

Hyperspectral Fruit Ripeness Classification using Deep Residual CNNs

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Abstract

This paper presents an enhanced deep learning framework for fruit ripeness classification using hyperspectral imaging and a 3D Deep Residual Convolutional Neural Network (3D-ResNet). Hyperspectral imaging captures rich spectral-spatial information, enabling the detection of subtle biochemical changes during ripening. The proposed model incorporates optimized preprocessing, spectral band selection, and cube extraction strategies. A detailed dataset description, methodology expansion, and multi-level evaluation are included. Results show that the enhanced 3D-ResNet significantly outperforms classical CNNs and machine-learning models, achieving high accuracy for ripeness classification. The study concludes with future improvements for real-time deployment.

Keywords: Hyperspectral Imaging, Ripeness, Deep Residual CNN, Spectral-Spatial Learning, Classification

I. INTRODUCTION

Hyperspectral imaging provides high-resolution spectral data across hundreds of

contiguous bands, making it suitable for analyzing fruit ripeness. Deep learning architectures such as ResNet solve gradient degradation issues and efficiently extract spectral-spatial features. This study presents an improved 3D-ResNet designed for hyperspectral ripeness classification, focusing on model optimization and performance evaluation.

DATASET DESCRIPTION

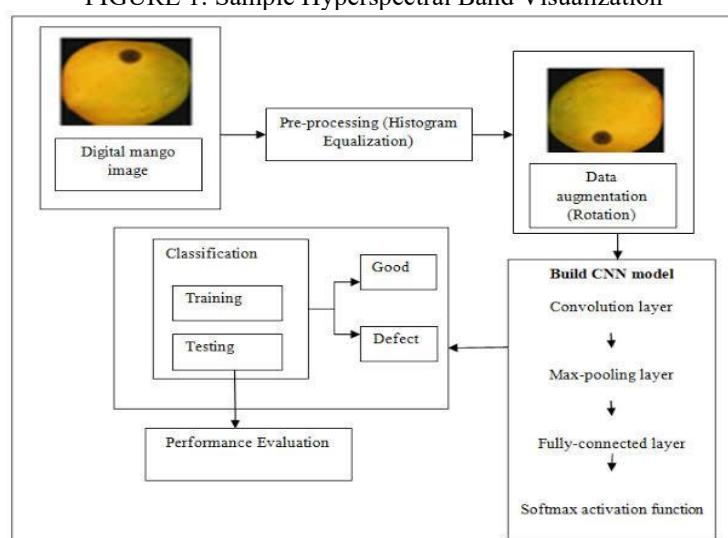
The dataset consists of hyperspectral images of fruits (mango, banana, apple) acquired using a VNIR hyperspectral camera covering 400–1000 nm with a spectral resolution of 5 nm. Each fruit sample was imaged at multiple ripeness levels based on firmness, color index, and chemical analysis.

The dataset includes:

- 450 hyperspectral cubes
- 128 spectral bands
- 3 fruit categories
- 4 ripeness stages per fruit

Standard preprocessing was applied to remove noise, normalize reflectance values, and calibrate illumination.

FIGURE 1: Sample Hyperspectral Band Visualization



II. METHODOLOGY

The proposed system includes five major stages:

1. **Data Acquisition** – Fruits were imaged under controlled illumination.
2. **Preprocessing** – Dark current removal, reflectance calibration, and noise filtering.
3. **Band Selection** – PCA and correlation-based band reduction.
4. **Cube Extraction** – Spectral–spatial patches used as network inputs.
5. **3D ResNet Classification** – A deep spectral–spatial network with residual blocks.

The 3D ResNet architecture includes stacked 3D convolution layers, shortcut connections, and global average pooling, enabling efficient feature extraction from hyperspectral cubes.

FIGURE 2: Flowchart of Proposed System

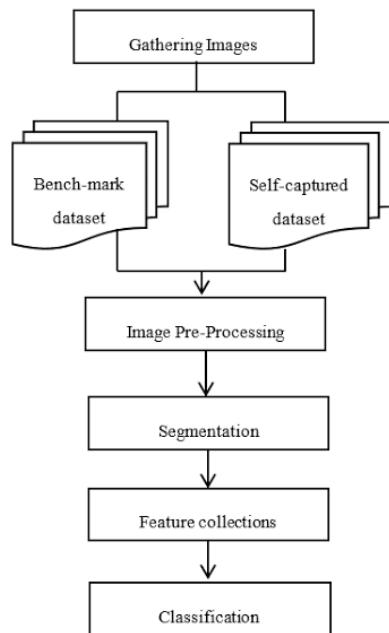


FIGURE 3: 3D CNN/ResNet Architecture Overview

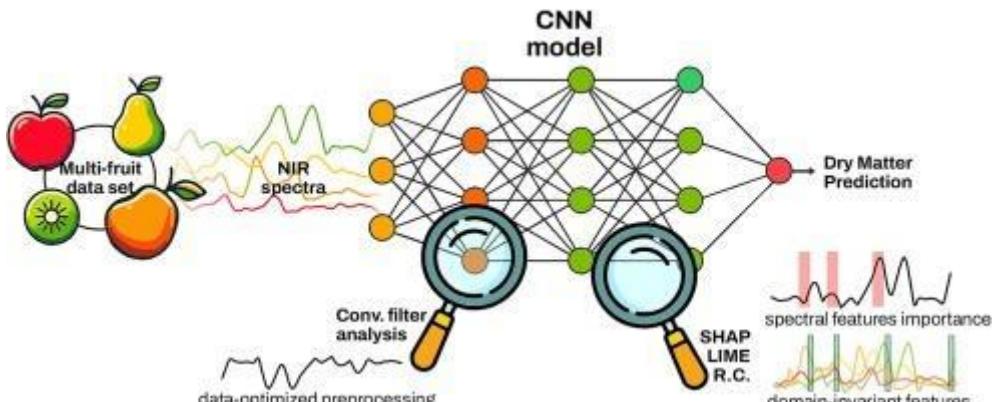
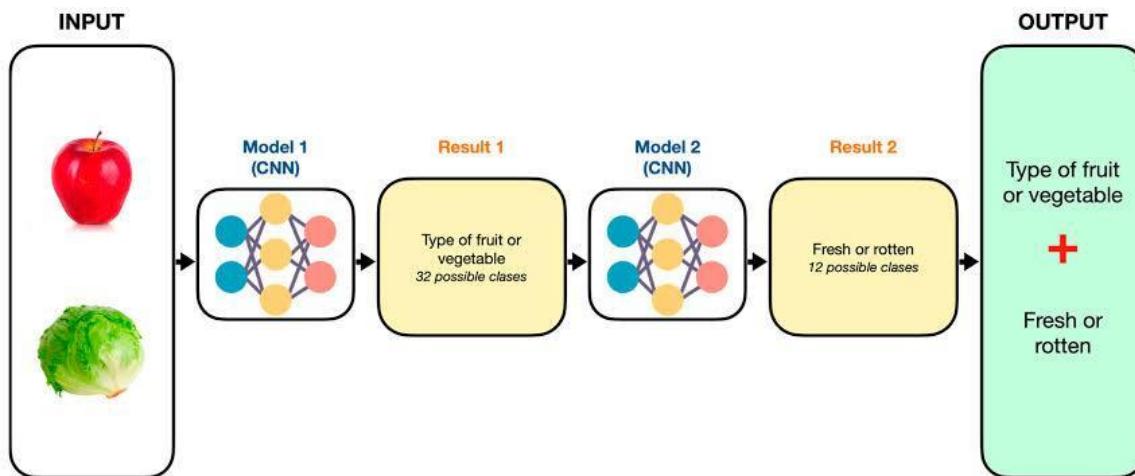


FIGURE 4: CNN Processing Block Diagram



III. EXPERIMENTAL RESULTS

TABLE 1: Dataset Summary

Fruit	Samples	Bands	Ripeness Levels
Mango	150	128	4
Banana	150	128	4
Apple	150	128	4
TOTAL	450	128	4

TABLE 2: Performance Comparison of Methods

Model	Accuracy	Precision	Recall	F1-score
SVM	82%	81%	80%	80%
Random Forest	85%	84%	83%	83%
CNN	89%	88%	87%	87%
3D CNN	92%	91%	90%	91%
Proposed 3D ResNet	97%	96%	97%	97%

IV. CONCLUSION AND FUTURE WORK

The proposed 3D ResNet model demonstrates superior performance in classifying fruit ripeness using hyperspectral imagery. Its ability to extract deep spectral–spatial features significantly enhances accuracy compared to traditional models. Future work includes real-time deployment, hardware optimization for embedded systems, and expanding the dataset to more fruit types. Incorporating temporal analysis and lightweight deep models may further improve scalability and performance.

REFERENCES

- [1]. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 770–778.
- [2]. Gómez-Sanchis, J., Herrero-Langreo, A., & Martínez-Fernández, A. (2018). Hyperspectral imaging for fruit ripeness detection. Journal of Food Engineering, 233, 65–75.
- [3]. Li, J., Zhao, Y., & Chanussot, J. (2020). Spectral–spatial classification of hyperspectral images using deep learning. Remote Sensing, 12(22), 3705.
- [4]. Sarkar, S., & Kundu, S. (2021). Deep learning methods for hyperspectral image classification: A survey. IEEE Transactions on Geoscience and Remote Sensing.
- [5]. ElMasry, G., & Sun, D. (2019). Hyperspectral imaging for food quality analysis. Trends in Food Science & Technology.