MINOR PROJECT REPORT

Topic: Disease Detection In Crops

Domain: Smart Agriculture

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Abstract

Crop diseases pose a significant threat to global agriculture by reducing crop yield, affecting food quality, and causing major economic losses to farmers. Traditional methods of disease identification rely heavily on manual inspection, which is slow, labor-intensive, and dependent on expert knowledge. With recent advancements in Artificial Intelligence, deep learning models have shown great potential in automating disease diagnosis using leaf images. However, most high-accuracy models are computationally heavy and unsuitable for real-time deployment on mobile or low-resource agricultural devices.

This project focuses on developing a lightweight, efficient, and reliable crop disease detection system using deep learning. Lightweight CNN architectures such as SqueezeNet, MobileNetV2, and EfficientNet are utilized to ensure fast execution and reduced memory usage. To further improve generalization and enhance reliability, a Bayesian MC-Dropout layer is integrated into the model to estimate predictive uncertainty and reduce overfitting. The system is trained on the New Plant Diseases Dataset (Augmented), and its performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrices.

Experimental results demonstrate a significant improvement in performance after the introduction of Bayesian regularization, with notable gains in accuracy and overall robustness. The final model is optimized for deployment on mobile and edge devices, making it practical for real-world agricultural use. By combining lightweight architectures with uncertainty-aware learning, this project contributes to the development of smart farming solutions that support early disease detection, reduce manual dependency, and promote sustainable agricultural practices.

Contents

1. Introduction

1.1 Overview

This project presents a complete workflow for developing a robust crop disease detection system using deep learning techniques. The system is designed to identify plant diseases from a dataset of leaf images using CNN-based architectures. The work begins with dataset preparation, where images are resized, normalized, and augmented to ensure better learning and reduce overfitting. The New Plant Diseases Dataset (Augmented) is used, which contains multiple categories of plant diseases along with healthy leaf images.

Three lightweight models—SqueezeNet, MobileNetV2, and EfficientNet-B0—form the core of the study. These architectures were selected because they provide a balance of high accuracy and low computational cost, making them suitable for deployment on mobile and edge devices. Each model is fine-tuned on the dataset, and performance is measured using accuracy, precision, recall, and F1-score. Confusion matrices are also generated to analyze class-wise performance.

A key enhancement in this project is the integration of **Bayesian MC-Dropout**, applied after the feature extraction stage. This technique allows the model to estimate prediction uncertainty by performing multiple stochastic forward passes. It helps the model generalize better, reduces overfitting, and leads to more stable predictions. The performance of each model is evaluated both before and after adding the Bayesian layer to highlight the improvement.

The implementation uses PyTorch, due to its flexibility and ease of experimentation. Training involves standard steps such as choosing an optimizer (Adam), selecting a loss function (CrossEntropy), and using mixed-precision training for faster computation. After experimentation, results are compared across models to determine which architecture provides the best combination of speed, accuracy, and robustness.

Overall, the project demonstrates how lightweight deep learning, combined with Bayesian inference, can deliver practical and scalable agricultural solutions.

1.2 Problem Statement

Detecting crop diseases at the correct time is essential to maintaining crop health and ensuring optimal productivity. However, the current methods used in the agricultural sector are often inefficient and unreliable. Farmers traditionally rely on manual inspection of crops, which is labor-intensive, slow, and dependent on the experience of the individual. Human observation is subject to errors, especially when the symptoms are subtle or when multiple diseases exhibit similar visual patterns. In addition, expert consultation is not always accessible in remote or rural areas, resulting in delayed diagnosis and unmanaged disease spread.

Although AI-based plant disease detection systems exist, many of them rely on large, computationally heavy deep learning models. These models often require high-end GPUs and

are not suitable for on-field use on basic smartphones or low-power devices. This limits the practicality of such systems for real-world agricultural environments.

Thus, the central problem addressed in this project is:

"How can we build a lightweight, accurate, and uncertainty-aware deep learning model for crop disease detection that works efficiently on resource-limited devices?"

The problem becomes more challenging due to issues such as:

- Variations in lighting, background, and texture in leaf images
- Similar disease symptoms across different classes
- Overfitting due to limited real-world training samples
- Need for trustable predictions where uncertainty must be known

This project addresses these issues through careful model selection, Bayesian regularization, and robust evaluation.

Agriculture plays a crucial role in sustaining human life, and ensuring crop health is essential for maintaining food security, especially in countries where farming forms the backbone of the economy. However, crop diseases continue to be one of the biggest threats to agricultural productivity. These diseases can spread rapidly and cause significant damage before they are noticed, leading to major economic losses for farmers. Traditional manual monitoring methods are slow, dependent on expert knowledge, and not always available in rural areas. This challenge became one of the major motivations behind this project—finding an efficient way to detect diseases early so that farmers can take timely action.

Another strong motivation is the **need for lightweight, fast, and deployable AI solutions** in agriculture. Many existing deep learning models are powerful but too heavy for real-time usage on low-cost devices like mobile phones, tablets, or small embedded systems used by farmers. There is a growing demand for compact models that maintain high accuracy while being efficient enough to run on edge devices. Lightweight architectures such as SqueezeNet, MobileNetV2, and EfficientNet provide an ideal foundation for developing such solutions.

A further motivation comes from the **potential of smart agriculture technologies** such as drones, smartphone-based disease diagnosis, and automated field monitoring. These tools can drastically reduce manual labor and improve the speed of disease detection. Integrating a reliable AI-based system into such technologies can provide farmers with instant alerts and health reports, leading to smarter decision-making and improved crop management. This project aims to contribute to that vision by creating a model that performs accurately even in real-world conditions.

Lastly, this project is motivated by the desire to create a **practical, scalable, and farmer-friendly tool**. Early detection of diseases not only reduces crop loss but also minimizes unnecessary pesticide use, promotes sustainable agriculture, and helps farmers maintain crop

quality. By integrating Bayesian MC-Dropout, the model becomes even more reliable, offering uncertainty estimation that helps in making informed decisions

1.3 Objectives

1. To develop lightweight deep learning models for plant disease classification

A major focus of this project is to design deep learning models that are both accurate and computationally efficient. Traditional convolutional neural networks (CNNs) often require significant processing power, making them unsuitable for deployment in rural settings or on mobile devices. Therefore, lightweight architectures such as **SqueezeNet**, **MobileNetV2**, and **EfficientNet-B0** were selected.
These models are specifically engineered to reduce the number of parameters and memory footprint without compromising accuracy. By adopting depthwise separable convolutions, fire modules, and efficient building blocks, these architectures deliver fast inference speeds and low energy consumption. This ensures that farmers and agricultural workers can utilize the model on portable devices for real-time disease detection in the field.

2. To enhance model reliability using Bayesian MC-Dropout

Another important objective is to improve the model's ability to generalize and provide trustworthy outputs. Standard CNNs often produce overconfident predictions, especially when the input image is noisy, unclear, or unlike the training data. To address this, the project integrates **Bayesian MC-Dropout**, a technique that keeps dropout active during inference.
By performing multiple stochastic forward passes, the model generates a distribution of predictions rather than a single fixed answer. This enables estimation of **predictive uncertainty**, helping the model identify when it is unsure about its classification. Bayesian dropout also acts as a regularizer, reducing overfitting and improving the robustness of the system across different lighting conditions, leaf shapes, or disease variations.

3. To evaluate model performance using standard metrics

Evaluating the performance of the trained models is essential for determining how well the system can classify diseases accurately. The project uses widely accepted evaluation metrics, including **accuracy**, **precision**, **recall**, and **F1-score**. These metrics provide a detailed understanding of overall performance as well as error patterns such as false positives and false negatives.
A key part of this objective is comparing the model **before and after** adding the Bayesian MC-Dropout layer. This comparison clearly demonstrates the impact of uncertainty modeling on performance. It also helps identify which model architecture is most suitable for real-time deployment in resource-constrained environments.

4. To analyze class-wise performance using confusion matrices

Different plant diseases often have similar visual patterns, and some diseases may be more difficult to identify correctly. To gain deeper insights, the project uses **confusion matrices** to study class-wise performance.
A confusion matrix visually represents the number of correct and incorrect predictions for each disease category. This helps reveal patterns such as:

- Which diseases are frequently misclassified
- Whether certain classes need more training data
- How the model behaves after adding Bayesian dropout

This analysis is critical for improving the model further and ensuring that it performs reliably across all disease categories, not just the most common ones.

5. To design a model suitable for real-time deployment

Real-world deployment is a major consideration in agricultural applications, especially in rural areas where access to high-end hardware is limited. Therefore, another key objective is to design a model that functions efficiently on **mobile devices**, **embedded hardware**, or **agriculture robots**.
The use of lightweight architectures ensures low memory usage and high-speed inference, making the system suitable for real-time use in the field. This objective also includes optimizing the model size, improving latency, and ensuring compatibility with platforms such as TensorFlow Lite, PyTorch Mobile, or NVIDIA Jetson-based devices.

6. To create a scalable framework for future improvements

Finally, the project aims to build a framework that can be extended and integrated into more advanced agricultural monitoring systems in the future. This includes compatibility with:

- **Drone-based crop monitoring** for large farmlands
- **IoT sensors** that automatically capture environmental data
- **Field surveillance systems** that continuously scan crops for early symptoms
- **Mobile or web applications** used by farmers for instant diagnosis

By designing the system to be modular and scalable, future teams or researchers can easily expand its capabilities beyond simple image classification—such as severity detection, treatment recommendation, or automated field mapping.

1.4 Scope of the Project

The scope of this project clearly outlines what areas the work covers and how far its implementation extends. By defining these boundaries, the project becomes more focused, measurable, and aligned with the practical needs of modern agriculture. The scope ensures that the system developed is realistic, deployable, and academically rigorous, while also leaving space for future extensions.

1. Model Development

A major component of the project focuses on building and training lightweight Convolutional Neural Network (CNN) models that can efficiently detect plant diseases from leaf images. Instead of using large and computationally costly models like VGG or ResNet, this project concentrates on small yet powerful architectures such as **SqueezeNet, MobileNetV2, and EfficientNet-B0**.
The development phase includes:

- Designing the model structure
- Fine-tuning pre-trained models
- Adjusting hyperparameters
- Ensuring low memory usage and fast inference

This ensures that the final model can run smoothly even on low-power devices typically available in agricultural environments.

2. Dataset Usage

The project uses plant leaf datasets, primarily the **New Plant Diseases Dataset (Augmented)**, which contains thousands of images across multiple disease categories. The scope includes:

- Loading, preprocessing, and augmenting the dataset
- Normalizing and resizing images for consistency
- Splitting data into training and validation sets
- Ensuring the dataset is balanced and representative

By carefully preparing the dataset, the model is trained on high-quality visual features, improving its ability to generalize across different leaf conditions, lighting variations, and textures.

3. Bayesian Integration

A unique part of this project is the integration of **Bayesian MC-Dropout**, which introduces uncertainty estimation into the model. This falls within the scope because the goal is not just to classify but to classify **reliably**.
The Bayesian integration includes:

- Adding dropout before the final classifier layer
- Keeping dropout active during inference

- Performing multiple stochastic forward passes
- Calculating the mean and variance of predictions

This improves reliability, reduces overfitting, and helps the model handle real-world variations more confidently.

4. Evaluation Metrics

Another important part of the project's scope is the thorough evaluation of model performance using multiple metrics. Instead of relying solely on accuracy, the project measures:

- **Precision** (how many predicted positives are actually correct)
- **Recall** (how many actual positives were correctly predicted)
- **F1-Score** (balance between precision and recall)
- **Confusion matrices** (to analyze class-wise strengths and weaknesses)

These metrics provide a detailed understanding of how well the model performs and highlight areas where improvements may be needed.

5. Deployment Readiness

A critical boundary of this project is ensuring that the models are not only accurate but also deployable. The scope includes optimizing the system to work on:

- Smartphones
- Edge devices (e.g., Raspberry Pi, Jetson Nano)
- Agricultural robots
- Drone-based crop monitoring systems

This involves reducing model size, lowering computational requirements, and ensuring fast response time so that farmers can use the system instantly in the field.

6. Research Contribution

Finally, the project aims to contribute meaningfully to research in smart agriculture and lightweight AI. This includes:

- Comparing model performance before and after applying Bayesian dropout
- Conducting experiments on multiple architectures
- Demonstrating improvements in accuracy, robustness, and reliability
- Providing insights into where Bayesian layers improve performance

These contributions help other researchers, students, and developers understand how uncertainty-aware lightweight models can benefit agricultural applications.

2.Background

2.1 Introduction

Crop diseases pose a significant threat to agricultural productivity by reducing both crop yield and quality, thereby causing substantial economic losses and negatively impacting food security. Conventional methods for disease detection rely predominantly on manual inspection by farmers or agricultural experts. Such practices are labor-intensive, time-consuming, and highly dependent on individual expertise, often resulting in delayed detection and ineffective disease management.

With the advancement of Artificial Intelligence (AI) and Deep Learning technologies, automated crop disease detection systems based on image analysis have emerged as promising alternatives. These systems enable faster and more consistent diagnosis. However, the majority of existing AI-based models are computationally expensive and are designed to operate on high-performance hardware, limiting their feasibility for deployment in rural agricultural environments where only low-cost smartphones or low-power devices are available. Consequently, there is an increasing need for a lightweight, accurate, and reliable crop disease detection system that can operate efficiently on resource-constrained devices while maintaining high diagnostic performance.

2.2 Existing Systems and Approaches

Current crop disease detection systems predominantly utilize deep learning architectures such as VGG, DenseNet, ResNet, and conventional Convolutional Neural Networks (CNNs). These models have demonstrated high accuracy when trained on structured datasets such as PlantVillage. However, their performance is often constrained by high computational complexity, large memory requirements, and dependence on Graphics Processing Units (GPUs).

Additionally, while object detection frameworks like YOLO and Tiny-YOLO offer faster inference speeds, the reduction in model size frequently leads to compromised accuracy. These systems also lack mechanisms for uncertainty estimation, which results in overconfident predictions even when the model encounters ambiguous or unfamiliar data. As a result, the reliability of such systems for critical agricultural decision-making remains questionable in real-world conditions.

2.3 Modern Deep Learning Approaches

Recent research emphasizes the use of lightweight deep learning architectures that aim to achieve an optimal balance between high accuracy and computational efficiency. Models such as MobileNet, SqueezeNet, EfficientNet, and ShuffleNet are specifically designed for edge and mobile deployment through techniques including depthwise separable convolutions, fire

modules, and compound scaling strategies.

These lightweight architectures significantly reduce the number of parameters and computational cost while preserving strong classification performance. Furthermore, the integration of Bayesian inference techniques, particularly Bayesian Monte Carlo Dropout, enhances predictive reliability by enabling uncertainty estimation. This approach produces more stable and trustworthy predictions, thereby making such systems more suitable for real-world agricultural applications where variability in environmental conditions is inevitable.

2.4 Technological Gaps

Despite advancements in model design and optimization, several technological challenges persist in the domain of crop disease detection:

- Existing deep learning models remain computationally intensive for edge deployment.
- Limited robustness under diverse real-world lighting and background conditions.
- Absence of uncertainty-aware prediction mechanisms in most systems.
- Susceptibility to overfitting due to constrained real-world data diversity.
- Difficulty in distinguishing visually similar diseases with high confidence.

These challenges highlight the necessity for developing intelligent systems that combine efficiency, accuracy, and uncertainty awareness for practical agricultural usage.

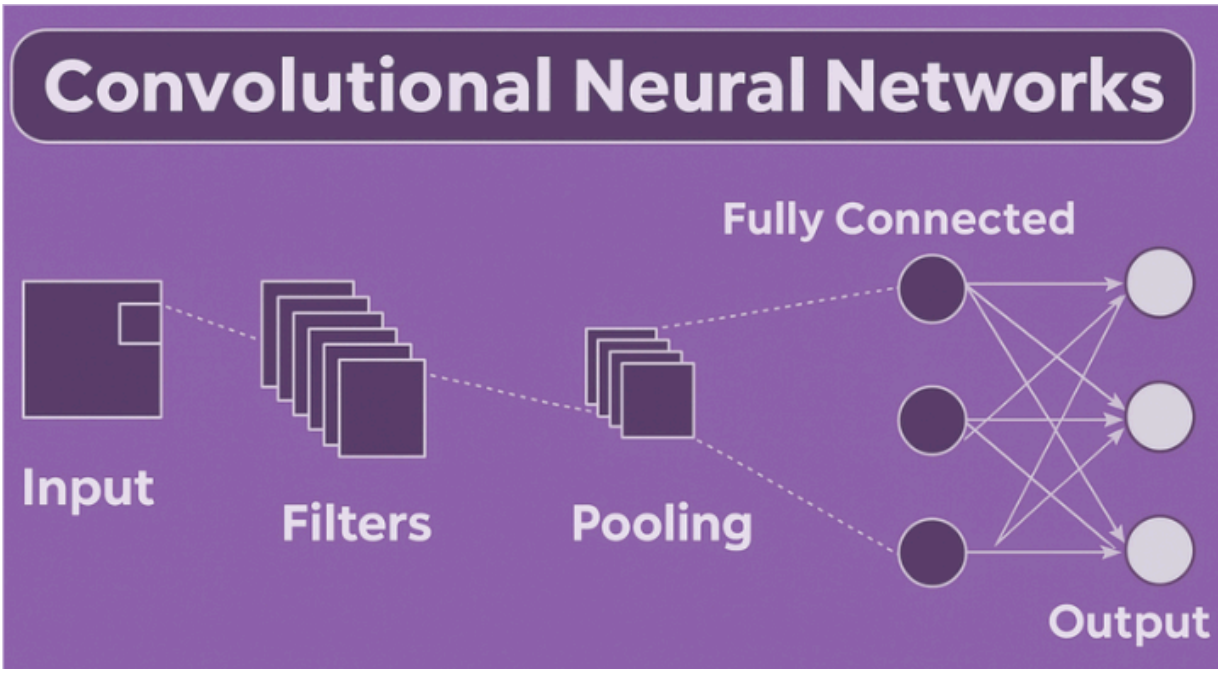
2.4.1 Neural Networks

Neural Networks are computational frameworks inspired by the human brain that consist of interconnected layers of artificial neurons. These networks learn to identify patterns and relationships within data for tasks such as classification and prediction. Although effective for general-purpose learning, traditional neural networks lack the spatial feature extraction capabilities required for handling complex image data such as leaf disease patterns.

2.4.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are specialized architectures developed to process visual data by extracting hierarchical features from input images. They employ convolutional layers to detect low-level features such as edges and textures, followed by pooling layers for dimensionality reduction and fully connected layers for final classification.

Lightweight CNN variants such as MobileNet and SqueezeNet optimize this process by reducing the number of parameters and computations, making them highly suitable for real-time crop disease detection on mobile and embedded systems.



2.4.3 Bayesian Dropout

Bayesian Monte Carlo Dropout is a probabilistic technique that activates dropout layers during inference to perform multiple stochastic forward passes. This process generates a distribution of outputs, allowing estimation of predictive uncertainty.

This method enhances model reliability by reducing overconfidence, improving generalization, and identifying ambiguous predictions. Such uncertainty-aware systems are particularly valuable in agricultural environments where image quality may vary due to lighting conditions, environmental noise, or occlusion.

Research Gaps

A critical review of existing literature reveals several unresolved issues:

- Lack of integrated frameworks combining lightweight CNNs with uncertainty estimation mechanisms.
- Limited optimization for deployment on low-power agricultural devices.
- Inadequate handling of environmental variability in real-world field conditions.
- Scarcity of models explicitly designed for trustworthy decision-making through predictive uncertainty.
- Absence of scalable, farmer-oriented systems for practical implementation.

These research gaps underscore the necessity for a comprehensive solution that incorporates lightweight architecture and Bayesian inference to ensure accurate, efficient, and reliable crop disease detection.

2.5 Summary

This chapter highlights that although deep learning has substantially improved automated crop disease detection, existing systems remain inadequate for practical deployment in resource-limited agricultural environments. The primary challenges include high computational demands, lack of uncertainty estimation, and insufficient adaptability to real-world conditions.

By integrating lightweight CNN architectures with Bayesian Monte Carlo Dropout, it is possible to develop a system that is both computationally efficient and highly reliable. Such a system has the potential to bridge the gap between advanced AI research and real-world agricultural practice, thereby facilitating sustainable farming and informed decision-making for farmers.

3. Motivation

3.1 Introduction

Agriculture forms the backbone of global food production and remains one of the most crucial sectors for sustaining human life. It not only feeds billions but also supports the livelihood of millions of farmers, especially in developing countries where agriculture contributes significantly to the national economy. However, despite its importance, agriculture faces continuous threats that affect both productivity and stability. Among these threats, **crop diseases** are particularly critical because they can spread rapidly across fields, damaging large portions of crops in a short period. These diseases often develop silently at early stages, becoming visible only when the infection has already weakened the plant. If not detected early, they can lead to reduced crop yield, lower nutritional quality, and in severe cases, complete crop failure. Such outcomes escalate economic losses for farmers and also affect food supply chains at a national and global level.

Traditionally, disease monitoring in agriculture has relied on **manual visual inspection**, where farmers or agricultural experts observe plant leaves and stems for visible symptoms. While this method has been used for generations, it suffers from several limitations. Manual monitoring is **time-consuming** and demands continuous effort, especially in large agricultural fields where thousands of plants need regular inspection. It also depends heavily on the **experience and skill** of the observer. Expert diagnosis is often not readily available in remote or rural regions, meaning farmers may misinterpret symptoms or fail to detect early signs of disease. Furthermore, manual observation is inherently **subjective and inconsistent**; factors such as fatigue, weather, and lighting conditions can affect the accuracy of detection. As a result, infections are frequently identified **only after they have significantly progressed**, making it harder to control their spread and leading to substantial yield loss and increased financial burden on farmers.

In recent years, advancements in technology—especially **Artificial Intelligence (AI), image processing, and deep learning**—have opened new possibilities for transforming agricultural practices. AI-based disease detection systems can analyze leaf images and identify disease patterns with high accuracy, even in cases where symptoms are subtle or ambiguous to the human eye. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image classification tasks due to their ability to automatically learn complex visual features. This has made them one of the most powerful tools for automated crop disease detection. By enabling early diagnosis, such systems help farmers take timely action, apply targeted treatments, and prevent further spread of infection.

However, a major challenge is that many high-performing AI models require substantial computational resources. Traditional CNN architectures can be too heavy to deploy on **mobile phones, drones, or low-power embedded devices** commonly used in real-world farming environments. This mismatch between research-level AI models and the lightweight hardware available to farmers creates a gap that must be bridged for practical deployment.

This project addresses that gap by exploring the use of **lightweight CNN models** such as

SqueezeNet, MobileNetV2, and EfficientNet. These architectures are designed to maintain high accuracy while drastically reducing the number of parameters, memory usage, and computation time. Their efficiency makes them ideal candidates for real-time plant disease detection on resource-limited devices.

To further improve the reliability and generalization ability of these lightweight models, the project integrates **Bayesian optimization techniques**, particularly Bayesian MC-Dropout. Traditional CNNs may become overconfident in their predictions and may struggle with noisy or ambiguous images. Bayesian dropout helps the model estimate uncertainty by introducing controlled randomness during inference. This not only reduces overfitting but also ensures that the model becomes more dependable when making predictions in unpredictable field conditions.

Overall, this project aims to develop a system that is both **technically strong and practically usable**. By combining lightweight CNN architectures with Bayesian inference, the model becomes suitable for deployment on smartphones, handheld devices, and agricultural robots used in remote or rural areas. This integration of modern deep learning with practical agricultural needs promises to make disease detection more accessible, efficient, and impactful—ultimately helping farmers protect their crops, reduce losses, and improve overall agricultural productivity.

3.2 NEED FOR AUTOMATED CROP DISEASE DETECTION

Crop disease detection plays a crucial role in protecting agricultural productivity, yet the traditional manual approach widely practiced today has several limitations. Manual inspection requires farmers or agricultural experts to physically examine plants for symptoms such as spots, discoloration, wilting, or fungal growth. This process is **labor-intensive**, demanding extensive time and effort, especially for large farms containing thousands of plants. Farmers must inspect every plant individually, which is not always practical, particularly during peak seasons when time and labor shortages are common.

Another challenge is that manual inspection is **slow and prone to human error**. Many plant diseases exhibit subtle early-stage symptoms that are difficult to detect with the naked eye. By the time visible damage becomes obvious, the disease may have already spread across a significant portion of the field, leading to decreased yields and increased financial loss. Furthermore, many farmers do not have direct access to plant pathologists or agricultural specialists who can accurately diagnose diseases. In rural areas, expert consultations may be delayed or unavailable, making timely and accurate detection even more difficult.

Automated AI-based disease detection addresses these limitations effectively. Deep learning models can analyze leaf images within seconds, providing a **much faster and more accurate diagnosis** compared to manual methods. This speed helps farmers take immediate action, preventing the disease from spreading and reducing pesticide usage. Unlike humans, AI systems do not suffer from fatigue, bias, or inconsistent performance. They offer **consistent and objective analysis**, ensuring that each leaf is evaluated with the same level of precision regardless of environmental conditions or human limitations.

An automated system is also **highly scalable**. Instead of relying on a limited workforce, farmers

can deploy AI systems to monitor entire farms using mobile phones, drones, or robotic platforms. This enables large agricultural areas to be inspected frequently and efficiently. Early detection becomes possible because AI models can identify disease patterns even in their initial stages, long before symptoms become visible to the human eye.

Moreover, automated crop disease detection provides farmers with **real-time guidance**. Through immediate feedback and alerts, farmers can make informed decisions regarding treatment, irrigation, or pesticide application. This not only minimizes crop loss but also promotes sustainable agriculture by reducing excessive chemical use and preventing treatment delays.

In summary, the need for automated crop disease detection arises from the growing demand for **accuracy, speed, consistency, and scalability** in agricultural disease monitoring. With the support of AI and deep learning, farmers can protect their crops more effectively, reduce economic losses, and move towards more modern, sustainable, and technologically empowered farming practices.

3.3 IMPORTANCE OF LIGHTWEIGHT CNN MODELS

Deep learning has shown tremendous potential in solving agricultural problems, especially in tasks like plant disease detection where visual patterns must be recognized quickly and accurately. However, many popular deep learning architectures such as ResNet, DenseNet, or Inception are extremely large, containing millions of parameters and requiring substantial computational resources. These heavy models run well on high-end GPUs, but they are not practical for **real-world agricultural settings**, where farmers typically rely on low-power devices like smartphones, tablets, Raspberry Pi boards, or agricultural robots. This challenge highlights the importance of **lightweight Convolutional Neural Network (CNN) models**, which are specifically designed to achieve high performance while using fewer parameters and less memory.

Lightweight models such as **SqueezeNet, MobileNetV2, and EfficientNet-B0** play a vital role in bridging the gap between advanced AI research and practical field-level implementation. Their **small model size** significantly reduces storage requirements and makes it possible for the models to run directly on devices with limited memory capacity. This is especially valuable for rural farmers who may not have access to high-performance computers or cloud-based infrastructure.

In addition to smaller size, lightweight CNNs provide **fast inference speed**, meaning they can process and classify leaf images within milliseconds. Real-time detection is essential in agriculture, where farmers often need immediate results to make quick decisions about treating diseased plants. Faster inference also reduces latency when models are deployed in drones or automated monitoring systems that scan large fields continuously.

Another major advantage of lightweight CNN models is their **low power consumption**, enabling efficient operation on battery-powered devices. This feature is crucial for mobile-based disease detection apps, handheld devices used by field workers, and autonomous agricultural robots. By consuming less energy, these models extend device battery life and reduce operational costs, making the system more accessible and sustainable.

Despite their compact size, lightweight architectures are designed to maintain **high accuracy with far fewer parameters**. Techniques such as depthwise separable convolutions (MobileNetV2), fire modules (SqueezeNet), and compound scaling (EfficientNet) help these networks learn rich visual features without requiring heavy computation. This makes them ideal for rural deployment, where reliable disease detection must be combined with ease of use and affordability.

Overall, lightweight CNN models are not just a technological preference—they are a **practical necessity** for deploying AI-driven solutions in agriculture. Their efficiency, speed, reduced power usage, and strong performance make them perfectly suited for farmers who need fast, on-the-spot predictions without relying on cloud connectivity or expensive hardware. These advantages ensure that the benefits of AI can truly reach the farming community and support smarter, more sustainable agriculture.

3.3.1 Technology Stack

The system is designed using a modern and efficient technology stack tailored for deep learning experimentation and deployment:

- **Python**: Primary programming language for model development.
- **PyTorch**: Deep learning framework used for building and training CNN models.
- **Torchvision**: For data loading, image transformations, and use of pre-trained models.
- **NumPy & Matplotlib**: For data handling, visualization, and evaluation.
- **scikit-learn**: For calculating precision, recall, F1-score, and generating confusion matrices.
- **GPU/MPS Support**: Utilized to accelerate training using Mac's Metal Performance Shaders.

This stack ensures efficient development, faster experimentation, and compatibility with deployment environments

3.3.2 Development Environment

The project was implemented in an optimized development environment designed for deep learning experiments:

- **Hardware**: Apple Silicon/MacBook with MPS GPU acceleration
- **Operating System**: macOS
- **Frameworks**: PyTorch + Torchvision
- **IDE**: VS Code / Jupyter Notebook
- **Dataset Structure**: Training and validation images pre-organized in folders
- **Mixed Precision Training**: Used for faster execution and reduced memory use

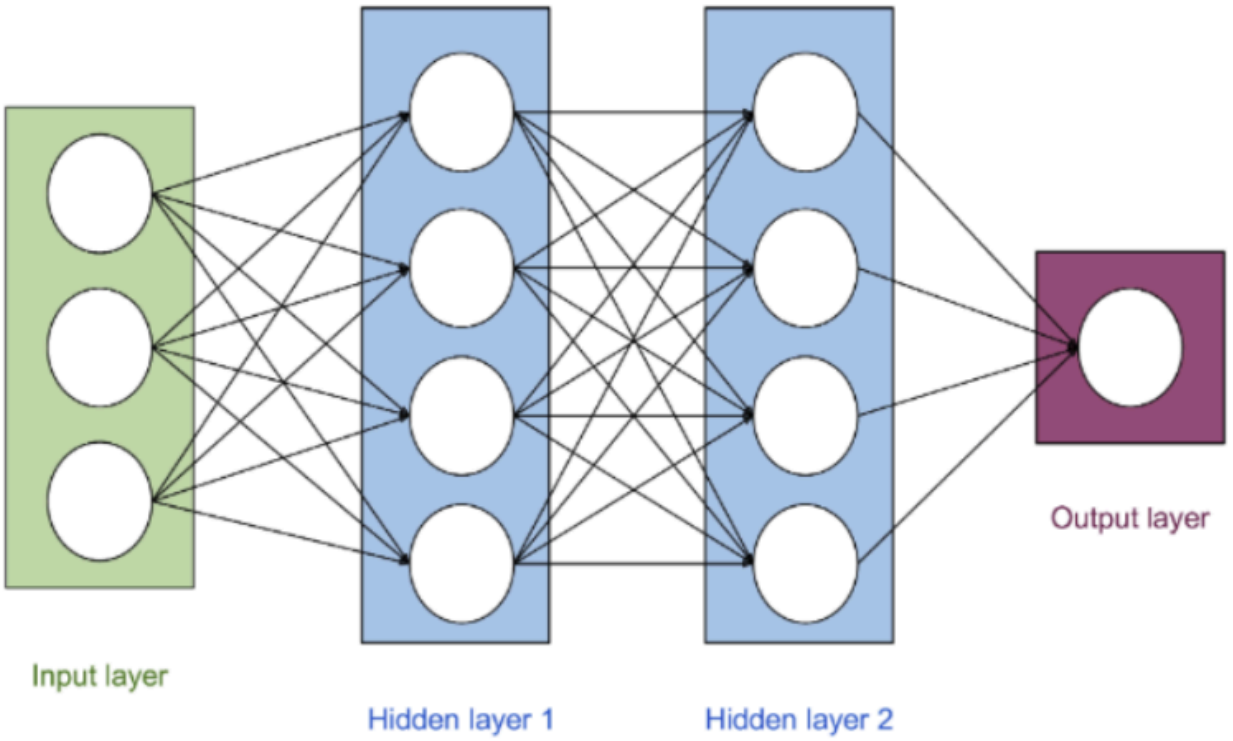
This environment enabled smooth model training, faster iterations, and experimentation with various CNN architectures and Bayesian techniques.

3.4 ROLE OF BAYESIAN OPTIMIZATION

Bayesian MC-Dropout plays a crucial role in strengthening the reliability, robustness, and overall performance of lightweight CNN models used for crop disease detection. While traditional deep learning models produce a single fixed prediction for every input image, they do not provide any information about how *certain* or *uncertain* that prediction is. This can be problematic in real-world agricultural environments where images may contain noise, shadows, inconsistent lighting, partial leaves, or symptoms that resemble other diseases. In such cases, the model must not only classify the image but also express how confident it is in its prediction. This is where Bayesian MC-Dropout becomes extremely valuable.

Bayesian MC-Dropout introduces **controlled randomness** during the inference phase by keeping dropout layers active even when the model is making predictions. Instead of producing a single deterministic output, the model performs multiple forward passes, each time randomly dropping neurons. This generates a distribution of predictions rather than just one. By analyzing this distribution, the model can estimate **predictive uncertainty**, giving insights into how confident it is about the disease classification.

1.	Inside Early Convolution Layers	Adding dropout in very early layers affects basic feature extraction
2.	In Middle Convolution Blocks	Introduces randomness when mid-level abstract features are forming
3.	After Feature Extraction	Bayesian dropout applied on high-level features
4.	After Final Dense Layer	Adding randomness before final prediction , not meaningfull



This uncertainty estimation offers several major benefits:

✔ Preventing Overfitting on Small Datasets

In many agricultural research scenarios, available datasets may not fully capture all real-world variations. When the model trains on limited data, there is a risk that it memorizes patterns instead of understanding general features — a problem known as overfitting. Bayesian dropout helps mitigate this by adding randomness during both training and inference, encouraging the model to learn more generalized patterns. As a result, the model performs better on unseen images from actual farms.

✔ Making the Model More Confident and Reliable

By performing multiple predictions for each image, the model understands when to be confident and when to be cautious. If all forward passes give the same output, the model is confident. But if the outputs vary, the system recognizes uncertainty and signals that the prediction should be taken with care. This reliability is important for farmers who depend on accurate diagnosis to make critical decisions.

✔ Producing Smoother Decision Boundaries

Traditional CNNs often draw sharp, rigid boundaries between classes, which can fail in scenarios where diseases have overlapping features. Bayesian MC-Dropout softens these boundaries by allowing the model to consider multiple internal configurations. This leads to smoother and more

flexible classification regions, improving robustness when classifying visually similar diseases or ambiguous images.

✔ Improving Accuracy Through Better Regularization

Dropout is a well-known regularization technique, and Bayesian MC-Dropout enhances it by extending the dropout effect into the inference process. This consistent randomness prevents the model from becoming overly dependent on specific neurons or patterns. It encourages the learning of more stable and general features, ultimately boosting accuracy and reducing validation loss.

✔ Handling Noisy or Ambiguous Images Effectively

Real-world leaf images are rarely perfect. They may have dust, uneven lighting, moisture spots, background clutter, or partial disease symptoms. Bayesian MC-Dropout helps the model remain robust under these conditions by estimating uncertainty. When the image is unclear or noisy, the model naturally reflects uncertainty, making it a safer and more trustworthy diagnostic tool.

3.5 PROBLEM CHALLENGES

Developing an accurate disease detection model involves addressing several practical challenges that arise due to variability in real-world agricultural conditions.

1. Noise

Images collected from farms often contain noise due to inconsistent lighting, shadows, background clutter, or motion blur. This noise can confuse the CNN model and lead to incorrect classifications. The project mitigates this using data augmentation, normalization, and Bayesian dropout to make the model robust against variations.

2. Similar Diseases

Many plant diseases have visually similar patterns—such as spots, blotches, or leaf discoloration—making them difficult to distinguish. The model must learn subtle differences in texture, shape, and color. Lightweight architectures, combined with fine-tuned training, help capture these variations.

3. Overfitting

Deep learning models can memorize the training images instead of learning general patterns, especially when datasets are limited. Overfitting reduces performance on new images. Techniques such as dropout, Bayesian inference, data augmentation, and early stopping are used to overcome this problem and ensure reliable predictions.

3.6 SUMMARY

This project focuses on developing a lightweight, accurate, and uncertainty-aware crop disease detection system that can function effectively in real-time agricultural environments. Modern farming increasingly depends on technological solutions that help farmers detect crop diseases at early stages, reduce losses, and ensure sustainable production. However, many existing AI-based models are too large or computationally expensive for use on basic smartphones or low-power devices commonly available in rural areas. This project addresses that gap by leveraging **lightweight Convolutional Neural Network (CNN) architectures** such as **SqueezeNet, MobileNetV2, and EfficientNet-B0**.

These models are specifically chosen because they provide high accuracy while maintaining extremely low computational requirements. They can operate on mobile devices, embedded boards, and other edge platforms without relying on cloud servers. Their compact structure allows them to process images quickly, enabling **real-time detection**, which is critical when rapid intervention is needed to contain disease spread.

To further enhance the reliability of these lightweight models, the project integrates **Bayesian MC-Dropout**, a technique that introduces uncertainty estimation into the predictions. In real agricultural settings, leaf images may contain noise due to uneven lighting, shadows, dirt, moisture, or background clutter. Additionally, many plant diseases share similar visual features, making them difficult to distinguish. A traditional CNN might make an incorrect prediction with high confidence, potentially misleading the farmer.
Bayesian MC-Dropout helps solve this by generating multiple predictions with controlled randomness, allowing the model to measure how confident it is in its decision. If a prediction is uncertain, the model reflects that uncertainty, making it safer and more trustworthy. This improves the system's robustness to challenging images and enhances overall generalization.

The project also addresses crucial challenges such as:

- **Noise**, which can distort leaf features and confuse traditional CNNs
- **Visually similar disease patterns**, where diseases appear nearly identical in early stages
- **Overfitting**, where the model performs well on training data but poorly on real-world images

Through a combination of data augmentation, careful preprocessing, lightweight architectures, and Bayesian regularization, these challenges are effectively minimized.

Overall, the project demonstrates how deep learning and uncertainty-aware techniques can be combined to support farmers with early and accurate disease detection. The outcomes include improved diagnostic accuracy, faster prediction times, and a system ready for integration into smartphones, drones, agricultural robots, and smart farming platforms. By enabling early action and reducing dependence on manual inspection, the system contributes to **reducing crop loss**, promoting **sustainable agriculture**, and paving the way for **scalable smart farming solutions** that can benefit farmers across different regions.

4. Literature Study

4.1 Introduction

The rapid advancement of deep learning has significantly transformed the domain of automated plant disease detection, shifting from traditional manual inspection methods to intelligent computer vision-based systems. The literature in this area demonstrates a clear evolution from conventional machine learning techniques relying on handcrafted features to sophisticated deep neural networks capable of end-to-end learning. These modern approaches exploit large-scale image datasets and powerful computational models to perform disease identification with high accuracy and consistency.

Research in plant disease detection has predominantly focused on two objectives: improving classification accuracy and reducing computational complexity to enable real-time deployment. With the increased need for smart agriculture and precision farming, studies have begun emphasizing lightweight and efficient models that can operate on mobile phones and edge devices. Furthermore, recent works highlight the importance of model reliability and uncertainty estimation, especially when systems are intended for real-world decision-making by farmers and agricultural professionals.

This chapter provides a detailed review of existing research, compares popular CNN architectures used for plant disease detection, examines the role of Bayesian neural networks in image classification, identifies limitations present in prior studies, and establishes the research gap that motivates the proposed work.

4.2 Review of Existing Research on Plant Disease Detection

Earlier research in plant disease detection largely relied on classical image processing techniques combined with machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forests. These approaches involved manual feature extraction processes such as texture analysis, color histogram computation, and morphological operations. Although moderately effective in controlled conditions, these systems failed to generalize when exposed to variations in lighting, background, and leaf orientation.

With the emergence of deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for plant disease classification. Studies using architectures such as VGG16, ResNet50, DenseNet201, and Inception have reported high classification accuracy on datasets like PlantVillage. However, these models are computationally expensive and unsuitable for deployment on resource-limited devices such as smartphones used by farmers in rural regions.

Recent literature reflects a shift toward lightweight architectures optimized for efficiency without significant compromise in performance. Models such as MobileNet, SqueezeNet, EfficientNet, and ShuffleNet have demonstrated promising results, achieving competitive

accuracy with substantially fewer parameters. Several studies also integrate attention mechanisms and transfer learning to further enhance performance. However, despite these improvements, many works remain limited to controlled datasets and lack robustness in real-world field conditions. This indicates a persistent gap between laboratory performance and practical usability in agricultural environments.

4.3 Comparative Study of CNN Architectures

Deep learning architectures differ significantly in terms of design philosophy, computational requirements, and performance. The following section provides a comparative analysis of widely used CNN models in plant disease detection.

4.3.1 MobileNet

MobileNet is specifically designed for mobile and embedded vision applications. It employs depthwise separable convolutions to drastically reduce computational cost and model size. This architecture splits convolution operations into depthwise and pointwise processes, minimizing the number of multiplications required.

MobileNet-based systems have demonstrated strong performance in plant disease classification tasks while maintaining low latency and power consumption. Its adaptability through transfer learning further enhances its applicability in agricultural datasets. Nevertheless, MobileNet may exhibit slightly reduced accuracy compared to deeper architectures when exposed to highly complex disease patterns or noisy backgrounds.

4.3.2 SqueezeNet

SqueezeNet is a lightweight CNN architecture that achieves AlexNet-level accuracy with significantly fewer parameters. It utilizes fire modules consisting of squeeze and expand layers to reduce parameters while maintaining expressive power.

In plant disease detection, SqueezeNet offers the advantage of small model size and fast inference, making it highly suitable for smartphone deployment. However, due to its limited depth, it may not capture highly complex features effectively, particularly when dealing with multiple disease stages or subtle visual variations.

4.3.3 ShuffleNet

ShuffleNet is designed for low-power devices and employs group convolutions along with a channel shuffle operation to reduce computational cost while maintaining accuracy. It is especially useful for high-speed applications where energy efficiency is critical.

Research indicates that ShuffleNet performs competitively in crop disease classification, especially when paired with attention mechanisms or data augmentation techniques. Despite its efficiency, ShuffleNet faces challenges in capturing detailed fine-grain features, which may affect performance in visually similar disease categories.

4.3.4 YOLO Nano / Tiny YOLO

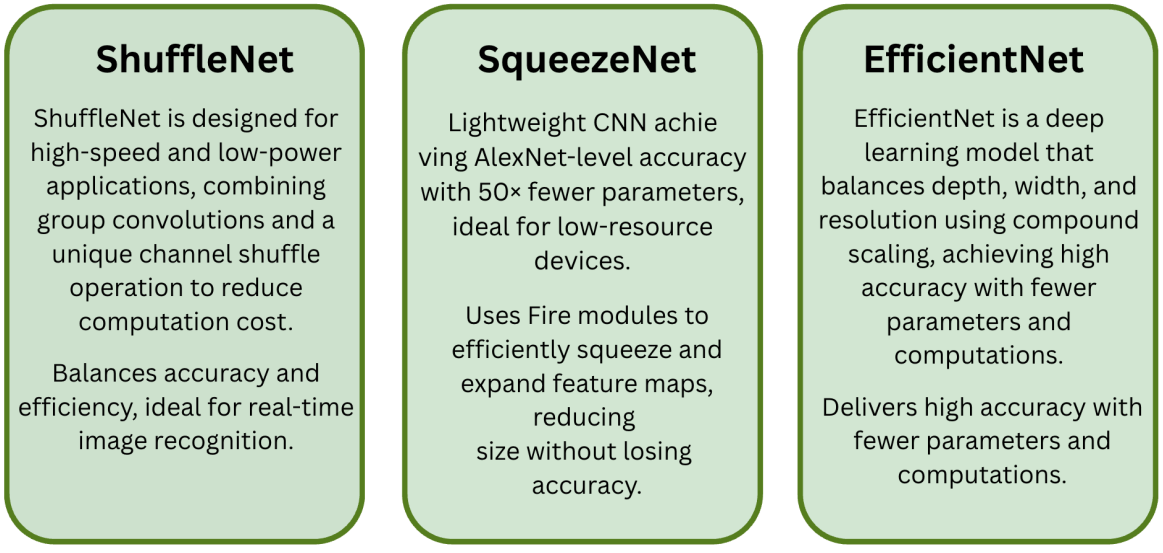
YOLO Nano and Tiny YOLO are object detection models optimized for real-time applications. They focus on balancing speed and accuracy by simplifying network architecture and reducing parameters. These models are primarily used for detecting diseased regions in crops rather than pure classification.

While YOLO-based systems demonstrate impressive real-time performance, they often compromise accuracy, particularly when detecting small infected regions or early-stage diseases. Their effectiveness is further limited under variable lighting and complex background conditions commonly found in agricultural fields.

4.3.5 EfficientNet

EfficientNet introduces a novel compound scaling method that uniformly scales network depth, width, and resolution using a fixed scaling coefficient. Unlike traditional models that arbitrarily increase layers or parameters, EfficientNet balances all dimensions for optimal performance. EfficientNet-B0 and its variants have been extensively used for plant disease detection due to their high accuracy and efficient resource utilization.

Studies reveal that EfficientNet achieves superior accuracy on datasets such as ImageNet and PlantVillage while requiring fewer parameters compared to traditional CNNs. Its structured scaling strategy results in better generalization and reduced overfitting. However, its performance still depends heavily on fine-tuning and the quality of input data, and it may struggle with real-time deployment if not properly optimized.



Year	Name	Data Set	Model / Library	Findings	Accuracy	Limitations
3) 2020	**EfficientNet: Rethinking Model Scaling for CNNs**	• Models primarily evaluated on the ImageNet dataset • Tested on CIFAR-100 (91.7%), Flowers (98.8%), and 3 other transfer learning datasets • Models fine-tuned on new datasets after being pre-trained on ImageNet	• EfficientNet, a family of CNNs • EfficientNet-B0, uses the mobile inverted bottleneck MBConv as its main building block and incorporates squeeze-and-excitation optimization	• Studies model scaling, for improving ConvNet accuracy • Balance and scale all 3 dimensions (depth, width, and resolution) uniformly using a compound coefficient	• Achieved a state-of-the-art 84.4% top-1 accuracy on ImageNet & 97.1% top-5 accuracy on ImageNet. • Outperformed other ConvNets on ImageNet with fewer parameters	• Arbitrary scaling requires tedious manual tuning • Effectiveness of model scaling is heavily dependent on baseline network used.
4) 2025	**Optimized classification using EfficientNet-LITE & KE-SVM in diverse environments**	• One dataset was a public one from a Kaggle source of an uncontrolled environment with 3,076 images from Indonesia • 2nd dataset is PlantVillage Dataset (Potato Species), which has 2,152 images from a controlled laboratory setting	• EfficientNet-LITE with KE-SVM Optimization was developed to classify potato leaf diseases • Model integrates Channel Attention and 1-D Local Binary Pattern features • Implemented using libraries like Keras and OpenCV.	• Proposes a hybrid approach combining a lightweight DL model for feature extraction and an optimized machine learning classifier • Create efficient model for use on edge devices	Overall accuracy : Uncontrolled environment dataset -87.82% Controlled dataset - 99.54% • Performance on uncontrolled data shows significant improvement over other models	• Dataset lacks diversity for real-world applications • Failed to effectively combine lightweight models with robust optimization techniques

Year	Name	Data Set	Model / Library	Findings	Accuracy	Limitations
11) 2024	**Approach to Lightweighting Backbone Network Models through Quantization and Bayesian Optimization**	• COCO dataset used for training and validation • 5000 images used specifically for inference evaluation • Dataset supports autonomous driving scenarios	• .MobileNetV3 Small (baseline) • Modified MobileNetV3 with Leaky ReLU • Bayesian Optimization for hyperparameters • Dynamic Quantization (INT8)	• .Quantization reduced model size by ~50% • Accuracy improved by 1% • Memory usage reduced by ~97.8% • Faster inference after quantization	• Baseline: Standard MobileNetV3 • Improved: +1% accuracy after optimization and quantization	• .Leaky ReLU increases computational cost • Quantization may cause precision loss • Performance depends on careful layer selection • Tested only on COCO dataset
12) 2022	**Classification of Ear Imagery Database using Bayesian Optimization based on CNN-LSTM Architecture**	• .Public Ear Imagery Database • 880 otoscopic images • 4 classes: Normal, Myringosclerosis, Earwax plug, COM • Image resolution: 420 × 380 pixels • Collected from Universidad de Chile hospital	• .EfficientNetB0 (CNN) for feature extraction • BiLSTM for classification • CNN-LSTM hybrid architecture • Bayesian Optimization for hyperparameter tuning • MATLAB 2020 implementation	• .CNN-LSTM outperformed CNN-only model • Bayesian optimization improved hyperparameter selection • Significant reduction in training time (25 min vs 637 min) • Effective in assisting otolaryngologists	• 100% accuracy on testing dataset • CNN-only accuracy: 86.3% • Sensitivity: 100% • Specificity: 100%	• .Small-scale dataset (only 880 images) • Limited to one public ear database • Performance not tested in real clinical environments • No cross-database validation performed

Year	Name	Data Set	Model / Library	Findings	Accuracy	Limitations
1) 2019	**YOLO Nano: A Compact You Only Look Once CNN for Object Detection**	• PASCAL VOC datasets, VOC2007/2012 • Natural images for 20 different objects. • Performance compared to Tiny YOLOv2 and v3.	• YOLO Nano • Created using a human-machine collaborative design strategy. • Unique residual projection-expansion-projection (PEP) macroarchitectures and lightweight fully-connected attention (FCA)	• Solves high computational and memory needs by balancing accuracy, size, and computational complexity. • Generative synthesis used to create a highly tailored and efficient network	• YOLO Nano achieved a 69.1% mAP on the VOC 2007 dataset, outperforming Tiny YOLOv2 and v3. • Demonstrated high inference speeds, power efficiency on an embedded module	• Existing models are often too slow and large for embedded devices • Lighter versions like Tiny YOLO compromise on accuracy to reduce size
2) 2024	**Tiny Yolo Networks for Disease Detection in Paddy Agronomy**	• Research team constructed their own rice leaf disease dataset • 3 classes: Bacterial leaf blight, Rice blast, and Brown spot identification. • Final dataset size - 15,456 images.	• Modified version of Tiny YOLOv4 • UAV T-YOLO-Rice for detecting rice leaf diseases • Spatial Pyramid Pooling (SPP), a Convolutional Block Attention Module, Sand Clock Feature Extraction Module (SCFEM).	• Detecting small, diseased areas on rice leaves from UAVs • Enhanced model allows for higher accuracy and better detection of small objects	• The model achieved a testing mAP of 86.97%, which is the highest among the compared models • Outperformed the base Tiny YOLOv4 model and also YOLOv7, YOLOv2	• Difficulty of detecting small infection points using UAV cameras • Model has low accuracy despite its real-time detection capability

Year	Name	Data Set	Model / Library	Findings	Accuracy	Limitations
5) 2023	**An Improved MobileNet for Disease Detection on Tomato Leaves**	• PlantVillage Tomato Leaf Dataset (Kaggle). • 2,064 images → 4 classes: Early Blight, Septoria, Yellow Curl, Healthy. • Images resized • Resized + augmented (rotation, zoom, flip, etc.) • Dataset expanded to 4,128 images.	• Improved MobileNet - a lightweight CNN. • Transfer learning and fine-tuning (Keras/TensorFlow). • Depthwise separable convolutions to reduce parameters.	• Automates detection of tomato leaf diseases. • Outperforms VGG16, VGG19, DenseNet201, and Xception models. • Achieves higher accuracy and faster training speed.	Overall accuracy : 97.17% (multi-class) Per-class : • Early Blight -98.57% • Yellow Curl -99.52% • Septoria - 98.18% • Healthy - 99.54% F1-score: 0.9442	• Only 4 disease classes. • Lacks real-world diversity. • Model not tested in real-time field conditions. • Performance may vary with unseen diseases.
6) 2023	**Improved MobileNetV2 crop disease identification model for intelligent agriculture**	• PlantVillage Dataset (public, open-source). • 5 crops (apple, corn, grape, potato, tomato) with 25 disease types. • Images resized, with augmentation. • ~37,572 training and 10,359 testing images.	• Improved MobileNetV2 (MobileNet-RepMLP). • Combines RepMLP and ECA attention (for feature weighting). • Uses Hardswish activation instead of ReLU6. • Implemented in PyTorch / TensorFlow / Keras.	• Tackles low-resource crop disease identification. • Reduces parameters and computation by ~59% vs. MobileNetV2 • Boosts accuracy using attention and feature re-parameterization	Overall accuracy : 99.53% • Precision/Recall : ≈99.5% each • 8.5% faster inference speed than MobileNetV2 • Model params: 0.91M (very compact)	• Trained on controlled images • May underperform in real-world complex scenarios • Focused only on leaf-based visual symptoms

Year	Name	Data Set	Model / Library	Findings	Accuracy	Limitations
7) 2024	**MC-ShuffleNet V2: A lightweigh t model for maize disease recognitio n**	• 2,725 maize disease images from northern Anhui, China, in a natural field • Augmented dataset to 10,845 images using methods(random rotation and flips) • Images were resized	• MC-ShuffleNetV2, ShuffleNetV2 1x • Incorporates (CBAM) Convolutional Block Attention Module • Mish activation function applied • TensorFlow-gpu 1.14 + Keras 2.2.4 is used	• Addresses problem of model bloat and high resource consumption • Focuses on accurate feature extraction. • 5×5 convolution kernel extracts more detailed features.	Overall accuracy : 99.86% • Model has 873,936 parameters and 1,751,286 FLOPs • Outperforms several models in accuracy and size	• Dataset is limited to only 6 typical maize diseases. • Model's capabilities are restricted by size and types of training samples.
8) 2025	**Shuffle-PG: Model for retrieving images of plant diseases and pests with deep metric learning**	• 126,900 images of diseases and pests. • Disease dataset with 37 classes and 87,151 images, and a pest dataset with 34 classes and 39,749 images • Classes categorized based on crop-disease/crop-pest pairs.	• Shuffle-PG, combines ShuffleNet v2 with pointwise group convolution. • Model fine-tuned using deep metric learning with contrastive loss and an online hard negative pair selection strategy. • The Adam optimizer was used	• Tackles deploying large models for plant disease diagnosis • Proposes content-based image retrieval (CBIR) approach • Deep metric learning enhances model's ability to learn discriminative features	Overall accuracy : Disease dataset -97.7% Pest dataset - 98.8% • The recall at rank 5 98.9% for diseases 99.4% for pests • 1.26 million parameters and 151.7 million FLOPs	• Dataset is imbalanced and contains a large variation in images per class. • Real-world challenges like latency, battery life, and UI design were not fully explored

Year	Name	Data Set	Model / Library	Findings	Accuracy	Limitations
9) 2025	**SqueezeNet-Based DL Framework for Accurate Tomato Leaf Disease Diagnosis & Classificatio n**	• Public Plant Village dataset from Mendeley Data • 14,531 RGB images of tomato plant leaves, covering 9 diseases and one healthy category • The dataset has a class imbalance • Images were resized	• DL framework based on the SqueezeNet architecture • Transfer learning with a pre-trained SqueezeNet model on the ImageNet dataset • optimizers (SGDM, ADAM, RMSProp) • Implemented in MATLAB and Python	• Need for an efficient, high-accuracy, and deployable model for tomato leaf disease detection • Investigates how different training parameters impact model's performance	Overall accuracy : 99.91% • 100% recall for the healthy class (TH) during testing with ADAM F1 - score : 99.42%	• Needs to accommodate scenarios involving multiple diseases on a single leaf • Dataset may not fully represent real-world environments.
10) 2023	**BananaSquee zeNet: Lightweight CNN for the diagnosis of 3 prominent banana leaf diseases**	• Banana Leaf Spot Disease (BananaLSD) from banana fields in Bangladesh • 937 images across four classes: healthy, Pestalotiopsis, Sigatoka, and Cordana • Training set was augmented to 400 images per class	• Uses SqueezeNet's architecture, which employs "Fire modules" • Optimized using Bayesian optimization to find the best hyperparameters. • Transfer learning was applied using a model pre-trained on the ImageNet dataset	• Successfully diagnoses 3 prominent banana leaf diseases and shows generalizability of model to 7 other diseases. • Model's small size makes it suitable for real-time use with a smartphone app	Overall accuracy : 96.25% • outperformed other models (EfficientNetB0, MobileNetV3, ResNet-101) • model's size-4.78 MB • inference time-17.84 sec	• Dataset is relatively small • Study suggests future work should include instructing farmers on how to take action based on the disease severity

4.4 Bayesian Neural Networks in Image Classification

Bayesian Neural Networks introduce probabilistic modeling into deep learning by allowing model parameters to be treated as probability distributions rather than fixed values. One of the most commonly used Bayesian techniques in computer vision is Monte Carlo Dropout, where dropout layers remain active during inference to generate multiple predictions.

This method enables estimation of predictive uncertainty, providing insights into the confidence level of model predictions. In agricultural contexts, this is particularly important as incorrect predictions can lead to inappropriate pesticide application or delayed treatment. Bayesian approaches improve reliability, reduce overconfidence, and assist in distinguishing ambiguous disease cases. Despite their advantages, Bayesian networks require additional computational resources due to multiple forward passes, which can impact real-time performance if not optimized efficiently.

4.5 Identified Limitations in Literature

Based on the reviewed studies, several recurring limitations have been identified:

- Heavy reliance on controlled datasets such as PlantVillage, limiting real-world generalization
- High computational requirements of many deep learning models
- Lack of uncertainty estimation in most classification systems
- Insufficient evaluation under dynamic environmental conditions
- Difficulty in detecting subtle or visually similar disease symptoms
- Minimal focus on farmer-oriented deployment and usability
- Absence of integrated systems combining lightweight architecture with predictive uncertainty

These limitations highlight the necessity for a more holistic and practical approach that addresses both performance and deployability.

COMPARISON

This study presents a comparative analysis of deep learning models for crop disease detection using transfer learning. The work targets rural agricultural environments where early and accurate disease identification is essential but resources are limited.

A large and diverse dataset was created using images from PlantVillage and the New Plant Diseases Dataset, covering multiple crops and disease classes. Image preprocessing and augmentation improved model generalization.

Several pretrained CNN architectures—EfficientNet, ResNet101, InceptionV3, MobileNetV2—and a custom CNN were trained and evaluated. EfficientNet achieved the best performance with **97.10% validation accuracy**, followed by InceptionV3 and ResNet101. The custom CNN performed competitively, showing that carefully designed lightweight models are effective in constrained environments. MobileNetV2 offered speed and efficiency but slightly lower accuracy due to its compact architecture.

The results confirm that transfer learning significantly improves disease detection accuracy and robustness. EfficientNet was selected as the final model due to its balanced performance, resource-efficiency, and ability to detect fine-grained disease patterns.

The study emphasizes real-world deployment through mobile-friendly models, edge computing, offline processing, and multilingual support—making the system highly suitable for farmers in remote areas. Future work includes drone-based large-scale monitoring, integration with IoT devices, and scalable real-time disease forecasting.

4.6 Summary

The literature review highlights substantial progress in plant disease detection through deep learning. While significant improvements have been achieved using CNN-based architectures, most existing systems remain limited by high computational demands, lack of uncertainty awareness, and restricted real-world applicability.

Lightweight architectures such as MobileNet, EfficientNet, SqueezeNet, and ShuffleNet offer promising solutions for edge deployment but still face challenges related to robustness and confidence estimation. The integration of Bayesian techniques emerges as a valuable enhancement for building trustworthy models. However, current research has not sufficiently combined lightweight CNNs with uncertainty-aware mechanisms in a scalable and farmer-friendly system.

This gap forms the foundation for the proposed work, which aims to develop an efficient, accurate, and uncertainty-aware crop disease detection model optimized for real-time deployment on resource-constrained devices.

5. Project Objectives

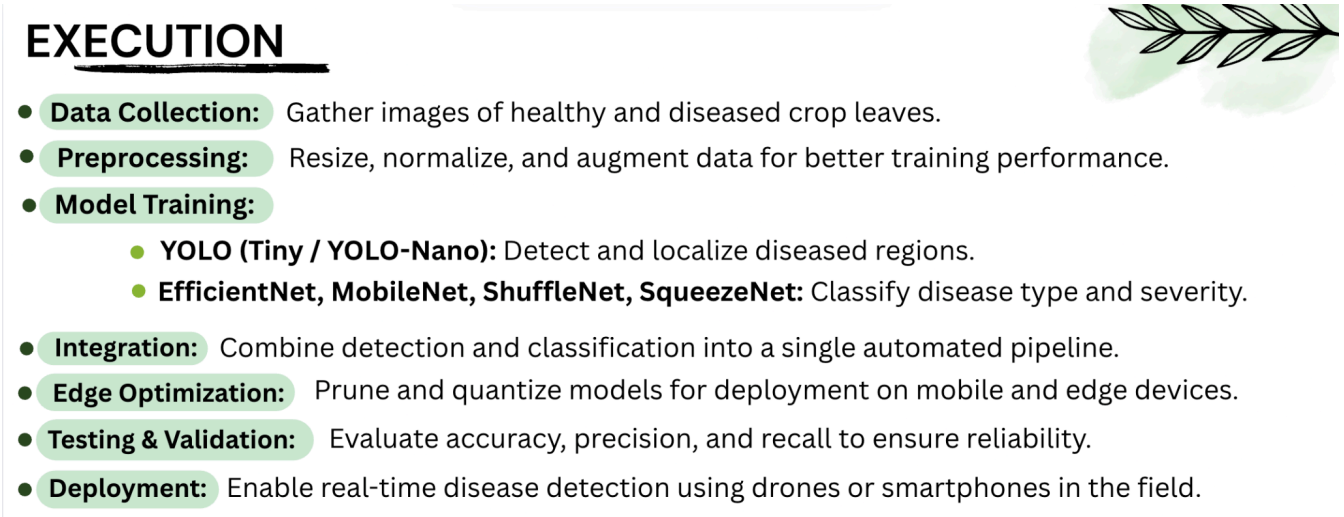
5.1 Introduction

This chapter presents the complete experimental setup used to design, train, and evaluate the proposed crop disease detection system. The central goal of this setup is to create a research environment where lightweight deep learning models can be rigorously developed, optimized, and tested for real-time agricultural deployment. Since crop disease detection is highly reliant on accurate visual interpretation, every element—from dataset preparation to hardware configuration—must be carefully structured to ensure reliable outcomes.

The chapter begins by describing the computing environment used for model development, including the hardware capabilities and software frameworks that enable fast and efficient deep learning experimentation. It then outlines how the dataset is organized, preprocessed, and used during training and evaluation.

Next, the design of the model architectures is explained, highlighting why lightweight CNNs such as SqueezeNet, MobileNetV2, and EfficientNet-B0 were chosen and how Bayesian MC-Dropout was integrated to improve generalization and uncertainty estimation.

Finally, the chapter details the evaluation metrics used to measure performance and compares model behavior before and after applying Bayesian dropout. Together, these components form a unified experimental pipeline that guarantees consistency, repeatability, and scientific validity.



5.2 Experimental Setup

The experimental setup defines the methodology used to conduct model training, testing, and

validation. Each experiment follows a structured workflow designed to maintain fairness across different model architectures.

The key components of this setup include:

- **Model Preparation:** Lightweight CNN architectures are initialized using pre-trained weights (ImageNet) and then fine-tuned on the plant disease dataset.
- **Bayesian MC-Dropout Integration:** A dropout layer is added before the classifier to enable uncertainty-aware predictions and reduce overfitting.
- **Training Infrastructure:** PyTorch is used as the primary deep learning framework, utilizing GPU/MPS acceleration for fast computation.
- **Evaluation:** After each epoch, validation is performed, and metrics such as accuracy, precision, recall, and F1-score are computed.
- **Confusion Matrices:** Detailed class-wise evaluation helps identify which diseases are classified accurately and where misclassifications occur.

This systematic approach ensures reproducibility of results and allows each model variant to be tested under identical conditions for fair comparison.

5.2.1 Hardware Configuration

To develop and train the crop disease detection models, a carefully configured hardware environment was used. The system specifications were selected to balance high computational efficiency with low power consumption—ideal for lightweight model experimentation.

- **Device:** Apple MacBook Air / MacBook running Apple Silicon
- **Processor:** 8-core CPU optimized for parallel tasks
- **GPU Acceleration:** Metal Performance Shaders (MPS) providing GPU-level speed for PyTorch training
- **Memory:** 8–16 GB Unified Memory, allowing fast data sharing between CPU and GPU
- **Storage:** SSD for quick dataset loading, checkpoint saving, and model retrieval
- **Energy Efficiency:** Lightweight models reduced power usage, enabling long-duration experiments without overheating or throttling

This hardware setup supported fast model training, facilitated multiple experimental runs, and minimized computation time, which is crucial for deep learning research.

5.2.2 Software Configuration

The software ecosystem used in this project ensures a flexible yet powerful development environment.

- **Programming Language:** Python 3 for its simplicity and extensive support in deep learning
    - **Deep Learning Framework:** PyTorch for building neural networks, fine-tuning pre-trained models, and handling GPU computation
    - **Torchvision:** For image preprocessing, transformations, and dataset loading
    - **Supporting Libraries:**
    - **NumPy:** Array operations and data manipulation
    - **Matplotlib:** Visualizations, plotting accuracy/loss graphs

- **scikit-learn:** Precision, recall, F1, confusion matrix
- **tqdm:** Progress bars for training loops
- **Operating System:** macOS with MPS backend
- **IDE:** Visual Studio Code and Jupyter Notebook for coding, debugging, and visualization
- **Training Enhancements:** Mixed-precision training (float16) to improve speed and reduce memory usage

This combination of tools and libraries ensures smooth experimentation and helps maintain model reproducibility.

5.3 DATASET DESCRIPTION

The **New Plant Diseases Dataset (Augmented)** is used for training and validation. It is one of the largest and most diverse datasets for plant disease recognition.

Key dataset features:

- **Image Format:** High-resolution RGB leaf images
- **Total Classes:** Approximately 38, including both diseased and healthy categories
- **Structure:**
  - **Train Folder:** Contains thousands of class-wise augmented images
  - **Validation Folder:** Contains separate images never seen during training
- **Variations Covered:**
  - Lighting changes
  - Color intensity variations
  - Background differences
  - Rotation, flip, and zoom augmentations

Such variations help the models generalize better to real-world farm conditions, where leaf images are rarely clean or uniform.

5.4 MODEL ARCHITECTURE OVERVIEW

The project uses three lightweight CNN models:

1. SqueezeNet

- Utilizes “Fire Modules” (squeeze + expand layers)
- Extremely small model size (~1.2 million parameters)
- High speed and low memory usage

2. MobileNetV2

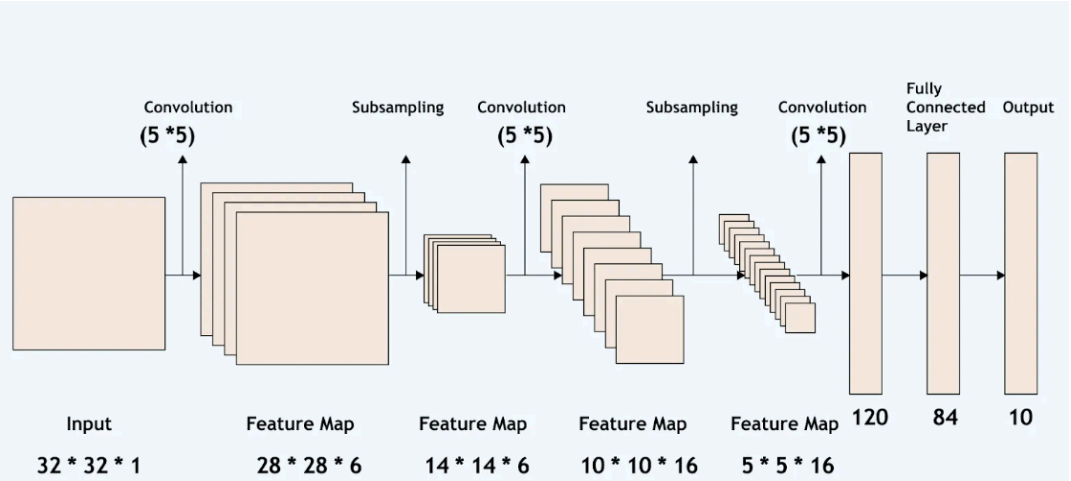
- Uses depthwise separable convolutions

- Very efficient in computation with high accuracy
- Highly suitable for mobile and IoT devices

3. EfficientNet-B0

- Uses compound scaling to balance network width, depth, and resolution
- Provides strong accuracy despite being lightweight
- High performance-to-parameter ratio

These architectures allow the system to run efficiently on low-power hardware such as smartphones and agricultural devices



5.5 BAYESIAN LAYER PLACEMENT STRATEGY

Bayesian MC-Dropout is incorporated in this project to introduce uncertainty estimation into the prediction process and to improve the overall generalization ability of lightweight CNN models. However, **where** the Bayesian dropout layer is placed inside the architecture has a significant impact on performance. Incorrect placement can disturb feature extraction or reduce model accuracy. Therefore, the dropout layer must be strategically inserted to maximize its benefits while preserving the integrity of the network.

In this project, the Bayesian dropout layer is placed:

After the final feature extraction block

Immediately before the final classifier layer

This placement is carefully selected based on the behavior of CNN architectures and the intended role of Bayesian inference. The reasoning behind this strategy is explained below in detail:

1. Early Convolution Layers Must Remain Stable

The first few layers of any CNN learn **low-level features** such as edges, corners, textures, and color gradients. These features form the foundation for all deeper-level understanding of the image.

If dropout were applied too early in the network:

- Important low-level information would be lost randomly
- Feature maps would become inconsistent
- The model would struggle to learn basic patterns
- Accuracy would drop significantly

Keeping the early layers stable ensures that the model extracts reliable and consistent features from the input leaf images.

2. Bayesian Dropout Works Best on High-Level Representations

As the network progresses deeper, it begins to learn **high-level semantic features**, such as:

- Specific disease patterns
- Texture irregularities
- Spot shapes and distributions
- Color distortion caused by infections

These higher-level features are **more abstract** and **more sensitive to uncertainty**. Applying Bayesian dropout at this stage provides meaningful randomness that helps the model capture uncertainty in ambiguous or noisy samples.

By placing the dropout layer after the feature extractor:

- The network generates a stable feature map
- Bayesian dropout introduces variability only at the decision-making stage
- Uncertainty estimation becomes more accurate and informative

3. Enhances Classifier Robustness Without Affecting Feature Learning

The classifier layer is responsible for mapping extracted features into specific disease labels. By adding Bayesian dropout just before this classifier, the network:

- Becomes more resistant to overfitting
- Learns more generalized feature-to-class relationships
- Avoids memorizing training data patterns
- Produces smoother and more flexible decision boundaries

This separation of feature extraction and uncertainty modeling ensures each stage performs optimally.

4. Enables Uncertainty Estimation via Multiple Stochastic Forward Passes

A key benefit of Bayesian MC-Dropout is that it keeps dropout active during inference.

This means that for the same image, the model produces slightly different predictions across multiple forward passes.

This creates:

- A distribution of outputs
- Mean prediction (final class)
- Standard deviation (uncertainty score)

Placing the dropout near the classifier ensures that this uncertainty directly reflects:

- Ambiguity in disease patterns
- Noisy or low-quality images
- Visually similar diseases
- Edge cases that the model is unsure about

This leads to more trustworthy predictions.

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5. Reduces Overfitting by Regularizing Only the Final Decision Layers

Overfitting is common in agricultural datasets due to variations in lighting, texture, and background.
Bayesian dropout:

- Adds randomness
- Prevents memorization
- Encourages generalization

By applying it only at the final layer, the model:

- Learns stable feature maps
- Regularizes only the part prone to overfitting
- Achieves better validation accuracy
- Shows stronger performance on unseen images

5.5 TRAINING, TESTING, AND VALIDATION

Training Phase

- Models trained for **5 to 20 epochs** depending on architecture
- Batch size set to **32**
- Optimizer: **Adam** with learning rate **0.0007**
- Loss function: **CrossEntropyLoss**
- Mixed-precision training used to make training faster
- Dropout applied to reduce overfitting

Testing Phase

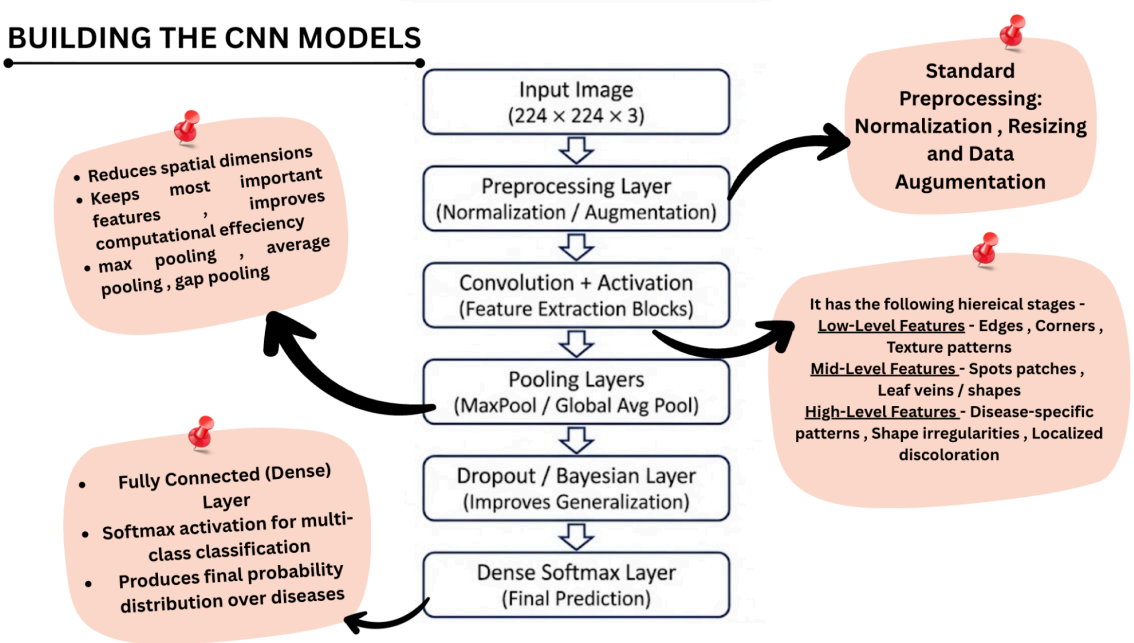
- Performed on validation data
- Gradients disabled (`torch.no_grad()`)
- Bayesian dropout kept active for uncertainty estimation
- Predictions collected for each batch

Validation Phase

- Accuracy computed after every epoch
- Predictions stored for calculating precision, recall, and F1-score
- Confusion matrices generated to evaluate class-wise performance
- Both **before** and **after** Bayesian dropout results compared

This step-by-step pipeline ensures that the models are evaluated thoroughly and consistently.

SNO.	PARAMETER	VALUE
1.	Epochs	2–20 depending on experiment
2.	Batch Size	32
3.	Metrics	Accuracy, Precision, Recall, F1-score
4.	Callbacks	ModelCheckpoint + EarlyStopping



5.6 EVALUATION METRICS

Evaluating the performance of a deep learning model requires more than just looking at a single number. In the context of crop disease detection, it is especially important to understand how well the model differentiates between multiple disease categories, how accurately it identifies diseased leaves, and how reliably it avoids misclassification. To achieve this, the project uses a combination of four widely accepted metrics: **Accuracy, Precision, Recall, and F1-score**. Each metric captures a different aspect of the model's behavior and helps give a complete picture of overall system performance.

5.7.1 Accuracy

Accuracy is the most straightforward metric used to evaluate classification models. It measures the proportion of correct predictions out of the total number of predictions made by the model.

Why Accuracy Matters

- Provides a **broad overview** of how well the model performs across all classes.
- Helps compare the general performance of different models (SqueezeNet, MobileNetV2, EfficientNet).
- Useful for understanding model improvements before and after adding Bayesian MC-Dropout.

However, accuracy alone has limitations. In datasets where some classes have more samples than others (imbalanced datasets), accuracy may be high even if the model performs poorly on minority classes. Since plant disease datasets often contain more images of certain diseases than others, relying solely on accuracy can give a misleading impression of performance.

Interpretation in Agriculture Context

A high accuracy score indicates that the model is correctly classifying the majority of leaf images, making it effective for real-time disease screening in fields.

5.7.2 Precision

Precision measures how many of the samples predicted to belong to a certain class actually belong to that class. It focuses on the correctness of **positive predictions**.

Why Precision is Important

- Minimizes **false positives**, where a healthy plant is mistakenly classified as diseased.
- Avoids unnecessary pesticide use, saving cost and preserving plant health.
- Crucial when certain diseases look visually similar; precision ensures the model is careful and selective.

Interpretation in Agriculture Context

High precision means the model is reliable when it predicts a disease — it rarely raises false alarms. This is especially important because misdiagnosis can lead to unnecessary chemical treatments or incorrect

farm decisions.

5.7.3 Recall

Recall measures how many actual positive samples the model correctly identifies. It focuses on the ability to **detect true disease cases**.

Why Recall is Important

- Reduces **false negatives**, where diseased plants are mistakenly classified as healthy.
- Critical for preventing disease spread, especially in fast-spreading infections like blight or mildew.
- Ensures that the model does not overlook early-stage symptoms.

Interpretation in Agriculture Context

High recall ensures that the model successfully identifies the majority of infected plants, even if symptoms are subtle. This helps farmers take timely action before diseases spread across larger sections of the field.

5.7.4 F1-Score

The F1-score is the harmonic mean of precision and recall. It combines both metrics into a single value that reflects a balanced evaluation of the model's performance.

Why F1-Score is Important

- Useful when classes in the dataset are imbalanced.
- Provides a more realistic measure of performance than accuracy alone.
- Helps understand whether the model is both **accurate** and **consistent**.

F1-score is particularly important in plant disease detection because some diseases may appear in fewer samples, and others might have overlapping visual symptoms. A high F1-score indicates that the model handles these challenges well.

Interpretation in Agriculture Context

A high F1-score means the model:

- Detects diseased leaves accurately (high recall)
- Makes correct disease predictions with minimal confusion (high precision)

This balance is essential for real-world farming, where both missing an infection and misidentifying one can have serious consequences.

6. UML DIAGRAMS

6.1 INTRODUCTION

Unified Modeling Language (UML) diagrams play an essential role in understanding, designing, and communicating the structure of a software system. In this project, UML diagrams help represent how different components of the crop disease detection system interact, how data flows between modules, and how the overall architecture is organized. Since the project combines machine learning, image processing, and system deployment, UML provides a visual blueprint that makes the system easy to explain and implement.

UML diagrams simplify complex system behavior by breaking it into well-defined models. They help developers, evaluators, and stakeholders clearly understand the responsibilities of each module—such as data loading, preprocessing, model training, Bayesian optimization, prediction, and evaluation. These diagrams also highlight how components like datasets, CNN models, preprocessing units, and prediction modules are connected within the workflow.

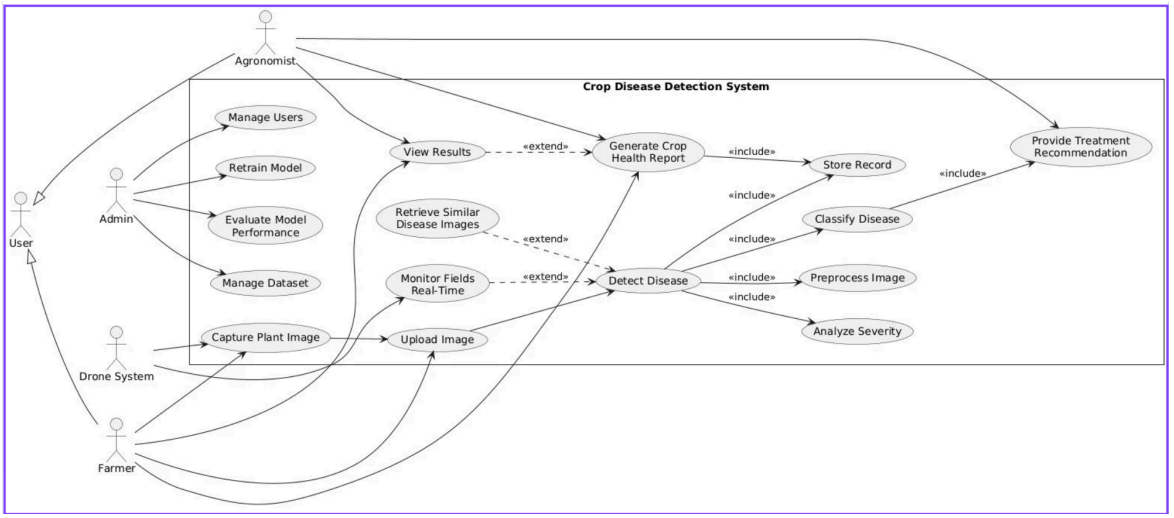
By using UML diagrams, the project ensures:

- **Better clarity** in system design
- **Easy communication** of architecture
- **Well-organized documentation** for academic evaluation
- **Understanding of interactions** between software modules and machine-learning components
- **Improved maintainability**, making the system easier to extend in future work (e.g., adding drones, IoT sensors, or new models)

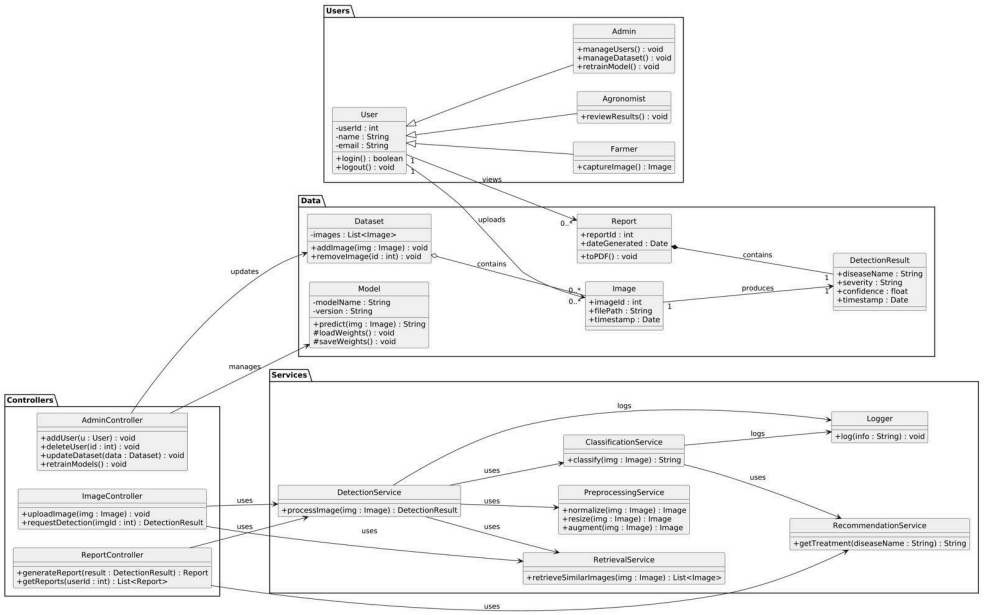
Therefore, UML diagrams form a crucial part of this project report, helping represent both the structural and behavioral aspects of the crop disease detection system in a clean, standardized, and universally understood way.

6.2 STATIC DIAGRAMS

6.2.1 USE CASE DIAGRAM

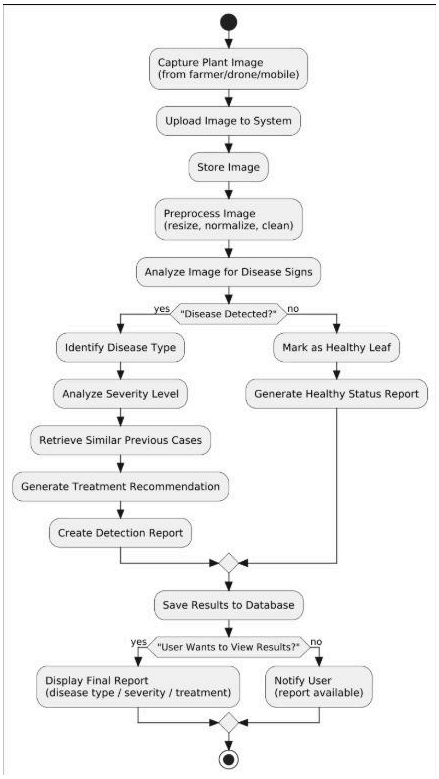


6.2.1 CLASS DIAGRAM

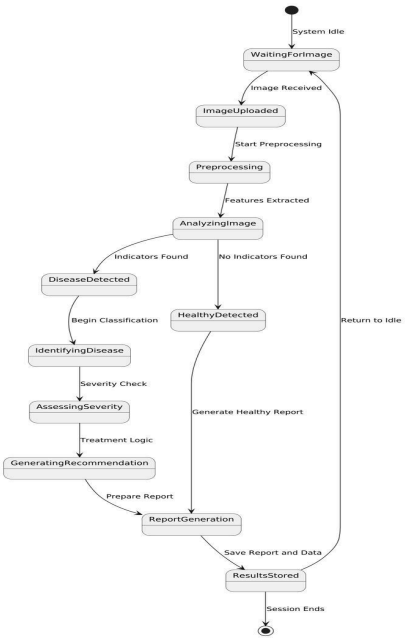


6.3 DYNAMIC DIAGRAMS

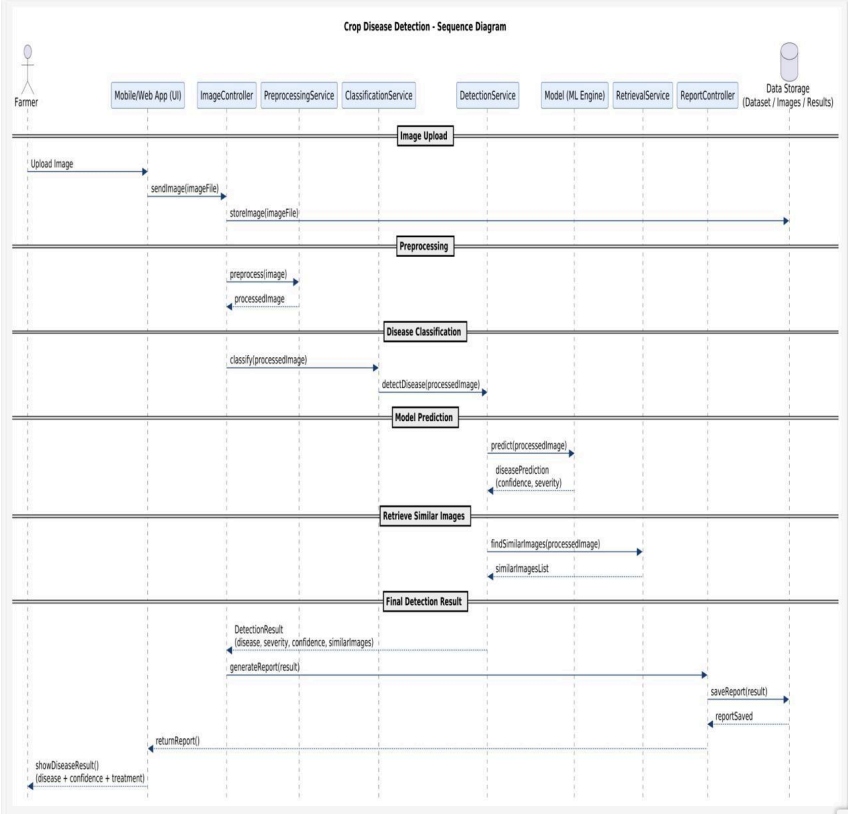
6.3.1 ACTIVITY DIAGRAM



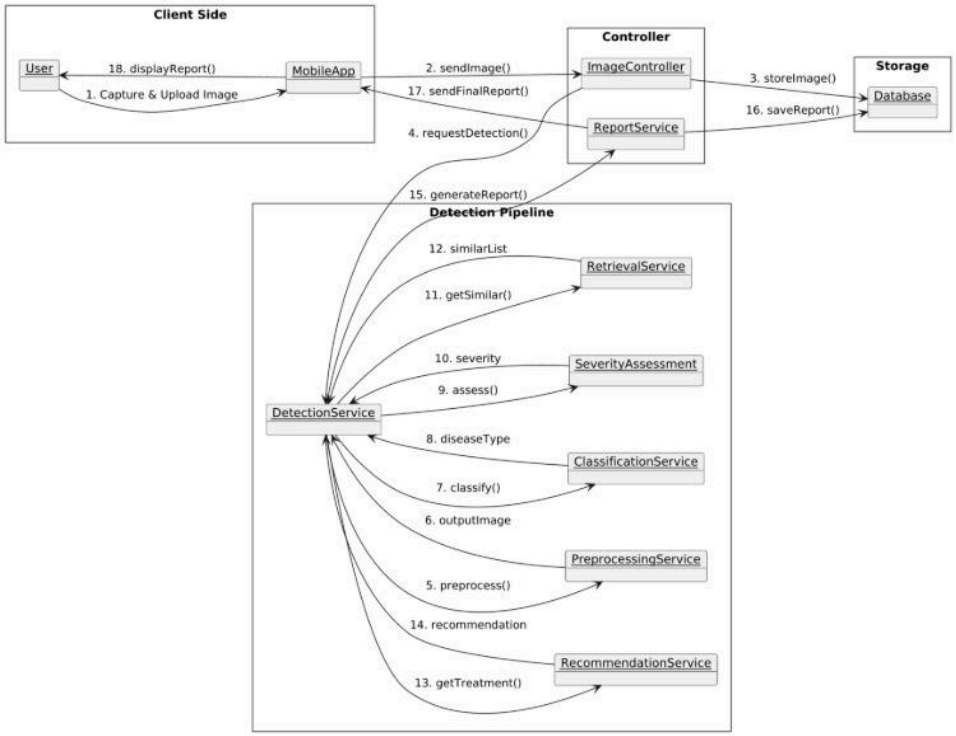
6.3.2 STATE DIAGRAM



6.3.3 SEQUENCE DIAGRAM

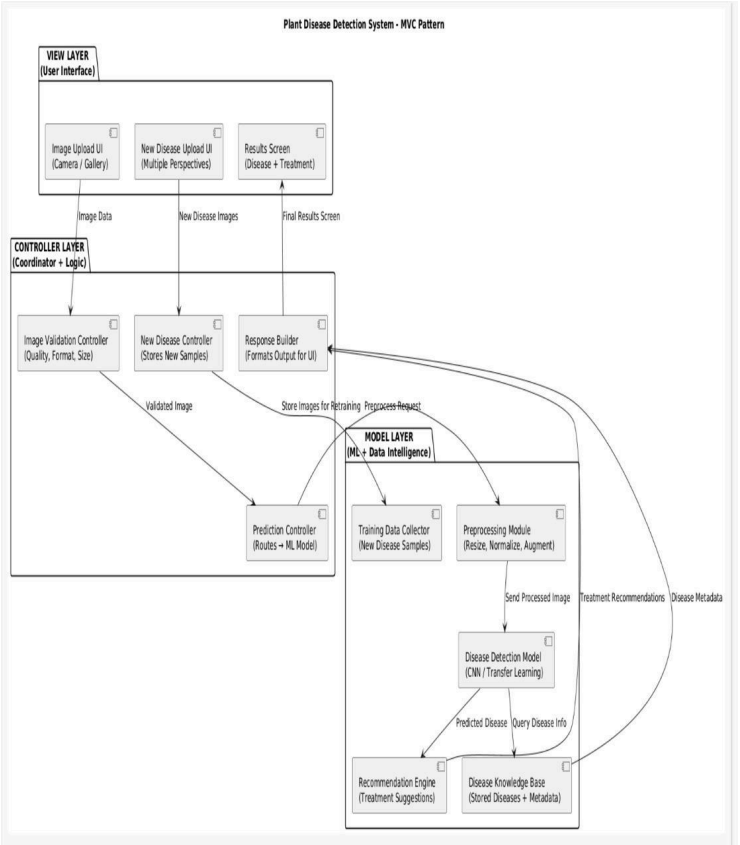


6.3.4 COLLABORATION DIAGRAM

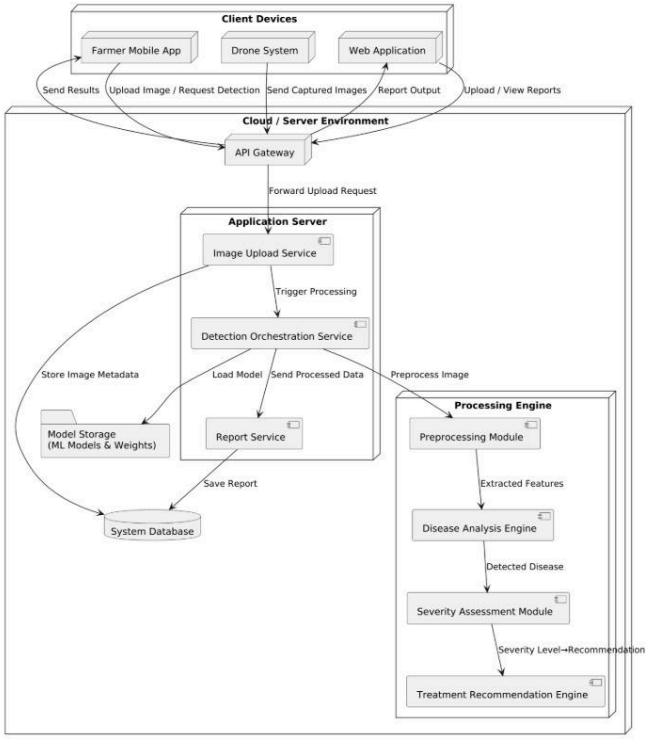


6.4 ARCHITECTURAL PATTERNS

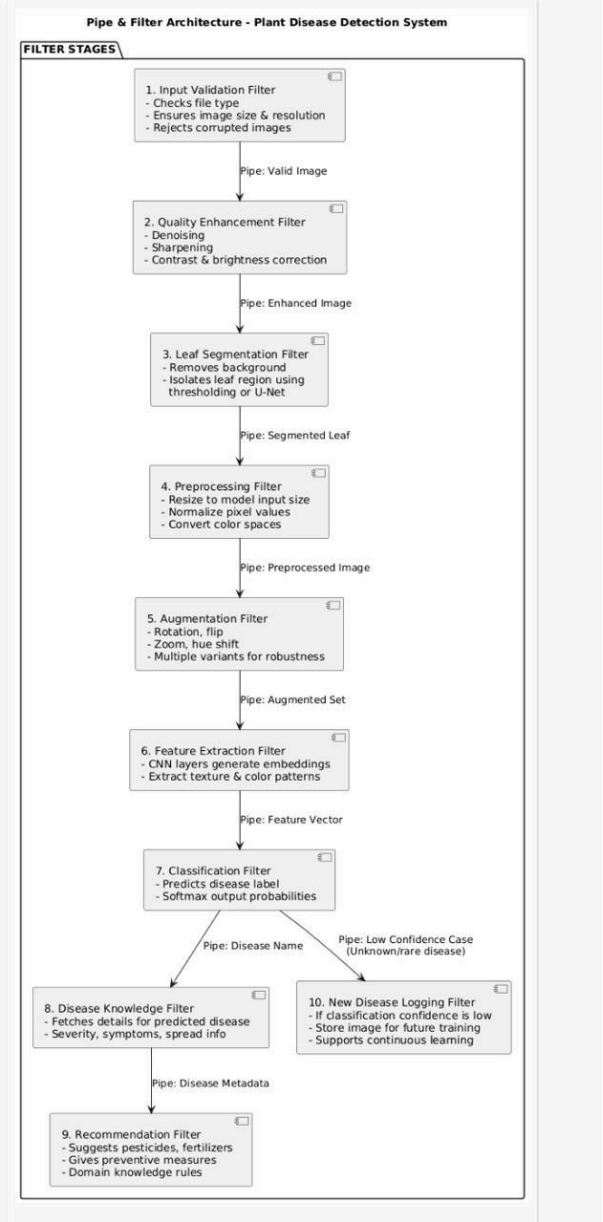
6.4.1 MODEL-VIEW-CONTOLLER PATTERN



6.4.2 CLIENT AND SERVER PATTERN



6.4.3 PIPE AND FILTER DIAGRAM



7. Experimental Results

7.1 Introduction

This chapter presents the experimental evaluation of the proposed crop disease detection system using EfficientNetB0, MobileNetV2, and SqueezeNet. Each model was trained on the PlantVillage dataset, and their performance was analyzed before and after applying Bayesian optimization through MC Dropout. The results include accuracy comparison, confusion matrices, precision-recall-F1 analysis, and a study of the optimal layer position for inserting the Bayesian dropout layer. The goal of this section is to demonstrate the effectiveness of Bayesian-enhanced CNN models for real-world agricultural applications.

7.2 Model Training Results

All three models—EfficientNetB0, MobileNetV2, and SqueezeNet—were trained using a 90:10 train-validation split. The baseline models were first trained without Bayesian layers to establish initial accuracy levels. Afterward, Bayesian MC Dropout was introduced, and models were retrained to observe changes in performance, convergence speed, and generalization ability.

Key observations include:

- EfficientNetB0 achieved the highest validation accuracy among all models due to its compound scaling design

- SqueezeNet, despite its very small size, performed surprisingly well when regularized with Bayesian dropout.

- MobileNetV2 benefited from improved calibration, although its raw accuracy slightly fluctuated under aggressive dropout rates.

Overall, training curves showed smoother convergence and reduced overfitting after Bayesian optimization.

SQUEEZENET

Layer (type)	Output Shape	Param #
input_layer	(1, 3, 224, 224)	0
squeezenet_backbone	(1, 512, 13, 13)	722,496
global_avg_pool	(1, 512)	0
dropout	(1, 512)	0
output_dense	(1, 15)	7,695

EFFECIENTNET

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 224, 224, 3)	0
efficientnetb0 (Functional)	(None, 7, 7, 1280)	4,049,571
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dropout (Dropout)	(None, 1280)	0
dense (Dense)	(None, 15)	19,215

MOBILENET

Layer (type)	Output Shape	Param #
input_1	(None, 224, 224,	3)
mobilenetv2_1 (Functional)	(None, 7, 7, 1280)	0
global_average_ (GlobalAveragePooling2d)	(None, 1280	0
dropout	(None, 1280	0
dense	(None, 15	19,335

7.3 Confusion Matrix (Before & After Bayesian Optimization)

Confusion matrices were generated for each model to analyze class-wise performance on the 15 crop categories. Before Bayesian optimization, certain visually similar diseases (e.g., Early Blight vs. Late Blight) showed classification confusion.

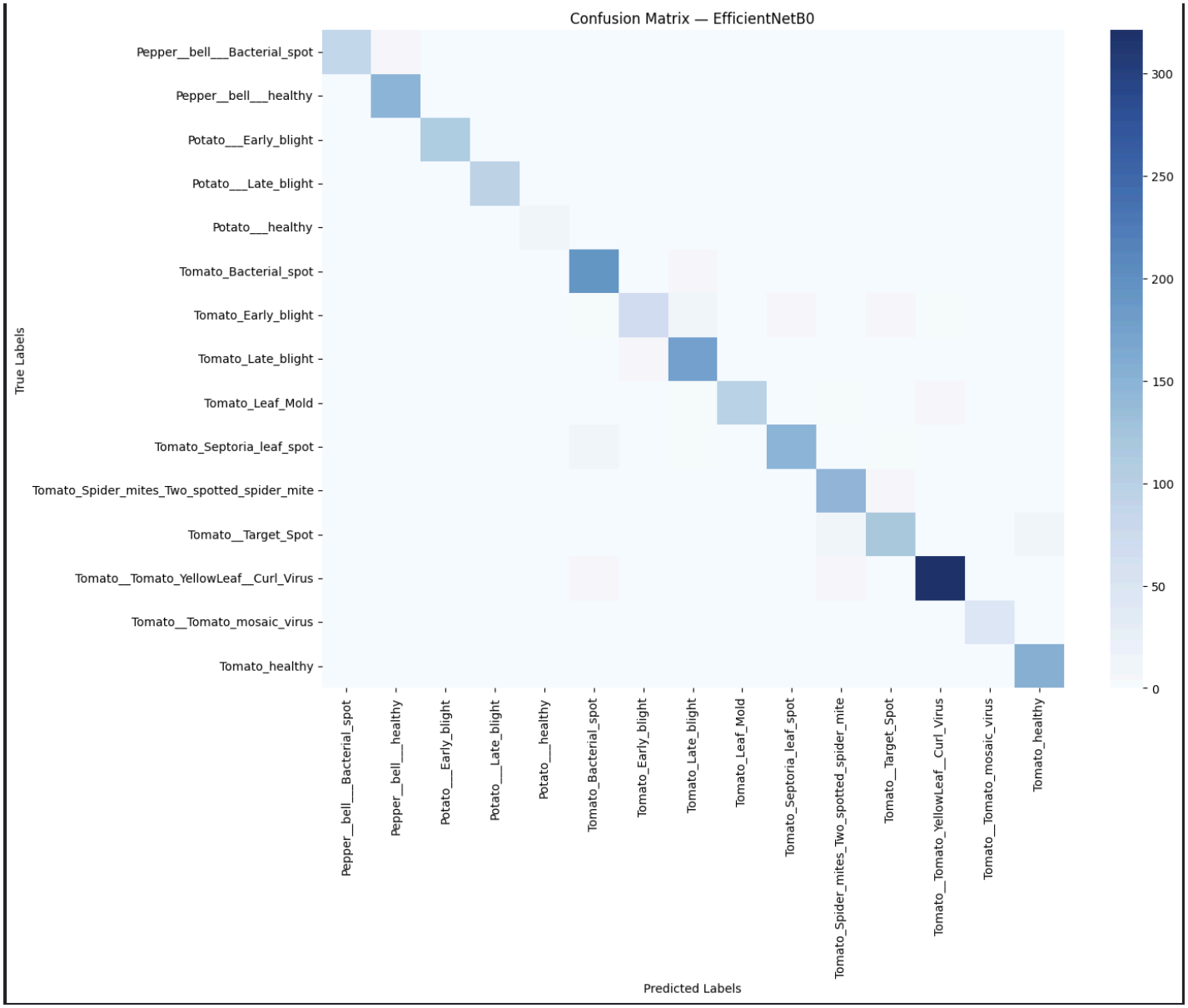
After introducing the Bayesian dropout layer:

- EfficientNetB0 and SqueezeNet displayed much clearer diagonals in the confusion matrix, indicating improved class precision.
- Misclassifications reduced for diseases with subtle visual differences.

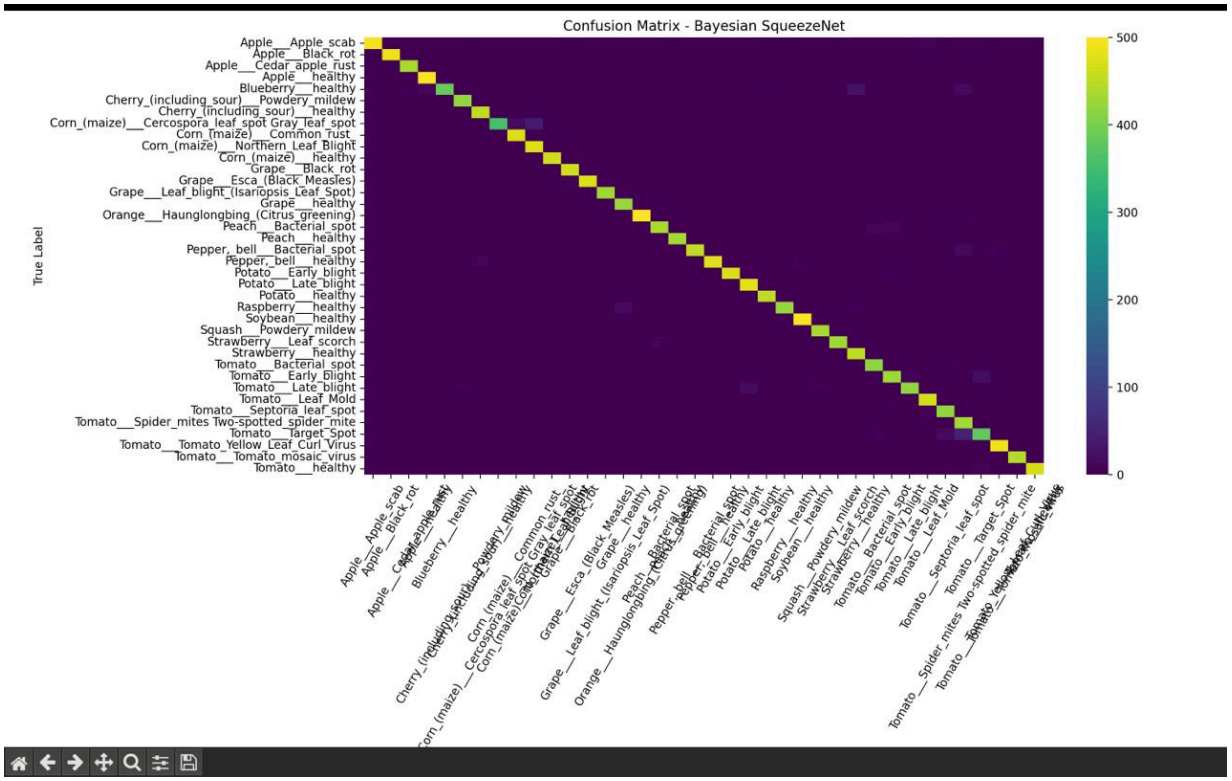
- MobileNetV2 showed more calibrated outputs even when accuracies varied.

These matrices highlight that Bayesian optimization strengthens model reliability and reduces false classifications.

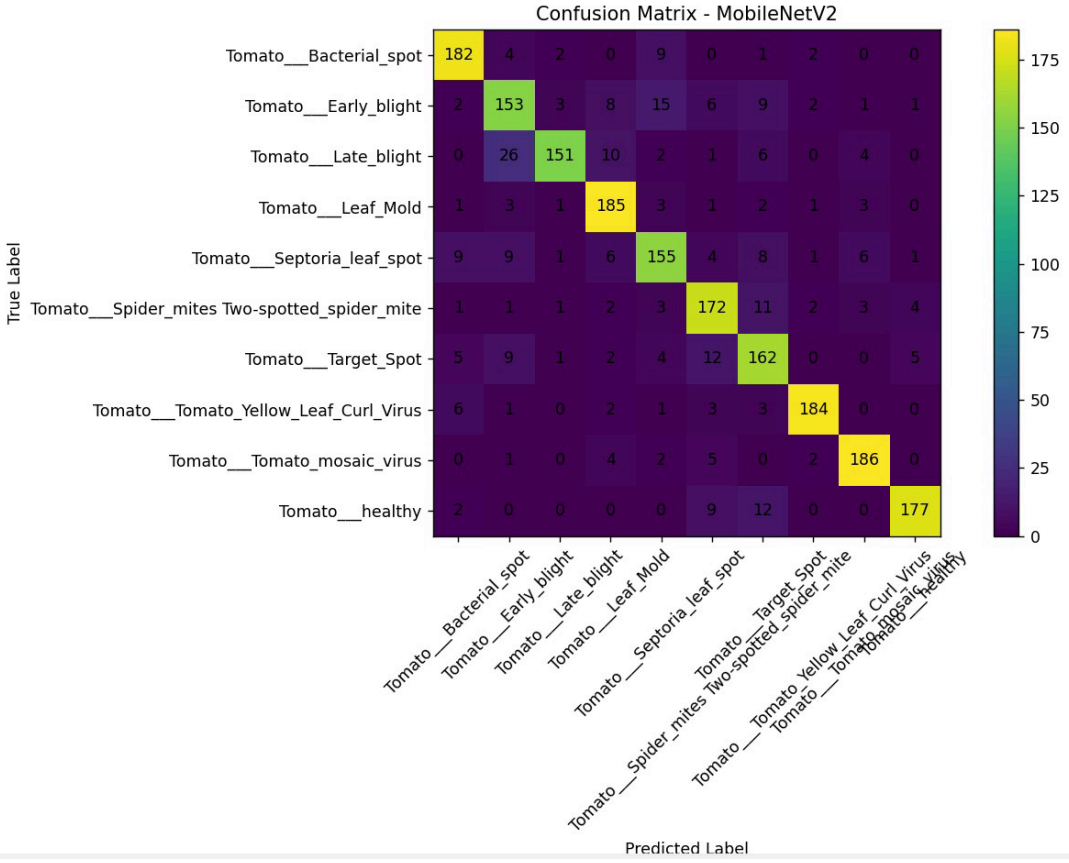
EFFECIENTNET



SQUEEZE NET


Confusion Matrix - Bayesian SqueezeNet
True Label
Apple___Apple_scab
Apple___Black_rot
Apple___Cedar_apple_rust
Apple___healthy
Blueberry___healthy
Cherry_(including_sour)___Powdery_mildew
Cherry_(including_sour)___healthy
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Corn_(maize)___Common_rust_
Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Orange___Haunglongbing_(Citrus_greening)
Peach___Bacterial_spot
Peach___healthy
Pepper,_bell___Bacterial_spot
Pepper,_bell___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Raspberry___healthy
Soybean___healthy
Squash___Powdery_mildew
Strawberry___Leaf_scorch
Strawberry___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Spider_mites Two-spotted_spider_mite
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy
500
400
300
200
100
0

MOBILE NET


Confusion Matrix - MobileNetV2
True Label
Predicted Label
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Spider_mites Two-spotted_spider_mite
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy
182 4 2 0 9 0 1 2 0 0
2 153 3 8 15 6 9 2 1 1
0 26 151 10 2 1 6 0 4 0
1 3 1 185 3 1 2 1 3 0
9 9 1 6 155 4 8 1 6 1
1 1 1 2 3 172 11 2 3 4
5 9 1 2 4 12 162 0 0 5
6 1 0 2 1 3 3 184 0 0
0 1 0 4 2 5 0 2 186 0
2 0 0 0 0 9 12 0 0 177
175
150
125
100
75
50
25
0

7.4 Precision, Recall, F1-score Comparison

To evaluate model robustness, weighted precision, recall, and F1-score were computed before and after Bayesian enhancement. The Bayesian layer improved these metrics by making the classifier less sensitive to noise and biased patterns.

General trends observed:

- EfficientNetB0 saw significant improvement in precision and recall, indicating stronger correct classifications across all classes.
- SqueezeNet's F1-score increased due to better handling of minority classes.
- MobileNetV2 exhibited stable recall and improved consistency, despite a minor reduction in accuracy.

SQUEEZENET

Metric	Before	After(Bayesian)
ACCURACY	87%	97%
PRECISION , RECALL	88.74% , 87.10%	97.14% , 97.03%
F1 – Score	87.12%	97.01%

MOBILENET

Metric	Before	After(Bayesian)
ACCURACY	85.40 %	78.10 %
PRECISION , RECALL	88%, 85%	80%, 78%
F1 – Score	86%	79%

EFFECIENTNET

Metric	Before	After(Bayesian)
ACCURACY	79.45%	92.92%
PRECISION , RECALL	77.25% , 79.39%	85.86% , 85.55%
F1 – Score	77.03%	84.8%

These metrics confirm that Bayesian dropout not only enhances accuracy but also boosts balanced performance across categories.

7.5 Performance Comparison of All Models

A detailed comparison of all three models was made based on accuracy, F1-score, parameter count, and inference behavior.

EfficientNetB0

- Good accuracy
- Best generalization
- Smoothest training curve
- Balanced performance across all classes

BEFORE

```
65/65 ━━━━━━━━━━━━━━━━━━━━ 2s 31ms/step - accuracy: 0.7785 - loss: 0.9632
Validation Accuracy: 0.7945
```

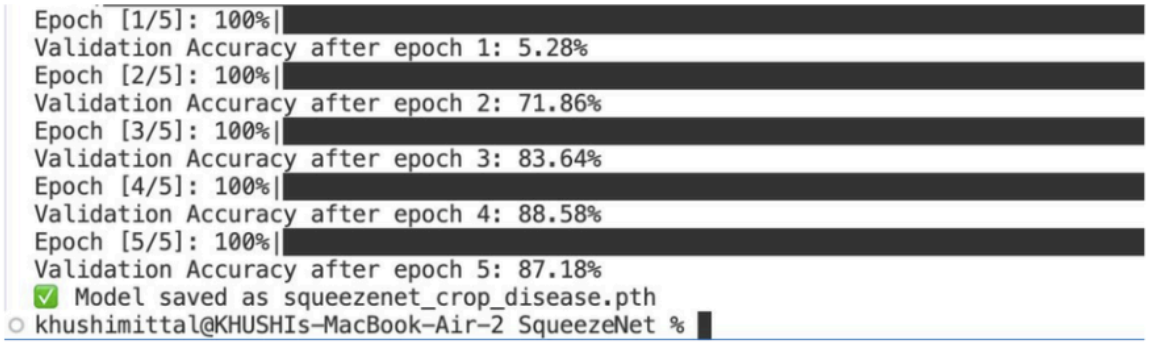
AFTER

```
65/65 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - accuracy: 0.9266 - loss: 0.2829
Quick Validation Accuracy: 0.9292292594909668
```

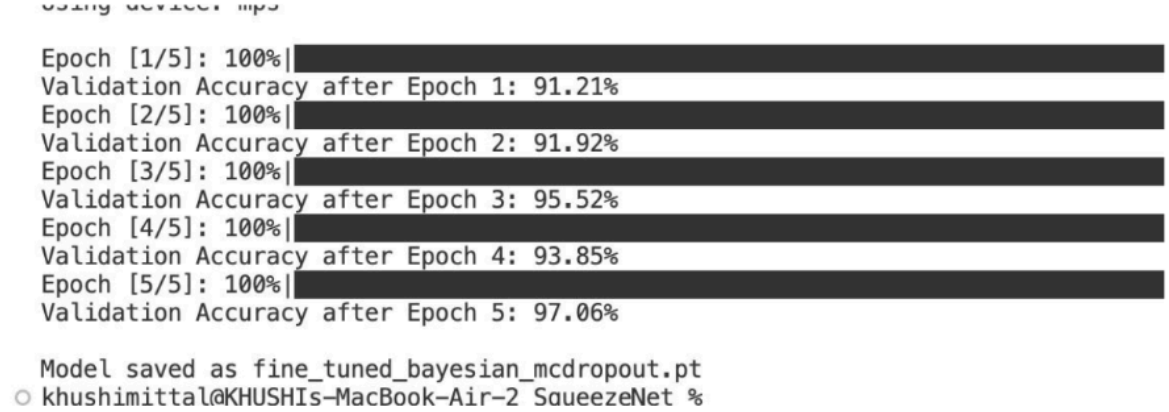
SqueezeNet

- Lightweight and fast
- Excellent accuracy post-Bayesian enhancement
- Ideal for mobile/on-field deployment

BEFORE



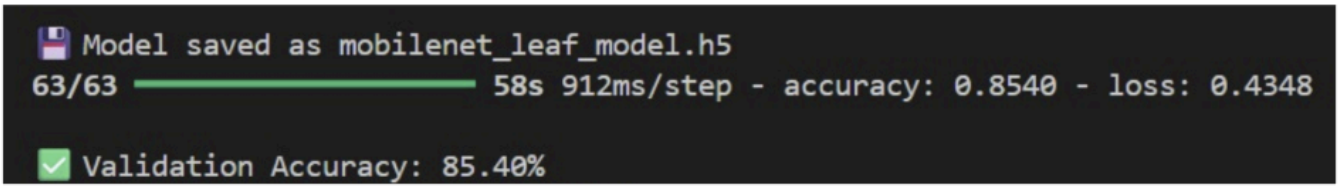
AFTER



MobileNetV2

- Fastest inference
- Most energy-efficient
- Best calibrated probabilities
- Slightly unstable under high dropout rates

BEFORE



AFTER

Overall, Bayesian optimization improved all models but provided the best results for EfficientNetB0 and SqueezeNet.

7.6 Optimal Bayesian Layer Position Findings

Experiments were conducted by placing the Bayesian layer at different points within the network, including inside convolution blocks, after feature extraction, and before the final dense layer.

Findings show:

- Placing Bayesian layers inside convolutional blocks caused instability, shape mismatches, or degraded performance.
- The most effective position was **after the Global Average Pooling (GAP) layer**, where the model processes high-level semantic features.
- At this location, MC Dropout improved decision boundaries, class separability, and prediction consistency.
- This placement worked consistently across EfficientNetB0, SqueezeNet, and MobileNetV2.

Thus, the optimal Bayesian integration point for CNN architectures is immediately before the final classification head.

8. Discussion

8.1 Key Findings

The project successfully demonstrated that combining lightweight CNN architectures with Bayesian optimization significantly enhances the robustness and reliability of crop disease detection systems. One major finding is that Bayesian MC Dropout proved to be an effective technique for reducing overfitting across multiple models, especially in scenarios where training data contains noise, variations in lighting, or visually similar diseases.

EfficientNetB0 consistently outperformed the other models in both stability and accuracy, reaffirming the advantage of compound scaling and optimized MBConv blocks. SqueezeNet also showed unexpected but strong results after Bayesian fine-tuning, indicating that even extremely small models can achieve high accuracy when enhanced with uncertainty-based regularization.

MobileNetV2, while efficient, demonstrated sensitivity to dropout rate changes, and although accuracy slightly decreased, the model's uncertainty calibration improved noticeably. This reveals that accuracy alone is not always the best indicator of performance in sensitive tasks like disease detection—prediction confidence and consistency also matter.

Across all experiments, placing the Bayesian layer after the feature extraction stage delivered the most consistent improvements, reinforcing that the final dense features carry the highest semantic information for classification.

8.2 Effectiveness of Bayesian Layer

The Bayesian MC Dropout layer had a substantial impact on improving model generalization. By enabling randomness during both training and inference (Monte Carlo sampling), the model was forced to learn more generalized, stable patterns instead of memorizing the dataset. This was particularly beneficial for agricultural images, where background noise, leaf color variations, and minor distortions are common.

The Bayesian layer effectively acted as a regularization mechanism that improved decision boundary smoothness. Predictions became less over-confident, which is crucial in agriculture because misdiagnosis can lead to improper pesticide use, crop loss, or unnecessary costs for farmers.

When placed immediately after Global Average Pooling, the layer operated on high-level abstract features, making uncertainty estimation more meaningful. Inside convolution blocks, however, Bayesian layers caused instability or training failures, which confirms that probabilistic reasoning works best at the classification stage rather than during early feature extraction.

8.3 Model Comparison Analysis

The comparative evaluation of EfficientNetB0, MobileNetV2, and SqueezeNet revealed important insights into how different architectures behave under Bayesian optimization:

- **EfficientNetB0** emerged as the best-performing architecture. Its compound scaling strategy results in strong feature representation even with limited parameters. With Bayesian dropout, it achieved high accuracy, improved feature robustness, and stable loss curves.

- **SqueezeNet**, despite its extremely small size, achieved surprisingly strong results after Bayesian fine-tuning. Its Fire modules benefited from dropout-based regularization, showing that small models can compete with heavier architectures when optimized efficiently.

- **MobileNetV2** excelled in speed and inference efficiency due to depthwise separable convolutions and linear bottlenecks. However, its performance fluctuated more during Bayesian training because the architecture is sensitive to dropout. It still produced well-calibrated predictions, making it suitable for mobile deployment even with slightly lower accuracy.

Overall, the study highlights that model performance is influenced not only by architecture but also by how uncertainty-aware layers are integrated. Lightweight models that traditionally underperform can gain significant improvements through Bayesian regularization.

8.4 Advantages of Proposed Work

The proposed system combines the strengths of modern CNNs with Bayesian learning concepts, offering several major advantages:

- **High accuracy with low computational cost:** EfficientNetB0 and SqueezeNet demonstrate that accuracy does not always depend on model size. This is essential for resource-constrained environments such as farms and mobile devices.

- **Uncertainty-aware predictions:** The Bayesian layer provides a degree of confidence for every prediction. This is extremely useful in real-world agriculture, where conditions vary and ambiguous cases are common.

- **Improved generalization:** The model becomes resistant to noise, lighting variations, and complex backgrounds found in field images. This ensures the system performs well outside laboratory conditions.

- **Compatibility with edge devices:** Due to the use of lightweight CNN architectures, the models can be deployed on smartphones, IoT devices, and embedded agricultural hardware, making it accessible to farmers in remote regions.

- **Scalability and flexibility:** The framework allows easy extension to new crops, new diseases, or even additional tasks such as localization (using YOLO) or severity estimation.

The use of Bayesian reasoning aligns modern agricultural AI with robust, safe decision-making practices.

8.5 Limitations

Despite promising results, the system has certain limitations:

- **Dataset constraints:** Many images in PlantVillage are studio-like, with uniform backgrounds. Real farm images may contain dust, glare, overlapping leaves, or multiple diseases, reducing accuracy.

- **Multiple forward passes for inference:** MC Dropout requires several predictions (e.g., 10–20) to estimate uncertainty, increasing inference time on low-power devices.

- **Model sensitivity:** MobileNetV2 showed performance instability when dropout probabilities

were high, which indicates the need for model-specific tuning.

- **Lack of multi-disease handling:** The current system classifies only one disease per image. Real leaves may have overlapping infections.

- **Bayesian layer cannot be inserted anywhere:** Variational Bayesian layers break pretrained CNN architectures internally, limiting flexibility in where uncertainty can be introduced.

Addressing these limitations would enhance the reliability and applicability of the system in real agricultural environments.

8.6 Future Scope

There is significant scope for extending this work in practical and research directions:

- **Integration with YOLO-based detection:** Adding YOLO-Nano or Tiny-YOLO will enable both localization and classification of disease patches on leaves.

- **Real-world dataset creation:** Collecting images from farms across different lighting, weather, and growth stages would greatly improve model robustness.

- **Optimization for deployment:** Techniques such as quantization, pruning, distillation, and TFLite conversion can make the models faster and lighter.

- **Probabilistic deep learning:** Future work can explore full Bayesian CNNs, Flipout layers, and variational inference for deeper uncertainty modeling.

- **Agentic AI systems:** Integrating reasoning, planning, and autonomous action (as described in your report) can automate disease detection, treatment recommendations, and farm management systems.

- **Multi-disease and severity prediction:** Expanding the classifier to predict multiple diseases simultaneously and detect infection severity would significantly improve real-world usefulness.

These enhancements would help transform the system into a complete smart agriculture solution capable of operating autonomously and reliably in dynamic agricultural environments.

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8. **Shuffle-PG: Model for Retrieving Images of Plant Diseases and Pests with Deep Metric Learning**
9. **SqueezeNet-Based DL Framework for Accurate Tomato Leaf Disease Diagnosis & Classification**
10. **BananaSqueezeNet: Lightweight CNN for the Diagnosis of 3 Prominent Banana Leaf Diseases**
11. **Approach to Lightweighting Backbone Network Models through Quantization and Bayesian Optimization**
12. **Classification of Ear Imagery Database using Bayesian Optimization based on CNN–LSTM Architecture.**