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Six Fruits Classification Using Deep Learning

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Abstract: *Fruit grading contributes to the improvement of self-pay and packaging systems in large companies and factories such as juice factories, pharmaceutical companies, fruit storage companies and supermarkets. Convolutional neural networks can automatically extract features by directly processing original images, which has attracted wide interest from researchers in fruit classification terms. However, it is difficult to obtain more accurate identification due to the complexity of class similarity.VGG16 has been used to recognize different types of fruit images. Next, the fruit data set which includes 6 classes also created for network model training and evaluation performance. Images of a group of fruits were collected and a deep convolutional neural network was built to identify six types of fruits. Indicating the feasibility of this model, the ratio reached 100%. Inclusive the approach to training real learning models on large, publicly available image data sets offers a clear path toward easy fruit classification. In this paper, a machine learning based approach is presented for classifying and identifying 6 different fruits with a dataset that contains 2677 images.*

Keywords: *Fruit Classification, Deep Learning, Classification, Detection*

1. INTRODUCTION

In food storage and manufacture, fruit is a major component of fresh produce. Fruit Shops Supermarkets or Shops helps in improving fruit screening and statistics and transportation systems. Fruit grading has always been a relatively complex problem, because of its wide variety and irregular shape, color in most cases. An enhanced convolutional neural network named VGG16 was proposed in this study for fruit classification and the main objective of this technique is with the perfect code and how you can use the already trained CNN (Convolutional Neural Network) to solve the fruit classification problem.. In this paper, we are identifying and classifying six of different type of fruits so we can take. As we mention in this paper we classify six different fruits, which are Pineapple, Pineapple Mini, Raspberry, Redcurrant, Strawberry and Strawberry Wedge[1].

2. STUDY OBJECTIVES:

Demonstrating the feasibility of using deep convolutional neural networks to classify fruits.

3. Materials and Methods:

1. Data set:
   A total of *2677* images were collected for the fruits to be classified. The images were downloaded from the Kaggle website to build the CNN . Every picture was crop it to 128, 128 pixels. Figure 1 shows the category and number of fruit images used in this study. For each type of fruit image use 70% from image for training and 15% from image for validation 15 % for testing. The generated model was trained based on the training set and evaluated using the test set.

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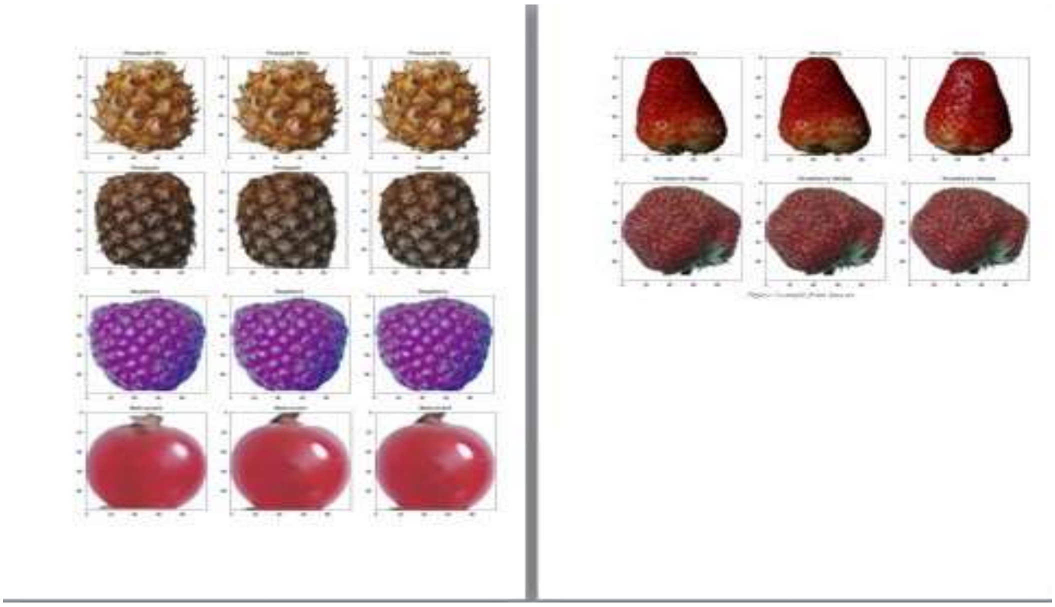

Figure 1: sample from data set

The output 6 classes as follow:

• class (1): Pineapple.

• class (2): Pineapple Mini

• class (3): Raspberry

• class (4): Redcurrant

• class (5): Strawberry

• class (6): Strawberry Wedge

The images were resized into 128 × 128 for faster computations but without compromising the quality of the data.

2. Convolutional Layer:
   The convolutional neural networks are a variant of deep networks, which automatically learn simple edge shapes from raw data, and identify the complex shapes within each image through feature extraction. The convolutional neural networks include various convolutional layers similar to the human visual system. Among them, the convolutional layers generally have filters with the kernels of 11 × 11, 9 × 9, 7 × 7, 5 × 5 or 3 × 3. The filter fits weights through training and learning, while the weights can extract features, just similar to camera filters [2-15].
3. Design :
   A CNN consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers [1-5]. Description of the process as a convolution in neural networks is by convention. Mathematically it is a cross correlation rather than a convolution. This only has significance for the indices in the matrix, and thus which weights are placed at which index[16-30].

4. Rectified Linear Unit (ReLU)Layer:
   is used as a non-linear activation function for each convolutional layer.ReLU suggests that, when the input value is less than zero, the output value will be set to zero. Using the ReLU, the convolutional layer is able to output the non-linear feature maps, thereby reducing the risk of overfitting[31-45].

5. Pooling Layer:
   The pooling layer is adopted for compressing the feature map after the convolutional layer.
   The pooling layer summarizes the output of the neighboring neurons, which reduces the activation
   Map size and maintains the unchanged feature. There are two methods in the pooling layer, i.e.

Maximum and average pooling. In this paper, the maximum pooling (mp) method was adopted. Typically, the mp method remains the maximum pooling area, and it is the most popular pooling Strategy[46-55].

6. Fully Connected and Dropout Layer:
Fully connected layer (FCL) is used for inference and classification. Similar to the traditional shallow neural network, FCL also contains many parameters to connect to all neurons in the previous layer. However, the large number of parameters in FCL may cause the problem of overfitting during training, while the dropout method is a technique to solve this problem. Briefly, the dropout method is implemented during the training process by randomly discarding units connected to the neural network. In addition, the dropout neurons are randomly selected during the training step, and its appearance probability is 0.25. During the test step, the neural network is used without dropout operation[56-60].

7. Model Structure and Training Strategy:
In this study, a convolutional neural network was created to classify fruits (Fig. 3). According to Fig. 3, the input image with a size of 128 × 128 × 3 was inserted into a network file. The convolutional neural network was a stacked structure integrating Three layers are fully connected(CNN, max pooling, fully connected)[61-65] (Fig. 2).

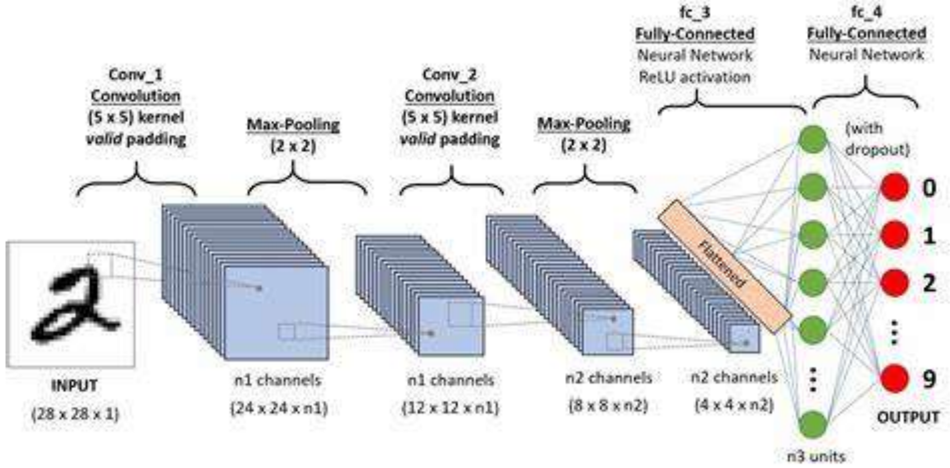

Figure 2:componnent CNN

- **Input Layer**: It represent input image data. It will reshape image into single diminsion array. Example your image is 64x64 = 4096, it will convert to (4096,1) array.
- **Conv Layer**: This layer will extract features from image.
- **Pooling Layer**: This layer reduce the spatial volume of input image after convolution.
- **Fully Connected Layer**: It connect the network from a layer to another layer
- **Output Layer**: It is the predicted values layer.

Notably, the last complete communication layer played a role as a classifier, which counts and outputs dozens of different fruits. To reduce errors, Adam's optimizer was also used in this study, which was superior in its high computational efficiency, low memory requirements and good suitability for large data or many parameters. The learning rate of the Adam optimizer was set to a constant of 0.00001, and Cross Entropy Loss as a cost function. Then, the proposed model was trained.

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```
58892288/58889256 [==============================] - 2s 0us/step
Model: "model_1"
_________________________________________________________________
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, 6)                 3078
=================================================================
Total params: 14,717,766
Trainable params: 14,717,766
Non-trainable params: 0
_________________________________________________________________
```

Figure 3: Model Arcjitucture

4. Results and Discussion:

In this section we describe the proposed solution as selected convolutional network (ConvNet) architecture and discuss associated design choices and implementation aspects

1. Loss and Accuracy rate:
   In terms of time and memory consumption in training the model, the curve of loss versus accuracy is effective feature. Figure 4 presents the loss rate results for a convolution neural network in the training and test sets in 10 repetitions. which indicates that the convolutional neural network learned the data effectively and can serve as a good model for fruit recognition.

```
Epoch 1/20
7/7 [==============================] - 17s 2s/step - loss: 24.9155 - accuracy: 0.2902 - val_loss: 7.8487 - val_accuracy: 0.4776
Epoch 2/20
7/7 [==============================] - 9s 1s/step - loss: 5.0280 - accuracy: 0.6373 - val_loss: 2.2414 - val_accuracy: 0.7488
Epoch 3/20
7/7 [==============================] - 6s 825ms/step - loss: 1.4915 - accuracy: 0.7969 - val_loss: 0.6747 - val_accuracy: 0.9104
Epoch 4/20
7/7 [==============================] - 7s 1s/step - loss: 0.5432 - accuracy: 0.9085 - val_loss: 0.1843 - val_accuracy: 0.9627
Epoch 5/20
7/7 [==============================] - 7s 977ms/step - loss: 0.2851 - accuracy: 0.9554 - val_loss: 0.1012 - val_accuracy: 0.9726
Epoch 6/20
7/7 [==============================] - 8s 1s/step - loss: 0.1339 - accuracy: 0.9621 - val_loss: 0.0533 - val_accuracy: 0.9900
Epoch 7/20
7/7 [==============================] - 6s 819ms/step - loss: 0.0516 - accuracy: 0.9911 - val_loss: 0.0337 - val_accuracy: 0.9950
Epoch 8/20
7/7 [==============================] - 6s 813ms/step - loss: 0.1413 - accuracy: 0.9732 - val_loss: 0.0202 - val_accuracy: 0.9950
Epoch 9/20
7/7 [==============================] - 6s 806ms/step - loss: 0.1012 - accuracy: 0.9723 - val_loss: 0.0149 - val_accuracy: 0.9925
Epoch 10/20
7/7 [==============================] - 5s 637ms/step - loss: 0.0706 - accuracy: 0.9849 - val_loss: 0.0154 - val_accuracy: 0.9950
Epoch 11/20
7/7 [==============================] - 5s 671ms/step - loss: 0.0239 - accuracy: 0.9955 - val_loss: 0.0152 - val_accuracy: 0.9950
Epoch 12/20
7/7 [==============================] - 5s 681ms/step - loss: 0.0410 - accuracy: 0.9911 - val_loss: 0.0188 - val_accuracy: 0.9950
Epoch 13/20
7/7 [==============================] - 5s 670ms/step - loss: 0.0074 - accuracy: 0.9978 - val_loss: 0.0229 - val_accuracy: 0.9925
Epoch 14/20
7/7 [==============================] - 5s 683ms/step - loss: 0.0187 - accuracy: 0.9924 - val_loss: 0.0217 - val_accuracy: 0.9925
Epoch 15/20
7/7 [==============================] - 4s 614ms/step - loss: 0.0088 - accuracy: 0.9975 - val_loss: 0.0184 - val_accuracy: 0.9925
Epoch 16/20
7/7 [==============================] - 7s 990ms/step - loss: 0.0051 - accuracy: 1.0000 - val_loss: 0.0125 - val_accuracy: 0.9950
Epoch 17/20
7/7 [==============================] - 6s 847ms/step - loss: 0.0252 - accuracy: 0.9955 - val_loss: 0.0071 - val_accuracy: 0.9975
Epoch 18/20
7/7 [==============================] - 6s 806ms/step - loss: 0.0114 - accuracy: 0.9955 - val_loss: 9.9914e-04 - val_accuracy: 1.0000
Epoch 19/20
7/7 [==============================] - 5s 779ms/step - loss: 0.0042 - accuracy: 0.9975 - val_loss: 5.5738e-04 - val_accuracy: 1.0000
Epoch 20/20
7/7 [==============================] - 5s 684ms/step - loss: 0.0021 - accuracy: 1.0000 - val_loss: 0.0010 - val_accuracy: 1.0000
CPU times: user 2min 8s, sys: 5.07 s, total: 2min 13s
Wall time: 2min 33s
```

Figure 4:Loss and Accuracy rate

2. Confusion Matrix:
In this work, the proposed deep learning network CNN was trained on the fruit dataset. Afterwards, the model was evaluated on the test set, which showed good performance. Figure 5 presents the confusion matrix of the classification results, where each row represents the actual category, while each column stands for the predicted result.

```
[[57  0  0  0  0  0]
 [ 0 37  0  0  0  0]
 [ 0  0 56  0  0  0]
 [ 0  0  0 56  0  0]
 [ 0  0  0  0 74  0]
 [ 0  0  0  0  0 62]]
```

Figure 5 Confusion Matrix

3. Comparison of Classification Performance:

To evaluate the effectiveness of these models, the as-proposed method was compared with the existing methods for modern deep learning. The models were evaluated on the test set by the accuracy rate, and avg F1-score (Figure 6). In Figure 6, the model VGG16 achieved lower false positive and false negative rates, which demonstrates the effectiveness.

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	precision	recall	f1-score	support
Pineapple	1.0000	1.0000	1.0000	57
Pineapple Mini	1.0000	1.0000	1.0000	37
Raspberry	1.0000	1.0000	1.0000	56
Redcurrant	1.0000	1.0000	1.0000	56
Strawberry	1.0000	1.0000	1.0000	74
Strawberry Wedge	1.0000	1.0000	1.0000	62
accuracy			1.0000	342
macro avg	1.0000	1.0000	1.0000	342
weighted avg	1.0000	1.0000	1.0000	342

Figure 6: Comparison of Classification Performance

4. System evaluation:

We used the original fruit dataset that consists of *2677* images after resizing the images to 128x128 pixels. We divided the data into training (70%), validation (15%), testing (15%). The training accuracy was 99.00% and the validation accuracy was 100% after 20 Epochs. As we shown in figure 7,8.

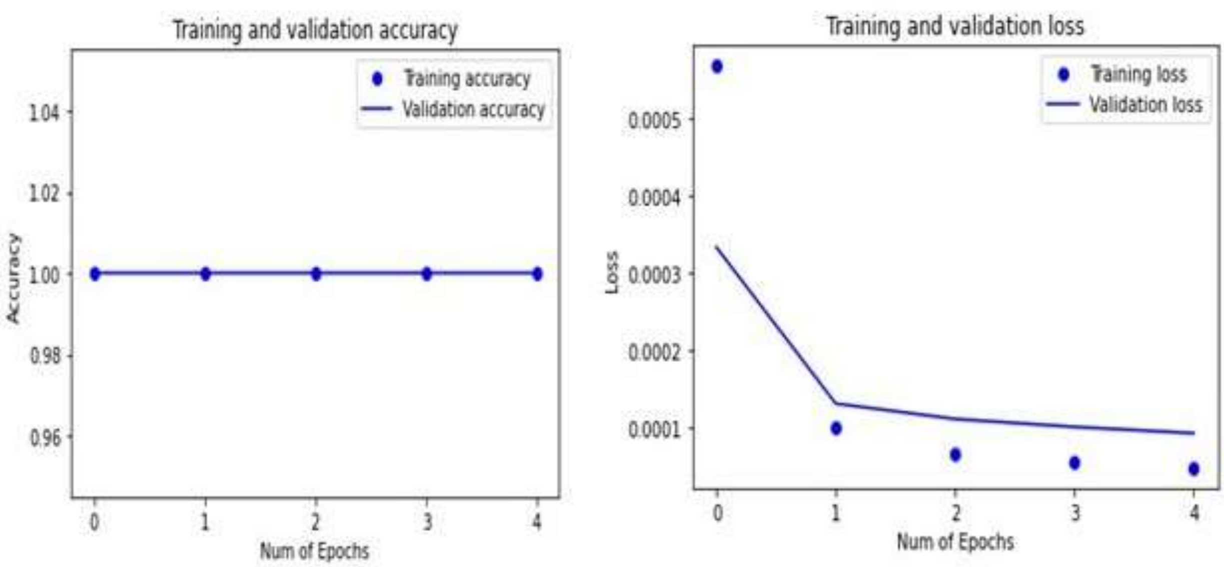

Figure 7, 8 training and validation accuracy, training and validation loss

CONCLUSION

Fruit classification in a very important task in many field such as industrial or agriculture. In this study, we proposed an approach that uses deep learning-based learning of images of six different fruit from Kaggle website. We use a pre trained CNN Model VGG16 fine-tuned. In this paper, we trained and validated the proposed model and tested its performance with un-seen dataset for testing. The Accuracy rate we achieved was 100%. This indicates that our proposed model can effectively predict and classify different fruit without error and with full performance.

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