Precision Health Assessment: Disease Detection using CNN Algorithms

Author 1. C Vinay Kumar , Research Scholar, ECE Department , JNTUH University College of Engineering Science and Technology Hyderabad
Author 2. Dr.D.Srinivasa Rao, Professor in ECE Department, JNTUH University College of Engineering Science and Technology Hyderabad

Abstract:
A country's growth relies on both agricultural and industrial development. In India, two of the most widely consumed vegetables are tomato and potato. This article focuses on the detection of diseases in the leaves of these plants, offering valuable benefits to farmers and related sectors. By identifying and addressing leaf diseases promptly, the article aims to support farmers in improving crop yields and safeguarding the agricultural sector, which, in turn, contributes to the overall economic development of the country and its allied industries. Leaf disease detection holds significant importance as it enables the identification of the specific type of disease affecting the plant's leaves. This crucial information allows farmers and plant experts to take appropriate and targeted measures to combat the disease effectively. By knowing the exact nature of the leaf disease, they can implement precise treatments, preventive measures, or management strategies, thereby safeguarding the overall health and productivity of the plant. In this study, a Convolution Neural Network (CNN) is employed to enhance the accuracy of plant disease diagnosis. By utilizing this advanced technology, the aim is to minimize crop loss caused by plant diseases. Often, early changes indicative of disease are not readily apparent, making it challenging for farmers to detect issues promptly. However, the CNN's capabilities allow for early detection, enabling farmers to take timely action and effectively control the spread of diseases, thus preventing significant losses in crop yield. Automated systems offer valuable assistance by accelerating the convergence rate and reducing training time in various tasks. Additionally, they contribute to the improvement of the final classification accuracy. These benefits are particularly advantageous in domains such as machine learning and artificial intelligence, where efficient and accurate model training is crucial for optimal performance.

Keywords: **Computer Vision, Recognition of plant Disease, Deep learning, Leaf Disease Detection, Convolution Neural Network,**
DOI Number: 10.48047/nq.2023.21.6.nq23176 **NeuroQuantology2023;21(6): 1775-1784**

I. Introduction:

India, with a majority of its population heavily reliant on agriculture, particularly emphasizes the cultivation of tomatoes, one of the most common vegetables used across the country. Tomatoes are highly valued for their rich content of vital antioxidants, including vitamin E, vitamin C, and beta-carotene, as well as being a good source of potassium, a crucial mineral for maintaining good health. The cultivation area for tomatoes in India covers around 3,50,000 hectares, producing approximately 53,00,000 tons of tomatoes annually, which makes India the third largest tomato producer in the world.

However, due to the sensitivity of tomato crops and varying climatic conditions, diseases pose a significant challenge during all stages of growth, resulting in a crop loss of 10-30% due to disease-affected plants. Efficient identification of diseases in tomato plants is vital to prevent heavy losses in yield and the overall agricultural output. Manual monitoring of these diseases proves difficult and time-consuming due to their complex nature. Therefore, there is a pressing need to reduce the manual effort required for disease detection, while ensuring accurate predictions, and ultimately providing hassle-free solutions for the farmers.

Traditional data augmentation methods, such as rotation, flip, and translation, have limitations in achieving satisfactory generalization results. However, a solution to this problem lies in employing an advanced method for real-time disease detection on plant leaves. By utilizing a CNN (Convolutional Neural Network) classifier, the proposed system can effectively identify four distinct tomato plant illnesses and accurately differentiate a healthy leaf in real-time. This improved approach to data augmentation and disease detection enhances the system's ability to provide reliable and swift diagnoses, making it a valuable tool for farmers and researchers in the agricultural sector. The use of CNNs allows for more sophisticated pattern recognition and better generalization, which is crucial for obtaining accurate results and facilitating proactive measures to combat plant diseases efficiently.

Farmers are facing increasing challenges in detecting these pathogens, and their lack of information about these diseases hampers their ability to take necessary precautions on certain plants. The diagnosis of tomato plant diseases typically involves a systematic approach. It begins with identifying the part of the plant that is infected, which could be the leaves, stems, or fruits. Once the infected area is located, farmers need to observe specific variations, such as the appearance of brown or black patches, lesions, spots, or holes on the plant. These visual cues can provide essential clues about the nature of the disease.

Furthermore, farmers should also be vigilant for any signs of insect infestations, as pests can often be carriers of plant diseases or exacerbate the spread of pathogens.

To improve disease detection and diagnosis, farmers can benefit from the use of advanced technologies, such as the real-time disease detection system mentioned earlier, which employs CNN classifiers. These technologies can aid in early and accurate detection of plant diseases, allowing farmers to implement timely and targeted measures to mitigate the impact of these diseases on their crops. Additionally, providing farmers with access to educational resources and expert advice can empower them to make informed decisions and effectively manage plant diseases on their farms.

II. LITERATURE SURVEY

Numerous studies have been conducted on the identification and prevention of plant diseases, with a particular focus on tomato leaves. However, these studies do have certain limitations. Nevertheless, deep neural networks have made substantial advancements in improving image recognition accuracy.

The author provides a method for feature extraction that uses the Gabor wavelet transformation approach and aids in the disease diagnosis of tomato leaves. The collected features were fed into an SVM classifier for training, which subsequently determined the disease kind of the affected tomato leaf. The photos were resized, noise was removed, and the backdrop was removed during the pre-processing stage. The paper used the Gabor modification to identify the afflicted leaf's textual patterns and extract relevant characteristics. SVM with different kernel functions was used to classify diseases, and performance was tested using the cross-validation technique. According to the results of the experiment, an accuracy of 99.5% has been demonstrated [1].

Grape is a very important food crop in India and is very dominant in the fruit market. Infection to its plant on stem, leaves lead to decreased crop health and overall productivity. Diseases in leaves are brought upon by bacteria, virus, fungi etc. Fruit production suffers a huge blow because of such diseases and sometimes they become incurable too. In order to get rid of these diseases, a timely detection of it has to be done in order to cure the plant. The theory paper, describes leaf diseases that occur in grape leaves and their segregation using Support Vector Machine (SVM) classification. In order to achieve this, the infected leaf region is discovered by k-means clustering. After clustering is done, color and texture fields are generated. Lastly, classification is done to understand and determine the type of disease that has occurred on the leaf. Accordingly, 88.89% is the accuracy with which this way of classification can determine the leaf disease [2].

Diseases in plants have transformed into an issue because it causes noteworthy decrease in standard and quantity of rural growth.70% of the populace rely upon agribusiness in India. Ranchers have wide scope of decent variety to choose reasonable Fruit and Vegetable yields. Administration of natural product crops requires close observing particularly for the administration of maladies that can influence creation essentially. The proposed workflow in this paper is as follows: - Masking of pixels is done on the basis of some value for threshold that are come across by Otsu's method, mostly pixels that are green are concealed. Furthermore, the pixels which have values for green, blue and red as zeroes are removed and also the edges of cluster which have pixels are also eradicated [3].

To address the issue raised in the preceding study, the authors of [3] offered several segmentation, feature extraction, and classification techniques that identify and detect the type of disease utilizing the sick image for classification. The leaf image that was fed into the system was pre-processed by smoothing it or boosting it with histogram equalization. Different segmentation algorithms, such as K-Means clustering, have been presented to obtain the impacted region. Following that, the features were collected from the segmented region and calculated using GLCM. Following feature extraction, illnesses can be recognized using Artificial Neural Networks (ANN) or Back Propagation Neural Networks. The disadvantage of utilizing K-Means clustering to segment the image is that the proposed process is semi-automated, as the user must actively select the cluster containing the diseased region [4].

In [5], The authors adopted a straightforward methodology to classify diseased tomato leaves into distinct categories, including Tomato late blight, Septoria spot, Bacterial spot, Bacterial canker, Tomato leaf curl, and Healthy. Their implementation was based on a dataset consisting of 383 images taken with a digital camera. Image segmentation was performed using Otsu's method. To extract relevant features, color information was derived from the RGB color components, shape features were obtained using the region props function, and texture features were extracted from the GLCM (Gray-Level Co-occurrence Matrix).The feature extraction module integrates all the extracted features. For classification, supervised learning techniques were employed, specifically by training the decision tree classifier. While achieving a high accuracy, the decision tree model has inherent drawbacks. It may encounter over fitting when dealing with noisy data, and the level of user control over the model is somewhat limited.

The deep convolution neural network algorithm was used to forecast potato crop illness from leaves. It is used with the Plant Village dataset. This dataset comprises photographs of over 50000 distinct plant leaves. However, in this study, they worked with 2250 photos of potato leaves. The deep convolution neural network detects two prevalent diseases of potato plants, early blight and late blight, as well as healthy potatoes. This approach achieves an accuracy of 98.33%. The F1 score is 0.9826, the precision is 0.9851, and the recall is 0.9809. It has a 97% accuracy for healthy sample plants [6].

The authors of the study proposed a novel and innovative model called "locally adaptive 1DCNN" to address the task of identifying potato diseases on leaves. This model represents a significant advancement in disease detection techniques for potatoes. Through rigorous experimentation and evaluation, the model was found to achieve an impressive accuracy rate of 97.72%.By leveraging the 1DCNN architecture, the model demonstrated the ability to effectively capture local patterns and features from the input data, which is crucial for precise disease identification. The locally adaptive approach allowed the model to adapt and focus on specific regions of interest in the potato leaf images, enhancing its ability to distinguish between various diseases[7].

In the study [8], Muhammad Sufyan Arshad conducted an extensive study focusing on disease detection in various crops, specifically corn, tomato, and potato. To accomplish this, they employed the powerful ResNet with Transfer Learning, a popular deep learning model known for its effectiveness in image recognition tasks. The study aimed to classify 16 different classes of plant leaf diseases across all three crops. By utilizing the ResNet50 architecture, an impressive accuracy of 98.93% was achieved, showcasing the robustness and reliability of their approach in accurately identifying and distinguishing between different types of plant diseases. This achievement marks a significant advancement in the field of agricultural technology and holds great potential in improving crop management and disease control strategies.

The image dataset employed in this study is the Plant Village dataset, which can be accessed from the Kaggle website. To facilitate the functioning of the model, several Python libraries such as TensorFlow, NumPy, Pandas, and Matplotlib were utilized. The images were divided into training and testing databases, maintaining a ratio of 60:40, respectively.

The primary goal of this research was to enhance the accuracy of the model while simultaneously reducing the loss function. By doing so, the model becomes more proficient in distinguishing between different classes of diseased tomato leaves and healthy ones, resulting in more reliable and precise predictions. This effort to increase accuracy and decrease the loss function ensures that the model can better generalize to unseen data and perform effectively in real-world scenarios. The iterative process of adjusting model parameters, hyper parameters, and optimization techniques was undertaken to achieve these objectives. The various techniques, such as data augmentation, regularization, hyper parameter tuning, and different architectures to find the optimal configuration that yields improved accuracy and minimized loss. By optimizing the model's performance, it becomes a valuable tool in assisting plant pathologists and farmers to detect and manage diseases effectively, contributing to more sustainable agricultural practices. [9].

The authors proposed a novel model based on the Mobile Net convolution neural network architecture for the identification of tomato leaf diseases. Through a series of experiments, they discovered that adjusting the learning rate significantly impacted the model's accuracy. By decreasing the learning rate to 0.01, they observed an improvement in accuracy, achieving an impressive 86.7% success rate. Encouraged by this progress, the authors decided to explore further and lowered the learning rate even more, setting it to 0.001. This adjustment resulted in a remarkable boost in accuracy, reaching an impressive 90.3%, demonstrating the model's capability to make highly accurate predictions when trained with the appropriate learning rate [10].

III. PROPOSED METHODOLOGY

The objective is to develop an automated system that can determine the health status of a given plant by analyzing images of its leaves. If the plant is found to be unhealthy, the system will also identify the specific disease affecting it, enabling prompt corrective actions. Timely detection will facilitate the implementation of preventive measures, which can significantly improve agricultural outcomes. Delayed detection, on the other hand, not only leads to wasted time but also adversely impacts the overall production rate.

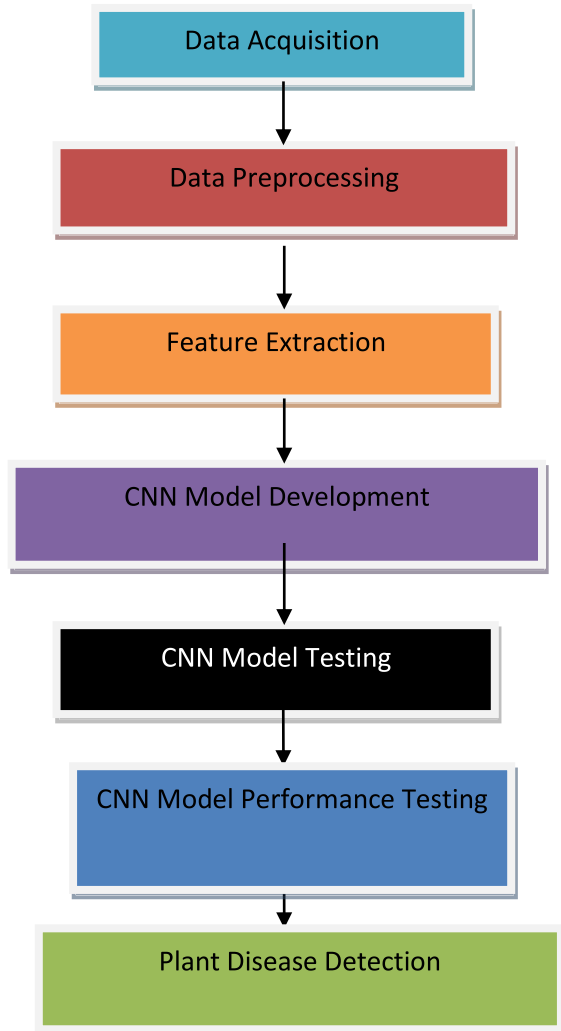

Fig.1. Proposed Block Diagram

System flow for disease detection:

The process of disease detection in plants initiates with the assembly of an image dataset containing plant leaf images as input pixels. Once the dataset is compiled, it undergoes pre-processing and feature extraction. Next, a convolutional neural network (CNN) model is developed, comprising three two-dimensional convolution layers, each consisting of 32 filters followed by max pooling with a stride of 2. Subsequently, the model's performance is evaluated using metrics such as precision, accuracy, and F1 score. If the model's performance meets the desired criteria, it is employed for predicting plant leaf diseases. Otherwise, adjustments are made through hyperparameter tuning to enhance its capabilities.

Data Acquisition:

The tomato leaf disease images used in this study were sourced from the Plant Village repository [5], a well-known database for plant disease images. To collect the necessary images for various diseases, a Python script was developed to download them efficiently. As a result, the acquired dataset encompasses a substantial number of approximately 18,160 images, categorically distributed into ten distinct classes representing different types of tomato leaf diseases. This extensive dataset ensures a comprehensive representation of various disease conditions, allowing for a more robust and accurate analysis and classification of tomato leaf diseases.

There are nine damaged tomato plant classes and one disease-free tomato plant class. This database is used for training and testing purposes. During installation, the training and testing picture databases are divided 60:40. The training set has 8842 photos in total, whereas the test set contains 4625 images in total. Images of all the main leaf diseases that potentially harm the tomato crop are included in the dataset. Each image that was downloaded was saved in the uncompressed JPG format and by default uses the RGB colour space.

Data pre-processing

Since the acquired dataset exhibited minimal noise, the need for noise removal as a preprocessing step was deemed unnecessary. To facilitate faster training and ensure computational feasibility, all images in the dataset were resized to a resolution of 60 × 60. Additionally, standardization of either the input or target variables was performed to expedite the training process and improve the numerical conditions of the optimization problem. This involved adjusting various default values related to initialization and termination to ensure their appropriateness for our specific purpose.

To normalize the images and bring all pixel values within the same range, we utilized the Z-score normalization technique. This process involved calculating the mean and standard deviation of the pixel values, allowing us to transform the image data into a standardized distribution. By applying the Z-score normalization, all images were prepared to have a consistent scale, which is essential for effective machine learning analysis and classification.

Convolutional Neural Network

The recommended model for leaf classification is Convolutional Neural Network (CNN). The activation functions utilized in this model are ReLU and softmax. ReLU eliminates negative inputs by setting them to zero, while softmax is employed since there are ten classes for classification, necessitating multi-class classification. The model's implementation relies on Python libraries such as TensorFlow, NumPy, Pandas, Matplotlib, and others to facilitate its functionality.

The initial layer in the CNN architecture is the convolution layer, responsible for feature extraction from the input image. It establishes correlations between the input pixels through a kernel or filter. The ReLU (Rectified Linear Unit) layer introduces nonlinearity to the CNN, enabling it to tackle more intricate tasks. Its mathematical representation is $f(x) = \max(0, x)$, effectively filtering out negative values. The Pooling Layer, which down samples the data, reduces the number of parameters while retaining crucial information for further processing. Here, max pooling is employed due to its selection of the most significant feature within a filter-defined area on the feature map.

Following the Pooling Layer, the Flattening Layer transforms the entire matrix into a vertical vector, which is then passed to the input layer [1]. Subsequently, the fully connected layer combines these features to create a model. Finally, an activation function like softmax or sigmoid is employed to define the model's outputs, enabling the interpretation and classification of the extracted features.

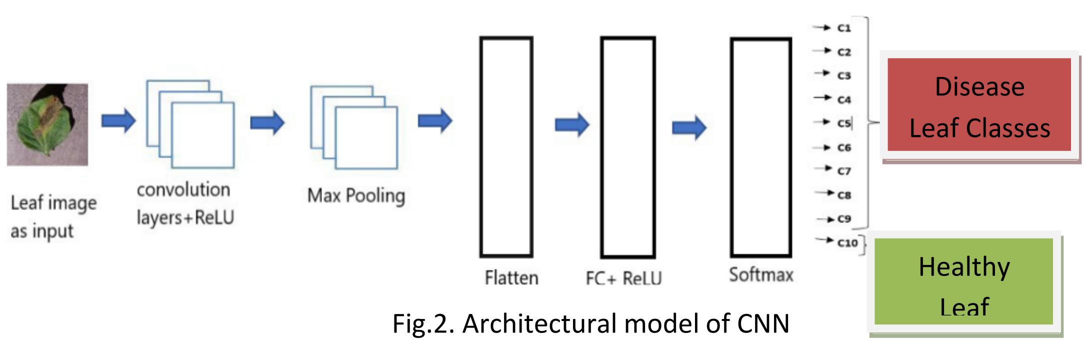

Fig.2. Architectural model of CNN

To construct a CNN model using open-source libraries like Keras and Tensor Flow GPU, we leverage the power of Tensor Flow, the widely-used open-source library for deep learning model development. Keras, a high-level programming interface, is employed to simplify the creation and training of deep learning models. It operates on top of TensorFlow, utilizing its computational capabilities and mathematical operations.

For training the model, we utilize Google Colab, a cloud-based Integrated Development Environment (IDE). This allows us to leverage the capabilities of TensorFlow GPU on the cloud for efficient and accelerated training of the CNN model.

By combining the strengths of these open-source tools, we can create and train a powerful CNN model for various image-related tasks with ease and efficiency.

The designed CNN model employs a sequence of layers to extract features from the input image. In the first layer, a 5*5 kernel is utilized to obtain 32 features. These features are then passed to the second layer, where a 3*3 kernel is applied to extract another set of 32 features from the outputs of the first layer. Moving on, the third layer utilizes a 3*3 kernel to extract 64 features from the second layer's outputs.

When using a single layer with a 5*5 kernel, the total number of parameters amounts to 25. On the other hand, employing two layers with 3*3 kernels results in a reduced number of parameters, specifically 18 (calculated as 3*3 + 3*3). This reduction in the number of parameters amounts to a significant 28% decrease, contributing to a more efficient model.

Dropout layers are incorporated in the model to mitigate over fitting by deactivating certain neurons during training, thus promoting generalization. Additionally, the softmax activation function is used to compute the probabilities of outputs, ensuring the final predictions are suitable for multi-class classification tasks.Throughout the layers, the CNN progressively reduces the number of parameters, allowing it to learn meaningful features and retain essential information while reducing redundancy. This characteristic results in a performance shape that decreases gradually, indicating the model's ability to uncover and understand critical patterns in the data as it progresses through the network.

Sample Test Image with Predicted and Expected Results

Picture Example	ResultsObtained	Expected Results
	- leaf mold passalora fulva 0.99999 - septoria leaf spot septorialycopersici 5.87832e06 - mosaic virus 2.34571e06 -late blight phytophthora infestans 1.02782e-06 - early blight alternariasolani 2.06558e-07	leaf mold passalora fulva

Strawberry Leaf | Potato Diseased Leaf | Grape Diseased Leaf | Tomato Diseased Leaf

IV.EXPERIMENTAL RESULTS:

The application of the convolutional neural network (CNN) approach to tomato plant leaves resulted in an impressive accuracy of 92% after conducting the experiment. The training and testing of the CNN model were carried out on the Google Colab platform. The training process involved iterating through 80 epochs to fine-tune the algorithm and optimize its performance.

This high accuracy showcases the effectiveness of the CNN method in accurately classifying tomato leaf diseases, demonstrating its potential as a powerful tool for plant disease diagnosis and monitoring. The utilization of Google Colab, a cloud-based platform with access to powerful computational resources, contributed to the successful training and evaluation of the CNN model. The use of 80 epochs allowed the model to undergo multiple iterations of learning, leading to the attainment of a robust and accurate classifier for tomato leaf disease recognition.

This proposed model is having efficient performance than the mentioned in which 87% of Train accuracy, Test Accuracy is 83%, and validation accuracy is 84% is obtained after identifying diseases in five classes. There are four disease classes while one is a healthy plant leaf class. Only 500 images of the dataset are covered.

By leveraging a substantial dataset, the proposed model can achieve more accurate disease classification. It is specifically designed to classify ten classes of tomato disease symptoms. The abundance of data ensures that the model can learn and generalize effectively; leading to improved accuracy in identifying the various disease conditions affecting tomato plants.

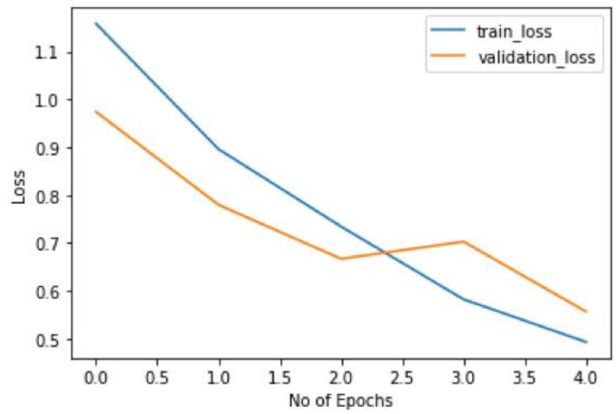

Fig.3.Training and Validation Loss

V. Conclusion:

The agricultural sector remains one of the most vital industries supporting a significant portion of the Indian population. As such, the detection of diseases in crops plays a crucial role in fostering economic growth and stability. Ensuring the health and productivity of crops through early disease detection can significantly impact the overall well-being of the agricultural sector and, in turn, the nation's economy.

Manual disease detection using leaf pictures is a laborious task for farmers, often yielding inaccurate results and consuming significant time. To overcome these limitations, there is a need for computational methods that automate the diagnostic and classification process using leaf drawings. The proposed approach involves utilizing a CNN model to observe leaf photos and accurately detect diseases in the shortest possible time.

To enhance the efficacy of this method, future work can focus on expanding the dataset by collecting more images of plant leaves. Additionally, the scope of this research can be extended by exploring various models and hybrid combinations to further improve disease detection accuracy. By applying this approach to other plant species and experimenting with different hyperparameter values, the potential impact and scope of this work can be amplified and diversified.

Future Scope:

In terms of Convolution neural network, modifications can be done by adjusting with different optimizers and loss functions. An increase in the number of layers can also be done. The scope of the number of diseases can be increased for a more expanded view on the subject by training the algorithm to accommodate a wide range of food and cash crops. A different architecture can also be used for implementing neural network such as Artificial Neural Network. More machine learning algorithms can be used to increase the accuracy of disease detection. An android application can also be created, which caters to a large user base.

Acknowledgement

Funding was provided by CSIR HRDG (Lt. No 23/(0037)/20/EMR-II). I would like to convey my

thanks to CSIR-HRDG-EMR-II.

VI. References:

1. Usama Mokhtar et al. “Tomato leaves diseases detection approach based on support vector machines”. In: Computer Engineering Conference (ICENCO), 2015 11th International. IEEE. 2015, pp. 246–250.
2. Pranjali B. Padol and Anjali A. Yadav, “SVM classifier based grape leaf disease detection”,pp. 3288-3294, 2016.
3. Smita Naikwadi and Niket Amoda, “Advances in Image ProcesingFor Detection of Plant Diseases”, pp. 168-175, 2013.
4. S. D. Khirade and A. B. Patil. “Plant Disease Detection Using Image Processing”. In: 2015 International Conference on Computing Communication Control and Automation. Feb. 2015, pp. 768–771. DOI: 10.1109/ICCUBEA.2015.153.
5. H Sabrol and K Satish. “Tomato plant disease classification in digital images using classification tree”. In: Communication and Signal Processing (ICCSP), 2016 International Conference on. IEEE. 2016, pp. 1242–1246
6. Ghosal, S., & Sarkar, K., “Rice Leaf Diseases Classification Using CNN With Transfer Learning,” in IEEE Calcutta Conference (CALCON), 2020.
7. Liu, F., & Xiao, Z., “Disease Spots Identification of Potato Leaves in Hyperspectral Based on Locally Adaptive 1D-CNN,” in IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), 2020
8. Arshad, M. S., Rehman, U. A., & Fraz, M. M., “Plant Disease Identification Using Transfer Learning,” in International Conference on Digital Futures and Transformative Technologies (ICoDT2), 2021.
9. Al-Tuwaijari, J. M., Jasim, M. A., & Raheem, M. A.-B., “Deep Learning Techniques Toward Advancement of Plant Leaf Diseases Detection,” in 2nd Al-Noor International Conference for Science and Technology (NICST), 2020.
10. Elhassouny, A., &Smarandache, F., “Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks,” in International Conference of Computer Science and Renewable Energies (ICCSRE), 2019.
11. Mohammad El-Helly, Ahmed Rafea, Salwa El-Gammal, “An Integrated Image Expert Processing System for Leaf Disease Detection and Diagnosis”, Central Lab. For Agricultural System (CLAES), Agricultural Research Center(ACR), Giza,Egypt.
12. Sachin D. Kirade and A. B. Patil,"Plant Disease Detection Using Image Processing," International Conference on

Computing Communication Control and Automation – 2015.

13. J. Liu and Xuewei Wang. "Tomato Diseases and Pests Detection Based on Improved YoloV3 Convolutional Neural Network". Frontiers in Plant Science, Vol. 11, No. 898, pp. 1– 12, 2020.
14. Yiping Chen, Jun Meng, and Wu Qiufeng.. "Dcgan-Based Data Augmentation for Tomato Leaf Disease Identification." IEEE Access, 2020, Vol. 8, pp. 98716–98728.
15. Y. Sook, L. Jaesu, SP. Dong, AF. Fuentes, and Y. Sook. Frontiers in Plant Science, Vol. 9, No. 1162, pp. 1–15, 2018. "High-Performance Deep Neural Network-Based Tomato Plant Diseases and Pests Diagnosis System With Refinement Filter Bank."
16. Xu P. ve ark., "Automatic wheat leaf rust detection and grading diagnosis via embedded image processing system", Procedia Computer Science, 107, 836-841, 2017.
17. Liming X. &Yanchao Z., "Automated strawberry grading system based on image processing", Computers and Electronics in Agriculture, 71S (2010), S32-S39, 2010.
18. Burgos-Artizzu X. P. ve ark., "Analysis of natural images processing for the extraction of agricultural elements", Image and Vision Computing, 28 (2010), 138-149, 2010.
19. David, H. E., Ramalakshmi, K., Gunasekaran, H., & Venkatesan, R., "Literature Review of Disease Detection in Tomato Leaf using Deep Learning Techniques," in 7th International Conference on Advanced Computing and Communication Systems (ICACCS), 2021.
20. Gehlot, M., & Saini, M. L., "Analysis of Different CNN Architectures for Tomato Leaf Disease Classification," in 5th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE), 2020.
21. Kibriya, H., Rafique, R., Ahmad, W., & Adnan, S., "Tomato Leaf Disease Detection Using Convolution Neural Network," in International Bhurban Conference on Applied Sciences and Technologies (IBCAST), 2021.
22. Radha, N., & Swathika, R., "A Polyhouse: Plant Monitoring and Diseases Detection using CNN," in International Conference on Artificial Intelligence and Smart Systems (ICAIS), 2021.
23. Al-Tuwaijari, J. M., Jasim, M. A., & Raheem, M. A.-B., "Deep Learning Techniques Toward Advancement of Plant Leaf Diseases Detection," in 2nd Al-Noor International Conference for Science and Technology (NICST), 2020.