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LeafGuard: Efficient Soybean Leaf Defect Classification in Indian Agriculture Using Fine-tuned CNN

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Abstract: Soybean leaf diseases have a significant impact on people's lives. With numerous distinct ailments, the process of detecting and categorizing them using artificial vision is both time-consuming and labor-intensive, leading to an increased risk of errors. While transfer learning-based algorithms have shown promising results in image categorization, they often struggle to extract all essential information, resulting in a decline in categorization accuracy. In this study, we propose a transfer learning-based approach to identify and classify soybean leaf diseases. We investigate how the performance of a classification system is influenced by the dataset size, emphasizing that a broader perspective can significantly enhance accuracy. To improve the categorization of soybean photos, we employ image creation techniques using well-known architectures such as VGG16-19, ResNet50, Xception, and InceptionV3. In our methodology, we incorporate Conv2d kernels and Leaky ReLU layers to reduce model parameters, resulting in improved efficiency. Our experimental results demonstrate that our model outperforms standard transfer learning networks on the test set, achieving a reduction in both parameters and training time. These findings affirm the effectiveness of our technique in the classification of soybean leaf diseases, offering a potential solution to the challenges posed by these diverse ailments.

Keywords: *Soybean, VGGNet, ResNet, Xception, Inception, CNN and Leaky ReLU.*

1. Introduction

Traditional machine learning techniques are being used more and more in plant disease prediction due to the fast advancement of computer technology. Researchers have looked at automated plant disease detection based on conventional machine learning techniques, such as random forest, k-nearest neighbour, and support vector machine [1,2], to increase the accuracy and speed of diagnostic findings. The Fabaceae family includes the bean, Phaseolus vulgaris L. in its botanical name. Soybean disease detection results in unnecessary financial losses because to delayed treatment, ineffective therapy, and a lack of knowledge [3].

The crop that is growing the fastest in India is the soybean, which is categorised as a Kharif crop. India's top three soybean-producing states are Rajasthan, Maharashtra, and Madhya Pradesh [4,5,6]. One of the greatest crops in the world is soybean. Its primary applications are for vegetable oil, animal feed, and protein. Soybean is recognised as an essential dietary component due to its high protein level (more than 40%) and high oil content (greater than 20 percent) [8,9]. Since soy protein contains enough of all essential amino acids, it is referred to as a complete protein. Soybean oil doesn't contain cholesterol. Low yield, which may be attributed to a variety of factors, including infections, is the biggest challenge confronting the country's soy industry. Soybean plants are susceptible to numerous diseases, which encompass conditions like downy mildew, pod and stem blight, phytophthora root and stem rot, brown spot, cercosporin leaf blight, purple seed stain, frogeye leaf spot, and various others [10,11].

The present deep learning and machine learning algorithms encountered several problems, including high computational complexity, greater training data cost, longer execution times, noise, feature dimensionality, lesser accuracy, slower speed, etc. The focus of this study is the classification of leaf diseases in soybean plants.

The Summary of the research paper is described as in the Section 1, the article underscores the significance of soybean leaf defect classification in agricultural practices, laying the groundwork for the development and evaluation of the LeafGuard model. Section 2, Related Work, provides a comprehensive overview of existing approaches in the field, highlighting the unique contributions and differentiators of LeafGuard. The meticulous curation of a robust dataset and the strategic design choices behind the proposed CNN architecture are detailed in Section 3, Materials and Methods. Section 4 delves into the proposed LeafGuard model, emphasizing its tailored approach for soybean leaf defect classification. The critical evaluation of the model's performance using key metrics is presented in Section 5, Result Analysis, showcasing its effectiveness and providing insights into its strengths and potential areas for improvement. Finally, the Conclusion, offers a concise summary of the study, emphasizing the model's real-world applicability, discussing practical challenges, and suggesting future directions for refining LeafGuard's performance in diverse agricultural contexts. Overall, the article presents a holistic exploration of soybean leaf defect classification, introducing an innovative CNN model and contributing valuable insights to the field of agricultural image analysis.

2. Related Works

This section discusses several models for the detection, classification, and prediction of soybean plant diseases. Also

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covered are the categorization models created by deep neural networks and machine learning methods.

A. S. Paymode et al [1] In his research proposal, a significant amount of emphasis is placed on the identification and classification of diseases that affect a variety of crops, with a particular focus on tomatoes and grapes. An important objective is to make an early diagnosis of the kind of disease that might affect the leaves of tomato and grape plants. Techniques based on the Convolutional Neural Network (CNN) are used to identify Multi-Crops Leaf Disease (MCLD). To extract information from the pictures, a model based on deep learning was used to differentiate between sick and healthy leaves. The Visual Geometry Group (VGG) model, which is based on CNN, is implemented to improve the performance metrics being measured. The researchers were able to correctly identify tomatoes 95.71 percent of the time and grapes 98.40 percent of the time.

M. S. A. M. Al-gaashani et al [2] The authors provide a method for diagnosing illnesses that may be found on tomato leaves. This method takes use of transfer learning as well as feature concatenation. The authors get features by utilizing pre-trained kernels to analyses data from MobileNetV2 and NASNetMobile (weights). After that, they use a technique called kernel principal component analysis to integrate these characteristics and reduce the dimensionality of the data. The next step is for them to combine these features into a standard instructional approach. The outcomes of the experiment provide credence to the assertion that the performance of classifiers may be improved using concatenated features. The authors conducted experiments with three of the most prevalent types of classical machine learning classifiers: random forest, support vector machine, and multinomial logistic regression. The multinomial logistic regression came out on top, outperforming the other methods with an accuracy rate of 97% on average.

P. Kaur, S. Harnal et al [3] Grapevine plant diseases are the focus of this research project. Grape vines are susceptible to four different diseases: leaf blight, black rot, stable, and black measles. There is no one who can offer a complete diagnosis of all four diseases; nevertheless, several earlier research concepts applying machine learning algorithms have been established to identify one or two diseases in the leaves of grape plants. Retraining the Efficient Net B7 deep architecture using pictures taken from the plant village dataset is done with the use of transfer learning. After the transfer learning step, the collected features are then down sampled with the use of a method called logistic regression. After 92 epochs, the most discriminating traits have finally been recognized with a maximum consistent accuracy of 98.7 percent owing to classifiers that are on the bleeding edge of technology.

M. Rudagi et al [4] The purpose of this article is to raise awareness about plant leaf diseases and educate farmers about innovative technologies that may help prevent plant disease. Additionally, this essay will educate farmers about innovative technologies. The tomato plant is only a widely accessible kind of produce; however, the techniques of machine learning and image processing, when combined with an appropriate algorithm, have been shown to be effective in identifying the diseases that affect the plant's leaves. This is because the tomato plant itself is only a widely accessible kind of produce. During our inquiry, we are taking into consideration several tomato leaves samples that contain diseases. Farmers can quickly detect infections based on the early signs because they use disorder samples collected from tomato leaves. These samples were taken. To enhance the overall quality of the tomato samples, first the size of the leaf samples is shrunk down to 256 by 256 pixels, and then histogram equalisation is performed on the samples. This is done to improve the overall quality of the tomato samples. In the conclusion, the categorization of the recovered features is carried out using machine learning techniques such as Support Vector Machine (SVM), Convolutional Neural Network (CNN), and K-Nearest Neighbour (K-NN). On tomato disordered samples, the accuracy of the proposed model is assessed using SVM (88 percent), K-NN (97 percent), and CNN (99.6 percent).

S. Ali, M. Hassan et al [5] Using feature fusion in combination with PCA-LDA classification, the author of this work provides a unique technique for the detection of agricultural illnesses (FF-PCA-LDA). When employing RGB photos, it is possible to generate unique hybrid and deep features. To get the deep features, the TL-ResNet50 method is used. Combining features that have been handmade, including hybrid and deep features, results in the generation of a fused feature vector. After the image's properties have been merged, the principal component analysis (PCA) is carried out to choose the characteristics that are going to be the most helpful in the process of creating the LDA model. As a case study for the validation of the technique, the identification of a leaf disease that was found to be harming a crop of potatoes was used. The constructed system is empirically tested by using the data from a potato crop leaf as a standard. This ensures that the system is accurate. On a dataset that has never been inspected before and that was not utilized in any manner during the training of the model, it obtains a remarkable accuracy of 98.20 percent, which is rather impressive.

M. A. Ganaie et al [6] This paper explores the most current deep ensemble models and offers scholars a comprehensive review of the topic. These models include explicit/implicit ensembles, homogeneous/heterogeneous ensembles, decision fusion approaches, unsupervised, semi-supervised, reinforcement learning, and online/incremental, multilabel based deep ensemble models. These groupings may be thought of as a rough division of the ensemble models.

W. Bao, T. Fan et al [7] The outcomes of this research suggest that an enhanced version of the Retina Net target detection and identification network, which the authors refer to as AX-Retina Net, needs to be put into operation. This would make it possible for the detection and diagnosis of diseases affecting tea leaves to be carried out in an automated form using photos obtained in their natural settings. This would make it feasible for the detection and diagnosis of diseases affecting tea leaves to be carried out. Because of the detection and identification work that was completed by AX-Retina Net, the F1-score value was found to be 0.954, and the mAP value was found to be 93.83 percent. Both values can be found in the table below. When compared to the initial network, there was an increase in both the mAP value and the recall value, as well as an improvement in the identification accuracy. The first two saw growth of over 4 percent, while the second and third had growth of 4 percent and over 1.5 percent, respectively. The fourth and fifth saw growth of over 1.5 percent.

D. Muller et al [8] In this study, the authors established a repeatable pipeline for categorizing medical pictures to investigate the influence that augmenting, stacking, and bagging ensemble learning algorithms have on performance. In addition to innovative pre-processing and photo enhancement methods, the pipeline has nine different deep convolution neural network architectures. It was used to four challenging medical imaging datasets that were well-known. In addition, 12 different processes for pooling data were investigated. These procedures ranged from simple statistical operations, such as unweighted averaging, to more complex learning-based operations, such as support vector machines. These functions were used so that a variety of forecasts may be combined. Their data indicate that stacking was the cause of the performance enhancement that resulted in an increase of up to 13 percent in F1 scores. Augmenting may be used to single model-based pipelines, and it has shown the capability to provide continuous improvements of up to 4 percent. Bagging, which is based on cross validation, demonstrated a significant performance improvement that was very close to that of Stacking. This resulted in an increase in the F1 score of up to +11 percent.

F. Wang, Z. Xu et al [9] This paper presents a technique for self-adjusting generative confrontation network image denoising. [Citation needed] [Citation needed] The solution incorporates both the GAN model for adaptive learning and noise reduction into a single process. The image is first pre-processed using the procedure, and then, with the help of image characteristics, the important information is extracted from the picture. After the edge signal has been categorized in accordance with the threshold value to avoid the problem of "excessive strangulation," the edge signal is then extracted to improve the effective signal in the high-frequency signal. This is done after the edge signal has been categorized. After that, the system will continue to train the image using a GAN model that features adaptive learning.

M. Saberi Anari et al [10] During the stage of feature extraction, this research recommends using a highly helpful structure that can be used to classify a variety of leaf diseases that might affect plants and fruits. To do this, it makes use of a modified version of a deep transfer learning model. To summaries, we derive characteristics via the use of model engineering (ME). When several support vector machine (SVM) models are used, the performance of the SVM models as well as their ability to discriminate between features is increased. During the stage of training, the model that is ultimately selected is the one that is used to determine the kernel parameters of the radial basis function (RBF). The Plant Village and UCI databases were used to conduct an analysis on six different leaf photo sets, including healthy and diseased leaves of apple, maize, cotton, grape, pepper, and rice.

S. M. Hassan et al [11] In the realm of machine vision, deep convolutional neural networks, more often known as CNNs, have shown very high levels of performance. Because of this, CNN models are used in this piece to identify and diagnose plant illnesses based on the leaves of the plants. Due to the structure of the model, standard CNN models need a high number of parameters, which in turn necessitates more expensive computations. During our inquiry, we decided to switch from utilizing conventional convolution to depth-separable convolution. This allowed us to cut down on the amount of money spent on computations as well as the number of parameters that were used. An easily available dataset was used to train the models that were produced. This dataset included 14 distinct plant species, 38 distinct categorical illness categories, and healthy plant leaves. To determine whether or not the models are accurate, a number of diverse criteria, including batch size, dropout, and a range of different numbers of epochs, were included into the analysis. The disease-classification accuracy rates that were achieved by the models that were implemented were, in order, 98.42 percent, 99.11 percent, 97.02 percent, and 99.56 percent, respectively. These rates were achieved by using InceptionV3, InceptionResNetV4, MobileNetV2, and EfficientNetB0, respectively. These rates were greater than what could be attained with traditional handmade feature-based methods.

I. H. Sarker et al [12] This article presents a methodical and comprehensive discussion of alternative methods to DL, including a taxonomy that takes into consideration the many types of supervised and unsupervised tasks that may be faced in the real world. Within this taxonomy, they classify deep networks as suitable for supervised or discriminative learning, unsupervised or generative learning, hybrid learning, and other applicable learning approaches. In addition to this, they present an overview of the many practical sectors in which deep learning approaches may be used. In addition to this, they provide research suggestions for ten distinct potential applications of the next generation of DL modelling.

M. Bansal et al [13] This study's objective is to improve the accuracy of image classification by combining deep features obtained using a well-known deep convolutional neural network known as VGG19 with other handmade feature extraction techniques such as SIFT, SURF, ORB, and the Shi-Tomasi corner detector algorithm. This will be accomplished by combining these techniques. In addition, the retrieved features from these approaches are categorized by employing a variety of machine learning classification techniques, such as Gaussian Naive Bayes, Decision Tree, Random Forest, and an extreme Gradient Boosting (XGB Classifier) classifier. These techniques are used to classify the features. The experiment is carried out using the standard dataset known as Caltech-101. When all the criteria are considered, the Random Forest algorithm achieves an accuracy of 93.73 percent, as determined by the outcomes of the experiments.

J. Xiao et al [14] Within the TensorFlow architecture, the VGG-19 approach is recommended, and over 3000 images are acquired for the purpose of model training and testing. With the use of the VGG-19 network model, three FC layers may be optimized into one flat layer and two FC layers that have fewer parameters each. In lieu of the SoftMax classification layer that was included in the initial model, a 2-label SoftMax classifier has been included. The results of the experiments indicate that the model has an accuracy of 97.62 percent and a recall of 96.31 percent respectively.

J. Hang et al [15] The advantages of the neural network may be exploited by the recommended approach to recognize the properties of sick parts and to categories the places of the sickness that are required. Combining the structures of an inception module, a squeeze-and-excitation (SE) module, and a global pooling layer was the method that was used to make the conventional convolutional neural network better able to accurately diagnose diseases. This improvement was achieved by adding a global pooling layer. The issues of a long training convergence time and overly large model parameters were resolved because of this solution. After then, medical conditions were determined by using the enhanced network. The feature data from the convolutional layer were blended on a variety of different scales using the Inception framework to increase the accuracy of the leaf disease dataset. This was done to improve the accuracy of the dataset. In the end, we decided to employ the globally average pooling layer rather than the fully connected layer to cut down on the overall number of model parameters. On the validation set, our model had an accuracy of 91.7% and performed much better than other standard convolutional neural networks. The answer to this question was found by comparing its performance to that of the other networks.

3. Materials and Methods

In the Materials and Methods section, the article details the careful curation of a comprehensive soybean leaf dataset and outlines the strategic design choices, including architecture specifications and preprocessing steps, employed in the development of the LeafGuard CNN model.

3.1. Dataset

The soybean leaf defects dataset used in this study was carefully curated from real images captured directly from farms, aiming to ensure authenticity and relevance to real-world conditions. The dataset curation process involved several steps.

Data Sources: The dataset incorporates images sourced from genuine photographs taken in real farm settings. This combination of sources aims to provide a comprehensive representation of soybean leaf diseases.

Preprocessing: To enhance the dataset's consistency and suitability for deep learning applications, a critical preprocessing step was employed. Specifically, the backgrounds of all images were manually blackened to remove any potential noise or distractions.

Image Resolution: In preparation for utilization in deep learning models, all images underwent resizing to a uniform resolution of 224 by 224 pixels. This standardization ensures that the dataset is compatible with a wide range of deep learning architectures.

Dataset Size: The dataset comprises a substantial collection of 20,000 soybean images. These images encompass a diverse range of soybean leaf conditions, categorized into 8 different classes.

Class Labels: To facilitate the study and categorization of soybean diseases, a clear table within the dataset was established, featuring various soybean illnesses as class labels. This systematic organization allows for efficient classification and analysis of the dataset shown in Table 1.

The representativeness of the dataset regarding diverse environmental and growth conditions is crucial for the model's generalization to real-world scenarios. The model is robust and capable of handling the complexities of real-world agricultural settings.

Table 1. Soyabean Disease Names

No	Type of leaf disease	Total Images
1	Bacterial Blight	2500
2	Rust	2500
3	Septoria brown spot	2500
4	Powdery mildew	2500
5	Downy mildew	2500
6	Southern blight	2500
7	Mosaic virus	2500
8	Healthy Soybean	2500
	Total	20000

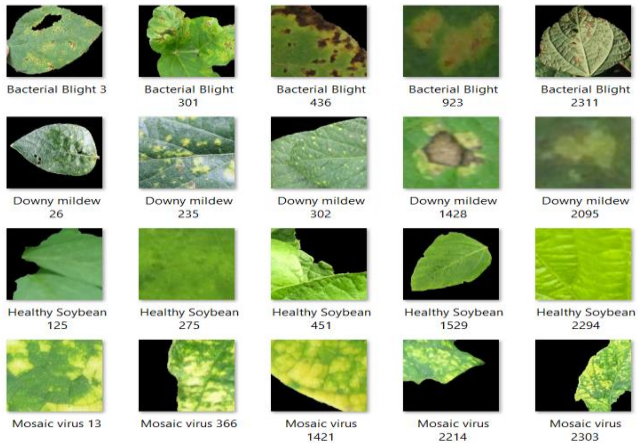


Fig 1. Dataset

3.2. Transfer Learning Models

AlexNet [1,3,4]: The Convolutional Neural Network was used for classification by every single one of the participants in the ImageNet competition, which began exactly one year after the introduction of AlexNet. The results of AlexNet show that a massive recurrent neural network (RNN) can reach excellent performance on an extremely challenging dataset using solely supervised learning techniques. This was shown by the fact that AlexNet was only able to do so.

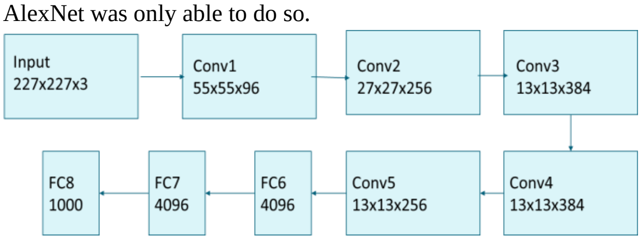


Fig 2. Alexnet Architecture [4]

ResNet [6,8,9,11]: It is a remnant from the building process with a shortcut connection, also known as a skipped link, that enables data to go through it without being altered in any way. A series of activation curve layers are used to perform the transformation from the input signal x to the output signal F. (x). This transition is comparable to something that's known as a skipped connection. The residual unit in this architecture demonstrates how the variations between the input signal x and the reference signal F are brought about by this design (x). When a network has previously approximated the output function that produces data on a certain layer, the signal will pass across the missing link with very little to no degradation consequently. This occurs when the network is said to have approximated that function. It's possible that the optimizer will bring the total weight of the remaining blocks on each level down to almost nothing.

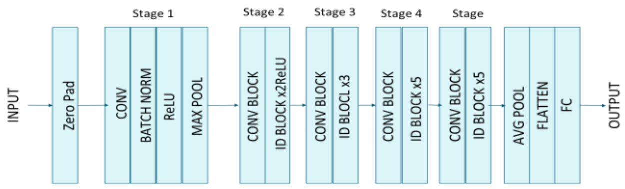


Fig 3. Resnet Architecture [8]

VGGNet [14,16,18]: This network, which is also known as the Visual Geometry Group (VGG), has an architecture that is like a deep convolutional neural network (DCNN) and has numerous convolutional layers. It is important to note the difference in total no. of convolutional layers between the VGG-16 and VGG-19 models. The VGG-16 consists of a total of 16 layers, whereas VGG-19 has a total of 19. On top of the VGG architecture, a modern object identification model is built from the ground up. The neural network architecture used to construct it is referred as as the Products Tend.

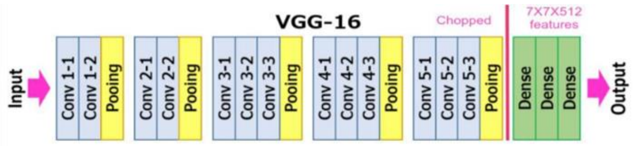


Fig 4. VGGNet Architecture [18]

Xception [16,19,21]: Within this convolutional neural network, there are 71 layers. An already trained version of the network may be found in the ImageNet database [1,3]. This version of the network was trained on more than one million images. The pretrained network is capable of classifying photographs into one thousand distinct item categories, some of which include a variety of animals, a computer keyboard, a mouse, and a pencil. Because of this, the network has been able to acquire comprehensive feature depictions for a diverse selection of picture types. Each side of the image that may be uploaded to the network must be exactly 299 pixels in length.

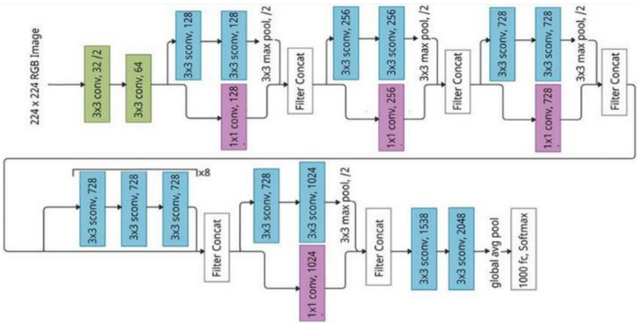


Fig 5. Xception model Architecture [21]

Inception: An inception network is a kind of deep neural network that has a specific architectural structure that is made up of repetitive pieces that are referred to as inception modules. On the ImageNet dataset, it has been shown that the image recognition model known as Inception v3 can achieve an accuracy that is more than 78.1 percent. The model is the product of several ideas that have been developed by a variety of different academics over the course of several years.

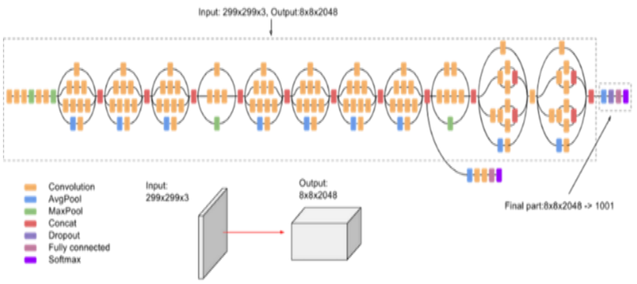


Fig 6. Inception V3 model Architecture [5]

3.3. Evaluation Parameters

Training loss [1,2]: In particular, for fitness data, the trained loss gauges how well the algorithm matches the information. However, the validation error assesses how often the model matches the fresh data when it comes to validation data.

Training Accuracy [2,6]: While accuracy rate is often represented as productivity gained when a model is applied to an initial dataset, checking quality is generally expressed as effectiveness gained when a procedure is developed to test the relevant data set. To determine if you have overtrained or undertrained, it may be beneficial to compare these.

Testing loss [7,9]: Making an incorrect prediction judgement will have negative effects. In other words, a loss is a no. which signifies in what way accurately the model estimate was at convinced point hip time. Alternatively, hazard is zero if the model's prediction is accurate; otherwise, the loss is greater.

Testing Accuracy [11,12]: According to the evidence, or training, data that was given, precision is a metric that is used to determine which machine learning model is the most accurate in identifying correlations and patterns across measurement scales.

Time [22]: The maximum length of time that a task may utilize the processor is specified. In other words, it determines the maximum amount of time that the task may use the CPU. It is a choice-based parameter. It may also be coded at the step and job levels.

4. Proposed Model

In this section the proposed CNN model is described along with the Leaky ReLU and kernels of convolution layers. The decision to select the Convolutional Neural Network (CNN) architecture instead of transfer learning models was driven by the specific requirements and objectives of our study. While transfer learning models can be effective in many scenarios, we chose to employ CNN because it allowed us to tailor the architecture to the unique characteristics of soybean plant leaf diseases. By designing a CNN from scratch, we could directly control and customize the layers, kernel sizes, and activation functions to optimize the model's performance for our specific dataset. This approach offered greater flexibility and a more targeted solution for the classification of soybean leaf diseases, aligning with the study's objectives.

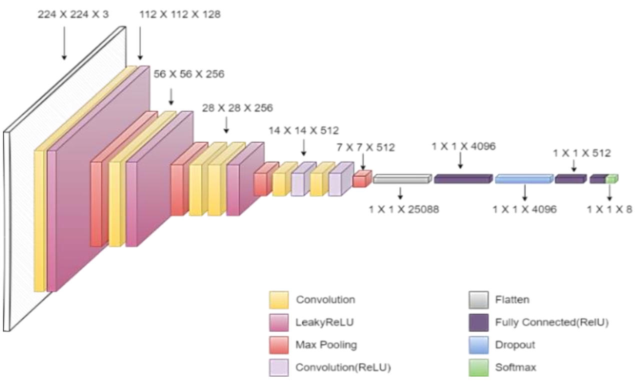


Fig 7. Proposed CNN Architecture

Figure 7 shows Convolution Neural Network architecture of Soyabean plan leaf disease classification model. Here in the first layer, we have used 7x11 kernel size in Conv2D and then apply Leaky ReLU in the second layer. Third layer is for Max Polling these steps are repeated three times in the network. At the last layer dense and SoftMax with indicate the disease of soyabean plant leaf class. The task of the kernel size in con2d is dividing the image into 7x11 blocks which gather micro pixel information from the image.

Key Components:

1. **Customized Convolutional Layers:** The architecture

consists of eight convolutional layers, each playing a crucial role in extracting hierarchical features from soybean leaf images. In the initial layer, a large 7x11 kernel size is employed in the Conv2D operation. This strategic choice helps in dividing the image into 7x11 blocks, allowing the model to capture micro pixel information efficiently.

2. Leaky ReLU Activation: Leaky ReLU activation is applied in three layers. This activation function is chosen for its unique characteristics, addressing the "dying ReLU" issue prevalent in traditional ReLU activations. The small, non-zero slope for negative values introduced by Leaky ReLU ensures that neurons remain active and responsive during training, preventing them from becoming completely inactive.

3. Max Pooling Layers: Four max-pooling layers are integrated into the architecture, strategically placed to down-sample the spatial dimensions of the input data. Max pooling aids in extracting essential features and reducing the computational load, enhancing the model's ability to recognize patterns and variations in soybean leaf images.

4. Dense and SoftMax Layers: The final layers of the architecture include dense layers followed by SoftMax activation. These layers facilitate effective classification of soybean leaf diseases based on the features learned throughout the convolutional layers.

Differences from Existing Approaches are Tailored CNN Approach, Strategic Kernel Size 7x11 Selection, Leaky ReLU for Robust Training, and detailed Hyperparameter Configuration.

The proposed CNN model provides a detailed set of hyperparameters in Table 2, showcasing transparency in model configuration. This allows researchers and practitioners to understand and potentially replicate the model's settings for further experimentation.

Table 2. Hyperparameter Used in Proposed CNN Model

Crops	soybean
Convolutional Layers	8
LeakyReLU Layers	3
Max Pooling Layers	4
Dropout Rate	0.50
Activation Function	LeakyReLU, ReLU, Softmax
Epoch	50
call-backs	Checkpoint, early stop
Optimizer	Adam (Default lr = 0.001)
Learning Rate	0.0001
Image Resolution	224 x 224 x 3
Batch Size	32

Leaky ReLU has two advantages: Due to the absence of zero-slope portions, it resolves the "dying ReLU" issue. It expedites instruction. There is proof that training goes more quickly when the "mean activation" is near to 0. Instead of being completely zero for negative values, Leaky ReLU has a minor slope. Leaky ReLU, for instance, may have y = 0.01x when x 0.

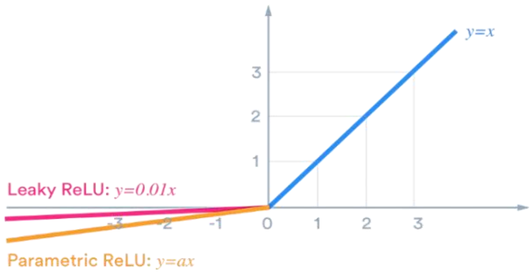


Fig 8. LeakyReLU [14]

Leaky ReLU function is used to fix a portion of the parameters to deal with gradient death, in accordance with the benefits of ReLU.

5. Result Analysis

In this section comparisons with baseline models or traditional machine learning approaches are discussed. Such comparisons are essential for contextualizing and assessing the effectiveness of the proposed Convolutional Neural Network (CNN) model in plant disease classification. To address this limitation, the following steps has been taken:

Baseline Models: To provide a meaningful point of reference, the paper should incorporate baseline models that are commonly used in plant disease classification. These may include traditional machine learning algorithms like VGG16, VGG19, ResNet152V2, Xception, InceptionV3, and InceptionResNetV2. Implementing these models allows for a direct comparison of CNN's performance against established techniques.

Performance Metrics: Specifically, we used metrics such as accuracy, precision, recall, and F1-score to gauge the model's overall classification performance. Accuracy provides a general measure of how well the model correctly classified disease instances, while precision assesses the model's ability to correctly classify disease cases among all positive predictions. Recall, on the other hand, measures the model's ability to identify all actual disease cases, minimizing false negatives. Additionally, the F1-score combines precision and recall providing a balanced evaluation of model performance, which is particularly important when dealing with imbalanced datasets.

Cross-Validation: To ensure the robustness of the results, cross-validation techniques can be applied. Cross-validation helps in minimizing the risk of overfitting and provides a more accurate evaluation of model performance.

Experimental Setup: Results from many models are presented in this part, along with a comparison analysis using various parameters. The workstation's Intel(R) Xeon(R) CPU E5-1650 @3.60 GHz 3.60 GHz Memory 32GB and GPU Nvidia Quadro P2000 - 5GB are used to collect the results.

Figure 7 shows the visualization of our proposed model Architecture. Model are training using below different Conditions:

Option 1: (Training: 70 %, Validation: 20 %, Test: 10 %) Train: Found 14000 pictures fit in to 8 types. Val: Found 4000 images belonging to 8 classes. Test: Found 2000 images belonging to 8 classes.

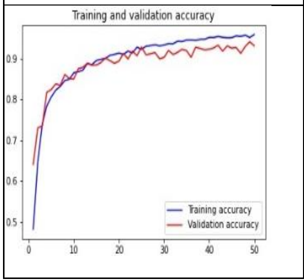
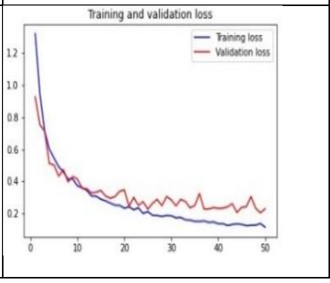
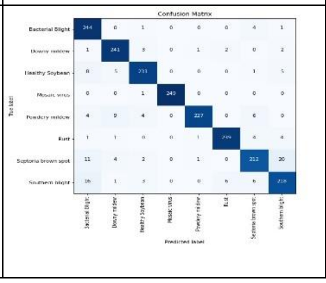
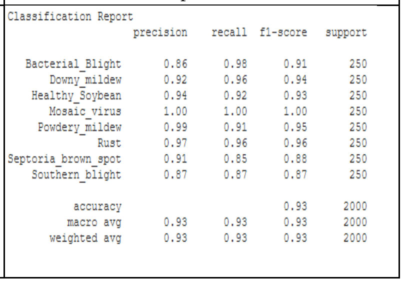
Option 2: (Training: 65 %, Validation: 25 %, Test: 10 %) Train: Found 13000 pictures fit in to 8 types. Val: Found 5000 images belonging to 8 classes. Test: Found 2000 images belonging to 8 classes.

Option 3: (Training: 60 %, Validation: 30 %, Test: 10 %) Train: Found pictures fit in to 8 types. Val: Found 6000 images belonging to 8 classes. Test: Found 2000 images belonging to 8 classes. Different Augment images are generated using Image Data

Generator function of TensorFlow library.

We can now apply learning to our problem statement by employing pre-trained deep learning models that was trained on huge datasets and applying the weights and architecture gained. Transfer learning refers to Table. 3 & 4.

Table. 3 Proposed Model Train using Split Image Dataset (Training: 70 %, Validation: 20 %, Test: 10 %)

AccVal_acc_New_Model _20_LR	LossVal_loss_New_Model _20_LR	Confusion_matrix_New_Model _20	Classification Report_New_Model _20
			

Classification Report

	precision	recall	f1-score	support
Bacterial_Blight	0.86	0.98	0.91	250
Downy_mildew	0.92	0.96	0.94	250
Healthy_Soybean	0.94	0.92	0.93	250
Mosaic_virus	1.00	1.00	1.00	250
Powdery_mildew	0.99	0.91	0.95	250
Rust	0.97	0.96	0.96	250
Septoria_brown_spot	0.91	0.85	0.88	250
Southern_blight	0.87	0.87	0.87	250
accuracy			0.93	2000
macro avg	0.93	0.93	0.93	2000
weighted avg	0.93	0.93	0.93	2000

Table. 4 Models Accuracy Analysis

For Validation data (50 Epochs)						
	Train-Validation - Test		**Train-Validation - Test**		**Train-Validation - Test**	
	70-20-10		**65-25-10**		**60-30-10**	
Model	**loss**	**accuracy**	**loss**	**accuracy**	**loss**	**accuracy**
VGG16	0.8043	0.7324	0.6993	0.7607	0.7900	0.7324
VGG19	0.7889	0.7148	0.8963	0.7011	0.6783	0.7568
ResNet152V2	0.9517	0.8203	1.3776	0.7402	1.4406	0.7470
xception	0.8984	0.7246	0.8081	0.7480	1.0949	0.6835
InceptionV3	0.7450	0.7666	0.8409	0.7441	1.0798	0.7109
InceptionResNetV2	0.7438	0.7871	0.5813	0.8212	0.6682	0.7968
Proposed Model	**0.1989**	**0.9365**	**0.2572**	**0.9229**	**0.2664**	**0.9160**
For Test data (50 Epochs)						
	Train -Validation - Test		**Train -Validation - Test**		**Train-Validation - Test**	
	70-20-10		**65-25-10**		**60-30-10**	
Model	**loss**	**accuracy**	**loss**	**accuracy**	**loss**	**accuracy**
VGG16	0.5009	0.8281	0.4200	0.8574	0.4754	0.8349
VGG19	0.5111	0.8242	0.5568	0.7988	0.4898	0.8212
ResNet152V2	0.6218	0.8759	0.8907	0.8261	0.8562	0.8300
xception	0.5521	0.8349	0.4863	0.8564	0.7171	0.7959
InceptionV3	0.5396	0.8378	0.6539	0.8134	0.6070	0.8046
InceptionResNetV2	0.5700	0.8437	0.4006	0.8720	0.5275	0.8388
Proposed Model	**0.1183**	**0.9658**	**0.1467**	**0.9599**	**0.2043**	**0.9355**

Transfer Learning Using CNN Models (50 Epochs)			
	Train -Validation - Test	**Train -Validation - Test**	**Train-Validation - Test**
	70-20-10	**65-25-10**	**60-30-10**
Model	**Accuracy (%)**	**Accuracy (%)**	**Accuracy (%)**
VGG16	82.81	85.74	83.50
VGG19	82.42	79.88	82.13
ResNet152V2	87.60	82.62	83.01
xception	83.50	85.64	79.59
InceptionV3	83.79	81.35	80.47
InceptionResNetV2	84.38	87.21	83.89
Proposed Model	**96.58**	**96.00**	**93.55**

Table. 5 Models Time Analysis

Proposed CNN Models Training Time (50 Epochs)						
	70-20-10		**65-25-10**		**60-30-10**	
Model	**Second**	**Hours**	**Second**	**Hours**	**Second**	**Hours**
Proposed Model	9551.789	02:39:12	9128.713	02:32:09	8565.548	02:22:46

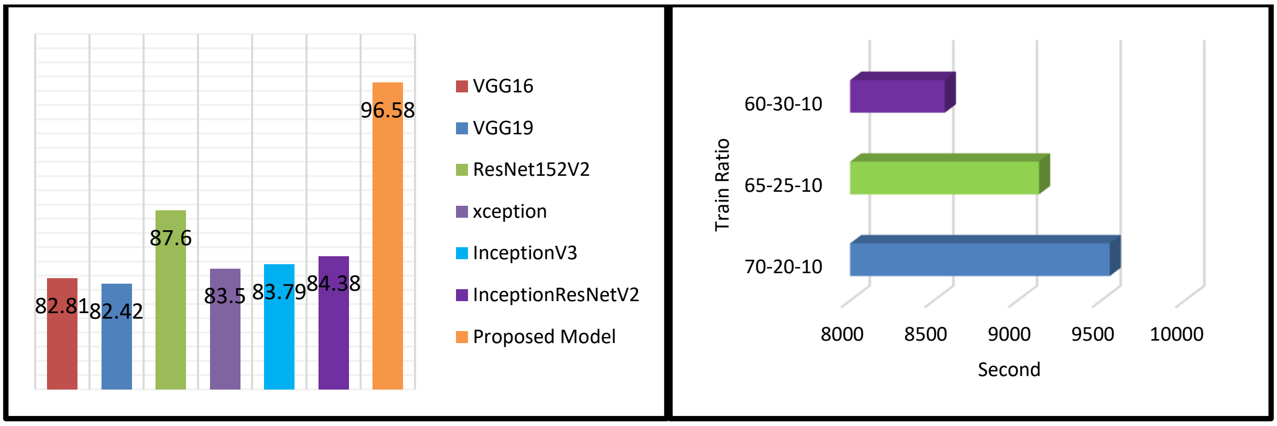


Fig 9. Analysis graph of Accuracy

For both the validation and test data, the Proposed Model consistently outperforms the other models in terms of accuracy and loss. It achieves the highest accuracy and the lowest loss across all data split ratios. The accuracy and loss values vary among the different CNN models and data split ratios. For example, ResNet152V2 performs relatively well on the 70-20-10 split but has higher loss and lower accuracy on the 65-25-10 and 60-30-10 splits. VGG16 and VGG19 also exhibit varying performance across different data split ratios but tend to have lower accuracy compared to the other models. The transfer learning results show that the Proposed Model achieves the highest accuracy across all data split ratios, demonstrating its effectiveness in utilizing pre-trained models for the given task.

Overall, the Proposed Model appears to be the best-performing model in this study, with high accuracy and low loss, suggesting that it might be a suitable choice for the specific task at hand.
From the Table 5 analysis it can be said that the proposed model gives 96.58% accuracy, which is best among all. While VGG19 model gives 82.42% accuracy which is worst case.

6. Conclusion

In conclusion, our research introduced a meticulously designed convolutional CNN model tailored for the precise recognition and classification of various diseases affecting soybean plant leaves. The innovative modification of the standard three-layer convolutional CNN, incorporating a Leaky ReLU activation and a 7x11 kernel, yielded promising outcomes, notably enhancing the model's classification accuracy when applied to soybean plant leaf disease datasets. This strategic adjustment not only demonstrated improved efficiency in training time and reduced memory requirements but also contributed to enhanced generalization capabilities.

Key Results and Discussion Points:

The replacement of the fully connected layer with Leaky ReLU and a 7x11 kernel showcased a notable increase in classification accuracy, reaching an impressive maximum of 96.58% on testing data. The Leaky ReLU layer's influence in reducing training time and memory requirements signifies potential efficiency gains, critical for real-world applications and on-farm deployment.

- **Acknowledging Limitations:** Variations in environmental conditions, diverse soybean plant varieties, and varying image qualities pose challenges for the model's performance in real-world settings.
- **Future Research Directions:** Strategies to address the identified limitations and enhance the model's robustness and accuracy in diverse agricultural scenarios need exploration in future research endeavors.
- **Practical Applications:** The research's potential impact on agriculture is substantial, offering an invaluable tool for early disease detection and plant health management across different crops, transcending soybean plants.
- **Versatility and Accuracy:** The model's adaptability to spatial shifts and its capability to recognize a wide range of plant diseases underscore its significance as a versatile asset in the agricultural sector.

In conclusion, our study marks a significant step forward in leveraging CNN models for agricultural applications, particularly in disease management and crop yield enhancement. With a solid foundation established, future research endeavors are poised to explore and apply this technology, fostering continuous advancements in the field of agriculture and contributing to more effective disease management practices.

7. References and Footnotes

Author contributions

Conceptualization—Mr. Kalpesh Patel and Dr. Atul Patel; Methodology—Mr. Kalpesh Patel; Software—Mr. Kalpesh Patel; Validation—Dr. Atul Patel; Formal Analysis—Mr. Kalpesh Patel and Dr. Atul Patel; Investigation—Dr. Atul Patel; Resources—Mr. Kalpesh Patel; data curation—Mr. Kalpesh Patel; Writing—review and editing—Mr. Kalpesh Patel and Dr. Atul Patel; Visualization—Mr. Kalpesh Patel; supervision—Dr. Atul Patel; Project administration—Mr. Kalpesh Patel.

Conflicts of interest

The authors declare no conflicts of interest.

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