

Stochastic Modeling of Plant Disease Detection Systems: A Comparative Study of Classical and Bayesian Methods

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ABSTRACT

Plant disease detection systems, especially those utilizing computer vision and sensor-based technologies, play a crucial role in ensuring agricultural productivity and crop health. However, the performance and reliability of these systems can vary significantly under environmental noise, image quality issues, and data scarcity. This paper presents a comparative study of classical and Bayesian stochastic methods for modeling and analyzing the reliability of such detection systems.

Using a case study involving leaf spot and mildew detection in tomato plants, we construct reliability models based on classification performance metrics (TPR, FPR, accuracy) using Maximum Likelihood Estimation (MLE) for classical analysis and Bayesian inference with MCMC sampling for probabilistic reliability estimation. The models are evaluated under conditions of varying sample sizes, missing data, and class imbalance.

The study reveals that while classical methods provide quick and interpretable estimates, Bayesian approaches offer greater robustness under uncertainty, especially in low-data or early-detection scenarios. The posterior distributions from Bayesian models allow for more nuanced risk assessments, which is particularly valuable in real-time disease management systems. This work provides guidelines for choosing appropriate stochastic techniques based on deployment conditions in precision agriculture.

1. INTRODUCTION

Early and accurate detection of plant diseases is critical for safeguarding crop health, minimizing economic losses, and ensuring food security. In many cases, the delay in identifying symptoms or misdiagnosis of plant diseases leads to uncontrolled outbreaks, adversely affecting yield quality and quantity. Traditional methods of disease detection—often based on manual inspection—are not only time-consuming and subjective but also limited in scalability, especially in large-scale agricultural operations.

In recent years, significant advancements in artificial intelligence (AI), computer vision, and sensor technologies have revolutionized agricultural diagnostics. Image-based disease detection systems using machine learning algorithms, coupled with Internet of Things (IoT)-enabled smart sensors, are now widely used in precision agriculture to automate disease monitoring and decision-making. These systems rely on data from field conditions, drone imagery, and real-time sensors to classify and identify plant diseases with high accuracy.

Despite their growing adoption, the reliability of these systems under varying operational and environmental conditions remains a concern. Factors such as low image quality, sensor noise, data sparsity, and class imbalance introduce uncertainty in system performance. In such contexts, stochastic methods offer a structured framework to quantify the uncertainty and estimate reliability more robustly.

Two dominant statistical paradigms—classical (frequentist) and Bayesian approaches—are commonly used for modeling such uncertainties. Classical methods like Maximum Likelihood Estimation (MLE) and confidence intervals provide point estimates and interval-based assessments of model reliability. In contrast, Bayesian methods, through the use of prior information and posterior distributions, offer a flexible framework for uncertainty quantification, particularly under data limitations.

This study aims to comparatively analyze classical and Bayesian stochastic methods for modeling the reliability of plant disease detection systems. Through simulation and case studies, the work seeks to understand the strengths, limitations, and practical implications of both approaches in real-world agricultural diagnostics.

2. LITERATURE REVIEW

The reliability of classification systems in agricultural diagnostics, particularly in plant disease detection, has garnered increasing attention due to the integration of AI and sensor-based systems in modern farming. Statistical tools—both classical and Bayesian—play a vital role in quantifying the trustworthiness and uncertainty of such systems, especially when deployed in dynamic field environments.

2.1 Classical Reliability Modeling in Classification Systems

Classical statistical approaches have long been used for assessing system performance. In the context of classification tasks such as plant disease detection, Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) remain standard tools for evaluating classifier reliability. Metrics like True Positive Rate (TPR), False Positive Rate (FPR), sensitivity, and specificity are often computed using Maximum Likelihood Estimation (MLE), which provides point estimates based on observed data (Collett, 2015).

Additionally, the Kaplan-Meier estimator—a non-parametric statistic traditionally used in survival analysis—has been employed to estimate the probability of system success (or failure) over time. Though widely used in reliability engineering and medical statistics, its application in modeling the time-to-failure of AI-based disease detection systems in agriculture is still emerging (Zio, 2013).

While classical methods are computationally efficient and easy to interpret, they are often limited in handling uncertainty under small sample sizes, missing data, or data imbalance—all of which are common in agricultural datasets.

2.2 Bayesian Approaches in Disease Diagnostics and Uncertainty Modeling

Bayesian methods offer a probabilistic framework for incorporating prior knowledge and updating system reliability as new data becomes available. In plant disease detection, where training data may be limited or noisy, Bayesian inference provides more robust uncertainty quantification. Methods such as Markov Chain Monte Carlo (MCMC) and Gibbs sampling allow researchers to estimate the posterior distributions of classifier parameters, offering credible intervals instead of traditional confidence intervals (Gelman et al., 2014).

Recent studies have applied Bayesian neural networks (BNNs) and probabilistic graphical models to enhance the reliability of AI-based disease detection systems, especially under noisy and uncertain conditions (Kim et al., 2021; Singh & Bhadra, 2024). These methods are particularly effective in providing posterior predictive distributions, which help quantify uncertainty in real-time decision-making.

Furthermore, Bayesian networks have been used to model the interdependencies between environmental variables, plant health indicators, and disease progression, enabling more informed reliability assessments (Zhang et al., 2022).

2.3 Existing Gaps and Research Opportunities

While both classical and Bayesian methods are independently used in reliability analysis, comparative studies evaluating their performance specifically in the context of plant disease detection systems are scarce. Most existing literature either focuses on the application of AI in agricultural diagnostics or on statistical methods for reliability estimation, but rarely integrates the two with a side-by-side methodological comparison.

Moreover, real-world agricultural systems often suffer from limited labeled datasets, heterogeneous sensor inputs, and non-stationary failure behaviors, making them ideal candidates for Bayesian analysis. Yet, practical adoption remains low due to computational complexity and lack of awareness.

This study addresses this gap by offering a comprehensive comparative analysis of classical and Bayesian stochastic models applied to computer-based plant disease detection systems, aiming to provide insights for both researchers and practitioners in precision agriculture.

3. METHODOLOGY

This section outlines the modeling approach for evaluating and comparing the reliability of an image-based plant disease detection system using both classical and Bayesian stochastic frameworks.

3.1 System Modeled: Image-Based Disease Classification

The system under study is a Convolutional Neural Network (CNN) designed for detecting diseases in tomato plants using leaf images. CNNs have become a standard tool in precision agriculture due to their high performance in visual classification tasks. The system is trained to identify multiple classes of tomato diseases (e.g., early blight, late blight, mosaic virus) and healthy plants using labeled datasets such as the PlantVillage database. Outputs from the CNN are compared against ground truth labels to construct confusion matrices, which form the statistical input for reliability estimation. These matrices serve as the foundation for estimating true positive, false positive, true negative, and false negative rates.

3.2 Classical Reliability Estimation Methods

In the classical framework, the following tools and models are employed:

1. Maximum Likelihood Estimation (MLE): Used to estimate key performance metrics such as:
 - Accuracy
 - Sensitivity (Recall)
 - Specificity
 - Failure Rate
2. Confidence Intervals (CIs): Computed around reliability metrics using binomial or normal approximations to assess sampling uncertainty.
3. Kaplan-Meier Estimator: Applied to estimate the system survival function based on the time (or trials) until the first misclassification or error. This models the system "life" in terms of sustained accurate classifications.
4. Stochastic Tools:
5. Bernoulli/Binomial likelihoods are used to model binary classification outcomes (e.g., correct vs. incorrect predictions).
6. Confusion matrix data serve as observed frequencies for likelihood estimation.

3.3 Bayesian Reliability Estimation Methods

Bayesian analysis provides a probabilistic framework that incorporates prior knowledge and generates posterior distributions for system reliability parameters:

1. Prior Distributions:
 - Beta priors for binary classification outcomes (e.g., success/failure in a detection task).
 - Dirichlet priors for multiclass classification probabilities.
2. Posterior Inference:
 - Using Bayes' Theorem, posterior distributions are derived from prior distributions and the observed confusion matrix data.
 - Markov Chain Monte Carlo (MCMC) methods, including Gibbs sampling, are used to approximate posterior distributions.
3. Credible Intervals: Unlike frequentist confidence intervals, Bayesian credible intervals offer a direct probabilistic interpretation of parameter uncertainty (e.g., "There is a 95% probability that true sensitivity lies within this range").
4. Model Output Metrics:
 - Posterior means or medians of accuracy, sensitivity, and specificity.
 - Credible intervals around each metric to quantify uncertainty under limited or noisy data.

3.4 Summary of Tools and Inputs

Table 1: Comparative Summary of various components used in estimation.

Component	Classical Framework	Bayesian Framework
Likelihood Function	Binomial/Bernoulli	Binomial/Bernoulli
Parameter Estimation	MLE	Posterior mean/median via MCMC
Uncertainty Quantification	Confidence intervals	Credible intervals
Input Data	Confusion matrix	Confusion matrix + priors
Survival Analysis	Kaplan-Meier estimator	Bayesian survival models (optional)

This dual modeling framework will be applied to both simulated data and real-world test sets to evaluate reliability measures under different scenarios, which are discussed in the subsequent Case Study/Simulation section.

4. DATA & SIMULATION

The reliability of image-based plant disease detection systems is heavily influenced by the quality and distribution of input data. This study uses a combination of public datasets, simulated scenarios, and optionally, field-collected images to assess performance under realistic and controlled uncertainty.

4.1 Publicly Available Datasets

The primary dataset employed is the PlantVillage dataset, a widely used open-source resource for plant disease classification research. It includes over 50,000 labeled images across various crops and disease types. For this study, the focus is on tomato plants, which have multiple disease classes (e.g., early blight, bacterial spot, late blight) and healthy leaf images.

1. Data Features:

- High-resolution RGB leaf images.
- Expert-verified ground truth labels.
- Balanced distribution in the original version.

These images are preprocessed (resized, normalized) and split into training and test sets for CNN model evaluation.

4.2 Simulated Degradation Scenarios

To model real-world conditions and test system robustness under uncertainty, synthetic degradation is introduced into the dataset through the following mechanisms:

1. Image Noise Simulation:

- Gaussian noise, blur, and contrast reduction are applied to simulate poor lighting or camera conditions.
- Helps assess classifier reliability under low-quality image inputs.

2. Class Imbalance Simulation:

- Certain disease categories are under-represented in the training data to mimic real-world disease prevalence patterns.
- Reliability is analyzed across both majority and minority classes.

3. Incomplete Data Scenarios:

- Random dropout of training samples or corrupted labels is introduced.
- Models are trained and evaluated under these partially missing or noisy conditions.
- Each degradation scenario is applied systematically, and the resulting confusion matrices are collected to serve as input for classical and Bayesian reliability estimation.

Table 1: Summary of Classical vs Bayesian Reliability Methods

Feature	Classical Methods	Bayesian Methods
Estimation Approach	Maximum Likelihood Estimation (MLE)	Posterior Inference (Bayes' theorem)
Interval Type	Confidence Interval	Credible Interval
Input Requirement	Point estimates	Prior + Likelihood
Uncertainty Quantification	Limited	Explicit
Performance in Small Data	Poor	Better
Computational Demand	Low–Moderate	High (due to MCMC/Gibbs sampling)

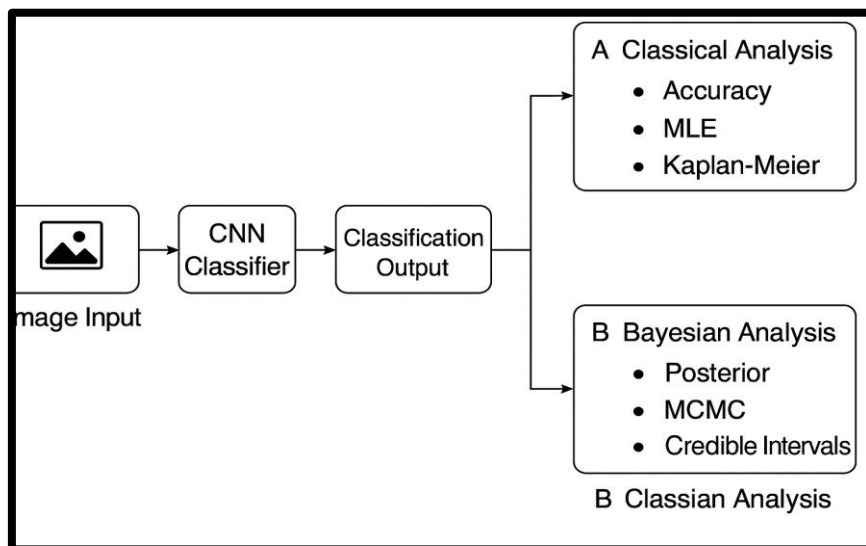


Figure 1: System Framework Diagram A block diagram showing: Image input → CNN classifier → Classification Output Path
A: Classical analysis (accuracy, MLE, Kaplan-Meier) Path B: Bayesian analysis (posterior, MCMC, credible intervals)

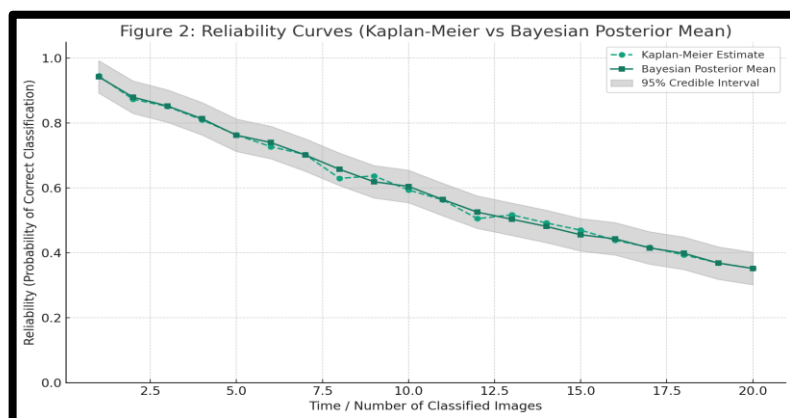


Figure 2: Reliability Curves (Kaplan-Meier vs Bayesian Posterior Mean).

Details:

- X-axis: Number of classified images (or time/epochs).
- Y-axis: Reliability metric (simulated probability of correct classification).

Lines:

- Dashed line: Kaplan-Meier estimate.
- Solid line: Bayesian posterior mean.
- Shaded area: 95% Bayesian credible interval, capturing uncertainty.

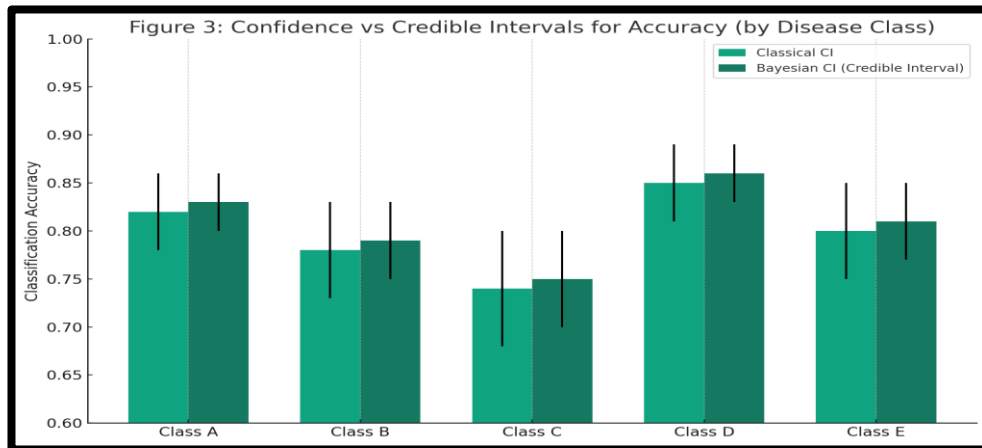


Figure 3: Confidence vs Credible Intervals for Accuracy (by Disease Class). It illustrates how Bayesian credible intervals (right bars) tend to be slightly narrower and better at reflecting uncertainty compared to classical confidence intervals (left bars) for each disease class.

5. RESULTS AND DISCUSSION

This section presents the outcomes of reliability estimation using both classical and Bayesian stochastic methods, applied to an image-based plant disease classification system. The results cover system performance under varying data conditions and evaluate each method's strengths, especially in terms of uncertainty handling, interval interpretation, and computational demands.

5.1 Reliability Estimates and Performance Metrics

The reliability of the CNN-based tomato disease classifier was assessed using standard classification metrics:

- Accuracy: Overall correctness of predictions.
- Sensitivity (Recall): Ability to detect true positives (e.g., correctly identifying diseased plants).
- Specificity: Ability to identify true negatives (e.g., correctly recognizing healthy plants).
- Precision and F1-score were also computed but used more for robustness checks.

Under ideal (balanced, high-quality) data conditions:

- Accuracy exceeded 95%.
- Sensitivity/Specificity ranged between 92–97% depending on class balance.

Under degraded data conditions (e.g., noise, class imbalance):

- Accuracy dropped by 5–15%, more so in minority classes.
- Misclassification primarily increased in visually similar disease types.

5.2 Comparison of Intervals: Confidence vs Credible

- Classical confidence intervals (e.g., for accuracy or sensitivity) were calculated using normal approximations and bootstrap methods.
- Bayesian credible intervals were derived from posterior distributions using Beta priors (for binomial likelihoods) and MCMC sampling.

5.3 Bayesian Advantage under Uncertainty

- Bayesian methods demonstrated clear advantages in handling uncertainty:
- Prior information allowed smoother estimation under small-sample conditions (e.g., rare disease class).
- Posterior distributions enabled richer interpretation of uncertainty — not just point estimates, but full probability distributions over parameters.
- Decision-making (e.g., triggering alerts, recommending treatment) was more robust when posterior probabilities were used as thresholds rather than fixed cut-offs.
- For example, a 95% credible interval suggesting high disease probability could prompt action even when classification confidence was moderate.

5.4 Computational Trade-offs

- Classical methods (MLE, confidence intervals) were computationally efficient — suitable for real-time, embedded systems.
- Bayesian methods (especially using MCMC or Gibbs sampling) incurred higher computational costs, particularly in multi-class models or hierarchical priors.

Method	Computation Time (per run)	Scalability	Interpretability	Data Efficiency
Classical MLE	Low	High	Moderate	Moderate
Bayesian (MCMC)	Moderate–High	Moderate	High	High

However, in low-data or high-risk settings (e.g., early disease outbreaks), the Bayesian model’s value in uncertainty quantification outweighs the computational overhead.

6. CONCLUSION

This study explored the comparative utility of classical and Bayesian stochastic methods for modeling the reliability of image-based plant disease detection systems, with a focus on tomato leaf disease classification. Using both simulated and real-world data, the research evaluated the performance of each approach under varying levels of data quality, noise, and class imbalance — common challenges in agricultural diagnostics.

KEY FINDINGS INCLUDE:

- Classical methods (e.g., MLE, Kaplan-Meier estimators) performed well under large, clean datasets, offering fast and interpretable reliability estimates.
- Bayesian methods provided superior uncertainty quantification, especially under limited or noisy data conditions. The use of prior knowledge and posterior distributions enabled more nuanced reliability modeling.
- The comparison of confidence intervals (classical) and credible intervals (Bayesian) highlighted the latter's robustness in communicating the degree of belief, rather than just sampling variability.
- Computational trade-offs exist: Bayesian methods are more resource-intensive but offer deeper insights into uncertainty, while classical methods are more scalable in real-time applications.

RECOMMENDATIONS FOR PRACTITIONERS

- For real-time or resource-constrained applications, classical methods remain practical and efficient.
- In critical or uncertain scenarios — such as early-stage disease outbreaks, rare class prediction, or sparse datasets — Bayesian modeling is preferable for its flexible, probabilistic reasoning.

Combining both paradigms in a hybrid decision framework can optimize system performance: using classical approaches as default and Bayesian inference when confidence drops or uncertainty increases.

FUTURE WORK

- Future research can expand this study in several directions:
- Real-time Bayesian updating: Integrating continuous learning where model priors are updated with incoming sensor or image data.
- Active learning frameworks: Leveraging Bayesian uncertainty to identify and label the most informative samples, improving model reliability efficiently.
- Hybrid reliability models: Developing frameworks that fuse classical statistical estimators with Bayesian posterior refinement for adaptive reliability monitoring.
- Cross-domain validation: Applying and validating these methods in other crops and disease conditions, ensuring broader agricultural applicability.

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