Fruit recognition based on near-infrared spectroscopy using deep neural networks

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1. Introduction
2. Data collection
3. Proposed methods
4. Experimental results
5. Conclusions

1. INTRODUCTION

1.1. Introduction

1.2. Related works and motivation

1. INTRODUCTION

1.1. Introduction

- ✓ Health protection trend.
- ✓ The demand for more fruits and vegetables to replace food of animal origin.
- ✓ Consumer choices and prices highly depend on fruit appearances and internal chemical attributes.
- ➢ There is a need for fast, non – contact, non destructive methods to extract internal quality features of fruits.

1. INTRODUCTION

1.2. Related works and motivation (1/2)

✓ **Fruit recognition: 2 main approaches**

- **Fruit appearances**: size, color and shape
- **Internal chemical attributes:** freshness, total soluble solid and acidity.

✓ **Traditional measurements**

→ **limit:** expensive, time-consumption, destructive and even dangerous for human health.

✓ **Spectroscopy:** measure the change in absorption or emission of a material for different wavelengths of light.

→ This spectrum is considered as the chemical fingerprint of the material.

✓ **NIR spectroscopy [1-3]** are noticeable: as non-invasive, safe and mostly low-cost tools.

1. INTRODUCTION

1.2. Related works and motivation (2/2)

✓ Some typical previous studies using NIRS technique:

- The investigation of agricultural product quality [4-8]
- Variety discrimination of agricultural products [9-10]

✓ Deep learning present its effectiveness in learning the essential features of a data set comprising a large number of redundant information such as images [11-12] or NIR spectra [13].

✓ No research on the combined use of NIRS and deep neural networks (DNNs) such as Convolutional Neural Network [11] or Residual Network [12] for the identity recognition and freshness detection of fruits.

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2. DATA COLLECTION

2.1. Texas Instrument’s DLP NIRscan Nano EVM

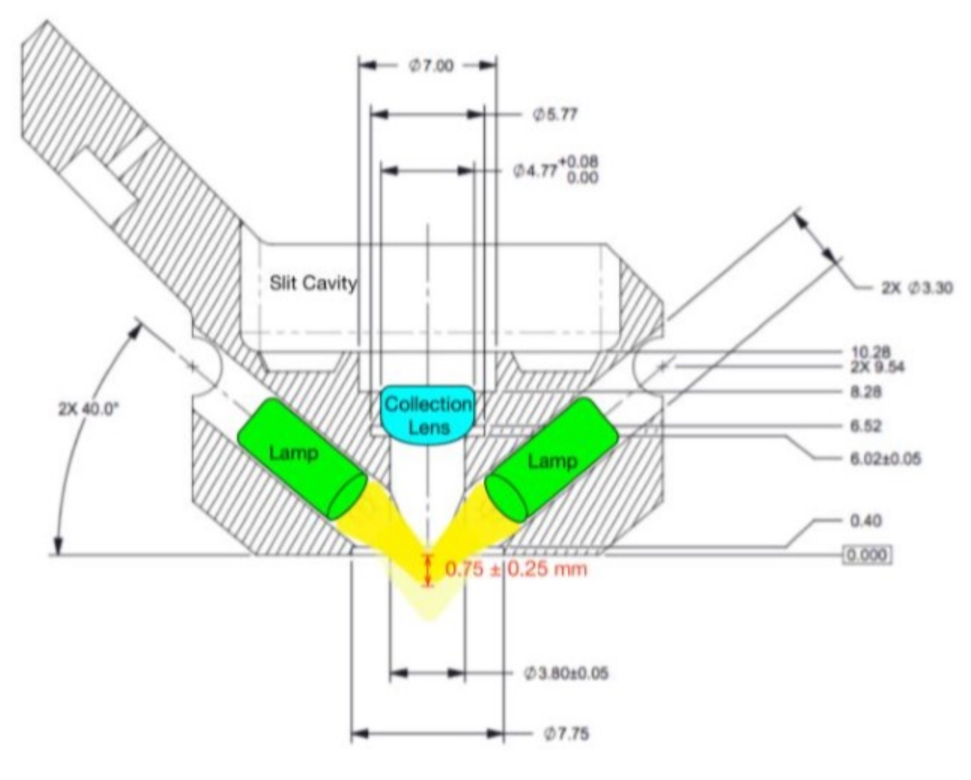
2.2. Scanning procedure

2.3. Self-built Database

2. DATA COLLECTION

2.1. Texas Instrument's DLP NIRscan Nano EVM

✓ Use Texas Instrument's DLP NIR scan Nano EVM supports a wavelength range of 900-1700 nm [16]



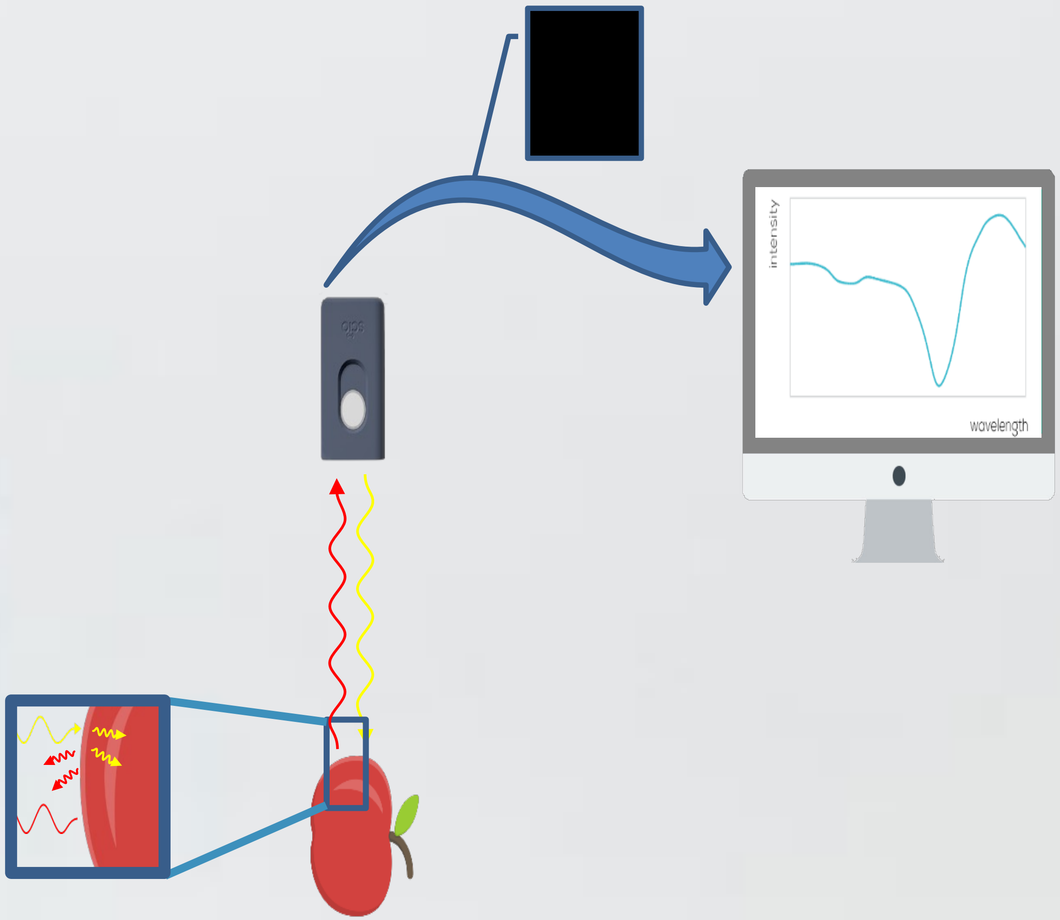
Spectrometer Operation

DLP NIRscan Nano EVM

2. DATA COLLECTION

2.2. Scanning procedure

- ✓ Three different NIR devices of the same type.
- ✓ Repeated the scanning operation 5 times at the center points around the body and 3 times at each of the two ends of a fruit sample.
- ✓ Data collection sessions across several days, from the day of buying them in total fresh condition to six days later and kept in room conditions.



Settings of NIR data collection sessions.

2. DATA COLLECTION

2.3. Self-built Database (1/2)

- **NIR data** were taken from **5 types** of fruits: Apple, Avocado, Dragon Fruit, Guava, and Mango.
- Different physical properties (e.g., shape and color) and flavours.
- Bought from the same distributor and have the same place of origin.
- Being kept in room conditions.
- The intensity spectrum was stored in a .csv file for each session.
- 1,979 NIR spectrum measurements, each of which has the dimension of 224 were taken and then divided into three sets: Training set, Validating set and Testing set.

2. DATA COLLECTION

2.3. Self-built Database (2/2)

Number of NIR spectrum measurements for each fruit type.

Fruit type	Training set	Validation set	Test set	All sets
Apple	246	102	66	414
Avocado	235	78	66	379
Dragon Fruit	240	78	66	384
Guava	251	73	66	390
Mango	266	80	66	412
Total	**1238**	**411**	**330**	**1979**

Settings of NIR data collection sessions.

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3. PROPOSED METHODS

3.1. Feature Extraction Techniques

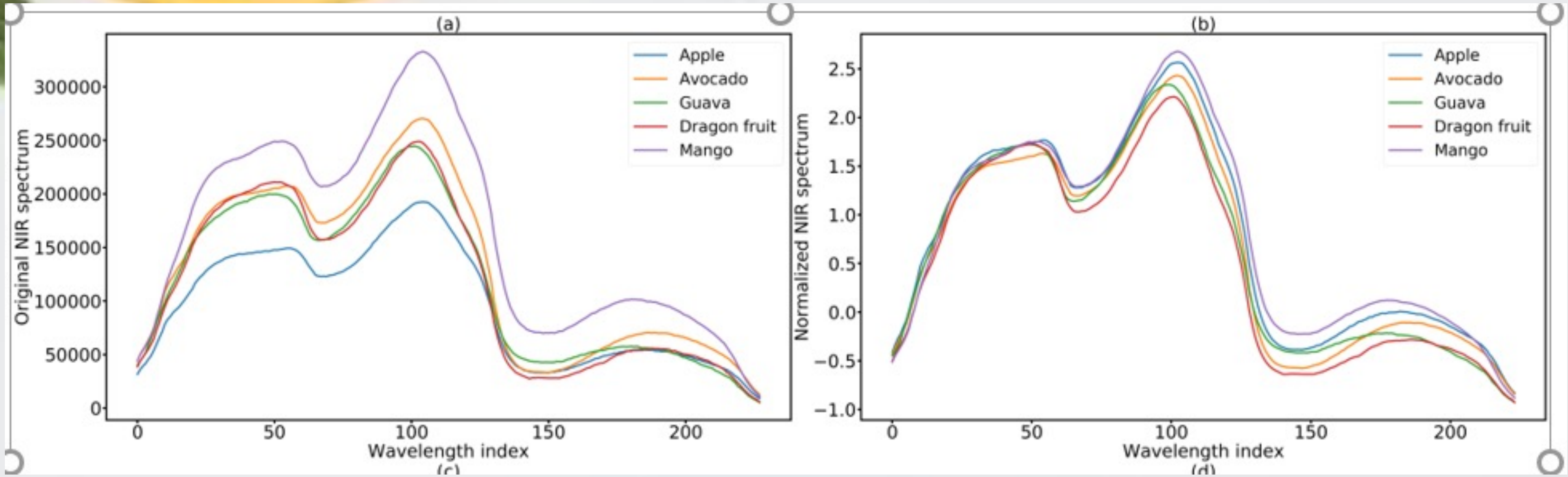
3.2. Deep Learning Model Architectures

3.2.1. Convolutional Neural Network (CNN) based model

3.2.2. Residual Network (ResNet) based model

3. PROPOSED METHODS

3.1. Feature Extraction Techniques (1/2)

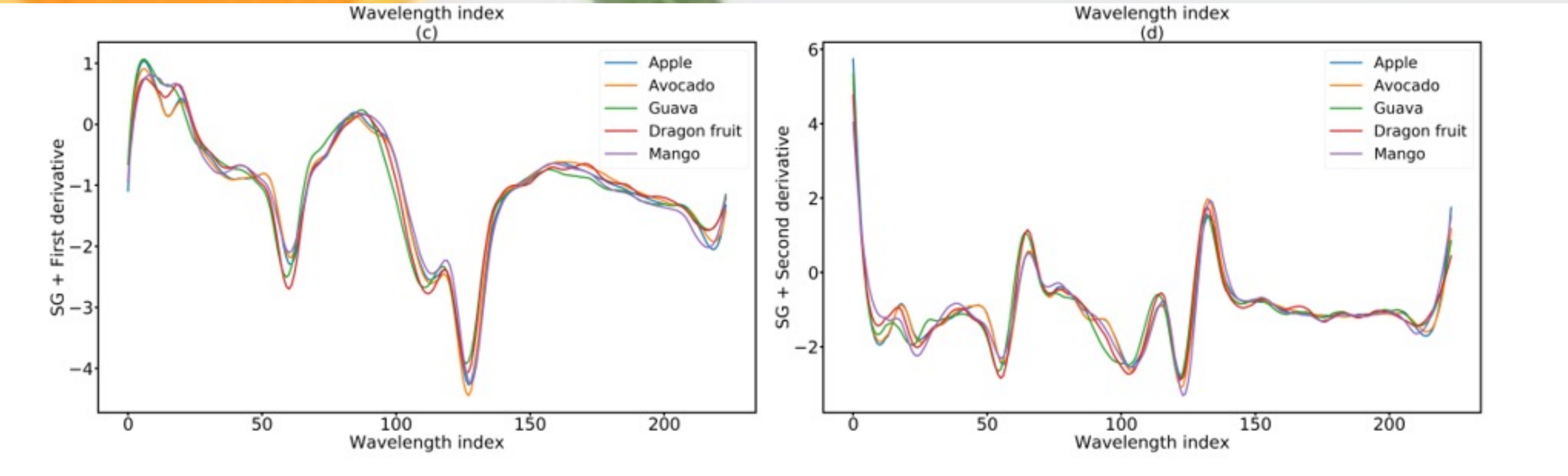


✓ Original and Normalized NIR spectra present **minor differences among** different types of fruits.

- Propose to include the first and the second derivatives of the normalized spectra. [17]

3. PROPOSED METHODS

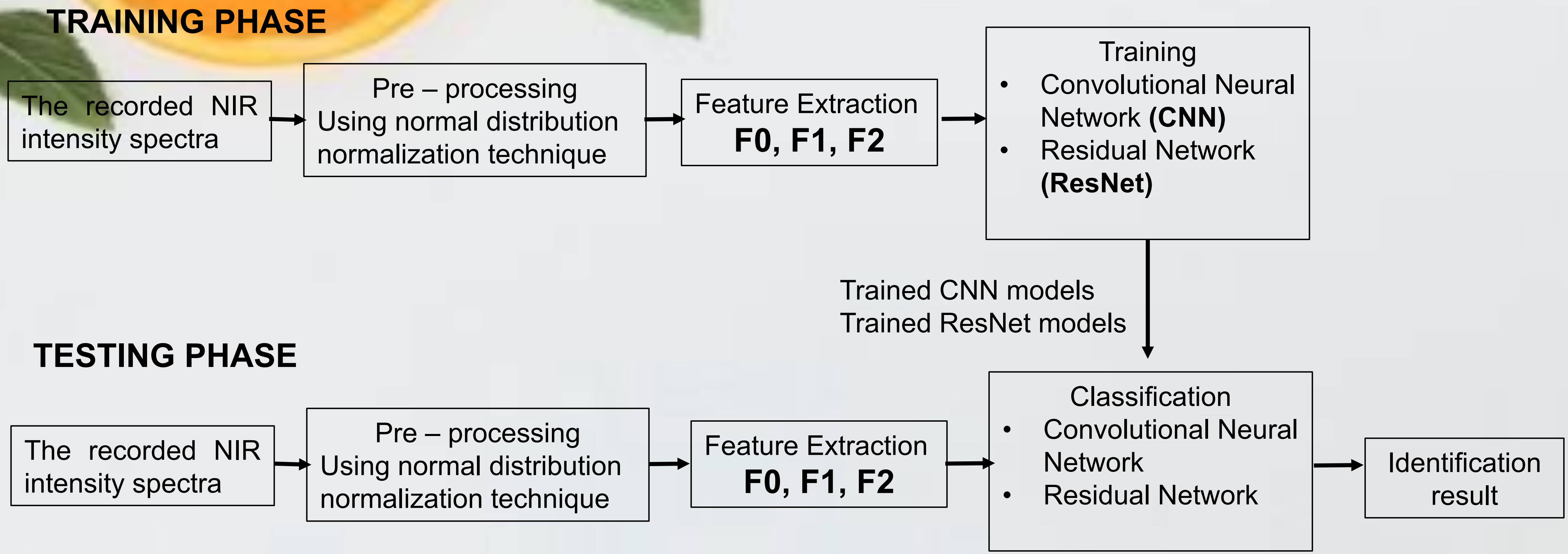
3.1. Feature Extraction Techniques (2/2)



- ✓ The derivatives of the normalized spectra will result in noisy data with lots of small variations.
  - Utilize the **Savitzky-Golay (SG) filter** [18] to smooth the normalized spectra without distorting its tendency.
  - SG filter parameters: Filter window length = 25, polynomial order = 5.
- ✓ The **full feature vector** of the total dimension of **672** includes:
  - The **normalized NIR spectra F0** (which has the dimension of 224);
  - The **first and second derivatives** of SG-smoothed normalized spectra **F1, F2** (which has the dimension of 448).

3. PROPOSED METHODS

3.2. Deep Learning Model Architectures



Overall diagram of our proposed deep learning models: Training and Testing phases

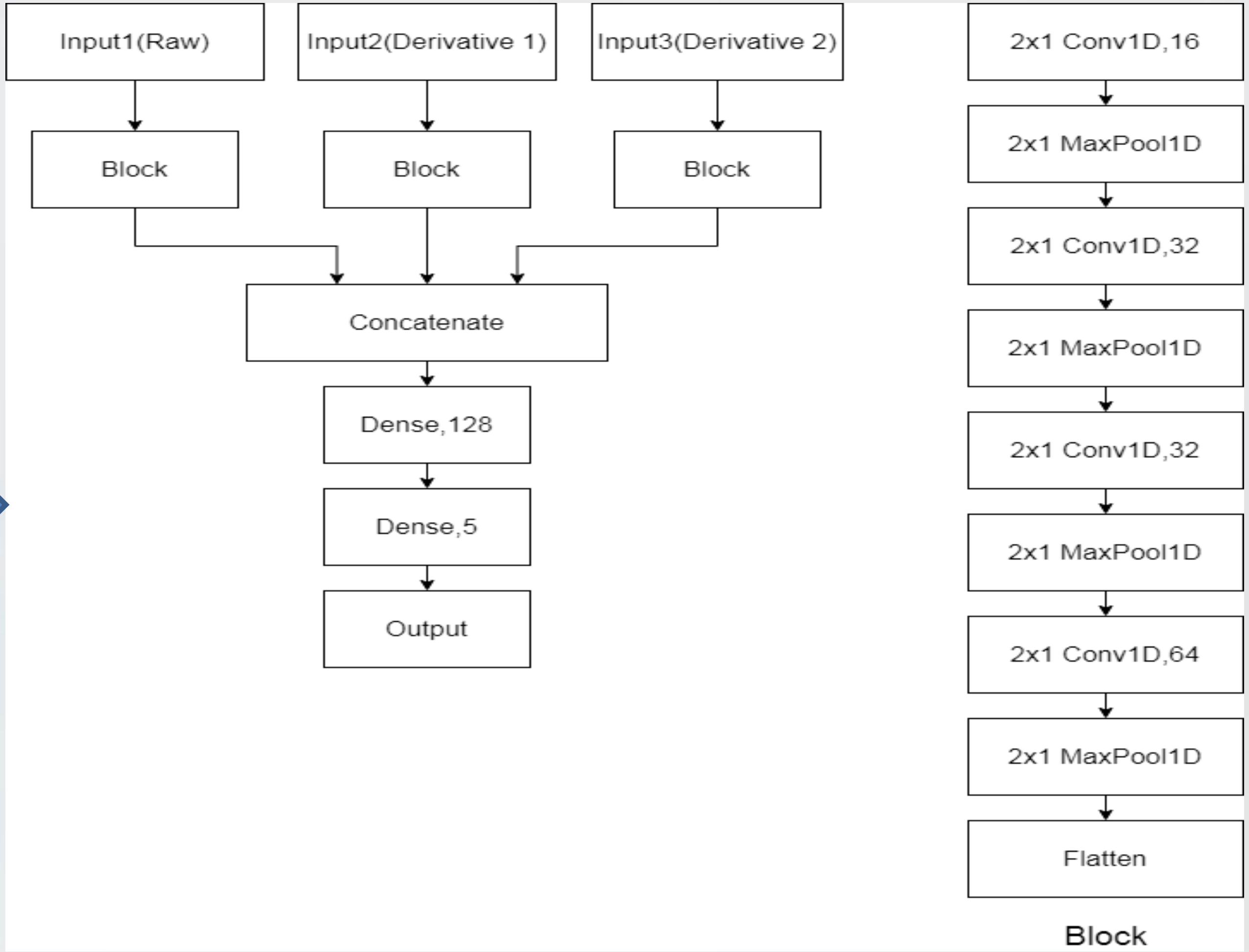
- The features extracted from the pre-processed spectras are used for training and testing, with Convolutional Neural Network **(CNN)** and Residual Network **(ResNet) models.**
- The trained models: classify the input spectra (testing dataset) → Identification result.

PROPOSED METHODS

3.2.1 Convolutional Neural Network (CNN) based model

✓ The model includes 3 input layers:
- 1st layer: Feature vector F1 of size 224x1
- 2nd layer: Feature vector F2 of size 224x1
- 3rd layer: Feature vector F3 of size 224x1

✓ The output feature vectors of three CNN-based blocks were concatenated into a single output vector of size 2496.

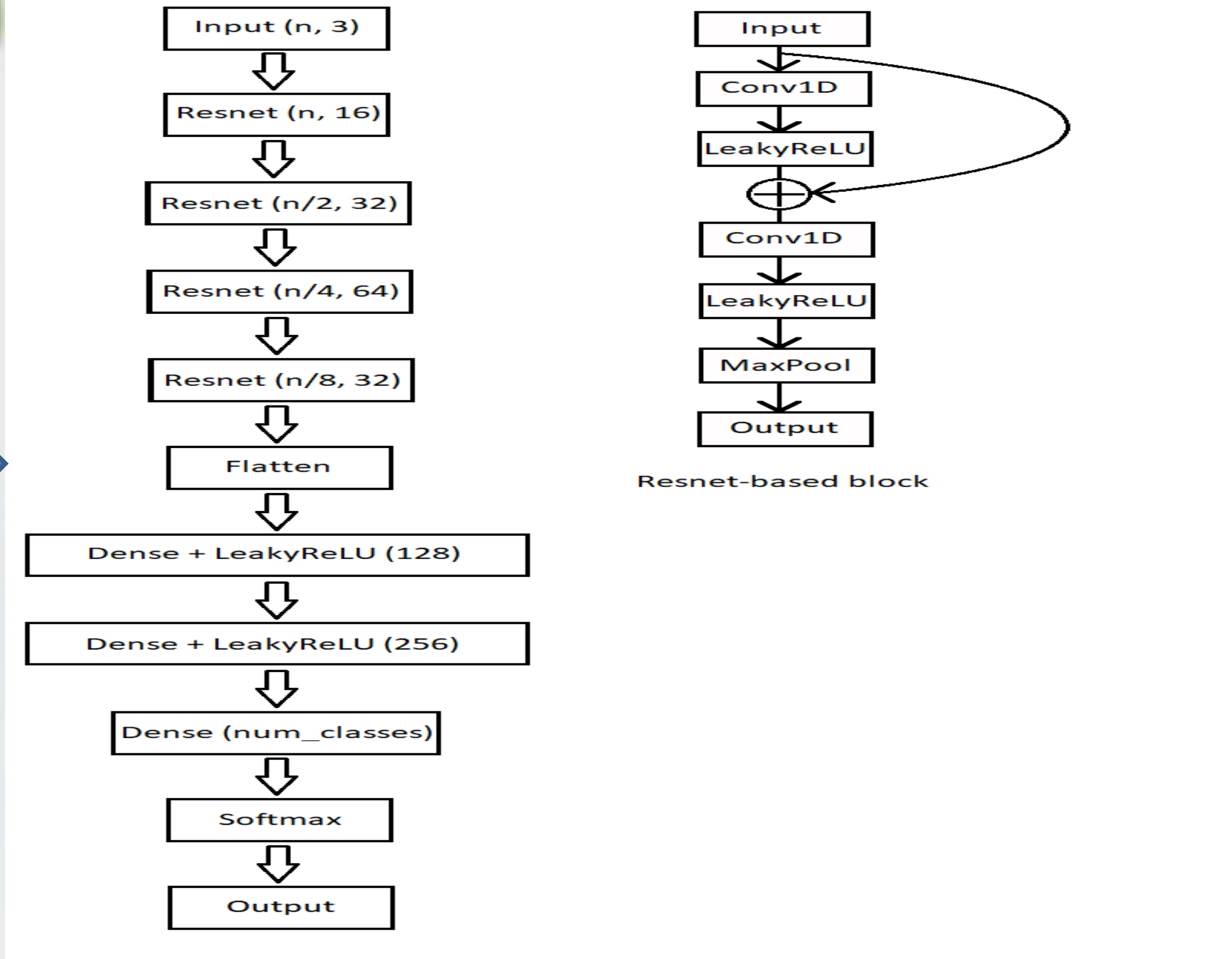


PROPOSED METHODS

3.2.2 Residual Network (ResNet) based model

✓ The model includes:

- 01 input layer containing a full feature vector of size 224x3.
- 04 ResNet based blocks :
  - 02 convolutional layers with kernels of size 3x1
  - Leaky ReLUs as the activation function.
- The number of output filters in 8 consecutive convolutional layers are 16, 32, 32, 64, 16, 32, 32 and 64.



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4. EXPERIMENTAL RESULTS

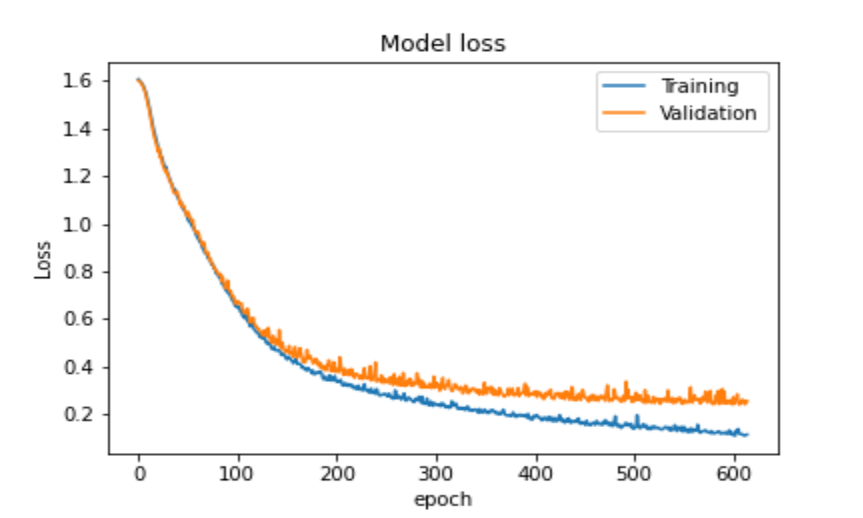
4.1. Comparisons between Proposed DNN models

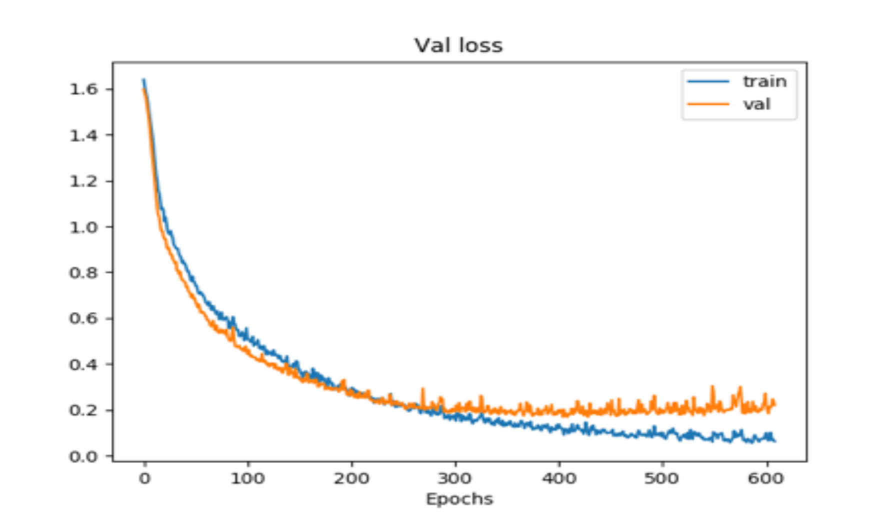
4.2. Effect of Proposed Feature Extraction Techniques

4.3. Comparisons with Traditional Machine Learning Models

4. EXPERIMENT RESULTS

4.1. Comparisons between Proposed DNN models





- ✓ **For training the proposed DNNs:**
  - Use Adam optimizer with a learning rate of 0.0001.
  - Use Keras, a deep learning API running on the top of the machine learning platform TensorFlow.
- ✓ Use proposed extracted features : **CNN_Fi and ResNet_Fi (i=0:2)**
- ✓ **The cross-entropy based loss function** of the two DNN models varied on the training and validation sets over training epochs.
  - Stop the training process after **600 epochs** to prevent over-fitting.

4. EXPERIMENTAL RESULTS

4.1. Comparisons between Proposed DNN models

Model	Training set	Validation set	Test set
CNN-based	99.4%	97.1%	98.2%
ResNet-based	97.0%	95.0%	99.0%

✓ **Recognition time :**

- 2 to 3 ms for predicting on a fruit sample tested on the same computer for both models.

✓ Total **number of trainable parameters**:

- ResNet-based model: 192,853
- CNN-based model: 342,293

✓ **ResNet-based model** presents slightly higher correct classification rate on the test set than **CNN-based one**.

4. EXPERIMENTAL RESULTS

4.2. Effect of Proposed Feature Extraction Techniques

Model	Training set	Validation set	Test set
CNN-based	91.6%	90.1%	89.8%
ResNet-based	90.9%	89.0%	90.2%

✓ **Replicating the experiment by using only normalized NIR spectra F1:**

- CNN-based model: 01 input layer of 224 neurons.
- ResNet-based model: 01 input layer of 224 neurons.

✓ The inclusion of features F2 and F3 helps improve the recognition accuracy on the test set of the proposed DNN models more than 8%.

4.EXPERIMENTAL RESULTS

4.3. Comparisons with Traditional Machine Learning Models

- ✓ Compare with **other traditional classifiers**: k-nearest neighbors, Naïve Bayes and SVM by using the **proposed feature extraction** techniques.
- ✓ The training and testing experiments used scikit-learn machine learning toolkit with the **same data subsets**.

Model	Main model setting	Accuracy (%)
KNN	K=6	90.0
	K=7	**91.5**
	K=8	88.5
NB	Gaussian NB	**86.5**
	Multinomial NB	85.2
	Bernoulli NB	81.1
SVM	Linear kernel	**90.2**
	Polynomial kernel	88.9
	Radial Basis Function kernel	84.0

➢ The recognition performance of these traditional classifiers is inferior compared to the two proposed DNN models.

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5. CONCLUSIONS

5.1. Conclusions

5.2. Recommendations & Future works

5. CONCLUSIONS

5.1. Conclusions

- ✓ Building **2 DNN models** for automatic recognition of five kinds of fruits in Vietnam: Apple, Avocado, Dragon Fruit, Guava, and Mango.
  - CNN-based model.
  - ResNet-based model.
- ✓ Constructing **new feature extraction techniques**:
  - **Normalized NIR spectra F1** (**224-dimensional vectors**);
  - The **first and second derivatives** of SG-smoothed normalized spectra **F2, F3** (224-**dimensional vectors for each one**).
- ✓ ResNet-based model achives slightly higher accuracy and is more compact than the CNN-based one.
- ✓ The recognition performance of the proposed DNN models surpasses that of traditional classifiers.
- ✓ The inclusion of F2 and F3 improves the recognition accuracy of the proposed DNN models by more than 8%.

5. CONCLUSIONS

5.2. Recommendations & Future works

- ✓ Our proposed methods can be applied for identifying the freshness of fruits based on NIR spectroscopy.
- ✓ Expanding our database: for different types of fruits, large number of samples, various sessions for different fresh level detection.

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Questions?

Thanks for the attention