

Automated Identification of Plant Bacterial Diseases Using Computer Vision Techniques

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ABSTRACT

Plant diseases pose a significant threat to global food security by reducing crop yield and quality. Accurate and early identification of such diseases is very important for effective management and prevention. Traditional disease identification methods rely on laboratory and visual inspection, which are time-consuming, labour-intensive, require expert knowledge and are often inaccurate. In recent years, computer vision and artificial intelligence (AI) have emerged as promising tools for automatically detecting plant diseases. This study presents an automated system for detecting plant bacterial diseases in leaf images via computer vision and deep learning. The datasets contain 1200 images representing healthy and infected leaves from crops such as tomatoes, rice and lemon, which were analyzed. Firstly, pest-associated symptoms were carefully screened and excluded through field level observations, integrating entomological knowledge to distinguish insect damage from bacterial infections. In addition, laboratory based bacterial isolation and biochemical characterization was performed to confirm presence of casual pathogens, ensuring the authenticity of the dataset. Image pre-processing techniques such as segmentation, resizing and normalization were applied to enhance the feature extraction. Convolutional Neural Networks (CNN) were used to classify bacterial diseases such as bacterial leaf blight, bacterial spot and citrus canker. The model achieved an overall accuracy of 93.4% with precision and recall values exceeding 90% for most disease categories. The results demonstrate that vision-computer-based systems can effectively differentiate between healthy and diseased plants based on visual symptoms such as discolorations, lesions and texture changes. This study highlights the potential of AI-driven

approaches in plant pathology, offering rapid, cost-effective and scalable solutions for disease detection at the initial stage. The integration of such technologies into agricultural practices can improve disease management, be cost-effective and reduce reliance on chemical treatments. Future research should focus on improving model generalization and real-time field deployment for sustainable agriculture.

Keywords: Computer Vision; CNN; Precision; Recall; Bacterial Diseases

INTRODUCTION

Agriculture plays a vital role in global food production. But plant diseases caused by bacterial pathogens represent a sustainable loss in crop yield every year globally. Crops such as tomatoes, rice and lemon are particularly vulnerable to bacterial infections, including bacterial leaf blight caused by *Xanthomonas oryzae*, bacterial wilt caused by *Ralstonia solanacearum* and citrus canker caused by *Xanthomonas citri* (Strange and Scott, 2005). These diseases result in significant economic losses and threaten food security, especially in developing countries.

Traditional methods for identifying plant bacterial diseases rely on visual diagnostic techniques such as biochemical assays, culturing and molecular methods (PCR). While these methods are reliable, they are also time-consuming, require specialized expertise and are not always feasible for large-scale monitoring (Bock et al., 2010). Moreover, visual diagnosis can be subjective and prone to error, particularly in the early stages of infection.

Recent advancements in artificial intelligence, particularly in computer vision and deep learning, have opened new avenues for automated plant disease detection. Computer vision techniques enable machines to interpret and analyze visual information from images, making it possible to identify disease symptoms based on colour, texture and shape features (Mohanty et al., 2016). Conventional Neural Networks (CNNs), a class of deep learning models, have demonstrated remarkable success in image classification tasks, including plant disease detection.

Several studies have reported high accuracy rates in detecting plant diseases using deep learning models. For example, Mohanty et al. (2016) achieved over 99% accuracy in classifying plant diseases using a large dataset of leaf images. Similarly, Ferentinos (2018) demonstrated the effectiveness of identifying multiple plant diseases with high precision.

Despite these advancements, limited research has focused especially on bacterial diseases, which often present subtle and overlapping symptoms. Therefore, the present study aims to evaluate the effectiveness of computer vision techniques in the automated identification of plant bacterial diseases using image-based analysis. Unlike existing studies (Table 1) that primarily focused on general plant disease detection using a controlled dataset, the proposed work specifically targets bacterial diseases, which are more challenging due to subtle visual symptoms.

Table 1: Literature Review

Author(s) & Year	Technique used	Dataset	Key Contribution	Accuracy/Findings
Sujatha et al., 2025	ML+DL hybrid approach	Leaf Dataset	Combined feature extraction and classification approach	Improved detection accuracy
Shafay et al., 2025	Advanced AI models	Multiple datasets	Discuss challenges and future directions	Highlights the need for robust real-time systems
Mishra et al., 2025	CNN, ResNet, EfficientNet	PlantVillage+Mango dataset	Comparative study of DL models	Accuracy upto~97%
Jelali et al., 2024	CNN-based model	Real-Field tomato datasets	Focus on real-world dataset challenges	Field conditions reduce accuracy
Pacal et al., 2024	Deep learning models	Multiple datasets	Survey of advanced DL architectures and challenges	Emphasis on scalability and dataset issues
Ramanjot et al., 2023	ML+DL hybrid approach	PlantVillage	Systematic review of classification techniques	DL outperforms ML traditional methods
Shoaib et al., 2023	Deep Learning (CNN, DL models)	Multiple datasets	Detailed review of DL models for identifying plant diseases	CNN is widely used with high performance

METHODOLOGY

Proposed System Architecture

The workflow of the proposed system is shown in Figure 1, which displays the automated plant disease detection using CNN computer vision techniques.

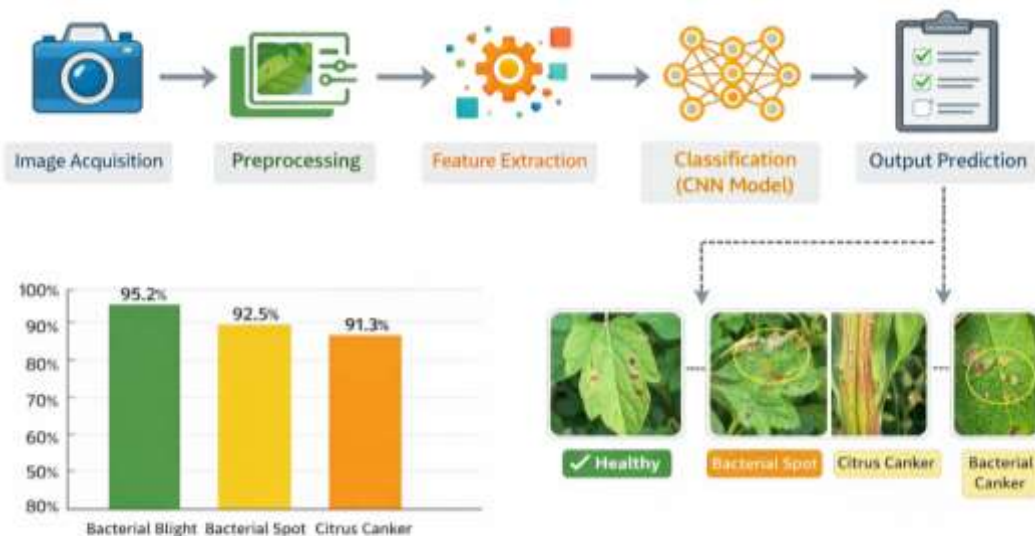


Figure 1: Proposed System Methodology

Screening of Bacterial and Non bacterial (Pest-associated) Symptoms

To ensure accuracy of the computer vision model, only bacterial diseases were included in the dataset. Field observations initially included a wide range of plant abnormalities such as insect feeding damage, fungal infections, and nutrient deficiencies. However, these conditions often produce symptoms similar to bacterial infections, including leaf spots, discoloration, and necrosis.

Therefore, a screening process was implemented to differentiate bacterial diseases from pest related and other non bacterial conditions. Samples exhibiting signs of insect infestation such as chewing marks, holes, frass deposition, or presence of larvae were excluded. Similarly, fungal infections characterized by powdery growth, concentric rings, or spore structures were removed. Only those samples showing water-soaked lesions, angular spots, or characteristic bacterial blight symptoms were selected for further analysis and model trainings (Agrios, 2005; Strange and Scott, 2005).

Bacterial Isolation and Identification

For laboratory confirmation, symptomatic leaf samples of rice, tomato, and lemon were collected and processed for bacterial isolation. Infected tissues showing typical lesions were surface sterilized using 70% ethanol followed by rinsing with sterile distilled water. Small sections from the lesion margins were macerated in sterile saline and streaked onto nutrient agar and selective media such as King's B medium. The inoculated plates were incubated at 28 ± 2 °C for 24-48hours to obtain discrete colonies.

Bacterial isolates were initially characterized based on colony morphology, including shape, size, color, and texture. Gram staining was performed to determine cell wall characteristics, while motility was examined using the hanging drop technique.

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Further identification was carried out using standard biochemical tests such as catalase, oxidase, Indol, methyl red, voges proskauer, citrate utilization, starch hydrolysis, and sugar fermentation assays. The obtained characteristics were compared with standard descriptions as per previous studies (Schaad et al., 2001; Agrios, 2005).

Dataset

The dataset used in this research work consists of 1200 images of plant leaves collected from publicly available repositories such as Plant Village and field observations. The dataset included images of healthy leaves and leaves infected with bacterial diseases, including bacterial leaf blight (Rice/*Oryza sativa*), bacterial spot (Tomato/*Solanum lycopersicum*), and citrus canker (Lemon/*Citrus limon*). Images were selected to represent different stages of infection and varying environmental conditions, ensuring model robustness (Figure 2).

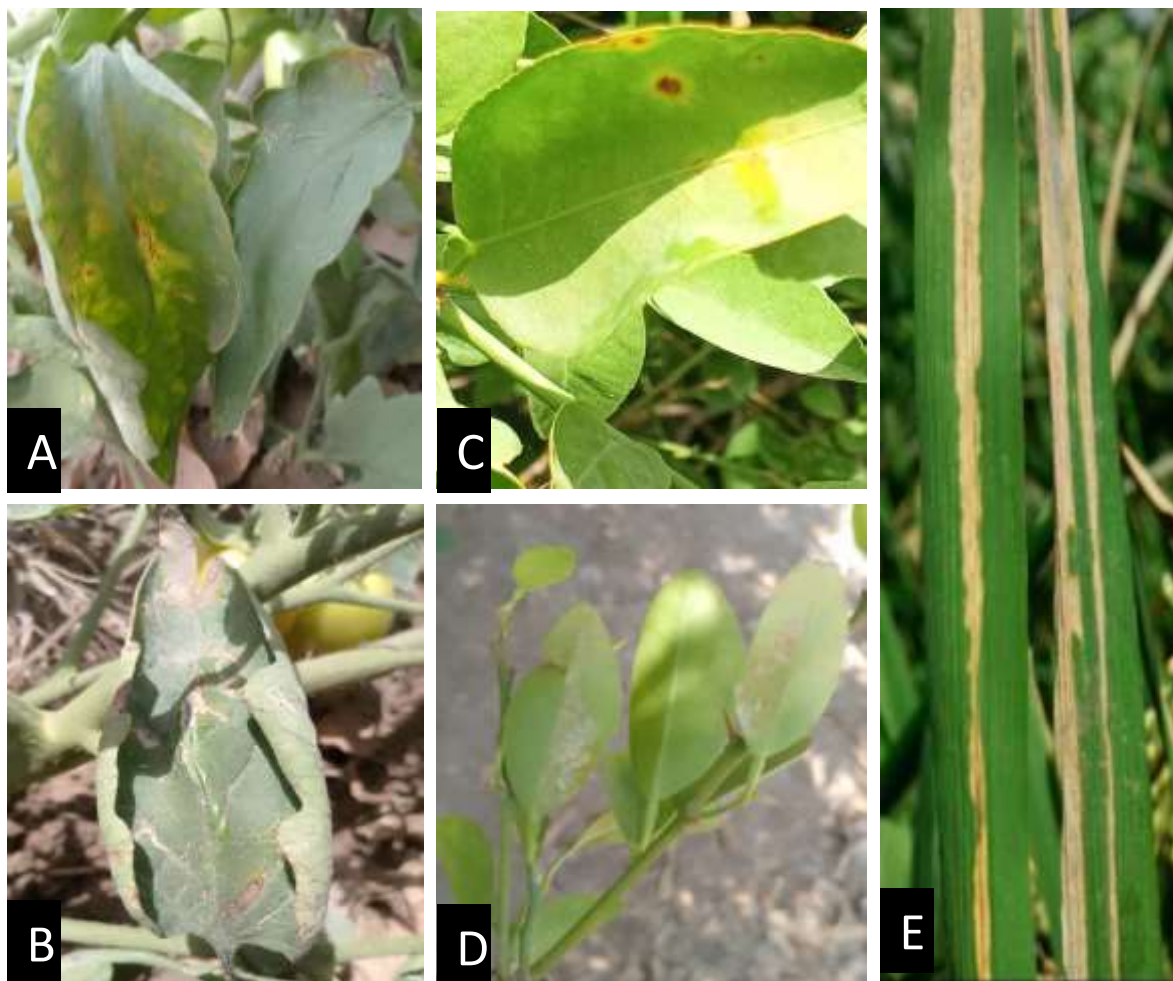


Figure 2: Diseased Leaves of crops: A, B (Tomato); C, D (Lemon); E (Rice)

Image Manipulation

All images were preprocessed before analysis. Pre-processing involved resizing images to a uniform resolution of 224^x224 pixels to standardize input for the neural networks. Image normalization between 0 and 1 was applied to scale pixel values, improving model convergence. Background noise was reduced using segmentation techniques, allowing the model to focus on relevant features such as lesions and discoloration.

Feature extraction was performed using a Convolutional Neural Network (CNN). The model consisted of multiple convolutional layers for detecting edges, textures, and patterns, followed by pooling layers to reduce dimensionality. Fully connected layers were used for classification. The dataset was divided into training (70%), validation (15%), and testing (15%) sets.

Model performance was evaluated using standard metrics, including accuracy, precision, recall, and F1-score. Confusion matrices were generated to assess classification performance across different disease categories. The model was implemented using Python and the TensorFlow framework.

RESULTS

Exclusion of Pest-associated Symptoms and Dataset Refinement

During field sampling and dataset preparation, a number of leaf samples exhibited symptoms caused by insect pests rather than bacterial infections. In rice, damage caused by the leaf folder and stem borer had resulted in folded leaves and feeding scars. In tomato, insect pests such as whiteflies and aphids produced chlorosis and leaf curling, while in lemon, leaf miner infestation caused serpentine mines that could be mistaken for disease symptoms.

Through careful visual inspection and laboratory verification, these pest related samples were excluded from the dataset. The screening process ensured that only bacterial disease symptoms were retained for analysis. This refinement improved the accuracy of the model by eliminating confounding factors and reducing misclassification between biotic stress caused by pests and bacterial infections. Consequently, final dataset used in this study represents true bacterial disease conditions, enhancing the reliability of the computer vision-based classification system (Agrios, 2005; Bock et al., 2010).

Laboratory confirmation of Bacterial Pathogens

The laboratory based isolation and identification procedures confirmed the presence of bacterial pathogens associated with the selected diseases. Colonies obtained on media were typically circular, smooth, and yellowish in appearance, consistent with *Xanthomonas* species. Gram staining revealed that all isolates were Gram negative rods, which is a characteristic feature of these pathogens. Biochemical tests showed positive catalase activity and variable oxidase reactions, further supporting their identification (Table 2).

Isolates from rice samples were identified as *Xanthomonas oryzae*, responsible for bacterial leaf blight, while those from lemon leaves corresponded to *Xanthomonas citri*, the causal agent of citrus canker. Similarly, bacterial isolates from tomato leaves were consistent with *Xanthomonas* spp. causing bacterial spot. These findings

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validated the visual symptoms used in the image dataset and confirmed that the samples used for model training were indeed bacterial in origin (Table 2).

Table 2: Cultural, Morphological and Biochemical Characteristics of Isolated Bacterial Pathogens

Identification characteristics	Diseae					
	Bacterial blight (Rice)	Leaf circular, mucoid	Bacterial (Tomato)	Spot round, raised	Citrus (Lemon)	Canker, yellow, mucoid
Colonial Characteristics	Yellow, smooth, colonies	circular, mucoid	Yellow, slightly colonies	round, raised	Bright convex, colonies	yellow, mucoid
Gram Reaction	Gram -ve		Gram -ve		Gram -ve	
Cell shape	Rods		Rods		Rods	
Catalase	+		+		+	
Oxidase	-		-		-	
Indole	-		-		-	
Methyl red	-		-		-	
Voges Proskauer	-		-		-	
Citrate utilization	+		+		+	
Key biochemical feature	Produces yellow pigment, starch hydrolysis positive		Gelatin liquefaction positive, non-fluorescent on King's B medium		Produces Xanthum gum, oxidizes glucose, starch hydrolysis positive	
Casual Organism	<i>Xanthomonas oryzae</i>		<i>Xanthomonas</i> spp.		<i>Xanthomonas citri</i>	

Overall Model Performance

The performance of the Convolutional Neural Network (CNN) model was evaluated using standard classification metrics (accuracy, precision, recall and F1-score, Table 2). The model showed an overall accuracy of 93.4%, indicating a high level of reliability in recognizing differences between healthy and diseased plant leaves. Precision (92.8%) reflects the model's ability to correctly identify true positive cases without misclassifying healthy as diseased. Similarly, the recall value (91.6%) demonstrates the model's effectiveness in identifying most of the actual disease cases present in the dataset. The F1-score (92.2%), representing the harmonic mean of precision and recall, further confirms the balanced performance of this model (Table 3).

The results obtained suggest that the implemented CNN architecture is capable of extracting meaningful visual features associated with bacterial infections, even when symptoms are subtle or vary across plant species. The high-performance metrics also indicate that the pre-processing steps, comprising image normalization and segmentation, contributed significantly to improving classification efficiency by suppressing background noise and enhancing disease-specific patterns.

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<http://amresearchreview.com/index.php/Journal/about>**Table 3: Performance Metrics of CNN Model**

Accuracy	Precision	Recall	F1-score
93.4%	92.8%	91.6%	92.2%

Disease-wise Classification Performance

A more detailed evaluation of the model revealed variation in classification accuracy among different bacterial diseases. The model performed best in identifying bacterial leaf blight, achieving an accuracy of 95.2%. This high accuracy can be attributed to the presence of distinctive visual symptoms such as elongated lesions and chlorotic streaks, which are relatively easier for the model to detect (Table 4).

For bacterial spot disease in tomato, the model achieved an accuracy of 92.5%, indicating strong but slightly lower performance compared to bacterial leaf blight. This may be due to overlapping symptoms with other foliar diseases, making classification more challenging. Similarly, the accuracy for citrus canker was 91.3%, which is comparatively lower but still within an acceptable range. The variations in accuracy across diseases highlight the influence of symptom variability and dataset diversity on model performance (Table 4).

Healthy leaves were also classified with high accuracy (94.6%), demonstrating that the model effectively differentiates between diseased and non-diseased samples. This is particularly important for reducing false positives in practical applications (Table 4).

Table 4: Disease-wise Accuracy Disease Accuracy (%)

Bacterial Leaf Blight	Bacterial Spot	Citrus Canker	Healthy Leaves
95.2%	92.5%	91.3%	94.6%

Feature Extraction and Visual Pattern Recognition

The CNN model demonstrated strong capability in identifying key visual features associated with bacterial diseases. These features included lesions, chlorosis, necrosis and a change in leaf texture. Lesions appeared as dark, irregular spots on the leaf surface, while chlorosis was characterized by yellowing around infected areas. Necrotic patches indicated advanced stages of infection, and texture changes reflected surface roughness caused by bacterial colonization (Table 5).

The ability of current model to detect these features suggests that it successfully learned hierarchical representations of image data, initiating from basic edges and shapes to more complex patterns. A fore mentioned hierarchical learning is a key advantage of deep learning models and contributes to their superior ability to perform image classification tasks.

Furthermore, the segmentation process ensured that the model focused primarily on the leaf region, minimizing the influence of background elements such as soil, shadows, or other plant parts. This improved the accuracy of feature extraction and

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reduced misclassification errors.

Table 5: Key Visual Features used for classification

Feature	Description
Lesions	Dark and irregular spots on the leaf surface
Chlorosis	Yellowing of leaf tissue
Texture	Changes in the rough or uneven leaf surface
Necrosis	Dead tissue patches

Distribution of predictions and misclassifications analysis

In this study, the confusion matrix represents the classification results for four classes: healthy, bacterial spot, bacterial blight and citrus canker. The diagonal elements of the matrix indicate correct classification, whereas, off-diagonal elements represent misclassification. An analysis of the confusion matrix revealed that most misclassifications occurred between bacterial spot and citrus canker. This can be explained by the similarity in visual symptoms such as small lesions and discoloration patterns, which can overlap under certain environmental conditions. Despite this minor error, the overall misclassification rate remained low, indicating robust model performance (Table 6).

Table 6: Distributions of predictions and misclassification analysis

Actual/Predicated	Healthy	Bacterial Spot	Blight
Healthy	98	1	0
Spot	2	95	2
Blight	1	2	96
Citrus Canker	1	1	0

The model also demonstrated consistency across different image conditions, although slight reductions in accuracy were observed in images with poor lighting or complex backgrounds. This highlights the importance of high-quality image acquisition for optimal model performance.

DISCUSSION

The results of the present study demonstrate that computer vision techniques, particularly convolutional neural networks, can successfully diagnose plant bacterial diseases with high accuracy. The achieved accuracy of 93.4% is comparable to previous studies that have utilized deep learning for plant bacterial disease detection (Mohanty et al., 2016; Ferentinos, 2018). However, unlike many earlier studies that focused on a broad range of plant diseases, this study specifically targeted bacterial diseases, which are often more challenging to diagnose due to their subtle and overlapping symptoms.

The high classification accuracy for bacterial leaf blight (95.2%) suggests that the model was able to effectively learn distinctive visual features associated with this

disease. These findings are consistent with studies by Brahimi et al.(2017), who reported that CNNs can accurately detect disease-specific patterns in plant leaves. Similarly, the relatively lower accuracy observed for citrus canker (91.3%) may be attributed to variations in symptom expression and environmental conditions affecting leaf appearance.

The use of image preprocessing techniques such as segmentation and normalization significantly improved model performance by enhancing relevant features and reducing noise. This aligns with previous research indicating that preprocessing plays a critical role in improving classification accuracy (Sladojevic et al., 2016). Additionally, the use of a balanced dataset contributed to the robustness of the model, minimizing bias toward specific classes.

One of the key advantages of the computer vision-based approaches is their ability to provide rapid and non-invasive diagnosis. Unlike traditional laboratory methods, which require huge resources and time, AI-based systems can analyze images in real time, making them suitable for large-scale agricultural applications. This is particularly important in regions where access to laboratory facilities is limited.

However, certain limitations were observed in this study. The model performance may be affected by the variations in lighting conditions, image quality, and background noise in real-world scenarios. Furthermore, the dataset used in this study, although diverse, may not fully represent field conditions where multiple stress factors coexist. Future research should focus on incorporating larger and more diverse datasets as well as integrating additional data sources such as environmental parameters.

Overall, the findings highlight the potential of computer vision techniques as reliable tools for automated plant disease identification. The integration of such technologies into precision agriculture systems can enhance disease management and improve crop productivity.

CONCLUSION

The present study demonstrates the effectiveness of computer vision techniques in the automated identification of plant bacterial diseases. By utilizing convolutional neural networks and image preprocessing methods, the developed model achieved high accuracy in classifying diseases such as bacterial leaf blight, bacterial spot and citrus canker.

The findings highlight the potential of AI-based approaches in transforming plant disease diagnostics by providing rapid, accurate, and scalable solutions. Compared to traditional diagnostic methods, computer vision techniques offer significant advantages in terms of speed, cost-effectiveness, and ease of deployment.

The integration of microbiological validation through bacterial isolation and biochemical identification, along with the exclusion of pest-related symptoms using zoological expertise, significantly enhanced the reliability and accuracy of the developed model. This interdisciplinary approach demonstrates the importance of combining computer vision with biological sciences for precise disease diagnosis.

Despite the promising results, further research is required to improve model generalization and adaptability to real-world conditions. The integration of advanced technologies such as hyperspectral imaging and IoT-based monitoring systems can

further enhance disease detection capabilities.

In conclusion, the adoption of computer vision techniques in agriculture has the potential to revolutionize plant disease management, contributing to sustainable farming practices and improved food security.

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