

Modern Trends in Deep Learning for Fruit Quality Analysis of Hyperspectral Images: A Review

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Abstract— Non-destructive testing techniques for fruit quality analysis have gained importance over the years. Hyperspectral image processing is one of the important non-destructive, cost-effective, rapid, and reliable quality testing techniques that provide both spatial as well as spectral information. Due to the automatic feature learning ability, deep learning is one of the most promising and powerful techniques with better classification accuracy for fruit applications. This paper starts by giving an overview of the quality concept of fruits and vegetables followed by fundamentals of hyperspectral imaging, and its potential applications. Then machine learning and deep learning techniques are highlighted followed by recent research work to illustrate the potential of hyperspectral imaging for fruit and vegetable quality analysis. Lastly, the research gap and future considerations are discussed to improve the analysis and applicability of hyperspectral imaging using deep learning for the quality assessment of fruits, and vegetables.

Index Terms— Hyperspectral imaging, HSI, fruit quality analysis, deep learning, convolutional neural network,CNN.

I. INTRODUCTION

Fresh fruits and vegetables are essential food products for nutrition due to the balanced supply of nutrients such as sugar, vitamins, fibers, and minerals. The quality and safety of fruits are crucial in terms of consumers, processors, and stakeholders. Behzad et al [1] discussed various fruit quality assessment parameters. Fruit quality is accessed by analysis of various physical, chemical, and biological parameters including taste, color, aroma, texture, freshness, firmness, sweetness, ripening rate, cleanliness, and presence of non-harmful chemicals and pesticides. The quality of fruit decides its market acceptance; hence it is directly affected by the storage conditions of fruits and vegetables. Testing of fruit quality has been a destructive, subjective, laborious, and cost-consuming process. Thus, many reliable and non-destructive imaging-based techniques have evolved over the years for internal and external fruit quality analysis. Over the past decade, non-destructive analysis of fruit quality parameters has been performed on hyperspectral images of many fruits and vegetables [2].

Hyperspectral imaging is a spectral sensing technique that integrates digital spectroscopy and imaging to obtain spatial as well as spectral information. HSI data is characterized by a number of distinct different spectral channels in each pixel, increasing the amount of data acquired beyond the human eye's capabilities [3]. Hyperspectral imaging systems provide a real-time, non-destructive, technique and provide an alternative to traditional methods that deliver cost-effective, rapid, reliable, and accurate results for fruit and vegetable quality analysis [2]. Quality parameters of fruits and vegetables include freshness, sweetness firmness, ripeness, chilling

injury, bruises, and pesticide residue detection [4-11]. This review focuses on the combination of the capability of hyperspectral image processing in the context of quality assessment in fruits and vegetables using deep learning techniques. The remainder of this review paper is organized into four sections. Section II introduces the fundamentals of hyperspectral imaging systems including components, structure, and potential applications of HSI. Section III presents a high-level description of the machine learning and deep learning techniques to illustrate the potential of hyperspectral imaging for fruit and vegetable quality analysis. Finally, based on the lessons learned throughout the paper, Section IV pinpoints some research gaps followed by future trends and scope for development to improve the analysis and applicability of hyperspectral imaging for quality assessment of fruits, and vegetables. Lastly, we have concluded the research work discussed in this review.

II. HYPERSPECTRAL IMAGING SYSTEMS

A. Fundamentals of Hyperspectral Imaging System

The human eye is able to see only a limited range of electromagnetic spectrum and can distinguish between objects based on their different spectral responses in that narrow spectral range [12]. However multispectral imaging sensors have been developed which can acquire images in visible and infrared segments of the electromagnetic spectrum and can uniquely identify material based on their unique spectral signatures. Images produced from hyperspectral sensors contain much more data than images from multispectral sensors which makes it suitable for fruit and vegetable quality analysis. Hyperspectral imaging or imaging spectrometry [13] is a spectral sensing technique in which an object is captured using several well-defined optical bands in a broad spectral range. It was originally implemented on airborne and satellite platforms for remote sensing applications but over last two decades, hyperspectral imaging has been applied to numerous applications including art conservation, military, defense and archaeology [14-15], medical diagnosis [16-17], analysis of crime scene detail, forensic analysis [18-19], medicine [20], water resources and agriculture control [21-22] and many more.

B. Structure and Components of Hyperspectral Imaging System

Fig 1 illustrates the configuration of a hyperspectral imaging system [23] and an example of the hypercube extracted from a hyperspectral image. In general, a hyperspectral image processing system consists of a light source, a detector, a device for the dispersion of wavelength, and a computer equipped with image acquisition software like Unscrambler, ENVI, etc. The configuration depends on the application type for which the HSI system is to be used for acquiring high-quality hyperspectral images. In most cases, tungsten halogen lamps are used as a source of light since it produces a stable, durable, uninterrupted, and low-cost spectrum [2].

Fig 2 represents the structure of the hyperspectral image. The hyperspectral image consists of a series of contiguous sub-images; each one represents the intensity and spatial distribution of the tested object at a certain wavelength. Any individual image can be selected at a particular wavelength covering the spectral sensitivity of the system. Therefore, a hyperspectral image described as $I(X, Y, \lambda)$ can be viewed either as a separate spatial image $I(X, Y)$ at each wavelength (λ), or as a spectrum $I(\lambda)$ at every pixel (X, Y). There is flexibility in the selection of any area of interest in a target object [24].

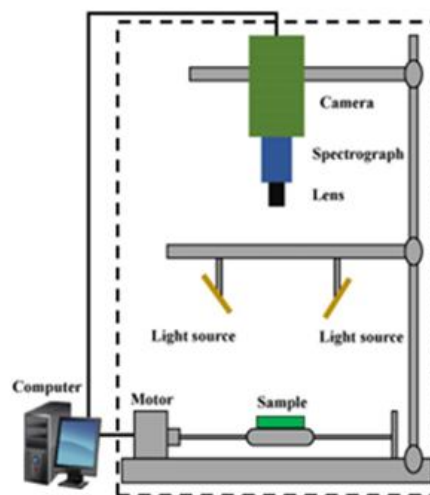


Fig 1. Components of hyperspectral imaging system.

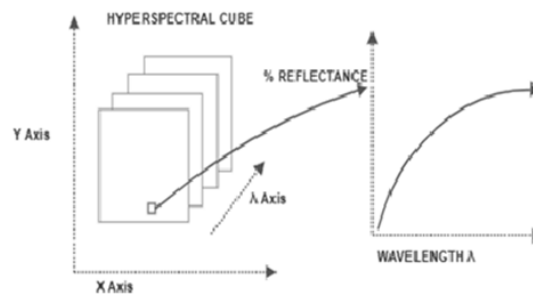


Fig 2: Structure of hyperspectral image

III. MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

Machine learning grew as a subdomain of artificial intelligence (AI) that consist of statistical models and algorithms that extract useful information from the data and utilize that information for making good classifications and predictions. Machine learning has gained popularity due to its reliability and accuracy. Machine learning is of three types including supervised, unsupervised, and reinforcement learning. In supervised learning, labeling of data is done to predict the results. Classification and regression are subdomains of supervised learning. Unsupervised learning deals with unlabeled data. Dimensionality reduction and clustering are subdomains of unsupervised machine learning. Reinforcement learning refers to the application of specific task-oriented algorithms in a manner to learn to achieve a goal. Supervised machine learning techniques include artificial neural network (ANN), Decision trees, Support vector machines (SVM), K-Nearest neighbor, Logistic Regression, etc. Examples of unsupervised machine learning techniques are k-mean clustering and dimensionality reduction techniques including principal component analysis (PCA) and independent component analysis (ICA) [2]. Deep Learning is a sub-domain of machine learning which deals with algorithms inspired by the structure and function of the human brain called artificial neural networks (ANN). In the last years, deep learning was widely used and improved the state of the art in many different application areas including food technology [2].

A. Introduction to Deep Learning

Deep learning is a branch of machine learning. It is based on artificial neural network (ANN) architecture. An artificial neural network or ANN consists of layers of interconnected nodes. These nodes or neurons work together to process the input and learn from the input data. In a fully connected deep artificial neural network, there is a single input layer and one or more hidden layers. These hidden layers are connected one after the other. Each neuron receives input from the previous layer neurons which is the input layer. The output of one neuron is fed as the input to other neurons in the next layer of the network. This process continues till the final layer produces the desired output. This allows the network to learn complex representations from the input data. The advantage of these deep learning techniques lies in their ability to learn features automatically rather than relying on manual feature learning, as in the case of more conventional machine learning techniques Ref. [25]. A common type of network for multidimensional data is a CNN as shown in Fig 3 typically consists of multiple convolutional layers.

A deep-learning CNN consists of a convolutional layer, a pooling layer, and a fully connected (FC) layer. The convolutional layer is the first layer, and the fully connected layer is the last layer. This complexity of CNN increases from the convolutional layer to the fully connected (FC) layer. This increasing complexity allows the CNN to successfully identify the object. NaranjoTorres et al. Ref. [26] specifically focus on the use of CNN for fruit image processing including fruit classification, detection, and quality control.

B. Studies Related to HSI Using Deep Learning

In this review, we focused on the research done in the last five years where convolutional neural network (CNN) of deep learning architecture has been exclusively used for the analysis of hyperspectral data of fruit and vegetable quality parameters including firmness, soluble solid content (SSC), bruises and internal mechanical damage detection.

- Wang et al. [27] specifically focused on the use of CNN for the detection of internal mechanical damage in blueberries. Wavelength selected was in the range of 400-1000 nm. In this work, Sub-sampling, image resizing and normalization was used for image pre-processing. ResNet and ResNeXt were used with a

convolutional layer filter size of 3x3; Stride 2 and activation function as Rectified Linear Unit (ReLU). The learning rate, decay rate, and decay step were 0.1, 0.1, 32,000 respectively. The training validation ratio was 80:20. Processing software used was MATLAB R2014a. The overall accuracy of the model was found 88%.

- Liu et al. [28] performed internal damage detection of cucumber in the spectral range of 400-1000 nm. Image thresholding was used as a pre-processing technique. Stacked Sparse Auto Encoder (CNN-SSAE) deep learning architecture was used. Greedy layer-wise pre-training was done with the stacking of an additional output layer on pre-trained SSAE. Training through gradient descent with backpropagation was done. Two neuron layers with 16 encoding neurons in each layer were considered. The training validation ratio was 80:20. The overall accuracy of the model was 91%.
- Yu et al. [29] predicted firmness and soluble solid content (SSC) of pear in the spectral range of 400-1000 nm. In this study, multiplicative signal correction (MSC) and successive projection algorithm (SPA) were used for spectral pre-processing. Image thresholding was used for image pre-processing. Features were extracted from hyperspectral data through a stacked autoencoder (SAE). The training validation ratio was 80:20. Processing software Matlab 8.1 and Python were used in this study. Observed accuracy was 89% for firmness and 92% for soluble solid contents (SSC).
- Liu et al. [30] performed a study on the detection of bruises in strawberries in the spectral range of 900 to 1700 nm. In this study, Savitzky–Golay filter was used for spectral pre-processing. The watershed algorithm was used for image segmentation. Two branch convolutional neural networks (2B-CNN) is used where 1st branch is 1D convolution of spectral features and 2nd branch is 2D convolution of spatial features. The training validation ratio was 80:20. The overall accuracy of the model was found as 99 %.
- Yun Xiang et al. [31] successfully predicted soluble solid contents of tomato using deep learning and hyperspectral imaging in the spectral range of 400 to 1000 nm. In this study, hyperspectral image pre-processing is done with multiple scattering corrections (MSC). A novel one-dimensional (1D) ResNet (Con1dResNet) based regression model is proposed and compared with the state of art methods. In this work, ReLu is used as an activation function, Adam is used as an optimizer and MSE is used as a loss function. Experimental methods show that with a large number of samples, the proposed technique is 26.4% better than the existing technique for soluble solid content and 33.7 % for firmness.
- Garillos-Manliguez, C.A. and Chiang, J.Y. [32] developed multimodal variants of deep learning models for a novel non-destructive, refined fruit maturity stage classification. The models utilized the multimodal input data cubes and exhibited very promising results in papaya fruit maturity estimation with up to 0.90 F1-score and as low as 1.45% top-2 error rate. Among the seven architectures examined, MD-VGG16 obtained the best performance, while MD-AlexNet and MD-VGG19 showed comparable outcomes. The results of this study offer great potential for multimodal deep learning and multimodal imaging to estimate fruit maturity in real time.
- Mesa, A.R. and Chiang, J.Y. [33] developed a non-invasive automated system for export-quality bananas, which utilized RGB, hyperspectral imaging, and deep learning techniques. A real dataset of pre-classified banana tiers based on quality and size (Class 1 for export quality bananas, Class 2 for the local market, and Class 3 for defective fruits) was utilized using international standards. Using combinations of CNN and MLP applied to features extracted using RGB and hyperspectral imaging, the multi-input model was able to classify tier-based bananas with an overall accuracy of 98.45% and an f1-score of 0.97570.

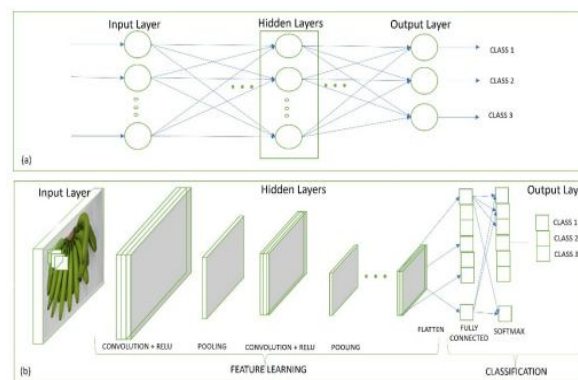


Fig 3: Neural network architecture, (a) a simple multilayer perceptron (MLP) architecture, and (b) basic convolutional neural network (CNN) architecture.

IV. RESEARCH GAP AND FUTURE CONSIDERATIONS

Hyperspectral imaging is a powerful tool for non-destructive assessment of fruits and vegetable quality because of its ability to capture spatial as well as spectral information but it is challenged with different limitations. There should be a standard way for proper sample selection, deciding sample size, use of efficient wavelength selection technique, model validation, and evaluation which define the success of the model developed for HSI processing. There are challenges in the availability and use of hardware and software for hyperspectral image processing. The cost of hyperspectral systems is very high to use for real-time applications. As hyperspectral images consist of huge volumes of data because of a number of wavelength bands, useful data extraction from huge amounts of data is a challenging task. There should be the use of spatial and spectral data for full utilization of hyperspectral image processing capability. Due to automatic feature learning, deep learning is one of the most promising and powerful techniques with better classification accuracy for fruit applications. In addition, applications of deep learning for fruit quality assessment are more present in research papers than in vegetables including leafy vegetables. Thus, the use of deep learning, certainly in combination with vegetable data analysis, is an interesting gap to explore in the near future.

V. CONCLUSION

It can be concluded that deep learning has tremendous potential for hyperspectral imaging systems, as it can automatically learn from features and can handle large volume of data. Although there are still many challenges to overcome including high computational cost, over fitting, and dependence on data quality, deep learning will certainly be further explored in the near future as it has high performance over traditional machine learning techniques.

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