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Papaya maturity Classification Using Deep Convolutional Neural Networks

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Abstract - *Papaya is a tropical fruit with a green cover, yellow pulp, and a taste between mango and cantaloupe, having commercial importance because of its high nutritive and medicinal value. The process of sorting papaya fruit based on maturely is one of the processes that greatly determine the mature of papaya fruit that will be sold to consumers. The manual grading of papaya fruit based on human visual perception is time-consuming and destructive. The objective of this paper is to the status classification of papaya fruits if it's mature or partially matured or unmatured. A deep learning technique that was extensively applied to image recognition was used. The trained model achieved an accuracy of 100% on a held-out test set, demonstrating the feasibility of this approach. Classification model of VGG16 achieved a 100% accuracy and 112 seconds of training time.*

Keyword: *Papaya, classification, deep learning, VGG16.*

1. Introduction

Papaya is known as one of the delicious tropical fruits and it grows in the tropics and is widely spread around the world. Although Mexico is considered the original home of this fruit, India produces the most amount of papaya in the world; Its production reached five million tons in 2013. Its scientific name is Carica papaya, and the fruit of the papaya grows on an evergreen tree, its height ranges from 2 to 10 meters above the surface of the earth, and its leaves are broad and grow in the form of a crown from the top, and the lower leaves begin to fall after their progress in Age, and the stem of the papaya tree is hollow and relatively soft, and this fruit is characterized by its sweet taste, bright color and ease of incorporation into meals. In addition, papaya fruit gives the body many benefits, such as reducing the risk of heart disease, diabetes or cancer, and contributes to maintaining healthy skin and hair. Papayas ripen within a few days at room temperature, even faster in a paper bag. Once ripe, the fruit will quickly turn very mushy, if not stored properly. When any of us look at a papaya picture, we can (usually) identify what it depicts with ease. Computers don't find this task quite as easy. They don't 'see' the world the same way that we do. Image classification, then, is a challenge for machines. Which is where deep learning comes in. Image classification is where a computer can analyze the papayas images and identify the 'class' the image falls under. Early image classification relied on raw pixel data. This meant that computers would break down images into individual pixels. The problem is that two pictures of the same thing can look very different. They can have different backgrounds, angles, poses, etcetera. This made it quite the challenge for computers to correctly 'see' and categories images. Image classification has a few uses and vast potential as it grows in reliability. The fruit classification and quality assessment by visual inspection causes error due to external influences such as fatigue, vengeance and bias. The identification of the maturity status of fruits relates to eating quality and determination of storage time before consumption. The determination of these properties with the help of human operators is time consuming and destructive. Thus, rapid, intelligent, and non-destructive techniques are required in this application domain. So here, using state of the art deep learning techniques, we demonstrated the feasibility of our approach by using a public dataset of 300 images of statuses of papayas, to produce a model that can be used in smartphones applications to identify 3 types of papayas statuses, with an accuracy of 100%.

2. Related Work

- In paper, Maturity status classification of papaya fruits based on machine learning and transfer learning approach, the authors suggested two approaches based on machine learning and transfer learning for classification of papaya maturity status. The VGG19 was perform with 100% accuracy and 1 min 52 s training time.
- In paper, Detection of passion fruits and maturity classification using Red-Green-Blue Depth images, the Authors Developed it detect passion fruits and identify maturity of the detected fruits using natural outdoor RGB-D images. A maturity stages of the fruits were divided into five categories: young (Y), near-young (NY), near-mature (NM), mature (M) and after-mature (AM). verified that the proposed method achieves 92.71% detection accuracy and 91.52% maturity classification accuracy.
- In paper, Image Based Tomato Leaves Diseases Detection Using Deep Learning, the Authors used deep learning to detect five tomato leaves diseases. They achieved a high accuracy in detecting the tomato disease.

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- In paper, Deep learning for plant identification in natural environment, the Authors implemented a 26-layer deep learning model consisting of 8 residual blocks in their classification of 10,000 images of 100 ornamental plant species with classification rates of up to 91.78%.

3. Deep learning

Deep learning is a machine learning approach that is restated as an outset to solve a different problem using the knowledge collected from an established model. The current study fine-tuned the pre-trained convolutional neural net-work (CNN) models based on transfer learning. The maturity status classification model for papaya fruits based on deep learning approach. Pre-trained networks are considered to evaluate their performance for classification of maturity stages of papaya fruits. The pre-trained network is VGG16.

The VGG network is characterized by its simplicity, using only 3 3 convolutional layers stacked on top of each other in increasing depth. Reducing volume size is handled by max pooling.

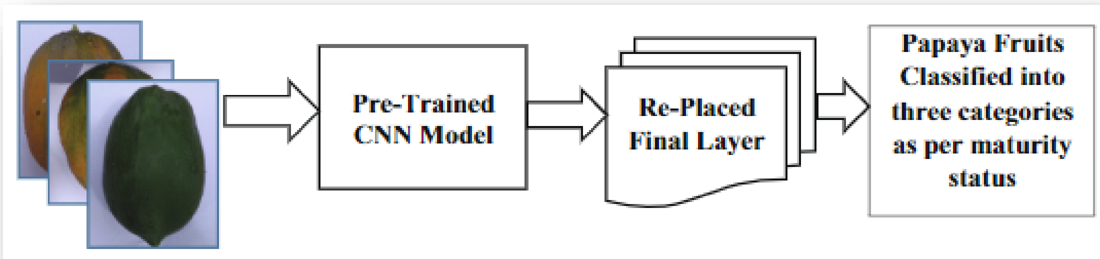

Figure 1 Papaya classification steps

4. convolutional neural network

4.1 An Introduction

a convolutional neural network (CNN, or ConvNet) is a class of artificial neural network. Based on biological processes, CNNs have been applied basically in digital image processing and intelligent image analysis.

Deep (CNN) are basically focused on applications like image classification, object detection, recommendation systems, and are also sometimes used for natural language processing.

The strength of DCNNs is in its own layers. It uses 3-d NN Process the RGB elements of the image at the same time.

The architecture of a Conv network consists of 4 kinds of layers: convolution, pooling, activation, and fully connected.

4.1.1 Convolution layer:

The convolution is the easy working of the input filter to the image to detect features of the image.

- A convolution: takes a group of weights and multiplies them with inputs from the NN.

- Kernels or filters: through the multiplication operation, a kernel or a filter passes over an image multiple time.

- Dot product: a mathematical operation performed through the convolution. Each filter multiplies the weights with various input values. The overall inputs are summed.

4.1.2 ReLU Activation Layer

A Rectified Linear Unit - The convolution maps are passed through a non-linear activation function that will output the input directly if it is positive, otherwise, it will output zero. In this layer we remove every negative value from the filtered image and replace it with zero.

4.1.3 The pooling layer

Is used to minimize the spatial dimensions, but not depth, on a CNN, model, reduce the size of the image and keeping only the most important information.

Minimizing the number of calculations and parameters in the network help Pooling layers control overfitting.

4.1.4 Fully Connected Layer

NN are a group of dependent non-linear functions. Each individual function consists of a neuron. In fully connected layers, the neuron applies a linear transformation to the input vector during a weight's matrix. A non-linear transformation is then

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applied to the product during a non-linear activation function f. The softmax function is applied at the end to the outputs of the fully connected layers, giving the probability of a class the image belongs to.

5. METHODOLOGY

In this department, show the proposed solution as selected convolutional network (ConvNet) architecture.

5.1 Dataset

We extracted our dataset from the well-known papaya dataset, which contains 300 labeled high-resolution images from 3 classes in total as follow:

* class (0): Mature.
* class (1): partially mature.
* class (2): unmature.

The images were resized into 128×128 for faster computations but without compromising the quality of the data, The images were collected from the web and labeled by human labelers.

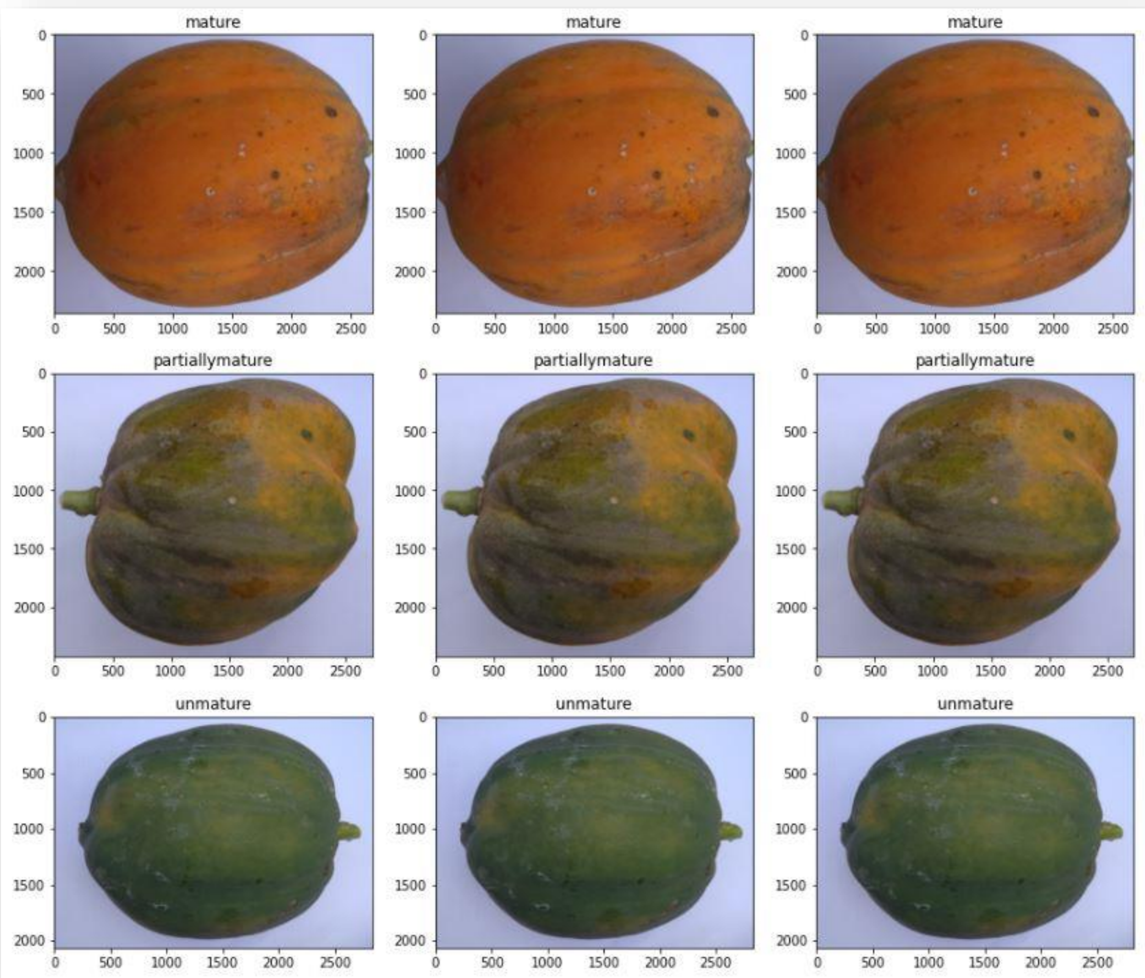

Figure 2 Images of the papaya statuses

5.2 Architecture

VGGNet is a well-documented and globally used architecture for convolutional neural networks.

VGG16 – Convolutional Network for Classification and Detection and it is a convolutional neural network model (CNN), a large visual database project used in visual object recognition software research. 'VGG' is the abbreviation for Visual Geometry Group and '16' implies that this architecture has 16 layers. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU's.

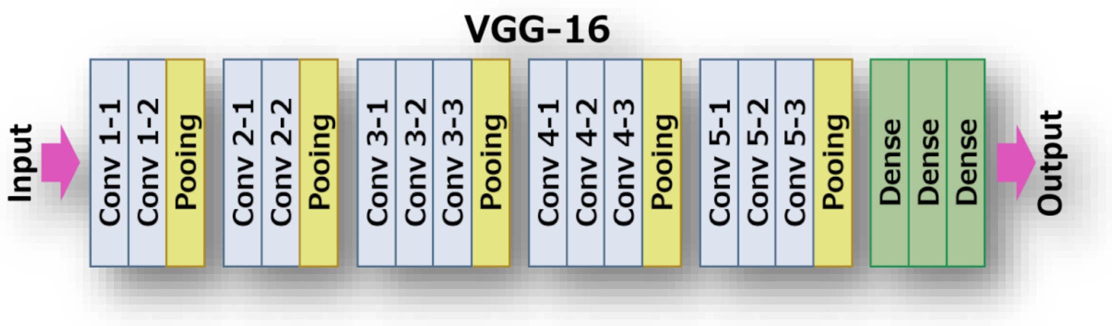

Figure 3 VGG16 layers

5.3 Design considerations

The original VGG16 must be modified to suit the current solution: the final fully-connected output layer must perform 3 classes only.

```
# load all images in memory
np.random.seed(91)

path = src_path +"/"
train_label = []
train_img = []
label2num = {'mature':0,'partiallymature':1,'unmature':2}

num_classes = 3

for i in os.listdir(path):
    print(i)
    label_number = label2num[i]
    new_path = path+i+'/'

    for j in fnmatch.filter(os.listdir(new_path), '*.*'):
        temp_img = image.load_img(new_path+j, target_size=(128,128))
        train_label.append(label_number)
        temp_img = image.img_to_array(temp_img)
        train_img.append(temp_img)

train_img = np.array(train_img)
train_y=pd.get_dummies(train_label)
train_y = np.array(train_y)
train_img=preprocess_input(train_img)

print('Training data shape: ', train_img.shape)
print('Training labels shape: ', train_y.shape)
```

```
mature
partiallymature
unmature
Training data shape:  (300, 128, 128, 3)
Training labels shape:  (300, 3)
```

Figure 4 load all images

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5.3.1 Preprocessing

Input images must be preprocessed by:

- Normalizing the pixel values to a [0,1] range.
- Balance the 3 different species
- Resizing the image to be 128x128 pixels.

5.3.2 Data augmentation

Data augmentation in data analysis are techniques used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data.

6. Model

Our model takes initial images as an input, so we used (CNNs) to extract features and call the VGG16 pre-trained Model, the details of the VGG16 convolutional base architecture, which are similar to simple convnets, is given in the summary shown below:

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 128, 128, 3)	0
block1_conv1 (Conv2D)	(None, 128, 128, 64)	1792
block1_conv2 (Conv2D)	(None, 128, 128, 64)	36928
block1_pool (MaxPooling2D)	(None, 64, 64, 64)	0
block2_conv1 (Conv2D)	(None, 64, 64, 128)	73856
block2_conv2 (Conv2D)	(None, 64, 64, 128)	147584
block2_pool (MaxPooling2D)	(None, 32, 32, 128)	0
block3_conv1 (Conv2D)	(None, 32, 32, 256)	295168
block3_conv2 (Conv2D)	(None, 32, 32, 256)	590080
block3_conv3 (Conv2D)	(None, 32, 32, 256)	590080
block3_pool (MaxPooling2D)	(None, 16, 16, 256)	0
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1180160
block4_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block4_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv2 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv3 (Conv2D)	(None, 8, 8, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0
global_max_pooling2d_1 (Glob	(None, 512)	0
dense_1 (Dense)	(None, 3)	1539

Figure 5 Model Summery

Here shows the testing final loss, testing final accuracy and total time for CPU and user

```
%%time
# Compute the final loss and accuracy
final_res = model.evaluate(X_test,Y_test)
print("Testing Final loss: {0:.4f}, Testing final accuracy: {1:.4f}".format(final_res[0], final_res[1]))

39/39 [==============================] - 0s 5ms/step
Testing Final loss: 0.0000, Testing final accuracy: 1.0000
CPU times: user 42 ms, sys: 7.9 ms, total: 49.9 ms
Wall time: 186 ms
```

Figure 6 compute final loss & accuracy

Here, a validation accuracy of about 100% is reached, much better than with a small model trained from scratch. But the plots also depict that overfitting happens almost from the start.

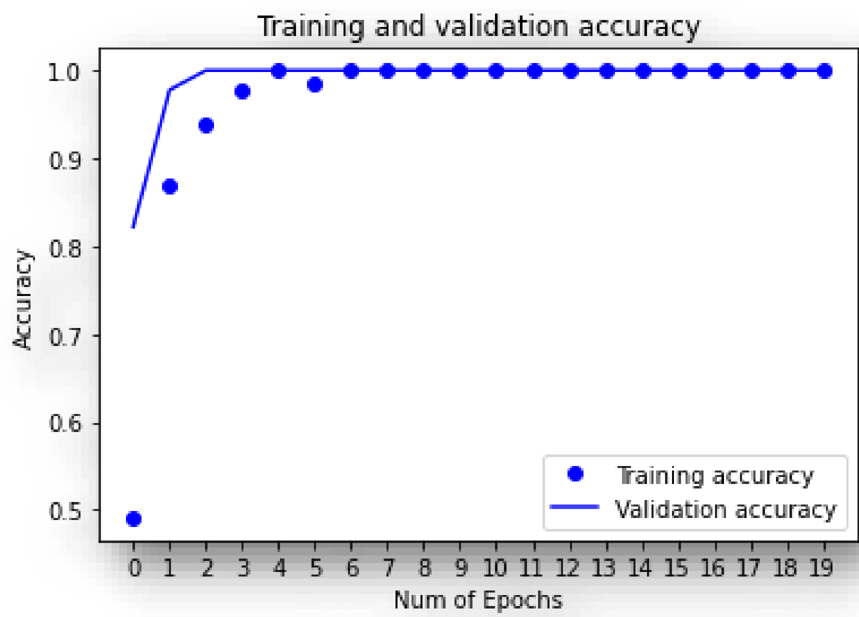

Figure 7 Training and validation accuracy for simple feature extraction

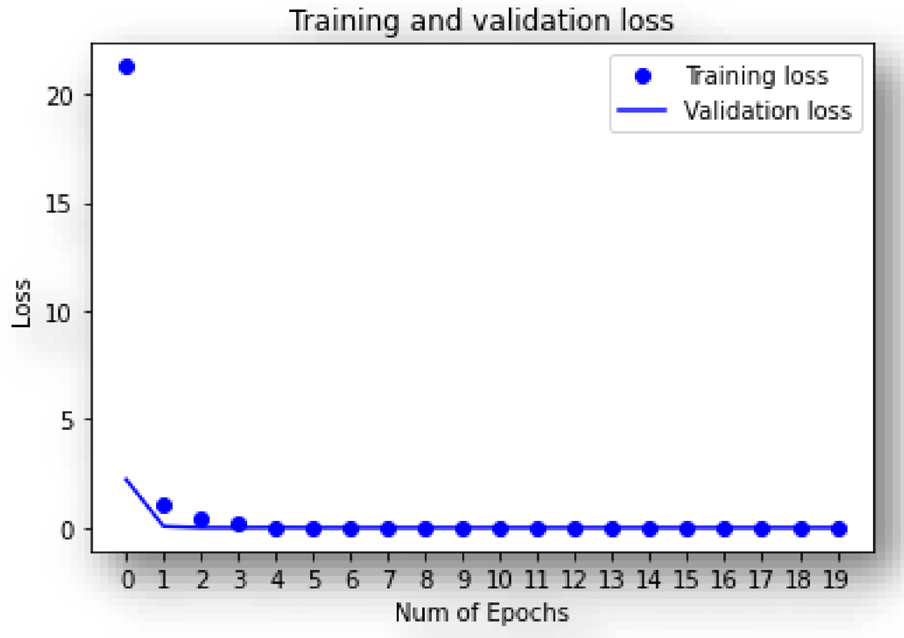

Figure 8 Training and validation loss for simple feature extraction

A Receiver Operator Characteristic curve is a graphical plot used to show the diagnostic ability of binary classifiers. It was first used in signal detection theory but is now used in machine learning.

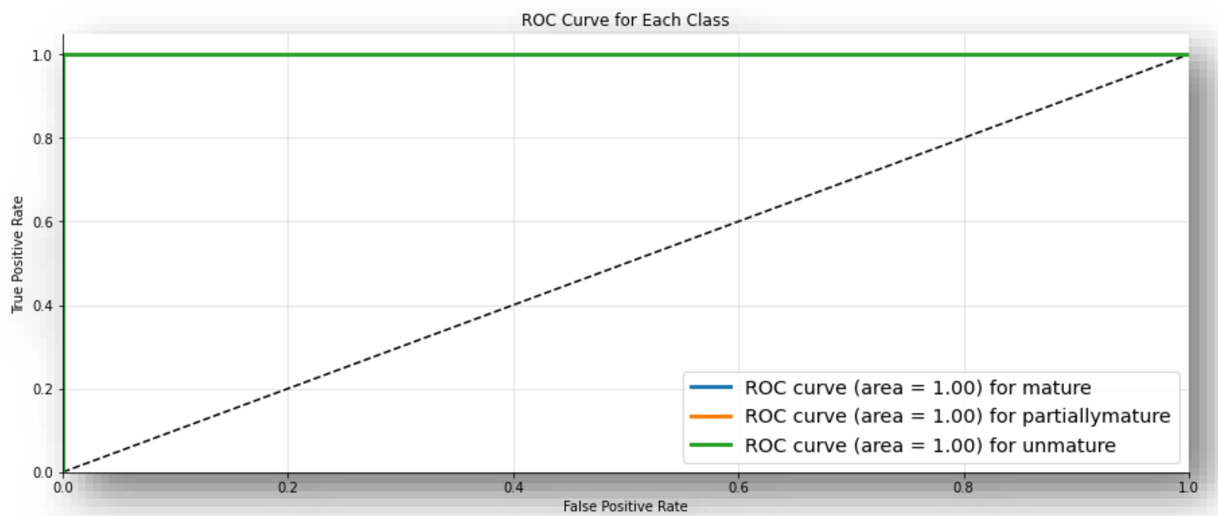

Figure 9 ROC Curve for each Class

Conclusion

This paper proposed a classification model for maturity status classification of papaya fruits by deep learning approach. In deep learning approach (VGG16).

Well, i.e., 100% accuracy with less time required for training, i.e., 1 min. 52 s. VGG16 is based on deep learning, there is no requirement of feature extraction and feature selection process. Although deep learning approach needs complex architecture, high training time and large datasets for but it is onetime only. Restricted data handing capability. However, the achieved accuracy in deep learning is 100%.

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