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Classification of pepper Using Deep Learning

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***Abstract**: This article presents a content-based image classification system to monitor the ripeness process of bell pepper via investigating and classifying the different maturity stages. Bell pepper is an important food crop, Bell pepper has a uniform shape with size and color, and the flavor can be sweet, mild, or very tart. Several recent studies have shown many health benefits of Bell pepper. It is an excellent source of dietary fiber and vitamin C which is necessary for the growth and repair of body tissue, as well as for the formation of collagen, a protein used for skin regeneration and the creation of blood vessels. Vitamin C is also needed for cartilage, bones, and teeth. Datasets of total 2368 images were used for both training and testing datasets. A deep learning technique that was extensively applied to image recognition was used. 70% from image for training and 15% from image for validation 15 % for testing. Our trained model achieved an accuracy of 100% on a held-out test set.*

Keywords: *Bell pepper Classification, Type of Bell pepper, Deep Learning, Classification, Detection*

1. INTRODUCTION:

Monitoring and controlling produce (fruits and vegetables) ripeness has become a very important issue in the crops industry since ripeness is perceived by customers as the main quality indicator. Also, the product's appearance is one of the most worrying issues for producers as it has a high influence on the product's quality and consumer preferences. However, up to this day, optimal harvest dates and prediction of storage life are still mainly based on subjective interpretation and practical experience. Bell peppers come in green, yellow, red varieties, Bell peppers are loaded with various vitamins and minerals, all of which give it special properties and benefits, which include: Eye Health, Prevent Cancer, Boosts Immunity, Balances Mood, Natural Sleep Aid, and Beautiful Skin.

2. BACKGROUND:

2.1. DEEP LEARNING:

Deep learning is a specific subfield of machine learning: a new take on learning representations from data that puts an emphasis on learning successive layers of increasingly meaningful representations.

The deep in deep learning isn't a reference to any kind of deeper understanding achieved by the approach; rather, it stands for this idea of successive layers of representations. How many layers contribute to a model of the data is called the depth of the model. Other appropriate names for the field could have been layered representations learning and hierarchical representations learning. Modern deep learning often involves tens or even hundreds of successive layers of representations and they're all learned automatically from exposure to training data.

Meanwhile, other approaches to machine learning tend to focus on learning only one or two layers of representations of the data; hence, they're sometimes called shallow learning. In deep learning, these layered representations are (almost always) learned via models called neural networks, structured in literal layers stacked on top of each other. The term neural network is a reference to neurobiology, but although some of the central concepts in deep learning were developed in part by drawing inspiration from our understanding of the brain, deep-learning models are not models of the brain. There's no evidence that the brain implements anything like the learning mechanisms used in modern deep-learning models. You may come across pop-science articles proclaiming that deep learning works like the brain or was modeled after the brain, but that isn't the case.

It would be confusing and counterproductive for newcomers to the field to think of deep learning as being in any way related to neurobiology; you don't need that shroud of "just like our minds" mystique and mystery, and you may as well forget anything you may have read about hypothetical links between deep learning and biology. For our purposes, deep learning is a mathematical framework for learning representations from data.

What do the representations learned by a deep-learning algorithm look like? Let's examine how a network several layers deep (see figure 1) transforms an image of a digit in order to recognize what digit it is.

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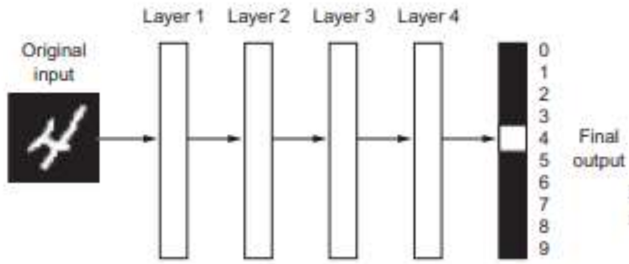

Figure 1:A deep neural netwok for digit classification

As you can see in figure 2, the network transforms the digit image into representations that are increasingly different from the original image and increasingly informative about the final result. You can think of a deep network as a multistage information-distillation operation, where information goes through successive filters and comes out increasingly purified (that is, useful with regard to some task).

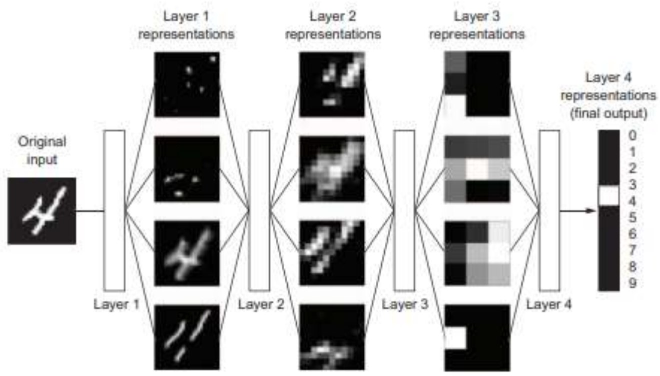

Figure 2: Deep representations learned by a digit-classification model

So that's what deep learning is, technically: a multistage way to learn data representations. It's a simple idea but, as it turns out, very simple mechanisms, sufficiently scaled, can end up looking like magic.[1]

2.2. CNNs:

A convolutional neural network, or CNN, is a deep learning neural network designed for processing structured arrays of data such as images. Convolutional neural networks are widely used in computer vision and have become the state of the art for many visual applications such as image classification, and have also found success in natural language processing for text classification.

Convolutional neural networks are very good at picking up on patterns in the input image, such as lines, gradients, circles, or even eyes and faces. It is this property that makes convolutional neural networks so powerful for computer vision. Unlike earlier computer vision algorithms, convolutional neural networks can operate directly on a raw image and do not need any preprocessing.

A convolutional neural network is a feed-forward neural network, often with up to 20 or 30 layers. The power of a convolutional neural network comes from a special kind of layer called the convolutional layer.

Convolutional neural networks contain many convolutional layers stacked on top of each other, each one capable of recognizing more sophisticated shapes. With three or four convolutional layers it is possible to recognize handwritten digits and with 25 layers it is possible to distinguish human faces.

The usage of convolutional layers in a convolutional neural network mirrors the structure of the human visual cortex, where a series of layers process an incoming image and identify progressively more complex features.

2.2.1. Convolutional Neural Network Design

The architecture of a convolutional neural network is a multi-layered feed-forward neural network, made by stacking many hidden layers on top of each other in sequence. It is this sequential design that allows convolutional neural networks to learn hierarchical features.

The hidden layers are typically convolutional layers followed by activation layers, some of them followed by pooling layers.[2]

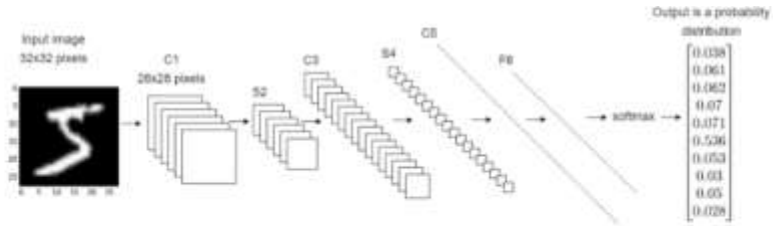

Figure 3:Convolutional Neural Network Design

2.2.2. VGG 16 Architecture:

A simple convolutional neural network that aids understanding of the core design principles is the early convolutional neural network VGG 16.

Of all the configurations, VGG16 was identified to be the best performing model on the ImageNet dataset. Let's review the actual architecture of this configuration.

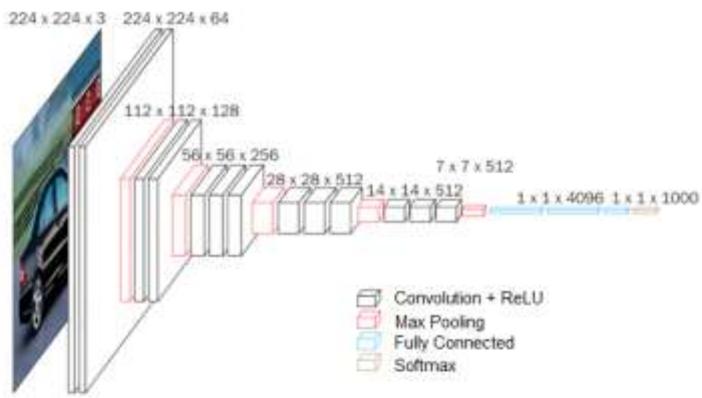

Figure 4: VGG 16 Architecture

The input to any of the network configurations is considered to be a fixed size 224 x 224 image with three channels – R, G, and B. The only pre-processing done is normalizing the RGB values for every pixel. This is achieved by subtracting the mean value from every pixel.

Image is passed through the first stack of 2 convolution layers of the very small receptive size of 3 x 3, followed by ReLU activations. Each of these two layers contains 64 filters. The convolution stride is fixed at 1 pixel, and the padding is 1 pixel. This configuration preserves the spatial resolution, and the size of the output activation map is the same as the input image dimensions. The activation maps are then passed through spatial max pooling over a 2 x 2-pixel window, with a stride of 2 pixels. This halves the size of the activations. Thus the size of the activations at the end of the first stack is 112 x 112 x 64.

The activations then flow through a similar second stack, but with 128 filters as against 64 in the first one. Consequently, the size after the second stack becomes 56 x 56 x 128. This is followed by the third stack with three convolutional layers and a max pool layer. The no. of filters applied here are 256, making the output size of the stack 28 x 28 x 256. This is followed by two stacks of three convolutional layers, with each containing 512 filters. The output at the end of both these stacks will be 7 x 7 x 512.

The stacks of convolutional layers are followed by three fully connected layers with a flattening layer in-between. The first two have 4,096 neurons each, and the last fully connected layer serves as the output layer and has 1,000 neurons corresponding to the 1,000 possible classes for the ImageNet dataset. The output layer is followed by the Softmax activation layer used for categorical classification.[3]

2.3. TRANSFER LEARNING:

Transfer learning is a machine learning technique that enables data scientists to benefit from the knowledge gained from a previously used machine learning model for a similar task. This learning takes humans' ability to transfer their knowledge as an example. If you learn how to ride a bicycle, you can learn how to drive other two-wheeled vehicles more easily. Similarly, a model trained for autonomous driving of cars can be used for autonomous driving of trucks.

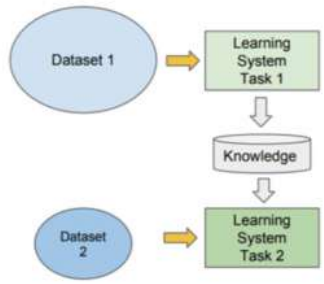

Figure 5:trasfer learning

2.4. IMAGENET:

ImageNet is formally a project aimed at (manually) labeling and categorizing images into almost 22,000 separate object categories for the purpose of computer vision research.

The goal of this image classification challenge is to train a model that can correctly classify an input image into 1,000 separate object categories.

Models are trained on ~1.2 million training images with another 50,000 images for validation and 100,000 images for testing.

These 1,000 image categories represent object classes that we encounter in our day-to-day lives, such as species of dogs, cats, various household objects, vehicle types, and much more.

3. METHODOLOGY:

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

3.1. DATASET:

A total of *2368* images were collected for the peppers to be classified. The images were downloaded from the Kaggle website to build the CNN. Every picture was Crop it to 128, 128 pixels. Image 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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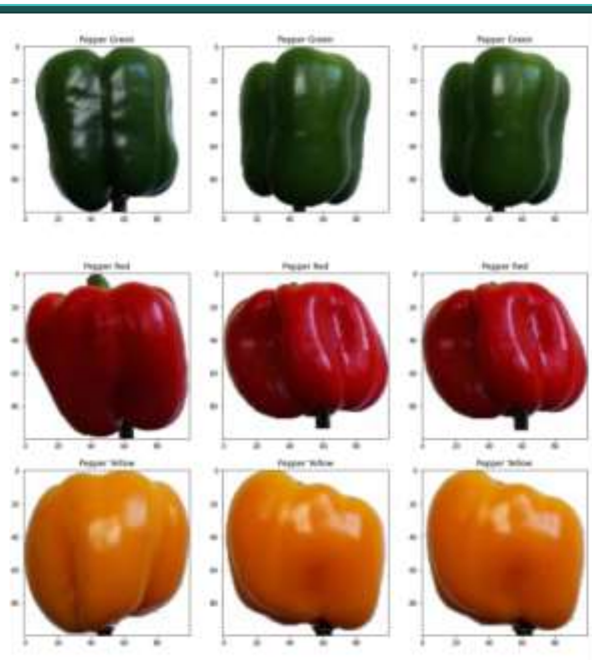

Figure 6:sample data set

3.2. EVALUATION:

The competition was a binary classification problem with area under the ROC curve between the predicted probability and the observed target as an evaluation matrix, since we want our submissions to be as close as possible to the actual probabilities, we used the binary cross entropy loss function with sigmoid as the last layer's activation function

3.3. VALIDATION METHOD:

In order to evaluate our model, we have to split the available dataset into training and validation sets, so we conducted an experiment to find the proper splitting method between simple hold-out validation and k-fold cross validation. In our experiment we trained and evaluated our model 5 times using simple hold-out validation method, and in each time we chose a different validation set. We observed a large diversity between the scores in the 5 times as shown in Fig. 7, so we concluded that the simple hold-out validation method is not suitable for this dataset, and we decided to use k-fold cross validation method instead.

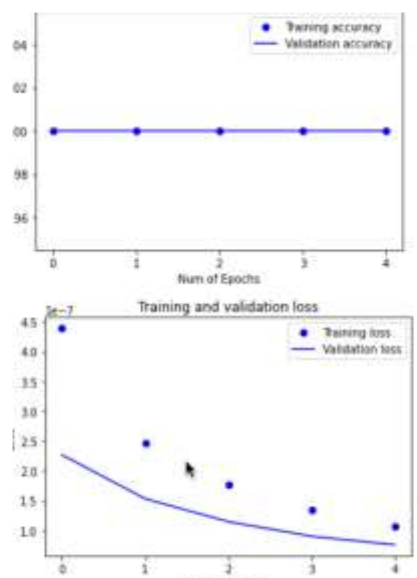

Figure 7: simple hold-out validation result

3.4. Loss and Accuracy rate:

In terms of time and memory consumption in training the model, the curve of loss versus accuracy is effective feature. Figure8 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 peppers recognition.

```
Epoch 1/10
6/6 [==============================] - 16s 3s/step - loss: 16.5354 - accuracy: 0.4766 - val_loss: 4.1524 - val_accuracy: 0.7416
Epoch 2/10
6/6 [==============================] - 9s 1s/step - loss: 2.3217 - accuracy: 0.8251 - val_loss: 0.4035 - val_accuracy: 0.9607
Epoch 3/10
6/6 [==============================] - 4s 708ms/step - loss: 0.4445 - accuracy: 0.9349 - val_loss: 0.0505 - val_accuracy: 0.9860
Epoch 4/10
6/6 [==============================] - 4s 708ms/step - loss: 0.1649 - accuracy: 0.9688 - val_loss: 0.0204 - val_accuracy: 0.9944
Epoch 5/10
6/6 [==============================] - 4s 714ms/step - loss: 0.0246 - accuracy: 0.9974 - val_loss: 0.0170 - val_accuracy: 0.9944
Epoch 6/10
6/6 [==============================] - 4s 720ms/step - loss: 0.0255 - accuracy: 0.9922 - val_loss: 4.1003e-04 - val_accuracy: 1.0000
Epoch 7/10
6/6 [==============================] - 4s 716ms/step - loss: 0.0039 - accuracy: 0.9974 - val_loss: 5.9472e-06 - val_accuracy: 1.0000
Epoch 8/10
6/6 [==============================] - 4s 715ms/step - loss: 1.2711e-05 - accuracy: 1.0000 - val_loss: 3.0506e-06 - val_accuracy: 1.0000
Epoch 9/10
6/6 [==============================] - 4s 696ms/step - loss: 9.2451e-05 - accuracy: 1.0000 - val_loss: 2.4939e-06 - val_accuracy: 1.0000
Epoch 10/10
6/6 [==============================] - 4s 719ms/step - loss: 1.5739e-07 - accuracy: 1.0000 - val_loss: 2.2761e-06 - val_accuracy: 1.0000
Time elapsed in seconds: 70.05654907226562
```

Figure 8: Loss and Accuracy rate

3.5. Confusion Matrix:

In this work, the proposed deep learning network CNN was trained on the pepper dataset. Afterwards, the model was evaluated on the test set, which showed good performance. Figure 9 presents the confusion matrix of the classification results, where each row represents the actual category, while each column stands for the predicted result.

```
[[ 64   0   0]
 [  0 107   0]
 [  0   0 131]]
```

Figure 9:confuson matrix

3.6. 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.

	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 10: Comparison of Classification Performance

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3.7. 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.

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_9 (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_9 (Glob (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 1539
=================================================================
Total params: 14,716,227
Trainable params: 14,716,227
Non-trainable params: 0
```

Figure 11: Fully Connected and Dropout Layer

4. CONCLUSION

Paper 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 3 different pappers 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 predicate and classify different peppers without error and with full performance.

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