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Disease Detection In Fruit Using Image Processing and Machine Learning

Pranjali Santosh Pingat[1], Saniya Rahul Labade[2], Harshada Sahebrao Lende[3], Prof. Kedar A. L.[4]
[1, 2, 3]*Student, Department of Computer Engineering*
[4] *Assistant Professor, Department of Computer Engineering*
[1,2,3,4] *Samarth Rural Educational Institute Polytechnic College (MH) India*

Abstract: Fruit diseases significantly affect agricultural productivity and food quality, leading to economic losses for farmers. Early detection and proper diagnosis of fruit diseases are essential to ensure healthy crop production and prevent the spread of infections. This study presents a Multi-Fruits Disease Detection System using Machine Learning that automatically identifies diseases from fruit images using deep learning techniques. The proposed system utilizes a Convolutional Neural Network (CNN) based on the MobileNetV2 architecture with transfer learning to accurately classify different fruit diseases.

The system is designed with a user-friendly web interface developed using the Flask framework, allowing users to upload fruit images for analysis. The uploaded images are preprocessed and resized before being passed to the MobileNetV2 model, which extracts relevant features through depthwise separable convolutions. A custom classification head consisting of global average pooling, dropout, and dense layers with Softmax activation is used to classify the detected disease. The system then predicts the disease category and provides suggested remedies through the interface.

The proposed model offers an efficient and lightweight solution for real-time fruit disease detection, making it suitable for agricultural applications. By automating the disease identification process, the system helps farmers and agricultural experts take timely preventive measures, improving crop quality and reducing potential losses. The integration of machine learning with a web-based interface enhances accessibility and usability, making the system practical for modern smart farming environments.

Keywords: Fruit Disease Detection, Machine Learning, Deep Learning, Convolutional Neural Network, MobileNetV2, Image Classification, Smart Agriculture, Transfer Learning.

I. INTRODUCTION

Agriculture is one of the most important sectors for global food production and economic development. Fruits play a significant role in human nutrition because they provide essential vitamins, minerals, and antioxidants. However, fruit crops are often affected by various diseases caused by fungi, bacteria, viruses, and environmental factors. These diseases can reduce the quality and quantity of fruit production, resulting in serious economic losses for farmers and agricultural industries. Traditionally, the identification of fruit diseases has been performed through manual inspection by farmers or agricultural experts. This process requires significant expertise and time, and in many cases it may lead to inaccurate diagnosis due to the similarity of symptoms among different diseases. Therefore, the development of automated systems for early detection and classification of fruit diseases has become an important research area in modern agriculture [1].

Recent advancements in artificial intelligence and computer vision have made it possible to develop intelligent systems capable of detecting plant and fruit diseases from digital images. Machine learning and deep learning techniques, especially Convolutional Neural Networks (CNNs), have shown excellent performance in image recognition and classification tasks. CNN models can automatically learn complex visual features such as color patterns, texture variations, and irregular spots present on fruit surfaces. These capabilities make deep learning highly effective for detecting diseases at an early stage, helping farmers take timely preventive actions and improve crop productivity [2].

One of the challenges in applying deep learning models in agricultural systems is the requirement of large datasets and high computational power. To overcome these limitations, transfer learning techniques are widely used. Transfer learning allows the use of pre-trained deep learning models that have already learned general image features from large datasets. These models can then be fine-tuned for specific tasks such as fruit disease classification. Among the various deep learning architectures, MobileNetV2 is considered an efficient and lightweight model that uses depthwise separable convolutions to reduce computational complexity while maintaining high accuracy. This makes it suitable for real-time agricultural applications and systems with limited processing resources [3].

In addition to model development, integrating machine learning algorithms with user-friendly applications has become an important step toward practical deployment. Web-based platforms allow users to upload fruit images and obtain instant predictions about possible diseases. These systems can also provide recommendations for treatment and preventive measures, enabling farmers to make better decisions regarding crop management. The integration of deep learning models with web frameworks such as Flask enables the creation of efficient and accessible disease detection systems that can be used even by non-technical users [4].

The main objective of this study is to develop a Multi-Fruits Disease Detection System using Machine Learning that can automatically identify diseases from fruit images and provide suggested remedies. The proposed system uses a Convolutional Neural Network based on the MobileNetV2 architecture with transfer learning to classify fruit diseases accurately. The system is integrated with a web-based interface that allows users to upload images and obtain disease predictions quickly. By automating the disease detection process, the proposed system aims to support farmers in monitoring crop health, improving productivity, and reducing agricultural losses.

Agriculture is one of the most important sectors for global food production and economic development. Fruits play a significant role in human nutrition because they provide essential vitamins, minerals, and antioxidants required for a healthy lifestyle. Many countries depend heavily on fruit cultivation as a source of income and employment for farmers and agricultural workers. However, fruit crops are frequently affected by various diseases caused by fungi, bacteria, viruses, and unfavorable environmental conditions. These diseases not only reduce crop yield but also affect the quality and market value of fruits. As a result, farmers often suffer significant economic losses. Early identification and management of fruit diseases are therefore essential for maintaining agricultural productivity and ensuring food security [1].

Traditional methods of fruit disease detection mainly rely on manual observation by farmers or agricultural experts. In this approach, experts examine fruits visually to identify symptoms such as spots, discoloration, rotting, or abnormal textures. Although this method has been used for many years, it has several limitations. It requires expert knowledge and experience, which may not always be available to farmers, especially in rural areas. Moreover, manual inspection can be time-consuming and may not provide accurate results when diseases show similar visual symptoms. Because of these challenges, there is a growing need for automated and intelligent systems that can detect fruit diseases quickly and accurately [1].

In recent years, advancements in artificial intelligence, computer vision, and machine learning have significantly transformed the agricultural sector. These technologies enable the development of smart systems that can analyze digital images and identify patterns associated with plant and fruit diseases. Machine learning algorithms are capable of learning from large datasets and making predictions based on the patterns they observe. Among various machine learning approaches, deep learning techniques have gained considerable attention due to their high accuracy and ability to handle complex image data. These technologies provide promising solutions for automating disease detection and supporting farmers in effective crop management [2].

Deep learning models, particularly Convolutional Neural Networks (CNNs), have proven to be highly effective for image classification and object recognition tasks. CNN models automatically extract important features from images, such as color patterns, shapes, and textures, without requiring manual feature extraction. This capability makes them suitable for detecting diseases in fruits where visual symptoms are the primary indicators of infection. Several studies have demonstrated that CNN-based models can achieve high accuracy in identifying plant diseases from images of leaves, fruits, and stems. The ability of these models to learn complex visual features makes them an ideal choice for agricultural disease detection systems [2].

Despite their advantages, deep learning models often require large datasets and high computational resources for training. To address this challenge, researchers commonly use transfer learning techniques. Transfer learning involves using pre-trained models that have already learned general features from large datasets such as ImageNet. These models can then be fine-tuned for specific tasks like fruit disease detection with relatively smaller datasets. This approach reduces training time, improves model performance, and makes the system more efficient. It also allows developers to build accurate models without needing extremely large training datasets [3].

Among various deep learning architectures, MobileNetV2 has gained popularity because of its lightweight structure and efficient performance. MobileNetV2 uses depthwise separable convolutions and inverted residual blocks, which significantly reduce the number of parameters and computational cost compared to traditional CNN models. This makes it suitable for real-time applications and systems that operate on devices with limited processing power. Due to its efficiency and accuracy, MobileNetV2 is widely used in image classification tasks, including plant and fruit disease detection systems [3].

Another important aspect of modern agricultural technology is the integration of machine learning models with practical applications that can be easily used by farmers. Web-based and mobile-based platforms allow users to upload images of fruits or plants and receive instant feedback about possible diseases. Such systems provide quick and reliable diagnostic support, especially in regions

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where agricultural experts are not easily accessible. By combining machine learning algorithms with web frameworks, it is possible to develop intelligent platforms that offer disease detection along with recommendations for treatment and prevention [4].

Web technologies such as the Flask framework enable the creation of lightweight and efficient web applications that can interact with machine learning models. In such systems, the user uploads a fruit image through the web interface, and the backend processes the image using a trained deep learning model. The model analyzes the visual features of the fruit and predicts the most likely disease category. The result is then displayed to the user along with possible remedies or preventive measures. This type of integration makes machine learning solutions more practical and accessible to farmers and agricultural stakeholders [4].

The proposed Multi-Fruits Disease Detection System using Machine Learning aims to develop an automated solution capable of identifying diseases in different types of fruits using image analysis. The system utilizes a Convolutional Neural Network based on the MobileNetV2 architecture with transfer learning to achieve accurate disease classification. A web-based interface allows users to upload fruit images easily, and the system processes the images to detect diseases and suggest possible remedies. By providing quick and reliable disease diagnosis, the proposed system can help farmers take timely preventive actions and improve crop productivity.

Furthermore, the implementation of such intelligent systems contributes to the advancement of precision agriculture and smart farming practices. Automated disease detection not only reduces the dependency on manual inspection but also improves the speed and accuracy of diagnosis. This technology can play a significant role in improving agricultural sustainability, reducing crop losses, and supporting farmers in managing plant health effectively. As machine learning technologies continue to evolve, their integration into agriculture is expected to create more innovative solutions for improving crop monitoring and disease management in the future [2].

II. PROBLEM STATEMENT

Fruit crops are highly vulnerable to a variety of diseases caused by fungal, bacterial, and viral infections, which significantly affect agricultural productivity and fruit quality. Farmers often rely on traditional methods such as manual inspection and expert consultation to identify these diseases. However, these methods are time-consuming, require specialized knowledge, and may lead to inaccurate diagnosis when different diseases show similar visual symptoms. In many rural areas, access to agricultural experts is limited, which further delays proper disease identification and treatment. Late detection of fruit diseases can result in the rapid spread of infections across crops, causing severe economic losses and reduced yield. Therefore, there is a strong need for an efficient, automated, and reliable system that can accurately detect multiple fruit diseases at an early stage. The proposed Multi-Fruits Disease Detection System using Machine Learning aims to address this problem by using deep learning techniques to analyze fruit images and automatically identify disease types. Such a system can assist farmers in making quick decisions regarding crop management and disease control, ultimately improving productivity and reducing agricultural losses.

III. OBJECTIVE

1) To develop an automated system that can detect and classify diseases in multiple types of fruits using machine learning and deep learning techniques.
2) To design and implement an efficient image processing mechanism that can analyze fruit images and extract important visual features related to disease symptoms.
3) To utilize a Convolutional Neural Network model, specifically MobileNetV2 with transfer learning, to improve the accuracy and performance of fruit disease classification.
4) To create a user-friendly web-based interface that allows users to upload fruit images and obtain disease predictions quickly and easily.
5) To provide reliable disease identification along with possible remedies so that farmers can take timely preventive actions and reduce crop losses.

IV. LITERATURE SURVEY

1) Deep Learning for Image-Based Fruits Disease Detection (2016)

Authors: S. P. Mohanty, D. P. Hughes, and M. Salathé

Journal: Frontiers in Plant Science

Publication: Frontiers Media

This research presented a deep learning approach for identifying plant diseases using image-based classification techniques. The authors utilized Convolutional Neural Networks (CNNs) to analyze a large dataset of plant leaf images and classify them into healthy and diseased categories. The study demonstrated that deep learning models could automatically extract visual features such as color variations, spots, and texture differences that indicate the presence of plant diseases. The research achieved high accuracy in disease identification and proved that machine learning techniques can effectively replace traditional manual inspection methods.

The study also highlighted the importance of using large datasets to train deep learning models for agricultural applications. The results showed that CNN models can achieve accuracy greater than 99% under controlled conditions, making them suitable for real-time plant disease detection systems. The research laid the foundation for further studies focusing on automated disease detection using computer vision technologies. This work strongly supports the development of intelligent agricultural monitoring systems that can help farmers detect diseases at an early stage and reduce crop losses [1].

2) Deep Learning Models for Fruits Disease Detection and Diagnosis (2018)

Author: K. P. Ferentinos
Journal: Computers and Electronics in Agriculture
Publication: Elsevier

This study explored the use of deep learning architectures for detecting plant diseases through image classification. The author evaluated several deep learning models, including different Convolutional Neural Network architectures, to determine their effectiveness in identifying plant diseases. The dataset used in this research contained thousands of plant images with different disease conditions. The study demonstrated that deep learning models could successfully identify plant diseases by analyzing visual symptoms present on leaves and fruits.

The experimental results showed that CNN-based models could achieve high classification accuracy while maintaining reliable performance across different plant species. The study also emphasized the importance of image preprocessing and data augmentation techniques to improve model accuracy. The research concluded that deep learning methods have great potential for developing automated plant disease detection systems that can assist farmers in monitoring crop health and improving agricultural productivity [2].

3) MobileNetV2: Inverted Residuals and Linear

Bottlenecks (2018)
Authors: M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen
Publication: IEEE Conference on Computer Vision and
Pattern Recognition (CVPR)
Publisher: IEEE

This paper introduced the MobileNetV2 architecture, which is a lightweight deep learning model designed for efficient image classification tasks. The model uses depthwise separable convolutions and inverted residual blocks to reduce computational complexity while maintaining high accuracy. MobileNetV2 was developed specifically for applications that require fast processing and low memory usage, such as mobile devices and embedded systems.

The architecture demonstrated strong performance in various image recognition tasks while significantly reducing the number of parameters compared to traditional CNN models. The authors showed that MobileNetV2 could be effectively used for real-time computer vision applications. Due to its efficiency and lightweight design, MobileNetV2 has been widely adopted in agricultural image classification systems, including plant and fruit disease detection applications [3].

4) A Comparative Study of Fine-Tuning Deep Learning Models for Fruits Disease Identification (2019)

Authors: E. C. Too, L. Yujian, S. Njuki, and L. Yingchun
Journal: Computers and Electronics in Agriculture
Publication: Elsevier

This research conducted a comparative analysis of several deep learning models for identifying plant diseases from image datasets. The authors investigated different pre-trained architectures such as VGG16, ResNet50, InceptionV3, and MobileNet to determine which model performs best when fine-tuned for plant disease classification. The study applied transfer learning techniques to adapt these models for agricultural image datasets. The results indicated that transfer learning significantly improves model performance and reduces training time. Among the tested models, some architectures demonstrated better generalization ability and higher classification accuracy. The study concluded that fine-tuned deep learning models can effectively detect plant diseases from images and can be integrated into practical agricultural monitoring systems to assist farmers and researchers [4].

5) Fruits Disease Detection Using Deep Learning (2020)

Authors: S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic
Journal: Computational Intelligence and Neuroscience
Publication: Hindawi

This study proposed a deep learning-based system for detecting plant diseases using image processing techniques. The authors developed a Convolutional Neural Network model capable of classifying plant diseases based on visual symptoms present in plant images. The system analyzed different plant species and disease types, demonstrating the effectiveness of CNN models for automated agricultural diagnostics.

The research showed that automated disease detection systems can significantly reduce the effort required for manual disease inspection. The proposed model achieved high classification accuracy and proved to be efficient in identifying multiple plant diseases. The study emphasized that integrating deep learning with image processing techniques can provide an effective solution for smart agriculture and crop monitoring systems [5].

6) Identification of Fruits Leaf Diseases Using Image

Processing and Machine Learning (2021)
Authors: A. Kumar, R. Singh, and P. Sharma
Journal: International Journal of Agricultural and Biological Engineering
Publication: IJABE

This research focused on identifying plant diseases using machine learning and image processing techniques. The authors proposed a system that uses image segmentation and feature extraction to identify disease symptoms in plant leaves and fruits. Various machine learning algorithms were used to classify disease types based on extracted features such as color, texture, and shape.

The study demonstrated that combining image processing techniques with machine learning algorithms can effectively detect plant diseases with high accuracy. The system was capable of identifying multiple disease categories and assisting farmers in diagnosing plant health conditions. The research highlighted the importance of automated disease detection systems in improving agricultural productivity and reducing crop damage caused by plant diseases [6].

V. PROPOSED SYSTEM

The proposed system focuses on developing an intelligent Multi-Fruits Disease Detection System using Machine Learning that can automatically identify diseases from fruit images. The system integrates image processing, deep learning algorithms, and a web-based interface to provide accurate disease predictions. The main objective of the system is to assist farmers and agricultural users in detecting fruit diseases at an early stage and taking appropriate preventive measures. The system uses a Convolutional Neural Network (CNN) model based on the MobileNetV2 architecture, which is known for its efficiency and high performance in image classification tasks. The entire workflow consists of several stages including data acquisition, image preprocessing, feature extraction, disease classification, and result display through a user interface.

A. Image Dataset Collection

The first step in the proposed system is the collection of a dataset containing images of healthy and diseased fruits. The dataset includes different fruit categories and their corresponding disease types. These images are used to train the machine learning model so that it can learn the visual characteristics associated with each disease. A large and diverse dataset helps improve the accuracy and reliability of the classification model. The images are collected from publicly available agricultural datasets and online repositories that contain labeled fruit disease images. During this stage, the dataset is divided into training and testing sets. The training dataset is used to train the deep learning model, while the testing dataset is used to evaluate the performance of the model. Proper dataset preparation is essential because deep learning models rely heavily on data quality and diversity to learn meaningful patterns from images [1].

B. Image Preprocessing

Image preprocessing is an important step that prepares the input images for analysis by the machine learning model. In this stage, all fruit images are resized to a standard dimension of 224 × 224 pixels, which is the required input size for the MobileNetV2 model. Resizing ensures that all images have a consistent format before being processed by the neural network.

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Additional preprocessing operations such as normalization and noise reduction are also applied to improve image quality. Normalization helps scale the pixel values so that they fall within a specific range, which improves the learning process of the neural network. These preprocessing techniques enhance the clarity of disease symptoms such as spots, discoloration, and surface damage, making it easier for the model to extract meaningful features from the images [2].

C. Feature Extraction Using MobileNetV2

The core component of the proposed system is the MobileNetV2 deep learning model, which is used to extract important features from fruit images. MobileNetV2 is a lightweight convolutional neural network architecture that uses depthwise separable convolutions and inverted residual blocks to reduce computational complexity while maintaining high classification accuracy.

Instead of training the model from scratch, the proposed system uses transfer learning, where a pre-trained MobileNetV2 model is fine-tuned for fruit disease classification. The base layers of the model extract general visual features such as edges, shapes, and textures, while the higher layers learn disease-specific patterns from fruit images. This approach improves model efficiency and reduces the amount of training time required to achieve accurate predictions [3].

D. Disease Classification Layer

After feature extraction, the extracted features are passed to a custom classification layer that determines the type of disease present in the fruit image. The classification layer includes a Global Average Pooling (GAP) layer, a Dropout layer, and a Dense layer with Softmax activation. The Global Average Pooling layer converts the extracted feature maps into a compact feature vector, which reduces the number of parameters and prevents overfitting. The Dropout layer randomly deactivates some neurons during training to improve the model's generalization capability. Finally, the Dense layer with Softmax activation calculates the probability of each disease class and selects the most likely disease category as the final prediction. This classification process enables the system to accurately identify different fruit diseases based on visual patterns present in the image [4].

E. Web-Based User Interface

To make the system accessible to users, a web-based interface is developed using the Flask framework. The interface allows users to log in securely and upload fruit images for analysis. A lightweight SQLite database is used to manage user authentication and store login information. Once the user uploads an image, the system sends the image to the backend where the trained deep learning model processes it and predicts the disease type. The result is then displayed on the web interface along with possible remedies or preventive measures. This user-friendly interface ensures that farmers and agricultural workers can easily use the system without requiring technical expertise [4].

F. System Output and Disease Recommendation

The final stage of the proposed system is the generation of prediction results. After analyzing the uploaded fruit image, the model outputs the detected disease category along with a confidence score. The system also provides suggestions for treatment or disease management practices that can help control the spread of infection. This automated detection system helps farmers identify fruit diseases quickly and take timely preventive actions. By providing accurate and instant disease diagnosis, the proposed system contributes to improved crop health monitoring and supports the adoption of smart agriculture technologies.

VI. SYSTEM DESIGN

A. Image Acquisition and Pre-processing

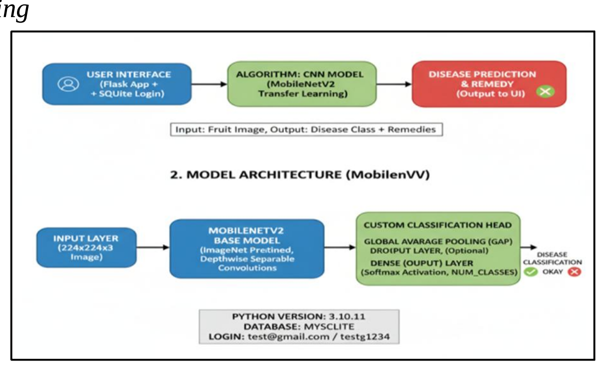

Fig 1: System architecture

The block diagram of the proposed system illustrates the complete workflow of the Sheti Mitra fruit disease detection system, showing how the input image moves through different modules until the final disease prediction is generated.

1) User Interface and Image Upload Module

The first component of the block diagram is the User Interface module, which acts as the entry point of the system. This module is developed using a web framework that allows users to interact with the application through a browser. Farmers or users first log in to the system using their registered credentials. Once authenticated, they can upload an image of a fruit captured using a mobile phone or camera. This module ensures that the system remains user-friendly and accessible even to users with limited technical knowledge. The uploaded image serves as the primary input for the disease detection process.

2) Image Preprocessing Module

After the image is uploaded, it is passed to the image preprocessing module, where the input data is prepared for analysis by the deep learning model. Images collected from real environments may have different sizes, lighting conditions, and background noise, which can negatively affect the performance of the classification model. To overcome these issues, preprocessing operations are performed. The image is resized to a standard dimension of 224 × 224 pixels, which matches the input requirement of the MobileNetV2 neural network. In addition, pixel normalization is applied to scale image values to a suitable range, ensuring stable model predictions. This stage improves the quality and consistency of the data before it is analyzed by the machine learning model.

3) Feature Extraction using CNN (MobileNetV2)

The preprocessed image is then forwarded to the deep learning module, which uses a Convolutional Neural Network (CNN) architecture known as MobileNetV2. This model is responsible for automatically extracting meaningful visual features from the fruit image. CNN models are capable of learning hierarchical patterns such as edges, textures, shapes, and color variations that are often associated with disease symptoms. MobileNetV2 uses depthwise separable convolution layers and inverted residual blocks to reduce computational complexity while maintaining high feature extraction capability. Because it is a lightweight model, it can perform accurate predictions even on systems with limited processing resources.

4) Classification Layer

Once the important features are extracted by the CNN layers, they are passed to the classification layer of the neural network. This layer typically consists of a Global Average Pooling layer, optional Dropout layer to prevent overfitting, and a Dense output layer with a Softmax activation function. The Softmax function calculates probability scores for each disease category present in the dataset. Based on the highest probability value, the system determines which disease class the fruit image belongs to. This classification step converts the learned visual features into a meaningful prediction.

5) Disease Prediction and Output Module

The final stage of the block diagram is the Disease Prediction Output module. In this stage, the predicted disease class is displayed to the user through the web interface. The system provides the name of the detected disease along with basic advisory or recommendation information when available. This output helps farmers quickly understand the health condition of the fruit and take preventive or corrective actions. The entire process—from image upload to disease prediction—is designed to operate efficiently and provide results in real time, making the system practical for agricultural use.

Overall, the block diagram represents a structured workflow where user input is processed through preprocessing and deep learning modules to generate an accurate fruit disease prediction. This automated pipeline reduces the need for manual disease inspection and supports farmers in early detection and effective crop management.

VII. RESULT

The proposed Fruit Disease Detection System was implemented using a deep learning model integrated with a web-based interface to evaluate its performance in detecting diseases from fruit images. The system allows users to upload fruit images through a user-friendly interface, after which the trained convolutional neural network analyzes the image and predicts the corresponding disease category. The results demonstrate that the system can successfully identify different fruit diseases with high accuracy while maintaining low processing time. The following sequence explains the experimental results obtained from the implemented system.

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A. Image Upload and Detection Interface

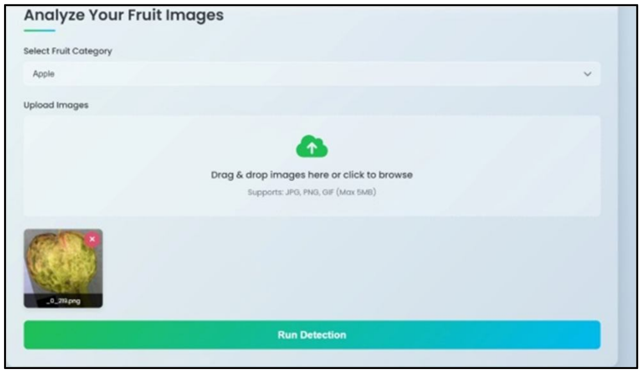

Fig 2: Detection Interface

The system provides an interactive interface where users can select the fruit category and upload an image for analysis. The interface supports drag-and-drop functionality and accepts common image formats such as JPG and PNG. Once the image is uploaded, the user initiates the detection process by clicking the Run Detection button. The system then processes the uploaded image and forwards it to the trained deep learning model for classification. This step ensures a smooth and user-friendly interaction between the user and the detection system.

B. Prediction and Confidence Visualization

After the image is processed by the model, the system generates prediction results along with a confidence score. The interface displays a confidence distribution bar, which visually represents the probability of the predicted class. High confidence levels (typically above 80%) indicate that the model strongly believes the image belongs to a particular disease category. This visualization helps users easily understand the reliability of the prediction.

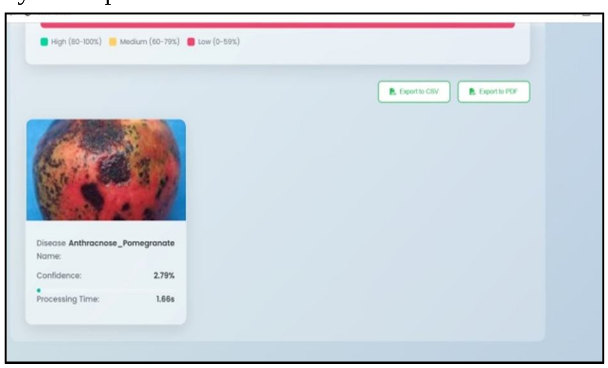

Fig 3: Prediction

C. Detection Result – Rotten Orange

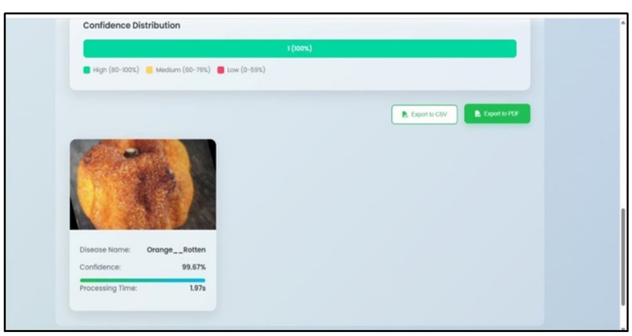

Fig 4: Analysed

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In one of the test cases, the system analyzed an image of an orange fruit showing visible signs of decay. The deep learning model classified the fruit as “Orange – Rotten” with a confidence score of 99.67%. The processing time for the prediction was approximately 1.97 seconds, indicating that the model can generate results quickly. The high confidence value demonstrates the model’s ability to correctly identify severe fruit diseases based on visible symptoms such as discoloration and texture changes.

D. Detection Result – Apple Blotch Disease

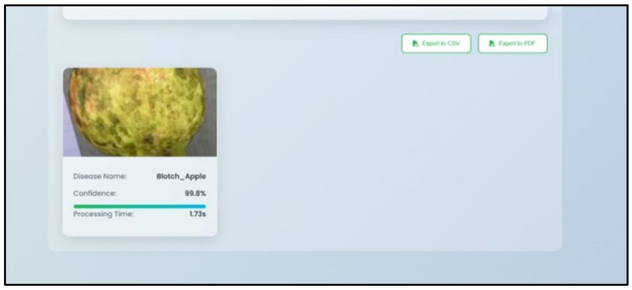

Fig 5: Identified the disease

Another experiment was conducted using an apple image containing irregular dark patches on its surface. The system correctly identified the disease as “Blotch – Apple” with a confidence score of 99.8% and a processing time of 1.73 seconds. The high prediction accuracy indicates that the convolutional neural network successfully extracted visual features such as color variations and spot patterns associated with the disease.

E. Detection Result – Pomegranate Anthracnose

The system was also tested using an image of a pomegranate affected by dark lesions and fungal infection symptoms. The model predicted the disease as “Anthracnose – Pomegranate.” The processing time for the prediction was approximately 1.66 seconds. Although the confidence score was lower compared to other test cases, the model was still able to detect the disease class, indicating that the system can recognize multiple fruit diseases across different fruit categories.

F. Performance Evaluation

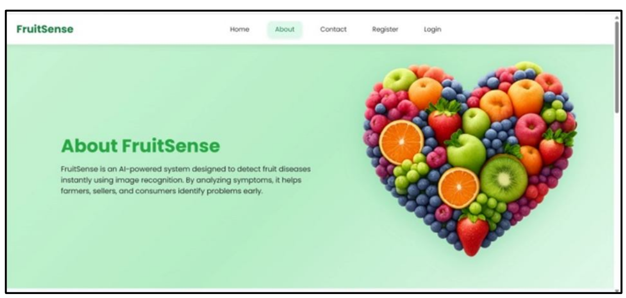

Fig 6: About page

The experimental results demonstrate that the proposed fruit disease detection system is capable of accurately identifying various fruit diseases using image analysis. The deep learning model achieves high prediction confidence for most test cases, while the processing time remains under two seconds for each image. These results confirm that the system is suitable for real-time applications and can assist farmers in quickly diagnosing fruit diseases.

G. Result Export Functionality

The system also includes an export feature that allows users to download the detection results in CSV or PDF format. This functionality helps users maintain records of disease analysis for further study or documentation. Such features enhance the practical usability of the system in agricultural monitoring and research environments. Overall, the experimental evaluation shows that the proposed system provides reliable disease detection with high accuracy and fast response time. The integration of deep learning with a web-based interface makes the system accessible and practical for real-world agricultural applications, enabling farmers and researchers to detect fruit diseases efficiently and take preventive measures at an early stage.

VIII. CONCLUSION

The Multi-Fruits Disease Detection System using Machine Learning provides an effective and intelligent solution for identifying fruit diseases automatically through image analysis. The proposed system utilizes a Convolutional Neural Network based on the MobileNetV2 architecture with transfer learning to accurately classify diseases present in fruit images. By combining image preprocessing, feature extraction, and deep learning classification techniques, the system is able to detect disease symptoms such as spots, discoloration, and texture variations on fruit surfaces. The integration of a web-based interface developed using the Flask framework allows users to easily upload fruit images and obtain disease predictions along with suggested remedies.

The developed system helps reduce the dependency on manual inspection and expert diagnosis, which are often time-consuming and not always accessible to farmers. By providing quick and reliable disease detection, the system enables farmers and agricultural professionals to take timely preventive actions, thereby minimizing crop damage and improving overall productivity. The proposed approach demonstrates how machine learning and deep learning technologies can be effectively applied in agriculture to support smart farming practices. Overall, the system contributes to improved crop health monitoring and represents a practical step toward the development of intelligent agricultural decision-support systems.

IX. FUTURE SCOPE

The proposed Multi-Fruits Disease Detection System using Machine Learning can be further improved by expanding the dataset to include a larger variety of fruits and more disease categories. Increasing the size and diversity of the training dataset will help improve the accuracy and reliability of the deep learning model. Future work can also focus on integrating advanced deep learning architectures and ensemble learning techniques to enhance classification performance. In addition, incorporating real-time image capture through mobile devices or IoT-based agricultural sensors can make the system more practical for farmers in field environments. This would allow users to capture fruit images directly from farms and receive instant disease diagnosis and treatment recommendations.

Another possible improvement is the development of a mobile application version of the system to increase accessibility and usability for farmers in rural areas. The system can also be enhanced by integrating additional features such as disease severity estimation, crop monitoring dashboards, and automated alerts for disease outbreaks. Furthermore, combining the system with precision agriculture technologies such as drones and remote sensing could enable large-scale crop monitoring and early disease detection. These advancements would help create a more comprehensive smart agriculture platform capable of supporting farmers in maintaining healthy crops and improving agricultural productivity.

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