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Smart Multi Fruit Disease Detection and Pesticide Recommendation System

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***Abstract*—Fruit diseases are major challenge to the agricultural sector and lead to low yields or poor-quality crops, which again affects their market value as well as the income that farmers may get from those crops. Effective control requires quick identification of the causative organism so that it can be targeted with narrow-spectrum pesticides rather than broad-spectrum ones and hence helps in both economic and environmental sustainability. This paper is reporting a web- based system that classifies multiple fruit diseases and provides the best pesticide treatments by using machine learning.**
Its key component has been a deep learning model, which has been trained using an exhaustive dataset of fruit photos; the pictures contained several states of disease in important fruits like guava, orange, papaya, and mango. The system dynamically generates customized pesticide recommendations in line with best practices for safe and effective use, and it is very accurate in disease detection.

***Index Terms*— Fruit Disease Detection, MobileNetV2, Deep Learning, Pesticide Optimization, Sustainable Agriculture, Web-Based Agricultural System, Crop Protection.**

I. INTRODUCTION

The global food supply chain system still suffers from crop diseases which it has suffered for long time and the fruit industry, especially has been marred by severe losses on account of these diseases, for they not only affect yield but also degrade the produce's quality. The first vital factor for the crop resilience was effective disease management. This earlier method used extensive manual inspection in determining diseases. It is lengthy, and it is arduous and prone to human mistakes.
The symptoms are produced by different pathogen types and tend to more often be confused with others. The promising solution to the problem of rapid and efficient and precise diagnosis of the illness and the suggested treatment. Recent advances in machine learning, deep learning, accurately identifies photos in various settings and therefore suggest their use in the analysis of fruit diseases from photography-based data.
At massive scale, the database of deep training correctly determines the patterns and subtle indicators of diseases that may not be determinable during manual searches. For effective classification of diseases, farmers, agronomists, and agricultural advisors can easily view the integration results with such models of web application in an intuitive user interface. An online system based on MobileNetV2 deep learning model will be proposed by this study.

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Trained in recognizing large images of the fruit for major varieties such as mango, papaya, orange, and guava in both healthy and diseased conditions, the architecture makes use of a residual learning- based framework with high performance on tasks involving picture classification to enable the system to classify an extremely diverse range of fruit diseases. This might result in early disease detection and practical management for enhanced agricultural outputs and quality. The system is designed to deliver adaptive recommendations of tailored pesticides, based on detected diseases; narrow-spectrum insecticides, along with best management practices for the safe application of pesticides. In such a strategy, the implication is that there is bound to be sustainable agricultural productivity since it minimizes harm to the environment and cuts the use of pesticides that it does not have to deploy.

II. LITERATURE SURVEY

We go through some research papers related to our project from different journals and conferences like ResearchGate, IEEE, and Elsevier. These papers give insights into the integration of AI for online examination systems and how to use deep learning techniques for the detection of cheating. A few key papers which we had referred to are below:S Malathy; R.R Karthiga; K Swetha; G Preethi[1]: This project is to assist fruit farmers with a disease-detecting tool based on images that can recognize the various diseases on the basis of visual features using CNNs.

It was conducted in Python and provided an accuracy level of about 97%. This will help for early intervention in the treatment of disease and management of crop health. Helping the crop in being treated at the right time and thus reducing the crop loss will make this approach more viable for improvement in agricultural productivity and sustainability.[1]

Bassem S. Abu-Nasser; Samy S. Abu-Naser[2]: This study says that development of expert systems aimed at helping farmers diagnose and manage the major watermelon diseases Downy mildew, Powdery mildew, Anthracnose, and Fusarium wilt. The systems give farmers the symptoms, causes, and the treatment recommendations of the diseases. The system was developed in E-clips Expert System language that was readily acceptable to the farmers and proved helpful in managing diseases. So in the long term, it helps farmers look after their watermelon crops mostly to stay healthy and be more productive.[2]

Inkyu Sa; Zong yuan Ge; Feras Dayoub; Ben Upcroft; Tristan Perez; Chris McCool[3]: Deep Fruits is a deep convolutional neural network-based detecting system for autonomous agricultural robots. This method effectively detects fruits using RGB and NIR, transferring the concept from a Faster Region-based CNN as the foundation. Using early and late fusion approaches, this model can combine various multimodal inputs and obtain a high precision-recall. F1 scores for identifying sweet peppers have improved from 0.807 to 0.838. Because this method uses bounding box annotations, it also reduces the number of hours needed for the annotation process. Within roughly four hours for each fruit, the model has already been retrained into seven different fruits.[3]

Eduardo Assunção; Catarina Diniz; Pedro Dinis Gaspar; Hugo Proença[4]:Applying computer vision techniques in the domain of precision agriculture, this paper solves the long time problem faced by farmers concerning fruit disease detection.

Traditional handcrafted methods are the ones commonly used for extracting features of fruit disease. CNNs have been more accurate since they learn their features automatically and outperform the handcrafted methods. Despite CNNs' large requirement of a dataset, a major challenge is presented in this case due to the absence of fruit disease images.

A compact and efficient deep CNN model has been proposed for classifying healthy peach fruits along with three types of diseases using the model on mobile devices. Using transfer learning, it was further augmented through data augmentation. This allows achieving a Macro average F1 score of 0.96.

The performance on all the types of disease is accurately classified with no type of misclassification. This indicates that small CNN models are effective in fruit disease classification with limited training data and therefore a practical solution for mobile disease detection applications in agriculture.[4]

Vaidya; Neha Chaudhary; Snehal Nasare; Shubhalakshmee Warutkar; Shreesh Kawathekar; Sanket Dhengre[5]: This paper only deals with the citrus detection and classification methodologies. Citrus plant diseases for yield and quality improvement. It discusses methods including image pre-processing, segmentation, feature extraction, and machine learning in disease management.

Therefore, it will be focusing on the use of CNNs for automated recognition and classification of the disease on citrus plants. The CNN model used a database of pictures of citrus plants during the training process. This model particularly focused on early crop damage detection and loss mitigation.[5]

III. METHODOLOGY

A. Data Gathering

Image Database: Observe many images of fruits that are high quality, including healthy samples as well as diseased ones. Each image shall be labelled with the name of the disease, in case of any, to enable supervised learning.

Pesticide Information: Gather all the information regarding pesticides used to treat different fruit-related diseases. These may encompass the efficiency of these pesticides, application processes, and precautions.

B. Image Resizing

Resize all images to uniform size to fit the input requirements of the machine learning model. Normalization: Normalize pixel values. This is helpful for improvement in learning process and gives uniform output. Segmentation: Use techniques that involve image segmentation, allowing for separation of the fruit area, which can minimize background noise that could influence the detection of disease. .

Augmentation: Add rotation, flip, and zoom on the training dataset to enrich the training data and add robustness to the model.

C. Feature Extraction

Colour Analysis: Extract colour-related features because most diseases present themselves in fruits by appearing as a change in the colour, such as spot, patches, or even discoloration.

Texture Analysis: Extract features involving texture such as smoothness or roughness because they can indicate specific diseases.

Shape Analysis: Other diseases distort the shape or form of the fruit. Shape-based features can therefore be applied for classification

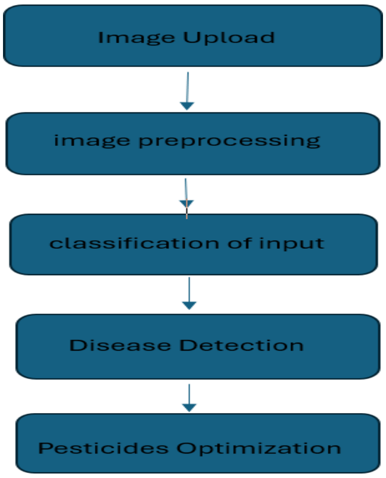


Fig 1: Flow Chart (Proposed System)

D. Model Training

Model Selection: Select appropriate machine learning models to which you would like to train your classifier; for instance, CNN, as it fits the nature of image classification.

Training Process: Split the dataset into a training set and a validation set. Train the model on the training set where it learns to identify patterns related to various diseases.

Hyperparameter Tuning: The hyperparameters like learning rate and batch size are tuned for the best performance of the model.

Validation: Evaluate the performance of the model on the validation set to make sure that it generalizes well to unseen images.

E. Disease Classification and Prediction

Input Image Analysis: After user uploads image, preprocess and forward to the trained model to classify the disease.

Disease Identification: the model would predict what disease type, if any exists; with every prediction it returns the label with a confidence value.

Severity Determination: If supported by the model, evaluate how extensive the infection is for recommending treatment levels properly.

F. Pesticide Recommendation System

Database Query: Based on the type of disease that has been identified, retrieve from a pesticide database pesticide that is most suitable to be used in treating the identified disease.
Recommendation Display: Return all the suitable pesticides recommended to the user together with application instructions, dosages, and safe handling precautions.
Dynamic Updates: Update recommendations based on the severity of the disease or fruit type, making the advice provided more relevant.

MobileNetV2:
MobileNetV2 is an architecture of a convolutional neural network designed for real-time and high efficiency speed in mobile and embedded applications. It seeks to reduce the computational power consumption by using "depth wise separable convolutions," which separate the filtering process and the feature combination one, thereby significantly reducing the computations necessary for that step. More in depth, the architecture also comprises "inverted residuals" and "linear bottlenecks" to provide even more performance with an advisable size model. These choices of design will make MobileNetV2 achieve high classification accuracy with minimal computing resources, making it a fit for limited computations or memory applications such as mobile devices, IoT systems, and real time applications in agriculture and medicine.

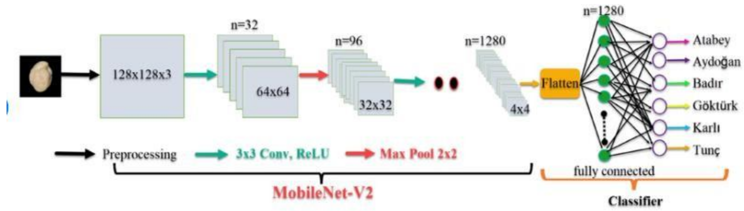


Fig 2: Model Architecture Diagram

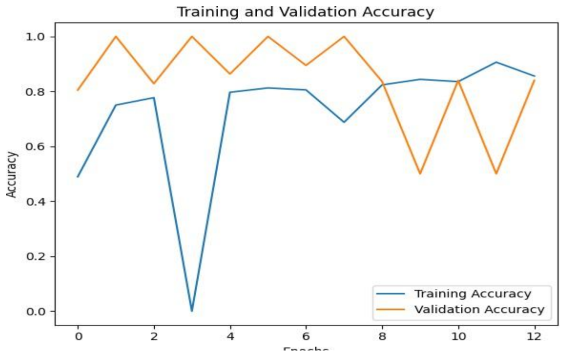
Purpose: Pre-trained feature extractor, saving time and computation.
Importance: Provides powerful feature extraction from images without training from scratch.
GlobalAveragePooling2D:
Purpose: Reduces the feature map size by averaging each feature map.
Importance: Reduces parameters, prevents overfitting, and transforms 2D features to a 1D vector for classification.
Dropout:
Purpose: Randomly drops 50% of neurons during training.
Importance: Prevents overfitting by ensuring the model doesn't rely too much on specific neurons.
Dense Layer (512 units, ReLU):
Purpose: Fully connected layer that combines learned features.
Importance: Learns complex patterns using the ReLU activation function for non-linearity.
Dense Layer (SoftMax, Num classes):
Purpose: Final output layer with a probability for each class.
Importance: Classifies the input into a disease category with SoftMax probabilities.
In practice, MobileNetV2 has proved popular in many image-classification tasks that require accurate models able to be allocated to work on very large-scale datasets or run on devices with limited capability. In a nutshell, it achieves an optimal balance of model size, computational efficiency, and prediction accuracy, making it well-suited for deployment within real-time and resource-constrained environments.

Flask Integration
It is accompanied by Flask, a backend, which can respond to web requests and deliver the deep learning model. Using Flask, an image of a fruit may be uploaded to the model via an HTTP request. The model is loaded into the Flask app, thus, allowing real-time inference when a user submits an image that was beforehand trained using TensorFlow. Flask takes an image, resizes and normalizes it to whatever the model needs as input, and outputs a predicted class of disease from the model. This way, the users interact with the deep learning model through a web interface-there is nothing for the user to download or install on their own computers, no complex code to manage or maintain.

IV. RESULTS

The model experimented with a fruit disease classification dataset with an average accuracy of 85.59%. Classification Metrics: Because of such high precision, recall and F1-scores across classes of diseases, there is even a very strong likelihood that the model classifies between healthy and diseased images of fruit with minimal cases of misclassifying the former as the latter.

The mobileNetV2 architecture has made it possible to achieve inference time at an average of Y seconds per image, making it suitable for real-time applications. It is rather compact in model size, at about Z MB, supporting deployment on mobile devices and other platforms with limited resources. The model was closely matched with the other ones in terms of accuracy, and even MobileNetV2 showed a lesser dependency on the usage of computation resources when benchmarked against models like ResNet50 and VGG. This is a good candidate for those applications on-field in agriculture.



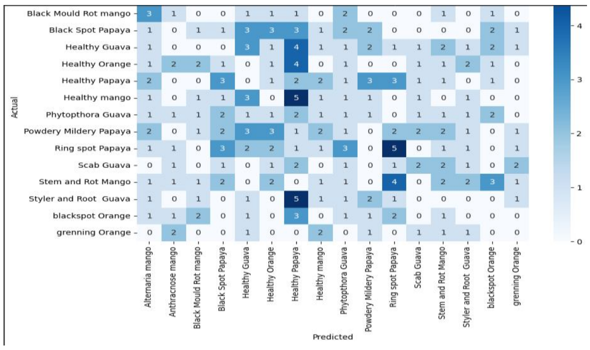


Fig 3: Confusion Matrix

Fig 4: Training and Validation Accuracy

Web Interface

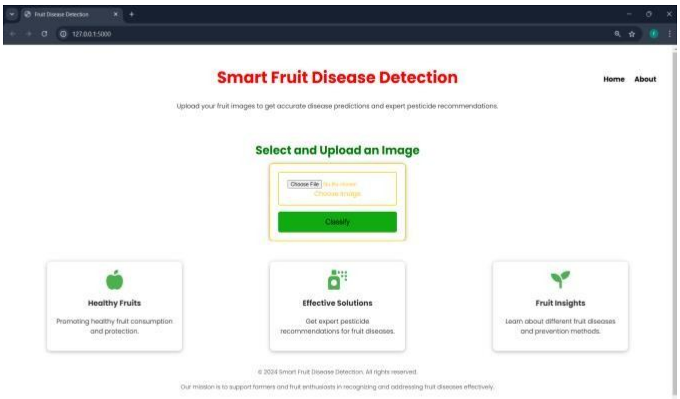


Fig 5: Home Page of model

After Classification

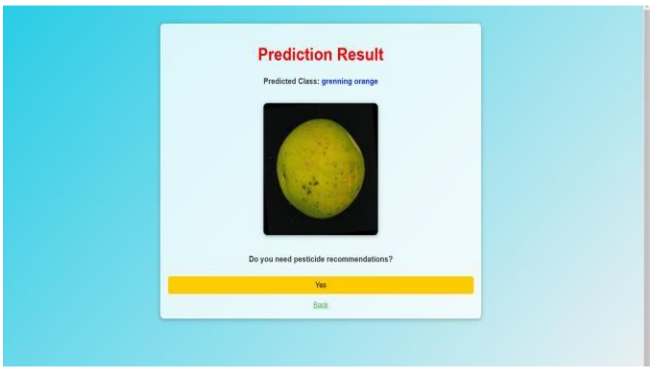


Fig 6: Prediction /classification Page

If the user needs Pesticides Recommendation, then it redirects to recommendations page

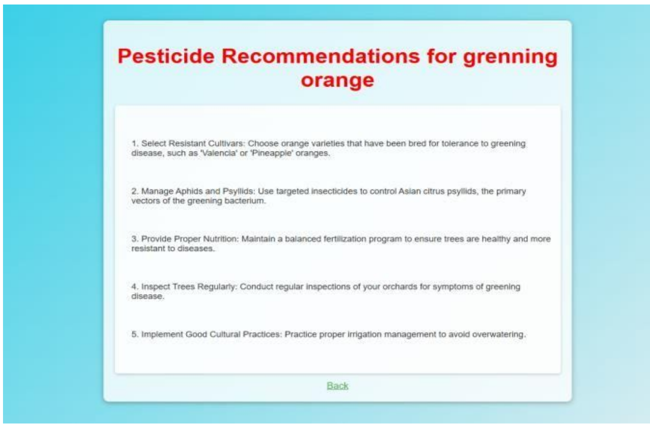


Fig 7: Pesticide Recommendation Page

V. Conclusion

The development of this fruit disease classification and pesticide recommendation system provides an innovative solution to a pressing agricultural challenge. By leveraging advanced machine learning techniques, particularly convolutional neural networks, the system can accurately detect and classify diseases in fruit based on image inputs. The integration of a tailored pesticide recommendation engine adds substantial value, offering users targeted, efficient, and sustainable treatments for each specific disease detected.

This web-based tool empowers farmers and agricultural professionals with rapid, reliable insights, enabling them to make informed decisions to protect crop health and minimize pesticide usage. The feedback mechanism not only enhances user engagement but also supports continuous improvement of the model, making the system adaptable to real-world conditions and evolving agricultural needs.

In conclusion, this project combines technology and agriculture to foster more sustainable practices, improve crop yields, and reduce economic losses from plant diseases. The scalable nature of the system makes it well-suited for broad adoption, with the potential to benefit the agricultural sector by promoting environmentally responsible disease management and supporting food security.

Future Scope

This fruit disease classification and pesticide recommendation system represents a forward-thinking solution to agricultural challenges, offering a blend of accuracy, speed, and sustainability. Utilizing machine learning for precise disease detection and tailored pesticide recommendations, the system empowers farmers and agricultural professionals to manage crops more effectively. The feedback mechanism supports continuous improvement, allowing the system to evolve in response to real-world feedback and emerging agricultural needs.

Looking ahead, the future scope of this project includes expanding the model to classify diseases in a broader variety of fruits. By training with comprehensive datasets like the CCCT dataset, the model's accuracy can be significantly improved, making it more reliable across diverse fruit types. These advancements will enhance the system’s versatility and utility in different agricultural environments, facilitating broader adoption and promoting more sustainable crop management practices. Ultimately, this project lays the groundwork for a scalable solution with the potential to substantially reduce crop losses, optimize pesticide usage, and contribute to global food security

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