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# Soybean Leaf Disease Detection Using Convolutional Neural Network

Aarti Pandurang Chavare<sup>1</sup>, Ajit B Patil<sup>2</sup>, Tanvi Gopinath Patil<sup>3</sup>, Dipti Prakash Swami<sup>4</sup>, Manasi Dipak Shirale<sup>5</sup>  
Department of Computer Science and Engineering Kolhapur Institute of Technology's College of Engineering, Kolhapur

**Abstract:** Soybean is one of the most important agricultural crops worldwide and serves as a major source of food, edible oil, and animal feed. The productivity and quality of soybean crops are significantly affected by various leaf diseases such as Caterpillar damage, Rust, Bacterial Blight, and Diabrotica Speciosa. These diseases reduce crop yield and negatively impact agricultural production and the economic condition of farmers. Therefore, early and accurate disease identification is essential for effective crop management and improved productivity. Traditional disease detection methods mainly rely on manual inspection by agricultural experts, which is time-consuming, costly, less efficient for large-scale farming, and prone to human error.

This paper presents an automated soybean leaf disease detection system using image processing and deep learning techniques. The proposed system utilizes Convolutional Neural Networks (CNN) for automatic feature extraction and classification of healthy and diseased soybean leaves. A Random Forest classifier is also implemented for comparative analysis to evaluate the performance of traditional machine learning approaches. The collected dataset undergoes preprocessing steps such as image resizing, normalization, filtering, and data augmentation techniques including rotation, zooming, and flipping to improve model performance and reduce overfitting.

Experimental results demonstrate that the CNN-based model achieves higher accuracy, precision, recall, and F1-score compared to Random Forest methods. The proposed system provides an efficient, reliable, and cost-effective solution for real-time soybean leaf disease detection. It can support smart agriculture systems and assist farmers in taking timely preventive measures to minimize crop damage and improve overall agricultural productivity.

**Index Terms:** Soybean, Leaf Disease Detection, Deep Learning, CNN, Image Processing, Softmax, Random Forest

## I. INTRODUCTION

Agriculture plays a vital role in the economy of many countries, especially India, where a large population depends on farming for their livelihood. Soybean is one of the most important commercial and oilseed crops due to its high protein content, nutritional value, and industrial applications. It is widely cultivated in agricultural regions such as Maharashtra, Madhya Pradesh, and Karnataka. Soybean contributes significantly to food production, edible oil industries, and animal feed. However, soybean crops are highly affected by various foliar diseases such as Rust, Bacterial Blight, Caterpillar damage, and Diabrotica Speciosa, which reduce crop quality and productivity. These diseases can spread rapidly under unfavorable environmental conditions and cause severe economic losses to farmers if not detected at an early stage.

Traditional disease detection methods mainly rely on manual visual inspection by farmers or agricultural experts. These methods are time-consuming, labor-intensive, subjective, and prone to human error, especially in large agricultural fields. Delayed or inaccurate disease identification can lead to severe crop loss and reduced agricultural productivity. In many rural areas, access to agricultural experts is limited, making timely disease diagnosis difficult.

Recent advancements in Artificial Intelligence (AI), image processing, and deep learning have provided efficient solutions for automated plant disease detection. Computer vision techniques combined with Convolutional Neural Networks (CNNs) can automatically identify disease patterns from leaf images with high accuracy. These techniques reduce human effort and provide faster and more reliable results compared to traditional approaches.

The main objective of this research is to develop an automated soybean leaf disease detection system using CNN and image processing techniques. The study also aims to compare CNN performance with Random Forest methods and improve disease classification accuracy for real-time agricultural applications.

## II. LITERATURE REVIEW

Several studies have been conducted on plant disease detection using image processing, machine learning, and deep learning techniques.

Traditional image processing methods used color, texture, and shape features for disease identification, but their performance was affected by lighting conditions and image quality [10], [19].

Machine learning techniques such as Random Forest and Logistic Regression improved classification accuracy but required manual feature extraction [2], [3]. These methods were less effective for complex disease patterns and large datasets. Recent deep learning approaches, especially Convolutional Neural Networks (CNNs), have shown better performance in plant disease detection. Models such as VGG16, ResNet, MobileNet, and YOLOv5 achieved high accuracy in soybean leaf disease classification [1],[4],[8]. Image augmentation and transfer learning techniques further improved model performance [5],[12].

Although previous studies achieved high accuracy, some challenges still remain, such as difficulty in detecting similar disease symptoms, high computational requirements, and lack of real-time implementation. The proposed system aims to overcome these limitations using an efficient CNN-based approach for accurate soybean leaf disease detection.

### III. METHODOLOGY

The proposed system consists of the following steps:

#### A. Data Collection

A dataset of soybean leaf images is collected containing both healthy and diseased samples. The dataset includes images captured under varying environmental conditions such as lighting, background, and leaf orientation to improve model generalization.

#### B. Dataset Description

The dataset used in this research contains soybean leaf images collected from online agricultural repositories and publicly available datasets. The dataset includes both healthy and diseased soybean leaf samples.

The images belong to the following classes:

- Healthy
- Rust
- Bacterial Blight
- Caterpillar Damage Softmax
- Diabrotica Speciosa

Σ

The dataset contains images captured under different lighting conditions, backgrounds, and leaf orientations to improve model robustness.

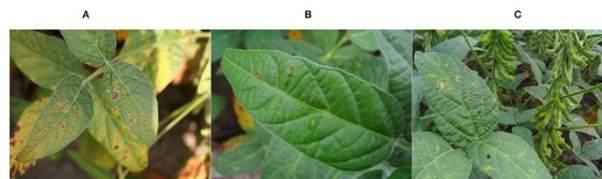


Fig. 1. Sample Images of Healthy and Diseased Soybean Leaves

#### C. Preprocessing

The collected images are resized to a fixed dimension (e.g., 224 × 224) to maintain uniformity. Pixel values are normalized to improve training efficiency. Noise is reduced using filtering techniques to enhance image quality. Additionally, data augmentation methods such as rotation, flipping, and zooming are applied to increase dataset diversity and prevent overfitting.

#### D. Feature Extraction

The CNN model automatically extracts important features from soybean leaf images without manual intervention. These features include color variations, texture patterns, and shape details that help distinguish between healthy and diseased leaves.

During this process, convolutional layers scan the image using filters to detect edges, spots, and disease-specific patterns. As the network goes deeper, it learns more complex and meaningful features, which are then used for accurate classification.

#### E. Model Architecture

A Convolutional Neural Network (CNN) is used for classification of soybean leaf diseases. The model consists of the following layers:

- Input Layer

- ConvolutionLayers
- ReLUActivation
- MaxPoolingLayer
- FullyConnectedLayer
- SoftmaxOutputLayer

The convolution layers extract important features from the images, while the ReLU activation function introduces non-linearity. The max pooling layer reduces the spatial dimensions and helps in feature selection. The fully connected layer processes the extracted features for final classification.

The Softmax classifier is used in the output layer to classify the images into multiple classes. It converts the output values into probability scores.

Softmax Function:

$$\text{Softmax}(z_j) = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$$

This function converts the output into a probability distribution and is used for multi-class classification.

#### F. Working of CNN

Convolutional Neural Networks (CNNs) are deep learning models mainly used for image classification tasks. CNN automatically extracts important features from images without manual feature engineering.

The convolution layer applies filters to the input image to identify important patterns such as edges, textures, and spots. The ReLU activation function introduces non-linearity into the model. Max pooling reduces image dimensions and computational complexity. Finally, fully connected layers and the Softmax classifier perform final disease classification.

CNN Architecture for Soybean Leaf Disease Detection

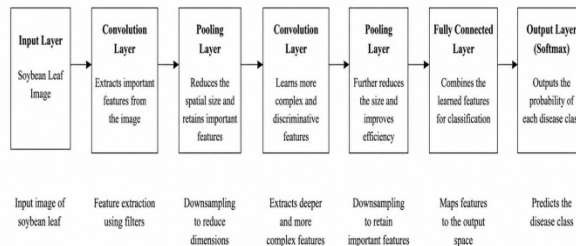


Fig.2. Proposed CNN Architecture for Soybean Leaf Disease Detection

#### G. Training

The model is trained using labeled data with cross-entropy loss and optimized using Adam optimizer.

### IV. SYSTEM ARCHITECTURE

The proposed soybean leaf disease detection system consists of multiple stages including image acquisition, preprocessing, feature extraction, CNN-based classification, and result prediction.

Initially, soybean leaf images are collected from the dataset and preprocessed using resizing, normalization, and augmentation techniques. The processed images are then passed to the CNN model for feature extraction and disease classification. Finally, the predicted disease result is displayed through the web-based interface.

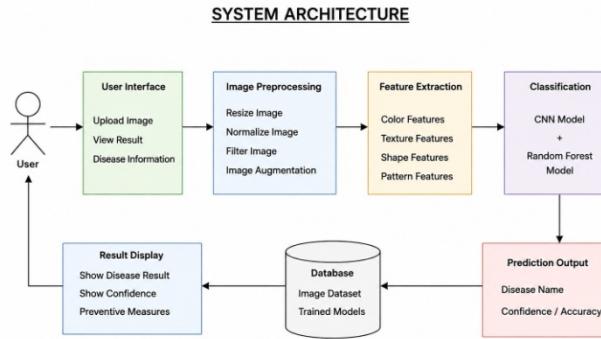


Fig.3.SystemArchitectureofProposedModel

### V. ALGORITHM

- Step1:Collectsoybeanleafimagedatasetcontaining healthy and diseased leaf samples.
- Step2:Performpreprocessingtechniquessuchasimage resizing, normalization, and noise removal.
- Step3:Applydataaugmentationmethodsincludingrota-tion, flipping, and zooming.
- Step4:Splitthedatasetintotrainingandtestingdatasets.
- Step5:TraintheCNNmodelusinglabeledsoybeanleaf images.
- Step6: Extract image features automatically using convo-lution layers.
- Step7:PerformclassificationusingtheSoftmaxoutput layer.
- Step 8: Evaluate model performance using accuracy, preci-sion, recall, and F1-score.

### VI. RESULTS AND DISCUSSION

Theproposedmodelachieveshighclassificationaccuracy. Experimental results show:

Accuracy:97%–99%

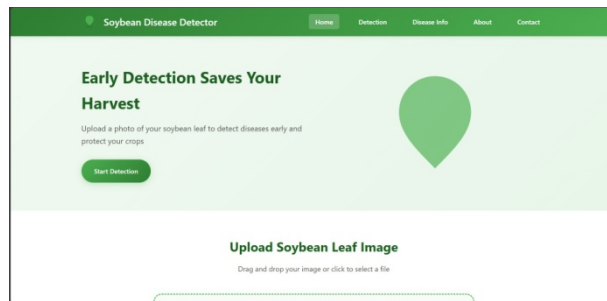


Fig.4.HomepageofSoybeanLeafDiseaseDetectionSystem

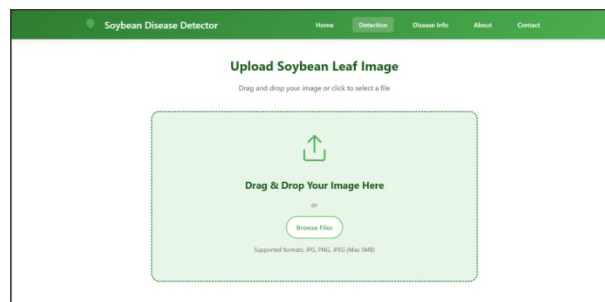


Fig.5.ImageUploadModule

Precision: High

Recall: High

The system performs well even with variations in lighting and background conditions.

TABLE I

PERFORMANCE COMPARISON OF MODELS

Model	Accuracy	Precision	Recall	F1 Score
CNN (Softmax)	96–98%	High	High	High
Random Forest	85–88%	Moderate	Moderate	Moderate

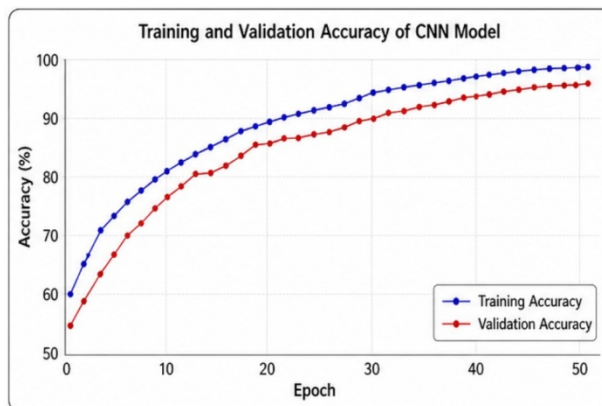


Fig. 6. Training and Validation Accuracy of CNN Model

Predicted: Diabrotica speciosa



```
for i, category in enumerate(categories):
    print(f"{category}: {prediction[0][i]*100:.2f}%")
```

Caterpillar: 0.43%  
 Diabrotica speciosa: 99.57%  
 Healthy: 0.00%

Fig. 7. Predicted Output Result

Observations:

- CNN performs better due to automatic feature extraction.
- Random Forest struggles with complex patterns.

- CNN handles image variations more effectively.
- CNN model has shown accuracy up to 99% in some plant disease datasets.

## VII. ADVANTAGES

The proposed system offers several benefits in soybean leaf disease detection:

- Automated detection of soybean leaf diseases
- High classification accuracy
- Real-time prediction capability
- Time-efficient and reduces manual effort
- Useful for farmers and agricultural experts

Why CNN is Better:

- Automatically learn spatial features from images
- Eliminates the need for manual feature extraction
- Effectively handles noise and variations in input data

Limitations of Random Forest:

- Requires manual feature extraction
- Limited performance when applied directly to image data
- Requires large dataset for training
- Performance depends on image quality
- High computational requirements during training

Applicability of Random Forest:

- Suitable for small datasets
- Requires lower computational resources

## VIII. CONCLUSION

This paper presents an automated soybean leaf disease detection system using Convolutional Neural Networks (CNN) and image processing techniques. The proposed model effectively identifies healthy and diseased soybean leaves with high accuracy, precision, and reliability. Experimental results show that the CNN-based approach performs better than traditional machine learning methods such as Random Forest due to its automatic feature extraction capability.

The system reduces manual effort and supports early disease detection, which can help farmers take timely preventive measures and reduce crop loss. The proposed method is efficient, cost-effective, and suitable for real-time smart agriculture applications. In the future, the system can be integrated with mobile and IoT-based platforms for practical field usage.

## IX. FUTURE WORK

Future improvements of the proposed soybean leaf disease detection system include:

- Integration with mobile applications for easy access and real-time disease diagnosis by farmers
- Real-time disease monitoring using IoT and smart agriculture devices
- Incorporation of video-based disease detection for continuous crop monitoring
- Extension of the model to detect diseases in multiple crop species
- Use of cloud-based storage and monitoring systems for large-scale agricultural analysis
- Improvement of model accuracy using larger and more diverse datasets
- Development of multilingual support systems for farmers from different regions

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