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AI-Powered Deep Learning Web Application for Automated Plant Disease Diagnosis with Rich Visual Analytics

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ABSTRACT

This work presents an AI system powered by artificial intelligence and based on deep learning for diagnosing and detecting plant diseases. Using a CNN that has been trained and optimized on the Plant Village dataset, major crops such as tomatoes, potatoes, and bell peppers can have their illnesses properly classified. The method provides comprehensive diagnostic data, including taxonomy, organisms responsible for the disease, nutritional deficit mimics, and external symptoms, in addition to illness class predictions. Innovatively, the system incorporates the Rich Python library, which enables a graphical, colour-coded command-line interface. Because of this, users can receive detailed, interactive feedback within the terminal itself. The programme was designed with easy use in mind and is intended for use by researchers, educators, and farmers in real-world agricultural settings. Facilitating the detection and understanding of plant health issues in real time aids in learning and practical decision-making. This study demonstrates how integrating AI with agricultural diagnostics can enhance interpretability, usefulness, and overall impact. Finally, it stresses how technology based on deep learning could revolutionize crop health monitoring and agricultural education.

Keywords: Plant Disease Detection; Deep Learning; Image Classification; Convolutional Neural Network (CNN)

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1. Introduction

Agriculture sustains billions worldwide and underpins national food security in many developing nations. Rising populations have amplified the demand for higher yields, healthier produce, and sustainable practices. However, plant diseases remain a persistent challenge to productivity^[1]. Modern deep learning models, particularly optimized convolutional neural networks (CNNs), have revolutionized diagnosis through accurate early recognition. Architectural innovations, such as squeeze-and-excitation (SE) blocks and depth-wise separable convolutions, enhance CNNs by reducing parameters for mobile deployment and focusing on critical disease features^[2]. These improvements enable efficient, lightweight models suited for real-time detection in resource-constrained agricultural settings^[3]. The emergence of Artificial Intelligence (AI) has further advanced plant disease detection with scalable and precise solutions. CNNs and transformer-based architectures now achieve over 95% accuracy across various crop diseases. Lightweight models such as MobileNet and Mobile Plant ViT support smartphone or edge deployment, while explainable AI (e.g., Grad-CAM) builds farmer trust by visually clarifying predictions. Platforms like YOLOv8 and DS_Fusion Net already support early-stage, field-level monitoring. In India, NITI Aayog and India AI initiatives, alongside new Centers of Excellence, emphasize AI in agriculture. Programs such as Kissan AI and Dhenu provide real-time, multilingual guidance, while pilot projects in Madhya Pradesh and Punjab demonstrate field deployment^[4]. These developments align with the goal of democratized precision agriculture. AI delivers critical advantages to farmers and society. By providing rapid, cost-effective, and highly accurate diagnostics, especially in rural areas, AI reduces dependence on extension services or experts^[5]. Timely detection mitigates yield losses, improves quality, and stabilizes income. Because many systems operate on smartphones or low-power devices, they are accessible and scalable, extending benefits to underserved communities. Widespread adoption promotes sustainable farming, food security, and reduced environmental impacts by optimizing the use of pesticides and fer-

tilizers^[6]. Moreover, AI strengthens agricultural education, digital infrastructure, and rural empowerment, while multilingual interfaces integrated with national e-agriculture platforms help bridge the digital divide. Traditionally, disease detection depended on manual inspections by farmers or officials^[7]. While experience-based, this method is subjective, time-consuming, labor-intensive, and reliant on expert availability. Delayed diagnosis often accelerates disease spread, causing significant economic losses^[8]. The integration of AI with high-resolution imaging and deep learning provides real-time, scalable, and reliable alternatives. Farmers can identify crop diseases with a smartphone camera, while these systems adapt through feedback and updated datasets, ensuring long-term relevance^[9]. This project, therefore, proposes an AI-driven tool that is lightweight, accurate, and user-friendly, specifically designed for mobile and edge deployment. It supports farmers, agricultural workers, and researchers in real-time field-based disease surveillance, enhancing crop health, sustainable practices, and food security. Globally, deep learning and transformer-based architectures^[10] continue achieving > 95% accuracy, while explainable AI enhances interpretability. Lightweight designs like MobileNet and Mobile Plant ViT extend reach to handheld devices, and field platforms such as YOLOv8 and DS_Fusion Net enable large-scale monitoring^[11]. In India, government programs under NITI Aayog and India AI, alongside pilot projects, reinforce AI-driven infrastructure, while initiatives like Kissan AI and Dhenu provide multilingual advisory systems. These developments signify crucial progress toward accessible, democratized diagnostics^[12]. The societal benefits of AI in plant pathology are profound. Farmers gain autonomy and efficiency, reducing reliance on traditional extension systems. Early intervention decreases losses, improves yield quality, and ensures income stability^[13]. At scale, these tools enhance sustainability, food security, and environmental protection. Beyond farming, they contribute to education, digital empowerment, and infrastructure development. Multilingual interfaces and integration with national e-agriculture frameworks ensure inclusivity. Plant diseases, often manifesting as leaf discoloration, stains, or fungal growth, pose major threats

to crop output. Manual inspection, though common, is limited and inconsistent^[14]. AI-powered solutions offer transformative alternatives by combining scalability, precision, and adaptability. By supporting early diagno-

sis, continuous improvement, and real-time deployment, these systems represent a paradigm shift for agriculture. Ultimately, they empower farmers, improve sustainability, and safeguard global food security (**Figure 1**).

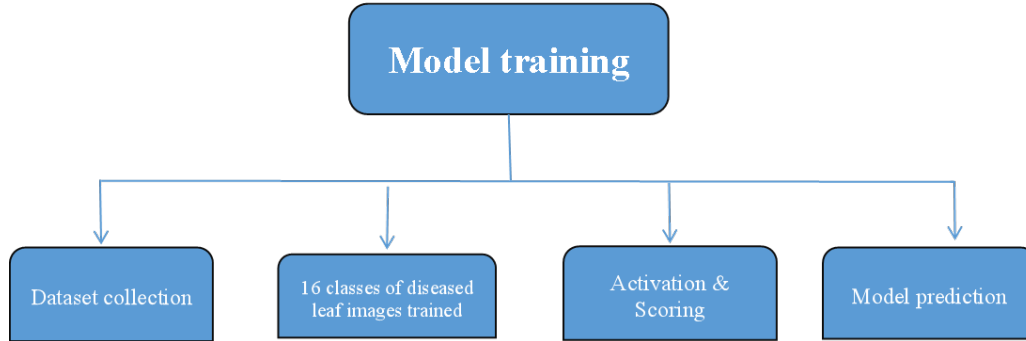


Figure 1. Model training of the plant village dataset.

Delays in diagnosing plant diseases allow rapid spread, leading to significant crop and financial losses^[15]. Recent advances in AI and computer vision have transformed plant disease detection, enabling farmers to identify illnesses using only a smartphone camera, combined with deep learning and high-resolution images^[16]. These AI-driven tools provide fast, scalable, and reliable diagnoses and can be deployed on mobile platforms linked with regional databases and advisory systems to monitor outbreaks. Continuous updates and user feedback further improve their accuracy and adaptability across various locations and seasons. This study focuses on developing a portable, precise, and user-friendly AI-based tool for real-time field diagnosis, supporting sustainable agriculture and food security.

2. Materials and Methods

2.1. Dataset

The dataset utilised in this study is sourced from the publicly available Plant Village. The dataset, a prominent and widely utilised benchmark repository in plant pathology and artificial intelligence, established and subsequently hosted on platforms like Kaggle, contains over 50,000 high-resolution images of plant leaves, annotated with labels indicating both healthy states and various disease categories. The photos contain 14 distinct crop species, including tomato, potato,

corn, grape, and bell pepper, and cover over 38 varieties of plant illnesses induced by pathogens such as fungus, bacteria, and viruses. This study specifically concentrated on three commercially significant and widely farmed crops: tomato (*Solanum lycopersicum*), potato (*Solanum tuberosum*), and bell pepper (*Capsicum annuum*). Fifteen unique classes were curated from the dataset, encompassing both healthy and diseased leaf photos for these crops. Every image underwent pre-processing and resizing to ensure uniformity throughout the dataset, hence optimising performance during model training and evaluation. The diversity, richness, and quality of the Plant Village dataset render it an optimal basis for training deep learning models to accurately identify and categorise plant diseases in a robust and scalable manner.

2.2. Preprocessing

To ensure optimal performance of the convolutional neural network model for plant disease diagnosis, a comprehensive preprocessing pipeline was implemented to prepare the Plant Village dataset images for training and inference. Preprocessing is a critical step in deep learning workflows, as it standardises input data, reduces computational overhead, and enhances model robustness against real-world variability. The preprocessing steps included image resizing, pixel value normalisation, data augmentation, conversion to NumPy ar-

rays, and batching. Each step was carefully designed to maintain the integrity of visual features essential for accurate disease classification while ensuring compatibility with the deep learning framework and minimising errors during training and inference^[17].

2.2.1. Image Resizing

All images in the dataset were resized to a uniform resolution of 126×126 pixels. This resolution was chosen as a balance between preserving essential visual features, such as leaf textures and disease-specific patterns (e.g., spots, discolouration, or wilting), and reducing computational complexity. High-resolution images, while rich in detail, significantly increase the memory and processing requirements of convolutional neural networks, which can be prohibitive for deployment on resource-constrained devices, such as smartphones or edge hardware used by farmers in rural settings^[11]. The 126×126 resolution ensures that critical diagnostic features, such as lesion shape and distribution, remain discernible while enabling efficient computation. Resizing was performed using bilinear interpolation, a method that smooths pixel transitions to prevent the loss of subtle disease indicators, ensuring that the resized images retain sufficient detail for accurate classification.

2.2.2. Pixel Value Normalisation

To enhance training efficiency and model convergence, pixel values of all images were normalised to a range of 0–1. Raw image pixel values typically range from 0 to 255 in RGB format, which can lead to numerical instability during gradient-based optimisation due to large value ranges. Normalisation was achieved by dividing each pixel value by 255, transforming the data into a standardised scale. This process stabilises the training process by ensuring that the gradients computed during backpropagation are within a manageable range, facilitating faster convergence and reducing the risk of vanishing or exploding gradients^[16]. Additionally, normalisation aligns the input data distribution with the expectations of the pre-trained MobileNet model, which was initialised with ImageNet weights, thereby improving the effectiveness of transfer learning for plant disease classification.

2.2.3. Data Augmentation

To increase the diversity of the training dataset and improve the model's robustness against real-world variations, a suite of data augmentation techniques was applied. These techniques simulate natural variations in field conditions^[18], such as differences in lighting, orientation, and perspective, which are common when farmers capture images using smartphones. The augmentation methods included:

- **Random Rotations:** Images were rotated by random angles between -30 and 30 degrees to account for variations in how leaves are photographed in the field. This helps the model generalise to images captured from different angles, such as tilted or upside-down orientations.
- **Horizontal and Vertical Flips:** Random flipping of images along the horizontal and vertical axes was applied to mimic natural variations in leaf positioning. This ensures that the model learns to recognise disease patterns regardless of the leaf's orientation.
- **Brightness Adjustments:** Random brightness shifts within a range of $\pm 20\%$ were applied to simulate variations in lighting conditions, such as images taken under sunlight, shade, or artificial light^[8]. This enhances the model's ability to handle diverse environmental conditions.
- **Zoom and Cropping:** Random zooming (up to 10%) and cropping were used to simulate partial leaf visibility or varying distances between the camera and the leaf, ensuring robustness to incomplete or close-up images.
- **Shear Transformations:** Slight shear transformations (up to 15 degrees)^[13] were applied to mimic distortions caused by camera angles, further enhancing model generalisation.

Data augmentation effectively increases the effective size of the dataset without requiring additional data collection, mitigating overfitting and improving the model's ability to generalise to unseen images. This is particularly important for the Plant Village dataset, which, despite its richness (over 50,000 images), may not fully capture the variability encountered in real-world agricultural settings^[19]. By applying these augmentations, the model be-

comes more resilient to challenges such as inconsistent lighting, varying image quality, and diverse leaf orientations, which are critical for practical deployment in field-based diagnostics.

2.2.4. Conversion to NumPy Arrays

Images were converted into NumPy arrays to facilitate efficient processing within the TensorFlow and Keras frameworks. NumPy arrays provide a compact and computationally efficient format for representing multidimensional image data, enabling seamless integration with the convolutional neural network model. Each image, originally in a standard image format (e.g., JPEG), was transformed into a three-dimensional array of shape (126, 126, 3), corresponding to the height, width, and RGB colour channels. This conversion ensures compatibility with the model's input layer and enables rapid matrix operations during training and inference^[20]. The use of NumPy arrays also simplifies data manipulation, such as batching and shuffling, which are essential for efficient model training.

2.2.5. Batching and Data Pipeline Optimisation

To streamline model training and inference, images were organised into batches of 32 samples. Batching reduces memory usage by processing data in smaller chunks, allowing the model to handle large datasets like Plant Village without overwhelming system resources. The dataset was split into training (70%), validation (20%), and testing (10%) sets to support model development and evaluation. A data pipeline was established using TensorFlow's `tf.data` API to automate the loading, preprocessing, and batching of images. This pipeline included shuffling to ensure the randomisation of training samples, prefetching to reduce I/O bottlenecks, and caching to minimise redundant preprocessing, thereby improving training efficiency^[21]. These optimisations ensured that the model could process the dataset quickly and consistently, reducing training time and enhancing scalability for real-time applications.

2.2.6. Rationale and Impact

The preprocessing pipeline was designed to address the unique challenges of plant disease diagnosis in real-world agricultural settings. By resizing images,

the system achieves computational efficiency, making it feasible for deployment on low-power devices commonly used by farmers. Normalisation ensures numerical stability, enabling the model to leverage pre-trained weights effectively. Data augmentation enhances robustness, allowing the model to handle diverse field conditions, such as varying lighting or camera angles, which are common in images captured by non-expert users. Conversion to NumPy arrays and batching optimise the data pipeline, ensuring compatibility with deep learning frameworks and enabling efficient training on large datasets^[19].

These steps collectively minimise errors during training and inference by ensuring data consistency and reducing the risk of overfitting. For example, augmentation mitigates the risk of the model memorising specific image patterns, while normalisation and batching improve convergence and computational efficiency. The preprocessing pipeline is particularly critical for the system's target audience—farmers, researchers, and educators in resource-constrained environments—where robust and efficient performance is essential for practical adoption. By addressing these technical requirements, the preprocessing steps lay a strong foundation for the CNN model to achieve high accuracy (~95%) in classifying plant diseases, as demonstrated in the results.

2.2.7. Considerations for Real-World Applicability

In designing the preprocessing pipeline, special attention was given to its applicability in real-world agricultural contexts. The choice of a 126×126 resolution ensures compatibility with low-resolution cameras found in budget smartphones, which are widely used in rural areas. Data augmentation techniques were selected to reflect common challenges in field photography, such as variable lighting and partial leaf visibility, ensuring that the model performs reliably under diverse conditions. Furthermore, the pipeline's modular design allows for easy adaptation to other datasets or crops, supporting future expansions of the system. For instance, additional augmentation techniques, such as colour jittering or noise injection, could be incorporated to handle specific environmental challenges, such as images taken in foggy or dusty conditions^[12].

The preprocessing steps also consider the constraints of edge devices, where computational resources are limited. By optimising image size and processing efficiency, the pipeline ensures that the system can operate on devices with minimal hardware specifications, such as low-end smartphones or embedded systems. This aligns with the project's goal of democratising precision agriculture, making advanced diagnostic tools accessible to farmers in under-resourced regions. Future improvements to the pipeline could include adaptive preprocessing techniques that adjust based on input image quality or device capabilities, further enhancing usability and performance.

2.3. Model Architecture

The core of the system is a pre-trained convolutional neural network based on the MobileNet architecture, fine-tuned for the specific task of plant disease classification.

Mobile Net’s lightweight design, utilising depth-wise separable convolutions, makes it ideal for deployment on resource-constrained devices like smartphones and edge hardware^[21]. The model was initialised with weights pre-trained on the ImageNet dataset, leveraging transfer learning to reduce training time and computational resources while achieving high accuracy.

The architecture was customised by adding dense layers tailored to the 15-class classification task. Squeeze-and-excitation (SE) blocks were incorporated to enhance feature recalibration, allowing the model to focus on disease-specific patterns in leaf images^[22]. The model outputs a probability distribution across the 15 classes, with the highest probability class selected as the predicted disease or healthy state. The Adam optimiser was used with a learning rate of 0.001, and categorical cross-entropy was employed as the loss function to handle multi-class classification (**Figure 2**).



Figure 2. Model accuracy of the plant village dataset.

2.4. Metadata Mapping and Enrichment

Each class label is linked to a structured dictionary containing detailed metadata, which includes:

- Plant type (e.g., Tomato, Potato, Bell Pepper)
- Taxonomical name (e.g., *Solanum lycopersicum*)
- Disease name and condition (e.g., Early Blight, Healthy)
- Cause or pathogen (e.g., *Alternaria solani*, *Xanthomonas* spp.)
- Nutrient deficiency symptoms that may mimic the disease
- Diagnostic features (e.g., leaf spots, mold appearance, leaf curling)

2.5. System Implementation

The system was developed using Python version 3.10 with TensorFlow and Keras for model training and inference. The Rich Python library was integrated to create a visually appealing, color-coded command-line interface. Upon receiving an input image, the system processes it through the Convolutional Neural Network model, generates a prediction, and displays the results in a structured panel. The panel includes the predicted disease, confidence score, and detailed metadata, formatted for clarity and accessibility. Matplotlib was used to display the input image alongside diagnostic outputs, enhancing user understanding. The application was designed for deployment on web and mobile platforms, with a focus on low computational requirements. This ensures compatibility with low-power devices commonly used by farmers in rural settings. The system's modular design allows for easy updates, such as adding new crop species or diseases, ensuring long-term relevance^[23].

3. Results and Discussion

The developed system accurately classifies plant diseases and generates informative diagnostic reports beyond a simple healthy/diseased outcome. Each prediction begins with the plant's scientific and common names, ensuring clarity for both farmers and researchers^[24]. The system then identifies the disease and its causal agent, while describing characteristic symptoms such as leaf

spots, wilting, chlorosis, or necrosis. This structured output supports field-based diagnosis, providing users with deeper insights into the problem. A notable strength of the system is its ability to reduce diagnostic confusion by addressing nutrient deficiency conditions that mimic diseases^[25]. For instance, nitrogen, potassium, or magnesium deficiencies may cause leaf yellowing or spotting, which resembles fungal or bacterial infections. By highlighting these overlaps and offering guidance on distinguishing nutrient stress from true disease, the tool helps minimize misdiagnosis. Another distinctive feature is the inclusion of a confidence score that quantifies the reliability of predictions^[26]. Expressed as a percentage, the score is categorized as high (> 85%), moderate (70–85%), or low (< 70%). For example, when analyzing a tomato leaf, the system might report: “Tomato (*Solanum lycopersicum*) – Diseased – Septoria Leaf Spot,” with details on typical symptoms, such as brown spots with grey centers and yellow halos, and a confidence level of 92% (high). If confidence is below 70%, the system advises expert consultation, preventing reliance on uncertain results^[27]. By combining scientific naming, causal agent identification, detailed symptom descriptions, differential diagnosis with nutrient deficiencies, and measurable confidence levels, the system delivers a holistic diagnostic framework^[28]. This approach not only improves diagnostic accuracy but also builds user trust, empowering farmers and researchers with actionable insights for sustainable crop management.

3.1. Visualization and User Interaction

The Rich Python package is utilised to develop an interesting and interactive command-line user experience (**Figure 3**). Upon prediction, the system presents the input image, succeeded by a structured panel that includes comprehensive diagnostic information. This improves the interpretability of the AI system, enabling users without a technical background to get benefits from the results.

For example, when an image of a tomato leaf with Septoria Leaf Spot is analyzed (**Figure 4**), the model accurately detects the condition, displays “Tomato (*Solanum lycopersicum*) – Diseased – Septoria Leaf Spot,” and includes the specific symptoms and causes associated with this disease.

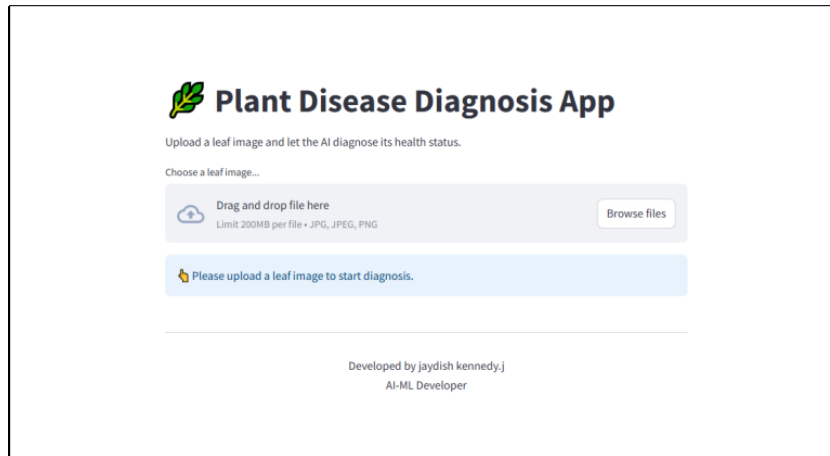


Figure 3. Home page of the web application.

Source: <https://plant-disease-diagnosis-5rbyj9jzfa4cbf2q2pn5j2.streamlit.app/>

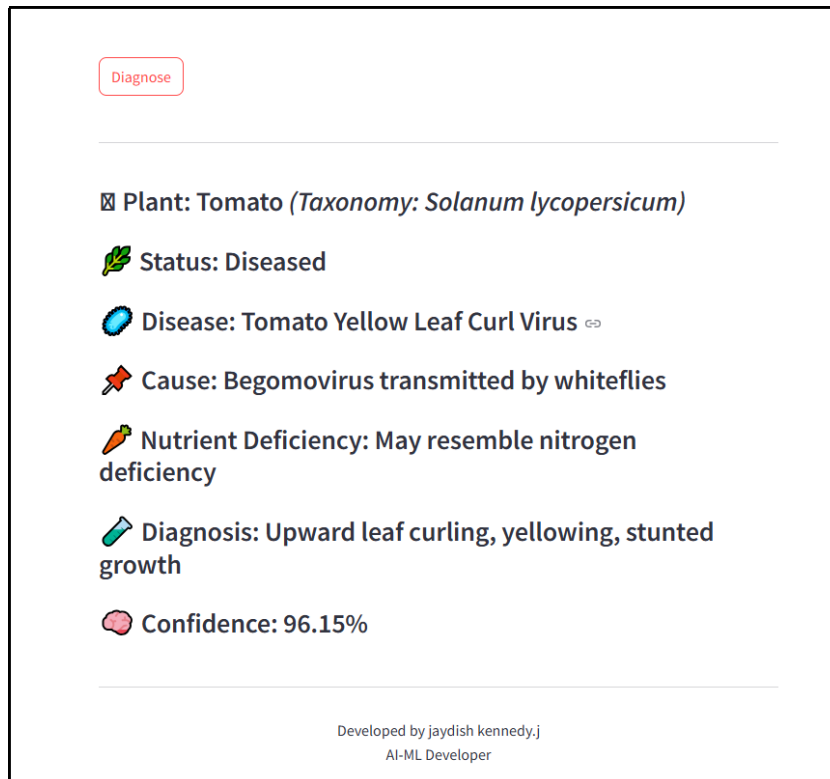


Figure 4. Result of uploaded image.

3.2. Visual Feedback

- Display of the original input image using Matplotlib.
- Styled console panel with diagnosis details.
- Highlighted confidence score with advisory if confidence is low.

3.3. Sample Input Images

- Tomato leaf.

- Alternaria leaf (**Figure 5**)

3.4. Model Summary

- Pre-trained Convolutional Neural Network model with custom final layers (**Figure 6**).
- Accuracy: ~95% on test set.
- Optimizer: Adam.
- Loss Function: Categorical Cross-entropy.

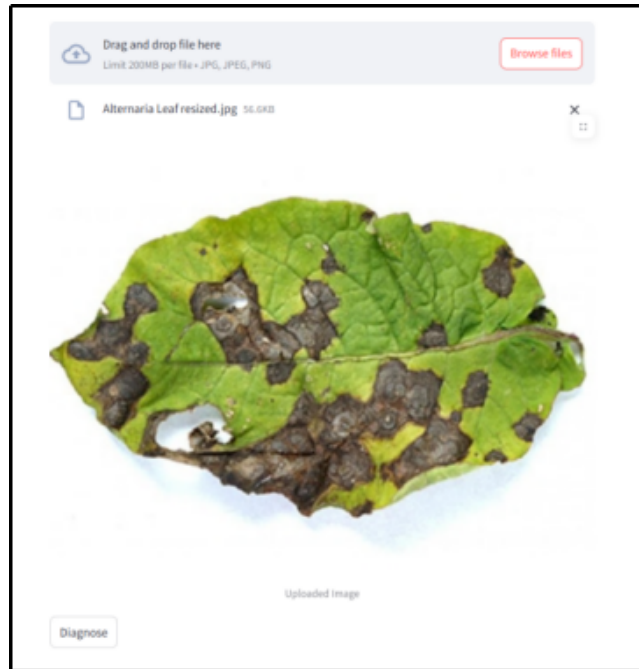


Figure 5. Uploaded image.

Model: "sequential"		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 256)	6,422,784
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 15)	3,855
Total params: 19,559,663 (74.61 MB)		
Trainable params: 6,519,887 (24.87 MB)		
Non-trainable params: 0 (0.00 B)		
Optimizer params: 13,039,776 (49.74 MB)		

Figure 6. Model summary.

3.5. Confidence Thresholds

- High confidence: > 85%.
- Moderate confidence: 70–85%.
- Low confidence: < 70% (prompt user to seek expert

validation).

The application of artificial intelligence (AI) in plant disease detection offers revolutionary benefits for contemporary agriculture. AI dramatically decreases

the time and labour historically necessary to diagnose crop illnesses through automation. Tasks that previously required hours or days of visual analysis by skilled plant pathologists can now be accomplished in seconds using a smartphone and a trained model^[29]. In agriculture, where prompt action can determine the preservation or total loss of a harvest, the swift response time is particularly advantageous. A notable advantage of these systems is their appropriateness for field deployment. In contrast to traditional laboratory diagnoses or expert consultations, AI-driven solutions can function on low-power mobile devices with minimal hardware specifications. This makes them particularly advantageous in remote and rural regions where access to agricultural extension agencies, laboratories, or skilled professionals is either limited or non-existent. In these situations, farmers can obtain immediate feedback by photographing a diseased leaf, which provides both disease categorisation and suggested interventions. The functionality of these systems is augmented by the integration of user interface libraries, such as Rich, which facilitate lively, organised, and interactive command-line or terminal outputs. Such functionality enhances user engagement and accessibility for persons with little technical proficiency—an essential consideration when developing applications intended for broad use by farmers, students, or educators. Enhancing the system's visual intuitiveness is essential for broad acceptance, particularly in multilingual, multi-literate agricultural communities^[30]. Nonetheless, despite the considerable advantages, existing solutions encounter specific restrictions. The AI model is trained on a predetermined dataset, signifying its capacity to identify a limited array of plant illnesses for designated crops. Should a novel illness arise or if the user provides an image of a plant absent from the training data, the system may yield erroneous results or be unable to generate a prediction. The model's accuracy is significantly contingent upon image quality. Blurry, inadequately illuminated, or partially concealed leaves may impede the classification process^[16]. Complicated real-world situations, including concurrent infections, pest infestations, or environmental stressors (e.g., nutrient deficiencies or climatic impacts), can undermine the system's reliability, as these

conditions may be inadequately represented in the training dataset. Notwithstanding these constraints, the existing system provides a solid basis for forthcoming advancements. Numerous improvements can be anticipated to broaden its reach and efficacy.

4. Practical Implications

The system's ability to deliver rapid and accurate diagnoses has significant implications for agriculture. Automating disease detection reduces the time and labour required compared to traditional methods, which can take hours or days. This is particularly critical in time-sensitive agricultural contexts, where early intervention can prevent widespread crop losses^[31]. The system's compatibility with mobile devices makes it accessible to farmers in remote areas, where access to extension services is limited. For example, a farmer in rural India can photograph a diseased leaf using a smartphone, receive an immediate diagnosis, and access recommendations for treatment, all without leaving the field. The integration of the Rich Python library enhances usability by presenting complex diagnostic information in an intuitive format. This is especially valuable in multilingual and multi-literate communities, where clear communication is essential for adoption^[32]. The system's educational value is further amplified by its detailed metadata, which can be used in agricultural training programmes to teach students and farmers about plant pathology and disease management.

5. Limitations and Challenges

Despite its strengths, the system has limitations that require careful consideration. The scope of the Plant Village dataset, which includes a finite set of crops and diseases, constrains the model's performance. Novel diseases or crops not represented in the dataset may lead to inaccurate predictions. Additionally, image quality is crucial; blurry, poorly lit, or partially obscured images can decrease the accuracy of classification^[33]. Additionally, real-world complexities, such as co-occurring diseases, pest damage, or environmental stressors, may not be fully captured in the training data, which can potentially affect

reliability. The system's reliance on a command-line interface, while innovative, may pose challenges for users unfamiliar with terminal-based applications. Future iterations aim to address those issues by developing a graphical user interface (GUI) for web and mobile platforms, further enhancing accessibility. Finally, the model's computational requirements, while optimised, may still be challenging for older or low-spec devices, necessitating further light-weighting efforts^[34].

6. Conclusions

This initiative demonstrates how AI and deep learning can significantly improve plant health management by providing fast, accurate, and reliable disease diagnosis. Using a CNN model combined with an intuitive console interface, the system empowers farmers, researchers, and agricultural consultants to quickly identify plant illnesses and take corrective action. By integrating biological taxonomy with diagnostic details, the tool not only supports decision-making but also enhances learning and awareness. Looking ahead, future developments include deploying the model as a mobile application, expanding the dataset to cover more crops and conditions, and adding multilingual support to make the technology accessible to diverse user communities, thereby advancing plant health improvements on a broader scale.

Future improvements will focus on expanding the dataset to include more crop species and diseases, adding multilingual support to reach diverse user groups, and developing a mobile app with an intuitive interface for easier use. The system will also integrate with IoT devices for real-time field monitoring and adopt explainable AI methods like Grad-CAM to offer graphic representations of predictions. Together, these enhancements will make the tool more scalable, accessible, and reliable across varied agricultural contexts.

Author Contributions

Conceptualization, J.J.K.; methodology, J.J.K.; software, J.J.K.; validation, J.J.K. and G.C.; formal analysis, J.J.K. and G.C.; investigation, G.C.; resources, G.C.; data curation, J.J.K.; writing—original draft preparation, J.J.K. and

G.C.; writing—review and editing, J.J.K. and G.C.; visualization, J.J.K.; supervision, J.J.K.; project administration, J.J.K.; funding acquisition, G.C. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Data Availability Statement

The dataset used in this study is publicly available from the Kaggle repository: *Plant Village Dataset* (<https://www.kaggle.com/datasets/emmarex/plantdisease>).

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Conflicts of Interest

The authors declare that there is no conflict of interest.

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