GREENLINK:
ADVANCING PLANT GROWTH WITH AI

A DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE
OF

MASTER OF TECHNOLOGY
IN
DATA SCIENCE

Submitted by

ANUSHKA UPADHYAYA

(2K22/DSC/03)

Under the supervision of

MR. RAHUL

DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi 110042

MAY, 2024

DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

CANDIDATE'S DECLARATION

I, Anushka Upadhyaya, Roll No. 2K22/DSC/03, hereby declare that the project Dissertation titled "GreenLink: Advancing Plant Growth with AI" which is submitted by me to the Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of degree of Master of Technology, is an authentic record of my own work carried out during the period from August 2022 to May 2024 under the supervision of Mr. Rahul.
This work has not previously formed the basis for the award of any Degree, Diploma, Fellowship or other similar title or recognition.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

Signature of Supervisor

DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

CERTIFICATE

I hereby certify that the Research Dissertation titled "GreenLink: Advancing Plant Growth with AI" which is submitted by Anushka Upadhyaya (2K22/DSC/03) to the Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the research work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: New Delhi — Mr. Rahul

Date: 27.05.2024 — **SUPERVISOR**

DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

ACKNOWLEDGEMENT

I wish to express our sincerest gratitude to Mr. Rahul for his continuous guidance and mentorship that he provided me during the research. He showed me the path to achieve the desired targets by explaining all the tasks to be done and explained to me the importance of this research as well as its industrial relevance. He was always ready to help and clear the doubts regarding any hurdles in this research. Without his constant support and motivation, this project would not have been successful.

Place: New Delhi Anushka Upadhyaya

Date: 27.05.2024

Abstract

The research is divided into two parts - The first part to the research involves Integrating K-Fold Cross-Validation with Convolutional Neural Networks (CNN) for Plant Species and Pathogen Detection, that focuses on precisely identifying and predicting various plant species using Artificial Intelligence (AI) techniques like CNN and K-fold Cross-Validation and also accurately diagnosing the disease that the plant under consideration is affected by. In the research, we utilized a rich dataset from the PlantVillage repository, and our models were trained on over 54,306 images that also cover 14 major crop species. The model identifies the plant and pathogens and then focuses on the accuracy of identifying the right kind of species and pathogens. The growth prediction model predicts the best conditions for the plant to grow. In the work, the results were successfully tested and witnessed 81 % accuracy in the Plant and Pathogen detection model and the growth prediction model's low mean squared error i.e. 21 % supports accurate trend forecasting for optimizing plant care. The second part to the research contributes towards Optimising Plant Health with Q-Learning, that introduces a novel approach to plant care, leveraging deep reinforcement learning (DRL) algorithms, such as Q-learning, to simulate diverse plant growth scenarios. The research aims to develop a system that provides a tailored approach to determine the best-case scenario for plant species' maximum or optimum growth or development. The PlantVillage dataset used for the research is well labeled and considered as it fulfills the set environment for the agent to produce rewards on. The research contributes significantly to environmental sustainability and ecological awareness, fostering a deeper connection between humans and the natural environment by providing AI-powered cultivation strategies.

Keywords: "Convolutional Neural Network, Q-Learning, PlantVillage Dataset, K-Fold Cross Validation, Plant and Pathogen Detection, Plant Health Management, Deep Reinforcement Learning, Cultivation Strategies"

Contents

List of Tables

List of Figures

List of Symbols, Abbreviations

%	Percentage
$\sum$	Summation
I	Input Image (or Input Matrix)
K	Kernel (or filter), a small matrix used for the convolution operation
i, j	Indices representing the position in the output feature map
m, n	Indices used to iterate over the elements of the input image and the kernel
x	The input to the activation function, which can be any real number
X	input vector from the flattened feature map
b	Bias Vector
W	Weight Matrix
O	Output Vector
z_i	The score for Class i
k	The number of times we need to iterate
s, a	State-Action Pair
Q	Q-Value
α	Learning rate
r	Immediate Reward
γ	Discount Factor
s'	The next state
a'	The next action
CNN	Convolutional Neural Network
AI	Artificial Intelligence
DRL	Deep Reinforcement Learning
ML	Machine Learning
DL	Deep Learning
A2C	Actor-Critic with Advantage
DQN	Deep Q-Networks
IoT	Internet of Things
DDQN	Double Deep Q-Networks
RL	Reinforcement Learning
DRQN	Deep Reinforcement Q-Network
RNN	Recurrent Neural Network
DSS	Decision Support Systems
VGG	Visual Geometry Group
SVM	Support Vector Machine
PI-GAN	Plant-Image Genetic Adversarial Network
PI-CNN	Plant-image Convolutional Neural Network
XAI	Explainable AI

DS	Data Science
1-D	One Dimensional
API	Application Programming Interface
MSE	Mean-Squared Error

Chapter 1

INTRODUCTION

1.1 Blueprint

We have built two models and used two approaches: First being the Plant Species and Pathogen Identification Model, which precisely identifies the correct plant species and the diseases caused to them, and the second is the Growth Prediction Model, which accurately detects the growth of plants. Our first approach is taken towards using K-fold cross-validation technique in Convolutional Neural Network to identify the plants and pathogen and the second approach deals towards maintaining the plant health care system using Q-Learning technique of Deep Reinforcement Learning.

1.2 Dataset

In the research we have utilised the PlantVillage dataset which contains all the required feature sets of different data points across PAN India. This dataset best determines the conditions optimal for a plant to grow in different regions across PAN India. The primary objective of the research is to provide an intuitive, scientifically backed, and easy-to-use model for plant enthusiasts, gardeners, and botanists. By consolidating vast botanical data and employing advanced AI algorithms, the research seeks to accurately simulate the best-case scenarios for the growth and development of any plant species and their specific needs, making plant care easy for any plant lover and resulting in optimal plant health.

1.3 Q-Learning

The DRL model intends to influence significantly by enacting sustainable gardening activities and increasing environmental awareness, as well as promoting biodiversity conservation. This influence will then be realized by educating people on how to care for plants in the most effective ways. Therefore, it impacts the relationship between people and nature which should be strengthened to facilitate an individual's well-being and enhancing the balance in the ecology. Botany coupled with Q-learning promotes new approaches to improving plant care practice. Q-learning allows the plants' decision-makers to get real and complex data by integrating extra learning tools to emulate a learning environment and learn from highly complex and frequently shifting contexts.

The DRL model for plant care can access numerous environmental factors, including temperature, light, humidity, and soil, and their impact on plant growth. Through the manipulation of these variables, Q-Learning acquires the ability to enhance maintenance decision-making, encompassing the effective management of nutrients, optimal timing of water supply, and judicious use of pesticides. Q-learning's ability to learn allows it to generate data-based recommendations for certain plants and growth stages, thereby substituting conventional approaches and advocating for permaculture techniques. The uniqueness of this technique is in its capacity to continuously adjust to new information, resulting in increasingly accurate and efficient facility solutions as time progresses.

1.4 Motivation

In recent years, the urge for plantation and love for plants have risen in many urban areas, especially during the rise of COVID-19. People have started knowing the importance of oxygen and, from it, the importance of plants in every household. This urge has led them to grow more and more plants, but not knowing which plants to grow in which conditions has become a significant problem. Information is available, but it isn't enough for us to get the best for our plant care; hence, we have developed a novel approach to train our model over a hasty number of images so that our model produces the required accuracy to build trust in our users. They gradually become experts at being plant moms.

The innovative feature of the model is its aspiration to function as a holistic plant care system. The objective is to provide users with knowledge on several elements of plant care, such as irrigation, soil choice, sunshine needs, and disease avoidance. This comprehensive approach encompasses all stages of plant care, providing a convenient option for both inexperienced gardeners and seasoned botanists.

While working on this project, we read and observed that approaches like CNN has been used earlier by researchers but no work has been done in the field of reinforcement learning using Q-Learning which motivated us to produce results and solve problems to maintain sustainability. Hence, the research contributes purely towards a novel understanding of the plant world. The objective is to solve the problem of our plant lovers, our professional botanists, and gardeners, who can quickly identify and recognize the detailed summary of any plant across PAN India.

In this advancing age of AI, where the whole world relies on technology and things that are easy for human use, why is it behind in terms of plants and botany? Hence, putting the best knowledge of AI into botany by using Machine Learning (ML) and Deep Learning (DL) techniques is a revolutionary way to interact with and identify plants. This is a research project aimed at utilizing these cutting-edge AI technologies that will reduce human effort and bring humans closer to nature, eventually leading to a healthy lifestyle and sustainable living.

Chapter 2

LITERATURE REVIEW

Jana Wäldchen et at [1] discusses about the efforts that are required to conserve biodiversity that is underway, but recognizing species is crucial for adequate protection, requiring thorough training and practice. Advances in image processing and pattern recognition technology can automate identification, providing invaluable support to the public, educators, researchers, and authorities.

The authors of [2] discusses how the crop diseases threaten food security, but detection infrastructure is lacking in many regions. With smartphone ubiquity and deep learning in computer vision by training on large, publicly available image datasets. The research further solves the problem discussed within.

Negin Katal et al. [3] discusses how the climatic changes pose an urgent danger to biodiversity, with wide-ranging impacts on species interactions, ecosystem functioning, and the formation of biotic communities. This paper is the inaugural comprehensive literature review that seeks to meticulously examine all major publications on DL methodologies. Authors have used a multi-stage procedure in works published over the past five years (2016–2021). After thoroughly examining this research, they have outlined the techniques based on the observed phenological phases, type of plant, geographical scale, data collection methods, and deep learning approaches. In addition, the have analyzed and explored current patterns in research, emphasizing potential areas for the future of development.

Aalt-Jan Van Dijk et al. [4] discuss in their paper the composition of plant cells resulted from genotypic variation and environmental variation. These factors subsequently impact physiological and developmental characteristics, such as the creation of organs and the growth of plants, and ultimately, qualities that are significant in agriculture, such as crop output and the ability to withstand stress. As a result, establishing a connection between genotypes and phenotypes provides valuable knowledge about controlling critical processes in plant growth and function.

The authors of the paper [5] discusses about the growing global population and the reality of climate change necessitate accurate agricultural productivity. In this study, authors have employed comprehensive algorithms that intricate interactions are inaccessible through repetition. Experiments are significantly influencing agricultural output fluctuations. Consequently, these interactions can potentially result in considerable gains in crop productivity. The methodology we employ can expedite agricultural research, detect and promote sustainable practices, and address the challenges posed by future food demands.

Zafar Salman et al. [6] through their work shows a survey that aims to document the notable progress made in disease identification using ML techniques. They have examined commonly used datasets and strategies for plant disease identification and emphasized new and developing approaches in this field. This paper overviews datasets of the plant disease, approaches related to DL, and the associated problems. The findings are a significant asset for scholars and practitioners. This study aims to provide valuable insights and stimulate future research endeavors, ultimately advancing precision agriculture techniques and optimizing crop health management.

The authors of the paper [7] discuss the rise of climate change and the increasing threat to the security of all countries that has increased the importance of climate action in many scientific studies. For this reason, climate data is an essential element in developing climate risk and impact assessment models. This study evaluated available spaces to determine the most suitable for the research field. Statistical methods such as discrepancy, and percentage variance were applied to meteorological data at three time scales (daily, weekly, and monthly).

Megali Lescot et al. [8] have talked about a database PlantCARE, a repository of plant, repressors, and promoters. The links to new cluster and motif studies are now available for studying gene clusters. Once new systems are managed, one can import and add them to the repository.

The authors of the paper [9] discuss the possibility of using another extension method, namely Actor-Critic with Advantage (A2C), which was not explored. This study used Deep Q-Network (DQN) and A2C methods with different static and dynamic control objectives.

Mariam Reda et al. in the paper [10] discuss how new and small-scale farmers and inexperienced and large-scale farmers identify the diseases that damage their plants. It aims to help farmers improve their knowledge in this area by providing additional agricultural training and co-training on basic plant care needed to identify, treat, and prevent Isola (type of disease). The work briefly compares the best CNN models for improvement of the accuracy and efficiency of classification decisions using transfer learning, which forms the basis of pre-training.

Przemyslaw Prusinkiewicz discusses in his paper [11] that the L-system theory proposed by Lindemeier in 1968 established a mature method for plant structural modeling. Many current engineering models provide insight into plant growth processes, including physiological processes such as carbon transport and distribution. Its goal is to interest plants in the face of plant biochemistry problems that do not affect all plant development.

Aldo Carl Leopold through his research [12] discusses in his book about botany. Each chapter is divided into several sections and further broken down by topic. Radiation in the physiological environment includes light, heat, and water. Plant physiologists often use the term "growth" loosely, and reviewers of this book do not quite understand the context. The development section of the book tends to focus on development policy.

The authors of the paper [13] talks about efficient irrigation which is vital for sustainable agriculture due to the scarcity of water resources. The A2C model reduced water consumption by 20 % compared to DQN, albeit with a slight decline in productivity. These findings suggest that on-policy models like A2C can enhance water savings in water-scarce regions. The BioD'Agro project will utilize IoT sensor data to train these models further, aiming to refine irrigation schedules and promote agrobiodiversity through efficient, environmentally conscious water management.

The authors of the paper [14] researched on how to meet global food demand by 2050, increasing agricultural productivity by 70 % that is essential, with fertilizer application playing a crucial role. However, traditional uniform fertilizer application wastes over 65 % of fertilizer, contributing to environmental problems. A Q-learning-based simulation tool is proposed to dynamically optimize fertilizer application by sensing the environment and adjusting to site-specific conditions. It is computationally efficient and matches or surpasses the performance of other deep learning methods like DQN, Double-Deep-q-Networks (DDQN), and dueling networks, providing a promising solution for sustainable fertilizer management. DDQN is a variant of DQN algorithm.

Oluwaseyi Ogunfowora and Homayoun Najjaran in their paper [15] talk about maintenance planning which is crucial for minimizing costs, extending equipment lifespan, and ensuring workplace safety. Reinforcement learning (RL) and deep reinforcement learning (DRL) have emerged as effective data-driven tools to optimize dynamic maintenance strategies by leveraging condition monitoring data. Graphical and tabular summaries offer insights into recent advancements and underscore areas ripe for further exploration, aiding both new and experienced researchers in navigating the evolving landscape of smart maintenance solutions.

Dhivya Elavarasan and P. M. Durairaj Vincent in their paper [16] discuss crop yield prediction and how it is essential for sustainable agriculture, yet existing models often struggle with directly mapping raw data to yield outcomes. DRL, combining RL and DL, offers a promising solution. The proposed Deep Recurrent Q-Network (DRQN) model leverages Recurrent Neural Network (RNN) and Q-learning to achieve a 93.75 % accuracy in yield prediction. The integration of DRL minimizes expert dependency and provides a holistic solution for accurate yield forecasting.

The authors of the paper [17] discuss RL, particularly multi-armed bandits, as a promising approach for improving crop management Decision Support Systems (DSS). Its ability to handle uncertainty and evaluate joint action sequences makes it well-suited for real-world agricultural challenges. However, limited contributions and challenges like data scarcity and multiple objectives have hindered adoption. A joint research effort between RL and agronomy experts, supported by ergonomists, is essential to overcome these obstacles. Collaboration will unlock RL's potential, enabling human-centered, interactive tools to better support farmers in addressing the evolving challenges of agriculture.

Faye Mohameth et al. in their paper [18] discusses how crop diseases pose a significant challenge to global food security, but advances in technology, specifically smartphone-assisted disease diagnosis powered by deep learning, offer promising solutions. The authors in this study applied deep feature extraction, and transfer learning to the PlantVillage Dataset, testing models like VGG16, GoogleNet, and ResNet50 for plant disease detection. Results showed that Support Vector Machines (SVM) are the best classifier for identifying diseases, achieveing high accuracy with efficient execution time. Future work will involve collecting a unique dataset from sub-equatorial zones to better understand plant behavior in hostile environments and refine disease detection methods for varying regions.

The authors of the research [19] through their study proposed a plant-image augmentation and classification approach using a novel PI-GAN (Plant-Image Genetic Adversarial Network) and PI-CNN (Plant-image Convolutional Neural network) method. By combining and enhancing input images, PI-GAN generated new plant images that improved classification accuracy over traditional augmentation methods. Experimental results using four open datasets verified that the PI-GAN and PI-CNN frameworks achieved higher classification accuracy compared to existing techniques. Future work will focus on incorporating explainable AI (XAI) methods to refine PI-CNN's classification accuracy and explore approaches to preserve class information during image augmentation.

The authors of the paper [20] investigated the inherent dataset bias present in the PlantVillage dataset for plant disease detection models. Training a machine learning model using just 8-pixel backgrounds yielded 49 % accuracy, revealing significant label-correlated noise. The dataset bias was attributed primarily to capture bias, affecting both the foreground and background. Background removal alone couldn't eliminate the bias, and adding data randomly didn't help either. Future research should follow robust experimental design principles to minimize noise factors and carefully extend the dataset while providing unbiased performance estimates.

The above-reviewed papers present insights and research done in our related field and highlights the future potential of AI and DL in plant science, covering all the major aspects of plant species, identification, prediction, phenotyping, and genomics. They are performed by recognised researchers in the field of Data Science (DS) and Artificial Intelligence. Hence, they add value and enhance our work and research in this domain.

Chapter 3

METHODOLOGY

3.1 Dataset Description

We have used the “PlantVillage” dataset for our research study [21]. The PlantVillage dataset consists of the following features:

- The feature set consists of ‘Image Data’ which has leaf images and ‘Labels’ in which each image is labeled with plant species, and if it carries any disease, then the disease types are also mentioned.

- The number of images (Rows) of the dataset contains 54,306 images, each representing a row in the context of a dataset.

- The number of columns is represented in a tabular view, where each row is an image, the dataset typically has columns named ‘Image’ which carries the pixel data or image file, and ‘Plant Species’ which carries the complete name of the species of that plant and the ‘Disease Type’ which shows the plant’s health or disease indicator, mentioned in case the plant is infected.

- The dataset overall covers 14 major crop species, The dataset contains 38 class labels, including those for healthy and diseased plants. The number of each category Tomato Leaf Images in PlantVillage Dataset is shown in Fig. 3.1.

No.	Name of Category	Number of Pictures
0	bacterial spot	2027
1	early blight	1000
2	late blight	1909
3	mold leaf	952
4	septoria leaf spot	1771
5	spider mites	1676
6	target spot	1404
7	tomato yellow curl virus	5357
8	tomato mosaic virus	373
9	healthy	1591

Figure 3.1: The number of each Category Tomato Leaf Images in PlantVillage Dataset

- The dataset contains features like temperature, soil, moisture, humidity, and water, and all of this is labeled data attached with each image.

- The dataset is used for enhancing and optimizing plant care management systems, and hence we have used it in building our deep reinforcement learning model using the Q-learning technique.

- The dataset contains annotated samples to show the region of interest as shown in Fig. 3.2.

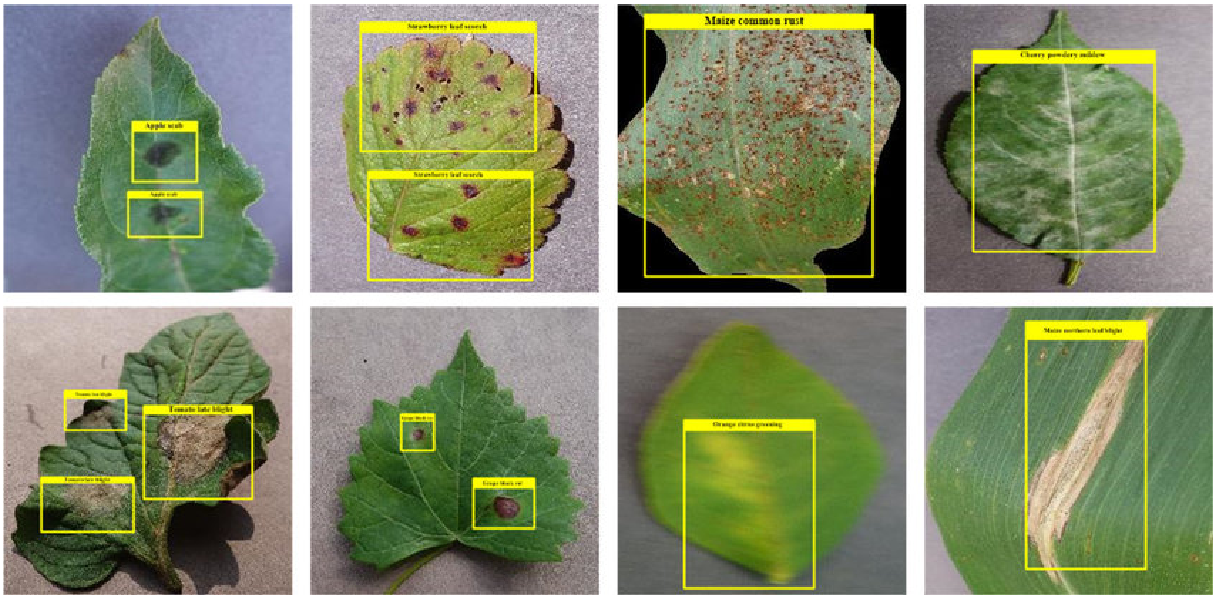


Figure 3.2: Annotated Samples of the PlantVillage Dataset to show the region of Interest

Timely disease detection in plants remains a challenging task for farmers. They do not have many options other than consulting fellow farmers. Expertise in plant diseases is necessary for an individual to be able to identify the diseased leaves as shown in Fig. 3.3. For this, Deep Convolutional Neural Networks based approaches are readily available to find solutions. One such solution is discussed below.

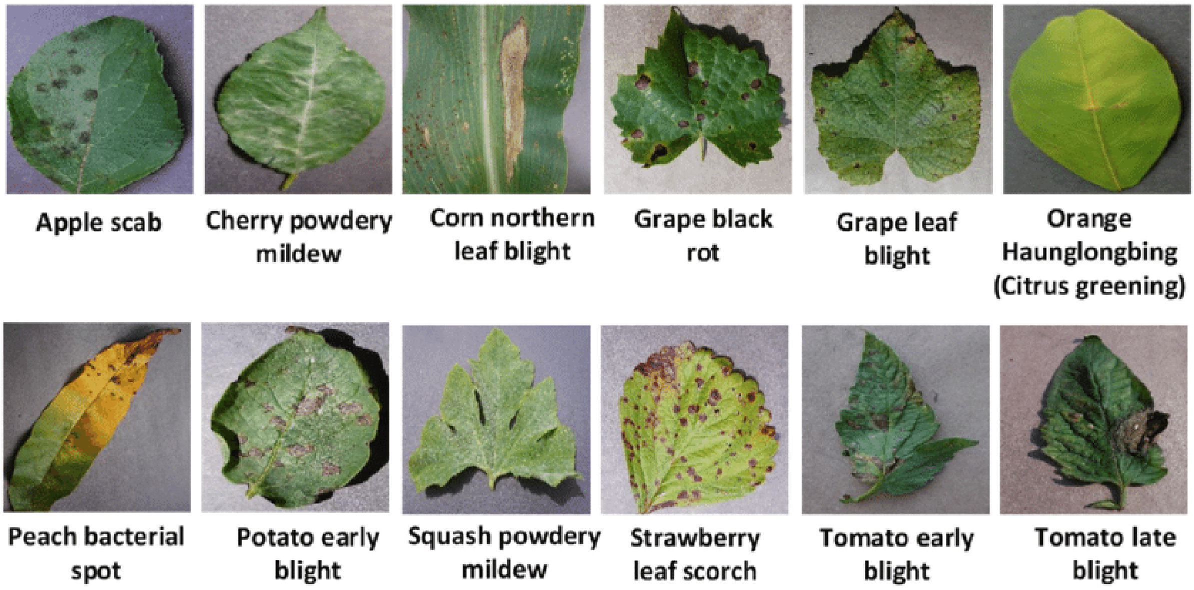


Figure 3.3: Different Types of Diseases from the PlantVillage Dataset

3.2 Building the Models

The initial step is creating a machine learning [22] CNN model to identify the images of the plants. We have chosen CNNs for plant identification as they excel in tasks related to image categorization. After the model is selected, it is trained over our PlantVillage Dataset, which consists of a wide array of plant photos encompassing different species and situations.

In this context, the feature extraction procedure is essential to discerning the fundamental attributes of plants from photographs as shown in Fig. 3.2. A single equation cannot fully capture CNNs in the context of picture categorization. CNNs comprise of numerous layers and processes that collaborate to classify images [23].

The dataset is split into two sets, one is the training dataset and another is the testing dataset. It is usually considered in the ration 8:2 respectively. To prevent over-fitting, we have used K-Fold Cross Validation technique for sampling of our data points into training set and testing set. This reduces the problem of over-fitting to a larger extent hence providing us with better accurate results.

We have then worked on our metrics o extract the results after running our model to fetch the Accuracy, Precision, Recall, F1-Score and Mean Squared Error (MSE) values to understand the performance of our model. Basis the MSE value, we built the growth prediction model.

Next, we have worked on the Reinforcement Q-Learning to maintain the best growth conditions for our plant's maximum health discussing along-way the best cultivation strategies. Our Q-Learning agent produces results after getting feedback from the action that it performs in the environment.

3.3 Convolutional Neural Network

3.3.1 Convolutional Operation

Equation 3.1 illustrates how to apply the operation across the entire image to create a feature map. The chosen CNN architecture can recognize patterns indicative of specific plant diseases [24]. The CNN architecture is as shown in Fig. 3.4.

$$(I * K)(i, j) = \sum_{m} \sum_{n} I(m, n).K(i - m, j - n) \tag{3.1}$$

3.3.2 Activation Function

ReLU (Rectified Linear Unit) Activation function is typically applied after each convolutional operation. ReLU is shown as given in Equation 3.2.

$$\mathbf{f(x) = max(0, x)} \tag{3.2}$$

3.3.3 Pooling

Pooling layers (e.g., max pooling) reduce special data dimensions. Equation 3.3 represents the Max pooling operation.

$$P(i,j) = max_{m,nwindow}.I(i+m, j+n) \tag{3.3}$$

3.3.4 Flattening

A fully connected neural network layer receives the output from the final pooling layer, which is flattened into a 1D vector.

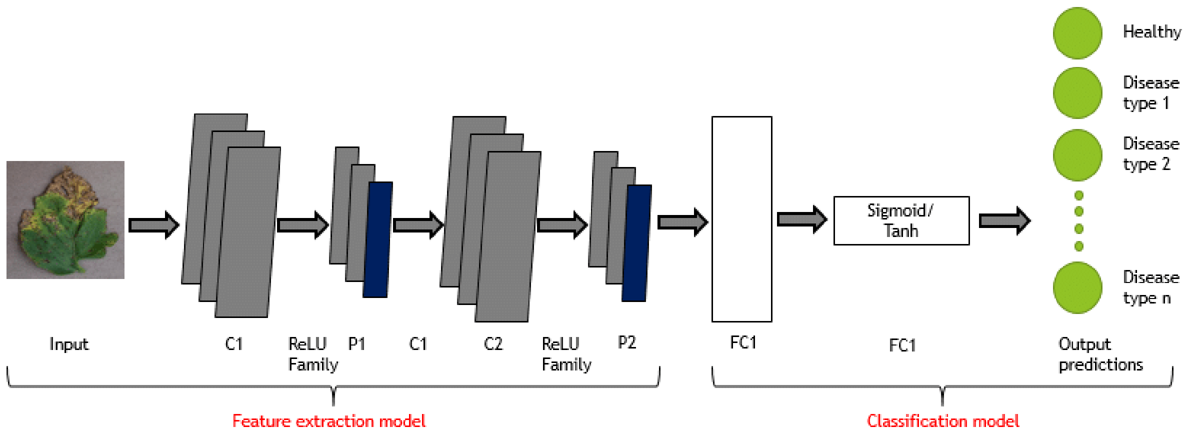


Figure 3.4: CNN Architecture in Plant Disease Detection

3.3.5 Fully Connected Layers

The neurons in these layers are fully connected to all activations in the previous layers. This can shown by Equation 3.4.

$$\mathbf{O} = \mathbf{W.\ X} + \mathbf{b} \tag{3.4}$$

Where,

- X is the input vector from the flattened feature map,
- b is the bias vector,
- W is the weight matrix, and
- O is the output vector.

3.3.6 Output Layers

For classification, the final layer is often a softmax layer, which converts output scores into a probability distribution, as represented in equation 3.5.

$$softmax(z)_i = \frac{e^{z_i}}{\sum_k e^{z_k}} \tag{3.5}$$

Where,

- zi is the score for class i, and
- the denominator is the sum of exponential scores for all classes.

3.4 K-Fold Cross Validation

K-fold cross-validation is a widely used method for assessing the performance of a machine learning model and ensuring that it generalizes well to new, unseen data. Resampling techniques are used while our dataset is split into training set and testing set, but there are high chances of repetition of sample set and hence over-fitting of our model could easily take place, hence for splitting the dataset and overcome the problem of over-fitting we have used resampling technique of Cross- Validation. It helps in estimating how well the model will perform on an independent dataset. The technique to Cross-Validation can also be depicted through the Fig. 3.5.

3.4.1 Concept

Dataset Splitting

- The dataset is divided into k equally sized subsets or "folds."
- The value of k is a hyper-parameter that needs to be chosen; common values are 5 and 10.

Model Training and Evaluation

- The model is trained and evaluated k times.
- In each iteration, one of the k folds is used as the test set, and the remaining $k-1$ folds are combined to form the training set.
- This process ensures that each data point is used exactly once as a test set and $k-1$ times as part of the training set.

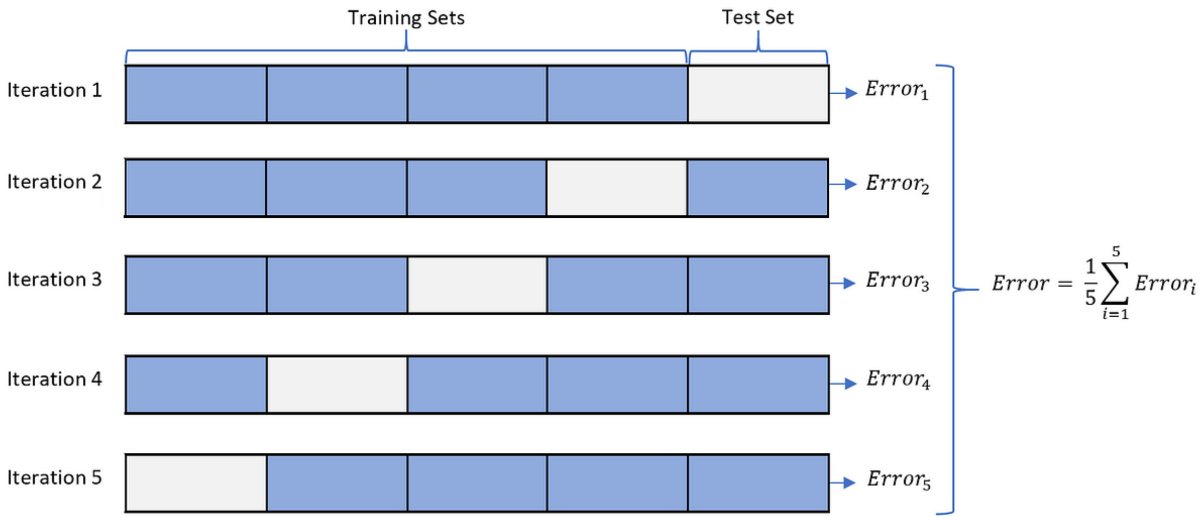


Figure 3.5: 5-Fold Cross Validation

Performance Metrics

- After each iteration, a performance metric (such as accuracy, precision, recall, F1 score, etc.) is calculated on the test set.
- These metrics are recorded and averaged over the k iterations to provide an overall performance measure.
- Additionally, the standard deviation of the performance metric can be calculated to assess the variability of the model's performance across different folds.

Steps of K-Fold Cross-Validation

- Randomly split the dataset into k folds of approximately equal size.
- For each fold i (where i ranges from 1 to k).
- Set the i-th fold aside as the test set.
- Combine the remaining $k-1$ folds to form the training set.
- Train the model on the training set.
- Evaluate the model on the test set using the chosen performance metric.
- Record the performance metric for this iteration.
- Calculate the mean of the performance metrics obtained from the k iterations.
- Calculate the standard deviation of the performance metrics to understand the variability.

3.4.2 Advantages

- Reduced Overfitting: By using multiple splits, K-fold cross-validation ensures that the model is tested on different subsets of the data, reducing the risk of overfitting to any particular subset.
- Efficient Use of Data: Unlike a single train-test split, K-fold cross-validation uses all the data for both training and testing, providing a more comprehensive evaluation.
- Performance Variability Insight: By calculating the standard deviation of the performance metrics, K-fold cross-validation provides insight into how stable the model's performance is across different subsets of data.

3.4.3 Disadvantages

- Computationally Intensive: Training and evaluating the model k times can be computationally expensive, especially with large datasets and complex models.
- Choice of k: The choice of k can influence the results. Smaller k values can lead to higher bias, while larger k values can lead to higher variance.

3.4.4 Typical Values of k

- 5-Fold Cross-Validation: Commonly used for general purposes, providing a good balance between bias and variance.
- 10-Fold Cross-Validation: Often used when more precision in performance estimation is required, though it is more computationally expensive.

3.5 Flowchart

We start the process by loading the dataset 'PlantVillage' and pre-processing the images. We have then built our CNN model using Keras Sequential API [25]. It consists of sequential layers using Adam optimizer and categorical cross-entropy loss. To generate augmented images of training, we performed data augmentation and nicely fit the model after preventing overfitting and putting checkpoints on epochs. To evaluate our model, we have used specific metric parameters like accuracy, recall, precision, mse, and f1-score. For visualization, we plotted our results using bar charts and line charts. The flow of events is depicted in the flowchart shown in Fig. 3.6.

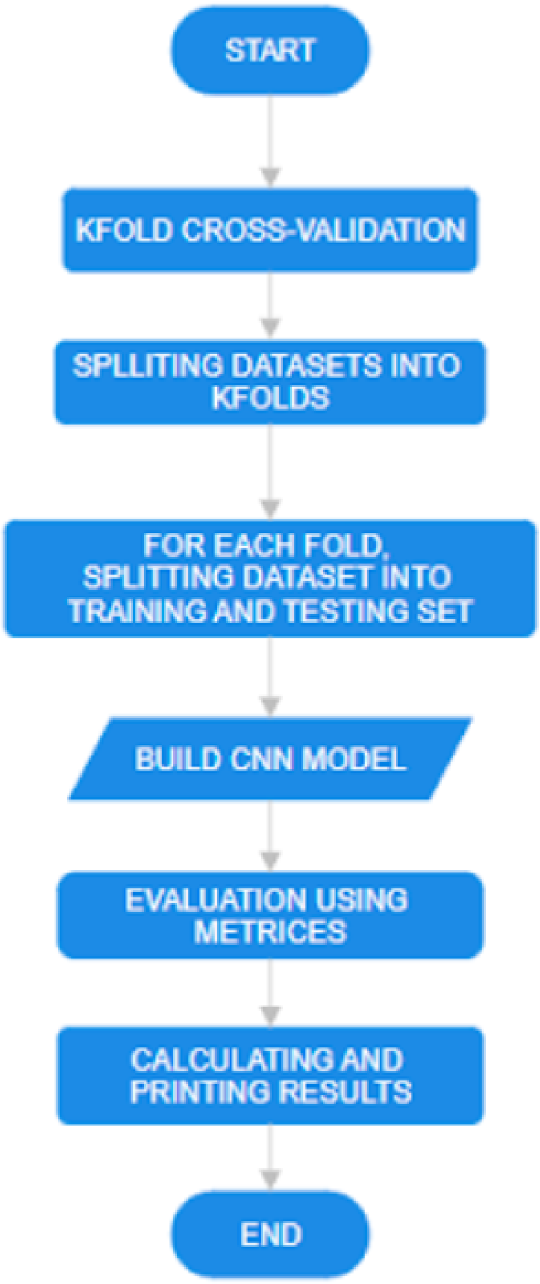


Figure 3.6: Optimized CNN Training and Evaluation Workflow with K-Fold Cross-Validation

3.6 Steps Towards Reinforcement Learning

3.6.1 Data Preparation

Images from the PlantVillage dataset [21] were preprocessed to normalize their pixel values and resized to a consistent format. Features such as color, texture, shape, and size were extracted from these images to serve as inputs to the DRL model.

3.6.2 Simulation Environment

A custom simulation environment was developed where different states represent the health conditions of plants (e.g., Mild disease, Moderate Disease, Severe Disease), and actions include treatments like fertilizing, watering, applying pesticides, and pruning [26]. The Q-learning algorithm was employed to learn optimal actions in each state based on the expected future rewards as shown in Fig. 3.7.

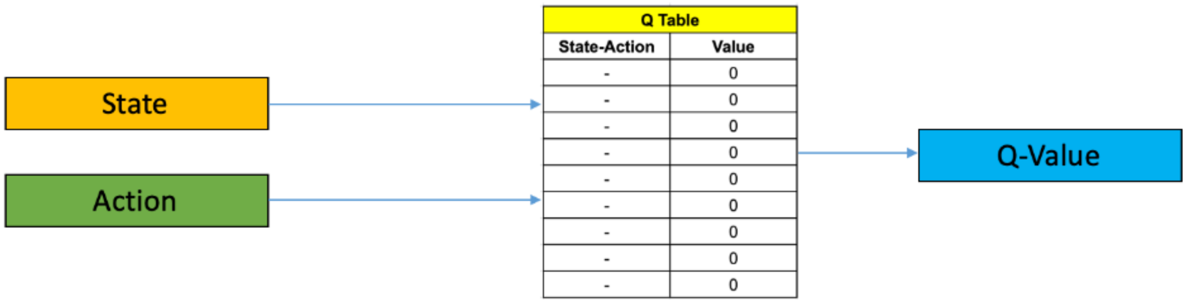


Figure 3.7: Q-Learning

3.6.3 Q-Learning Implementation

The Q-table was initialized to store Q-values representing the expected utility of taking actions in specific states. Actions were chosen based on the policy derived from the Q-table, aiming to maximize the expected reward.

The learning involved updating the Q-table entries based on the reward received after taking action and observing the resulting new states. Q-learning is A value-based reinforcement learning algorithm that seeks to learn the Value of the best action in a given state. It's represented by the Q-function, updated as given in equation 7.

$$Q(s,a) \leftarrow (1-\alpha)\cdot Q(s,a) + \alpha \cdot \left(r + \gamma \cdot \max_{a'} Q(s',a')\right) \tag{3.6}$$

where:

- $Q(s,a)$ is the Q-value for state-action pair (s,a),
- α is the learning rate,
- r is the immediate reward,
- γ is the discount factor,
- s' is the next state,
- a' is the next action.

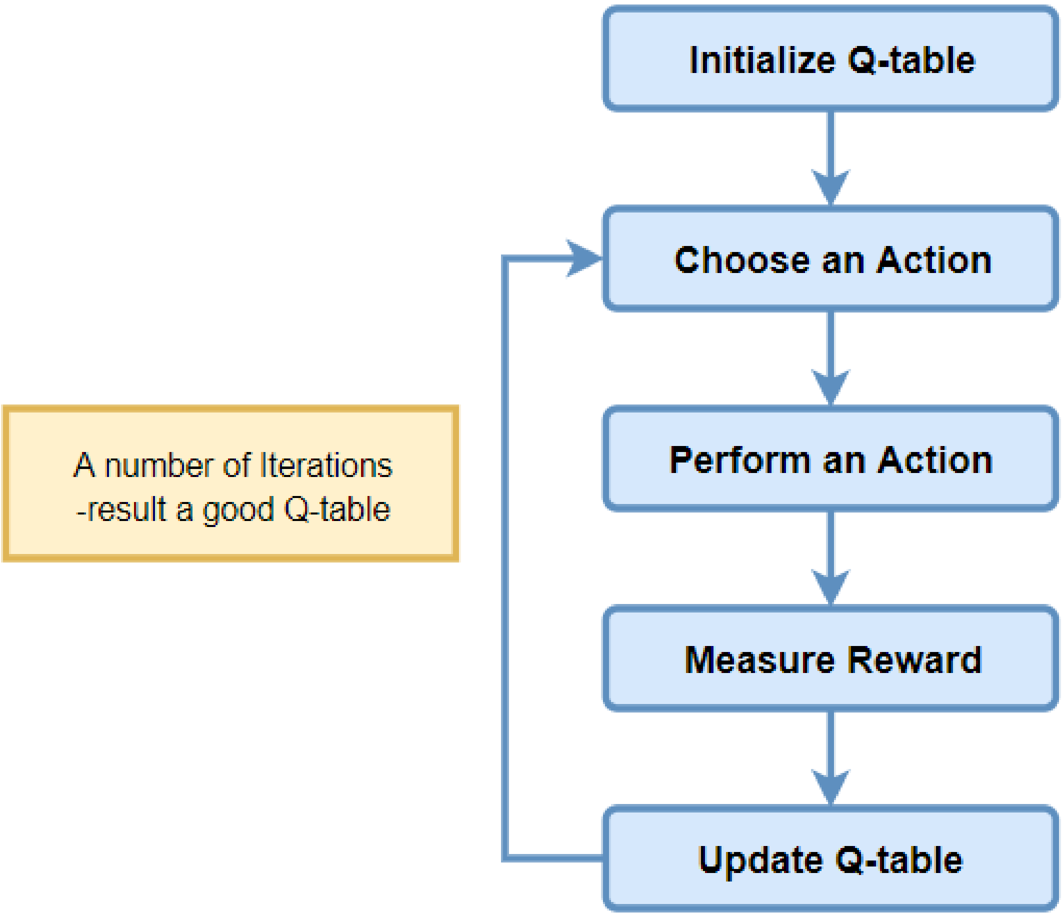


Figure 3.8: Step-wise Q-Learning Implementation

In the implementation process as shown in Fig. 3.8 , these algorithms are coupled with neural networks to handle plant growth's high complexity and non-linearity under various environmental conditions. The neural networks serve as function approximators for the Q-function in Q-learning or the policy in policy gradients. Hyperparameter tuning (adjusting learning rates, discount factors, exploration rates, etc.) is an integral part of training these models to achieve optimal performance. Dealing with the over-fitting of the model, we have used methods like early stopping and drop-out techniques to fetch better results and manage the plants well.

3.7 Confusion Matrix

A confusion matrix is a table used to evaluate the performance of a classification algorithm. It provides a detailed breakdown of the model's predictions compared to the actual outcomes. Each row of the matrix represents the instances in an actual class, while each column represents the instances in a predicted class (or vice versa). The tale 3.1 shows the confusion matrix.

A confusion matrix is a tool used to evaluate the performance of classification models by summarizing the results of predictions in a tabular format. It compares the actual target values with the predicted values generated by the model, allowing you to see where the model is getting things right and where it is making mistakes. Here are the types of errors that can be observed in a confusion matrix:

3.7.1 Terms in a Confusion Matrix

- **True Positive (TP):** The number of instances correctly predicted as positive.

- **False Negative (FN):** The number of instances incorrectly predicted as negative, when they are actually positive.

- **False Positive (FP):** The number of instances incorrectly predicted as positive, when they are actually negative. Type I Errors.

- **True Negative (TN):** The number of instances correctly predicted as negative. Type II Errors.

Table 3.1: Confusion Matrix

−−−−−−	**Predicted Positive**	**Predicted Positive**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

3.7.2 Metrics Derived from a Confusion Matrix

Accuracy

The proportion of correct predictions (both true positives and true negatives) among the total number of cases. The accuracy is calculated as shown in Equation 3.7.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.7}$$

Precision

The proportion of true positives among the predicted positives. The value for precision is calculated as shown in Equation 3.8.

$$Precision = \frac{TP}{TP + FP} \tag{3.8}$$

Recall (Sensitivity or True Positive Rate)

The proportion of true positives among the actual positives. The recall value is calculated as shown in Equation 3.9.

$$Recall = \frac{TP}{TP + FN} \tag{3.9}$$

Specificity (True Negative Rate)

The proportion of true negatives among the actual negatives. The specificity is calculated as shown by equation 3.10.

$$Specificity = \frac{TN}{TN + FP} \tag{3.10}$$

F1 Score

The harmonic mean of precision and recall, providing a single metric that balances both. The F1-Score is calculate as shown by equation 3.11.

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3.11}$$

3.7.3 Types of Errors

False Positives (FP)

- These are instances where the model incorrectly predicts the positive class.
- This error indicates that the model has predicted a positive outcome when the actual outcome is negative.
- In medical diagnostics, a false positive might indicate that a person is diagnosed with a disease they do not have, leading to unnecessary stress and potentially harmful treatments.

False Negatives (FN)

- These are instances where the model incorrectly predicts the negative class.
- This error occurs when the model fails to predict a positive outcome that is actually present.
- In medical diagnostics, a false negative could mean a patient with a disease is not diagnosed, resulting in a lack of treatment and potentially severe health consequences.

3.7.4 Implications of Errors

False Positive Rate (FPR)

The proportion of actual negatives that are incorrectly classified as positive. It is calculated as shown in equation 3.12 below:

$$FPR = \frac{FP}{FP + TN} \tag{3.12}$$

False Negative Rate (FNR)

The proportion of actual positives that are incorrectly classified as negative. It is calculated as shown in equation 3.13 below:

$$FNR = \frac{FN}{FN + TP} \tag{3.13}$$

Balancing Errors

In practice, the cost and consequences of false positives and false negatives vary depending on the application. Therefore, it is often necessary to balance these errors by adjusting the decision threshold of the model or choosing an appropriate evaluation metric.

3.7.5 Multiclass Confusion Matrix

For multiclass classification problems, the confusion matrix extends to an $n \times n$ matrix, where n is the number of classes. Each element (i, j) in the matrix represents the number of instances of class i that were predicted as class j as shown in table 3.2.

Example

In the matrix shown in table 3.2:

- 50 instances of class A were correctly predicted as A (True Positives for A).
- 2 instances of class A were incorrectly predicted as B.
- 3 instances of class A were incorrectly predicted as C.
- And so on for classes B and C.

Table 3.2: The Confusion Matrix for a Three-class classification problem (classes A, B, and C)

− − −−	**Predicted A**	**Predicted B**	**Predicted C**
Actual A	50	2	3
Actual B	4	45	6
Actual C	7	3	40

Understanding the types of errors in a confusion matrix is crucial for evaluating and improving the performance of a classification model. By analyzing false positives and false negatives, and using appropriate metrics like precision, recall, and F1 score, we made informed decisions on how to optimize our model based on the specific needs and consequences of errors in our application domain.'

3.7.6 Mean Squared Error (MSE)

Mean Squared Error (MSE) is a common metric used to evaluate the performance of a prediction model, including growth prediction models for plants. MSE measures the average of the squares of the errors—that is, the average squared difference between the actual observed values and the values predicted by the model. Here's a step-by-step explanation of how we calculated the MSE for a plant growth prediction model:

Step-by-Step Calculation of MSE

Calculate the Errors

- For each observation i, calculate the difference (error) between the actual value and the predicted value: $e_i = y_i - \hat{y}_i$.

Square the Errors

- Square each error: e_i^2.

Calculate the Mean of Squared Errors

- Sum all the squared errors: $\sum_{i=1}^{n} e_i^2$.
- Divide this sum by the number of observations n: $MSE = \frac{1}{n} \sum_{i=1}^{n} e_i^2$.

Interpretation

A lower MSE value indicates that the model's predictions are closer to the actual values, signifying better model performance. However, it is essential to compare the MSE value in the context of the specific dataset and problem domain, as what constitutes a "low" or "acceptable" MSE can vary.

MSE is a useful metric for evaluating the accuracy of growth prediction models for plants. It provides a single number that summarizes the average squared differences between predicted and actual values, facilitating easy comparison between different models or configurations.

Chapter 4

RESULTS AND DISCUSSION

The research aims to integrate advanced AI technologies with plant care and disease management. This research's conclusions and possible outcomes are broadly categorized into technological advancements, practical applications, and broader impacts. The comparison of results of all the evaluated metrics and the level of correctness received in the species and pathogen detection model and the growth prediction model is given in Table 4.1 below.

The results as shown in Table 4.1 of different performance metrics across the two main models in the project: the Species and Pathogen Detection Model and the Growth Prediction Model.

Table 4.1: Comparative Analysis of the Performance of Metrics

Metrics	Species Detection Model	Growth Prediction Model
Precision Metric	0.99	−−
F1-Score Metric	0.89	−−
Accuracy Metric	0.81	−−
Recall Metric	0.81	−−
MSE Metric	−−	0.21

Fig. 4.1 helps us visualize the results obtained and compare them between all the metrics. The high precision highlights that whenever the model predicts a positive instance, it is 99.02 % of the time correct.

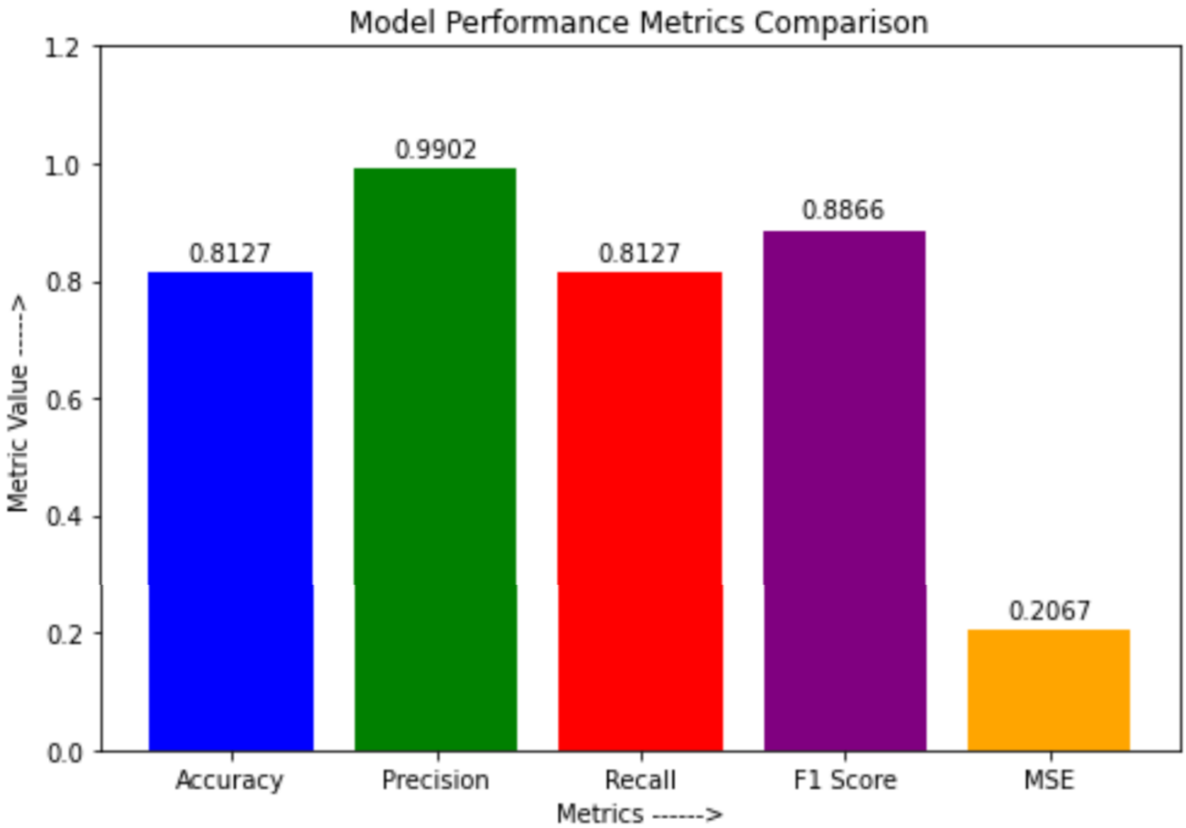


Figure 4.1: Quantitative Evaluation of Predictive Accuracy and Error Metrics in Convolutional Neural Network Performance

It is visible that the highest performance metric for both the models, i.e., the plant and pathogen detection models, is precision, followed closely by f1-score, recall, and accuracy as shown in Fig. 4.2. The high precision combined with good accuracy and recall suggests that this model is highly effective in scenarios where false positives are high. The balance observed in the f1-score indicates that the model is suitably calibrated for the task, effectively minimizing both types of errors [27].

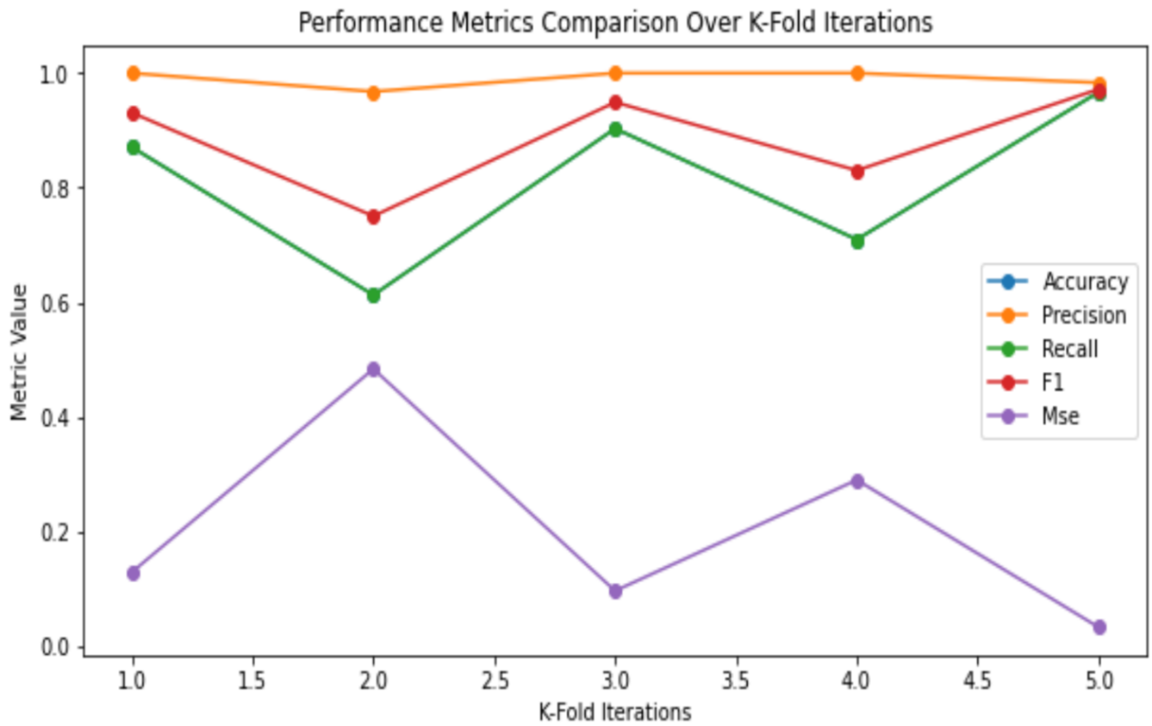


Figure 4.2: Dynamic Evaluation of CNN Diagnostic Accuracy and Error Metrics Across Multiple K-Fold Validation Cycles

The simulation demonstrated fluctuations in plant health indices over time, indicative of the response to the treatments applied based on the learned Q-learning policy [25]. The health indices showed variability, suggesting that the treatments' effectiveness [28] depended significantly on the specific conditions and application timing.

The research confirmed that DRL [29] could effectively learn and suggest optimal plant care strategies under varying conditions. However, the variability in plant health indices suggests that while the model can adjust to changes, there is room for improvement in the stability and consistency of the model's proposed care strategies.

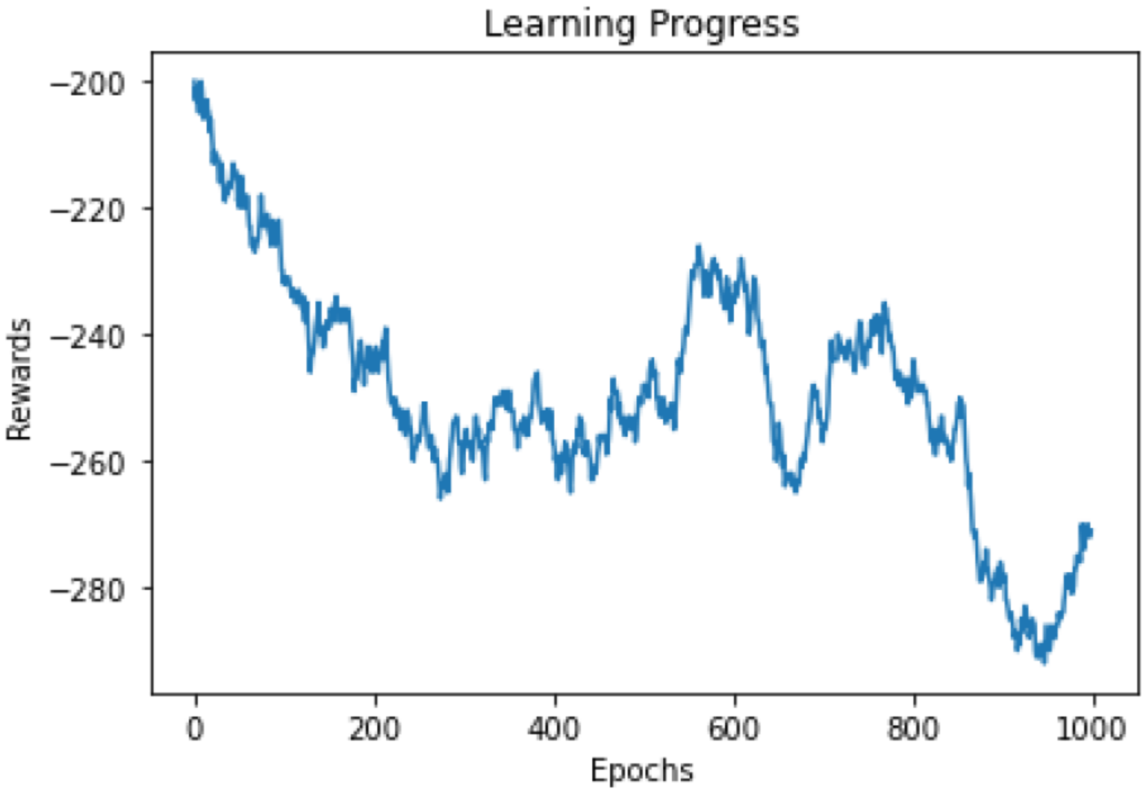


Figure 4.3: The Progress Report of the Learning Curve Demonstrated by a Graphical Representation

Fig. 4.3 shows the learning curve and its progress as our agent learns from the environment and rewards itself by taking action. With each iteration, our agent is learning. Either it produces positive feedback or negative feedback.

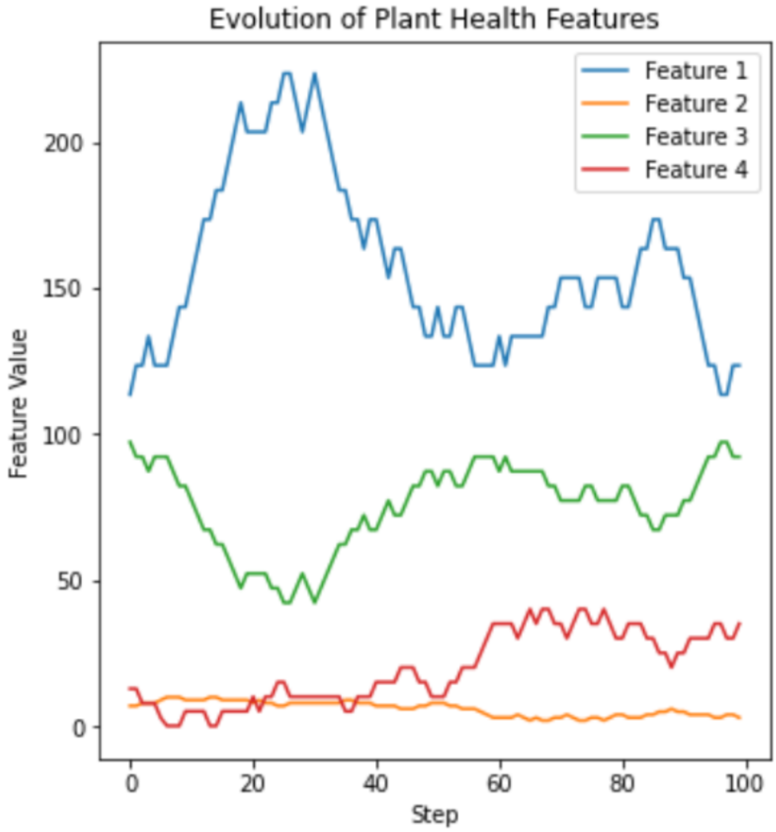


Figure 4.4: Evolution of Plant Care Features: A Graphical Demonstration.

Fig. 4.4 shows the trend in changing plant care features and how, after performing the feature extraction, the care in the plant management system changes with time, indicating different features.

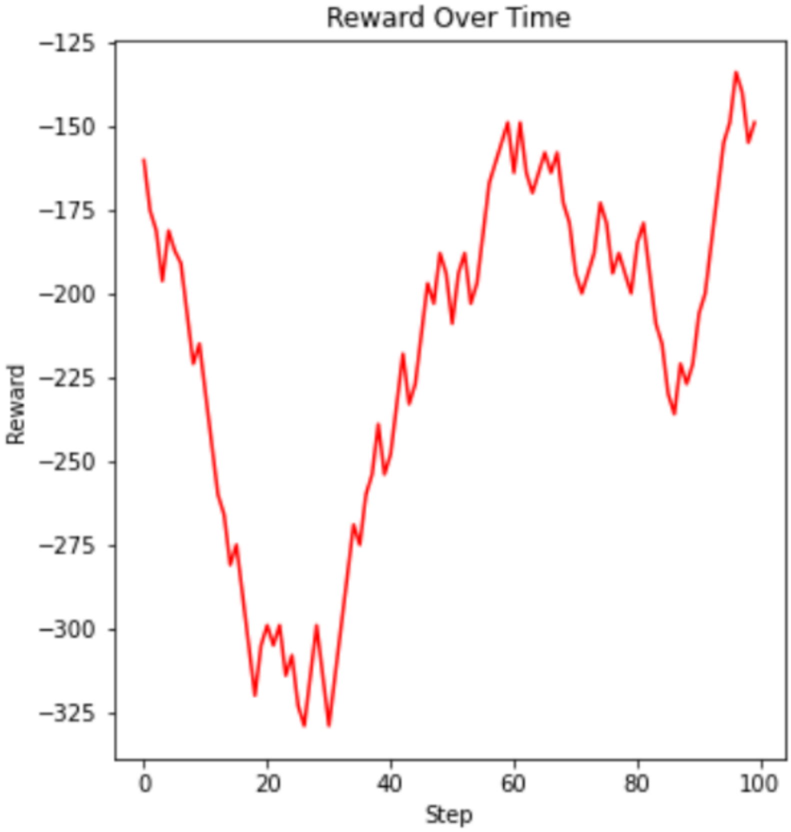


Figure 4.5: Evolution of Reward Over time: A Graphical Demonstration.

The following graph in Fig. 4.5 shows the reward our agent is getting after performing actions on the environment and learning from the feedback loop, improving its efficiency with time.

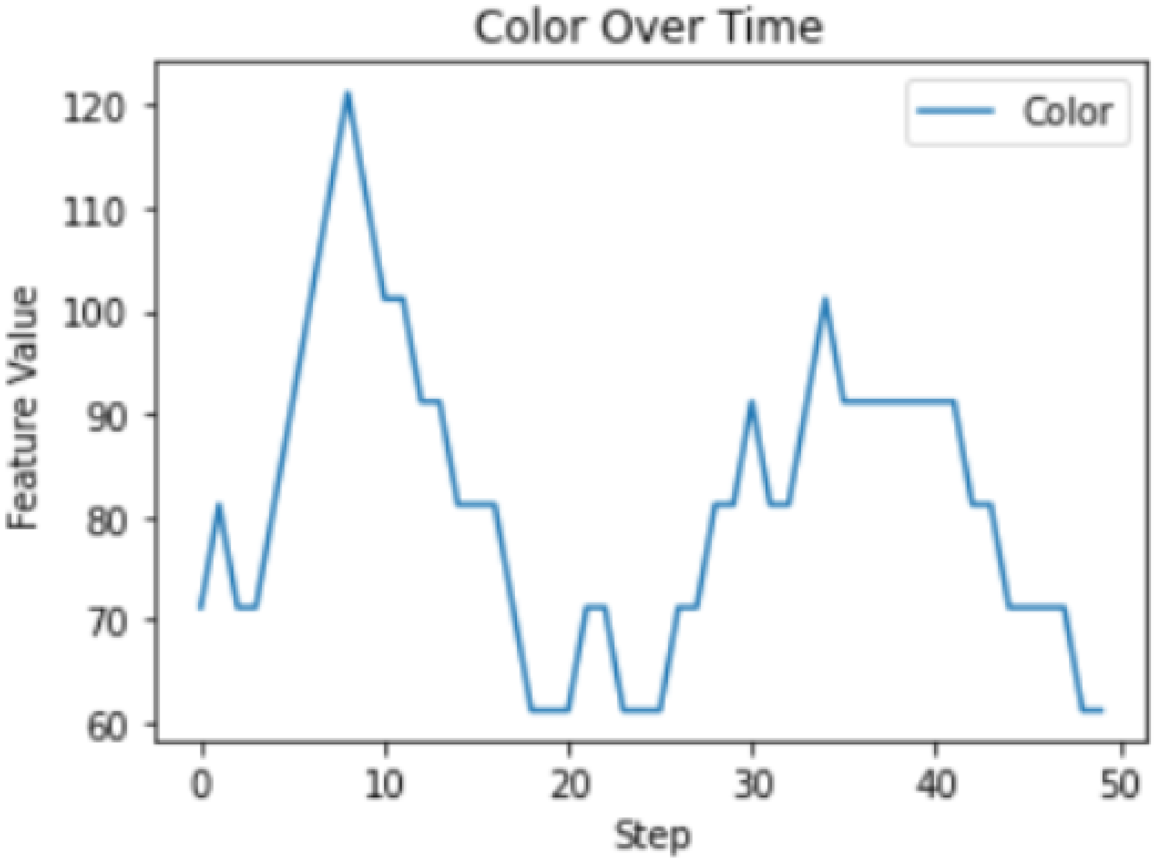


Figure 4.6: A Graphical Representation of: Color over time

Fig. 4.6 to Fig. 4.10 shows different features that change over time, like color, texture, size, and shape of the plant and leaf. It also shows the health changes of the plant and the reward changing with time.

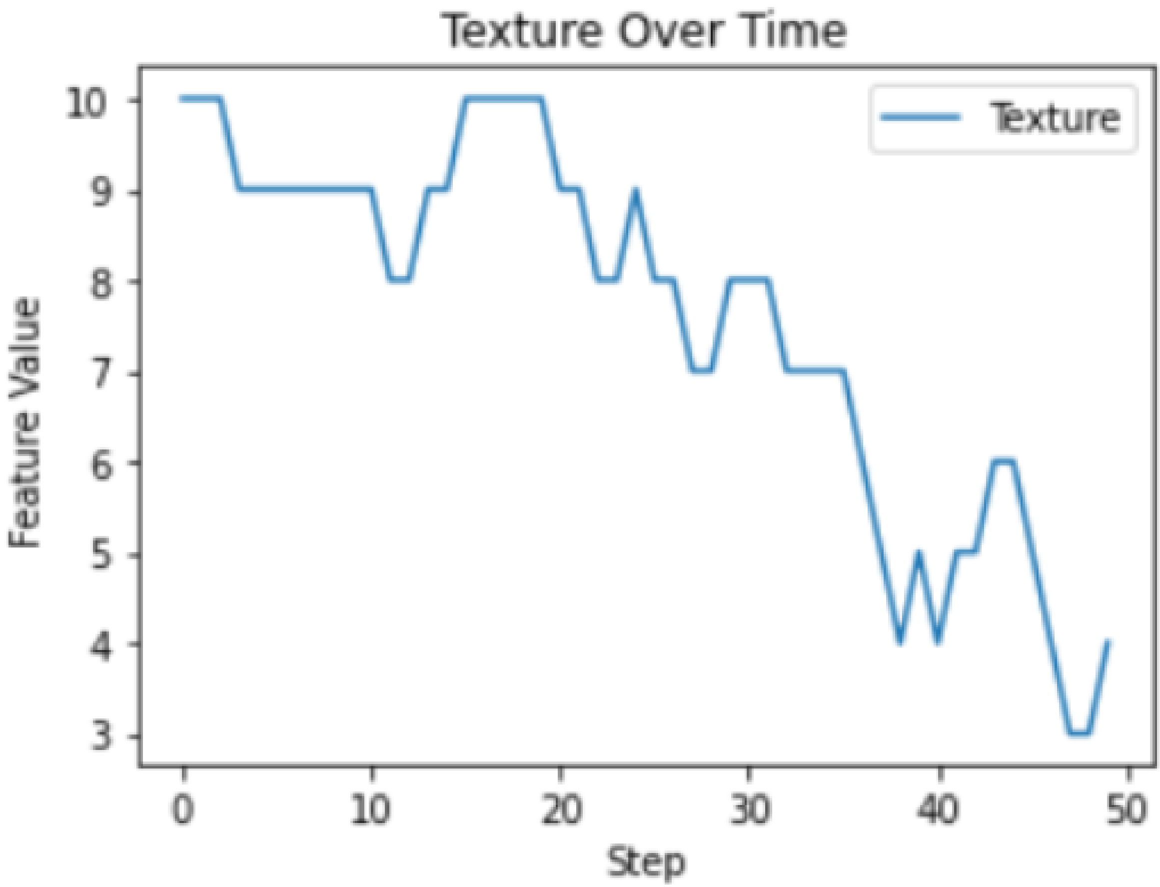


Figure 4.7: A Graphical Representation of: Texture Over Time

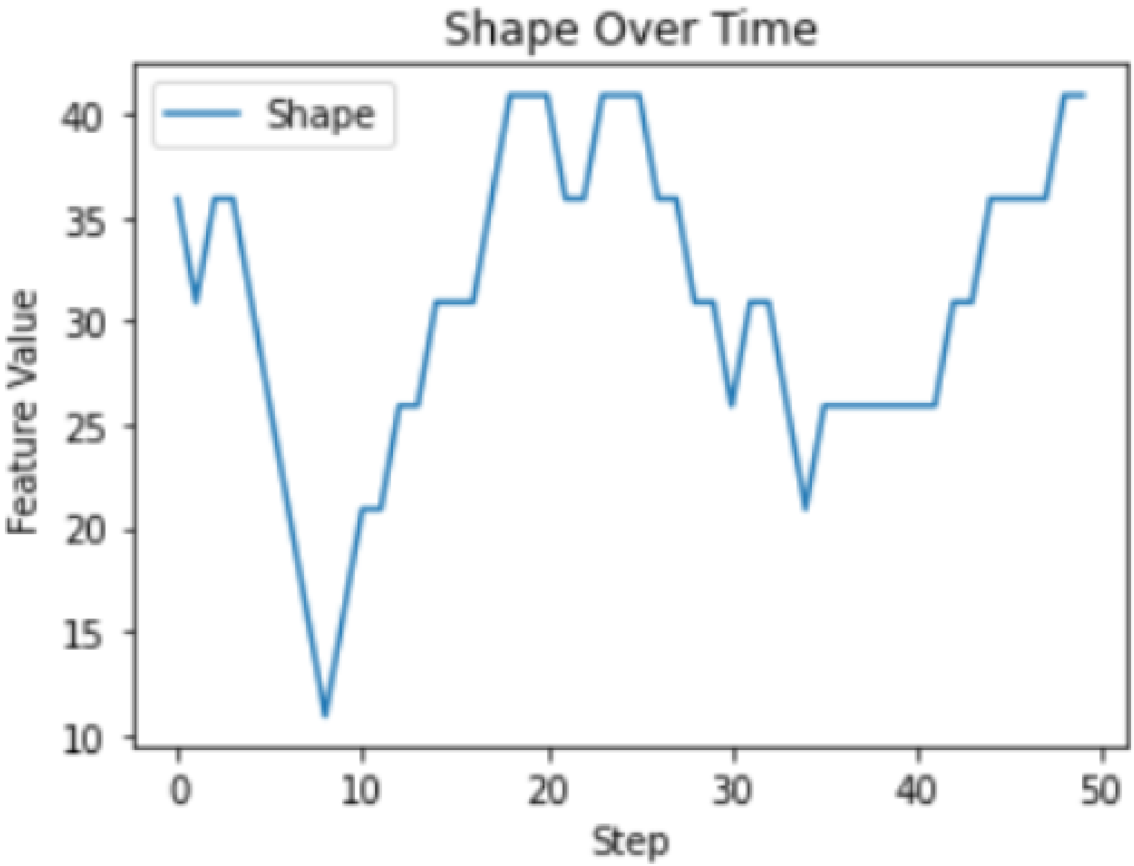


Figure 4.8: A Graphical Representation of: Shape over time

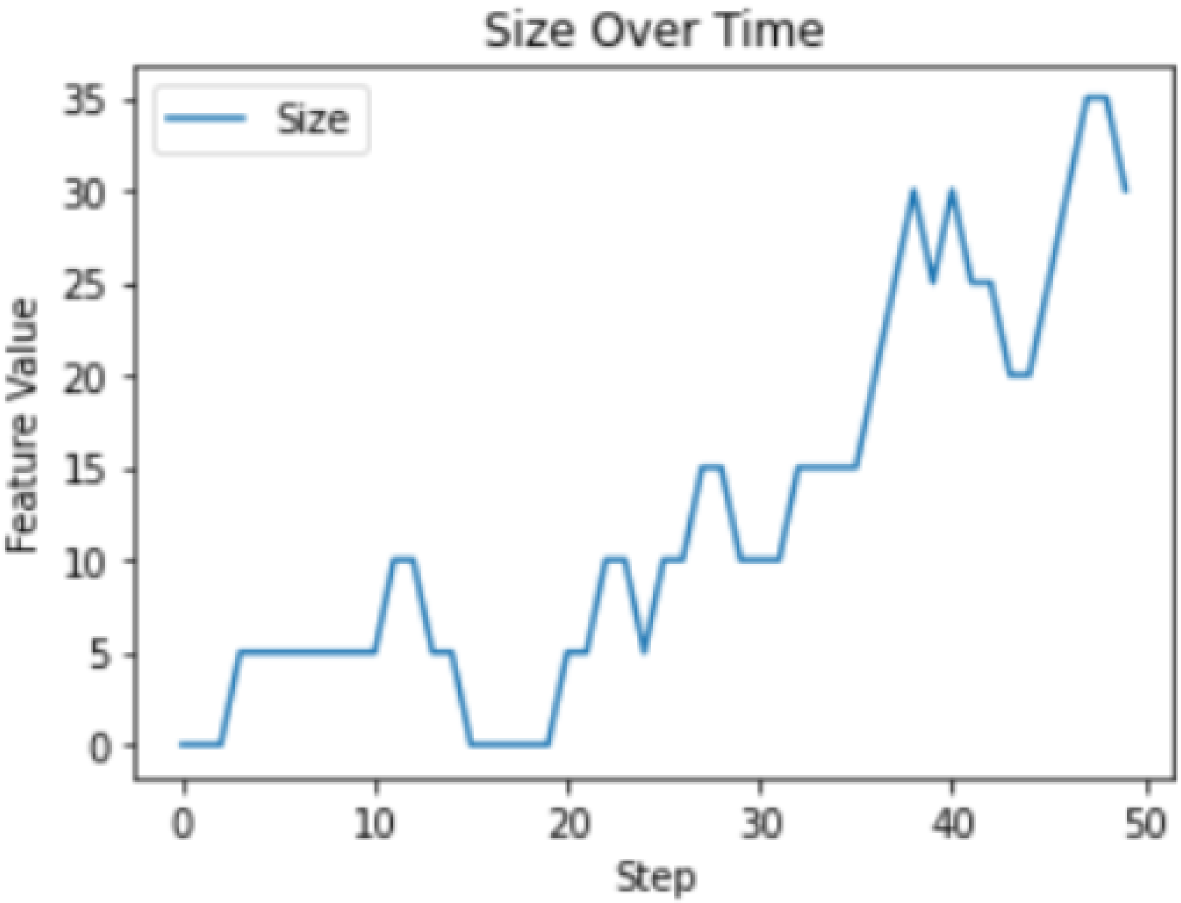


Figure 4.9: A Graphical Representation of: Size over time

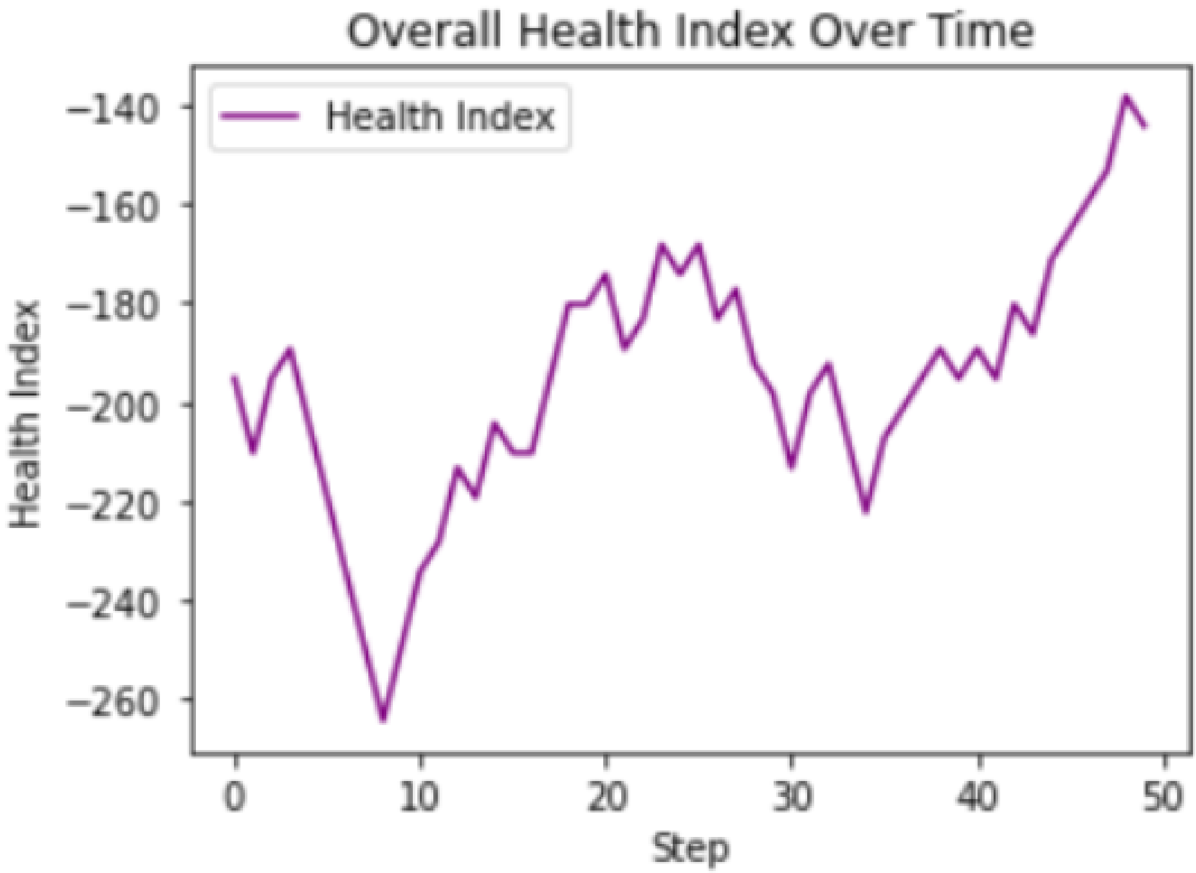


Figure 4.10: A Graphical Representation of: Overall Health Index over time

Figure 4.11: A Visual Representation of Distribution of Rewards

Fig. 4.11. shows how the reward is distributed as the agent performs actions on the environment and learns continuously from the feedback received.

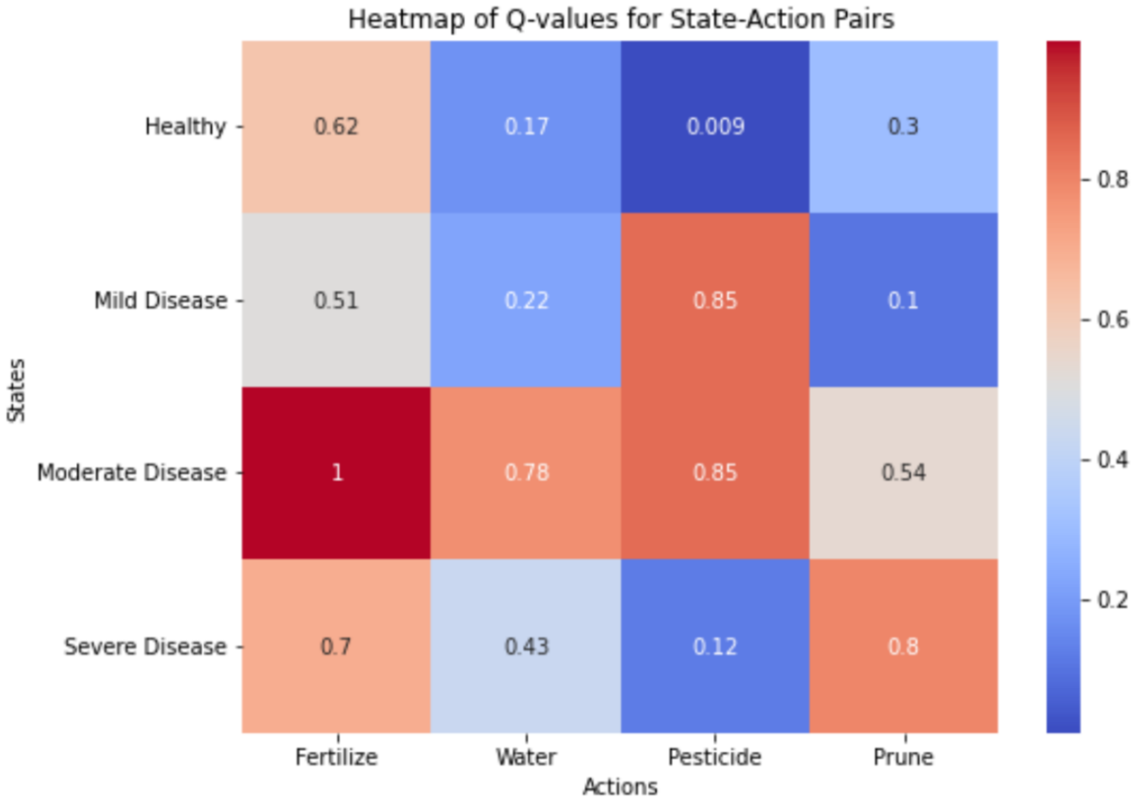


Figure 4.12: Heatmap of Q-Values for State-Action Pairs in the Q-Learning Process.

Fig. 4.12 shows the heatmap of Q-values for State-Action pairs. The highest Q-values appear in actions such as "water" in the "healthy" state (0.98), suggesting that watering is highly beneficial or optimal when the plant is healthy. Similarly, "prune" in the "severe disease" state shows a high value (0.75), indicating that pruning might be considered a beneficial action in managing severe disease conditions.

Low values, as shown in Fig. 4.12 in certain states like "Fertilize" in the "Severe Disease" state (0.39), suggest that fertilizing is less effective or potentially detrimental when the plant is severely diseased.

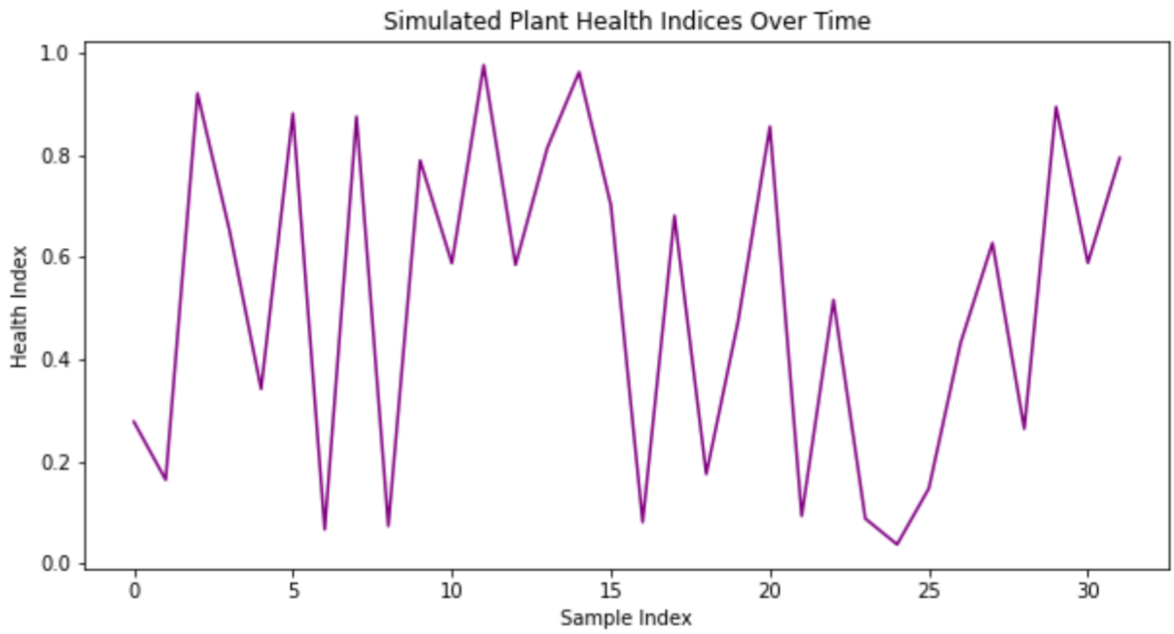


Figure 4.13: Visual Representation of Simulated Plant Health Indices Over Time

The graph shown in Fig. 4.13 visually represents how plant health might vary over time under simulated conditions, offering insights that could be used to refine models, adjust experimental setups, or develop better plant care protocols in various applications.

The research aims to integrate advanced Q-Learning with plant care and cultivation and health management strategies. This research's conclusions and possible outcomes are broadly categorized into technological advancements, practical applications, and broader impacts.

4.1 Effective Cultivation Strategies for Plant Health Management

Effective cultivation strategies are essential for managing plant health, enhancing growth, and ensuring optimal yields. Here are some key strategies:

4.1.1 Soil Management

- **Soil Testing:** Regularly test soil for pH, nutrient levels, and contamination. Adjust pH with lime (to raise) or sulfur (to lower) and amend soil with organic matter or fertilizers based on test results.
- **Crop Rotation:** Rotate crops to prevent soil depletion and reduce pest and disease cycles.
- **Cover Cropping:** Use cover crops to improve soil structure, increase organic matter, and suppress weeds.
- **Mulching:** Apply mulch to conserve soil moisture, regulate temperature, and reduce weed growth.

4.1.2 Water Management

- **Irrigation Systems:** Use efficient irrigation systems like drip or sprinkler systems to ensure uniform water distribution and reduce water wastage.
- **Water Scheduling:** Schedule watering based on plant needs and weather conditions to avoid overwatering or underwatering.
- **Rainwater Harvesting:** Collect and store rainwater for irrigation to reduce dependency on groundwater and municipal water sources.

4.1.3 Nutrient Management

- **Balanced Fertilization:** Apply balanced fertilizers based on soil test results to provide essential nutrients without over-fertilizing.
- **Organic Amendments:** Use compost, manure, and other organic amendments to enhance soil fertility and microbial activity.
- **Foliar Feeding:** Apply nutrients directly to plant leaves for quick absorption, especially during periods of nutrient deficiency.

4.1.4 Pest and Disease Management

- **Integrated Pest Management (IPM):** Use a combination of biological, cultural, mechanical, and chemical control methods to manage pests and diseases sustainably.
- **Resistant Varieties:** Choose plant varieties resistant to common pests and diseases.
- **Sanitation:** Remove and destroy diseased plants and plant debris to reduce sources of infection.
- **Beneficial Insects:** Encourage beneficial insects like ladybugs and predatory wasps to control pest populations naturally.

4.1.5 Crop Selection and Genetic Diversity

- **Diverse Cultivation:** Plant a diverse range of crops to reduce the risk of widespread disease and pest outbreaks.
- **Heirloom and Native Varieties:** Use heirloom and native plant varieties adapted to local conditions and resistant to local pests and diseases.

4.1.6 Climate Adaptation

- **Micro-climate Modification:** Use windbreaks, shade cloths, and row covers to modify the micro-climate and protect plants from extreme weather.
- **Season Extension:** Use greenhouses, high tunnels, and cold frames to extend the growing season and protect plants from adverse weather.

4.1.7 Proper Planting Techniques

- **Correct Spacing:** Plant at proper spacing to ensure adequate air circulation, reduce disease incidence, and allow for healthy root development.
- **Planting Depth:** Plant at the correct depth to ensure proper root establishment and prevent stem rot.

4.1.8 Regular Monitoring and Record-Keeping

- **Frequent Inspections:** Regularly inspect plants for signs of stress, pests, and diseases.
- **Record-Keeping:** Maintain detailed records of planting dates, treatments applied, and observations to identify patterns and make informed decisions.

4.1.9 Sustainable Practices

- **Organic Farming:** Adopt organic farming practices to reduce chemical inputs and promote ecological balance.
- **Conservation Tillage:** Use conservation tillage methods to reduce soil erosion and improve soil health.

4.1.10 Education and Training

- **Continuous Learning:** Stay updated with the latest research and advancements in plant health management.
- **Farmer Training:** Participate in workshops and training programs to enhance knowledge and skills in sustainable cultivation practices.

Implementing these strategies helps create a holistic approach to plant health man- agement, promoting resilient and productive agricultural systems.

Chapter 5

CONCLUSION AND FUTURE SCOPE

The research aims to integrate advanced AI technologies with plant care and disease management. This research's conclusions and possible outcomes are broadly categorized into technological advancements, practical applications, and broader impacts.

It is evident that the highest performance metric for both models, i.e., the plant and pathogen detection models, is precision, followed closely by F1-score, recall, and accuracy. The high precision combined with good accuracy and recall suggests that this model is highly effective in scenarios where false positives are high. The balance observed in the F1-score indicates that the model is suitably calibrated for the task, effectively minimizing both types of errors.

The evaluation of the species and pathogen detection and growth prediction model reveals significant advancements in their accuracy and precision. The detection model achieves a precision of 99%, ensuring that positive predictions are accurate while maintaining a balanced F1-score 89% and recall 81%, minimizing both false positives and negatives.

This balanced performance allows efficient disease management with minimal waste. The growth prediction model's low mean squared error 21% supports accurate trend forecasting for optimizing plant care. These models hold substantial potential for improving resource efficiency, reducing environmental impact, and cutting costs through precise interventions and accurate yield predictions.

The simulation demonstrated fluctuations in plant health indices over time, indicative of the response to the treatments applied based on the learned Q-learning policy. The health indices showed variability, suggesting that the treatments' effectiveness depended significantly on the specific conditions and application timing.

The research confirmed that DRL could effectively learn and suggest optimal plant care strategies under varying conditions. However, the variability in plant health indices suggests that while the model can adjust to changes, there is room for improvement in the stability and consistency of the model's proposed care strategies.

The Q-Learning model has effectively learned optimal care strategies, significantly adapting to plant health's dynamic conditions. The simulation data show that the effectiveness of interventions, such as watering, and fertilizing, varies significantly, based on the timing and specific environmental conditions.

The evolution of plant care features, such as color, texture, and size, indicates that the model can effectively track and respond to changes over time. The heatmap of Q-values demonstrates that specific actions (e.g. watering in healthy states and pruning in severely diseased states) are more beneficial. Overall, the model is a success indicative of the best care management that needs to be performed for the maximized growth of the plant.

Despite the overall success, the variability in plant health indices suggests room for improvement in the stability and consistency of the model's outputs [30]. Given the fluctuations and the diverse responses observed in the plant health indices, there is a significant potential to refine the model to achieve more consistent and predictable results.

Enhancing the DRL model by incorporating more detailed features and possibly using more complex models like Deep Q-Networks (DQNs) [31] as shown in Fig. 5.1 or combining them with other AI techniques such as convolutional neural networks for better feature extraction from images. Expanding the dataset with more varied images under different environmental conditions will train the model to handle a broader range of scenarios.

Incorporating IoT devices for real-time monitoring of plant conditions can provide continuous input to the DRL model for dynamic adjustment of care strategies. Conducting field trials to validate the effectiveness of the recommended strategies under real-world conditions.

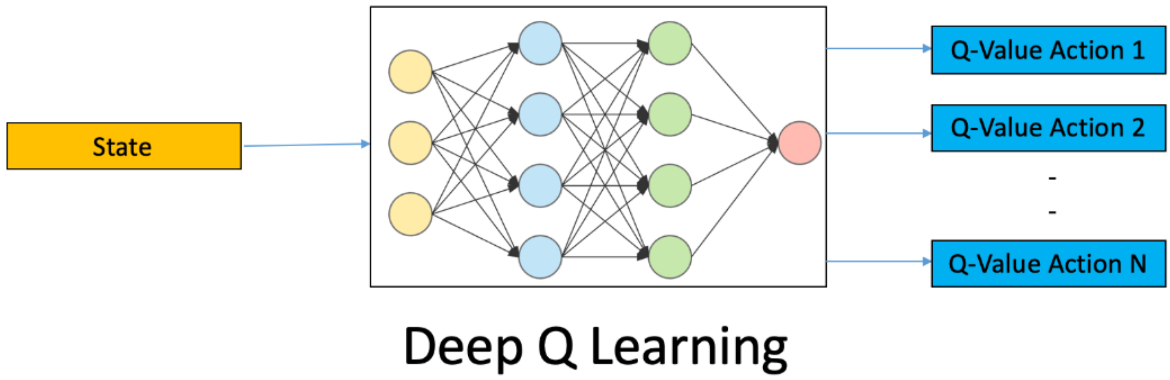


Figure 5.1: Deep Q-Learning

We can improve our work into a user-friendly application where one can scan the image of the plant and identify its exact species. Similarly, one can detect the disease the plant is carrying [32] and further, we can also classify our model based on the geographical locations using machine learning classification techniques.

We can further advance our application by providing a complete guide to maintaining the plant's best health conditions based on geographical locations and improvising our model using DRL algorithms like Q-learning and Deep Q-Networks.

Appendix A

K-Fold Cross Validation with CNN for Species Classification and Pathogen Detection

Import Libraries Importing the required libraries

Data Loading Load the dataset

Data Preprocessing Preprocess the data (normalization, resizing, etc.)

K-Fold Cross-Validation Setup Define the number of folds k

CNN Model Building Build the Convolutional Neural Network architecture

Main Execution Block `each fold in K-Fold Cross-Validation`

Data Augmentation Apply data augmentation techniques on the training data

Training Train the CNN model on the training split of the current fold

Prediction and Metrics Evaluation Evaluate the model on the validation split.

Collect Metrics Store the calculated metrics for this fold

Print Metrics Calculate and print the average metrics across all folds

Visualization Visualize the results (e.g., accuracy, loss curves)

Appendix B

Plant Health Optimisation using Q-Learning.

Convert image to RGB Convert the image from other color spaces to RGB

Convert image to grayscale Convert the RGB image to a grayscale image

Compute GLCM Calculate the Gray Level Co-occurrence Matrix (GLCM)

Compute contrast from GLCM Extract the contrast feature from the GLCM

Find contours Detect contours in the grayscale image

Calculate area of the largest contour Measure the area of the largest contour

Image size as a proxy for plant size Use image dimensions to approximate size

Example feature extraction for the first image Extract features.

Assuming 4 features: color, texture, shape, size Define four main features.

These ranges are arbitrary for demonstration. Specify ranges for each feature.

max values for each feature Set the maximum values for normalization

initial random state Initialize the state of the plant randomly

Four possible actions Define the set of possible actions.

Ideal state (perfect health conditions) Define the optimal state.

Action effects (simplified) Specify how each action affects the state variables

Apply action effects to the state Update the state based on the chosen action

Calculate reward Compute the reward based on the state after action

Reset the state to a new random state Randomly reinitialize the state.

Simulate 10 steps each step in 1 to 10

Randomly choose an action Select an action randomly from the action set

Hypothetical function to simulate the effect of an action on the state

Assuming each action randomly improves or worsens the state

Negative sum of absolute differences from ideal state Calculate the reward.

Assuming 4 actions and 4-dimensional state Define the state and action spaces

To track state and reward history for visualization Maintain history of states.

Reset the state to a new random state within bounds Reinitialize the state

Apply action effects to the state Update the state based on the chosen action

Plot the evolution of plant features and rewards over time Visualize changes

State_size should be adjusted based on actual discretization Adjust the state

Simplified state representation for indexing Q-table Use a simplified state

Plotting each feature evolution over time Visualize changes in individual features

Plotting overall health index Visualize the overall health index of the plant

Plotting rewards Visualize the rewards obtained over time

Assuming the dataset is organized under 'dataset_directory' Defining dataset

Modify these based on actual needs Adjust based on specific requirements

Example function to simulate reward calculation for an episode

Reward decreases slightly with each episode due to increasing difficulty

Simulating the reward calculation for 100 episodes each episode in 1 to 100

Calculate reward Compute the reward for the episode

Plotting the learning curve Visualize the learning progress over episodes

Assume these lists are filled with data from your simulation

Calculating the required metrics Compute performance metrics

Printing the results Output the results of the simulation

Path to the image Specify the image path for loading

Appendix C

List of Publications

- ”Integrating K-Fold Cross-Validation with Convolutional Neural Networks for Plant Species and Pathogen Detection”, in the International Conference on Intelligent Computing and Communication Techniques (ICICCT), 2024 (Accepted)

- ”Optimizing Plant Health with Q-Learning: A Deep Reinforcement Learning Approach”, in the 15th International IEEE Conference on Computing, Communication and Networking Technologies (ICCCNT), 2024 (Accepted)

Bibliography

[1] J. Wäldchen, M. Rzanny, M. Seeland, and P. Mäder, "Automated plant species identification—trends and future directions," *PLoS Computational Biology*, vol. 14, no. 4, p. e1005993, 2018. [Online]. Available: https://doi.org/10.1371/journal.pcbi.1005993

[2] S. P. Mohanty, D. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in Plant Science*, Sep. 2016. [Online]. Available: https://doi.org/10.3389/fpls.2016.01419

[3] N. Katal, M. Rzanny, P. Mäder, and J. Wäldchen, "Deep learning in plant phenological research: A systematic literature review," *Frontiers in Plant Science*, Mar. 2022. [Online]. Available: https://doi.org/10.3389/fpls.2022.805738

[4] A. D. J. van Dijk, S.-H. Shiu, and D. De Ridder, "Editorial: Artificial intelligence and machine learning applications in plant genomics and genetics," *Frontiers in Artificial Intelligence*, Jun. 2022. [Online]. Available: https://doi.org/10.3389/frai.2022.959470

[5] S. Mourtzinis, P. D. Esker, J. E. Specht, and S. P. Conley, "Advancing agricultural research using machine learning algorithms," *Scientific Reports*, Sep. 2021. [Online]. Available: https://doi.org/10.1038/s41598-021-97380-7

[6] S. Zafar, M. Abdullah, M. J. Piran, and D. Han, "Crop-saving with ai: Latest trends in deep learning techniques for plant pathology," *Frontiers in Plant Science*, Aug. 2023. [Online]. Available: https://doi.org/10.3389/fpls.2023.1224709

[7] P. Setiya, M. Singh, and A. S. Nain, "Evaluating the performance of the grid imd, nasa power, and marksim time-series weather datasets for uttarakhand climatic conditions," *Theoretical and Applied Climatology*, vol. 155, pp. 2657–2668, 2024. [Online]. Available: https://doi.org/10.1007/s00704-023-04787-5

[8] M. Lescot, P. Déhais, G. Thijs, K. Marchal, Y. Moreau, Y. Van de Peer, P. Rouzé, and S. Rombauts, "PlantCARE, a database of plant cis-acting regulatory elements and a portal to tools for in silico analysis of promoter sequences," *Nucleic Acids Research*, vol. 30, no. 1, pp. 325–327, 2002. [Online]. Available: https://doi.org/10.1093/nar/30.1.325

[9] R. Mukhopadhyay, S. Bandyopadhyay, A. Sutradhar, and P. Chattopadhyay, "Performance analysis of deep q networks and advantage actor-critic algorithms in designing reinforcement learning-based self-tuning PID controllers," in *2019 IEEE Bombay Section Signature Conference (IBSSC)*, 2019, pp. 1–6.

[10] M. Reda, R. Suwwan, S. Alkafri, Y. Rashed, and T. Shanableh, "A mobile-based novice agriculturalist plant care support system: Classifying plant diseases using deep

learning," in *2021 12th International Conference on Information and Communication Systems (ICICS)*, 2021, pp. 411–418.

[11] P. Prusinkiewicz, "Modeling plant growth and development," *Current Opinion in Plant Biology*, vol. 7, no. 1, 2004. [Online]. Available: https://doi.org/10.1016/j.pbi.2003.11.007

[12] A. C. Leopold, *Plant Growth and Development*, english ed. New York, San Francisco, Toronto, and London: McGraw-Hill Book Co., 1967, 466 pp.

[13] K. Alibabaei, P. D. Gaspar, E. Assunção, S. Alirezazadeh, T. M. Lima, V. N. G. J. Soares, and J. M. L. P. Caldeira, "Comparison of on-policy deep reinforcement learning A2C with off-policy DQN in irrigation optimization: A case study at a site in portugal," *Computers*, Jun. 2022.

[14] Z. Mei, R. R. Vatsavai, and R. Chirkova, "Q-learning-based simulation tool for studying the effectiveness of dynamic application of fertilizer on crop productivity," Online, Nov. 2023.

[15] O. Ogunfowora and H. Najjaran, "Reinforcement and deep reinforcement learning-based solutions for machine maintenance planning, scheduling policies, and optimisation," *Journal of Manufacturing Systems*, Oct. 2023.

[16] "Crop yield prediction using a deep reinforcement learning model for sustainable agrarian applications," IEEE Journals & Magazine — IEEE Xplore, 2020. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9086620

[17] R. Gautron, O. A. Maillard, P. Preux, M. Corbeels, and R. Sabbadin, "Reinforcement learning for crop management support: Review, prospects, and challenges," *Computers and Electronics in Agriculture*, Sep. 2022.

[18] M. Faye, B. Chen, and K. A. Sada, "Plant disease detection with deep learning and feature extraction using plant village," *Journal of Computer and Communications*, Jan. 2020.

[19] G. Batchuluun, S. H. Nam, and K. R. Park, "Deep learning-based plant-image classification using a small training dataset," *Mathematics*, Aug. 2022.

[20] M. A. Noyan. (2022, Jun.) Uncovering bias in the plantvillage dataset. arXiv.org. [Online]. Available: https://arxiv.org/abs/2206.04374

[21] T. Emmanuel, "Plantvillage dataset," Kaggle, 2018. [Online]. Available: https://www.kaggle.com/datasets/emmarex/plantdisease

[22] Rahul, P. Kedia, S. Sarangi, and Monika, "Analysis of machine learning models for malware detection," *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 23, no. 2, pp. 395–407, 2020. [Online]. Available: https://doi.org/10.1080/09720529.2020.1721870

[23] M. Hema, N. Sharma, Y. Sowjanya, C. Santoshini, R. Durga, and V. Akhila, "Plant disease prediction using a convolutional neural network," *Emitter International Journal of Engineering Technology*, Dec. 2021.

[24] S. Sagar *et al.* (2023, Dec.) Leaf-based plant disease detection and explainable ai. arXiv:2404.16833v1 [cs.CV]. [Online]. Available: https://arxiv.org/pdf/2404.16833

[25] S. Parmar and R. ., "Chess piece classification via convolutional neural networks," 10 2023, pp. 36–42.

[26] Y. Hitti, "Growspace: A reinforcement learning environment for plant architecture," *Volume 214*, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169924000048

[27] C. Goutte and E. Gaussier, "A probabilistic interpretation of precision, recall, and f-score, with implications for evaluation," *Lecture Notes in Computer Science*, Jan. 2005.

[28] R. Cook, "Advances in plant health management in the twentieth century," *Annual Review of Phytopathology*, Sep. 2000.

[29] R. . and R. Katarya, "A systematic review on predicting the performance of students in higher education in offline mode using machine learning techniques," *Wireless Personal Communications*, vol. 133, pp. 1–32, 01 2024.

[30] M. Daughtrey and D. M. Benson, "Principles of plant health management for ornamental plants," *Annual Review of Phytopathology*, Sep. 2005.

[31] P. Dwivedi and A. Upadhyaya, "A novel deep learning model for accurate prediction of image captions in fashion industry," in *2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, 2022, pp. 207–212. [Online]. Available: https://doi.org/10.1109/Confluence52989.2022.9734171

[32] M. Munnangi, "Crop: Plant disease identification using mobile app," Towards Data Science, Oct. 2019. [Online]. Available: https://towardsdatascience.com/crop-plant-disease-identification-using-mobile-app-aef821d1a9bc

ANNEXURE-IV

DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

PLAGIARISM VERIFICATION

Title of the Thesis GREENLINK: ADVANCING PLANT GROWTH WITH AI

Total Pages 81 Name of the Scholar ANUSHKA UPADHYAYA

Supervisor (s)

(1) MR. RAHUL

(2)

(3)

Department SOFTWARE ENGINEERING

This is to report that the above thesis was scanned for similarity detection. Process and outcome is given below:

Software used: TURNITIN Similarity Index: 14%, Total Word Count: 10689

Date: 27/05/2024

Candidate's Signature

27/5/24
Signature of Supervisor(s)

PAPER NAME

AI_Enhanced_Plant_Health_Thesis_Anushka_2k22dsc03 (2).pdf

WORD COUNT	CHARACTER COUNT
10689 Words	60186 Characters
PAGE COUNT	FILE SIZE
82 Pages	2.2MB
SUBMISSION DATE	REPORT DATE
May 30, 2024 11:25 PM PDT	May 30, 2024 11:26 PM PDT

14% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

- 11% Internet database
- 6% Publications database
- Crossref database
- Crossref Posted Content database
- 12% Submitted Works database

Excluded from Similarity Report

- Bibliographic material
- Quoted material
- Cited material
- Small Matches (Less then 10 words)

14% Overall Similarity

Top sources found in the following databases:

- 11% Internet database
- 6% Publications database
- Crossref database
- Crossref Posted Content database
- 12% Submitted Works database

TOP SOURCES

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	dspace.dtu.ac.in:8080 Internet	3%
2	Delhi Technological University on 2024-05-01 Submitted works	<1%
3	researchgate.net Internet	<1%
4	University of Salford on 2023-05-12 Submitted works	<1%
5	fastercapital.com Internet	<1%
6	University of Adelaide on 2024-03-21 Submitted works	<1%
7	Brunel University on 2024-02-14 Submitted works	<1%
8	mdpi.com Internet	<1%

9	Tilburg University on 2024-05-21 Submitted works	<1%
10	Kennesaw State University on 2023-09-23 Submitted works	<1%
11	dspace.bracu.ac.bd Internet	<1%
12	Delhi Technological University on 2024-05-09 Submitted works	<1%
13	cornellius.substack.com Internet	<1%
14	Juan Wen, Yangjing Shi, Xiaoshi Zhou, Yiming Xue. "Crop Disease Clas... Crossref	<1%
15	Liverpool John Moores University on 2023-06-10 Submitted works	<1%
16	medium.com Internet	<1%
17	University of Edinburgh on 2022-08-11 Submitted works	<1%
18	Brunel University on 2013-04-05 Submitted works	<1%
19	Thi-Thu-Huong Le, Rini Wisnu Wardhani, Dedy Septono Catur Putranto,... Crossref	<1%
20	res.mdpi.com Internet	<1%

21	Brunel University on 2014-02-18 Submitted works	<1%
22	Monash University on 2024-05-21 Submitted works	<1%
23	Technological University Dublin on 2023-07-24 Submitted works	<1%
24	pdffox.com Internet	<1%
25	"Data Analytics for Smart Grids Applications—A Key to Smart City Deve... Crossref	<1%
26	University of New England on 2013-04-25 Submitted works	<1%
27	University of Southampton on 2024-05-03 Submitted works	<1%
28	University of Colorado, Denver on 2018-11-30 Submitted works	<1%
29	Cornelia Caragea, Jivko Sinapov, Vasant Honavar, Drena Dobbs. "Asse... Crossref	<1%
30	Manchester Metropolitan University on 2023-12-08 Submitted works	<1%
31	scholarworks.unr.edu:8080 Internet	<1%
32	Ganbayar Batchuluun, Se Hyun Nam, Kang Ryoung Park. "Deep Learnin... Crossref	<1%

33	Latvia University of Life Sciences and Technologies on 2023-12-05 Submitted works	<1%
34	Loughborough University on 2021-05-03 Submitted works	<1%
35	Rochester Institute of Technology on 2024-02-18 Submitted works	<1%
36	Universitat Politècnica de València on 2023-05-24 Submitted works	<1%
37	University of Huddersfield on 2024-05-04 Submitted works	<1%
38	as-proceeding.com Internet	<1%
39	easychair.org Internet	<1%
40	link.springer.com Internet	<1%
41	techscience.com Internet	<1%
42	www2.mdpi.com Internet	<1%
43	University of Ghana on 2024-02-08 Submitted works	<1%
44	University of Glasgow on 2024-04-21 Submitted works	<1%

45	etd.repository.ugm.ac.id Internet	<1%
46	ijaiem.org Internet	<1%
47	ijraset.com Internet	<1%
48	"Second International Conference on Image Processing and Capsule N... Crossref	<1%
49	Berlin School of Business and Innovation on 2023-06-30 Submitted works	<1%
50	CSU, San Marcos on 2018-12-14 Submitted works	<1%
51	Charles Sturt University on 2023-04-23 Submitted works	<1%
52	Liverpool John Moores University on 2017-03-31 Submitted works	<1%
53	The University of Memphis on 2019-02-27 Submitted works	<1%
54	University of Birmingham on 2024-04-08 Submitted works	<1%
55	University of Leeds on 2019-09-18 Submitted works	<1%
56	machinelearningmodels.org Internet	<1%

57	orca.cardiff.ac.uk Internet	<1%
58	biorxiv.org Internet	<1%
59	frontiersin.org Internet	<1%
60	oreilly.com Internet	<1%

DECLARATION

We/I hereby certify that the work which is presented in the Major Project-II/Research Work entitled INTEGRATING K-FOLD CROSS VALIDATION USING CNN FOR PLANT DETECTION in fulfilment of the requirement for the award of the Degree of Bachelor/Master of Technology in DATA SCIENCE and submitted to the Department of SOFTWARE ENGINEERING, Delhi Technological University, Delhi is an authentic record of my/our own, carried out during a period from 2022-2024, under the supervision of MR. RAHUL.

The matter presented in this report/thesis has not been submitted by us/me for the award of any other degree of this or any other Institute/University. The work has been published/accepted/communicated in SCI/ SCI expanded/SSCI/Scopus indexed journal OR peer reviewed Scopus indexed conference with the following details:

Title of the Paper: INTEGRATING K-FOLD CROSS VALIDATION USING CNN FOR PLANT & PATHOGEN DETECTION
Author names (in sequence as per research paper) ANUSHKA UPADHYAYA ; MR. RAHUL
Name of Conference/Journal: INTERNATIONAL CONFERENCE ON INTELLIGENT COMPUTING & COMMUNICATION TECHNIQUES
Conference Dates with venue (if applicable): 28th JUNE 2024 ; JNU, NEW DELHI
Have you registered for the conference (Yes/No)?: YES
Status of paper (Accepted/Published/Communicated): ACCEPTED
Date of paper communication: MAY 11, 2024
Date of paper acceptance: MAY 29, 2024
Date of paper publication:

Student(s) Roll No., Name and Signature
ANUSHKA UPADHYAYA
2K22/DSC/03

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I, further certify that the publication and indexing information given by the students is correct.

27/5/24

Supervisor Name and Signature

Place: NEW DELHI

Date: 27/05/2024

NOTE: PLEASE ENCLOSE RESEARCH PAPER ACCEPTANCE/ PUBLICATION/COMMUNICATION PROOF ALONG WITH SCOPUS INDEXING PROOF (Conference Website OR Science Direct in case of Journal Publication).

DECLARATION

We/I hereby certify that the work which is presented in the Major Project-II/Research Work entitled OPTIMISING PLANT HEALTH WITH Q-LEARNING: A DRL APPROACH in fulfilment of the requirement for the award of the Degree of Bachelor/Master of Technology in DATA SCIENCE and submitted to the Department of SOFTWARE ENGINEERING, Delhi Technological University, Delhi is an authentic record of my/our own, carried out during a period from 2022-2024, under the supervision of MR. RAHUL.

The matter presented in this report/thesis has not been submitted by us/me for the award of any other degree of this or any other Institute/University. The work has been published/accepted/communicated in SCI/ SCI expanded/SSCI/Scopus indexed journal OR peer reviewed Scopus indexed conference with the following details:

Title of the Paper: OPTIMISING PLANT HEALTH WITH Q-LEARNING: A DEEP REINFORCEMENT LEARNING APPROACH
Author names (in sequence as per research paper) ANUSHKA UPADHYAYA ; MR. RAHUL
Name of Conference/Journal: THE 15TH INTERNATIONAL IEEE CONFERENCE ON COMPUTING, COMMUNICATION & NETWORKING TECHNOLOGIES
Conference Dates with venue (if applicable): 28th JUNE 2024 ; JNU, NEW DELHI
Have you registered for the conference (Yes/No)?: YES
Status of paper (Accepted/Published/Communicated): ACCEPTED
Date of paper communication: MAY 13, 2024
Date of paper acceptance: MAY 30, 2024
Date of paper publication:

Student(s) Roll No., Name and Signature
ANUSHKA UPADHYAYA
2K22/DSC/03

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I, further certify that the publication and indexing information given by the students is correct.

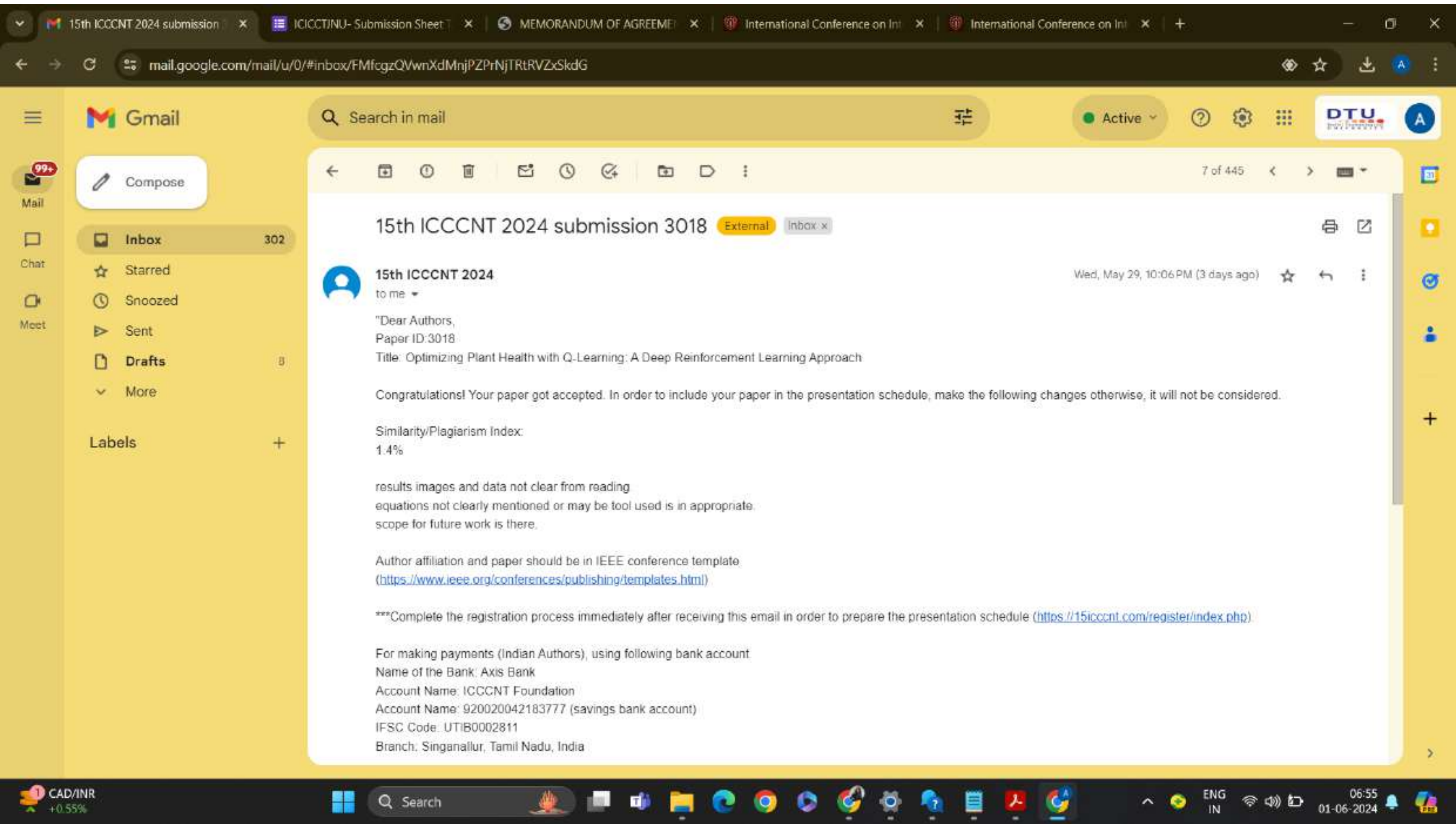
27/5/24

Supervisor Name and Signature

Place: NEW DELHI

Date: 27/05/2024

NOTE: PLEASE ENCLOSE RESEARCH PAPER ACCEPTANCE/ PUBLICATION/COMMUNICATION PROOF ALONG WITH SCOPUS INDEXING PROOF (Conference Website OR Science Direct in case of Journal Publication).



15th ICCCNT 2024 submission 3018

External | Inbox

15th ICCCNT 2024

to me

Wed, May 29, 10:06 PM (3 days ago)

"Dear Authors,
Paper ID:3018
Title: Optimizing Plant Health with Q-Learning: A Deep Reinforcement Learning Approach

Congratulations! Your paper got accepted. In order to include your paper in the presentation schedule, make the following changes otherwise, it will not be considered.

Similarity/Plagiarism Index:
1.4%

results images and data not clear from reading
equations not clearly mentioned or may be tool used is in appropriate.
scope for future work is there.

Author affiliation and paper should be in IEEE conference template
(https://www.ieee.org/conferences/publishing/templates.html)

***Complete the registration process immediately after receiving this email in order to prepare the presentation schedule (https://15icccnt.com/register/index.php)

For making payments (Indian Authors), using following bank account
Name of the Bank: Axis Bank
Account Name: ICCCNT Foundation
Account Name: 920020042183777 (savings bank account)
IFSC Code: UTIB0002811
Branch: Singanallur, Tamil Nadu, India

Transaction Successful
08:34 pm on 30 May 2024

Paid to

ICCCNT Foundation — ₹8,600
XXXXXXXXXXX3777
Axis Bank

Transfer Details

Transaction ID
T2405302034306767329634

Debited from
XXXXXXX1451 — ₹8,600
UTR: 415194125354

Powered by
UPI AXIS BANK

The ICCCNT 2024 Conference themes, grouped in three tracks, are the following (but are not limited to)

Computing	Communication	Networking			
Track Id	**Tracks**	**Track Id**	**Tracks**	**Track Id**	**Tracks**
1	Image Processing - click to view tracks	26	Professional Communication	51	Social Networks
2	Deep Learning - Click to view tracks	27	Wireless CommunicationTopics	52	Wireless NetworkingTopics
3	Machine Learning - Click to view tracks	28	Optical Communication	53	Network Security
4	Natural Language Processing - Click to view tracks	29	Remote Sensing	54	Sensor Network
5	Big Data	30	VLSI / ULSI / MEMS	55	Computer Networks
6	Data Science	31	RF System	56	Power DistributionNetworks
7	Data Mining	32	Signal Processing	57	Optical Networks
8	Computer Science Topics	33	Digital System Design	58	Ubiquitous Networks
9	LIDAR - Click to view tracks	34	Smart Grid	59	Cyber Physical Systems (CPS)
10	Medical Imaging - Click to view tracks	35	Control System	60	Heterogeneous Wireless Networks
11	Test-Bed	36	Robotics, Drones, UAV	61	Measurement and Performance analysis
12	Computer Graphics - Click to view tracks	37	Information Theory & Coding	62	High Speed Networks
13	Cyber Security - Click to view tracks	38	5G, 6G and beyond	63	Network Applications
14	Internet of Things	39	Future Technologies	64	Network Based Architectures
15	Biometrics - Click to view tracks	40	Fake news detection	65	Vehicles to everything (V2X) Autonomous car
16	Start-Up	41	QoS provisioning and Architectures	66	AR/VR streaming
17	Electronic Package Topics - Click to view tracks	42	Communication technologies for animals, animal	67	Next Generation Internet
18	Photonics – Click to view tracks	43	Machine Learning forCommunications	68	AI/ML techniques for Computer Networks
19	Quantum Photonics	44	Industrial Applications	69	Novel Networking protocols
20	Artificial Intelligence	45	Terahertz Communication	70	Network softwarization for 5G/6G
21	Women in Computing	46	Green CommunicationNetworks	71	Socio-economic impact and regulations for softwarization
22	Data Visualization	47	Multimedia Communicationand Software	72	Machine -to- Machine communication networks
23	3D, AutoCAD	48	Cognitive Radio	73	Security/privacy issues
24	AI in Education	49	Information System Security	74	5G /6G in Education
25	Augment Reality, Virtual Reality	50	Communication Theory	75	Cryptography

Publication

15th ICCCNT 2024 IEEE Conference proceedings will be published in IEEE Xplorer and indexes in scopus

Qualified paper will be recommended to special issue journals

Venue

Notification of acceptance of paper id 782

External Inbox

Microsoft CMT <email@msr-cmt.org>
to me

Wed, May 29, 12:17 AM (3 days ago)

Dear Dr./ Prof. Anushka Upadhyaya,

Congratulations...

Your paper / article paper id 782: Integrating K-Fold Cross-Validation with Convolutional Neural Networks for Plant Species and Pathogen Detection has been accepted for publication in International Conference on Intelligent Computing and Communication Techniques at JNU New Delhi, India.

Kindly save your paper by given paper id only (eg. 346.docx, 346.pdf, 346_copyright.pdf)

Registration Link:

https://forms.gle/mSsHa8GMLtMkWuaq8

Please ensure the following before registration and uploading camera ready paper.
1. Paper must be in Taylor and Frances Format.
Template and copyright with author instruction are given in below link: https://icicct.in/author_inst.html

2. Minimum 12 references should be cited in the paper and all references must be cited in the body. Please follow the template.
3. The typographical and grammatical errors must be carefully looked at your end.
4. Complete the copyright form (available at template folder).
5. The regular fee (Available in registration section) will be charged up to 6 pages and after that additional Rs.1000 for Indian authors / 10 USD for foreign authors per additional page will be charged.
6. Reduce the Plagiarism below 10% excluding references and AI Plagiarism 0%. The Authors are solely responsible for any exclusion of publication if any.
7. Certificate will be issued by the name of registered author (Single author only).
8. Certificates may be issued to all other authors on the extra payment of 1000/- INR per author.
9. Last Date of registration and uploading copyright and camera-ready copy: 31/05/2024.

Transaction Successful
07:17 PM on 01 Jun 2024

Paid to

Evedant Foundation ₹7,000
XXXXXXXXXXXX2900
Punjab National Bank

Transfer Details

Transaction ID
T2406011917378831398852

Debited from
XXXXXXX5862 ₹7,000
UTR: 415392469135

Powered by
UPI ICICI Bank

About The *ICICCT*

ICICCT-2024 is a non-profit conference and the objective is to provide a platform for academicians, researchers, scholars and students from various institutions, universities and industries in India and abroad, to exchange their research and innovative ideas in the field of Cloud, Communication and Internet of Things. We invite all students, research scholars, academicians, engineers, scientist and industrialist working in the field of Intelligent Computing, Communications and Techniques from all over the world. We warmly welcome all the authors to submit their original research in upcoming conference ICICCT-2024 to share their knowledge and experience among each other in collaboration with JNU and EVedant Foundation.

Papers submitted to ICICCT-2024 will undergo a strict double-blind review process. All papers that are accepted and presented in ICICCT-2024 will be published in the ICICCT-2024 Conference Proceeding. The proceeding will be published by Taylor & Francis and Indexing in Scopus.

International Conference on Intelligent Computing and Communication Techniques (ICICCT-2024)

Date : 28th to 29th June, 2024

Certificate of Participation

This is to certify that **Anushka Upadhyaya** of **Delhi Technological University** has presented his/her research paper titled **"Integrating K-Fold Cross-Validation with Convolutional Neural Networks for Plant Species and Pathogen Detection"** in the ICICCT-2024 organized by Jawaharlal Nehru National University, New Delhi in collaboration with E-Vedant Foundation held from **28th to 29th June, 2024**.

Dr. D. K. Lobiyal **General Chair** ICICCT-2024	**Dr. Karan Singh** **Conference Chair** ICICCT-2024	**Dr. Arvind Dagur** **Conference Chair** ICICCT-2024	**Mr. Avanish Kumar** **Director** EVedant Foundation