Fruits classification and analysis using Hyperspectral Imaging with the help of Deep learning

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Abstract

Hyperspectral imaging (HSI) is most efficient way of retaining information using Deep learning concept. It is very intricate task to identify the rotten fruits without destructing it, HSI is non-destructive way of collecting data of fruits, which ease the process of sorting with an help of Algorithm. Deep Learning employs neural network method to exploit the connection between the spatial context and spectral context. HSI stores the wavelength of refracted, reflected and absorbed light in several bands which also contain noise produced by machinery used that is filtered using SMV(Standard normal variate). Filtered information is represented by hyperspectral cube(3D). An image pre-training convolution neural network (CNN) is used on dataset and then tunned to provide classifier. In this model most dataset (70%) collected is used to train the neural network, while (30%) dataset for verifying the process. The obtained proves that this process of analysis using CNN algorithm is more accurate (>90%) and effective.

Keywords: Hyperspectral Imaging; AlexNet; ResNet-50; VGG-19

Introduction

In Harvest and Storage of fruits we can't neglect the damage caused by scrape, brevity, tremble. Customers are paying attention only for the external quality of fruits. Moreover, food industry is facing some issues in maintaining good quality standards and assuring safety of fruit which are characterized by physical, chemical and biological attributes of fruit to attain this constraint we're moving towards an emerging technique Hyper Spectral Imaging along with Deep learning. There are some non-destructive approaches like x-rays, thermal imaging, electrical impedance for detecting damaged sample but they are not effective. Machine learning has the ability to detect the sample attributes like shape, size, color, texture precisely. Visible Imaging sensor (RGB color image) creates image that reproduce human vision in which the images are captured in red, green, blue wavelength but they cannot capture image in night and dim light. NIR (Near Infrared) is a segment of electromagnetic spectrum which are intangible to human eyes, the visible range is from 0.4 to 0.7 um while the near infrared spectrum band is from 0.7 to 1um. The multispectral imaging (MSI) includes both visible and invisible wavelength (ultraviolet, infrared) but its spectral information is bounded. Hyperspectral Imaging aka spectroscopic or chemical imaging has massive growth and application in multiple fields and it's superior to typical RGB, NIR, multispectral imaging (MSI) which has the capability to collect broad and comprehensive spatial and spectral information and it also has the ability to extract features that are difficult for traditional computer vision system.

Hyperspectral Imaging (HSI) incorporates with spectroscopy and imaging used for the estimation of internal and external attributes of fruit. Therefore, effective chemometric and algorithm are required for reducing the dimension of HSI data to enhance HSI adaption in real time application. Deep learning is the machine learning technique which performs fast analysis of HSI data due to that, the whole system can run in online and real time conditions. Convolutional Neural Network algorithm comprises of many layers like convolutional layers, pooling layers and fully connected layers. The pixel of image is fed into convolutional layer which performs convolutional operation and functions are applied on the resultant convolved map then the image is processed, distinct pooling layers is used to identify the individual parts of image, this pooled feature map is compressed and fed into fully connected layer to get the output. It's an artificial neural network which is used in training machine in such a way so that it will learn from its own experience and realize data or image like human brain. It also has the ability to identify important aspects without human inspection. Thus, CNN learns everything from training dataset implicitly, it works by getting data, deputing some weightage according to the attribute of image and discriminate each other. It prefers less pre-processed data while comparing with other algorithms. It's more accurate and effective than other algorithms. This algorithm minimizes the computation time and process, enhance the performance and also reduce irrelevant variables and redundancies in order to obtain robustness. This paper presents the integrated aspects of Hyperspectral imaging and Deep learning technique in fruit quality analysis which is an onerous mission to detect the rotten fruits without destructing it.

Materials and methods

Dataset

Data Acquisition

The data set used in this analysis contains 3306 images of fruits. All images were taken with a resolution of 100x100 pixels with Specim hyperspectral sensor sw 3.6218722 camera. These hyperspectral images are collected as dataset. We come across a variety of challenges when acquiring images like light, sunshine, darkness, the camera capturing artifacts, shadows, pose variations and lighting changes. Same category of images were taken at various times and days, which makes the scenario more realistic. Figure 1 shows the sample image and the image specifications are shown in Table 1 respectively.

Figure 1. Image of sample data

Table 1. List of fruit images

S.NO	Fruit name	Image Count
1.	Apple	450
2.	Avocado	440
3.	Banana	513
4.	Blue Berry	507
5.	Guava	693
6.	Kiwi	250
7.	Orange	453

Data Preparation

In this part, the dataset containing 3306 images of fruits is splitted into 70 and 30 percent as training dataset and test dataset. An efficient analytical method is required along with pre-processed hyperspectral images for analyzing the information contained in the images like spectral, spatial and texture features therefore to make the data suitable for deep learning we are performing data preprocessing. This will also increase the accuracy and efficiency of the learning model.

Experimental Procedure

Methods

In this work, we use a variety of models with a hyperspectral picture data set. Our primary goal is to classify the rotting fruits with the best degree of accuracy. In order to enhance the amount of training data sets and hence the accuracy, we first apply data augmentation to the given data. The spectral pictures that were afterwards acquired were divided into training and test processes in a 7:3 ratio. The accuracy and precision achieved from several models, including AlexNet, ResNet, and VGG19, are then compared. Figure 2 shows the working set model's flowchart.

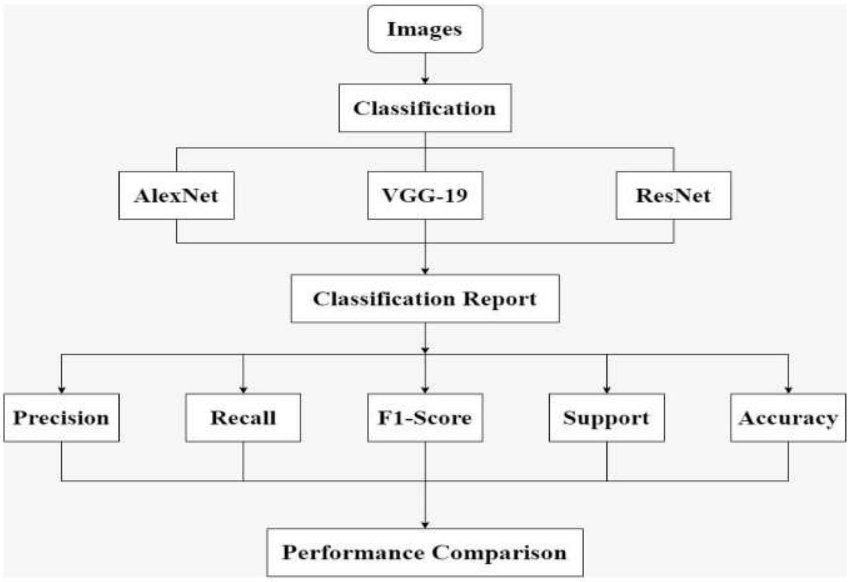

Figure 2. Flowchart of working set model

A. AlexNet

AlexNet is an eight-layer convolutional neural network design with parameters that may be learnt. With the exception of the output layer, each of the model's five levels uses relu activation together with max pooling and three completely connected layers. It was discovered that the relu activation function boosted training speed by a factor of roughly six. Additionally, they included dropout layers to prevent their model from overfitting. Figure 3 shows the architectural diagram for AlexNet.

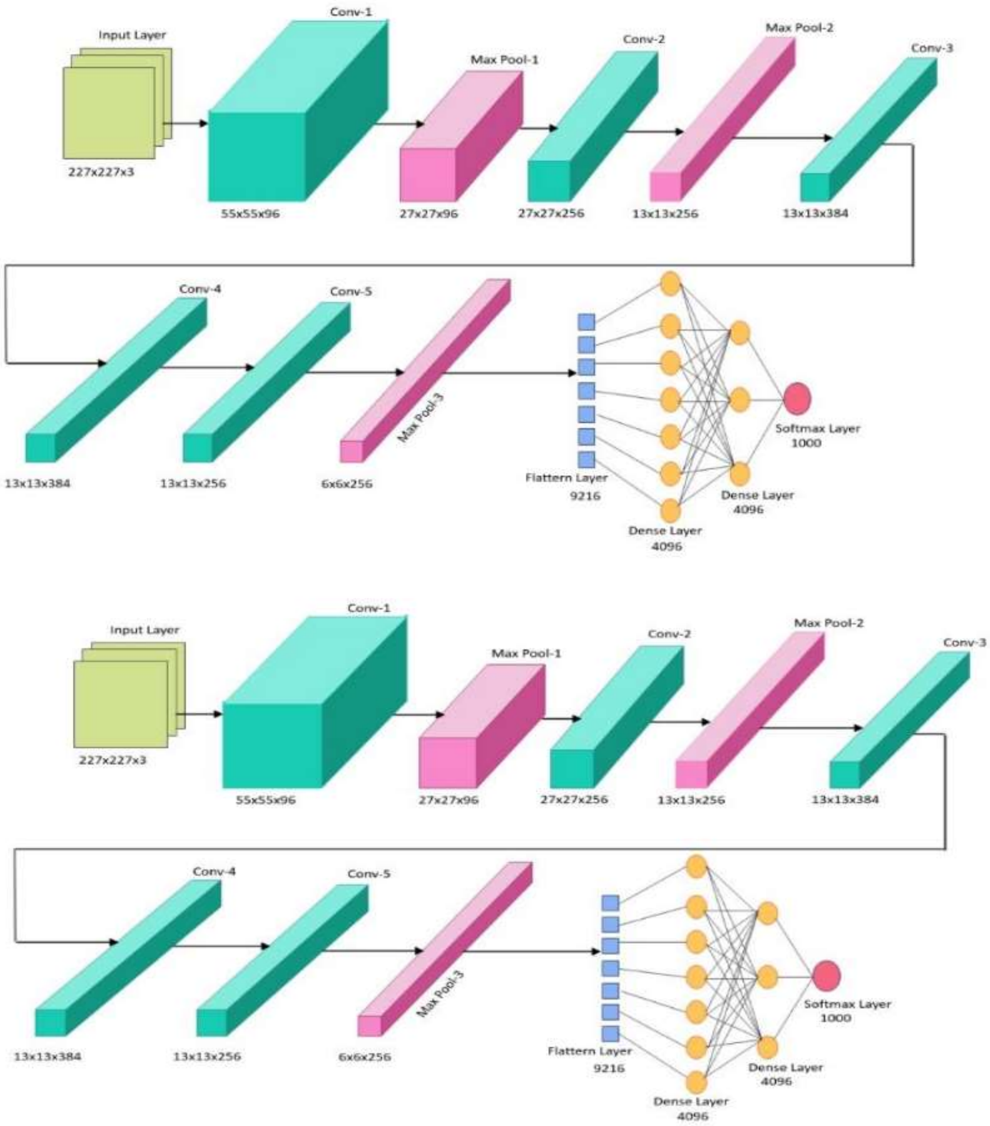

Figure 3. AlexNet architecture

B. VGG-19

VGG-19, is the most established of the models we considered. The VGG-19 model outperforms the VGG-16 in several ways. 19-layer convolution neural network model. Convolutions are stacked together to create the model, however the decreasing gradient problem restricts the model's depth. Deep convolution networks are challenging to train as a result of this problem. The model, like the other candidates, was honed using ImageNet to classify 1,000 different categories of objects. Using VGG-19, we examined feature extraction and amplification. The best outcomes were obtained by feature extraction utilizing only VGG-19. In our situation, VGG-19 does not react to retraining and fine-tuning. Figure 4 gives the architecture diagram of VGG-19 model.

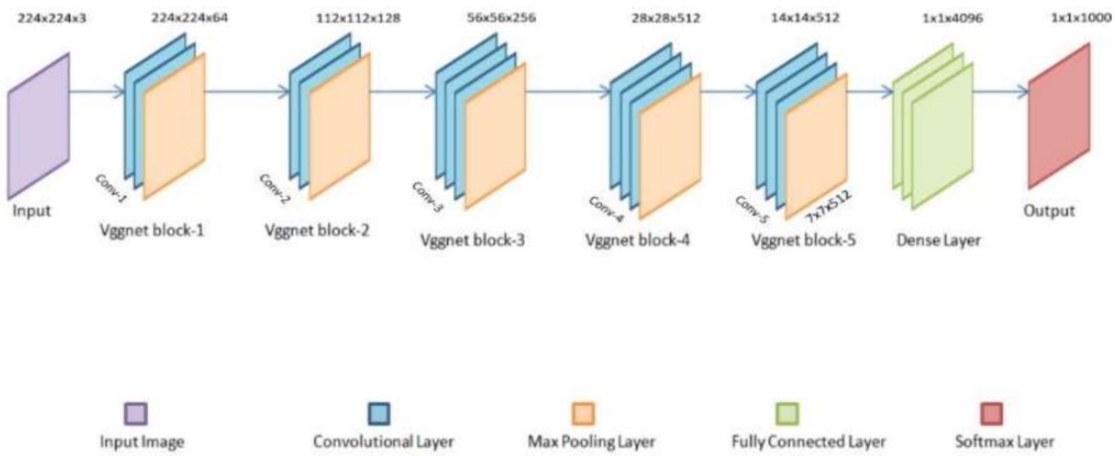

Figure 4. VGG-19 architecture

C. ResNet-50

The Resnet model was suggested as a solution to the gradient-decreasing problem. The intention is for the model to continue training by skipping the connection and passing the residual to the following layer. CNN models can get even more granular using Resnet models. There are other Resnet model modifications, but we went with Resnet-50 in this instance. The best outcome from Resnet 50 is retraining around 40% of all the parameters. Figure 5 shows the architecture diagram of ResNet-50.

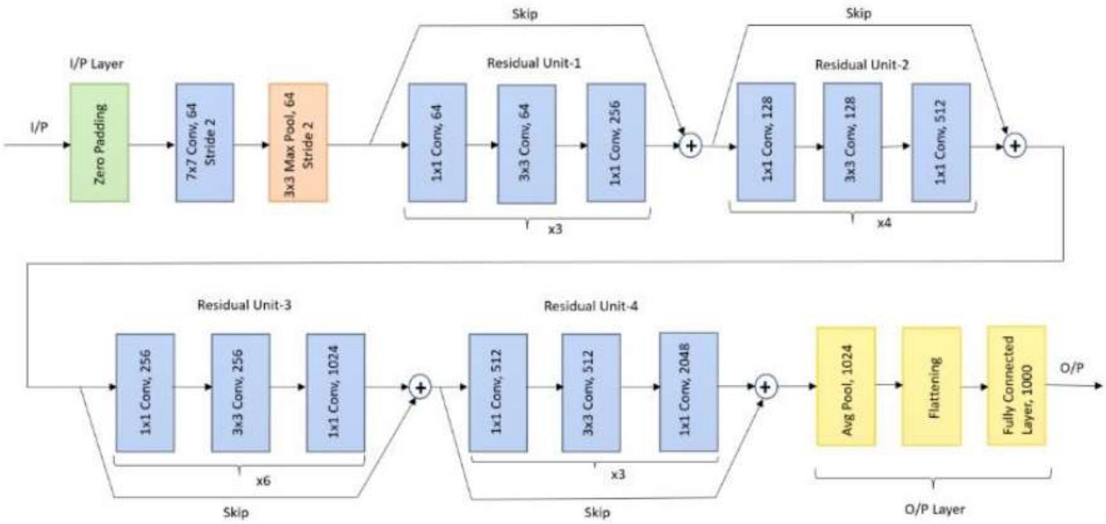

Figure 5. ResNet-50 architecture

D. Training

For training, all 7 different fruits used have approximately same. We apply horizontal flip, rotation, shear shift, zoom as augmentation technique. Hyperspectral images is resized int 100*100 pixels. The neural network is optimized with Adabound using 1e-3 as learning rate. For training we used the batch size of 128.

Adam optimizer is used as it adapt for learning rate scale for different layers instead of hand picking. And to measure the loss value we use categorical-crossentropy while to measure the all the pixel value effectively padding is taken as 'same', and to reduce the size of convolutional layer maxpooling is done with different window size and stride value a 2.

Formula used for calculating the size of convolutional layer is:-

$$\text{Convolutional layer size} = \frac{N-2*P-f}{S}$$

Where, N stands for size of image, P is value of padding, f is total number of filters and s means stand strides value.

Formula for calculating accuracy is:-

$$\text{Accuracy} = \frac{\text{Correct prediction}}{\text{Total cases}} * 100$$

$$\text{Accuracy} = \frac{(Tp+Tn)}{(Tp+Tn+Fp+Fn)} * 100$$

where Tp is True-Positive, Tn is True Negative, Fp is False-Positive and Fn is False-Negative.

Formula for calculating Precision is:

$$\text{Precision} = \frac{\text{True Positives}}{\text{All predicted positives}} * 100$$

Formula for calculating Recall is:-

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives +False Negatives}} * 100$$

Formula for calculating F1score is:-

$$\text{F1 score} = 2 * \frac{\text{Precisions * Recall}}{\text{Precisions +Recall}} * 100$$

After applying all the parameter, we tabulated the accuracy obtained by different models.

Table 2. Accuracy of different models for all samples

Fruit name	Model name	Precision	recall	F1-score	support
Apple	AlexNet	1	0.45	0.27	136
	VggNet	1	0.94	0.97	174
	ResNet50	0.97	0.83	0.89	136
Avocado	AlexNet	1	0.45		143
	VggNet	0.94	1	0.97	116
	ResNet50	1	0.94	0.97	127
Banana	AlexNet	1	0.45	0.87	142

	VggNet	1	1	1	146
	ResNet50	1	1	1	154
Blueberry	AlexNet	1	0.45	0.87	141
	VggNet	1	1	1	140
	ResNet50	0.99	1	1	141
Guava	AlexNet	1	0.45	0.87	143
	VggNet	0.40	1	0.80	60
	ResNet50	1	1	1	141
Kiwi	AlexNet	1	0.45	0.87	139
	VggNet	1	0.47	0.64	278
	ResNet50	0.42	1	0.59	136
Orange	AlexNet	1	0.45	0.87	141
	VggNet	0.97	1	0.99	132
	ResNet50	1	0.01	0.01	166

E.Test

We tested seven different fruits on three models. The model were a AlexNet, VggNet, and ResNet-50, a convolutional neural network architecture with identity shortcut connections and 50 layers. The test set has 30% of labelled hyperspectral images which is further being validated by $(1/3)^{rd}$ part of data set. It is found that VggNet model not perform well in case of "Guava" while for all other fruits it shows more than 90% accuracy. Whereas ResNet model perform well with all the fruits.

Results and Discussions

In this paper, a hyperspectral deep learning model was evaluated to obtain accuracy in classifying rotten fruits. We begin by dividing the 3306 samples into the training and test sets in a 7:3 ratio. Then AlexNet, vggNet, and ResNet were applied to establish models to evaluate the fruit quality. We have done preprocessing, which leads to increased accuracy and efficiency of the learning model. Following that, we used data augmentation on hyperspectral images to resize the HSI to 100 * 100 pixels. For training, we used a batch size of 128. We examine the training and prediction performance of three deep CNNs, i.e., AlexNet, vggNet, and ResNet. We compare and evaluate the performance of these models in terms of precision, recall, and F1-Score. The overall accuracy of the models AlexNet, vggNet, and ResNet is 67.42, 92.072, and 97.342, respectively. Table 3 shows the models and their results in terms of precision, recall, F1-Score, and support.

Table 3. The accuracy and loss value obtained by different models

Model	Loss	Accuracy(%)
AlexNet	1.0047	67.42
VggNet-19	0.1779	92.072
ResNet-50	0.0676	97.342

AlexNet

Table 2 shows that the AlexNet model gives good results for banana, blueberry, guava, kiwi, and orange with an F1-Score of 0.87. As seen in the table, the F1-Score of the proposed AlexNet model does not improve performance drastically compared to the other two models, i.e., vggNet and ResNet, using the same dataset. As compared with the other two models, the accuracy of the AlexNet model is average. The overall accuracy of the AlexNet model is 67.42%, and the loss value is 1.0047. The AlexNet model performs poorly with Apple.

VggNet

Table 2 shows that VggNet performs best for fruit bananas and blueberries with F1-scores of 1 and poorly for kiwis with a F1-score of 0.64. It is found that the VggNet model does not perform well in the case of guava, while for all other fruits it shows more than 90% accuracy. The VggNet model's overall accuracy is 92.072, and the loss value is 0.1779. In comparison to other existing models, VggNet outperformed AlexNet but not the ResNet model. Figure 6 shows the classification accuracy of the VggNet model in terms of accuracy and loss value.

ResNet

As seen in Table 3, among the three models, ResNet gives the highest accuracy. With an F1-Score of 1, the ResNet model performed well in the cases of banana, blueberry, and guava. In comparison with two other models, ResNet performs well in terms of F1-Score, recall, and loss value. As seen in the table, the F1-Score of the Resnet model improved the performance drastically compared to the other two existing models, i.e., VggNet and AlexNet, using the same dataset. The ResNet model's overall accuracy is 97.342, with a loss value of 0.0676. However, the ResNet model outperforms the other two models in terms of overall accuracy and performs well with all fruits. Figure 7 shows the classification accuracy of the ResNet model in terms of accuracy and loss value.

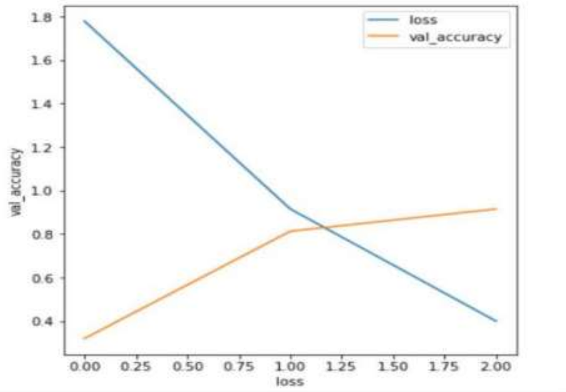

Figure 6. VggNet classification accuracies.

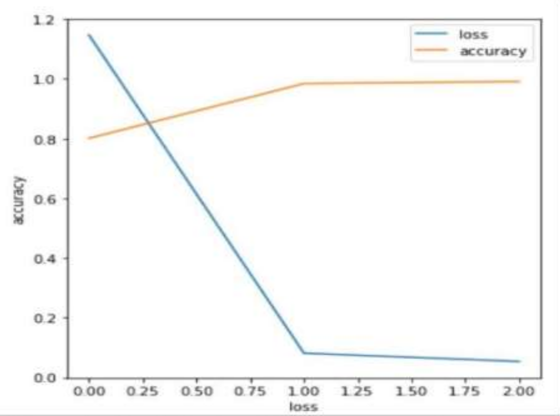

Figure 7. ResNet classification accuracies.

Conclusion

In this research, we developed a hyperspectral deep learning model to assess fruit quality using HSI. A Secim hyperspectral sensor SW 3.6218722 camera was used to capture 3306 images of seven different fruits at a resolution of 100 by 100 pixels for the dataset used in this analysis. Our main objective is to classify the rotting fruits with the best degree of accuracy. First, in order to enhance the number of training datasets while decreasing data redundancy, we apply data augmentation to the acquired data. The outcome demonstrates how highly promising the suggested models are for that kind of application. The performance of each classification approach was then assessed using three distinct models: AlexNet, VggNet, and ResNet. With an accuracy of 95.97%, the ResNet model outperformed the other two in terms of classification abilities. VggNet is a useful model to assess the fruit's quality because of its overall accuracy. However, the research community in hyperspectral classification is currently facing many significant obstacles.

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Conflict of Interest:

According to the authors, there is no conflict of interest.

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