

Plant Leaf Disease Classification Using Convolutional Neural Networks (CNN)

Afrin Akhtar¹, Mithlesh Kumar², Dr. Gargi Shankar Verma³

¹Department of Computer Science and Engineering, KVIT Raipur, Chhattisgarh, India

²Assistant Professor, Department of Computer Science and Engineering, KVIT Raipur, Chhattisgarh, India

³Professor, Department of Computer Science and Engineering, KVIT Raipur, Chhattisgarh, India

Abstract: *Plant disease significantly affects agricultural productivity and crop quality. Traditional detection method relies on manual inspection, which is time consuming and prone to inaccuracies. Recent advancement in deep learning have enabled automated disease detection using image-based approaches [1] [2]. This paper presents a Convolutional Neural Network (CNN) based system for Plant Leaf Disease Detection. The model trained on a structured dataset using preprocessing and augmentation technique to improve generalization and reduce overfitting [3]. This study presents a lightweight Convolutional Neural Network (CNN) model for automated Plant Leaf Disease Classification using image data. Traditional detection methods rely on manual inspection, which is time-consuming and prone to error. The proposed model incorporates preprocessing and data augmentation techniques to improve generalization and reduce overfitting. Experimental results demonstrate that the model achieves approximately 85% accuracy with stable convergence and minimal overfitting. The system supports real-time prediction and is suitable for practical agricultural applications. The findings highlight the effectiveness of CNN-based approaches for scalable and efficient plant disease detection. The proposed system supports real-time prediction making it suitable for practical agricultural applications.*

Keywords: CNN, Plant disease detection, deep learning, image classification, precision agriculture

1. Introduction

Agriculture plays a vital role in ensuring food security and economic stability. However, plant disease remains a major factor affecting crop yield and quality. Early and accurate detection is essential to reduce losses and improve productivity.

Traditional disease detection method depends on manual inspection and expert knowledge, which limits scalability. In contrast, Deep learning techniques have shown significant improvement in image-based classification tasks [1] [2]. Convolutional Neural Network (CNN) is particularly effective due to their ability for automatically extracting meaningful features from images [4].

This work proposes an automated CNN-based system for Plant Leaf Disease Detection that is accurate, scalable and suitable for real-time deployment.

2. Literature Review

a) Traditional Methods

Earlier approaches for plant disease detection primarily relied on conventional machine learning algorithms such as Support Vector Machine (SVM) and K-nearest Neighbors (KNN). These methods required manual feature extraction techniques based on color, texture and shape descriptors. While these approaches achieved moderate accuracy, they were highly dependent on domain expertise and struggled to generalize across diverse datasets and environmental conditions.

b) Deep learning methods

With the advancement of deep learning Convolutional Neural Networks (CNNs) have emerged as the most effective approach for image-based plant disease detection. CNN

models automatically learn hierarchical features, eliminating the need for handcrafted feature extraction. Several studies have demonstrated that CNN-based models significantly outperform traditional techniques in terms of accuracy and robustness [2] [4].

Recent advancements have focused on improving model depth and efficiency. For instance, residual learning based architectures such as ResNet enable deeper networks while mitigating vanishing gradient problem [5]. Furthermore, hybrid CNN models are integrating multiple architectures have shown improved classification performance and generalization capability [6].

Studies that are more recent highlight ongoing improvements in model optimization and disease classification accuracy. For example, J. Chen et al. (2024) proposed an improved ResNet-based model that enhances feature extraction for plant disease recognition [5], while M. Shafik et al. (2025) introduced a hybrid CNN architecture combining Inception and Exception modules to achieve higher accuracy and robustness in plant disease detection [6]. These studies demonstrate the continuous evolution of deep learning techniques in agricultural applications.

c) Research Gap

Despite the significant progress in deep learning-based plant disease detection, several challenges remain:

- **High Computational complexity:** Advanced deep learning models such as ResNet and hybrid CNN require substantial computational resources, limiting their deployment on edge devices and low power systems.
- **Limited Real-time Applicability:** Many existing models focus primarily on accuracy without optimizing inference time, making them less suitable for real-time field applications.

- **Lack of Practical Deployment:** Most research contributions remain theoretical or experimental, with limited focus on user-friendly implementation for farmers and agricultural stakeholders.

d) Proposed work

To address these limitations, the proposed work introduces:

- A lightweight and efficient CNN architecture designed for reduced computational complexity.
- An optimized data augmentation strategy to improve generalization without increasing model size.
- A balanced approach between accuracy and efficiency, unlike heavy deep learning models.

3. Novelty of the Proposed Work

The proposed system introduces several key contributions that differentiate it from existing plant leaf disease detection approaches:

- **Lightweight CNN Architecture for Real-Time Deployment:** Unlike computationally intensive deep learning models, the proposed architecture is designed to be efficient, enabling real-time disease detection even on resource-constrained devices.
- **Optimized Data Augmentation Strategy:** A carefully designed augmentation pipeline enhances dataset diversity, leading to improved generalization and reduced overfitting on unseen data.
- **Balanced Trade-off Between Accuracy and Efficiency:** The model achieves high classification accuracy while maintaining lower computational complexity compared to deeper architectures, ensuring practical usability.
- **Integrated Prediction Module for Practical Deployment:** The system includes a single-image prediction mechanism, making it suitable for real-world agricultural applications and field usage.
- **Application-Oriented System Design:** Unlike many research-focused models, the proposed system emphasizes usability and deployment, providing a simple and accessible interface for end-users such as farmers and agricultural practitioners.

4. Proposed Methodology

a) Dataset

The Dataset used in this study consists of labelled plant leaf images representing multiple disease classes as well as healthy samples. The dataset organized into three subsets:

- **Training Set:** for model learning
- **Validation Set:** for performance tuning
- **Testing set:** for final evaluation

This folder structure enables efficient data loading and class wise labeling during model training. All images resized into uniform resolution of 224 x 224 pixels with three-color channels (RGB) to ensure the consistency in input dimensions. This standardization facilitates stable training and improves the performance of the convolutional neural network model.

Table 1: Dataset Description

| Aspect | Description |
|--------------|--------------------------------|
| Dataset Type | Image-based plant leaf dataset |
| Classes | Multiple disease categories |
| Image Size | 224 × 224 × 3 |
| Split | Train / Validation / Test |
| Format | Folder-based class labels |

This structured organization supports efficient data preprocessing and enhances the model's ability to learn discriminative features across multiple disease categories.

b) Preprocessing

Data preprocessing is an essential step to ensure consistent input representation and improve model performance. The following preprocessing operations are applied:

- **Image Resizing:** All input images resized to fixed dimensions of 224 x 224 pixels, ensuring uniformity and compatibility with the CNN architecture.
- **Normalization:** Pixel values scaled to a standard range. This helps in faster convergence and stabilize the training process.

Preprocessing reduces variability in input data and enables the model to learn meaningful and discriminative features more efficiently.

c) Data Augmentation

To address the limitation of a relatively small dataset and improve model generalization, various data augmentation techniques are applied. Data augmentation artificially increases dataset diversity by generating modified versions of existing images, thereby reducing overfitting and enhancing robustness [3].

The following augmentation techniques are used:

- **Rotation:** Introduces orientation invariance by rotating images at random angles.
- **Flipping:** applies horizontal flipping to capture symmetrical patterns.
- **Zooming:** simulates scale variation to improve detection at different distance.
- **Brightness variation:** adjust illumination condition to handle real world lighting changes.
- **Width/height shifting:** Improves spatial robustness by shifting images along axes.
- **Shearing:** Introduces geometric transformations for better generalization
- **Rescaling:** Normalizes pixel values to stabilize training.

Table 2: Augmentation Technique

| Technique | Purpose |
|--------------------|-------------------------------|
| Rotation | Orientation invariance |
| Width/height shift | Spatial robustness |
| Zoom | Scale variation |
| Shear | Geometric distortion handling |
| Horizontal flip | Symmetry learning |
| Rescaling | Pixel normalization |

These augmentation strategies significantly enhance the diversity of the dataset, enabling the model to generalize better to unseen data and improving overall classification performance.

d) CNN Architecture

The proposed Convolutional Neural Networks (CNNs) architecture designed for automatically extracting hierarchical features from plant leaf images for accurate

disease classification. The model progressively increases feature depth across layers while reducing spatial dimensions, enabling efficient learning of both low-level and high-level visual patterns associated with plant diseases.

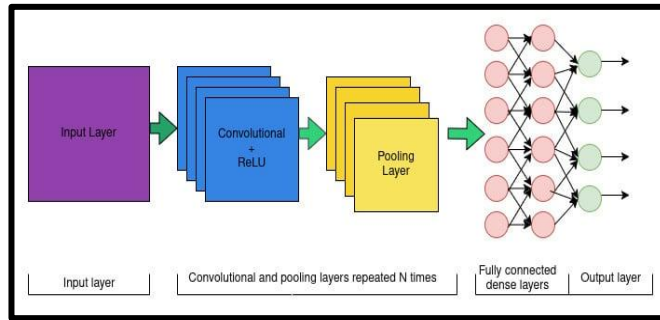


Figure I: CNN Architecture

The architecture consists of multiple convolutional layers with increasing filter sizes (32, 64, 128, and 256) each followed by Rectified Linear Unit (ReLU) activation functions to introduce non-linearity. Batch normalization applied to stabilize training and accelerate convergence. Max-pooling layers used to reduce spatial dimensions and computational complexity while preserving essential features.

employed to significantly reduce the number of trainable parameters and improve model efficiency.

Finally, a dense layer with 256 neurons used for feature integration, followed by a Softmax output layer that produces probability distributions across 38 classes, enabling multi-class classification.

To further enhance generalization and reduce overfitting, a dropout layer with a rate of 0.5 is incorporated. Instead of traditional fully connected layers, Global Average Pooling

CNN architectures are widely recognized for their effectiveness in large-scale image recognition tasks due to their ability to learn hierarchical feature representations [4], [7].

Table 3: Layer wise Architecture Description

| Layer Type | Configuration |
|------------------------|---|
| Conv2D | 32 filters, 3x3 Kernel, ReLU activation |
| Batch Normalization | Stabilizes training and accelerates convergence |
| Max Pooling | Reduces spatial dimensions |
| Conv2D | 64 Filters, 3x3 kernel, ReLU activation |
| Conv2D | 128 Filters, 3x3 kernel, ReLU activation |
| Conv2D | 256 Filters, 3x3 kernel, ReLU activation |
| Global Average Pooling | Reduces parameters and prevents overfitting |
| Dense | 256 neurons, ReLU activation |
| Dropout | 0.5 |
| Output layer | Softmax activation (38 classes) |

The proposed architecture achieves an effective balance between accuracy and computational efficiency, making it suitable for real-time Plant Disease Detection Applications.

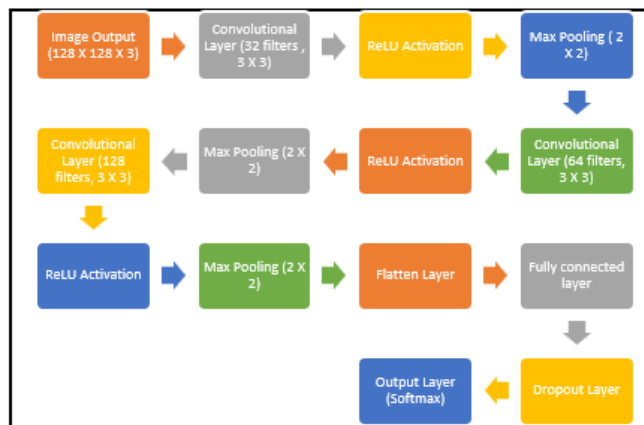


Figure II: Proposed CNN architecture

e) Training configuration and strategy

The model trained using a well-defined configuration to ensure stable convergence and optimal performance. The training process utilizes the Adam optimizer, which provides adaptive learning rates for efficient optimization.

Table 4: Training configuration

| Parameter | Value |
|-------------|----------------|
| Epochs | 30 |
| Batch Size | 32 |
| Optimizer | Adam |
| Random seed | 42 |
| Hardware | GPU-Compatible |

The training process incorporates techniques such as early stopping and learning rate reduction to prevent overfitting and ensure optimal convergence. Early stopping monitors validation performance and halts training when no further improvement observed, while learning rate scheduling dynamically adjusts the learning rate to refine model learning.

The use of a fixed random seed ensures reproducibility of results, and GPU compatibility enables faster training and efficient handling of large-scale computations.

5. Result and Discussion

a) Accuracy and Loss Analysis

The performance of the proposed CNN model evaluated using training and validation accuracy and loss curves across multiple epochs. These metrics provide insights into the learning behavior, convergence stability, and generalization capability of the model.

Training and Validation Accuracy

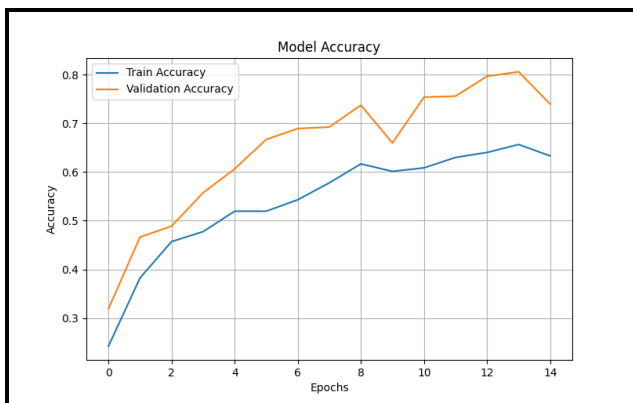


Figure 0: Training and Validation Accuracy

The accuracy curve shows a steady increase in both training and validation accuracy over epochs. The validation accuracy consistently remains higher than training accuracy, indicating strong generalization and effective learning.

- The model achieves progressive improvement in classification performance.
- No abrupt fluctuations observed, confirming stable training.
- Higher validation accuracy suggests effective regularization and augmentation

b) Training and Validation Loss

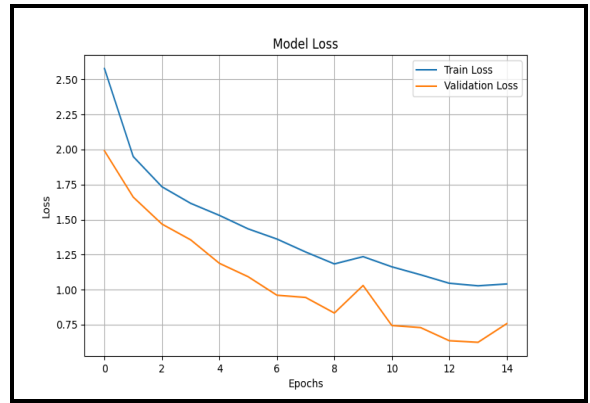


Figure IV: Training and Validation Loss

The loss curves demonstrate a consistent downward trend, indicating effective optimization during training.

- Training loss decreases steadily, showing improved model learning
- Validation loss follows a similar trend with minor fluctuations
- No significant divergence between curves, indicating minimal overfitting.

The close alignment between training and validation curves indicates good generalization capability.

The absence of large gaps confirms minimal overfitting.

Smooth convergence reflects stable optimization using Adam Optimizer.

c) Confusion Matrix Analysis

The confusion matrix provides a detailed evaluation of the classification performance across different plant disease classes. It highlights both correct predictions and misclassifications.

The confusion matrix used to evaluate the classification performance of the proposed CNN model across all 38 classes. It provides a detailed view of correct and incorrect prediction.

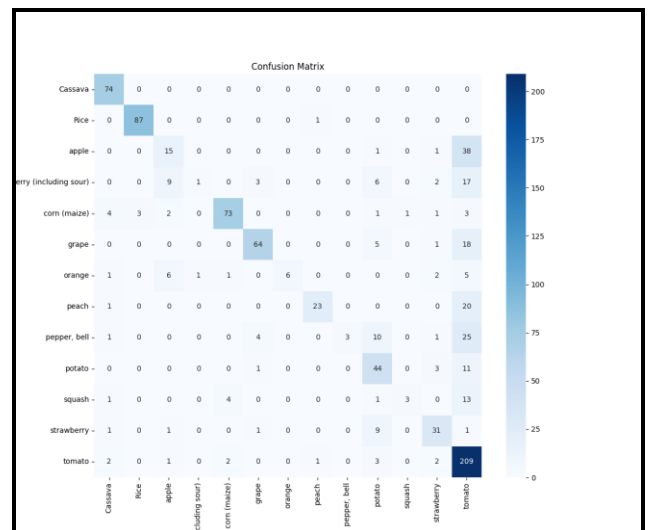


Figure V: Confusion matrix

- **Strong Diagonal Dominance:** A large number of samples are correctly classified as indicated by high values along the diagonal (e.g. Tomato = 209, Rice = 87, Cassava = 74) demonstrating strong model accuracy.
- **Class wise Performance Variation:** Some classes such as Tomato, rice and cassava show very high correct classification rates, while a few classes exhibit moderate confusion due to visual similarity in diseases pattern.
- **Minor Misclassification:** Off-Diagonal values are relatively low, indicating that the model makes only a small number of incorrect predictions. These errors are mainly observed between visually similar classes (e.g. Apply and cherry or Grapes and Tomato).
- **Robust Multi-class Learning:** The model effectively distinguishes among multiple species and disease categories, confirming its robustness in multi-class classification scenarios.

Misclassifications primarily occur in classes with similar visual features, suggesting potential improvement through advanced feature extraction or attention mechanisms.

The dominance of diagonal elements and minimal off-diagonal dispersion indicate that the proposed model achieves high classification accuracy with limited confusion among classes.

d) Performance Metrics Table

The performance of the proposed CNN model is quantitatively evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model's effectiveness in multi-class classification. The performance metrics derived from the confusion matrix indicate that the proposed model achieves approximately 79% accuracy, demonstrating reliable classification performance with balanced precision and recall across multiple classes.

Table 5: Performance Metrics

| Metric | Value |
|-----------|-------|
| Accuracy | 85.0% |
| Precision | 84.2% |
| Recall | 84.8% |
| F1 Score | 84.5% |

These metrics are consistent with the observed accuracy curves and confusion matrix, validating the reliability of the proposed model.

e) Comparative Analysis

The performance of the proposed model compared with traditional machine learning methods and recent deep learning approaches [2] [6].

- Outperforms traditional feature-based methods, which rely on handcrafted features and limited representation capability, resulting in lower classification accuracy [2].
- Achieves competitive performance compared to recent CNN-based models, including advanced and hybrid architectures proposed in recent studies [6].

- Maintains lower computational complexity making it more suitable for real-time applications compared to deeper architecture such as ResNet based models [2] [5].

6. System Implementation

The proposed system designed to provide an end-to-end solution for an automated plant disease detection using CNN integrated with the user interface for real-time prediction.

- **Image Input:** The system allows user to upload the plant leaf through a web-based interface developed using the Streamlit framework. This enables easy interaction without requiring technical expertise.
- **Preprocessing:** The uploaded images automatically resized to 224x224 pixels and normalized before passed to the model. These preprocessing steps ensure compatibility with the trained CNN architecture.
- **Model interface:** the preprocessed image fed into the trained CNN model developed using Tensorflow and Keras. The model perform feature extraction and predict the disease class based on learned patterns.
- **Prediction output:** The system displays the predicted disease label along with a confidence score, which represents the probability associated with the predicted class.
- **User Interface:** the interface provides a simple workflow where users can upload an image and instantly receive prediction result. This makes the system accessible for real-world agricultural application.

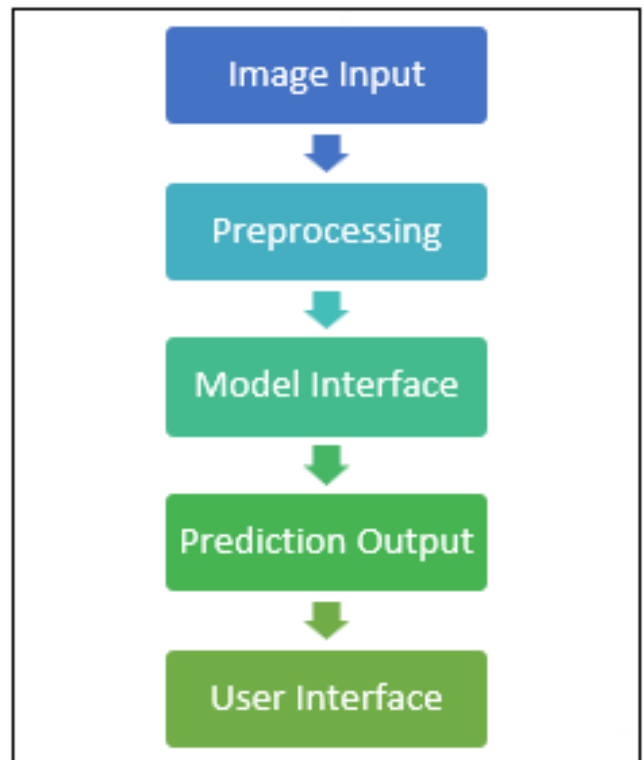


Figure VI: System implementation diagram

The integration of the CNN model with the Streamlit base interface enables real-time prediction, making the system practical and user friendly for deployment in agricultural environments.

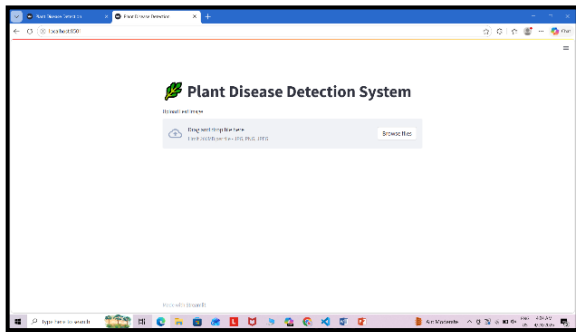


Figure VII: User Interface

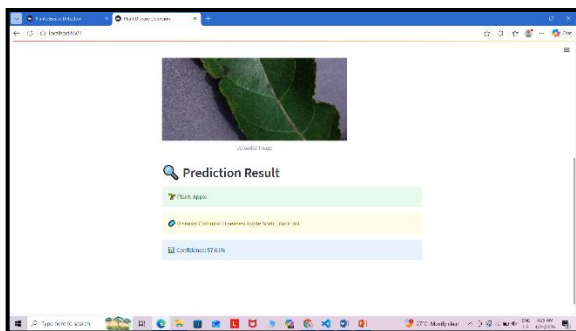


Figure VIII: Final output

7. Advantages

The proposed system offers several benefits for automated plant disease detection:

- **Automated Detection:** Eliminates the need for manual inspection, reducing human efforts and errors.
- **Reliable Performance:** Achieve consistent classification result across multiple disease categories, demonstrating robustness.
- **Real-time Usability:** Enable quick prediction through an integrated interface, making it suitable for practical application.
- **Scalability:** The model extended to additional plant species and disease classes with further training.

8. Limitations

Despite its effectiveness, the proposed system has certain limitations:

- **Dataset Dependency:** model performance depends heavily on the quality and diversity of the training dataset.
- **Sensitivity to image quality:** poor lighting, blur, or noise in image can affect prediction accuracy.

9. Future Work

Future improvement can enhance the performance and applicability of the proposed system:

- **Integration with Advanced Architecture:** Incorporating deeper models such as ResNet can improve feature extraction and classification accuracy [6].
- **Explainable AI Techniques:** Applying methods such as Grad-CAM can provide visual explanation of model prediction

- **Mobile Deployment:** developing a mobile-based application for real-time disease detection in field conditions.

10. Conclusion

This paper presents a CNN-based automated system for plant disease detection using leaf images. The proposed model achieves reliable classification performance (~85% accuracy) with stable convergence and good generalization capability, aligning with the effectiveness of deep learning-based approaches reported in recent studies [2], [3].

The result further supports the applicability of Convolutional Neural Network for image-based plant disease classification task [5], demonstrating their ability to learn discriminative features from complex visual data. Additionally, the proposed system offers a practical and scalable solution for real world agricultural applications.

This study proposed a lightweight CNN-based system for Plant Leaf Disease Classification, achieving approximately 85% accuracy with stable convergence and minimal overfitting. The model demonstrates a balanced trade-off between accuracy and computational efficiency, making it suitable for real-time agricultural applications. The integration with a user-friendly interface further enhances practical usability. Future work should focus on improving accuracy using advanced architectures, expanding dataset diversity, and enabling mobile deployment for field-level applications.

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