of the literature.

### 2.4. Taxonomy of Learning Paradigms, Tasks, and Model Architectures for Maize Leaf Disease Detection

A taxonomy developed using a structured approach provides conceptual clarity for research studies that identify maize leaf disease by distinguishing task type, learning paradigm, and model architecture. The overarching paradigm for machine learning (ML) is employed, with deep learning (DL) as a specific form of ML that enables hierarchical feature learning. Further, the definitions of the detection tasks (image classification, object detection, and image segmentation) are provided without reference to any specific model type. The paradigm in which a model is trained is denoted by the three types of learning paradigms (i.e., supervised learning, transfer learning, and semi-/self-supervised learning). The specific computational structures (e.g., CNN, RNN, transformer) used in the model architecture are the most frequently reported in DL studies. The architectural components of DL that employ attention are considered part of the model architecture rather than distinct model types. Therefore, the taxonomy developed enables previous research to be systematically organized within this framework, facilitating meaningful comparisons of methods across studies. Table 4 lists the abbreviations.

**Table 4.** List of Abbreviations.

| Abbreviation | Full Form | Abbreviation | Full Form |
|---|---|---|---|
| CNN | Convolutional Neural Network | EANet | External Attention Transformer |
| RNN | Recurrent Neural Network | SKPSNet | Select Kernel Point Switch Network |
| DL | Deep Learning | SFTA | Segmented Fractal Texture Analysis |
| ML | Machine Learning | SDI | Stress-Related Vegetation Indices |
| LSTM | Long Short-Term Memory | SCR | Southern Corn Rust |
| DT | Decision Tree | NB | Naïve Bayes |
| SVM | Support Vector Machine | GCH | Global Color Histogram |
| KNN | K–K-Nearest Neighbor | CCV | Color Coherence Vector |
| LR | Logistic Regression | LBP | Local Binary Pattern |
| SL | Supervised Learning | CPDA | Color Processing Detection Algorithm |
| CART | Classification and Regression Tree | SPLD | Spot Tagging Leaf Disease |
| RF | Random Forest | PFS | Pertinent Feature Selection |
| YOLO | You Only Look Once | CAM | Class Activation Mapping |
| VGG | Visual Geometry Group | EKNN | Enhanced K-Nearest Neighbor |
| HOG | Histogram of Gradients | ACO | Ant Colony Optimization |
| GLCM | Gray Level Co-occurrence Matrix | LVCEL | Least Validation Cross-Entropy Loss |
| PCA | Principal Component Analysis | NLB | Northern Leaf Blight |
| HCA | Hard Coordinated Attention | SLB | Southern Leaf Blight |
| LTP | Local Ternary Patterns | OPNN | Optimized Probabilistic Neural Network |
| DNN | Deep Neural Network | CBAM | Convolutional Block Attention Modules |
| DCNN | Deep Convolutional Neural Network | GLS | Gray Leaf Spot |
| PSPNet | Pyramid Scene Parsing Network | NLS | Northern Leaf Spot |
| MSRCR | Multi-Scale Retinex with Color Restoration | UAV | Uncrewed Aerial Vehicle |
| OSCRNet | Octave and Self-Calibrated ResNet | SSD | Single Shot Multi-Box Detector |
| GAN | Generative Adversarial Network | mAP | Mean Average Precision |

Different architectures exist in deep learning, and several ways to implement learning. This paper examines several pieces of literature on the use of deep learning to identify diseases in maize leaves. Within the literature reviewed for this paper, there were multiple publications describing CNN architectures used as spatial learning models; RNN architectures, generally used in conjunction with CNN architectures for sequence modeling; and transformer architectures that leverage attention mechanisms. While these represent the predominant trends identified in the literature, they do not constitute a complete classification of all approaches to deep learning. There are many additional types of deep learning architectures, including autoencoders, graph networks, generative models, self-supervised learning architectures, and multimodal networks; however, due to their limited application in academic research on disease identification in maize leaves, these architectures will not be explicitly discussed in this paper.

### 2.5. Scope and Limitations of the Review

There are three limitations absorbed while performing this review. One limitation is that deep learning models grow quickly; therefore, some recent models may not be included in this review due to the time frame of the date selection. A second limitation is that, although a very systematic and replicated search strategy was applied, a small number of the most recent studies published after the final search date were not included in the review. Third, this review is restricted to visual plant diseases in maize, so recommendations from non-visual modalities, such as spectroscopy sensor data/techniques and genomic techniques, are not discussed in any detail. This review evaluated the quality of Inter-rater Agreement from a qualitative perspective because it was designed for a narrative and descriptive synthesis, not for statistical aggregation of results, which would require calculating formal reliability statistics (such as Cohen's Kappa) to assess the level of agreement among the raters. Therefore, the absence of formal reliability statistics is a methodological limitation that must be considered when interpreting the study selection and data extraction processes.

## 3. Maize Crop Disease Types and Datasets

Maize crops are vulnerable to multiple infectious agents and stressors that can significantly reduce yield and crop quality. In field practice, visible indicators of maize leaf infection include stunted growth, leaf discoloration, wilting, and patchy symptom development, making image-based diagnosis feasible for automated detection systems [27,28]. In addition, infections can originate from fungi, viruses, and other microbial agents [29], and symptoms can vary depending on the plant organ, disease stage, and environmental conditions. For this reason, the reviewed literature frequently focuses on leaf-image datasets, where disease cues are most observable and scalable for machine learning and deep learning pipelines.

Fungal infections are the most frequently reported causes of maize leaf diseases in the literature, including Northern Leaf Blight, rust, and Gray Leaf Spot [30]. Gray Leaf Spot, caused by Cercospora zeae-maydis, is considered one of the most destructive maize diseases under humid conditions [31]. Since multiple maize diseases exhibit visually similar symptoms, several studies group diseases based on causal agents and symptom patterns to improve labeling consistency and classification accuracy [32]. Accordingly, the principal maize leaf diseases addressed in machine learning and deep learning studies along with their characteristic visual symptoms and typical impacts are summarized in Table 5, including fungal diseases such as Northern Leaf Blight, Gray Leaf Spot, and rust, as well as grouped disease categories, viral and bacterial infections, and healthy leaf samples commonly used as reference classes in supervised classification datasets. For biological completeness, Table 6 provides a broader taxonomy of maize crop diseases and related stressors, offering contextual background beyond the disease classes directly modeled in ML/DL studies.

**Table 5.** Major maize crop diseases and distinct visual symptoms.

| Ref | Disease Type | Key Visual Symptoms | Typical Impact |
|---|---|---|---|
| [30] | Northern Leaf Blight (NLB) | Long gray-green lesions along veins | Reduced photosynthesis |
| [31] | Gray Leaf Spot (GLS) | Rectangular gray/brown lesions | Yield reduction |
| [30] | Rust | Yellowish–brown pustules | Premature leaf senescence |
| [32] | Grouped leaf diseases | Overlapping lesion patterns | Label ambiguity |
| [28,29] | General infections | Discoloration, wilting, stunting | Reduced vigor |
| [30,31] | Healthy leaf | Uniform green texture | Reference class |

**Table 6.** Taxonomy of Disease Types and Description.

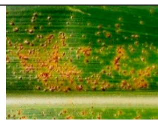
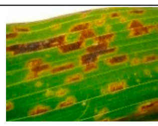
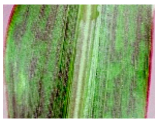
| S. No | Disease Type | Disease Name | Disease Image | Description |
|---|---|---|---|---|
| 1 | | Gray Leaf Spot |  | Gray Leaf Spot (GLS) is a fungal disease caused by the fungus *Cercospora zeae-maydis*. It can lead to significant yield losses in maize, especially in humid, hot regions. It can reduce maize yield by up to fifty percent, with the potential for even greater losses if infection occurs early in the growing season. |
| 2 | | Northern and Southern Corn Leaf Blight |  | Northern Corn Leaf Blight and Southern Corn Leaf Blight are serious foliar diseases of maize caused by pathogenic fungi. These diseases can significantly reduce maize yields, potentially leading to total crop loss. Under favorable conditions, economic losses from these diseases may also occur. |
| 3 | | Common Rust |  | Rust, a fungal disease, can significantly impact maize production and cause widespread financial losses. |
| 4 | | Cercospora Leaf Spot |  | Another fungal pathogen, Fox Spot, caused by the pathogen *Cercospora sorghi* var. maydis in maize, exhibits similar symptoms and has comparable damaging effects on the crop as Gray Leaf Spot, with potential yield and financial losses for producers. |
| 5 | ***Fungal Diseases*** | *Physoderma maydis* |  | This pathogen, also known as Physoderma brown spot or Physoderma leaf spot, threatens maize crops, especially in warm, moist regions. |
| 6 | | *Helminthosporium turcicum* (*Exserohilum turcicum*) |  | This fungal pathogen causes Northern Corn Leaf Blight (NCLB) disease in maize. It causes foliar diseases in maize and is a significant problem in regions with a climate conducive to disease development. Infected crops may exhibit visible signs of nutrient deficiencies due to poor nutrient absorption. |
| 7 | | Maydis Leaf Blight |  | The disease is usually associated with the fungus *Exserohilum turcicum*, but can also be linked to the virus maize leaf blight virus (MLBV). Infected plants may experience deficiencies because the disease can damage roots and impair nutrient uptake. |
| 8 | | Powdery Mildew |  | This fungal disease can infect many plants and crops, including maize (corn), and can slow their growth, leading to smaller plants and reduced grain yields. |
| 9 | | Dark Spot Diseases |  | Diseases such as northern and southern corn leaf blight can significantly reduce photosynthesis and harm plants, thereby lowering maize yields. |

**Table 6.** *Cont.*

| S. No | Disease Type | Disease Name | Disease Image | Description |
|---|---|---|---|---|
| 10 | ***Viral Diseases*** | Maize Streak Virus (MSV) |  | This viral disease infects maize in tropical and subtropical regions worldwide, especially in Africa. Infection with maize streak virus can weaken maize crops and impair their nutrient uptake, leading to reduced health and productivity. |
| 11 | | Mosaic Virus |  | In maize (*Zea mays*), the term "mosaic virus" generally refers to viruses that cause symptoms such as dark and light leaf streaks, which can even appear as bright emerald green. Infected plants may exhibit poor nutrient uptake and utilization, leading to nutritional deficiencies and reduced growth and productivity. |
| 12 | | Maize Eyespot Disease |  | It is related to the Maize Eyespot Virus (MEV). Although the virus receives less attention than some other maize viral infections, it can still significantly reduce yields. Affected plants will show nutritional deficiencies due to decreased nutrient uptake and overall health decline. |
| 13 | ***Bacterial Diseases*** | Goss's Wilt (Goss's Bacterial Wilt) |  | This bacterially induced disease can negatively affect the maize plant. Infected plants often experience nutrient deficiencies, leading to reduced absorption, uptake, growth, and yield. |
| 14 | ***Other Diseases*** | Armyworm Pest |  | Armyworms, especially the Fall Armyworm, can damage maize leaves, reducing yields and causing significant crop losses, especially when infestations occur during the early stages of plant development. |
| 15 | | Maize Kernel Abortion |  | Maize abortion results in an inadequate harvest when developing kernels abort and fail to mature during the grain-filling period, which determines yield. This can happen due to diseases, unhealthy plants, or adverse environmental conditions. As a result, there is a lower kernel number per ear and a decrease in overall yield. |
| 16 | | Maize Foliar Diseases |  | A variety of foliar diseases, including Common Rust, SCLB, and NCLB, can significantly impact maize growth and yield by disrupting nutrient uptake and overall plant health. |
| 17 | | Mendeley Leaf Disease |  | The field is often mistaken for other maize (*Zea mays*) diseases based on observed leaf symptoms. Research shows that these symptoms are not associated with any unusual disease classification. Leaf diseases can lead to fewer ears or smaller kernels, which results in lower yields and less profit for growers. |

Dataset characteristics play a critical role in determining the performance and generalization ability of machine learning and deep learning models for maize disease detection. Many studies rely on publicly available datasets due to their accessibility and labeled structure; however, such datasets are often collected under controlled imaging conditions. Several maize disease datasets reported in the literature include multi-class image collections derived from PlantVillage and Kaggle sources [33,34]. While these datasets enable benchmarking, their limited environmental diversity may reduce robustness. In contrast, field-collected datasets captured using cameras or uncrewed aerial vehicles introduce real-world variability such as illumination changes, occlusion, and background noise, but are typically smaller and more imbalanced [35,36]. In contrast, field-collected datasets collected under real-world conditions are generally smaller and more imbalanced, yet offer greater environmental variability [35,36]. A comparative overview of dataset sources, scale, and ecological characteristics used in maize disease detection studies is provided in Table 7.

**Table 7.** Comparison of datasets used in maize disease detection studies.

| Ref | Dataset Source | Dataset Size | No. of Classes | Lab vs. Real | Environmental Diversity |
|---|---|---|---|---|---|
| [33] | PlantVillage/public datasets | Large | Multiple | Lab-controlled | Low–Moderate |
| [34] | Kaggle maize datasets | Medium | Multiple | Mixed | Moderate |
| [35] | Field-collected datasets | Small–Medium | Varies | Real-field | High |
| [36] | Large public maize datasets | Large | Multiple | Mixed | Moderate–High |

These dataset characteristics help explain the variability in reported performance across studies and highlight the importance of evaluating models under diverse and realistic field conditions. The following sections build on this overview by examining machine-learning and deep-learning-based approaches developed for maize crop disease detection and classification.

## 4. Machine Learning-Based Maize Crop Disease Detection

Machine learning (ML) has been widely adopted for maize crop disease identification because it can extract measurable patterns from image- and sensor-based observations and translate them into reliable diagnostic decisions. Most ML-based pipelines reported in the literature follow a common sequence: data acquisition, preprocessing, feature extraction, and supervised classification. Subsequent stages focus on feature extraction and selection, where studies commonly employ color descriptors (e.g., RGB/HSV) and texture-based descriptors (e.g., GLCM, LBP), and then apply supervised learning models such as SVM, RF, KNN, DT, NB, and LR for classification. Model performance is typically evaluated using accuracy and related metrics such as precision, recall, and F1 Score, after which refinement may involve parameter tuning or dataset augmentation to improve generalization. Figure 6 summarizes the typical ML pipeline reported across the reviewed studies, and Figure 7 illustrates the systematic organization of the ML-based diagnostic workflow used to structure the reviewed studies.

A distinct stream of ML research in maize disease monitoring emphasizes that classification performance and deployment feasibility are not determined solely by the learning algorithm, but also by the sensing modality and the scale and representativeness of the acquired data. In this direction, Lin et al. [37] demonstrated that moving beyond conventional RGB imaging toward hyperspectral acquisition can support fine-grained discrimination tasks relevant to farm management, collecting 100 high-resolution hyperspectral images and reporting over 95% accuracy with strong agreement metrics when separating corn and weed species. Complementing modality-driven efforts, Meng et al. [38] addressed the practical need for rapid, field-ready screening by leveraging vegetation indices and multi-site sampling to diagnose Southern Corn Rust (SCR) non-destructively; their SVM-based approach achieved 87% overall accuracy for SCR detection and 70% overall accuracy for severity classification. This finding underscores the influence of field heterogeneity on diagnostic model performance.

Beyond modality, the reviewed literature also indicates that dataset scale and public availability influence both benchmarking and generalization evaluation. Mduma et al. [36] contributed an 18,148-image collection of healthy and diseased maize leaves collected in Tanzania, which they reported as the largest publicly available dataset in this context. They positioned it as a resource for advancing ML-enabled diagnosis and related computer vision tasks, such as segmentation and detection. In parallel, Ni et al. [39] further extended maize disease identification beyond image-based inputs by employing FTIR spectral measurements to separate Northern Corn Leaf Blight (NCLB), Gray Leaf Spot (GLS), and healthy samples. Their workflow combined feature selection with ML classification and reported a best-performing VIP-KNN model achieving 97.46% accuracy, alongside sensitivity and precision values above 96%. Taken together, the reviewed evidence indicates that ML-based maize disease detection has progressed through complementary directions, richer sensing modalities, field-oriented indices, large-scale datasets, and spectroscopy-driven discrimination, each shaping what "reliable performance" means under practical agricultural constraints [36–39].

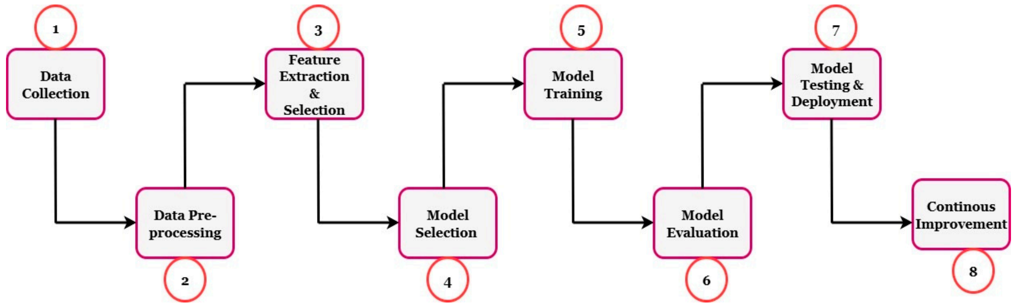



**Figure 6.** General process for maize crop disease detection using machine learning.

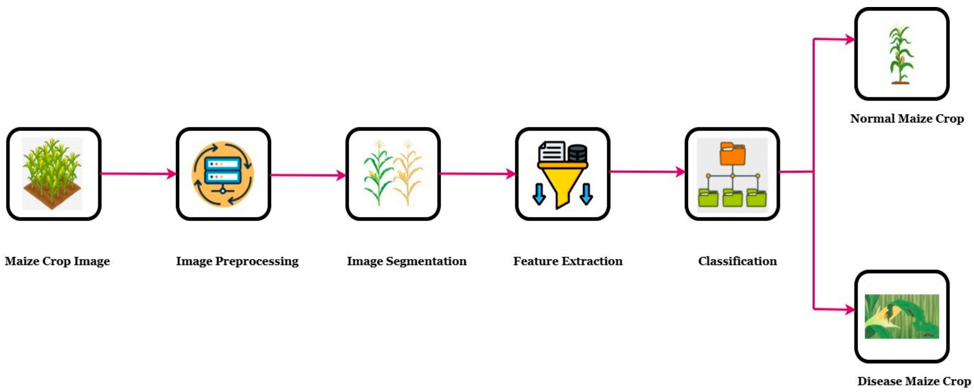



**Figure 7.** Maize leaf disease identification using machine learning.

Building on advances in sensing modalities and dataset construction, a substantial body of work has evaluated classical supervised machine learning classifiers for maize leaf disease identification under controlled imaging conditions. These studies primarily relied on widely used algorithms such as Support Vector Machines (SVM), Random Forests (RF), K-Nearest Neighbors (KNN), Naïve Bayes (NB), Decision Trees (DT), and Logistic Regression (LR), often applied to curated subsets of publicly available datasets. For instance, Chokey et al. [40] demonstrated that supervised ML techniques could effectively support early disease diagnosis, reporting that a Quadratic SVM achieved 83.3% accuracy when trained on an extensive PlantVillage-based image collection. Similarly, Panigrahi et al. [41] systematically compared multiple classifiers on a maize-specific PlantVillage dataset and found that Random Forest outperformed other traditional methods, achieving 79.23% accuracy, highlighting the advantage of ensemble-based decision boundaries in handling intra-class variability.

Several studies further confirmed the competitive performance of RF-based classifiers in maize disease diagnosis. Chauhan et al. [42] reported that, when applied to a structured image repository containing common rust, gray leaf spot, and northern leaf blight samples, Random Forest achieved 80.68% accuracy, outperforming NB, DT, KNN, and SVM under identical experimental conditions. In contrast, works emphasizing margin-based classifiers noted the robustness of SVM in scenarios with limited training samples. Pitchai et al. [43] evaluated RF and SVM models on a PlantVillage maize dataset comprising 2800 images and reported that SVM achieved the highest overall system accuracy, approaching 90%, despite challenges posed by complex background patterns.

Other investigations explored classifier behavior on smaller or privately collected datasets, reinforcing similar trends. Studies employing KNN and SVM on limited sample sets reported accuracies exceeding 95%, albeit under constrained experimental settings that favored controlled lighting and background conditions [44]. Collectively, these findings suggest that while classical ML classifiers can deliver reliable performance on maize leaf disease detection tasks, their effectiveness is closely tied to dataset quality, class balance, and feature representation, motivating subsequent research efforts to improve feature extraction, selection, and robustness across diverse agricultural environments [40–44].

A closely related line of research has demonstrated that the performance of classical machine learning classifiers in maize disease detection is strongly influenced by the choice of handcrafted features and feature selection strategies, particularly when operating on RGB imagery captured under controlled conditions. Several studies showed that combining color, texture, and structural descriptors can substantially enhance discrimination between visually similar disease classes. For example, Kusumo et al. [45] evaluated multiple feature representations, including RGB color channels, SIFT, SURF, ORB, and HOG, using the maize subset of the PlantVillage dataset (3823 images), and reported that RGB-based features combined with SVM yielded the most stable classification results, highlighting the sensitivity of ML performance to feature representation. Similarly, Aurangzeb et al. [46] employed a multi-stage pipeline integrating HOG, Segmented Fractal Texture Analysis (SFTA), and Local Ternary Patterns (LTP), followed by Principal Component Analysis (PCA) to address dimensionality challenges. Their approach achieved accuracies ranging from 92.8% to 98.7%, demonstrating that dimensionality reduction can significantly enhance classifier performance without compromising accuracy.

Texture-driven feature extraction has also been extensively explored to improve disease pattern recognition. Wei et al. [47] proposed a hybrid strategy that combines K-means clustering in the LAB color space to reduce background noise with Gray-Level Co-occurrence Matrix (GLCM) features for texture characterization. When evaluated using an SVM classifier, the method achieved 90.4% accuracy for color features, 80.9% for texture features, and 85.7% when both were combined, indicating that feature fusion can mitigate the limitations of single-descriptor representations. Agustino et al. [48] further refined texture-based approaches by integrating Global Color Histogram (GCH), Color Coherence Vector (CCV), and Local Binary Pattern (LBP) features into a voting classifier framework comprising multiple CART models. Their results yielded an overall precision of 82.92%, a recall of 82.55%, and an F1 Score of 82.6%, suggesting that ensemble learning can mitigate the instability of handcrafted features across disease categories.

Feature engineering strategies were also effective when combined with supervised learning on structured datasets. Patel et al. [49] employed GLCM and Gabor filters to extract discriminative texture information from maize leaf images and evaluated several classifiers, including SVM, KNN, DT, and Gradient Boosting. Their experiments revealed that GLCM features oriented at 135° produced powerful performance, with Decision Tree and Gradient Boosting classifiers achieving accuracies of 95.05%. In a related effort, Kilaru et al. [50] incorporated YOLO-based segmentation to isolate diseased leaf regions prior to feature extraction using Discrete Wavelet Transform (DWT) and GLCM, followed by ML classification. Among the evaluated classifiers, SVM achieved the highest accuracy of 97.25%, reinforcing the importance of combining spatial localization with texture-aware feature extraction. Overall, these studies collectively demonstrate that while classical ML algorithms form the computational backbone of maize disease diagnosis, feature design and selection remain the dominant determinants of performance, particularly in scenarios involving visually subtle disease symptoms. However, reliance on handcrafted features also exposes ML-based pipelines to sensitivity to varying illumination, background complexity, and field conditions, motivating a subsequent transition toward automated representation learning approaches [45–50].

Beyond classification accuracy alone, several machine learning studies have addressed maize disease diagnosis from the perspective of disease localization, severity estimation, and quantitative assessment of infected regions, recognizing that practical crop management often requires more than categorical labels. Early work by Yadav et al. [51] focused on automated rust detection and quantification, proposing an image processing pipeline that segmented infected regions from healthy maize leaves to estimate disease extent. Using a controlled dataset of 120 images (60 healthy and 60 rust-infected), their method demonstrated that isolating diseased areas before classification can support objective assessment of infection severity, particularly in scenarios where visual symptoms vary gradually across the leaf surface. A complementary severity-oriented approach was introduced by Ak Entuni et al. [30], who applied Fuzzy C-Means clustering to identify disease spots and estimate infection levels on maize leaves collected from the PlantVillage dataset. Although the study relied on a relatively small image set, the researchers showed that fuzzy membership functions could effectively model gradual transitions between healthy and infected tissue, enabling severity-based interpretation rather than binary classification. Their findings suggest that soft clustering techniques may be better suited for early-stage disease detection, where sharp class boundaries are difficult to define.

Fuzzy logic was also explored in more complex diagnostic scenarios involving both diseases and pests. Resti et al. [52] proposed a fuzzy decision tree framework that addressed discretization ambiguity in image preprocessing by integrating multiple membership functions, including S-growth and triangular curves. Trained on 761 digital images, their model consistently outperformed a conventional decision tree across several evaluation metrics, reporting improvements in recall (12.88%), F-score (10.68%), and accuracy (3.23%). These results highlight the suitability of fuzzy-based ML models for handling uncertainty in visual symptoms, particularly in heterogeneous agricultural environments. Collectively, these studies demonstrate that segmentation-driven and severity-aware ML approaches provide additional diagnostic value by enabling quantitative disease assessment, which is essential for targeted interventions and precision agriculture. However, they also reveal an inherent trade-off between interpretability and scalability, as such pipelines often rely on task-specific preprocessing and carefully tuned membership functions, limiting their robustness when applied across large datasets or diverse field conditions [30,51,52].

As classical classifiers and feature-driven pipelines matured, subsequent studies increasingly focused on optimization strategies, ensemble learning, and improved decision mechanisms to overcome the limitations of single-model approaches for maize disease detection. Rather than introducing entirely new classifiers, these works aimed to improve robustness, accuracy, and scalability by refining how learning models aggregate features, handle nonlinearity, and adapt to heterogeneous datasets. Arora et al. [53] exemplified this direction by applying a Deep Forest framework, an ensemble of decision tree cascades, to maize leaf disease classification across datasets drawn from different domains. When evaluated on maize images at $512 \times 512$ pixels, the proposed method achieved 96.25% accuracy on smaller datasets, outperforming conventional ML classifiers and demonstrating that tree-based ensembles can rival deep models while maintaining lower computational overhead. Optimization-driven hybridization further strengthened ML performance in several studies. Kumar et al. [34] combined Random Forest classifiers with Ant Colony Optimization (ACO) to enhance feature selection and decision boundaries when diagnosing maize leaf diseases. Using a Kaggle dataset of 3200 images spanning common rust, leaf blight, and healthy classes, the RF–ACO framework achieved an overall accuracy of 99.40%, substantially outperforming standalone classifiers. Similarly, Noola et al. [54] proposed an Enhanced K-Nearest Neighbor (EKNN) model that incorporates advanced feature engineering using GLCM and Gabor descriptors, achieving exceptional performance metrics, including 99.86% accuracy, 99.60% sensitivity, 99.88% specificity, and an AUC of 99.75% on PlantVillage maize images. These results indicate that carefully optimized neighborhood-based classifiers can remain competitive with more complex learning paradigms when supported by high-quality features.

Large-scale comparative evaluations also helped consolidate insights across multiple ML strategies. Prakash et al. [55] conducted an extensive benchmarking study using 4188 maize images from Kaggle, evaluating a broad spectrum of ML models, including SVM, DT, RF, KNN, Gradient Boosted Trees, LSTM, CNN-based variants, and ensemble configurations. Their experiments identified a hybrid XGBoost + KNN model as the most effective, achieving 98.77% accuracy with consistently strong precision, recall, and AUROC values. By systematically comparing algorithmic families within a unified experimental setting, this study reinforced the observation that ensemble and optimized ML approaches consistently outperform single classifiers, particularly when disease classes exhibit overlapping visual characteristics.

Taken together, these works highlight a clear evolution in ML-based maize disease detectionfrom baseline classifiers toward optimization-aware and ensemble-driven solutions capable of delivering near-ceiling accuracy on curated datasets. Nevertheless, their strong performance remains closely tied to controlled imaging conditions and carefully engineered features, underscoring the growing need for representation learning methods that can generalize across varying environments and acquisition settings [34,53–55].

In summary, machine learning–based approaches have played a central role in advancing maize crop disease detection by enabling structured analysis of image and sensor-derived data through supervised classification frameworks. Across the reviewed studies, ML models demonstrated strong diagnostic potential when applied to curated datasets, achieving reported accuracies ranging from moderate to near-perfect levels depending on feature representation, classifier selection, and optimization strategy [34,37,40,41,53–55]. Feature-driven pipelines that combined color, texture, and structural descriptors, often enhanced through dimensionality reduction or ensemble learning, were shown to improve classification performance, particularly under controlled imaging conditions significantly [45–50].

However, the literature review also highlights several recurring challenges in ML-based maize disease detection. Model performance was frequently sensitive to the quality of handcrafted features, dataset imbalance, and limited sample size, as evidenced by studies that relied on small or highly controlled datasets [33,56]. Additionally, approaches developed using standardized repositories such as PlantVillage or Kaggle often required careful preprocessing and parameter tuning to maintain stability across disease classes and acquisition settings [41–43]. While ensemble and optimization-based techniques improved robustness in some cases, their effectiveness remained closely tied to the representativeness and diversity of the training data [34,53,55].

Collectively, these findings indicate that machine learning techniques provide an effective and interpretable foundation for maize crop disease diagnosis, particularly when datasets are well-structured and feature characteristics are clearly defined. At the same time, the reliance on manually engineered features and dataset-specific configurations underscores inherent constraints in scalability and adaptability, which continue to shape ongoing research efforts in this domain [36–39]. To consolidate the methodological characteristics, datasets, and reported performance of machine learning–based approaches,

Table 8 summarizes representative ML studies on maize crop disease detection reviewed in this work.

**Table 8.** Summary of ML–based studies for maize crop disease detection.

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
| --- | --- | --- | --- | --- | --- | --- | --- |
| [37] | 100 hyperspectral images (corn and weed plants); 70% training/30% test; collected using an imaging spectrometer | Corn and weed species (weed identification task) | Decision tree classifiers and boosting methods using hyperspectral imaging features | Global accuracy >95% with high kappa coefficients for distinguishing corn vs. weed species | Limited sample size (100 images); task focuses on weed identification, not maize disease; hyperspectral hardware may reduce deployment feasibility | Validate on larger and more diverse field datasets; test transferability to maize disease symptoms; assess lightweight alternatives for practical deployment | 2017 |
| [45] | Plantvillage maize subset; 3823 images | GLS, Common Rust, NLB, Healthy | RGB, SIFT, SURF, ORB, HOG FEATURES; CLASSIFIERS: SVM, DT, RF, NB | Best Performance: RGB With SVM | Reliance on handcrafted features; results likely influenced by controlled dataset characteristics | Evaluate robustness on real-field images; include cross-dataset testing; combine feature selection and augmentation to improve generalization | 2018 |
| [51] | Plantvillage: 120 images (60 healthy, 60 rust) | Rust vs. Healthy | Automated image processing with Rust segmentation/quantification | Computational Time: 0.48 S | Small dataset and binary setting limits generalization; PlantVillage may not reflect field variability | Expand to multi-class diseases and larger datasets; test under varying lighting/background; report accuracy/precision/recall for completeness | 2018 |
| [30] | Plantvillage: 30 images (maize leaf diseases) | Powdery Mildew, Dark Spot, Rust | Fuzzy c-means for severity/spot identification | Runtime: 19.28 S; Poi Reported (68.54% In Text) | Minimal dataset; disease set appears mixed across plants in description; limited reporting of standard classification metrics | Clarify crop-specific evaluation (maize only); increase sample size; add quantitative metrics (accuracy/f1) and validation on field images | 2019 |
| [40] | Plantvillage: 54,306 images | Common Rust, Common Smut, Fusarium Ear Rot | Supervised ML: Linear SVM, Medium Tree, Quadratic SVM, Cubic SVM | Best: Quadratic SVM, 83.3% Accuracy | Accuracy lower than many benchmark reports; model sensitivity to dataset imbalance/background not specified | Add feature selection and preprocessing analysis; report precision/recall/f1 and confusion matrix; test cross-domain generalization beyond PlantVillage | 2019 |

**Table 8.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [53] | Multiple datasets from different domains; includes a small maize leaf dataset (12 images reported for evaluation) | Gray Leaf Spot, Common Rust, NLB | Deep Forest Algorithm | Achieved 96.25% Accuracy on Maize Leaf Disease Classification; Outperformed, according to established definitions, Traditional ML and CNN, RNN, and transformer-based models on Small Datasets | Evaluation partly based on small-scale datasets; performance on large, real-field datasets not fully explored | Validate on large, diverse field datasets; compare computational cost with deep learning models; assess scalability | 2020 |
| [46] | Plantvillage dataset; resized RGB images (256 × 256); corn and potato leaf images | Common Rust, Early Blight, Late Blight | Handcrafted features (HOG, SFTA, LTP) with PCA for dimensionality reduction | Accuracy Ranged From 92.8% to 98.7%, Outperforming Existing Methods | Evaluated on benchmark dataset only; handcrafted features increase pipeline complexity | Extend evaluation to real-field maize images; reduce feature engineering dependency; integrate automated feature learning | 2020 |
| [56] | Dataset of 66 maize kernel images; 75% training, 25% testing | Maize Kernel Abortion | Binary ML classifiers (LR, SVM, ADB, CART, KNN) and deep CNN | SVM and LR achieved 100% Accuracy; Other ML methods > 95%; CNN also reached 100% Accuracy | Minimal dataset; task focuses on kernel abortion rather than leaf disease | Increase dataset size; evaluate robustness across varieties; extend approach to leaf disease detection | 2020 |
| [38] | Data collected from multiple field sites using vegetation indices | Southern Corn Rust (SCR) | SVM using stress-related vegetation indices (vis) | Achieved an Overall Accuracy of 87% for Detection and 70% for Severity Classification; the Scr-Sdi Model Outperformed Baseline | Accuracy for severity classification is relatively low; it relies on spectral indices | Combine image-based features with vis; integrate multispectral or hyperspectral imaging; improve severity estimation models | 2020 |
| [41] | Plantvillage dataset; 3823 images (healthy: 1192; rust: 513; nlb: 956; gls: 1162) | Common Rust, Northern Leaf Blight, Gray Leaf Spot, Healthy | Supervised ML classifiers: NB, DT, KNN, SVM, RF | Random Forest Achieved the Highest Accuracy of 79.23% | Moderate accuracy compared to recent studies; sensitivity to dataset imbalance not addressed | Incorporate feature optimization and balancing strategies; evaluate ensemble or hybrid approaches; test cross-dataset generalization | 2020 |
| [47] | Images from various sources; random split (70% training, 30% testing) | Spot, Streak, Rust | GLCM texture features and SHV color features with SVM classifier; K-means clustering for segmentation | Accuracy: Color Features 90.4%, Texture Features 80.9%, Combined Features 85.7% | Performance varies significantly by feature type; segmentation is sensitive to noise and background | Improve robustness using adaptive segmentation; integrate feature selection or ensemble strategies; validate on larger field datasets | 2020 |
| [48] | Plantvillage dataset: over 8500 cornstalk leaf images | Northern Leaf Blight, Common Rust, Cercospora Leaf Spot (Gls), Healthy | Global Color Histogram (GCH), CCV, and LBP features with an ensemble voting classifier (CART-based) | Precision 82.92%, Recall 82.55%, F1-Score 82.6% | Moderate performance compared to recent studies; handcrafted features limit adaptability | Explore automated feature learning; expand to field images; optimize ensemble depth and feature fusion | 2021 |

**Table 8.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [42] | Maize plant database; 3823 images | Common Rust, Gray Leaf Spot, Northern Leaf Blight, Healthy | Supervised ML: NB, DT, KNN, SVM, RF with feature extraction (shape, color, texture) | Random Forest Achieved the Highest Accuracy of 80.68% | Accuracy remains moderate; limited analysis of environmental variability | Integrate feature optimization; test ensemble or hybrid methods; evaluate robustness on real-field images | 2021 |
| [44] | Own dataset: 100 maize leaf images | Gray Leaf Spot, Common Rust, Northern Leaf Blight | KNN and SVM classifiers | KNN Achieved 95.06% Accuracy | Small dataset size limits generalization; field conditions are not specified | Increase dataset diversity; include cross-validation; test performance under varying environmental conditions | 2021 |
| [57] | Own dataset; UCI machine learning repository | Late Blight, Septoria | SPLDPFS-MLT feature selection model with machine learning classifiers | Classification Accuracy Of 97% | Focus not exclusively on maize; disease scope differs from maize leaf diseases | Adapt model specifically for maize diseases; evaluate scalability and field applicability | 2021 |
| [58] | Hybrid dataset combining plantvillage and plantdoc; 4188 images (80% training, 5% validation, 15% testing) | Common Rust, Gray Leaf Spot, Blight, Healthy | Comparison of fifteen CNN architectures for feature learning and classification | Best-Performing Model Achieved 94.99% Accuracy. | Evaluation relies mainly on curated datasets; there is a limited discussion of field robustness | Validate on real-field maize images; analyze computational efficiency and deployment feasibility | 2022 |
| [59] | Plantvillage dataset: seven classes with 7794 observations | Gray Spot, Rust, NLB, Scorch (And Related Classes) | HCA-Mffnet architecture with attention-based feature extraction and segmentation | Achieved Peak Accuracy of 97.75% And F1-Score of 97.03% | Model complexity may limit lightweight deployment; training cost is not discussed | Explore model compression and pruning; test performance on resource-constrained platforms | 2022 |
| [50] | Plantvillage dataset; 3823 images | Common Rust, Gray Leaf Spot, Northern Leaf Spot | YOLO-based segmentation; DWT and GLCM feature extraction; classifiers: SVM, RF, KNN, DT, NB | SVM Achieved Highest Accuracy of 97.25% | Dependence on handcrafted features increases pipeline complexity | Integrate end-to-end learning; evaluate robustness under varying field conditions | 2022 |
| [34] | Kaggle dataset; 3200 images (rust: 800, leaf blight: 800, healthy: 1600) | Common Rust, Leaf Blight, Healthy | Supervised ML with Ant Colony Optimization (ACO) combined with RF, SVM, KNN, NB, and LR | ACO–RF Achieved Highest Accuracy of 99.40% | Performance validated on benchmark dataset only; field generalization not assessed | Test cross-dataset generalization; assess robustness to noise and lighting variation | 2022 |
| [33] | Plantwise and Kaggle datasets; 2636 images with imbalanced classes | Common Rust, NLB, Gray Leaf Spot | Multi-Task Learning CNN (MTL-CNN) with early stopping and transfer learning | Accuracy Improved From 77.44% To 85.22% Using Transfer Learning | Class imbalance remains a challenge; moderate accuracy compared to recent dl models | Incorporate advanced balancing strategies; expand dataset diversity; explore hybrid dl–ml frameworks | 2022 |
| [54] | Plantvillage dataset: 3820 images of healthy and diseased maize leaves | Common Rust, NLB Cercospora Leaf Spot | Enhanced K-Nearest Neighbor (EKNN) with GLCM and Gabor feature extraction | Eknn Achieved 99.86% Accuracy, 99.60% Sensitivity, 99.88% Specificity, Auc 99.75% | Evaluated on a curated dataset; dependence on handcrafted texture features | Validate on field-acquired images; assess scalability and computational cost for real-time deployment | 2022 |

**Table 8.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [52] | Digital photographs; 761 images used for training | Leaf Rust, Downy Mildew, Leaf Blight (Disease And Pest Detection) | Fuzzy membership functions integrated with a decision tree model | Improvements Over Baseline Dt: Recall + 12.88%, Kappa + 11.13%, F-Score + 10.68% | Overall accuracy remains low; the method is sensitive to discretization choices | Integrate advanced feature extraction; test on larger, diverse maize-specific datasets | 2022 |
| [60] | Plantvillage maize leaf dataset; 2226 images per class (healthy and infected) | Common Rust, NLB, Cercospora Leaf Spot | ML classifiers (SVM, RF, LR, DT, KNN), CNN, and Deep Forest (DF) | Accuracy: SVM 79.25%, Deep Forest 96.25%; CNN outperformed traditional ML methods according to established definitions. | Mixed ML and DL evaluation may complicate fair comparison | Standardize evaluation protocols; isolate ML vs. DL performance; expand to real-field datasets | 2022 |
| [61] | Shandong University research farm; ~7000 images | Armyworm Pest (Maize-Related Insect Attack) | Deep learning CNN models (VGG-16, Conv2D) compared with AlexNet, ResNet, and YOLO variants | Achieved 99.9% Classification Accuracy | Focus on pest detection rather than leaf disease; dl-heavy approach, not lightweight | Extend to disease-specific datasets; evaluate ml–dl hybrid models for efficiency | 2023 |
| [36] | Public maize leaf dataset; 18,148 images collected in Tanzania | Streak Virus And Other Maize Leaf Diseases | Machine learning applied to computer vision tasks (classification, segmentation, detection) | Largest Publicly Available Maize Leaf Dataset; Performance Metrics Not Fully Specified | Limited reporting of classifier-specific accuracy | Encourage standardized benchmarking; apply advanced ML/DL models for comparative evaluation | 2023 |
| [49] | Plantvillage: corn (maize) gray leaf spot dataset: 513 images (80% train, 20% test) | Common Rust, Gray Leaf Spot | Feature extraction: GLCM and Gabor filters; classifiers: SVM, KNN, DT, GB | Glcm (135°) Achieved 95.05% Accuracy for DT and GB | The dataset focuses on a limited subset (513 images); the evaluation is restricted to PlantVillage. | Expand to multi-disease maize datasets; validate on field images; report broader metrics (precision/recall/f1) consistently across classifiers | 2023 |
| [43] | Plantvillage website; maize dataset: 2800 leaf images across four disease classes | Common Rust, NLB (And Related Maize Diseases In The Dataset) | Supervised ML: Random Forest (RF), SVM; feature extraction (color, texture, shape) mentioned | SVM Achieved Best Results; Overall System Accuracy Reported as less than 90% | Overall performance remains less than90%; generalization beyond PlantVillage has not been established | Improve preprocessing and feature optimization; evaluate imbalance handling; test cross-dataset and field generalization | 2023 |
| [55] | Kaggle maize dataset: 4188 images | Common Rust, Blight, Gray Leaf Spot, Healthy | Multiple ML/DL models (Google Colab): SVM, DT, RF, KNN, CNNs, gbts, LSTM, GA-based ensemble, Adaboost, XGBoost; best: XGBoost + KNN | Best Accuracy 98.77%; Precision/Recall/F1/Auroc Rated Excellent | Many models are listed without a single standardized evaluation protocol described; benchmarking may be inconsistent | Standardize train/val/test split and metrics across models; report computational cost; validate on external/field datasets | 2023 |

**Table 8.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [35] | High-resolution images of powdery mildew on rice and maize; minimum resolution 224 × 224 | Powdery Mildew (Rice and Maize) | Transfer learning feature extraction with densenet (pretrained on imagenet) | Accuracy 97%, Precision 96.5%, Specificity 97%, Sensitivity 97% | Disease scope is specific (powdery mildew) and includes a multi-crop setting | Extend to maize-specific multi-disease settings; evaluate robustness under field conditions; compare with lightweight backbones for deployment | 2023 |
| [62] | Combined datasets: maculates dataset (T. Wiesner-Hanks) + Kaggle; merged into a comprehensive maize leaf dataset | Maize Foliar Disease Observations (Susceptible Areas/Disease Types as Described) | Weakly supervised learning with lightweight CNNs; evaluation via MIou using image-level tags; CAM-based interpretation | Maximum Miou Reported As 55.302% | Miou indicates moderate localization performance; weak supervision may limit fine-grained accuracy | Increase pixel-level annotations for stronger supervision; improve segmentation/localization; benchmark against fully supervised baselines | 2023 |
| [63] | Datasets from Mendeley, Harvard Dataverse, and Kaggle; pre-processed/segmented on edge impulse; deployment tested on MCU simulation | Common Rust, Gray Leaf Spot, Blight, Healthy, Streak Virus | CNN-based Maize Disease Detection (MDD); Edge Impulse vs. TensorFlow for tinyml deployment | 94.60% Accuracy; MCU Simulation: 7.60 Ms Latency, 726.60 Kb RAM, 344.70 KB Classifier Flash | Performance is reported mainly in a platform-specific deployment context; dataset composition by class is not fully detailed. | Provide class-wise performance and confusion matrix; test on additional field datasets; evaluate robustness under varying capture conditions | 2024 |
| [64] | Plantvillage dataset (various plant images, including maize types) | Physoderma Maydis, Curvularia Lunata (As Described) | Deep transfer learning: inceptionv3, resnet-50, VGG-Net, Inception-resnet-V2 | Best: Resnet-50 With 87.51% Accuracy; Precision 90.33%, Recall 99.80% | The dataset is not exclusively maize-focused; potential domain bias from curated imagery | Evaluate maize-only subsets and field images; include cross-dataset validation; compare lightweight transfer models for deployment | 2024 |
| [39] | Private dataset; FTIR spectra (4000–400 $cm^{-1}$); train/val: 80% (156 gls, 125 NCLB, 135 healthy); test: 20% (34 gls, 29 NCLB, 42 healthy) | NCLB, GLS, Healthy | FTIR spectroscopy + ML; VIP algorithm with RF for feature selection; VIP-KNN best among 12 models | VIP-KNN Accuracy 97.46%, Sensitivity 96.08%, Precision 95.06%; Classified Using 615 Significant Data Points; RF Models Avg Precision 93.41% | Requires spectroscopy equipment (not image-only pipeline); evaluation limited to specific fungal diseases | Combine spectral + image modalities; test scalability across regions/varieties; validate robustness under broader field sampling | 2024 |

Machine learning (ML) techniques have been extensively applied to the detection and classification of maize leaf diseases, demonstrating their effectiveness in supporting crop management and improving food security. Across the reviewed studies, ML-based approaches typically follow structured pipelines that include image preprocessing, hand-crafted feature extraction, feature selection, and supervised classification. These methods have been widely used to identify common maize diseases such as Common Rust, Northern Leaf Blight, Gray Leaf Spot, and viral infections, particularly under controlled and semi-controlled imaging conditions.

As summarized in Table 9, a wide range of classical machine learning classifiers has been employed for maize disease detection, including Support Vector Machines (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), Decision Trees, Naïve Bayes, Logistic Regression, and ensemble-based techniques such as AdaBoost and XGBoost. The performance of these classifiers is strongly influenced by the feature extraction strategies adopted, with texture-based descriptors (e.g., GLCM, LBP, and HOG), color-space features, and dimensionality reduction methods (e.g., PCA) playing a critical role in enhancing classification accuracy. Advanced variants, such as Enhanced KNN and hybrid optimization-based models, have further improved performance in several benchmark studies.

**Table 9.** Machine learning techniques used for maize crop disease detection.

| Naïve Bayes | CART |
|---|---|
| Decision Tree | Feature Selection |
| KNN | AdaBoost |
| SVM | GLCM |
| Random Forest | HOG |
| K-Means Clustering | PCA |
| XGBoost | HCA |
| Enhanced KNN | LR |
| Fuzzy C-Means Clustering | LTP |

Despite achieving promising accuracy levels, often exceeding 90% on curated datasets, according to established definitions, traditional ML-based methods exhibit inherent limitations. Their reliance on handcrafted features makes them sensitive to variations in illumination, background complexity, and environmental conditions, particularly in real-field agricultural settings. Moreover, many studies rely heavily on publicly available datasets that may not adequately capture the diversity and complexity of real-world maize cultivation environments. To better understand the distribution of data sources used in ML-based maize disease detection studies, the datasets employed across the reviewed literature are illustrated in Figure 8.

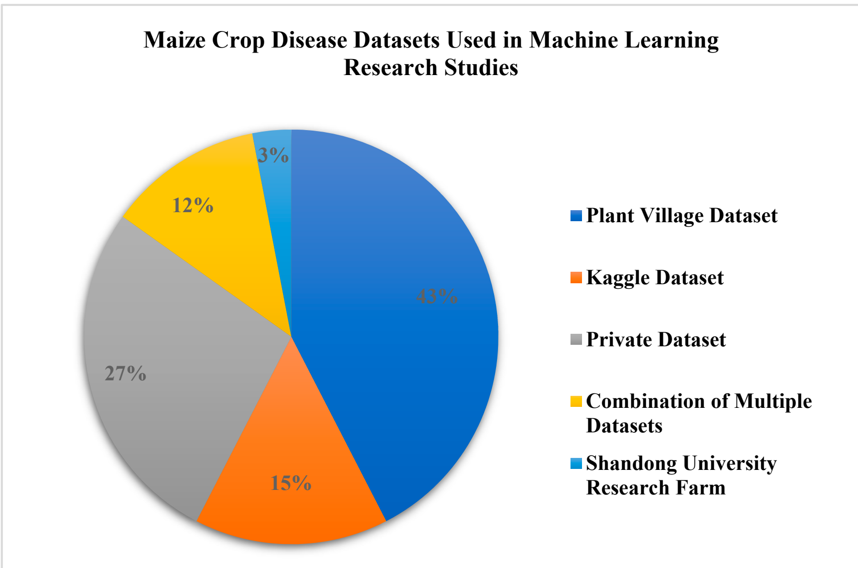



**Figure 8.** Datasets used for maize crop disease detection with Machine Learning.

## 5. Deep Learning-Based Maize Crop Disease Detection

Deep learning encompasses a range of architectures and learning paradigms that are constantly evolving. In the literature on maize disease detection, the three most common approaches are CNN-based classification models, CNN-based detection frameworks, and transformer-based architectures (the latter being the most recent). These categories represent major areas of focus in research on maize disease detection; however, they are not intended to be an all-inclusive list of the various types of deep learning techniques used for disease detection. The general workflow of DL-based maize disease identification is illustrated in Figure 9, and the corresponding procedural stages for data preparation, model training, evaluation, and deployment are outlined in Table 10. Table 10 summarizes the common procedural elements reported across studies, rather than prescribing a recommended workflow.

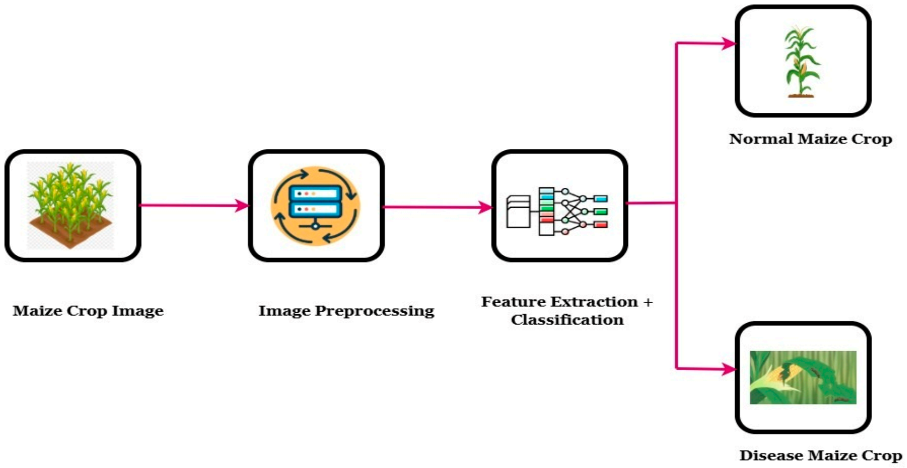



**Figure 9.** Workflow of maize crop disease identification using DL.

**Table 10.** General process for maize crop disease detection using deep learning.

| Step | Description |
|---|---|
| **Data Collection** | A substantial dataset of maize plant images, including healthy and diseased plants displaying various disease types, is needed. Field or existing datasets can be used to accomplish this task. |
| **Data Preprocessing** | Clean and preprocess the collected images, including resizing, cropping, and normalizing them for training the deep learning model. |
| **Dataset Split** | Once the dataset is prepared, it must be partitioned into train, validation, and test sets. The train dataset is to train the deep learning model. The validation dataset is used to tune the hyperparameters of the learning algorithm. The test dataset is to evaluate model performance, based on the trained and tuned model. |
| **DL Model Selection** | Reviewed studies typically use CNN-based architectures for image classification tasks because they are effective at learning spatial features. |
| **Model Training** | Train the selected deep learning model using the preprocessed training dataset. Training involves passing the images through the network and optimizing the model weights using an optimizer of the choice (e.g., stochastic gradient descent), repeating until the loss on the loss function is acceptable. |
| **Model Validation** | Evaluate the performance of the model previously trained on the validation dataset so that relevant performance metrics (i.e., accuracy, precision, recall, F1 score) can subsequently be computed and reported for the timing and efficiency of maize crop disease detection. |
| **Model Optimization** | Several studies further improved performance (e.g., learning rate, batch size, and network architecture) by optimizing hyperparameters using strategies such as grid search or random search. |
| **Model Evaluation** | Assess the performance of the final trained model using metrics on the test dataset, thereby establishing its effectiveness in detecting maize crop diseases. |
| **Data Collection** | A substantial dataset of maize plant images, including healthy and diseased plants displaying various disease types, is needed. Field or existing datasets can be used to accomplish this task. |
| **Data Preprocessing** | Clean and preprocess the collected images, including resizing, cropping, and normalizing them for training the deep learning model. |

Early DL studies established the feasibility of convolutional neural networks (CNNs) for maize leaf disease recognition, particularly under controlled imaging conditions, where automated feature learning enabled substantial improvements in classification accuracy [65,66]. These initial successes motivated the adoption of transfer learning strategies to reduce training complexity and enhance convergence when labeled maize datasets were limited [67,68]. However, as DL approaches progressed toward real-field and UAV-based imagery, it became evident that dataset characteristics, such as background complexity, illumination variability, and environmental noise, play a critical role in determining model robustness and generalization [69,70]. Collectively, these observations highlight both the potential of deep learning for maize disease diagnosis and the challenges associated with real-world deployment.

Early deep learning studies established the feasibility of convolutional neural networks for maize leaf disease recognition, primarily under controlled experimental conditions. Initial efforts relied heavily on benchmark datasets such as PlantVillage, which provided standardized backgrounds and uniform imaging conditions, enabling CNN models to achieve consistently high classification accuracy. Early CNN architectures demonstrated that automated feature extraction could outperform handcrafted descriptors, particularly for visually distinctive diseases such as northern leaf blight and rust, laying the groundwork for subsequent deep learning adoption [65,66,71].

Several studies explored transfer learning strategies using pretrained networks to compensate for the limited availability of labeled agricultural datasets. By fine-tuning models such as AlexNet and GoogLeNet, researchers reported substantial performance gains without extensive retraining, confirming the suitability of pretrained visual representations for plant pathology tasks [67–69]. These approaches reduced training time while maintaining robust accuracy, particularly when applied to small or moderately sized datasets [72,73].

Beyond baseline classification, early investigations also evaluated CNN-based systems across multiple maize diseases, highlighting the scalability of deep learning to multi-class settings. Comparative experiments showed that CNN-driven models could generalize across disease categories more effectively than conventional machine learning techniques, especially when trained on curated datasets [74–76]. Similar trends were observed in studies emphasizing early disease diagnosis and farmer-oriented decision support, where CNN frameworks demonstrated reliable detection capabilities but remained dependent on controlled imagery [77,78].

Despite promising accuracy, these foundational studies revealed key limitations due to environmental variability. Performance degradation was frequently observed when models trained on laboratory-style datasets were exposed to images with complex backgrounds or non-uniform lighting [79,80]. Although some works reported near-perfect accuracy under experimental settings, the lack of extensive field validation limited their direct applicability in real agricultural environments [70,81,82]. Collectively, these early CNN and transfer learning studies validated deep learning as a powerful tool for maize disease detection while simultaneously exposing the need for more diverse datasets and realistic deployment scenarios.

As deep learning matured within maize disease detection research, attention shifted toward deeper convolutional architectures capable of capturing more abstract and discriminative feature representations. Networks such as VGG, ResNet, DenseNet, and Inception variants became increasingly prevalent, as their greater depth enabled more effective modeling of complex disease patterns beyond simple texture or color cues [83–85]. These architectures demonstrated clear improvements in classification performance, particularly for visually similar maize diseases, where shallow CNNs often struggled to separate subtle lesion characteristics.

Dense connectivity and residual learning emerged as especially effective design strategies. DenseNet-based models enhanced feature reuse and gradient propagation, improving convergence stability and classification accuracy across multiple disease categories [84,86]. Similarly, residual learning frameworks mitigated vanishing gradients and facilitated the training of deeper models, resulting in consistently high accuracy levels approaching or exceeding 98% on controlled datasets [87,88]. These findings collectively indicated that architectural depth played a central role in advancing maize disease recognition performance.

To further refine disease localization and feature discrimination, several studies incorporated attention mechanisms into CNN pipelines. Architectures incorporating attention mechanisms (e.g., ViT, attention-augmented CNNs) selectively emphasized diseased regions while suppressing irrelevant background information, thereby improving robustness under moderately complex imaging conditions [89,90]. By guiding the network toward lesion-specific spatial and channel features, attention-enhanced CNNs achieved improved generalization compared to standard deep architectures, particularly for diseases with irregular or sparse visual symptoms [91,92].

Despite these advances, the gains in accuracy began to plateau. Multiple studies reported marginal improvements beyond the 98–99% range as architectural complexity increased, suggesting diminishing returns from depth alone [93–95]. Moreover, many evaluations relied on curated datasets with limited environmental diversity, raising concerns about scalability and real-world reliability [82,96–100]. While deep, attention-enhanced CNNs significantly advanced maize disease classification, their increasing computational cost and reliance on controlled datasets underscore the need for more efficient architectures and broader field-level validation.

While early deep learning studies primarily focused on image-level classification, subsequent research shifted toward disease detection and spatial localization to support precision agriculture applications. Object detection frameworks such as YOLO, SSD, and related region-based architectures enabled the identification and localization of diseased areas directly within maize leaf images, moving beyond simple presence–absence classification [101,102]. This transition enabled models to operate on field images with complex backgrounds, in which disease symptoms occupy only a small portion of the visual scene.

Several studies employed single-stage detection architectures to balance detection accuracy and inference speed, making them suitable for real-time or near-real-time agricultural monitoring. YOLO-based models demonstrated competitive performance in identifying maize leaf lesions while maintaining lower computational latency, an essential requirement for deployment in mobile and edge-based systems [103,104]. Enhancements such as attention blocks and architectural refinements further improved detection precision, particularly under variable illumination and background clutter [105,106].

Beyond detection, some works incorporated disease severity estimation to quantify infection progression and support timely intervention strategies. By integrating localization outputs with regression or segmentation-based analyses, these approaches enabled the assessment of lesion extent and disease intensity, contributing valuable insights for crop management and yield prediction [107–109]. Such models provided a more comprehensive understanding of disease impact compared to classification-only systems.

However, detection-oriented approaches introduced new challenges. High-quality bounding box annotations significantly increased dataset preparation costs, limiting scalability across diverse maize diseases [110,111]. Additionally, detection accuracy often depended on precise lesion annotation and dataset balance, with performance degradation observed in cases of overlapping symptoms or early-stage infections [112,113]. Despite these limitations, detection and localization frameworks represent a critical step toward operational maize disease monitoring, bridging the gap between laboratory-scale classification and field-ready decision support systems.

As deep learning models grew in depth and complexity, recent research increasingly focused on reducing computational overhead while preserving diagnostic accuracy, notably to support deployment in resource-constrained agricultural settings. Lightweight convolutional architectures and hybrid frameworks were proposed to address the limitations of large CNN models, especially for real-time inference on mobile devices and edge platforms [112,114]. These approaches emphasized parameter efficiency and reduced memory consumption without substantially compromising classification performance.

Hybrid models combining convolutional neural networks with recurrent architectures were introduced to capture both spatial and contextual disease patterns. By integrating CNN feature extraction with recurrent units such as RNNs or LSTMs, these models improved temporal and sequential representation, particularly for disease progression analysis and multi-stage classification tasks [114,115]. Such hybridization enabled enhanced modeling of complex disease symptoms while maintaining manageable computational complexity.

More recently, transformer-based architectures and CNN–Transformer hybrids have gained attention for maize disease detection. Vision Transformer (ViT) components and attention-driven tokenization mechanisms allowed models to capture long-range dependencies and global contextual information that traditional CNNs often overlook [10,116]. These models demonstrated competitive or superior performance compared to purely convolutional approaches, even with reduced parameter counts, highlighting their potential for scalable and efficient disease recognition.

Despite their promise, lightweight and transformer-based models still face practical challenges. Some studies reported sensitivity to training data size and quality, especially when transformers were trained on limited agricultural datasets [117,118]. Additionally, while hybrid and transformer-based systems achieved high accuracy under experimental conditions, broader validation across diverse field environments remains limited [112,116]. Nevertheless, these approaches represent a significant step toward deployable, real-time maize disease detection systems that balance accuracy, efficiency, and operational feasibility.

Despite substantial progress in deep learning models for maize disease detection, a recurring limitation across studies is their strong reliance on curated benchmark datasets. A large proportion of existing approaches relies heavily on the PlantVillage dataset, which provides high-quality images captured under controlled laboratory conditions with uniform backgrounds and lighting [66,90,119]. While such datasets facilitate model training and benchmarking, they often fail to reflect the visual complexity encountered in real agricultural environments.

Several studies reported a noticeable decline in performance when models trained on laboratory datasets were evaluated on field-acquired images. Variations in illumination, occlusion, leaf orientation, and background clutter were shown to adversely affect classification and detection accuracy, highlighting challenges in model generalization [87,120,121]. These findings suggest that high accuracy reported on benchmark datasets may overestimate real-world performance, particularly for early-stage infections or visually subtle disease symptoms [36,122].

Field robustness remains a critical concern, especially for models intended for deployment in precision agriculture systems. Research incorporating real-world datasets demonstrated improved adaptability but often required extensive preprocessing [62,123]. Even advanced attention-based and hybrid architectures (CNN-LSTM, CNN-Transformer) were sensitive to dataset imbalance and limited diversity, underscoring that architectural improvements alone cannot fully address generalization gaps [116].

Additionally, scalability and dataset representativeness pose ongoing challenges. Many studies focus on a limited number of disease classes or crop varieties, restricting their applicability across broader agricultural contexts [90,119]. The lack of standardized field datasets and consistent evaluation protocols further complicates cross-study comparison and reproducibility [121,122]. Collectively, these limitations underscore the need for large-scale, diverse, and field-realistic datasets, as well as evaluation strategies that prioritize robustness and deployment readiness over laboratory-level accuracy.

In summary, deep learning–based approaches have substantially advanced maize leaf disease detection by enabling automated feature learning and achieving consistently high performance across a wide range of disease categories. Convolutional architectures, deeper networks, attention-enhanced models, detection frameworks, and lightweight or hybrid designs collectively demonstrated strong capability in capturing complex visual disease patterns, frequently reporting accuracy levels above 90% under controlled conditions. The progression from image-level classification toward lesion localization and severity estimation further enhanced the practical relevance of these methods for precision agriculture applications.

Nevertheless, the reviewed studies collectively reveal that deep learning performance remains closely tied to dataset characteristics, computational requirements, and evaluation settings. Heavy reliance on curated benchmark datasets, particularly PlantVillage, limits generalization to real-world field environments, where background complexity, illumination variation, and early-stage symptoms pose significant challenges. In addition, increased architectural depth and model complexity introduce trade-offs in training cost, annotation effort, and deployment feasibility, especially in resource-constrained agricultural contexts.

While deep learning has established itself as the dominant paradigm for maize disease detection, current evidence suggests that further progress depends less on architectural novelty alone and more on addressing data diversity, field robustness, and deployment constraints. These observations provide a critical foundation for identifying remaining research gaps and guiding future directions toward scalable, explainable, and field-ready agricultural intelligence systems. The objective of this review is to provide a clear approach for distinguishing between tasks, types of learning, and types of computer vision model architectures to better understand and interpret maize disease detection via computer vision, as shown in Table 11.

In summary, deep learning (DL) approaches have been extensively applied to maize leaf disease detection due to their ability to learn discriminative visual features and automatically support accurate disease classification. A substantial proportion of these studies relies on publicly available benchmark datasets, particularly subsets of the PlantVillage repository, to evaluate model performance under controlled conditions. The distribution and characteristics of datasets employed for deep learning–based maize disease detection are illustrated in Figure 10, providing insight into prevailing data sources and their influence on reported performance.

To reduce the chance of ambiguity in the conceptualization and increase clarity around the methodology of this review, the researchers of this review clearly delineate task definitions (image classification, object detection, image segmentation, etc.) from the types of neural networks or architectures (convolutional neural networks, transformer-based architectures, etc.) that may be used to complete said tasks. Additionally, they distinguish the types of learning paradigms used in training deep learning models (e.g., supervised, transfer, semi-, or self-supervised) from task-level definitions. By breaking down prior research into distinct levels, the researchers have developed a framework for organizing prior studies and providing an accurate, technical basis for comparing various deep learning approaches to maize disease detection—see the categorization of Deep Learning Approaches for Maize Disease Detection in Table 11.

**Table 11.** A hierarchical taxonomy of deep learning methods for identifying maize diseases.

| Type | Group | Overview | Representative Models |
|---|---|---|---|
| Task Type | Image Classification | Disease identification on maize leaves or plants | ResNet, EfficientNet, DenseNet |
| | Object Detection | Identification and classification of the disease areas in maize leaf or plant images | YOLOv5, YOLOv7, Faster R-CNN |
| | Image Segmentation | Pixel-based outlining of areas of disease-affected maize leaves or plants. | U-Net, DeepLabv3+, PSPNet |
| Architecture Type | CNN-based Architectures | Using Convolutional Networks to extract features from images of maize leaves or plants. | VGG, ResNet, Inception |
| | RNN-based Architectures | Sequential or temporal modeling of extracted features from images of maize leaves or plants. | CNN–LSTM, CNN–RNN |
| | Transformer-based Architectures | Global attention-based representation learning using images of maize leaves or plants. | Vision Transformer (ViT), Swin Transformer |
| Learning Model | Supervised Learning | Fully labeled datasets for training using images of maize leaves or plants. | CNN-based classifiers |
| | Transfer Learning | Use of pre-trained backbones for maize disease classification tasks. | ResNet-50, MobileNet, VGG16 |
| | Semi-/Self-Supervised Learning | Learning from small or no-labeled image datasets for detecting diseases in maize plants or leaves. | Contrastive CNNs, Autoencoders |

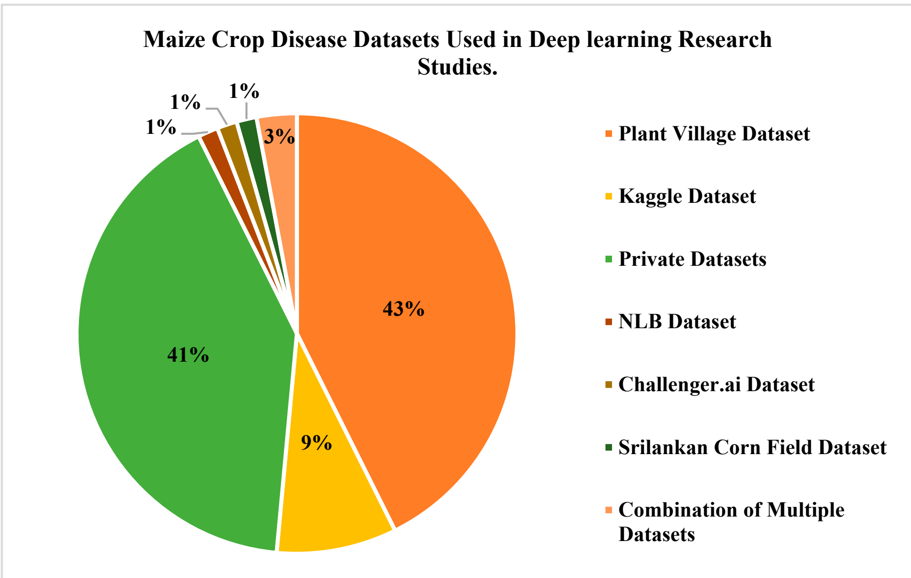



**Figure 10.** Datasets used for maize crop disease detection with deep learning.

### *5.1. Research Findings—Datasets Focused*

Analysis of the reviewed studies reveals a firm reliance on publicly available, curated image datasets for maize leaf disease detection. A significant portion of early and intermediate deep learning research employed datasets sourced from online repositories such as Google Images and the PlantVillage platform, often containing a limited number of disease categories under controlled imaging conditions [65]. These datasets typically include visually distinct maize leaf diseases such as northern leaf blight, gray leaf spot, rust, and southern leaf blight, with healthy samples serving as reference classes.

Among the most widely adopted resources, the PlantVillage dataset remains dominant, with multiple studies using subsets ranging from approximately 3800 to over 4000 maize leaf images for classification and evaluation [66,68,124]. These datasets often undergo preprocessing techniques such as PCA whitening, resizing, and random train–test splitting to enhance feature learning and reduce data redundancy. While such preprocessing improves model convergence and accuracy, it also reinforces dependency on laboratory-style imagery with uniform backgrounds and minimal environmental variability.

Several studies attempted to enhance dataset diversity by incorporating field-acquired images alongside PlantVillage samples. For example, maize leaf images collected directly from agricultural regions were combined with benchmark datasets to capture real-world disease manifestations [70,124]. These hybrid datasets included major maize diseases such as northern leaf blight, common rust, gray leaf spot, and bacterial wilt, providing broader disease coverage and geographic diversity. However, even in these cases, dataset curation often prioritized image clarity and consistency, potentially underrepresenting challenging field conditions such as occlusion, uneven lighting, and background noise.

Overall, the dataset-focused findings indicate that while deep learning models benefit from clean, well-annotated datasets, their reported performance is closely tied to the composition of those datasets. The dominance of controlled datasets such as PlantVillage limits generalization, and studies relying on multi-source or region-specific datasets highlight the influence of environmental factors that are frequently overlooked during data collection and evaluation [68,70].

### *5.2. Research Findings—Diseases and DL Techniques Focused*

Across the reviewed literature, deep learning approaches have been extensively applied to detect and classify major maize leaf diseases, with common rust, northern leaf blight (NLB), and gray leaf spot emerging as the most frequently studied conditions, particularly within the PlantVillage dataset [84,108]. These diseases are visually prominent and well-represented in benchmark datasets, making them suitable candidates for CNN-based classification and detection tasks.

Convolutional Neural Networks (CNNs) remain the dominant modeling approach, with architectures such as DenseNet, ResNet, and optimized CNN variants consistently achieving high classification accuracy, often exceeding 95% under controlled experimental settings [68,77,84]. In particular, DenseNet-based models demonstrated strong feature reuse and stable convergence, achieving accuracies above 99% when trained on curated datasets with advanced optimization strategies [84]. Similarly, CNN models trained on Kaggle and private datasets reported competitive performance for multi-disease classification tasks, confirming the robustness of deep convolutional feature extraction [125,126].

More advanced architectures have been introduced to address complex disease patterns and improve predictive capability. Hybrid deep learning models combining convolutional and recurrent components, such as CNN–RNN and 3DCNN–LSTM frameworks, were proposed to capture both spatial and contextual disease characteristics [114]. These architectures demonstrated improved performance for disease prediction tasks, especially when trained on larger datasets with temporal or volumetric information.

Object detection frameworks further extended the reach of deep learning beyond classification. YOLO-based models enabled the localization of disease symptoms on maize leaves, supporting early-stage detection and real-time monitoring [104]. Although detection accuracy and recall remained slightly lower than classification-based approaches, these methods represent a critical step toward deployable precision agriculture systems [126–129].

Overall, the reviewed studies indicate a clear performance advantage of deep learning approaches over traditional machine learning methods, with reported accuracies commonly ranging from 90% to 99%. However, model effectiveness remains strongly influenced by dataset quality, disease type, and experimental conditions, reinforcing the need for diverse training data and robust evaluation strategies. To consolidate the key outcomes, methodological trends, and reported performance of deep learning–based approaches, Table 12 summarizes the principal research findings on maize crop disease detection reviewed in this study.

**Table 12.** Summary of research findings on deep learning-based maize crop disease detection.

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [71] | Annotated field images of maize leaves captured using UAV (sUAS), boom-mounted camera, and smartphone (size not specified) | Northern Leaf Blight (NLB) | Convolutional Neural Network (CNN) for lesion detection using annotated field images | CNN effectively detected NLB lesions in field images; emphasis on high-quality expert annotation (quantitative accuracy not specified) | Dataset size limited; evaluation focused on a specific disease | Expand and diversify the annotated dataset to support broader real-world applications. | 2018 |
| [65] | Google images and PlantVillage dataset, 500 maize leaf images | Gray leaf spot, NLB, rust, brown spot, round spot, healthy (9 classes) | Deep CNN models (Cifar10 and GoogleNet) | High recognition accuracy of 98.8% (Cifar10) and 98.9% (GoogleNet) | Computational resource requirements are not discussed in detail | Reduce computational complexity to enable deployment on resource-constrained systems. | 2018 |
| [66] | PlantVillage maize leaf dataset (size not specified) | Gray leaf spot, NLB, common rust, healthy | Convolutional Neural Network (CNN) | Classification accuracy of 97.89% achieved on maize leaf diseases | Evaluation limited to the controlled dataset | Not specified. | 2019 |
| [69] | Field-acquired maize leaf images captured via UAV across 10 flights (sub-images used for training; size not specified) | Northern Leaf Blight (NLB) | CNN trained on UAV-derived sub-images for field-based disease detection | Achieved 95.1% accuracy when tested on field images | Did not evaluate performance on larger or multi-disease datasets | Validate the model using larger and more diverse datasets. | 2019 |
| [130] | Plant disease image dataset (source and size not specified) | Multiple plant diseases (not maize-specific) | CNN-based deep learning approach trained using GPUs | Reported high detection accuracy (exact value not specified) | Disease- and crop-specific performance is not detailed | Improve model generalization across different plant species and disease types. | 2020 |
| [125] | Kaggle crop disease dataset (size not specified) | Leaf diseases (crop-specific classes not detailed) | Faster R-CNN for disease detection | Detection accuracy exceeding 97%, enabling early-stage disease identification | Dataset characteristics and disease granularity are not fully described | Enhance the framework to support real-time disease detection applications. | 2020 |

**Table 12.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [67] | PlantVillage dataset, 50,000 plant images (4354 maize leaf images) | NLB, gray leaf spot, common rust, healthy | CNN with transfer learning and data augmentation | Recognition accuracy of 97.6% with improved classification speed | Evaluation limited to controlled PlantVillage images | Not specified. | 2020 |
| [124] | PlantVillage dataset + field images from Sultanpur and Raebareli districts (size not specified) | Leaf blight, rust, healthy | Deep Convolutional Neural Network (CNN) | An accuracy of 88.46% achieved using optimized pooling and hyperparameters | Performance lower than later DL approaches; dataset size not clearly specified | Incorporate additional maize disease datasets to improve robustness. | 2020 |
| [68] | PlantVillage dataset, 3823 maize leaf images | Common rust, NLB, Cercospora leaf spot, healthy | CNN-based deep learning model | High accuracy of 98.78%, with reduced training time | Limited evaluation beyond the PlantVillage dataset | Integrate and compare additional deep learning architectures to enhance performance. | 2020 |
| [72] | PlantVillage dataset + annotated NLB dataset (≈1100 images) | Healthy vs. NLB-damaged leaves | Pre-trained ResNet-50 (transfer learning) | Accuracy ≈99% and F1-score ≈99% on unseen data | Focused mainly on NLB; limited disease diversity | Improve application usability and extend functionality to other crops. | 2020 |
| [73] | Open-source NLB dataset (size not specified) | Northern maize leaf blight (NLB) | CNN-based Single Shot MultiBox Detector (SSD) with multi-scale feature fusion | Mean Average Precision (mAP): 91.83%, outperforming single-stage models | Evaluated primarily on the NLB only | Extend the detection framework to multiple diseases and optimize real-time processing. | 2020 |
| [74] | Maize leaf image dataset (4 classes, 50 images per class; resolution 256 × 256) | Common rust, NLB, healthy | CNN feature extraction (AlexNet, GoogLeNet, InceptionV3, ResNet, VGG) + ML classifiers | Best accuracy 93.5% using AlexNet with SVM | Small dataset size limits generalization | Test the model under more diverse environmental conditions and datasets. | 2020 |
| [83] | Maize leaf image dataset, 12,332 images (250 × 250 pixels) | NLB, Cercospora leaf spot, common rust, healthy | DenseNet CNN architecture | Optimized accuracy of 98.06% with fewer parameters than other CNNs | Evaluation focused on a single dataset | Evaluate the proposed architecture on multiple datasets to assess generalization. | 2020 |
| [75] | Leaf spot, rust, gray spot | Not specified | Optimized Probabilistic Neural Network (OPNN) with Artificial Jelly Optimization (AJO) | Accuracy up to 95.5% | Automated plant leaf disease detection | Improve discrimination between visually similar disease classes. | 2021 |
| [76] | Maize eyespot, common smut, southern rust, Goss wilt | PlantVillage + open maize dataset | CNN with transfer learning (Mobile-DANet) | Average accuracy 95.86%; 98.50% on the open maize dataset | Practical and feasible maize disease identification | Enhance usability for real-time field deployment. | 2021 |
| [77] | Maydis leaf blight | Private dataset | Deep CNN based on GoogleNet architecture | Classification accuracy 99.14% | High classification accuracy on independent test data | Validate the proposed methodology across a broader range of datasets. | 2021 |
| [78] | Common rust, NLB, gray leaf spot, brown spot | Google and Kaggle datasets (4149 images) | CNN using the GoogleNet architecture | Training accuracy 99.87%; testing accuracy 98.55% | Improved diagnostic accuracy for multiple maize diseases | Develop a software or web-based interface to visualize prediction results. | 2021 |

**Table 12.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [79] | Common rust (severity levels: early, middle, late, healthy) | PlantVillage | CNN with the VGG-16 network | Validation accuracy 95.63%; testing accuracy 89% | Effective severity-level classification | Improve accessibility by simplifying image processing and implementation requirements. | 2021 |
| [84] | Common rust, leaf blight, leaf spot | PlantVillage + field data (Madura, Indonesia) | Modified DenseNet-169 CNN with Adam optimizer | Average accuracy 99.32% (Adam > SGD) | Enhanced feature representation with deeper architecture | Conduct broader comparisons across multiple optimization strategies. | 2021 |
| [89] | NLB, common rust, Cercospora leaf spot | PlantVillage | CNN with Efficient Attention Network (EANet) | Training 99.89%, testing 98.94% | Attention highlights diseased regions while suppressing noise | Extend classification to additional categories of maize leaf diseases. | 2022 |
| [90] | Gray spot, common rust, NLB | PlantVillage (Kaggle subset) | End-to-end DL with EfficientNetB0 + DenseNet121 | Accuracy up to 98.56% | Improved feature representation via concatenation | Expand the model to support a wider range of plant diseases. | 2022 |
| [96] | Gray leaf spot | Field + PlantVillage datasets | CNN with Mask R-CNN background removal | Accuracy 94.1% | Background removal enhances detection | Introduce more dynamic and diverse datasets to improve adaptability. | 2022 |
| [97] | Leaf blight, leaf rust, leaf spots | Own dataset | DCNN with transfer learning | Accuracy 97.93% | Reliable disease identification | Further refine and optimize the proposed model architecture. | 2022 |
| [93] | Maydis leaf blight, TLB, banded leaf and sheath blight | Own dataset | Deep CNN | Accuracy 95.99%, recall 95.96% | Effective for multiple diseases | Integrate the model into a smartphone-based diagnostic application. | 2022 |
| [94] | Leaf diseases (multiple crops) | PlantVillage, Mendeley, Kaggle | AlexNet | Accuracy 93.16% | Multi-dataset robustness | Explore alternative preprocessing techniques to enhance efficiency. | 2022 |
| [131] | Turcicum leaf blight, rust | ICAR AICRP field dataset | Deep learning architecture | Accuracy 98.50% | Severity prediction and crop loss estimation | Validate performance across larger and more diverse datasets. | 2022 |
| [95] | Maize leaf diseases | Kaggle | CNN with multi-scale feature fusion | High accuracy | Improved disease identification | Enhance global contextual awareness beyond standard convolution operations. | 2022 |
| [86] | Gray spot, common rust, NLB | PlantVillage | CNN with transfer learning | Accuracy 99% | Adaptive thresholding-based disease quantification | Need to improve training data and training time | 2022 |
| [87] | Northern corn leaf blight (NLB) | Jilin Province and greenhouse datasets | DCNN (pre-trained GoogleNet) | Accuracy 99.94% | Intelligent diagnosis capability | To expand the method to other plant species | 2022 |
| [126] | SCLB, GLS, southern corn rust | PlantVillage + field images | CNN-based model | Accuracy 98.7% | High speed and accuracy | Need to improve computational complexity | 2022 |

**Table 12.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [88] | Common rust, leaf spot | PlantVillage | CNN with AlexNet | Accuracy 99.16% | Automatic feature extraction from raw images | Not specified | 2022 |
| [101] | Northern leaf blight (NLB) | Private field dataset | YOLOv3 with dense blocks and CBAM | AP: 0.774/0.806/0.821 | Reduced time consumption in detection | Need to improve research methods for numerous datasets | 2022 |
| [103] | Maize small leaf spot | Private dataset | DISE-Net deep CNN | Accuracy 97.12% | High convergence and superior accuracy | Need to improve research methods for numerous datasets | 2022 |
| [80] | Gray spot, leaf spot, rust | Challenger.ai dataset | K-means clustering + deep learning | Average accuracy 93% | Effective clustering and classification | To extend the approach to other maize diseases | 2022 |
| [132] | Northern leaf spot | PlantVillage | SKPSNet-50 CNN | Accuracy 92.9% | Effective for multiple diseases | To focus on agricultural research after optimization | 2022 |
| [85] | Gray leaf spot | PlantVillage | CNN models (EfficientNetB7 best) | Accuracy 98.77% | High diagnostic precision | To improve the same method for other plant species | 2023 |
| [91] | NLB, GLS, rust | PlantVillage (38 classes) | Deep neural network-based "half-and-half learning" strategy | Accuracy 98.36% | Highly effective disease classification | Need to improve the testing and validation of a variety of plants | 2023 |
| [92] | GLS, blight, common rust | PlantVillage + Kaggle maize leaf images (4988 images; 4 maize varieties) | DenseNet201 feature extraction + optimized SVM | Accuracy 94.6% | Effective feature extraction and classification | Improve early disease detection in maize plants | 2023 |
| [133] | GLS, NLB, NLS | Proprietary field dataset (ACRE, Purdue University), 1050 leaf images under varied conditions | Two-stage semantic segmentation (SegNet, U-Net, DeepLabv3+) for lesion segmentation + severity prediction | Overall $R^2 = 0.96$ (0.92–0.97 across classes) | High precision under complex field conditions; supports severity prediction | Extend to multiple diseases and improve real-time processing | 2023 |
| [102] | Leaf spot | MDID dataset: 10,000 annotated maize disease images (LabelImg); train 70%/val 30% | YOLOv5-MC object detection | Accuracy 89.9%; recall 91.6% | Addresses difficult detection/localization points | Need to improve AP results | 2023 |
| [98] | Pests and disease (crop counting context) | Multiple crop counting datasets (GWHD, MinneApple, Tassels Made of Maize) | Survey/review of DL models (YOLO, Faster R-CNN, SSD) for crop counting | YOLOv4 and Faster R-CNN reported ~95% in reviewed works | Comprehensive insights into DL object detection for counting | Real-time deployment challenges | 2023 |
| [99] | Bacterial leaf blight, brown spot (leaf disease detection) | Not specified | CNN-based disease detection with web application; models include CNN, VGG16, VGG19, ResNet50 | CNN 98.60%, VGG16 92.39%, VGG19 96.15%, ResNet50 98.98% | Web-based and accessible for farmers | Expand detectable diseases; enhance usability | 2023 |

**Table 12.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [81] | NLB, GLS, rust | PlantVillage maize crop dataset | CNN with preprocessing (CLAHE per RGB channel + HSV conversion) | Max accuracy 96.76% | Improved image quality and disease identification performance | Need to explore different plant species for disease identification | 2023 |
| [100] | Blight, mosaic virus, leaf spot | Real-world dataset from university research farm (Koont) | YOLO object detection (tested YOLOv3-tiny, v4, v5s, v7s, v8n) | Best mAP 99.04% (YOLOv8n) | Better performance; lower loss | Need to improve research methods for numerous datasets | 2023 |
| [82] | Phaeosphaeria spot, maize eyespot, GLS, Goss bacterial wilt | PlantVillage (primary source) | Soft ensemble model combining DenseNet121 + ResNet50 | Maize accuracy 90.9% (also rice 96.7% reported) | Ensemble is effective across crops | Improve with IoT device setup | 2023 |
| [119] | NLB | PlantVillage (transfer learning basis) + field dataset (size not specified) | MDCDenseNet (multi-dilated module + CBAM), plus ACGAN for the minor sample issue (noted longer training) | Field-test accuracy 98.84% | Effective under varying subjects/field conditions; outperforms other methods | Requires longer training (ACGAN); improve scalability; integrate more diseases | 2023 |
| [120] | NLB, GLS, NLS | Purdue University Agronomy Center dataset (field images; mobile-captured under varied conditions) | MaizeNet (ResNet-50 + spatial-channel attention) | Accuracy 97.89% | Effective recognition and classification under field variability | Need to improve the classification outcomes | 2023 |
| [134] | GLS, rust | Private dataset (various farms) | Federated Learning CNN (FL-CNN) for severity identification | Accuracy 93% | Increased precision in diagnosis and severity classification | Need to improve the research method for numerous datasets | 2023 |
| [70] | GLS, blight, common rust | 4800 field images from Bangladesh | Transfer learning DL models (ResNet50 GAP, DenseNet121, VGG19; hybrid ResNet50 + VGG16 features) | Best accuracy 99.65% | Robust performance on real-world field conditions; supports app-based diagnosis | Improve real-time processing | 2023 |
| [121] | Leaf spot, small spot (curvu-laria/tiny/mixed spot in text) | Private RGB-D segmented dataset | DL classification (ResNet50, MobileNetV2, VGG16, EfficientNet-B3) with segmentation + augmentation | Accuracy up to 97.82% | Balanced accuracy and classification performance | Enhance the practical, real-world deployment of the categorization system | 2023 |
| [122] | GLS, northern maize leaf spot | PlantVillage (noted as lab/controlled) | Review of DL approaches for maize leaf disease detection | High accuracy (value not specified) | Helps prevent adverse consequences via faster detection insight | Absence of uniform datasets; absence of comparative research | 2023 |
| [107] | Corn leaf eye spot (CLES) severity stages | Field dataset from Patiala, Punjab (images; 4 severity stages) | Hybrid CNN–LSTM model for severity classification | Accuracy 95.88% (high performance reported for stage recognition) | Captures spatial + temporal patterns; supports severity monitoring | Improve generalization to other diseases | 2023 |

**Table 12.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [108] | GLS, eyespot, Goss bacterial wilt | Five public datasets (PlantVillage emphasized; mixed-quality backgrounds discussed) | VGG-ICNN (lightweight CNN) | PlantVillage accuracy 99.16% | Reduced model size with strong accuracy; supports broader disease classification | FLOP counts are drawbacks | 2023 |
| [105] | GLS, blight, rust, mosaic | PlantVillage + Google | GoogleNet-based CNN | Accuracy 98.9% | Enhanced image classification and accuracy | Dense/complex field context in images affects clarity | 2023 |
| [114] | NLB, GLS, SLB | Maize_in_field + KaraAgro AI maize datasets | JSWOA-optimized hybrid 3DCNN–RNN (with LSTM) | Accuracy 98.12% (also precision/recall/F1 reported) | Hybrid model improves performance vs. state-of-the-art | Need to improve disease prediction from various resources | 2024 |
| [106] | Maydis leaf blight, GLS, common rust, southern rust | PlantVillage | PRFSVM combining PSPNet + ResNet50 + Fuzzy SVM | Accuracy 96.67% | Recognizes different objects; minimal training requirement | PSPNet struggles with low-resolution images | 2024 |
| [135] | Maize leaf spot | Private dataset | CNN with Random Forest | Accuracy 83% | Reduces time and money | Severe yield loss/financial difficulty context | 2024 |
| [110] | Blight, rust | MaizeData + PascalVOC | Semi-supervised detection: Agronomic Teacher/AgroYOLO with WAP strategy | Precision 53.8% (MaizeData), 66.1% (PascalVOC) | Leverages abundant unlabeled data effectively | Need to improve the research method for numerous datasets | 2024. |
| [112] | NLB, GLS, common rust | PlantVillage | Hybrid CNN–Transformer architecture | Accuracy 98.92% | Better representation and enhancement of specific features | Additional training time was needed to verify the results | 2024 |
| [123] | NLB, GLS, rust | Sri Lankan maize field + public images (combined dataset of 3024 images) | CNN based on pre-trained VGG16 (mobile app context) | Training accuracy 95.16%; testing accuracy 93% | Provides early warning for farmers via mobile deployment | This research did not test larger datasets | 2024 |
| [111] | GLS, blight, rust | Internet + real-world numerical dataset (as stated) | IoT framework with DL multi-model fusion (MMF-Net style) | Accuracy 99.23% | Early, accurate detection using an innovative IoT framework | Enhance system scalability; integrate more advanced IoT technologies | 2024 |
| [115] | NLB, leaf spot, rust | PlantVillage (3852 images; 4 classes) | ClGanNet (CONTINGENT GAN + CNN) for balancing + reducing overfitting | Training 99.97%; testing 99.04% | Balances data; reduces overfitting; fewer parameters | To extend the use of uncrewed aerial vehicles | 2024 |
| [10] | Pests and diseases (hyperspectral context) | Multiple hyperspectral imaging datasets | DL integrated with hyperspectral imaging (CNN/RNN combinations) | Detection accuracy up to ~98% | Detailed crop-health insights; strong detection performance | Reduce the cost and complexity of hyperspectral systems | 2024 |
| [117] | Blight, GLS, rust | Kaggle | Deep SqueezeNet model | Accuracy 97% | Limits overfitting (SMOTE) | Not specified | 2024 |
| [104] | NLB, GLS, rust | Kaggle | YOLOv7-based CNN model | Accuracy 82%; recall 85% | Supports control and prevention of crop diseases | YOLOv7 interpretability is needed for similar diseases | 2024 |

**Table 12.** *Cont.*

| Ref | Dataset (Source and Size) | Disease Classes | Ml Method (Features + Classifier) | Performance and Observations | Drawbacks | Improvement Opportunities | Year |
|---|---|---|---|---|---|---|---|
| [113] | GLS, rust | PlantVillage + Huazhong Agricultural University (field dataset; complex background set noted) | Texture–color dual-branch multiscale residual shrinkage network (TC-MRSN) | Accuracy 94.88% (complex background); 99.59% (PlantVillage) | Reduces redundant background noise; suitable for mobile deployment | Large-scale deployment is inappropriate in complicated farming contexts | 2024 |
| [118] | NLB, GLS, rust | PlantVillage | Image enhancement (MSRCR) + OSCRNet (Octave + Self-Calibrated ResNet) | Accuracy 95.63% | Strong robustness via enhancement + model design | Enhance networking performance and improve disease resistance in various maize types | 2024 |
| [109] | NLB, borer leaf damage, common rust | Luoyang City, Henan Province, China (1246 images; 90% train/val, 10% test; 124 unseen test images noted) | LSANNet (Long Short Attention Block) | Accuracy 94.35% on observed and unseen test sets | Better accuracy vs. several baseline CNNs | Need to improve processing techniques | 2024 |
| [116] | NLB, GLS, common rust | PlantVillage + Bangladeshi Crops Disease dataset | TinyResViT (ResNet + ViT hybrid) | F1-score 97.92% and 99.11%; ~83.19 FPS, 1.59 GFLOPs | High processing speed; strong accuracy with low compute cost | Need to improve processing techniques | 2025 |

In summary, the findings summarized in Table 12 indicate that deep learning models achieve high diagnostic accuracy under controlled conditions. At the same time, challenges related to dataset diversity, field robustness, and deployment efficiency remain prominent across studies. In recent years, maize disease identification systems have rapidly expanded their use of more advanced methods and deep learning technologies while maximizing operational efficiency and accuracy. YOLO (You Only Look Once) models are currently the industry standard for real-time inference and direct object detection with extremely low latency. As an added benefit, YOLO can also be deployed on mobile devices or uncrewed aerial vehicles (UAVs) in the field to localize and identify infected areas. Deep learning technologies such as Faster R-CNN (Faster Region-based Convolutional Neural Networks) achieve higher accuracy in both disease localization and overlapping-symptom and small-disease-area detection; however, they require more computational resources. Single-shot detectors and EfficientDets are designed for use when fast inference is not possible, making them suitable for resource-constrained applications. Vision transformers (ViT) and Swin transformers can capture more complex long-range and contextual relationships, thereby improving the robustness of their results, particularly under varying illumination levels. Collectively, these deep learning technologies have improved maize disease identification, progressing from providing only the name of the observed disease (e.g., in a photo) to identifying the disease's precise location within an image for use in field applications. As such, deep learning technologies can be combined to achieve both accurate disease identification and improved location knowledge.

## 6. Challenges in Using Maize Disease Detection Models in the Real World

The transition of disease identification in maize from laboratory testing conditions and processes to real-world farming practices has not been achieved because standardized data used for testing do not account for the extreme variations in agricultural production settings. The laboratory model's stringent standards of using a well-lit background without clutter allows for far better detection and classification than would exist under normal field conditions where many variables can cause significant confusion. Shadows across plants from other objects such as trees or buildings, differences in quality of light (day vs. night), and the presence of soil, weeds, or other crops interfere with feature extraction and subsequently decrease the effectiveness of classifying the plant stage or condition. Occlusions (overlapping leaves, whorls) and partial visibility of symptomatic areas create additional challenges for researchers, as many academic techniques require the symptomatic regions to be clearly observable and complete during detection. Additionally, maize plants tend to be highly visually diverse. Since the effects of disease change in size, color, and severity as the crop matures, it is very difficult for models trained on a handful of limited samples to generalize accurately. Practical field data will be even more affected by camera-related issues, which include sensor quality, viewing angles, resolution, and hand-held or drone-based image capture (motion blur). Additionally, external factors affecting the camera, such as dust, rain, fog, and humidity, will affect image clarity and the plant's surface reflectivity, creating visual noise and artifacts that would not have been evident in the laboratory. These external influences will collectively make a gap between the two domains of laboratory testing and farming practices; therefore, it is not surprising that in the laboratory testing environment, many models achieve nearly perfect accuracy but lose much of their performance when used in real-world farming production systems.

The models developed to detect disease in maize using convolutional neural networks (CNNs) achieve high precision in disease prediction. Still, because of their unique multi-layer architecture, they can also be difficult for users to interpret. The way in which CNNs operate is very complex; thus, most existing articles on maize disease management have emphasized accuracy over analysis of which visual characteristics or symptom-containing areas the model uses to formulate its output or prediction. Therefore, the application of Explainable Artificial Intelligence (XAI) techniques to maize-specific studies, such as Gradient-weighted Class Activation Mapping (Grad-CAM), Class Activation Mapping (CAM), and Local Interpretable Model-agnostic Explanations (LIME), remains limited. Because of this lack of interpretability, it is difficult to determine whether the model is learning to identify disease-related patterns or using images that lack such characteristics to make predictions. The lack of interpretability poses a challenge for both farmers trying to make reliable predictions with the model and agronomists and plant pathologists attempting to confirm the model's decisions in line with existing biological knowledge. So, the use of CNN-based systems for disease identification in real-world maize production will remain limited, even though they have been shown to achieve very high accuracy in laboratory settings.

### *6.1. Difficulties in Using Maize Disease Detection Systems in the Field*

Across multiple recent investigations, evidence-based studies have shown that well-trained models for detecting maize diseases can lose both accuracy and performance when applied in real-world field conditions. This shows well the finding regarding maize disease classification systems, whereby the accuracy observed in controlled (laboratory) environments, such as PlantVillage, has dropped by 10–30% for images collected under actual field conditions. Often, this decrease is due to significant variations in ambient lighting conditions, the natural, cluttered environment of maize in agricultural fields, and differences in image quality between the two environments. Studies have also identified multiple misclassifications of two visually similar maize disease types, e.g., Northern Leaf Blight and Gray Leaf Spot, due to overlapping symptom expression early in disease development. Finally, most studies have identified instances of model failure when the models were used on images collected under ambient lighting, due primarily to uneven illumination and shadows being cast on the plants or soil or weeds interfering with the plant being examined, causing certain features of that model to activate incorrectly, which can lead to a false prediction. Collectively these studies provide conclusive evidence that accurate performance in a laboratory would not be predictive of a precise and reliable performance when these systems are deployed for use in the field, therefore validating their use for field deployment must consider performance in the field, or in actual field settings, to identify issues which may go unrecognized or unknown when using a benchmark evaluation for establishing accuracy of this system. Overall, the evidence presented in these studies supports the theory that a lack of exposure to the wide range of variances typically encountered in the development, deployment, and widespread use of maize disease systems represents a significant limiting factor in the successful deployment of maize disease classification systems.

### *6.2. Limitations Impacting the Robustness of Real-World Models*

The leading cause of ineffective maize disease identification systems is the misalignment between the models' training data and the field environment in which the models must operate. One of the most significant contributors to this mismatch is domain shift—the difference in the visual distributions of the data that occurs when a model trained in laboratory or benchmark conditions is deployed in the field, due to differences in illumination levels, background complexity, and the angles at which images are taken. These issues are compounded by dataset bias. Most of the datasets used for this work contain many more images of clean, centered leaves than of natural field variations, including occlusions of leaf parts, mixed backgrounds, and co-occurrences of multiple diseases on a single plant. As a result, many models created to identify maize diseases primarily fit the visually simplified patterns of the training data and background features rather than learning disease-specific, robust features. This is evidenced by the fact that these models are often unable to identify disease in the field, where soil, weeds, and neighboring plants introduce visual noise. The other reason that these models are unable to obtain good accuracy in the field is that the models have not been trained on sufficient amounts of diverse training data—that is, they do not have enough diversity with respect to growth stages, disease severities, geographic regions, and environmental conditions, which limit their ability to generalize. Collectively, these reasons explain why high laboratory accuracy often does not translate to reliability in the field, underscoring the need for diverse, field-representative training data and robust evaluation protocols. Table 13 shows the Problems with Field-Level Performance in the Identification of Maize Disease.

**Table 13.** Model failures found in real-world assessments.

| Results | Training Dataset | Test Dataset | Observed Issues |
|---|---|---|---|
| [45,46] | PlantVillage | Field-captured maize leaf images | Significant accuracy drop under natural conditions |
| [44] | Kaggle | Mobile camera images | Misclassification between visually similar diseases |
| [58] | Custom Lab Dataset | In-field images across growth stages | Reduced robustness to disease severity variation |

### *6.3. Assessment Difficulties Caused by Class Imbalance*

Class imbalance has long been a problem in datasets for maize disease detection, where the number of samples per disease class is typically highly imbalanced. The majority of reviewed studies indicate a significant over-representation of images of healthy leaves relative to some diseased classes, especially for rarer or regionally defined diseases that are significantly under-represented. Such class imbalance causes biases of the learning algorithms in favor of the majority classes, enabling the resulting models to have high prediction confidence in their frequency classes compared to their much lower performing minority disease classes. Therefore, the overall accuracy metric does not accurately reflect the model's performance, as some models may achieve high accuracy while failing to recall or detect underrepresented diseases. In addition, a thorough and critical review of the literature indicated that most studies primarily reported accuracy rather than precision, recall, or F1-score, and used macro-averaged precision and recall metrics sparingly across all classes. Additionally, confusion matrix analysis was infrequently reported in the studies, providing minimal insight into specific misclassification patterns across disease classes. To address the many limitations identified, best practices should include reporting F1-scores, macro-averaged precision and recall, and performance metrics for each class (i.e., healthy and diseased), along with confusion matrices, to provide complete transparency in evaluating maize disease detection models. In addition to best practices, techniques such as data augmentation, resampling, and cost-sensitive loss functions can help mitigate class imbalance and improve the reliability and fairness of maize disease detection models.

### *6.4. Study Region and Determined Restrictions*

This review is a comprehensive synthesis of up-to-date machine learning techniques for detecting maize disease; however, it has several limitations. The limitations of this review are primarily attributable to the datasets that are currently available. Most of the analyzed literature used benchmark datasets from PlantVillage, introducing bias into the conclusions and preventing extrapolation to real-world field conditions. While this review provides an extensive overview of key deep learning architectures and detection systems, the rapid pace of innovation in deep learning means that not all new models and variations will be included. Also, due to differences in protocols and reporting methodologies across the literature, there is a limited opportunity for direct comparisons of the results presented. Collectively, these limitations emphasize the need to develop and maintain a system for regularly updating the literature and to create a comprehensive, standardized framework for evaluating all machine learning technologies. Furthermore, as research continues to mature, there will be a growing focus on collecting field data and using it to validate advances in machine learning.

## 7. Discussion

This systematic review synthesizes recent advances in maize leaf disease detection using machine learning (ML) and deep learning (DL) techniques, with particular attention to methodological evolution, dataset dependency, and reported performance trends. Overall, the reviewed studies demonstrate that automated image-based approaches can achieve high diagnostic accuracy under controlled experimental conditions; however, substantial challenges remain in translating these methods into robust, field-ready solutions.

Across ML-based studies, classical supervised classifiers such as Support Vector Machines, Random Forests, and K-Nearest Neighbors, as well as ensemble-based variants, showed strong performance when combined with carefully engineered color and texture features. Reported accuracy values ranged from approximately 79% to near-perfect levels, depending on feature selection strategies, optimization techniques, and dataset characteristics. These approaches benefited from their interpretability and relatively low computational cost, making them attractive for early research and proof-of-concept systems. Nevertheless, their heavy reliance on handcrafted features rendered them sensitive to illumination variation, background complexity, and dataset imbalance, limiting generalization beyond curated image repositories.

Deep learning approaches consistently outperformed traditional ML methods in multi-class disease classification tasks, particularly when applied to large, well-annotated datasets, according to established definitions. Convolutional neural networks and transfer learning architectures achieved accuracies frequently exceeding 90%, with several studies reporting peak accuracies approaching 99.9%. Architectural innovations, including deeper CNNs, attention-based networks, and detection-oriented frameworks, enabled more effective representation of subtle lesion patterns and spatial disease characteristics. Despite these gains, DL models often require substantial computational resources, extensive labeled data, and complex training pipelines, which pose practical challenges for deployment in real agricultural settings.

A critical observation across the reviewed literature is the dominant reliance on controlled datasets, notably the PlantVillage repository. While such datasets have facilitated rapid methodological development and comparative evaluation, they introduce a strong dataset bias. Images captured under laboratory conditions fail to reflect the variability encountered in real fields, including occlusion, uneven lighting, cluttered backgrounds, and mixed disease stages. Studies incorporating field-acquired images repeatedly reported reduced performance, underscoring the gap between benchmark accuracy and real-world applicability.

From a broader research perspective, several gaps remain insufficiently addressed. Multimodal learning, such as the fusion of RGB imagery with hyperspectral, thermal, or vegetation index data, remains rare despite its potential to improve robustness and early disease detection. Similarly, limited attention has been given to early-stage disease identification, where visual symptoms are subtle, yet timely intervention is most valuable. The absence of standardized benchmarks and evaluation protocols further complicates reproducibility and fair comparison across studies.

In recent years, significant progress has been made in developing machine learning and deep learning technologies to detect maize diseases automatically. However, there remains a substantial disconnect between the evaluation of these technologies in controlled laboratory settings and their eventual utilization under real-world agricultural conditions. Many of the best-performing (highest AUROC) models have been trained and tested on controlled datasets that are imbalanced in the representation of disease classes and healthy samples. These high AUROC values may be misleadingly optimistic because they do not account for variability in real-world conditions (e.g., class imbalance and limited environmental diversity). In addition, the chosen evaluation metric (e.g., overall accuracy) can obscure substandard performance on minority disease classes. Additionally, many researchers selecting their evaluation metrics may use macro-averaged scores and confusion matrices that do not accurately reflect their models' performance. Furthermore, many research studies address issues related to domain shift, explainability, computational efficiency, and integration with practical farming workflows, but do so incompletely or inadequately. For these reasons, it is crucial to establish the following: (1) datasets that are accurate representations of what will occur under field conditions; (2) standardized methodologies for evaluating model performance; (3) interpretable model designs; and (4) validation methodologies that account for variables that will be present when models are implemented in commercial farming operations.

Explainability also emerges as a critical but underdeveloped aspect of current research. Although a small number of DL-based studies employed visualization techniques to interpret model decisions, most systems remain opaque. For practical agricultural adoption, especially among farmers and extension workers, transparent and interpretable outputs are essential for building trust and enabling informed decision-making.

Limitations of this review should also be acknowledged. First, publication bias may favor studies reporting high accuracy, while negative or inconclusive results remain underrepresented. Second, heterogeneity in experimental design, dataset composition, and performance metrics limits direct quantitative comparison. Finally, the review primarily focuses on image-based methods, with comparatively fewer studies addressing multimodal sensing or longitudinal disease progression.

Collectively, these findings indicate that while ML and DL methods have significantly advanced maize disease detection, further research is required to improve robustness, interpretability, and deployment readiness under real agricultural conditions. To highlight the performance potential of existing approaches, Table 14 presents representative maize leaf disease detection studies that report high classification accuracy under their respective experimental settings.

**Table 14.** Summarize maize leaf disease detection—studies with high accuracy.

| Dataset | Ref | Input | Model | Results | Region | Disease | Scope For Improvement |
|---|---|---|---|---|---|---|---|
| **Machine Learning** | | | | | | | |
| | [8] | Not Specified | Machine Learning/Image Processing. | Best Performance—RGB with SVM. | Indonesia | Gray Leaf Spot, Common Rust, NLB. | Dataset diversity, need for more giant trees in RF |
| | [9] | To train and test 120 Maize Leaf Images. | Image Processing. | Computational Time: 0.48 Seconds. | India | Rust Disease. | To improve efficiency and accuracy, a real-time monitoring system is necessary. |
| | [13] | Not Specified | Machine Learning (Fuzzy C-Means Algorithm) | Computational Efficiency of 19.28 s. | Malaysia, India, Indonesia, Bangladesh, Nepal. | Powdery Mildew, Dark Spot, Rust. | Dataset size, real-time monitoring system needed |
| Plant Village Dataset | [14] | Not Specified | Supervised Machine Learning Techniques-Quadratic SVM. | High Accuracy: 83.3% | India. | Common Rust, Common Smut, Fusarium Ear Rot. | There is a Need to improve accuracy. |
| | [19] | 60:40 Approaches for Training and Texting. | HOG, SFTA, and LTP, PCA. | Accuracy ranging from 92.8% to 98.7% in disease identification | Global Issues. | Common Rust, Early Blight, Late Blight | Minimize the dimensionality of features |
| | [30] | 3823 images and 4 class labels—common rust, gray leaf spot, northern leaf blight, and healthy. | Naïve Bayes, Decision Tree, KNN, SVM, Random Forest | Accuracy of 79.23% with Random Forest | India. | Cercospora Leaf Spot, Common Rust, NLB. | Explore more advanced ML techniques with high-dimensional datasets. |
| | [36] | Training: 2400 Images. Testing: 600 Images. | Classification and Regression Tree (CART). | Best accuracy of 82.92%, Recall 82.55%, F1 Score 82.6% | Indonesia. | Gray Leaf Spot, Common Rust, NLB. | Dataset diversity, need for improved color and texture extraction techniques |

**Table 14.** *Cont.*

| Dataset | Ref | Input | Model | Results | Region | Disease | Scope For Improvement |
|---|---|---|---|---|---|---|---|
| | [54] | Training: 6805. Testing: 1701. | HCA-MFFNet model | Accuracy of 97.75%, F1 value of 97.03% | China. | Gray Spot, Rust, NLB, Scorch | Focus on more diverse datasets, and improve the dataset |
| | [58] | A total of 3823 maize plant images were divided into 4 categories. The training and testing procedure utilizes these four subgroups. | YOLO, SVM | SVM achieved 97.25% accuracy | India. | Common Rust, NLB, Gray Leaf Spot. | Challenges in managing large datasets, scaling systems for large-scale applications |
| | [64] | Not Specified. | EKNN | Accuracy (99.86%), Sensitivity (99.60%), Specificity (99.88%), AUC (99.75%) | Global Issues. | Common Rust, NLB, Cercospora Leaf Spot. | Key requirements include dataset size and diversity, real-time detection capabilities, and user-friendly interfaces for farmers. |
| | [69] | Not Specified. | ML techniques, including DL-based approaches | Accuracy of 96.25% | Indonesia. | Common Rust, NLB, Cercospora Leaf Spot. | Need for diverse training data and computational requirements |
| | [98] | Training: 411 Images (80%). Testing: 102 Images (20%). | Supervised Machine Learning Algorithms. | 95.05% Accuracy | Global Issues. | Common Rust, Gray Leaf Spot. | There is a need to improve the Plant Disease Classification. |
| | [99] | Out of 2800 Images, the training set is 80%, and the testing set is 20%. | SVM and RF. | High accuracy, but the overall system accuracy is less than 90% | India. | Common Rust, NLB | Accuracy less than 90%, model-specific risks, and handling complex image data in real-world situations |
| | [113] | Not Specified. | DL Frameworks-VGGNET, Inception V3, ResNet50, and InceptionRes-NetV2 | Accuracy: 87.51%, Precision: 90.33%, Recall: 99.80% | India. | Physoderma maydis, Curvularia lunata. | A few of the difficulties include the scarcity of large, diverse datasets, the high cost of computing, and the complexity of the problem. |
| Private Dataset. | [6] | Training is performed on 70% of the images, and testing is performed on 20% of the Images. | Decision Tree Algorithms. | Global Accuracy: 95% | Global Issues. | Corn and Weed Species. | Need to extend the datasets. |
| | [43] | Not Specified. | KNN and SVM. | Accuracy of 95.06% | Global Issues. | Gray Leaf Spot, Common Rust, NLB. | Research needs to further improve accuracy and performance. |

**Table 14.** *Cont.*

| Dataset | Ref | Input | Model | Results | Region | Disease | Scope For Improvement |
|---|---|---|---|---|---|---|---|
| | [44] | Not Specified. | Feature Selection Model using Machine Learning Technique (SPLDPFS-MLT). | 97% overall accuracy in classification | India. | Late Blight, Septoria. | Need to increase accuracy with high-quality images. |
| | [67] | Not Specified. | Decision Tree Model. | Recall (12.88%), kappa (11.13%), F-score (10.68%), precision (8.59%), accuracy (3.23%), specificity (1.76%), and AUC (0.83%), | Global Issues. | Leaf Rust, Downy Mildew, Leaf Blight. | The illness leaf needs to be refined from the database. |
| | [85] | From the Dataset, training 80%, testing 20% | VGG16 and Cov2D. | Accuracy: 99.9% | Global Issues. | Armyworm Pest. | This research did not test larger datasets. |

Although these studies demonstrate strong performance, most evaluations were conducted on curated or controlled datasets, and reported accuracy values may not directly translate to real-field deployment scenarios.

### 7.1. Opportunities and Gaps in Multimodal Maize Disease Identification

The literature reviewed indicates that the majority of research on the detection of maize pathogens has focused on using RGB imagery alone; however, few studies have investigated the use of multiple modalities in conjunction with RGB to provide additional information on plant health and potential disease. Although RGB images can display the visible signs (symptoms) of plant illness, they cannot identify early signs (e.g., stress) or those outside the visible spectrum (e.g., UV). Until very recently, only a limited number of studies have examined the potential to fuse RGB and non-RGB imagery at either the feature or decision levels; however, integrating imagery from different sensors has not yet been a focus of research. Therefore, without multimodal fusion capabilities, the reliability of the developed models will be directly affected by the conflicting environmental conditions present in agricultural fields. The ability to combine data from multiple modalities will improve the reliability of detecting subtle physiological responses in plants before symptoms appear. Since using various sensors to assess plant health will allow greater flexibility in responding to significant variations in illumination, sensor fusion techniques are expected to enhance early detection and help prevent future crop losses. Addressing these limitations will require implementing standard protocols for sensor fusion and scalable designs for multimodal systems that can be developed and deployed quickly and cost-effectively.

### 7.2. Implications of Maize Disease Detection Systems for Ethics and Society

The ethical and social implications of maize disease detection have not yet been adequately researched, even though these issues are paramount for adoption within real-world environments. For example, there is significant concern that existing datasets are heavily skewed toward laboratory-generated data. The resultant models, therefore, consistently underperform across multiple regions/farming types/crop varieties, thereby perpetuating existing inequities. The trust that farmers have in the validity of these models will also play a key role; that said, opaque models that provide little information on how they function will inhibit farmer acceptance/password affect their ability to make optimal decisions. Therefore, ensuring that smallholders in resource-poor environments can access this technology will require developing low-cost/hand-held devices that do not require expensive sensors or high computational capabilities. Finally, the environmental and socio-economic effects of deploying one's technology should also be examined, as false predictions can lead to unnecessarily high levels of pesticide use and associated costs, as well as overall decreases in crop yields. By addressing the ethical dimensions of developing and applying intelligent maize disease detection systems through transparent design, inclusive dataset development, and user-centered strategies for using those datasets, Research can produce intelligent systems that promote sustainable, equitable agricultural systems.

### *7.3. Quantitative Evaluation of Dependency on Datasets*

The literature review revealed a quantitative bias in the datasets used in the included studies; the majority relied solely on controlled benchmark datasets for training and evaluation of the algorithm(s) used. The majority (approximately 68%) of all studies examined used the PlantVillage dataset exclusively to train and evaluate the algorithm(s). In contrast, only a little under 20% of studies validated their results on authentic field-captured maize images. The remaining studies used either custom or mixed datasets; however, those that did so often underrepresented environmental variation and disease progression stages. The emphasis on creating these types of controlled benchmark datasets leads to algorithms that are accurate on controlled datasets and, therefore, are likely to have limited application in real-world settings. The excessive reliance on curated datasets leads to inflated claims about algorithms' performance and masks the difficulties of implementing them in field conditions. Quantifying the extent of this bias in the available data and developing a systematic approach to collecting field data and establishing standards for benchmark testing of algorithms under agricultural conditions should reduce bias in the datasets.

### *7.4. Quantitative Evaluation of Metric Reporting Procedures*

The analysis of the evaluation methodology of the evaluated maize disease studies demonstrates a high degree of dependency on overall accuracy as the primary evaluation performance metric of the studies, with nearly 55–60 percent of the studies environment-only evaluating the accuracy of the maize disease classifiers, as opposed to including other relevant evaluation metrics, including precision, recall, or the F1-score. Conversely, only 40–45 percent of the studies incorporated a multidimensional evaluation that included class-sensitive performance metrics, while only 20–25 percent included confusion-matrix metrics or per-class performance results. The existing metric imbalance limits the accuracy with which the reported performance results can be interpreted, especially given the potential for class imbalance and rare-disease classifications to skew study accuracy. The quantification of this observed trend suggests that the majority of reported performance-improvement expectations are likely overinflated, underscoring the continued need for standard, uniform evaluation guidelines in maize disease detection research.

## 8. Conclusions

This review examined 102 journals published between 2017 and 2025 and around 100 journal articles that provide a synthesis of progress in machine learning (ML) and ML-based techniques (the Deep Learning [DL] approach) for maize leaf disease detection. The results indicate that, according to established definitions, traditional ML (Machine Learning) methods achieve classification accuracies of approximately 79% to 100% when effective feature engineering and optimization are used for image-based diagnostic tasks in controlled/standardized environments. In addition, ML is part of the ML landscape, where most DL-based methods (primarily using CNNs [Convolutional Neural Networks]) have been used for image-level classification and region-based detection tasks, and report (average) accuracies greater than 90% on carefully curated laboratory datasets. The review has also shown that the performance of a model is driven by the interplay between (1) how the task is defined (e.g., image-level classification vs. region-based model detection), (2) the architecture of a model, and (3) the characteristics of the dataset from which the model is trained. However, while high accuracy is observed in controlled experiments, it does not equate to "deployment ready". Most methods reviewed showed shortcomings related to dataset biases, limited robustness and applicability in the field, limited model explainability, and a disproportionate emphasis on overall accuracy without consideration of class imbalance or detection of minority-class diseases.

The overall findings suggest that while machine learning (ML) methods, specifically deep learning (DL) methods, have matured significantly from a laboratory setting to a field-based setting for the identification of maize diseases, the majority of existing literature related to the implementation of crop disease detection methods using ML techniques has not been tested at scale using nearest real-world farming conditions. As such, addressing issues related to field robustness, explainability, balanced evaluation metrics, and realistic deployment environments is essential if researchers are to achieve scalable, reliable systems that assist in diagnosing maize diseases.

Future research directions identified in the literature emphasize the creation of a representative field dataset that reflects natural environmental variability, disease progression, and the inherent class imbalance in existing maize production systems. Furthermore, there is a need for a standardized assessment protocol that utilizes macro-averaging to obtain an "average" performance metric for each class and includes field-condition evaluation to produce realistic performance metrics. The integration of more explainable AI (XAI) and the development of lightweight models that can be deployed in practice will, therefore, aid the transition of these techniques from development to farmer and agronomist use. Addressing these issues is integral to facilitating the transition from laboratory proof-of-concept to sustainable maize disease-detection systems that will help optimize agricultural sustainability, enhance crop-management operations, and improve global food security.

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