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Abstract

The diseases on sesame leaves have a huge implication on the production and earnings of farmers particularly in the developing areas. It is important to ensure that the disease is properly managed by identifying it early and correctly. The purpose of this study is to create a deep learning-based framework that could be used to categorize four of the most common scenarios involving sesame leaves, i.e. Healthy Leaf, Leaf Spot Disease, Yellowing Leaf Syndrome, and Leaf Damage by Insects using high-resolution images acquired in Pabna, Bangladesh. The preprocessing, augmentation and split of a set of 3,540 images were performed into training and validation sets. The pre-trained convolutional neural networks models were trained and tested on five models inceptionV3, EfficientNetB3, ResNet50, MobileNet, and DenseNet121 by measuring the metrics such as accuracy, precision, recall, and F1-score. MobileNet achieved the highest accuracy of 96.33%, precision of 96%, recall of 96%, and the F1-score of 96%, which is the best amongst them. The findings indicate that deep learning architectures

are capable of classifying the sesame leaf diseases in a reliable and precision-oriented way that is not affected by different environmental circumstances. The study facilitates the creation of the automated, efficient methods of detecting the disease at an early stage, cutting down the number of pesticides used and enhancing crop control. Future direction will be to enlarge the dataset, add temporal data and to implement lightweight models so that it can be deployed to real-time field projects

Keywords:
Computer Vision; Sesame Leaf Disease; Deep Learning; Image Classification Smart Farming.

1. Introduction

Sesame is among the most ancient oil seed crops that are grown around the globe with superior nutritional value, yielding high oil, and financial importance among mainly the farmers of the developing world. Sesame is one of the crops that is tremendously affected by foliar infections by fungi, bacteria and viruses. All these diseases such as Leaf Spot Disease, Yellow-ing Leaf Syndrome, and Insect Leaf Damage could materially diminish output, crop quality, and farm profits in case they are not identified and controlled on time. The common strate-gies that farmers use to identify their diseases include visual assessment and through the assessment of trained experts in agriculture which are highly subjective, time consuming and are not accurate particularly in the preliminary stages when symptoms are not apparent. This paper will create an effective model of deep learning-based early identification and classification of sesame leaves diseases. The research uses Convolutional Neural Net-works(CNNs) to detect four key disease types on the basis of a large resolution image database in an attempt to enhance detection efficiency and precision over the traditional counter-parts. The study is concerned with the prospects of using higher-level computer vision and artificial intelligence in precision agriculture. The suggested system can diagnose diseases real-time, respond to the farmers in time, minimize the excessive use of pesticides and enhance management of the crops and concretize scientific detection of disease agents that rely on microscope. This robotic system has the capability of improving the decision making, sustainable agricultural process and above all enhancing the overall productivity and profitability of sesame production.

1.1. Background

In this paper a deep CNN architecture was proposed to classify sesame disease in leaves. Their dataset was composed of 2,300 original images gathered in the largest agricultural research institutions in Ethiopia, to which further 9,200 were added with the help of augmentation methods. Some of the steps involved in workflow were preprocessing utilizing median filtering, contrast enhancement, and leaf segmentation using SegNet. An augmented data was

implemented and classified by a customicle CNN, which was trained and tested. The model was highly accurate: 98% during the training, 97.78% during validation and 96.67% during the testing. The custom model had a higher performance than the pretrained models, such as Xception, which are a likely indication that in a real-life agricultural environment; this model can be put into practice (Nibret et al., 2025).

In this paper, the authors introduced a CNN-based system that is able to detect the three common conditions of the sesame leaf, namely bacterial blight, phyllody and healthy leaves. The data consisted of 540 images of leaves as recorded in natural light by mobile phones. Its methodology was based on preprocessing a video to get the better contrast and noise reduction, then segmenting, adding few augmented points, and using a multi-layer CNN to do classification. The model had an accuracy of 99% on training and 98% on testing, a good indication of it being robust in spite of its somewhat small data. The design was straightforward yet sufficient enough that it could be used in the field. The findings of this study indicate the potential of deep learning on small scale and real time
agricultural use-cases (Abeje et al., 2022).

This project involved the application of transfer learning not only to the classification of the sesame disease but also with the help of the ResNet50 architecture. There were 1,453 images of leaf of sesame classified in three groups. To display better results, it was decided to pretrain the model on the ImageNet dataset and then fine tune it on the data of the Cas-sava disease before completing the training on sesame pictures. The overall precision achieved 96.7%, which showed that the multistage pretraining approach to domain adaptation can be rather effective. The author also used the regular data augmentation to increase generalization. This piece offers a workable outline to the formation of reasonable models under labeled conditions (Ibrahimssd, 2023).

This paper built on the previous ResNet based methodology by resolving the problem of overfitting through unsupervised pretraining. The project experimented on the hypothesis that models that were pretrained with unlabeled data through contrastive learning would be able to learn better visual representations. The dataset was not large, yet the overall approach of the transfer learning and self-supervision produced more consistent and generalizable results. Although it was not compared with large models, it nevertheless outpaced simple fine-tuning

strategies. The present experiment promises to improve sesame disease models in data-limited settings, particularly the rural settings, where it is challenging to obtain labeled data (Musa, 2024).

The authors compared their proposed CNN architecture with the common Xception one as a part of their significant study. On the same dataset, they determined that Xception would attend to approximately 94% training accuracy and the testing accuracy was approximately 93.3%. This was not as good as their usual performance on CNN (96.67% test accuracy), yet nonetheless was respectable. The comparison also showed that a highly customized model trained specifically for sesame data can outperform a very broad pretrained, large model. Moreover, the localized CNN had fewer parameters, training required less time, thus making it viable to deploy in a local scale (Nibret & Atnafu, 2025).

The topic of the present review paper was on the application of CNNs to the detection of disease in oilseed crops, including sesame. On a dataset of 1,695 images of sesame leaves a six layer CNN was tested and a training accuracy of 90.8% and a testing accuracy of 88.5% was achieved. Researchers contrasted it with classic expert systems and demonstrated the excellence of CNN in its adaptability and the speed of classification. The credits of present research already focused on the usefulness of preprocessing and the necessity of more quality datasets. It was efficient and suitable for low-resource activity compared to other deep models even though the accuracy was less (Sharma & Patel, 2021).

The study did not focus on sesame; however, it suggested a CNN-LSTM hybrid model to be trained on a variety of crops containing more than 87 thousand leaf images and 38 disease classes. The method used spatial characteristics extracted by the CNN, and the temporal dependence that is expressed by the LSTM. With training accuracy and validation accuracy of 99.1% and 96.4% respectively, it is effective in generalized classification of disease in plants. This design can be modified into designing of sesame disease classification, in particular, where the progression of the symptoms of the disease with time is a factor. In the paper, the potential of deep hybrid networks in the solving of complex agricultural problems was emphasized (Kanakala & Pothuganti, 2025).

The study presented a hybrid model nicknamed PlantXViT and uses the CNN and the Vision Transformer (ViT) models to perform the detection of leaf disease. The model reached an

accuracy of up to 98.33% although it was trained on maize, apple, and rice. It had explainable output by Grad-CAM and LIME and so it would be useful in trustable agriculture AI systems. With less than 1 million parameters, the architecture was not only lightweight but efficient as well. Its clarity and explainability show that it could be a good option in adapting to the transparency and accountability of sesame leaf classification (Thakur et al., 2022).

A deep CNN was trained on more than 147,000 augmentedimages belonging to 58 plant disease classes in this work. The techniques including GANs and neural style transfer helped achieve augmentation and make the models much more robust. The CNN demonstrated a very high proportion of accuracy of 99.97% that affirmed using artificial data to enhance performance. The procedures can be applied directly to small sesame dataset to generate synthetic training samples, although sesame was not considered. The importance of augmentation is highlighted in this paper to produce almost flawless outcomes in detecting plant disease (Zhang et al., 2022).

This establishment paper trained a deep CNN by using the PlantVillage dataset that consists of more than 54,000 images of 14 crops and 26 diseases. Under ideal conditions, the model attained a test accuracy of 99.35% but when field images were tested, its accuracy went to 31%, a fact that showed the restriction of domain shift. The article is important in relation to the influence of training and testing conditions on the reliability of a model. It set up the framework that was later referenced in subsequent models such as the one used in handling sesame and how real-world information is very considerably used in developing the model (Mohanty et al., 2016).

In this paper, the medicine plant leaves diseases have been detected with a correctness rate of 92.7% with a shallow architecture of CNN. Its efficiency was low because the model was simple to implement on the device having limited resources. Although it is tested on other non-sesame crops, its results can be applied to detect sesame diseases in other areas where there is low infrastructural development in marginal lands of agriculture. The research also showed the effect of preprocessing and data balancing as far as performance is concerned. It supports the idea that the need of complex models may not be necessary when data is good (Roy & Sinha, 2023).

In this conference paper, the early-stage detection system was reported with an early source of overall-plant leaf data trained deep CNN. It emphasized on light architecture and quick processing to allow mobile applications. The system design and methodology are easily adaptable although not focused on sesame. The research confirmed that preprocessing such actions as downsizing and normalization play a considerable role in the CNN performance. It is especially applicable in development of early-warning tools in the field of agriculture where it should be possible to detect a disease before the symptoms get too intense (Islam & Haque, 2021).

1.2. Aim

This study will produce an effective and precise deep learning-based system to confirm the classification of diseases in Tahini sesame leaves with high-resolution images. Through an accumulation of a rich dataset and the usage of different pretrained convolutional neural network models, the study will aim at finding the optimal architecture that will be applicable in the early and reliable detection of the disease. Also, the research will work toward improving model performance in preprocessing and augmentation techniques, which will eventually offer a viable tool that would help the farmers diagnose the health of the crop in time and manage it more satisfactorily.

2. Data Description

The Sesame Leaf Disease Dataset consists of 3,540 high-resolution images purposefully sample-selected in the fields of sesame crop cultivation on the territory of Pabna, Bangladesh. The Photographs were taken under natural conditions without any particular environmental conditions to capture natural representation of how sesame leaves appear in different ways in real life conditions. According to Fig. 1, they were the direct photos of the areas in which the sesame plants grow, and the dataset represents the measuring of the fields.



Figure1: The Sesame field from where the images of the dataset were taken

In the dataset used, there are four categories where each category indicates a certain condition of the sesame leaf: Leaf Spot Disease, Healthy Leaf, Yellowing Leaf Syndrome, and Leaf Damage by Insects. These classes will facilitate proper training and assessment of the machine-learning models to achieve proper diagnosis of a disease. Table 1 shows the summary of distribution of the images over these classes.

Table 1: Statistics of the sesame leaf dataset

Serial No	**Classes (Leaf)**	**Number of Images**
1	Healthy Leaf	1335
2	Leaf Spot Disease	587
3	Yellowing Leaf Syndrome	894
4	Insect Leaf Damage	724
Total		**3,540**

Table 1 below indicates the specifics of the dataset such as the number of images in the different classes, a brief description and sample images to represent each category.

Table 2: Dataset Summary of Sesame Leaf

Class	**Total Images**	**Description**
Healthy Leaf	1335	Sesame plant growth with good yield, and photosynthesis as well as distribution of nutrients and content of oil need healthy leaves.
Leaf Spot Disease	587	The problem of leaf spot is a result of different fungus pathogens which as a consequence generate brown or black spots that weaken the photosynthesis capacity of the plant.
Yellowing Leaf Syndrome	894	A disease caused by the yellowing of sesame leaves occurring because of a lack of nutrients or illness or stresses on the saplings. It is an indicator of a low plant vitality.
Insect Leaf Damage	724	Places in the leaves of sesame such as holes or scratches that are the result of insect pests. It influences the plant structure and growth of the leaf.



Figure 2: Sample Images from the Sesame Leaf Disease Dataset.

It is an automated recognition of sesame leaf diseases image dataset, which is built in 3,540 high-resolution images. These images are categorized into four classes which depict the conditions of leaf in four ways: Healthy Leaf, Leaf Spot Disease, Yellowing Leaf Syndrome, and Leaf Damage by Insects. This more comprehensive classification as compared to a simpler one divides into healthy and diseased groups only means more precise and earlier detection of the disease, which helps manage its crops and decisions.

The data was gathered during the course of April 2025 to May 2025, and the imaging on different days and times varied so that to get a diverse lighting environment and weather conditions. The sampling points used in the collection of data were chosen to represent the variety of the actual field symptoms in sesame crops. Also, important information like the type of leaf, weather, date, time, temperature and the gadgets used to take the photos were also noted. Table 3 provides the information.

Table 3: Collection Details of sesame Leaf Dataset

Date	Class Name	Weather	Temperature	Camera Device	Location
20 April, 2025	HealthyLeaf	Sunny	34°C	Realme 8 (55%) and the Redmi Note 10 Pro (45%)	Pabna
27 April, 2025	Leaf Spot Disease	Partly Cloud	31°C	Realme 8 (60%) and the Redmi Note 10 Pro (40%)	Pabna

5 May, 2025	Yellowing Leaf Syndrome	Cloudy	29°C	Realme 8 (70%) and the Redmi Note 10 Pro (30%)	Pabna
15 May, 2025	Insect Leaf Damage	Light Rain	27°C	Realme 8 Rain (85%) and the Redmi Note 10 Pro (15%)	Pabna

3. Methodology

Technique includes collecting the data, preprocessing data, enlarging it, and classification of sesame leaf diseases employing five states of the art deep learning models.

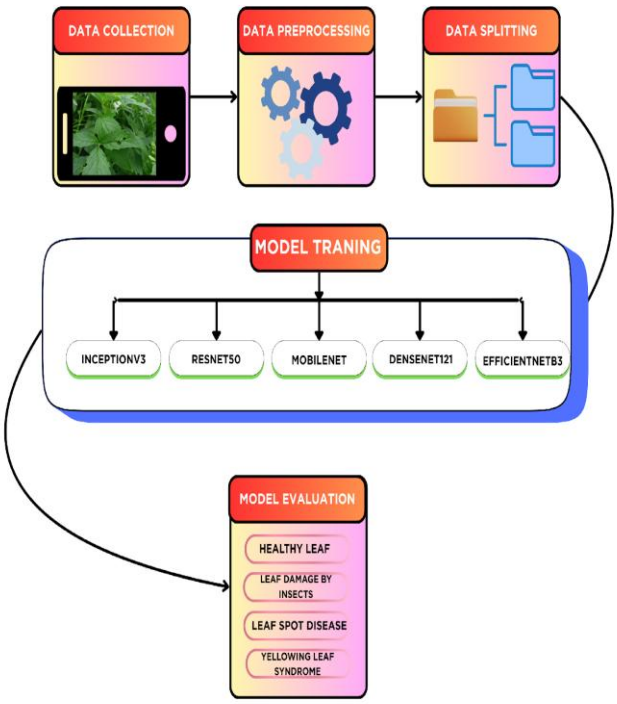


Figure 3: Flowchart for Early Detection of Sesame Leaf Diseases

3.1. Data Collection

We have used a training dataset comprising of images of sesame leaves which we have obtained in Kallyanpur area of Sujanagar upazila of Pabna district. The timing of the data collection was

in April 2024-May 2025. Crisp views of the sesame plants were taken in natural light using several smart-phone cameras in direct contact with the plants. The research team then uploaded these images into a central repository. The data contains unhealthy and healthy leaves which are affected by frequent diseases like Leaf Spot Disease, Yellowing Leaf Syndrome and Insect Leaf Damage. To be robust and diverse, the images have been captured in different categories of environmental and lighting conditions so as to be very similar to real-life conditions. The geographical locations of the sites of collection are the following ones:

1. Kallyanpur, Sujanagar, Pabna
   Latitude: 23.987907, Longitude: 89.557542



Figure 4: Geo. Locations of Datasets

After obtaining the images, the raw images obtained have had various processes of preprocessing coupled with the need to have uniformity and quality. All images were re-sized to similar standard-resolution of 1024x1024 pixels, and some background noise elimination was done by insertion of plain white background. The image normalization was used to make them consistent against different lighting conditions and different specifications of different devices. Duplicate and poor-quality images were removed leaving high quality and only

relevant images in order to train the model. Then the dataset was divided into 80% training and 20% validation datasets. To label the task, five publicly known pre-trained deep learning models were applied: InceptionV3, EfficientNetB3, ResNet50, Mobilenet, and DenseNet121. These models were applied to classify the pictures into 4 categories of diseased leaves of sesame. Accuracy, precision, recall, and F1-score, were used as evaluation metrics to evaluate performance of each model. This pipelined framework shows the efficacy of deep learning in diagnosing diseases of sesame leaves in a realistic environment.

3.2. Materials (Camera Specifications)

In order to achieve a high-quality acquisition of the images, the dataset as regards sesame grape leaf has been collected with the aid of two mobile phones, including the Realme 8 and the Redmi Note 12 Pro. These devices were chosen because of the sophisticated camera features such as high sensor resolution and macro that will be important in obtaining the leaf details and symptoms of the disease. Comparing it with Table 5, Realme 8 has a 64 MP primary lens that has an aperture of f/1.79, whereas Redmi Note 12 Pro sensor has 50 MP and a wide aperture to accept more light. The macro photography functionality present in both devices also enables the photographer to take intimate photos where the details of the leaf surface can be observed like it has discoloration, lesions, and fungal patterns.

3.3. Image Pre-processing and Classification

The collected images were classified according to their types, resized into a standardized 1024x1024 pixels, and named as per the class to which it falls, which comes next to the process of categorizing them before training those models. This provided quality, diversity and relevance of the dataset to the detection tasks in the real world. The scheme was expected to reproduce the conditions of real-life farming and create a powerful model that could reliably recognize new information. Fig.3 shows the illustration of the main working steps involved in storing raw pictures to supply final processed data that could eventually be used to train a model.

These were:

1. **Field Selection:** The fields were selected among the various regions of Pabna to have the representation of the different disease severity and the environmental condition.

2. **Leaf Collection:** Sesame healthy and diseased leaves were collected by a painstaking procedure of collecting healthy and diseased leaves with the least possible physical damage to the physiology of the leaves.
3. **Image Capturing:** The image was taken at a high resolution in natural light in order to reduce the shadows and reflections in images, and clear visibility of disease symptoms was guaranteed.
4. **Image Organization:** The captured images were uploaded to a secure place and put into well-placed folders to facilitate fast processing.
5. **Image Resize:** All images were downscaled into a single size of 1024 × 1024 pixels.
6. **Image Labeling:** All pictures were classified as Healthy Leaf, Leaf Damage by Insects, Leaf Spot Disease and Yellowing Leaf Syndrome.
7. **Classification:** Just like it was done before, labeled images were classified into distinct folders to automatize the training process.

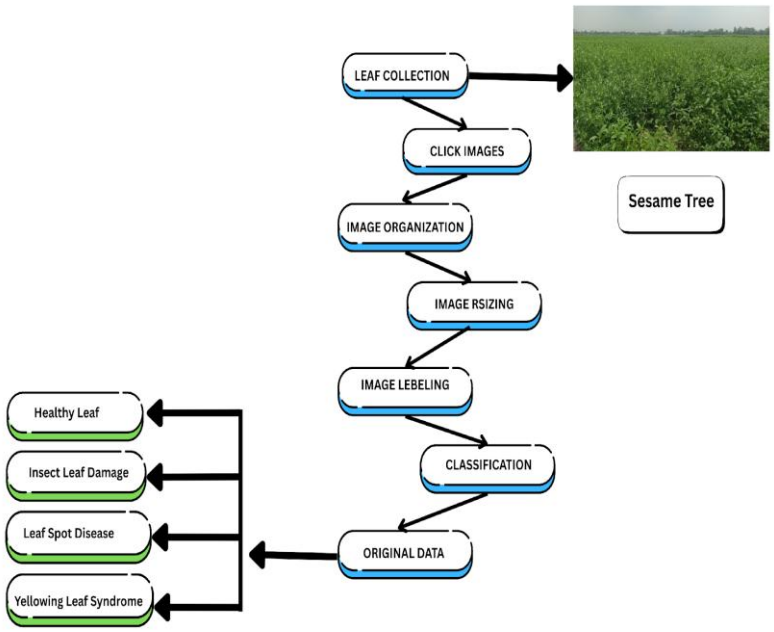


Figure 5: Workflow of image pre-processing and classification.

3.4.Techniques of Image Augmentation

These additions play a vital role in increasing the strength and generalization skills of deep-learning models when the Sesame Leaf Disease data is considered in training. This necessitated

the need to increase the size of the dataset that was originally small in size in order to achieve robust performance in a wide array of real-world scenarios. In our work, we used various augmentation strategies including rotation, flipping, scaling, contrast manipulation, blurring, shearing, zooming, and noise addition as the means of enhancing the data diversity and raising predictive accuracy of the models. Through these sorts of transformations, the dataset was augmented and brought more closely to natural field variations.

The augmentation process was used to appropriately overlay various transformations to achieve the conditions whereby sesame leaves are reproduced in real-world conditions. To reproduce differences in orientation and point of view, horizontal and vertical flipping was used. Angular variability was introduced by rotation to 45deg and size variability models degree of scaling between 0.8-1.2. Gaussian blur of radius 0.5 to 2.5 were used to replicate low-quality or shaky images captures. Random contrast variations in 0.7-1.3 were used to cope with different lighting conditions to make the models resistant to variations in brightness. Tilt factors of -0.3 to +0.3 caused some distortion because the leaves are usually taken at an angle. A zoom of 1.5x was then followed by cropping to enable the models limit their interest to disease patterns at finer levels of interest. Lastly, the range of -60 to +60 was added to random noise to simulate the real-world image defects like background interference or low-resolution image capture.

With these augmenting methods, there was an expansion of the original dataset of 3,540 images to about 12,000 images. The balance was considered by adding samples to each class until each one reached 3,000 images, we did not have imbalance in classes in the final dataset. Table III provides the schemas of the initial and added classifications of images.

Table 4: Number of Original and Augmented Images in the Sesame Leaf Dataset

Serial No	Class Name	Original Images	Augmented Images
1	Healthy Leaf	1335	3,000
2	Leaf Spot Disease	587	3,000
3	Yellowing Leaf Syndrome	894	3,000
4	Insect Leaf Damage	724	3,000
Total		**3,540**	**12,000**

The process of augmenting the dataset not just fixed the class imbalance, but also added wide variability to the dataset. The resulting trained models trained with this augmented data were therefore less likely to overfit and more apt to extrapolate to novel field conditions. The dataset,

by capturing various changes, was critical in developing powerful models to detect the sesame leaf diseases accurately, which is a critical move towards precision agriculture and good management of the diseases.

3.5.Dataset Structure

The data is categorized into two primary folders, Original Images and Augmentation Images with four subfolders Healthy Leaf, Leaf Damage by Insects, Leaf Spot Disease and Yellowing Leaf Syndrome. The Original Images is the folder that contains original, raw images and Processed Images is one where after being resized, cleaned, and increased the brightness, images are ready to be used to train models. Fig 5 displays the overall structure of the dataset.

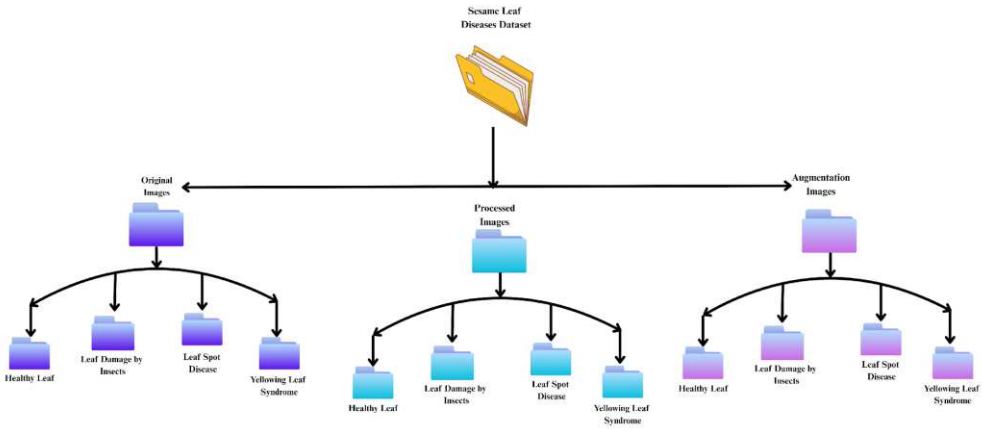


Figure 6: Sesame Leaf Disease dataset organization.

4. Results/Findings

The five CNN models had good performance with regard to classifying the sesame leaf conditions. MobileNet provided the best and trustworthy prediction followed by EfficientNetB3 and ResNet50. The general conclusions suggest the responses to the efficiency of deep learning in the automation of identifying diseases in agricultural fields.

4.1.Model Validation

Since these five pre-trained CNN networks are known to have good performance, they were applied to check their prediction performance regarding the class of disease on the sesame leaf

into four categories: Healthy Leaf, Leaf Spot Disease, Yellowing Leaf Syndrome, and Leaf Damage by Insects. We trained the models with 32 in the batch size and 30 epochs and apply an adaptive learning rate of 0.001 to avoid overfitting and gain better training stability. The pre-processed dataset consisted of 3,540 images that were divided in the 80:20 training-validation ratio in preparing the models. Plots of accuracy and loss of the training and validation sets were also obtained during training. Such graphs are crucial to trace the learning process during which I will be able to get an idea about the quality of model generalization to novel data. They as well are capable of helping to detect problems with a model that yields good results on training data but fails on validation data, e.g. overfitting; or does not learn enough compared to the data, e.g. underfitting. We resorted to standard metrics to gauge the extent of characterization accuracy of the models, namely accuracy, precision, recall, and F1-score. These measures offer a clear interpretation of how well the models can arrive at the right classification of each of the classes and handle skewed datasets, as well. The particular formula for calculating these metrics are:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP - FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

with TP, TN, FP, and FN being True Positives, True Negatives, False Positives and False Negatives, respectively.

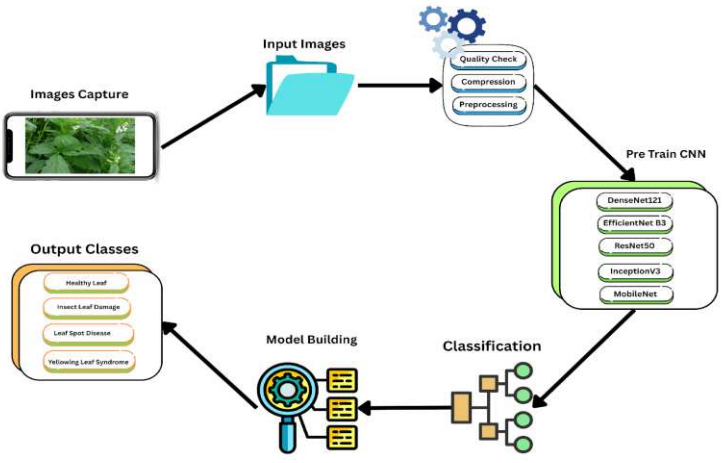


Figure 7: The visual abstract for Sesame Leaf classification.

Table 5 shows the performance of the MobileNet model when it classifies sesame leaves into four categories namely: Healthy Leaf, Leaf Spot Disease, Yellowing Leaf Syndrome and Insect Leaf Damage. It achieves an accuracy of 96.33%. Fig. VI plots the MobileNet loss and accuracy curve, and Fig. VII the MobileNet confusion matrix.

Table 5: Performance metrics of the MobileNet model on the Sesame Leaf Dataset

Class Name	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Accuracy%**
Healthy Leaf	95	96	96	96.33
Insect Leaf Damage	98	97	97	96.33
Leaf Spot Disease	94	94	94	96.33
Yellowing Leaf Syndrome	98	98	98	96.33

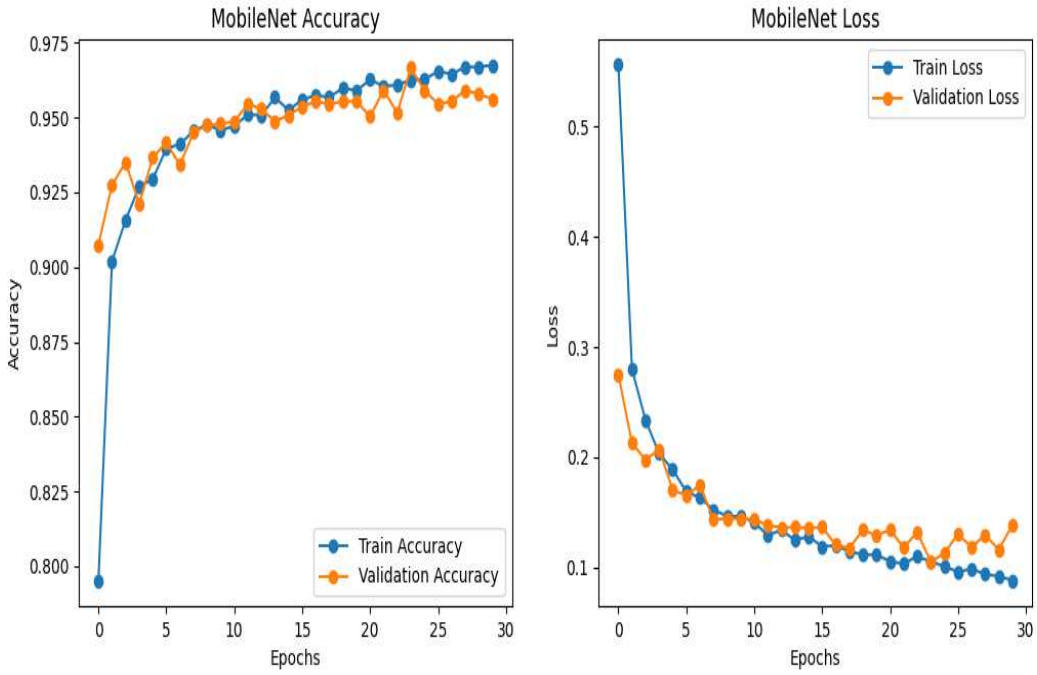


Figure 8: Accuracy and loss curve for MobileNet.

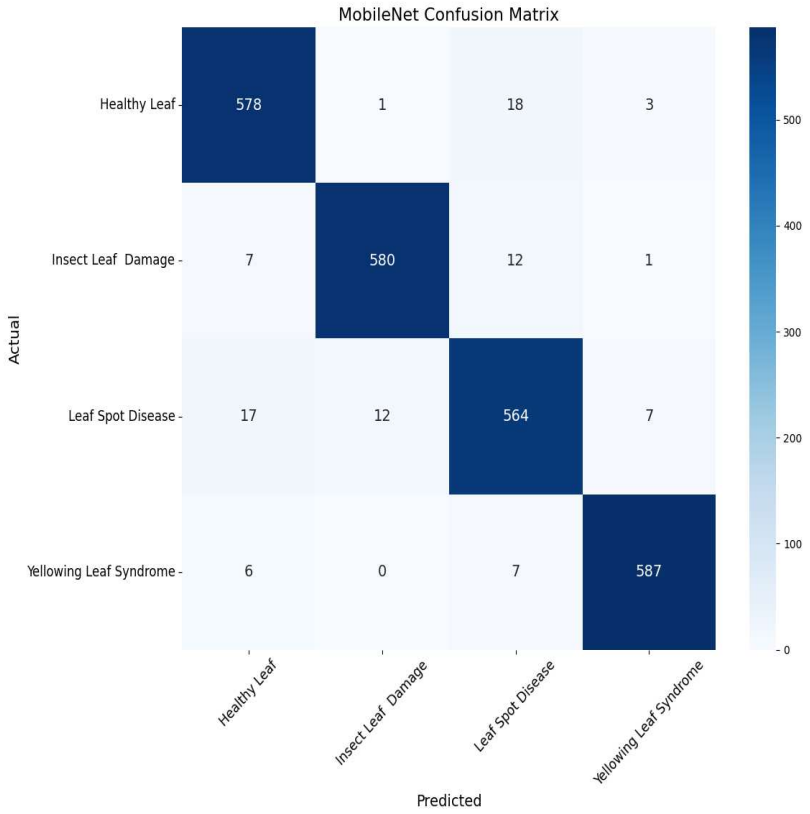


Figure 9: Confusion matrix for MobileNet.

Table 5 presents the precision of each model. With all model performances analyzed, we can observe that MobileNet was the highest-performing model because of the high 96.33% accuracy.

Table 6: Comparison of accuracy models

Models	**Precision**	**Recall**	**F1-Score**	**Accuracy**
DenseNet121	0.95	0.95	0.95	0.9529
EfficientNet B3	0.95	0.95	0.95	0.9521
MobileNet	0.96	0.96	0.96	0.9633
ResNet50	0.96	0.96	0.96	0.9596
InceptionV3	0.91	0.91	0.91	0.9137

Based on the scores reported in the table, all five models performed well and consistently in the classification of sesame leaf diseases. DenseNet121 reached a precision, recall and F1-score of 95% with an accuracy of 95.29%. EfficientNetB3 had similar results, achieving 95% in precision, recall, F1 with an accuracy of 95.21%. MobileNet achieved a performance gain against previous models with a precision, recall and F1-score of 96% and a maximum accuracy of 96.33%. ResNet50 also performed very well, getting a precision, recall and F1-score of 96% with an accuracy of 95.96%. In contrast, InceptionV3 achieved slightly smaller values: 91% in precision, recall and F1 score, and an accuracy of 91.37%. Overall, although differences between models were small, all models showed good classification performance and could be used successfully for the identification of sesame leaf diseases.

5. Discussion

The research shows that MobileNet and ResNet deep learning model could be used to meaningfully predict disease in sesame leaves. Their high-end architectures have facilitated feature extraction on high-resolution image whereas preprocessing and data augmentation methodologies contributed to the enhancement of the robustness of models to lighting, relative leaf orientation, and environmental changes. The similarity in the results of lightweight models such as MobileNet supports the view that it is possible to put disease detection tools into mobile or embedded devices which can be very helpful to farmers in the regions with few resources. Nevertheless, training was done on a rather small dataset and on static images, thus potentially lacking the reality of the entire spectrum of situations in the real world: time-wise dis-ease development or geographical areas. Additional research in the future can increase the diversity of the data and implement time-series or multispectral data into the dataset to reap greater accuracy. Also, the use of such models in mobile applications that are easy to use to the user could increase early disease detection and timely crop management of crops to minimize losses as a step towards sustainable agriculture.

6. Conclusion

To sum up, this research has proven that deep learning models are effective in classifying the disease in sesame leaves. MobileNet demonstrated the most comprehensive performance, among the reviewed architectures, and was in close competition with EfficientNetB3 and ResNet50. Preprocessing and augmentation of the images used increased the capability to generalize their models to diverse conditions within the field. The precision, recall, and F1

scores of all models were balanced, which proves accurate detection of various types of diseases. This automated method can be very helpful to the farmers as we can get early diagnosis, and the accuracy can be high ditching the human inspection. Also, the light models such as the MobileNet have good prospects of application in mobile and embedded systems. Future development may address larger data and real-time application that has broader applicability. In sum, the study promotes the use of deep learning as an effective concept that can be used to promote precision agriculture in the management of the sesame crop.

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