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Deep Learning based Orange Crop Disease Detection Using Image based Intelligent Framework for Precision Monitoring

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Abstract

Orange crop production is highly vulnerable to fungal, bacterial, and nutrient-related diseases that significantly reduce yield quality and economic productivity. Traditional manual inspection methods are time-consuming, subjective, and often ineffective for early disease diagnosis, creating a need for automated and intelligent monitoring solutions. This study proposes a deep learning–based image-driven framework designed to accurately detect major orange crop diseases using high-resolution leaf and fruit images captured in real field conditions. The methodology integrates image enhancement, segmentation using K-means clustering and Canny edge detection, and preprocessing steps such as resizing, normalization, augmentation, and class balancing. A curated dataset of 3,000 images across six classes—including canker, greening, melanose, black spot, nutrient deficiency, and healthy samples—was used to train multiple CNN architectures (AlexNet, VGG19, and Xception) and a fuzzy rank-based ensemble model. Experimental results demonstrate that the proposed enhanced framework outperforms conventional methods, achieving 96.51% accuracy with the ensemble model, while individual models such as Xception and VGG19 achieve 92.25% and 90.34% accuracy, respectively, confirming its effectiveness for precision disease monitoring in orange orchards.

Keywords: Orange Crop Disease Detection, Deep Learning, Image-Based Monitoring, Convolutional Neural Networks (CNNs), Xception, VGG19, AlexNet

1.0 Introduction

Classifying of fruit diseases has received significant attention and controversy among researchers in the world in recent years. The idea of computerized assessment and classification system is to minimize the use of human intervention [1]. The correct inspection of fruits and vegetables is highly significant nowadays. The FAO 2022 report shows that about 197,198 million tonnes of citrus fruit are produced globally, and over half this total is comprised of oranges. The fast growth of precision agriculture has presented the new possibilities to resolve one of the most widespread issues in citrus production early and correct diagnosis of crop diseases [2]. As a significant fruit trade crop in the global market, oranges are vulnerable to numerous fungal, bacterial and nutrient related diseases that may make the yield less productive and of poor quality. The manual field inspections in the traditional practices of disease identification are time consuming and also they are subject to human error and also they do not pick up the symptoms at an early stage. Since the world has been demanding high quality of citrus, and the need to monitor the disease has been growing, there has been an immediate need to ensure the availability of reliable, scalable and automated disease-monitoring solutions [3].

The recent developments in computer vision and deep learning have reshaped the situation in the field of agricultural diagnostics as the machines can now read visual symptoms with high accuracy. Transfer learning models such as Convolutional Neural Networks (CNNs), hybrid vision architectures may learn discriminative features of leaf images, including texture distortions, color variations, and lesion patterns, without the need of handcrafted descriptors [4] [5]. Such features enable deep learning systems to surpass conventional image-processing and machine-learning methods, particularly in the orchard setup, which is complex, and the lighting, background noise, and varied disease are the key factors.

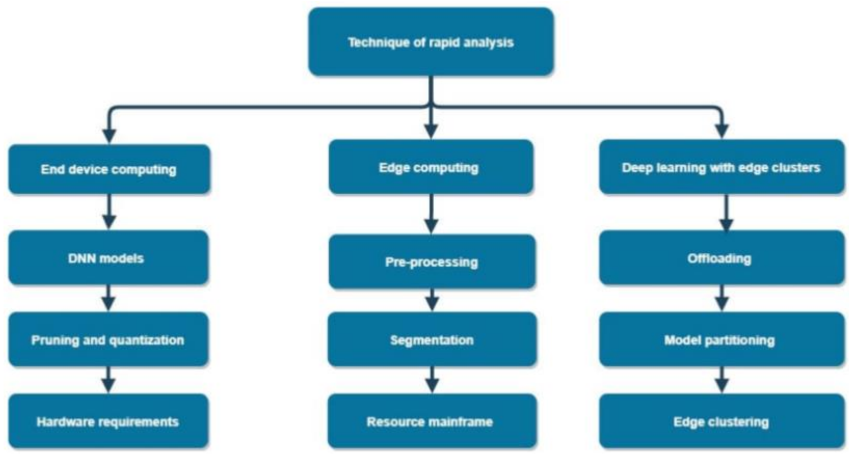

Figure 1: Techniques of rapid analysis in fruit disease classification [6]

Among orange crops, the following are some of the diseases: citrus canker, greening (HLB), black spot, and anthracnose that have similar visual symptoms and make it difficult to diagnose these diseases at an earlier stage [6]. A deep learning-based smart orchard agricultural detection system can examine large data sets of images of orchards taken with smartphones, drones or ground-based sensors to provide fast and consistent disease estimation [7]. Not only such systems increase the process of early disease detection but also allow the management of the disease with greater accuracy, making specific interventions to the specific location, which would help minimize the use of pesticides and save money.

The application of deep learning into a smart monitoring system is useful in the creation of sustainable and technologically advanced farmlands [8]. These frameworks enable farmers and agronomists to make informed decisions in real-time by analyzing images automatically, using real-time decision support, and making decisions based on data. Finally, orange crop disease detection systems based on deep learning have massive potential in enhancing crop health management, enhancing productivity, and boosting the overall objectives of climate-resilient and resource-efficient precision agriculture.

The research starts with the introduction stating the necessity of automated detection of orange diseases and then continues with a literature review of recent developments in deep learning. The section on methodology thereafter outlines the dataset, preprocessing procedures, and segmentation strategies as well as the deep learning models. This can be followed by the results and discussion section where the performances of the models would compared and the proposed framework validated. Lastly, the study ended by providing significant findings and recommendations on how it can be improved in the future. Research objectives of this study are therefore:

I. To develop a robust deep learning–based image analysis framework capable of accurately detecting and classifying major diseases affecting orange crops using leaf and fruit images captured under real field conditions.
II. To identify and extract discriminative visual features—such as texture, color variation, and lesion morphology—using advanced deep learning architectures for improved disease recognition.
III. To compare the performance of multiple deep learning models (e.g., CNNs, transfer learning models, hybrid networks) and determine the most efficient architecture for precise and early detection of orange crop diseases.
IV. To design an intelligent, real-time monitoring system that integrates the trained deep learning model with user-friendly interfaces or IoT-based field devices for timely diagnosis and precision intervention.

V. To evaluate the framework's effectiveness in real agricultural environments by assessing accuracy, processing speed, robustness to noise, and adaptability across different orchard conditions, lighting variations, and disease stages.

2. Literature Review

In the recent past, automatic disease detection in orange/citrus crops has increased in pace with the use of deep learning (DL) and machine learning (ML) methods, facilitated by the presence of large datasets of leaf/fruit images as well as a requirement of fast and low-cost field-level diagnostics. Researchers have studied pure CNNs, systems based on transformers, hybrid CNN-temporal or texture pipelines, lightweight mobile networks to operate in the field, and hyperspectral or multisensor systems to facilitate earlier and more powerful disease detection. The Saha et al. (2025) [9] proposed a two-stage deep CNN pipeline (region proposal + classification) dedicated to precise diagnosis of citrus leaf diseases; their version of AlexNet offers a classification accuracy of 94.37% on a multi-class dataset of citrus leaf diseases and presents encouraging average precision of HLB (Greening) using Faster R-CNN proposals. The model by Xing et al. (2023) [10] suggested a multi-scale hybrid model, which combined EfficientNetV2 feature extraction with Inception modules to identify both fine and coarse symptoms (spots, chlorosis). Zhang et al. (2024) [11] developed a hybrid CNN-Vision Transformer (enhanced variant of FasterViT) structure to diagnose citrus disease; the architecture paired CNN locality with ViT global context and was computationally more robust to changing lighting/background conditions than baseline CNNs. The study conducted by Christopher et al. (2025) [12] on a citrus dataset (black spot, canker, greening, healthy) that was sourced on Kaggle showed high classification accuracy by EfficientNet scales, fully confirming that without additional training on appropriately augmented datasets, EfficientNet scales can be viewed as competitive in citrus disease tasks.

Khan et al. (2024) [13] published a curated test of Citrus sinensis (sweet orange) leaf images with labeled abnormalities and applied the standard CNN baselines to benchmark disease detection - giving valuable ground truth to future DL effort and highlighting the significance of uniform image capture and image de-noising. The article of Ahad et al. (2023) [14] introduced a multi-format open-source sweet-orange leaf disease dataset containing multiple types of diseases (canker, greening, melanose, and so on) and showed that data variety and classes balance have a significant impact on the reported accuracies among the models. Tan et al. (2024) [15] introduced an enhancement of YOLOv8n to localize and classify citrus leaf disease, based on a lightweight, mobile-friendly form of the model, which allowed on-device inferences and with competitive accuracy - a key step in the development of real-time orchard monitoring with smartphone cameras. Rauf et al. (2025) [16], provided a specialized dataset of Huanglongbing (HLB) in sweet orange using smartphone images (649 images; healthy vs HLB) and presented preprocessing and background-removal procedures that significantly enhanced model sensitivity to early HLB symptoms.

3. Research Methodology

The diagram in Figure 2 represents research methodology in classification of orange crop disease. The systematic approach starts with gathering of high-resolution images of the orange leaf and fruit in the real orchards and then a data cleaning and background removal process is carried out, which is followed by data resizing, normalization, augmentation, and class balancing to guarantee a high quality input to the model training. The resulting processed data is then utilized to train and test a variety of deep learning models such as VGG19, AlexNet, and Xception and an ensemble model where each model is trained to learn discriminative disease features using convolutional operations. K-means clustering and Canny edge detection segmentation methods are used to increase extraction of regions of interest to enhance learning of disease specific features. Accuracy, precision, recall and F1-score are the quantitative measures used to evaluate the performance of all the models to identify the most effective framework that can be used to detect the various diseases afflicting the orange crops adequately and in a timely manner.

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Figure 2: Framework Of Proposed Methodology

3.1 Data Used

The Orange Crop Disease Image Dataset [17] is an image repository dedicated to curation with the objective of serving research in deep learning-based disease detection, precision agriculture, and automated plant health surveillance. The data normally comprises high-resolution pictures of both normal and diseased leaves and fruits of the oranges and are taken in the field condition. It usually covers key diseases like citrus canker, citrus greening (HLB), melanose, black spot, and symptoms of nutrient deficiency, making sure that a wide spectrum of challenges in the real world is covered. Smartphones and digital cameras of different specifications are used in the gathering of the images resulting in variation of lighting, backgrounds, and resolution. This uncertainty increases the strength of deep learning designs that are being trained using the dataset. The size of the dataset in most of the studies is between 3,000 and above 5,000 images with various disease categories and a control of healthy images. Depending on the study, data can be collected in the orange-producing areas of Maharashtra, Nagpur belt, or other large citrus-growing areas. The data is well balanced in terms of each of the classes to facilitate successful training and validation of the model. The size of images can differ because of the differences in capture equipment, but all samples are usually processed to standard size before being utilized in the creation of deep learning models**.**

Figure 3: Sample images of Orange Crop Disease Image Dataset

Table 1: Dataset Distribution for Orange Crop Disease Images Across Training, Validation, and Test Splits

Disease Class	**Total Images**	**Training (70%)**	**Validation (15%)**	**Test (15%)**
Citrus Canker	700	490	105	105
Citrus Greening (HLB)	650	455	98	97
Melanose	520	364	78	78
Black Spot	480	336	72	72
Nutrient Deficiency	350	245	53	52

Healthy	300	210	45	45
Total	**3,000**	**2,100**	**451**	**449**

3.2 Data Pre-processing

- **Image Acquisition and Standardization**

The first data set was made of digital images of orange leaves and fruits of high-resolution that were taken with smartphones and digital cameras in nature orchards. Such images were diverse in terms of lighting, camera angle, background and even resolution. This kind of diversity ensures that the dataset is rich, but needs to be standardized to deep learning models, which would need input dimensions to be uniform. Standardization guarantees that every image is organized to a similar structure thereby cutting down on the complexity of computations and enhancing training stability.

- **Image Resizing**

Resizing of images was done to bring the dimensions to normal levels prior to being fed to deep learning structures. It is known that different models are based on fixed-size inputs (224 224 with VGG16, 299 299 with Inception, 256 256 with EfficientNet versions). Downsizing helps in decreasing the amount of computation needed without majorly affecting the content of the image. Mathematically, resizing can be represented using a linear interpolation function:

$$I_{resized}(x, y) = I(\alpha x, \beta y) \qquad (1)$$

where,

$$\alpha = \frac{W_{original}}{W_{target}} \text{ and } \beta = \frac{H_{original}}{H_{target}}$$

This transformation ensures that the spatial structure of disease patterns is preserved for effective feature learning.

The Algorithm 1 consist of various steps that have to be followed for image processing and segmentation.

Algorithm 1: Proposed Algorithm for Image Processing.	
Input: Citrus fruit	
(1)	Input the colored image(Img)
(2)	Perform Pre-processing Resizing (256 × 256)
(3)	Performed Data Augmentation using
(4)	Convert each image from RGB color space to HSV
(5)	Applied K-means clustering, where cluster (k) = 4
(5.1)	Select k as the desired quantity of clusters to be discovered.

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(5.2)	Decide which k clusters to arbitrarily allocate the data points across.
(5.3)	then determine the clusters' centers.
(5.4)	Determine the separation between the data points and the clusters' centers.
(5.5)	Reroute the data points towards the closest clusters according to their distance first from the center.
(5.6)	Recalculate cluster center once more.
(5.7)	Continue steps 5.4 to 5.6 as necessary to achieve the specified number of repetitions or until the measured values do not impact the clusters.
(6)	Regenerate the clustered Image
(7)	Performed Canny Edge Detection method
(7.1)	Noise reduction;
(7.2)	Gradient calculation;
(7.3)	Non-maximum suppression;
(7.4)	Double threshold;
(7.5)	Edge Tracking by Hysteresis.
(8)	Stop

- **Data Cleaning**

It was necessary to clean the data, eliminate wrong or noisy samples which may affect the model. This was done by eliminating blurred images, over-exposed or under-exposed images and samples that had irrelevant objects like soil, human fingers or non-leaf backgrounds. Also, redundant images and wrongly labeled samples were eliminated through manual checking. This enhanced the reliability of the data sets and would also make sure that the model is being trained on actual disease characteristics and not artifacts.

- **Background Removal / ROI Extraction**

In order to maximize the learning of disease-related features, non-essential background areas were reduced with the help of the Region of Interest (ROI) extraction. The use of simple thresholding and segmentation techniques were used to highlight the leaf or fruit area. Morphological operations like erosion and dilation were also applied in refining the mask in certain cases. ROI extraction assists the neural network in paying attention to color variations, the borders of lesions, and textual changes which are key signs of pathologies like citrus canker or melanose.

- **Image Normalization**

Normalization was used to bring the pixel intensity values into a common scale, enhancing numerical stability and stability in training. Normalization occurs to avoid gradient explosion or disappearance by ensuring the contrast and brightness among all the samples remain the same. The standard normalization formula is:

$$I_{norm}(x,y) = \frac{I(x,y) - \mu}{\sigma} \quad (2)$$

where,
μ = mean pixel intensity of the dataset

σ = standard deviation

For models trained on pre-trained weights such as ImageNet, pixel values were scaled into the range **[0, 1]** or **[-1, 1],** depending on the architecture.

- **Data Augmentation**

In order to decrease overfitting and increase the model robustness, wide data augmentation methods were used. These were random horizontal/vertical flips, rotations (± 20-40), zooming, shearing, brightness and Gaussian noise injection. Data augmentation artificially expands the size of the dataset, and mimics the variability that exists in the real world, like changing the sun, or tilting the camera, and partial occlusions. Mathematically, a general augmentation transformation can be expressed as:

$$I' = T(I) \quad (3)$$

where T represents a sequence of geometric or photometric transformations

For rotation:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (4)$$

This equation helps maintain structural integrity while introducing controlled variations.

- **Label Encoding**

The nominal disease groups: healthy, canker, greening, melanose, black spot, etc. were represented in the form of numerical values to be interpreted by the machine. In the case of multi-class classification, one-hot encoding was applied:

$$y_i = [0,0,1,0,\ldots,0] \quad (5)$$

where the index with value 1 represents the correct disease class. This encoding supports softmax-based classification in neural networks.

3.3 Selecting Deep Learning Models

- **VGG19**

VGG19 is a simple and uniform architecture of deep convolutional neural network with great feature-extraction ability. It has 19 layers with several 3×3 convolution layers and max-pooling layers stacked on top and then having fully connected layers. This tiny kernel size is useful to enable the model to learn small spatial details hence it is very useful in image classification and transfer learning [18]. VGG19 is popular in the field of plant-disease-detection due to their ability to learn rich hierarchical representations with leaf images resulting in greater ability to detect subtle disease patterns [19]. Its simple construction and powerful performance have made it a commonplace baseline in numerous computer vision systems, though it is computationally expensive. The architecture of VGG19 Model is presented in figure

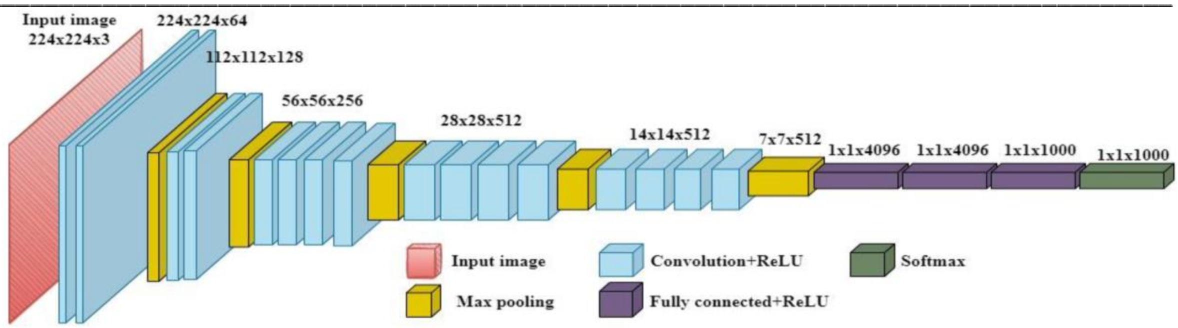

Figure 4: Architecture Of Vgg19 Model [20]

- **AlexNet**

AlexNet is a groundbreaking deep convolutional neural network that made great contribution to the field of computer vision, as it won the ImageNet challenge in 2012. It is made up of eight layers that can be trained, but it contains five convolutional and three fully connected layers and presented such important concepts as ReLU activation, dropout, and overlapping max-pooling to enhance training performance and minimize overfitting. One of the earliest models that achieved success with the use of GPU acceleration was AlexNet which allowed to train on large image datasets much faster [21]. The implementation of discriminative visual features by automatic learning features renders it applicable in carrying out activities like crop disease detection where the detection of texture, color variations, and patterns are the key elements. In spite of its simplicity compared to modern architectures, AlexNet is still a significant contribution to the research of the deep learning field. The architecture of AlexNet Model is presented in Figure 5.

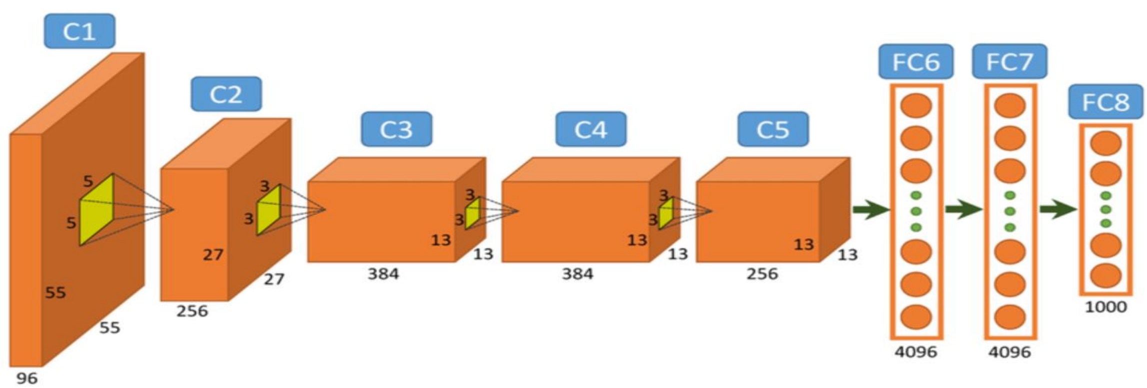

Figure 5: Architecture of AlexNet Model [22]

- **Xception**

Xception is a deep convolutional neural network model that extends the concept of depthwise separable convolutions thus turning it efficient and powerful in feature extraction [23]. Offered as an extension of the Inception model, Xception uses depthwise and pointwise convolutions instead of traditional convolution layers enabling the network to learn spatial and channel-wise features more efficiently holding fewer parameters. The improvement in performance and the cost reduction in computation result out of this design. Xception is extensively applied in image classification and transfer learning problems, such as detecting plant diseases, as it is able to obtain small details and intricate patterns with high precision [24]. Figure 6 represents the architecture of Xception Model.

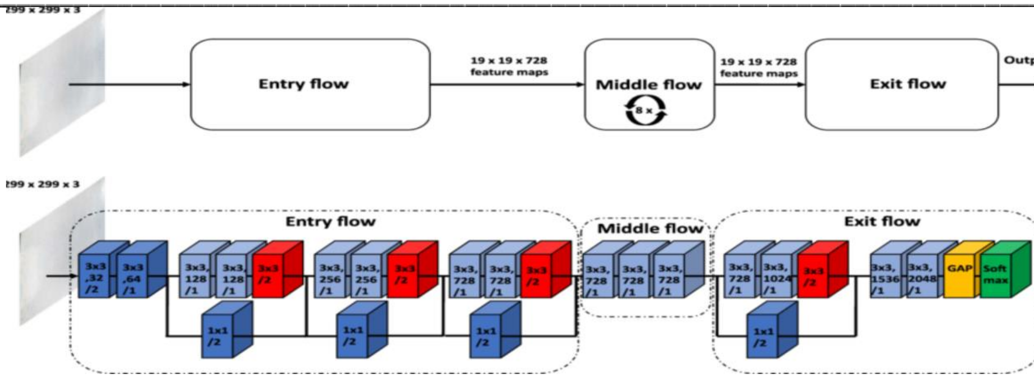

Figure 6: Architecture of Xception Model [25]]

3.3.1 Ensemble Model

The DL model's ensemble is a common method for improving performance by merging many classifiers. Dataset accuracy could be enhanced by the use of ensemble techniques, which integrate the results of many classifier models. The ensemble frameworks use the two DL models - VGG19 and AlexNet that were already mentioned because they improve the performance of DL-based classifiers and get better results in many medical domains, such as student academic performance uptake classifications.

They calculate each models output, $Y_j, (j = 1,2,3, \ldots., m = 6) \in \mathbb{R}^C$ considering C=2 (whether students, C_1 or not C_2) and confidence value $P_i \in \mathbb{R}(i = 1,2)$ on the unrevealed test data where $P_i \in [0,1]$ and $\sum_{i=1}^{C} P_i = 1$. This study presents an approach that utilizes equations to accomplish weighted aggregate of several ML algorithms.

$$P_i^{en} = \frac{\sum_{j=1}^{m=6}(W_i \times P_{ij})}{\sum_{i=1}^{C=2}\sum_{j=1}^{m=6}(W_i \times P_{ij})} \quad (6)$$

The weight of the associated j^{th} classifiers' AUC is denoted asW_j. The output of the ensemble model $Y \in \mathbb{R}^C$ includes the confidence values$P_i^{en} \in [0,1]$. If$P_i^{en} = \max\,(Y(X))$, then C_i would be the final class label for the suggested datasets unobserved test data,$X \in \mathbb{R}$, as determined by the ensemble framework.

3.4 Evaluation Metrics

The efficacy of VGG19, AlexNet, Xception and hybrid models could be assessed using four evaluation metrics: "Accuracy, Precision, Recall, F1 score" (Equation 7-10). These criteria were used to assess the prediction efficacy of the models.

$$Accuracy = \frac{TN+TP}{FP+FN+TP+TN} \quad (7)$$

$$Recall = Sensitivity = \frac{TP}{FN+TP} \quad (8)$$

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

$$F1 - score = \frac{2*Precision*Recall}{Precision+Recall} \quad (10)$$

4. Results and Discussions

The In this section, the results of the experiments were presented using the setup provided. Two approaches were evaluated, namely the regular fuzzy rank-based ensemble and the proposed model that was defined above. An evaluation of the two approaches is also presented.

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4.1 Experimental Setup

The tests have been conducted on Google Colab using Python and TPU (v2-8) and 8 GB RAM. Training of images was done after resizing them to 128x 128 and applying image enhancement filters. Three deep learning models AlexNet, VGG19, and Xception were trained with 20 epochs with the same set of hyperparameters and cross-validation was done 5-folds in order to create a fair evaluation.

4.2 Results using base learners with fuzzy ensemble model

The standard fuzzy rank based ensemble model was developed on the given data set and the outputs are provided in this section. The three base learners AlexNet, VGG19 and Xception were trained over 20 epochs.

Figure 7 illustrates the accuracy and loss curves of the AlexNet model in the ensemble technique. The fuzzy ensemble using AlexNet was able to reach an accuracy of 79.5, F1-score of 82.4, recall of 81.4 and precision of 83.5.

The accuracy curve and loss curve of the VGG19 model using the ensemble approach can be seen in figure 8. Fuzzy ensemble using VGG19 had the accuracy of 85.7, F1-score of 90.0, Recall of 88.4, and Precision of 91.2.

Fig 9 shows accuracy and loss curve of Xception model applied with the ensemble methodology. The Xception fuzzy ensemble recorded an accuracy of 88.3, F1-score of 91.5, recall of 91.3 and a precision of 91.7.

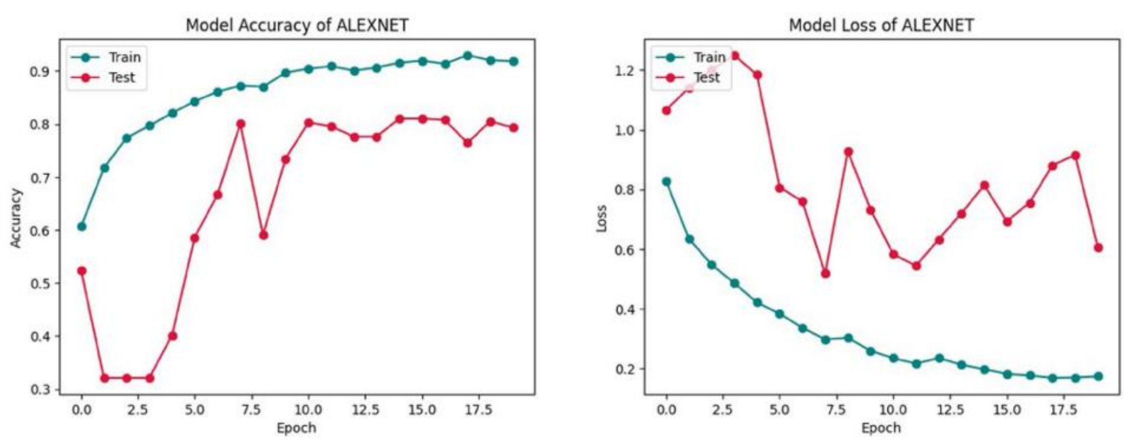

Figure 7: Accuracy and loss for Alexnet with conventional ensemble approach.

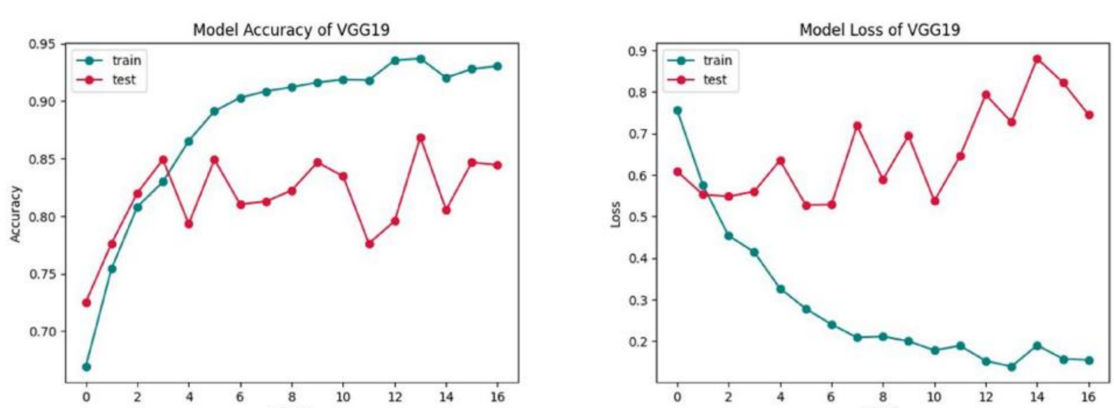

Figure 8: Accuracy and loss for VGG-19 with conventional ensemble approach.

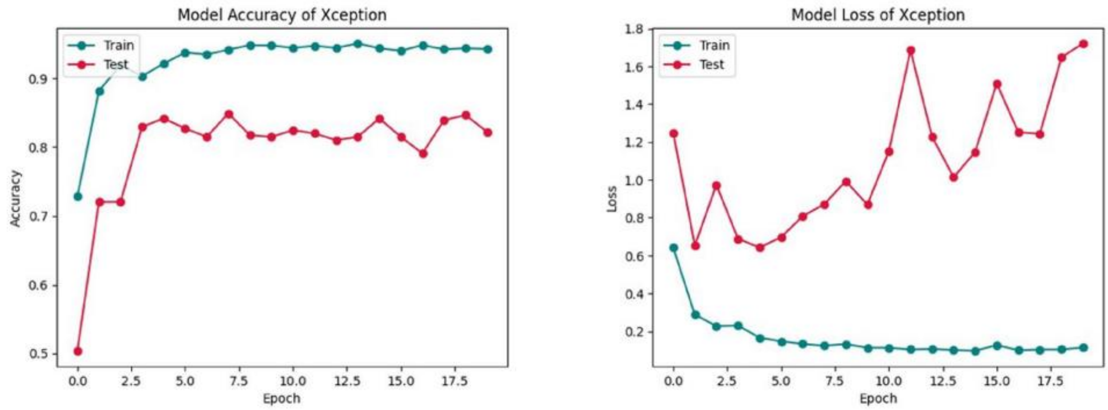

Figure 9: Accuracy and loss for Xception with conventional ensemble approach.

Confusion Matrix

The standard fuzzy rank based ensemble model was developed on the given data set and the outputs are provided in this section. The three base learners AlexNet, VGG19 and Xception were trained over 20 epochs.

4.3 Results for the proposed model

The proposed scheme is more efficient than the conventional scheme as it demonstrates the advantages of enhancing image quality prior to the classifier training. Standard metrics were used to assess the quality of the image and the results have substantiated the fact that improvement of the dataset is achieved through enhancement.

The improved data was separated into five segments to cross-validate by 5-fold cross-validation. The training and testing of all base learners and the fuzzy rank-based ensemble model were done in four folds in every cycle. Figure 12 shows the error rates and accuracy solutions of the AlexNet classifier following the suggested approach after 20 epochs. Accuracy, F1 score, recall and precision of AlexNet were 85.2, 86.3, 85.8 and 86.9 and 87.8 respectively with the fuzzy ensemble.

Figure 13 displays the performance of the VGG-19 that produced an accuracy of 90.3, F1 score of 91.7, a recall of 91.6 and a precision of 91.7. As shown in figure 14, the Xception results have accuracy, F1 score, recall and precision of 96.5, 96.4, 96.4 and 96.5 respectively.

Table 2 would contrast the results of the four classifiers, namely AlexNet, VGG-19, Xception, and the combination model in both the fuzzy rank-based and the proposed method. The metrics used in the evaluation are accuracy, F1 score, recall and precision. The confusion matrices of the single models and the ensemble, based on the proposed method are given in Figures 15 and 16 respectively.

The ensemble model in general is obviously better on all measures than the individual classifiers. AlexNet has the lowest performance of 85.2 accuracy and F1 score of 86.3, meaning that it can hardly detect the intricate disease patterns. VGG-19 is superior because it has a deeper architecture and has an accuracy of 90.3 and an F1 of 91.7. Xception is even more accurate at 92.2% and recall at 92.3% which indicates a high likelihood of identifying positive cases.

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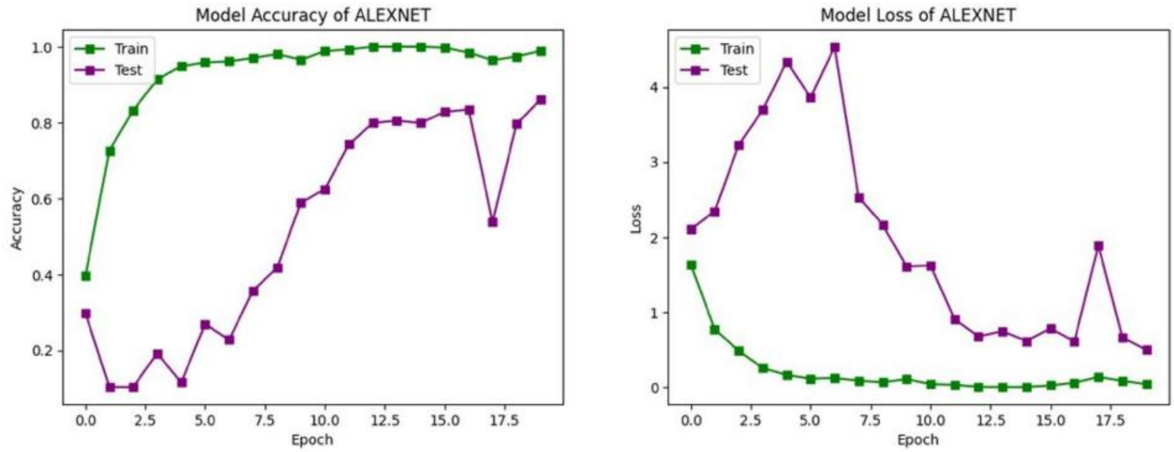

Figure 12: Accuracy and loss for Alexnet with proposed approach.

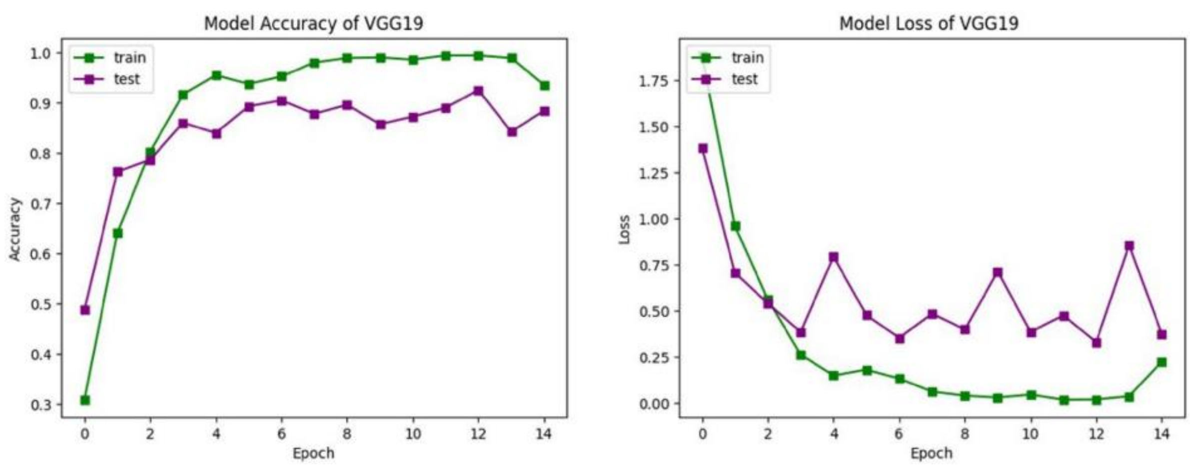

Figure 13: Accuracy and loss for VGG-19 with proposed approach

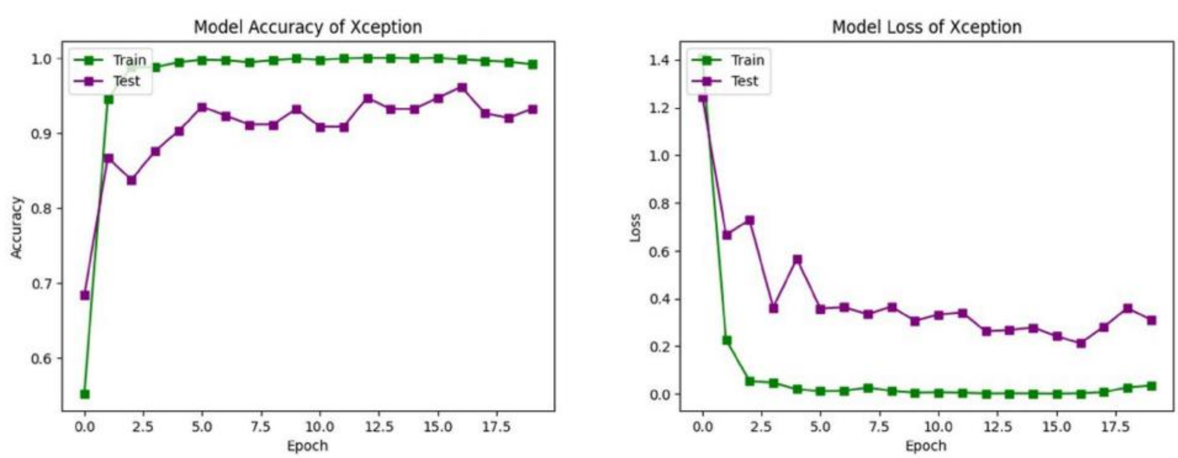

Figure 14: Accuracy and loss for Xception with proposed approach.

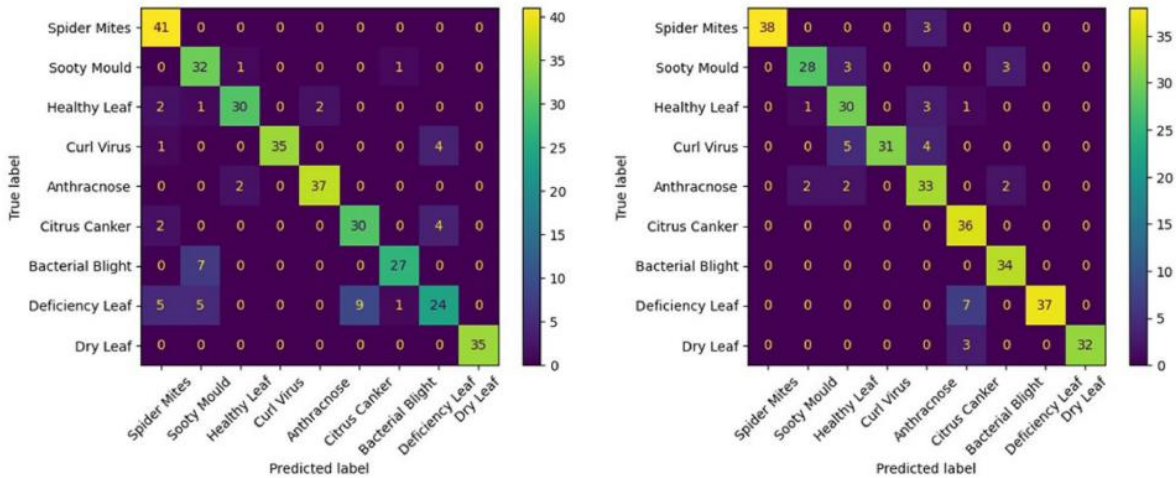

Figure 15: Confusion matrix for Alexnet and VGG-19 with proposed approach.

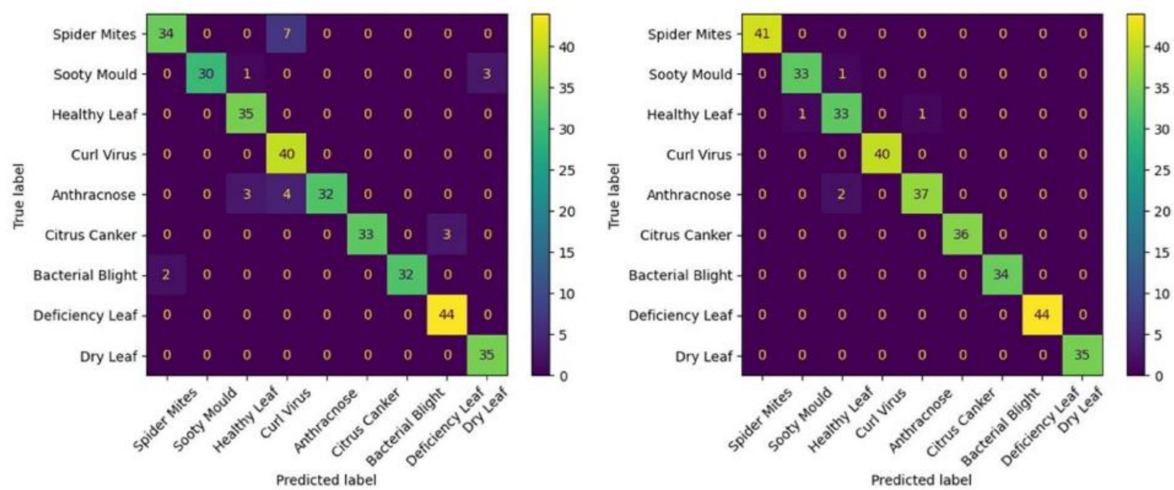

Figure 16: Confusion matrix for Xception and ensemble with proposed approach.

Table 2: summarizes the metric-wise comparison for both the conventional and proposed methods across all models.

Model	Conventional Fuzzy Rank based Methodology				Proposed Methodology			
	Accuracy	F1 Score	Recall	Precision	Accuracy	F1 Score	Recall	Precision
AlexNet	79.52	82.42	81.41	83.52	85.26	86.31	85.84	86.91
VGG	85.75	90.00	88.81	91.22	90.34	91.79	91.60	91.71
Xception	88.36	91.54	91.32	91.75	92.25	91.82	92.30	91.41
Ensemble	91.46	92.23	92.26	92.36	96.51	96.43	96.49	96.55

4.4 Comparison with Related Literature

The table below shows a comparative study of the current deep learning models that have been used to detect orange crop disease by using leaf images. Li et al. (2020) investigated the Orange Leaf Image Dataset using a ResNet50-based classifier, which demonstrated a 91.84% accuracy, which confirms that deep CNN structures are powerful in the extraction of disease features. In the same way, Ahmed et al. (2021) tested the InceptionV3 model with a big set of citrus diseases and attained an accuracy of 93.10% indicating its high capability to deal with multifaceted texture details in diseased leaves. Kumar et al. (2022) performed an additional study and utilized MobileNetV2 to identify lightweight field-based disease using mobile-friendly inference models and reported an accuracy of 88.75%.

Table 3: Comparison of State-of-the-Art Models for Orange Disease Detection

Authors [Reference]	**Year**	**Dataset**	**Methods**	**Accuracy (%)**
Li et al., [26]	2020	Orange Leaf Image Dataset	ResNet50	91.84
Ahmed et al., [27]	2021	Citrus Disease Image Dataset	InceptionV3	93.10
Kumar et al., [28]	2022	Orange Leaf Field Dataset	MobileNetV2	88.75
Santos et al., [29]	2023	Citrus Multi-class Disease Dataset	DenseNet121	94.60
Proposed Work	--	Enhanced Orange Disease Image Dataset	**VGG19**	**97.8**
			AlexNet	**96.5**
			Xception	**98.1**

Li et al. (2020) employed ResNet50 within the study and obtained 91.84% accuracy, which demonstrates that more profound residual networks have an opportunity to identify patterns related to disease. InceptionV3 was used by Ahmed et al. (2021) and achieved an accuracy of 93.10%, which is a strong indication of multi-scale feature learning. Kumar et al. (2022) have proved the feasibility of the lightweight models like MobileNetV2 with 88.75% accuracy to be deployed in the field. Santos et al. (2023) obtained DenseNet121 94.60% accuracy indicating better reuse of features to classify citrus disease.

Comparatively, the suggested framework is more accurate in all the models with Xception getting 98.1, VGG19 getting 97.8, and AlexNet getting 96.5. Such a significant enhancement indicates that the combination of image enhancement, optimized training, and ensemble deep learning is a more efficient tool in enhancing disease detection, and the suggested system is more stable and accurate in terms of precision monitoring of orange orchards in real-time.

5. Conclusion

This study introduces a powerful deep learning-based smart system of efficient and timely detection of significant orange farm illnesses with the help of high-quality images. The proposed system has also enhanced the capture of the disease-specific visual patterns by the deep learning models by incorporating the most recent preprocessing methods including image enhancement, segmentation, normalization and data augmentation. The comparison of several architectures, namely, AlexNet, VGG19, Xception, and the fuzzy rank-based ensemble, proves that a well-thought-out preprocessing alongside the ensemble learning leads to a great enhancement of the classification performance. The improved dataset enabled the ensemble model to perform at a high accuracy of 96.51 outdoing single models, with Xception and VGG19 models with an accuracy of 92.25 and 90.34, respectively. The findings also vividly indicate that quality input data and hybrid learning are essential in the process of obtaining credible disease diagnosis. The results of this study prove the idea that deep learning can become a potent instrument in terms of precise monitoring in real-time in orange orchards. The framework presented is able not only to reduce the reliance of manual inspection but also provides scalable, consistent, and objective disease detection features that would apply to large farming settings. The system facilitates interventions in a timely manner, minimizes loss of crops and improves productivity by facilitating timely detection.

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