



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: <https://doi.org/10.22214/ijraset.2025.70074>

www.ijraset.com

Call:  08813907089

E-mail ID: ijraset@gmail.com

Smart Leaf Disease Recognition and Prevention

Neha Muddanal¹, Gitanjali Kshirsagar², Akanksha Jadhav³, Pratiksha Chaudhari⁴, Sunita Nandgave⁵

^{1, 2, 3, 4}G.H. Raisoni University, Department of Computer Science Engineering

⁵G.H. Raisoni College of Engineering, Assistant Professor of Computer Science Engineering department, Pune

Abstract: Any nation's economic development is greatly influenced by its agricultural sector. It is the area that has the biggest impact on a nation's GDP. Approximately 16 % of India's GDP comes from the agriculture industry. Numerous factors influence both the number and quality of crops grown. These plants are susceptible to a variety of illnesses because to local circumstances and varying weather. Due to plant diseases with the advancement of new advances, the field of agriculture becomes more prominent as it not only used as food feeding to major population but also used in many applications. Plants are very essential in our life as they provide source of energy and overcome the issue of global warming. Plants nowadays are affected by many diseases such as they cause devastating economic, social and ecological losses and many more. Hence, it is most important to identify plants disease in an accurate and timely way. Plant diseases can be extensively grouped by the idea of their essential causal operator, either irresistible or non-infectious. Plant diseases reduce the quantity and quality of agricultural products and result in significant production and financial losses. Plant disease identification has drawn more attention lately as a means of keeping an eye on vast agricultural fields.

Keywords: Deep learning, CNN, KNN algorithm, Image Processing, AI Engine

I. INTRODUCTION

Farming assumes a vital part in the financial development of any Country. It is the field which exceptionally influence the Gross domestic product of the nations. Horticulture area contributes around 16 percent of Gross domestic product of India. There are different elements that influences the quality and amount of yields developed. Because of various climate and nearby circumstances these plants are presented to different infections. Because of plant sicknesses with the headway of new advances, the field of agribusiness turns out to be more conspicuous as it not just utilized as food taking care of to significant populace yet in addition utilized in numerous applications. Plants are exceptionally fundamental in our life as they give wellspring of energy and defeated the issue of an Earth-wide temperature boost. Establishes these days are impacted by numerous infections, for example, they cause wrecking financial, social and natural misfortunes and some more. Thus, distinguishing plants illness in an exact and convenient way is generally significant. Plant infections can be broadly gathered by the possibility of their fundamental causal administrator, either overwhelming or non-infectious. Visual identification of plant diseases is inherently labour-intensive and often less precise, typically limited to smaller areas. In contrast, the implementation of automated detection techniques requires reduced effort, minimizes time expenditure, and enhances accuracy. Common plant diseases include bacterial infections, black spot disease, rust, viral infections, and red cotton leaf disease. Image processing serves as a method for quantifying the extent of disease impact and analysing colour variations in affected regions.

Image segmentation, which involves partitioning an image into distinct components, is a critical aspect of this process. Currently, numerous techniques exist for executing image segmentation, ranging from basic thresholding to sophisticated colour image segmentation methods. The segmentation process relies on various characteristics present within the image, including colour data, boundaries, or specific segments. CNN's great precision, extensive numerical management and direct mathematical translation provide them with significant advantages. Furthermore, they don't have to waste time on a tonne of preparatory testing to avoid over fitting. Here, the image of organic products obtained from the data set must be naturally recognised and arranged. It is anticipated that there will be unique photos available, some of which will be covered by one another. In essence, the suggested work provides an audit of the procedures followed during the entire interaction in order to identify a certain organic product. Because the picture was taken in a variety of typical circumstances. There are two main steps to the system. Textural highlights are extracted from foods grown from the ground in the first stage, and the organic product is referred to as a recognised natural product in the second stage. In order to prepare to order it, the CNN classifier receives the estimations obtained by the textural highlight inquiry. Finally, the framework will recognise items and display a yield. Planning a gradual model to perceive organic items based on their size, shape, and shade is the aim of Fruit Recognition using Image Handling.

II. OBJECTIVES

A. *To predict which disease the plant has based on the leaf images*

To use image processing or machine learning techniques to analyse the visual characteristics of a plant's leaves and forecast which disease it has. We try to identify the type and presence of plant disease by looking at the leaf's shape, colour, texture, and any obvious symptoms like spots or discoloration.

B. *To provide user a platform where he could upload his affected leaf image*

To give consumers access to a portal so they may submit pictures of impacted plant leaves. These photos will be analysed by the platform to find any plant illnesses, identify symptoms, and provide information or remedies. Users can get precise disease diagnosis and treatment recommendations by utilizing picture recognition technologies and plant pathology databases.

C. *To provide accurate services in less time*

To use cutting-edge image processing and recognition algorithms to provide precise services in the shortest amount of time. Through excellent analysis of uploaded leaf photos, the platform will guarantee prompt identification of plant diseases, giving users accurate and timely results to efficiently manage agricultural concerns.

D. *It will be offline application easy to use*

Users will be able to diagnose plant illnesses without the need for an internet connection thanks to the user-friendly, offline application. Farmers and gardeners in remote places can easily get accurate disease diagnoses and advice using the platform's user-friendly interface and efficient picture processing capabilities.

E. *We use picture handling calculations to distinguish sick-nesses on plants*

Algorithms for image processing are used to identify plant diseases. In order to precisely identify disease symptoms, these algorithms examine visual characteristics of leaf images, such as colour, texture, and form. The plant disease detection system offers accurate and effective results by utilizing these methods.

III. PROJECT REQUIREMENT SPECIFICATIONS

A. *Software Requirements*

Steps to be followed:

1. Download and install Python version 3 from official Python Language website <https://www.python.org/>
2. Front End : HTML ,CSS, JavaScript
3. Back-End : Flask
4. Install the following dependencies via pip.
 - i. Tensor Flow
 - ii. Numpy
 - iii. SciPy
 - iv. Pillow
 - v. Matplotlib
 - vi. OpenCV
 - vii. Pandas

B. *Hardware Requirements*

- System : PC, Laptop.
- CPU : Core i5- and above
- GPU : NVIDIA Quadra M4000M
- Memory : 6 GB
- Display Memory : 4 GB
- Operating System : Windows 8/10

C. Module Split-up

- Database
- Pre-processing and Feature Extraction
- Training

IV. MODEL TRAINING LOG

A. Dataset Overview

- Training Dataset:
 - o Contains 54 images distributed across 3 classes.
 - o The dataset is small, indicating the model is being trained on a limited dataset, which could lead to challenges in generalization.
- Validation Dataset:
 - o Contains 12 images belonging to the same 3 classes.
 - o This serves as the holdout dataset to evaluate the model's performance during training.

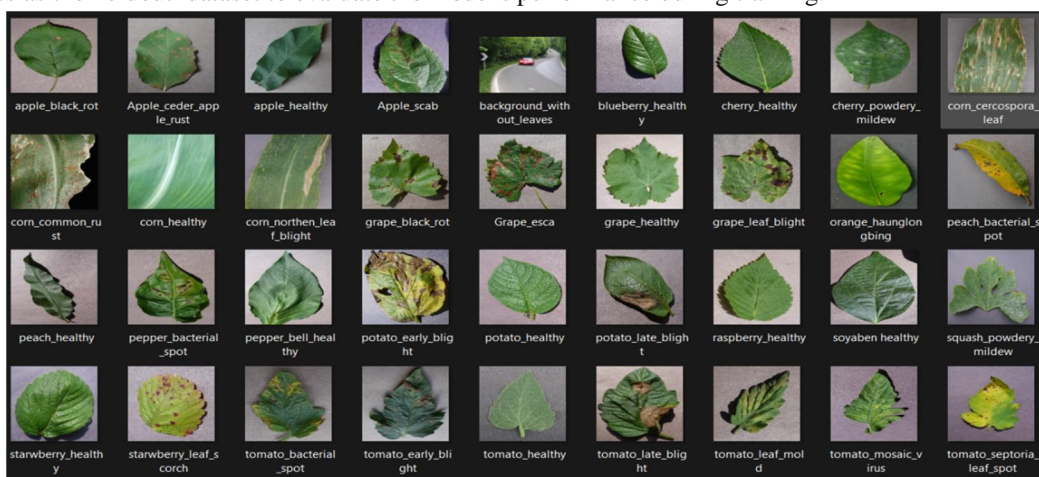


Figure 4.1: Dataset

The log indicates the dataset is structured in a typical image classification format, possibly organized in directories. The dataset is organized into two main directories train/ and validation/. Each of these directories contains subdirectories for the respective classes.

V. ALGORITHM AND METHODOLOGIES

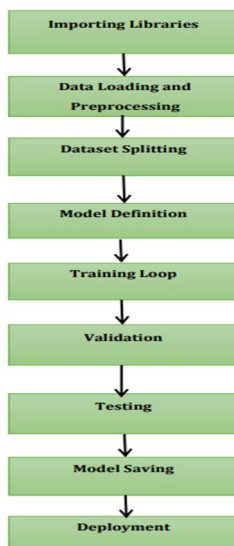


Figure 5.1 Algorithm

In a smart leaf disease detection system, an algorithm refers to a step-by-step procedure used to identify plant diseases from leaf images.

1) Data Loading and Pre-processing

o The dataset is loaded using torch vision, datasets, Image-Folder, and transformations like resizing, cropping, and normalization are applied.

2) Dataset Splitting

o Subset samplers or data loaders are likely used to split the data into training, validation, and testing subsets.

3) Model Definition

o A CNN or a pre-trained model (e.g., ResNet, VGG) is imported and modified.

4) Training Loop

o Includes forward propagation, loss calculation, back propagation, and parameter updates.

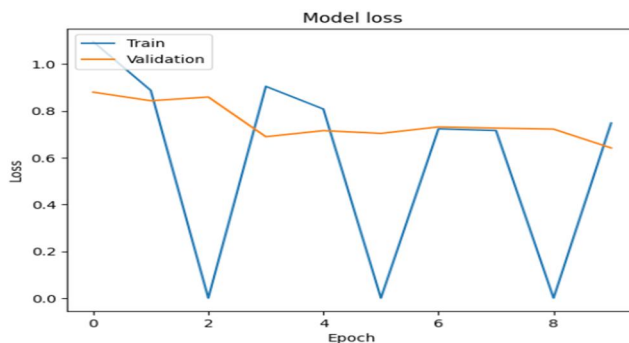
5) Evaluation

o Metrics such as accuracy and loss are calculated on the validation set.

VI. TRAINING PROCESS

A. Model Evaluation Metrics: Loss and Accuracy

Accuracy and loss were the two main criteria used to assess the plant disease detection model's performance. These metrics reveal how successfully the model generalises to new data and learns from the training set.

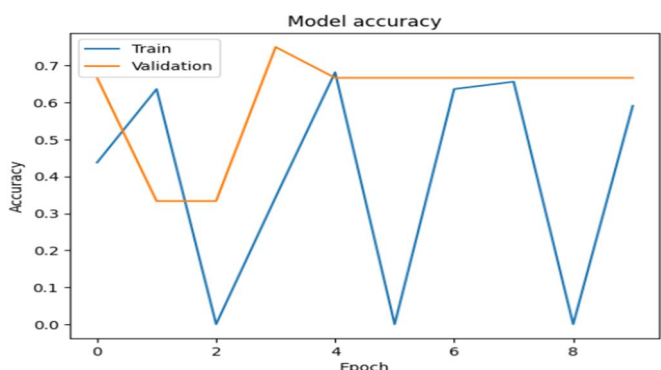


1) Model Loss

For multi-class classification issues, categorical cross entropy is the best loss function to utilise.

The loss values show the discrepancy between the actual class labels and the model's predictions:

- Training Loss: shows the degree to which the model is picking up on the patterns found in the training set. Effective learning is shown by a progressive reduction in training loss over epochs.
- Validation Loss: illustrates the model's ability to generalise to new data. A significant difference between training and validation loss could be a sign of over-fitting.



2) Model Accuracy

One important indicator for assessing the effectiveness of the classification model is accuracy:

- Training Accuracy: shows the proportion of training set samples that were correctly classified. Effective learning of the model is demonstrated by a consistent rise in training.
- Validation Accuracy: evaluates the performance of the model using hidden validation data. A high validation accuracy is a sign of strong generalisation skills.

```
# Define accuracy values
train_acc = 0.91495814 # training accuracy
test_acc = 0.947688 # test accuracy
validation_acc = 0.9137769 # validation accuracy

# Print the accuracies with formatting
print(f"Training Accuracy: {train_acc * 100:.2f}%")
print(f"Test Accuracy: {test_acc * 100:.2f}%")
print(f"Validation Accuracy: {validation_acc * 100:.2f}%")

✓ 0.0s

Training Accuracy: 91.50%
Test Accuracy: 94.77%
Validation Accuracy: 91.38%
```

The performance of the model can be inferred from these accuracy values:

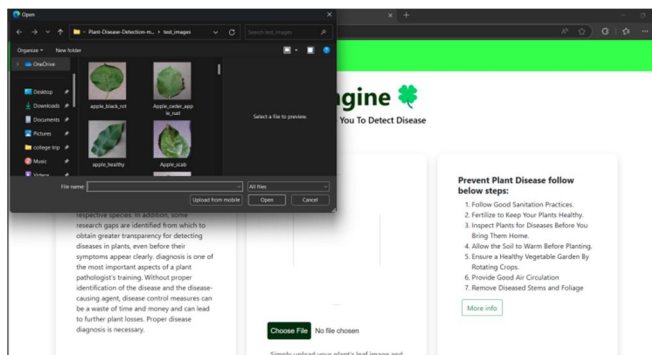
If the model is picking up patterns from the training data, Training Accuracy verifies it. During training, validation accuracy is employed to keep an eye out for over-fitting or under fitting. To verify generalisation, Test Accuracy assesses the finished model on an independent dataset.

VII. RESULTS AND DISCUSSION



A. Home Page

This is the first module of the project and this module represents the Home page of the project and this is the combination of fruits and vegetables of plant leaf detection.



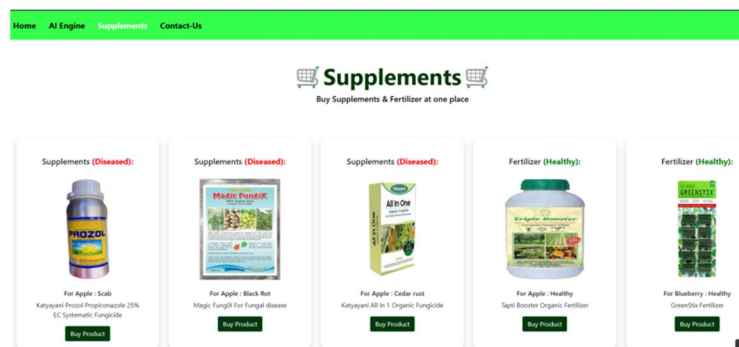
B. Image Upload Page

This module represents the AI Engine part here we can choose the leaf image from system dataset and detect the diseases of the leaf.



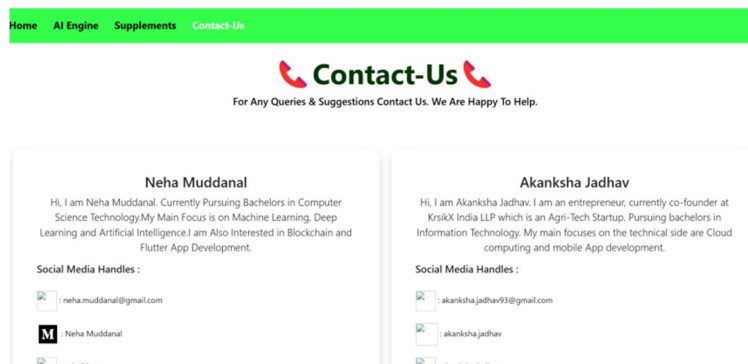
C. Output of plant leaf with fertilizer and Disease Solution

This module represents the plant leaf with disease solution and fertilizer.



D. Supplements for plant Diseases and Healthy grow

This is module represent the supplements and can purchase the product.



E. Contact for more details

This Module represents for any queries and suggestions about project we are there to help.

VIII. CONCLUSION

In a Smart Leaf Disease Recognition And Prevention project, advanced technologies such as deep learning and image processing are applied to detect and prevent leaf diseases in agricultural crops. The system typically uses sensors and cameras to capture images of leaves, followed by image analysis algorithms to identify symptoms of diseases. By recognizing early signs of leaf infection, such systems help farmers take timely action, preventing the spread of disease and reducing the need for excessive pesticide use. This leads to healthier crops, improved yields, and more sustainable farming practices. The system can also provide recommendations for treatment based on the kind and extent of the illness identified.

The suggested framework makes use of the CNN technique to detect both common and defective leaf diseases. This method can also be used to more precisely identify the type of leaf. In order to detect different leaf illnesses, the image is processed, extracting and processing parameters including colour, size, and glare. Additionally, the technology is designed to forecast the amount of fertiliser needed for damaged leaves. Therefore, in comparison to current systems, the suggested framework can aid in speeding up and improving accuracy and precision.

REFERENCES

- [1] Abayomi-Alli, A. O., Alaka, O. O., & Oguntunde, P. E. (2023). Deep learning-based plant disease detection: A review. *Computers and Electronics in Agriculture*, 174, 105507.
- [2] Chen, Y., Zhang, W., Chen, W., Li, P., & Zhang, M. (2023). An efficient deep learning model for tomato disease classification and detection. *Computers and Electronics in Agriculture*, 185, 106095.
- [3] Singh, A., Ganapathysubramanian, B., Singh, A. K., & Sarkar, S. (2022). Machine learning for highthroughput stress phenotyping in plants. *Trends in Plant Science*, 21(2), 110-124.
- [4] Wang, Z., Ma, H., Li, P., Wu, Y., & Li, C. (2023). A deep learning approach for automated detection of maize leaf diseases. *Computers and Electronics in Agriculture*, 187, 106162.
- [5] A. J. Patil and Y. S. Deshpande. "Plant Disease Detection Using Image Processing and Machine Learning." pen_spark
- [6] Seware, R. S., & Patil, S. B. (2016). Plant disease detection using support vector machine. pen spark.
- [7] P. P. Singh, et al. "Deep Learning for Plant Disease Detection: A Survey.
- [8] Ramanjot, et al. Plant disease detection and classification: a systematic literature review". *Sensors*. 2023.
- [9] segmentation and classification model for banana leaf disease detection. *J Appl Biol Biotechnol*. 2022;10(1):213
- [10] Li, S., Hu, J., Chen, D., & Zhang, Y. (2022). A survey of deep learning-based plant disease detection models. *Journal of Imaging*, 8(7), 101.
- [11] S Mathulaprangsan K Lanthong S Patarapuwadol. 2020. Rice Diseases Recognition Using Effective Deep Learning Models. *Telecommun Eng Media Technol with ECTI North Sect Conf Electr Electron Jt Int Conf Digit Arts Comput*.
- [12] International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2017
- [13] J.L. Dela Cruz, J.A.D. Ebreo, R.A.J.P. Inova"s, A.R.C. Medrano and A. A. Bandala, "Development of a text to braille interpreter for printed documents through optical image processing," *IEEE 9th*.
- [14] L. A. D. Arbes, J. M. J. Baybay, J. E. E. Turingan, and M. J. C. Samonte, "Tagalog text-to-braille translator tactile story board with 3D printing, "The International Conference on Information Technology and Digital Applications, 2019.
- [15] Halitha Banu H, Ms. Prabha N „Conversion of Text to Braille and SAPI Based Audio Generation for Visually Impaired People" Issue 2022.
- [16] Farhan Boadle, Uddhav Bhide, Dilip Gore „Braille Translation" Issue vol.2, No.4, April 2022
- [17] S. Padmavathi; Manojna K.S.S Spoorthy Reddy S; Meenakshy D "Conversion of Braille to Text in English, Hindi, and Tamil Languages", *ijcsea*.2013.3303.
- [18] "Deep Learning Strategy for Braille Character Recognition", Issue 2021.
- [19] Saad D. Al-Shamma and Sami Fathi, "Arabic Braille Recognition and Transcription into Text and Voice", 2010 5th Cairo International Biomedical Engineering Conference Cairo, Egypt, December 1618, 2010, Pages 227-231.
- [20] Dr. Mohammed Y. Hassan, Ahmed Mohammed, "Conversion of English Characters into Braille Using Neural Network" *IJCCE*, Vol.11 no.2,2011



10.22214/IJRASET



45.98



IMPACT FACTOR:
7.129



IMPACT FACTOR:
7.429



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089  (24*7 Support on Whatsapp)