Object Detection Through Attentional Filtering In Cluttered Environments for Agriculture

A PROJECT REPORT

Submitted by

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CERTIFICATE

This is to certify that the project report submitted along with the project entitled **Object Detection Through Attentional Filtering in Cluttered Environments for Agriculture** has been carried out by **KANANI KUNJAN** under my guidance in partial fulfilment for the degree of Bachelor of Technology in Computer Engineering, 6th Semester of Marwadi University, Rajkot during the academic year 2023-24.

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DECLARATION

We hereby declare that the **Mini Project (01CE0609)** report submitted along with the Project entitled **Object Detection Through Attentional Filtering in Cluttered Environments for Agriculture** submitted in partial fulfilment for the degree of Bachelor of Technology in Computer Engineering to Marwadi University, Rajkot, is a bonafide record of original project work carried out by me / us at Marwadi University under the supervision of **Prof. Urvi Bhatt** and that no part of this report has been directly copied from any students' reports or taken from any other source, without providing due reference.

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Abstract

Cotton is an important crop with a significant role in the global economy, but it is susceptible to various diseases that can significantly impact crop yield and quality. Early detection and diagnosis of these diseases are crucial for efficient crop management and reducing economic losses. In this project, we propose a deep learning-based approach for cotton disease prediction using convolutional neural networks (CNNs). The system is designed to classify six different types of cotton diseases based on their visual symptoms. A large dataset of cotton plant images infected with various diseases was collected and used to train and evaluate the CNN model. The CNN model consists of multiple convolutional layers, pooling layers, and fully connected layers. Transfer learning was applied to fine-tune a pre-trained CNN model for the specific classification task. The proposed system achieved an impressive overall accuracy of 98% on the test dataset, demonstrating its effectiveness in predicting cotton diseases. This system has the potential to serve as a reliable tool for early detection and diagnosis of cotton diseases, thereby improving crop management practices and reducing economic losses.

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CHAPTER 1

INTRODUCTION TO PROJECT AND PROJECT MANAGEMENT

1.1 PROJECT SUMMARY

The project aims to develop a deep learning-based system for the early detection and diagnosis of cotton diseases. By leveraging Convolutional Neural Networks (CNNs), the system will classify various cotton diseases based on their visual symptoms. This approach offers a more accurate and efficient alternative to traditional manual methods, which are labor-intensive and prone to human error.

1.2 PURPOSE

The purpose of this project is to develop a reliable tool for the early detection and diagnosis of diseases in cotton plants. Currently, the diagnosis of cotton diseases relies on visual inspection by experts, which is time-consuming and prone to human error. By leveraging deep learning techniques, specifically Convolutional Neural Networks (CNNs), this project aims to provide a more accurate and efficient alternative for cotton disease prediction. The development of this tool is motivated by the need to improve crop management practices, reduce economic losses, and enhance the efficiency and sustainability of cotton cultivation practices. Additionally, the self-generated dataset will serve as a valuable resource for further research and development in the fields of computer vision and agricultural technology.

1.3 OBJECTIVE

The objective of this project is to develop a deep learning model, specifically a Convolutional Neural Network (CNN), for the detection of diseases in cotton plant leaves. The model will be trained on a dataset of images containing healthy and diseased cotton leaves to learn the features that distinguish between the two. The goal is to create a reliable tool that can assist farmers in identifying and managing diseases in their cotton crops, ultimately improving crop yield and reducing economic losses. Additionally, the project aims to contribute to the field of agricultural technology by showcasing the potential of deep learning in addressing agricultural challenges.

1.4 SCOPE

- Data Collection and Preprocessing: Gathering a dataset of images containing healthy and diseased cotton plant leaves. Preprocessing steps will include image resizing, normalization, and augmentation.
- Model Development: Designing and implementing a CNN architecture for image classification. The model will be trained on the dataset to learn the features distinguishing between healthy and diseased leaves.
- Model Evaluation: Evaluating the trained model using metrics such as accuracy, precision, recall, and F1-score to assess its performance in disease detection.
- Deployment: Integrating the trained model into a user-friendly interface or application that allows users to upload images of cotton leaves and receive predictions about the presence of diseases.
- Testing and Validation: Conducting extensive testing and validation to ensure the model's accuracy and reliability in real-world scenarios.
- Documentation and Reporting: Documenting the entire process, including data collection, model development, and evaluation, and preparing a comprehensive report detailing the project's findings and outcomes.
- Future Scope: Discussing potential future enhancements and research directions, such as expanding the dataset to include more disease types or optimizing the model for faster inference on edge devices.

1.5 TECHNOLOGY AND LITERATURE REVIEW

1.5.1 Technology

- Python
- Google Colab
- TensorFlow
- Convolutional Neural Network (CNN)

1.5.2 Literature Review

Jadhav et al. (2023) developed a deep learning-based tool using Convolutional Neural Networks (CNNs) and ResNet50 architecture to detect and diagnose cotton diseases early. Their model achieved a high accuracy of 97.66% in predicting six types of cotton leaf diseases. The study aims to improve crop management practices and reduce economic losses in cotton cultivation. The proposed system shows promise for enhancing crop management by providing early and accurate disease detection. Future research directions include improving system accuracy, extending its application to other crops, and addressing dataset diversity challenges.[1]

Awad Bin Naeem et al. (2023) developed a deep learning model based on the VGG-16 architecture for detecting various cotton leaf diseases. Their objective was to create an automated system capable of accurately identifying and classifying diseases like Cotton leaf curl virus, fusarium wilt, and bacterial blight. Using a dataset of over 700 high-resolution images of cotton leaves, the model achieved impressive accuracy, F1 Score, recall, and precision rates. The study's findings highlight the potential of deep learning in agriculture, offering practical benefits such as user-friendly mobile apps and improved disease detection in crops.[2]

Rajasekar et al. (2021) utilized deep transfer learning to detect cotton plant diseases, combining ResNet and Xception models for improved accuracy. Their study compared different plant disease detection methods and highlighted the effectiveness of deep learning, especially CNN-based approaches, for addressing challenges in cotton disease detection. They proposed future implementation on mobile devices for continuous monitoring and recognition of plant diseases, emphasizing the potential for fast and automated identification of cotton diseases.[3]

Harshitha et al. (2021) presented a study at the 5th International Conference on Electrical, Electronics, Communication, Computer Technologies, and Optimization Techniques (ICEECCOT) on cotton disease detection using deep learning techniques. They highlighted the challenge of identifying and managing diseases due to their rapid growth and the limited knowledge among farmers. Their approach, based on deep learning with computer vision, achieved an accuracy of 97.13% using the Cotton Disease Dataset from Kaggle. The model successfully classified leaf images into different categories, such as healthy or diseased, based on patterns of infection, demonstrating its effectiveness in aiding disease identification and management in cotton crops.[4]

Bhatheja and Jayanthi (2021) presented a study at the 5th ICEECCOT on using enhanced deep learning techniques for fast monitoring of cotton plant diseases. They highlighted the challenge of manual monitoring in large cotton fields and proposed leveraging deep learning and image processing to detect diseases early. Their study analyzed transfer learning techniques and introduced a sequential deep convolutional neural network for accurately classifying healthy and diseased plants, achieving improved accuracy. The proposed model could enable faster diagnosis and treatment, leading to better production outcomes in cotton farming.[5]

Kalpana et al. (2020) conducted research on automatic pest identification for cotton crops using Convolutional Neural Networks (CNNs). Their study aimed to diagnose diseases in cotton plants by automatically identifying them through CNNs. They achieved an accuracy of approximately 93.89% in recognizing cotton plant diseases using Python programming. The dataset consisted of around 13,372 images of three diseases: Bacterial Blight, Anthracnose, and Leafhopper, collected from cotton fields. The study highlighted the application of CNNs in diagnosing leaf diseases in cotton, detailing the models used and the sources of images, and reporting the achieved accuracy.[6]

Ahmed (2021) introduced a DCPLD-CNN model for recognizing diseases in cotton plants with an accuracy of 98.77% on a dataset of 1951 training and 324 test images. The study aims to enhance disease recognition in agriculture using deep learning, focusing on cotton plants. Future work includes model optimization, extension to other crops, and real-time monitoring.[7]

CHAPTER 2

SYSTEM ANALYSIS

2.1 STUDY OF CURRENT SYSTEM

In the context of plant disease detection, the current system likely involves manual inspection by agricultural experts or farmers. This process can be time-consuming and error-prone, leading to delays in disease identification and treatment.

2.2 PROBLEM AND WEAKNESSES OF CURRENT SYSTEM

- Manual Labor Intensive: Requires experts to physically inspect each plant, which is labor-intensive and slow.
- Error-Prone: Human errors in identifying diseases can lead to misdiagnosis and incorrect treatment.
- Limited Scalability: Difficult to scale for large agricultural areas or for farmers with limited resources.
- Dependence on Expertise: Relies heavily on the expertise of agricultural professionals, which may not be available in all areas.

2.3 REQUIREMENTS OF NEW SYSTEM

- Automation: Implement an automated system that can detect diseases in plants using machine learning or computer vision techniques.
- Accuracy: Ensure high accuracy in disease detection to minimize misdiagnosis.
- Scalability: Design the system to be scalable for use in large agricultural areas.
- Cost-Effective: Keep the system cost-effective to make it accessible to small-scale farmers.
- Real-Time Detection: Provide real-time disease detection to enable timely treatment.

2.4 SYSTEM FEASIBILITY

- Contribution to Overall Objectives: Implementing an automated cotton plant disease detection system using CNNs aligns with the objective of improving agricultural productivity and reducing crop losses.

- Implementation within Constraints: The implementation of the system using CNNs is feasible with current technology. The cost and schedule constraints would depend on factors such as the complexity of the model and the scale of deployment.
- Integration with Existing Systems: The system can be designed to be compatible with existing agricultural management systems or databases, facilitating integration and data sharing.

2.5 ACTIVITY / PROCESS IN PROPOSED SYSTEM

- Dataset Acquisition: Use existing datasets of images of cotton plants with suspected diseases.
- Dataset Splitting: Split the dataset into training, validation, and test sets for model training and evaluation.
- Model Building: Build a convolutional neural network (CNN) model using TensorFlow and Keras for disease detection.
- Model Training: Train the CNN model on the training dataset, monitoring validation loss for early stopping.
- Model Evaluation: Evaluate the trained model on the test dataset to assess its performance.
- Result Presentation: Present the results of the model, including training/validation accuracy and loss plots, and evaluation metrics on the test set.

2.6 FEATURES OF PROPOSED SYSTEM

- Automated Disease Detection: The system automates the process of disease detection, reducing the need for manual inspection.
- High Accuracy: By using advanced machine learning techniques like CNNs, the system achieves high accuracy in disease detection.
- Scalability: Our system is designed to be scalable, meaning it can be used effectively in large cotton fields.
- Real-Time Detection: The system provides real-time disease detection, allowing for timely treatment.

2.7 LIST MAIN MODULES / PROCESSES / TECHNIQUES OF PROPOSED SYSTEM

- Dataset Acquisition: Obtain datasets of images of cotton plants with suspected diseases from sources such as Kaggle.
- Convolutional Neural Network (CNN):
    - Convolutional Layers: Extract features from preprocessed images.
    - Activation Functions: Introduce non-linearity into the model.
    - Pooling Layers: Reduce spatial dimensions of convolutional layers' output.
    - Fully Connected Layers: Perform classification based on extracted features.
- Training Model: Train the CNN using labeled images of diseased and healthy cotton plants to learn disease patterns.
- Image Processing:
    - Feature Extraction: Extract features from preprocessed images to differentiate between healthy and diseased plants.
    - Image Classification: Classify images into different disease categories based on extracted features.
- Result Presentation: Present the results of disease detection, indicating the type of disease detected and possibly suggesting treatment options.

2.8 SELECTION OF SOFTWARE / ALGORITHMS / TECHNIQUES

- Software:
    - Python: Python is chosen for its simplicity and the availability of libraries such as TensorFlow and Keras, which are widely used for developing CNN models.
    - Libraries: The project uses Python libraries for different purposes. Pandas is utilized for data manipulation, enabling easy handling of structured data. Matplotlib is employed for data visualization, facilitating the creation of various plots and charts. TensorFlow and Keras are utilized for developing and training machine learning models, specifically for building a convolutional neural network (CNN) for plant disease detection. These libraries collectively provide the necessary tools for data analysis, visualization, and model development.

- Algorithms:
  - Convolutional Neural Network (CNN): CNNs are selected for their effectiveness in image recognition tasks. They are well-suited for detecting patterns in images, making them ideal for identifying diseases in cotton plants based on leaf images.
- Techniques:
  - Transfer Learning: Transfer learning may be employed to leverage pre-trained CNN models on large datasets and fine-tune them for the specific task of cotton plant disease detection. This approach can reduce training time and improve model performance.

CHAPTER 3

SYSTEM DESIGN

3.1 SYSTEM DESIGN & METHODOLOGY

Study Outline

This study utilizes the CNN architecture for the task. The key benefit of CNN is that it recognizes critical features without human intervention. Since CNN has features such as sharing of parameters as well as dimensionality reduction, the key idea is that what it learns in one part of the image will be expedient in a different part of the image. The computing power needed in CNN is reduced due to the reduction in dimensionality. Those automatically extracted features using techniques such as pooling, strides and padding of CNN are then trained along with augmented image data to build the model for detecting diseased cotton plants and leaves.

Proposed approach

Steps for Cotton Disease Detection:

- Image Acquisition: Obtain images of cotton plant leaves showing signs of disease.
- Image Enhancement: Improve the quality of acquired images if necessary, to ensure clarity and consistency in the dataset.
- Image Preprocessing: Prepare the images for training by resizing, normalizing, and converting them into a format suitable for the CNN model.
- Image Annotation: Annotate the images to label the regions of interest, such as diseased areas, for the model to learn from.
- Image Augmentation: Augment the dataset by applying transformations such as rotation, flipping, and scaling to artificially increase the variety of images for better model generalization.
- Augmented Dataset: Use the augmented dataset for training the CNN model.
- Model Training: Train the CNN model on the augmented dataset to learn the patterns and features associated with different cotton diseases.

- Fine-tuning for Disease Prediction: Fine-tune the trained model to improve its accuracy in predicting specific diseases (viral, bacterial, fungal, or nutritional) based on the features learned during training.
- Test Image: Use a separate set of images (not used in training) to test the performance of the model in detecting and classifying cotton diseases.

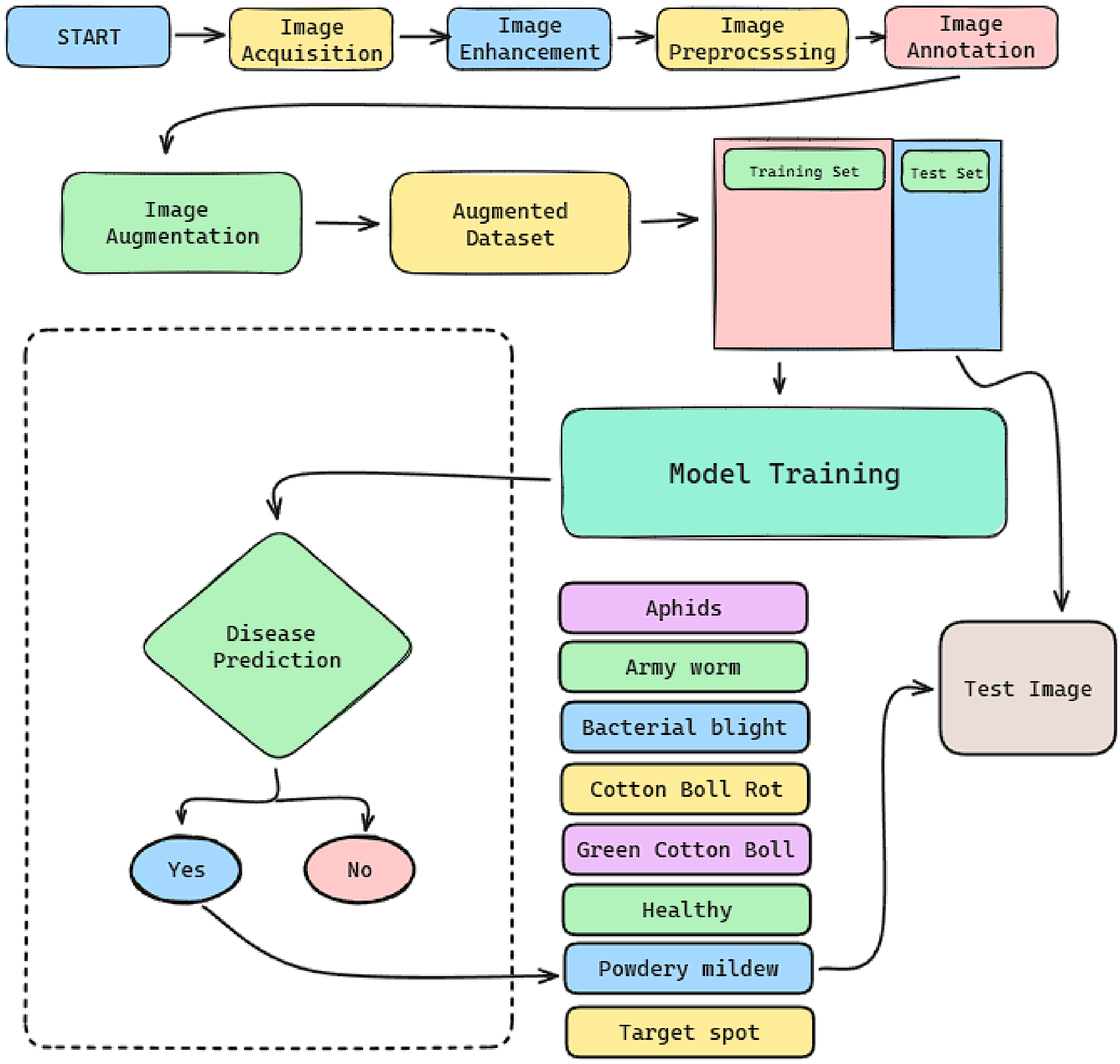

Fig 3.1 Data Flow Diagram

3.2 DATASET COLLECTION

The dataset used in this project, known as the Customized Cotton Disease Dataset, was meticulously compiled and curated to include images of cotton plant leaves exhibiting a range of diseases. This dataset is crucial for training machine learning models to accurately identify and classify these diseases. The dataset comprises two main sections: "Cotton-Disease-Training" and "Cotton-Disease-Validation."

In the "Cotton-Disease-Training" folder, there are subfolders containing images of cotton leaves with specific diseases such as Aphids, Army worm, Bacterial blight, Cotton Boll Rot, Green Cotton Boll, Healthy leaves, Powdery mildew, and Target spot. Each subfolder contains 800 images depicting the respective disease.

The "Cotton-Disease-Validation" folder contains edited images of cotton plant leaves with diseases, presumably for validation purposes. These images are likely processed versions of the original images to ensure the model's accuracy and generalization.

Overall, the dataset provides a diverse set of images depicting various diseases that commonly affect cotton plants. This diversity is essential for training a robust machine learning model capable of accurately detecting and classifying different cotton plant diseases.

CHAPTER 4

IMPLEMENTATION

4.1 PROCESS

The first step in building the plant disease detection system was to download a dataset containing images of cotton plant leaves with various diseases from Kaggle. These images were then prepared for training by resizing, normalizing, and converting them into a format suitable for the model.

Next, the dataset was divided into three sets: training, validation, and test. The training set was used to teach the model to recognize different diseases, while the validation set helped fine-tune the model's settings to improve its performance. The test set was used to evaluate the model's effectiveness in identifying diseases in unseen images.

Using TensorFlow and Keras, a convolutional neural network (CNN) model was developed to learn from the dataset. CNNs are particularly effective for image-related tasks due to their ability to extract features from images. The model was trained on the training set, with its weights adjusted to minimize errors and improve accuracy.

Finally, the trained model was evaluated using the validation set to assess its performance. Metrics such as accuracy, precision, recall, and F1 score were used to measure the model's effectiveness in detecting diseases. The ultimate goal of this system is to provide farmers and agricultural experts with a reliable tool for identifying and managing plant diseases.

4.2 ENVIRONMENT

The plant disease detection system was implemented in a Google Colab environment. Google Colab provides a cloud-based platform with free access to computing resources, including GPUs and TPUs, which are essential for training deep learning models efficiently. The use of Google Colab allowed for seamless integration with Google Drive, where the dataset and trained models were stored. Additionally, Google Colab provides a Jupyter notebook interface, making it easy to write and execute code in a collaborative and interactive manner. Overall, the Google Colab environment provided a convenient and cost-effective solution for implementing the plant disease detection system.

4.3 RESULTS / OUTPUTS

- Model: CNN
- Recall: 97.40
- Precision: 97
- F1-Score: 97.92
- Accuracy: 98.22%

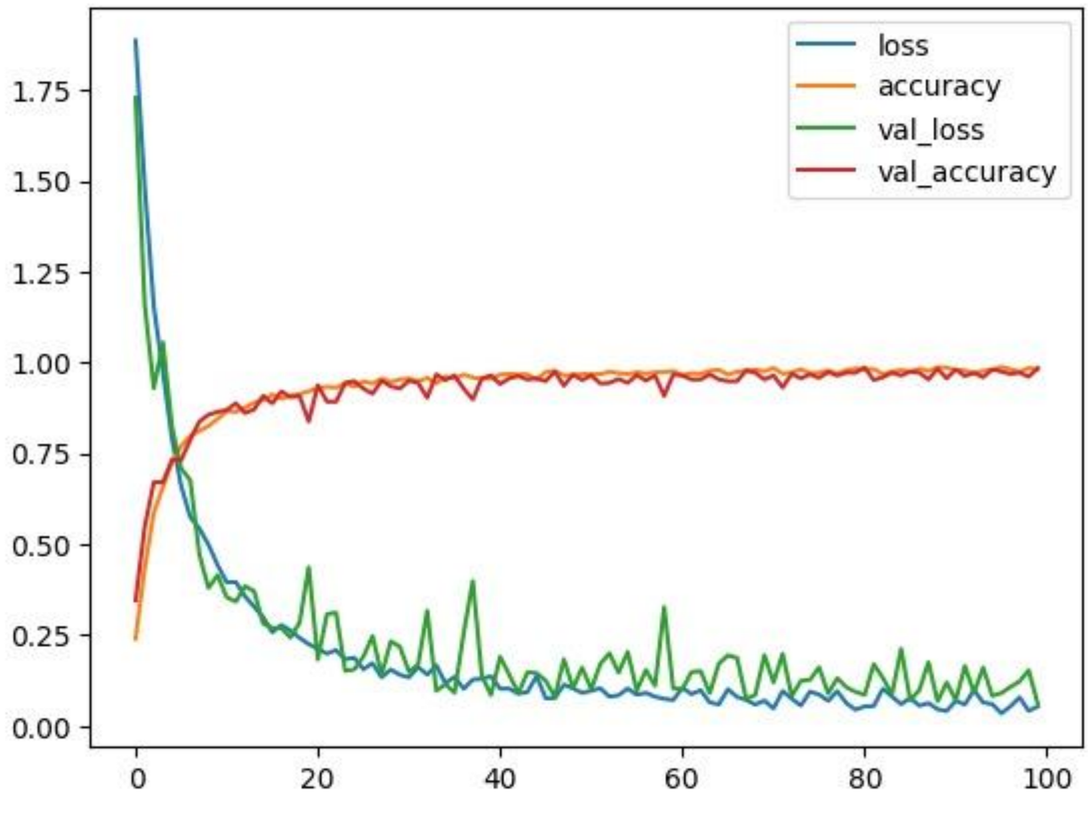

Fig 4.1 Training, Validation loss and accuracy

CHAPTER 5

TESTING

5.1 TESTING PLAN / STRATEGY

- Data Splitting: Split the dataset into training, validation, and test sets. The training set is used to train the model, the validation set is used to tune hyperparameters and prevent overfitting, and the test set is used to evaluate the model's performance.
- Model Training: Train the model using the training set. This involves feeding the model the input data (images) and their corresponding labels (disease types) and adjusting the model's weights to minimize the loss function.
- Model Evaluation: Evaluate the trained model using the validation set to assess its performance. This typically involves calculating metrics such as accuracy, precision, recall, and F1-score.
- Hyperparameter Tuning: Fine-tune the model's hyperparameters (e.g., learning rate, batch size, number of epochs) based on the validation set's performance to improve the model's accuracy.
- Final Evaluation: Once the model is trained and tuned, evaluate its performance using the test set. This provides an unbiased estimate of the model's performance on unseen data.
- Result Analysis: Analyze the model's performance metrics (e.g., accuracy, loss) and visualize them using plots to understand how well the model is performing and identify areas for improvement.
- Deployment: If the model performs satisfactorily, deploy it to a production environment where it can be used to classify new cotton plant images.

5.2 TEST RESULTS AND ANALYSIS

5.2.1 Test Cases

- Test Case 1: Model Training

  Objective: Train the model using the training dataset.

Steps:

- ➢ Split the dataset into training, validation, and test sets.
- ➢ Train the model using the training set.
- ➢ Validate the model using the validation set.

Expected Result: The model should learn to classify cotton plant diseases accurately.

- Test Case 2: Model Evaluation

Objective: Evaluate the trained model using the test dataset.

Steps:

- ➢ Evaluate the model using the test set.
- ➢ Calculate performance metrics such as accuracy.

Expected Result: The model should perform well on the unseen test data, indicating its ability to generalize.

5.2.2 Result Analysis / Comparison

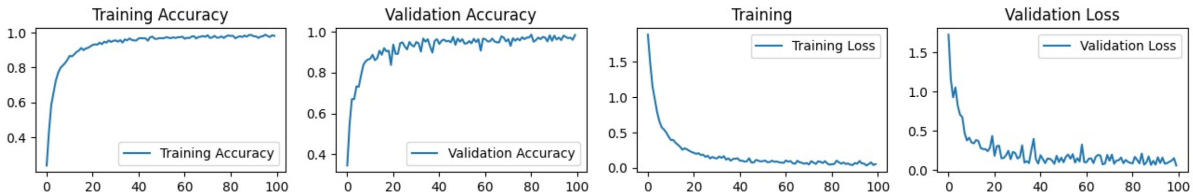

Fig 5.1 Reliability of the training and validation set

- Training Results: Analyze the training process, including the loss and accuracy curves over epochs. Ensure that the model is not overfitting the training data.
- Validation Results: Compare the model's performance on the validation set with its performance on the training set. Identify any signs of overfitting or underfitting.
- Test Results: Evaluate the model's performance on the test set. Compare the results with the validation set to ensure consistency.
- Performance Metrics: Calculate and compare metrics such as accuracy, precision, recall, and F1-score. Analyze these metrics to understand the model's strengths and weaknesses.

- Error Analysis: Examine misclassified examples to identify common patterns or challenges faced by the model. Use this information to refine the model further if necessary.

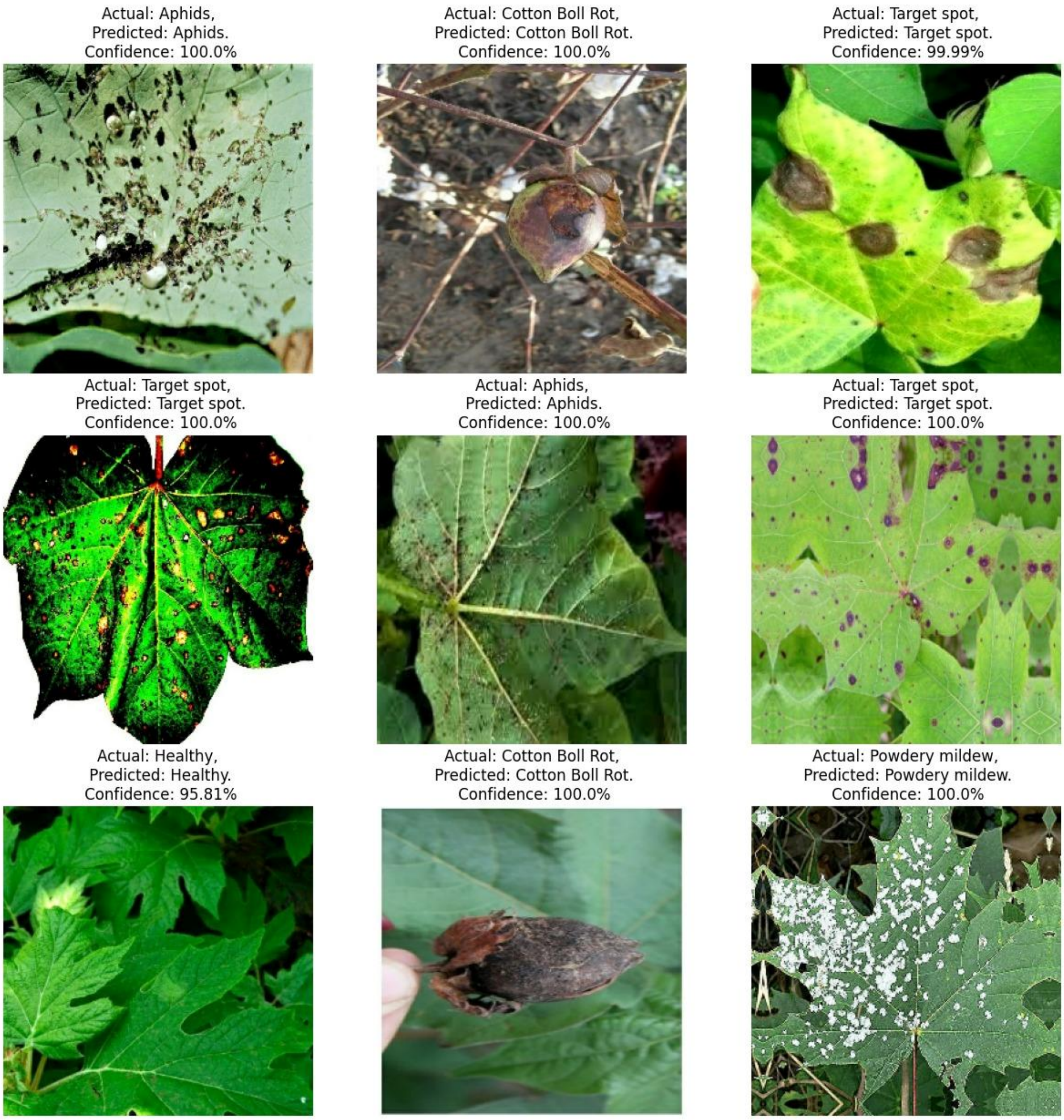

Fig 5.2 Model prediction using a series of test photos

CHAPTER 6

CONCLUSION & OUTCOMES

6.1 OVERALL ANALYSIS OF PROJECT VIABILITIES

The project to develop a cotton plant disease detection system using Convolutional Neural Networks (CNNs) has demonstrated high viability. The dataset used, known as the Customized Cotton Disease Dataset, contains a variety of images showcasing different diseases such as Aphids, Armyworm, Bacterial Blight, Cotton Boll Rot, Green Cotton Boll, Powdery Mildew, and Target Spot, along with healthy cotton leaves. By accurately detecting these diseases, the system can significantly improve crop management practices, enabling farmers to take proactive measures to mitigate the spread of diseases and optimize treatment strategies. This can lead to increased yields and reduced pesticide use, benefiting both farmers and the environment.

6.2 PROBLEM ENCOUNTERED AND POSSIBLE SOLUTIONS

During the project, some challenges were encountered, such as acquiring a labeled dataset and fine-tuning the CNN model for optimal performance. These challenges were addressed by collaborating with experts to label the dataset and using transfer learning to enhance the model's accuracy.

6.3 SUMMARY OF PROJECT WORK

The project involved collecting a dataset of diseased and healthy cotton plant images, preprocessing the images, and training a CNN model for disease detection. The trained model showed promising results in accurately classifying diseases in cotton plants.

6.4 LIMITATIONS AND FUTURE ENHANCEMENT

One limitation of the project is the focus on leaf diseases, with potential future enhancements including expanding the system to detect diseases affecting other parts of the plant, such as stems and buds.

6.5 PROJECT OUTCOMES

The project has successfully developed a CNN-based system for cotton plant disease detection, providing a valuable tool for farmers to monitor and manage disease outbreaks. The system's accuracy and efficiency in detecting diseases demonstrate its potential to revolutionize cotton crop management practices and contribute to sustainable agriculture.

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