Fruit Plants Disease Severity Detection and Pesticide Recommendation Using Deep Learning

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Abstract
Agriculture is considered to be essential for keeping economic stability in the world. The condition of the fruit plants affects the phenomenon of cultivation directly, regard for the quantity and quality of fruits. The infringement of plants should be observed early and correctly judged to prevent the fruit farmers from economical damage, and to possess a sustainable cultivation. In this work, a deep learning based model for disease detection of fruit plants and the evaluation, estimation of severity level with the proposing of pesticide solution is developed. CNN categorized a classifier by MobileNetV2 base architecture to discriminate over 23 classes, including healthy and unhealthy fruit leaves like apple, banana, grape, mango, orange and strawberry, and we find a multi class type of the classification based on the two search modes. The severity levels of the infections are calculated according to the Confidence scores, based on the scores suitable pesticide is recommended. The top visual CNN feature map, Grad-CAM inspired, is employed on CNN model explained what location command the prediction of CNN. Based on severity and scourge class, the possible medicine use is also advised to aid farmers. The MobileNetV2 choice is as a lightweight model, merely takes a few and consumes low time. Our system achieved a state-of-art accuracy of 98.29% with a precision, recall and F1-score of 0.98.

Keywords: Fruit Leaf Disease Detection, Deep Learning, CNN, MobileNetV2, Image-Based Classification, Severity Estimation, Pesticide Suggestion, Precision Farming, Computer Vision, Smart Farming

INTRODUCTION

Agriculture is one of the most important field which drives to the development of nation and the world food system. The health of crops is directly related to the yield and the standard of quality of the products. Plant diseases play a major role in this area and are the result of large reductions of yield and price on the market. It would be helpful, in order to achieve a better and more efficient result.

With the development of artificial intelligence in recent years, deep learning has been widely employed in automatic plant leaf diseases detection and recognition [13], [14]. The application of CNNs, a typical deep learning model which does very well in image data analyzing, can be identified without a doubt in the field of plant leaf diseases detection.

A lot of deep learning based methods have been developed in fruit leaf disease classification. More "powerful" deep learning classifiers with high accuracy of classification including those based on hierarchy learning and feature selection methods can achieve higher classification accuracy among many kinds of fruits[1]. Meanwhile, the "light" deep learning methods with less parameters, such as MobileNet, have also been interested in as they could achieved accuracy with less computational expense[2], [5]. Transfer learning style methods (using pre-train networks such as VGG16, ResNet, Inception) also achieve great results on multi-category classification[3], [9].

Further benefits were also successfully provided by attention mechanism and hybrid models. Attention mechanisms, such as, help to enhance feature representations by locally and globally weighing important parts while hybrid models can balance using both deep learning and classic machine learning approaches for simultaneous classification [5], [12]. Recently, new approaches have been developed based on Vision Transformers offer more effective feature extraction, but can incur significant additional computational overhead [15]. Other than the common fruit crops, some of the specific fruit crops are also investigated, such as apple, grape, banana and mango. Especially deep learning based approaches have demonstrated high accuracy in disease recognition of these fruit crops; however, the robustness of these models declines under the illumination variation, mixed background and noise of the images. For the detection of the diseases of banana, grape and mango, the dedicated models perform well in the classification task, but there's still some gap of the generalization ability when used for the practical application [8], [10], [11], [12].

However, still some short comings are there. For example, various existing techniques are dependent on hand tuned data set and only limited number of techniques are useful in a real field environment. Further, higher the accuracy, the more computation heavy the models are and they cannot be used in low powered devices [6], [15].
To get rid of the problems of performance and availability of these methods, a deep learning based fruit leaf disease detection framework (focus on performance and efficiency) is proposed in this paper which can achieves an accurate classification at the same time cost less computational resources for application in real-time.
The rest of the paper will beorganized as follows: 2 will be spent on the survey of literature., In Section III, the method introduced the method that we used, in section IV, we proposed the system in the paper, we show our system and function, then we give the result and conclusion in section V.

LITERATURE SURVEY

Table 1: Summary of Existing Methods

Ref. No.	Authors (Year)	Dataset Used	Proposed Method	Key Findings / Results
[1]	Rehman et al. (2023)	Fruit leaf datasets (Apple, Grape, Peach, Cherry)	Hierarchical Deep Learning with Darknet53 + Butterfly Optimization	Achieved **99.6%** accuracy; improved feature selection and classification performance
[2]	Pantha (2024)	3,642 apple leaf images (Kaggle)	CNN (MobileNet)	Achieved **~95%** accuracy; efficient lightweight model
[3]	Saurav N. Shende et al. (2025)	Plant dataset (16 classes)	Transfer Learning (VGG16, ResNet50V2, InceptionV3, Xception)	Achieved **>99%** accuracy; Xception performed best
[4]	Zheng et al. (2019)	Apple & peach leaf dataset	CNN + Sobel Image Enhancement	Achieved **92.1%** accuracy; image enhancement improved classification
[5]	Subburaj et al. (2025)	Multi-crop dataset	Plantention (MobileNetV2 + Dual Attention)	Achieved **98.34%** accuracy; lightweight model (~7.3M parameters)
[6]	Pathan & Pandey (2025)	Small dataset (291 images)	Multiple CNNs (AlexNet, VGG, DenseNet, MobileNet, ShuffleNet)	Overall accuracy **~99%**; ShuffleNet achieved **99.96%**
[7]	Juyal et al. (2025)	Fruit and plant datasets	CNN Model	Strong classification performance for healthy and diseased leaves
[8]	Biibosunov et al. (2022)	Banana leaf dataset	KNN, SVM, AlexNet	AlexNet achieved **96.73%** accuracy; deep learning outperformed traditional ML
[9]	Sangeetha et al. (2024)	PlantVillage + orchard dataset	Transfer Learning (ResNet50, VGG16, InceptionV3)	InceptionV3 achieved the best performance (**~93%** accuracy)
[10]	Ravi et al. (2024)	Grape leaf dataset	Deep CNN	Accurate classification of multiple grape leaf diseases
[11]	Vidhya & Priya (2025)	Banana leaf dataset	KNN, SVM + AlexNet	AlexNet achieved **~96.73%** accuracy and outperformed ML models
[12]	Jain & Jaidka	Mango leaf dataset	Hybrid SVM + Deep	Achieved **97.7%** accuracy with hybrid feature

	(2023)		Features	extraction
[13]	Sladojevic et al. (2016)	Custom dataset (13 classes)	CNN (Caffe)	Achieved **96.3%** accuracy for plant disease recognition
[14]	Chouhan et al. (2019)	Real-time plant dataset	Multilayer CNN	Outperformed traditional machine learning methods in disease detection
[15]	Borhani et al. (2022)	Multiple plant disease datasets	CNN, Vision Transformer (ViT), Hybrid CNN + ViT	Hybrid CNN+ViT achieved a good balance between accuracy and computational efficiency

METHODOLOGY

In this work, we propose a complete framework for fruit leaf disease detection by integrating deep learning techniques with image processing and rule-based decision support module. The framework architecture has a systematic flow from data preparation and Image cleaning to feature extraction using CNN model, to disease classification and severity assessment, then to pesticide recommendation.

1. Dataset Overview

The data has been tabulated from online public agriculture database of leaf images of fruits. It contains number of different categories of fruits. Categories used are Apple, Banana, Mango, Grape, Orange, Cherry and Strawberry. Number of disease classes for the categories used above varies. Hence the problem becomes a Multi-class classification problem based on fruit name and disease class.

Some sample classes include:

- Apple – Scab, Black Rot, Rust
- Banana – Sigatoka, Cordana
- Mango – Anthracnose, Powdery Mildew
- Grape – Leaf Blight, Black Rot
- Orange – Canker, Greening

The overall data set contains a total of 23 classes out of which the total number of images of leaves are 30579. All data has been further divided into three categories, i.e., training set 21517 images, validation set 6543 and for testing the performance of the system 2519 images.

2. Dataset Organization & Splitting

The data will be stored in nested folder structure, in which we have separated folder for training, validation and testing folder.

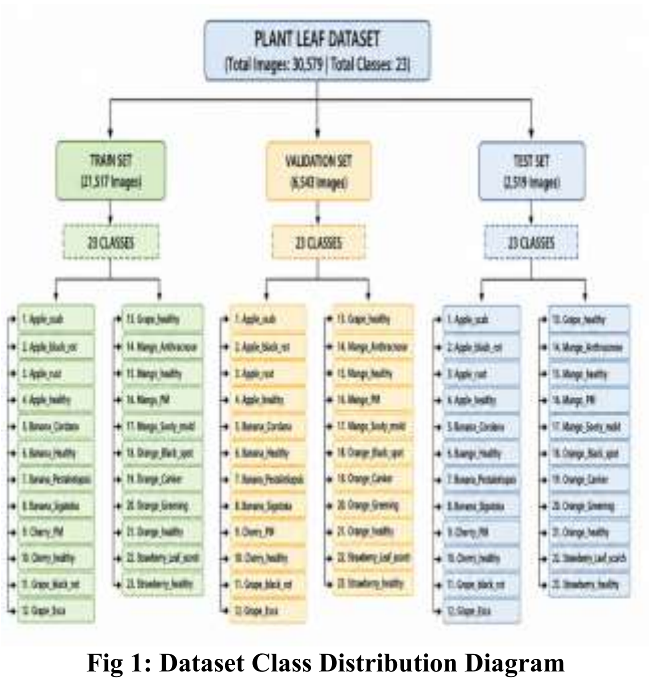

Fig 1: Dataset Class Distribution Diagram

The dataset is split into three parts to enable experimentation; 70% for model training; 20% for evaluation of its learning and 10% for testing, which is used after training. This appropriately partitioned dataset would facilitate model training, hyperparameter tuning and unbiased performance evaluation.

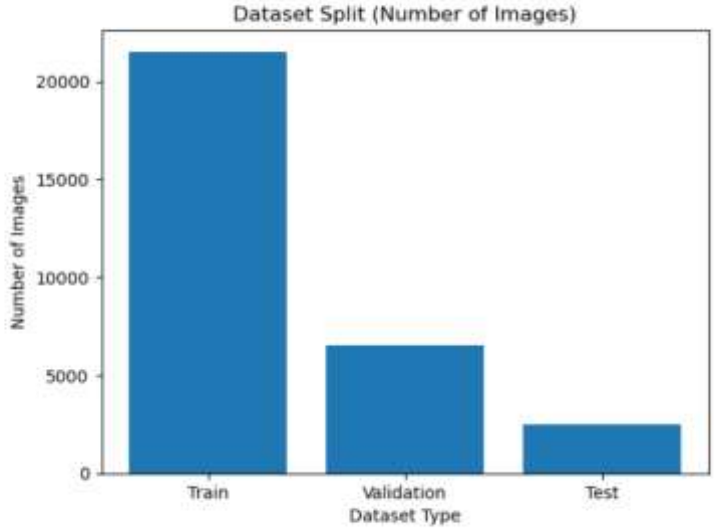

Fig 2: Dataset Split (Training, Validation, and Test Sets)

3. Image Preprocessing and Augmentation

Prior to the deep learning model being feeding, images for training the model are base processed repeated times so the images are set a standard. The base processing is.. Scaling each pixel to 224 x 224x 3, normalizing each pixel to a ranges between 0 and 1 and conversion image to tensor.

Various other data augmentation methods are also used during training to further help improve the generalization of the model to reduce over-fitting as.

- Rotation (±20°)

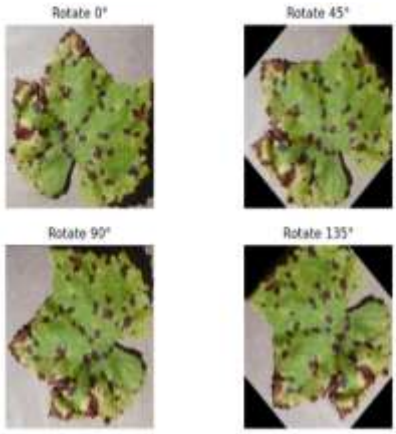

Fig 3: Image Rotation Augmentation (0°, 45°, 90°, 135°)

- **Horizontal and vertical flipping**

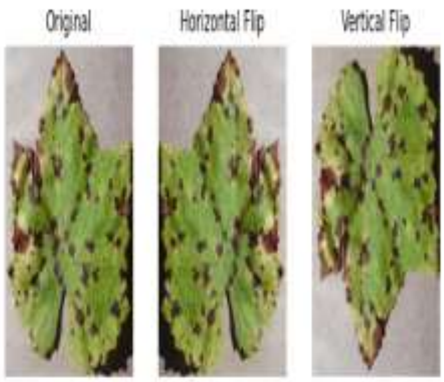

Fig 4: Image Flip Augmentation (Original, Horizontal Flip, Vertical Flip)

- Zoom (0.2 range)

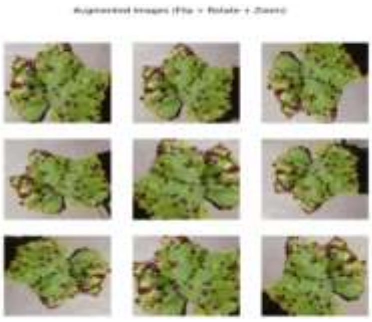

Fig 5: Combined Image Augmentation Samples

4. Model Architecture and Training

The proposed approach adopts a MobileNetV2-based convolutional network to handle feature learning and classification. Its compact structure and efficiency in computation make it an effective choice for image-based tasks, especially in scenarios that require fast processing with minimal hardware resources.

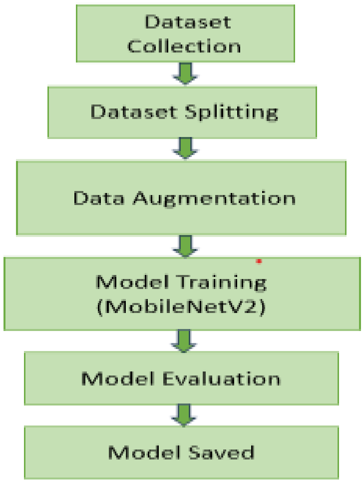

Fig 6: Training Pipeline

For training, the Adam optimizer is utilized along with a categorical cross-entropy loss function. The model processes data in batches of 72 samples and is trained for 10 complete iterations over the dataset. Through this process, the system extracts relevant features from images and categorizes them into appropriate disease labels.

5. Evaluation Metrics

To evaluate how effectively the proposed approach performs, several standard performance measures are considered:

Accuracy: Indicates the proportion of total predictions that are correctly identified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: It represents the reliability of positive predictions by indicating how many predicted positive cases are actually correct.

$$Precision = \frac{TP}{TP + FP}$$

Recall: This measure shows the model's capability to capture all actual positive instances within the dataset.

$$Recall = \frac{TP}{TP + FN}$$

F1-score: Provides It combines precision and recall into a single value, providing a balanced evaluation of the model's performance.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Corresponding mathematical expressions are used to compute each metric. Together, these measures give a complete assessment of classification performance.

PROPOSED SYSTEM

1.System Architecture

A new system has been developed for automated detection of fruit leaf disease based on a set of powerful deep learning algorithms, image analysis as well as a rule based advisory module. The system has a combination of Intelligence and Integration as it is a prediction system in addition to an advisory system.

Preprocessing stage, In this step the raw leaf image is prepared for input into the network. Several augmentation techniques are used to prepare the images after the image is resized to a uniform size, and following pixel normalization. The different techniques used in model.

After the preprocessing, the image will be passed onto the model which will make the prediction. The model used is a CNN (Convolutional Neural Network) which has being trained with a MobileNet V2 architecture. The CNN looks at the image and captures the relevant visual features of the leaf, then in predict the type of disease it has. In order to understand the CNN decision, the technique Grad-CAM is used, this approach will produce heat map visualizations of the areas the CNN took into account to make the prediction.

The severity of the diagnosed disease is graded based on the prediction confidence score of the model. The higher the confidence score, the more are the features of the diagnosed disease clustered into a given image and hence the severity is rated higher. Severity diagnosis is classified into mild, moderate and severe based on the classification. The severity estimation is visualized via the grad-cam classification.

In the final phase, an output of suggestions in terminologies of knowledge-base recommendation module, such as suggestions for pesticide usage amount, ratio and novel pesticide selection. Moreover, prediction information such as disease identification, severity and visual explanation are also presented in a userfriendly web interface for the farmers.

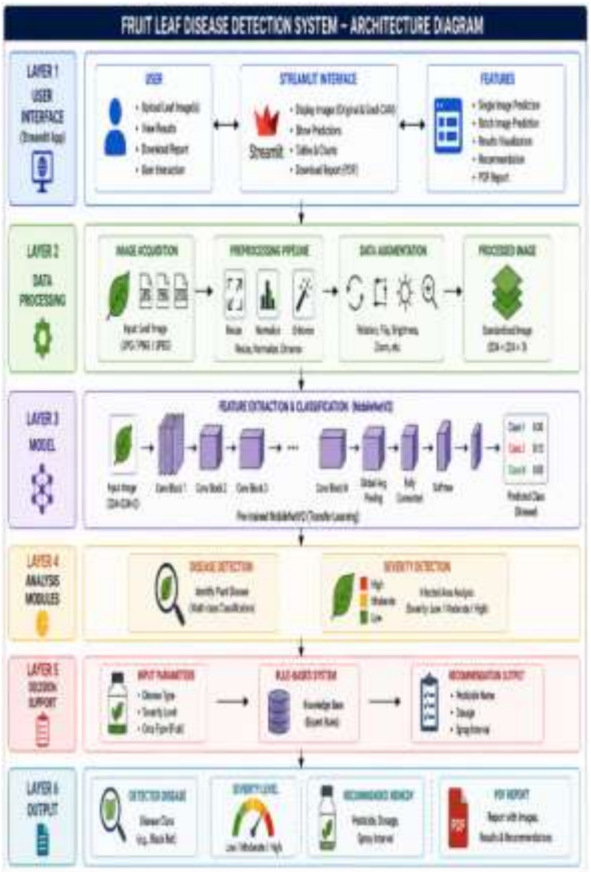

Fig 7: System Architecture

2. System Workflow

The working process of the proposed solution follows a structured sequence that transforms an input leaf image into meaningful outputs. The flow begins with image acquisition, followed by preparation of the data, analysis using a neural network, and finally generation of insights and recommendations.

Input Image → Preprocessing → CNN Model → Disease Prediction → Severity Estimation → Pesticide Recommendation → Result Display

This pipeline ensures a smooth and automated flow from raw input to actionable output.

3. Disease Prediction

The deep learning network analyzes the given leaf image by capturing important visual patterns such as texture, color variations, and irregularities. Based on these learned features, the system determines the type of disease affecting the plant.
Along with the predicted category, the model also produces a probability value that reflects how confident it is in the decision. This value helps in understanding the certainty level of the prediction.

4. Severity Estimation
Classification level is directly related to the infection by the confidence level in the classification. The more infected a disease is the higher confidence values in the classification. Because the confidence scores, the greater the disease features are obvious and identifiable to (corresponding to in severity levels). This advantage is computationally far more efficient compared to pixel-wise annotation that require very expensive labeling effort.
Severity Levels:

- Mild: Confidence < 60%
- Moderate: Confidence between 60% and 80%
- Severe: Confidence > 80%

This approach avoids the need for complex image segmentation, making it efficient and practical for field-level applications. To further support this analysis, visualization techniques are used to indicate the most affected portions of the leaf.

5. Pesticide Recommendation
The system incorporates a knowledge-based recommendation module using an external dataset (Excel/CSV format). This dataset maps:
Disease + Severity → Pesticide + Dosage + Spray Interval
Based on the identified condition and its severity, the system provides suitable recommendations, including pesticide type, quantity, and application schedule. This assists farmers in taking timely and effective action.

6. Model Interpretability (Grad-CAM)
However, to improve the explainability of this system, a visualization method called Grad-CAM is used. This method generates a heatmap on the input image indicating which region has contributed the most.
When this is checked it will give the user a visual indication of what the system predicted; this will build the users faith in the system and their understanding of how it works.

7. Result Visualization
The above results are displayed through a simple web-interface. The web-interface was developed having in mind farmers and agricultural specialists and all the above results are displayed in a clear way.
The final output includes:

- Predicted Disease: The identified disease class of the input fruit leaf image using the trained deep learning model.
- Confidence Score: The probability score indicating the model's certainty in its prediction.
- Severity Level: The stage of disease progression (mild, moderate, or severe), determined using a confidence-based estimation approach, where higher confidence corresponds to more prominent disease patterns.
- Recommended Pesticide: Recommended pesticide along with usage details
- Grad-CAM Heatmap Visualization: Heatmap showing affected regions on the leaf

System is integrated into an intuitive, user-friendly web UI implemented with Streamlit, an open-source app framework. Users are able to feed images into the deep learning model and get prediction results, as well as download the report for next step.
Real-time output is also a feature of the system, the output is original image, the Grad-CAM heatmap, prediction of diseased classes and the confidence score, severity level and recommended pesticide use . In addition, the system has the generate report function, which can generate the report in PDF format, all output is summarized and analyzed for field uses.
The engine is a user friendly so has several access points, making it more accessible to users that are not experts such as farmers or agronomists.
Key Advantages

- End-to-end automated pipeline
- Multi-class disease classification
- Severity-aware analysis
- Real-time predictions using Streamlit
- Integration of Explainable AI (Grad CAM)

RESULTS & DISCUSSION

A. Performance Metrics
Our Fruit plant disease detection model that we have trained, gives very high prediction accuracy (about 98.29% when tested). This very high value achieved from our Fruit plant disease detection model shows that the model is good enough in practical way to differentiate different plant leaf disease types.

The general improvement could be a result of either one of the following: increased learning of important visual features by the CNN, or better generalization brought about by augmentation techniques used in training. In conclusion, the results find that the system is performing relatively well and could be trusted to be practical to use in an agricultural setting.

Metric	Value
Accuracy	**98.29%**
Precision	**98.00%**
Recall	**98.00%**
F1-Score	**98.00%**

Table 2: Model Performance Metrics

B. Training Performance Analysis

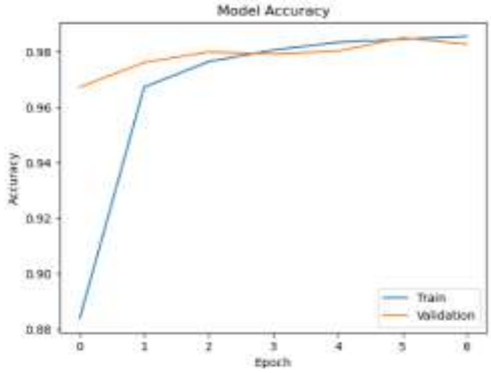

Fig 8: Graph illustrating accuracy trends during training and validation phases

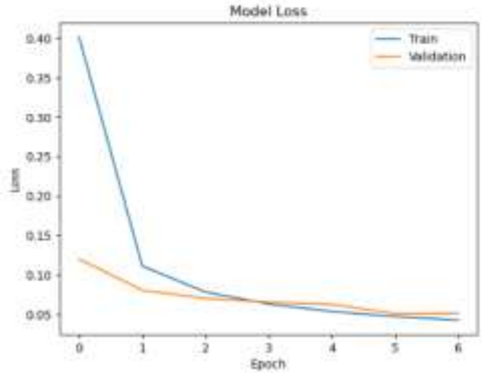

Fig 9: Graph showing loss variations across training and validation

These graphs provide insight into how well the model learns over time and help evaluate its performance and stability.

- Training Accuracy: Increased from ~88.38% to ~98.54% across epochs
- Validation Accuracy: Improved from ~96.71% to ~98.49%
- Training Loss: Decreased from ~0.40 to ~0.04
- Validation Loss: Reduced from ~0.12 to ~0.05

Interpretation

- consistent increase in training, validation accuracy indicates stable and effective learning.
- simultaneous decrease in training and validation loss suggests good convergence of the model.
- Unlike earlier observations, the model shows minimal overfitting, as validation performance closely follows training performance.

Conclusion

The model demonstrates strong generalization capability with minimal overfitting, indicating that it performs well on both training and unseen data.

C. Class-wise Performance Analysis

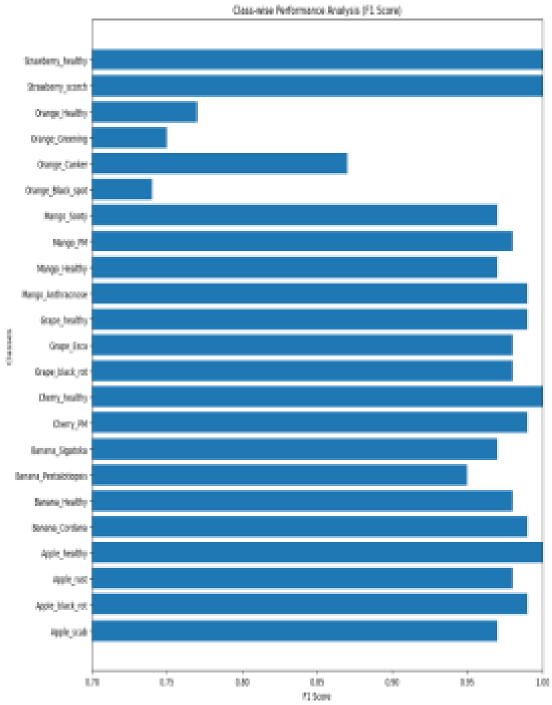

Fig 10: Class-wise Performance Analysis (F1 Score)

The bar graph representing class-wise F1-scores shows that:

- Most classes achieve very high performance (close to 0.98–1.00)
- A few classes (particularly some orange disease categories) show relatively lower scores

Interpretation

- High F1-scores across most classes indicate excellent balance among precision and recall.

D. Confusion Matrix Analysis

The confusion matrix offers a clear breakdown of how the model performs across different disease categories by comparing actual labels with predicted outcomes. Instead of just giving overall accuracy, it helps in understanding where the model performs well and where errors may occur.

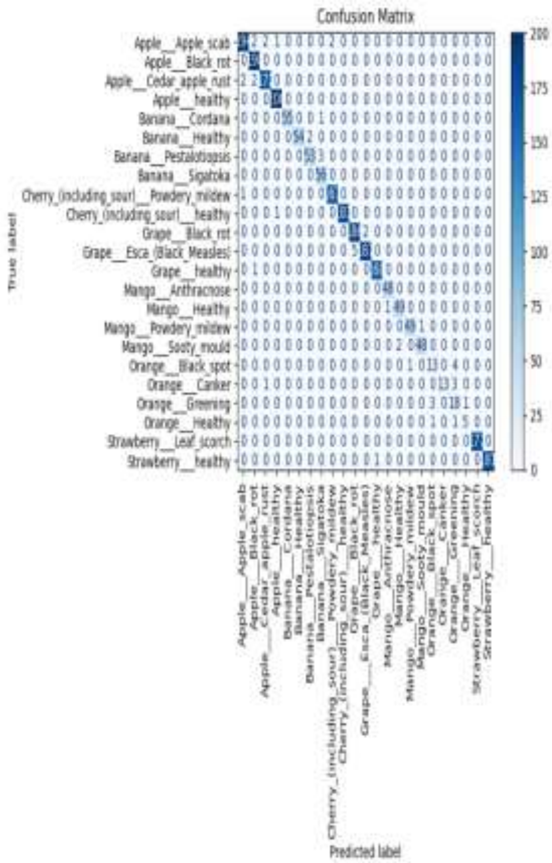

Fig 11: Confusion Matrix of Model Predictions

Observations

- A large number of correct predictions can be seen where the actual and predicted values match, showing that the model performs reliably across most classes.
- Most plant disease classes, such as apple, banana, cherry, grape, mango, and strawberry, exhibit very high classification accuracy with minimal misclassification.

E. System Interface and Practical Results

The application written in Streamlit is the field test of the system implemented. It shows the working of a solution at a real life situation where end user can put the image of leaf and get the prediction with other details.

1. Single Image Prediction Results :

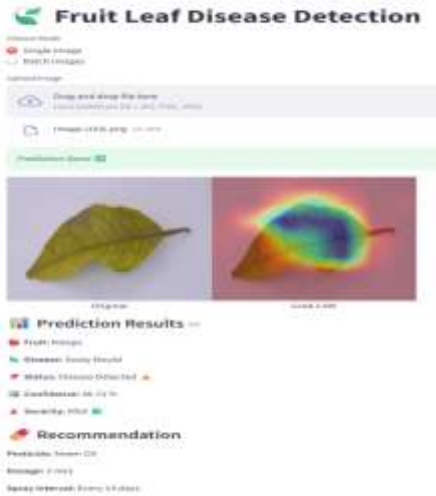

Fig 12: Web Interface – Low Severity Case

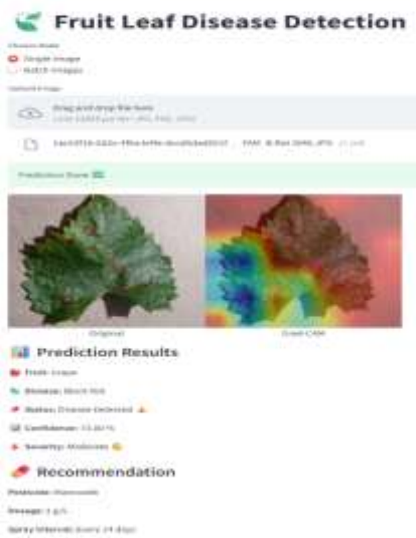

Fig 13: Moderate Severity Case

Fig 14: High Severity Case

2. Batch Image Prediction Result

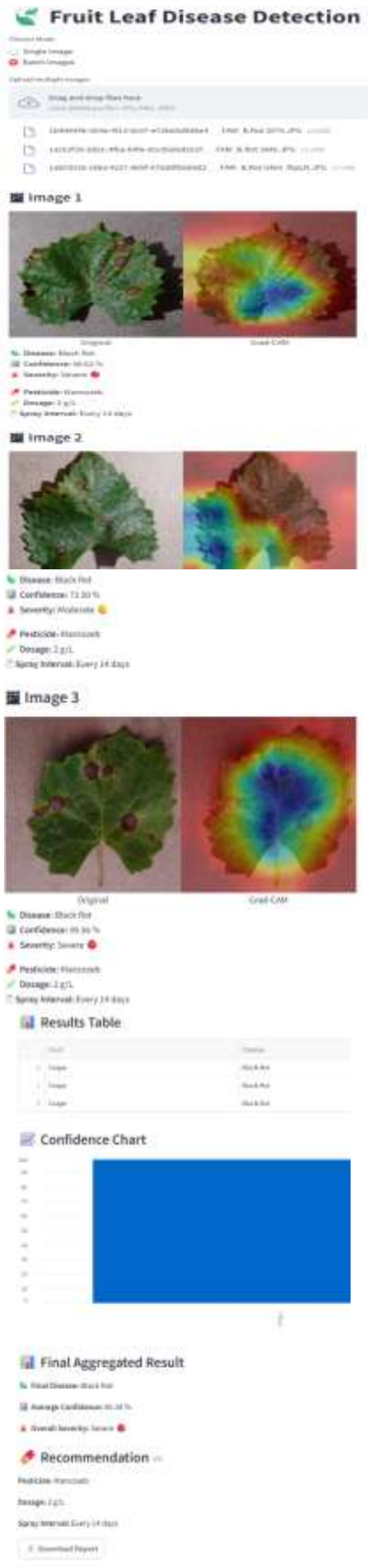

Fig 15: Batch Processing Output

Observed Outputs from System Interface :
The system interface demonstrates effective functionality in detecting and analyzing plant leaf diseases. From the experimental screenshots, the following key observations are made:

- The interface supports user-friendly image upload, enabling both single and multiple image inputs.

- Upon processing, the system generates comprehensive outputs including:
- Disease Classification, accurately identifying the plant disease category.
- Severity Estimation, indicating the level of infection spread.
- Prediction Confidence, reflecting the certainty of the model's output.
- Treatment Recommendation, providing actionable pesticide solutions with dosage and application intervals.
- Explainable AI Output (Grad-CAM), visually highlighting critical regions influencing the model's prediction.

This with high accuracy in prediction and visual explainability will be highly usable for this in practical fields of agriculture. Our system for detection of diseases in fruit plants.

Second, severity analysis could aslo perform well in prediction accuracy and usability in the wild. The system is trained with images in leaves form, which able to discriminate different kinds of diseases, and detect special characteristics in the leaves images to identify the healthy and infected plant with high accuracy.

Based on the evaluation results, it can be seen that the model performs quite well on all different evaluation parameters such as precision, recall, andF1-score. Low errors are found on the predictions and the results can be extended to new, unseen data sets which is an essential requirement for real environments based on agriculture where there are often the noises in images caused by some factors like lighting conditions, background etc and location of leaves.

An additional feature of the proposed system that could be of interest is that we attempt to quantify the severity of a disease rather than simply it exists. Rather than using complex segmentation method, severity is estimated indirectly by the extent of confidence of the model when making a prediction. Typically, higher confidence would suggest presence of more prominent disease characteristics and severity. This is a simple yet robust idea.

A further unique advantage of the use of Grad-CAM is that it shows us the part of the leaf which the model was focusing on to make its prediction. The images give the user a better understanding of the model and make them more confident in the results.

The second feature that may be potentially useful in our project is recommendation pesticide. After identification of disease and the intensity of occurrence, it suggested the techniques and doses of applying the pesticide.

However, the accuracy of the model depends on the training data, (e. g. uneven distribution of diseases). However, if some diseases are not well known there will be less accurate class predictions. In addition, bad pictures or bad environment condition could affect the class prediction. In conclusion, this system appears to meets the requirement for accuracy, speedy and user-friendly one. It offers effectively combined diagnosis, grade and treatment advices, which could be quite helpful to be adjunct of contemporary procedures.

F. Comparative Analysis with Existing Methods

Comparison of the suggested model with the existing state-of-art models for plant disease classification indicates that the system achieves the accuracy of 98.29% which is comparable to or better than many traditional CNN models and has achieved the same accuracy as many attention-mechanism based models. To enhance the usability of the system, the proposed system also includes the Grad-CAM visualization and recommendation module.

Table 3: Comparison with Existing Methods

Dataset / Classes	Model Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
3642 Apple Leaf Images (Kaggle Dataset)	CNN (MobileNet)	**95.00**	**94.00**	**96.00**	**96.00**
Multi-crop Datasets (Rice, Wheat, Tea, Banana, Sugarcane)	Plantention (MobileNetV2 + Dual Split Attention)	**98.34**	**98.74**	**99.19**	**99.02**
Custom Plant Leaf Dataset (13 Disease Classes)	Deep Convolutional Neural Network (CNN) using Caffe	**96.30**	**91–98**	**–**	**–**
Custom Fruit Leaf Dataset (23 Classes, 30,579 Images – Train: 21,517, Validation: 6,543, Test: 2,519)	MobileNetV2 + Grad-CAM + Recommendation System	**98.29**	**98.00**	**98.00**	**98.00**

CONCLUSION

In this paper, we proposed the system to detect the disease of fruit leaf. The system work show the promising result presenting the different species of disease with high accuracy with low computational complexity which appropriate for the light-weight model. Moreover, the system not only perform the detection task but also give the system to support the newly, special treatment methods which make the system more alive with its real farm fields. To make the system more proper for many users, the web interface also is added with the streamlit system which any user can upload the image with their own and predicts the disease very efficiently. The experimental results from the practical implementation show the system able to work efficiently in the real environment. Further, the system can be upgraded by increasing the size of the dataset, adding more varieties of the crop or even automating the system by using the connected camera and device. Finally, this project can be sum up that the combination of the accuracy of the system along with the usability in real farm field environment.

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