KLE Technological University
Creating Value, Leveraging Knowledge
Dr. M. S. Sheshgiri Campus, Belagavi

Department of
Electronics and Communication Engineering

Minor Project - 2 Report

on

Crop Health Assessment through Image Processing

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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

CERTIFICATE

This is to certify that the project entitled "Crop Health Assessment through Image Processing" is a bonafide work carried out by the student team of "Rohan Anvekar 02FE21BEC074, Rohit M Hosalli 02FE21BEC075, Samruddhi Shindolkar 02FE21BEC083, Ujwala V T 02FE21BEC105". The project report has been approved as it satisfies the requirements with respect to the mini project work prescribed by the university curriculum for B.E.(VI Semester) in the Department of Electronics and Communication Engineering of KLE Technological University Dr. M. S.Sheshgiri CET Belagavi campus for the academic year2023 2024.

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-The project team

ABSTRACT

Traditional methods of crop health assessment often rely on visual inspection by farmers, which can be subjective and time-consuming. Early detection of diseases or nutrient deficiencies is crucial for taking timely corrective actions and minimizing crop losses. This system can address the limitations of traditional methods by offering real-time monitoring and objective disease detection. Further research and development can improve the generalizability of the model and optimize its performance for resource-constrained devices, paving the way for wider adoption in precision agriculture.

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Chapter 1

Introduction

The agricultural sector faces significant challenges in maintaining crop health and maximizing yields, with disease detection and nutrient management being critical components. Traditionally, farmers have relied on visual inspections to assess crop health, a method fraught with subjectivity and inconsistency. These manual inspections are not only labor-intensive but also prone to human error, leading to delayed or incorrect diagnoses.

Timely and accurate detection of crop diseases and nutrient deficiencies is essential to prevent significant yield losses and ensure sustainable farming practices. However, the limitations of traditional methods necessitate the development of more reliable and efficient solutions.

Advancements in technology offer promising alternatives to manual inspections. Real-time monitoring systems, incorporating machine learning algorithms and remote sensing technologies, provide objective and accurate assessments of crop health. These systems can analyze vast amounts of data rapidly, enabling early detection of issues and allowing for prompt intervention.

Despite the potential benefits, the adoption of such technologies in precision agriculture faces challenges. Key among these is the need for models that can generalize well across different crop types and environmental conditions. Additionally, the optimization of these systems for resource-constrained devices is crucial to ensure their feasibility and affordability for widespread use by farmers.

1.1 Motivation

The motivation for developing a crop health assesment is to address the limitations of traditional crop health assessment methods, which are often subjective, time-consuming, and prone to human error. By developing a system that offers real-time monitoring and objective disease detection, the project aims to enable timely corrective actions, minimize crop losses, and improve the efficiency and accuracy of crop health assessments. This, in turn, supports sustainable agricultural practices and enhances overall productivity. Additionally, the project seeks to make such advanced technologies accessible and practical for farmers, especially in resource-constrained settings, through further research and development to improve model generalizability and optimize performance for widespread adoption in precision agriculture. The project aims to develop a system for real-time monitoring and objective disease detection, enabling timely corrective actions, reducing crop losses, and enhancing assessment efficiency and accuracy. This supports sustainable farming and boosts productivity. Additionally, the project focuses on making advanced technologies accessible and practical for farmers, particularly in resource-constrained settings, through further research to enhance model generalizability and optimize performance for precision agriculture.

1.2 Objectives

- Develop a Real-Time Monitoring System: Create a system capable of continuous real-time monitoring of crop health to provide immediate feedback on the status of the crops.
- Achieve Objective Disease Detection: Utilize advanced technologies such as machine learning and remote sensing to identify diseases and nutrient deficiencies accurately and objectively.
- Enhance Assessment Efficiency and Accuracy: Improve the speed and precision of crop health assessments compared to traditional visual inspection methods.
- Model Generalizability: Conduct research and development to enhance the model's ability to generalize across different crop types and varying environmental conditions.

1.3 Literature survey

Table 1.1: Literature Review

SI.No	Paper Title	Objective	Algorithm used	Limitations
1	[5]	Effective for over 15 plant types and 51 diseases, achieving over 93 percent accuracy despite noisy images.	Tensor flow framework by CNN model	Complex Deep Learning model.
2	[3]	This paper aims for eliminate the need for farmers to rely solely on visual inspection.	Machine Learning Histogram of oriented Gradients(HOG)	systems ability to detect limited diseases on limited plants.
3	[1]	This paper aims on agricultural productivity, mentioning specific examples like black spot and rust.	Deep Learning Convolution Neural Networks(CNNs)	Results may signify and works only for limited dataset.
4	[2]	This paper aims on Artificial Intelligence with the potential to revolutionize plant disease diagnosis.	Deep Learning	require significant computational resources and processing power.
5	[4]	This paper aims on real-time data on environmental factors (air temperature, humidity, soil moisture, pH).	Raspberry Pi 3 with camera Machine learning (SVM) algorithm	requires optimization for real-time applications.

1.4 Problem statement

The agricultural sector is pivotal to global food security, yet it faces significant challenges in maintaining crop health and maximizing yields. Key to addressing these challenges is the ability to detect diseases and nutrient deficiencies early and accurately. Traditionally, farmers have relied on visual inspections to assess crop health. However, this method is inherently subjective, time-consuming, and prone to human error, often leading to delayed or incorrect diagnoses and subsequent crop losses. This project aims to develop such a system to revolutionize crop health assessment. By integrating cutting-edge technologies, the project seeks to enhance the efficiency and accuracy of crop health monitoring.

1.5 Application in Societal Context

- Enhanced Food Security: By enabling early detection and accurate diagnosis of crop diseases and nutrient deficiencies, the project can help ensure more stable and higher crop yields. This contributes to global food security by reducing the risk of crop failures and increasing the overall food supply.

- Sustainable Agriculture: The system promotes sustainable farming practices by optimizing the use of resources such as water, fertilizers, and pesticides. This not only improves crop health and yields but also minimizes environmental impact, supporting long-term agricultural sustainability.

- Economic Benefits for Farmers: By improving the efficiency of crop health monitoring and reducing losses due to disease and nutrient deficiencies, farmers can achieve better productivity and profitability. The system can lead to cost savings and increased income for farmers, particularly in resource-constrained settings.

- Public Health: By reducing the reliance on chemical pesticides through more precise application based on accurate crop health data, the project can contribute to safer food production and lower the exposure of farm workers and consumers to harmful chemicals.

- Global Competitiveness: By integrating advanced technologies into agriculture, the project can help nations enhance their agricultural competitiveness on the global market. Improved crop yields and quality can boost export potential and strengthen the agricultural economy.

- Educational Advancement: The implementation of this technology can foster knowledge transfer and skill development among farmers, agricultural professionals, and students. It encourages the adoption of modern agricultural practices and continuous learning.

1.6 Organization of the report

- Introduction: - Brief overview and rationale for the project.
- Literature Review: - Summary of existing machine learning algorithms , Deep learning algorithms and applications.
- Objectives: - Clear definition of project goals and objectives.
- Methodology: - Explanation of the algorithm design process, and optimization strategies.
- Algorithm Methodology: - Detailed explanation of algorithmic design principles, emphasizing optimization considerations.
- Simulation Testing: - Overview of testing procedures and presentation of simulation results.
- Ethical Considerations: - Discussion of ethical considerations related to data security.
- Results and Discussion: - Summary of key findings, comparative analysis, and optimization impact.

Chapter 2

System design

2.1 Functional block diagram

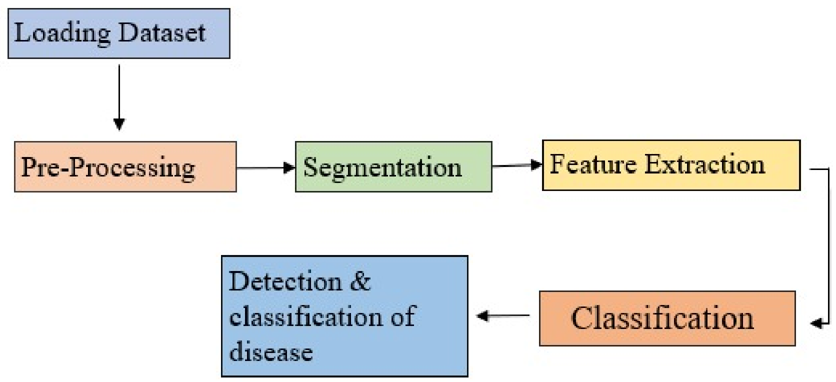

Figure 2.1: Block Diagram of crop image processing

2.2 Design alternatives

- Support Vector Machines (SVM): SVM is effective for small to medium-sized datasets, finding optimal hyperplanes to separate data points. However, it struggles with large-scale image datasets and noisy data due to high computational costs.

- Deep Learning Models: Deep learning includes various architectures beyond CNNs, such as RNNs, LSTMs, and Autoencoders. These models are highly flexible and can learn complex patterns, making them suitable for a range of applications. However, they require substantial computational resources and extensive training data.

- Histogram of Oriented Gradients (HOG): HOG is a feature descriptor used for object detection. It captures the distribution of gradient orientations within localized portions of an image. HOG is computationally efficient and suitable for real-time applications on resource-constrained devices, but it may not perform as well as deep learning models for complex image classification tasks.

- Convolutional Neural Networks (CNN) CNNs are specialized deep learning models designed for image processing tasks. They are highly effective in capturing spatial hierarchies in images and can achieve high accuracy in classification tasks. CNNs can generalize well across different plant types and disease conditions, handling noisy images, diverse backgrounds, and varying disease coverage.

2.3 Final design

We select one of the optimal solutions based on its working and ease of the implementation.

- Working:

  The CNN model was ultimately selected for its high accuracy and ability to generalize well across different plant types and disease conditions. CNNs offer robust performance in handling noisy images, diverse backgrounds, and varying disease coverage.

- Ease of Implementation:

  Despite the higher computational requirements, CNNs can be optimized for deployment on low-powered devices. Techniques such as model quantization, pruning, and hardware acceleration can be employed to mitigate computational limitations.

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Chapter 3

Implementation details

3.1 Specifications and final system architecture

Specifications for CNN Model

Input:

- Image Details: About 87K RGB images of healthy and diseased crop leaves categorized into 38 different classes.
- Dataset Split: The total dataset is divided into an 80/20 ratio for training and validation sets, preserving the directory structure.
- Test Set: A new directory containing 33 test images is created later for prediction purposes.

Processing Steps:

Model Training: Use a Convolutional Neural Network (CNN) model and Trained the model for 15 epochs with a learning rate of 0.0001.

Output:

- The output includes the detection of the leaf as either healthy or diseased, along with the specific name of the disease if applicable.

Usage:

- Dataset Preparation: The user needs to download the original dataset from the provided GitHub repo and apply offline augmentation to recreate the dataset.
- Model Training: Train the CNN model using the prepared training and validation sets.
- Prediction: Use the model to predict the health status of the leaves in the test set.

Dependencies:

- TensorFlow/Keras for building and training the CNN model.
- NumPy for numerical operations.
- Matplotlib for plotting results (if needed).

Adjustable Parameters:

- Learning Rate: The learning rate used in the CNN model training (0.0001).
- Epochs: The number of epochs for which the CNN model is trained (15).

Visualization:

- Training and Validation Accuracy: The accuracy results can be visualized using plots to show the training and validation accuracy over epochs.
- Test Predictions*: The predictions on the test set can be displayed along with the actual images for comparison.

3.2 Algorithm

Training Dataset:

- Load the Training and Validation Dataset from the defined path.

Model Setup:

- Architecture: Build a CNN with Conv2D, MaxPooling2D, Dropout, Flatten, and Dense layers. Compile with Adam optimizer, learning rate 0.0001, categorical cross-entropy loss, and accuracy metric.

Train the Model:

- Training: Train the model with the training and validation datasets for 15 epochs. And Print model summary.

- Performance: Evaluate and print training and validation loss and accuracy.

  Save Model and History:

  Save the model in keras format
  Visualization: Plot training and validation accuracy over epochs.

  Confusion Matrix and Report:

  – Matrix and Report:
  – **C**ompute and print confusion matrix and classification report.
  – **P**lot confusion matrix heatmap.

  New Image Prediction:

  – Load model from "trained $_model.keras$".

3.3 Flowchart

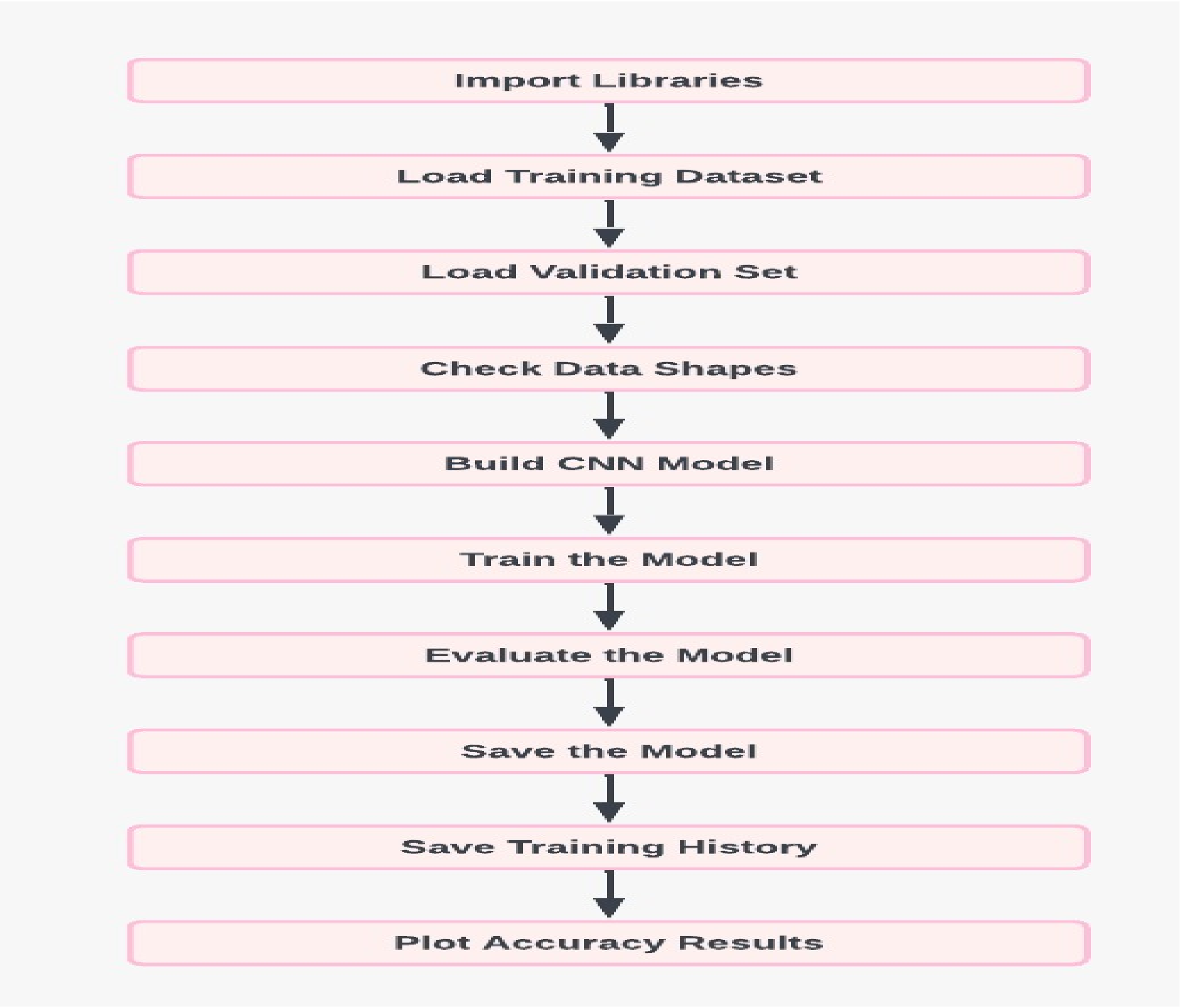

Figure 3.1: Flow Chart of crop image processing

Chapter 4

Optimization

4.1 Introduction to optimization

- To optimize the CNN model for detecting healthy and diseased crop leaves, several strategies can be implemented beyond adjusting the learning rate. These optimizations can enhance model performance, reduce overfitting, and improve training efficiency.
  Learning rate schedulers adjust the learning rate during training, which can help in converging faster and avoiding local minima. A common approach is to reduce the learning rate when a metric has stopped improving.

4.2 Types of Optimization

Hyperparameter Optimization:

* Used a reduced learning rate of 0.0001 and dynamic adjustment with ReduceLROnPlateau.

Architectural Optimization:

* Higher filter sizes (32, 64, 128, 256, 512) for better feature extraction and adding more layers to capture more complex patterns.

Regularization Techniques:

* Prevents overfitting by randomly dropping units during training and implemented batch normalization, improving performance and convergence.

Learning Rate Schedulers:

* Adjusts the learning rate dynamically based on validation loss and used this scheduler to adapt learning rates during training.

4.3 Selection and justification of optimization method

Justification for Selection:

* Batch Normalization: Selected to stabilize and accelerate the training process by normalizing inputs of each layer. This helps in faster convergence and better generalization.

Justification for Selection:

* Learning Rate Adjustment: The dynamic adjustment via ReduceLROnPlateau helps to fine-tune learning, preventing overshooting the minimum and allowing finer adjustments as training progresses.

Justification for Selection:

* Increased Filter Sizes: More filters in Conv2D layers enable the model to learn more complex features, improving its ability to classify images accurately.

Justification for Selection:

* Dropout Regularization: Applied to prevent overfitting, ensuring that the model does not become too dependent on any particular set of neurons during training.

Chapter 5

Results and discussions

5.1 Result Analysis

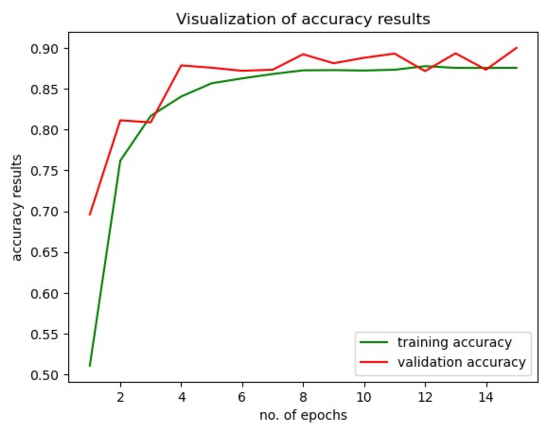

Figure 5.1: Result before optimization

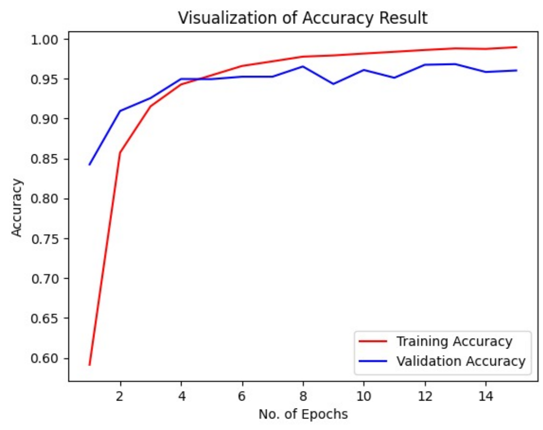

Figure 5.2: Result after optimization

5.2 Output

Figure 5.3: test image

Figure 5.4: Results of prediction

5.3 Discussion on Optimization

Batch Normalization:

* Led to improved stability and faster convergence. It helped in maintaining a smooth learning curve and preventing gradient issues.

Learning Rate Scheduler:

* The use of ReduceLROnPlateau allowed the model to lower the learning rate dynamically, helping in achieving a better minimum loss and preventing the model from plateauing too early.

Architectural Changes:

* Increasing the number of filters and adding more Conv2D layers allowed the model to capture intricate details in the images, leading to improved accuracy.

Regularization:

* Dropout effectively reduced overfitting, ensuring that the model generalizes well to unseen data..

Chapter 6

Conclusions and future scope

6.1 Conclusion

In conclusion, the implementation of advanced systems in agriculture presents a significant leap forward from traditional methods, providing real-time monitoring and objective disease detection. By focusing on further research and development, these systems can achieve greater generalised and efficiency, particularly for use in resource-constrained environments. This progress will enable broader adoption of precision agriculture techniques, ultimately leading to more sustainable and productive farming practices worldwide.

6.2 Future scope

* Integration with Internet of Things (IoT): Expanding the system to integrate with IoT devices can enhance data collection and monitoring capabilities. IoT sensors can provide real-time environmental data such as soil moisture, temperature, and humidity, further improving the accuracy and comprehensiveness of crop health assessments.
* Geographic and Crop Diversity: Extending the system's applicability to a wider range of geographic regions and diverse crop types can improve its generalizability. Research and development can focus on adapting the system for different climates, soil types, and farming practices globally.
* Economic and Impact Analysis: Conducting comprehensive economic and impact analyses can demonstrate the system's benefits in terms of cost savings, yield improvements, and environmental impact. This can help in securing funding, support from stakeholders, and encouraging widespread adoption.
* Collaboration with Agricultural Research Institutions: Partnering with agricultural research institutions can provide valuable insights and accelerate the development and refinement of the technology. Collaborative research can enhance the system's scientific foundation and practical effectiveness.

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