Journal of Chemical Health Risks

www.jchr.org

JCHR (2025) 15(1), 368-375 | ISSN:2251-6727

The Rose's Mysteries: An Extensive Examination of Rose Leaf Illnesses

Jyoti Bhosale*[0000-0002-1704-0805], Suraj Damre2, Madhavi Panchakshari3, Priti Pancholi4

**Vilasrao Deshmukh Foundation, Group of Institutions,School of Enginerring and Technology,Latur, India-413512*
2,4 M.S.Bidve Enginerring college,Latur,India-413512
3STMEI'S Sandipani Technical Campus Faculty of Engineering, Kolpa, Latur, India-413512

(Received: 16 November 2024 Revised: 11 December 2024 Accepted: 11 January 2025)

KEYWORDS

Rose leaf diseases,

Plant pathology,

Disease management,

Integrated pest management,

Symptom Identification

ABSTRACT:
Rose plants, cherished for their vibrant blooms and fragrant essence, are susceptible to various diseases that can severely impact their health and aesthetic appeal. This research paper provides a comprehensive analysis of common rose leaf diseases, focusing on their causes, symptoms, and management strategies. Through a combination of literature review, field observations, and expert insights, this study aims to enhance our understanding of rose leaf diseases and equip gardeners, horticulturists, and researchers with effective tools for disease prevention and control. The findings highlight the importance of early detection, proper sanitation practices, and integrated pest management techniques in maintaining the vitality and beauty of rose plants. Accuracy without transfer learning (87.82%) significantly outperforms that with transfer learning (64.53%). The highest accuracy was achieved without transfer learning (95.00%), compared to 81.56% with transfer learning. Without transfer learning, the model achieves 87.15% accuracy, while with transfer learning, it is limited to 67.28%. Accuracy without transfer learning (94.37%) is markedly better than with transfer learning (72.88%). The characteristic rust-colored spots on leaves are better detected with a specialized model. Across all four diseases, models trained without transfer learning consistently outperform those utilizing transfer learning. This emphasizes the importance of disease-specific training for accurate detection. While transfer learning is often advantageous in scenarios with limited data, its effectiveness diminishes when pre-trained features fail to generalize to domain-specific tasks, such as rose disease detection.

,

1. Introduction

On our globe, starvation and food insecurity are largely caused by crop diseases. Plant diseases are thought to be responsible for annual worldwide crop output losses of up to 16%. Importance of roses and the impact of leaf diseases on plant health. Roses have been cultivated for centuries, and their cultural, aesthetic, and economic significance cannot be overstated. They are cherished for their diverse colors, captivating fragrances, and the emotional messages they convey. The cultivation and trade of roses contribute significantly to the horticultural industry and local economies. Methods based on DNA sequencing and microscopies are useful for identifying and understanding many diseases.

A promising solution is a smartphone-based gadget that aids in crop disease diagnosis by taking and automatically analyzing an image of a plant leaf. Small, chlorotic dots that are surrounded by leaf veins are the first signs of the disease, which then progresses to thin, dark streaks.

However, rose plants are prone to various diseases, with leaf diseases being a common challenge faced by growers worldwide.

1.1. Cultural Significance

Roses have a deep-rooted cultural significance in many societies around the world. They have been associated with love, beauty, and romance for centuries. Roses are often used as symbols of affection, making them popular choices for expressing emotions and conveying messages. In literature, art, and music, roses frequently appear as powerful symbols, evoking feelings of passion, elegance, and purity. Various cultural celebrations and events, such as weddings, anniversaries, and Valentine's Day, are incomplete without the presence of roses. They hold a special place in human culture, representing beauty, love, and emotional connection.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2025) 15(1), 368-375 | ISSN:2251-6727

1.2. Economic Importance

The economic significance of roses cannot be overlooked. The global rose industry generates substantial revenue through the production, trade, and consumption of rose flowers. Commercial rose cultivation creates employment opportunities for farmers, workers in nurseries, and individuals involved in the flower trade. The cut flower market heavily relies on roses, with high demand for bouquets, floral arrangements, and decorative purposes. Rose exports contribute significantly to the economies of countries known for their rose production, such as Colombia, Ecuador, Kenya, and the Netherlands. The economic impact of roses extends beyond the flower industry, as they also contribute to related sectors like tourism and hospitality.

1.3. Horticultural and Landscape Value

Roses are highly valued in horticulture and landscaping for their aesthetic appeal, versatility, and adaptability. They come in a wide range of colors, sizes, shapes, and fragrances, allowing for creative and diverse landscape designs. Roses can be grown as standalone plants, hedges, or climbers, enhancing the visual appeal of gardens, parks, and public spaces. Their ability to bloom repeatedly throughout the growing season makes them popular choices for adding vibrant colors and textures to land scapes. Additionally, certain rose varieties are cultivated for their attractive foliage, such as those with variegated or colorful leaves, adding visual interest even when not in bloom. The horticultural and landscape value of roses lies in their ability to trans- form outdoor spaces into captivating, inviting environments.

2. Objectives

To solve the aforementioned problems, we offer a deep learning-based method for categorizing and locating roses leaf diseases. We demonstrate that the framework is made up of two key parts: classification based on deep learning and picture pre-processing.

3. Literature review

B. Dan et al. [8] conducted research on 11 different diseases and pests affecting lycium barbarum (also known as goji berry) plants. To increase the network's capacity, they unveiled a better iteration of MobileNet V2's image recognition technology. Their suggested approach included the MobileNet V2 network's SE (Squeeze-and-Excitation) module that comes before the final pooling layer and convolution layer.

The researchers gathered 1,955 pictures in all of lycium barbarum and made use of spatial adjustments to increase the collection to 18,720 photos. They evaluated the performance SEMobileNet V2, the method they suggested, achieved 98.23% accuracy. This accuracy was higher than trials conducted in the same field.

A. L. P. de Ocampo and E. P. Daios [9] concentrated on computational light neural network models in their experiment. In two steps, they trained their model using the ImageNet dataset. With the use of this dataset, the researchers trained their model, which had an accuracy of 89.0%. They used computational methods to create a simple neural network model that was capable of handling the task at hand. In their investigation, S. Ghoury et al. [10] used the transfer learning technique and Single Shot Multi Box Detector (SSD) MobileNet v1 and Faster R-CNN Inception v2 are two pre-trained deep learning models.

In their particular work, the researchers discovered that SSD MobileNet v1 was not particularly helpful for real-time categorization. The Faster R-CNN Inception v2 model outperformed the others, nevertheless. In their experiment, the accuracy rate for classifying the test images utilising a faster R-CNN Inception v2 was up to 95.57%.

A 78% to 99% range of exactitude was shown by the model. However, it should be noted that this model required more time to process. In conclusion, S. Ghoury et al. [10] used transfer learning using already-trained deep learning models to conduct their research. In real-time classifications, SSD MobileNet v1 proved ineffective, while the Better results were obtained by the quicker R- CNN Inception v2 model, which had an accuracy rate of up to 95.57%. However, it was associated with longer processing times. Convolutional neural networks were used by R. Gandhi et al. [11] to categories plant diseases. They employed two CNN models, Inception V3 and MobileNet, to boost their accuracy, which was 88.6% and 92%, respectively, and GANs to increase the size of their image collection.

To identify tomato illnesses, A.K. Rangarajan et al. [12] used deep learning architectures, particularly AlexNet and VGG16. Their dataset consisted of 13,262

Journal of Chemical Health Risks
www.jchr.org
JCHR (2025) 15(1), 368-375 | ISSN:2251-6727

images. With the AlexNet architecture, the researchers were able to attain an accuracy of 97.49%, while the VGG16 design produced a result of 97.29%. To improve their accuracy, they used the Inception V3 and MobileNet CNN models, which was 88.6% and 92%, respectively, and GANs to increase their picture dataset [13]. Regarding the detection of crop diseases in general, they worked with both the MobileNet and Inception V3 architectures. J. Amara et al. achieved an accuracy of 99.04% using MobileNet [14], while O. Kulkarni achieved an accuracy of 99.45% using Inception V3 [14].

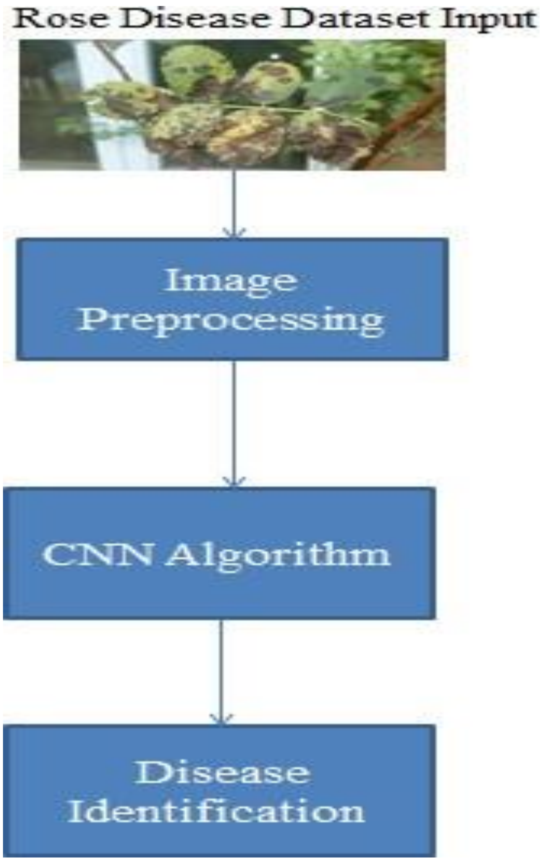
L. G. Nachtigall et al. [15] utilised CNN as it was first Architecture AlexNet to discover apple tree problem. They made use of a brand-new dataset with labelled predecessors, which had 2539 pictures of six cognitive illnesses. Their experiment's accuracy percentage is 97.3% [15].

To diagnose tomato disease, they employ 13262 pictures. To increase accuracy, they use VGG16 net (97.29%) and AlexNet (97.49%). The Inception ResNet-v2 network, which has already been trained using the ImageNet dataset to identify nutrient shortages in plants, was implemented using transfer learning by L. A. Wulandhari et al. [17]. They accomplish accuracy using a fine-tuning strategy, with 96% accuracy for training and 86% accuracy for testing, respectively. To diagnose tomato disease, they employ 13262 pictures. To increase accuracy, they use VGG16 net (97.29%) and AlexNet (97.49%). One of them gets 97.33% accuracy in diagnosing tomato leaf illnesses when they employ their suggested CNN-based technique to identify various forms of agricultural leaf diseases [18]. The experimental results, according to Bhosale, J. D. et al., demonstrate that the recommended model outperforms previously trained models like VGG16 and InceptionV3. According to, the categorization accuracy ranges from 76% to 100%.

4. Methods

Lorem Our process entails creating a data collection that is smeared with labelled photos of the four declensions of disease that often impact rose plants. The embodiment process of this work is represented in this part. The embodiment process is broken down into several steps, including the collection of picture data, preparation of the image dataset, training, and performance assessment of the suggested model Fig. 1 depicts the work's implemented process.

Fig. 1. Manifestation of the Technique for Recognizing Rose Plant Diseases



4.1 Image preprocessing

In the dataset we provide, which is displayed in Fig. 2 below, we include four photographs of rose plant diseases together with their English names and symptoms.

The collection includes several pictures of both healthy and diseased leaves that are saved in local or worldwide repositories. The photos were captured with a common digital camera. Red (R), green (G), and blue (B) are the three channels that make up an image. In our research, we'll examine the compatibility of our technique with both RGB and gray-scale images. We perform a preprocessing step to accomplish this in which we reduce each image in our dataset to 60 * 60 pixels and convert them all to gray-scale.

.

4.2 Categorization based on deep learning

Neurons are grouped in layers in neural networks. The neurons in the neighbouring layers are interconnected. CNNs are renowned for their resilience to inputs with

Journal of Chemical Health Risks
www.jchr.org
JCHR (2025) 15(1), 368-375 | ISSN:2251-6727

little change, and their execution requires little pre-processing.

They can do discrimination while concurrently extracting the proper features. The three crucial components of a CNN are convolution, pooling, and fully connected layers. The convolution and pooling layers extract information the fully connected layer performs the categorization operation from the input photos. The automatic feature extraction from each input image is convolution's main objective. The dimensionality of these characteristics is reduced by the pooling layer.

Neurons are grouped in layers in neural networks. The neurons in the neighbouring layers are interconnected the CNNs. The model's final fully connected layer with a soft max activation function classifies the input photos into predetermined groups using the ingested high-level features. We shall describe these two elements in more depth in the following paragraphs.

- Model Feature extraction model.

Using the feature extraction method, the network picks up on a number of high level features from the input photographs. It is made up of several convolutional and pooling layers. Each filter accounts for the blue, green, and red color channels is applied to the image's raw pixel values using the sliding window method, and the dot product between the filter pixel and the input pixel is calculated. This will result in the feature map, a two-dimensional representation of the filter's activation.

We'll talk about these two elements in more detail in the sentences that follow. In the classification stage of the convolution neural network, we use fully connected layers, where each neuron provides a complete connection to each learnt feature map released from the previous layer. To establish the class scores, these connected layers are based on the soft max activation function. We'll discuss the experiments we ran and their findings.

- Experimental Evaluation.

We carried up a series of experiments utilizing a genuine dataset of rose illnesses gathered from the Plant Village project in order to confirm the efficacy of the indicated strategy.To assess the robustness of our suggested approach and its capacity to prevent over fitting, we chose to explore a wide variety of train and test set splits in our experiments. Because of this, just a portion of the entire dataset is used for training, and the remainder is used for testing to ensure that the suggested technique actually works as intended. Using an actual dataset of rose illnesses received from the Plant Village project, we carried out a series of tests.

To assess the robustness of our suggested approach and its capacity to prevent over fitting, we chose to explore a wide variety of train and test set splits in our experiments.

A small number of training inputs are randomly selected as part of the SGD algorithm's operation. This is what we mean by the batch size, which is 10 at the moment. In the majority of test splits, beginning with iteration 25, the model stabilizes and, in the final iteration, achieves a high level of accuracy.

Fig. 2. A case of rose diseases

4.3 Preprocessing of Image Dataset.

We used scaling, labeling, and augmentation techniques in this stage of the implementation process. Large datasets are often needed for deep learning techniques; however, it might be challenging to collect this type of data. To address this issue, we employed augmentation as a helpful technique. We applied augmentation techniques to a real dataset to enhance its quality and quantity. Among other augmentation approaches, Rotation, zooming, shearing, flipping, cropping, adaptive histogram equalization, and other techniques were applied. and contrast adjustment with histogram equalization. These techniques were employed to improve and expand our dataset. Following the augmentation process, we were able to successfully increase our dataset for each class from 100 to 500 photos. Consequently, we obtained 2000 augmented images in total for the implementation phase. The expanded labelled dataset was scaled to make training and testing easier. With a ratio of 0.8 to 0.2, the training set and the testing set were created by randomly dividing the dataset.

Journal of Chemical Health Risks

www.jchr.org

JCHR (2025) 15(1), 368-375 | ISSN:2251-6727

4.4 Proposed Model Description.

The Mobile-Net architecture, a thin deep convolutional neural network (CNN), is the foundation of our suggested model. Mobile-Net is specifically designed to have a smaller model size and faster performance compared to many other models. It achieves this by utilizing depth-wise separable convolutions, where filtering and consolidation are split into separate layers. This reduction in model size helps to decrease computational requirements.

For our task of detecting rose diseases, we employed the Mobile-Net architecture along with transfer learning techniques. We also experimented without transfer learning using the Mobile-Net architecture alone. In both cases, we leveraged the pre- trained weights of the Image-Net dataset, which has 1000 distinct classes, was used to train Mobile-Net.

Since our dataset contains only 4 classes corresponding to roses diseases, we re- moved the 1000 neurons from the output layer of the Mobile-Net architecture and replaced them with 4 neurons. We made each layer of the Mobile-Net architecture with transfer learning trainable. To reduce overfitting, we additionally added a fully connected layer to the model.

4.5 Performance Assessment.

In this stage of the implementation, we evaluated the freshly trained models using test data. Table 1 contains the 4*4 confusion matrix. We create a class set to assess the effectiveness of our experiment, which includes powdery mildew, rust.

All of the formulas used to determine the precision, recall, accuracy, and F1- score are shown in Table 2. The accuracy of transfer learning using Mobile-Net accession, which is shown in Table 3, is the highest of the two techniques at 95.63 percent. Additionally, we determined the F1 score for the method we used to construct the performance evaluation criteria for each of the four denominations. The F1 ratings for rust are 87.15% for rose dieback, 87.82% for black spot, and 95.7 % for powdery mildew are saved in Table 4 for transfer learning using the Mobile-Net approach. The Mobile-Net with transfer learning technique yields the best outcomes for each class.

Table 1. Formation of Binary for the Confusion Matrix

Name of class	Process	True Positive	False Positive	False Negative	True Negative
Black Spot	Mobile Net without Transfer Learning	62	11	58	289
Powdery Mildew		88	28	12	292
Rose Dieback		75	47	25	273
Rust		76	33	24	287
Black Spot	Mobile Net with Transfer Learning	84	7	16	293
Powdery Mildew		97	5	3	295
Rose Dieback		93	21	7	279
Rust		91	2	9	298

Table 2. Formulas

Metrics	Formula
Recall	Recall = True Positive / (True Positive + False Negative)
Precision	Precision = True Positive / (True Positive + False Positive)
Accuracy	Accuracy= (True Positive + True Negative) /(True Positive +False Positive+ True Negative +False Negative)
F1- score	F1-score = 2 True Positive / (2 True Positive + False Positive + False Negative)

Journal of Chemical Health Risks
www.jchr.org
JCHR (2025) 15(1), 368-375 | ISSN:2251-6727

5. Result

The upper left corner of the graph, which has the highest true positive rate (TPR) and the lowest false positive rate (FPR), is the optimal placement, according to the ROC curve. Another crucial indicator is the area under the curve (AUC), where a higher AUC denotes better performance. Fig 3 includes the Python source code. This demonstrates that, in terms of performance, the Mobile-Net with the transfer learning technique surpasses the Mobile-Net without the technique. When dealing with multi-label classification, the ROC curve, which is a valuable tool for binary classification, needs to be adapted to handle multiple labels. To achieve this, we must first binaries the output by treating each label as a separate binary classification task. To evaluate the multi-label classification performance, two commonly used averaging techniques are micro and macro averaging. These techniques yield slightly different measurements and interpretations. With macro averaging the measure is calculated separately for each class, and then an overall average is taken. This method does not take into account class imbalance and treats all classes equally. In contrast, micro averaging determines the average measure by adding the contributions from all classes.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

# Assuming you have the true labels and predicted probabilities for the test set
# true_labels: array of true labels (0 or 1) for each test sample
# predicted_probs: array of predicted probabilities for the positive class for each test
sample

# Compute false positive rate (FPR), true positive rate (TPR), and threshold values
fpr, tpr, thresholds = roc_curve(true_labels, predicted_probs)

# Compute the area under the ROC curve (AUC)
roc_auc = auc(fpr, tpr)

# Plotting the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' %
roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

Fig. 3. Code for ROC curve

This method weighs classes with more instances by taking into account the overall performance across all labels. Micro averaging is frequently seen as a more suitable measurement technique in the context of multi-label categorization. It provides a holistic assessment of the classifier's performance by considering all labels and their respective contributions to the overall evaluation. Table 3 compares the outcomes.

Table 3. Result Comparison

Rose Disease	Accuracy with Transfer Learning	Accuracy without Transfer Learning
Black Spot	64.53 %	87.82 %
Powdery Mildew	81.56 %	95.00 %
Rose Dieback	67.28 %	87.15 %
Rust	72.88 %	94.37 %

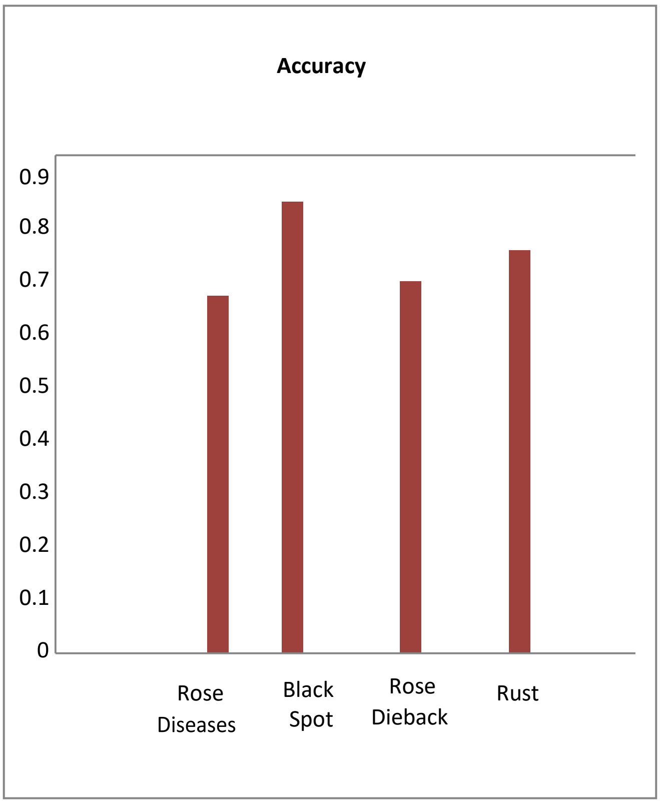


Fig. 4. Accuracy graph without transfer learning

Journal of Chemical Health Risks

www.jchr.org

JCHR (2025) 15(1), 368-375 | ISSN:2251-6727

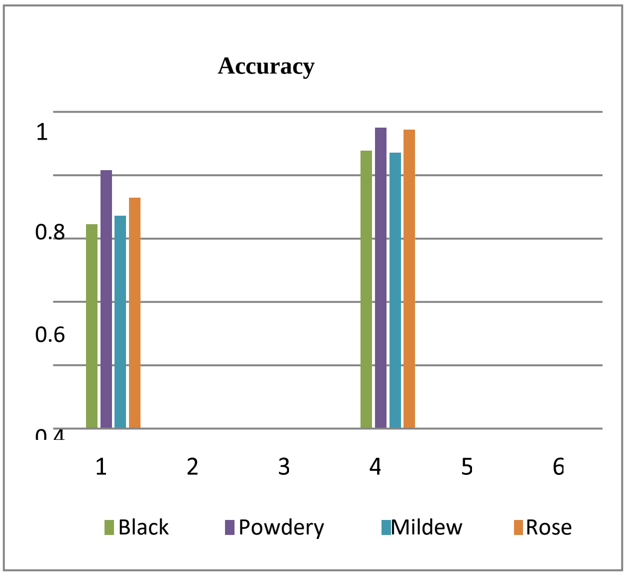


Fig. 5. Accuracy graph with and without transfer learning

6. Discussion

Plant diseases, which lower output and yield quality, are a serious issue in agriculture. Early detection of plant diseases with cost-effective and user-friendly technologies is urgently required. In order to achieve this, we introduced a method in this paper that uses convolutional neural networks to recognize and categorize rose illnesses.

The suggested model can help farmers recognize the disease in the rose plant by acting as a decision support tool. After multiple tests, our system was able to produce accurate categorization outcomes. As a result, it has been demonstrated that the suggested strategy can considerably aid in the precise diagnosis of leaf diseases with minimal computing effort. The accuracy is shown in figures 4 and 5 with and without transfer learning. Diseases of plants have been estimated to be resulting in up to 16% yearly agricultural yield losses over the world. Inspired by our findings, we hope to use our model to evaluate similar rose and plant diseases in future studies. By implementing preventive strategies, gardeners can reduce disease incidence, improve plant health, minimize economic losses, and promote sustainable and environmentally friendly gardening practices.

Refrences

1. Sun, Y., Ruh, M., & Gómez-Chova, L. (2017). Deep learning-based classification for hy- perspectral images. Remote Sensing, 9(1), 67.
2. Singh, A., Ganapathysubramanian, B., & Singh, A. K. (2016). Machine learning for high-throughput stress phenotyping in plants. Trends in Plant Science, 21(2), 110-124.
3. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.
4. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. Computa- tional Intelligence and Neuroscience, 2016, 3289801.
5. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311-318.
6. Bhagat, A. A., Badgujar, C. D., Bhosale, S. S., & Supe, V. S. (2019). An economics analy- sis for export of fresh cut rose flowers from India. Journal of Pharmacognosy and Phyto- chemistry, SP2, 291-298.
7. Haque, M. A., Miah, M. A. M., Hossain, S., & Alam, M. (2013). Profitability of rose culti- vation in some selected areas of Jessore district. Bangladesh J. Agril. Res, 38(1), 165-174.
8. Dan, B., Sun, X., & Liu, L. (2019). 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.
9. Ocampo, A. L. P., & Dadios, E. P. (2018). Mobile platform implementation of lightweight neural network model for plant disease detection and recognition. In 2018 IEEE 10th In- ternational Conference on Humanoid, Nanotechnology, Information Technology, Commu- nication and Control, Environment and Management (HNICEM), pp. 1-4, IEEE.
10. Ghoury, S., Sungur, C., & Durdu, A. (2019). Real-Time Diseases Detection of Grape and Grape Leaves using Faster R-CNN and SSD MobileNet

Architectures. In International Conference on Advanced Technologies, Computer Engineering and Science (ICATCES 2019).

11. Gandhi, R., Nimbalkar, S., Yelamanchili, N., & Ponkshe, S. (2018). Plant disease detec- tion using CNNs and GANs as an augmentative approach. In 2018 IEEE International Conference on Innovative Research and Development (ICIRD) (pp. 1-5). IEEE.
12. Rangarajan, A. K., Purushothaman, R., & Ramesh, A. (2018). Tomato crop diseases classi- fication using pre-trained deep learning algorithm. Procedia computer science, (133), 1040-1047.
13. Amara, J., Bouaziz, B., Algergawy, A. (2017). A deep learning-based approach for banana leaf diseases classification. In Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband.
14. Kulkarni, O. (2018). Crop disease detection using deep learning. In 2018 Fourth Interna- tional Conference on Computing Communication Control and Automation (ICCUBEA), pp. 1-4, IEEE.
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. K. Rangarajan, R. Purushothaman, A. Ramesh,”Tomato crop diseases classification us- ing pre-trained deep learning algorithmn,” Procedia computer science, no. 133, pp. 1040-1047, 2018.
17. L. A. Wulandhari, A. A. S. Gunawan, A. Qurania, P. Harsani, T. F. Tarawan, R. F. Her- mawan, "Plant nutrient deficiency detection using deep convolutional neural network," ICIC Express Letters, vol. 13, no. 10, pp. 971-977, 2019.
18. A. Elhassouny, F. Smarandache, "Smart mobile application to recognize tomato leaf dis- eases using Convolutional Neural Networks," In 2019 International Conference of Com- puter Science and Renewable Energies (ICCSRE), pp. 1-4. IEEE, 2019.
19. Bhosale, J. D., Thorat, S. S., Pancholi, P. V., & Mutkule, P. R. (2023). Machine Learning-Based Algorithms for the Detection of Leaf Disease in Agriculture Crops. International Journal on Recent and Innovation Trends in Computing and Communication, 11(5s), 45–50.