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Original Article

Proactive Soybean Disease Detection through YOLO Leaf Extraction and ResNet-50 Classification to Reduce Crop Loss and Boost Productivity

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Abstract - *Agriculture contributes 18% to India's GDP, with soybean production at 14 million metric tons annually, making it a major crop for farmers, though the sector's share is decreasing. Bacterial, fungal, and viral diseases, along with nematode infestations, can affect soybeans throughout the growing season. Accurate disease identification and appropriate treatment improve soybean production by stopping the spread of infections, reducing crop loss, enhancing plant health, boosting yields, and providing better economic benefits for farmers. The fifty different soybean farms in Maharashtra were surveyed to construct a dataset on the major diseases affecting the soybean crop. The collected images are preprocessed through resizing for uniformity, data augmentation for diversity, and normalization to scale pixel values, facilitating efficient training. The collected dataset is used to train several deep learning algorithms, such as AlexNet, VGG-16, Inception-v3, EfficientNetV2B0, and ResNet-50, to predict diseases. To evaluate the model's effectiveness, the study analyzed the training and validation loss and accuracy. The real-time soybean plant images were utilized, and YOLO was employed for leaf extraction, generating test images that were then fed into the trained models. The outcomes show that ResNet-50 predicts soybean conditions from the captured pictures from the soybean farm more effectively than cutting-edge methods. Performance metrics for classification were calculated for each model, with ResNet-50 yielding the most accurate predictions across all metrics. A confusion matrix was also generated to assess the model's classification accuracy, further confirming ResNet-50's robustness. These results suggest that deep learning models, especially ResNet-50, can serve as effective tools for early and accurate detection of soybean diseases, offering valuable support for precision agriculture.*

Keywords - *Soybean, Disease, Prediction, AlexNet, VGG, Inception, EfficientNet, ResNet, YOLO.*

1. Introduction

In most parts of India, water resources are scarce, and agriculture relies primarily on rainfall, a practice known as rainfed farming. Farmers in these regions grow crops that can withstand limited water during low rainfall and are resilient to floods during heavy rain [1]. Soybean is one of the most commonly cultivated crops during the rainy season in India and serves as a vital livelihood source for farmers in regions with low rainfall. Numerous diseases pose a threat to soybean cultivation, often leading to reduced yields and economic losses for farmers [2]. Approximately 14 million metric tons of soybeans are produced in India each year, which makes it a major crop cultivated by farmers. As a Kharif crop, soybeans are sown in June or July during the rainy season and harvested in October or November. Throughout the growing season, soybeans can be affected by bacterial, fungal, and viral diseases, as well as nematode infestations. However, in order to increase production and preserve soil health, successful soybean farming demands appropriate management practices, uch as pest control, disease management, and optimum irrigation. In order to increase production and reduce environmental effects, modern technologies like automated systems and precision agriculture are being implemented in response to the growing need for sustainable farming practices [3]. The estimated costs, production, and profit for soybean farming are presented in Table 1.

Table 1. Economic breakdown of soybean farming: costs, production, and profits

Ploughing and sowing	4000
Soybean Seed cost for sowing	2000
natural fertilizer and Chemical Fertilizer [nitrogen (N), phosphorus (P), and potassium (K)]	5000
Pesticide spraying/application	5000
Weeding	3000
Labour cost for irrigation	3000
Harvesting (dry soybean plant collection and harvesting machine rent)	7000
Electricity cost (4 Months)	6000
Other	2000
Total cost per acre (4840 square yards.)	37000
Soybean production per acre in KG	1400
Soybean selling price (average rate 50 INR per KG)	70000
Profit per acre in INR	33000

The appearance of soybean diseases on leaves can be similar, making it challenging to visually identify the specific disease accurately. A summary of the most prevalent soybean diseases and their descriptions is provided below [4].

1.1. Bacterial Pustule (BP)

Xanthomonas axonopodis pv. glycines is the reason for bacterial pustule, which develops in the middle to late season during warmer weather. The lesions, which start out small with pale green patches having elevated centers, can be seen on the outer leaves and gradually become larger.

1.2. Frogeye Leaf Spot (FLS)

The young soybean leaves are particularly susceptible to frogeye leaf spot, which is caused by the fungus Cercospora sojin, whereas older leaves usually have greater resistance.

1.3. Rust

The fungus Phakopsora pachyrhizi causes the most common disease called soybean rust, which appears on the lower surface of leaves after the plants have flowered. Lesions initially appear on the lower leaf surfaces as small gray spots that then change to a reddish-brown color.

1.4. Sudden Death Syndrome (SDS)

Toxins produced by the fungus Fusarium virguliforme that spread from the roots to the leaves lead to sudden death syndrome. SDS arises on the uppermost leaves of the soybean plant after flowering, appearing in the spaces between the veins. The little yellow-haloed dots develop into brownish-tan lesions that enlarge until the leaf is dead.

1.5. Target Leaf Spot (TLS)

Target spot is a common disease that affects almost all plants and is caused by the fungus Corynespora cassiicola. Reddish-brown, spherical to irregularly shaped lesions are the target spot on leaves, which are frequently encircled by yellow halos. Target spots get their name from the formation of concentric rings in more developed lesions. Severe infections that begin in the bottom canopy and progress upward can cause defoliation.

1.6. Yellow Mosaic (YM)

Young leaves, mostly affected by the mosaic virus, pucker along the veins and curl downward. The lower seed size, fewer pods per plant, and plant stunting are all potential consequences of the mosaic virus [5].

Farmers face numerous challenges while growing soybean crops, which are outlined below.

- The symptoms of many soybean diseases are identical, making it challenging to differentiate between them just by visual inspection [6].
- Many times, accurate identification needs specialized expertise and knowledge that not all producers have, particularly in isolated or resource-constrained places.
- Although molecular and serological diagnostic techniques are available, not all farmers have access to them due to their high cost and need for specialist equipment [7].
- Some diseases have a high rate of transmission within a field or between fields; thus, prompt and correct diagnosis is essential for controlling such diseases.
- Small-scale farmers, in particular, may find it difficult to properly detect and manage soybean conditions due to the high expense of tests for diagnosis and disease management [8].

The study introduces a soybean disease prediction method that accurately forecasts diseases, allowing farmers to take prompt action. The collected 5,600 images of infected plants represented six common diseases, and data augmentation was employed to enhance the diversity of the training dataset and improve the model's robustness. Various deep learning models, including AlexNet, VGG-16, Inception-v3, EfficientNetV2B0, and ResNet-50, were implemented to assess prediction accuracy. The YOLO for real-time leaf extraction was used to prepare 70 test pictures for six disease classes for assessment in order to simulate real-world situations. The performance of different trained models is evaluated using training and validation results, classification metrics, and the confusion matrix. The comparison, based on accuracy, precision, recall, and F1 score, revealed that ResNet-50 outperforms the other models, providing more accurate predictions for soybean diseases.

2. Literature Survey

Advancements in deep learning have made it easier to build a variety of models aimed at detecting diseases in plant leaves. Right now, there are few approaches available for identifying soybean leaf diseases, and most of them rely on machine learning techniques. In order to more reliably identify soybean leaf diseases, Q. Wu et al. [9] presented an improved deep learning network model that is divided into three parts: extracting features, calculating attention, and categorization. To increase the network's resilience, the dataset was initially diversified using data augmentation methods such as random masking.

This method reduced background noise, strengthened the network's capacity to focus on differentiating features, and made use of the attention module's LeakyReLU activation function to prevent neuron learning failures in the context of negative inputs. Improved soybean leaf disease classification accuracy has been obtained by combining the extracted features with a fully connected layer to predict the disease category. The enhanced network model achieved an accuracy of 85.42%, compared to 66.41% for ConvNeXt, 72.22% for ResNet50, 72.92% for SqueezeNet, 59.89% for ShufeNetV2, and 67.27% for MobileNetV3.

Although soybeans are an essential source of protein and oil, their yields are vulnerable to environmental changes, infections, and inappropriate fertilization. For this reason, an accurate assessment of leaf damage is crucial to applying pesticides, fertilizer selection, and yield forecasting. The YOLOv5s model [10] trained on a dataset contains 2930 soybean leaf images for five diseases with a size of 600 × 800 pixels. For approximately thirty parameters, the Genetic Algorithm (GA) was utilized for hyperparameter optimization. The model achieved 89%, 87%, 83%, 82%, and 93% for the five disease categories, respectively.

Conventional deep learning models have restricted recognition accuracy, and detecting soybean diseases by chemical analysis is a time-consuming approach. Furthermore, human assessment and interpretation usually struggle to ensure the correctness of the purpose. M. Yu et al. [11] presented a quick detection approach for soybean diseases based on a new residual attention network (RANet) model. The OTSU approach was implemented to eliminate the background from the original image, subsequently augmenting the sample dataset with pictures of soybean conditions. A Residual Attention Layer (RAL) with shortcut connections and attention mechanisms has been developed and incorporated into the ResNet 18 model. Research results revealed an F1-score of 98.52 and a recognition time of 0.0514 seconds; the average recognition accuracy was 98.49%, indicating the development of a precise, quick, and effective model for soybean leaf disease identification.

The agriculture industry is crucial to ensuring food quality while additionally contributing significantly to economic and demographic growth. However, plant diseases can have a significant influence on the availability of foods and the diversity of species. By using precise or automated techniques, early diagnosis of plant diseases may mitigate financial losses and enhance the quality of food produced. J. Andrew et al. [12] used the well-known PlantVillage dataset, which comprises 54,305 picture samples of many different crop disease species in 38 categories, to train CNN-based pre-trained models such as DenseNet-121, ResNet-50, VGG-16, and Inception V4. The evaluations revealed that DenseNet-121 achieved superior performance compared to leading models, attaining an accuracy of 99.81%. The outcome demonstrates that the DenseNet-121 model appeared to be simple to train due to its lesser computational complexity and fewer trainable parameters.

In order to forecast the development of soybean Sudden Death Syndrome (SDS) disease, L. Bi et al. [13] present a Gated Recurrent Unit (GRU)-based model that primarily takes into account the crop's current condition and makes use of satellite photos gathered from PlanetScope. Instead of depending on individual static images, the GRU-based model transfers the original images into time-series data. The severity of soybean disease predictions was performed under different data scenarios, and the results were compared with those achieved using fully connected deep neural networks and XGBoost techniques. The proposed GRU-based model yields 82.5–90.4%, while XGBoost and FCDNN yield 76.3–85.5% and 80.6–89.2%, respectively.

M. Baljon et al. [14] conducted a study analyzing fungal diseases of thirty-two varieties, viral, physiological disorders, and parasites affecting onions, peppers, and tomatoes in Saudi Arabia. This research focuses on accurately diagnosing plant diseases by fine-tuning the hyperparameters of frequently utilized various classifiers and models. The preprocessing stage includes median filtering for noise reduction, brightness improvement, and eliminating backgrounds employing HSV color space segmentation. With the help of several optimizers, the best CNN model can achieve an F1 score of 1.00 and 99.5% classification accuracy for pepper disease.

The combination of the upgraded GoogleNet architecture with the Adam optimizer offered superior improvement in distinguishing between images of good and infected tomato leaves, resulting in a remarkable F1 score of 0.997 and a validation accuracy of 99.5%. One of the most essential components of maintaining a country that has grown its agricultural economy is being able to identify plant diseases. Plant diseases must be identified quickly and effectively in order to maintain a profitable and healthy agricultural industry and avoid squandering money or other resources. Using a dataset of 10,000 images from a plant village, Md. M. Islam et al. [15] evaluated CNN, VGG-16, VGG-19, and ResNet-50 models to identify crop infection. The models' accuracy scores were 98.60%, 92.39%, 96.15%, and 98.98%, respectively. To distinguish between leave categories, such as healthy or infected, and identify the type of disease currently present, the suggested application fundamentally implements the outperformer ResNet50 transfer learning model.

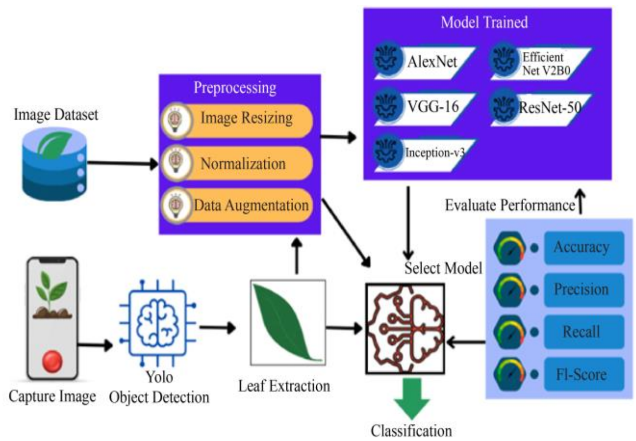


Fig. 1 Soybean disease prediction architecture

For sustainable crop management, early and precise assessment of leaf health is essential to minimizing its effects and ensuring immediate action. Recent efforts to overcome these difficulties have been made possible by the advancement of deep learning and its efficiency in the recognition of images. For the objective of detecting plant leaf diseases, S. Padshetty et al. [16] present a distinctive approach called the Leaky Rectilinear Residual Network (LRRN), which combines the ResNet architecture with the Leaky ReLU activation.

It is built on three fundamental modules: pre-processing, feature extraction, and categorization. The obtained results were benchmarked against cutting-edge techniques, showing higher performance with an accuracy of 94.56%, precision of 93.48%, F1-score of 92.83%, recall of 93.12%, and specificity of 92.58%.

3. Methodology

The dataset of 5600 collected pictures from different farms for soybean diseases covers six major diseases. Preprocessing techniques, including scaling, normalization, and augmentation, were applied to the collected dataset. A number of deep learning algorithms were trained and analysed using metrics for classification to discover the top-performing model.

Then, using real-time data, this selected model was used for the classification of soybean conditions. Using the YOLO object detection method, leaf images were extracted from captured plant photographs. After applying the preprocessing described in Figure 1, the images have been provided to the selected model for disease diagnosis.

3.1. Dataset

A dataset including 5600 photographs was collected, which represented six distinct diseases of soybeans. To ensure variety and capture varied symptoms of disease, these photos were collected from different farms. The images in Figure 2 illustrate different soybean diseases and their appearances.

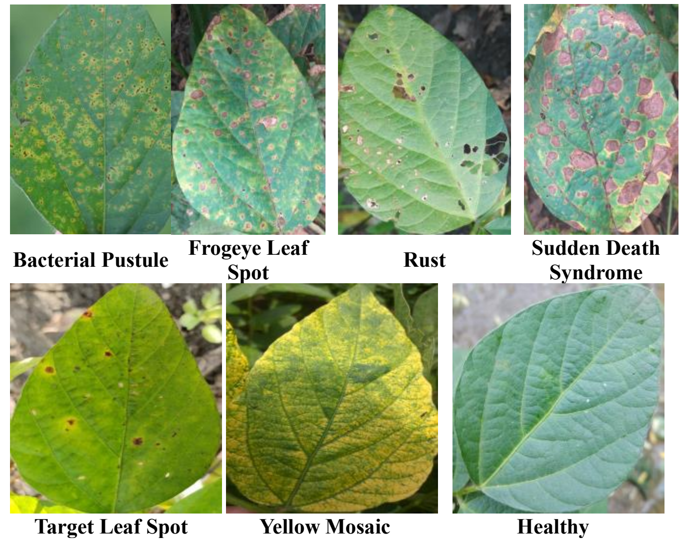


Fig. 2 Soybean disease prediction architecture

3.2. Preprocessing

In order to prepare the dataset for deep learning algorithm training, preprocessing techniques such as augmentation, normalization, and scaling were applied [17]. Normalization standardized pixel values for better convergence during training, while augmentation incorporated variations, such as rotations and flips, to help the models become more robust and less prone to overfitting.

3.3. Model Training

The several state-of-the-art deep learning models, such as AlexNet, VGG-16, Inception-v4, EfficientNetV2B0, and ResNet-50, were trained and assessed carefully. Their performance in disease classification was rigorously analysed using a range of evaluation metrics, allowing for a comprehensive comparison of their effectiveness.

3.3.1. AlexNet

AlexNet transformed the field of computer vision by showcasing the capabilities of deep convolutional networks, establishing a new standard for image classification through its innovative deep learning methods. With the objective of processing images for classification tasks, the architecture is comprised of five convolutional layers and three fully linked layers. To capture extensive features from the input images, the architecture initially uses a large kernel size in its first convolutional layer [18]. The successive convolutional layers further extract and enhance these features, while max-pooling layers minimize spatial dimensions, preserving crucial information. AlexNet traverses several convolutional, pooling, and fully connected layers when processing an initial input size of 227x227x3 and producing a final classification size of 1x1000 with 60 million parameters [19].

3.3.2. VGG-16

A renowned CNN architecture known for its depth and effectiveness in image classification applications is VGG16.

In order to efficiently capture image features, it is made up of 16 layers, consisting of 3 fully connected layers and 13 convolutional layers. A small 3x3 convolution filter with ReLU activation functions is used in the architecture to improve the model's capacity to identify complex patterns in the data [20]. Following the convolutional layers, max-pooling layers reduce computational complexity and spatial dimensions without losing important features. In the end, the fully connected layers generate probability distributions by transferring the learned features to output classes with the use of a softmax layer. Approximately 138 million parameters make up VGG16, which accepts input images with a fixed size of 224x224 pixels with three colour channels [21].

3.3.3. Inception

Inception is a deep CNN architecture with the objective to increase the effectiveness of deep learning models employing a multi-scale feature extraction approach. The use of "Inception modules," which enable the network to simultaneously apply numerous filter sizes (1x1, 3x3, and 5x5) coupled with max pooling, is its primary innovation [22]. This parallel structure reduces dimensionality using 1x1 convolutions, allowing the model to collect a wide range of features without substantially raising processing needs. The 224x224x3 is the usual input size for the Inception model. The outcome is a vector with a dimension of 1x1000 that is usually used by the model to represent class probabilities in classification tasks. An Inception module uses different convolutional filter sizes and pooling operations to process input data in parallel rather than stacking layers sequentially.

This increases the network's capacity to identify different visual patterns without significantly affecting computational cost by allowing it to extract both fine and coarse features from the same input [23]. A typical Inception module performs a number of concurrent tasks. 1x1 convolutions are utilized to minimize computational costs by reducing the number of input channels before applying bigger convolutions, as well as for feature extraction and dimensionality reduction. 3x3 convolutions are used to extract medium-scale patterns like edges and texturing. 5x5 convolutions are applied after dimensionality reduction with 1x1 convolutions in order to capture larger, more complex features that require greater computational resources. 5x5 applied after dimensionality reduction with 1x1 convolutions in order to capture larger, more complex features that require greater computational resources. By downsampling the input, the max pooling process captures spatial correlations while minimizing the feature map's size. The downsampled features are often further processed using a 1x1 convolution after the max-pooling step [24].

3.3.4. EfficientNet

EfficientNet is a CNN architecture that relies on a unique scaling technique to consistently scale the network's depth, width, and resolution, resulting in a balanced model that maximizes accuracy while preserving efficiency [25]. Inspired by MobileNetV2, EfficientNet additionally uses mobile inverted bottleneck convolution (MBConv) layers, which further improve efficiency, assist in lowering the number of parameters and computational expenses, and make EfficientNet perfect for large-scale datasets [26]. EfficientNet achieves good accuracy in classifying image applications, such as plant disease identification, with substantially fewer FLOPs (floating point operations) and parameters than typical CNN architectures by eliminating redundancy and computational waste [27].

3.3.5. Resnet-50

A deep learning model that is popular for its potential to resolve the vanishing gradient issue is ResNet-50, a part of the Residual Networks family. The 50 layers that makeup ResNet-50 have primarily been built with convolutional and identity blocks, which enable the model to retain accuracy as the network depth grows [28]. Figure 3 demonstrates the layers in ResNet-50, as well as the input and output sizes of each layer, filter size, stride, activation, etc.

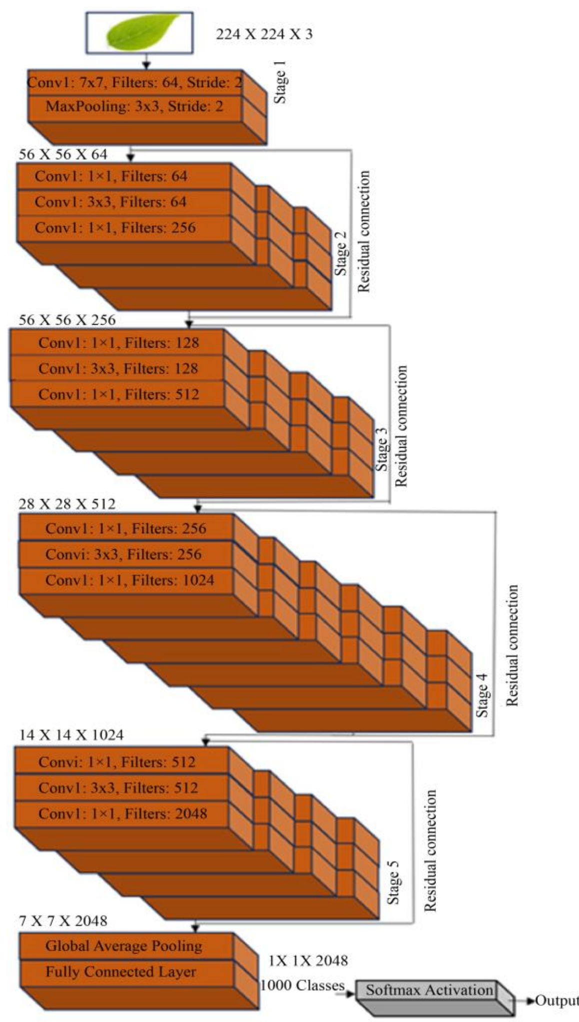


Fig. 3 ResNet-50 architecture

Convolution Layer

The convolution layer conducts element-wise multiplication and summing between the filter and a subset of the input by sliding a small filter, also known as a kernel, over the input image [29]. Padding is used to regulate the spatial size of the output, while the stride specifies how far the filter moves across the input image at each step. A convolutional layer's basic function can be expressed as follows [30]:

$$y_{i,j,k} = \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{c=1}^{C} x_{i+m,j+n,c} . w_{m,n,c,k} + b_k \quad (1)$$

Where $x_{i,j,c}$ refers to the input at the place [i,j] from the c^{th} input channel. $y_{i,j,k}$ refers to the output at place [i,j] for the k^{th} filter. $w_{m,n,c,k}$ refers to the weight for the k^{th} filter at position [m,n] for channel c. The bias term is represented as b_k for the k^{th} filter. This summation covers all C input channels and M×N spatial dimensions.

Residual Learning

A residual block is a series of layers in which a shortcut connection, often referred to as a skip connection, transfers the block's input directly to the output. The network learns the residual mapping F(x)=H(x)-x in a residual block rather than a mapping H(x). Equation 2 expresses the residual block's output (y).

$$y = F(x, W) + x \quad (2)$$

The convolutional layers output F(x,W) and block input x, which is added element-wise to the output of F(x).

Batch Normalization

In order to normalize the activations and ensure faster convergence while minimizing the sensitivity to initialization, batch normalization is applied after each convolution [31]. Equation 3 represents the batch normalization transformation for activation x_i.

$$\widehat{X} = \frac{x_i - \mu\beta}{\sqrt{\sigma_\beta^2 + \epsilon}} \quad (3)$$

Where μ_β and σ_β^2 are the mean and variance of the batch. To avoid division by zero, a small constant ϵ gets added [32].

ReLU Activation

Rectified Linear Unit (ReLU), the non-linear activation function used in ResNet, includes non-linearity to the network while eliminating the problem of gradient vanishing [33].

$$f(x) = \max(0, x) \quad (4)$$

Global Average Pooling

This layer efficiently summarizes the data over the whole image by minimizing the spatial dimensions of the feature map to a single value per feature map channel [34].

$$yk = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{i,j,k} \quad (5)$$

The K^{th} feature map's activation at point [i,j] is denoted by Xi, and the feature map's spatial size is represented by H×W.

Loss Function

ResNet50 usually utilizes the cross-entropy loss function for classification tasks. Equation 6 is used to compute the cross-entropy loss for a single training sample.

$$L(y, \hat{y}) = -\sum_{i=1}^{C} y_i log \hat{y}_i \quad (6)$$

Where y_i represented the actual label, $\hat{y}_i$ represents the predicted probability for class i, and C is the number of classes [35].

3.3.6. Object Detection

The powerful object identification framework YOLO (You Only Look Once) is renowned for its real-time capability and performance in processing pictures in a single pass. The input image is divided into an S×S grid by YOLO's architecture, with each grid cell predicting a fixed number of bounding boxes and their confidence scores, along with class probabilities for each object spotted [36]. YOLOv8 offers a number of layer enhancements intended to improve detection and performance. YOLOv8 typically receives input images with different sizes (e.g., 640x640) and resizes them to a consistent resolution that can be processed. After being normalized, the input image is run through the network to extract features. In order to extract spatial information from the image, such as edges, textures, and patterns that are essential for object detection, YOLOv8 uses numerous convolutional layers with a combination of 3x3 and 1x1 convolution filters.

After every convolutional layer, YOLOv8 keeps using batch normalization, which helps to stabilize and speed training by normalizing the activations and assuring that each layer receives input on a common scale. With SiLU (Sigmoid Linear Unit) or Leaky ReLU as its activation function, YOLOv8 achieves faster training and convergence by facilitating better gradient flow, particularly in deeper layers. YOLOv8 involves residual blocks inspired by ResNet to preserve information flow and enhance the training of deeper networks. With the use of CSPNet (Cross Stage Partial Network) architecture, YOLOv8 enhances feature fusion by dividing feature maps into two parts, processing one of the parts via the network, and then combining them later to increase learning efficiency. YOLOv8 uses a Path Aggregation Network (PANet) for feature fusion and employs upsampling layers to improve the resolution of feature maps during the detection process. YOLOv8's final detection head layers are responsible for class probabilities, bounding box predictions, and abjectness scores [37]. Figure 4 displays the YOLO leaf detection along with the bounding box.

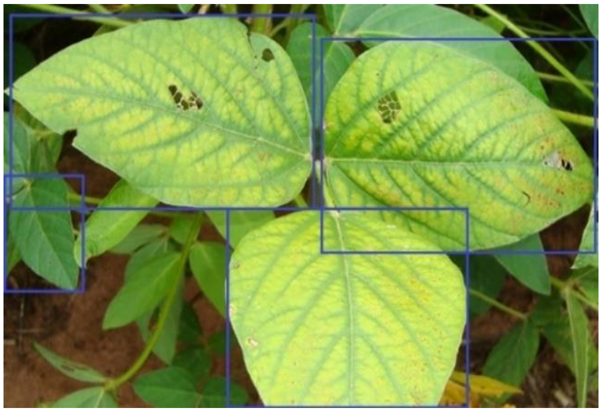


Fig. 4 YOLO leaf detection with bounding box

3.4. Performance Evaluation

The classification metrics, such as precision, recall, F1-score, and accuracy, are employed to assess the model's performance and reliability in appropriately identifying various disease categories [38]. Accuracy expressed in Equation 7 represents the proportion of true predictions for class instances to all instances, offering a comprehensive measure of the model's predictive performance. Precision expressed in Equation 8 assesses the proportion of correctly predicted true class instances among all instances predicted as positive, reflecting the accuracy of positive predictions [39].

Recall expressed in Equation 9, also known as sensitivity, measures the proportion of actual true class instances that were accurately predicted by the model. Equation 10 for the F1 score offers a balanced measure of a model's performance by considering both precision and recall [40].

$$\text{Accuracy} = \frac{Correctly\ Predicted\ Instances[TP+TN]}{Total\ Instances[N]} \tag{7}$$

$$\text{Precision} = \frac{True\ Prediction\ as\ Positive\ Instance[TP]}{Number\ of\ Positive\ Prediction\ [TP+FP]} \tag{8}$$

$$\text{Recall} = \frac{Correctly\ Predicted\ True\ Instances[TP]}{Number\ of\ Positive\ Prediction\ [TP+FP]} \tag{9}$$

$$\text{F1Score} = 2 * \frac{[\text{Product of Precision and Recall}]}{[\text{Sum of Precision and Recall}]} \tag{10}$$

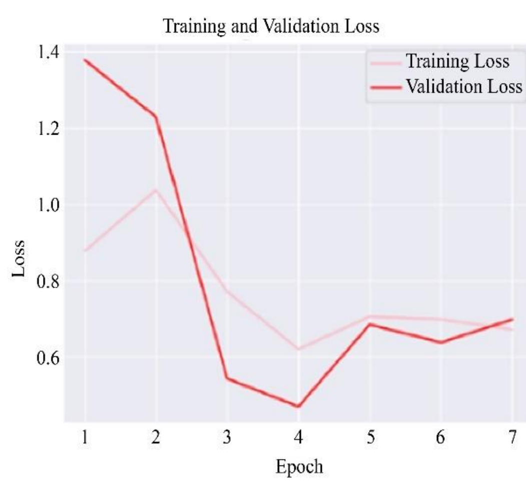
4. Result and Discussion

In the present study, we evaluated several kinds of deep learning models for soybean disease prediction, including AlexNet, VGG-16, Inception, EfficientNet, and ResNet-50. A total of 5600 pictures representing six soybean diseases were collected, of which 4200 images were used for training and 1400 for validation. The models were trained using GPU resources from Google Colab to ensure effective performance.

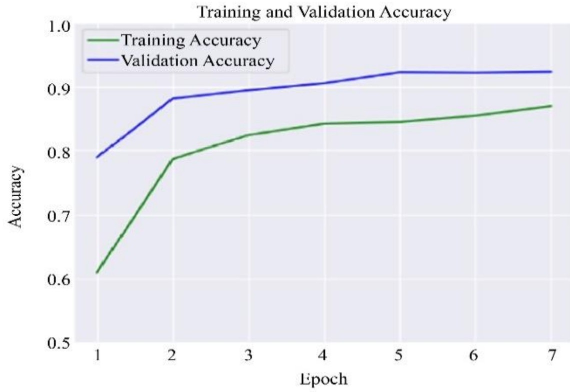
The training and validation accuracy, along with the loss for each model, were visualized against the number of epochs to describe several model performances shown in Figure 5. ResNet-50 performed better than the other models and attained the highest accuracy. The accuracy and loss curves for training and validation clearly demonstrate this performance benefit. YOLO was utilized for real-time leaf extraction in order to mimic real-world situations, and a test set of 70 photos was created for each disease class.

This made it possible to assess the model's performance more realistically. Each model's performance was evaluated using assessment metrics, and the results are presented in Table 2. The output demonstrated that ResNet-50 performed better than the other tested models in each assessment metric. This indicates that when integrated with YOLO for real-time leaf extraction, ResNet-50 performs better for precise disease classification. In comparison to shallower models like AlexNet or VGG-16, its strong feature extraction capabilities allow for more accurate predictions. The combination of YOLO for leaf detection and ResNet-50 for disease classification outperforms alternatives, as shown by the performance evaluation results.

AlexNet Accuracy vs Epoch

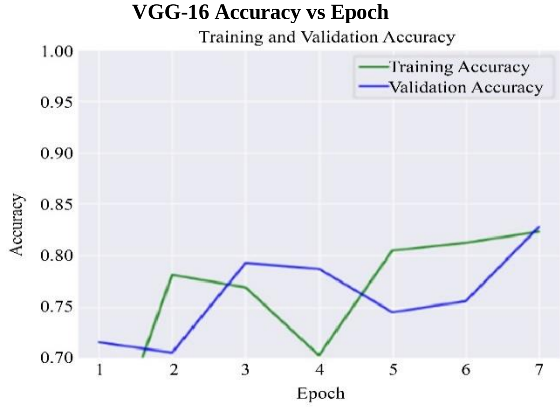


AlexNet Loss vs Epoch

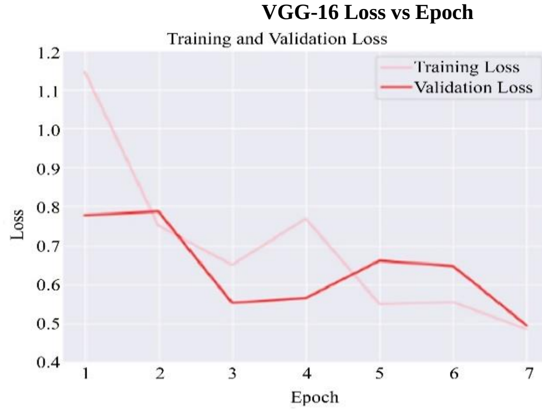


VGG-16 Accuracy vs Epoch

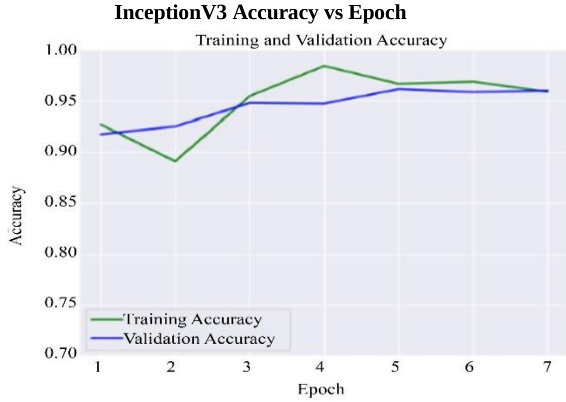
VGG-16 Loss vs Epoch



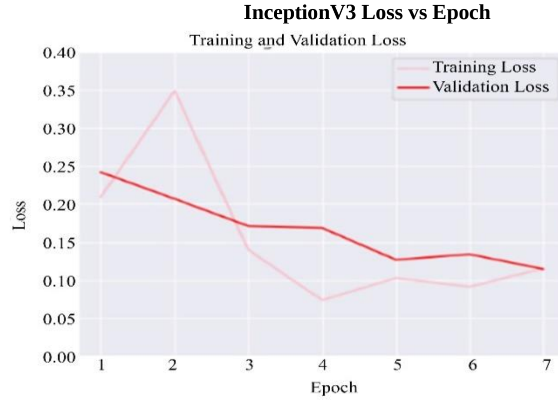
InceptionV3 Accuracy vs Epoch



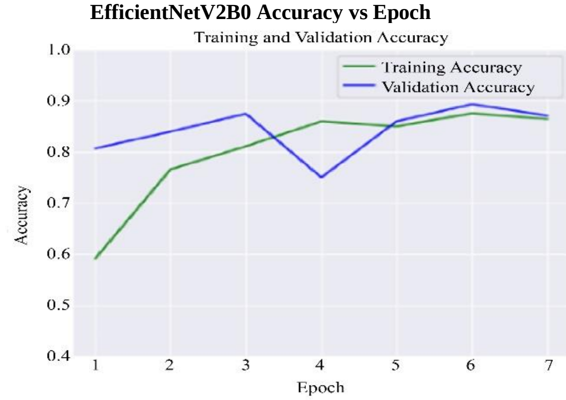
InceptionV3 Loss vs Epoch



EfficientNetV2B0 Accuracy vs Epoch



EfficientNetV2B0 Loss vs Epoch



ResNet-50 Accuracy vs Epoch

ResNet-50 Loss vs Epoch

Fig. 5 Training and validation performance of the models

Table 2. Comparative performance of models based on assessment metrics

Model	Accuracy	Precision	Recall	F1-Score
Alexnet	0.7429	0.7571	0.7429	0.7440
VGG-16	0.9000	0.9105	0.9000	0.9023
InceptionV3	0.9286	0.9309	0.9286	0.9284
EfficientNetV2B0	0.9429	0.9489	0.9429	0.9425
ResNet50	0.9857	0.9870	0.9857	0.9857

Table 3. Confusion matrix for test dataset

True Label	BP	FLS	Healthy	Rust	SDS	TLS	YM	
BP	9	0	1	0	0	0	0	**AlexNet**
FLS	0	10	0	0	0	0	0	
Healthy	0	1	6	0	0	0	3	
Rust	1	2	2	5	0	0	0	
SDS	0	0	0	3	7	0	0	
TLS	0	0	2	0	0	8	0	
YM	0	0	2	0	1	0	7	
BP	9	0	1	0	0	0	0	**VGG-16**
FLS	0	8	0	1	0	1	0	
Healthy	0	2	8	0	0	0	0	
Rust	0	0	0	10	0	0	0	
SDS	0	1	0	0	9	0	0	
TLS	0	0	0	0	0	10	0	
YM	0	0	1	0	0	0	9	
BP	10	0	0	0	0	0	0	**InceptionV3**
FLS	0	8	1	0	0	0	1	
Healthy	0	0	9	1	0	0	0	
Rust	0	0	0	10	0	0	0	
SDS	0	1	0	0	9	0	0	
TLS	0	0	0	0	0	10	0	
YM	0	0	1	0	0	0	9	
BP	10	0	0	0	0	0	0	**EfficientNetV2B0**
FLS	1	9	0	0	0	0	0	
Healthy	0	1	8	0	0	1	0	
Rust	1	0	0	9	0	0	0	
SDS	0	0	0	0	10	0	0	
TLS	0	0	0	0	0	10	0	
YM	0	0	0	0	0	0	10	
BP	10	0	0	0	0	0	0	**ResNet-50**
FLS	0	9	0	0	0	0	1	
Healthy	0	0	10	0	0	0	0	
Rust	0	0	0	10	0	0	0	
SDS	0	0	0	0	10	0	0	
TLS	0	0	0	0	0	10	0	
YM	0	0	0	0	0	0	10	

Predicted Label

Using a test set of images for the six soybean disease classes, a confusion matrix was created to assess the performance of the ResNet-50 model in more detail. The confusion matrix presents the true positives, false positives, and false negatives for each disease category, offering an in-depth assessment of the model's classification performance. Almost all predictions made by the ResNet-50 model were properly classified, demonstrating excellent prediction accuracy across all six classes. This demonstrates the model's strong potential to differentiate between similar disease symptoms and accurately predict the presence of each soybean disease. When it comes to disease classification in soybean crops, the model's highly accurate performance in the confusion matrix demonstrates its reliability and effectiveness in real-world applications. Table 3 presents the Confusion Matrix, illustrating the classification performance of various techniques on the test dataset.

5. Conclusion

In order to forecast soybean diseases, this study investigated the use of many deep learning models, including AlexNet, VGG-16, Inception, EfficientNet, and ResNet-50. The models trained and validated 4200 and 1400 photos, respectively, from a dataset of 5600 images that represented six different disease classes. ResNet-50 outperformed the other models in terms of precision, recall, and F1-score, and it proved to be the most accurate model among those who participated in the testing. Additionally, the integration of YOLO for real-time leaf extraction enables the testing of the models practically with seventy photos for each disease class. The integration of deep learning and object detection ensured effective disease classification, enhancing the system's efficiency. ResNet-50 is an excellent alternative for soybean disease prediction because of its effective feature extraction capabilities, which efficiently reduce false negatives while preserving a high level of overall accuracy. Further study attempts could involve expanding this methodology to incorporate new crops and diseases, integrating additional real-time data, and refining the models to enhance both speed and accuracy. Furthermore, farmers may benefit greatly from the real-time deployment of drone-based automated disease monitoring systems in agricultural fields. This approach could be used in various agricultural domains by being adapted to detect a wider range of plant diseases.

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