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Research Article

Implementation of a CNN-Based Model for Soybean Leaf Diseases

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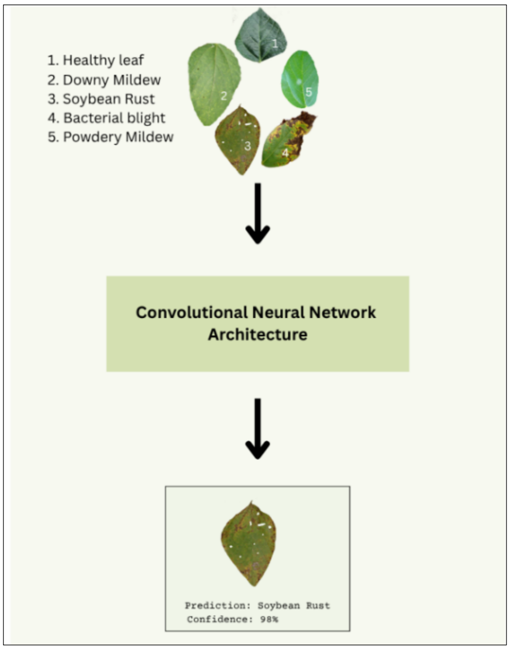
Abstract— Soybean ranks among the most vital crops grown in India, especially in Madhya Pradesh, where it significantly contributes to the agricultural economy and supports nutritional security. Nonetheless, the yield of soybean crops is greatly affected by several leaf diseases, including bacterial blight, downy mildew, soybean rust, southern blight, and powdery mildew. Timely and precise detection of these diseases is crucial to reduce crop damage. Conventional disease identification techniques are often slow, require considerable manual effort, and are susceptible to human error. To address this issue, this study proposes the implementation of a Convolutional Neural Network (CNN)-based deep learning model to detect and classify common soybean leaf diseases using image data. A total of 5,917 images were utilized in the dataset, divided into five disease categories and one healthy category. The dataset was preprocessed and augmented to enhance model performance and divided into training (70%), validation (10%), and testing (20%) sets. The CNN model was trained over 20, 40, and 50 epochs to assess its performance across varying training durations. It demonstrated high classification accuracy, highlighting its effectiveness as a dependable method for the early detection of soybean leaf diseases.

Keywords— Convolutional Neural Network, Machine Learning, Keras, TensorFlow, Plant Disease Identification.

Graphical Abstract-



Early and accurate disease detection to support crop management

Purpose- The graphical abstract visually simplifies the research approach, showcasing the classification of soybean leaf diseases through a Convolutional Neural Network (CNN). It demonstrates how the model processes images of both healthy and diseased leaves to accurately identify specific conditions. The visual emphasizes the efficiency of the proposed technique in facilitating early disease detection, aiding prompt decision-making, and enhancing crop health management.

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1. Introduction

Figure 1. Healthy Leaf

From the fertile plains of Madhya Pradesh, the Indian Soybean Research Institute (IICR) stands as a beacon of agricultural innovation. Golden seeds yield soybeans — a key to nutritional security. Soybeans are a valuable crop for both humans and animals, being one of the richest sources of essential nutrients and high-quality protein. India produces soybeans in large quantities. They are highly productive and rich in vitamins, minerals, and various antioxidants. Soybeans also play a crucial role in nitrogen fixation in the soil, making them vital for sustainable agriculture. In terms of production, India ranks fifth in the world after the United States, Brazil, Argentina, and China. Within India, Madhya Pradesh is the largest producer of soybeans, consistently meeting high demand. Production is currently on the rise, driven in part by the growing trend of veganism in Western countries. Commercial soybean cultivation is concentrated primarily in the Malwa region of central India.

The Indian Council of Agricultural Research (ICAR) has acknowledged the success of this crop, attributing it to the continuous efforts of farmers, scientists, and government initiatives that add value to the harvest. The All India Coordinated Research Project on Soybeans is considered a milestone in the history of soybean cultivation in India. Launched with the primary objective of advancing technology and research to boost soybean production and productivity, the project also aimed to establish a strong national research infrastructure. Soybeans, legumes originating from East Asia, have a wide range of applications that enhance the nutrition of living organisms. The plant is upright with multiple branches and can grow up to 2 meters tall. This crop thrives particularly well in warm climates with diverse climatic zones and soil types.

Taxonomically, soybeans fall under two subgenera: Glycine and Soja, which include both the cultivated soybean (Glycine max) and its wild relatives. Nutritionally, soybeans provide approximately 446 calories per 100 grams, consisting of 20% oil, 40% protein, 35% carbohydrates, and 5% minerals. Beyond raw consumption, soybeans are processed into oil, which is fundamental for culinary use, industrial applications, and even biodiesel production.

Soybean leaves are versatile and are useful in various ways. It adds nutrition to multiple dishes. Fresh soy leaves can be tossed into a salad, giving a unique flavour. These can even be used to add texture and nutrition to soups by steaming or just sautéing. Soybeans are native to East India and have been an essential part of the Asian diet for centuries. Culturally, soybeans are a key element in culinary traditions, often featured prominently in religious and traditional ceremonies. Moreover, they offer multiple benefits, as the notable amounts of iron, calcium, magnesium, potassium, and selenium in soybeans promote skin health, help regulate blood pressure, strengthen bones, and assist in the treatment of anaemia.

To tackle the increasing difficulty of accurately and swiftly identifying diseases in soybean leaves, this study introduces a deep learning-based approach using Convolutional Neural Networks. The model's performance was examined by training it for 20, 40, and 50 epochs, allowing a comparative analysis of how training duration affects key metrics such as accuracy, loss, and processing time. This evaluation helps determine the most effective balance between computational efficiency and model accuracy. The broader objective of this project is to create a reliable, automated detection system that can assist farmers and agricultural professionals in early-stage disease identification, consequently minimizing crop loss and promoting healthier yields.

1.1 Diseases

1.1.1 Bacterial blight is a common soybean disease that manifests as small, water-soaked spots with yellow halos on the leaves. Over time, these spots enlarge and turn brown, often leading to torn or fallen leaves. It typically affects plants during cool, wet weather conditions, particularly in the early to mid-growing season. This disease is caused by Pseudomonas species and easily spreads through splashing water, making it prevalent after rain or irrigation.

1.1.2 Soybean rust is a disease that affects soybeans and other legumes. It is caused by two types of fungi, Phakopsora pachyrhizi, commonly known as Asian soybean rust, and Phakopsora meibomiae, commonly known as New World soybean rust. It typically affects plants during cool, moist weather conditions, particularly in the early to mid-growing season when extended leaf wetness.

1.1.3 Downey mildew is a fungal disease affecting soybean plants, caused by Peronospora manshurica, a fungus-like organism. This disease manifests on the leaves of soybeans and is most prevalent in rainy and humid weather conditions. It survives on the seed surface. The potential loss for 100 kg of soybeans could reach up to 30 per cent at the maximum stake [6].

1.1.4 Powdery mildew is a soybean leaf disease that appears as white or grey powdery fungal patches on the upper surface of leaves. Infected leaves may become curled, distorted and fall off prematurely. The disease is favored by low humidity and moderate temperatures, usually appearing at the end of the season. It is caused by several fungal species and is more common when air flow is restricted.

1.1.5 Southern blight is a soil-borne fungal disease that affects the stem base of soybean plants. It is characterized by a white, cottony fungal growth near the base and small, brown, mustard seed-like sclerotia. The disease causes stem rot, plant wilting, and eventual collapse. Southern blight is most active in hot and humid conditions, especially during the mid to late stages of plant growth. It is caused by Sclerotium rolfsii, which can survive in the soil for years.

Table 1. Soybean Production in Madhya Pradesh

Year	Area (Hectare)	Production (1000Tons)	Yield (Tons/Hectare)
2014-2015	5000	4000	0.80
2015-2016	4500	3500	0.78
2016-2017	5500	4500	0.82
2017-2018	5000	5000	1.00
2018-2019	4500	4500	1.00
2019-2020	5500	5500	1.00
2020-2021	6000	6000	1.00
2021-2022	5500	5500	1.00
2022-2023	6000	6000	1.00
2023-2024	6500	6500	1.00

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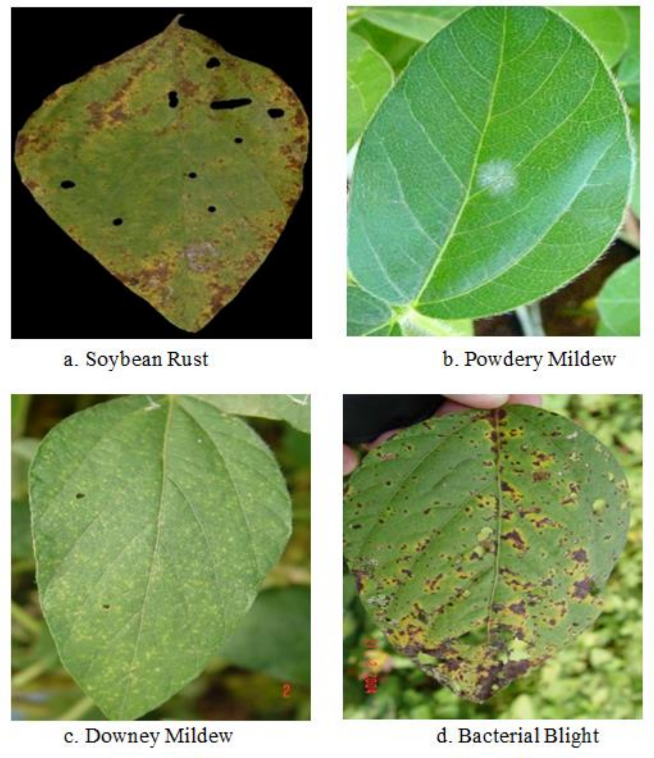

Figure 2. Images of Infected Soybean Leaves

As the agricultural industry increasingly adopts smart farming and precision agriculture, advanced technologies such as Artificial Intelligence and Deep Learning are proving to be game-changers. Automated detection of plant diseases plays an essential role in delivering timely and accurate crop health evaluations, minimizing dependence on traditional manual methods that are often labor-intensive and error-prone. By integrating deep learning models into modern farming practices, farmers gain access to intelligent systems capable of real-time monitoring and diagnosis. This study contributes to the ongoing advancement of Agri-tech by offering a scalable, practical solution aimed at improving both crop productivity and long-term sustainability.

2. Related Work

The application of advanced image-based techniques and deep learning has significantly improved plant disease detection and diagnosis. Several studies have made significant contributions to this field, highlighting the use of image processing, machine learning, and deep learning approaches.

Al-Hiary proposed a system that includes image-processing techniques for the classification and detection of plant diseases [3]. The study focused on segmentation, feature extraction, and classification steps, achieving computationally efficient and accurate results. This work is cost-effective and uses fast methods for disease identification.

Ferentinos explored the use of convolutional neural networks for plant disease detection [4]. The study employed an extensive dataset comprising 87,848 images from 25 plants and 58 disease categories, achieving a classification accuracy of 99.53%. This research illustrated the delivery of accurate disease diagnosis in real-world agricultural conditions.

Saradhambal introduced an image processing approach based on k-means clustering and segmentation for the early detection of plant diseases. The study identified diseases such as Alternaria and Anthracnose measured the affected leaf area. By combining traditional clustering algorithms with feature extraction, the research provided a simple yet effective methodology for detecting plant diseases in real-time [5].

Park presented a CNN-based mechanism for determining strawberry diseases using smartphone-acquired images of leaves and fruits [6]. The study achieved 92% accuracy in classifying healthy and diseased plants, including powdery mildew and gray mold rot. The system also provided dynamic feedback to farmers, enhancing its practical utility in real-world smart farming scenarios.

These studies collectively illustrate the evolution of plant disease detection techniques from traditional image processing [1] to deep learning methods [2], [4]. While [1] emphasized computational efficiency, [2] and [4] highlighted the scalability and accuracy of deep learning models. Additionally, [3] bridged the gap by integrating clustering and feature extraction techniques to address simpler agricultural applications. The works of Ferentinos [2] and Park et al. [4] particularly stand out for their use of extensive datasets and real-time applications. Despite significant advancements, challenges such as dataset imbalance, model generalization across diverse environments, and real-time processing remain. Future research could focus on expanding datasets, integrating IoT technologies, and leveraging edge computing to enhance the accessibility and scalability of plant disease detection systems.

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3. Proposed Model

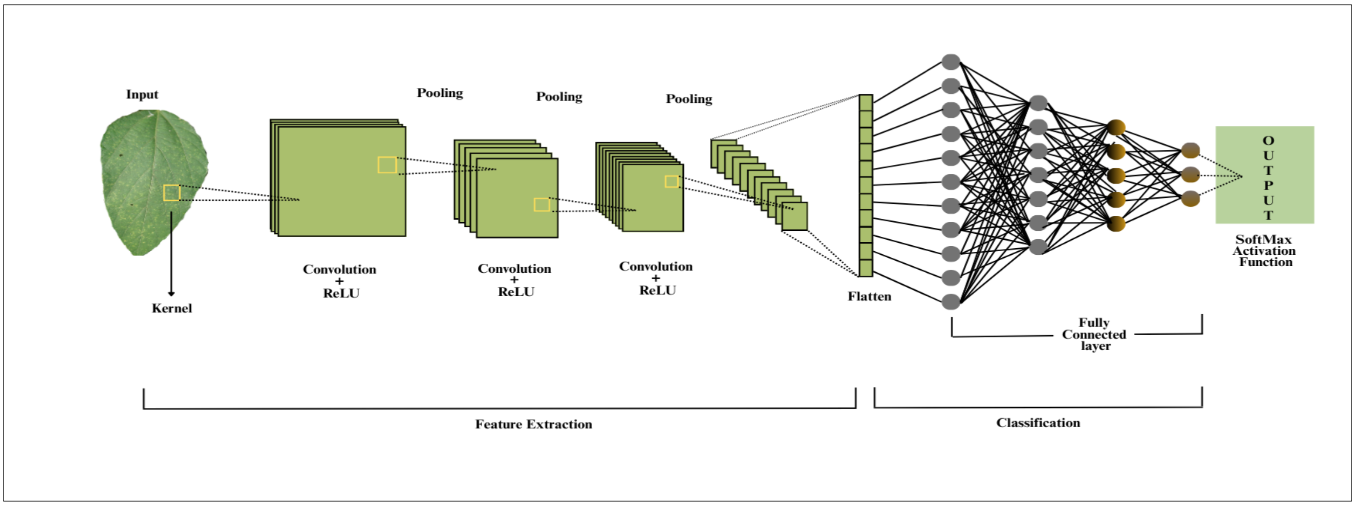

Figure 3. Proposed CNN Model for Soybean Leaf Disease Detection

The proposed model is a Convolutional Neural Network (CNN)-based architecture designed for the classification of soybean leaf diseases. It follows a sequential design comprising three convolutional layers with increasing filter sizes (32, 64, and 128), followed by max-pooling layers to reduce spatial dimensions while retaining essential features. The model takes input images resized to 150x150 pixels, normalizes them, and applies data augmentation techniques such as rotation, zoom, shear, and flipping to enhance generalization. The extracted features are flattened and passed through a fully connected dense layer with 512 neurons and a dropout layer to prevent overfitting. The final output layer uses a SoftMax activation function to classify images into one of the five disease categories. The model is compiled using the Adam optimizer with categorical cross-entropy loss and trained over multiple epochs with validation using a split of the dataset. This architecture balances complexity and performance, making it suitable for image-based disease detection tasks.

4. Convolutional Neural Network

The core of the soy disease classification system is based on a folding network (CNN), which is highly effective for image recognition tasks. CNNS is a class of deep neuronal networks that can be developed specifically for processing pixel data, allowing folding layers to extract spatial hierarchies of properties. In this project, the proposed CNN architecture consists of three layers of folding, followed by a maximum pooling layer to reduce spatial dimensions and calculations. The network starts with a folding layer with 32 filters of size 3, followed by layers with either 64 or 128 filters. These layers are activated using the Relu function and introduce nonlinearity. The output flattens out of the folding block and is induced by a dense layer of 512 neurons, followed by a layer of failure to prevent excessive adaptation at a rate of 0.5. Finally, the output layer classifies the input images in one of the predefined disease categories using the SoftMax activation function. This architecture effectively records important patterns in leaf photographs, so the model accurately distinguishes healthy and sick leaves.

4.1 Equation

4.1.1 Convolution Operation

$$S\ (i,j) = \sum_m \sum_n X(i+m, j+n). K(m,n).. \quad (1)$$

• X: Input image
• K: Kernel, a small matrix that slides over the input
• (i,j): Position in the output feature map
• (m,n): Indexes within the kernel
• $S\ (i,j)$: Output value.

4.1.2 ReLU Function

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

- x: Output value from the convolution operation
- f(x): Activated output

4.1.3 Max Pooling

$$P(i,j) = \max_{m,n\in R} F(i+m, j+n) \ldots\ldots\ldots\ldots\ldots (3)$$

- F: Input feature map
- R: Pooling region (usually 2×2)
- P (i, j): Maximum value in region R

4.1.4 SoftMax Function

$$\sigma(z_i) = \frac{e^{zi}}{\sum_{j=1}^{K} e^{z_j}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

- z_i: Raw output from the final layer for class iii
- K: Total number of
- $\sigma(z_i)$: Probability

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5. Tools

5.1 Python

Python is open-source programming language known for its design for readability, and it has some similarities to the English language. It was created by Guido van Rossum and released in 1991. Python is a dynamically typed language used for web development, software development, and mathematics.

5.2 TensorFlow and Keras

TensorFlow is a library of machine learning used to create and train neuronal networks. It is the most popular deep learning framework. Free open-source software available under Apache license 2.0. It is a flexible framework that can be provided on a variety of platforms such as CPU, GPU, TPU, and more, and is typically used for tasks such as deep learning, image detection, and natural language processing.

5.3 Numpy

Numpy is a powerful Python library that supports multidimensional arrays and matrices, along with a large collection of high-level mathematical features to work with these arrays. It provides a wide range of functions for mathematical manipulation, data manipulation, and scientific computer tasks [26].

5.4 Matplotlib

Matplotlib is a data visualization library for Python, which was written by John D. Hunter. Matplotlib provides an object-oriented API which allows you to embed plots into apps made with GUI tools like Tkinter. It is a free and open-source plotting library.

5.5 TKINTER

TKINTER is a standard GUI library for Python (graphic user interface) written by Steen Lumholt. It provides a quick and easy way to create desktop applications. It helps users upload images and classification results in real time.

5.6 Keras Image Data Generator

Image data generator is useful for expanding real data. It was used to create training and validation data departments that scale pixel values, perform random transformations (rotation, zoom, flipping, etc.) and improve model generalization.

5.7 Kaggle

Kaggle is a well-known online platform for data science and machine learning that hosts data records, competition and community discussions. Numerous curated datasets are available for researchers and practitioners. In this project, data records were associated with Kaggle soy leaf disease, including classified images of healthy soybean leaves. Data records were essential for training and evaluation of the performance of CNN models.

6. Implementation

Implementation of the Soy Disease Classification System was performed in several phases, from preparing modeling data via a graphical user interface (GUI). The entire project was developed along with several supporting libraries and frameworks along with the Python programming language.

6.1 Data Preprocessing

Kaggle's data records are in the form of images divided into several classes, such as various types of soy blade disease and healthy leaves. To maintain uniformity, each image was modified with a solid dimension of 150 x 1550 pixels. Data augmentation techniques such as rotation, flipping, zooming, and moving were used using Keras's image utility. These enhancements were important to improve the generalisation of the models and to prevent them from being adapted.

6.2 Model Architecture

A Convolutional Neural Network (CNN) was designed and implemented using TensorFlow and Keras. The architecture consisted of three convolutional layers with ReLU activation functions followed by max-pooling layers. These layers helped in extracting spatial features from the images. The output from the convolutional layers was flattened and passed through a dense layer with dropout regularization to reduce overfitting. The final layer used a SoftMax activation function to predict the probability distribution over the output classes.

Model Summary

- Input Layer: 150x150x3 image
- Convolutional Layer (32 filters, 3x3) → MaxPooling2D
- Convolutional Layer (64 filters, 3x3) → MaxPooling2D
- Convolutional Layer (128 filters, 3x3) → MaxPooling2D
- Flatten → Dense (512 neurons, ReLU) → Dropout (0.5)
- Output Layer: Dense with SoftMax activation (based on number of disease classes)

The model was compiled using the Adam optimizer and categorical cross-entropy loss function. The accuracy metric was used to evaluate performance during training.

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6.3 Model Training and Evaluation

Using the training subgroup of data records, the models were trained at a batch size of 32. A validation set consisting of 20% of the original data was used to monitor the power of the model and prevent over-regulation. Accuracy and losses were applied using MATPLOTLIB to visualize the learning curve. If previously trained models are available, they were loaded directly to save computing time. Otherwise, the new model was trained and saved in .h5 format for future use.

6.4 Graphical User Interface (GUI)

A user-friendly desktop application was developed using Tkinter to allow end-users to upload images and receive instant predictions. Upon uploading an image, it is resized and normalized, then passed to the trained CNN model for prediction. The GUI displays the predicted class along with the confidence level as a percentage. The interface also displays the uploaded image for visual confirmation

7. Results

The performance of the Convolutional Neural Network-based model for soybean leaf disease classification was evaluated over three different training durations: 20, 40, and 50 epochs.
The objective was to observe the impact of increased training epochs on model accuracy, validation performance, and training stability. Figure 4 depicts how training and validation accuracy evolve over epochs, showing a consistent improvement in training accuracy that indicates the model's effective learning from the provided data. Despite minor fluctuations, the validation accuracy generally trends upward, indicating that the model can generalise well to unseen data while minimising overfitting, as evidenced by the convergence of both accuracy curves.

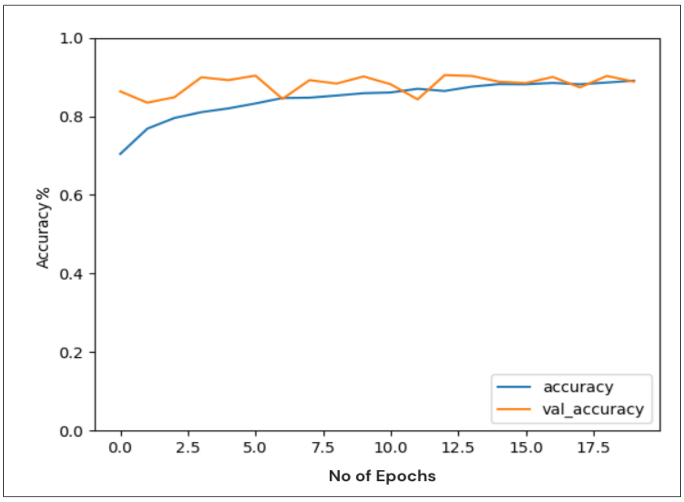

Figure 4. Epoch Accuracy Graph

Figure 5 displays the training and validation loss over epochs, showing a consistent decrease in training loss and some variability in validation loss that may result from the complexity and variability of the dataset.
The parallel behavior of the loss curves confirms that the model is training stably. Comprehensive classification metrics like accuracy, precision, recall, and F1-score for each soybean leaf disease type are provided in Table 2. The model achieved the highest accuracy in detecting Soybean Rust, while performance was relatively lower for Powdery Mildew, likely due to symptom overlap with other diseases like Downy Mildew. The macro F1-score indicates the model's balanced and trustworthy performance, emphasizing its suitability for automated detection of soybean leaf diseases.

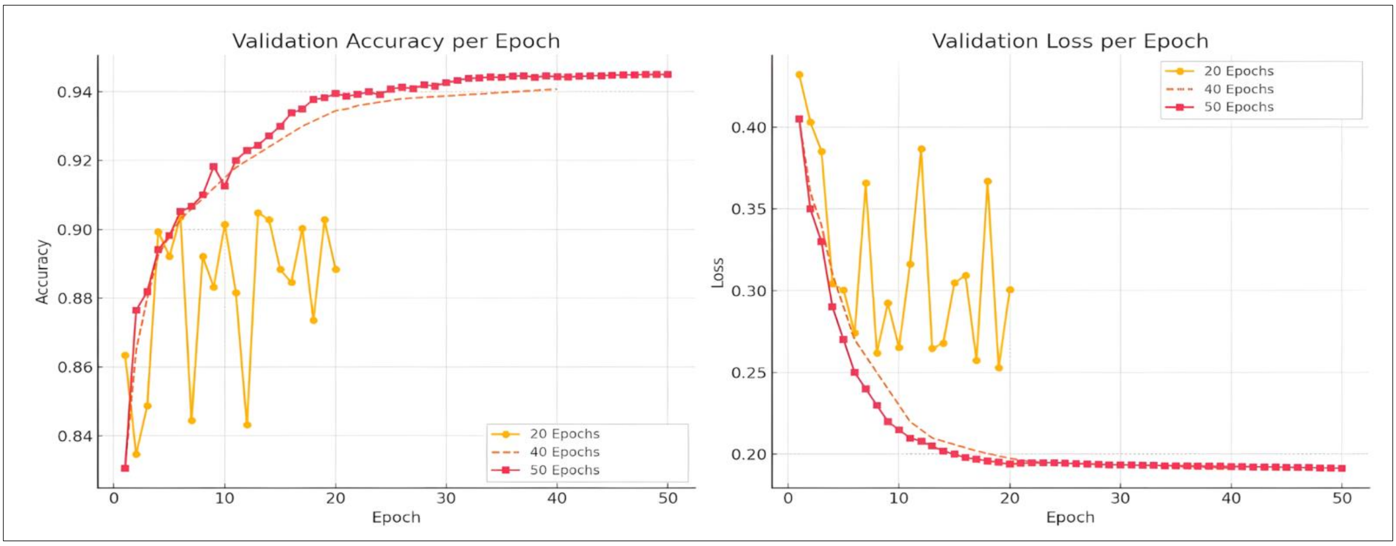

Figure 5. Comparison of Validation Accuracy and Loss for CNN Models Trained for 20, 40 and 50 Epochs

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Table 2. Comparative Analysis of CNN Models Trained on Leaf Datasets.

Model	No. of Epochs	Accuracy (%)	Average (%)	Loss (%)	Time per Epoch (Seconds)
M1	20	0.8840	0.1116	0.3007	575
M2	40	0.9175	0.0825	0.2751	585
M3	50	0.9302	0.698	0.2702	594

8. Conclusion

In this project Convolutional Neural Network was developed for the classification of soybean leaf disease. Using data records obtained from Kaggle, the system was trained to identify several disease categories with high accuracy. The model architecture was carefully developed with several foldable and bundling layers, followed by dense layers that could not reduce over adaptation. Image magnification technology was used to improve the robustness of the model to variations in input data. The proposed convolutional neural network model was trained using a publicly available soybean leaf disease dataset from Kaggle and evaluated across different training durations (20, 40, and 50 epochs). It was observed that training the model for a greater number of epochs resulted in higher classification accuracy and a decline in validation loss. Training the model for 50 epochs yielded the best results, with a recorded accuracy of 93.02% and a validation loss of 0.2702. These outcomes demonstrate the model's ability to generalize well to unseen data, confirming its robustness and effectiveness in the early detection of soybean leaf diseases. To enhance usability a user-friendly GUI has also been developed with TKINTER, allowing end users to easily upload and classify images. Experimental results show that the proposed model effectively extracts relevant features and provides reliable predictions, indicating that it is a promising tool for early detection and diagnosis of diseases in soybean systems. This system can support farmers and farm professionals with real-time information from a decision-making perspective, ultimately contributing to improved harvest and nutritional safety.

9. Future Work

The system effectively classifies soybean leaf diseases using a Convolutional Neural Network (CNN) and provides a user-friendly desktop interface. There are some instructions for future improvements. Extending the data records to more diverse real images taken under different environmental conditions can greatly improve the generalization of the model. Providing a system as a mobile application could support farmers by increasing the ease of use in remote agricultural environments. Additionally, both accuracy and efficiency can be improved by introducing advanced CNN architectures such as resets and mobile sets, or using forwarding learning techniques. Integrating explanatory AI technologies such as Grad-CAM further increases the transparency of the system by highlighting the image areas that affect predictions. Furthermore, tools for non-English language users, including multilingual support in the user interface, are more accessible, especially in rural communities.

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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