

Deep Learning enabled Fruit Quality Assessment with Spatial-Spectral Feature Fusion

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Abstract—In this paper, a novel method is proposed to high-light hyperspectral imaging (HSI) for the analysis of multiple characteristics of fruits. The goal is to use this method to establish the level of maturity and quality in fruits. This new approach combines deep features obtained from a pre-trained residual network-18 layers (ResNet-18) with handcrafted features, e.g. texture, spectral reflectance, surface defect score, and moisture index. This would allow for the capture of the spatial and spectral characteristics of fruits accurately. These features are combined into one unified framework and are run through a multi-task learning approach to accomplish both the classification of maturity and the regression of quality at the same time. A balanced loss function is used for convergence stability across both tasks. The experimental testing showed very strong chances of predictive success, and the correlation analysis demonstrated that both moisture and texture have a positive impact on overall quality, whereas ripeness and defects have an inverse relationship. Overall, the proposed framework provides a solid and scalable solution to the automated assessments of fruit quality in precision agriculture systems.

Index Terms—Hyperspectral Imaging (HSI), Multi-Attribute Analysis, Fruit Ripeness Classification, Quality Estimation, Spectral Reflectance.

I. INTRODUCTION

Accurate, non-destructive and real-time measurement of fruit quality has become very important due to the increase in demand for precision agriculture and automated food supply chains. Traditional fruit ripeness and quality evaluation methods require extensive manual inspection, laboratory testing and are time-consuming, subjective, and cannot scale. The inconsistency of fruit grading in commercial applications directly affects their market value, storage determinations, and efficiency within the supply chain. An automated, objective and dependable system capable of evaluating multiple fruit attributes simultaneously (such as ripeness, firmness, moisture content, and overall quality) is therefore urgently required.

Advancements in computer vision plus deep learning have substantially increased our ability to classify fruit and analyze fruit quality. One of the best methods for accomplishing this is through the use of convolutional neural networks (CNNs) and other deep-learning CNN-type architectures like residual networks (ResNets), which have a unique capability to extract features from images as they create hierarchical representations of image based features [1]. The limitations that many techniques utilizing only RGB color images face

is that they cannot capture and represent chemical properties of fruits internal to the fruit; rather, these techniques can only capture surface-level properties of the fruit.

This paper proposes a hyperspectral multi-attribute analysis technique that uses physically interpretable features in conjunction with deep feature extraction. This is accomplished using a deep neural network (DNN) to extract features from texture value, spectral reflectance, surface defect value index, and moisture pointer index [2], [3]. As a result, improved accuracy of predictions is achieved. A multi-task learning approach has been applied to predict the ripeness and quality of fruits. Therefore, duplication in the prediction process are avoided to detect the process, thus improving the efficiency of the overall deep learning model. The comprehensive goal of this unified methodology is to provide a scalable and reliable way for automated fruit analysis in precision agriculture applications and food quality monitoring systems.

II. RELATED WORKS

Recently, hyperspectral imaging (HSI) has begun to emerge as a very powerful technique to overcome this limitation by allowing the spectral data for a fruit to be collected across many wavelengths (e.g. from 400 nm to 1000 nm) and used to create a comprehensive and complete characterization of both internal and external fruit characteristics. It can also provide detailed information regarding the unique biochemical composition of that fruit [4]–[6]. Many researchers have investigated the combination of hyperspectral imaging along with machine learning techniques. For example, hyperspectral-based methods have demonstrated success in determining fruit ripeness, bruise detection, and defect detection; all of which utilize the unique spectral signatures of the fruit that correlate to the unique biochemical and chemical compositions [4]. Additionally, classical feature extraction methods, such as Gray Level Co-occurrence Matrix (GLCM) and various texture analysis techniques, have been widely used for classification of images based on texture [7]. Similarly, spectral indices such as normalized difference water index (NDWI) have been used to estimate the moisture content of fruits, which is considered a key determinant for freshness and quality of fruits [8], [9]. Most current methodologies mainly focus on single-task prediction using either deep learning or handcrafted features, and do not fully utilize the complementary benefits offered

by combining both types of features. In addition, numerous systems do not integrate multiple attributes (e.g. texture, moisture, and defects) into a single prediction framework.

III. PROPOSED METHODOLOGY

The proposed methodology involves spectral characterization of a fruit's flesh and skin in order to create an accurate ripeness and quality score by combining deep learning with meaningful visual cues based on spectral analysis. To accomplish this goal, a series of steps will be carried out that include preprocessing hyperspectral images, extracting relevant features from the images, calculating the features, integrating the features, and then generating a multi-task prediction through deep learning.

A. System Overview

The system will take a hyperspectral image cube as input and provide the following outputs: ripeness level (classification), and fruit quality score (regression). On the other hand, intermediate attributes that are computed as follows: texture score, spectral reflectance of the surface, surface defect score, and moisture index. Unlike the typical RGB image-based systems that use visual representation only of the surface of a fruit to derive its attributes, this system takes into account both the visual (on the surface) and nonvisual spectral data (skin and flesh) attributes in the prediction process through the use of hyperspectral imagery

B. Hyperspectral Preprocessing

The initial hyperspectral image cube $I \in \mathbb{R}^{H \times W \times B}$ (where H , W and B represent the height, width and spectral bands, respectively) will be preprocessed to guarantee uniformity and minimise noise.

- Spatial Normalization: Each image must be resized to standard resolution (e.g. 224×224).
- Spectral Normalization: Each band within the cube will be normalized via:

$$l_b^{norm} = \frac{l_b - \mu_b}{\sigma_b} \quad (1)$$

where:

l_b = Normalized spectral band value
 μ_b = Mean of spectral band
 σ_b = Standard deviation of spectral band

- Noise Reduction: Optional smoothing may be applied to each band.
- Dimensionality Reduction: If the number of bands is high, principal component analysis (PCA) or a 1×1 convolution will be used.

This stage of the process is important because it prepares the hyperspectral data for the extraction of deep features.

C. Feature Extraction and CNN Backbone

The backbone of the feature extraction process is a pre-trained ResNet-18. The preprocessed hyperspectral image cube will be provided as an input to the ResNet-18 network and will produce feature maps of the image [10]:

$$F = \phi(l_p) \quad (2)$$

where:

F = Feature maps
 ϕ = CNN mapping function (ResNet-18)
 I_p = Preprocessed hyperspectral image

These feature maps will then be flattened and converted to a common latent representation between all feature maps:

$$f = \text{Dense}(\text{Flatten}(F)) \quad (3)$$

where:

f = Latent feature vector
 $\text{Flatten}()$ = Converts feature maps into 1D vector
 $\text{Dense}()$ = Fully connected layer

These new representations will encode both high-level spatial and spectral groupings of information.

D. Computation of Features

In addition to deep features, a number of other physically interpretive attributes are now calculated:

1) Texture Score (GLCM-based)

Texture is computed using the Gray-Level Co-occurrence Matrix:

$$T = \sum_{i,j} P(i,j)(i-j)^2 \quad (4)$$

where:

T = Texture Scores
 $P(i,j)$ = Probability of pixel pairs (GLCM)
 $\{i,j\}$ = Pixel intensity levels

2) Spectral Reflectance

$$S = \frac{1}{N} \sum_{i=1}^N R(\lambda_i) \quad (5)$$

where:

S = Mean spectral reflectance
 $R(\lambda_i)$ = Reflectance at wavelength λ_i
 N = Number of spectral bands

3) Surface Defect Score

$$D = \frac{A_{\text{defect}}}{A_{\text{total}}} \quad (6)$$

where:

D = Defect score
 A_{defect} = Defective area
 A_{total} = Total fruit area

4) Moisture Index (HSI-based)

$$M = \frac{R(\lambda_1) - R(\lambda_2)}{R(\lambda_1) + R(\lambda_2)} \quad (7)$$

where:

M = Moisture index
 $R(\lambda_1), R(\lambda_2)$ = Reflectance at selected wavelengths

These features provide meaningful insights into fruit condition and improve interpretability.

E. Feature Fusion

All features are now combined into a unified representation:

$$f_c = \text{concatenate}(f, T, S, D, M) \quad (8)$$

where:

f_c = Combined feature vector
 f = Deep features
 $\{T, S, D, M\}$ = Handcrafted features
 $\text{concatenate}()$ = combine different features

This fusion allows the model to utilize both learned and handcrafted features simultaneously.

F. Multi-Task Prediction

The framework performs two main predictions:

1) Ripeness Prediction

$$R = \text{Softmax}(W_r f + b_r) \quad (9)$$

where:

R = Ripeness class output
 W_r = Weight matrix (ripeness)
 b_r = Bias term
 $\text{Softmax}()$ = Classification activation function

2) Quality Prediction

$$Q = \text{Sigmoid}(W_q f_{\text{combined}} + b_q) \quad (10)$$

where:

Q = Quality score
 W_q = Weight matrix (quality)
 b_q = Bias term
 $\text{Sigmoid}()$ = Regression activation

Ripeness prediction is based on mainly deep features, while quality prediction is both deep and computed features.

G. Loss Function Optimization

The training of the model is done through the use of a combined loss function: where:

$$L_{\text{total}} = \nu_1 L_{\text{ripeness}} + \nu_2 L_{\text{quality}} \quad (11)$$

where:

L_{total} = Total loss
 ν_1, ν_2 = Weighting coefficients
 L_{ripeness} = Cross-entropy loss
 L_{quality} = Mean Squared Error (MSE)

This method provides optimal balance of the tasks being optimized.

H. Training and Optimization

The model was trained by the use of optimization based on Stochastic Gradient Descent (SGD), the model went through the following process

- 1) Forward pass – to produce predictions.
- 2) Loss was computed based on the predictions.
- 3) Back-propagation to adjust parameters.
- 4) Adjusted parameters based upon the computed loss.

Regularization was applied through a combination of dropout and data augmentation to prevent overfitting.

I. Algorithmic Representation

Algorithm 1 Hyperspectral Multi-Task Feature Analysis

```

1: Input: Hyperspectral image cube  $I$ 
2: Normalize and resize  $I$ 
3: if  $B > 3$  then
4:    $I_p \leftarrow \text{DimensionalityReduction}(I)$ 
5: else
6:    $I_p \leftarrow I$ 
7: end if
8:  $F \leftarrow \text{ResNet18}(I_p)$ 
9:  $f \leftarrow \text{Flatten}(F)$ 
10:  $f \leftarrow \text{Dense}(f)$ 
11:  $T \leftarrow \text{Compute GLCM}(I_p)$ 
12:  $S \leftarrow \text{Mean Spectral Response}$ 
13:  $D \leftarrow \frac{\text{DefectArea}(I)}{\text{TotalArea}(I)}$ 
14:  $M \leftarrow \frac{R(\lambda_1) - R(\lambda_2)}{R(\lambda_1) + R(\lambda_2)}$ 
15:  $f_c \leftarrow \text{Concatenate}(f, T, S, D, M)$ 
16:  $R \leftarrow \text{Softmax}(W_r f_c + b_r)$ 
17:  $Q \leftarrow \text{Sigmoid}(W_q f_c + b_q)$ 
18: Return:  $(R, T, S, D, M, Q)$ 

```

The proposed algorithm 1 processes bananas, apples, pears, cherries, and cucumbers via hyperspectral imaging within a series of structured tasks designed to evaluate their ripeness as well as quality. The first task performed preprocesses the hyperspectral image cube by either resizing or normalizing (standardizing) the hyperspectral spectral bands so that they are consistent across all three dimensions. For large numbers of spectral bands, dimensionality reduction techniques are utilized to reduce the number of measurements made without losing significant information. After preprocessing the hyperspectral images, a summary of high-level spatial and spectral data is obtained for all images via a residual neural network, i.e. ResNet-18. In addition to computed spectral data, additional information is obtained in the form of several features, including texture (using grey level co occurrence matrices), spectral reflectance, surface defect score, moisture index, which are then compiled into a single feature representation; as such, this feature representation can now be used as the input for predicting ripeness through classification (ripeness class) and/or estimating an overall quality score through regression (overall quality score). This process aids in striking a balance between accuracy and cost/profitability while maximizing the

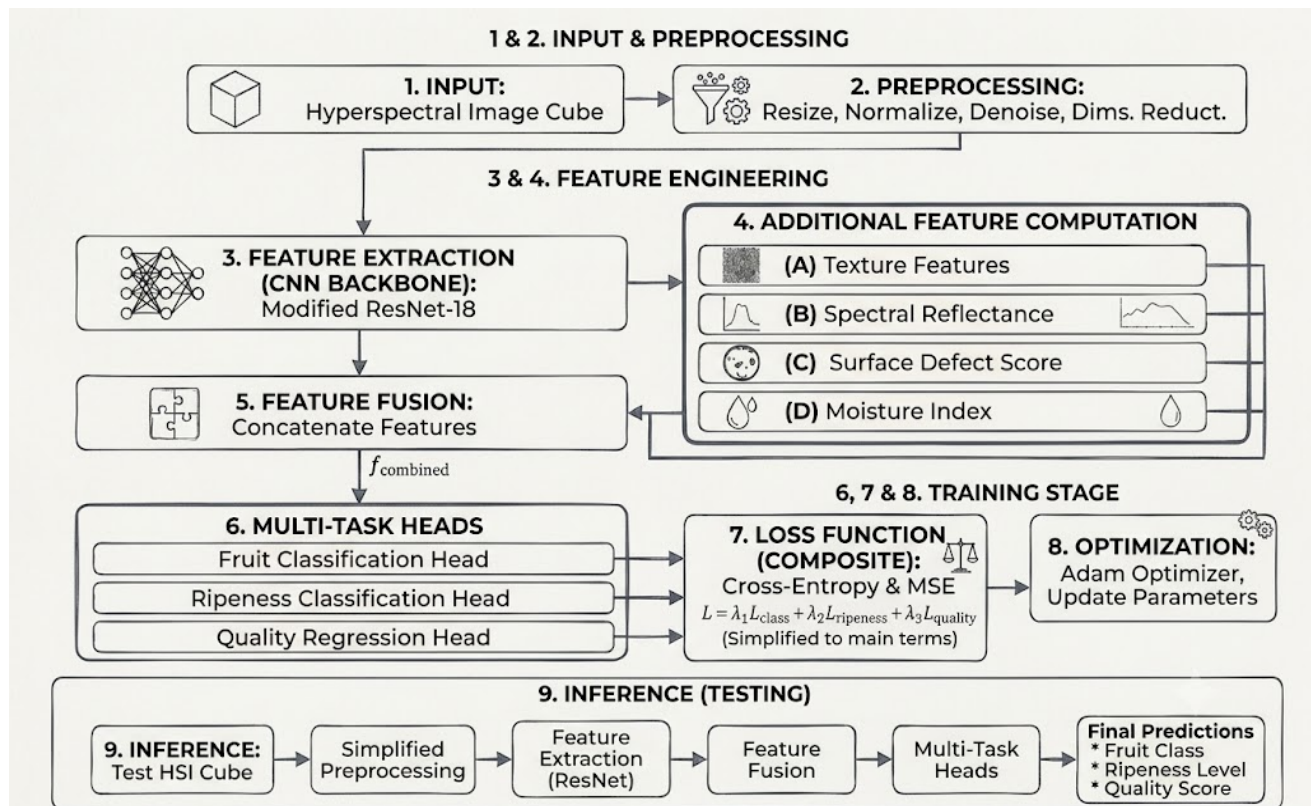


Fig. 1: Proposed Hyperspectral Multi-task Framework

ID	Fruit	Image	Ripeness (0-4)	Texture Score (GLCM-based)	Spectral Reflectance (VIS)	Surface Defect Score	Moisture Index (NDWI-like)	Quality
A1	Apple		0	0.88	4620	0.05	0.85	0.9142
A2			1	0.85	4450	0.09	0.81	0.8657
A3			2	0.80	4205	0.16	0.75	0.7841
A4			3	0.75	3940	0.24	0.68	0.6923
A5			4	0.68	3680	0.34	0.60	0.5126
B1	Banana		0	0.92	5150	0.02	0.90	0.9456
B2			1	0.86	4890	0.06	0.84	0.8778
B3			2	0.78	4580	0.11	0.76	0.7685
B4			3	0.70	4220	0.21	0.66	0.6547
B5			4	0.60	3820	0.33	0.52	0.4389
P1	Pear		0	0.89	4260	0.06	0.86	0.9261
P2			1	0.83	4070	0.12	0.78	0.8376
P3			2	0.77	3865	0.20	0.71	0.7352
P4			3	0.71	3680	0.28	0.64	0.6428
P5			4	0.64	3425	0.37	0.54	0.4683
C1	Cucumber		0	0.93	5360	0.03	0.93	0.9563
C2			1	0.88	5120	0.07	0.87	0.8892
C3			2	0.81	4765	0.14	0.79	0.7925
C4			3	0.74	4350	0.21	0.69	0.6534
C5			4	0.66	3890	0.29	0.58	0.4778
CH1	Cherry		0	0.90	4125	0.04	0.85	0.8974
CH2			1	0.87	4050	0.07	0.80	0.8412
CH3			2	0.83	3980	0.11	0.74	0.7615
CH4			3	0.79	3890	0.17	0.67	0.6147
CH5			4	0.72	3750	0.25	0.59	0.4256

Fig. 2: Dataset showing Fruit Attributes including Ripeness, Texture, Spectral Reflectance, Surface Defect and Moisture Index

Fruit	ID	Step 1	Step 2	Step 3	Step 4	Step 5	Final Quality
Apple	A3	0.4351	0.4782	0.5327	0.5632	0.6954	0.7841
Banana	B1	0.5621	0.6152	0.7335	0.7835	0.8521	0.9456
Pear	P1	0.5214	0.5743	0.6489	0.7012	0.8125	0.9261
Cucumber	C1	0.6012	0.6675	0.7523	0.8146	0.9021	0.9563
Cherry	CH3	0.4025	0.4558	0.5213	0.5987	0.6824	0.7615

Fig. 3: Ablation Study: Quality Progression across Model Enhancements

efficiency of fruit evaluation via automated systems. The flowchart depicting the overall framework is given in Fig. 1.

IV. RESULTS AND DISCUSSION

The performance evaluation of the hyperspectral multi-dimensional attribute model outlined in this paper are documented here. Five different fruit types (i.e. apple, banana, pear, cucumber, and cherry) are included in a database (see [11]) created on five levels of ripeness. This section discusses the results based on feature relationships, spectral characteristics, and reliability of the models tested.

A. Data Representation

This data set contains the following 6 features that are used to characterize individual fruit samples: ripeness (of fruit), texture scores, spectral reflectance values, surface defects, moisture index, and quality score.

From Fig. 2, it is evident that the relationship between the different 6 attributes remains constant regardless of the fruit (i.e., there are stable and predictable relationships within the data):

- Texture score decreases with increasing ripeness
- Spectral reflectance decreases as fruits mature
- Surface defects increase with ripeness
- Moisture index decreases, indicating loss of freshness
- Quality score declines progressively

These stable or predictable changes in each of the 6 attributes support that the data resulting from these features correspond to the same behavior seen in real-world examples.

B. Ablation Study

The ablation results in Fig. 3 show that having moisture and texture features together provide the greatest improvement over quality estimation alone. Finally, using a multi-task learning framework, all features are combined to predict the current ripeness level and quality at once.

C. Correlation Analysis

On the correlation heatmap in Fig. 4 there are numerous relationships between the features we extracted:

Positive Correlation (strong):

- Moisture to Quality (~ 0.98)
- Texture to Quality (~ 0.94)

Negative Correlation (Strong):

- Ripeness to Quality

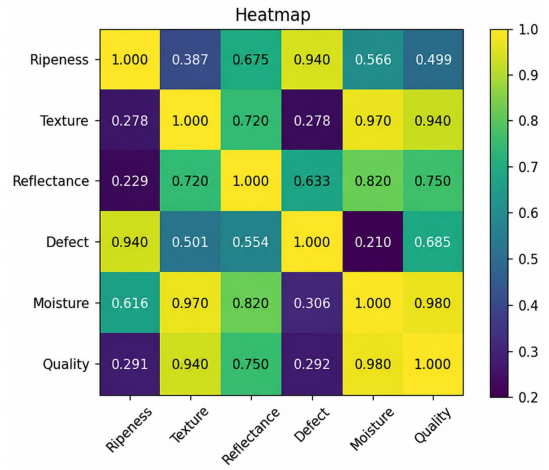


Fig. 4: Correlation Heatmap showing Relationships among Ripeness, Texture, Reflectance, Defect, Moisture, and Quality

- Defect to Quality

Moderate Correlation:

- Reflectance to Quality (~ 0.75)

From correlation analysis we can deduce that:

- Quality depends a lot on moisture and that moisture and texture are highly related.
- Defects and ripeness have an inverse effect on quality.
- Spectral features influence quality but they are not independent from one another.

D. Hyperspectral Reflectance Analysis

Reflectance curve in Fig. 5 (a) differ across 400-1000 nm:

- Cucumber has the highest reflectance which means it has the most water content.
- Cherry has the lowest reflectance which is due to dark color.

All fruits have the same trend:

- Dip around ~ 500 nm
- Peak at $\sim 700 - 750$ nm
- Rapid decline as wavelengths approach near infrared.

This reinforces hyperspectral data's importance in capturing biochemical properties.

E. Reflectance vs. Ripeness Analysis

The graph in Fig. 5 (b) exhibits a steady decline of reflectance over time with the fruits ripening. Fruits that are less ripe have higher levels of reflectance due to:

- High levels of moisture
- The intact structure of cells

As fruits ripen more:

- The concentration of pigment increases
- The internal structure breaks down
- The level of reflectance drops

All of the major fruit types follow these patterns and show that the spectral features are consistent.

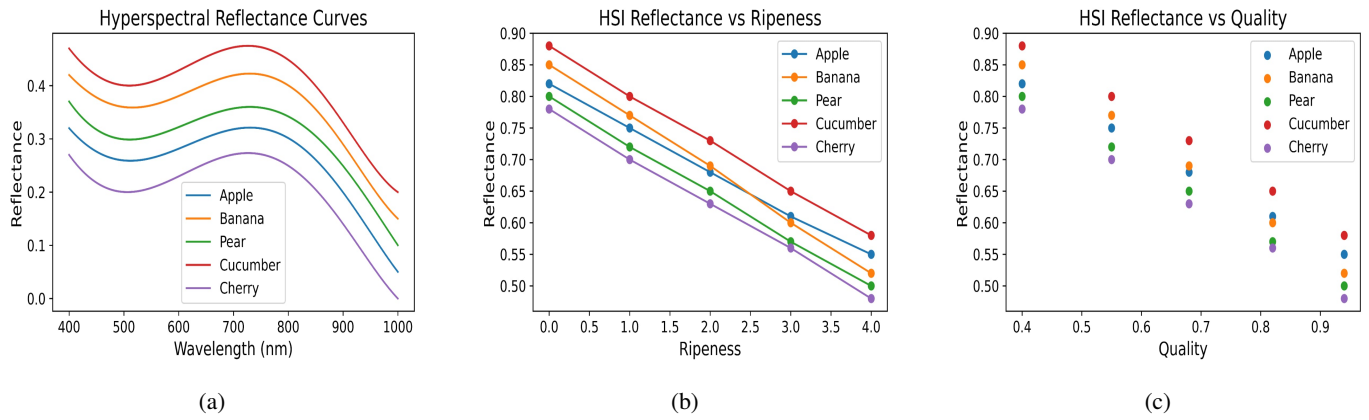


Fig. 5: (a) Hyperspectral Reflectance Curves of Different Fruits, (b) HSI Reflectance vs. Ripeness of Different Fruits, and (c) HSI Reflectance vs. Quality of Different Fruits

F. Reflectance vs. Quality Analysis

The scattered plot in Fig. 5 (c) shows a positive relationship between reflectance and fruit quality:

- Greater levels of reflectance have higher quality of fruit
- Lower levels of reflectance indicate lower quality of fruit

Therefore:

- Reflectance can be used as an accurate gauge of freshness of fruit
- Quality of fruit can be predicted from reflectance data.

G. General Discussions

The cumulative results from the data listed in above figures suggest:

- **Feature Consistency:** All features extracted demonstrate logical trends consistent with biological behaviour of fruit.
- **Hyperspectral Value:** Spectral reflectance are critical to evaluating internal characteristics.
- **Multi-Feature Dependency:** Quality is not dependent solely on one feature but a combination of Moisture, Texture, Surface defect, and Spectral Reflectance.
- **Model Reliability:** The framework successfully integrates deep and handcrafted features, producing stable and interpretable outputs.

CONCLUSION

This paper proposes a novel framework to automate the assessment of fruit ripeness and type of quality using hyperspectral imaging in combination with deep learning techniques, including interpretable characteristics of texture, moisture index value, reflected spectral energy, and physical defect score. The methodology uses deep learning and interpretable feature engineering. Using a ResNet-18 backbone and features that are created specifically to work with these fruit types, it analyzes various features such as surface defects, moisture indices, texture (using GLCM), and spectral reflectance. Analysis of these results produce high correlations between moisture and quality (~ 0.98), texture and quality (~ 0.94), and a moderate

correlation between spectral reflectance and quality (~ 0.75). In summary, the strong correlations indicate that moisture and texture significantly contribute to the quality ratings of the fruit. The results of an ablation study on the integration of spectral features with hand-craft features demonstrate that the addition of spectral features improve the prediction of fruit quality from a baseline of ~ 0.43 to ~ 0.94 (for banana) as more features are integrated into the database. Therefore, the new method presents an accurate, reliable, and scalable methodology for precision agriculture. Future research will be focused on extending the method to implement it in the field and at real-time intervals.

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