A HEURISTIC APPROACHES TOWARDS CITRUS FRUIT AND LEAVES DISEASE DETECTION USING MACHINE LEARNING & ARTIFICIAL INTELLIGENCE TECHNIQUES

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Abstract: *Citrus fruit and foliage detection using deep learning techniques is an emerging frontier in agricultural technology. This article explores the application of deep learning models for automated recognition and analysis of citrus fruits and leaves in agricultural sector. The primary focus is on utilizing enhanced deep learning Convolutional Neural Networks (CNNs) model to accomplish tasks of object detection. The susceptibility of citrus plants to diseases underscores the importance of effective disease management strategies. Various pathogens, such as fungi, bacteria, and viruses, can infect citrus trees and their fruits. These pathogens can cause symptoms ranging from leaf spots and cankers to more severe issues like fruit rot and tree decline. Early identification of ailments in citrus plants aids in thwarting their spread within orchards, thereby reducing financial setbacks for farmers. The dataset contains images of citrus fruits and leaves depicting both healthy specimens and plants afflicted with diseases such as Black spot, Canker, Scab, Greening, and Melanoses. . In this study, we employed deep learning models including CNN, EfficientNet, VGG16, and ResNet. The primary focus was on developing a CNN model tailored to distinguish between healthy citrus fruits and leaves and those affected by prevalent diseases such as black spot, canker, scab, greening, and melanoses. According to the experimental results, the CNN Model excels in a variety of evaluation metrics compared to its competitors. Boasting a training accuracy of 99.66 and test accuracy of 84.40 percent, the CNN Model is an invaluable decision support resource for farmers diagnosing citrus fruit/leaf diseases.*

Keywords: CNN, VGG16, ResNet, EfficientNet, Deep Learning, Object Detection

I INTRODUCTION

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Citrus fruits, which include a variety of well-known types such as oranges, lemons, limes, grapefruits, and tangerines, are globally beloved for their invigorating flavours and health benefits. However, the cultivation of citrus trees encounters substantial difficulties due to a range of diseases affecting both the fruits and leaves. These diseases can lead to significant agricultural losses, impacting both small-scale farmers and large commercial enterprises. Citrus canker, caused by the bacterium Xanthomonas citrus, is one of the most widespread and destructive diseases. It appears as lesions on the leaves, stems, and fruits, characterized by an oily, water-soaked look with a distinctive yellow halo. The disease not only affects the aesthetic and commercial value of the fruit but also induces premature fruit drop, causing yield losses. Another major threat is Huanglongbing (HLB), or citrus greening, caused by the bacterium Candidatus Liberibacter, which is carried by the Asian citrus psyllid. HLB symptoms include the yellowing of leaves, which imitates zinc deficiency, along with the production of malformed, bitter fruits. Infected trees suffer from stunted growth and eventually die, making HLB one of the most damaging citrus diseases with no known treatment. The management and control of these citrus diseases necessitate a multifaceted strategy that encompasses good agricultural practices, chemical treatments, biological control, and regulatory measures. Sanitation measures, such as the regular removal and destruction of infected plant material, are essential to prevent the spread of pathogens. Chemical control, involving the application of fungicides and bactericides, acts as a preventive or curative measure against various diseases. The use of disease-resistant citrus varieties, when available, provides a sustainable solution to mitigate the impact of certain pathogens. Biological control methods, utilizing natural predators or antagonists to target disease vectors and pathogens, are gaining popularity as environmentally friendly alternatives. Cultural practices, including proper irrigation, fertilization, and pruning, help maintain tree health and reduce stress, making the trees less vulnerable to infections. Despite these efforts, the fight against citrus diseases continues, with ongoing research directed at developing more effective management strategies and disease-resistant cultivars. The resilience of the citrus industry hinges on integrating advanced scientific research with practical agricultural techniques. This comprehensive approach not only improves disease management but also ensures the sustainability and profitability of citrus cultivation. The global citrus community, made up of researchers, farmers, and industry stakeholders, must collaborate to tackle the challenges posed by citrus diseases, ensuring the continued production of high-quality citrus fruits for consumers worldwide.

Farmers and agronomists visually examine plants for symptoms such as spots, lesions, discoloration, and deformities by gathering samples of leaves, fruits, and stems for further scrutiny. Microscopic methods, such as Light Microscopy, are useful for studying the structure of pathogens in plant tissues. Furthermore, Electron Microscopy offers detailed images of pathogens at a cellular level. These approaches are crucial for accurately identifying citrus diseases, facilitating early intervention and effective management techniques to reduce their impact on citrus crops. Computer vision technologies utilize sophisticated algorithms to analyze images of plants and automatically detect disease symptoms. This approach involves capturing images of citrus fruits and leaves and processing them to identify patterns and anomalies indicative of diseases. Deep learning models, particularly convolutional neural networks (CNNs), are trained on extensive datasets containing images of both diseased and healthy plants. These models learn to distinguish between different types of diseases with high accuracy. By integrating these advanced algorithms into mobile applications, farmers can leverage the power of their smartphone cameras and artificial intelligence to diagnose plant diseases in real-time, directly in the field. This empowers farmers with immediate, actionable insights, helping them to take timely measures to manage and mitigate the spread of diseases.

II RELATED WORK

Caserta et al[1]. indicate significant progress in the development of disease-resistant citrus varieties using biotechnological methods, which promise to enhance the sustainability and productivity of citrus cultivation. The authors explore various biotechnological approaches, including Genetic Engineering, RNA Interference (RNAi) AND CRISPR/Cas9 for precise genome editing to introduce disease resistance traits. Ashok Kumar et al[2]. revolves around the various methodologies and technological advancements used in the detection and classification of diseases affecting citrus leaves. The paper provides a comprehensive survey of the existing techniques and approaches, emphasizing the importance of early and accurate disease identification to ensure effective management and treatment. Liujun Li et al [3] focuses on innovative techniques for identifying citrus diseases using advanced machine learning and neural network methods and emphasis on the effectiveness of the proposed models in terms of accuracy, robustness, and computational efficiency compared to existing methods. Narayani et al[4]. is centred around evaluating and comparing different methodologies for detecting and classifying diseases in fruits. Ramanathan Lakshmanan et al [5] explained the use of machine learning techniques for the predictive analysis of citrus diseases based on visual symptoms is to provide a comprehensive review of how machine learning techniques can be effectively utilized for symptom-based predictive analysis in citrus orchards, highlighting the potential to enhance disease detection and management practices in agriculture.

III METHODOLOGY

The main goal of employing deep learning to predict citrus fruit and leaf diseases is to create a precise, efficient, and scalable system capable of identifying and diagnosing different diseases in citrus crops. This system aims to improve early detection, enable timely intervention, reduce crop losses, and enhance yield quality. In order to guarantee accessibility for farmers in the field, the model is tailored for real-time deployment across a variety of platforms. The goal of combining this technology with already-available agricultural technologies to offer a comprehensive monitoring system. The solution also provides farmers with actionable insights to help them choose efficient treatments and management techniques.

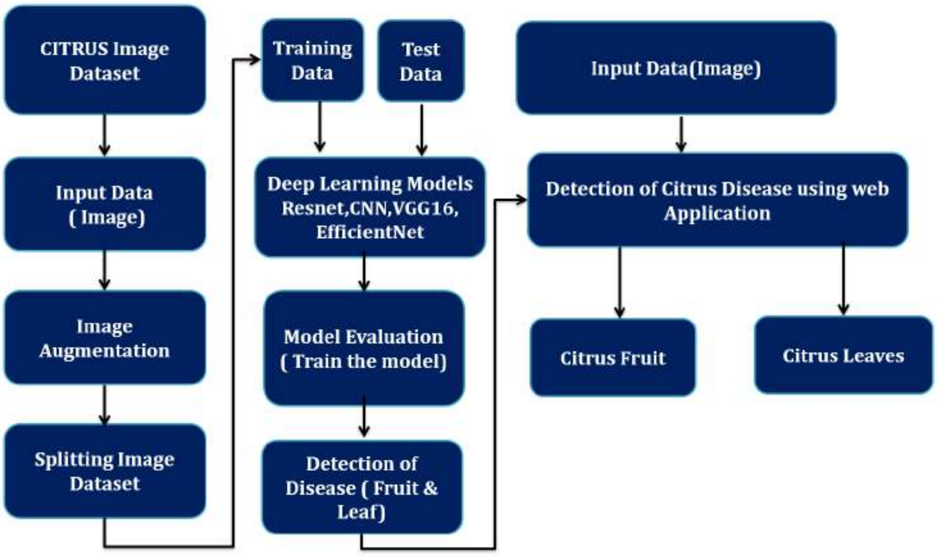

Figure 1: Architecture of Citrus Fruit and Leaves detection

The process begins with the collection of standard images. Next, data pre-processing is conducted as an essential initial step to enhance the quality of the fruit and leaf images. Following this, image segmentation is performed to facilitate easier analysis and interpretation while preserving image quality. For model implementation, deep learning techniques such as CNN, EfficientNet, VGG16, and ResNet are employed. The proposed algorithm is then evaluated using various performance metrics. Finally, the system classifies and detects diseases in citrus fruits and leaves. The overall process can be shown as

Data Collection: This is the initial phase where high-resolution images of citrus fruits and leaves are collected. These images serve as the foundational data required to train and test the deep learning models.
Data Preprocessing: In this step, the collected images undergo preprocessing, which includes standardizing sizes, normalizing pixel values, and potentially enhancing image quality. Ensures the dataset is clean, consistent, and suitable for further processing and model training.
Image Augmentation: This involves applying various transformations to the images, such as rotation, flipping, scaling, and colour adjustments. Augmentation increases the diversity of the dataset, helping the model become more robust and generalize better to new, unseen images.
Image Segmentation: Segmentation involves dividing the images into meaningful parts, often isolating the areas that show symptoms of disease. Helps the model focus on the relevant parts of the images, improving its ability to detect and classify diseases accurately.
Feature Selection and Extraction: This step involves identifying and extracting the most relevant features from the pre-processed and augmented images. Reduces the complexity of the dataset and highlights the features that are most indicative of specific diseases, improving model performance.

Deep Learning Algorithms (CNN, ResNet, VGG16, EfficientNet): These are the core algorithms used to train the models. They include various types of Convolutional Neural Networks (CNNs), such as ResNet, VGG16, and EfficientNet. These models learn to recognize patterns and features associated with different diseases from the training data.
Data (Train/Test Split): The dataset is split into training and test sets. The training set is used to train the model, while the test set is used to evaluate its performance, ensuring it can generalize well to new data.
Model Deployment: Once trained, the model is deployed for real-world use. Enables the practical application of the trained model for disease detection in citrus fruits and leaves.
Model Evaluation: The model is evaluated on the test data to assess its accuracy, precision, recall, and overall performance. Ensures the model is reliable and performs well before it is deployed.
Citrus Fruit and Leaves Prediction: The final output of the system, where the deployed model is used to predict diseases in new images of citrus fruits and leaves. Provides users, such as farmers and agricultural experts, with accurate disease diagnoses to take appropriate actions.

Thus, the system for detecting diseases in citrus fruits and leaves incorporates high-resolution image collection. It utilizes advanced deep learning models, especially Convolutional Neural Networks (CNNs), which are trained on a diverse dataset to accurately identify diseases. A mobile application with real-time processing capabilities allows farmers to capture images and receive immediate diagnoses, supported by edge computing for low-latency performance. Additionally, a centralized monitoring platform offers a comprehensive dashboard to track disease prevalence and analyze trends. Continuous learning mechanisms enable the models to improve over time through user feedback and new data. This comprehensive approach aims to enhance disease management, resulting in healthier crops and increased agricultural productivity.

IV EXPERIMENTAL RESULTS

The experiment to detect the citrus fruit and leaves carried out on high computing machine with 32GB of RAM , 2.8Ghz processor and 4GB graphics. The python programming is used along with the flamework flask to create the web application. Many of the python packages such as NumPy, pandas, matplotlib, seaborn , scikit-learn , pillow , keras , TensorFlow, computer vision-based packages are used. The computer vision functions such as threshold, erode and dilate are used to crop the images. The dataset of Citrus is collected from the different resources and the data has categorised as Citrus leaves with classes Black Spot Leaves, Canker Leaves, Greening Leaves, Healthy Leaves and Melanose Leaves. The citrus fruit classes are Black spot Fruit, Canker Fruit, Greening Fruit, healthy Fruit and Scab Fruit. The dataset is divided into training data with 1115 images and test data size being 1091images. The dimensions are batch size =32, image height =256, image width=256 are used . The image data displayed in the visualization in figure 2.

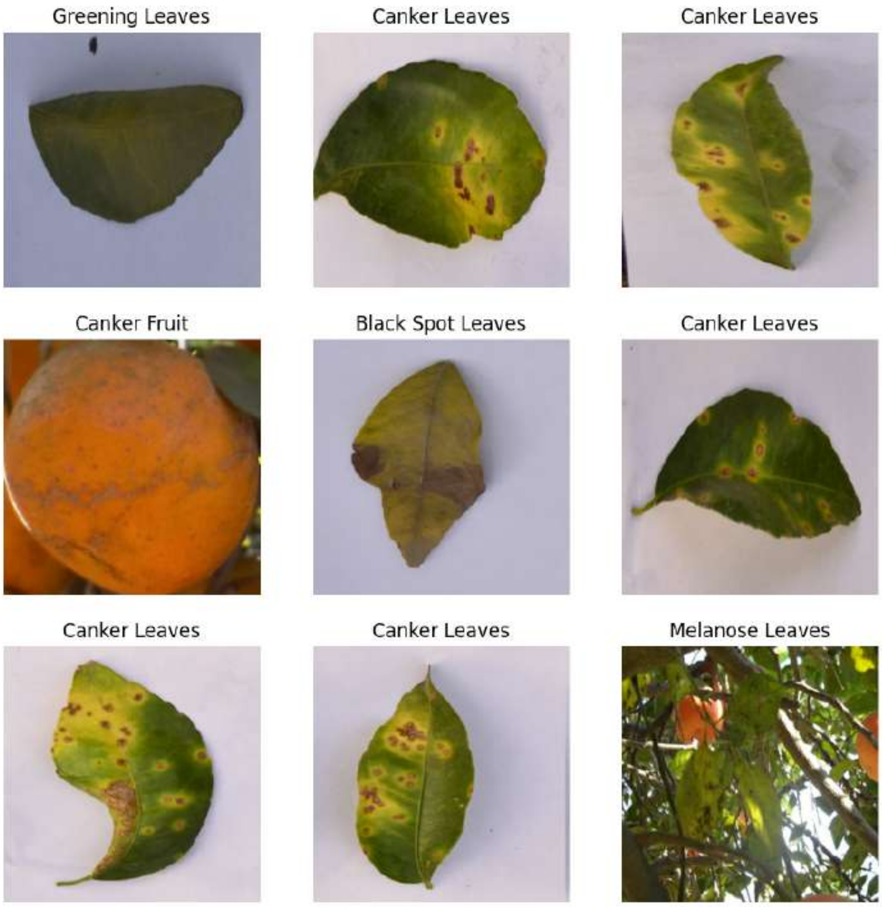

Figure 2: Samples of Dataset

The denomination of the training dataset can be seen in figure 3 and the testing dataset can be seen in figure 4. The Neural Network model using CNN has developed. The summary of parameters can be shown as in figure5 as follows. The total number of epochs are 10 are used to train the model.

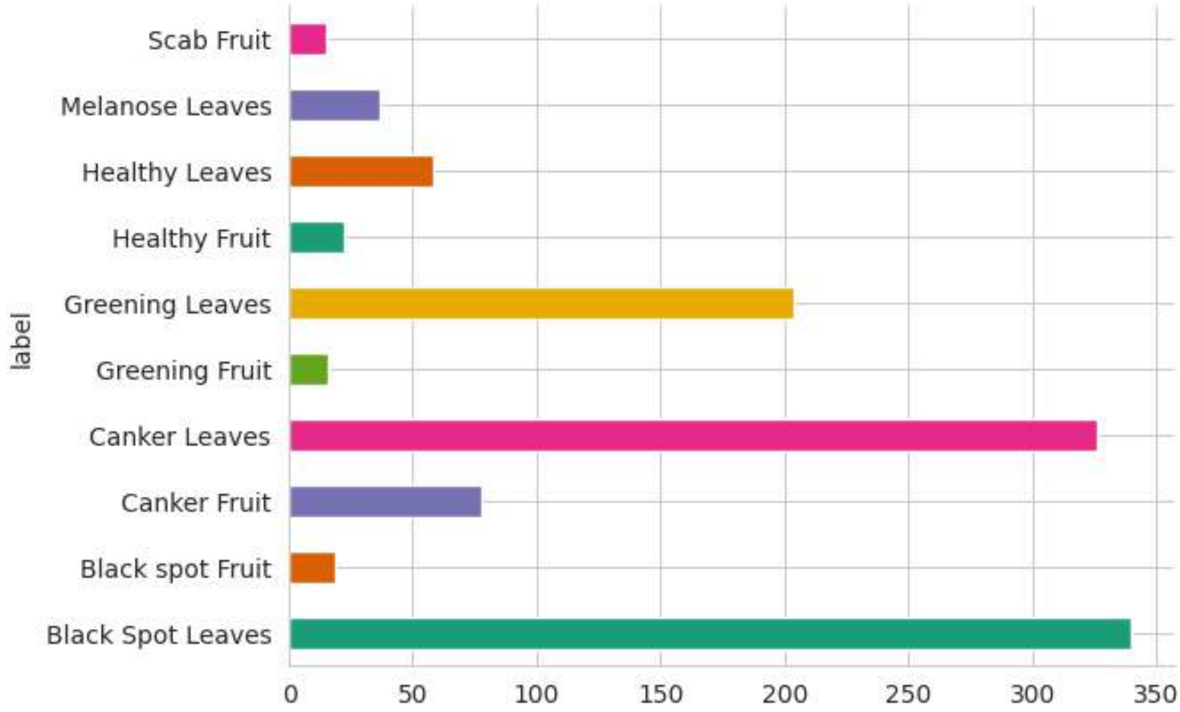

Figure 3: Training dataset

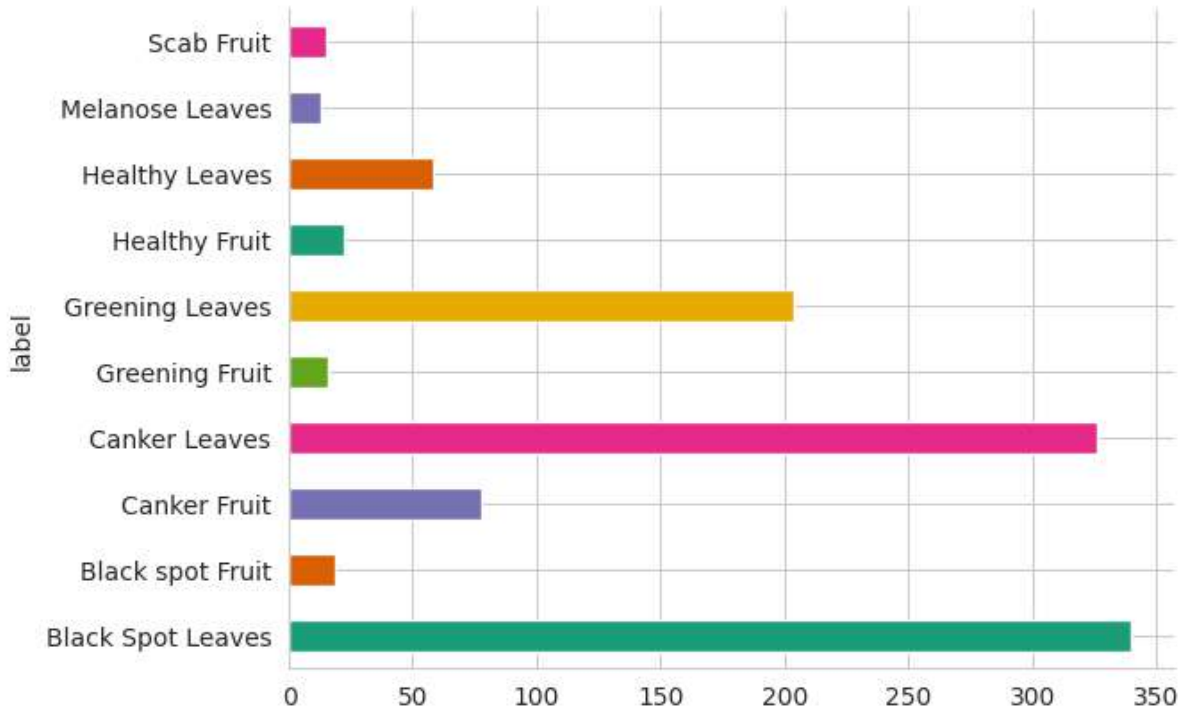

Figure 4: Testing dataset

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_1 (Rescaling)     (None, 256, 256, 3)       0

 conv2d (Conv2D)             (None, 256, 256, 16)      448

 max_pooling2d (MaxPooling2  (None, 128, 128, 16)      0
 D)

 conv2d_1 (Conv2D)           (None, 128, 128, 32)      4640

 max_pooling2d_1 (MaxPoolin  (None, 64, 64, 32)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 64, 64, 64)        18496

 max_pooling2d_2 (MaxPoolin  (None, 32, 32, 64)        0
 g2D)

 flatten (Flatten)           (None, 65536)             0

 dense (Dense)               (None, 128)               8388736

 dense_1 (Dense)             (None, 10)                1290

=================================================================
Total params: 8413610 (32.10 MB)
Trainable params: 8413610 (32.10 MB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 5 : Summary of CNN Neural network Model

Data augmentation techniques are performed using random flip (Horizontal and vertical) , Radiomutation and Random zoom functions. The compilation of the model is done through the Adam's optimizer, the loss function as sparse_categorical_crossentropy and accuracy of the model has calculated. Finally, model is saved using .h5 module and it can be used in the web application. The comparison table of the models are shown here in figure 6.

Sl No	**Model**	**Training Accuracy**	**Test Accuracy**
1	**CNN (Improved & Enhanced)**	**99.66%**	**84.40%**
2	VGG16	88.50%	93.26%
3	ResNet	52.84%	53.22%
4	EfficientNet	94.53%	83.98%

Table 1: Comparison table of Deep Learning Algorithm

The web Application is created using python flask framework to demonstrate the experimental outcomes of citrus fruit and leaves detection. The results can be shown in the below figures 6, 7 & 8.

Figure 6: Detection of Canker Fruit

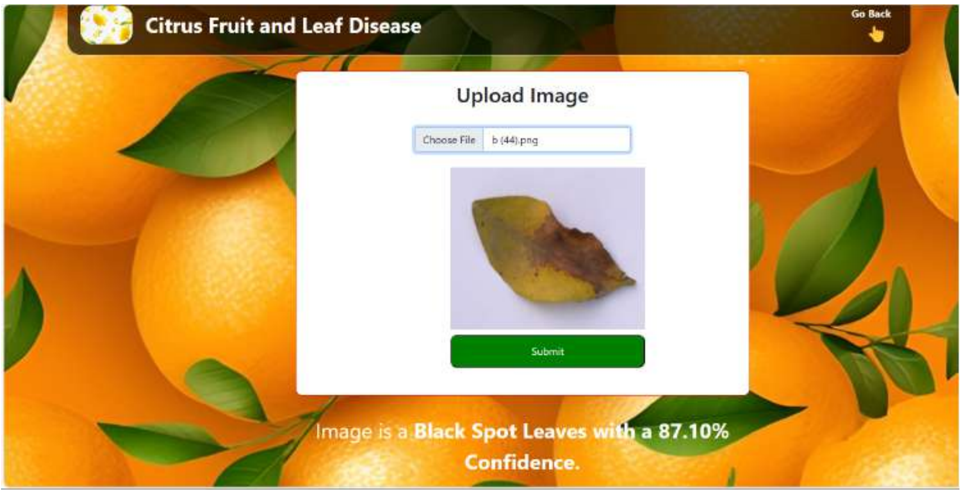

Figure 7: Black Spot Leaves detection

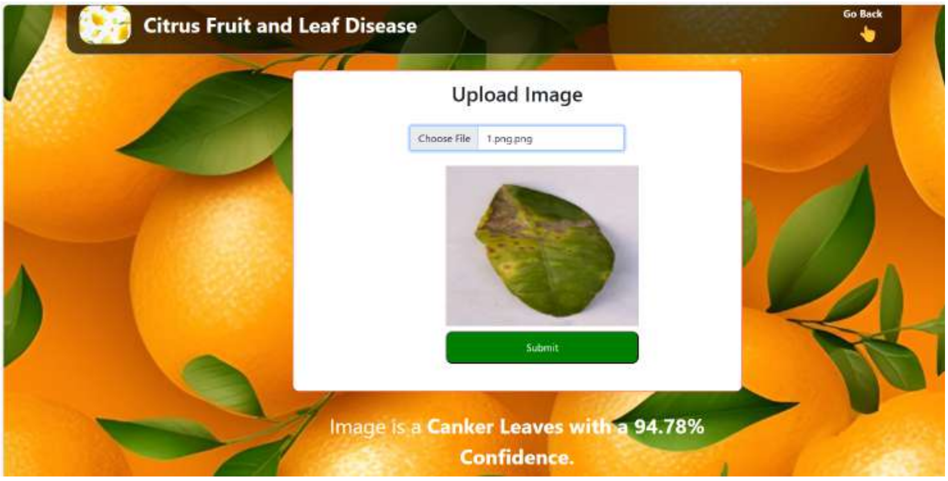

Figure 8: Canker Leaves Detection

CONCLUSIONS

Using deep learning models such as CNN, VGG16, ResNet, and EfficientNet for predicting diseases in citrus fruits and leaves has yielded promising results. These models effectively classify various citrus diseases like canker, greening, and scab, and differentiate healthy fruit and leaves. By harnessing the power of convolutional neural networks, these models can learn complex patterns and features from images, allowing them to make accurate predictions. CNN acts as a foundational architecture, offering a robust baseline for image classification tasks. VGG16, with its deeper structure, captures more intricate features, while ResNet's residual connections enable the training of even deeper networks, addressing the vanishing gradient problem. EfficientNet, by balancing depth, width, and resolution, delivers superior performance with fewer parameters, making it ideal for resource-limited environments.

FUTURE ENHANCEMENT

By adapting the learnt features to the unique characteristics of citrus illnesses, performance can be improved by fine-tuning pre-trained models such as VGG16, ResNet, or EfficientNet on datasets particular to citrus. By utilizing various architectures and learning representations, ensemble methods—which merge predictions from many models—can further improve prediction accuracy and robustness. Furthermore, when data relevant to citrus is scarce, incorporating transfer learning strategies from related domains like plant pathology or agricultural imagery might enhance model performance.

REFERENCES

[1]. R. Casertaa, N.S. Teixeira-Silva a, L.M. Granatoa, S.O. Dortaa, C.M. Rodriguesa, L.K. Mitrea,b, J.T.H. Yochikawaa, E.R. Fischera, C.A. Nascimentoa,b, R.R. Souza-Netoa,b, M.A. Takitaa, R.L. Boscariol-Camargoa, M.A. Machadoa, A.A. De Souzaa, "Citrus biotechnology: What has been done to improve disease resistance in such an important crop?", Biotechnology Research and Innovation (2020) **3,** 95---109, 2020.

[2]. Ashok Kumar Sainia, Roheet Bhatnagarb, Devesh Kumar Srivastavac, "Detection and Classification Techniques of Citrus Leaves Diseases: A Survey", Turkish Journal of Computer and Mathematics Education, Vol.12 No.6 (2021), 3499-3510,2021.

[3]. Ruoli Yang, Tingjing Liao, Peirui Zhao1 , Wenhua Zhou, Mingfang He1 and Liujun Li, "Identification of citrus diseases based on AMSR and MF-RANet", Plant Methods, Yang et al. Plant Methods, 2022.

[4]. Sathya Priya. G , Narayani. V, "A Comparative Analysis of Fruit Disease Detection and Classification" International Journal of Research Publication and Reviews, Vol 3, no 5, pp 112-116, May 2022.

[5]. P Dinesh, Ramanathan Lakshmanan, "Symptoms Based Image Predictive Analysis for Citrus Orchards Using Machine Learning Techniques: A Review", International Journal on Recent and Innovation Trends in Computing and Communication, ISSN: 2321-8169 Volume: 11 Issue: 8, 2023.

[6]. Williams, H.A.; Jones, M.H.; Nejati, M.; Seabright, M.J.; Bell, J.; Penhall, N.D.; Barnett, J.J.; Duke, M.D.; Scarfe, A.J.; Ahn, H.S.; et al. Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms. Biosyst. Eng. 2019, 181, 140–156.

[7]. Santos, T.T.; de Souza, L.L.; dos Santos, A.A.; Avila, S. Grape detection, segmentation, and tracking using deep neural networks and three-dimensional association. Comput. Electron. Agric. 2020, 170, 105247.

[8]. Monzurul Islam, Anh Dinh, Khan Wahid, Pankaj Bhowmik "Detection of Potato Diseases Using Image Segmentation and Multiclass Support Vector Machine", IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE),2017.

[9]. Vijai Singh A.K. Misra, \"Detection of plant leaf diseases using image segmentation and soft computing techniques\", Information Processing In Agriculture 4 (2017) 41–49, Elsevier, 2017.

[10]. Sharada Prasanna Mohanty, David Hughes and Marcel Salathé, \" Using Deep Learning for Image-Based Plant Disease Detection, \"April 15, 2016.

[11]. Noa Schor, Avital Bechar, Timea Ignat, Aviv Dombrovsky, Yigal Elad, and Sigal Berman, \"Robotic Disease Detection in Greenhouses: Combined Detection of Powdery Mildew and Tomato Spotted Wilt Virus\", IEEE Robotics And Automation Letters, Vol. 1, No. 1, January 2016.

[12]. Lucas G. Nachtigall and Ricardo M. Araujo, "Classification of Apple Tree Disorders Using Convolutional Neural Networks", IEEE 28th International Conference on Tools with Artificial Intelligence, 2016.

[13]. Santanu Phadik are and Jaya Sill, "Rice Disease Identification using Pattern Recognition", Proceedings of 11th International Conference on Computer and Information Technology,2008.