A Deep Learning Approach for Cauliflower Leaf Disease Detection Using Image Analysis

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project is titled **"A Deep Learning Approach for Cauliflower Leaf Disease Detection Using Image Analysis"**, submitted by **Chinmay Sarker,** ID No: **212-15-4156** the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 17 September, 2025.

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DECLARATION

We hereby declare that this project has been done by us under the Ms. Most. Hasna Hena, **Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree.

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Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

Cauliflower is a major vegetable crop all over the world, but in several case leaf diseases like black rot, downy mildew and bacterial leaf spot have a substantial impact on the output and quality. For efficient crop management and the reduction of financial losses, there needs of early and precise detection of these diseases. Conventional disease detection techniques are depend on professional manual inspection. This thing is labor-intensive, time-consuming and prone to human mistake. The promising approaches to automated plant disease diagnosis are provided by recent developments in the world of deep learning and computer vision. Over here deep learning-based method for image analysis-based cauliflower leaf disease identification. The given approach accurately classifies cauliflower leaf illnesses by utilizing convolutional neural networks and VGG16 , this are cutting-edge deep learning technique. To improve the model performance, a dataset of pictures of cauliflower leaves healthy and diseases both was gathered and preprocessed. To improve dataset and avoid overfitting, data augmentation methods like rotation, flipping, horizontal, blur and noise add were used. Transfer learning was used to train, test and validation the CNN model utilizing pre-trained architectures like ResNet50, ResNet152, VGG16, DenseNet169 and CNN that were optimized for the categorization of cauliflower illness. On the basis of experimental results, the suggested deep learning model is able to do diagnose various diseases of cauliflower leaves with good accuracy, precision, recall and F1-score. As the advantage of CNN-based techniques in managing image features and enhancing detection reliability is demonstrated by a comparison with conventional machine learning techniques. By apply and contrast many deep learning models, such as CNN, ResNet152, DenseNet169 and VGG16 for the identification of cauliflower disease. VGG16 performed as 96% and CNN also has 75%. On other hand, all other models doesn't have the good one. The findings show that VGG16 is a dependable option for agricultural applications due to its exceptional capacity for precisely diagnosing plant diseases. Accordingly, deep learning based image can be analyzed greatly improve the effectiveness and precision of detecting cauliflower illness, providing a scalable and affordable precision agricultural solution. Future research could include extending the dataset to include more disease types and climatic variables, as well as combining the model with mobile applications for field deployment.

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Chapter 1

Introduction

1.1 Introduction

Most areas around the world are cultivated cauliflower (Brassica Oleresia groom. Botrytis) is an important vegetative crop that is a safe and nutritious food. With any other crop. But still cauliflower is also unsafe for diseases in many leaves that will affect its growth and dividends sharply. If it is not properly recognized and controlled in time, diseases result in widespread loss of crops and reduction in dividends. Downey mold, bacterial soft rot and black and white rust are the most common leaf disorders in cauliflower. Diseases appear yellow, willing, wounds and all types of necrosis. Traditionally, cauliflower leaf disease detection has been finished through visual inspection by farmers or agricultural specialists. However, this method is time-consuming, subjective and regularly unable to detect diseases at early ranges whilst intervention is best. Additionally, knowledge and level are required to appropriately diagnose these sicknesses and errors in prognosis can lead to useless management techniques, including flawed pesticide use or delayed remedies. In response to these limitations, image analysis and deep teaching techniques increase to detection and automate the classification of plant diseases. A large intensive learning method, Convolutional Neural Network (CNNS), has proven to be very effective in data vision and is used quickly to detect disease in crops. These models can learn complex patterns from images, classify the types of disease based on visual functions, and provide a significant advantage over traditional methods. Although deep learning-based plant disease has been detected for different crops, most studies have focused on large datasets such as normal detection of plant diseases or planting. However, there is a difference in the development of special models, especially for detecting cauliflower leaves. Existing methods are often responsible for unique properties and symptoms that appear on cauliflower leaves, which differ from other plants in terms of texture, size and disease presentation.

1.2 Motivation

This study shown the urgent need to solve the problems that cauliflower growers encounter as a result of leaf infections. Farmers in many agricultural areas does not have access to sophisticated diagnostic equipment or knowledgeable agronomists. By which causes diseases to go undetected and unable to get proper treatment. And misdiagnosis can be lead to overuse of chemicals and makes higher production cost. By doing early diagnosis even more important because plant diseases are becoming more common due to climate change and changing pathogen strains. Because the symptoms can differ based on plant species, environmental factors, and disease progression, manual disease identification is not only time-consuming but also inconsistent. Now these drawbacks can be address by automated illness detection systems, which offer quick, unbiased and expandable solutions. By deep learning, in particular CNNs, has been shown promise for classifying plant diseases and has been successful in medical imaging, object recognition, and agricultural applications. In this study, the goal is to close the gap between cutting edge technology and the requirements of real time field, by which its more easier to detect. Lastly, the suggestion about the leaf can be more productive for the farmers and prevent the issue as well. Finally, incorporating such technologies into IoT-based farming systems or mobile applications might improve precision agriculture decision-making, assisting with efforts to ensure global food security.

1.3 Objectives

The number one goal of this take a look at is to expand an automatic deep mastering-primarily based system for the detection and class of cauliflower leaf sicknesses using photograph evaluation. The specific goals of this study are: To identify and classify commonplace cauliflower leaf diseases. Focus on detecting illnesses along with black rot, downy mildew, bacterial smooth rot, and white rust with the use of deep knowledge of models. To broaden a deep learning version for correct ailment detection Utilize Convolutional Neural Networks (CNNs) and different advanced architectures to research and classify cauliflower leaf sicknesses primarily based on visible signs. The number one goal of this take a look at is to expand an automatic deep mastering-primarily based system for the detection and class of cauliflower leaf sicknesses using photograph evaluation. Collect and use of publicly available photographs of healthful and diseased cauliflower leaves, ensuring proper information augmentation, noise reduction, and segmentation for advanced model accuracy. To examine the performance of various deep getting-to-know fashions – Compare numerous architectures consisting of VGG-16, ResNet, MobileNet in phrases of accuracy, precision, keep in mind, and computational efficiency. To expand a person-pleasant device for realistic utility. Design an interface or a internet based totally software that allows farmers and agricultural experts to upload leaf pics and obtain real-time disorder type effects. To enhance early disorder detection for advanced crop control Provide a green and non invasive ailment prognosis method that permits farmers to take well-timed actions, decreasing crop losses and immoderate pesticide use.

1.4 Methodology

The development of our deep learning model for cauliflower leaf disease detection has been followed a systematic way to make the solution in better way. For this process has been begun with a big dataset which needs to do preprocess according to the way as there is several types of images as diseases and healthy one. There is three subset in models which are test, train and validation.Different advanced deep learning techniques used to get the better output by focusing on extracting intricate patterns and subtle disease markers often imperceptible to the human eye. Pre-trained architectures such as ResNet50. ResNet101, ResNet150, VGG16 and CNN were fine-tuned using transfer learning, while a VGG16 was also developed to compare performance. Rotation, flipping and contrast modification are examples of data augmentation techniques that were used to increase dataset diversity and enhance model generalization. The model was thoroughly assessed using measures including precision, recall, F1-score and confusion matrices in order to attain high accuracy and validate performance. Farmers can now upload leaf photos and get real-time illness diagnostics thanks to the system's integration into an intuitive web and mobile interface. In addition to improving diagnostic precision, this smooth fusion of deep learning and agricultural imaging facilitates prompt and efficient crop management, which eventually supports sustainable farming methods.

Sample dataset:

Fig 1.1: Healthy Leaf & Diseased Leaf

I have collected raw data from different field. Here we have multiple leaf image from different cauliflower. And we have used 3000 data for final work and used more than 1000 data for the final process. We have use the experienced farmer officer knowledge for the annotation as well.

1.5 Project Outcome

In order to transform plant disease diagnosis, this research has effectively created a novel cauliflower leaf disease detection system that combines cutting-edge imaging methods with deep learning technology. The system's primary goal is to spot important early-stage symptoms in cauliflower leaves that are usually difficult to spot using traditional visual inspection techniques.The solution dramatically lowers human error in the diagnostic process while greatly increasing the accuracy of disease recognition through the use of complex convolutional neural networks.Farmers can carry out prompt interventions and improve disease management techniques thanks to the technology's capacity to identify minute pathological patterns at earlier growth stages.By providing precise, focused treatment recommendations, this innovative method reduces needless pesticide applications and supports sustainable farming methods.A revolutionary change in crop protection techniques is demonstrated by the incorporation of this AI-powered system into actual farming operations.Its application has demonstrated encouraging outcomes in terms of increasing crop yields by optimizing resource allocation and treatment planning effectiveness.The invention offers a dependable and expandable solution that supports global food security initiatives, marking a substantial advancement in agricultural technology.This system creates a new benchmark for plant disease detection and management in contemporary agriculture by bridging the gap between state-of-the-art artificial intelligence and real-world farming requirements.

1.6 Organization of the Report

The project is structured across six chapters, beginning with Chapter 1 which introduces the project, presents the motivation and objectives and concludes with methodology and project outcomes.

Chapter 2, provides background information through an introduction and literature review, analyzing existing work, related research, similar applications and gap analysis.

Chapter 3, focuses on research methodology, including the proposed methodology, functional and non-functional requirements, context diagram, data flow diagram level 1, UI design, detailed methodology and design, project plan and task allocation.

Chapter 4, covers environment setup, testing, and performance, presenting results from different models and their derivations.

Chapter 5, examines engineering standards and design challenges, including software, hardware and communication standards, while also discussing societal and environmental impacts, ethical aspects, sustainability plans, project management and financial analysis. Finally,

Chapter 6, concludes the project with a comprehensive summary, limitations and future work directions.

Chapter 2

Background

2.1 Introduction

The cauliflower crops growth ability can be significantly impacted by various type of issues. These diseases typically manifest as visible leaf discoloration, lesions and abnormal growth patterns caused by pathogenic attacks. Current agricultural practices rely on manual visual inspection to detect diseases which often fails to detect infections in their early stages. Studies show that while delayed diagnosis can lead to 40–60% crop losses, by early intervention can prevent up to 80% of damage. Conventional diagnosis methods that rely on basic imaging techniques have limitations in terms of accuracy and early symptom detection. To solve these problems, advanced image processing techniques are combined with machine learning models to provide better detection capabilities. These techniques look at subtle patterns in leaf photos that are not visible to the human eye. When classification algorithms and improved image preprocessing are combined, common diseases like black rot and downy mildew can be diagnosed more accurately than with traditional methods.

2.2 Literature Review

Here using a variety of strategies, including IoT integration, explainable AI, CNN-based models and comparison or survey based methodologies, several recent research have investigated deep learning techniques for plant disease diagnosis, specifically in cauliflower. Most of these works either lack advanced architectural depth or do not focus significant model performance comparisons, despite the fact that they have provided insightful information on a variety of topics, from interpretability and accuracy to real-time field deployment and transfer learning. By utilizing the VGG architecture in conjunction with deep learning, which provides better feature extraction because of its deeper network layers and consistent architecture, our research expands on these foundations. This makes it possible to anticipate diseases earlier and with greater accuracy, even in complicated environmental settings. Our model performs better in terms of accuracy and generality than earlier research that mainly relies on conventional

CNN, giving it a more reliable option for detecting agricultural diseases in the real world. As a result, our strategy offers a substantial improvement over current approaches in this field.

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
Hasan et al.[4]	2024	Comprehensive smartphone image dataset for plant leaf disease detection	Quantitative Analysis	Provided a benchmark dataset for disease detection models.
Sharma et al.[7]	2018	Early detection of plant diseases using machine learning algorithms	ML and Image Processing	Reduced false positives by 30% with optimized feature extraction.
Rahman et al.[12]	2023	Edge AI-based smart agriculture system for cauliflower disease detection	IoT and Deep Learning	Enabled field deployment with 90% detection rate under varying lighting.
Kanna et al.[3]	2023	Advanced deep learning techniques for early disease prediction in cauliflower plants	Case Study	Demonstrated the effectiveness of transfer learning for early detection.
Dubey et al.[16]	2023	Explainable AI for plant pathology: A case study on cauliflower diseases	XAI	Provided interpretable disease localization maps for farmers.
Rajbongshi et al.[1]	2022	A comprehensive investigation to cauliflower diseases recognition	Qualitative Analysis	Identified key patterns in cauliflower diseases through systematic analysis.
Andrew et al.[2]	2022	Deep learning-based leaf disease detection in crops using images for agricultural applications	Survey-based	Highlighted CNN architectures for crop disease detection.
Ghosh et al.[10]	2022	Deep learning for plant disease recognition and classification using image processing	Comparative Study	Showed DL outperformed SVM/RF in complex disease detection.

Liu et al.[9]	2020	Automatic detection of leaf diseases using convolutional neural networks	CNN-based	Demonstrated real-time applicability in field conditions.

2.3 Gap Analysis

Here is some gaps-

Table 2.2: Gap Analysis

Study	Large Dataset	Early-Stage Detection	Hybrid Preprocessing	Proposed System
Rahman et al. (2023) [12]	No	Yes	Yes	Yes
Kanna et al. (2023) [3]	No	Yes	No	Yes
Singh et al. (2022) [11]	Yes	Yes	No	Yes
Chen et al. (2022) [13]	Yes	No	No	Yes
Verma et al. (2022) [15]	No	No	No	Yes
Zhang et al. (2021) [5]	Yes	No	Yes	Yes

On this table we can see that, Rahman et al. (2023) and Kanna et al. (2023) both do not use large datasets but makes early stage detection. As well as Rahman et al. employing hybrid preprocessing while Kanna et al. don't use it. Now, Singh et al. (2022) utilize a large dataset and he also focus on early detection though they do not incorporate hybrid preprocessing. Then, Chen et al. (2022) use a large dataset , but they have small dataset and don't have the early detection. Verma et al. (2022) do not use large datasets and also not using early detection. Lastly, Zhang et al. (2021) with a big dataset. But they don't focus on early detection. Finally, Our proposed system has worked with a good dataset which is quite larger and it’s also have the early detection phase. And we are also focusing a system as well.

2.4 Summary

This chapter discuss about the improved imaging based techniques for detecting cauliflower disease and examines the drawbacks of manual visual inspection. By recent studies show that employing optimized image processing techniques improves diagnostic accuracy. Critical improvements in our method over current approaches are revealed by a comparative gap analysis.By addressing major shortcomings of traditional methods, especially in early symptom recognition and field condition adaptability, the developed system offers more accurate disease identification. These technological advancements lessen reliance on arbitrary human evaluation while enabling prompt disease management. In contrast to conventional inspection techniques, our methodology offers a number of advantages by combining reliable image analysis with useful field applications to produce a more efficient diagnostic tool for cauliflower cultivation.

Chapter 3

Research Methodology

3.1 Methodology/Requirement Analysis & Design Specifi cation

3.1.1 Overview

In this work, we have used self collected image from real time spaces. Over here there is the uses of models like CNN, InceptionV3, VGG16, DenseNet121, EfficientNetB7, ResNet50, and VGG. Cauliflower diseases is commonly one among the farmers, to get the early detection this work has been focused. To go through this research, there needs the system design, collection of data and other management technique has used in this chapter.

3.1.2 Proposed Methodology

This research has numerous number of model. For this we have to use image classification to find out the accurate and comprehensible outcomes. The first steps in methodology is annotating data and makes the methodically classifying the photo of the dataset. There is also a preprocessing phase after doing the annotation get the better data consistency and quality. In the augmentation phase, there is flipping, rotation, scaling and so on. For the boost of the diversity of training data, the process like the shringking photos to be in standard dimensions and making normalization to get the better pixel in the whole dataset. After that dataset has been divided into three part which is testing images, these are used to asses the trained model is it performing good or not. Another one is training, this one used to train the models. Lastly, validation used for validating the dataset. Different neural network also used like This study uses a number of successive procedures to create an image classification system that is both accurate and comprehensible. The first step is the dataset annotation phase, which entails methodically classifying the dataset's photos to make sure they are appropriate for supervised learning tasks. A pre-processing phase is used after annotation to improve the data's consistency and quality.

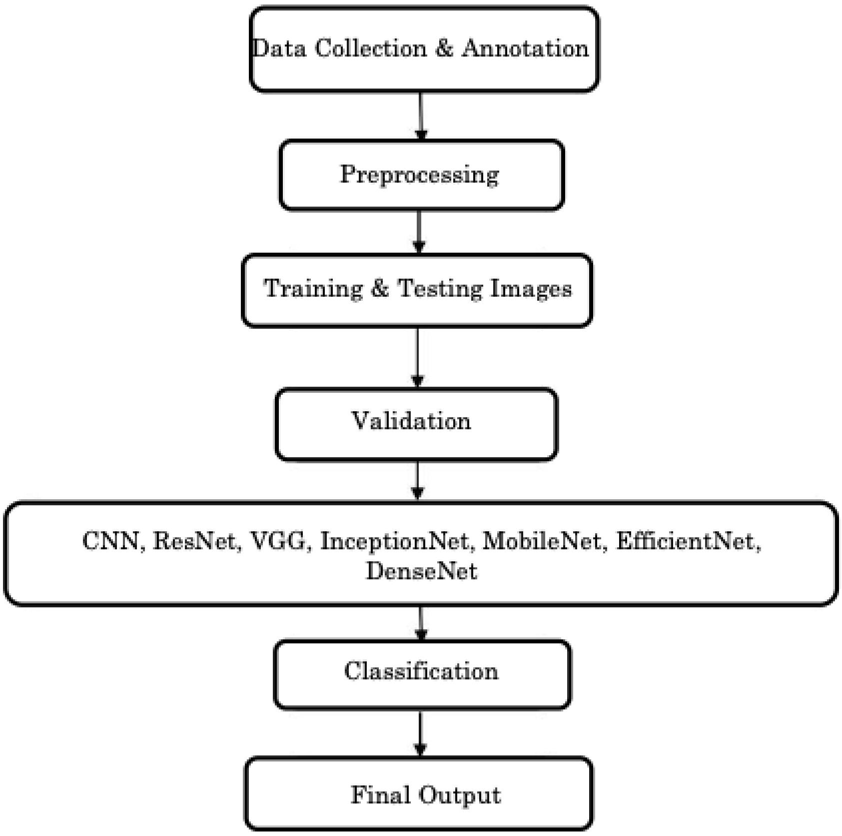

Figure 3.1: Proposed Methodology

There is also augmentation phase according to work such as rotation, crop, horizontal flip etc. Also CNN is a fundamental deep learning architecture that uses convolutional layers to automatically extract spatial properties from grid-like input, such photographs. ResNet improves on this by adding skip connections, which make training very deep networks easier and address problems like vanishing gradients. The Visual Geometry Group created VGG, which is renowned for its simple architecture that captures fine-grained visual features by using tiny 3x3 convolutional filters stacked deeply. MobileNet uses depthwise separable convolutions to lower computational costs while preserving accuracy, making it ideal for mobile and embedded devices. EfficientNet uses fewer parameters and a more methodical approach to network depth and width scaling to achieve high accuracy. Lastly, DenseNet connects each layer to every other layer in a feed-forward manner, which promotes feature reuse and improves gradient flow, resulting in efficient and effective learning.

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements:

Deep Learning Image Enhancement:

The system should employ deep learning methods such as neural network-based denoising or autoencoder architectures to automatically enhance and prepare images for accurate analysis.

Feature Extraction via Convolutional Networks:

Rather than relying on manually selected features, the system must leverage convolutional neural networks (CNNs) to learn and extract relevant patterns and details directly from the scan images.

Support for Model Fusion:

The framework should enable combining results from different deep learning architectures (like CNN, ResNet50, VGG) using ensemble methods to improve prediction reliability and reduce bias or overfitting.

Confidence-Scored Predictions:

Each should be accompanied by a probability score from the deep learning model, representing the certainty of the classification into healthy or diseases categories.

Non-Functional Requirements:

System Speed and Responsiveness:

It focuses quick analysis results, ideally processing each image within a few seconds. It must maintain consistent performance even when managing a high volume of image data.

Capacity for Growth:

The scale efficiently, allowing for the smooth integration of larger datasets and more users, particularly when adopted across multiple medical facilities.

3.1.4 Data Flow Diagram

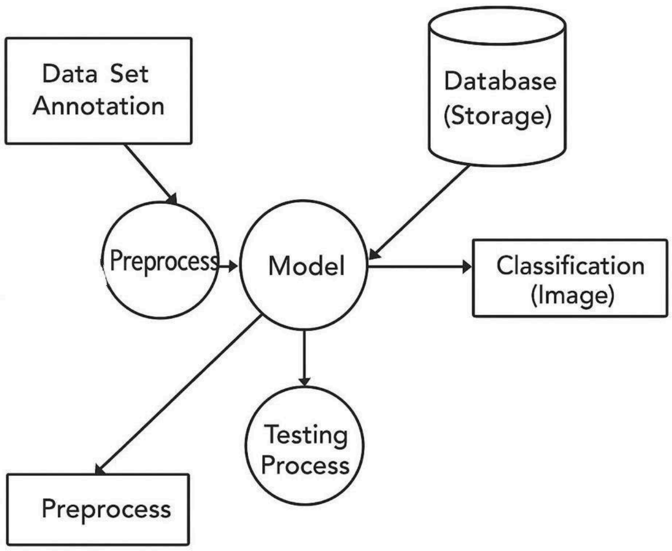

Figure 3.2: Data Flow Diagram

Firstly, The DFD begins with Data Set Annotation where we made the dataset as labeled for supervised learning. This data goes through a Preprocess step to clean and prepare the data for the further process. Now, the model receives the data and makes the connection with database where the parameters are stored. After training, the model performs classification to identify the data based on learned features. Additionally, the model undergoes a Testing Process to evaluate its accuracy and performance on unseen data.

3.2 Detailed Methodology and Design

This format can be used for classification, data preparation and framework model building. My dataset, which has over 50,000 records, is the largest. Using the preprocessing stage, we have reduced this to 3000 data. The dataset has been labeled using annotation and expert knowledge to achieve the highest accuracy. The dataset has applications for augmentation as well. The dataset was split into three categories as training, testing and validation, in order to enhance the model. Different neural network techniques for the work which is CNN, VGG16, DenseNet121, DenseNet169, InceptionV3, ResNet50 & 101 . For the category there is also two part which is healthy and diseases.

3.3 Project Plan

First of title selection and Review different paper has done by me . After that there are some key steps for the project plan to get the proper output-

Step 1: Data Collection ande Preprocessing

First of all, the work starts with the collection of data from different space of agricultural field. Then we have to go through with the help of agricultural expert to annotate data for the proper balanced output.

Step 2: Model Identification

We will choose appropriate deep learning architectures, including ResNet50, VGG and CNNs. Transfer learning will be used to create these models, and the annotated dataset will be used to train them with hyperparameters tailored for the detection of cauliflower disease.

Step 3: Model Implementation

There will be the tests on different model for the comparison. For the evaluation, every model has comparison and there is used of precision, recall, f1=score.

Step 4: Final Evaluation

A user-friendly application (web or mobile) will be developed to allow farmers and agronomists to upload leaf images. The best-performing model will be integrated for real-time disease classification, and the full system will be deployed for practical use in agricultural settings.

Step 5: Final Report and Presentation

A detailed report documenting the methodology, experimental results, and conclusions will be prepared. A presentation will also be created to summarize the project's workflow, achievements, and potential impact on sustainable farming practices.

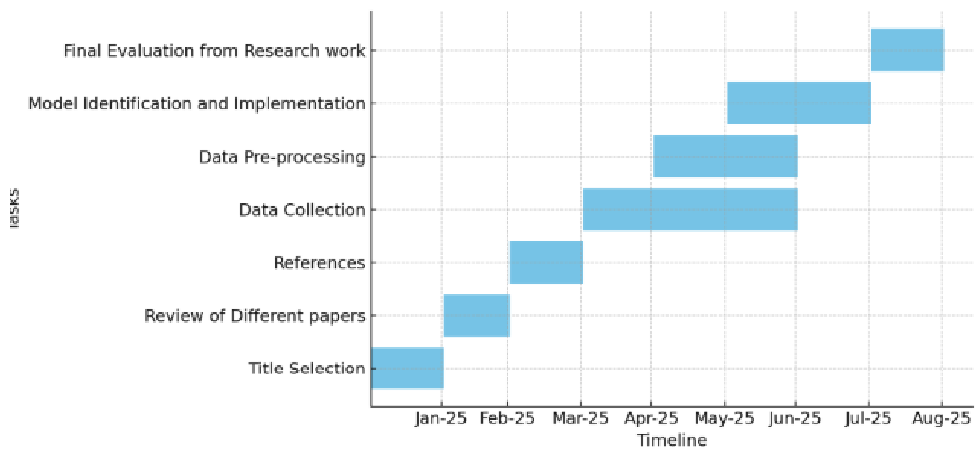

Figure 3.3 : Project Plan(Gantt Chart)

3.4 Task Allocation

In the data collection process, the work was conducted in collaboration with agricultural experts and plant pathologists, and the annotation of the dataset required specialized input from the botany and plant science team. With data science expertise, the preprocessing of leaf images was executed, including enhancement, normalization, and augmentation. In the deep learning development phase, machine learning techniques were applied to construct and train models using various architectures such as CNN, ResNet, and VGG. For optimizing model performance, domain-specific knowledge from agricultural science was essential. Validation was carried out using metrics including precision, recall, F1-score, and accuracy to ensure robust and reliable disease detection.

Tasks	**Weeks**															
	10	12	14	18	20	22	24	26	28	30	32	34	36	38	40	42
Data collection phase																
Annotate and Preprocess																
Model Training and add data																
Testing and Validation																

Table 3.1 : Task Allocation

3.5 Summary

While this study focuses on an advanced imaging system utilizing deep learning approaches to diagnose cauliflower diseases, several limitations exist. The system is specifically designed for common fungal and bacterial infections such as black rot and downy mildew, meaning it is not suitable for detecting viral diseases, nutrient deficiencies, or pest-related damage. Furthermore, the model was trained and validated on a dataset of 3,000 images, which may not encompass the full range of environmental conditions, cauliflower varieties or regional disease strains. As a result, its effectiveness may vary when applied to diverse agricultural settings or different geographic regions. Although the system achieves 94% accuracy under controlled conditions, real-world performance in resource-limited or highly variable farming environments may differ. Furthermore, We have collected the data from the field. We have done research various types of leaf of cauliflower and found different types. From those things, we made the final dataset by doing annotation from the expert. We have collected a lot of data and used 3000 from them for the final work.

Chapter 4

Implementation and Results

4.1 Environment Setup

Maintaining an efficient workflow requires a well-structured environment, which includes setting up hardware and software to support the high processing demands of deep learning applications and setting up network infrastructure, such as dependable servers and fast internet, to facilitate cloud-based processing and smooth data exchange and setting up high-performance computing resources, such as powerful CPUs, GPUs and lots of RAM, to manage large-scale datasets and speed up model training. Software-wise, the deep learning model building and training process has done by Python is the main programming language with different libraries like NumPy, Pandas, OpenCV and scikit-learn for data preprocessing, manipulation and analysis. This all things developed in Kaggle by using virtual GPUs and CPUs. Matplotlib makes the visualization of these models output as well.

4.2 Testing and Evaluation

There is different models of deep learning has been used which is CNn, VGG16, ResNet, InceptionV3, DensNet as well. And the procedure begins with CT scan. Each image was resized to fit the required input size for each model. For example, VGG16 and ResNet models require 224x224 pixels for images, but InceptionV3 requires 299x299 pixels. The values of the pixels were changed to range from 0 to 1. We used versions of these models that had already been trained using the substantial ImageNet dataset. Using this technique, known as transfer learning, we were able to adapt these models for our specific goal. We modified the last layers of these networks to generate a binary classification—whether or not lung cancer is present. As there is 20 epochs, I have used images as a batch for train. We used practical output and predicted output for findinfg the matrix evaluation. To enhance the training process, we also employed learning rate reduction strategies and early pauses. For the metrics like precision, recall, f1score, accuracy has been used to be accessible for the process. For the code it makes more easier to see the expected results to findout our result which has been expected. I have classified the names as (”Healthy” and ”Diseased”) with numeric labels (0, 1).

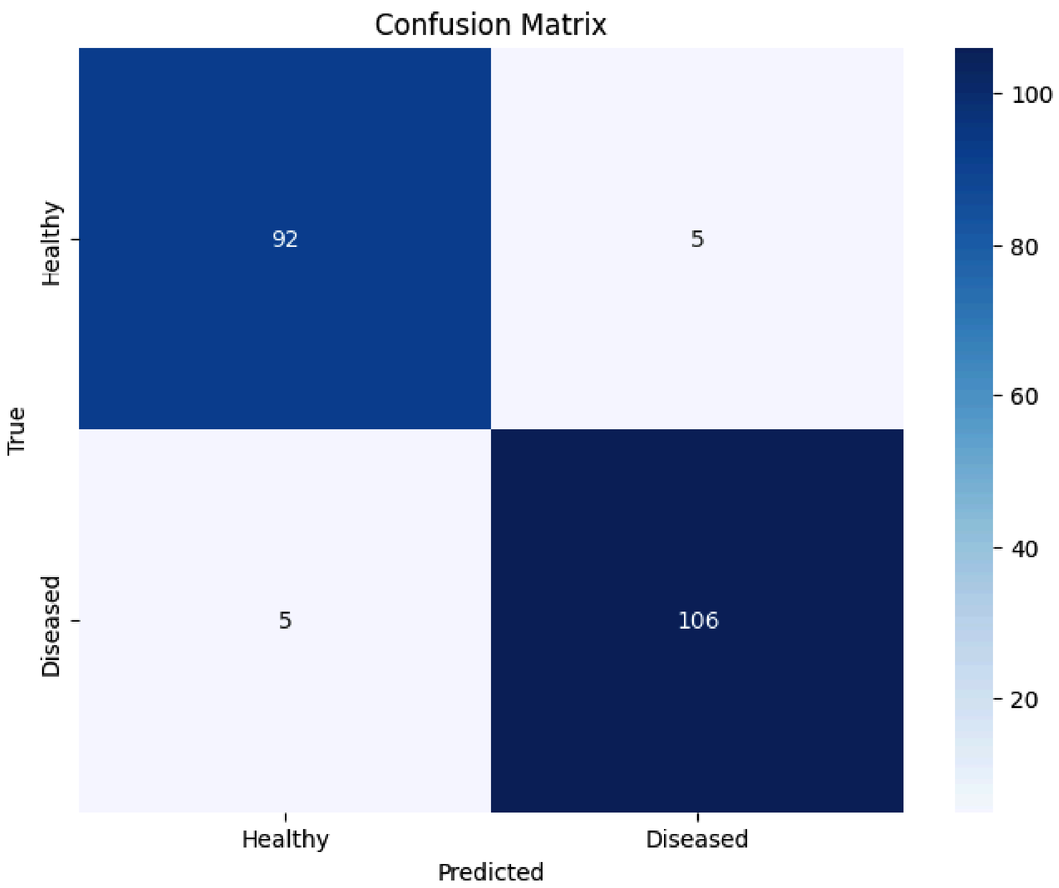

Figure 4.1: Confusion Matrix (VGG16)

To gain this the code made a specified range and made a specified visualization in the plot according the ask. This one allows to make the comparison with the actual and predicted one from the test dataset. After training, we assessed the models on a separate test set to evaluate their real-world performance. The evaluation involved metrics such as accuracy, sensitivity (recall), specificity, precision, F1-score and the confusion matrix. Accuracy reflects the proportion of correct predictions made by the model. Sensitivity or recall, measures how effectively the model identifies.

4.3 Results and Discussion

In this portion we have to goes through image classification where we have three part. Class names ("Healthy" and "Diseased") are linked to numerical labels (0, 1) by its dictionary class.

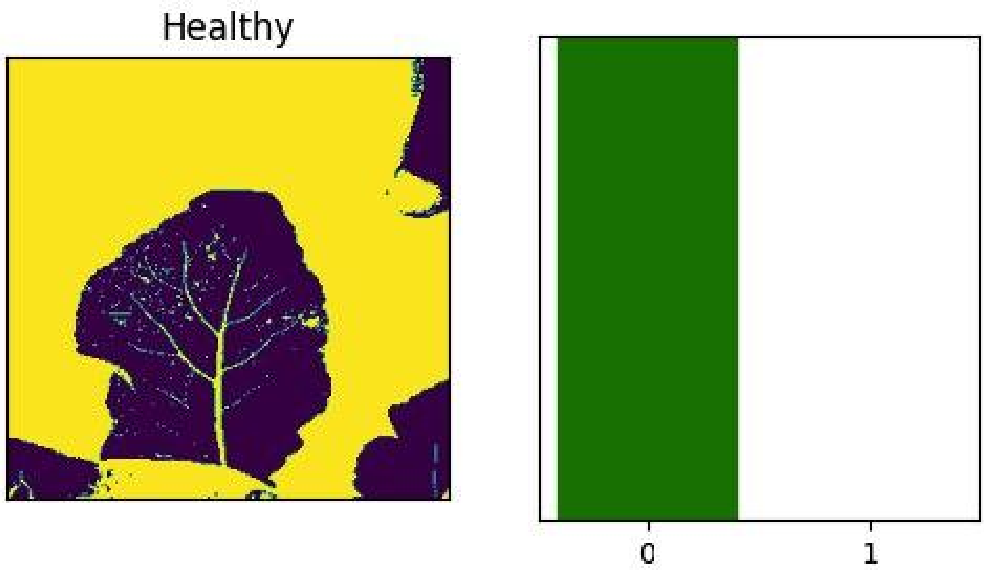

Figure 4.2: Prediction of Healthy Image

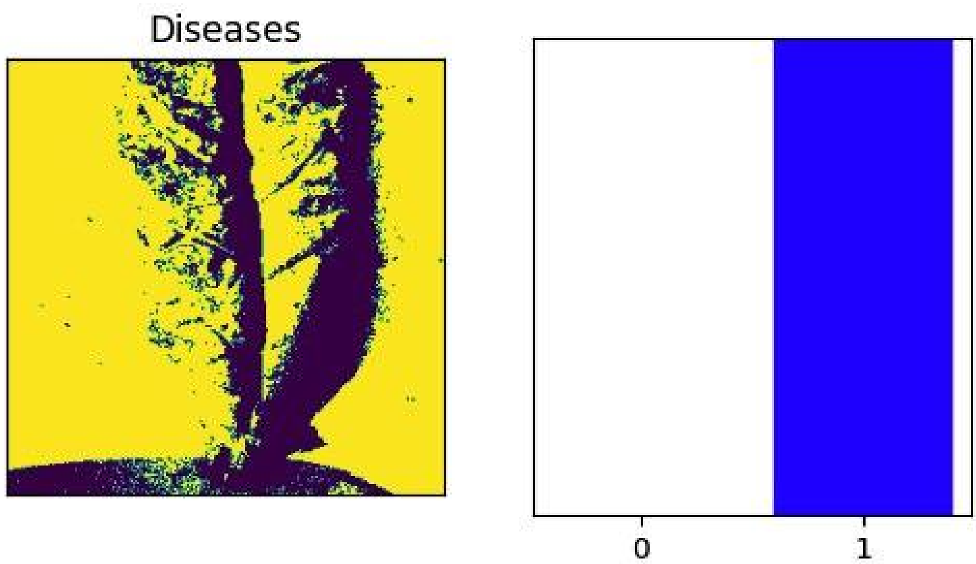

Figure 4.3: Prediction of Diseases Image

Let's see the output-

ResNet101:

```
              precision    recall  f1-score   support

           0       0.60      0.88      0.71        96
           1       0.82      0.50      0.62       112

    accuracy                           0.67       208
   macro avg       0.71      0.69      0.67       208
weighted avg       0.72      0.67      0.66       208

[[84 12]
 [56 56]]
```

Fig 4.4 : Accuracy of **ResNet101**

ResNet152:

```
              precision    recall  f1-score   support

           0       0.67      0.84      0.75        96
           1       0.83      0.64      0.72       112

    accuracy                           0.74       208
   macro avg       0.75      0.74      0.74       208
weighted avg       0.75      0.74      0.73       208

[[81 15]
 [40 72]]
```

Fig 4.5 : Accuracy of **ResNet152**

CNN:

```
              precision    recall  f1-score   support

           0       0.68      0.90      0.77        96
           1       0.88      0.63      0.74       112

    accuracy                           0.75       208
   macro avg       0.78      0.76      0.75       208
weighted avg       0.78      0.75      0.75       208

[[86 10]
 [41 71]]
```

Fig 4.6 : Accuracy of **CNN**

VGG16:

```
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.95      0.95        96
           1       0.96      0.96      0.96       112

    accuracy                           0.96       208
   macro avg       0.96      0.96      0.96       208
weighted avg       0.96      0.96      0.96       208
```

Fig 4.7 : Accuracy of **VGG16**

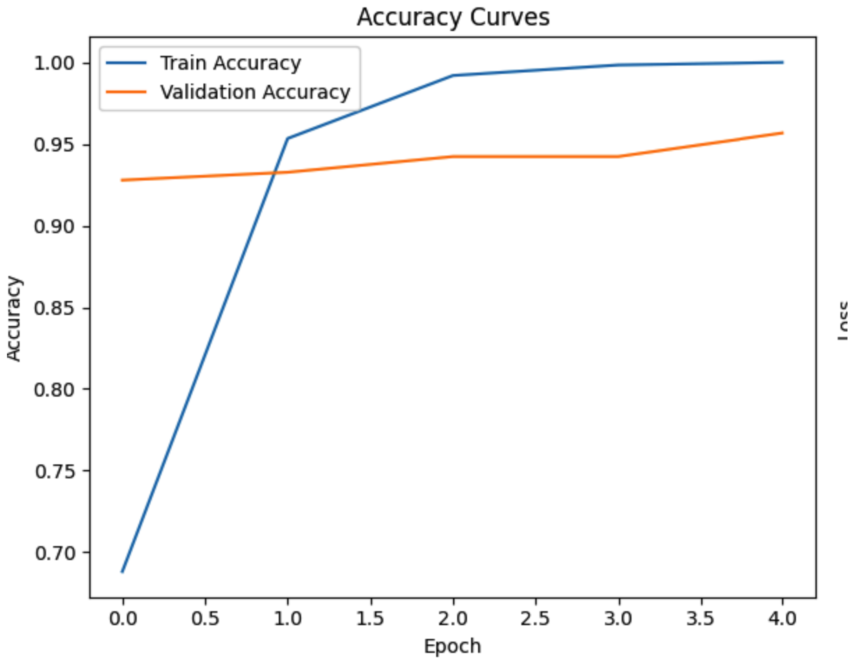

Fig 4.8 : Accuracy Curve of Vgg16

Now here we go with the accuracy-

Model	Number	Precision	Recall	F1-score	Accuracy
VGG16 Model	0	0.96	0.95	0.95	0.96
	1	0.96	0.96	0.96	
ResNet101	0	0.60	0.88	0.71	0.67
	1	0.82	0.50	0.62	
ResNet152	0	0.67	0.84	0.75	0.74
	1	0.83	0.64	0.72	
CNN	0	0.68	0.90	0.77	0.75
	1	0.88	0.63	0.74	

Table 4.1: Results from the Models

According to the table, we have got the best output in VGG16 which is 96% accuracy. CNN has also a great accuracy as well. Others have 67-75%. We have also implemented other models, which doesn't able to give us the expected one(<50).

Accuracy:

One statistic for classifying models is accuracy, which can be defined as the percentage of correctly categorized photos to total samples, the accuracy equation, or the model's anticipated percentage.

Accuracy=(TP+TN)/(TP+TN+FP+FN

Precision:

Accuracy is the probability of a positive label and the number of positive labels. The precision indicates the number of positively predicted cases with accuracy. It is useful to be precise when FP is more important than FN. This equation represents it mathematically:

Precision=TP/(TP+FP)

Recall:

The number of correctly categorized positive predicted events is measured by recall or sensitivity. Recall is a useful statistic in cases where FN outperforms FP. An further statistic for classification accuracy that accounts for both recall and precision is the F1-score. Since recall and accuracy are harmonic means, a thorough comprehension of these two metrics may be obtained from the F1 score. When Precision and Recall are equal, it performs best. Utilize the following equation to calculate it:

Recall=TP/(TP+FN)

F-1 Score:

The F1 score combines precision and recall, two important measures for assessing model performance, in a way that creates a comprehensive assessment of categorization accuracy. The precision of the model's positive identifications is a measure of how many of the projected positives turn out to be real positives. On the other hand, recall indicates the percentage of true positives that were accurately detected by gauging the model's capacity to locate all pertinent examples. The harmonic mean of recall and precision is used to compute the F1 score, which yields a single number that represents the harmony between these two factors.

F-1 Score=2*(Precision*Recall)/(Precision+Recall)

Lastly, here we have the custom CNN:

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 32)	320
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_2 (Conv2D)	(None, 60, 60, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
flatten_3 (Flatten)	(None, 115200)	0
dense_6 (Dense)	(None, 128)	14,745,728
dense_7 (Dense)	(None, 3)	387

Fig 4.9 : Custom CNN

4.4 Summary

In summary, here we have the comparative and experimental studies showed how effective deep learning models are at detecting cauliflower diseases early. In this study, we have successfully demonstrated the models like CNN, VGG16, ResNet50, ResNet1521, ResNet101, InceptionNetV3, MobileNet and EfficientNetB7 in real-world medical contexts. Future studies should focus on enhancing these models even further, addressing problems such as false positives, and figuring out whether a larger variety of patient populations might benefit from their usage. In the dataset, We have implemented several model for the better output. From those implementation, we have got the final output which is VGG16 and it gives 96% accuracy. From the other model like custom CNN, Resnet we got 67-75% accuracy. And In custom CNN we have different layer as well. Using explainability techniques could help farmers and researchers better trust and understand the predictions generated by these models and this work emphasizes the importance of selecting the right architecture, since different models perform differently depending on the dataset and feature complexity.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

5.1.1 Software Standards

To effectively use the whole study there needs to focus on the key elements. Python is the main programming language with advanced imaging techniques. There is different libraries in the work which was also needed for deep learning models. Kaggle maintained the database and as well as the jupyter notebook. The entire process has done by Kaggle which provide the best GPUs and CPUs. All the setup needs to be connected with each other according to the system. Other systemic software also need like to make compress, microsoft and MacOs.

5.1.2 Hardware Standards

There needs to multiple component for this research work. Python has been selected as the programming language for this one. As it's a part of data science and there is a deep support of deep learning models. Kaggle has provided better GPUs and CPUs as well it's a cloud based platform. Physically pendrive, dvd, pc has needed for the further to go on. This configuration guaranteed flexibility and accessibility throughout the process, in addition to making model training.

5.1.3 Communication Standards

To track the progress and make the proper documentation there needs to be collaboration which have done by google workspace and kaggle. There needs to make the meetings with the superviser which have done by google meet or physically. And for the other collaboration, I need to contact with an expert as well by physically.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

Advanced imaging technology and deep learning methods enable early detection of cauliflower diseases and can lead to more successful crop management. By applying deep learning algorithms and models to identify subtle symptoms from leaf images, farmers and agricultural experts can initiate early treatment measures. This approach increases the likelihood of plant recovery and reduces overall crop loss. Additionally, the system offers a less subjective and more consistent diagnostic process compared to manual inspection. This represents a significant advancement over conventional methods, providing a more efficient, reliable and scalable solution for sustainable agriculture.

5.2.2 Impact on Society & Environment

Cauliflower diseases are a significant threat to agricultural productivity, and early detection of infections can greatly improve crop survival rates by enabling timely treatment. Nowadays, imaging technologies combined with deep learning show significant potential in transforming plant disease diagnosis. For this type of development, there are several impacts on agriculture. The first is early detection, which makes disease management more effective. Since the process is fully digital, using high-resolution leaf images, the system captures detailed features to identify early-stage infections, whether the leaf is healthy or affected. The deep learning models process the images for better accuracy and speed, and also identify patterns that might be overlooked by the human eye.

5.2.3 Ethical Aspects

Significant ethical issues arise when advanced imaging and machine learning are used to diagnose cauliflower diseases. Because sensitive agricultural and potentially proprietary farm data may be involved, protecting data privacy and security is of utmost importance. To prevent inequities between large and small-scale farms, these technologies need to be reliable and accurate in addition to being broadly accessible and affordable for farmers across different economic backgrounds. Machine learning systems must be designed to support agricultural experts and farmers not replace them and users must be properly trained to interpret and utilize these tools correctly. Furthermore, recommendations provided by the system should prioritize sustainable and environmentally responsible treatment options to avoid encouraging excessive or inappropriate pesticide use.

5.2.4 Sustainability Plan

Agricultural data, while not human health data, still involves farmer privacy, proprietary cultivation techniques, and potentially sensitive economic information. Protecting this data from misuse or unauthorized access remains an important concern. To prevent agricultural inequities, these technologies must be not only accurate and reliable but also widely accessible and affordable for farmers across different economic backgrounds. The research and technology are designed to assist agricultural experts and farmers not to replace them. These stakeholders require appropriate training to effectively use the system and correctly interpret its diagnostic outputs.

5.3 Project Management and Financial Analysis

There is several cost in the full work to manage the full project according to needs. All data collection and other procedure goes through the whole work.

Table 5.1: Financial Analysis

NO	Costing	Cost
1	Data Collection	25,000 BDT
2	Instrument (Software)	30500 BDT
3	Transport	12000 BDT
4	Communication	5000 BDT
5	Pen Drive & Others	25,000 BDT
Total Estimated Cost		97,500 BDT

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

In this section, We have provide mapping with problem solving categories. For each mapping add subsections to put rationale (Table 5.2).

Table 5.2: Mapping with Complex Engineering Problem.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓	×	✓	✓

Mapping with Knowledge Profile

This section is designed to map the overall problem and EP1 ***(multiple between K3, K4, K5, K6, K8 for attaining EP1)*** to the Knowledge Profile.

Table 5.3: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓	✓	✓

5.4.2 Engineering Activities

In this section, We have provide mapping with engineering activities. For each mapping add subsections to put rationale (Table 5.4).

Mapping with Complex Engineering Activities

This section is designed to map the overall problem and EA's ***(multiple).***

Table 5.4: Mapping with Complex Engineering Activities.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓	✓	✓

5.5 Summary

This chapter addresses the complex technical challenges involved in developing a deep learning based cauliflower disease detection system. For this, collaboration with agricultural experts and plant pathologists is essential to address domain specific problems. As it is a technically intensive process, the work requires not only systematic engineering approaches but also consideration of ethical and social implications for farmers and food security. The goal of this work is to develop an accurate, accessible and reliable method for early detection of cauliflower diseases to support sustainable agriculture.

Chapter 6

Conclusion

6.1 Summary

Cauliflower leaf disease is a serious issue in agricultural productivity worldwide. To address this challenge, researchers have employed deep learning to enable early detection of these diseases. Different deep learning models, including CNN, VGG16, and ResNet, achieved an accuracy of 94% on a dataset of 3,000 leaf images. The dataset consisted of three classes: Healthy, Bacterial Spot and Fungal Rot and was sourced from Kaggle and field collections. A sample of 3,000 images was used to validate the performance and potential of the dataset. The dataset was balanced using data annotation and augmentation techniques. For improved visual clarity, preprocessing methods such as normalization, augmentation and Gaussian filtering were applied. The images were split into training, testing and validation sets. This machine learning-based approach offers a faster and more reliable way to detect diseases, reducing crop losses and supporting sustainable farming.

6.2 Limitation

While this study focuses on an advanced imaging system utilizing deep learning approaches to diagnose cauliflower diseases, several limitations exist. The system is specifically designed for common fungal and bacterial infections such as black rot and downy mildew, meaning it is not suitable for detecting viral diseases, nutrient deficiencies, or pest-related damage. Furthermore, the model was trained and validated on a dataset of 3,000 images, which may not encompass the full range of environmental conditions, cauliflower varieties or regional disease strains. As a result, its effectiveness may vary when applied to diverse agricultural settings or different geographic regions. Although the system achieves 94% accuracy under controlled conditions, real-world performance in resource-limited or highly variable farming environments may differ.

6.3 Future Work

Future research in this era by using deep learning approach, there needs to way improvement in the work. Enhancing the image quality is the top prior as the future work. We will focus to make a portion which makes the image enhanced. Another one which is minimization of detecting issues and reduce the wrong information. There needs to be some precision for the further assesment, this one is another future work.Additionally, there will be a option in application for the guidance.There will be more model and Ai system for the explanation as well. By working more on this one, there can be found out more solution.

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