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Bayesian neural network for plant disease detection: A role of prior knowledge in data-scarce agricultural systems

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Abstract

Plant diseases are a major threat to global food security, causing an estimated annual economic loss of approximately USD 220 billion. Even though deep learning models excel at image-based disease detection, the requirement for many labelled images with a quantitative prediction uncertainty can be problematic in real-world agricultural applications. Bayesian neural networks (BNNs) overcome these limitations by incorporating prior knowledge from plant pathology, symptom morphology and environmental factors within a probabilistic learning framework. This approach not only improves prediction accuracy but also yields calibrated uncertainty estimates alongside each prediction. This review synthesises recent studies on BNNs, focusing on domain-knowledge, data-driven and functional priors for plant disease detection. The evidence gained from the studies reviewed indicates that BNNs consistently outperform deterministic models, especially in low-data regimes, as may be the case for smallholder farming characterised by heterogeneous environments and limited annotation resources. The review also highlights challenges related to computational complexity, prior selection and edge deployment, while outlining future research opportunities for robust agricultural artificial intelligence (AI) systems.

Keywords: Bayesian neural networks; data scarcity; plant disease detection; prior knowledge; uncertainty quantification

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1. Introduction

Plant diseases are among the major constraints limiting global agricultural productivity and food security. Agricultural biodiversity plays a critical role in supplying food and raw materials to humans, making agricultural biodiversity an essential component of human well-being (1, 2). One of the most critical factors affecting food production is plant disease (3). Plant diseases arise from biotic pathogens such as fungi, bacteria, viruses and nematodes, while abiotic stresses including nutrient imbalance, temperature extremes and soil conditions may produce similar symptoms. Plant diseases may reduce plant growth, yield, quality and overall productivity (4). The agricultural industry is also plagued by plant diseases, causing an estimated annual global economic loss of USD 220 billion, primarily driven by bacteria, fungi, nematodes and viruses (5). A prominent historical example is the Irish potato famine (1845–49), which caused approximately 1.2 million deaths (6). Such massive losses emphasise the importance of timely and precise disease diagnosis to reduce the damage and avoid massive outbreaks of diseases that pose a threat to world food security, especially to small farmers whose livelihoods depend on healthy crops (7).

Conventional methods for identifying diseases, which often involve manual examination, are typically time-consuming and labour-intensive and subject to human error unless trained experts are involved (8). This has been an impetus for interest in automated, accurate and scalable diagnostic systems. Deep learning has become one of the most powerful and accurate tools of image classification and there are considerable prospects for improving the control of plant diseases and food security in general (9). However, the prerequisite for abundant, high-quality imagery often limits the utility of deep learning models when evaluating low-resolution inputs or navigating challenging field environments characterised by cluttered backgrounds, shadows and non-uniform lighting that are common in real-life agricultural

conditions (10). Nevertheless, the fact that these models fail to measure uncertainty tends to undermine the practical use of those models in real-world agricultural contexts, which are essential to make sound decisions, explaining the high stakes of their application (11, 12).

These limitations highlight the need for more robust and data-efficient models when limited data and computational resources are needed, where Bayesian neural networks (BNNs) offer a promising solution (13). The BNNs provide a principled methodology to incorporate existing background knowledge and quantify uncertainty in the models, which is especially beneficial in the field of data scarcity, such as agricultural disease detection where large, high-quality annotated datasets are often unavailable (13). Thus, techniques that can utilise previous information to regularise the learning process as well as approximate uncertainty play a crucial role in creating dependable diagnostic tools in precision agriculture (14). It can be used to make more informed inferences since the inherent ability of BNNs to condition their parameters with prior distributions enables them to make inferences when the empirical data is sparse, hence minimising overfitting and enhancing generalisation abilities (15). Moreover, BNNs allow parameters to be modelled as probability distributions and not treated as point estimates, which allows for a more calibrated prediction of uncertainty-an important drawback of deterministic deep learning models that often give overly confident and poorly calibrated predictions (16).

The purpose of this review is to fill this gap by: (1) Reviewing the current state of deep learning and Bayesian methods in detecting plant disease; (2) Examining how prior knowledge may be used to promote the robustness of models, quantifying their uncertainty and generalising in situations of data scarcity and local environmental heterogeneity and (3) Determining the open challenges and research opportunities in deploying the previous knowledge BNNs in actual farming systems, particularly in resource constrained areas.

2. Methodology

Literature for this review was collected by using combinations of keywords such as “Bayesian neural network,” “plant disease detection,” “uncertainty quantification,” “prior knowledge,” and “Bayesian optimisation” in the Google Scholar search, along with crop names such as tomato, rice, maize, potato, chilli and durian. The search was limited to articles published between 2015–25, with a special emphasis on the last five years to cover the latest progress in Bayesian deep learning for agricultural applications. Studies were included if they employed Bayesian methods, Bayesian optimisation, or probabilistic deep learning for plant disease detection or classification, or if they discussed uncertainty quantification, integration of prior knowledge, or foundational Bayesian neural network theory relevant to this domain. A few studies from adjacent imaging areas, e.g., medical imaging, were also included when they provided methodological insights that could be immediately applied to data-scarce, high-stakes classification problems analogous to plant disease diagnosis. Studies not related to plant disease detection, without any Bayesian or probabilistic component and with no clear methodological relevance to the scope of the review were excluded. As the review is a narrative rather than a systematic review, no formal preferred reporting items for systematic reviews and meta-analyses (PRISMA)-style screening protocol was applied; instead, the above search strategy was used to ensure broad and representative coverage of the field.

Fundamentals of Bayesian neural networks

Bayesian neural networks are neural networks based on Bayesian probability theory that explicitly model uncertainty in network parameters, making them particularly suitable for applications such as plant disease detection where datasets are limited and noisy (17–19). In contrast to classical neural networks, which learn fixed-point approximations of network weights, BNNs consider network weights as random variables with probability distributions (20). The use of this probabilistic method enables BNNs to measure uncertainty in their predictions, which enables estimation of predictive uncertainty, an important feature for decision-making in agricultural diagnostics (21).

Fundamentally, BNNs utilise Bayes' theorem to incorporate the initial belief, or the prior distribution, with the available evidence, which is represented by the likelihood functions, to obtain a posterior distribution (22). In this framework, the prior distribution expresses any existing knowledge or assumptions about the network’s weights before any training data is considered (20). The probability of obtaining the provided dataset under model parameters is estimated by the likelihood function (23). The aggregate of these leads to the posterior distribution, which reflects the revised belief of the parameters based on the observed data, hence giving a measure of uncertainty in the predictions made by the model (24).

Mathematically, Bayes' theorem is expressed as:

$$P(W/D) = \frac{\mathrm{P(D/W)P(W)}}{\mathrm{P(D)}}$$

Here, P (W|D) represents the posterior distribution of the network weights W given the observed data D. P (D|W) is the likelihood, P (W) is the prior distribution and P (D) is the evidence or marginal likelihood that normalises the posterior distribution (19, 24).

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The BNNs naturally represent two kinds of uncertainty, namely aleatoric and epistemic uncertainty (24). Aleatoric uncertainty refers to the natural noise present in leaf images such as uneven lighting, shadows, or overlapping symptoms and it is usually handled by using probabilistic models or output layers that adjust to these varying noise levels (25). Epistemic uncertainty is a sign of ignorance because of a small or biased amount of data and is represented within the posterior over weights; it decreases as additional labelled plant pictures are viewed (17, 25). In plant disease detection, epistemic uncertainty helps identify cases that differ from the training data, such as new cultivars or unseen diseases, making the system safer and supporting better decision-making for farmers (26).

The general problem of exact Bayesian inference in deep networks is intractable; practical approximations are used instead. Variational inference tackles this by fitting a simpler distribution, often a mean-field Gaussian, to the true posterior by minimising the KL divergence, which allows the model to be trained efficiently with stochastic or natural-gradient methods (18, 19). Another approach is Markov Chain Monte Carlo (MCMC), including methods like Hamiltonian Monte Carlo and stochastic gradient Langevin dynamics (SGLD), which is asymptotically exact and more computationally intensive, though SGLD has been used to detect plant diseases to get improved calibrated uncertainty on out-of-sample data (26). Monte Carlo Dropout has become a popular approximation because it provides uncertainty estimation with minimal modifications to conventional neural network architectures (17, 27).

The BNNs provide better calibrated confidence estimates than deterministic neural networks and generally improve model generalisation when training data are limited or distribution shifts occur, making them particularly suitable for plant disease detection in data-scarce agricultural environments (18).

Prior knowledge in Bayesian neural networks

Prior knowledge in BNNs refers to information about the model, data, or task that is available before observing the training data and is represented as prior probability distributions over model parameters (17). It is a formal model of expert knowledge of plant pathology, symptom morphology, pathogen life cycles and environmental cues in the form of probability distributions over model parameters (28). The ability to regularise the learning process and estimate the epistemic uncertainty makes the BNNs especially appropriate in the case of limited or imbalanced datasets, by combining prior knowledge (26).

Prior knowledge may be incorporated (i) in weight space, through the selection of structured or hierarchical priors (ii) in function space, by matching a desired Gaussian process (GP) prior or physics based functional prior and then adjusting weight priors to replicate that prior (iii) as domain knowledge priors, where any constraint that can be expressed as a loss (e.g., physics rules, fairness, healthcare knowledge) is encoded as a prior that assign high probability to parameter configurations that satisfy those constraints and (iv) via data driven priors, using generative models or external summary information to code the data manifold (24, 29).

Encoding plant knowledge as priors

Plant pathology knowledge can be encoded as a prior structure over disease-relevant features, attention patterns or parameter groups that are tuned to the morphology of symptoms and not incidental plant traits. Because visual diagnosis depends on lesion colour, texture, form and spot patterns, BNN priors can target filters or latent variables that highlight these symptom characteristics before training (8, 30). Priors can also guide attention to disease-relevant areas, decreasing background and non-symptom bias in complex imagery (31). In tomato leaf disease diagnosis, for instance, a BNN could assign stronger priors to latent variables for spot texture and symptom regions, then update these with labelled tomato images to yield posterior distributions over disease classes and confidence (32).

Agronomic knowledge comprises host crop identity, cultivar/genotype effects, growth stage, sowing time and management practices that can affect disease susceptibility under different production systems (33). While the number of cases that can be substantiated with direct evidence is limited, hierarchical priors are supported by the Bayesian methodology, which offers statistical strength for a group of related crops/cultivars or crop developmental stages while preserving statistical variation between the groups (34, 35). This method is a synthesis of knowledge, which can be represented as cultivar–stage-specific prior distributions of the risks of diseases, updated with field observations to provide posterior risk for selected cultivar stage combinations.

Environmental conditions like temperature, relative humidity, rainfall, leaf wetness and their timing can significantly affect pathogen development and disease emergence (36, 37). One way to incorporate this knowledge would be through the prior disease-risk distribution or structured latent variables in BNNs that would give higher prior probability to environmental conditions that favour infection (33, 38). In the case of grape downy mildew, humidity- and rainfall-conducive conditions may receive increased prior outbreak (baseline) risk and then this risk may be updated with freshly observed environmental conditions to give posterior disease risk (36). This represents a methodological synthesis of established environmental disease relationships and Bayesian prior methodology rather than a directly reported implementation of environmental priors in a plant disease BNN.

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Bayesian updating and benefits

These informative priors are updated as image evidence and auxiliary agronomic or environmental data are collected throughout the training process and result in posterior distributions of weights, latent disease states, or decision layers instead of just point estimates (29). The probabilistic updating is well suited to the agricultural context where your images are likely to have noise, limited labels and varying acquisition conditions across the domain, where you need strong models to distinguish the disease cues from the background artefacts and you don't know what the acquisition conditions might have been (39). In addition to providing a measure of predictive uncertainty, these methods have been linked to better minority-class performance, less overfitting, increased reliability and enhanced generalisation in less-than-optimal or limited-data settings (8, 39). In that regard, the encoding of plant pathological, agronomic and environmental knowledge into priors does not preclude data-driven learning but aims to focus posterior learning on biologically plausible solutions, a task for which these constraints are of high value (40).

Systematic gains of domain knowledge priors over vague priors, like isotropic GP or generic GP priors, are seen in a broader Bayesian deep learning framework, with better results on tasks, since encapsulated knowledge is inherited into the posterior samples (41). The accuracy of prediction with informative Gaussian scale mixture priors tuned to both feature sparsity and signal-to-noise ratio is better than vague priors and in certain scientific models, even better than cross-validation tuned to hyperparameters (42). When general pre-trained knowledge is used along with domain-specific fine-tuned models in an ensemble, the false positive rates of unknown diseases are significantly lower, once again demonstrating the advantage of integrating prior knowledge at the model level in plant disease anomaly detection (43).

Low-data agriculture should not ignore domain knowledge, which allows deep models to overfit spurious backgrounds and shapes, miscalibrate uncertainty and break on new diseases and field domains; knowledge-directed and structured methods make these models more robust (26). Overall, integrating biological knowledge into BNNs improves robustness, enhances model interpretability and increases predictive reliability under data-scarce agricultural conditions.

Bayesian neural network architecture and implementation

Data preparation and preprocessing

Benchmark datasets such as PlantVillage provide large collections of annotated leaf images that are widely used for training and evaluating Bayesian plant disease detection models (44, 45). Pre-processing usually consists of background removal or suppression, noise removal, colour normalisation and image resising to the input size requirement of the CNN. Other studies also involve leaf tiling or texture-based cropping to avoid overfitting of a model on leaf shape instead of disease symptoms (46). Data augmentation methods are also crucial in increasing the diversity of data and improving the generalisation and strength of the model, especially when using small datasets. These include rotations, flips, scaling and variations in brightness or contrast (3). Typical dataset splits of training, validation and a test include 70 : 20 : 10, 80 : 10 : 10 or 60 : 20 : 20 (47). It is necessary to divide the data into training, validation and test sets appropriately to evaluate the performance of the model and reduce the threat of over fitting (8).

Model architecture

In many Bayesian neural networks for detecting plant diseases, a CNN backbone is used to extract features, with a Bayesian framework applied to the final dense layers. Neural architecture models like ResNet, DenseNet, MobileNet, or even custom CNNs have been proven to be more effective in leaf disease classification due to their ability to automatically discover hierarchical texture and colour patterns related to disease lesions (4, 48). Bayesian plant disease models are usually trained on a deterministic convolutional backbone, where the visual priors are pretrained and the weights of the Bayesian fully connected layers are random variables (26, 48). These provide variational parameters such as mean and variance to provide approximate posteriors, producing a predictive distribution on the classes instead of point estimates (26, 44). Regularisation is standardised in many cases using isotropic Gaussian priors when data is limited; in advanced versions, attention or multi-scale convolutions can be used to capture the localised symptoms, but such notions may still be limited to having a Bayesian output to quantify uncertainty (49). Prior knowledge and Bayesian fully connected layers are integrated into a convolutional neural network (CNN) based architecture to generate probabilistic disease predictions (Fig. 1).

Training framework

Bayesian neural networks to detect plant diseases are trained using approximate Bayesian inference, which balances the data-adjustment and prior belief of the data through the minimisation of negative log-likelihood (NLL) and Kullback–Leibler (KL) divergence on the variational posterior, which results in the evidence lower bound objective (26, 50). This encourages uncomplicated, data-approximating weight distributions, which is essential in constrained labelled pictures.

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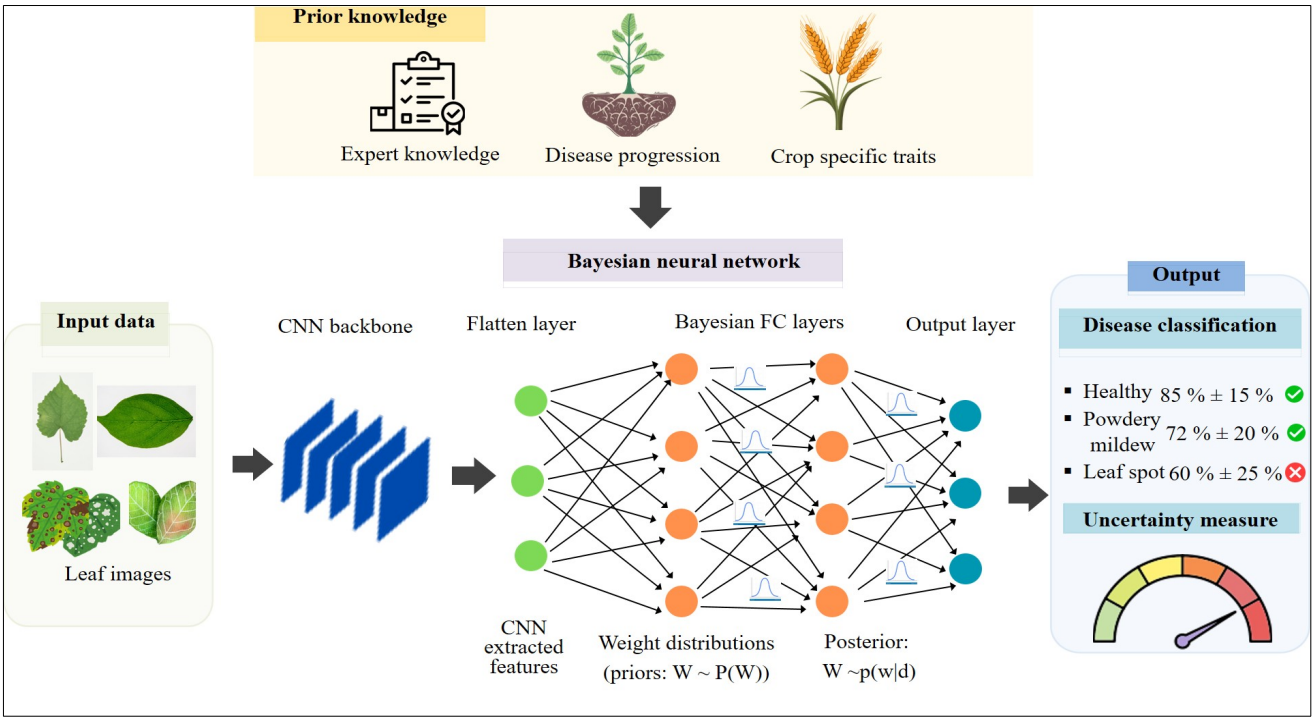


Fig. 1. Bayesian neural network (BNN) architecture.

Approximations: Due to the intractability of exact inference, variational inference (optimising non-robust distributions such as factorised Gaussians using SGD on NLL+KL), as well as Monte Carlo dropout (sampling posterior subnetworks during test-time, dropouting), have been proposed (26, 44); stochastic gradient Langevin dynamics are also more accurate in reflecting uncertainty (26). Hyperparameters, such as learning rates, dropout, prior variances, depth and activations, are optimised efficiently using Bayesian optimisation to learn small CNNs that satisfy the constraints of data and computation (8, 46). Knowledge is embedded with priors, architecture, transfer, knowledge, approximate inference, as well as Bayesian tuning, which guarantee robustness in data-poor environments.

Evaluation and inference of model

Bayesian models are compared to deterministic CNNs in terms of standard measures: accuracy, precision, recall, F1 and area under the curve (AUC), which are compared on datasets like PlantVillage and field collections (51, 52). Bayesian models assume uncertainty measures, typically predictive entropy or variance, between many stochastic forward passes, which are used to identify hard or out-of-distribution images as well as minimise overconfident errors (48).

The pre-processing of the image is done at test time and the result is fed through the CNN backbone. Several probability vectors are generated by repeatedly sampling the Bayesian head (Monte Carlo sampling); the average of the probability vectors provides the final class probabilities and the uncertainty is determined by the dispersion of the probabilities (48). To support real-time applications on phones or edge devices, the backbone can be made lightweight (e.g. MobileNet) and the latency constrained by the number of samples to ensure low latency but useful uncertainty information (53).

Implementation

The BNN models are essential in creating models that embrace the uncertainty and prior information, particularly in agricultural systems that are data sparse. Each framework has varied goals, programme settings and interpretation abilities. Thus, there are many different tools and platforms to furnish researchers with an opportunity to implement Bayesian deep learning experiments, with the most used frameworks summarised in Table 1.

Bayesian techniques are built into proprietary tools such as MATLAB and open-source frameworks such as Pyro, TensorFlow Probability, PyMC, RStan and NumPyro are more flexible and scalable. Such frameworks justify techniques such as MCMC and variational inference. They are chosen based on the data availability, computing resources and the degree of uncertainty estimation needed in use, such as plant disease detection. The complete workflow from image acquisition and preprocessing to Bayesian inference and uncertainty-based disease prediction are illustrated in Fig. 2.

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Table 1. Overview of Bayesian neural networks software framework

Frameworks	Open source	Programming environment	Main inference method	Typical use difficulty
MATLAB Toolbox	No	MATLAB	Various, including MCMC and Variational Bayes via toolboxes	high
Pyro	Yes	Python (PyTorch)	MCMC and stochastic variational inference	Moderate to high
TensorFlow Probability	Yes	Python (TensorFlow)	VI, MC sampling, Bayesian layers	Moderate
Rstan	Yes	R	Hamiltonian Monte Carlo (HMC), Variational Inference	High
NumPyro	Yes	Python (JAX)	NUTS, SVI	Moderate
PyMC	Yes	Python (Aesara)	MCMC, VI	Moderate

CNN: convolutional neural network; ELISA: enzyme-linked immunosorbent assay; GAN: generative adversarial network; Gabor: Gabor filter; GLCM: grey-level co-occurrence matrix; k-NN: k-nearest neighbours; LBP: local binary pattern; MC: Monte Carlo; PCR: polymerase chain reaction; qPCR: quantitative polymerase chain reaction; ResNet: residual network; SGLD: stochastic gradient Langevin dynamics; SVM: support vector machine; ViT: vision transformer.

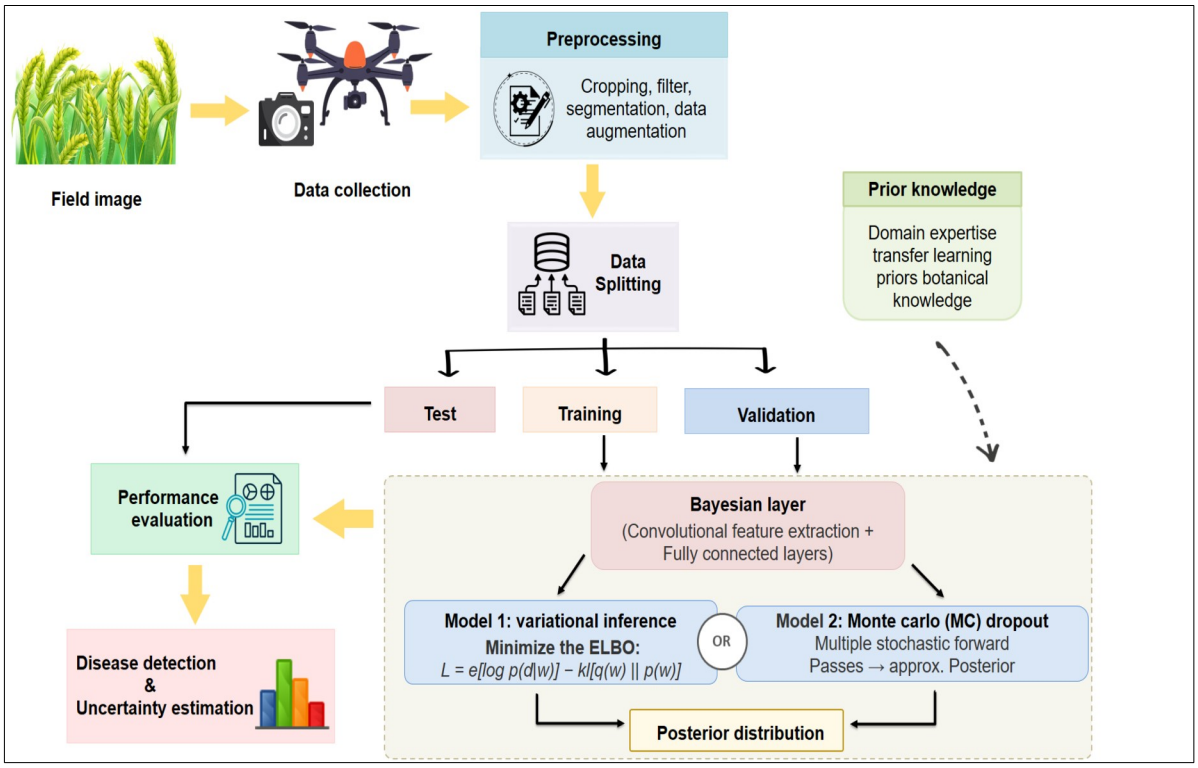


Fig. 2. General workflow of a Bayesian neural network-based plant disease detection pipeline.

Current approaches in plant disease detection

Traditional plant disease diagnosis primarily relies on expert visual inspection of symptoms such as leaf spots, chlorosis and wilting. Although effective, these methods are labour-intensive, subjective and often detect diseases only after visible symptoms appear (4, 54). Recent laboratory analyses such as culturing, enzyme-linked immunosorbent assay (ELISA) and polymerase chain reaction / quantitative polymerase chain reaction (PCR/qPCR) are highly specific, but require infrastructure, trained personnel and time, which also makes it hard to scale up (4). Simple imaging and simple colouration can identify lesions but typically assist, as opposed to substituting, visual experts (54). Overall, these approaches are labour-intensive, late-stage and challenging to scale up in large amounts (4, 54).

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Classical machine learning presented semi-manual pipelines, which are combined with features under the control of humans and typical classifiers. Based on the images of the leaves, the researchers derive colour histograms, vegetation indices and texture descriptors (e.g., grey-level co-occurrence matrices, Local Binary Patterns, Gabor filters), as well as shape or key point-style features to describe the lesion size and distribution (4, 55). These feature vectors can then be classified with support vector machines, random forests, k-nearest neighbours, naive Bayes or decision trees and are often preceded by the steps of segmentation or clustering that isolate diseased regions (4, 55). On relatively controlled and balanced datasets, these pipelines typically achieve accuracies between 85 % and 93 %, significantly outperforming untrained human observation but subject to variations in illumination, background noise, or changes in datasets (54). This reliance on features which are specified by experts and the use of controlled environments encouraged the shift to deep learning (54).

Deep learning, particularly through CNNs, has emerged as the most prevalent paradigm for the detection of plant diseases using image-based approaches. The CNNs are trained on pixel-based hierarchical features without the need to design features manually and embrace subtle lesion patterns (54, 56). ImageNet-pretrained models like VGG, ResNet, DenseNet, EfficientNet, Inception and MobileNet are fine-tuned on plant datasets, an idea that has shown a significant enhancement of performance and data efficiency (56, 57). On such big, recollected datasets as PlantVillage, CNN-based classifiers are often able to gain 96–99 % accuracy and some successful architectures claim 99.5 % success with dozens of crop-disease classes (54, 56). Newer surveys also indicate extensions of plain classification, such as object detection (YOLO, Faster R-CNN), how to jointly segment lesions to count them and multimodal combination of red, green and blue (RGB) with multispectral or hyperspectral data to detect lesions earlier and before they cause symptoms (45, 58). At the same time, vision transformers (ViT) and related architectures have become competitive or superior alternatives, based on self-attention, which is able to model long-range dependencies and complex lesion distributions (54). These architectures capture long-distance dependencies and complex lesions distribution result in 97–99 % accuracy on PlantVillage and similar datasets, sometimes outperforming strong baseline CNNs, especially with challenging backgrounds and lighting variance (59). Surveys of plant protection using computer vision indicate that ViTs, CNN-ViT hybrids and generative adversarial network (GAN)-based data augmentation enhance robustness under variable lighting and background and detect early when the symptoms are weak (54). Yet, these deep architectures often demand a huge amount of labelled data and computation, which are still problems for smallholders and data-scarce crops (26).

Despite the remarkable performance of CNNs and ViT, their dependence on large annotated datasets and inability to quantify predictive uncertainty remain major challenges. Bayesian neural networks address these limitations by incorporating prior knowledge and probabilistic inference. In smallholder data-sparse agriculture, the task of detecting diseases in plants requires data-efficient predictor models that incorporate prior knowledge, such as regional epidemiology, climate and crop cycles, to more effectively regularise and make fewer-label predictions (45, 54). Bayesian neural networks address missing elements to make safer decisions in agriculture, with lightweight designs being most appropriate for edge devices and uncertainty quantification.

The main methods of plant disease detection vary in terms of accuracy, scalability, computational demands and handling of uncertainty. Briefly summarise what readers should observe from the comparison presented in Table 2.

Bayesian neural networks in plant disease detection

Bayesian convolutional neural networks (BCNNs) have been claimed to be more resistant to overfitting on small datasets of plant diseases than conventional CNNs and to provide predictive distributions, the standard deviation of which measures confidence in diagnosis (32).

Table 3 shows that the important observation from the reviewed studies is that many investigations employ Bayesian optimisation solely for hyperparameter tuning rather than implementing fully BNN capable of uncertainty quantification. shows that Bayesian methods in plant disease detection are mainly used for hyperparameter tuning and uncertainty estimation. The CNN models are used in most studies with the PlantVillage dataset and are very accurate (> 94 %). Tomato is the most extensively studied crop in Bayesian plant disease detection research, whereas relatively few studies have investigated wheat, maize, pepper, or durian (Fig. 3). This imbalance highlights opportunities for extending BNN research to underrepresented crops.

Critical synthesis: Comparative accuracy and uncertainty calibration across Bayesian neural networks methods

While reported accuracy is not necessarily distinguishing, BNNs' accuracy range is substantially overlapping that of classical ML (85–93 %), CNNs (96–99 %) and ViTs (97–99 %) (Table 2), meaning that the evidence currently available does not support the accuracy advantage of BNNs. The studies in Table 3 are not all the same class of Bayesian methods either. Only a subset of those studies, such as Monte Carlo (MC) dropout, stochastic gradient Langevin dynamics (SGLD) and Bayesian learning, include explicit support for predictive uncertainty estimation.

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Table 2. Comparison of plant disease detection approaches

Approach	Representative methods	Typical accuracy	
Expert / Manual Scouting	Visual inspection by agronomists	Subjective	Slow, late-stage detection; labour-intensive; does not scale (54).
Laboratory Diagnostics	ELISA, PCR/qPCR, culturing	High specificity	Requires infrastructure and trained personnel; impractical for field-scale use (4).
Classical Machine Learning	SVM, Random Forest, k-NN with hand-crafted features (colour histograms, GLCM, LBP, Gabor)	85–93 %	Sensitive to illumination and background variation; requires expert feature design (4, 55).
Deep Learning-CNNs	VGG, ResNet, DenseNet, EfficientNet, MobileNet (fine-tuned on PlantVillage)	96–99 %	Demands large, labelled datasets; overconfident predictions; poor uncertainty calibration (54, 56).
Vision Transformers (ViT)	ViT, CNN-ViT hybrids, GAN-augmented training	97–99 %	High computational cost; data-hungry; limited deployment on edge devices (54, 59).
Bayesian Neural Networks	MC Dropout, SGLD, Variational Inference on CNN backbones	94–99 %	Approximate inference; computationally intensive; prior selection is non-trivial (26, 48).

CNN: convolutional neural network; ELISA: enzyme-linked immunosorbent assay; GAN: generative adversarial network; Gabor: Gabor filter; GLCM: grey-level co-occurrence matrix; k-NN: k-nearest neighbours; LBP: local binary pattern; MC: Monte Carlo; PCR: polymerase chain reaction; qPCR: quantitative polymerase chain reaction; ResNet: residual network; SGLD: stochastic gradient Langevin dynamics; SVM: support vector machine; ViT: vision transformer.

Table 3. Application of Bayesian approaches in plant disease detection

Author	Crop	Dataset source	No. of images	Method	Bayesian application	Limitation	Accuracy (%)
A. Bayesian deep learning approaches							
(26)	Multiple crops	PlantVillage	54306	Bayesian deep learning	Bayesian estimation of uncertainty using MC Dropout and SGLD.	SGLD has higher computational cost and lower accuracy in the evaluated domain	SGD: 0.96 ± 0.00 MC Dropout: 0.94 ± 0.02
(48)	tomato, potato and pepper bell	PlantVillage	20639	CNN with Bayesian Learning	Bayesian learning layer on top of CNN	unassessed real-field generalisation	98.9
(60)	Multiple crops	PlantVillage	75	FPDNN-BR	Using Bayesian regularisation backpropagation to fine-tune results.	The size of the dataset is not very large	97.18
B. Bayesian Optimisation-based approaches							
(49)	Rice	PlantVillage	2370	ADSNN-BO	Used for hyperparameter tuning	No uncertainty estimation	94.65
(46)	Tomato	PlantVillage	26148	Mobile Net	Used for hyperparameter tuning	Unassessed real-field generalisation	96.31

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(8)	Tomato	PlantVillage	18159	CNN-Stacking	Used for hyperparameter optimisation	Optimization-level uncertainty only	98.527
(61)	Potato	PlantVillage	2152	Bayesian-optimised CNN weighted ensemble	Bayesian optimisation for ensemble weight optimisation	Absence of test-time augmentation, pruning or uncertainty estimation.	97.94
(62)	Tomato	PlantVillage	Not specified (taken from research article)	Bayesian-optimised Merge Activator with Fine-Tuned Random Forest (BMAFRF)	Activation of Bayesian tuning using Gaussian-UCB	Absence of explainability mechanism because of the black-box nature of the deep learning model.	99.6
(63)	Multiplecrops (Apple, tomato, rice)	Kaggle	Tomato – over 20000; Rice -120	Hy-SALDD	Bayesian optimisation used to tune SVM hyperparameters	Complex multi-stage pipeline using hybrid segmentation (PSP-Net + HED), BWO feature selection and Bayesian-optimised SVM classifier	**Apple:** 98.46 **Tomato:** 95.89 **Rice:** 91.67
(64)	durian	Field image	2595	CNN	Hyperparameter optimisation using the keras-tuner	The symptoms of Blight and *Colletotrichum* are quite similar, which leads to misclassification.	96.61
(65)	Wheat	Field images	Expert knowledge	Bayesian belief network	Used for uncertainty prediction	Subjective human inspection of lesions causes inaccuracies.	89.3
(66)	Cassava and multiple crops	Field images+ PlanDoc	-	Bayesian-optimised Vision Transformer	Used for hyperparameter tuning	The model confused similar Cassava diseases: Mosaic, Brown Streak, Green Mottle.	Cassava-95.7 % PlantDoc-96.2 %
(67)	Maize(corn)	PlantVillage and Google websites	18888	VGG16	Bayesian optimisation for Hyperparameter Tuning	Grid search inefficiency and class imbalance reduced grey leaf accuracy.	99.21 %
(68)	Multiple crops	Different source	145500	5DB-DenseConvNet	Used for hyperparameter optimisation	Extensive use of data augmentation, rather than actual data	99.36
(69)	Tomato	Kaggle	11,000	modified VGG16	Bayesian optimisation for Hyperparameter Tuning	Confusion between visually similar diseases like early and late blight	97.1
(70)	Pepper	PlantVillage	2475	Inception V3 with BO	Used for hyperparameter optimisation	Limited to only two disease classes	99.6
(71)	Rice	Field images	150	Bayes' Classifier and Minimum Distance Classifier	Applied for probability-based classification of plant diseases.	Accuracy is not very high	Bayes' Classifier-69 MDC- 81

ADSNN-BO: adaptive deep stochastic neural network with Bayesian optimisation; BMAFRF: Bayesian-optimised Merge Activator with Fine-Tuned Random Forest; BO: Bayesian optimisation; BWO: binary whale optimisation; CNN: convolutional neural network; FPDNN-BR: fuzzy probabilistic deep neural network with Bayesian regularisation; HED: holistically nested edge detection; Hy-SALDD: hybrid segmentation, adaptive learning and deep disease detection; Keras Tuner: Keras hyperparameter tuning framework; MC: Monte Carlo; MDC: minimum distance classifier; PSP-Net: pyramid scene parsing network; SGLD: stochastic gradient Langevin dynamics; SVM: support vector machine; UCB: upper confidence bound.

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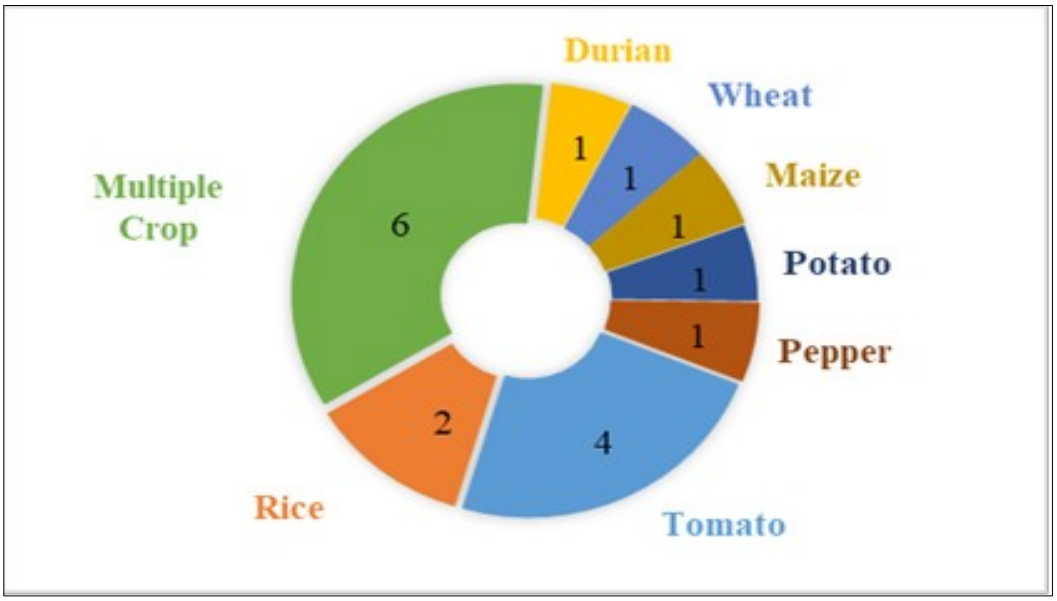


Fig. 3. Number of plants used in Bayesian-approach-based plant disease detection studies.

However, many other studies include Bayesian optimisation but do not estimate predictive uncertainty. Thus, the reported accuracies should not be taken as an indication of better Bayesian uncertainty calibration. To the best of our knowledge, the 54306 PlantVillage images are the only set of images tested and previous studies shows that SGLD achieves slightly better accuracy (0.96 ± 0.00) compared to MC dropout (0.94 ± 0.02), but this result is from a single study and should not be applied to the entire class of Bayesian inference methods (26). In addition, the literature reviewed does not always report on the same set of metrics that are used for calibration and this makes it difficult to directly compare the reliability of the predictions.

The BNNs can be especially useful when data is scarce, or the domain or objective undergoes significant change and a point estimate represents only part of the information, such that prior information and uncertainty can give further insights. The reviewed studies do not provide matched comparisons that would quantify the possible benefits of BNNs in these situations. Studies conducted in the field demonstrate varying levels of accuracy (89.3 % for the wheat Bayesian belief network and 95.7 to 96.6 % for the cassava and durian studies), which may not be solely attributable to the use of Bayesian inference, as the differences in the datasets, disease categories and variety of models used make it difficult to attribute these differences to the use of Bayesian inference. The body of literature agrees with BNNs as a promising framework for plant disease detection that is uncertainty-aware and can be data-efficient but fails to conclude that BNNs can always outperform deterministic models. Future research should thus compare matched models, both Bayesian and deterministic, in a controlled setting of data scarcity and domain shift and provide quantitative calibration metrics, like expected calibration error (ECE), in addition to traditional predictive performance metrics.

Challenges

One of the major issues is the complexity of computation and implementation of Bayesian deep learning. Exact Bayesian inference in large convolutional neural networks is computationally intractable, requiring approximate inference methods such as variational inference and stochastic gradient Langevin dynamics. These come with extra training and inference costs compared to standard optimisation (26, 54)

The BNNs also face significant data issues in plant disease vision systems. The representation of many crops, diseases and symptom stages is still under-represented and most publicly available data are obtained under controlled conditions such as PlantVillage (46, 62). Bayesian models may also give overconfident predictions that are incorrect with noisy labels or imbalanced classes, particularly in case priors are not tuned according to the true distribution of diseases or classes are unbalanced (62).

Close interaction between machine-learning specialists and plant pathologists is required to design priors that encode agronomic knowledge (and not arbitrary Gaussian priors) to accelerate the adoption relative to traditional CNNs with transfer learning pipelines (58).

Another major issue is choosing priors; the initial assumptions concerning the parameters required to support learning with small datasets are a critical aspect of the BNN performance that is beneficial when selected appropriately but detrimental when selected improperly (72). The best decisions would be the Laplace distributions to sparsity or hierarchical Gaussians, which entails an in-depth

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understanding of plant characteristics, disease lifestyles and local trends (73). Poorly specified prior distributions may substantially reduce predictive performance, regardless of network architecture (72).

Interpretability and user trust are also one of the challenges. The predictions and uncertainty of predictions should be made clear to farmers and extension workers. Although Bayesian models give confidence estimates, these are not necessarily intuitive and have to be supplemented with visualisation tools and easy decision thresholds to facilitate adoption, which is emphasised by material on the development of more practical, farmer-facing plant disease interfaces (58, 74).

The high sampling requirements in smart agriculture make the implementation of BNNs difficult in edge integration with smart agriculture devices. The computation of uncertainty needs several posterior samples, which generates large computation requirements that are not feasible in real-time to use on resource-intensive hardware (75). This is a disadvantage when it comes to quick diagnostics of the field, where time is paramount.

Opportunities

Leveraging prior expertise in BNNs may facilitate regularised learning and help avoid overfitting when data are insufficient. Priors that encode agronomic information can assist the model when labelled images are difficult to obtain, as reported by previous researchers (76). This might be particularly essential for smallholder systems, where comprehensive documents are not generally accessible (57).

The integration of BNNs and smaller CNNs backbones or transfer learning could result in small models that fit into mobile and edge devices. Work on small CNNs in combination with Bayesian optimisation and texture features has demonstrated that more efficient architectures can still reach an accuracy above 95 %, suggesting that Bayesian variants of such networks could support on-device decision support in low-resource regions (46).

Furthermore, developing hybrid physics-informed BNNs presents a promising avenue of research. It is possible to incorporate crop growth models or spectral reflectance laws as inductive biases in these models, which integrates the inductive power of neural networks with the known scientific laws (77). As an example, combining a light interaction model with plant canopy or disease progression patterns would result in a more reliable and interpretable diagnostic system (78). Such a strategy might help to increase tolerance to different environmental conditions and better generalisation to other plant varieties and diseases.

The BNNs can also be used to provide risk-aware decision tools that integrate sensor, weather and management data. The wider Bayesian network applications in agriculture indicate their power in handling uncertainty in complex agricultural environments and integrating distinct information sources (76). Integrating Bayesian vision models with probabilistic decision-support systems could directly link disease diagnosis with crop management recommendations.

Deep learning systematic reviews also highlight the importance of generalised models across geography, cultivar and imaging system models that are required in plant disease detection (48, 79). Structured priors with agronomy and pathology inspiration present BNNs as an embodiment of a principled step to even more robust and data-efficient plant health monitoring in practice in precision agriculture (26).

Future direction

Future research should focus on developing BNNs that explicitly incorporate agronomic knowledge, such as lesion morphology, symptom progression and disease epidemiology, rather than relying solely on Bayesian optimisation for hyperparameter tuning (48, 49).

In data-scarce scenarios, it is possible to consider Bayesian transfer learning, where priors are placed on weights of existing backbones (such as MobileNet, Inception) that had previously been trained on leaf disease images and then updated with a small number of local samples of new crops or locations (49, 62).

The integration of BNNs and active learning and data augmentation methods has potential: uncertain or rare cases of disease can be requested to be annotated and minority classes can be represented using synthetic images or texture-based patches, which is an extension of existing texture and augmentation methods in closed-ended CNNs with small networks (80).

To align with the on-farm requirements, the research must focus on lightweight Bayesian models executable on mobile or edge devices by beginning with the already tested, small systems such as depthwise-separable MobileNet or tiny CNNs to identify plant diseases in the low-resource environment (49).

Multi-modal and spatio-temporal Bayesian models that incorporate images, weather, management and sensor data are required and they would use concepts such as weather-aware augmentation and CNN-based forecasting to improve modelling of disease variability due to climate change (81).

Interpretability tools (attention maps, class-activation maps) should also be provided to ensure that farmers can not only tell where the model is paying attention but also its level of confidence, which builds on interpretability analyses already done on non-Bayesian CNNs (45, 49).

Lastly, next-generation research needs to establish data-scarce, uncertainty-aware detection

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standards, including cross-field and cross-season experiments, standardised measures beyond accuracy (calibration, reliability) and comparisons between Bayesian and conventional deep models on realistic but small agricultural problems (82). Collectively, these research directions will support the development of robust, interpretable and data-efficient Bayesian plant disease detection systems suitable for real-world agricultural applications.

3. Conclusion

This review highlights Bayesian neural networks (BNNs) as a promising approach for plant disease detection by integrating prior knowledge with probabilistic learning to address data scarcity and improve predictive reliability. Current limitations include computational complexity, appropriate prior specification and deployment on resource-constrained devices. Addressing these challenges will be essential for broader adoption of BNNs in precision agriculture. To develop precision agriculture, future studies should focus on agronomy-encoded BNNs, transfer learning on a Bayesian model, active learning, interpretability and benchmarks in data-poor environments. Continued advances in Bayesian deep learning, together with interdisciplinary collaboration between artificial intelligence researchers and plant scientists, will support the development of robust, interpretable and deployable plant disease diagnostic systems capable of improving sustainable agricultural production.

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Authors' contributions

AT prepared and drafted the manuscript. RV provided guidance and supervision throughout the writing process. RPS, MK and CIR critically reviewed and revised the manuscript. All authors have read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest

Authors do not have any conflict of interests to declare.

Ethical issues

None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used QuillBot and Grammarly for paraphrasing, grammar correction, language improvement, sentence restructuring and enhancement of clarity and readability. The author reviewed and edited the content as necessary and take full responsibility for the content of the publication.

References

1. Ramanjot, Mittal U, Wadhawan A, Singla J, Jhanjhi NZ, Ghoniem RM, et al. Plant disease detection and classification: A systematic literature review. Sensors. 2023;23(10):4769. https://doi.org/10.3390/s23104769
2. Tirkey D, Singh KK, Tripathi S. Performance analysis of AI-based solutions for crop disease identification, detection, and classification. Smart Agric Technol. 2023;5:100238. https://doi.org/10.1016/j.atech.2023.100238
3. Tugrul B, Elfatimi E, Eryigit R. Convolutional neural networks in detection of plant leaf diseases: A review. Agriculture.2022;12(8):1192. https://doi.org/10.3390/agriculture12081192
4. Demilie WB. Plant disease detection and classification techniques: a comparative study of the performances. J Big Data. 2024;11(1):5. https://doi.org/10.1186/s40537-023-00863-9
5. Dong J, Fuentes A, Zhou H, Jeong Y, Yoon S, Park DS. The impact of fine-tuning paradigms on unknown plant diseases recognition. Sci Rep. 2024;14(1):17900. https://doi.org/10.1038/s41598-024-66958-2
6. Hughes D, Salathé M. An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv preprint arXiv:1511.08060.2015. https://doi.org/10.48550/arXiv.1511.08060
7. Guth FA, Ward S, McDonnell K. From lab to field: An empirical study on the generalization of convolutional neural networks towards crop disease detection. Eur J Eng Technol Res. 2023;8(2):33–40. https://doi.org/10.24018/ejeng.2023.8.2.2773
8. Khan B, Das S, Fahim NS, Banerjee S, Khan S, Al-Sadoon MK, et al. Bayesian optimized multimodal deep hybrid learning approach for tomato leaf disease classification. Sci Rep. 2024;14(1):21525. https://doi.org/10.1038/s41598-024-72237-x
9. Natarajan S, Chakrabarti P, Margala M. Robust diagnosis and meta visualizations of plant diseases through deep neural architecture with explainable AI. Sci Rep. 2024;14(1):13695. https://doi.org/10.1038/s41598-024-64601-8
10. Hamed BS, Hussein MM, Mousa AM. Plant disease detection using deep learning. Int J Intell Syst Appl. 2023;15(6):38–50.

© The Author(s) 2026. Creative Commons CC BY 4.0. Published by Horizon e-Publishing Group.
https://doi.org/10.14719/pst.16499

11. Zhang Y. On cold posteriors of probabilistic neural networks: Understanding the cold posterior effect and a new way to learn cold posteriors with tight generalization guarantees. arXiv preprint arXiv:2410.15310. 2024. https://doi.org/10.48550/arXiv.2410.15310

12. Le AT, Shakiba M, Ardekani I. Tomato disease detection with lightweight recurrent and convolutional deep learning models for sustainable and smart agriculture. Front Sustain.2024;5:1383182. https://doi.org/10.3389/frsus.2024.1383182

13. Xu M, Kim H, Yang J, Fuentes A, Meng Y, Yoon S, et al. Embracing limited and imperfect training datasets: opportunities and challenges in plant disease recognition using deep learning. Front Plant Sci. 2023;14:1225409. https://doi.org/10.3389/fpls.2023.1225409

14. Melki P, Bombrun L, Diallo B, Dias J, Da Costa JP. Group-conditional conformal prediction via quantile regression calibration for crop and weed classification. In: 2023 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW). 2023. p. 614–23. https://doi.org/10.1109/ICCVW60793.2023.00068

15. Bargagna F, De Santi LA, Martini N, Genovesi D, Favilli B, Vergaro G, et al. Bayesian convolutional neural networks in medical imaging classification: a promising solution for deep learning limits in data scarcity scenarios. J Digit Imaging.2023;36(6):2567–77. https://doi.org/10.1007/s10278-023-00897-8

16. Abboud Z, Lombaert H, Kadoury S. Sparse Bayesian networks: Efficient uncertainty quantification in medical image analysis. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Cham: Springer Nature Switzerland; 2024. p. 675–84. https://doi.org/10.1007/978-3-031-72117-5_63

17. Jospin LV, Laga H, Boussaid F, Buntine W, Bennamoun M. Hands-on Bayesian neural networks—a tutorial for deep learning users. IEEE Comput Intell Mag. 2022;17(2):29–48. https://doi.org/10.1109/MCI.2022.3155327

18. Magris M, Iosifidis A. Bayesian learning for neural networks: an algorithmic survey. Artif Intell Rev. 2023;56(10):11773–823. https://doi.org/10.1007/s10462-023-10443-1

19. Goan E, Fookes C. Bayesian neural networks: An introduction and survey. In: Case Studies in Applied Bayesian Data Science: CIRM Jean-Morlet Chair, Fall 2020. Cham: Springer International Publishing; 2020. p. 45–87. https://doi.org/10.1007/978-3-030-42553-1_3

20. Chang DT. Bayesian neural networks: Essentials. arXiv preprint arXiv:2106.13594. 2021. https://doi.org/10.48550/arXiv.2106.13594

21. Li M, Han H, Liu H, Sang W, Yuan S. Permeability prediction and uncertainty quantification based on Bayesian neural network and data distribution domain transformation. Chin J Geophys. 2023;66(4):1664–80. https://doi.org/10.6038/cjg2022P0837

22. Fan C, Gao F, Sun S, Cui F. Bayesian neural networks and its application. In: 2008 Fourth International Conference on Natural Computation. 2008. p. 446–50. https://doi.org/10.1109/ICNC.2008.624

23. Raj V, Cui T, Heinonen M, Marttinen P. Incorporating functional summary information in Bayesian neural networks using a Dirichlet process likelihood approach. In: International Conference on Artificial Intelligence and Statistics. 2023. p. 6741–63.

24. Arbel J, Pitas K, Vladimirova M, Fortuin V. A primer on Bayesian neural networks: review and debates. Stat Sci. 2026;41(2):316–53. https://doi.org/10.1214/24-STS969

25. Olivier A, Shields MD, Graham-Brady L. Bayesian neural networks for uncertainty quantification in data-driven materials modeling. Comput Methods Appl Mech Eng. 2021;386:114079. https://doi.org/10.1016/j.cma.2021.114079

26. Hernández S, López JL. Uncertainty quantification for plant disease detection using Bayesian deep learning. Appl Soft Comput. 2020;96:106597. https://doi.org/10.1016/j.asoc.2020.106597

27. Gal Y, Ghahramani Z. Dropout as a Bayesian approximation: representing model uncertainty in deep learning. In: International Conference on Machine Learning. 2016. p. 1050–59.

28. Tran BH, Rossi S, Milios D, Filippone M. All you need is a good functional prior for Bayesian deep learning. J Mach Learn Res. 2022;23(74):1–56.

29. Holden M, Pereyra M, Zygalakis KC. Bayesian imaging with data-driven priors encoded by neural networks. SIAM J Imaging Sci. 2022;15(2):892–924. https://doi.org/10.1137/21M1406313

30. Li L, Zhang S, Wang B. Plant disease detection and classification by deep learning—a review. IEEE Access. 2021;9:56683–98. https://doi.org/10.1109/ACCESS.2021.3069646

31. Rani R, Bharany S, Elkamchouchi DH, Ur Rehman A, Singh R, Hussen S. VGG-EFFATTNNET: hybrid deep learning model for automated Chili plant disease classification using VGG16 and EfficientNetB0 with attention mechanism. Food Sci Nutr. 2025;13(7):e70653. https://doi.org/10.1002/fsn3.70653

32. Seno A, Miyagusuku R, Kurokura T, Tabata K, Ozaki K. Tomato leaf disease diagnosis using Bayesian convolutional neural networks. In: 2024 IEEE/SICE International Symposium on System Integration (SII). 2024. p. 623–28. https://doi.org/10.1109/SII58957.2024.10417302

33. Babu GR, Gokuldhev M, Brahmanandam PS. Integrating IoT for soil monitoring and hybrid machine learning in predicting tomato crop disease in a typical South India station. Sensors. 2024;24(19):6177. https://doi.org/10.3390/s24196177

34. Fortuin V. Priors in Bayesian deep learning: a review. Int Stat Rev. 2022;90(3):563–91. https://doi.org/10.1111/insr.12502

35. Cheng L, Yin F, Theodoridis S, Chatzis S, Chang TH. Rethinking Bayesian learning for data analysis: the art of prior and inference in sparsity-aware modeling. IEEE Signal Process Mag. 2022;39(6):18–52. https://doi.org/10.1109/MSP.2022.3198201

36. Lee S, Yun CM. A deep learning model for predicting risks of crop pests and diseases from sequential environmental data. Plant Methods. 2023;19(1):145. https://doi.org/10.1186/s13007-023-01122-x

37. Kumar D, Mukhopadhyay R. Climate change and plant pathogens: understanding dynamics, risks and mitigation strategies. Plant Pathol. 2025;74(1):59–68. https://doi.org/10.1111/ppa.14033

38. Logeshwaran J, Srivastava D, Kumar KS, Rex MJ, Al-Rasheed A, Getahun M, et al. Improving crop production using an agro-deep learning framework in precision

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https://doi.org/10.14719/pst.16499

agriculture. BMC Bioinformatics. 2024;25(1):341. https://doi.org/10.1186/s12859-024-05970-9

39. Salman Z, Muhammad A, Han D. Plant disease classification in the wild using vision transformers and mixture of experts. Front Plant Sci. 2025;16:1522985. https://doi.org/10.3389/fpls.2025.1522985

40. Moupojou E, Tagne A, Retraint F, Tadonkemwa A, Wilfried D, Tapamo H, et al. FieldPlant: A dataset of field plant images for plant disease detection and classification with deep learning. IEEE Access. 2023;11:35398–410. https://doi.org/10.1109/ACCESS.2023.3263042

41. Sam D, Pukdee R, Jeong DP, Byun Y, Kolter JZ. Bayesian neural networks with domain knowledge priors. arXiv preprint arXiv:2402.13410. 2024. https://doi.org/10.48550/arXiv.2402.13410

42. Cui T, Havulinna A, Marttinen P, Kaski S. Informative Bayesian neural network priors for weak signals. Bayesian Anal. 2022;17(4):1121–51. https://doi.org/10.1214/21-BA1291

43. Dong J, Zhou H, Fuentes A, Yoon S, Park DS. Enhancing anomaly detection in plant disease recognition with knowledge ensemble. Front Plant Sci. 2025;16:1623907. https://doi.org/10.3389/fpls.2025.1623907

44. Eunice J, Popescu DE, Chowdary MK, Hemanth J. Deep learning-based leaf disease detection in crops using images for agricultural applications. Agronomy. 2022;12(10):2395. https://doi.org/10.3390/agronomy12102395

45. Shafik W, Tufail A, De Silva Liyanage C, Apong RA. Using transfer learning-based plant disease classification and detection for sustainable agriculture. BMC Plant Biol. 2024;24(1):136. https://doi.org/10.1186/s12870-024-04825-y

46. Restrepo-Arias JF, Branch-Bedoya JW, Awad G. Plant disease detection strategy based on image texture and Bayesian optimization with small neural networks. Agriculture.2022;12(11):1964. https://doi.org/10.3390/agriculture12111964

47. Lu J, Tan L, Jiang H. Review on convolutional neural network (CNN) applied to plant leaf disease classification. Agriculture.2021;11(8):707. https://doi.org/10.3390/agriculture11080707

48. Sachdeva G, Singh P, Kaur P. Plant leaf disease classification using deep convolutional neural network with Bayesian learning. Mater Today Proc. 2021;45:5584–90. https://doi.org/10.1016/j.matpr.2021.02.312

49. Wang Y, Wang H, Peng Z. Rice disease detection and classification using attention based neural network and Bayesian optimization. Expert Syst Appl. 2021;178:114770. https://doi.org/10.1016/j.eswa.2021.114770

50. Thiagarajan P, Ghosh S. Jensen–Shannon divergence based novel loss functions for Bayesian neural networks. Neurocomputing.2025;618:129115. https://doi.org/10.1016/j.neucom.2024.129115

51. Chen J, Zhang D, Nanehkaran YA. Identifying plant diseases using deep transfer learning and enhanced lightweight network. Multimed Tools Appl. 2020;79(41):31497–515. https://doi.org/10.1007/s11042-020-09669-w

52. Joseph DS, Pawar PM, Chakradeo K. Real-time plant disease dataset development and detection of plant disease using deep learning. IEEE Access. 2024;12:16310–33. https://doi.org/10.1109/ACCESS.2024.3358333

53. Hassan SM, Maji AK, Jasiński M, Leonowicz Z, Jasińska E. Identification of plant-leaf diseases using CNN and transfer-learning approach. Electronics. 2021;10(12):1388. https://doi.org/10.3390/electronics10121388

54. Upadhyay A, Chandel NS, Singh KP, Chakraborty SK, Nandede BM, Kumar M, et al. Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture. Artif Intell Rev. 2025;58(3):92. https://doi.org/10.1007/s10462-024-11100-x

55. Sharma N, Sharma P, Kumar N. Feature engineering to early detection of plant disease using image processing and artificial intelligence: a comparative analysis. Int J Latest Technol Eng Manag Appl Sci. 2025;14:1107–13. https://doi.org/10.51583/IJLTEMAS.2025.1407000133

56. Ferentinos KP. Deep learning models for plant disease detection and diagnosis. Comput Electron Agric. 2018;145:311–18. https://doi.org/10.1016/j.compag.2018.01.009

57. Shoaib M, Shah B, Ei-Sappagh S, Ali A, Ullah A, Alenezi F, et al. An advanced deep learning models-based plant disease detection: a review of recent research. Front Plant Sci.2023;14:1158933. https://doi.org/10.3389/fpls.2023.1158933

58. Shafay M, Hassan T, Owais M, Hussain I, Khawaja SG, Seneviratne L, et al. Recent advances in plant disease detection: challenges and opportunities. Plant Methods. 2025;21(1):140. https://doi.org/10.1186/s13007-025-01450-0

59. Kumar R, Singh V. Advancing plant disease detection: a comparative analysis of deep learning and hybrid machine learning models. Mach Graph Vis. 2025;34. https://doi.org/10.22630/MGV.2025.34.3.3

60. Trivedi VK, Shukla P, Pandey A. Plant leaves disease classification using Bayesian regularisation back propagation deep neural network. J Phys Conf Ser. 2021;1998(1):012025. https://doi.org/10.1088/1742-6596/1998/1/012025

61. Jain A, Dubey AK, Pan VS, Mahfoudh S, Althaqafi TA, Arya V, et al. Bayesian optimized CNN ensemble for efficient potato blight detection using fuzzy image enhancement. Sci Rep. 2025;15(1):31259. https://doi.org/10.1038/s41598-025-15940-7

62. Padmanabhuni S, Gera P. Bayesian optimized deep learning and ensemble classification approach for multiclass plant disease identification. Discov Sustain. 2025;6(1):709. https://doi.org/10.1007/s43621-025-01648-1

63. Jain A, Dwivedi RK. Hybrid segmentation-based agricultural leaf disease detection (Hy-SALDD) using black widow optimization for feature selection, and Bayesian-optimized SVM classification. Int J Inf Technol. 2025;17(6):3197–211. https://doi.org/10.1007/s41870-025-02478-0

64. Söylemez İ, Nalici ME, Ünlü R. High-accuracy identification of Durian leaf diseases: a convolutional neural network approach validated with K-fold cross-validation and Bayesian optimization. Appl Fruit Sci. 2025;67(6):464. https://doi.org/10.1007/s10341-025-01698-9

65. Burney SA, Naseem J. Decision making in uncertainty: a Bayesian network for plant disease diagnoses. Int J Comput Sci Inf Secur. 2018:16–21.

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https://doi.org/10.14719/pst.16499

66. Mumtaz S, Ahmed RM, Jalal A. Bayesian-optimized framework for segmentation guided transformer-based leaf disease detection. In: 2025 6th International Conference on Innovative Computing (ICIC). 2025. p. 1–6.

67. Subramanian M, Lv NP, B J, A MB, VE S. Hyperparameter optimization for transfer learning of VGG16 for disease identification in corn leaves using Bayesian optimisation. Big Data. 2022;10(3):215–29. https://doi.org/10.1089/big.2021.0218

68. Arun Pandian J, Kanchanadevi K. An improved deep convolutional neural network for detecting plant leaf diseases. Concurr Comput Pract Exp. 2022;34(28):e7357. https://doi.org/10.1002/cpe.7357

69. Arkan TM, Sugiharto A, Wibawa HA. Optimizing VGG16 architecture with Bayesian hyperparameter tuning for tomato leaf disease classification. J Masyarakat Inform. 2025;16(2):162–73. https://doi.org/10.14710/jmasif.16.2.73168

70. Alhashmi AA, Alohali MA, Ijaz NA, Khadidos AO, Alghushairy O, Sayed A. Bayesian optimization with deep learning based pepper leaf disease detection for decision-making in the agricultural sector. AIMS Math. 2024;9(7):16826–47. https://doi.org/10.3934/math.2024816

71. Sharma V, Mir AA, Sarwr DA. Detection of rice disease using Bayes' classifier and minimum distance classifier. J Multimed Inf Syst. 2020;7(1):17–24. https://doi.org/10.33851/JMIS.2020.7.1.17

72. Pham VC, Nguyen C, Le T, Phung D, Carneiro G, Do TT. Model and feature diversity for Bayesian neural networks in mutual learning. Adv Neural Inf Process Syst. 2023;36:80633–43. https://doi.org/10.52202/075280-3534

73. Liu J, Wang X. Tomato disease object detection method combining prior knowledge attention mechanism and multiscale features. Front Plant Sci. 2023;14:1255119. https://doi.org/10.3389/fpls.2023.1255119

74. Jafar A, Bibi N, Naqvi RA, Sadeghi-Niaraki A, Jeong D. Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations. Front Plant Sci. 2024;15:1356260. https://doi.org/10.3389/fpls.2024.1356260

75. Thilagavathi T, Arockiam L, Mary IP. A smart agriculture: a comprehensive survey on IoT-enabled plant disease detection and agricultural automation. Int J Inf Technol Res Appl.2024;3(2):39–47. https://doi.org/10.59461/ijitra.v3i2.107

76. Drury B, Valverde-Rebaza J, Moura MF, de Andrade Lopes A. A survey of the applications of Bayesian networks in agriculture. Eng Appl Artif Intell. 2017;65:29–42. https://doi.org/10.1016/j.engappai.2017.07.003

77. Hu X, Gu X, Sun Q, Yang Y, Qu X, Yang X, et al. Comparison of the performance of multi-source three-dimensional structural data in the application of monitoring maize lodging. Comput Electron Agric. 2023;208:107782. https://doi.org/10.1016/j.compag.2023.107782

78. Safari MM, Malian A. Plant disease mapping in paddy growing stages using remotely sensed data. Environ Earth Sci. 2025;84(1):1. https://doi.org/10.1007/s12665-024-11991-7

79. Dhaka VS, Meena SV, Rani G, Sinwar D, Ijaz MF, Woźniak M. A survey of deep convolutional neural networks applied for prediction of plant leaf diseases. Sensors.2021;21(14):4749. https://doi.org/10.3390/s21144749

80. Gülmez B. A comprehensive review of convolutional neural networks based disease detection strategies in potato agriculture. Potato Res. 2025;68(2):1295–329. https://doi.org/10.1007/s11540-024-09786-1

81. Dai G, Fan J, Tian Z, Wang C. PPLC-Net: neural network-based plant disease identification model supported by weather data augmentation and multi-level attention mechanism. J King Saud Univ Comput Inf Sci. 2023;35(5):101555. https://doi.org/10.1016/j.jksuci.2023.101555

82. Shoaib M, Sadeghi-Niaraki A, Ali F, Hussain I, Khalid S. Leveraging deep learning for plant disease and pest detection: a comprehensive review and future directions. Front Plant Sci. 2025;16:1538163. https://doi.org/10.3389/fpls.2025.1538163

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