Enhancing the Leaf Disease Detection through Convolutional Neural Network

Deep Rohit[1[0009-0000-2792-9467]], Mohini Darji[2[0000-0002-1508-605X]], Sachi Joshi[3[0000-0002-1663-8872]], and Upesh Patel[4[0000-0003-4872-553X]]

[1] Devang Patel Institute of Advance Technology and Research, Charotar University of Science and Technology, Changa, Anand, India.
[2,3] Devang Patel Institute of Advance Technology and Research, Charotar University of Science and Technology, Changa, Anand, India.
[4] Chandubhai S. Patel Institute of Technology, Charotar University of Science and Technology, Changa, Gujarat, India.
deeprohit2163@gmail.com
mahi.darji1992@gmail.com
sachi20shah@gmail.com
upeshpatel.ec@charusat.ac.in

Abstract. In India, agriculture is the main contributor to GDP. Reduced agricultural output due to crop diseases is a major contributor to both global economic losses and food insecurity. Major losses in both output and revenue are incurred as crop diseases reduce agricultural output both in terms of quality and quantity. Crop diseases are a major threat to food security. Early diagnosis of crop diseases using accurate or automated detection techniques can improve food production quality and reduce economic losses. Using a public dataset of 87,867 images divided into 38 healthy and diseased leaves collected under controlled conditions. This model is trained on a deep convolutional neural network to detect and classify many plant species. The proposed system can identify diseases of 14 crops i.e. apple, blueberry, acerola, maize, etc. Classification precision and average score were used to assess the model's effectiveness. The evaluation showed outstanding global classification accuracy, with about 97% trained on convolutional neural networks (CNNs). This paper also highlights challenges and future directions in the field, to provide valuable information to researchers and practitioners related to agricultural technology and management. plant diseases.

Keywords: Disease classification, Deep Learning, ConvNet, Detection.

1 Introduction

India is an agrarian country where most of the population depends on agriculture. Research aimed at increasing food productivity and quality at reduced costs and increased profits. Crop diseases are a significant menace to global agriculture, causing significant yield losses and impacting food production. Many studies show that the quality of agricultural products can be reduced due to crop diseases. [4] Time-consuming, subjective, and prone to human error, traditional disease detection systems rely on the physical examination of skilled agronomists to identify problems. The demand for reliable, time-saving automated methods to detect leaf diseases is rising. This page gives a summary of the relevant literature, with an emphasis on current findings.

In general, various pests such as insects, weeds, nematodes, animals, and diseases are estimated to cause crop yield losses of about 20-40%. Specifically, the data show that crop disease leads to an average yield loss of 42% for most important food crops. The conventional approach to crop disease diagnosis poses challenges for reliable crop evaluation. The conventional method of diagnosing plant diseases begins with hiring an expert to come to the field and examine the crop with optical equipment. This method takes a lot of time and effort. In addition, it requires constant monitoring of cultures. Another major difficulty is that some farmers do not have access to specialists. Plant diseases cannot always be detected by optical surveillance. Traditional techniques will not provide a reliable assessment of plant diseases.[2]. Plant diseases need to be detected early to limit disease transmission and take effective control measures. Effective crop management depends on assessing the disease status of the plant, including predicting treatment methods and application models. Agronomists rely on computerized methods to identify and diagnose crop diseases. Diagnosis of the disease can still be made subjectively using outdated methods. On the other hand, modern technologies provide an objective method of identifying plant diseases. Agricultural diseases can be detected accurately and reliably using automated methods, such as Deep Learning, saving time and money. Early and accurate detection of damaged leaves is an important topic in computer vision due to disease and environmental change [2].

This study proposes the use of a convolutional neural network (CNN), which has become a very effective and promising method in modern agriculture, to identify diseases in young leaves. CNNs are deep learning models created mainly for extracting and recognizing complex patterns from images. The ability of these networks to learn hierarchical patterns allows them to accurately classify and identify a wide variety of foliar diseases. The CNN model can automatically learn the distinct characteristics that indicate different diseases by looking at photos of job interruptions. The network changes internal parameters during training to reduce misclassification, allowing it to efficiently generalize images of fresh and unexplored leaves. This powerful technology helps farmers identify diseases quickly, allowing for more targeted and precise treatment. It also speeds up the diagnostic process.

To reduce the risk of total crop destruction, this study focused on the early detection of foliar diseases. Manual leaf examination and disease prediction are two traditional disease detection techniques. However, farmers cannot use this method to accurately identify diseases. Therefore, it is possible to identify leaf diseases through reliable disease image processing algorithms. These are modern methods, that use modern technology, and give accurate results.

The summarization of this paper is given below:

- Applying a deep learning model, author can identify leaf diseases in numerous fruit and vegetable crops, including apples, blueberries, cherries, corn, grapes, oranges, peaches, peppers, potatoes, raspberries, soybeans, Squash Powdery_moldew, strawberries, and tomatoes.
- Optimal hyper-parameter configuration led to the enhancement of performance metrics.
- CNN multilayer model accuracy of 97%.
- The proposed research offers agricultural sector advancements, leading to increased production.

The paper's structure for the subsequent sections is as follows: Section 2 covers the literature survey. Section 3 explains the methodologies utilized in this study. Section 4 displays the results and outcomes. Lastly, Section 5 provides the paper's conclusion.

2 Literature Survey

The paper "Diagnosing leaf diseases using convolutional neural networks" presents an automatic disease detection system on plant leaves, providing farmers around the world with quick and accurate disease diagnosis. The proposed system focuses on disease identification in major crops such as maize, sugar, wheat, and grapes using the MobileNet model, a type of convolutional neural network (CNN). The study highlights the importance of early detection of agricultural diseases to minimize damage caused by pests or nutrient deficiencies. Traditional manual disease detection methods are time-consuming and less accurate. Therefore, modern techniques using image processing and deep learning technologies are needed. This article reviews the relevant literature on CNN's crop disease detection, highlighting methods and results from previous studies. The authors then present their recommendation system, which uses the TensorFlow and Keras libraries to preprocess the data and train the CNN. Experimental results show high accuracy in disease classification for some crops, while others require further improvement in training and dataset size. Overall, the proposed system is a promising method to help farmers effectively manage crop health [1].

This research introduces a novel approach, the "Self-Attention Convolutional Neural Network (SACNN)", for efficient and reliable leaf disease recognition. The difficulties posed by poor contrast between scores and medical history and complex histories that limit recognition accuracy are discussed. SACNN is made up of two networks: one that extracts generic features and one that uses self-attention to zero in on details specific to lesions. Extensive testing on the AES-CD9214 and MK-D2 datasets shows that the recognition accuracy of SACNN is 95.33% and 98.0%, respectively, better than the modern 2.9 methods. %. SAC-NN's self-attention mechanism allows it to identify important image regions, thereby improving recognition accuracy and reliability. The authors discuss the influence of self-attention network parameters on recognition performance, providing insights for future research. SACNN exhibits strong anti-interference ability when tested with noisy AES-CD9214 images. Overall, the proposed SACNN offers high accuracy and reliability in the identification of crop diseases, making it valuable for agricultural applications [2].

This paper highlights the use of AI in agriculture to detect and classify foliar diseases, especially in tomatoes and grapes. The proposed method using CNN, including the VGG model, achieved high accuracy (98.40% for grapes and 95.71% for tomatoes) in classifying diseased leaves. Research highlights the importance of early disease detection and classification to support agricultural advancement and increase food production [3].

This study introduces a mechanized methodology for the identification of plant diseases through the analysis of picture features and the implementation of single-class classification. The approach employed in this study involves the utilization of local binary (LBP) models to extract features. Furthermore, it employs dedicated single-class classifiers for each specific plant health condition, including healthy, late blight, and diseased states. Algorithms trained on grape leaves exhibit highly generalizable behavior, successfully identifying diseases in different crops. The proposed method achieved an impressive overall success rate of 95% for the 46 combinations of plant conditions tested. Conflict resolution techniques are also introduced to deal with ambiguous data patterns. The study highlights the potential of AI-based methods to accurately and efficiently diagnose plant diseases in agriculture [4].

This paper presents an image segmentation technique to detect tree diseases using the K-Means clustering algorithm. The proposed method effectively identifies and conceals predominantly green pixels in the leaf image, focusing on specific disease areas. The algorithm removes noisy and boundary data from infected clusters, allowing for more accurate disease classification and identification. The experimental results demonstrate the robustness and effectiveness of the proposed technique, making it a promising tool for detecting foliar diseases in agriculture [5].

This paper presents a method to detect and classify tomato leaf diseases using the CNN model and LVQ algorithm. The dataset contains 500 images with four disease symptoms. The CNN model extracts features from the RGB and LVQ components that act as classifiers. The results show that it is effective in identifying 4 diseases on tomato leaves. This approach has the potential to detect agricultural diseases early, thereby improving crop yields and management. Presented at the International Conference on Computing and Engineering 2018 [6].

This study presents a novel deep learning metamodel that aims to effectively and precisely detect illnesses occurring on cotton leaves. The dataset comprises a total of 2385 photos depicting both healthy and diseased leaves, which have been augmented to enhance overall performance. The proposed model integrates meta CNN, VGG16 Transfer Learning, ResNet50, and a proprietary Deep Learn approach to attain a classification accuracy of 98.53% on the Cotton dataset. Deep learning and transfer learning are crucial components in the realm of plant health assessment and disease identification. The primary objective of this study is to establish a comprehensive and dependable framework for the accurate detection and classification of several illnesses affecting cotton leaves. [7].

This review discusses the use of deep learning for plant pest detection, compares it with traditional methods, and highlights its advantages over functional machine learning. It describes plant disease research and deep learning-based pest detection, including classification, detection, and segmentation networks. Generic datasets and performance comparisons are provided. Practical application challenges are discussed and potential solutions and future trends are proposed [8].

This study investigates the application of deep learning technology in the identification of agricultural diseases through picture analysis, which poses a significant challenge to the global food security. A deep convolutional neural network was employed to train on a dataset consisting of 54,306 photos, with the objective of accurately identifying 14 distinct crop species and 26 different illnesses. The most optimal model demonstrated a remarkable accuracy of 99.34% in a sequence of successful evaluations. This study showcases the capacity of utilizing smartphones for disease diagnostics on a global scale, hence providing advantages to small-scale farmers and enhancing global food production. [9].

This study proposes an efficient plant disease detection technique that uses image processing and machine learning technology with 93° accuracy to detect 20 diseases on 5 common crops. This method consists of pre-processing the RGB image through a Gaussian filter, Otsu threshold, and morphological transformations to extract the foreground. The shape, texture, and color features are then extracted and the HSV color space is used to quantify the green color of the image. The publicly available Plant Village dataset is used for testing purposes, providing an efficient and cost-effective computational solution for large-scale crop disease monitoring [10].

3 Methodology

Dataset Collection: The Kaggle database was utilized by the author for the purposes of training and testing. This database contains a variety of images, each associated with their respective class names. Table 1 presents comprehensive information regarding the database, including details such as the number of layers and accompanying photos for each layer. The database has a total of 38 distinct classes derived from 14 distinct plant species, encompassing both healthy and damaged leaves. The individual is experiencing an illness. The provided visual representations are depicted in Figure 1.

Table 1. Different Data Collection

Classes	No of Images
Apple	7771
Blueberry	1816
Cherry	13,985
Corn	21,301
Grape	28,523
Orange	2010
Peach	3566
Bell Pepper	3901
Potato	5702
Raspberry	1781
Soybean	2022
Squash Powdery_moldew	1736
Strawberry	3598
Tomato	18,345

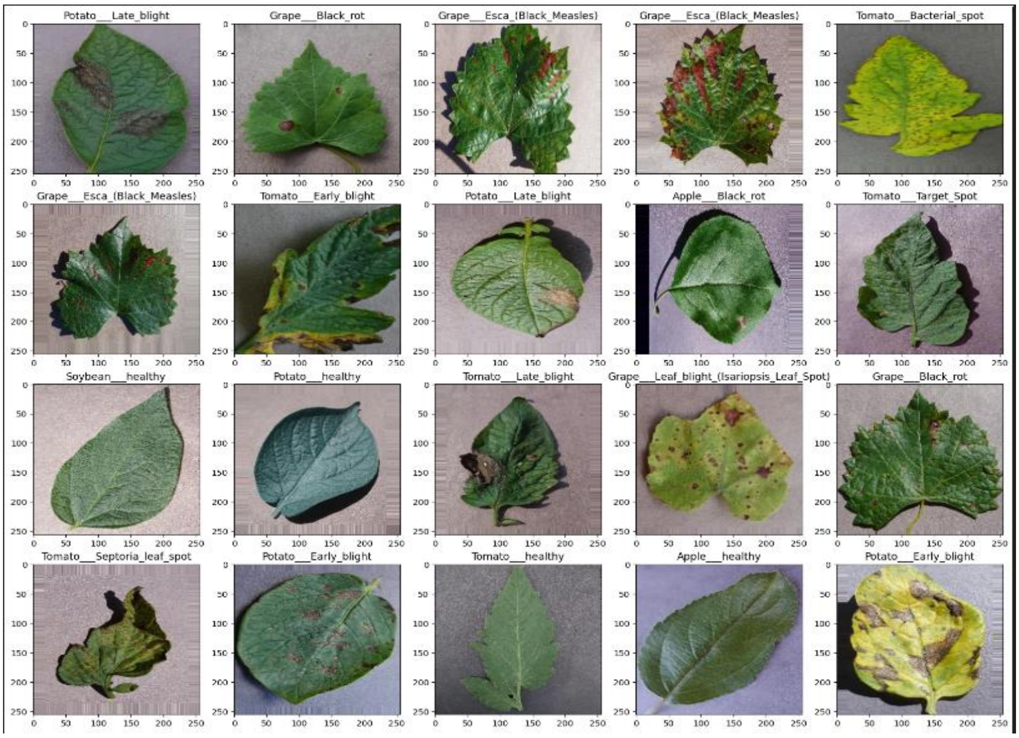


Fig. 1. Dataset Sample.

Data Pre-Processing: This arrangement divides a total of 87,867 image datasets belonging to 38 classes into training and testing. Of this total, 70,295 images are used for training and the remaining 17,572 images are used for model testing. The dataset is scaled 80:20 for prediction. The results of this model are prepared and checked for accuracy.

Classification: The preceding process involved utilizing convolutional neural networks (CNN) to classify images. CNNs are extensively employed for image classification and detection tasks. These artificial neural networks find application across various domains and data formats. The CNN model is notably employed for pixel manipulation and serves as an organizational strategy for complex learning computations on a large scale.

Model: The proposed model involves passing the input through a deep learning embedded network. Within this network, image features are extracted and preprocessed for training, utilizing Maxpooling and Softmax layers. Specific layers for cultured diseased images are incorporated. In the final CNN classifier, Softmax classes are employed (as shown in eq.1), converting the output into class probabilities. Maxpooling layers are utilized to extract crucial information. This amalgamation ensures precise disease classification, efficient model performance, and facilitates early diagnosis and management.

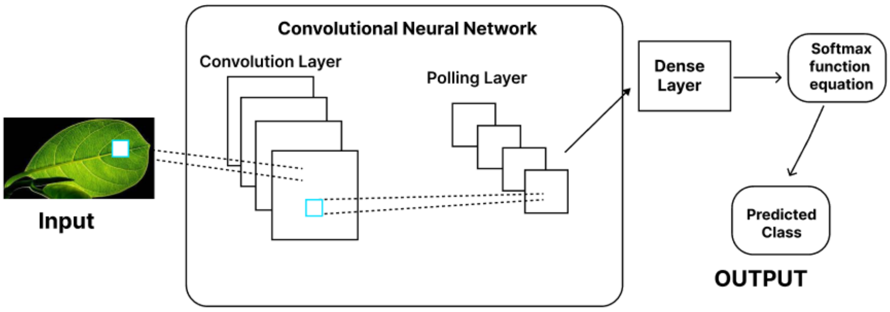


Fig. 2. CNN Architecture

$$P(x) = \frac{e^{x^t}w^l}{\sum_{k=1}^{k} e^{x^t}w^l} \qquad (1)$$

```
# CNN building.
model = Sequential()
model.add(Conv2D(32, (5, 5),input_shape=input_shape,activation='relu'))
model.add(MaxPooling2D(pool_size=(3, 3)))
model.add(Conv2D(32, (3, 3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(512,activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(128,activation='relu'))
model.add(Dense(num_classes,activation='softmax'))
model.summary()
```

Fig. 3. Model Summary

The architecture of the supplied CNN is designed for picture categorization. It includes three different sets of convolutional layers and max-pooling layers that gradually decrease the number of spatial dimensions while deepening the learned features. The model first applies two convolutional layers with 32 filters each, followed by max-pooling, and then a third convolutional layer with 64 filters, again followed by max-pooling, starting with a base 252x252 RGB picture. After flattening the output, the design adds 512 neurons to a dense layer, integrates dropout for regularization, and finishes with a final dense layer for prediction. A thorough understanding of the model's intended use and performance is limited by the absence of particular activation functions and output neuron characteristics in the about 11.9 million parameter model, which shows its potential for complex feature identification.

4 Results

Early halting when training the model on 15 epochs resulted in a 97% accuracy rate. Figures 4 provide a visualization of training and validation accuracy as well as training and validation loss. Figure 6 depicts the results of identifying and recognizing a maize, apple, and tomato leaf.

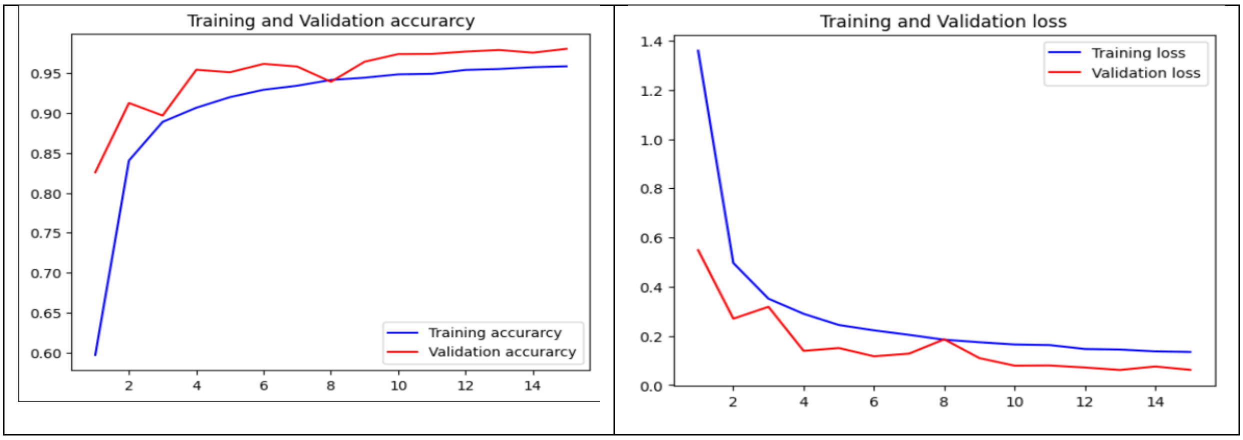
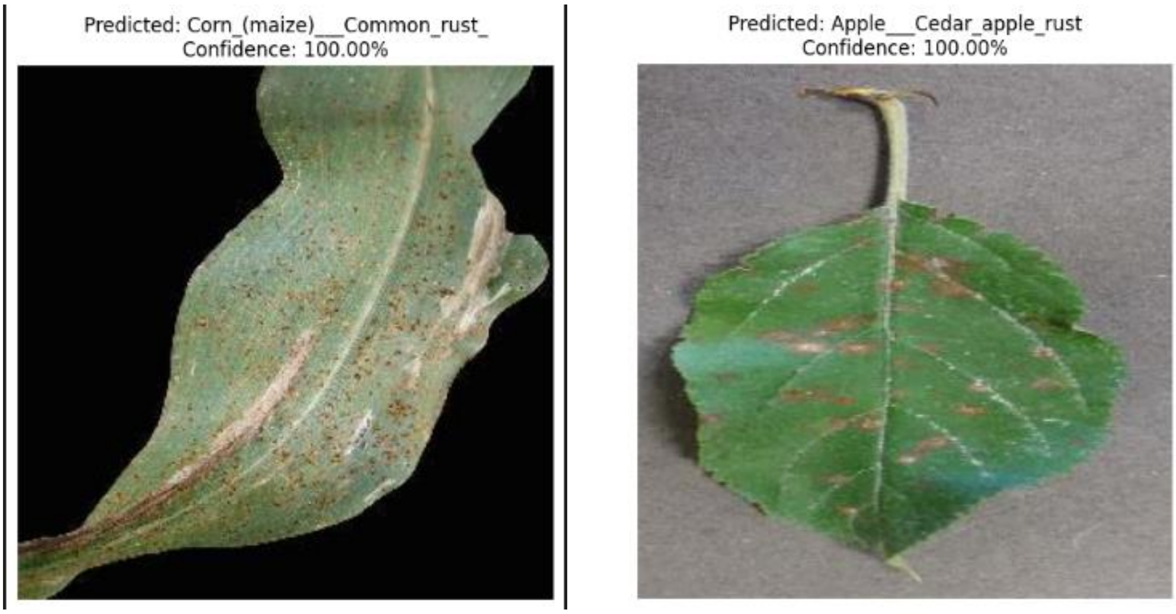


Fig. 4. Model Accuracy and Loss



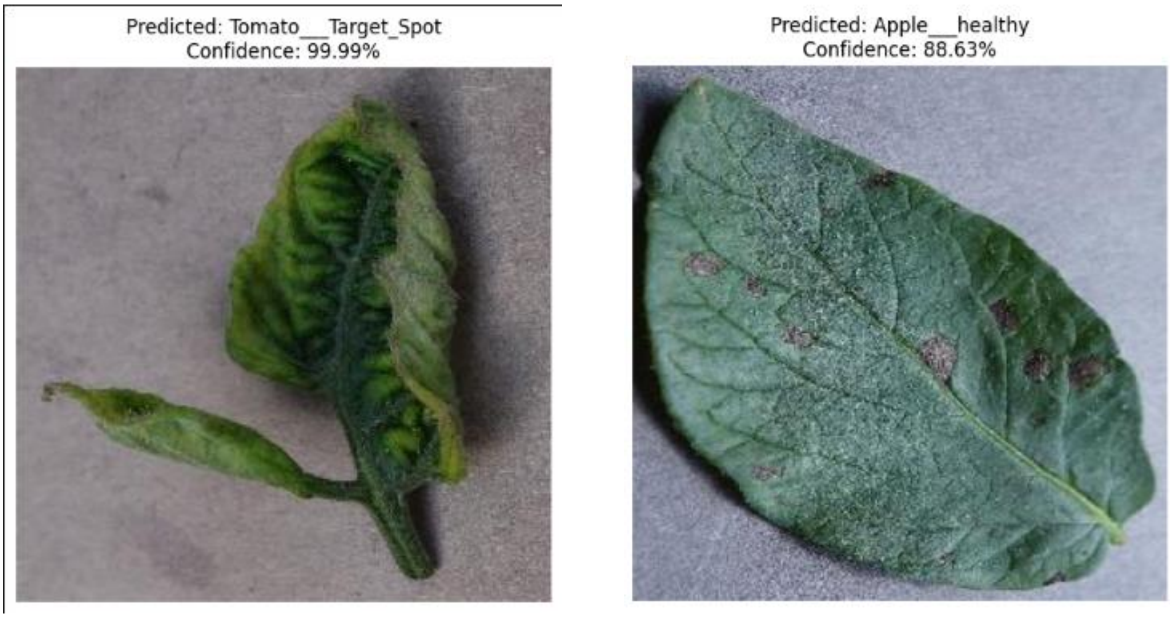


Fig. 6. Output Images

5 Conclusion

The author has successfully devised disease classification techniques for detecting plant leaf diseases. A deep learning model capable of automatic detection and classification of these diseases has been formulated. The model has been tested on 14 species including Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Bell Pepper, Potato, Raspberry, Soybean, Squash Powdery_moldew, Strawberry, and Tomato, encompassing 38 plant classes for identification. This CNN-based system holds potential for real-world agricultural implementation, boasting a recommended model validation of 97% globally. This article is poised to enhance disease classification and early detection, ultimately improving crop yields. In conclusion, this paper significantly contributes to plant pathology, offering insights to enhance plant health management.

References

1. Bharath, S., Kumar, K.V., Pavithran, R., Malathi, T.: Detection of plant leaf diseases using CNN. In: 4 Computer Science and Engineering. , Chennai. India (2020).
2. Zeng, W., Li, M.: Crop leaf disease recognition based on Self-Attention convolutional neural network. Computers and Electronics in Agriculture. 172, (2020).
3. Paymode, A.S., Malode, V.B.: Transfer learning for multi-crop leaf disease image classification using convolutional neural network VGG. Artificial Intelligence in Agriculture. 6, 23–33 (2022). https://doi.org/10.1016/j.aiia.2021.12.002.

4. Pantazi, X.E., Moshou, D., Tamouridou, A.A.: Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers. Comput. Electron. Agric. 156, 96–104 (2019). https://doi.org/10.1016/j.compag.2018.11.005.
5. Jaware, T.H., Badgujar, R.D., Patil, P.G.: Crop disease detection using image segmentation. World Journal of Science and Technology. 2, 190–194 (2012).
6. Sardogan, M., Tuncer, A., Ozen, Y.: Plant leaf disease detection and classification based on CNN with LVQ algorithm. In: 2018 3rd International Conference on Computer Science and Engineering (UBMK). IEEE (2018).
7. Memon, Muhammad Suleman, Pardeep Kumar, and Rizwan Iqbal. "Meta deep learn leaf disease identification model for cotton crop." Computers 11, no. 7 (2022): 102.
8. Liu, J., Wang, X.: Plant diseases and pests detection based on deep learning: a review. Plant Methods. 17, 22 (2021). https://doi.org/10.1186/s13007-021-00722-9.
9. Mohanty, S.P., Hughes, D.P., Salathé, M.: Using deep learning for image-based plant disease detection. Front. Plant Sci. 7, 1419 (2016). https://doi.org/10.3389/fpls.2016.01419.
10. Kulkarni, P., Karwande, A., Kolhe, T., Kamble, S., Joshi, A., Wyawahare, M.: Plant disease detection using image processing and machine learning, http://arxiv.org/abs/2106.10698, (2021).
11. Eunice, Jennifer, Daniela Elena Popescu, M. Kalpana Chowdary, and Jude Hemanth. "Deep learning-based leaf disease detection in crops using images for agricultural applications." Agronomy 12, no. 10 (2022): 2395.
12. Gavhale, K.R., Gawande, U.: An overview of the research on plant leaves disease detection using image processing techniques. Iosr Journal of Computer Engineering (iosrjce). 16, 10–16 (2014).
13. Pantazi, X.E., Moshou, D., Tamouridou, A.A.: Automated leaf disease detection in different crop species through image features analysis and Class Classifiers. Computers and electronics in agriculture. 156, 96–104 (2019).