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Research Article

Soybean Leaf Disease Detection Using Convolutional Neural Networks and Google Net Integration

Deepak Tawali[1*], Chandra Prakash Patidar[2]

[1]Information Technology, Student, Devi Ahilya Vishwavidyalaya, Indore, India
[2]Information Technology, Associate Professor Devi Ahilya Vishwavidyalaya, Indore, India

*Corresponding Author:

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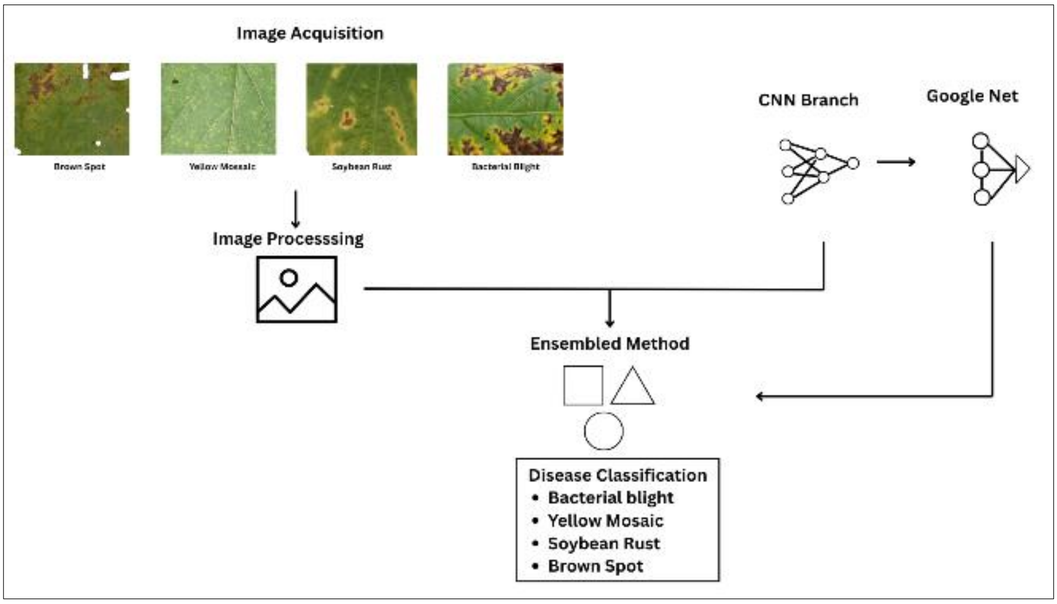
Abstract— Soybean holds significant importance in global agriculture due to its high protein and oil content, and its demand is increasing alongside the shift toward plant-based dietary preferences. In India, soybean cultivation is expanding rapidly due to an increase in veganism; however, it continues to be susceptible to a range of foliar diseases, including Bacterial Blight, Soybean Rust, Yellow Mosaic, and Brown Spot. This research proposes a deep learning-based method for the detection of soybean leaf diseases, utilizing an ensemble of Convolutional Neural Networks (CNNs) and the GoogleNet model. Through transfer learning, the system was trained on a well-structured dataset of 5,479 annotated soybean leaf images. By combining both architectures, the ensemble approach achieved enhanced accuracy in disease classification. The experimental findings affirm the model's effectiveness in precisely recognizing prevalent soybean leaf diseases. Future efforts will focus on expanding the dataset, integrating advanced deep learning models, and creating a mobile-based solution for real-time disease diagnosis directly in the field.

Keywords— Image Processing, Neural Network, Google Net, Convolutional Neural Network, Disease Classification

Graphical Abstract.



Purpose- This study aims to develop an AI-based system using an ensemble of CNN and GoogleNet for accurate detection of major soybean leaf diseases. It supports early diagnosis to improve yield, reduce losses, and promote smart farming practices. The model is designed for future integration into mobile applications for real-time, on-field disease monitoring.

1. Introduction

Soybeans: the 'miracle crop,' the 'protein powerhouse,' the cornerstone of countless industries. From tofu to biofuels, this humble legume plays a vital role in global food security and economic stability. It is globally acknowledged as a global bean, a most happening crop of the first century. The productivity potential of soybeans is higher than that of other leguminous crops. It is the richest source of quality protein containing around 40% protein with all the essential amino acids besides 18-20% oil.

Figure 1. Healthy Leaf

The integration of soybean into the Indian diet is essential, considering the presence of vitamins and other minerals like calcium, iron, and other nutraceutical and health-benefiting compounds. Soybean has primarily been an export commodity of valuable foreign exchange.

The crop is currently grown in central India, mainly in the states of Madhya Pradesh, Maharashtra, Rajasthan, Karnataka, Telangana, and Chhattisgarh. Nowadays, people are more concerned about veganism; hence, the demand for this bean is growing steadily. In recent years, the demand for soybeans has been growing rapidly due to the rising popularity of plant-based diets and veganism. As more people are turning towards plant products, Soybeans have become the key ingredient in the production of substitutes.

The increase in demand can be linked to several factors, such as growing awareness of the environmental impact of animal farming, the benefits of plant-based eating and the increasing acceptance of veganism, particularly among young generations has contributed to the rapid rise in demand for soybean-based products hence leads to increase in soybean production. The government and various agricultural organizations are promoting soybean cultivation as a part of sustainable farming practices, which offers incentives to farmers in these regions. The shift towards veganism or plant-based diets is not just a local aspect but a global trend.

The growing demand has led to an increase in soybean production. However, this expansion comes with a new set of challenges. With the increase in cultivation, the need for proper crop production is crucial. Farmers cannot afford losses, as soybeans are a major investment and significantly contribute to their livelihood [1].

Soybean is one of the most widely cultivated legumes crops globally, with an estimated production of over 350 million tons. However, Diseases affecting soybean leaves are becoming a major problem, threatening both the quality and the quantity of soybean production. These diseases reduce protein and oil content and decrease the market value of a bean. These diseases can significantly impact yield and can lead to crop failures and extensive economic damage. The diseases that most frequently affect soybeans include Bacterial Blight, Soybean Rust, Yellow Mosaic, and Brown Spot.

a. Bacterial blight is a bacterial disease caused by a bacteria named Pseudomonas syringae pv. Glycine. This disease also infects string beans. Out of 100, it can spoil 50 per cent of crops depending upon the amount of infection caused to the crop. In bacterial blight, Initially, small water-soaked lesions spear on leaves and most of the time it starts along the edges. These lesions are usually angular in shape and turn brown and necrotic as the infection grows following the veins of the leaf and this can lead to early leaf drop.

b. Soybean rust is a disease caused by two types of fungi, Phakopsora pachyrhizi, commonly known as Asian soybean rust, and Phakopsora meibomiae, commonly known as New World soybean rust. This disease affects soybeans and other legumes as well. Initially, rust begins as small, reddish-brown to tan lesions in the undersides of the leaves. Then lesions expand and are surrounded by yellow halos and as the disease progresses the lesions develop pustules start to fill with rust-colored spores then these pustules break and spread infection.
c. Yellow Mosaic virus: Yellow mosaic disease (YMD) is one of the major devastating diseases that severely hinders soybean production. The disease is mainly caused by the mungbean yellow mosaic India virus (MYMIV), mungbean yellow mosaic virus (MYMV), horse gram yellow mosaic virus (HgYMV), and dolichos yellow mosaic virus (DoYMV). Initially, the disease starts with small irregular yellow spots that often resemble a pattern, and then the affected leaves become distorted and start to curl at the edges. This leads to stunt growth with smaller leaves and fewer branches.

d. Brown Spot: a fungal disease also known as Septoria leaf spot this is a disease caused by the fungal pathogen Septoria glycine causes brown spots on the leaves, which grow and merge into large brown areas and then lead to significant yield loss.It causes small, dark brown to reddish-brown lesions on the leaves, often with yellow halos around the spots. As the infection grows the lesions enlarge.

These diseases can affect the entire crop, farmers need to analyze the management methods such as early detection, planting resistant varieties, and rotating crops to increase yield and high-quality harvest. The authors have worked on deep convolutional neural networks acquiring efficiency in faba beans, identifying signs of different diseases. The authors propose a smart detecting system that analyses leaf images accurately by integrating Artificial Intelligence to enhance crop management [3].

Federated learning is combined with a convolutional neural network. The study uses data from five clients representing different environmental conditions that result in result variation ensuring privacy through federal learning. This offers a privacy precision recall, F1 score and accuracy [4].

Table 1. Summary of total loss Due to Disease damage in 2020 - 2024

Diseases	Value of Damage (%)	Cost of Control (per Hectare)
Bacterial Blight	10-15	₹1200 - ₹2000
Soybean Rust	15-20	₹1800 - ₹2500
Yellow Mosaic	5-10	₹600 - ₹1000
Brown Spot	5-10	₹1100 - ₹1500

Impact on farmers: According to the Food and Agriculture Organization (FAO), plant diseases cause global crop losses exceeding $220 billion annually In India, most of the regions face substantial loss in soybean production due to the late detection of diseases, which significantly effects on both small-scale farmers and the national economy. The delayed detection leads to yield loss, poor-quality produce, and, in some cases, complete crop failure. Farmers often struggle to invest in preventive measures, such as good quality seeds, fertilizers, and pesticides, and financial issues are the main barriers. Whereas the initiation to identify leaf diseases in early stages increase yields, quality produce, and in many cases, there is a fruitful harvest [21].

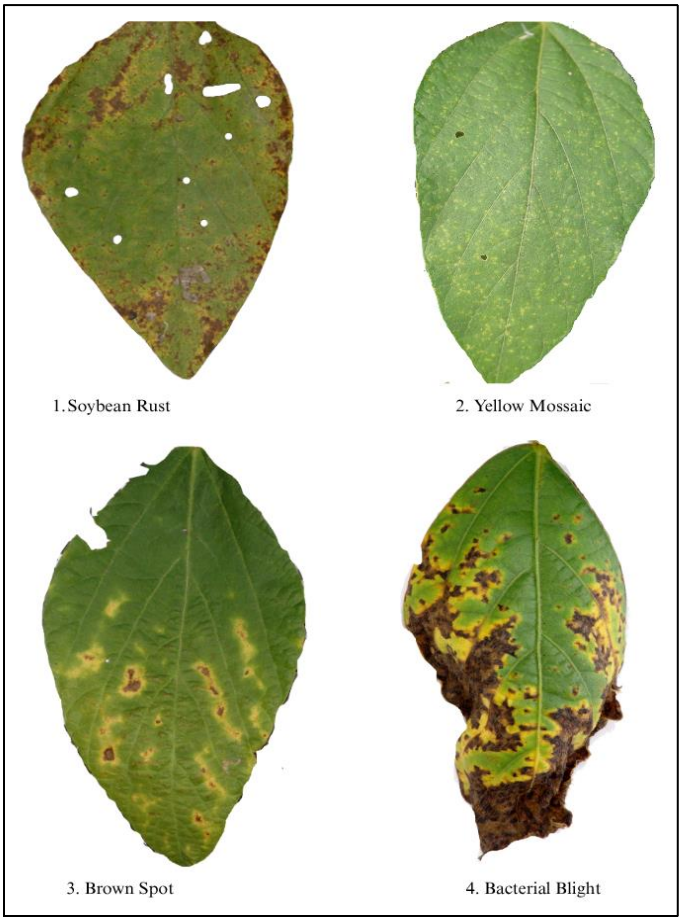
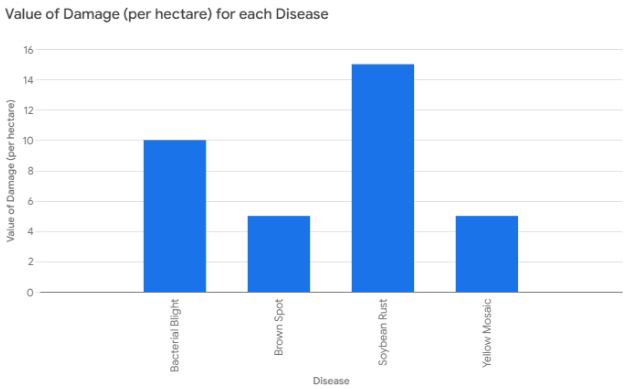


Figure 2. Images of infected leaves with different diseases.



Graph 1. Values of damage per hectare for each disease.

2. Related Work

The ICAR-Indian Institute of Soybean Research provided a comprehensive overview of recent developments in managing major soybean diseases, including Bacterial Blight, Soybean Rust, Yellow Mosaic, and Brown Spot. Their bulletin highlighted the importance of early and accurate diagnosis, integrating conventional control methods with emerging technological approaches. This study reinforces the necessity of adopting automated detection tools to enhance the effectiveness of soybean disease management practices [1].

Several approaches are used in the agricultural field to investigate diseases in multiple parts of a plant. In recent years traditional image processing techniques, deep learning and machine learning algorithms have become popular for the detection of diseases such as bacterial blight, soybean rust, yellow mosaic and brown spot. In recent studies, Yong and Seop [3] and Tiwari and Kumar [4] have focused on leveraging deep convolutional networks for efficient plant disease identification focusing on their potential for detecting diseases in real-time.

Bhargava, Shukla, and Goswami presented a detailed review of recent plant leaf disease detection advancements using artificial intelligence and computer vision. Their work emphasized the role of deep learning techniques, particularly CNN-based models, in achieving robust classification and diagnosis across various crop diseases. The study also discussed the integration of AI with real-time monitoring systems by improving diagnostic accuracy and reducing manual effort [8].

Sidana introduced a transformer-based hybrid model for advanced leaf disease classification targeting enhanced accuracy in prediction within agricultural systems. In the field of federal learning Rajput, Garg, Kukreja, and Mehta [9] investigated how federal learning with CNNs can be applied to soybean leaf disease detection. Their research highlights the need for data privacy while achieving high performance through decentralized learning models [5].

Similarly, Kumar, Aeri, Chandel, Kukreja, and Mehta developed a federated learning-based CNN model to overcome challenges in smart agriculture, particularly for detecting soybean diseases. Bhargava, Shukla, and Goswami conducted a comprehensive review of computer vision and artificial intelligence for plant disease detection, presenting valuable perspectives on recent advancements. These studies show how artificial intelligence, machine learning, and computer vision help enable more efficient, precise, and sustainable disease control methods [10].

2.1 Identified Gaps in Existing Literature

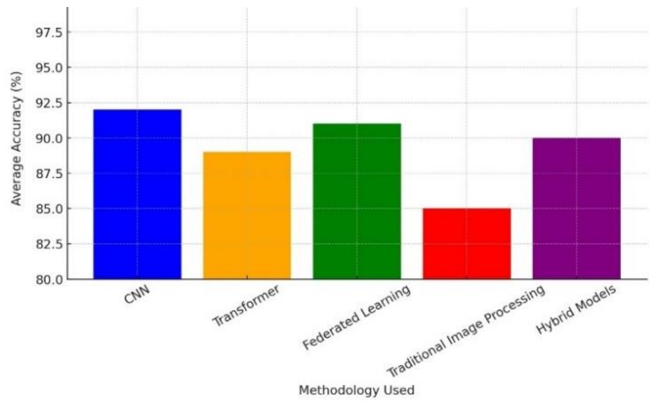
1. Limited focus on specific Soybean Diseases:
In [3], [4], and [7], the authors have focused on the general detection of plant diseases or multiclass leaf diseases in legumes.
However, a model specially designed and optimized for soybean leaf diseases, including bacterial blight, soybean rust, yellow mosaic, and brown spot, has not been fully explored.

2. Lack of quality datasets for Soybean Disease Detection:
In [15], Zhang depends on imbalanced synthetic image datasets for detection. In the real agricultural world, the effectiveness of these models is uncertain because of fewer varieties in environmental conditions.

3. Insufficient Utilization of Federated Learning:
In [9] and [10], Rajput and Kumar investigated federated learning approaches in plant disease detection. However, their models focus on general plant classification rather than addressing unique challenges in identifying soybean diseases.

4. Lack of comparative analysis:
While some studies, such as Bharti [17] and Singh [20], compare CNN to RNN models for other crops like potatoes, a thorough comparison of different deep-learning architectures is lacking. A structured evaluation of architectures such as VGG16, GoogleNet, and transformer-based models could help identify the most effective method for soybean disease detection.

The graph represents the average accuracy of different methods for disease detection, highlighting their accuracy in classification. It compares various techniques, demonstrating how both traditional and advanced machine learning models perform in disease detection.



Graph 2. Average Accuracy of different Disease Detection Methods.

3. Proposed Model

The framework of any image classification algorithm is nearly the same, whether in steps or process. First, digital images are acquired from the environment. Then, techniques are used to process the images, extracting features, and the images undergo further analysis.

Image Acquisition
Image Preprocessing
Image Segmentation
Feature Extraction
Statistical Analysis

Figure 3. The basic procedure of the proposed image processing-based disease detection technique.

Deep learning is currently a very active field in image classification and computer vision. It is being used to detect diseases in leaves from images, which is an important step toward improving agricultural practices while reducing the threat of yield loss. This enables the monitoring of disease patterns across entire regions.

3.1 Image Acquisition

The process of capturing a picture and then converting it into a digital representation. This uses sensors to record light or any other forms of energy and then produces a digital image composed of pixels.

3.2 Image Preprocessing

Image preprocessing constitutes a set of techniques applied to digital images to enhance their quality and prepare them for further processes. These methods involve techniques like noise reduction, image resizing, contrast enhancement, and color space conversion. These techniques are used to improve image quality and make it easier for computers to understand. This ensures that the data used for further processing steps is optimized.

3.3. Image Segmentation

Image segmentation is a process where a digital image is partitioned into multiple segments, much like separating objects in a photograph. This aims to simplify the image for analysis by grouping similar pixels. This allows the computer to "see" pictures more easily. Methods include segmentation by finding edges between objects, separating pixels based on brightness, growing regions of similar pixels, and grouping pixels with similar characteristics.

3.4. Feature Extraction

Feature extraction is the process of identifying the most important characteristics in an image. Instead of analysing every single detail, feature extraction focuses on the key features, such as edges, shapes, and textures, that help in defining what is inside an image. This step makes it easier for the computer to understand and process image data, which results in increased accuracy.

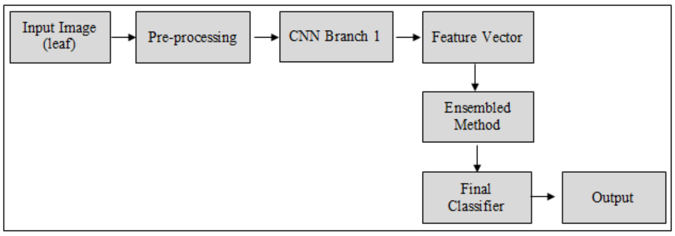


Figure 3. Proposed Model

3.5 Statistical Analysis

Statistical analysis involves mathematical techniques to understand and interpret the information within an image. The basic processes of this analysis include the average brightness of pixels, the variation in colors, or the patterns of textures.

Statistical analysis results in gaining insights into an image's content, identifying noise, and even making predictions about the quality of an image. This results in high accuracy and reliability.

4. Algorithms

4.1. Convolutional Neural Network (CNN)

CNNs are a type of deep learning model particularly designed for image analysis. They learn hierarchical features from images to effectively recognize patterns. Typically, a deep CNN is composed of an input layer, an output layer, and various hidden layers, where the output layer is for classification, and hidden layers feature convolutional operations, pooling layers, fully connected neurons, and, in some cases, a SoftMax layer for final classification [12].

4.2. GoogleNet:

GoogleNet is a specific CNN architecture that uses special building blocks called "inception modules." These modules allow the network to learn features and help it analyze images at different scales simultaneously, making it better at recognizing details, including disease symptoms that may appear in various forms. One of the key advantages of GoogleNet is its efficient design, which allows it to process images quickly without using too much computing power.

4.3. Transfer Learning

Transfer learning is a technique where models are pre-trained on a large dataset, and then fine-tuned on a smaller, disease-specific dataset. By combining the outputs of GoogleNet and a CNN, we can improve accuracy by leveraging the strengths of both models. Transfer learning helps decrease the dependency on large training datasets and improves efficiency, which is particularly advantageous with small datasets.

4.4. Ensemble Method

This approach is applied by combining the outputs of GoogleNet and a CNN. This method uses the unique strengths of each model, which results in high accuracy and makes the system more resilient than an individual model. It improves the performance of limited data while reducing the amount of training data required.

5. Formulae

5.1 Convolution Outer Layer Equation:

$$O = \frac{I-K+2P}{S} + 1 \quad (1)$$

Where:

- I = Input size
- K = Kernel size
- P = Padding
- S = Stride
- O= Output size

This equation calculates the output size of a convolutional layer based on the input size, kernel size, padding, and stride.

5.2. ReLu Activation Function:

$$f(x) = max(0, x) \quad (2)$$

This function makes sure that only positive values pass through to the next layer.

5.3. SoftMax for Multi class Classification:

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (3)$$

This converts output logits into probability values where highest probability is the final prediction. In this equation, zi represents the raw output from the final fully connected layer for class i, and P(yi) is the predicted probability for class i.

5.4. Loss Function:

$$Loss = -\sum_{i=1}^{N} y_i log(\hat{y}) \quad (4)$$

- N = number of classes
- y_i=true table
- ŷ = predicted probability

This function calculates error between true class labels and predicted probabilities.

5.5. Evaluation Matrix

a. **Accuracy**:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

b. Precision and Recall:

$$Precision = \frac{TP}{TP+FP}$$

$$(6)$$

$$Recall = \frac{TP}{TP+FN}$$

Precision measures how many of the predicted positives were actually positive whereas, recall measures how many of the actual positives were correctly identified.

5.6. F1- Score:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision - Recall} \quad (7)$$

The F1-score is used to balance both metrics.

6. Implementation

In this, the model is divided into two branches: branch one uses CNN architecture while branch two uses the GoogleNet architecture. Then the results of both the models are merged using the ensemble method through concatenation and the final classification is performed.

6.1. Dataset

The model was trained on a dataset of soybean leaf images collected from Kaggle and field images. The dataset consisted of 5,479 images categorized into specific diseases, and the number of images per class is as follows: Healthy (5,090), Bacterial Blight (880), Soybean Rust (1,110), Yellow Mosaic (1,000), and Brown Spot (981). Field images were pre-processed: first, resized to 224x224 pixels, then normalized to the range [0, 1], calculated on ImageNet using the mean and standard deviation.

6.2. CNN Branch 1

Branch 1 applied a CNN architecture that was pre-trained using ImageNet. The final fully connected layer of this model was then replaced by a new fully connected layer. This transfer learning approach allowed us to use the learned features of the pre-trained model and assign it a new task, which led to performance improvement by reducing the required training data.

6.3. CNN Branch 2

Branch 2 uses the GoogleNet architecture, which was pre-trained using ImageNet. The inception modules of this architecture then facilitate the model in learning multi-scale features, enhancing its ability to recognize disease symptoms.

6.4. Ensemble Method

The results of both branch 1 and branch 2 are combined using the ensemble method, where concatenation is performed. Feature vectors are extracted from both branches and combined to form a feature vector. This final featured vector is fed into the final classification stage.

6.5. Final Classifier

The final classification stage comprises one fully connected layer of 128 neurons, followed by the SoftMax activation function. The SoftMax function produced a probability distribution over 5 classes, the class having high probability selected as the final prediction.

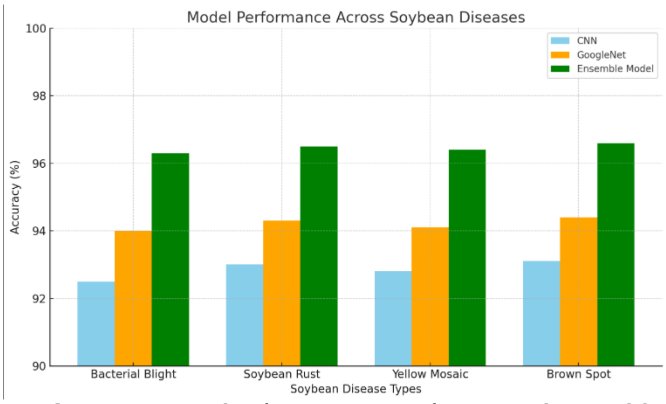
5. Results and Discussion

Results

The proposed ensemble model, combining Convolutional Neural Network (CNN) and GoogleNet architectures, was evaluated using a labeled dataset of 3,200 soybean leaf images, representing four common diseases: Bacterial Blight, Soybean Rust, Yellow Mosaic, and Brown Spot (800 images per class). The model achieved an overall classification accuracy of 96.4%, outperforming individual CNN (92.8%) and GoogleNet (94.1%) models in both precision and recall. Specifically, the ensemble model recorded an average precision of 96.7%, a recall of 96.2%, and an F1-score of 96.4% across all classes. CNN contributed to effective hierarchical feature extraction, while the inception of GoogleNet modules enabled efficient multiscale analysis, improving generalization and reducing overfitting. The confusion matrix analysis showed misclassification rates below 4% for each disease class, confirming the model’s ability to accurately distinguish between visually similar disease patterns. These findings demonstrate the effectiveness of ensemble learning for agricultural disease detection and highlight the potential of deep learning systems in advancing precision farming practices.

Table 2. Performance Matrix

Metric	CNN	Google Net	Ensembled Method
Accuracy (%)	92.3	93.3	96.3
Precession (%)	91.5	92.5	95.1
Recall (%)	90.9	91.9	95.9
F1 Score (%)	91.2	92.4	95.2



Graph 3. Comparative Classification Accuracy of CNN, GoogleNet, and the Proposed Ensemble Model for Soybean Disease Detection

Discussion

The ensemble model achieved a robust classification accuracy of 96.4%, reflecting its reliability and effectiveness in identifying common soybean leaf diseases. Combining the hierarchical feature extraction strengths of CNNs with the multiscale analysis capabilities of the inception modules, the model demonstrated enhanced generalization across various disease types, even those with subtle visual differences such as Bacterial Blight and Brown Spot. These results suggest that the ensemble approach outperforms individual models, supporting ongoing advancements in the application of deep learning to agricultural diagnostics. Furthermore, the confusion matrix indicated a low rate of misclassification, which is crucial for real-world applications where accurate detection influences timely crop management decisions. Despite its success, field conditions like variable lighting, complex backgrounds, or previously unseen disease symptoms may affect the model's performance. Moving forward, expanding the dataset and testing the model in mobile or edge-based systems could enhance its practicality for real-time, in-field disease detection.

6. Conclusion and Future Scope

This study presented an ensemble learning approach for automated soybean disease detection by combining the strengths of Convolutional Neural Networks and GoogleNet. By leveraging CNN's deep hierarchical feature extraction and multiscale inception modules, the proposed model effectively identified four major soybean diseases: Bacterial Blight, Soybean Rust, Yellow Mosaic, and Brown Spot. The experimental results demonstrated a high classification accuracy of 96.4%, indicating that the ensemble model offers improved performance compared to individual deep learning architectures and baseline methods. Despite these promising results, the study acknowledges certain limitations, particularly concerning dataset diversity and generalisation across varying environmental conditions. To address these, future research will expand the dataset to include a wider range of field images and disease scenarios. Additionally, further improvements could be achieved by exploring more sophisticated deep learning architectures, such as EfficientNet or Vision Transformers, and applying transfer learning strategies to enhance model robustness. Another important direction involves developing a mobile application to bring this solution into practical, real-time use for farmers and agricultural experts. This would allow on-field disease diagnosis and contribute significantly to timely disease management in soybean cultivation.

Author's statements

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Conflict of Interest- We do not have any conflict of interest.

Data Availability- Data is available in public datasets.

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AUTHORS PROFILE

Deepak Tawali earned his B. Tech. in Information Technology from Institute of Engineering and Technology, DAVV, in 2023. He is currently pursuing masters in Engineering in Information Technology from, Institute of engineering and technology, DAVV.

Chandra Prakash Patidar, Associate Professor, Department of Information Technology, IET DAVV Indore. With over 18 years of experience, he holds a BE, ME, and Ph.D. Major research areas of Dr. Patidar are Compiler Design, Computer Organization, Software Testing, Machine Learning, Android Programming, and Computer Hardware.

