ROSE DISEASE CLASSIFICATION USING TRANSFER LEARNING

BY

AL MUNTASIR AHMED REYAD
ID:181-15-1854

AYESHA SIDDIKA
ID:191-15-2441

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Al Amin Biswas
Senior Lecturer
Department of CSE
Daffodil International University

Co-Supervised By

Md. Sabab Zulfiker
Senior Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

JANUARY 2023

APPROVAL

This Project/internship titled **"Rose disease classification using transfer learning"**, submitted by Ayesha siddika, ID No:191-15-2441 and Al Muntasir Ahmed Reyad, ID No:181-15-1854 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 01 February 2023.

BOARD OF EXAMINERS

4/2/23

Chairman

Dr. Touhid Bhuiyan
Professor and Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner

Tania Khatun (TK)
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner

1.2.23

Ms. Lamia Rukhsara (LR)
Senior Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

External Examiner

Dr. Mohammad Shorif Uddin
Professor
Department of Computer Science and Engineering
Jahangirnagar University

DECLARATION

I hereby declare that, this project has been done by me under the supervision of **Al Amin Biswas, Senior Lecturer, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Alim 22/01/2023

Al Amin Biswas
Senior Lecturer
Department of CSE
Daffodil International University

Submitted by:

Reyad

Al Muntasir Ahmed Reyad

ID: 181-15-1854

Ayesha
Ayesha Siddika

ID: 191-15-2441

Department of CSE

Daffodil International University

ACKNOWLEDGEMENT

First, I express my heartiest thanks and gratefulness to Almighty Allah for His divine blessing which makes me possible to complete the final year project/internship successfully.

I really grateful and wish my profound indebtedness to **Al Amin Biswas**, **Senior Lecturer** and **Md. Sabab Zulfiker, Senior Lecturer** Department of CSE, Daffodil International University, Dhaka, deep knowledge & keen interest of my supervisor in the field of Machine Learning to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stage have made it possible to complete this project.

I would like to express my heartiest gratitude to **Dr. Touhid Bhuiyan**, Head**,** Department of CSE, for his kind help to finish our project and also to other faculty members and the staffs of CSE department of Daffodil International University.

Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

In many sectors, plant life has proven to be a useful resource for human existence for many years. Currently, plant diseases are wreaking havoc on our agriculture sector. Consequently, farmers are suffering significant losses. Manually detecting rose diseases requires expert knowledge, which is very complex, time-consuming, and exhausting. An early detection and treatment process for plant diseases can reduce substantial economic suffering. The purpose of this study is to describe CNN-based, robust deep-learning model that classifies rose diseases photos into four categories. Unsolicited regions of rose disease are eliminated, quality is enhanced, and the disease is tinted by removing artifacts, decreasing noise, and enhancing the image. Two augmentation approaches are used to expand the dataset. Several CNN architectures are used to analyze the augmentation dataset, namely VGG16, VGG19, MobileNet, MobileNetV2, and InceptionV3. VGG-16 offers the highest level of precision in this instance. The proposed hyper-tuned VGG16 produced the best results, with a train accuracy of 99.01% and a test and validation accuracy of 98.21%.

Keywords: Transfer Learning, Deep Learning, Convolutional Neural Network.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

There is no doubt that the rose is one of nature's most magnificent works of art. Among all flower species, it reigns supreme as the cutest and most unrivaled queen. Rose is a member of the Rosacea family, which has shown to be a successful business concept around the globe. People in many different nations have been growing roses for an untold amount of time and in many different climates. A significant capability for manufacturing roses blossoms on a commercial scale in order to satisfy the growing demand in the market as a result of their widespread use. India is responsible for 46.54% of the world's cut roses market, whereas China is responsible for 23.68%, Ecuador for 6.74%, Kenya for 3.58%, Mexico for 2.35%, and Italy for 2.02%, among other countries [1]. Both the oil and water of roses are utilized in the production of fragrances and cosmetics, two industries that generate significant revenue for their producers. The growing of roses in Bangladesh results in the annual production of 2423 tons of rose blooms over 111 hectares [2]. However, the rate of making a profit from roses is declining as a result of a number of illnesses. The cultivation of roses is suffering quite severely as a result of these illnesses. Due to a lack of familiarity with the illnesses in question, the farmer is unable to determine the nature of the issue immediately. As a direct consequence of this, the farmer is looking at substantial losses. In order to take some of the burden off of the shoulders of farmers, several machine learning techniques have been perfected and are being used to accurately diagnose illnesses. Transfer learning was one of the strategies that we used in order to alleviate some of the anxiety. Reusing previously taught models to solve a new challenge is an example of transfer learning, a strategy that is supported by machine learning algorithms. In the actual world, the process of collecting data for a large dataset is challenging. Therefore, we will use the transfer learning approach to solve the mystery. In particular, it can be used to train a deep neural network with limited data. As part of this research, we use the VGG-16 model on picture datasets to identify illnesses that affect rose plants through transfer learning methods. We were able to achieve an accuracy of around

95.63% in the diagnosis of rose illnesses by combining the VGG-16 with the transfer learning approach. In addition to that, we have computed the F1 and performed additional calculations. This study aims to identify and categorize rose disease hooked on black spot, botrytis blight, powdery mildew, and rose mosaic virus at an early stage, thereby reducing the danger of extreme loss. It is crucial to remove noise and artefacts to accomplish excellent execution from a CNN model. Moreover, the similarity between impenetrable normal roses and diseased areas may cause problems in the interpretation process. By adapting raw image brightness and contrast levels, it can improve the visibility of diseased lesions. This study proposed VGG16, a highly automated and reliable deep learning approach that relies on transfer learning, to classify rose disease in images.

1.2 RESEARCH OBJECTIVES

a) To analyze research flaws in existing deep learning-based techniques for accurately classifying various types of rose disease and their categories.
b) To enhance the precision of class separation by using a straightforward deep learning-based approach.

1.3 RESEARCH QUESTIONS

a) What is the best technique for analyzing the flaws in existing deep learning-based classification systems that correctly classify certain types of rose diseases?
b) How can we implement a deep learning-based strategy to enhance the accuracy of correctly identifying rose disease types and their categories?

1.4 REPORT LAYOUT

Chapter 1 Introduce the study, its objectives, and the relevant research questions.

Chapter 2 Provides a concise description of relevant literature.

Chapter 3 In-depth evaluation of the proposed methodology.

Chapter 4 Perform an analysis and comparison of the results with previous work.

Chapter 5 Briefly summarizes the research findings and makes recommendations for future research.

CHAPTER 2
RELATED WORK

2.1 LITERATURE REVIEW

Despite the fact that many researchers are researching transfer learning strategies to identify a variety of items, mobile Net models have not been used to identify rose illnesses either through transfer learning or without such an approach. The majority of plant disease detection research has been conducted in this area. As observed in the most recent deep CNN, this phenomenon is restricted to computers with massive accumulation receptivity and resource computation. This is the case for almost all of the research that has been done in this field. B. Dan and colleagues [3] worked on the 11th genre of lyceum barb arum diseases and initiate a slightly newer edition of the Mobile Net V2 algorithm for image identification. In their proposed methodology, the SE module is implemented after the convolution layer and the final pooling layer of Mobile Net V2. Intentionally, this is done in order to increasing the capacious area of the network. During the course of this research, a total of 1,955 photographs were taken, but after going through the process of spatial transformation, they became 18,720. The accuracy achieved by their suggested method, Sembilan V2, is 98.23%, which is greater than the accuracy achieved by earlier trials in this sector. A. L. P. de Ocampo and E. P. Daios [4] decided to establish computational models of light neural networks for the purpose of the experiment. In this instance, they utilized a two-step training approach on the ImageNet dataset, and their model achieved a precision of 89.0%. S. Ghoury, et al. [5] accomplished their goal by combining transfer learning with the pre-trained deep learning models Faster R-CNN Inception v2 and Single SSD MobileNet v1. These models are part of the transfer learning technique. The Faster R-CNN Inception v2 model is more competent than the SSD Mobile Net v1, despite the possibility that the SSD Mobile Net v1 will not be effective for real-time identification in their work. In their experiment, Faster R-CNN Inception v2 was able to classify test images with an accuracy rate ranging from 78 to 99%. However, the processing time was somewhat lengthy. Convolutional neural networks were used by R. Gandhi et al. [6] in order to categorize the many types of plant diseases. For the purpose of enhancing their picture dataset, they make use of Generative Adversarial Networks, or GANs. They use Inception v3 and MobleNet, both of which are CNN-based models. They achieve an accuracy of 88.6% when they use Inception V3, and they get an accuracy of 92% when they use the MobileNet model. AlexNet and VGG16 net are examples of architectures that are powered by deep learning and were used by A.K. Rangarajan et al. [7]. When diagnosing tomato disease, they employ 13262 different photos. They see an increase in accuracy when they use AlexNet, which is 97.49%, and when they use VGG16 net, which is 97.29%. M. M. Gazi et al. utilized a deep convolutional neural network in conjunction with the transfer learning approach [8] in order to identify the various plant species. GoogleNet, AlexNet, and VGGNet are the names of the three powerful deep learning brickwork scilicets that they deployed. The combined system improved its accuracy to an overall level of 80%. CNN that was trained on AlexNet stonework was used by L. G. Nachtigall and colleagues [9] to identify apple tree disorder. They employed a unique dataset with annotated antecedents that was comprised of 2539 photos from 6 different disorders. They found that their experiment was accurate 97.3% of the time [9]. The approach that was presented by P. K. Kosamkar and colleagues [10] is geared at identifying crop leaf diseases and making recommendations on the usage of pesticides. Tensor flow technology was used in conjunction with convolutional neural networks in order to facilitate the ramification of illnesses and the imparting of pesticides. The proposal that they have proposed focuses on preprocessing and removing any peculiarities from the leaf pictures that are collected from a collection of plant data from a hamlet. When they used the tensor flow approach, a five-layer model that was run for 15 epochs produced the best results (95.05%) for their experiment, while a five-layer model that was run for 20 epochs produced the best results (89.67%) for their validation. CNN was used by G. Suresh and colleagues to detect many illnesses that affect grape plants [11]. Comparative analysis of their three distinct CNN architectures is performed in order to identify plant diseases. Convolutional neural networks were utilized by A. P.

Marcos et al. [12] and S. S. Hari et al. [13] in order to construct a model that could identify plant illnesses based only on photographs of the leaves of the plants. As part of their image processing work, they use free and open-source libraries, which are published on a website. In order to test their CNN access for rust detection, they created a dataset consisting of 159 images of coffee leaves. The dataset consisted of photographs of coffee leaves. The work that was done in [13] is put into practice by having 10 different kinds of plant diseases. An accuracy rate of 86% has been determined for the work. A. Elhassouny and F. Smarandache, as well as S. Machha et al. [15], have proposed a method and algorithms based on MobileNet [16] for identifying illnesses affecting tomato leaf and plant leaf. Based on their proposed CNN-based technique, they achieved an accuracy of 88.4% in the classification of tomato leaf diseases [14] and 97.33% in the detection of various crop leaf diseases [15]. L. A. Wulandhari et al. [17] implemented the Inception ResNet-v2 network, which had been trained on the ImageNet database to identify plant nutrient deficiencies, using transfer learning. Using an approach to fine-tuning, they were able to achieve training accuracy of 96% and testing accuracy of 86%, respectively. Deep learning is a technique proposed by J. Amara et al. [18] and O. Kulkarni [19] for differentiating between various agricultural illnesses. They were able to identify illnesses affecting banana leaves by using LeNet architecture and inception v3 [18]. Work on MobileNet and Inception V3 to improve their illness detection capabilities and achieve an accuracy of 99.04% and 99.45%, respectively [19].

2.1.1 PROBLEM STATEMENT

As said before, when it comes to rose disease, time is crucial in protecting plants' lives. There is a lack of technology and resources to provide timely rose disease monitoring, diagnosis, and treatment services. Numerous tactics and approaches have been proposed for detection and diagnosis, but these approaches often produce false or negative results. This study aims to reduce workload and misdiagnosis rates by improving imaging models and preprocessing methods. Developing a quick and inexpensive method could help save plant life in developing, underdeveloped, and even advanced countries. It is described how to get high accuracy of rose diseases using the most suitable image preprocessing techniques and models.

2.2 CHALLENGES

This study has several research challenges, which include the following:

a) **Data Collection:** To train deep learning systems for the detection of rose disease, large datasets are required, but our research encountered some difficulties collecting large amounts of data. In this study, 190 images were analyzed, which is insufficient for the model proposed. Thus, collecting image data from the rose disease field was time-consuming.

b) **Raw Image Processing**: Considering that the rose disease dataset images contain a significant amount of noise and artifacts, this study aims to improve the model's accuracy by utilizing image processing techniques. Image processing is the first step in training a deep-learning model since images are typically filled with noise and artifacts.

c) **Select deep learning Approach**: In order to accomplish tasks efficiently, several researchers have utilized deep-learning techniques. Therefore, selecting the optimal deep learning technique that can effectively classify rose diseases is difficult.

d) **Accuracy Improvement:** An additional challenge is to enhance the accuracy of the deep learning model and to select the optimal model.

CHAPTER 3

MATERIALS AND METHODS

3.1 WORKING PROCESS

To complete the task, there are four different steps to follow. They are as follows:

a) Original Datasets
b) Image Pre-processing
c) Model Selection
d) Result Analysis

Figure 1 depicts the entire working process, from image collection to analysis results, and elaborates on it in the following sections.

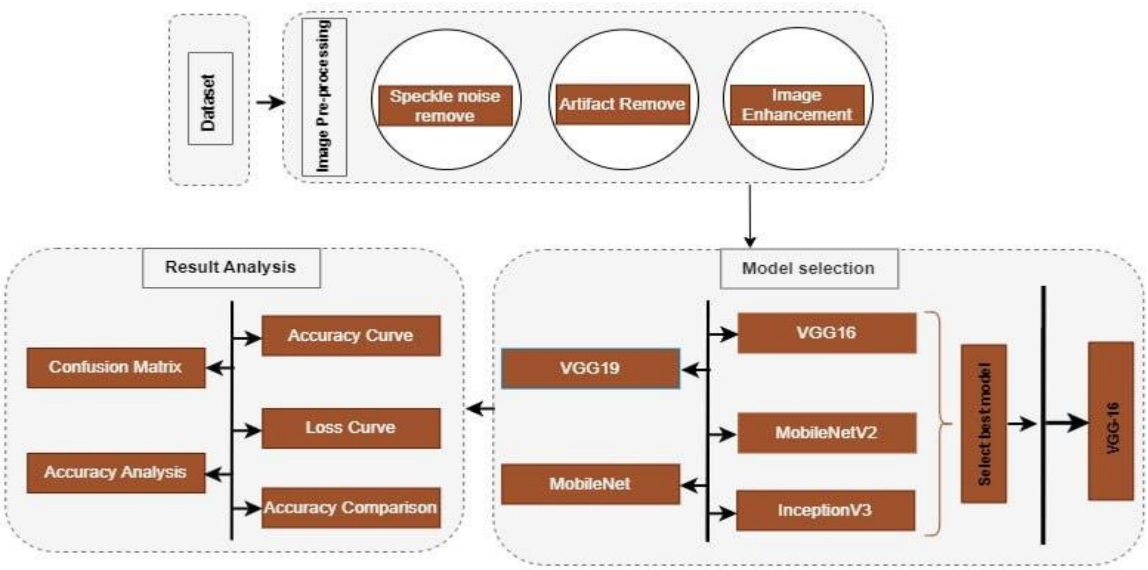


Figure 1. An overview of the entire classification process

3.2 DATASET PREPARATION

The dataset consists of 190 images that were analyzed for this study. In the dataset, there are four categories: black spot, botrytis blight, powdery mildew, and rose mosaic virus. The black spot class consists of 72 images, the botrytis blight class consists of 17, the powdery mildew class consists of 46 images, and the rose mosaic virus class consists of 55 images. Different pixel sizes are contained in the datasets. Dataset image collected from the 5-rose garden. Here is a detailed description of the dataset as shown in Table 1:

Table 1. Description of the dataset utilized in this research

Name	**Description**
Total Number of Images	190
Average Dimensions	3000 x 4000
Color Gradings	RGB
Data Formats	JPG
Black spot	72
Botrytis blight	17
Powdery mildew	46
Rose mosaic virus	55

3.3 IMAGE PRE-PROCESSING

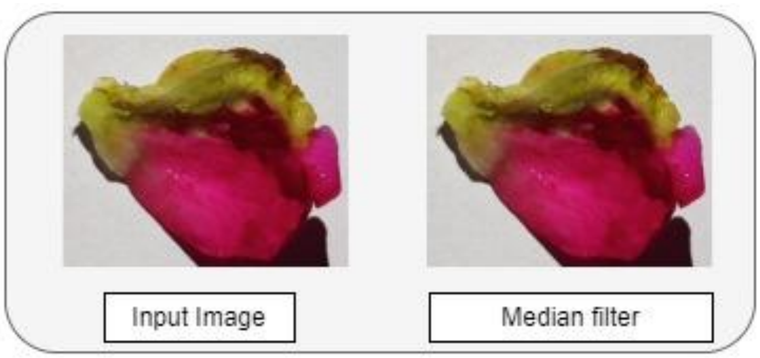
Images of rose disease data sets are collected using mobile cameras. As a result, the images contain a significant amount of noise and artifacts; thus, this study focuses on enhancing the model's precision through image processing. Image processing, despite the fact that images frequently contain noise and artifacts, is the first step in training a deep-learning model. To remove artifacts from this image, a morphological closure is used first, followed by a median filter to remove noise.

3.3.1 IMAGE RESIZING

Through the process of resizing, we can reduce the size of an image without losing quality. When an image's dimensions are changed, it often results in a loss in quality and an increase in file size [33]. With smaller images, our transfer learning models can train more quickly. If the dimension of the input image is doubled, our network will have to learn from eight times as many pixels, which takes more time. In our dataset there are many large and small combined images. We resized our dataset’s images into 224 X 224 [34] from 3000 X 4000 pixels to get the perfect shape of images.

3.3.2 MEDIAN FILTER

As previously mentioned, the dataset contains some noise. Median filters can be used to remove speckle noise. Consequently, the median filter is applied to this dataset in order to ensure that the images are free of speckle noise. The median filter is a simple nonlinear filter that reduces noise. The method is renowned for its excellent ability to remove noise of all types, including Gaussian, random, and salt-and-pepper. A visual representation of this procedure is shown in image 2.



. **Figure 2.** Output of the median filter

3.3.3 MORPHOLOGICAL CLOSING

Additionally, morphological operations are performed in order to remove artifacts from the rose disease dataset [23]. Artifacts can be eliminated using a variety of morphological operations. However, this study focuses on morphological opening techniques. In accordance with the intended procedure, the kernel size of the filter varies. To extract artifacts from an image, cv2.getStructuringElement is used to construct a rectangular kernel. This approach is depicted in image 3.

Figure 3. An output from the morphological closing process

3.3.4 CLAHE

The Clahe technique is used in order to calculate complete contrast. Adaptive histogram equalization is accomplished using the Clahe method. Clahe was established to enhance the quality of images of complex structures [24]. Enhancement of local contrast improves the legibility of images [25]. This step's output is depicted in image 4.

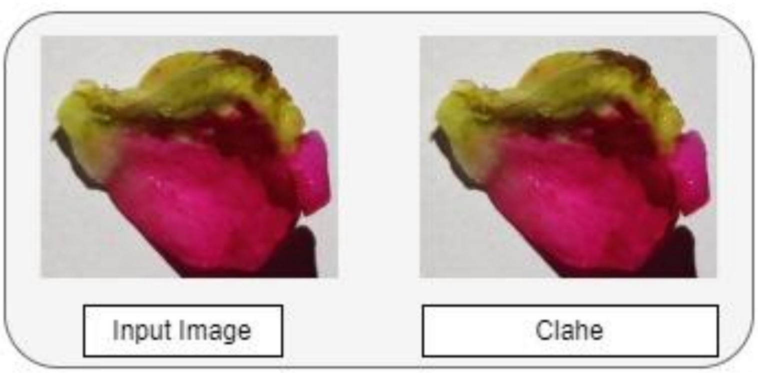


Figure 4. Output of the Clahe

Considering an image size of M x M, and a tile size of m x m, the number of tiles is calculated as follows:

$$D = \frac{M \times M}{m \times m}$$

Clip limit $C_L = M_{CL} \times M_{avg}$ is used to construct the histograms for these tiles.

Where,

M_{CL} = Limit of normalized contrast.

M_{AVG} = Number of pixels on average

The equation of average pixel is (3):

$$M_{AVG} = \frac{Mx \times My}{Mg}$$

Where,
Mg = Intensity of gray
Mx and My = The total number of pixels along the x and y axes

$$M_{CP} = \frac{M \sum cl}{Mg}$$

Where,
C_L = Clipped pixels.

$$M_r = \frac{M_g}{M_r}$$

Where,
M_r represents the number of pixels that remain after clipping
Where P × Q is the image size and L is the highest concentration level and the clahe formula:

$$(p, q) = \mathrm{D}\ (\iota(p, q) = \frac{(L-1)}{PQ} \sum_j^K n_j$$

3.4 PRE-PROCESSED IMAGE VERIFICATION

There is the possibility of losing a significant amount of image quality when using many different image preprocessing algorithms. In order to determine whether image quality has been compromised, various types of numerical evaluation are performed, including PSNR, SSIM, MSE, and RMSE.

3.4.1 MSE

According to MSE, each pixel in the two compared images has an accumulated squared error. Images with values near 0 are considered to be of superior quality. An image that does not contain noise has a value of 0. When the value exceeds 0.5, there is a degradation in quality.

$$MSE = \frac{1}{xy} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} (O(m,n) - P(m,n))^2$$

Where,

O indicates the ground truth (original image), P indicates the processed image, x and y indicate the pixels in O and P, and m, n represent the rows of pixels in x and y, respectively.

3.4.2 PSNR

Before calculating PSNR, it is necessary to determine MSE. In order to determine the quality of an image, the power of a signal is divided by the power of corrupting noise. Following are the steps involved in calculating PSNR:

$$PSNR = 10 \log_{10} \left(\frac{Q^2}{MSE} \right)$$

The input image data type Q has the highest fluctuation. The max is 255 pixels [26].

3.4.3 SSIM

Preprocessing algorithms reduce image quality, as measured by SSIM. A score of 1 reveals "perfect structural similarity" and a result of 0 indicates no structural similarity [26].

$$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_{xy} + c_2\right)}{(\mu_x^2 + \mu_x^2 + c_1)\,(\sigma_x^2 + \sigma_x^2 + c_2)}$$

Where,

x, y is two images , σ_x^2, σ_y^2 is variance, σ_{xy} is covariation between the images and μ_x, μ_y utilizes the Gaussian window to evaluate the average of two images.

3.4.4 RMSI

In RMSE, the original image is compared to the processed image in order to estimate the quality of the image. An image with an RMSE rate near 0 is considered to be of superior quality and contains fewer errors.

$$RMSE = \sqrt{\sum_{J=1}^{N}(d_{fi} - \frac{d_d)^2}{N}}$$

Where, d_{fi} indicates the difference of predicted, d_d indicates the actual value, and N indicates the dataset size.

Table 2. MSE, RMSE, PSNR, SSIM values for 5 images

Image	MSE	RMSE	PSNR	SSIM
Image_1	13.82	0.11	39.31	0.966
Image_2	15.21	0.13	37.79	0.963
Image_3	12.47	0.10	40.36	0.969
Image_4	15.37	0.13	37.36	0.962
Image_5	13.37	0.11	39.28	0.967

3.5 PROPOSED MODEL

As previously mentioned, this study tested a total of five models in order to identify the optimal network based on its accuracy in order to determine the most effective transfer learning model for the classification problem. The transfer learning model comprises five pre-trained networks - InceptionV3, MobileNetV2, MobileNet, VGG16, and VGG19 - that have been trained on training data and validated on testing data.

3.5.1 VGG 16

VGG-16 is one of the most effective approaches to transfer learning. The VGG16 is a DCNN model proposed by Simonyan and Zisserman [28]. On the basis of the ImageNet dataset, the model achieved 92.7% top 5 test accuracy. According to studies on the feasibility of transfer learning [30], a pre-trained VGG16 achieved significantly higher accuracy than a fully trained network. Utilizing the enhanced depth of the VGG model, the kernel can learn characteristics that are more detailed.

3.5.2 VGG 19

VGG19 is a form of the VGG model that contains 19 layers. There are three consecutive FC levels in the VGG19 model, bringing the total to 19 layers, each containing 4096, 4096, and 1000 neurons. As well as this, there are five Maxpool layers and one Softmax layer. A characteristic of convolutional layers is the activation of the ReLU..

3.5.3 INCEPTIONV3

The purpose of InceptionV3, an enhanced version of the original algorithm, is to reduce the amount of computing power consumed by earlier versions of Inception. Several techniques can be used to reduce the computational cost, including regularizing, reducing the dimension, factorizing convolutions, and parallelizing calculations. The InceptionV3 algorithm features 77 convolutional layers and an auxiliary classifier for transmitting label information down the network. By using InceptionV3, smaller convolutions replace larger ones to shorten training time.

3.5.4 MOBILENET

In MobileNet, discrete convolutions are implemented depth-wise. The number of variables is drastically reduced when compared to networks that use standard convolutions of the same depth. Consequently, transportable deep neural networks have been developed. In order to generate depth-separable convolutions, two strategies are employed. In this method, there are two types of convolution, one dealing with in-depth convolution, and the other dealing with convolution at a specific point. For training our ultra-short and ultra-fast classifiers, we use the CNN class MobileNet, which is freely licensed by Google.

3.5.5 MOBILENETV2

MobileNetV2 has been recommended by the Google community. It contains two types of blocks, each one with three levels. Within each block, there are 11 convolutional layers, with 32 filters in the first, third, and second layers. In order to prevent non-linearity from corrupting a large amount of data, longitudinal bottlenecks are required between layers. Each block has a different stride, with block 1 having a stride of one and block 2 having a stride of two.

3.5.6 TRAINING APPROACH

In order to train a model, the batch size is 16 and the maximum number of epochs is 100[31]. The "callback" function of Keras was utilized during training to retain the weights of an optimal model [31]. Adam has been employed as an optimizer with a 0.001 percent learning rate. For multiclass problems, categorical cross-entropy is the default loss function [31]. To predict the probability of each class, a Softmax activation is performed. Considering that Softmax normalizes all values between 0 and 1, their sum is always 1.

$$Softmax(y_i) = \frac{\exp(y_i)}{\sum_j \exp(y_i)}$$

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 RESULTS AND DISCUSSION

The mathematical formulas for these performance metrics are as follows:

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

$$recall = \frac{TP}{TP + FN}$$

$$precision = \frac{TP}{TP+FP}$$

$$F1 - score = 2(\frac{Precision \times Recall}{Precision+Recall})$$

$$FPR = \frac{FP}{FP+TN}$$

$$FNR = \frac{FN}{FN+TP}$$

4.2 MODEL ACCURACY

In Table 2, the results of the five transfer learning models' training accuracy, test accuracy, and validation accuracy are summarized, along with their train, test, and validation losses. According to table 3, the most accurate model is the VGG-16. The information there makes this quite evident.

Table 3. Accuracy table of models

Model	Train Accuracy	Train Loss	Validation Accuracy	Validation Loss	Test Accuracy	Test Loss
VGG-19	96.67	0.22	95.63	0.21	95.24	0.23
VGG-16	**97.77**	**0.18**	**96.83**	**0.12**	**96.13**	**0.19**
Mobile Net	95.43	0.18	94.23	0.28	94.24	0.33
Mobile Net V2	95.76	0.25	94.63	0.32	94.59	0.39
InceptionV3	76.86	0.421	76.21	0.392	76.21	0.384

4.3 STATISTICAL EVALUATION:

Table 4. Showing the statistical evaluation of the proposed best model VGG-16

Configuration	Value
Image sizes	224 x 224
Epochs	92
Optimization Functions	Adam
Learning rates	0.001
Batch sizes	32
Activation functions	Softmax
Dropouts	0.5
Momentums	0.9
Accuracy	98.21

Table 5. Performance Analysis and Statistical Analysis of best Proposed Model VGG16

Accuracy	FPR (%)	FNR (%)	FDR (%)	KC (%)	MCC (%)	MAE (%)	RMSE (%)	Precession (%)	Recall (%)	Specifity (%)	F1 Score (%)
98.21	1.55	2.41	2.56	99.04	88.39	2.11	5.57	96.26	96.42	97.55	96.55

CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

In order to train deep learning systems for rose disease detection, massive datasets are required. Overly high costs are obstructing the development of artificial intelligence in rose disease (time and expertise). Several transfer learning techniques have been studied in order to train a competitive classifier at a minimal cost. Transfer learning techniques allow models to identify and categorize new data using information obtained from large datasets. This study proposes a system to more accurately classify rose disease using a transfer learning model, thereby reducing the danger of extreme loss. In this study, various preprocessing techniques are used to reduce speckle noise and artifacts from the image. A total of five transfer learning models were tested on the rose disease dataset. The proposed model achieved the highest precision due to proper hyperparameter tuning. Following that, we can say that rose disease prediction is an important aspect of rose cultivation and disease prevention. Predictive models can accurately predict the onset of rose diseases, assisting farmers in identifying and preventing them. Using machine learning models, growers can accurately predict the onset of rose diseases in time, allowing them to take the necessary precautions to prevent disease spread and ensure a healthy and high-quality crop.

5.2 LIMITATIONS AND FUTURE WORK

In this study, transfer learning models for multiclass classification performed significantly better than conventional classifiers. Despite the study's major limitations, the dataset is inadequate for the proposed model. In the future, the effectiveness of the proposed model can be evaluated using expanded quantities of unprocessed images. However, in most tests, the proposed model from this research accurately categorizes the four types of rose disease. Despite a few minor drawbacks, such as inadequate data and a relatively small dataset, the suggested model could still accurately categorize four different types of rose disease in most tests.

REFERENCES

[1] A. A. Bhagat, C. D. Badgujar, S. S. Bhosale and V. S. Supe, “An economics analysis for export of fresh cut rose flowers from India,” Journal of Pharmacognosy and Phytochemistry SP2: 291-298, 2019.

[2] M. A. Haque, M. A. M. Miah, S. Hossain and M. Alam, “Profitability of rose cultivation in some selected areas of Jessore district,” Bangladesh J. Agril. Res, vol. 38(1), pp. 165-174, 2013.

[3] B. Dan, X. Sun, L. Liu, “Diseases and pests’ identification of lycium barbarum using se-mobilenet v2 algorithm,” In 2019 12th International Symposium on Computational Intelligence and Design (ISCID), vol. 1, pp. 121-125, IEEE, 2019.

[4] A. L. P. de Ocampo, E. P. Dadios, “Mobile platform implementation of lightweight neural network model for plant disease detection and recognition,” In 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), pp. 1-4, IEEE, 2018.

[5] S. Ghoury, C. Sungur, A. Durdu, “Real-Time Diseases Detection of Grape and Grape Leaves using Faster R-CNN and SSD MobileNet Architectures,” International Conference on Advanced Technologies, Computer Engineering and Science (ICATCES 2019), 2019.

[6] R. Gandhi, S. Nimbalkar, N. Yelamanchili, S. Ponkshe, "Plant disease detection using CNNs and GANs as an augmentative approach, " In 2018 IEEE International Conference on Innovative Research and Development (ICIRD), pp. 1-5, IEEE, 2018.

[7] A. K. Rangarajan, R. Purushothaman, A. Ramesh,” Tomato crop diseases classification using pre-trained deep learning algorithmn,” Procedia computer science, no. 133, pp. 1040-1047, 2018.

[8] M. M. M. Ghazi, B. Yanikoglu, E. Aptoula, “Plant indentification using deep neural networks via optimization of transfer learning parameters,” Neurocomputing, vol. 235, pp. 228-235, 2017.

[9] L. G. Nachtigall, R. M. Araujo, G. R. Nachtigall, "Classification of apple tree disorders using convolutional neural networks." In 2016 IEEE 28th International Conference on Tools with Artificial Intelligence (ICTAI), pp. 472-476, IEEE, 2016.

[10] P. K. Kosamkar, V. Y. Kulkarni, K. Mantri, S. Rudrawar, S. Salmpuria, N. Gadekar "Leaf disease detection and recommendation of pesticides using convolution neural network," In 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), pp. 1-4, IEEE, 2018.

[11] G. Suresh, V. Gnanaprakash, R. Santhiya, "Performance Analysis of Different CNN Architecture with Different Optimisers for Plant Disease Classification," In 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), pp. 916- 921, IEEE, 2019.

[12] A. P. Marcos, N. L. S. Rodova, A. R. Backes, "Coffee leaf rust detection using convolutional neural network,"In 2019 XV Workshop de Visão Computacional (WVC), pp. 38-42, IEEE, 2019.

[13] S. S. Hari, M. Sivakumar, P. Renuga, S. Karthikeyan, S. Suriya, "Detection of plant disease by leaf image using convolutional neural network," In 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN), pp. 1-5, IEEE, 2019.

[14] A. Elhassouny, F. Smarandache, "Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks," In 2019 International Conference of Computer Science and Renewable Energies (ICCSRE), pp. 1-4. IEEE, 2019.

[15] S. Machha, N. Jadhav, H. Kasar, Prof. S. Chandak, "Crop leaf disease diagnosis using convolutional neural network," International Journal of Trend in Scientific Research and Development (IJTSRD), vol. 4, 2020.

[16] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, H. Adam, "Mobilenets: Efficient convolutional neural networks for mobile vision applications," arXiv preprint arXiv, pp. 1704.04861, 2017.

[17] L. A. Wulandhari, A. A. S. Gunawan, A. Qurania, P. Harsani, T. F. Tarawan, R. F. Hermawan, "Plant nutrient deficiency detection using deep convolutional neural network," ICIC Express Letters, vol. 13, no. 10, pp. 971-977, 2019.

[18] J. Amara, B. Bouaziz, A. Algergawy, "A deep learning-based approach for banana leaf diseases classification," Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband, 2017.

[19] O. Kulkarni, "Crop disease detection using deep learning," In 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), pp. 1-4, IEEE, 2018.

[20] J. Amara, B. Bouaziz, A. Algergawy, "A deep learning-based approach for banana leaf diseases classification," Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband, 2017.

[21] O. Kulkarni, "Crop disease detection using deep learning," In 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), pp. 1-4, IEEE, 2018.

[22] Schmeelk, J., 2002. Wavelet transforms on two-dimensional images. *Mathematical and computer modelling*, *36*(7-8), pp.939-948.

[23] Abbas, A.H.; Kareem, A.A.; Kamil, M.Y. Breast Cancer Image Segmentation Using Morphological Operations. Int. J. Electron. Commun. Eng. Technol. 2015, 6, 8–14.

[24] Wang, X.; Liang, G.; Zhang, Y.; Blanton, H.; Bessinger, Z.; Jacobs, N. Inconsistent Performance of Deep Learning Models on Mammogram Classification. J. Am. Coll. Radiol. 2020, 17, 796–803.

[25] Zheng, Y. Breast Cancer Detection with Gabor Features from Digital Mammograms. Algorithms 2010, 3, 44–62.

[26] Van Droogenbroeck, M.; Buckley, M.J. Morphological Erosions and Openings: Fast Algorithms Based on Anchors. J. Math. Imaging Vis. 2005, 22, 121–142.

[27] Beeravolu, A.R.; Azam, S.; Jonkman, M.; Shanmugam, B.; Kannoorpatti, K.; Anwar, A. Preprocessing of Breast Cancer Images to Create Datasets for Deep-CNN. IEEE Access 2021, 9, 33438–33463.

[28] Wang, P.; Wang, J.; Li, Y.; Li, P.; Li, L.; Jiang, M. Automatic classification of breast cancer histopathological images based on deep feature fusion and enhanced routing. Biomed. Signal. Process. Control 2021, 65, 102341.

[29] Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. arXiv 2014, arXiv:1409.1556.

[30] Shuyue, G.; Murray, L. Breast cancer detection using transfer learning in convolutional neural networks. In Proceedings of the 2017 IEEE Applied Imagery Pattern Recognition Workshop (AIPR), Washington, DC, USA, 10–12 October 2017; pp. 1–8.

[31] Shallu; Mehra, R. Breast cancer histology images classification: Training from scratch or transfer learning? ICT Express 2018, 4, 247–254.

[32] Hameed, Z.; Zahia, S.; Garcia-Zapirain, B.; Javier Aguirre, J.; María Vanegas, A. Breast Cancer Histopathology Image Classification Using an Ensemble of Deep Learning Models. Sensors 2020, 20, 4373.

[33] Lorencin, I.; Šegota, S.B.; Andeli´c, N.; Mrzljak, V.; ¯Cabov, T.; Španjol, J.; Car, Z. On Urinary Bladder Cancer Diagnosis: Utilization of Deep Convolutional Generative Adversarial Networks for Data Augmentation. Biology 2021, 10, 175.

ROSE DISEASE CLASSIFICATION

ORIGINALITY REPORT

23%	13%	15%	7%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	8%
2	Md Harun or Rashid, Salma Akter, Amatul Bhusra Akhi. "BrainNet-7: A CNN Model for Diagnosing Brain Tumors from MRI Images based on an Ablation Study", International Journal of Advanced Computer Science and Applications, 2022 Publication	7%
3	Aditya Rajbongshi, Toma Sarker, Md. Meraj Ahamad, Md. Mahbubur Rahman. "Rose Diseases Recognition using MobileNet", 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), 2020 Publication	3%
4	www.mdpi.com Internet Source	2%
5	www.researchgate.net Internet Source	1%

6	"Artificial Neural Networks and Machine Learning – ICANN 2018", Springer Science and Business Media LLC, 2018 Publication	<1 %
7	cybersecurity.springeropen.com Internet Source	<1 %
8	Submitted to University of Hertfordshire Student Paper	<1 %
9	Sidratul Montaha, Sami Azam, Abul Kalam Muhammad Rakibul Haque Rafid, Pronab Ghosh et al. "BreastNet18: A High Accuracy Fine-Tuned VGG16 Model Evaluated Using Ablation Study for Diagnosing Breast Cancer from Enhanced Mammography Images", Biology, 2021 Publication	<1 %
10	dr.ntu.edu.sg Internet Source	<1 %
11	danielstern20.medium.com Internet Source	<1 %
12	scholarworks.umass.edu Internet Source	<1 %
13	Dongmei Guo, Liang Ye, Guang Yan, Huasong Min. "CCD-BSM:composite-curve-dilation brush stroke model for robotic chinese calligraphy", Applied Intelligence, 2022	<1 %

Publication

14	link.springer.com Internet Source	<1%
15	"Pattern Recognition and Computer Vision", Springer Nature America, Inc, 2018 Publication	<1%
16	"Third International Conference on Image Processing and Capsule Networks", Springer Science and Business Media LLC, 2022 Publication	<1%
17	Yuan Yuan, Lei Chen, Huarui Wu, Lin Li. "Advanced agricultural disease image recognition technologies: A review", Information Processing in Agriculture, 2021 Publication	<1%