Determination of Fruit Freshness Using Near-Infrared Spectroscopy and Machine Learning Techniques

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Abstract. This paper addresses the problem of fruit freshness categorization in the context of fruit quality assessment during short storage periods. As it is hard to handle by using computer vision technology, we propose a novel method by using absorbance near-infrared spectroscopy combined with machine learning (ML) techniques. We collected several samples of five popular fruits with various properties and classified them into three degrees of freshness based on the storage duration. We then examined multiple combinations of feature extraction and machine learning techniques. Experimental results show that the proposed Convolutional Neural Network (CNN) architecture were superior to other traditional ML models regardless of the selected feature vector. In particular, the proposed CNN when trained on the concatenated first and second derivatives of the pre-processed absorbance spectrum achieved the highest accuracy of 80.0%. The obtained classification performance was evaluated on a variety of fruits, which shows the potential of our approach.

Keywords: Near-infrared spectroscopy · Absorbance spectrum · Feature extraction · Machine learning · Fruit freshness classification

1 Introduction

Accurate recognition of fruit freshness is highly important because it affects consumer health as well as economic activities. It is estimated that nearly one-third of fruit costs are spent on fruit spoilage [1]. In addition, spoiled fruit will also damage consumers' health due to the decreased concentration of amino acids, vitamins, sugar/glucose and some nutrients. Fruit quality is often manually examined based on fruit appearance observation or internal destructive analysis methods. However these methods are subjective, laborious, inconsistent, time-consuming and costly.

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Currently, fruit freshness grading via computer vision technology is the most common method for solving the automatic freshness determination problem. Machine learning (ML) and deep learning (DL) models trained on large datasets of digital images of a variety of fruits with various textures, colors and shapes can obtain classification results with the accuracy ranging from 70% to 100% [1, 5, 6, 8]. In spite of the high accuracy, this approach does not analyze internal characteristics affecting the freshness of the fruit such as dry matter, acidity, heavy metals, dissolved solids, etc. Rather, it fully depends on the appearance of fruits. Consequently, the performance of computer vision based freshness classification systems is highly dependent on how considerably the color, texture and shape of fruits varies during their growing or spoilage process, making this technology suitable for particular kinds of fruits (e.g., papaya [8], gooseberry [5], palm oil fresh fruit bunch [6]) or for long time spans of fruit maturation/ deterioration process (e.g., in weeks).

In this study, we considered the problem of fruit freshness categorization in the context of fruit quality assessment under usual storage conditions (i.e., without any climate-controlled system) for consumption at homes or for sale at street markets during short time periods. For this aim, we investigated five popular fruits with various appearances and flavors (including western apple, avocado, dragon fruit, guava, and mango) during a short interval of observation of six days. In particular, we classified collected fruit samples into three degrees of freshness based on the storage duration from the time of buying at the supermarket in fresh states to the time of six days later after being kept in room conditions in completely unfresh states. For fruits such as western apple and dragon fruit, their appearances exhibit little change during this period, making computer vision based methods hard to predict their freshness. We thus leveraged near-infrared (NIR) spectroscopy technology to solve the fruit freshness determination problem.

Recently, several studies have employed NIR spectroscopy techniques for evaluating chemical and micro-biological attributes of food products due to its simplicity, speedity and non-destructive nature [3]. NIR spectra may contain lots of information reflecting internal properties of fruits. Researchers have exploited NIR spectroscopy in combination with ML techniques to classify fruits not only into organic and inorganic categories but also into different geographical origins [4]. Besides, the combined DL models and NIR spectra have shown the effectiveness for the prediction of dry matter in mango fruit [2] or for the recognition of different fruits [7]. However, none of previous studies using the NIR approach focused on determining the freshness of fruits.

This paper presents the first attempt in detecting fruit freshness using absorbance NIR spectroscopy combined with ML techniques. We examined multiple combinations of feature extraction techniques and ML/DL models. The paper has following contents. Previous works on NIR spectroscopy and ML techniques in fruit examination are reviewed in Sect. 2. The collection of NIR data is detailed in Sect. 3. Section 4 presents our methods and Sect. 5 describes experimental results. The last section gives the conclusion and future work.

2 Related Works

NIR radiation consists of wavelengths ranging from 780 to 2500 nm in the electromagnetic spectrum. When the radiation hits a fruit sample, it may be reflected, transmitted or absorbed, resulting correspondingly a NIR spectrum in the reflectance, transmittance or absorbance mode. Each of these spectra can reflect some physical attributes and chemical composition of the sample. Consequently, many studies have leveraged NIR spectroscopy for fruit quality evaluation over the last decades [3].

Gupta et al. [4] presented an approach that uses visible and NIR spectroscopy to identify various properties of products such as variety, farmer and organic category. Combining spectral data of over 75,000 fruit and vegetable samples with support vector machine (SVM) technique gave a high accuracy of 90–98% and 98–99% for organic/inorganic classification and farmer recognition, respectively. Besides, NIR spectroscopy is also combined with DL to predict dry matter in mango [2]. This study gives the root mean square error of prediction (RMSEP) with the lowest is 0.79% and the highest is 0.84%. In addition, Ninh et al. [7] proposed to combine NIR spectra and deep neural networks to recognize several types of fruit including apple, avocado, dragon fruit, guava and mango. By using the derivative features of NIR spectra, these DL based models achieved the recognition accuracy as high as 99.0%.

There are many other studies in literature that leveraged NIR technology to analyze and classify food and agricultural products. However, none of the previous researches has employed NIR spectra for classifying the freshness of fruits. In the next sections of the paper, we will present our novel approach in details.

3 Data Collection

In this study, we performed the classification of the freshness of five fruits including western apple, avocado, dragon fruit, guava, and mango. For each fruit, we bought eight samples from the same supermarket to ensure they have the same origin as this factor may have some affect on spectral data. However these samples were purchased at different times (at least ten days apart from each purchase) for the diversity of sample data. We created three different levels of freshness: (i) “Fresh” for samples on the day of purchase in their fresh condition; (ii) “Not very fresh” for samples stored in room conditions from two to three days after the day of purchase; (iii) “Not fresh at all” for samples stored in room conditions from four to six days after the purchasing day. Figure 1 illustrates five types of fruit with three freshness labels for several samples. It could be observed that some fruits, particularly western apple and dragon fruit, exhibited almost no change in their appearances during this short storage period.

We used a portable NIR spectrometer named DLP NIRscan Nano EVM from Texas Instrument to collect the NIR spectrum of fruits. The fruit sample to be measured is placed close to the sapphire glass of the instrument. During each measurement, the sample absorbs a certain amount of NIR light emitted by the scanner, while the unabsorbed light is reflected into the scanner’s lens and converted by the optical processing module into a spectrum containing 228 wavelengths with a range of 900–1700 nm. The spectral data is transmitted from the measurement instrument to a computer using a USB cable as.csv files containing three types of spectra: intensity, reflectance, and absorbance. Among the three spectra, the absorbance spectrum gained highest performance in fruit freshness classification in our initial experiments. Therefore, we only employed absorbance spectra in this study. Physically, the absorbance spectrum indicates how well the molecules in fruits absorb electromagnetic waves (i.e., NIR light), thus it can reflect the freshness of fruits to a certain degree. The collection of the NIR spectrum of a fruit sample is shown in Fig. 2a.

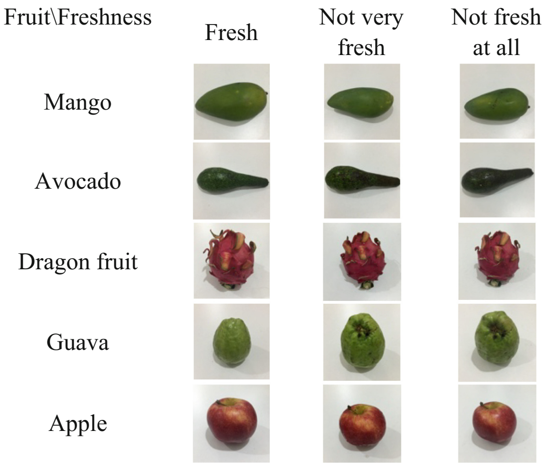
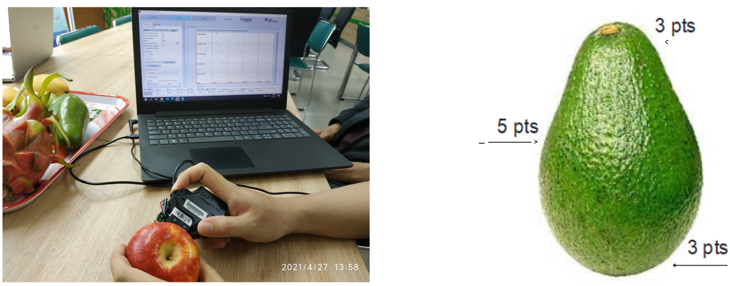


Fig. 1. Example samples of five fruits with three freshness labels.

For each fruit sample, we collected its absorbance spectrum in three freshness states. Moreover, we measured the spectrum at different positions on the fruit to take into account the measurement position. In particular, the measurements were carried out at 11 different positions on the sample, including five points around the body and six points around the two ends (Fig. 2b). As a result, we have collected 1320 NIR absorbance spectra from forty fruit samples with three freshness states. After removing those suffered from data errors (i.e., containing negative values), we obtained a total of 1252 valid spectra measurements for data modeling as listed in Table 1.



(a) (b)

Fig. 2. Setup of the NIR spectrum collection (a) and 11 measurement positions (b).

Table 1. Number of valid NIR absorbance spectra per fruit and per freshness label.

Fruit\Freshness level	Fresh	Not very fresh	Not fresh at all	Total
Apple	88	88	88	264
Avocado	88	88	86	262
Dragon fruit	88	88	88	264
Guava	88	66	66	220
Mango	88	88	66	242
Total	**440**	**418**	**394**	**1252**

4 Proposed Methods

Our fruit freshness classification system was carried out by using supervised ML framework. We examined multiple combinations of feature extraction schemes and ML models to seek for the optimal one. We trained a common ML model for different fruits, thus the spectral data of different fruits were pooled and used for modeling and validation. The system includes three stages: pre-processing, feature extraction, and model building.

4.1 Pre-processing

In the pre-processing stage, all of the collected NIR absorbance spectra were smoothed by a Savitzky-Golay (SG) filter (with the window length of 25 and the polynomial order of 5) to remove spectral noise. The smoothed spectra then were calibrated by the standard normal variate correction (i.e., z-score normalization) to eliminate the deviations caused by particle size and scattering. These are two techniques widely used for pre-processing NIR spectra [3].

4.2 Feature Extraction

Relevant features need to be extracted for building classification models. For a fruit sample, its pre-processed NIR spectrum is a certain choice as the feature vector for freshness identification. We further examined the derivatives of the pre-processed spectrum to see if they can help to differentiate levels of freshness. Figure 3 illustrates the originally collected spectra, spectra pre-processed by SG-smoothing and normalizing, first and second derivatives of pre-processed spectra of a fruit sample in three freshness states. We investigated four types of feature vector based on the concatenation of the pre-processed spectrum and/or its derivatives as described in Table 2.

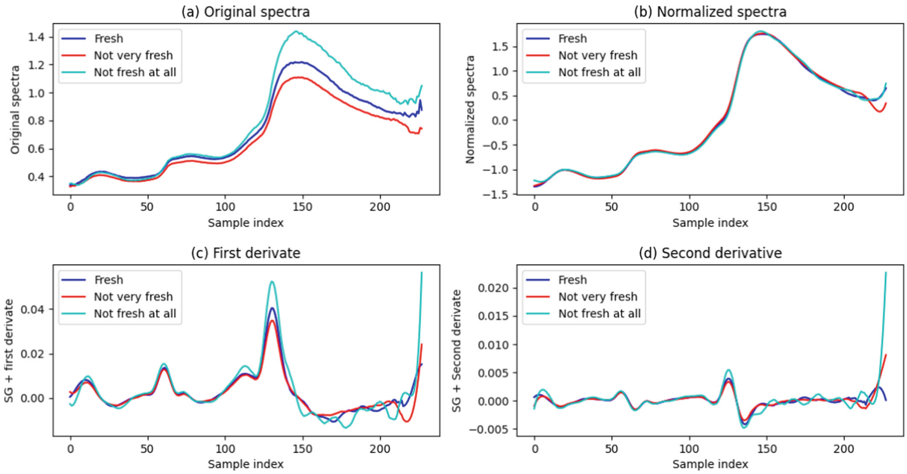


Fig. 3. Originally collected absorbance spectra (a), spectra pre-processed by SG-smoothing and normalizing (b), first (c) and second (d) derivatives of pre-processed spectra of a fruit sample in three freshness states.

Table 2. Four types of feature vector with their vector sizes and descriptions.

Feature type	Vector size	Description
x	228	Pre-processed spectrum
d1	228	1st derivative of pre-processed spectrum
d1_d2	456	1st and 2nd derivatives of pre-processed spectrum
x_d1_d2	684	Pre-processed spectrum + its 1st and 2nd derivatives

4.3 Machine Learning Models

In the training stage, the extracted spectral features of training fruit samples were used as the training data, and the three levels of freshness were used as the labels. We used both the traditional ML and modern DL approaches to build classification models and compared their performances. For the traditional ML approach, five algorithms were experimented including decision tree (DT), random forest (RF), gradient boosted trees (GBT), k-nearest neighbors (KNN), and support vector machine (SVM).

For the DL approach, we proposed a Convolutional Neural Network (CNN) whose architecture is illustrated in Fig. 4. Note that this CNN architecture was utilized regardless of the type of the feature vector. The model includes one input layer contains N neurons as input data, representing the feature vector of size N $\times$ 1 (N can be set to 228, 456, or 684 depending on the chosen feature). The CNN includes two convolutional layers with 16 and 32 filters, consecutively. They used kernels of size 2 $\times$ 1 and ReLU (Rectified Linear Unit) activation functions. In the following max pooling layers, a pool size of 2 $\times$ 1 along with a stride length of 2 was employed. The conversion from a 2D filter matrix into an 1D feature vector with a size of N $\times$ 8 was carried out by a flatten layer.

The 1D feature vector was then fed into two fully connected (FC) layers, both having 128 neurons and a ReLU activation function. Lastly, the third FC layer equiped with 3 neurons and a softmax activation function performs the classification to output the freshness label.

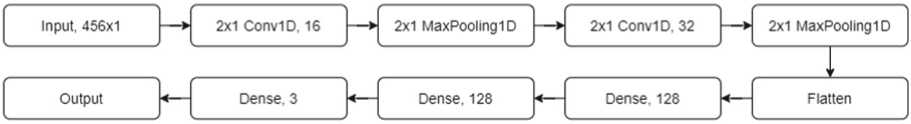


Fig. 4. Proposed CNN architecture (the size of input feature vector N is 456 in this case).

5 Experimental Results

5.1 Results of Proposed CNN Model

We set up experiments with the proposed CNN model by using functions of the deep learning library Keras. The collected spectral dataset were randomly divided into three sets for training, validating, and testing CNN models according to the ratio 3:1:1, correspondingly. In each set, the quantity of samples among fruit types as well as among freshness levels were kept balanced. A loss function based on cross-entropy and an Adam optimizer were utilized for training CNNs. The learning rate was initially set to 0.001 and to be reduced by a factor of 0.8 when the training result was not progressing. Moreover, the validation set was used for stopping the training process. Figure 5 shows the variation of the loss function on the training and validation sets over training epochs when trying with the feature vector d1_d2. In this case, the training process was stopped after 400 epochs since the loss function on the validation set converged at this point. We applied the same procedure for training CNN models regardless of the feature types to prevent model over-fitting.

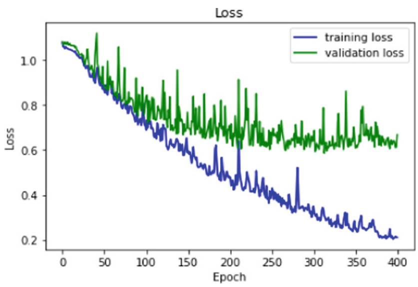


Fig. 5. Variations of loss function on training and validation sets over epochs of training CNNs.

Table 3 shows the full performance of CNN models. We can find that the model achieved the best performance when the feature vector d1_d2 was used (the accuracy is 80% on the test set with F1-score of 0.801).

Table 3. Performance of CNN models.

Feature vector	Accuracy (%)			Other metrics on test set		
	Training set	Validation set	Test set	Precision	Recall	F1-score
x	70.1	52.3	60.7	0.612	0.623	0.614
d1	93.0	73.0	78.5	0.805	0.792	0.798
d1_d2	91.0	80.1	**80.0**	0.801	0.800	**0.801**
x_d1_d2	85.0	61.0	70.0	0.710	0.721	0.710

5.2 Results of Traditional ML Models

The proposed CNN models were compared with other five traditional classifiers mentioned in Sect. 4.2. The ML training experiments were conducted with the scikit-learn toolkit. As model parameters can have significance influence on the performance of these ML algorithms, grid search procedures using four fold cross validation on the training set were carried out to produce the optimal models. Then the accuracies as seen on the test set were reported. Here, we combined the training and validation sets for constructing the CNN models into the training set for building the traditional ML models while keeping the test set identical for both cases. Table 4 lists set of parameters used in the grid searching for the optimal ML models.

Table 4. Set of parameters used in the grid searching for the optimal traditional ML models.

Model	Set of parameters (values in parentheses are those of the optimal models)
DT	Maximum depth of the tree (9), minimum number of samples at a leaf node (4)
RF	Maximum depth of a tree (5), minimum number of samples at a leaf node (9), number of trees in the forest (29)
GBT	Step size shrinkage (0.1), maximum depth of a tree (3), minimum sum of instance weight needed in a child (10), number of boosting rounds (57)
KNN	Number of neighbors (9)
SVM	Regularization parameter (100), kernel type (polynomial)

Table 5 summarizes the classification accuracy on the test set of the optimal model for each traditional ML algorithm regarding the feature types in comparison with that of the proposed CNN. It can be observed that the performance of all traditional ML models were inferior to that of the CNN model whatever the feature type was used. Among the traditional ML models, the GBT trained on d1 feature achieved the highest accuracy of 64.9%, much lower than the best performance of the proposed CNN when trained on d1_d2 feature with the accuracy of 80.0%. All of the models meet the real-time classification with the recognition time shorter than 0.4 s when running on Google's Colab platform.

Table 5. Classification accuracies (%) of ML/DL models on the test set.

Feature vector	Model					
	DT	RF	GBT	KNN	SVM	CNN
x	50.9	59.6	56.6	52.6	56.6	60.7
d1	55.7	61.0	**64.9**	52.2	60.5	78.5
d1_d2	50.0	60.5	62.3	53.1	60.5	**80.0**
x_d1_d2	53.1	60.5	61.4	50.9	55.7	70.0

6 Conclusion

We have presented the first attempt in fruit freshness categorization based on absorbance NIR spectra of fruits. For a short period of six-days storage during consumption time, many fruits exhibit little or no change in their appearances, making computer vision techniques hard to deal with the freshness prediction problem. Consequently, NIR spectroscopy technology shows its advantage in this context thanks to its capability in characterizing internal properties of fruits. We have examined multiple combinations of feature extraction schemes and ML models to seek for the optimal one. Experimental results show that the proposed CNN architecture were superior to other traditional ML models regardless of the feature vector type. In particular, the proposed CNN when trained on the concatenated first and second derivatives of the pre-processed absorbance spectrum achieved the highest accuracy of 80.0%. The obtained classification performance was tested on a variety of fruits, which shows the potential of our approach. The additional use of chemometrics methods (such as those suggested in [2]) would be helpful to improve the capability of ML models in grading the freshness of fruits based on NIR spectra.

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