Deep Learning-Based Multiclass Classification of Diseases in Cucumber Fruit: Enhancing Agriculture Diagnosis

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Agriculture plays a key role in the economies of many developing nations. Cucumber is a cultivated vegetable that is grown in large quantities, but the production is regularly affected by diseases, with its yield loss impacted by diseases which include Belly Rot and Pythium Fruit Rot. Early and accurate disease diagnosis is critical for minimizing economic losses and improving crop quality. Traditional method techniques are based on visual identification and are time-consuming and often inaccurate, especially for the early stages of the disease. In this work, we aim to tackle these problems and present an automatic cucumber disease classification system by transfer learning. Three convolutional neural network models (pre-trained VGG16, MobileNetV2, and ResNet-50) were retrained on a set of 2400 images containing two disease classes and one normal class. The images were preprocessed with contrast-limited Adaptive Histogram Equalization (CLAHE) and background removal by deep learning segmentation to eliminate the background noise and focus only on the informative feature of the image. The models were trained and tested by using training, validation, and test sets with the respective accuracies of 95.28%, 98.06%, and 57.5%. MobileNetV2 showed superior performance to all other models including the highest precision, recall, and F1 score of 0.98, confirming that it was robust and appropriate for real-time disease classification. The results demonstrate that the transfer learning method is conducive to improving the issues of lack of labeled samples and variations in image acquisition and strength, thus providing a reliable model for early disease detection in cucumbers. The system we propose can support farmers and agronomists in early disease management decisions and reduce chemical usage. In the future, we will increase the data set with more disease classes, and develop a mobile APP for field-level disease detection.

Keywords: Cucumber diseases classification, Transfer learning, Deep learning, MobileNetv2, VGG16, ResNet50, Preprocessing, Clahe, Convolutional Neural Network (CNN), Machine learning.

Introduction:

Farming is central to the economy of many developing countries. Now, the agriculture of fruits and vegetables in fresh conditions can be produced and commercialized worldwide. To meet the rising demand for food, the food manufacturing industry has developed and used new technology. Governments invest billions of dollars every year to bring these technologies into place. Assessing and grading fruits is a difficult task. [1] Disease in cucumber plants is a disease that causes farm yield to face a threat all over the world in agricultural production. And contributes significantly to the cost of goods. Fruit diseases cause a 1015 percent decrease in food production. Cucumber is a highly susceptible fruit with different diseases (Belly rot, Fresh cucumber, and Pythium Fruit Rot). Classification of the disease process is time-consuming and requires experts to identify it. Farmers evaluate damage from diseases and apply treatment in their fields, but plant pathologists' analysis and diagnosis are mistakenly used most of the time. Hence, cucumbers need an accurate recognition method for disease [2]. To address these issues, it is necessary to establish an accurate and efficient disease diagnosis model. Scientists have been exploring mechanisms to monitor large fields with crops for diseases using different computer algorithms. The objective is to design a robust recognition model that most farmers can conveniently use. For those situations, it is important to have a computer program capable of diagnosing cucumber disease with a higher degree of accuracy, quicker, and reliably, to allow farmers to take the necessary steps to protect their produce promptly.

The most powerful methods in the cucumber varieties classification were initially traditional machine learning techniques, e.g., SVM and common neural networks. [3] These techniques were primarily based on hand-crafted features based on color, shape, and texture, and reasonably resulted in good classification accuracy with structured datasets. However, deep learning with transfer learning, in particular, has greatly improved the results of image classification. Transfer learning Transfer learning is performed by reusing pre-trained deep learning models, e.g., VGG-16, MobileNet, and ResNet-50, that have been trained on large image datasets like ImageNet. Such models can automatically learn complex and hierarchical features from images without requiring manual feature engineering. Using them as pre-trained models and finetuning them for cucumber classification has greatly improved the classification accuracy and overall accuracy of these models. The preferred one is transferring learning. Improvements in classification precision and overall.

Limitation:

Deep learning-based cucumber disease detection suffers from a lack of high-quality images, which can be used to train the model effectively. Due to a lack of images, the model cannot identify some diseases correctly, which makes the predictions biased. Furthermore, differences in illumination, background content, and plant arrangement might cause the model to fail in recognizing diseases under realistic settings, where the images are not always acquired under perfect conditions. Another barrier is that deep learning models are computationally intensive, meaning they need high-performance computers or graphics processing units (GPUs) for training and processing. This renders the technique slow and expensive.

Significance:

The value of the work comes from the new practice of applying transfer learning in the cucumber disease classification, which results in an effective solution to the difficulties in disease detection in agriculture. Transfer learning makes it possible to reuse the pre-trained model from a big, general dataset. It saves time and resources (especially labeled datasets, which are rare in most agricultural cases). Such pre-trained models are further adapted to the target task of cucumber disease accuracy. As a result, transfer learning has become a preferred method. [1]

Problem Statement:

Cucumber is one of the most important vegetable crops, and it is frequently subjected to various diseases. These diseases destroy the leaves and fruit of the plant, causing poor crop quality and reduced production. If farmers can't identify these diseases early, they can lose a significant part of their crop. Disease detection through organic glass is observed with the naked eye in most cases. This method is time-consuming, labor-intensive, and more often untrue, particularly at the early stage of the disease or for the unobvious symptoms. This problem can be addressed by using deep learning and image processing in the image-based plant disease identification process. However, deep learning has a few obstacles within that approach. One major problem is that we lack clear and labeled disease images for cucumber disease to train the model. Some diseases have very few photos. Hence, the model might not learn to identify them correctly. The other challenge is that real-world images may come with various lighting, angles, and backgrounds. These changes could mislead the model and degrade its performance. Also, deep learning models often rely on powerful computers or GPUs, which are cost-prohibitive and not widely accessible to everyone, particularly small farmers. For all these reasons, there is a high demand for a robust, accurate, and user-friendly system that could perform cucumber disease detection based on images, even if the photos were shot under normal field conditions.

Classification in the research enhances the accuracy and efficiency of disease detection and makes it achievable for farmers who do not have enough financial capital. In addition, this research shows how transfer learning can successfully be used for fruit disease classification, a step forward in the development of machine learning methods in the field of agriculture. The successful deployment of transfer learning in this context can open up new lines of research, with large-scale solutions that contribute to the development of healthy crop management, improving yield quality, and reducing harmful pesticides.

Contribution:

1) **Enhanced Cucumber Disease Classification Efficiency:** An important contribution of this work is to investigate the accuracy and efficiency of cucumber disease classification, which is based on images, developed with transfer learning techniques. More specifically, it uses VGG16, MobileNet, and ResNet-1
architectures to improve the accuracy and speed of the detection of diseases.

2) **Comparison of Transfer Learning models:**
In this research, we compared the three transfer learning models, ResNet-50, MobileNet, and VGG-16, based on their accuracy and computational requirements. The comparison is informative as to the capacities and performance of the models.

3) **Hyperparameter Optimization for Enhanced Results:** This work contributes to finding the best hyperparameters and training settings for transfer learning models that achieve the best results in classifying cucumber diseases. This abatement makes the model practical and reliable.

Literature Review:

In [4], authors adopted two transfer learning models of VGG16 and InceptionV3 framework for feature extraction from cucumber plant disease images. The selected features were subsequently fused to integrate the merits of the two models and further optimized using the Whale Optimization Algorithm (WOA) to obtain the optimal feature subsets. Several classifiers were compared, and the KN-CNN (K-Nearest Neighbors Convolutional Neural Network) classifier outperformed the others with an accuracy rate of 95%, thus gaining the leading place for cucumber disease classification in the state-of-the-art accuracies. This result demonstrates the effectiveness of feature fusion, optimization, and classifier selection in enhancing model performance for this task. The author in [5], shows that image Capturing is the pre-stage of computer vision. In this experiment preprocessing techniques are applied since the need of the features must be a fixed size for the model, it's important to be a normal size so use image resize during the training the filter techniques, use clip limit for class, use the clay technique for contrast enhancement, apply Segmentation and then apply different ml approach and different transfer learning and used different transfer learning over the InceptionV3, MobileNetV2, and VGG16 for our work. The more accurate model is 93.5% of MobileNetV2. In another research [6], authors used an extraction feature by comprehensive color, that is, the HSV color space and the lab color space, which is used to find disease spots and remove the background. With the help of segmentation, all the images are resized to 20 x 20 x 3 due to a small spot on the images, and then they are run through the DCNN model for classification, and the model accuracy is 85 %. In one study [7], the FruitVision model is presented for cucumber disease classification, employing advanced preprocessing techniques to enhance image contrast, such as Contrast Limited Adaptive Histogram Equalization (CLAHE).

Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied for image enhancement, while Otsu's segmentation method is used to reduce noise. In a related study [5], the model is trained using MobileNetV3, with two optimizers: Munsanet for improved feature extraction and NetAdapt for adaptive model complexity during training. These techniques not only obtained a different level of performance but also 98% accuracy in this case/model. However, it is to be noted that it was trained on a single view angle of the dataset and hence would not be able to directly generalize to different points of view of the cucumber fruit in real-world scenarios. In [8], a model is suggested that classifies whether an apple is good or bad. Firstly, we take different types of texture features, i.e., DWS, HOG, LTE, GLCM, and Sure and Temura features. This method is used, followed by other classifications like SVM and K-NN. It is not better than the others, but the accuracy of the SVM classification is good. The model's accuracy on the Apple dataset is 97%. The work [9], uses the Tawan AI Cup 2020 dataset, which was used to train a model. The research itself mostly focused on data preprocessing, such as resizing the input images, scaling, and normalization. Remove background noise using R-CNN MASK and augment the data to get the dataset. Then a ConvAE-Clfs, `3'-ConvAE-Clfs, consists of 3 parts: encoding, decoding, and classifying. Later, a model was trained on transfer learning (VGG11), but that model did not provide accuracy. The accuracy of the model introduced by this student is 81 %, and the accuracy of the model accuracy by this student is 82.5%. Authors in [10], used a common methodology in this research, including different mathematics, color, and most texture features, to recognize the category of mangoes on the basis of grading behavior. kNN, SVM, AND ANN techniques of machine learning.

Although all methods yield results, the Support Vector Machine (SVM) model demonstrates the highest accuracy among all the evaluated models. Implementation of the service System in [11] using a multi-class disease detection model. The system output will be used for both the model's input and output. The first one is the image that represents the disease, and the treatment model that we provide. Input as an Image: To preprocess the image, we use histogram equalization to enhance the image and apply a segmentation technique to the processed RGB images, which are converted into Lab* color space. Then, using different CNN transfer learning methods to figure out the best one. There are so many models in transfer learning, but we considered and compared three pre-trained models: InceptionV3, MobileNetV2, and VGG16 for our work. From these two approaches, we observed that the transfer learning point of the MobileNetV2 model has the highest accuracy of 93.23%. Another research paper [1] uses two different techniques: traditional machine learning and deep learning technique. The machine learning approach achieves an accuracy of 84%, whereas the deep learning technique, utilizing transfer learning, attains a higher accuracy of 93%.

Proposal Methodology:

Our proposal methodology, Transfer learning, is implemented using pre-trained convolutional neural networks (CNNs) such as VGG16 and ResNet50. Figure 1 presents the flow diagram of the proposed method.

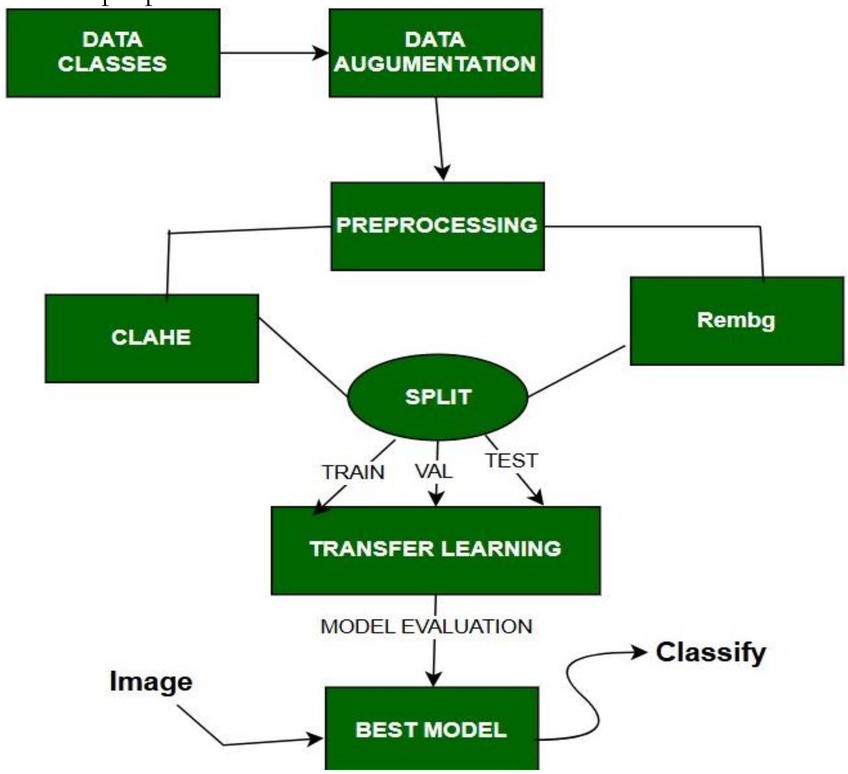

Figure 1. Proposed Model

Dataset:

The open-source cucumber fruit disease dataset https://www.kaggle.com/datasets/sujaykapadnis/cucumbe r-disease-recognition-dataset from Kaggle with the augmented images in it already. The complete dataset consists of 2,400 images, between three categories (Pythium Fruit Rot, Belly Rot, Fresh fruits): 800 images for Pythium Fruit Rot, 800 images for Belly Rot, and 800 images for Fresh fruits, a perfect class balance. Every image in the Kaggle repository is kept at a 256×256 resolution (before any additional preprocessing).

Model Flow Diagram:

This is the flow diagram 1 for our proposed model, which shows the sequence of the multiple process steps.

Data Pre-Processing:

Contrast-limited Adaptive Histogram Equalization (CLAHE) is applied to image preprocessing for cucumber fruit disease symptom enhancement. The CLAHE in essence divides the image into small sub-images and does contrast manipulation based on each sub-image. It brightens dark areas and dims overly bright ones, so you can see things like Belly Rot or Pythium Fruit Rot lesions much better. We then removed everything but the cucumber fruit following contrast enhancement using CLAHE. Figure 2 presents the preprocessing method.

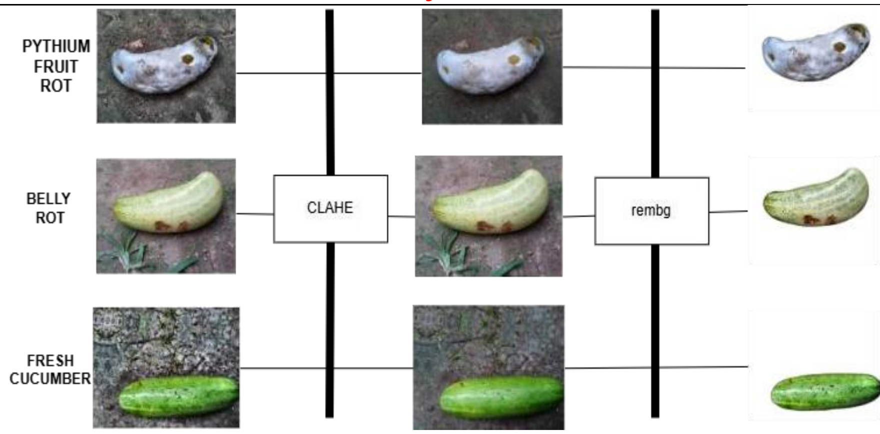

Figure 2. Overall Preprocessing Method

This is done by using the Rembg library which is based on the U-2-Net deep-learning model, a model designed to separate the fruit (foreground) from the background. By removing the background, the model can then concentrate only on the features of the fruit during training. By clearing away background noise in this manner, we help the network to learn true disease patterns in a more reliable way, which in turn achieves better generalization and higher classification accuracy.

Convolutional Neural Network (CNN):

CNN is a deep learning model that can capture discriminative features automatically from images. It finds patterns, like edges and shapes, by churning through data in layers of so-called convolutional layers. These patterns pass through some special functions, such as ReLU and pooling layers, to aid the model in paying attention to the most important parts. For multiclass problems, such as the three classes of cucumber disease, the last layer of the CNN is a softmax layer. This layer turns the raw results of the previous layer into probabilities that detail how confident the model is about each class. CNNs can learn directly from images and can accommodate changes, such as in angle and size, so they are very useful for the automatic recognition of cucumber diseases.

Transfer Learning Model:

This is not very costly – advanced deep learning models require plenty of data and high processing capacity for transfer learning. It applies pre-trained CNN models such as those trained on ImageNet and fine-tunes them for related tasks. This is time and resource-effective as there is no need to construct CNN models taken by CNN features from zero to one. This method is beneficial in the cucumber-fruit classification under a low-data availability situation. Although ImageNet is the focus of the literature on natural images, using transfer learning for cucumber fruit classification with certain modifications on fruit images is adopted. It solves such challenges as the statistically-impaired training data and enhances image recognition. Fine-tuning of pre-trained models, where the original layers and learned weights are retained for final classification. This approach helps to improve CNN models by using information from tasks learned before and applying it to new tasks, e.g., identifying cucumber fruit diseases.

VGG16:

VGG16 is a deep learning model that has a good performance in image classification. It has 16 layers, 13 of which are convolutional layers for image processing, and 3 are fully connected layers for decision-making. VGG16 uses smaller 3x3 filters to scan the image in finer detail and learn what are known as features, such as shapes, textures, and edges. Although VGG16 is strong in feature extraction, it demands immense computational power for training. But with transfer learning, the model can build on the expertise it learned from the large dataset so that it can classify cucumber fruits by tweaking its parameters a bit. The transfer of learned features allows faster training and higher efficiency, especially when the dataset is small or resources are limited.

Resnet_50:

ResNet50 is another Deep Learning model with 50 layers. The special thing about it is that it uses residual connections, which enable information to jump over some layers and let the model learn on shorter paths, faster and more efficiently. These shortcuts are designed to ease a deep learning phenomenon, called the vanishing gradient problem, which happens when a network becomes really, really deep. ResNet50 is especially appropriate for intricate assignments such as cucumber fruit classification since it can describe image features in fine detail without losing useful information. Thanks to task-specific model finetuning, you can obtain great performance despite having small datasets.

Mobilenetv2:

MobileNetV2 is a small-sized deep learning model, which facilitates faster/smoother service in mobile phones with constrained resources. It employs a method known as depthwise separable convolutions, which minimizes the number of calculations required so that the model runs faster and still performs well. MobileNetV2 fits real-time scenarios such as mobile or tire photoelectron cucumber fruit sorting. Turn on: Speedy... This is a good option when you have few resources and still want to operate on images quickly.

Evaluation Method:

It is then necessary to assess the performance of the model, particularly in the image classification (cucumber fruit classification) tasks. Classic values like accuracy, precision, recall, or F1-score are computed from the confusion matrix, where true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are summarized.

Confusion Matrix:

The confusion matrix is the basis of evaluation methodology to judge the performance of a classification model by using the actual labels and predicted labels, while dealing with multi-class problems, such as cucumber fruit disease classification.

Table 1. Confusion matrix illustrating the classification performance of a multi-class model across three classes.

Actual \ Predicted	Class 1	Class 2	Class 3
Class 1	True Positives (TP)for Class 1	Class1 misclassified as Class 2	Class1 misclassified as Class 3
Class 2	Class2 misclassified as Class 1	True Positives (TP)for Class 2	Class2 misclassified as Class 3
Class 3	Class3 misclassified as Class 1	Class3 misclassified as Class 2	True Positives (TP)for Class 3

Accuracy:

Accuracy tells you how frequently the classifier is correct for your data. It is the proportion of hair predictions that were accurate (either positive or negative) to the total number of predictions made.

$$Accuracy = \frac{I \qquad i}{\sum_{i=1}^{k}(\mathrm{TP}_i+\mathrm{FP}_i+\mathrm{FN}_i)} \sum^{K}{}_{=}1\ TP$$

A high accuracy means the model predicts most samples correctly.

Precision:

Precision measures the accuracy of positive predictions for each class, quantifying how many of the predicted samples for a class are correct. For class III, precision is calculated as:

$$Precision_i = \frac{TP_i}{TP_i + FP_i}$$

High precision indicates a low false positive rate, which is important to avoid misclassifying healthy fruits as diseased or confusing different disease categories.

Recall:

Recall measures the ability of the model to identify all relevant instances of a class correctly. Recall is given by:

$$Recall_i = \frac{TP_i}{TP_i + FN_i}$$

High recall ensures that most diseased fruits are detected, reducing false negatives, which is critical for early disease intervention.

F1-score:

The F1-score balances precision and recall by calculating their harmonic mean. This metric is especially useful when there is a trade-off between accuracy and recall:

$$F1_i = 2 \times \frac{Precision_i \times Recall_i}{Precision_i + Recall_i}$$

A higher F1 score indicates a better balance between precision and recall for each class.

Result Analysis and Discussion:

This study evaluates the effectiveness of pre-trained CNN models—VGG16, MobileNetV2, and ResNet50—in classifying cucumber fruit diseases. The dataset consists of 2400 cucumber fruit images representing three classes: Pythium, Fresh (healthy), and Belly Rot. All images were resized to 224 × 224 pixels to maintain consistency for model input and facilitate accurate feature extraction. VGG-16 utilizes a 3x3 convolution kernel, contributing to 138 million hyperparameters. MobileNetV2 utilizes modules to reduce convolutional layers and computational complexity, while ResNet50 accommodates numerous layers without significantly increasing training error. The cucumber fruit images were preprocessed and evaluated using metrics such as accuracy and loss. The analysis was conducted using 1680 images for training, 150 images for validation, and 150 images for testing on Google Colab. This study proposes an innovative approach using feature ensembles for the accurate classification of cucumber fruit diseases, surpassing existing CNN-based methods. Our proposed model, MobileNetV2, achieved a higher accuracy of 98.06%, compared to previous studies. Across VGG16, MobileNetV2, and ResNet50, accuracy scores of 95%, 98%, and 58% were achieved.

VGG16 Model Implementation:

Figure 3 presents the true label data and predicted label data. The confusion matrix for the VGG16 model demonstrates its classification performance across the three cucumber fruit disease classes: Belly Rot, Fresh, and Pythium. The model correctly classified 112 samples of Belly Rot, 116 samples of Fresh, and 115 samples of Pythium. Misclassifications were minimal, with a few samples of Belly Rot predicted as Fresh (7) and some Pythium samples misclassified as Belly Rot (5).

Figure 4 illustrates the training and validation accuracy of the VGG16 model over 20 epochs. The training accuracy shows a steady increase from approximately 39% at the first epoch to around 88% by the final epoch, indicating effective learning of the model over time. Validation accuracy begins at a higher level, near 72%, and progressively improves, reaching close to 89% by the end of training. The close alignment between training and validation accuracy curves throughout the epochs suggests that the model maintains good generalization capability without significant overfitting.

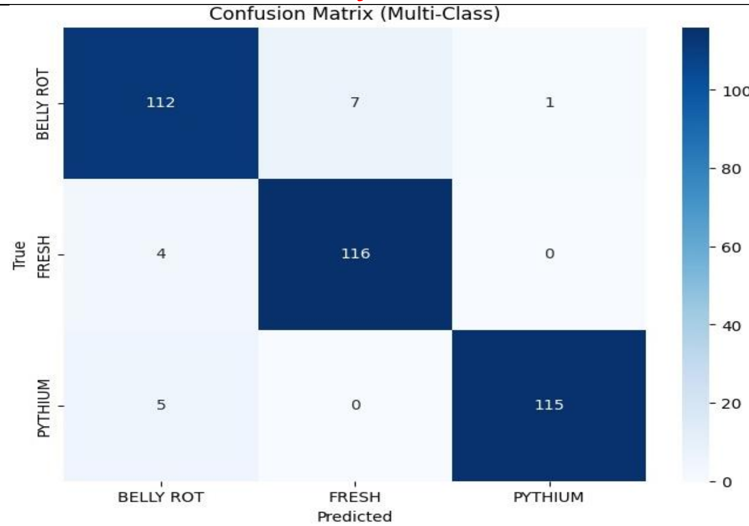

Figure 3. True table and prediction table for Vgg16

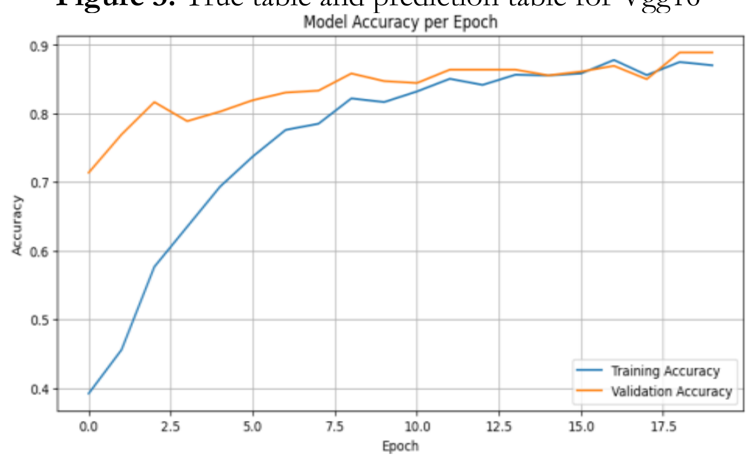

Figure 4. Training and validation accuracy of VGG16

Figure 5 shows the training and validation loss curves over 20 epochs. The training loss starts at approximately 1.18 and consistently decreases to around 0.40 by the final epoch, demonstrating effective minimization of the error during training. Similarly, the validation loss begins at about 0.98 and gradually declines to approximately 0.37, closely tracking the training loss throughout the epochs.

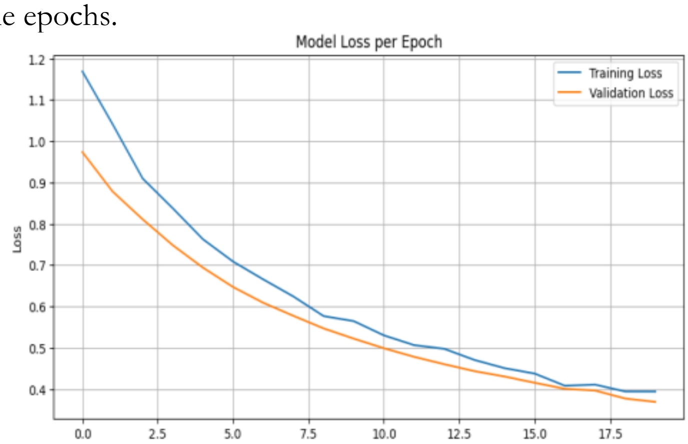

Figure 5. Training and validation loss of VGG16

Table 2 shows that the model achieved an overall accuracy of 95.28%, indicating that it correctly classified the majority of cucumber fruit images across the three disease classes. The weighted precision score of 95.34% reflects the model's ability to minimize false positives, demonstrating high reliability in its positive predictions across all classes. Similarly, the weighted recall score of 95.28% shows that the model successfully identified most of the actual positive cases, effectively reducing false negatives—the weighted F1 score is 95.29%.

Table 2. Evaluation Matrix Of VGG16

MODEL	Accuracy	Precision	Recall	F1 score
VGG16	0.9528	0.9534	0.9528	0.9529

Mobilenetv2 Model Implementation:

Figure 6 presents the true label data and predicted label data.

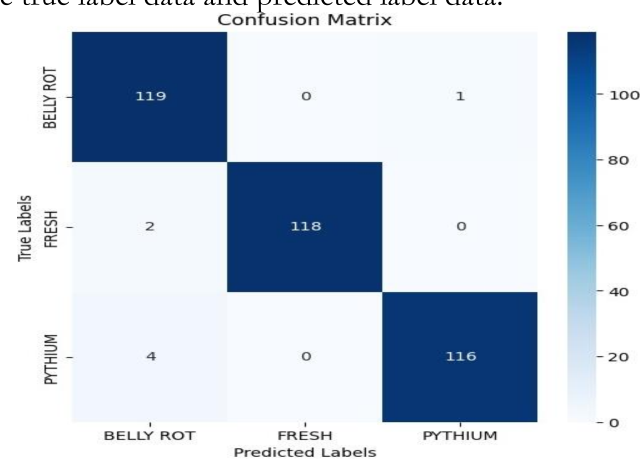

Figure 6. True table and prediction table for Mobilenetv2

The confusion matrix for the final model shows excellent classification performance across the three classes. Out of 120 Belly Rot samples, 119 were correctly identified and only one was misclassified as Pythium, with none confused with Fresh. For the Fresh class, 118 of 120 healthy fruits were correctly predicted, while two were misclassified as Belly Rot. In the Pythium class, 116 out of 120 diseased fruits were correctly recognized, and four were wrongly labeled as Belly Rot.

Figure 7 presents the accuracy curves of the final model, demonstrating rapid learning and strong generalization over 20 epochs. Training accuracy begins around 66% in the first epoch, rises sharply to approximately 86% by epoch 1, and continues climbing steadily to nearly 98% by the final epoch. Validation accuracy starts at about 92%, increases quickly to over 95% by epoch 2, and remains consistently high, peaking close to 98% around epoch 14, before stabilizing just below this level.

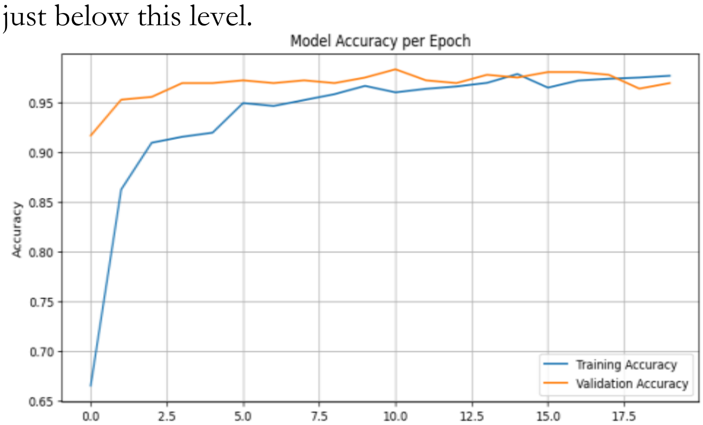

Figure 7. Training and validation accuracy of MOBNETV2

Figure 8 illustrates the loss curves for the final model demonstrating rapid error reduction and stable convergence over 20 epochs. Training loss begins at approximately 0.75 in the first epoch and drops sharply to around 0.39 by epoch 1. From there, it continues a steady decline, reaching roughly 0.17 by epoch 5 and tapering off near 0.07 by the final epoch.

Validation loss mirrors this trend, starting at about 0.35, descending to 0.23 after the first epoch, and gradually decreasing to approximately 0.11 by epoch 5 before settling around 0.07 toward the end of training.

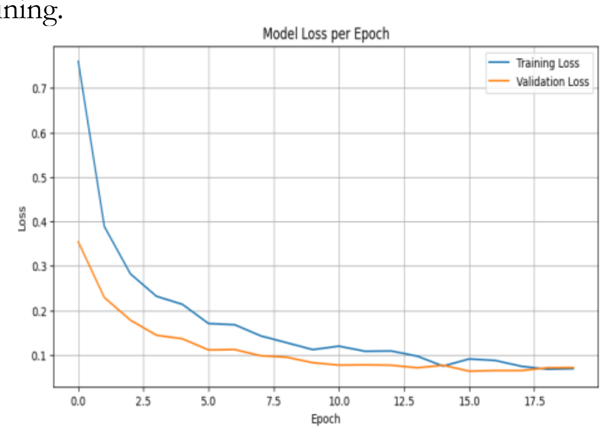

Figure 8. Training and validation LOSS of MOBNETV2

Table 3 shows the final evaluation of the test set yielded an overall accuracy of 98.06%, indicating that the model correctly classified nearly all cucumber fruit images across the three disease categories. The precision of 0.98 reflects a very low rate of false positives—when the model predicts a disease, it is almost always correct. The recall of 0.98 indicates a similarly low rate of false negatives—rarely does the model fail to detect an actual disease. The F1- score, also 0.98, balances these two measures, confirming that the model maintains both high sensitivity and high specificity.

Table 3. Evaluation Matrix of VGG16

MODEL	Accuracy	Precision	Recall	F1 Score
Mobnetv2	0.98	0.98	0.98	0.98

Resnet_50 Model Implementation:

Figure 9 presents the true label data and predicted label data.

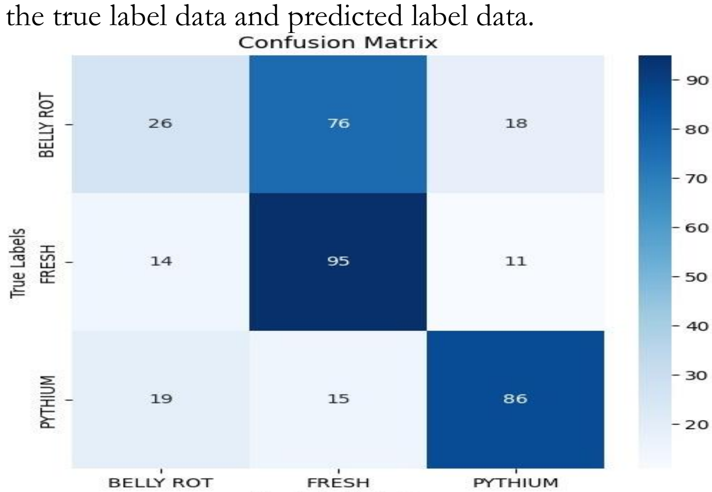

Figure 9. True table and prediction table Resnet_50

The model demonstrated the highest accuracy in predicting the Fresh class, correctly classifying 95 samples, while misclassifying 14 and 11 samples as Belly Rot and Pythium, respectively. In contrast, the Belly Rot class exhibited a higher degree of confusion, with only 26 samples accurately identified and 76 and 18 samples misclassified as Fresh and Pythium, respectively. The Pythium class was predicted with moderate accuracy, correctly classifying 86 samples, but with some misclassifications into Belly Rot (19 samples) and Fresh (15 samples).

Figure 10 presents the training and validation accuracy of the model which was monitored over 20 epochs to evaluate learning progress and generalization capability. Initially, the training accuracy started at approximately 32% and demonstrated a steady increase, reaching around 53% by the final epoch, indicating progressive learning on the training data. The validation accuracy, while generally higher than the training accuracy, exhibited considerable fluctuations throughout the training process, ranging between 45% and 55%.

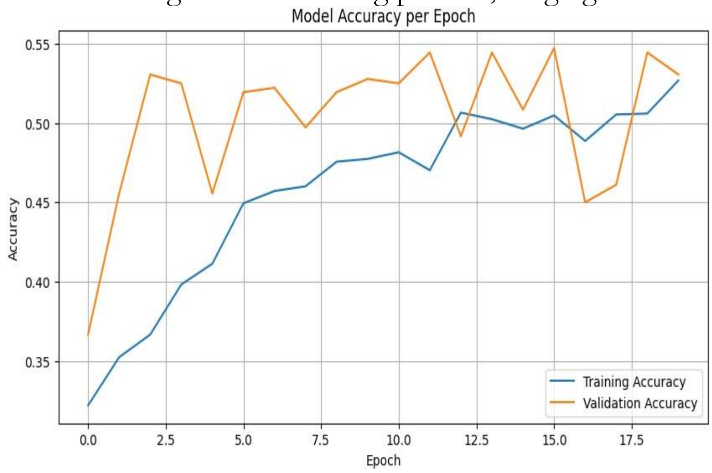

Figure 10. Training and validation accuracy of Resnet_50

Below Figure 11 shows the model's training and validation losses were evaluated across 20 epochs to assess the optimization process. The training loss began at approximately 1.35 and steadily decreased to around 0.97 by the final epoch, indicating progressive improvement in the model's ability to fit the training data. Similarly, the validation loss started at a lower value of about 1.08 and gradually declined to nearly 0.96, showing a consistent reduction in prediction error on unseen data.

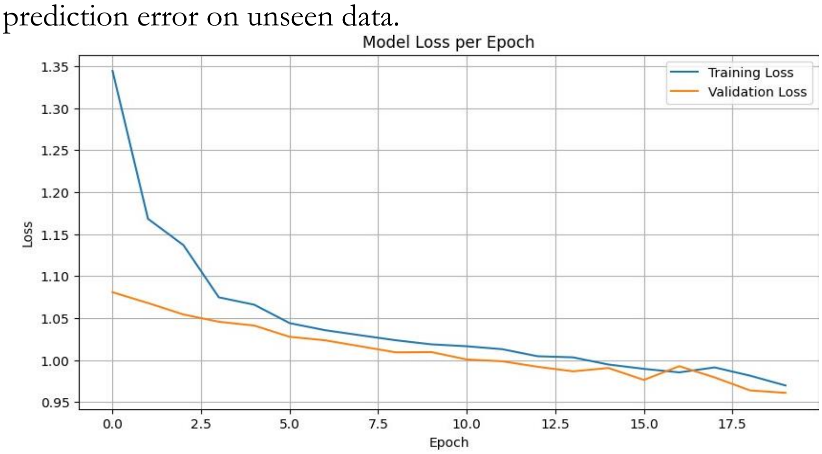

Figure 11. Training and validation losses across 20 epochs

Table no 4 shows the evaluation matrix of ResNet-50. The model achieved an accuracy of 57.5%, indicating that it correctly classified the samples slightly more than half of the time. Both precision and recall were measured at 0.57, suggesting that the model's predictions were correct 57% of the time when it identified a positive case, and it successfully detected 57% of all actual positive cases. The F1- score, which balances precision and recall, was 0.55, reflecting a moderate overall performance.

Table 4. Evaluation Matrix of ResNet-50

MODEL	Accuracy	Precision	Recall	F1 score
Resnet_50	0.57	0.57	0.57	0.55

Discussion:

Table No 5 summarizes the performance metrics of three deep learning models—MobileNetV2, VGG16, and ResNet- 50—applied to cucumber disease classification. MobileNetV2 achieved the highest accuracy of 98%(BLOW FIGURE), followed by VGG16 with 95%, while ResNet-50 attained 57%. In terms of precision, which reflects the correctness of positive predictions, MobileNetV2 and VGG16 scored 0.98 and 0.95, respectively, indicating reliable identification of diseased samples. Recall values, measuring the ability to detect actual positive cases, were similarly high for MobileNetV2 (0.98) and VGG16 (0.95), whereas ResNet-50 showed a considerably lower recall of 0.57, suggesting many disease instances were missed. The F1 score, balancing precision and recall, further confirms the superior performance of MobileNetV2 (0.98) and VGG16 (0.95), compared to ResNet-50 (0.55). Although ResNet-50 has achieved tremendous success across different image classification problems, its performance was much lower compared to MobileNetV2 and VGG16 in our study.

The reason for that is that ResNet-50 is a large model with a large number of parameters (≈25 million), which was prone to overfitting especially when trained on a relatively small dataset that included only 2400 images. This was not the case as severe in MobileNetV2 which possesses fewer parameters and is built for efficient performance on less data. Ultimately, despite background removal, the underlying variability in image conditions (e.g. lighting, angle, and quality) could have differentially impacted ResNet-50's generalizability. More compact models, like MobileNetV2, are often better to mediate such variety and are more appropriate to this type of real-world classification task. These results demonstrate that MobileNetV2 outperforms the other models in accurately and consistently classifying cucumber diseases, making it the most suitable model for this task. Figure 12 shows the results of proposed model.

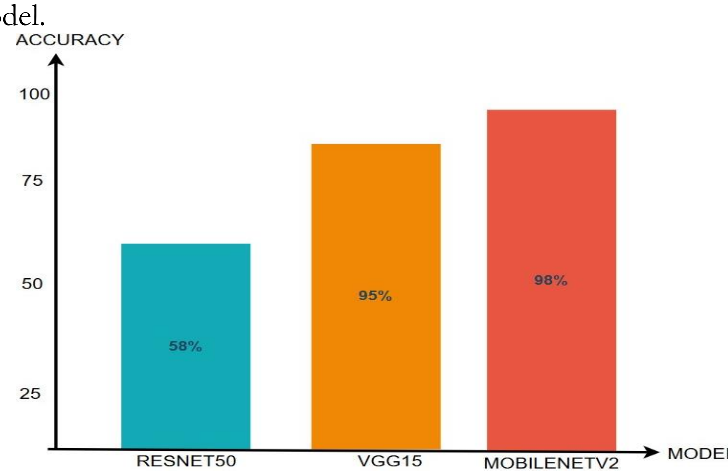

Figure 12. Model Result

Table 5. Study Results of All Models

MODEL	Accuracy	Precision	Recall	F1 score
MOBILENETV2	0.98	0.98	0.98	0.98
VGG16	0.95	0.95	0.95	0.95
RESNET-50	0.57	0.57	0.57	0.55

Comparative Analysis:

The summary of the comparative study on the current techniques for classification is presented in Table 6. Previous works employed different deep-learning models with mixed results.[12] This work used VGG16 transfer learning and fine-tuning to improve the accuracy but the VGG16 model showed an accuracy of 94%. [13] In this paper researcher uses two different techniques machine learning and deep learning. For preprocessing using k-mean base segmentation then apply a random forest model, accuracy is 89% and deep learning accuracy is 93%. [14] In this paper using preprocessing, remove the noise of the fruit image, and then extract eight different features after using CNN mode, the accuracy is 84%. Based on this work, the MobileNetV2 model used also enhanced the accuracy and was rated at 98%, which showed that the detection and classification of cucumber diseases had been greatly improved.

Table 6. Study Results of All Models

Reference	Model	Result
[12]	VGG16	94%
[13]	MOBILNET	93%
[14]	CNN	84%
Proposed model	MOBILENETV2	98%

Conclusion and Future:

This research proves that the MobileNetV2 model performs best in detecting cucumber diseases with 98% accuracy. On the basis of transfer learning and image preprocessing, the model is well-trained even though the training dataset is limited. Farmers could use this to sense disease and help save crops rapidly. In the future, we will include more types of diseases and images from various conditions to enhance the model. We also want to make a simple mobile app for farmers to check diseases in the field easily. Incorporating other data and making the model more legible will make it more valuable. This work enables more advanced farming and reduces reliance on harmful chemicals.

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