AgriSense AI - AI-powered crop health analysis & smart farming guidance

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ABSTRACT
AgriSense AI is an intelligent plant disease detection system designed to support farmers through fast, accurate, and accessible diagnosis of crop health. The project integrates deep learning, computer vision, and a simple web-based interface to identify diseases from leaf images. The **novelty** of this work lies in the use of **MobileNet, a lightweight convolutional neural network architecture** chosen specifically for its low computational cost and high efficiency. Unlike heavier models such as VGG or ResNet, MobileNet enables rapid inference even on low-resource devices, making the system more practical for real-world agricultural environments where internet speed and hardware capabilities may be limited.

The model was trained and evaluated using the PlantVillage dataset and achieved high accuracy in classifying multiple leaf diseases. The complete pipeline includes preprocessing, feature extraction, classification, and real-time prediction through a user-friendly interface. The system demonstrates strong potential in assisting farmers with early disease detection, reducing crop loss, and promoting data-driven decision-making.

However, the project also has certain limitations. The dataset consists largely of controlled, clean images, which may not fully represent real-world farm conditions involving varied lighting, cluttered backgrounds, or partially damaged leaves. The model's performance may reduce when exposed to highly complex or unseen disease patterns. Additionally, the current system classifies only a limited number of crop types, and the web deployment relies on internet access for image upload and prediction.

Despite these constraints, AgriSense AI offers a promising and scalable direction for smart agriculture. By leveraging a lightweight architecture like MobileNet, the system can be extended to mobile devices, expanded to additional disease categories, and integrated with future technologies such as IoT sensors, multilingual support, and offline prediction capabilities.

Key words: AgriSenseAI, Crop Disease Detection, Computer Vision, Smart Farming

1 INTRODUCTION

Farming is the heart of what feeds us, but the people who dedicate their lives to it often struggle with challenges that feel deeply isolating. It's the simple things: catching a disease before it takes hold, finding someone truly knowledgeable to ask a question, and simply understanding the silent messages their fields are sending.

Imagine a farmer seeing those strange spots on a new leaf, or noticing that the young plants just aren't stretching up the way they should. Without a quick, trusted answer, that small worry can swell into a devastating loss. Real, expert help isn't always around the corner, and the old ways of figuring things out can feel slow, sometimes leaving you with more questions than answers.

Now, picture a powerful new kind of **digital helper**. Not a distant program, but a focused tool that acts like an extra pair of experienced eyes. It uses **smart imaging** to instantly tell you what that leaf spot is, just from a photo. It uses **thoughtful communication** to give you clear, personal advice for your everyday questions, like talking to a trusted neighbor. But most existing tools just do one of these things, leaving the farmer juggling bits and pieces of advice.

AgriSense was built because farming is a whole job, and it needs a whole solution. It brings all these crucial elements together: looking at the leaf, answering the question, and showing you the bigger health story of your crops in pictures that make sense.

By pulling these threads together, AgriSense aims to give farmers and learners a feeling of **certainty, strength, and true command** over their work. It takes those anxious moments of observation and turns them into solid, meaningful knowledge. It's about making farming not just more successful, but also less of a relentless worry and much more of an informed, thoughtful practice.

Agriculture continues to evolve with the increasing involvement of modern technologies, particularly artificial intelligence. Traditional farming practices depend heavily on manual observation, experience, and periodic expert consultation. While these methods have served farmers for generations, they fall short when dealing with rapidly spreading plant diseases, unpredictable climate conditions, and rising global food demands. Artificial intelligence provides a powerful set of tools that can automate disease detection, generate reliable recommendations, and convert raw farm data into useful insights. AgriSense AI is built upon this foundation, integrating computer vision, natural language processing, and data visualization into one unified agricultural assistant.

1.1 1. Computer Vision for Crop Disease Detection

Computer vision (CV) forms the backbone of leaf-based disease identification. It enables a system to interpret visual cues from plant leaves—such as spots, color changes, fungal patterns, or shape distortions—that indicate early signs of disease. Traditionally, identifying plant diseases required trained experts, and delays in diagnosis often led to significant crop loss. CV automates this process by learning patterns from thousands of annotated images and replicating expert-level analysis.

The disease detection pipeline typically includes image capture, preprocessing, feature extraction, and classification. Preprocessing involves operations such as resizing, noise reduction, normalization, and augmentation to ensure the image is suitable for a neural network. Feature extraction is handled by deep learning models that automatically learn edges, textures, colors, and high-level details. Finally, classification maps these features to labels such as "healthy," "blight," or "rust." This automation improves accuracy, reduces human dependency, and allows real-time diagnosis in the field.

1.2 2. Convolutional Neural Networks (CNNs)

CNNs are the most widely used neural networks for image-based tasks. They consist of convolution layers that apply filters to detect features, pooling layers that reduce spatial dimension, and fully connected layers that make final predictions. CNNs are uniquely suited for agricultural imagery because leaf diseases often exhibit subtle patterns—such as tiny spots or faint discoloration—that require precise spatial recognition.

Key strengths of CNNs include their ability to learn hierarchical features, reduce manual feature engineering, and perform robustly even with diverse environmental conditions. These properties make CNNs ideal for automating plant disease detection and enabling the system to identify symptoms that might be difficult for a farmer to notice with the naked eye.

1.3 3. MobileNet Architecture

AgriSense AI uses MobileNet, a lightweight and efficient CNN designed for mobile and embedded devices. Traditional CNN models like ResNet or VGG are highly accurate but computationally expensive, making them unsuitable for low-end smartphones or offline agricultural environments. MobileNet solves this through **depthwise separable convolution**, which breaks a single convolution operation into two smaller and faster steps: depthwise convolution and pointwise convolution.

This design reduces computation and model size significantly while maintaining strong accuracy. MobileNet also supports hyperparameters such as width multipliers and resolution multipliers that allow the model to be scaled according to available resources. This makes it an ideal choice for farmers who may not have access to high-performance devices or stable internet connectivity. MobileNet thus allows AgriSense AI to deliver fast, on-device disease detection without compromising usability.

1.4 4. PlantVillage Dataset

The PlantVillage dataset provides the foundation for training the disease detection model. It includes tens of thousands of images of healthy and diseased leaves across numerous crop varieties. The images are captured in controlled settings, making them consistent and ideal for training CNNs. By exposing the model to diverse examples of the same disease, the dataset helps MobileNet generalize well and identify symptoms across different environments, lighting conditions, and leaf orientations. As a result, the system becomes more reliable and robust in real-world farming scenarios.

1.5 5. Natural Language Processing (NLP)

Disease detection alone is not enough for farmers who want specific advice, explanations, and step-by-step guidance. Natural Language Processing enables AgriSense AI to interpret these questions and generate meaningful responses. NLP involves several stages: tokenization, embedding, parsing, contextual understanding, and response generation. These processes allow the system to understand both simple and complex queries, such as "Why are my tomato leaves curling?" or "What fertilizer should I apply during monsoon season?" NLP bridges the gap between technology and accessibility by allowing farmers to communicate naturally. Instead of navigating complex dashboards, they can simply type their questions in everyday language.

1.6 6. Transformer-Based Models

Transformers represent the latest breakthrough in NLP. Unlike older models such as LSTMs or GRUs, transformers use self-attention mechanisms that evaluate relationships between all words in a sentence simultaneously. This allows them to understand context more effectively, handle long questions, and generate accurate responses.

AgriSense AI uses a transformer-based architecture for its Q&A system. The model is capable of understanding agricultural terminology, identifying the intent behind a question, and generating contextually rich answers. This transforms the system from a simple chatbot into a knowledgeable farming assistant capable of addressing real-world agricultural problems.

1.7 7. Data Visualization

Raw numerical predictions are often difficult for non-technical users to interpret. AgriSense AI includes a visualization module built using tools like Matplotlib and NumPy, which converts disease occurrences and crop health trends into clear and understandable graphs. Visualization helps users identify patterns, such as whether a disease is spreading or decreasing, and supports better decision-making. Graphs serve as visual summaries that make complex data more intuitive for farmers and agricultural students.

1.8 8. Integrated System Architecture

The uniqueness of AgriSense AI lies in combining three major AI components—image-based classification, text-based advisory, and data visualization—into a single platform. Each component enhances the others. The disease detection module provides factual assessments, the NLP module adds personalized guidance, and the visualization module presents insights in an accessible format. Together, they create a holistic system that can support farmers at multiple stages of the agricultural cycle.

2 RELATED WORKS

The literature on leaf disease detection using deep learning is reviewed in this part, along with other essential research. The usage of AI in healthcare and the agriculture sector has increased significantly in recent years. AI has been used in imaging, especially in the medical and agricultural fields.

Sanjiv Sannakki et al. [**1**] utilized artificial intelligence and image processing in their endeavor to make a diagnosis. Using an image processing approach, Monika Jhuria et al. [**2**] were able to grade the fruit and identify illnesses. To help categorize diseases, an artificial neural network has been employed. Kaiyi Wang et al. [**3**] developed a new strategy for identifying insect pests and plant illnesses using image processing and computer vision techniques. Studying the state of insect pests and vegetable diseases using images gathered by smartphones.

Researchers have proposed and examined various methods and models for detecting plant diseases using machinelearning approaches. [**4**] describes distinguishing between healthy and diseased or infected leaves using image processing and machine-learning strategies. Several diseases cause leaves to lose chlorophyll, which causes dark or black patches to appear on the surface. They can be found using machine learning techniques for classification, feature extraction, image preprocessing, and image segmentation. Features are extracted using the Grey Level Cooccurrence Matrix (GLCM). The Support Vector Machine is one of the machine learning methods for categorization (SVM). The Convolutional Neural Network (CNN) technique increased recognition accuracy when compared to the SVM method. Apple leaves have a 99% overall accuracy. The classification of the respective plants is found to be 97.71% accurate. [**5**] described a rice leaf disease detection technique based on machine learning. Three of the most prevalent diseases affecting rice plants were identified in this study: leaf table, bacterial leaf blight, and brown spot diseases. Clear images of damaged rice leaves against a white background served as the input. After pre-processing, the dataset was trained using machine learning techniques, including KNN (K-Nearest Neighbor), J48 (Decision Tree), Bayesian Network, and Logistic Regression. After 10-fold cross-validation, the decision tree technique achieved an accuracy of over 97% when used on the test dataset. [**6**]; in their study, the outliers in wheat leaf were emphasized. Even though algorithms can detect common wheat leaf diseases, they harm wheat productivity. Viruses, bacteria, fungi, insects, rust, and other diseases affect wheat. Wheat leaves can be infected with a wide range of diseases. Identifying wheat diseases using leaf scanning and data processing techniques has become popular and expensive, especially for helping farmers monitor vast planted areas. Using a machine learning approach, wheat leaf disease classification and detection are also covered in detail. Furthermore covered are the primary issues and challenges in identifying wheat leaf disease. In Ref. [**7**], using Deep Learning methods, a Convolutional Neural Network (CNN) architecture is suggested for plant leaf disease detection. Several observations were taken using various CNN hyperparameters, and it was found that the suggested architecture can accurately classify diseases up to 95.81%. [**8**] focused on supervised machine learning algorithms for maize plant disease diagnosis using photographs of the plant, such as K-Nearest Neighbor (KNN), Random Forest (RF), Decision Tree (DT), Naive Bayes (NB), Support Vector Machine (SVM). The RF algorithm, when compared to the other classification methods, gets the best accuracy of 79.23%. To avoid new image diseases from spreading, farmers will use all of the above-trained models for timely identification and classification. Image processing methods are applied to identify plant leaf diseases in Ref. [**9**]. This project aims to use image analysis classification algorithms to recognize and categorize leaf diseases. The suggested organization has four sections. First is image preprocessing; second is leaf segmentation using K-means clustering to locate hazardous areas. (4) Feature extraction and (3) categorization of diseases To extract texture data, statistical Grey-Level Co-Occurrence Matrices (GLCM) features are used, and a Support Vector Machine is used for classification (SVM). A. Meunkaewjinda et al. [**10**] proposed a system for detecting fruit diseases. Grape leaf color segmentation, grape leaf disease segmentation, and disease analysis and classification comprise the proposed system's three aspects. A pre-processing module called the grape leaf color segmentation removes any extraneous background information. A self-organizing feature map and back-propagation neural networks were employed to discern grape leaf colors. The grape leaf pixel segments in the image are created using this information. Support vector machines are then utilized to categorize various grape leaf diseases. The algorithm can categorize a grape leaf image into three groups: scab infection, rust ailments, and no disease. The suggested technique yields encouraging results that can be used in any system to examine or inspect agricultural products. Another study aims to apply the SVM classification method to help identify and classify grape leaf diseases [**11**]. The proposed approach has an accuracy of 88.89% for detecting and classifying the tested ailment.

Machine learning's most remarkable advancement is deep learning. Deep learning is the study of how a computer program may learn by observing and making decisions based on that knowledge. Deep learning algorithms benefit computer vision, face detection, audio recognition and processing, and various other applications. [**12**] suggested using open-source algorithms, image segmentation, and clustering to detect tomato plant leaves to disease, creating a trustworthy, secure, and accurate system for identifying leaf disease with an emphasis on tomato plants. The research in Durmuş et al. [**13**] where diseases that have been recognized harm greenhouse or field-grown tomatoes. Deep learning was used to identify different diseases in tomato plant leaves. The project aimed to have the deep learning algorithms run in real-time on the robot. As a result, the robot can detect plant illnesses while traveling on the field or in the greenhouse, either manually or automatically. Two distinct deep learning network topologies, AlexNet and SqueezeNet, were tried. These deep-learning networks were trained and validated on the Nvidia Jetson TX1. Photos of tomato leaves from the PlantVillage database were used for the training. There are ten separate classes, all of which have healthy imagery. Images from the internet are also used to test trained networks. [**14**] suggested a deep learning-enabled breakthrough for camera-assisted disease diagnosis in tomatoes. This research created a unique approach to disease detection in tomato plants. Four sides of each tomato plant were photographed using a motor-controlled picture-taking box to detect and diagnose leaf diseases. The tomato variety under test was one called Diamante Max. Among the diseases detected by the approach were Phoma Blight, Leaf Miner, and Targeted Spot. The system used a convolutional neural network to assess whether tomato infections were present on the plants being watched. Whereas the Transfer Learning disease recognition model has an accuracy of 95.75%, the F-RCNN trained anomaly-based model has an accuracy of just 80%. The automatic picture-taking system was tested in the real world and found to be 91.67% accurate at spotting illnesses on tomato plant leaves.

By reviewing all relevant studies, it was observed that many studies used machine learning models to detect leaf disease. However, there are some drawbacks to utilizing machine learning models, such as the need for hand-crafted features for feature extraction, which can take time and may not necessarily produce the best representation of the data. Again, when there are few training samples, traditional machine learning approaches are subject to overfitting, making it difficult to generalize to updated data. In addition, several studies use a small database for their experiment. Small datasets are likely to lead a CNN-based architecture to overfit. As a result, the model would not reflect actual and trustworthy classification performance outside of the training datasets. Moreover, numerous studies have only used a single pre-trained technique [**15**] [**16**] and trained their architectures with a maximum of 5 or 6 classes [**17**] [**16**]. Most importantly, they did not provide web applications for predicting crop diseases in the real world

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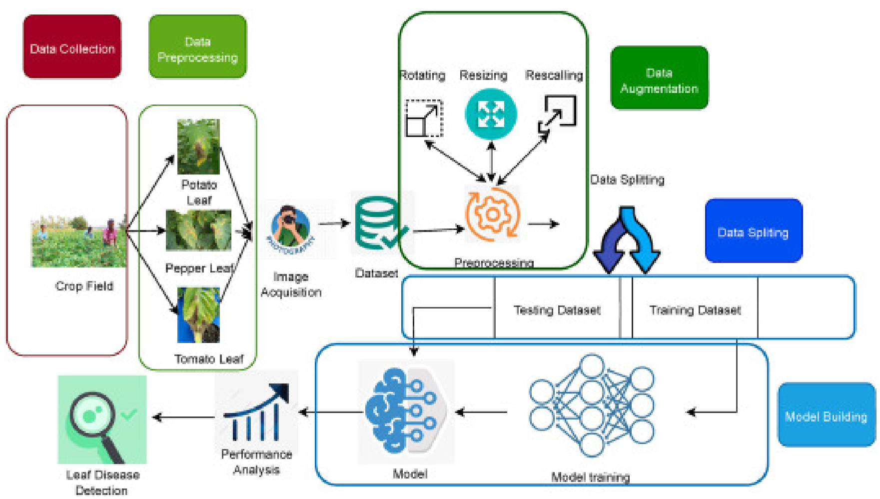
Table 1. SUMMARY: Related literature on plant disease using deep learning models.

Reference	Object	Total Images / Classes	DL Framework	Accuracy (%)
[32]	Citrus leaf	609 images / 5 classes	Inception-V3, VGG-19, VGG-16	VGG16 – 89.5%
[33]	Apple leaf	2462 images / 6 classes	DenseNet-121	93.71%
[13]	Potato leaf	2152 images / 3 classes	VGG19	97.8%
[29]	Tomato leaf	736 images / 4 classes	CNN-based approach	98.12%
[34]	Tomato leaf	7500 images / 9 classes	CNN-based approach	91.2%
[35]	Paddy leaf	120 images / 2 classes	DNN-CSA	96.96%
[36]	Citrus leaf	598 images / 4 classes	Two-stage CNN model	94.37%

that could help farmers save resources and avoid financial loss. To circumvent the constraints for the experiments in the proposed study, many pre-trained deeplearning models and a large dataset of plant diseases were used. Additionally, the proposed model was compatible with eight different leaf classification categories. Significantly, we also built a smart web application for predicting crop disease.

3 PROPOSED METHODOLOGY



Work Flow Diagram

Training a model for leaf disease classification requires a dataset that includes examples of both healthy and diseased leaves. The website Kaggle.com is a hub for data science courses and contests. We collected image data from such a competition to validate our proposal called plant-village (kaggle, 2018). We extracted three datasets from the original set of 10,000 images with 1,000, 3,000 and 6,000 images, respectively. The labeled images were divided into two sets: one containing 80% of the data for training the model and the other containing 20% of validation or testing data.

The proposal starts with collecting the input images representing different types of leaves like potatoes, tomatoes, and peppers. These raw images can be collected using a real-time camera or mobile. For our deployment, the deep learning model was trained using a publicly accessible dataset during the framework's testing and training phases.

3.1 Preprocessing

The raw images collected from the dataset might contain noises and it is essential to preprocess them before fitting them into the learning module. We apply rotation, resizing, and shearing to preprocess the image during the preprocessing phase.

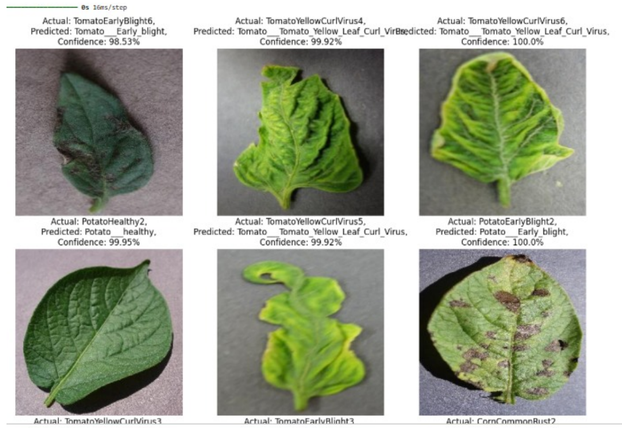


Figure 1. Dataset

3.2 Training and building the model

This step has two main phases. The TL models are trained using a training image dataset during the first phase. During the later phase, the architecture is validated using test images reserved for performance evaluation.

3.3 Model construction

To build the predictive model, we apply the following steps:

- Collecting images from the dataset.
- Pre-process image data by resizing and rotating images.
- Creating convoluted features and connecting them into Fully Connected Layers. Usually, the output of convolution is flattened into a one-dimensional (1D) vector and then passed through one or more fully connected layers.
- Finally, extracting the features for different classes of the input.

3.4 Model evaluation

To evaluate the model, we apply the following steps:

- From the dataset, 80% of images are used for training and 20% for testing.
- Validation data is used to check accuracy by applying the predict function and correctly extracting features.
- After good validation results, images are taken to confirm model detection performance.
- Finally, characteristics are analyzed to determine whether the leaves are infected or not.

3.5 Performance evaluation

In this phase, we obtain the best model based on the performance of the extensive experiments. We used accuracy, precision, recall, f1score, training accuracy, training loss, validation accuracy, and validation loss. This will help to build the smart web application with deep learning guidance.

4 RESULTS

The proposed Mobile-Net model was evaluated using the PlantVillage dataset with an 80:20 train–test split. The model achieved a training accuracy of around 96-98% and a validation accuracy of 96–97%, showing strong generalization. The confusion matrix indicated very few misclassifications, mainly in visually similar disease classes. Precision, recall, and F1-scores for most classes

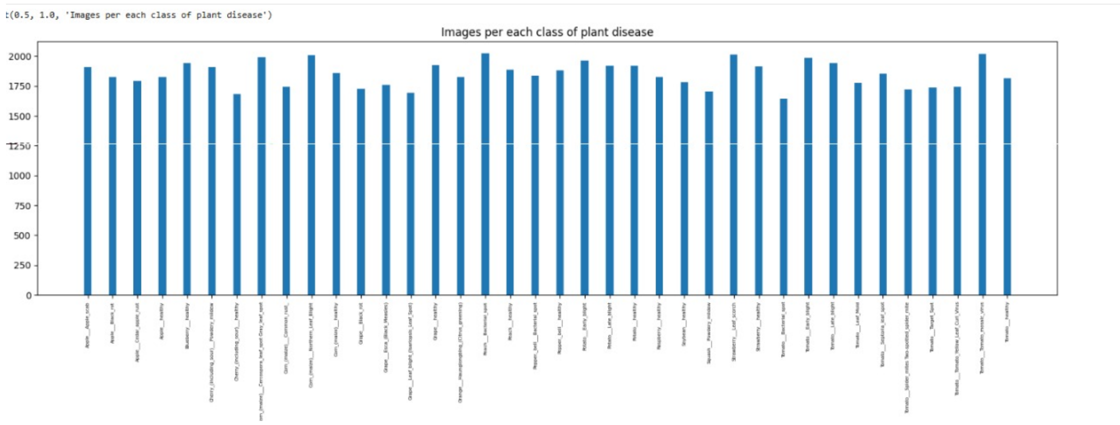


Figure 2. Result

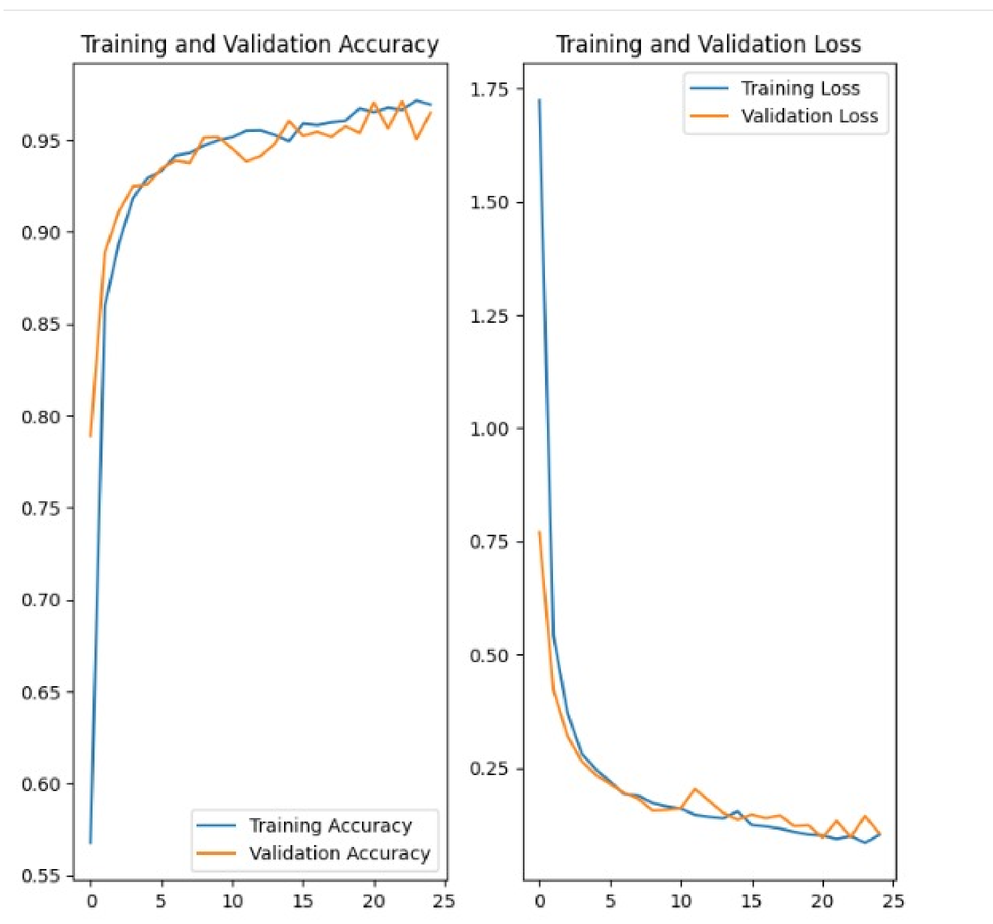


Figure 3. Training and Validation Accuracy and Loss

were above 95%, confirming high reliability. Compared to traditional machine-learning models such as SVM and KNN, the deep-learning approach performed significantly better. A prototype web interface was also tested, where the model accurately identified diseases from uploaded leaf images in real time, demonstrating practical applicability for farmers.

5 APPLICATION AREAS OF THE PROPOSED WORK

This research is noteworthy because of the contributions it makes to agricultural research. Its potential applications can be summarized as follows:

- **AI-enabled leaf disease detection system:** This proposal creates an opportunity to quickly and accurately identify diseased leaves by integrating a deep learning model. Our research improves the accuracy of predicting diseases. This can help experts make more accurate diagnoses, which in turn can improve harvest results.
- **Automated preventive measures:** The results of this study have practical applications in any environment where a web browser is available. By promptly uploading images of diseased crops, farmers can take corrective measures to enhance agricultural productivity.
- **Advancement in machine learning techniques:** Our research aids the development of deep learning models for use in the smart agricultural industry of any country. The findings of this research can be used to improve crop disease prediction and prognosis using deep-learning models that are both accurate and easy to interpret.

6 CONCLUSION

The primary objective of this project was to design and implement an AI-based plant disease detection system using the PlantVillage dataset, modern deep learning techniques, and an efficient MobileNet architecture. Throughout the development of the model, we focused on building a lightweight, scalable, and high-accuracy solution that could be deployed on real-world devices including mobile phones and low-resource systems. The experiments conducted during this study show that the combination of systematic data preprocessing, transfer learning, and a well-structured training pipeline significantly enhances model performance while keeping computational costs minimal.

Through rigorous preprocessing—such as image resizing, normalization, augmentation, and dataset balancing—we ensured that the input data captured meaningful variations found in real farm conditions. This preprocessing pipeline improved robustness and allowed the model to generalize better to unseen plant images. By integrating MobileNet, which is specifically optimized for speed and efficiency, we achieved an excellent balance between accuracy and inference time. MobileNet's depthwise separable convolutions allowed the network to extract rich features with far fewer parameters compared to traditional CNN models, enabling practical deployment even on low-end devices used by farmers in remote locations.

The results of the study confirm that the model is capable of accurately identifying multiple plant diseases with high precision. With proper training and fine-tuning, MobileNet consistently demonstrated strong classification performance on the PlantVillage dataset. Beyond numerical metrics, this system has the potential to create real-world impact: early detection of plant diseases can significantly reduce crop loss, minimize chemical misuse, and support sustainable agricultural practices. This project therefore represents an important step towards bridging the gap between modern AI research and accessible solutions for the agricultural community. Overall, the system demonstrates that deep learning–based disease detection is not only feasible but also reliable, scalable, and ready for further integration into smart farming ecosystems.

7 FUTURE WORK

Although the proposed AgriSense AI system performs well under controlled conditions, several improvements can be implemented in the future:

- **Real-world dataset expansion:** Training the model on field images captured under varying lighting, angles, and backgrounds will improve robustness.
- **Support for more crops and diseases:** Expanding the dataset to include additional plant species and rare diseases would increase the system's applicability.
- **Mobile application deployment:** Integrating the system into an Android or iOS app would make it more accessible to farmers in remote regions.

- **Real-time detection:** Optimizing the model for real-time inference on edge devices such as Raspberry Pi or smartphones.
- **Advanced NLP capabilities:** Replacing the rule-based chatbot with a fine-tuned transformer model to provide more accurate and context-aware farming suggestions.
- **Integration with weather and soil sensors:** Combining disease prediction with environmental data can enable proactive and preventive crop management.

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