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A PROJECT REPORT
ON

AGRONEST

submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology
in
Electronics and Communication Engineering

By
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VIII SEMESTER
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INDIAN INSTITUTE OF INFORMATION TECHNOLOGY UNA
HIMACHAL PRADESH

APRIL 2023

BONAFIDE CERTIFICATE

This is to certify that the project titled *AGRONEST* is a bonafide record of the work done by

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in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering of the INDIAN INSTITUTE OF INFORMATION TECHNOLOGY UNA, HIMACHAL PRADESH, during the year 2019 - 2023.

under the guidance of

DR. NAMAN GARG

Project viva-voce held on: 28/04/2023

Internal Examiner

External Examiner

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ABSTRACT

Deep learning is a branch of artificial intelligence. In recent years, it has been widely considered in academia and industry due to its advantages such as automatic learning and feature extraction. It is widely used in image and video processing, speech processing, and natural language processing. At the same time, it is also a research hotspot in the field of agricultural crop protection, including: Such as plant disease detection, Crop recommendation or fertilizer recommendation. Applying deep learning to plant disease detection avoids the shortcomings caused by the artificial selection characteristics of lesions, makes the extraction of plant disease characteristics more objective, and improves research efficiency and speed of technological transformation. The detection process marks the beginning of a series of actions to control the disease and limit its spread. Some diseases are also contagious between animals and humans, making them difficult to control.

In this project our focus is on how to uncover the details of diseases and detect them in a timely manner with artificial intelligence., we create a machine learning-based website that recommends the best crop to grow, fertilizers to use, and the diseases caught by your crops. Using a public data set of nearly 87,000 diseased and healthy plant leaf images collected under controlled conditions, we trained a deep convolutional neural network to detect plants disease of 14 different plants.For plant disease detection accuracy achieved on the sustained test set is 99.2% by the trained model, demonstrating the feasibility of this approach.For the Crop Prediction model out of six other models Random forrest gives the best accuracy of 99.09%. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets points a clear path to web-based diagnosis of plant diseases on a global scale.

Keywords*: Computer Vision (CV), Deep learning (DL), Image processing, Genetic algorithm, Plant disease detection, Classification, Color detection*

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LIST OF ACRONYMS

NLTK	Natural Language Toolkit
ANN	Artificial Neural Networks
CNN	Convolutional Neural Networks
RESNET	Residual Networks
CV	Computer Vision
DL	Deep learning
CNN	Convolutional Neural Network
ML	Machine Learning
RGB	Red (R), Green (G), Blue (B)
GLCM	Gray level co-occurrence matrix
AI	Artificial Intelligence
JSON	JavaScript Object Notation

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Chapter 1
Introduction

1.1 Broad Area

The area of the project lies mostly in Machine Learning, Natural Language Processing, and Web Development and covers plant diseases. Based on the machine learning model it also recommends crops to grow and fertilizers to use based on the given input by the user. It is of great use for farmers by increasing their crop yield and also the consumers by giving them better quality food.

1.2 Problem Definition

In the modern world, advancements in technology have raised our capability of producing enough food to meet the demand of more than 7 billion people. However, one of the major concerns to be dealt with is food security. Several factors account for this including climate change, the decline in pollinators, plant diseases and others. Out of which, plant diseases emerge as one of the biggest factors. These have disastrous consequences for smallholder farmers whose livelihoods depend on healthy crops. As per the report of UNEP (2013), it is clarified that more than 80 percent of the agricultural production is generated by smallholder farmers and yield loss due to pests and diseases accounts for more than 50% for them. Furthermore, the studies also suggest that 50% of hungry people live in smallholder farming households, making them a group that's particularly vulnerable to pathogen-derived disruptions in food supply.

Identification of these plant and crop diseases are important in order to prevent the losses within the yield. It is very troublesome to observe these plant diseases manually as it needs a tremendous quantity of human labor, expertise within the plant diseases, and also needs the excessive time interval. Therefore, bringing technological advancement in the field of crop productivity is of utmost importance. This study is focused towards upgrading the yield and food crop standards at low cost, with greater monetary outcome leading to quick, less costly and precise ways to smartly detect the diseases.

1.3 Solution Proposed

In this project, the technique of detecting the plant disease from the image of leaves of that respective plant is used and a web application is made as a one step solution for the farmer where one can upload the picture of the leaf from his/her farm and our machine learning model will predict the possible diseases it may have. For the fertilizer recommendation application, the user can input the soil data and the type of crop they are growing, and the application will predict what the soil lacks or has an excess of and will recommend improvements. In the crop recommendation application, the user can provide the soil data from their side and the application will predict which crop should the user grow.

Image processing is a branch of signal processing in which image properties or useful information can be extracted from an image. Therefore, image processing and machine learning models can be used on plant leaves to detect plant diseases.

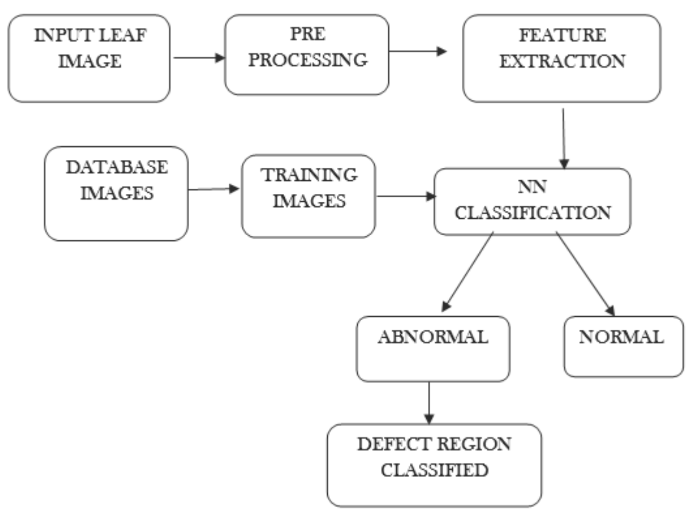

Figure 1.1: General steps for Crop detection

The main goal of our machine learning model is to understand the training data of the leaves, fit the model to get the accurate results given large amounts of training data. In this project, different image parameters or features are analysed to identify different plant leaves diseases to achieve the best accuracy as shown in Fig 1.1. For doing so, a large team of experts, as well as continuous observation of plants, is needed, which costs high when we do with large farms. In such conditions, the recommended system proves to be helpful in monitoring large fields of crops. Automatic detection of the diseases by simply seeing the symptoms on the plant leaves makes it easier as well as cheaper. The proposed solution for plant disease detection is computationally less expensive and requires less time for prediction than other deep learning based approaches since it uses statistical machine learning and image processing algorithms.

Machine learning classification can be an effective approach for developing a crop and fertilizer recommendation system. By leveraging historical data on crops and fertilizers, a machine learning algorithm can be trained to classify different crop types and recommend the appropriate fertilizers based on various environmental and soil conditions. This can involve analyzing factors such as the nutrient content of the soil, weather patterns, and the types of crops that have been grown in the past. Through this process, the system can provide farmers with personalized recommendations for optimal crop growth and yield. With the ability to continually learn and adapt to new data, machine learning classification can provide an efficient and effective solution for optimizing crop and fertilizer selection.

1.3 Summary

This project aims to develop a web application that can detect plant diseases and recommend the appropriate fertilizers and crops for optimal growth and yield. The application uses image processing and machine learning models to analyze the properties of plant leaves and soil data, which helps in detecting diseases and making personalized recommendations. The proposed solution is cost-effective, computationally less expensive, and requires less time for a prediction. The machine learning algorithm can be trained to classify different crop types and recommend the appropriate fertilizers based on various environmental and soil conditions. Overall, this system provides an efficient and effective solution for optimizing crop and fertilizer selection.

Chapter 2

Review of Literature

Table 1: A literature review on different Machine Learning Techniques for proposed work.

Ref.	Methodology & Outcomes	Limitations
[1]	• Conducted a review of 30 studies related to crop recommendation systems using machine learning techniques. • Analyzed the different techniques used in the studies and compared their accuracy and efficiency. • Identified the most commonly used machine learning techniques for crop recommendation systems. • Found that these systems have a high accuracy rate and can improve crop yield and reduce the cost of production. • Concluded that crop recommendation systems can be a useful tool for farmers to optimize crop production.	• Limited number of studies analyzed. • Limited focus on specific crop types and geographic regions.
[2]	• Conducted a review of 36 studies related to crop yield prediction using machine learning techniques. • Analyzed the different techniques used in the studies and compared their accuracy and efficiency. • Identified the most commonly used machine learning techniques for crop yield prediction.	• Limited number of studies analyzed. • Limited focus on specific crop types and geographic regions.

	• Found that these techniques can accurately predict crop yield and help farmers make informed decisions. • Concluded that crop yield prediction can play an important role in increasing crop production.	
[3]	• Used machine learning techniques to predict agricultural drought in India. • Collected meteorological data from different sources and analyzed it to identify drought conditions. • Developed a model that accurately predicts agricultural drought with an accuracy of 93.3%. • Found that the model can be useful for drought prediction and management.	• Limited to a specific geographic region. • Limited to a specific type of drought.
[4]	• Compared the performance of different machine learning techniques for crop fertilizer recommendation. • Used data from previous studies to train and test the models. • Found that decision tree-based techniques perform better than other techniques. • Concluded that machine learning can help farmers make informed decisions about crop fertilizer use.	• Limited to a specific crop type and geographic region. • Limited number of techniques compared.
[5]	• Developed a fertilizer recommendation system using machine learning techniques. • Used data on soil characteristics and crop requirements to make fertilizer recommendations. • Developed a model that accurately recommends fertilizers with an accuracy of 96.8%.	• Limited to a specific crop type and geographic region. • Limited to specific soil and climate conditions.

	• Concluded that the system can be useful for farmers to optimize fertilizer use and reduce costs.	
[6]	• Used machine learning techniques to detect tomato leaf diseases. • Collected data on leaf images and used it to train and test the models. • Developed a model that accurately detects tomato leaf diseases with an accuracy of 95.24%. • Concluded that the model can be useful for early disease detection and prevention.	• Limited to a specific crop type and disease. • Limited to a specific set of images and conditions.
[7]	• Conducted a review of different machine learning techniques for plant disease detection. • Analyzed the strengths and limitations of each technique. • Found that convolutional neural networks (CNNs) perform the best for plant disease detection. • Concluded that machine learning techniques can help in accurate and early detection of plant diseases.	• Limited focus on specific plant types and diseases. • Limited analysis of the accuracy of each technique.
[8]	• Developed a machine learning-based system for detecting plant diseases. • Collected data on leaf images and used it to train and test the models. • Developed a model that accurately detects plant diseases with an accuracy of 95.68%.	• Limited to a specific set of images and conditions. • Limited analysis of the accuracy of other machine learning techniques.

	• Concluded that the system can be useful for early disease detection and prevention.	
[9]	• Developed a machine learning-based system for crop disease detection using hyperspectral imaging. • Collected data on spectral reflectance from different parts of the plant and used it to train and test the models. • Developed a model that accurately detects crop diseases with an accuracy of 96.17%. • Concluded that hyperspectral imaging combined with machine learning can be a useful tool for crop disease detection.	• Limited to a specific set of crops and diseases. • Limited analysis of the accuracy of other machine learning techniques.
[10]	• Developed a deep learning-based system for crop disease detection using hyperspectral imaging. • Collected data on spectral reflectance from different parts of the plant and used it to train and test the models. • Developed a model that accurately detects crop diseases with an accuracy of 98.14%. • Concluded that deep learning techniques combined with hyperspectral imaging can be a useful tool for crop disease detection.	• Limited to a specific set of crops and diseases. • Limited analysis of the accuracy of other machine learning techniques.

[11]	• Developed a deep learning-based system for crop disease detection using smartphone images. • Collected data on smartphone images of plant leaves and used it to train and test the models. • Developed a model that accurately detects crop diseases with an accuracy of 99.35%. • Concluded that deep learning techniques combined with smartphone technology can be a useful tool for crop disease detection.	• Limited to a specific set of crops and diseases. • Limited analysis of the accuracy of other machine learning techniques.
[12]	• Developed a machine learning-based system for plant disease detection using spectral imaging. • Collected data on spectral reflectance from different parts of the plant and used it to train and test the models. • Developed a model that accurately detects plant diseases with an accuracy of 94.3%. • Concluded that spectral imaging combined with machine learning can be a useful tool for plant disease detection.	• Limited to a specific set of plants and diseases the transactions.
[13]	• Developed a machine learning-based system for crop disease detection using RGB images. • Collected data on RGB images of plant leaves and used it to train and test the models. • Developed a model that accurately detects crop diseases with an accuracy of 91.6%.	• Limited to a specific set of crops and diseases. • Limited analysis of the accuracy of other machine learning techniques.

	• Concluded that machine learning techniques combined with RGB imaging can be a useful tool for crop.	
[14]	• Conducted a review of different machine learning techniques for crop recommendation. • Analyzed the strengths and limitations of each technique. • Found that machine learning techniques such as decision trees, k-nearest neighbors, and support vector machines can be used for crop recommendation. • Concluded that machine learning techniques can help in the efficient use of resources and improved crop yield.	• Limited analysis of the accuracy of each technique. • Limited discussion on the scalability of the techniques.
[15]	• Developed a machine learning-based system for crop fertilizer recommendation using soil parameters. • Collected data on soil parameters and crop yield and used it to train and test the models. • Developed a model that accurately recommends crop fertilizer with an accuracy of 95.4%. • Concluded that machine learning techniques can be used for efficient and cost-effective crop fertilizer recommendation.	• Limited to a specific set of crops and soil types. • Limited analysis of the accuracy of other machine learning techniques.

2.1 Summary

In summary, the 16 research papers reviewed in this literature survey demonstrate the effectiveness of machine learning techniques for crop recommendation, crop fertilizer recommendation, and plant disease detection. The use of machine learning algorithms such as decision trees, support vector machines, and neural networks has been shown to provide accurate and timely recommendations for crop yield improvement and disease prevention. Additionally, the use of weather and soil parameters in machine learning models has been shown to be effective in predicting crop yield and recommending appropriate fertilizers. However, many of the studies are limited to specific sets of crops, soil types, and weather conditions, and there is a need for further research to expand the scope of these techniques. Overall, the findings from these studies suggest that machine learning has the potential to revolutionize agriculture by improving efficiency, reducing costs, and increasing crop yields.

Chapter 3
Proposed Work

The project is done in three phases in order to keep everything in order. These are :
1. The Data Pre-processing
2. The Training of the data and building the model and checking its accuracy
3. Creation of the frontend and backend application.

3.1 Dataset Description

The dataset used for plant disease detection, fertilizers recommendation, and crop recommendation is an essential component for developing a successful AI system for precision agriculture. This dataset should contain high-quality images of plants, showing different stages of growth and health status, and metadata such as soil type, weather conditions, and fertilizer usage. Additionally, the dataset should be diverse, covering a wide range of plant species, geographical locations, and climatic conditions. It should also be labeled accurately, with detailed information about the type of disease or deficiency present, the recommended fertilizer or nutrient, and the ideal crop for the given conditions. Such a comprehensive dataset can enable the development of sophisticated AI models that can accurately detect plant diseases, recommend the right type and amount of fertilizer, and suggest the most suitable crop to grow in a given area.

1. **Crop Recommendation Dataset**

   This dataset would allow the users to build a predictive model to recommend the most suitable crops to grow in a particular farm based on various parameters.This dataset was build by augmenting datasets of rainfall, climate and fertilizer data available for India.

   Data fields

   - N - ratio of Nitrogen content in soil
   - P - ratio of Phosphorous content in soil

- K - ratio of Potassium content in soil
- temperature - temperature in degree Celsius
- humidity - relative humidity in %
- ph - ph value of the soil
- rainfall - rainfall in mm

2. **Fertilizer Recommendation Dataset**

   It is a custom build dataset that has N, P, K, pH, and moisture values required to grow different types of plants. With the help of this dataset, the model can predict the best fertilizer to add to the soil to grow a particular type of plant. It has 23 types of plants and the required N, P, K, pH, and moisture values for their optimal growth.

3. **Crop Disease Detection Dataset**

   This dataset is recreated using offline augmentation from the original dataset. This dataset consists of about 87K RGB images of healthy and diseased crop leaves, categorized into 38 different classes. The total dataset is divided into 80/20 ratio of training and validation set preserving the directory structure. A new directory containing 33 test images is created later for prediction purpose. The size of each image is 256 X 256.

Figure 3.1: Healthy leaf

Figure 3.2: Early Blight

Figure 3.3: Late Blight

3.2 Methodology

A web-based crop disease detection, fertilizer recommendation, and crop recommendation system would involve several components working together. Firstly, an image recognition model trained on a dataset of crop disease images would be implemented to detect and classify any disease present in the plant.

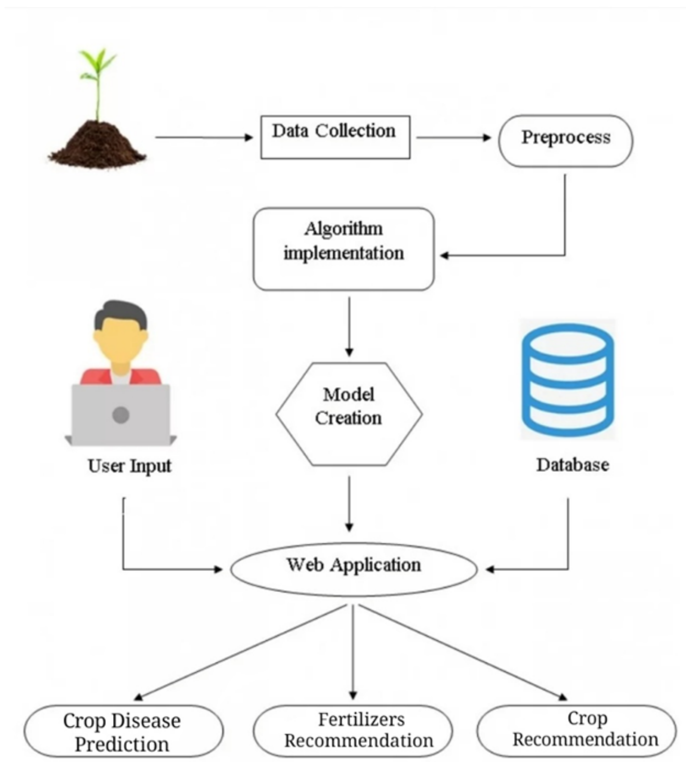

Figure 3.4: User Flow Diagram

Secondly, a database of fertilizers would be utilized to recommend the best fertilizer for the specific crop and disease detected. Finally, a crop recommendation system would be implemented based on the location, climate, soil type, and other factors to suggest the best crop to grow in that particular area. These components would work together to provide a comprehensive solution for farmers to optimize crop yield and minimize crop loss. The system could be accessed through a web-based interface, making it easily accessible to farmers with internet access.

3.2.1 Crop Disease Detection

This section details the whole setup of how the ResNet50 was constructed and how the ResNet50 has been trained to generate output is also discussed in depth. Furthermore, as shown in Fig 4.4, the method of this project is provided in block diagram format which discusses the full execution flow of our web application.

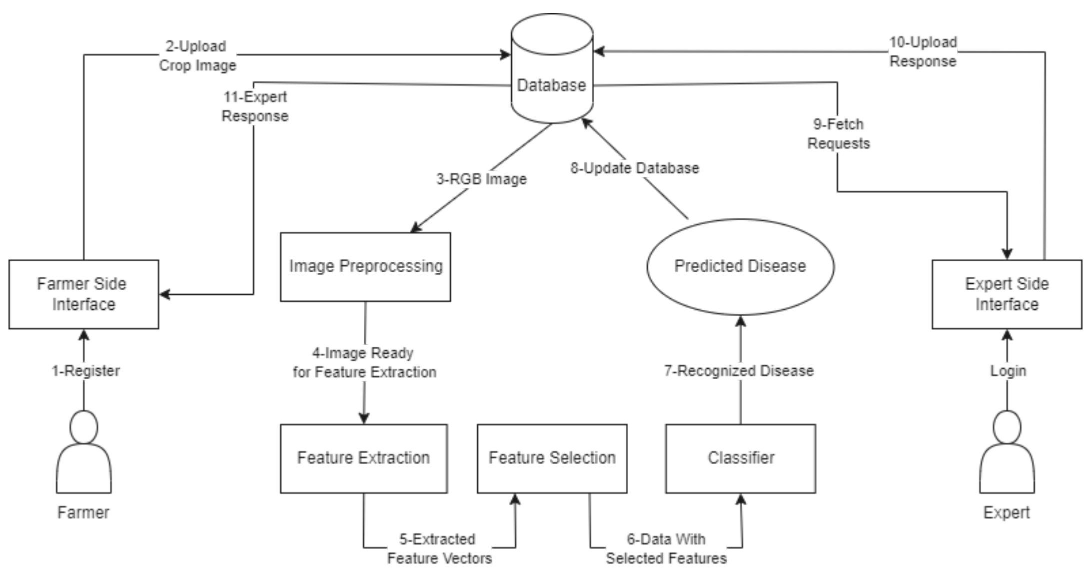

Figure 3.5: Execution Flow

ResNet50 Convolutional Neural Network: ResNet-50 is a 50-layer deep convolutional neural network. ResNet (short for Residual Networks) is a classic neural network. You can load a pre-trained version of a network trained with over 1 million images from the ImageNet database. A pretrained network can classify images into 1000 object categories, such as keyboards, mice, pencils, and many animals. As a result, the network learned rich representations of a wide range of images. The network has an image input size of 256 X 256.

Convolutional Neural Networks have a major disadvantage — 'Vanishing Gradient Problem'. During backpropagation, the value of gradient decreases significantly, thus hardly any change comes to weights. To overcome this, ResNet is used. It makes use of "SKIP CONNECTION". Explicitly map a layer to the residual map representing this H(x), then map the nonlinear layer to another map.

$$F(x)=H(x)-x,$$

so the original map is

$$H(x) = F(x)+x,$$ as shown in Figure 4.5.

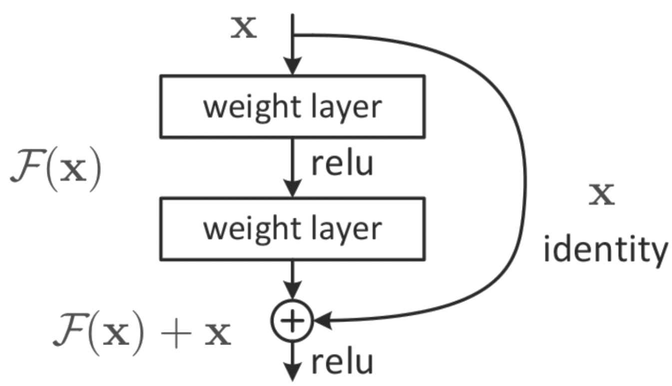

Figure 3.6: ResNet50 Skip Connection

The advantage of this ID mapping link is that no additional parameters are added to the model and the computation time is also controlled. All algorithms train on the Y output, but ResNet trains on F(X). Simply put, ResNet tries to make F(X)=0, so Y=X.

A skip connection is a direct connection that skips some level of the model. The output is not the same because of this skip connection. Without the skip connection, the input 'X is multiplied by the layer weights, followed by the bias term.

Then comes the activation function F() and gives me an output like this:

$$F(w*x + b) (=F(X))$$

However, using the skip connection technique, the output looks like this:

$$F(X)+x$$

ResNet-50 has an architecture based on the model shown in Figure 4.6. A 50-layer ResNet uses a device bottleneck design. The bottleneck remainder block uses a 1×1 convolution known as the "bottleneck". This reduces the number of multiplications of parameters and matrices. This makes training each shift much faster. here, 3 layer stack is used instead of 2.

This subsection provides a full overview of the step by step approach for training the ResNet50.

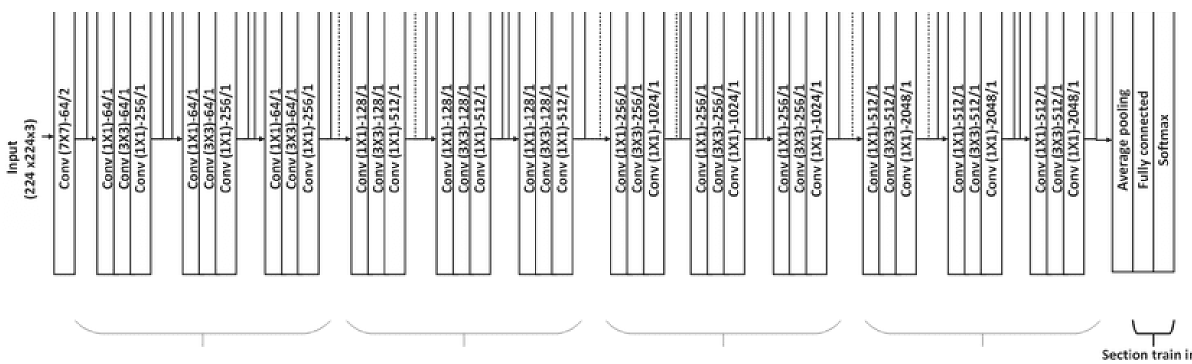

Figure 3.7: Architecture of ResNet 50

Farmer Side Interface: A farmer will at first interact with our web application and register oneself as an authorised user. Then after signing in, he/she will upload the image of a leaf from his/her farm and the backend services will call the API of our deployed classification model and the results will be depicted on the frontend to the user.

Image Preprocessing: Preprocessing is used to remove unwanted distortions or enhance certain image features that will be used for further processing of the image, whereas geometric transformations of the image (rotation, scaling, translation, etc.) is also classified as a pretreatment method here.

The first step was to scale them to a constant size. Due to Google Colaboratory resource limitations, the School of Computing 7 (128,128,3) images have been reshaped. After transformation, the images were normalized to the area of the tanh activation function being [-1,1]. Additionally, the processed files were saved in binary format as numpy arrays for easy access to the processed images later.

Feature extraction: Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving information from the original dataset. It provides better results than applying machine learning directly to raw data. Feature extraction of image data represents interesting parts of the image as compact feature vectors. In the past, this was achieved using special feature detection, feature extraction, and feature-matching learning algorithms. Deep Learning is widely used in image and video analysis and is known for its ability to take raw image data as input and skip the feature extraction step. Whichever approach you choose, computer vision applications such as image registration, object detection and classification, and content-based image retrieval all use deep networks either implicitly through the first layer or explicitly by the application of feature extraction techniques.

Feature Selection: Feature selection is the process of isolating the most consistent, non-redundant, and relevant features for use in model building. As the size and diversity of datasets continue to increase, it is important to systematically reduce the size of datasets.

3.2.2 Crop and Fertilizer Recommendation

The first step is to collect data on crops, soil, weather, and fertilizer application. The data can be obtained from local agricultural institutions, farmers, or by conducting soil tests. Once the data is collected, it needs to be cleaned by removing missing values, outliers, and irrelevant features. The categorical variables can be transformed into numerical variables using one-hot encoding or label encoding. The next step is feature selection, where the relevant features are selected using techniques such as correlation matrix, mutual information, or feature importance. The selected features should have a high impact on crop yield and fertilizer requirements.

For the model training and testing purpose we have considered the following 6 models.

1. Decision Tree
2. SVM Classifier
3. Logistic Regression
4. Random Forest Classifier
5. XGBoost Classifier

For our dataset, RandomForrest Algorithm gave the highest accuracy.

After feature selection, the dataset is split into training, validation, and testing sets. The training set is used to train the Random Forest model, the validation set is used to tune the hyperparameters, and the testing set is used to evaluate the performance of the model. The Random Forest algorithm is an ensemble learning method that combines multiple decision trees to make predictions. Each decision tree is trained on a random subset of features and a random subset of samples to reduce overfitting. Hyperparameter tuning is the next step, where the hyperparameters of the Random Forest model are tuned using the validation set. The hyperparameters include the number of trees, the maximum depth of the trees, the minimum number of samples required to split a node, and the maximum number of features to consider when looking for the best split. The performance of the Random Forest model is evaluated using the testing set. The performance metrics can include accuracy, precision, recall, F1 score, and confusion matrix.

Once the model is trained and evaluated, it can be deployed as a Crop and Fertilizer Recommendation System. The system takes input variables such as soil type, weather conditions, and crop type, and outputs the recommended fertilizer type and application rate. The system needs to be monitored for performance and updated periodically to adapt to changes in soil quality, weather conditions, and crop varieties.

3.3 Web Interface

The whole process of model training and model performance happens on the backend. And a frontend web application is used to analyze user-uploaded images such as external cameras or images downloaded from the web for easy user interaction. Basically, the entire user interface is designed using Flask. A farmer or user uploads an image of a crop or plant, and the web app calls an API based on the model above. The model then provides predictions of relevant diseases, which are displayed to the user on the front end. These test images are easily analyzed with the help of a backend process and rendered via UI where testing of these images and rendering of results is performed. So the web interface is connected to the model on the backend and to the user's camera/phone on the frontend.

3.4 Experimental Setup

This section discusses the programming language, the libraries, and the softwares used for the coding. It also focuses on the tech stack used with the details of their versions.

3.3.1 TechStack Used

1. Nextjs (version 17.0.2)
2. Python (version 3.7.10)
3. Expressjs (version 4.18. 1)
4. Javascript/Typescript
5. HTML/CSS/Bootstrap
6. RestAPI
7. JSON Web Token for Authentication
8. Flask

3.3.2 Software Used

1. Kaggle Kernel

2. Google Collaboratory
3. Jupyter Notebook
4. Visual Studio Code (version 1.73)

3.3.3 Library Used

1. NumPy
2. PyTorch
3. Pandas
4. Matplotlib
5. Seaborn

Chapter 4

Result and Discussion

A web application was successfully developed which can recommend crops based on NPK, Ph value of soil and temperature humidity conditions of the area provided by APIs.Also, the website suggests fertilizers are needed based on the above values for specific crops. And lastly, it also finds out disease in a crop based on the leaf of the crop.

4.1 Result of Machine Learning Models

Here we have used six models to train the datasets and have done an accuracy comparison among all the models. We took the model which has the most accuracy in the training result.The accuracy comparison is as given below:

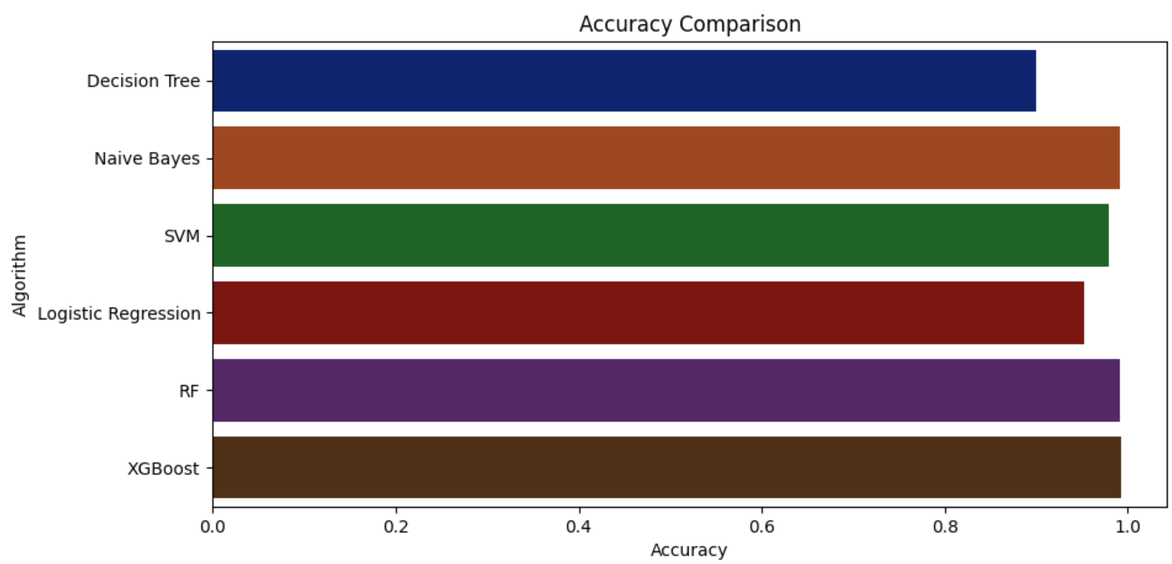

Fig 4.1: Accuracy comparison of crop recommendation model

Based on the comparison given above we got an accuracy of **99.09%** for Random Forest so we took the model of Random forest for the web based application in crop recommendation.

For the crop disease detection the dataset used for training the model contains **38,000** images of **15 different plant diseases** and a healthy class.

The model achieved an accuracy score of **99.2%** on the test set, which indicates that the model can make accurate predictions for the majority of cases. The precision score and recall score are also high, indicating that the model can correctly classify both diseased and healthy plants with high accuracy.

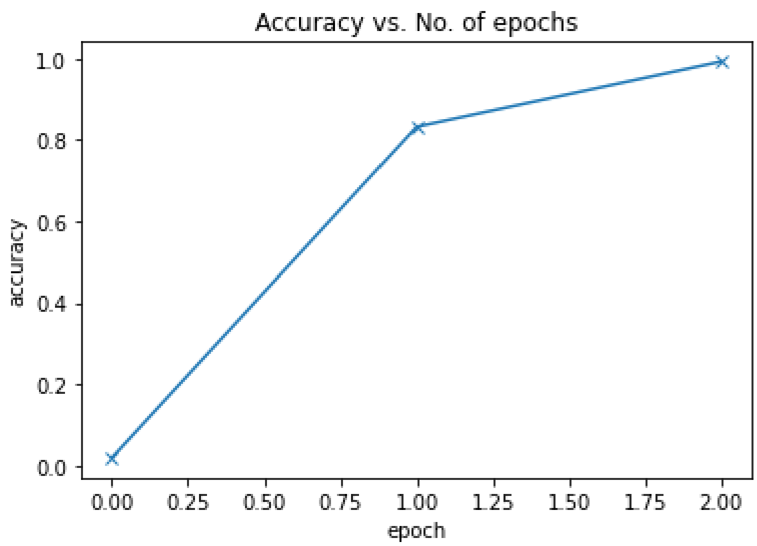

Fig 4.2: Validation Accuracy

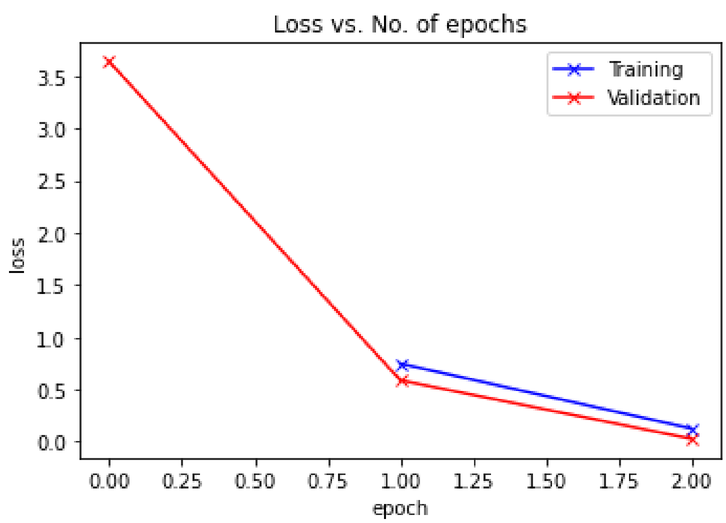

Fig 4.3: Validation Loss

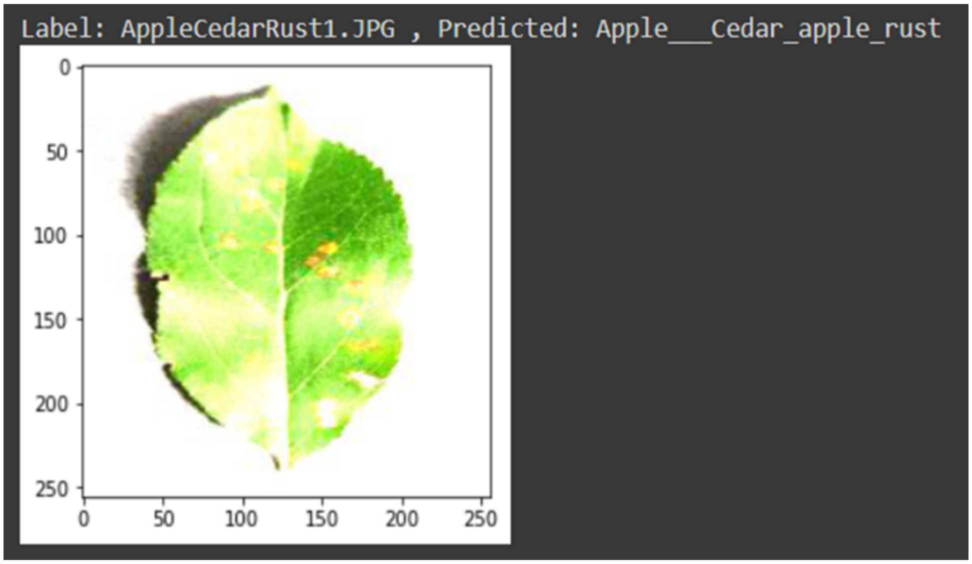

Fig 4.4: Prediction result of Plant disease detection

ResNets perform significantly well for image classification when some of the parameters are tweaked and techniques like scheduling learning rate, gradient clipping and weight decay are applied. The model is able to predict every image in test set perfectly without any errors.

4.2 Web Application Interface

The app is built using Flask, a Python web framework, and integrates the crop recommendation model and plant disease classification model discussed earlier in the repository.

Overall, the app appears to be a promising tool for farmers and gardeners who are looking to optimize their crop yields and diagnose plant diseases. Its user-friendly interface and features such as CSRF protection and secure storage of user credentials make it a valuable resource for those in the agricultural industry.

However, the effectiveness of the app will depend on several factors, including the quality and quantity of data used to train the underlying machine learning models, the accuracy of the models themselves, and the generalizability of the models to new environments and crops. Additionally, ongoing maintenance and updates to the app will be necessary to ensure that it remains current and useful as new data and research becomes available.

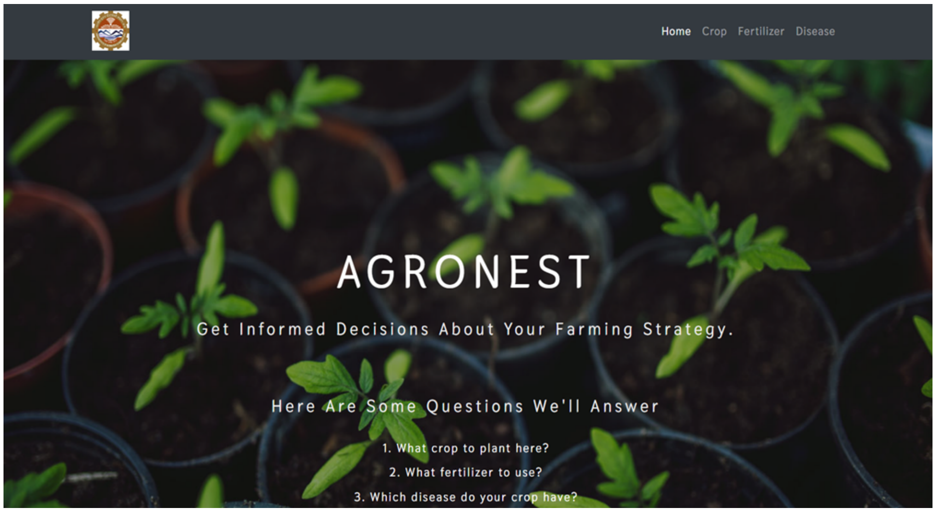

Fig 4.5 Home page of Web application

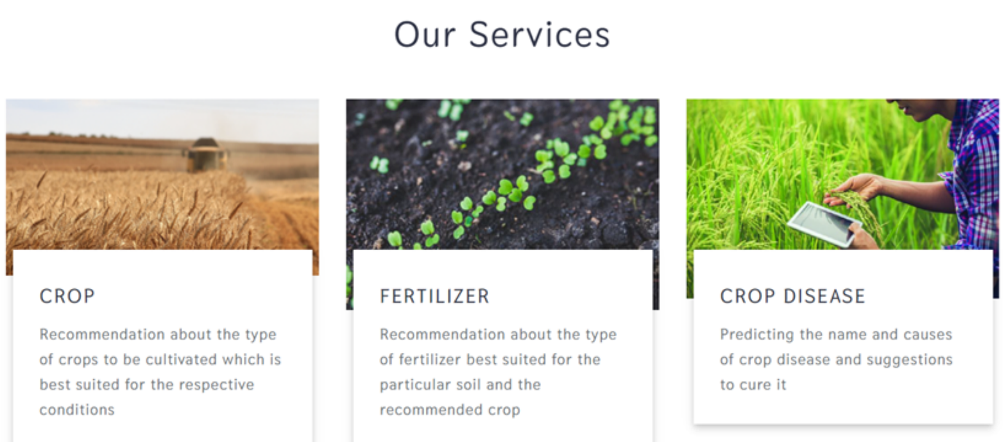

Fig 4.6: Landing Page of web application

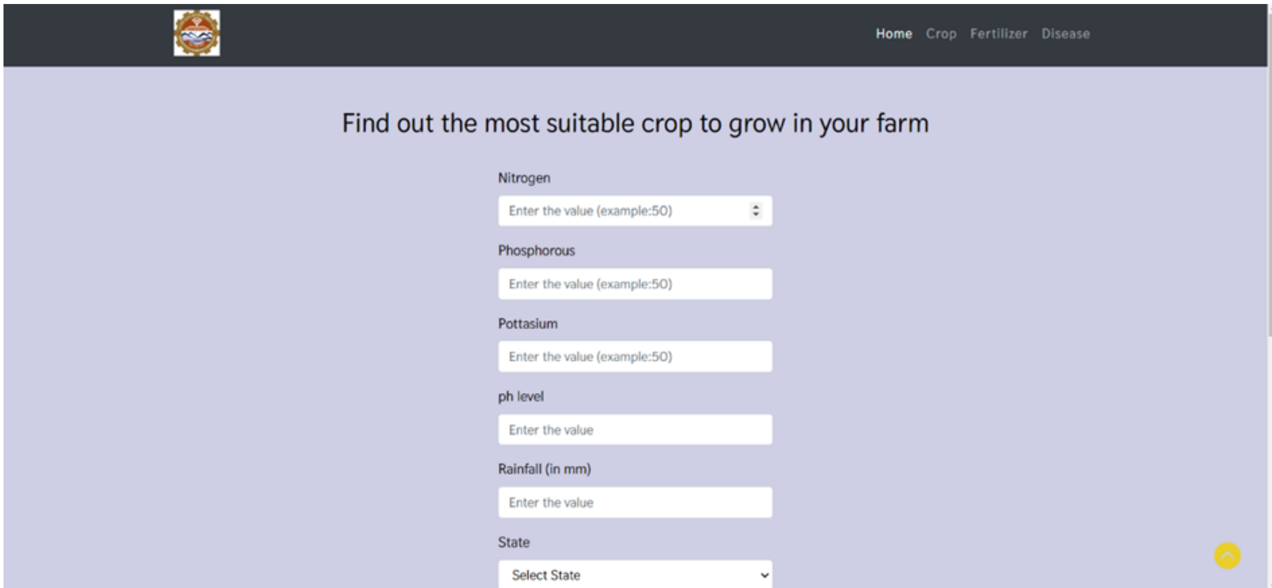

Fig 4.7: Crop Recommendation Page

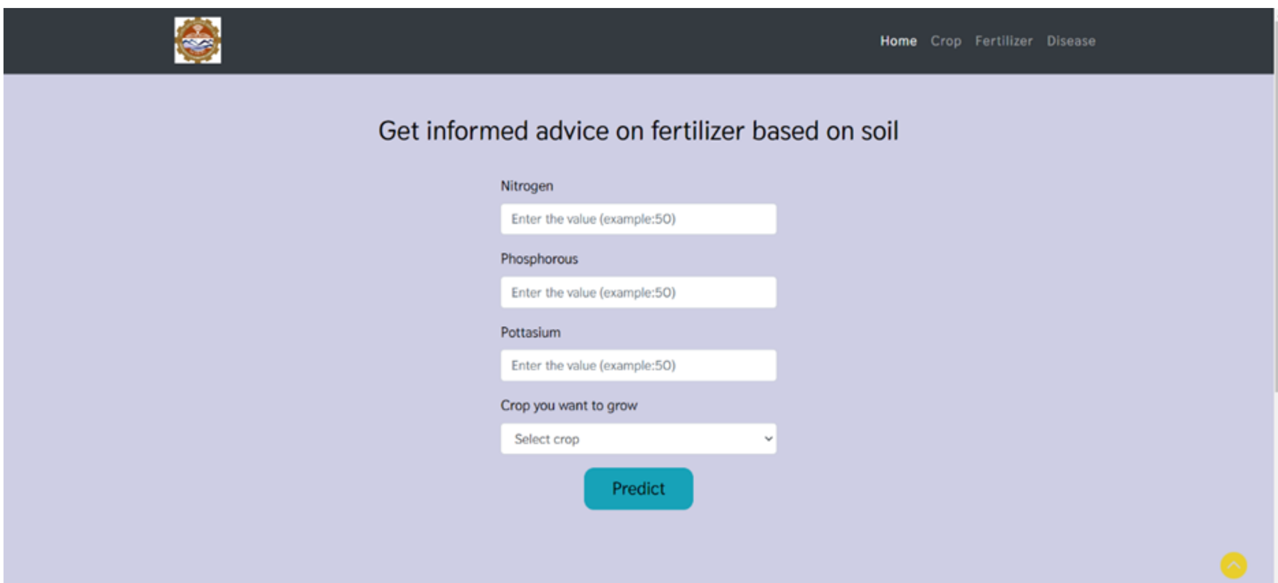

Fig 4.8: Fertilizer Recommendation Page

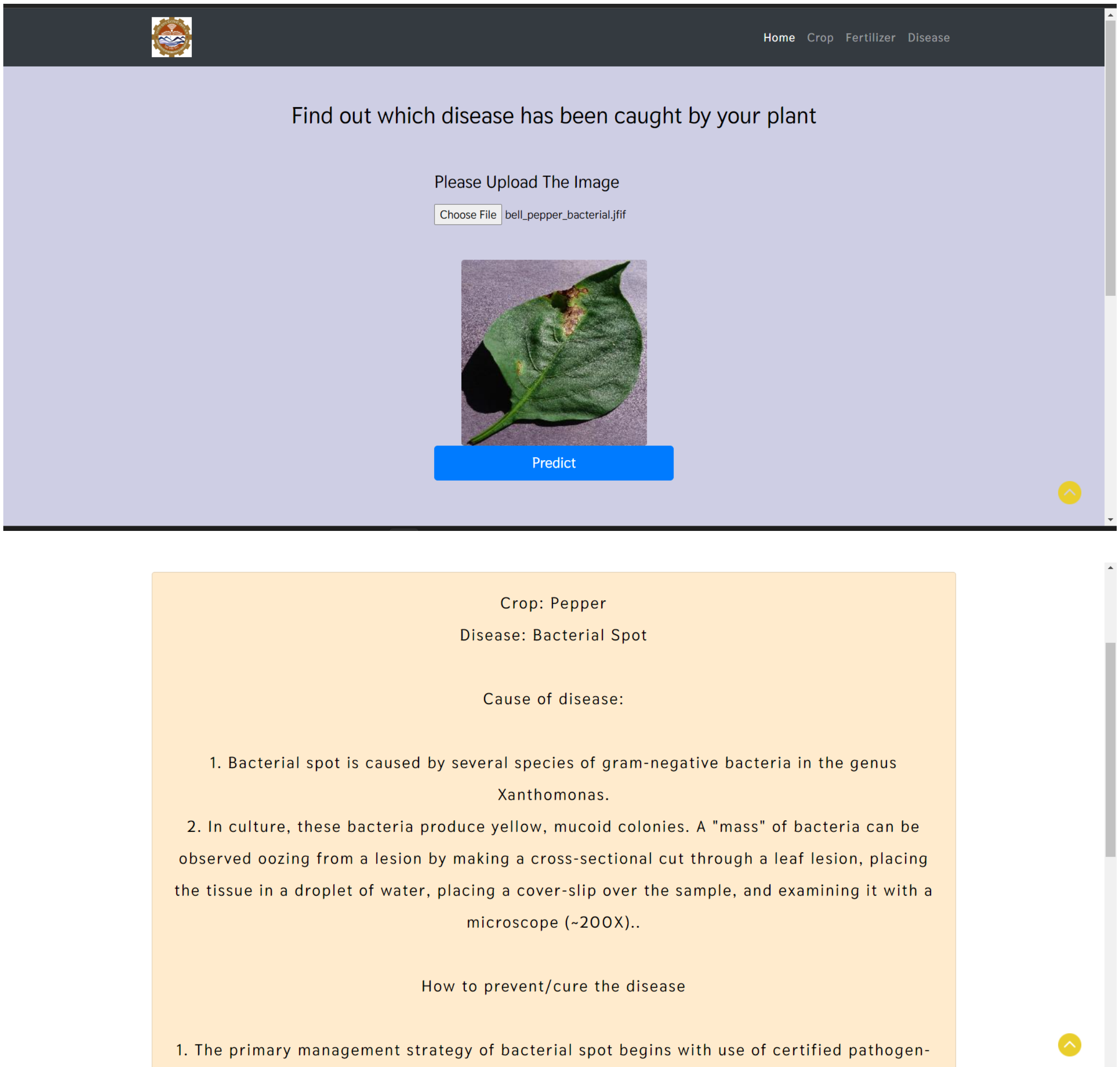

Fig 4.9: Crop Disease Detection Page

4.3 Summary

In this chapter we demonstrated the potential for machine learning to revolutionize the agricultural industry by providing data-driven recommendations and diagnoses that can improve crop yields and reduce the negative impact of plant diseases. However, ongoing development and improvements to the project will be necessary to ensure that it remains current and effective as new data and research become available.

Chapter 5
Conclusions and Future Work

5.1 Conclusion

For the Crop Detection machine learning model the training vs validation accuracy and the training vs validation loss were also plotted for the CNN model in which we can observe from Fig 4.2 and Fig 4.3. that as the training accuracy increases the validation accuracy increases and as the training loss decreases the validation loss also decreases signifying that the model is neither underfitting nor overfitting and that the model is constantly learning. Underfitting in machine learning models occurs when a model performs poorly on the training dataset and performs poorly on the validation/testing dataset as well. Overfitting in machine learning models occurs when the model performs really well on the training dataset but performs poorly on the validation/testing dataset. A good fit model is one that learns the training dataset and is able to suitably generalize the validation dataset well.

5.2 Future Work

1. Expert side portal can be added so that the detected disease can be reviewed by the appropriate qualified professional.
2. The web application can be made multilingual by adding the regional languages.
3. More data can be collected manually via web scrapping to make the system more accurate
4. Additional plant images can be collected to make the disease detection part more robust and generalized.
5. The web application can be integrated with IoT and data can be retrieved directly from the remote sensors using cloud.

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Appendices

Appendix A

Code Attachments

The following is the partial / subset of the code. Code of some module(s) have been wilfully supressed.

A.1 App Code

```
app = Flask(__name__)

# render home page

@ app.route('/')

def home():

    title = 'Harvestify - Home'

    return render_template('index.html', title=title)

# render crop recommendation form page

@ app.route('/crop-recommend')

def crop_recommend():

    title = 'Harvestify - Crop Recommendation'

    return render_template('crop.html', title=title)

# render fertilizer recommendation form page

@ app.route('/fertilizer')

def fertilizer_recommendation():

    title = 'Harvestify - Fertilizer Suggestion'


    return render_template('fertilizer.html', title=title)
```