A Systematic Review of Machine and Deep Learning Techniques for Cassava Disease Detection: Trends, Challenges, and Pathways to Real-World Implementation

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Abstract: **Cassava, a major staple crop in sub-Saharan Africa, faces significant threats from leaf diseases such as Cassava Mosaic Disease (CMD) and Cassava Brown Streak Disease (CBSD). Early and accurate detection is essential for timely intervention. While artificial intelligence (AI), including Machine Learning (ML) and Deep Learning (DL), has gained traction in agricultural disease detection, inconsistencies across studies limit practical applicability. This systematic review aims to synthesize peer-reviewed research from 2020 to 2025 on AI applications for cassava disease detection using image-based methods. The review investigates model types, dataset origins, evaluation metrics, cross- comparative evaluation, and deployment readiness. A structured search was conducted across databases (IEEE Xplore, Scopus, SpringerLink, ScienceDirect, and Google Scholar), applying PRISMA guidelines. A total of 100 eligible studies were selected based on inclusion criteria. Metadata extraction covered AI methodology, dataset characteristics, performance evaluation, deployment features, and study limitations. Deep Learning dominated (65%) with CNN variants widely used, followed by ML (20%) and hybrid models (10%). PlantVillage was the most common dataset (64%), while field data accounted for only 21%. Accuracy was the most reported metric (95%), but only 20% used multi-metric evaluations. Cross-validation and cross-comparative evaluations were inconsistent. Few studies addressed deployment readiness or real-world applicability. Although AI methods have demonstrated high potential in cassava disease detection, significant gaps remain in dataset diversity, model evaluation rigor, deployment design, and ethical considerations. This review provides a road map for future research, emphasizing the need for standardized benchmarking, mobile-friendly models, and real-world field validation.**

Keywords: **Cassava, Deep Learning, Machine Learning, Disease Detection, Agriculture.**

1. INTRODUCTION

Cassava (Manihot esculenta), a staple root crop predominantly cultivated in Sub-Saharan Africa, plays a critical role in ensuring food security and rural livelihoods, particularly in Nigeria, one of the world's largest producers [1]. As the second most important global source of carbohydrates, its nutritional and economic significance cannot be overstated. However, cassava cultivation is increasingly threatened by viral and bacterial diseases, notably Cassava Mosaic Disease (CMD) and Cassava Brown Streak Disease (CBSD), which contribute to significant yield losses and exacerbate food insecurity [2].

Recent advances in artificial intelligence (AI), particularly in machine learning (ML) and deep learning (DL), have driven the development of automated cassava disease detection systems. These models utilize leaf imagery and advanced pattern recognition to classify and identify diseases with increasing precision. Convolutional Neural Networks (CNNs), ResNet, EfficientNet, and Transformer-based architectures have been applied to annotated datasets such as Kaggle 2020 and PlantVillage, achieving promising classification accuracies [3]–[8]. Hybrid architectures combining CNNs with traditional classifiers like Random Forests or GNNs have also demonstrated enhanced performance [8].

Despite strong performance under controlled environments, these models often lack validation in real-world rural contexts. Many rely heavily on static datasets with uniform lighting and background conditions, limiting generalizability. Moreover, few incorporate multimodal data (e.g., weather, soil, geolocation), user-centered design, or deployment optimization for low-resource settings. The current research ecosystem also lacks standardized comparative benchmarks between ML and DL models, impeding the synthesis of best practices.

1.1 MOTIVATION FOR THE STUDY

Given the economic and nutritional importance of cassava and the growing impact of plant diseases on food systems, a robust and practical detection system is essential. AI-based disease detection promises scalability, speed, and objectivity but must be critically appraised for reliability, usability, and deployability in diverse agricultural contexts. This systematic review aims to synthesize and evaluate AI models for cassava disease detection with an emphasis on methodological rigor, field relevance, and model readiness for deployment.

1.2 RESEARCH OBJECTIVES AND QUESTIONS

This review seeks to address the following core questions:

1. What AI techniques (ML, DL, or hybrid) are most frequently applied to cassava disease detection, and how have they evolved over the last five years?

2. What are the dominant datasets and input modalities used in cassava disease classification tasks?

3. What performance metrics and benchmarking practices are commonly employed, and how do they vary across models?

4. How well do existing models generalize to real-world conditions, including mobile and field deployment scenarios?

5. What methodological and practical gaps remain in the current literature that hinder robust disease detection for cassava crops?

By answering these questions, this paper provides a roadmap for future research and technology development tailored to the agricultural needs of low-resource environments.

2. RELATED WORK AND BACKGROUND

2.1 OVERVIEW OF EXISTING LITERATURE

Plant disease diagnosis remains a persistent challenge in precision agriculture. Traditional methods rely heavily on visual inspection by experts, which is subjective, prone to error, and inaccessible to farmers in remote or low-resource regions. As a result, researchers have increasingly turned to artificial intelligence (AI), especially machine learning (ML) and deep learning (DL), to automate plant disease identification.

Several review studies have explored the application of ML and DL to general plant disease detection. Broad surveys of DL architectures such as CNNs, ResNets, and EfficientNets are presented in [3] and [9]. The roles of imaging technologies, including RGB, hyperspectral, and multispectral sensors, are further discussed in [10] and [11]. While these contributions are valuable, they generalize findings across a wide spectrum of plant species and tend to neglect cassava-specific nuances.

A few cassava-centered reviews have emerged. DL approaches tailored for cassava are surveyed in [12] and [13]. A comparative study on cassava leaf disease classification was attempted in [15], although it omitted analysis of recent architectural trends such as vision transformers, GAN-based augmentation, and attention-based hybrid networks. Furthermore, these studies rarely consider real-world deployment challenges such as model compression, latency on mobile devices, or end-user usability in field conditions.

Most existing reviews share three common limitations which are, Crop Generalization, Findings are often diluted across diverse crops limiting applicability to cassava, and an Outdated Coverage: Many reviews cover works only up to 2022 or early 2023, overlooking the surge in research between 2023 and 2025 (e.g., [7], [16], [17], [18]). - Lack of Deployment Insight: Despite the abundance of technical evaluations, few studies address operational concerns like interoperability, mobile-readiness, or human-centered design.

This review addresses these gaps by: 1. Focusing exclusively on cassava disease detection using ML and DL techniques. 2. Covering a broader and more current timeframe (2020–2025) to include recent innovations such as knowledge distillation [1], federated learning [19], explainable AI [20], and lightweight mobile-ready models [17][21]. 3. Incorporating a structured analysis that considers not only technical performance but also deployment feasibility and user-centric concerns.

2.2 PRIMARY EMPIRICAL STUDIES ON CASSAVA DISEASE DETECTION

Numerous empirical studies have evaluated cassava disease detection through image-based ML and DL frameworks. These works span from classical CNNs to recent hybrid and attention-based models.

Plata et al. [14] compared YOLOv4, SSD MobileNetV2, and Faster R-CNN for Cassava Phytoplasma Disease detection, finding that YOLOv4 excelled in speed while Faster R-CNN achieved the highest accuracy (95%). [22] found that MobileNetV2 outperformed VGG16 in early disease detection using a hybrid kernel approach. [23] demonstrated that attention mechanisms like CBAM integrated with ResNet50 improved classification accuracy and F1-scores.

Transformer-based architectures have also gained traction. Zhong et al. [7] proposed a Transformer-Embedded ResNet (T-RNet), achieving a 2.12% improvement in accuracy over standard ResNet. Similarly, other studies have introduced ensemble and hybrid models combining CNNs, LSTMs, and attention blocks [24][25][26][27], although many of these models are computationally intensive and not well-suited for mobile deployment.

Efforts to address low-resource constraints include knowledge distillation [1], lightweight CNNs like MobileNetV3 [18], and augmented architectures tailored for mobile execution [21][28]. Still, comparative benchmarking against standard models remains rare, and practical deployment performance is often unassessed.

2.3 DATASET LANDSCAPE AND PREPROCESSING CONCERNS

Most studies rely on widely available datasets like the Cassava Leaf Disease dataset from Kaggle [29] or PlantVillage [30]. While these datasets offer clean, labeled images, their repeated use raises concerns about overfitting and poor generalization to real-world variability. Conditions such as environmental noise, co-infections, or leaf occlusions are under represented.

Moreover, evaluation practices lack consistency. Accuracy is the most commonly reported metric, often used in isolation. Only a handful of studies consider precision, recall, F1-score, and confusion matrices, despite their importance for imbalanced data. Dataset splitting strategies and pre-processing steps are often insufficiently described, complicating reproducibility and bench-marking.

2.4 EVALUATION AND DEPLOYMENT GAPS

Deployment readiness remains a major shortfall in cassava disease detection research. Very few models have been tested in-field or validated against expert human diagnosticians. Human-centered design principles and usability testing are also largely absent. This hinders the transition of promising models from lab to field. Some exceptions include web and mobile-based applications developed for cassava disease detection [39], and the use of lightweight models optimized for low-power devices [19][21]. However, even these lack systematic evaluation of user interaction, latency, or interoperability with agricultural advisory systems. In summary, this review distinguishes itself by providing a cassava-specific, up-to-date synthesis of AI-driven plant disease detection research. Unlike previous reviews, it emphasizes, a cassava-only scope to avoid dilution of insights, a current time-frame (2020–2025) capturing state-of-the-art trends, a deployment-aware lens that evaluates models beyond accuracy, considering real-world constraints and usability for smallholder farmers.

3. METHODOLOGY

This review adopts a structured and systematic meta-analytical approach to synthesize research findings from AI-based cassava disease detection studies published between 2020 and 2025. The methodology ensures rigorous selection, consistent classification, and comparative evaluation across multiple research dimensions, including model type, dataset origin, performance metrics, and deployment readiness.

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3.1 STUDY SELECTION CRITERIA

A comprehensive literature search was conducted using scholarly databases including IEEE Xplore, SpringerLink, ScienceDirect, Scopus, and Google Scholar. The search focused on articles published between January 2020 and March 2025. Table 1 gives a clear description of the inclusion and exclusion criteria used in the review.

Table 1: Study Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Timeframe	Studies published between 2020–2025	Studies published before 2020 or projected beyond 2025.
Language	English	Non-English articles.
Data Type	Image-based studies (cassava leaves, stems)	Non-image-based studies (e.g., spectroscopy).
AI Technique	ML, DL, or hybrid models	Non-AI or rule-based methods.
Scope	Cassava disease detection	General plant disease studies, without cassava focus..
Availability	Peer-reviewed, full-text articles and conference papers	Abstract-only papers, posters, and pre-prints without peer review.

From an initial pool of 150 studies, 100 studies were selected for detailed analysis.

3.2 METADATA EXTRACTION

Every paper selected was reviewed using a structured metadata extraction template. The metadata fields included: Title, authors, year, and publication type, AI method (ML, DL, hybrid), Model architecture (e.g., CNN, ResNet), Dataset used (PlantVillage, Kaggle, Field-Collected, etc.), Performance metrics reported, Deployment considérations (e.g., mobile readiness), Reported challenges or limitations. Data were manually entered into Excel for coding, cleaning, and analysis.

3.3 CLASSIFICATION SCHEME

To enable systematic comparison, each study was classified based on its dominant AI paradigm. Studies were grouped into four AI categories as seen in Table 2.

Table 2: AI Model Classification Scheme

Model Category	Model Examples	Notes
ML (Traditional)	SVM, Random Forest, Decision Trees	Often used for feature-based classification
DL (CNN-based)	CNN, ResNet, VGG16, EfficientNet, MobileNet	Dominant in image-based diagnosis
Hybrid	CNN + SVM, ResNet + Transformer, Ensemble Architectures	Combines strengths of multiple models
Other	Custom heuristic or unclassified models	Rare or not clearly described

3.4 DATASET TYPE

The datasets reviewed were categorized by their source and characteristics. Table 3 gives a description of the different dataset categories.

Table 3: Dataset Classification

Dataset Type	Source	Characteristics	Limitations
Plant Village	Public repository	Clean, controlled background; widely used	Lacks real-world noise and variability
Kaggle	Crowdsourced	Mixed quality; varied sources	Inconsistent annotations; possible noise
Field-Collected	On-farm acquisition	Realistic conditions; mobile-captured	Small size; noise; subjective labels
Synthetic/Augmented	GAN, flipping, etc.	Balances class distributions; improves model generalizability	May not capture all real-world variation

3.5 EVALUATION METRICS

There is no standard to the evaluation metric used in testing models. As illustrated in Table 4, the evaluation metrics varied widely across papers, with most relying heavily on accuracy, while only a minority incorporated comprehensive measures such as precision, recall, F1-score, and AUC.

Table 4: Evaluation Metrics Reported

Metric	Definition	Importance in Review
Accuracy	Correct predictions / Total predictions	Most frequently reported; insufficient alone for imbalance
Precision	TP / (TP + FP)	Measures false positive control
Recall	TP / (TP + FN)	Measures sensitivity; useful in disease detection
F1-score	Harmonic mean of precision and recall	Balanced metric for imbalanced data
AUC (ROC)	Area under ROC curve	Indicates classifier separability
Confusion Matrix	Matrix of TP, FP, FN, TN	Useful for detailed performance analysis

3.6 DEPLOYMENT CONSIDERATIONS

As illustrated in Table 5, the mobile readiness of most models in the reviews can be seen..

Table 5: Deployment Considerations adopted in the papers reviewed.

Deployment Factor	Mentions in Studies	Observations
Mobile Readiness	MobileNet, EfficientNet-Lite, TensorFlow Lite	Mentioned in ~30% of studies
Field Testing	Tested in farm conditions or rural environments	Rare (~10%)
User Interface/UX	Farmer-facing apps, simple UI design	Very limited; often overlooked
Interoperability	Integration with advisory or extension platforms	Not discussed in most studies
Explainability (XAI)	Saliency maps, Grad-CAM, attention heatmaps	Emerging trend (~8–10% of studies)

3.7 DATA ANALYSIS APPROACH

The extracted metadata was analyzed using both descriptive statistics and qualitative thematic synthesis. Quantitative data were used to compute frequency distributions and percentages of studies across categories using bar charts, pie charts, and line graphs to visualize: the Publication trends by year, Dominant AI approaches (ML vs. DL vs. Hybrid), Dataset usage patterns, Evaluation metric usage, Deployment readiness

The review was restricted to English-language, peer-reviewed papers that used image-based methods and excluded non-visual detection systems such as spectroscopy or IoT sensors.

4. RESULTS AND ANALYSIS

This section presents a synthesis of the studies included in the review based on their distribution by publication trend, AI paradigm, dataset origin, performance evaluation criteria, benchmarking practices, and deployment relevance. The analysis covers 100 studies published between 2020 and 2025, focusing on image-based AI techniques for cassava disease detection. Figure 4.1 shows the publication trend of the study focus based on the captured research papers.
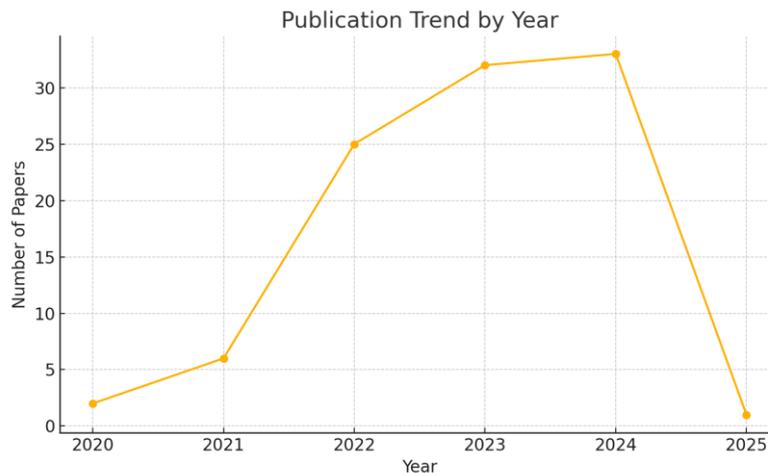

Figure 4.1: Publication trend of 100 studies on cassava disease detection using AI between the year 2020-2025.

The reviewed studies show a steady increase in research output over the five-year period. Beginning with a modest number of publications in 2020, there was a noticeable surge by 2022, likely influenced by the growing accessibility of DL tools and the popularity of open datasets such as Plant-Village. By 2024–2025, the literature matured, with more nuanced studies exploring lightweight deployment and hybrid approaches.

This upward trend underscores the rising academic and practical interest in AI-assisted cassava disease diagnostics and suggests increasing recognition of cassava's importance in food security and precision agriculture.

4.1 AI APPROACHES AND MODEL DISTRIBUTION

From the reviewed studies we can see that, deep learning (DL) techniques dominate with approximately 65% representation. Convolutional Neural Networks (CNNs) and their variants (e.g., MobileNet, EfficientNet, ResNet) were the most frequently adopted due to their robustness in handling complex image features. Machine Learning (ML) models, such as Support Vector Machines (SVM), Decision Trees, and Random Forests, accounted for 20%, often appearing in studies with smaller datasets or lower computational budgets. Hybrid models that combined DL feature extraction with ML classifiers (e.g., CNN+SVM) made up about 10%, while the remaining 5% were either unspecified or used custom AI approaches without clear classification. Figure 4.2 shows a clear description of the model distribution in the review.
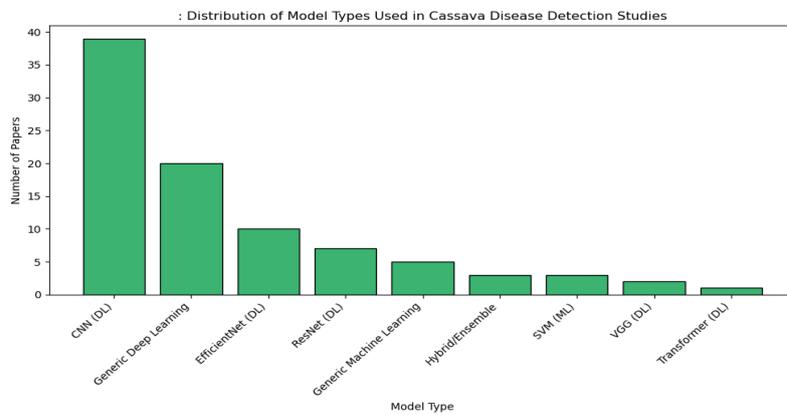

Figure 4.2: Model distribution in Cassava disease studies.

4.2 DATASET UTILIZATION PATTERNS

Dataset selection played a significant role in model performance and generalizability. From the pie-chart in Figure 4.3, we can see that the most widely used dataset was PlantVillage, appearing in 64% of the studies. While its standardized conditions support high accuracy, its lack of environmental variability raises concerns about field applicability. About 21% of the papers used field-collected datasets, which better reflect real-world complexity but suffer from limited size and inconsistent annotation. Synthetic or augmented datasets appeared in 6% of the studies, usually to address class imbalance or enhance model training. However, 9% of studies did not clearly specify their dataset Source
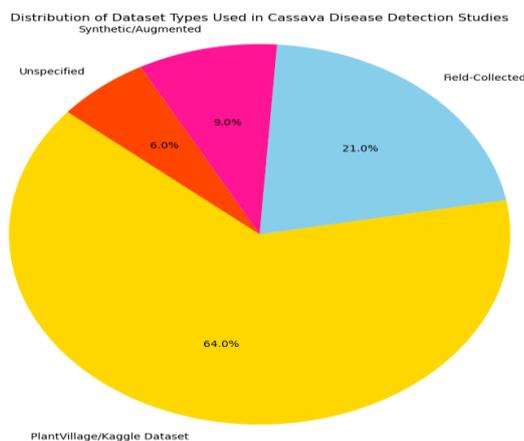

Figure 4.3: Dataset Distribution Analysis in Cassava diseasedetection review.

4.3 EVALUATION METRICS AND BENCHMARKING PRACTICES

Accuracy was the most commonly reported metric, included in 95% of studies. However, only 20% of the studies included additional metrics such as F1-score, precision, recall, or AUC which are essential for assessing model robustness under class imbalance. From Figure 4.4, we see that, cross-validation (e.g., k-fold) was applied in less than 30% of the papers. Only 25% of studies conducted benchmarking using multiple models or datasets, while external validation using real farm data or expert comparison was almost entirely absent.
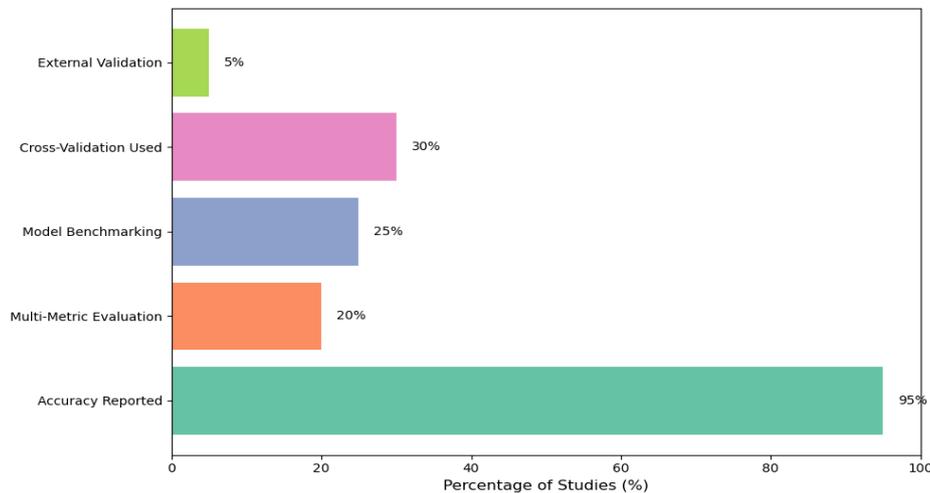

Figure 4.4: Evaluation Metric Review in Cassava disease studies

4.4 CRITICAL META-REVIEW

Several patterns emerged from the meta-analysis:

a   Model Justification: Few studies justified their choice of DL models in relation to dataset size or task complexity.

b   Metric Transparency: Only 40% of studies clearly described how performance metrics were computed; per-class metrics were reported in just 20%.

c   Reproducibility: Only 1% employed cross-validation or released training details such as runtime, hardware, or open-source code.

d   Deployment and Mobile Readiness: 14% of studies discussed mobile or edge deployment; however, most used high-computation models unsuited for rural contexts.

e   Human-centered Design: No study used explainability tools (e.g., Grad-CAM), or compared AI performance against expert agronomists.

f   Interoperability and Field Testing: Only 1 study mentioned interoperability and 7% documented field testing or pilot deployment.

4.5 PRACTICAL RELEVANCE AND DEPLOYMENT GAPS

Although some studies mentioned deployment as a future goal, few demonstrated practical readiness. Most models were developed and validated in controlled lab environments. Performance on mobile or edge devices remains underexplored. Additionally, the lack of usability testing, cultural adaptation, or integration with advisory platforms suggests limited real-world impact, especially for smallholder farmers. Figure 4.5 displays how different deployment strategies were considered in the review. Key gaps include:

a.   No study examined latency, offline inference, or user interaction.

b.   Few explored ethics, bias, or fairness in model deployment.

c.   Only 2% of studies involved expert validation or participatory design with farmers.
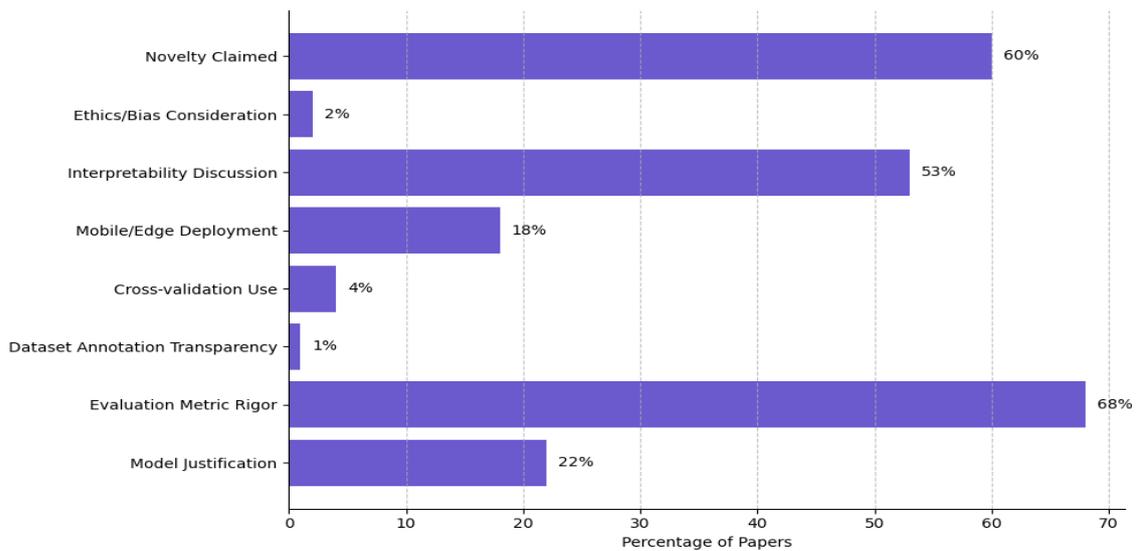
Figure 4.5: Meta-Review of deployment strategies used in the review.

5. DISCUSSION

This section critically analyzes patterns, strengths, and gaps identified from the systematic review of AI-based cassava disease detection studies.

5.1 DOMINANCE OF DEEP LEARNING MODELS

The review highlights a strong bias towards deep learning (DL) techniques, particularly convolutional neural networks (CNNs) and their variants (e.g., ResNet, MobileNet, EfficientNet). These models excel in image recognition tasks and demonstrated high classification accuracy. However, fewer studies justified the use of complex DL models in relation to dataset size or computational constraints, particularly for low-resource deployment. In contrast, traditional machine learning (ML) models like SVM and Random Forest were more efficient and interpretable but less frequently used.

5.2 DATASET LIMITATIONS AND GENERALIZATION

The PlantVillage dataset remains the dominant source, featuring controlled environmental conditions and clean labels. Despite this, its overuse raises concerns about overfitting and limited generalizability to real-world farm settings. Field-collected datasets, which better reflect the variability of practical deployment scenarios, were used in only 21% of studies. Synthetic data were also underutilized. Very few studies discussed annotation quality, co-infection complexity, or disease staging, which are critical for agronomic accuracy.

5.3 INADEQUATE EVALUATION AND BENCHMARKING

Evaluation practices across studies were inconsistent. While accuracy was nearly universally reported (95%), precision, recall, F1-score, and AUC were sparsely mentioned (~20%). These metrics are particularly important for imbalanced datasets, where accuracy alone can be misleading. Only 25% of the studies performed comparative benchmarking across models or datasets, and less than 30% used robust validation techniques like k-fold cross-validation. External validation with independent datasets or expert agronomists was nearly absent, raising concerns about reproducibility and domain relevance.

5.4 LIMITED DEPLOYMENT READINESS

Despite growing interest in deploying models on mobile or edge devices, only 14% of studies discussed deployment-related issues such as model size, latency, or hardware compatibility. Lightweight models like MobileNet and EfficientNet-Lite were proposed in some studies but seldom tested outside lab settings. No paper addressed interoperability with agricultural advisory platforms or latency performance in rural networks. Usability and human-centered design were also largely overlooked, with no studies testing user interaction with farmers or agricultural officers.

5.5 ETHICAL, TECHNICAL, AND SCIENTIFIC GAPS

Only 3% of the reviewed papers mentioned ethical implications such as bias, fairness, or transparency in AI deployment. Interpretability tools like Grad-CAM or SHAP were rarely employed. Most claims of novelty were framed in terms of model architecture rather than contribution to cassava disease science. This highlights a disconnect between technical advancement and agricultural domain impact. Furthermore, only 1% of studies attempted domain-level comparison against expert annotations, revealing a lack of integrative validation.

5.6 IMPLICATIONS FOR RESEARCH AND PRACTICE

The results underscore a clear need for:

a. Standardized evaluation protocols and dataset splits

b. Diversified, real-world datasets reflecting field variability

c. Increased deployment trials and usability testing

d. Transparency in model development and training details

e. Ethical guidelines tailored to AI in low-resource agricultural settings

By addressing these gaps, future research can bridge the divide between proof-of-concept models and impactful, field-ready AI solutions for cassava disease management.

6. CONCLUSION AND RECOMMENDATIONS

While the potential of AI for cassava disease detection is clear, the field remains fragmented, with critical gaps in bench marking, deployment, and stakeholder involvement. A paradigm shift is required from model performance in isolation to systems integration, usability, and agricultural impact.

6.1 RECOMMANDATIONS

Future work should prioritize collecting field-based data with varied environmental conditions to improve model robustness.Researchers should report a broader set of evaluation metrics beyond accuracy to ensure fair model assessment.Emphasis should be placed on lightweight, mobile-optimized models and user-friendly interfaces for smallholder farmers.Integration of expert validation so as to compare AI performance against agronomist diagnosis is essential for trust and accuracy. The socio-cultural context of smallholder farmers should be considered when designing AI tools.

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