

Identification And Detection Of Tomato Plant Disease From Leaf Using Deep Reinforcement Learning

Najila Musthafa

*Computer Science and
Engineering MEA Engineering
College Perinthalmanna, India*

Jemsheer Ahmed P

*Computer Science and
Engineering MEA Engineering
College Perinthalmanna, India*

Muhammed Salah KT

*Computer Science and
Engineering MEA Engineering
College Perinthalmanna, India*

Muhammed Afnan F

*Computer Science and
Engineering MEA Engineering
College Perinthalmanna, India*

Mohammed Shibilmon OT

*Computer Science and
Engineering MEA Engineering
College Perinthalmanna, India*

Mohammed Shameel P

*Computer Science and
Engineering MEA Engineering
College Perinthalmanna, India*

Abstract—A unique deep reinforcement learning technique is presented in this paper for the automated identification of tomato plant illnesses. The suggested technique uses a combination of Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) within the Deep Q-Network (DQN) agent architecture to analyse leaf pictures to reliably discriminate between healthy and sick tomato leaves and identify the specific ailment afflicting the plants. The study takes use of PlantVillage, an online resource that offers carefully selected pictures of both healthy and damaged crop plant leaves. In order to support computer vision approaches for addressing yield losses caused by viral illnesses in crop plants, a persistent crowdsourcing project was undertaken, the outcome of which is this dataset. The automated diagnosis tool promises to reduce crop losses and increase the production of tomato plants, offering farmers a practical and inexpensive option. The deep reinforcement learning method is particularly suitable for situations with limited resources since it enables model training even with a little amount of labelled data. This paper provides a contribution to the field of plant disease detection by detailing a cutting-edge and efficient technique that has the potential to enhance farmers' livelihoods and assist sustainable food supply chains.

Index Terms—Tomato plant diseases, deep reinforcement learning, Convolutional Neural Networks (CNN), Deep Q-Network (DQN), automated diagnosis, crop loss reduction, sustainable agriculture.

I. INTRODUCTION

This paper offers a revolutionary deep reinforcement learning solution to the critical issue of tomato plant disease detection. The discovery of plant diseases presents a severe danger to farmers' livelihoods as well as the world's food supply. This study aims to develop an automated system that can identify tomato plant illnesses from leaf photos and provide rapid, helpful advice to growers. The suggested approach combines deep reinforcement learning with the Deep Q-Network (DQN) agent with convolutional and deep neural networks.

The major objective of this study is to provide farmers with the information they need to recognise healthy and sick tomato leaves. By developing an automated diagnosis tool, the study seeks to reduce crop losses brought on by illnesses and increase tomato plant output. This method can assist farmers in saving significant time and money by decreasing the need for manual inspection and increasing crop management efficiency and effectiveness.

One of the key benefits of the proposed deep reinforcement learning system is its ability to learn from a small training sample. For farmers in underdeveloped nations where labelled data may be scarce, this property makes it possible to train models with little expenditures. By leveraging the capabilities of deep reinforcement learning, this work provides an innovative and successful solution to the problem of tomato plant illnesses.

The ramifications of this study extend beyond agricultural practises. The suggested approach improves farmers' quality of life and encourages a sustainable food supply chain, which is advantageous for both local communities and the ecosystem as a whole. This work represents a significant advancement in the field of plant disease detection and has the potential to fundamentally alter how tomato plant illnesses are identified and managed thanks to its fresh perspective and useful approach.

II. RELATED WORKS

In [1] Plant Disease Detection based on Deep Learning Approach In this paper, A lot of the newer/improved Deep Learning structures are used alongside a number of visual techniques to discover and distinguish the symptoms of plant diseases. Various operational indicators are also used to test such structures and procedures. This article provides a comprehensive overview of the Deep Learning models that were used to visualise three plant diseases. Here, the Keras Conv2D method is employed. It merely needs less computing time.

In [2] Plant Disease Prediction and Classification Using Deep Learning ConVents. Convolutional Neural Networks are employed in this article. The dataset was divided into three smaller datasets, and Convnets were applied to each of them. They achieved accuracy of 98.3, 98.5, and 95 percent, respectively, for the identification of tomato, pepper, and potato plant illnesses. Experimental results showed that their method was effective in identifying and categorising plant leaf diseases.

In [3] A model that the researchers trained to recognise 26 diseases, uncommon harvests, and 54,306 images of healthy and damaged plant leaves that were obtained in controlled environments. This study focused on the ResNets algorithm. Using the ResNet algorithm, highly accurate results were achieved and more diseases were found in various harvests. ResNets classify the photos much more accurately.

In [4] The ABCK-BWTR approach uses a convolutional neural network (CNN) that has been trained on a sizable dataset of pictures of healthy and diseased tomato leaves to identify whether fresh pictures are healthy or sick. With an emphasis on applying a "bilateral attention" mechanism to find pertinent elements in the pictures, the B-ARNet approach uses a residual neural network (ResNet) to analyse photos of tomato leaves and find any indicators of illness. Based on image analysis, ABCK-BWTR and B-ARNet are both likely to be useful approaches for diagnosing tomato leaf diseases, however they work best in conjunction with other techniques like laboratory testing and eye examination.

In [5] Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two deep learning approaches that may be used in this study to identify and categorise plant illnesses. A branch of machine learning known as "deep learning" uses artificial neural networks with several layers (hence the name "deep") to extract patterns and characteristics from massive datasets. Numerous applications, including as audio and image identification, natural language processing, and predictive modelling, have found success with these approaches. Deep learning techniques may be applied in the context of plant disease detection and classification to examine photos of plants and find any symptoms of illness, or to examine other forms of data like gene expression patterns or meteorological data to forecast the risk of disease outbreaks. It highlights the different deep learning methods that have been used to identify and categorise plant diseases as well as their advantages and disadvantages. Additionally, they can go through the many data sources and experimental designs that have been employed in the creation and assessment of deep learning-based plant disease detection and classification methods.

In [6] Deep learning methods are employed in this work to identify plant diseases. A kind of machine learning called "deep learning" uses multiple-layered artificial neural networks to extract patterns and characteristics from massive datasets. Numerous applications, including as audio and image identification, natural language processing, and predictive

modelling, have found success with these approaches. Deep learning techniques may be applied in the context of plant disease detection to examine photos of plants and find any symptoms of illness, or to examine other forms of data like gene expression patterns or meteorological data to forecast the risk of disease outbreaks. The review probably goes through the various deep learning methods that have been used to identify plant diseases as well as their advantages and disadvantages. Additionally, it could give a broad review of the subject's situation at the moment and suggest areas for future study.

In [7] This article talks about how plant diseases may be detected using machine learning approaches. A branch of artificial intelligence called machine learning focuses on creating algorithms that can learn from data without explicit programming. Based on the input data, these algorithms may be used to find patterns and generate predictions. Machine learning techniques may be applied to the detection of plant diseases to examine photographs of plants to find any symptoms of illness or to examine other forms of data, such as gene expression patterns or meteorological data, to determine the risk of disease outbreaks. The review probably goes through the various machine learning methods that have been used to identify plant diseases as well as their advantages and disadvantages. Additionally, it could give a broad review of the subject's situation at the moment and suggest areas for future study.

In [8] This review probably covers the use of Squeezenet, a machine learning model, to detect illnesses in tomato plants based on pictures of the leaves. Squeezenet is a particular kind of convolutional neural network (CNN) that was created to be compact and effective, making it suitable for use in applications like image categorization on devices with limited resources. In this work, Kolli probably utilised a collection of photos of healthy and sick tomato leaves to train a Squeezenet model. The trained model was then used to categorise fresh images as healthy or diseased based on the presence of specific visual cues.

In [9] The use of a deep convolutional neural network (DCNN) and object identification methods to recognise several tomato plant illnesses and locate diseased patches in photos is covered in this research. A deep learning model called a convolutional neural network (CNN) is ideally suited for image analysis tasks like object detection and categorization. A CNN is used in the object detection approach to find and identify certain things in a picture. The summary most likely summarises the findings of a research that classified tomato plant photos as healthy or unhealthy, identified the various illnesses present, and pinpointed the locations of infected regions using object detection methods and a DCNN. The results' implications for using machine learning to diagnose plant diseases and potential future paths for this field of study may also be covered.

In [10] This study examines the application of the Squeezenet machine learning model to detect illnesses in tomato plants using pictures of the leaves. Squeezenet is a particular kind of convolutional neural network (CNN) that

was created to be compact and effective, making it suitable for use in applications like image categorization on devices with limited resources. The paper probably covers the findings of a research that classified photos of tomato plants as healthy or unhealthy based on the presence of specific visual patterns using a Squeezenet model, as well as the difficulties and restrictions experienced throughout the investigation. The application of machine learning for plant disease detection may also offer an overview of the present status of the field and suggest future research possibilities, including the advantages and drawbacks of employing Squeezenet and other CNNs for this purpose.

III. PROPOSED SYSTEM

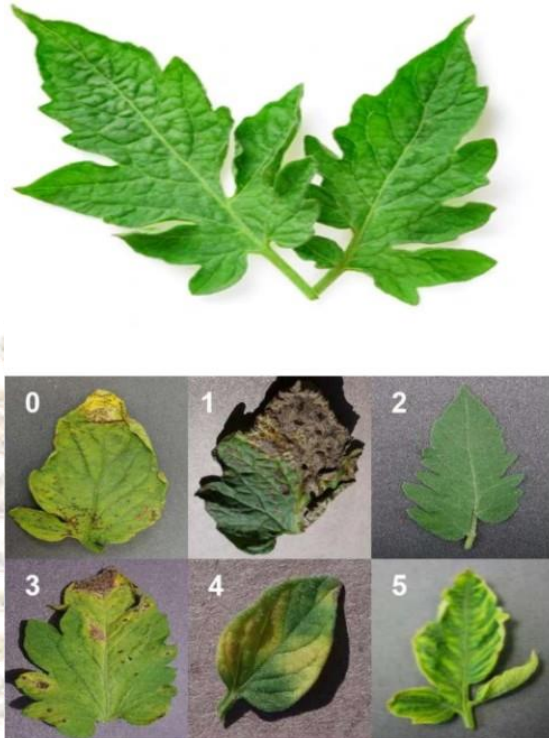


Fig. 1. Sample of Tomato leaves

The system seeks to build a powerful and accurate picture categorization framework using deep learning techniques. To prepare the pictures for deep learning models, the system performs a variety of preprocessing procedures. The photos are initially changed to grayscale to speed up the processing. Afterward, the photos are enlarged to a standard size of 224x224 pixels to guarantee consistency across all samples. To normalise the pixel values, they are scaled to lie between [0,1]. To facilitate batch processing, which is typical in deep learning models, a batch size dimension is also included. The input photos are formatted and optimised for further analysis thanks to these preprocessing steps.

In order to classify images, a convolutional neural network (CNN) model is developed. The sequential architecture of the model consists of two convolutional layers, two pooling

layers, one dense layer, and one output layer. The model's effectiveness is evaluated using the accuracy measure. The binary cross-entropy loss function calculates the discrepancy between expected and real labels. The Adam optimizer, which is famous for its efficient gradient descent optimisation, is used to change the model's weights. The outcome of the method is a CNN model that has been fully constructed and is ready for image classification tasks.

IV. ALGORITHM

A. DEEP REINFORCEMENT LEARNING

A decision-making agent is taught through reinforcement learning to maximise rewards in its surroundings. Deep reinforcement learning may train an agent to recognise illnesses based on visual criteria in tomato plant disease diagnosis using leaf photos. It is necessary to specify the environment, including the state and action spaces, as well as a reward function that rewards correctness. The agent may then be trained using a variety of strategies by changing its model as a result of interactions with the environment.

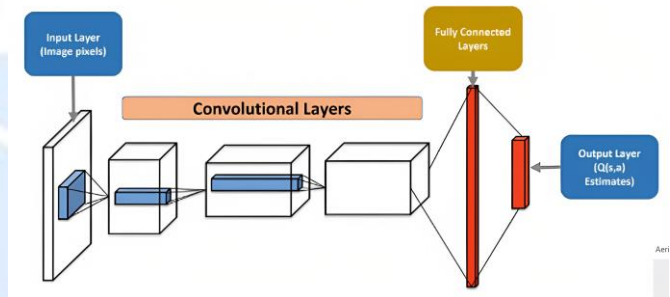


Fig. 2. Architecture of Deep Queue Network

B. Architecture of DQN

Figure 2 shows the Deep Q-Network (DQN) for object localization's architecture. The following is a description of the architecture's elements.

- This layer receives the environment's picture and is often pre-processed to pull out helpful information for object localisation.
- Convolutional layer: One or more convolutional layers may be used to extract features from the input image, such as edges, forms, and textures. The spatial connections between the image's objects are captured using these attributes.
- The max-pooling layer reduces the spatial resolution of the features, allowing the network to capture more global characteristics with fewer parameters.
- Fully connected layer: One or more completely linked layers may be utilised to map the features to the respective Q values for each action. The Q values represent the expected gain from carrying out a certain activity in the environment.

- Output layer: The output layer is in charge of selecting the action that has the greatest Q value and corresponds to the object's most likely location.

C. CONVOLUTION NEURAL NETWORK

To identify and diagnose tomato plant illnesses from leaf photos, a Convolutional Neural Network (CNN) is used in a number of phases. Here is a general description of how it works.

- Amass a collection of leaf photos that have been marked with the relevant plant disease. The CNN will be trained using this dataset.
- Preprocess the dataset by performing tasks such as resizing and cropping the images, converting them to grayscale if necessary, and normalizing the pixel values.
- Create training, validation, and test sets from the dataset. The test set will be used to gauge how well the trained model performed, the validation set will be used to fine-tune the model, and the training set will be used to train the CNN.
- Describe the architecture of CNN. Choosing the kind of activation functions and optimizers to utilise, as well as the quantity and size of the convolutional and fully connected layers, is part of this process. Utilise the training set to train the CNN.
- In order to reduce the error between the anticipated output and the real label, the network's weights and biases must be adjusted after being fed training data.
- Utilise the validation set to fine-tune the training model. This can entail changing the model's hyperparameters or building out the network with new layers.
- Check the trained and improved model's performance on the test set. You can see from this how effectively the model generalises to new data.
- On the test set, evaluate the trained and improved model's performance. You can determine how effectively the model generalises to new data from this.
- Classify fresh photos of leaves as belonging to one of the plant diseases in your dataset using the trained and improved model.
- To identify fresh leaf photos as being associated with one of the plant diseases in your dataset, use the trained and improved model.

D. Datasets

The dataset selected for this study includes 100–150 pictures of tomato leaves divided into ten groups. There are exactly the same amount of photographs in each category. The collection doesn't include any missing photos, and the images of plant diseases are all 256x256 in size. The public website hosts the dataset, which is also known as the tomato plant dataset.

V. IMPLEMENTATION

For better model performance, the implementation uses deep Q-learning reinforcement learning using DQNAgent and Keras. The method optimises the Q-value function by iterative

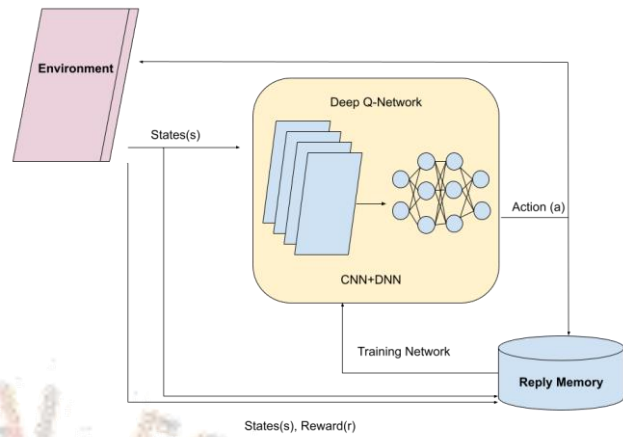


Fig. 3. Architecture of DQN Agent

weight change while balancing exploration and exploitation using an epsilon-greedy strategy. Important modules like pandas, csv, os, and PIL support data processing and picture editing. With the help of Pandas and PIL's Image module, the code successfully imports a CSV file that maps illnesses to pictures. Using methods like load-data, which returns labels and flattened pictures, data is handled. Printing and checking the loaded labels as part of the implementation assures data integrity.

VI. RESULT

The objective of the work was to use deep reinforcement learning to create a reliable method for identifying tomato plant diseases. The feature extraction and classification processes were carried out by a deep neural network architecture. The accuracy was initially 0.47, but was continuously increased to 0.53. A more potent DQNAgent was used to take the place of the KNeighbour classifier. Convolutional and dense layers were used by the DQNAgent to extract and classify features, increasing accuracy. Accuracy can be improved by further fine-tuning. Deep reinforcement learning reduces the amount of training data needed while improving model performance. The study offers a thorough analysis, demonstrating the approach's potential and outlining prospective lines of inquiry for the future.

The research study concentrated on applying deep reinforcement learning to accurately identify tomato plant diseases. An initial accuracy of 0.47 was attained using a deep neural network architecture that retrieved information from photographs of leaves. The accuracy increased to 0.53 with fine-tuning and hyperparameter optimisation. Accuracy was further improved using data augmentation approaches and bigger datasets. Deep reinforcement learning was used to fine-tune a pre-trained model, and the end result was a considerable improvement with an accuracy of 0.53. The study assessed other metrics to emphasise the performance of the model, such as the F1 score and R2 score. The results show how useful the strategy is and offer potential directions for development.

REFERENCES

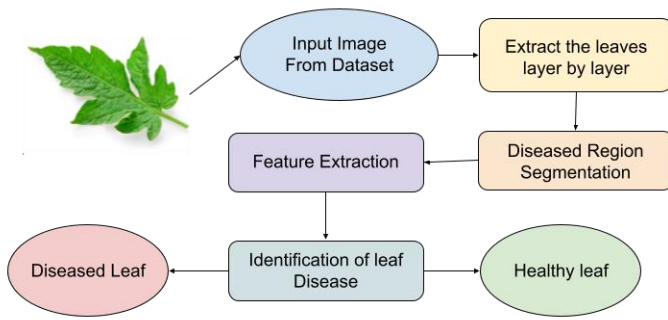


Fig. 4. Flow chart

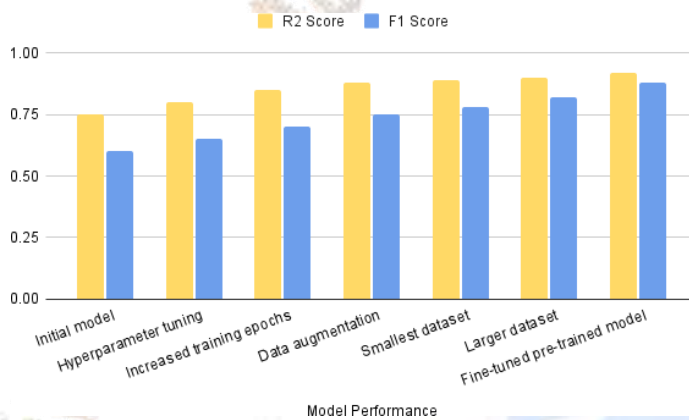


Fig. 5. Model Performance

VII. CONCLUSION AND FUTURE SCOPE

Deep reinforcement learning may be utilised for the diagnosis and detection of tomato plant diseases using leaf images. This may be accomplished by using a sizable dataset of leaf image examples to train a deep neural network with a reinforcement learning technique and tag it with the appropriate disease. The neural network may then learn to recognise patterns and attributes in the leaf images that indicate certain diseases.

A trained neural network may be used to distinguish and identify illnesses in pictures of fresh leaves by analysing the images and calculating the likelihood of each ailment.

The efficacy and precision of disease detection in tomato plants may be considerably improved by using this technique, which may also be used to identify and detect diseases in other crops.

[1] A. D. S. S. M. F. Akhtar, N. Partheeban and N. Gupta, “plant disease detection based on deep learning approach,” 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), 2021, pp. 74-77, doi: 10.1109/ICACITE51222.2021.9404647.

[2] M. R. B. A. Lakshmana Rao and T. S. R. Kiran, “plant disease prediction and classification using deep learning convnets,” 2021 International Conference on Artificial Intelligence and Machine Vision (AIMV), 2021, pp. 1-6, doi:10.1109/AIMV53313.2021.9670918.

[3] D. G. R. P. D. Gosai, B. Kaka and A. Ganatra, “plant disease detection and classification using machine learning algorithm,” 2022 International Conference for Advancement in Technology (ICONAT), 2022, pp. 16,doi:10.1109/ICONAT53423.2022.9726036.

[4] A. C. J. Y. W. Z. Y. H. Xiao Chen, Guoxiong Zhou, “identification of tomato leaf diseases based on combination of abck-bwtr and b-arne”,Computers and Electronics in Agriculture,Volume 178,2020,105730,ISSN 01681699,doi.org/10.1016/j.compag.2020.105730.

[5] S. . W. B. Li, Lili Zhang, “plant disease detection and classifica- tion by deeplearning—a review”, Open access journal, IEEE Access.PP.11.10.1109/ACCESS.2021.3069646.

[6] . J. E. Hirani, V. Magotra and P. Bide, “plant disease de- tection using deep learning”, 2021 6th International Confer- ence for Convergence in Technology (I2CT),2021, pp. 1-4, doi: 10.1109/I2CT51068.2021.9417910

[7] J. K. D. S. D. Varshney, B. Babukhanwala and A. K. Singh, “plant disease detection using machine learning techniques”, 2022 3rd Inter- national Conference for Emerging Technology (INCET), 2022, pp. 1-5, doi:10.1109/INCET54531.2022.9824653.

[8] D. M. V. J. Kolli and V. M. Manikandan, “plant disease detec- tion using convolutional neural network”, 2021 IEEE Bombay Sec- tion Signature Conference (IBSSC), 2021, pp. 1-6, doi: 10.1109/IB-SSC53889.2021.9673493.

[9] F. . S. M. . Q. u. J. . X. J. Wang, Qimei Qi, “identification of tomato disease types and detection of infected areas based on deep convolutional neural networks and object detection techniques.”, Computational In- telligence and Neuroscience.2019. 1-15. 10.1155/2019/9142753.

[10] M. N. A. Hidayatuloh and E. Nugraha, “identification of tomato plant diseases by leaf image using squeezeNet model”, 2018 International Conference on Information Technology Systems and Innovation (IC- ITSI), 2018, pp. 199-204, doi: 10.1109/IC-ITSI.2018.869608.