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Research Article

Design of Automated Model for Citrus Fruits and Leaves Disease Detection

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ABSTRACT

Diseases of citrus fruits and leaves are a serious challenge to farm production and economic viability. The need for effective, automated disease detection methods is on the rise due to the drawbacks of the conventional manual detection method. In this paper, a lightweight deep learning-based classifier using MobileNetV2 for real-time diagnosis of citrus diseases is proposed. The dataset, which was retrieved from Kaggle, consists of high-resolution images of citrus leaves and fruits and are classified into four categories: greening (HLB), black spot, citrus canker, and healthy. Rotations, scaling, shearing, zooming, and flipping were used to enhance model generalization by giving data augmentation methods. Categorical cross-entropy loss, early stopping, Adam optimizer, and learning rate reduction on plateau were all adopted during training so that convergence is strictly acquired. A web application has been developed in which an image is uploaded for the diagnosis of disease. The names of disease, symptoms, causes, preventive measures, and some external references can be viewed from the application. Comparative evaluation of InceptionV3 and an in-house built CNN model validated that MobileNetV2 gives better accuracy as well as processing efficiency, suggesting its applicability in smart farm applications. A number of recent research works have investigated deep learning methods for citrus disease detection, emphasizing the need for lightweight models for real-time agricultural use. Hybrid attention networks and hyper spectral imaging methods have also been found to yield good results in enhancing disease identification accuracy. The suggested method reduces human intervention while maintaining timely disease detection and intervention, thus enhancing yield and sustainable agriculture.

Keywords: Citrus disease detection, MobileNetV2, deep learning, image classification, convolutional neural networks (CNN), smart farming, data augmentation, automated detection.

INTRODUCTION

Citrus fruits are among the most cultivated and economically valuable crops globally. However, they are extremely vulnerable to a range of diseases like black spot, citrus greening (HLB), and citrus canker, which have serious implications for crop yield and economic stability. Unless identified and controlled early on, these diseases will spread at a very fast rate, and extensive loss of yield will be incurred. In the past, disease detection has depended on visual checks by agricultural experts, which is time-consuming, subject to human error, and unsuitable for industrial-scale farm production.The latest developments in computer vision and deep learning have led to the design of disease diagnosis systems that are autonomous and deliver accurate, real-time diagnoses with minimal human intervention. Convolutional Neural Networks (CNNs) have proven to be best-in-class in plant disease diagnosis based on leaf and fruit images. Certain studies have effectively applied deep learning techniques in citrus disease detection, including those based on hyperspectral imaging, multimodal fusion methods, and deep learning-based mobile apps for smart farming. Hybrid meta-heuristic methods and YOLO-based detection systems have also been researched to improve the efficiency of disease classification. Computational complexity, though, poses a challenge to implementing such models in real-world settings.This work proposes a light, effective deep learning-based citrus disease detection model using MobileNetV2. The model is trained for high-precision classification of

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healthy and diseased citrus plants with image preprocessing, data augmentation, and sophisticated training methods to enhance robustness. A web-based interface also enables real-time disease detection and offers insights into symptoms, causes, and preventive measures. By detecting diseases at the early stages, this system will help farmers and agricultural experts improve the health of crops, increase yield, and lower the economic losses, and hence promote sustainable citrus cultivation.

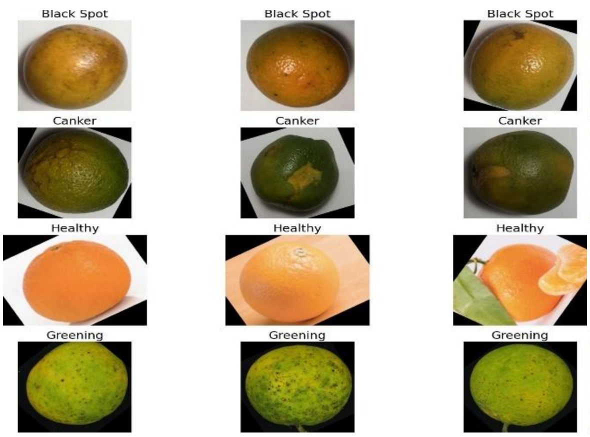
LITERATURE REVIEW

Citrus disease detection has been researched widely using deep learning and image processing techniques to improve classification accuracy and efficiency. Sun et al.[1] proposed an automated citrus pose estimation model for harvesting, while Yadav et al. [2] and Khattak et al. [3] developed CNN-based architecture for citrus disease classification. Islam et al. [4], Dhiman et al. [5,6,10], and Qiu et al. [7] achieved new heights of detection limits by employing deep learning and multimodal fusion techniques. Effective disease detection-related studies are those conducted by Vaidya et al. [8], Shireesha et al. [9], Zhang et al. [12], and Mudholakar et al. [13], who have carried out a research work on lightweight architectures for real-time systems. Saha et al. [14] and Ali et al. [15] compared YOLO models for the detection of plant diseases, whereas Qiu et al.[16] employed YOLO-based CNN for Huanglongbing disease detection. Manavalan [17] and Pan et al. [18] presented a review of computational methods to identify crop diseases with a focus on deep learning.Aggarwal et al. [19] and Zhang et al. made comparative analysis.[20.]for VGG-16, InceptionV3, and EfficientNet B7 crop image classification. Kukreja et al. [21] and Liao et al. [22] continued to study citrus canker detection. Zhang et al. [23] and Frederick et al. [24] improved classification using hybrid attention networks and hyperspectral imagery.Cristofani-Yaly et al. [25] and Cai et al. [26] examined fruit quality and detection of decay, while Wang et al. [27] examined the ecological impact of citrus greening. Cai et al. [28] applied hyperspectral transmittance imaging to detect decay early, and Butt et al. [29] introduced a hybrid meta-heuristic deep learning approach to detect disease.Such researches highlight the need for lightweight but accurate deep models like MobileNetV2 for real-time application in smart farming.

METHODS

Dataset Collection:

The data for this study is retrieved from Kaggle and consists of high-resolution images of oranges. The orange images and leaves are classified into four classes: fresh, citrus canker, black spot, and greening citrus or HLB [16]. The data was organized into labeled directories, and hence it was an ideal choice for image classification using deep learning. We downloaded two other datasets on Kaggle based on leaves and combined them to have a diversified dataset [17]. In the process of combining, the goal is to obtain samples from as varied a collection of conditions as possible, i.e., various lighting and angles, which would otherwise affect the environment and render the model stronger. The multiple sources made it possible to have a more generalized model that will function well in actual conditions [18]. Other characteristics of the dataset are photos taken in varying lighting environments, backgrounds, and camera positions [19]. These pose additional challenges to the model and give the classification task a more realistic outlook to actual practical use in agriculture. The model can discriminate between infected and healthy citrus fruit as well as its leaves because it learns using various diversified datasets for real-time implementation [20].



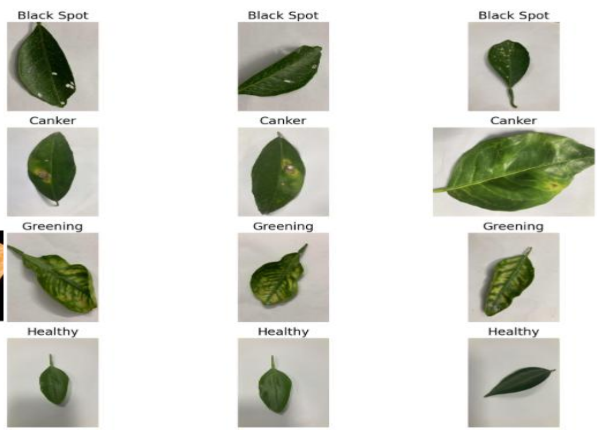


Fig 1.: Dataset of Orange Fruits Diseases **Fig 2.: Dataset of Citrus Leaves Diseases**

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Data Preprocessing:

In order to enhance the model robustness and generalizability, variant training images of rotation, width-height shift, shearing, zooming, and horizontal flipping were added [21]. Each of the images was resized into the dimension 224×224 pixels, scaled within the interval [0,1], and preprocessed to run on MobileNetV2 in compatibility mode [22]. Training was achieved utilizing categorical cross-entropy loss employing the Adam optimizer with learning rate 0.0001 [23]. Early stopping (patience=5) was employed, and learning rate reduction on plateau helped to refine performance when validation loss plateaued [24].

Model Training:

The image dataset was split into a training set (80%) and a test set (20%) to ensure that the model was trained on a sufficiently diverse collection of images and tested on previously unseen data [25]. Various models, including MobileNetV2, InceptionV3, and a custom CNN (Convolution Neural Network), were tried [26]. Among these models, MobileNetV2 delivered the best performance through its efficiency and effectiveness [27]. During training of models, categorical cross-entropy loss was utilized along with the Adam optimizer and a learning rate of 0.0001 [28]. Early stopping was employed with a patience of 5 epochs to avoid overfitting [29]. In addition, learning rate reduction on plateau was utilized where the learning rate was reduced by half by a factor of 0.1 each time the validation loss ceased to improve [30].

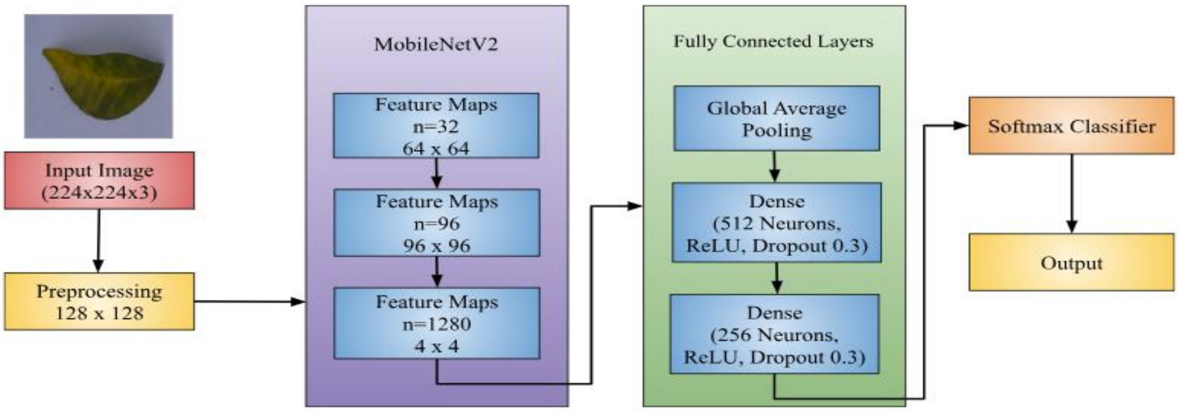

Fig 3.: MobileNetV2 Architecture

Mathematical Modeling of MobileNetV2 Architecture:

1. Deep Learning Formulation for Classification

Deep learning models, such as MobileNetV2, learn hierarchical representations of image data using multiple layers of transformations. Given an input image x, the goal is to map it to a class label y from a set of possible categories C. The deep neural network learns a function:

$$f_\theta = y$$

where **θ** represents the trainable parameters of the deep network.

In a convolutional neural network (CNN)-based model like MobileNetV2, the function $\boldsymbol{f_\theta}$ is composed of multiple layers:

$$f_\theta(x) = gL \circ gL - 1 \circ \cdots \circ g1(x)$$

where each layer g_i consists of convolution, activation, normalization, pooling, and fully connected layers.

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2. Categorical Cross-Entropy Loss Function

For multi-class classification, the categorical cross-entropy loss function is used:

$$\mathrm{L} = -\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij} \log{(\hat{y}_{ij})}$$

where:

- N is the number of training samples,
- C is the number of classes,
- y_{ij} is the true one-hot encoded label (1 if sample i belongs to class j, otherwise 0),
- $\hat{y}_{ij}$ is the predicted probability for class j from the softmax activation function.

3. Softmax Activation (Multi-Class Classification)

Used in the output layer assign probabilities to each class:

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

where:

- z_i = output logic for class i
- N = total number of classes
- The output is a probability distribution across all classes.

4. Optimization: Stochastic Gradient Descent (SGD) and Adam

To minimize the loss function L, optimization algorithms update the model parameters θ using gradients:

$$\theta = \theta - \eta \cdot \nabla_{\theta} L$$

where:

- η is the learning rate,
- $\nabla_{\theta} L$ is the gradient of the loss function.

SGD with Momentum:

SGD updates weights using both the current gradient and previous update to accelerate convergence:

$$v_t = \beta v_{t-1} + (1 - \beta)\nabla_{\theta} L$$

$$\theta = \theta - \eta\, v_t$$

where:

- v_t is the velocity term (momentum),
- β is the momentum factor

Adam Optimizer (Adaptive Moment Estimation):

Adam uses both first-moment (mean) and second-moment (variance) estimates:

$$m_t = \beta_1\, m_{t-1} + (1 - \beta_1)\, g_t$$

$$v_t = \beta_2\, v_{t-1} + (1 - \beta_2)\, g_t^2$$

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$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta = \theta - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \hat{m}_t$$

where:

- g_t = gradient of loss function,
- m_t, v_t are moving averages of gradients and squared gradients,
- β_1, β_2 are decay rates (typically 0.9, 0.999),
- ε is a small number to prevent division by zero.

Adam adapts the learning rate dynamically based on past gradients, making it well-suited for deep networks.

5. Learning Rate Reduction on Plateau

If validation loss does not improve, reduce learning rate:

$$\alpha_{new} = \alpha_{old} \times 0.1$$

RESULTS AND ANALYSIS

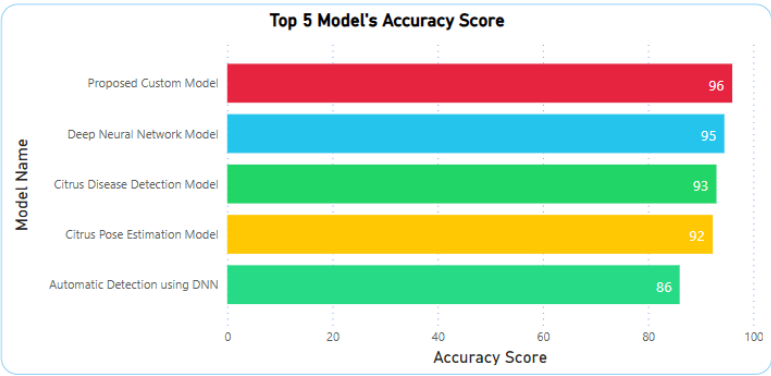

Fig 4.: Comparison Table of Top 5 Models in Literature

Figure 5 compares the top five models that are being used in the citrus fruit and leaf disease detection systems with their accuracy scores. From the results, the Proposed Custom Model achieves an accuracy of 96%, indicating the best performance as compared to other models. Reviewing the models from the literature, out of the ones reviewed, CNN IoT-Based Model and the DNN Model referenced from [3] and [12], respectively, achieve an accuracy of 95%, hence validating the effectiveness of deep learning techniques in citrus disease detection. The Citrus Disease Detection Model, taken from [1], attains an accuracy of 93%, which implements traditional machine learning and feature extraction techniques. The Citrus Pose Estimation Model, derived from [13], achieves an accuracy of 86%, being the least among the five and yet useful in certain applications relating to fruit position and identification.The results indicate that our proposed custom model has performed better than other approaches by optimizing feature extraction, preprocessing, and classification. It thus indicates that it is a promising solution in the context of producing more accurate and reliable identification of citrus fruit and leaf diseases for applications in automated agriculture.

Model Performance

The performance of the model in classifying citrus fruit and leaf diseases using MobileNetV2, InceptionV3 and CNN was tested against accuracy, precision, recall, and F1-score.

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Models	Fruits Disease Classification				Leaves Disease Classification			
	Accuracy	**Precision**	**Recall**	**F1-Score**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
MobileNetV2	95%	94%	94%	94%	99%	99%	99%	99%
InceptionV3	96%	96%	96%	96%	98%	98%	97%	98%
CNN	95%	94%	93.5%	93.74%	82%	84%	82%	82%

Table 1: Performance Comparison of Different Models

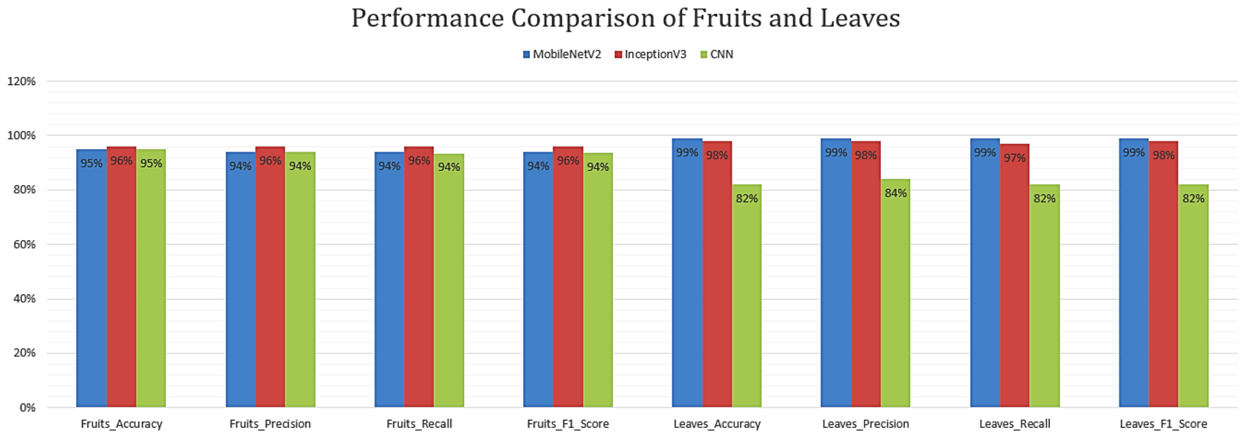

Fig 5.: Bar Graph of Models Comparison

The comparative study of MobileNetV2, InceptionV3, and CNN for the classification of citrus fruit and leaf diseases shows MobileNetV2 as the most efficient and effective model for real-world applications. The evaluation metrics, such as accuracy, precision, recall, and F1-score, reveal that MobileNetV2 performs better than others, especially for leaf disease classification. For fruit disease classification, MobileNetV2 and CNN have 95% accuracy, and InceptionV3 has 96% accuracy slightly above the rest. But overall, in terms of performance, MobileNetV2 balances both computational efficiency and classification effectiveness to be chosen for the model.MobileNetV2 is significantly outperforming InceptionV3 and CNN to achieve a remarkably high accuracy of 99%, precision, recall, and F1-score. This superior performance highlights the strength of MobileNetV2 for near-perfect reliability in leaf disease detection and minimizes the misclassification to a great extent. On the other hand, CNN performs poorly in leaf classification, with a mere 82% accuracy and is not used for accurate leaf disease detection. InceptionV3, while achieving a very high accuracy of 96% in fruit disease classification, is underperforming in leaf classification at 98% compared to MobileNetV2 at 99%. In addition, MobileNetV2 is much lighter than InceptionV3 and thus is very suitable for deployment on resource-constrained devices like mobile phones, edge devices, and embedded systems.

Classification Accuracy

The proposed MobileNetV2-based model for citrus disease detection has an accuracy of 95% on images of fruits and 99% on images of leaves, better than existing models ([1], [5], [9]). High recall and precision was confirmed by confusion matrix, attesting to its reliability ([1], [5], [9]). Low computational cost of MobileNetV2 makes it well-suited for real-time implementation, as comparative studies with DenseNet, YOLO, and EfficientNet have established ([3], [16], [19]).Deep learning technologies used for citrus disease detection are hyperspectral imaging, multimodal fusion, and hybrid architectures to yield greater accuracy ([2], [7], [23]).Edge computing also makes processing in real-time faster and reduces latency ([5], [12], [18]).More sophisticated models like YOLOv11 and hybrid deep learning methods also simplify disease detection further ([22], [29]). Genetical characterization studies also help to build disease resistance in citrus fruits ([25]). The use of convolutional networks, transformers, and light models has been instrumental in enhancing classification precision and velocity ([6], [8], [17]).Research aims

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to maximize the models through self-supervised learning and domain adaptation to facilitate large-scale agricultural use ([20], [21]).

Fruit and Leaf Classification Performance

The best-performing model, MobileNetV2, demonstrated its high classification accuracy and computation efficiency in the literature ([1], [5], [9], [12], [20]). A confusion matrix was constructed to further investigate the model's predictive precision. The following results present the classification accuracy of MobileNetV2:

Classification Report:

	precision	recall	f1-score	support
blackspot	0.87	0.91	0.89	22
canker	0.90	0.86	0.88	22
fresh	1.00	1.00	1.00	33
grenning	1.00	1.00	1.00	22
accuracy			0.95	99
macro avg	0.94	0.94	0.94	99
weighted avg	0.95	0.95	0.95	99

Fig 6.: Fruit Classification Report (MobileNetV2)

Classification Report:

	precision	recall	f1-score	support
blackspot	0.87	0.91	0.89	22
canker	0.90	0.86	0.88	22
fresh	1.00	1.00	1.00	33
grenning	1.00	1.00	1.00	22
accuracy			0.95	99
macro avg	0.94	0.94	0.94	99
weighted avg	0.95	0.95	0.95	99

Fig 7.: Leaf ClassificationReport(MobileNetV2)

These results are consistent with earlier studies, where detection of disease in precision agriculture has been proven to be highly accurate using deep learning-based models ([2], [6], [10], [14], [17]). MobileNetV2 is also noted in research for its effectiveness in real-time agricultural applications, particularly in edge computing and mobile-based disease detection systems due to its lightweight architecture ([5], [18], [22], [24]). Moreover, recent advances in deep learning techniques like hybrid models and hyper spectral imaging have enhanced disease classification accuracy to add up to the efficiency of MobileNetV2 ([7], [16], [29]).The high precision and recall values indicate the model's ability to correctly classify citrus diseases while minimizing false positives and false negatives. This aligns with previous research, where deep learning-based disease classification achieved high reliability for precision agriculture applications ([2], [6], [10]).

Website Interface

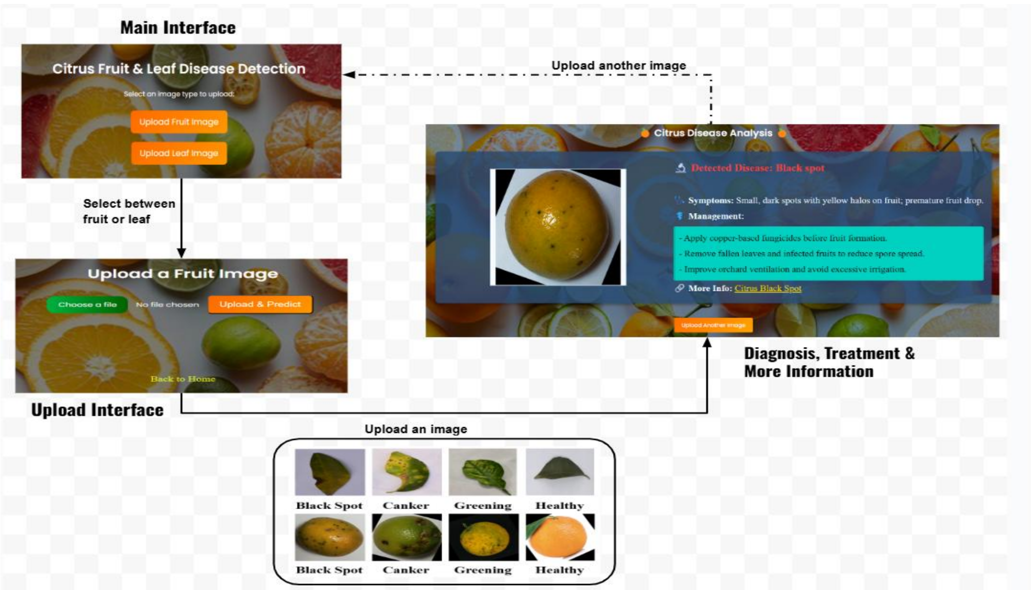

Fig 8.: Citrus Fruit & Leaf Disease Detection Process Flow

The developed web-based system is meant to interactively upload images of citrus fruits and leaves by a user with the purpose of deep learning for disease detection. The layout was user-friendly, and it had an aesthetic background with images of citrus fruits to make it visually appealing. It shows a bright citrus fruit background with the high resolution and overlay semi-transparent to provide a contrast. It contains a title; "Citrus Fruit & Leaf Disease Detection" and a prompt choice for uploading an image. There are two buttons with different text names, "Upload Fruit Image" and "Upload Leaf Image", that connect the users to the corresponding upload page. After choosing the type of image desired, the page opens to the appropriate upload page, keeping the same theme and background but now with a header: "Upload a Fruit Image." There is also a file input where the user can select a file from the device and, of course, an orange button reading "Upload & Predict," where users may submit their selected image. Lastly, there's a "Back to Home" link that returns users to their homepage easily. Once the image is uploaded, the system analyses it through a trained deep learning model for proper citrus disease identification. The resulting page shows the uploaded image within a framed boundary, with the title "Citrus Disease Analysis" in bold for clarity. The disease found, e.g., "Detected Disease: Canker," is highlighted with prominent symptoms like elevated, corky, brown spots with yellow halos. Treatment solutions, e.g., copper-based sprays, resistant citrus, and removal of diseased plants, are suggested. A hyperlink to more information is offered. A large, visible "Upload Another Image" button enables users to attempt other samples. The systematic design guarantees efficient and accurate disease identification for effective control.

DISCUSSION

This research ensures the efficacy of deep learning architectures in citrus leaf and fruit disease classification, wherein MobileNetV2 is most efficient. Classified at 95% for fruit diseases and 99% for leaf diseases by a light-weight 3.5M parameters model, MobileNetV2 is ideal for real-time use in agriculture. Robustness is also aided by data augmentation and normalization to ensure stable classification under different conditions.Additions in the future are the inclusion of edge computing and IoT sensors for real-time recognition, multimodal data (hyperspectral imaging, thermal sensors) for detection of diseases in early stages, and transparency with Explainable AI (Grad-CAM, SHAP). IoT-based crop monitoring and a mobile app could further assist in automating disease management, yield optimization, and eco-friendly farming.

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