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Research Article

Assessing Dragon Fruit Pulp Health Through Machine Learning and Deep Learning

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ABSTRACT

Dragon fruit is having high nutritional value and health benefits and it is increasingly popular worldwide. This fruit is rich in antioxidants, minerals, and vitamins, supports immunity, digestion, and skin health. Dragon fruit, though nutritionally beneficial, is susceptible to various diseases that affect its yield and quality. In India, around 2-5% of dragon fruit farmers have reported the fruit defect which causing a formation of white structure within a dragon fruit pulp, leading to concerns over fruit health and market value. The formation of white structure can be termed as "meshy" pulp formation in the fruit.

This research focuses on detecting the meshy structure within dragon fruit pulp, which indicates poor fruit health. 120 fruits were sampled, cut, and imaged to create a dataset for analysis. To classify pulp health based on image data, a hybrid approach is developed with deep learning and machine learning techniques. Specifically, we utilized feature extraction layers from two deep learning models-Inception and ResNet. These models, known for their accuracy in image feature detection and gives intricate details in the pulp texture. The extracted features from the Inception and ResNet models were integrated with a machine learning-based classification layer to identify meshy versus non-meshy pulp.

This hybrid model provides an effective solution for detecting presence of the meshy structure from images, facilitating a quick and reliable health assessment of the fruit. This research offers a valuable solution for the dragon fruit processing industry by enabling automated identification of pulp health, ultimately enhancing product standards and reducing the need for manual inspection.

Keywords: Dragon Fruit, Deep learning, Machine learning, Image processing, Fruit pulp, Food Processing.

1. Introduction

Cultivation of dragon fruit is expanding globally, with major production areas in countries like Vietnam, Thailand, and Malaysia. India has also emerged as a significant producer, particularly in states like Maharashtra, Gujarat, Karnataka, and Andhra Pradesh. As Indian farmers increasingly recognize the economic potential of this fruit, its cultivation has grown rapidly, driven by both domestic demand and export potential. Dragon fruit pulp is increasingly popular in various food and health products because of its rich nutritional profile and vibrant, visually appealing colour. The pulp, which contains vitamins, minerals, antioxidants, and dietary fibre, makes it ideal for a wide range of applications. One of the most common uses is in beverages like smoothies, juices, and fruit blends. These drinks benefit from the dragon fruit's natural sweetness, adding a healthful twist to traditional fruit beverages. In dairy products, dragon fruit pulp is often incorporated into yogurts, ice creams, and frozen desserts, offering both flavour and colour. The pulp's mild sweetness and unique texture make it a desirable ingredient, appealing to consumers who wants natural flavours and nutritious additions to their diets. In baking, dragon fruit is used to add natural colour and a subtle flavour to cakes, pastries, and even bread, providing a visual appeal without artificial additives [1].

The wellness industry also takes advantage of dragon fruit pulp, which is often dried and turned into powder. This form is easy to incorporate into smoothies, teas, or supplement blends, allowing consumers to enjoy its nutritional benefits in a concentrated form. Furthermore, health-conscious food manufacturers sometimes incorporate dragon fruit pulp into snack bars and granola, where it complements other fruit and nut ingredients for a healthful snack. The pulp's high antioxidant content and digestive health benefits make it a favoured choice in functional foods aimed at boosting wellness. Overall, dragon fruit pulp is a versatile ingredient in various sectors, offering both visual and health benefits. Its inclusion in products enhances nutritional value while also catering to consumer demand for natural, colourful, and nutrient-rich foods and supplements.

Dragon fruit, though nutritionally beneficial, is susceptible to various diseases that affect its yield and quality. Some common diseases include *Anthracnose*, caused by *Colletotrichum* species, which results in dark spots and rotting on the fruit; *Stem Canker*, often linked to fungal pathogens, affecting the plant's stems and reducing fruit production; and *Bipolaris Cactus Rot*, a disease that leads to decay, especially in humid climates. Additionally, *Neoscytalidium Dimidiatum* infection causes blight and dieback, further impacting dragon fruit cultivation and market quality [1].

In India 2-5% farmers observed one defect which cause white mesh structure formation in dragon fruits, this white meshy structure forms when seeds cluster in one area rather than being evenly distributed throughout the pulp as shown in Fig 1. This clustering appears as a fibrous white network, altering the fruit's appearance, texture, and overall appeal. also this affect the taste, it results in reducing the smoothness, sweetness and it may lower nutritional content as well. Fruits with this defect are less desirable for consumers, as the texture and flavour are compromised, making them unsuitable for both fresh consumption and for processed products.

(a) (b)

Fig 1. (a) Non Meshy (Healthy) fruit (b) Meshy (Diseased) fruit

The objective of this research is to develop an efficient solution for dragon fruit processing industries, enabling accurate and automated assessment of fruit pulp quality. Typically, fruits are sliced open to use the pulp and peel in products, making it necessary to identify any internal defects, such as the meshy structure indicative of poor fruit health. Manual inspection of pulp quality can be labour-intensive and inconsistent, especially when done on a large scale [2]. By implementing image processing techniques, industries can automate the detection of such defects. This approach could streamline quality control, reduce labour costs, and improve the consistency of fruit processing operations by providing a fast and reliable method to ensure that only high-quality fruit pulp enters production lines.

The introduction outlines the importance of dragon fruit and the challenges associated with pulp defects, emphasizing the need for advanced detection techniques. Following this, the literature review examines existing studies, highlighting methodologies and advancements that provide context and inspiration for the research presented in this paper.

Patil et al. (2021) explored the use of machine learning algorithms like CNN, ANN, and SVM for dragon fruit grading and sorting, focusing on fruit quality detection using various features. They utilized a Raspberry Pi board and depth camera for hardware, while internet images served as the dataset. The future goal was to develop a real-time grading system for dragon fruits [3]. Kulkarni et al. (2022) introduced a method for detecting dragon fruit diseases and ripeness using R-CNN, which involved image processing to extract features related to color, shape, and defects. However, their dataset lacked sufficient labeled samples. They aimed to create a more diverse and accurate dataset for improved classification and ripeness detection [4].Wismadi et al. (2019) developed a VGG-Net-Like deep learning network for detecting dragon fruit ripeness, suggesting future real-time detection systems [5]. Lado et al. (2021) compared neural networks and random forest classifiers for dragon fruit disease classification, emphasizing the need for more diverse datasets [6]. Nguyen et al. proposed a CNN-based system achieving over 96% accuracy in classifying dragon fruit by external features, enhancing labor efficiency [7]. Vijayakumar et al. employed ResNet 152 for ripeness assessment of dragon fruit, achieving AUROC of 1.0, outperforming other methods [8]. Dong et al. integrated FCM and 2D OTSU algorithms for disease segmentation, achieving high accuracy for detecting diseases in dragon fruits [9]. Hakim et al. (2021) used SVM and k-NN for detecting diseases in dragon fruits stem, reaching 87.5% accuracy [10]. Prasetyo et al. (2018) combined neural networks with MATLAB image processing for ripeness detection of red dragon fruit, achieving 100% accuracy for ripe fruit and proposing mobile adaptation [11]. Shakil et al. (2023) explored feature selection and machine learning, with Random Forest and AdaBoost performing best for disease detection of dragon fruit [12]. Yusamrun et al. (2023) introduced DIP-CBML for Thai dragon fruit species classification, showing potential in robotic harvesting [13]. Maltare et al., (2023) explored the rainfall pattern and groundwater level and predicted a rise in the groundwater level using SARIMA, multi-variable regression, ridge regression, and KNN regression [21]

2. Materials and Methods

2.1 Proposed Methodology

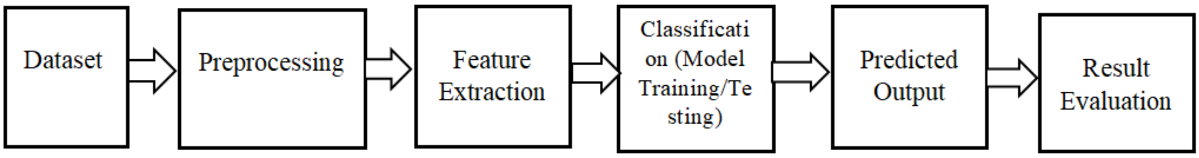

Fig 2. Bock Diagram of Proposed Methodology

2.1.1 **Dataset**: The dataset for this study was collected in month of August 2023 at ICAR-National Institute of Abiotic Stress Management, Malegaon Khurd, Maharashtra, India. A total of 120 dragon fruits were selected, consisting of 60 healthy (non-meshy) and 60 diseased (meshy) pulp samples as shown in Sample Test Images Fig 3. Images of cut fruits were captured using a Nikon camera to ensure high-resolution quality, which is essential for accurate feature extraction and analysis. From dataset images 80% images used for training the model and 20% images are used for testing.

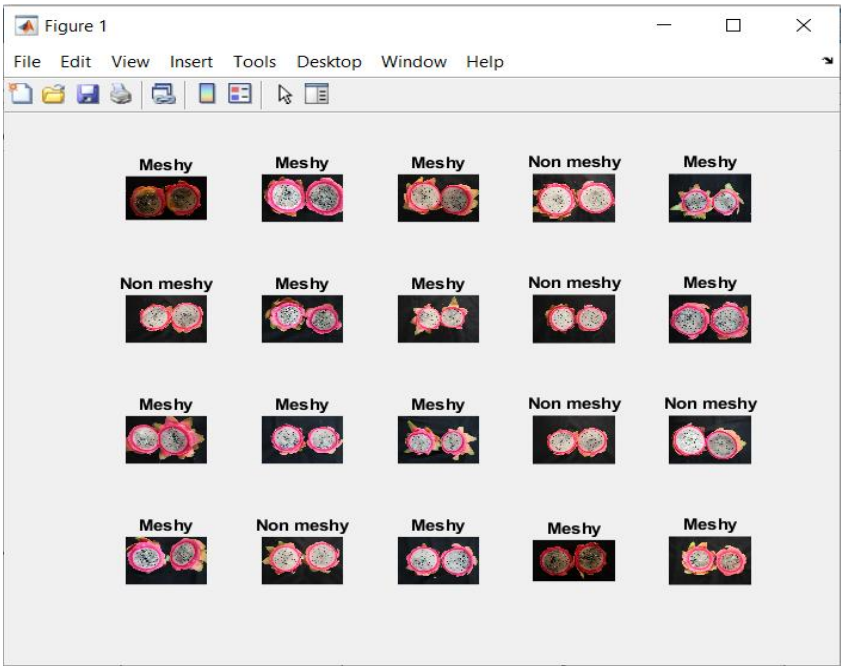

Fig 3. Sample Test Images

2.1.2 **Pre-processing**: In this step, images undergo cleaning and normalization to enhance quality and consistency. Adjustments are made to size, brightness, and contrast to ensure uniformity. These steps improve feature detection by minimizing image noise and artefacts, preparing the data for effective feature extraction. Additionally, data augmentation techniques are applied to expand the dataset and improve the model's generalization capability. This includes resizing images to match the input layer dimensions of the pre-trained model, as well as performing operations such as rotation, scaling, and translation. These transformations simulate variations in real-world scenarios, making the model more robust to changes in orientation, size, and position of objects within the images.

2.1.3 **Feature Extraction**: In this stage, we leverage deep learning by utilizing pre-trained models, specifically InceptionV3 and ResNet101, which are known for their robust feature detection capabilities. These models are used to extract detailed attributes from the images, such as texture and structural features, essential for analysing pulp health. To enhance the feature extraction process, we employ feature fusion, combining the strengths of both architectures.

The InceptionV3 architecture uses inception modules, which employ convolutional layers of varying filter sizes in parallel, enabling it to capture features at multiple scales. Meanwhile, ResNet101 incorporates residual connections, allowing the model to train deeper networks without the risk of vanishing gradients and to extract complex hierarchical features effectively.

In the fusion process, we extract feature maps from the respective feature layers of both models specifically, the output of the final convolutional layers before the classification heads. These feature maps are then concatenated or combined through advanced fusion techniques, such as weighted averaging or bilinear pooling, to create a unified representation of the image. This fused feature set leverages the multi-scale detection capability of InceptionV3 and the deep hierarchical understanding of ResNet101, resulting in a comprehensive feature map for downstream analysis. This approach not only captures fine-grained details but also improves the robustness and accuracy of the model.

2.1.4 **Classification (Model Training/Testing)**: A hybrid approach combines deep learning and machine learning to classify the images. The extracted features are fed into a machine learning-based classification layer, specifically designed for this task. This layer is trained and tested on MATLAB to differentiate healthy and defective pulp images, enhancing the model's accuracy and applicability for industry use.

2.1.5 **Predicted Output**: Once trained, the model generates a predicted output for each image, classifying it as either non-meshy/healthy or meshy/diseased.

2.1.6 **Result Evaluation**: The final step is assessing the model's performance by evaluating metrics like accuracy, error rate, sensitivity, specificity and F-score. These results provide insights into the model's reliability and efficiency, validation.

2.2 Deep learning models

i) **Inception Model**: Developed by Google, the Inception model (notably InceptionV3) is designed for high accuracy in image classification tasks. Its architecture includes multiple convolutional filters at each layer, enabling it to capture diverse image features across scales. This model's ability to identify detailed patterns makes it ideal for recognizing complex textures in the dragon fruit pulp images.

ii) **ResNet Model**: The ResNet model, short for Residual Networks, introduced by Microsoft, is known for its innovative skip connections, which help overcome the "vanishing gradient" issue common in deep networks. ResNet's structure allows it to learn deeper features effectively without losing accuracy, which is essential for distinguishing subtle differences in pulp texture between healthy and diseased samples.

By using the feature layers of these models, we capture fine-grained characteristics from the images, enhancing the model's ability to classify pulp health accurately. The extracted features are then used within a machine learning classification layer.

2.3 Decision Tree Bagger

In this research, we use a Decision Tree Bagger as the machine learning classification layer. The Decision Tree Bagger, also known as Bootstrap Aggregating (or Bagging), combines multiple decision trees for improving classification accuracy and reduce overfitting. By training multiple decision trees on random subsets of the dataset, the model averages their predictions to produce a final, robust classification output. This approach works well for handling complex data patterns and enhances the hybrid model's ability to accurately classify meshy and non-meshy dragon fruit pulp based on the deep learning features extracted from the Inception and ResNet models.

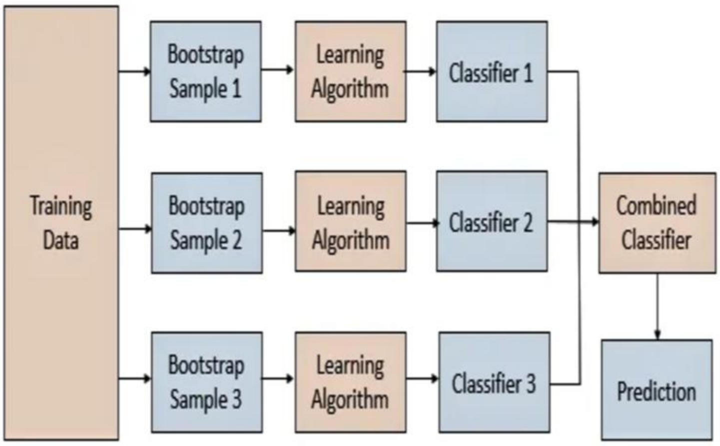

Fig 4. workflow of Decision tree bagger

2.4 Result Evaluation Matrices

i) **Accuracy**: Accuracy measures the proportion of correctly classified samples to the total samples. It is calculated as:

$$\text{Accuracy} = \frac{\text{True Positives+True Negatives}}{\text{Total Samples}}$$

This metric is crucial here as it indicates the overall effectiveness of the model in identifying both healthy and diseased pulp samples correctly.

ii) **Error Rate**: It indicates the proportion of misclassified samples. It is calculated as:

$$\text{Error Rate} = 1 - \text{Accuracy}$$

This value highlights the rate of incorrect predictions, helping to identify areas where the model might need improvement.

iii) **Sensitivity**: Sensitivity, or recall, is the measure of the model's ability to correctly identify true positives (diseased samples). It is calculated as:

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives+False Negatives}}$$

In this context, sensitivity is significant as it ensures diseased fruits are detected, minimizing the chance of flawed fruit entering production.

iv) **Specificity**: Specificity measures the model's ability to identify true negatives (healthy samples). The formula is:

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives+False Positives}}$$

Specificity is important here to ensure that healthy samples are not mistakenly classified as diseased, reducing waste and increasing efficiency.

v) **F-Score**: The F-score, or F1 score, balances precision and recall, offering an overall measure of model performance. It is calculated as:

$$\text{F-Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}}$$

The F-score is valuable in contexts with class imbalances, providing a comprehensive metric that balances the need for high sensitivity and specificity.

vi) **Receiver Operating Characteristic (ROC) curve**: The Receiver Operating Characteristic (ROC) curve is a visual tool used to assess the effectiveness of binary classification models. It represents the relationship between the True Positive Rate (TPR), also known as sensitivity, and the False Positive Rate (FPR) across different threshold values. By showcasing the balance between sensitivity and specificity, the ROC curve offers an insightful depiction of a model's ability to differentiate between the two classes. Models with ROC curves nearer to the top-left corner are considered more accurate, indicating superior performance in classification.

Key Metrics in ROC Curve:

i. True Positive Rate (TPR) (Sensitivity or Recall):

$$TPR=\frac{TP}{TP+FN}$$

Where,

TP: True Positives

FN: False Negatives

ii. False Positive Rate (FPR):

$$FPR=\frac{FP}{FP+TN}$$

Where,

FP: False Positives

TN: True Negatives

iii. Formula for ROC Curve: The ROC curve is created by plotting TPR (y-axis) Vs FPR (x-axis) for different decision thresholds θ:

$$ROC=\{(FPR(\theta),TPR(\theta))|\theta\in R\}$$

Each point on the ROC curve corresponds to a specific threshold value, reflecting the classifier's performance at that threshold.

iv. Area Under the Curve (AUC): The Area Under the Curve (AUC) is a single scalar value summarizing the ROC curve's performance. AUC values range from 0 to 1, where:

AUC=1: Perfect classifier.

AUC=0.5: Random guessing.

$$AUC=\int_0^1 TPR(FPR)d(FPR)$$

3. Results and Discussions

3.1 Experimental Setup

The experimental setup for this research was carried out using MATLAB R2021b, utilizing various built-in toolboxes to support the machine learning and image processing tasks. The Classification Learner app in MATLAB was used to run the machine learning algorithms, allowing for easy implementation and comparison of different classification models. In addition, the study incorporated several MATLAB toolboxes, including Deep Learning, Statistics and Machine Learning, Computer Vision, and Image Processing, to facilitate tasks such as feature extraction, image processing, and model training. These tools provided a robust environment for analyzing and processing the data, ensuring the effective deployment of machine learning models for classification tasks in the study.

3.2 Evaluation Metrics

Table 1 shows evaluation metrics obtained after applying proposed approach on the dataset images.

Table 1. Evaluation Metrics of experiment

Evaluation Matrices	Obtained Values
Accuracy	95.8333

Error rate	4.1667
Sensitivity(Recall/ hit rate)	91.6667
Specificity	100
F-Score	98.2143

3.3 Result Analysis

Confusion matrix shown in Fig 6. Shows for the testing phase, a total of 24 dragon fruit pulp images were analysed to classify them into meshy and non-meshy categories. The confusion matrix results indicate that the proposed method achieved the following outcomes:

- **True Positives (TP)**: Out of the 24 images, 11 meshy pulp images were correctly identified as meshy. This indicates the model's strong ability to identify and classify meshy pulp.
- **True Negatives (TN)**: The model correctly classified 13 images as non-meshy, showcasing its reliability in identifying healthy pulp.
- **False Negatives (FN)**: 1 image, which was actually meshy, was misclassified as non-meshy. This reflects a minor limitation in sensitivity.
- **False Positives (FP)**: No non-meshy pulp images were misclassified as meshy, demonstrating a perfect precision for non-meshy pulp classification.

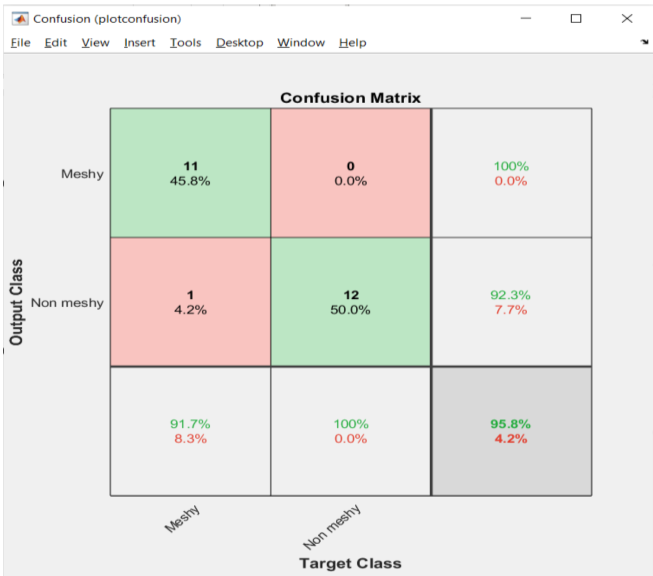

Fig 6. Confusion Matrix

The confusion matrix reflects that the classification results are highly reliable, with the model excelling in specificity and overall accuracy. The small number of misclassifications (1 FN) indicates a minor area for improvement, but the results are overall very strong, demonstrating the model's suitability.

Fig 7. shows ROC curve for meshy classification with a TPR of 0.9167 and an FPR of 0, the ROC curve for this classification task would start at the origin (0,0) and rise sharply to near the top-left corner, representing a high True Positive Rate with no False Positive Rate. Since this model classifies Meshy instances very accurately, the ROC curve will likely show a near-ideal performance, and the AUC value would approach 1, indicating excellent discrimination between the two classes (Meshy and Non-Meshy). The AUC provides a clear measure of the model's ability to correctly classify both Meshy and Non-Meshy cases, with higher values suggesting better classification accuracy.

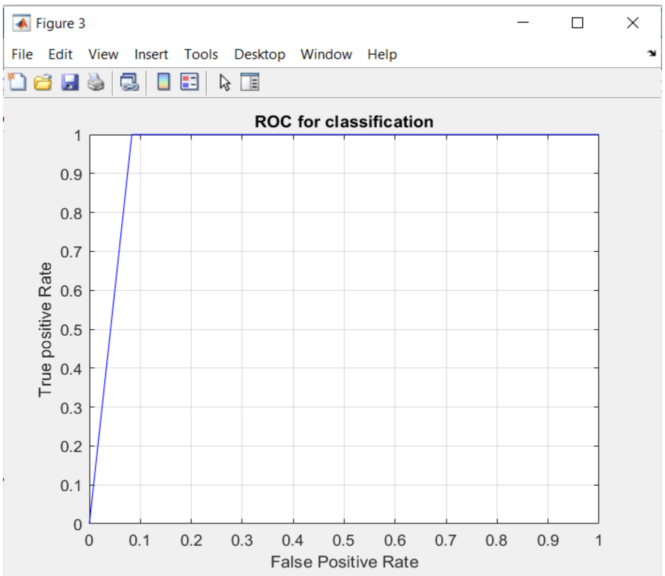

Fig 7. ROC Curve for Meshy Classification

3.4 Discussion and Future Prospects

There is a lack of existing literature focusing specifically on dragon fruit pulp disease detection using machine learning techniques. While there has been considerable research on the pulp quality assessment of other fruits like apples, mangoes, durian, banana, tomatoes etc. This research pioneers the use of advanced machine learning algorithms for the precise identification and classification of healthy and diseased dragon fruit pulp. The application of feature fusion techniques from models like InceptionV3 and ResNet101 enhances the model's ability to detect subtle patterns, achieving 95.83% accuracy. This work not only fills a significant gap in the current agricultural research but also provides a foundation for future studies

Future research could focus on further improving model accuracy by incorporating larger and more diverse datasets, experimenting with advanced deep learning architectures, and expanding the system to detect additional fruit diseases. This approach could also be adapted for other fruits, enhancing quality assessment across agricultural industries. Additionally, real-time implementation of this model in portable devices or mobile applications could revolutionize on-site fruit quality assessment.

4. Conclusion

In conclusion, this research successfully demonstrates a hybrid deep learning and machine learning approach to classify the health of dragon fruit pulp based on its meshy structure, achieving an accuracy of 95.83%. By integrating the Inception and ResNet models for feature extraction with a Decision Tree Bagger classifier, we were able to capture subtle differences in pulp texture, effectively distinguishing healthy from diseased samples. This approach offers a practical and efficient solution for the dragon fruit processing industry, enabling automated quality assessment and reducing the need for manual inspection.

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