iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 **Issue:** II **Month of publication:** February 2024

DOI: https://doi.org/10.22214/ijraset.2024.58500

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue II Feb 2024- Available at www.ijraset.com

Crop Disease Detection and Recommendation of Pesticides and Secondary Crops using Deep Learning

J. Benita[1], G. Shyamsundar Reddy[2], K. Venkata Rao[3], V. Bharath Kumar[4], P. Anil Kumar [5]
[1, 2, 3, 4, 5] Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Krishnan koil, Virudhunagar, India

Abstract: In India, so many people belong to an agricultural background. Nowadays crop disease detection is a very crucial topic in analysis. Crop diseases are one of the major issues for the depletion of the quality and quantity of the crop. So, detecting and giving suitable solutions for crop disease is very important to increase the quality and quantity of the crops. In this research work, we use Deep Learning Algorithms such as Convolutional Neural Networks to train the crop disease dataset and we use image pre-processing techniques to pre-process the image and to detect the crop disease. In this project, we selected the convolution neural network to get better accuracy for the system. Here, crop leaf images that are affected by diseases are given as input to the system, and after pre-processing that image, it will detect whether there is a disease or not for the crop. If a disease is detected then it will give the name of the disease. After, it will show the suitable pesticides and chemicals that reduce the crop diseases for good yield of the crop. In this project, we also suggest to the farmers some alternative crops that provide various benefits such as improve yield, soil fertility, pest management, etc. These alternative crops often have unique characteristics that complement the yield and growth of main crops
Keywords: CNN, Pesticides, Secondary Crops, Pre-processing

I. INTRODUCTION

In India, agriculture is the primary industry. Around sixteen percent (16%) of India's GDP and ten percent(10%) of its exports come from it. Approximately 60% of Indians rely on agriculture for their living, either directly or indirectly. It belongs to the Indian economy's primary sector. It is the primary source of food, fuel, and fodder. India ranks second globally in terms of the overall area of arable land, with over 60% ofthe total land area dedicated to agriculture. However, the quantity and quality of the agricultural product are declining as a result of numerous diseases. Some agricultural illnesses are not visible in the early stages,which causes the crop to be destroyed as a whole.

The automatic identification of crop illnesses, which recognizes the diseases from the symptoms that appear on the crop leaves, is a highly relevant analysis issue today. One of the problems that results in a decrease in the quantity and quality of crop production is crop diseases. People may become starved as a result of this. The identification and classification of crop diseases are essential activities for increasing plant productivity and the economic process. It's essential to spot disease and apply pesticides to crops correctly. They vary in size, shape, and color when they contracta disease. Manual examinations of these symptoms are possible, but not in sufficient numbers. Therefore,different image processing techniques can identify illnesses on plant stems and leaves. Plants' changes in color, texture, or shape can be used to determine the exact level of disease using image processing techniques. Then, by applying machine learning algorithms, we can categorize these disorders andoffer a treatment.

II. LITERATURE SURVEY

The paper authored by Pranali K. Kosamkar, Shubham Rudrawar, Dr. V.Y. Kulkarni, Shubhan Salmpuria, Krushna Mantri, and Nishant Gadekar, titled "Leaf Disease Detection and Recommendation of Pesticides using Convolution Neural Network," handles an important issue in agriculture. Building on earlier researchin this field, it uses Convolutional Neural Networks (CNNs) to identify plant illnesses in leaf photos. The study highlights the value of deep learning in managing plant diseases and demonstrates how it might improve crop health and productivity. However, it is crucial to recognize the demand for reliable datasets and the need for pesticide usage ethics as future research objectives [1].

In their article titled "Plant Leaf Disease Prediction," authors Vaishnavi Monigari, G. Khyathi Sri, and T. Prathima discuss the significant difficulty of forecasting illnesses in plant leaves. They make use of a sizableand varied dataset made up of different plant leaf photos. They use a specialized form of artificial intelligence known as a Convolutional Neural Network (CNN) to generate predictions. The findings of theirstudy demonstrate amazing precision in spotting illnesses in plant leaves. The importance of this discoveryfor agriculture lies in the fact that it offers a useful tool for early plant disease detection, protecting agricultural production, and ensuring there is enough food for everyone [2].

Habiba, S. U., & Islam, M. K. et al. proposed to use of a deep learning-based method for diagnosing tomatoplant diseases from images of their leaves presented in the research. After extracting information from eachimage with a convolutional neural network (CNN), the authors utilized a support vector machine (SVM) tocategorize the images into four groups: healthy, bacterial spot, early blight, and late blight. On a dataset containing 1,500 to 3,000 photos of tomato leaves, the authors tested their method and got an accuracy of 95.6%. This is a major improvement over earlier methods, which often had accuracy levels of 80% or higher [3].

Radha, N., & Swathika, R. proposed to use Convolutional neural networks (CNNs) are used in the researchto show a system for plant monitoring and disease detection in a polyhouse. The system is made up of a camera that takes images of the plants, a CNN that helps to determine whether they are healthy or sick, anda control system that responds to the predictions made by the CNN. Polyhouses are greenhouses that have a transparent covering like plastic or glass. This allows the plants to get more heat and sunshine, which mayresult in greater crops. A CNN model is trained using a collection of photos of healthy and sick plant leavesto increase accuracy. It is possible to improve and analyze the dataset's photos to get improved prediction outcomes. Future research contest this technique with different plant species [4].

Sagarika, G. K., Prasad, S. K., & Kumar, S. M. The method for classifying and predicting rice plant diseasesusing convolutional neural networks (CNNs) is presented in the research. A camera takes images of the plants, a CNN learns to identify if they are healthy or sick, and a prediction model is developed to determinehow severe the sickness will be. The proposed method is evaluated in the research using a dataset of images of both healthy and unhealthy paddy plants. The results indicate that the system can categorize images withan accuracy of 95% and predict the severity of a disease with an accuracy of 85% [5].

Bhagat, M., Kumar, D., Mahmood, R., Pati, B., & Kumar, M. The method for classifying diseases of bell pepper leaves explained in this study uses convolutional neural networks (CNNs). A camera takes images ofthe leaves, a CNN is taught to determine if they are healthy or unhealthy, and a web application shows the results. The outcomes demonstrate that the system can categorize images with an accuracy of 96% [6].

The study by Swathika, S. Srinidhi., N. Radha and K. Sowmya. (2021) addresses the crucial task of diseaseidentification in paddy leaves, leveraging Convolutional Neural Networks (CNNs) within the domain of deep learning. The authors contribute to this area by applying CNNs to paddy leaf disease identification, potentially enhancing accuracy and efficiency in comparison to traditional methods. Their work aligns withthe broader trend of employing advanced technologies to address agricultural challenges. The study also highlights the interdisciplinary nature of research, combining computer vision and agriculture to foster innovation in precision farming practices [7].

Deep convolutional training of neural networks was done by S.P. Mohanty et al by using a public database,to identify 26 illnesses and 14 species of crops in 54,306 picture datasets. The practiced model understood a 99.35% accuracy rate. When put to the test on some pictures instead of those that were utilized from the web the model still achieved a 31.4% performance for training. Ferentinos trained numerous CNN architectures, including using an open database, such as Alex Net, VGG, and Google Network has 58 different plant or disease pairings. The experimental findings showed that the most effective VGG convolution neural network served as the model architecture. This achieved a 99.53% success rate [8].

H. Park, J. S. Eun, and S. H. Kim et al. [9], released a paper in 2017 on the detection and prediction of cropdiseases using pictures and deep learning methods. Experts use a conventional method that is obvious to theunaided eye to locate and identify sugarcane leaf disease. However, large farms are not able to use this agricultural method. It can be costly and time-consuming to hire a specialist in underdeveloped countries like the Philippines. Sixty epochs were used to record 95% of the validation accuracy throughout training [9].

"Detection of Potato Diseases Using Segmentation of Images and Multiple classes Support Vector Machine"was the title of an article published in 2017 by Khan Wahid, Anh Dinh, Pankaj Bhowmik, and Monzurul Islam et al. Using action image processing and machine learning, they describe methods in this work for accepting a diagnosis based on leaf images. Food security and property agriculture can be achieved with theuse of trending phenotyping and disease identification. This algorithmically generated technique often diagnoses potato diseases using "Plant' Village," a publicly available plant photo collection. We report thatwe were able to classify 300 ill photographs with Vector with 95% accuracy [10].

III. ARCHITECTURE DIAGRAM

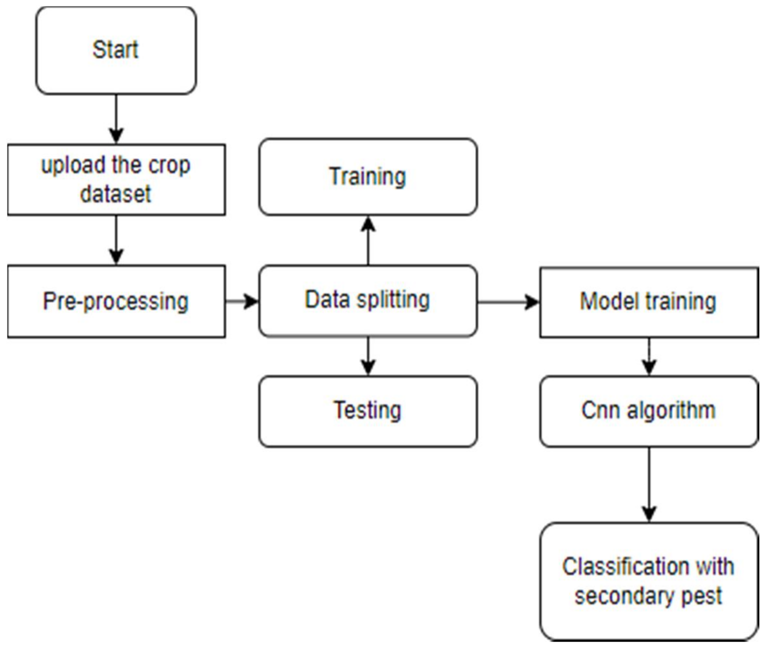

Fig. 1: System Architecture

This is the workflow of our project, first we collect the dataset which is having crop diseases images then we pre-process the images to enhance the images then we trained the convolutional neural network model with the crop disease dataset. After training the model we evaluate the performance of the model and we test our model by giving some healthy and disease crop images to know whether it predict the disease correctly or not. After finding the disease it compare with the data in python code which is having pesticidesand secondary crop solutions suitable for the predicted disease. After comparing the solution it can give thesolution to the user.

IV. PROPOSED SYSTEM

A. User Input

In this project we create user friendly frontend website using HTML, CSS and JavaScript in which we havevarious sections like Home page, Sign up, Sign in, upload image and Live prediction options. First user needto sign up to the website by giving their Name, Email, Phone number, Password and Location. After this the user need to login using the credentials like email and their password. After this the user entered into the upload image option in which the user need to upload the disease image of the crop to detect the disease. In this project we also provide live prediction which take the image of the crop using camera.

B. Classification of The Disease Using CNN

After the upload of the image by the user in the user interface it will be compared with the model which was trained by the convolution neural network deep learning algorithm using the crop disease dataset. In this crop disease dataset we are using 7 crops namely Apple, Grapes, Tomato, Corn, Peach, Blueberry and orange. Under each crop we have several diseases and healthy leaves images to train the CNN model. Aftercompare with the CNN trained model it will classify the disease of the crop leaves image and gives diseasename to the user in the user interface. In this Project we are using convolution neural network deep learningAlgorithm and python language to train the model with crop disease dataset. Before training the model we have to preprocess the dataset to make the training process easier and faster.

C. Recommendation Of Pesticides And Secondary Crops

After detecting the disease name of the crop which was uploaded by the user in the user interface, the system provide the pesticides list which was helpful to kill the disease or decrease the disease of the crop. Along with the pesticides the system also provide secondary crops list which was helpful to the main crop to improve its yield and also the secondary crops are helpful in controlling the pests which was reason for the crop disease.

V. PROPOSED METHODOLOGY

The major goal is to create a system that can effectively identify illness from diseased leaves, suggest appropriate pesticides for the disease that has been found, and suggest appropriate secondary crops for the crop that has been chosen in order to increase production and reduce disease. We employ two phases for that purpose: the first is called training, and the second is called testing. Phase 1 includes CNN-based training, image preprocessing, and image acquisition. Phase two involves acquiring images, pre-processingthem, classifying them, identifying diseases, and recommending pesticides and secondary crops. We have used datasets related to plant diseases for our experiments. The 50,000 photos above are contained in the data records. Seven crop species are represented in the images: orange, tomato, blueberry, corn, grape, apple,and peach.

A. Image Pre-Processing

Prior to being sent to the algorithm for testing and training, the image should be processed. In order to achieve this, the image in this project has been resized to 250 by 250 pixels. The color image we utilized eliminates the need for color conversion processes, and the pre-processed image is sent straight to the algorithm for testing and training.

B. Convolutional Neural Network

Following pre-processing, CNN is utilized for training, and the result is a trained model. Tensor flow is used to help write that CNN approach. We categorize the image that the system receives after pre- processing the test image by employing this model. The specific disease name, or the name of a healthy leaf if the leaf is free of disease, is then sent to a web application. Using this information, the web application identifies specific pesticides and secondary crops, enabling farmers to take the appropriate action to reduce the percentage of disease

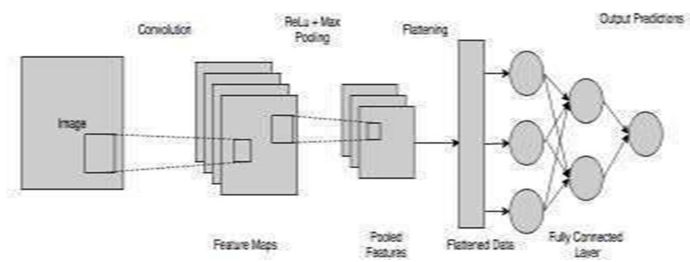

Fig. 2: Architecture of CNN

1) CNNs Consist of Several key Components

The core of CNNs consists of these layers. To the input image, they apply a collection of learnable filters, or kernels. To create feature maps, each filter performs element-wise multiplications while scanning the image in a sliding window fashion. The results are then added together. These feature maps record diversepatterns at different scales, including edges, textures, and forms. Being the first layer to do so, the convolutional layer uses a filter to apply to an array of pixels in order to extract features from the input image. Using small squares of input data, this layer will learn visual attributes and maintain the association between the pixels. In essence, this is a mathematical process that takes two inputs, the image matrix and the filter and outputs a feature map.

After convolution, an activation function like ReLU (Rectified Linear Unit) is applied element by elementto the network to introduce non-linearity. CNNs may learn intricate correlations in the data by doing this.By down sampling, pooling layers decrease the spatial dimensions of the feature maps. For example, max- pooling reduces computing complexity while preserving the most significant information by choosing themaximum value within a small region. CNNs usually consist of one or more fully connected layers following a number of convolutional and pooling layers. These layers carry out conventional neural network functions and flatten the high-dimensional feature maps into a vector. It is their duty to forecast the future based on the features that have been retrieved.

2) The Training Process of a CNN Involves

a) *Forward Propagation:* The network is fed forward with input data during training. A loss function (suchas cross-entropy for classification tasks) is used to calculate the error between the predicted and actual labels once predictions are made.
b) *Backpropagation:* Gradient descent optimization techniques are then used to transmit the error backwardthrough the network. To reduce error, this procedure modifies the filter and fully linked layer weights.
c) *Training Iterations:* The network goes through many iterations, adjusting the weights to improve its ability to recognize patterns and features in the data. This continues until the loss converges to a minimum.

C. Feature Extraction

After successfully completed the training of convolution neural network model with the crop disease dataset, we extract the features from the images of that data which was trained with the help of convolution neural network and this features will be helpful to detect the disease of the crop image which was uploaded by the user through the user interface.

D. Recommendation of Pesticides and Secondary Crops

After detecting the disease from the crop it compare with the data which have solutions which means pesticides and secondary crops suitable for the disease detected by the trained model using convolution neural network. The database include crop names, crop diseases, suitable pesticides and secondary crops forparticular diseases. The below table shows the pesticides and secondary crops suitable for particular crop disease.

Table 1: Pesticides and Secondary crops details

S.NO	CROP NAME	DISEASES NAME	PESTICIDES NAME	SECONDARY CROP
1	APPLE	Apple scab	Chlorothalonil, Captan, Miclobutanil	Herbs and Vegetables, Flowering plants, grains
		Apple black rot	Captan, Miclobutanil, Boscalid	
2	BLUEBERRY	Blueberry healthy	Malathion, Abamectin, copper-based fungicides	Grasses, Cover crops, Small fruits
3	CORN	Common rust	Triazoles, Strobilurnis, Mixed-model fungicides	Forage crops, Root crops, Vegetables
		Northern leaf blight	Methyl Benzimidazole Carbamates (MBCs)	
4	GRAPE	Black rot	Mancozeb, Strobilurins, Boscalid	Herbs and Vegetables, Flowering plants, grains
		Grape Esca(Black measles)	Bordeaux mixture, Tebuconazole	
5	ORANGE	Huanglongbing (Citrus greening)	Neonicotinoids, Organophosphates, Bactericides	Herbs and flowers, Grasses, Legumes
6	PEACH	Bacterial spot	Streptomycin, Copper-based sprays	Grasses, Cover crops, Small fruits
		Healthy	Insecticides, Bactericides, Fungicides	
7	TOMATO	Bacterial spot	Copper-based sprays, Streptomycin	Basil, Marigolds, Lettuce, Nasturtiums
		Early blight	Azoxystrobin, Mancozeb, Chlorothalonil	

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue II Feb 2024- Available at www.ijraset.com

VI. RESULT

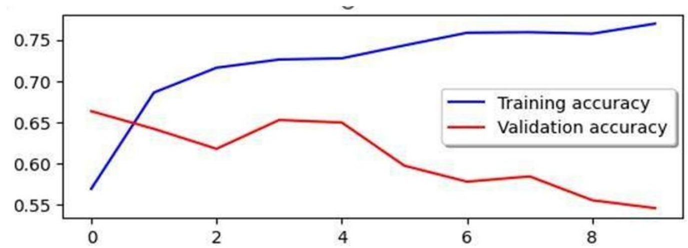

Fig. 3: Training and Validation Accuracy graph

The above Fig 3 indicates the training and validation accuracy of the convolutional neural network model after training the model with the crop disease dataset with 10 epoch values. The accuracy of the model increasing by increasing the epoch value. The training and validation accuracy of the model comes around 75%.

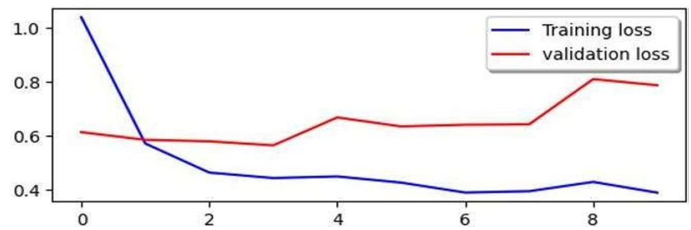

Fig. 4: Training and Validation Loss Graph

The above Fig 4 indicates the training loss and validation loss of the convolutional neural network model after training the Model with the crop diseases dataset with 10 epoch values. The Loss of the model decreasing by increasing the epoch value. 1/1 [==============================] - 0s 369ms/step True label: Corn_(maize) Northern_Leaf_Blight Predicted label: Corn_(maize)__Northern_Leaf_Blight

Fig. 5: Testing image of CNN

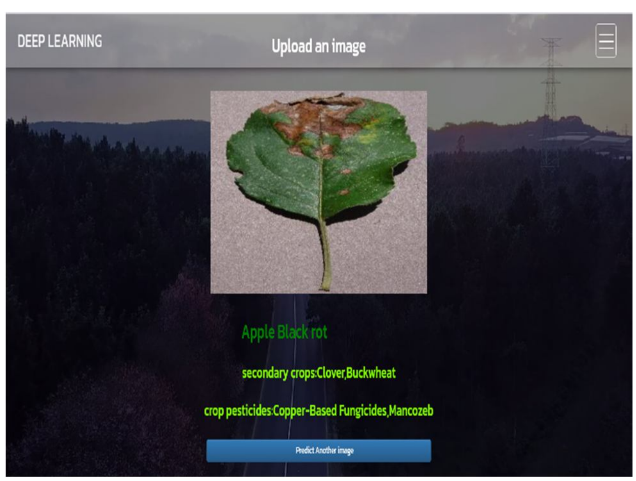

Fig. 6: Solutions Output

VII. CONCLUSION

Convolutional Neural Networks (CNNs) have proven to be remarkably effective in the identification of agricultural diseases, to sum up. The model efficiently recognizes and categorizes illnesses, allowing forprompt intervention to reduce losses to agriculture. CNN integration has increased disease prediction accuracy, assisting farmers in making well-informed decisions regarding crop management. Sustainablefarming methods have much to gain from the combination of technology and agriculture, as cutting-edge technologies have the ability to transform crop disease control and guarantee the world's food security.

VIII. FUTURE WORK

In future if there is any error occur in the system while detecting the crop disease it may be due to the lack of data of crop disease. We can overcome this issue by continuously training the convolution neural networkmodel with new data with better accuracy rates. After training the model with new crop disease data we canalso update the data of pesticides and secondary crop details suitable to the updated crop diseases. In futurewe can also recommend solutions from relational database by connecting it to the trained CNN model and user interface.

REFERENCES

[1] Kosamkar, P. K., Kulkarni, V. Y., Mantri, K., Rudrawar, S., Salmpuria, S., & Gadekar, N. (2018, August). Leaf disease detection and recommendation of pesticides using convolution neuralnetwork. In 2018 fourth international conference on computing communication control and automation (ICCUBEA) (pp. 1-4). IEEE.

[2] Monigari, V., Sri, G. K., & Prathima, T. (2021). Plant Leaf Disease Prediction. International Journal for Research in Applied Science and Engineering Technology, 9, 1295-1305.

[3] Habiba, S. U., & Islam, M. K. (2021, February). Tomato plant diseases classification using deep learning based classifier from leaves images. In 2021 international conference on informationand communication technology for sustainable development (ICICT4SD) (pp. 82-86). IEEE.

[4] Radha, N., & Swathika, R. (2021, March). A polyhouse: plant monitoring and diseases detection using cnn. In 2021 International conference on artificial intelligence and smart systems (ICAIS) (pp. 966-971). IEEE.

[5] Sagarika, G. K., Prasad, S. K., & Kumar, S. M. (2020, November). Paddy Plant Disease Classification and Prediction Using Convolutional Neural Network. In 2020 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT) (pp. 208-214). IEEE.

[6] Bhagat, M., Kumar, D., Mahmood, R., Pati, B., & Kumar, M. (2020, February). Bell pepper leaf disease classification using CNN. In 2nd international conference on data, engineering and applications (IDEA) (pp. 1-5). IEEE.

[7] Swathika, R., Srinidhi, S., Radha, N., & Sowmya, K. (2021, February). Disease Identificationin paddy leaves using CNN based Deep Learning. In 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV) (pp. 1004-1008).IEEE.

[8] Yu, H., Liu, J., Chen, C., Heidari, A. A., Zhang, Q., Chen, H., ... & Turabieh, H. (2021). Cornleaf diseases diagnosis based on K-means clustering and deep learning. IEEE Access, 9, 143824- 143835.

[9] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-basedplant disease detection. Frontiers in plant science, 7, 1419.

[10] Sandika, B., Avil, S., Sanat, S., & Srinivasu, P. (2016, November). Random forest based classification of diseases in grapes from images captured in uncontrolled environments. In 2016 IEEE 13th international conference on signal processing (ICSP) (pp. 1775-1780). IEEE.

[11] Dwivedi, R., Dey, S., Chakraborty, C., & Tiwari, S. (2021). Grape disease detection networkbased on multi-task learning and attention features. IEEE Sensors Journal, 21(16), 17573-17580.

[12] Sharma, R., Singh, A., Jhanjhi, N. Z., Masud, M., Jaha, E. S., & Verma, S. (2022). Plant Disease Diagnosis and Image Classification Using Deep Learning. Computers, Materials &Continua, 71(2).

[13] Harakannanavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. (2022). Plant leaf disease detection using computer vision and machine learning algorithms. GlobalTransitions Proceedings, 3(1), 305-310.