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Image-Based Detection Using Deep Learning and Google Colab

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***Abstract**: The application of neural networks and image processing techniques for detecting using images dataset is presented in this paper. An image-based detection of diverse nuts types has been observed and shown using Deep Learning (DL). Artificially using image augmentation, additional training images generated by various processing methods or combinations of multiple processing, such as random rotation, moves, shearing and flipping. The DL model is developed based Convolutional Neural Networks (CNN) using Python in Google Colaboratory, or "Colab" platform. Using Google's environment provides a free access to GPUs as well as a few configurations is required. A dataset of 1595 images of four different classes of nuts were used for training, validating and testing in the model. The trained model reached an accuracy of 100% on testing set, representing viable approach in detection and classifications applications.*

Keywords: Deep Learning, Convolutional Neural Networks, Detection, Classification

1. INTRODUCTION

The rapid development of computer vision and the availability of image datasets would benefit the research in detection and classification field (1). Image processing is an effective method for the identification of agricultural products and is commonly used in DL (2). Identifying products, particularly as per our research data set of nuts, is a key step in the effective automating product identification which contributes in economic development because it is more efficient than manual operation and saves time (3). As outstanding DL algorithm, the CNNs is commonly used in the development of the deep leaning models related to image classification and identification (4). Graphics Processing Unit (GPU) computing architecture is a promising platform as a DL tool that can work with learning algorithms (5). In our research, we demonstrated the viability of our method using state-of-the-art DL techniques by using a public dataset of 1595 images to produce a model that can be used in applications to classify 4 types of nuts, with an accuracy of 100 % on a testing dataset.

2. STUDY PURPOSES

- **Viability and usage:** To demonstrate the feasibility of using deep CNNs to identify small organic objects.
- **Development and testing:** To develop a DL model that can be used for applications to detect fruits types such as nuts.

3. DATASET

Our dataset contains 1595 images of 4 nut classes which have a resolution of 256×256 pixels as shown in Figure *1*. The classes in total are categorized according to the following:

- Class (1): Hazelnut.
- Class (2): Nut Forest.
- Class (3): Nut Pecan.
- Class (4): Walnut.

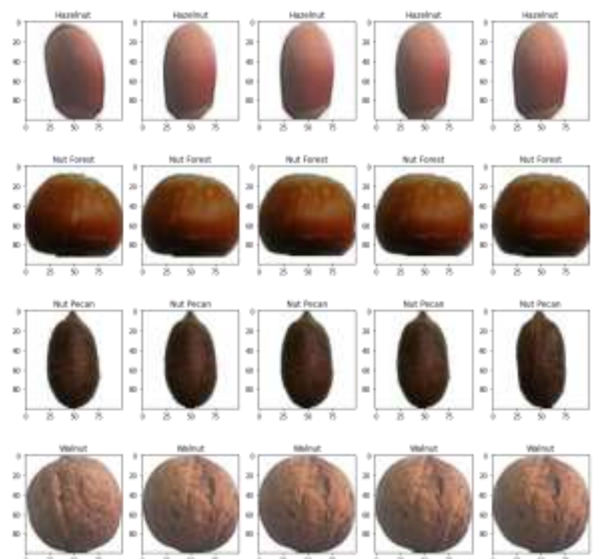

Figure 1 *Dataset Samples*

4. CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural Networks (CNNs or ConvNets) in Computer Vision (CV) is an emerging technology that use Artificial Neural Networks (*Figure 2*) concept in image processing in Machine Learning (ML) and DL (6). CNNs are part of a wider family of methods known as DL, a common group of neural networks designed to effectively process image data (7). In the last decade, numerous improvements to CNNs, from input representation, number of layers, types of pooling, optimization techniques, and applications to different tasks, have been active research topics (8). Improvements in CNNs includes convolution operations, convolution layers, architecture design, loss functions, and advanced applications (9). For grid-structured data is a 2-dimensional image, CNNs function best to extract

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important characteristics from the spatial correlation and dependencies data using multi-layer perceptrons (10) (11).

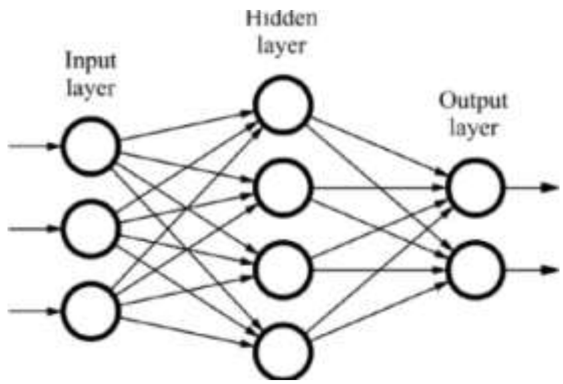

Figure 2 *Artificial Neural Network*

CNNs are made up of multiple essential elements, including convolution layers, pooling layers, and fully connected layers (Figure *3*), and are built using a backpropagation algorithm to learn spatial hierarchies of features automatically and adaptively (12).

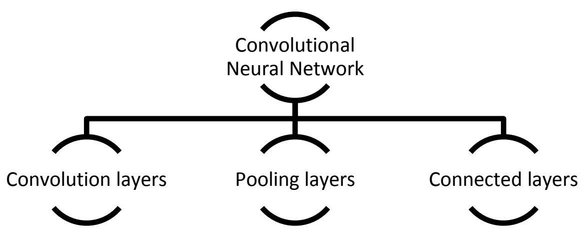

Figure 3 *Layers in CNNs*

A convolution can be represented as a method from the original image that generates an new image representation. Using the kernel matrix representing the weight, it generates multiple feature maps, and then continues with classification. Mathematically, the convolution is achieve through a kernel of N * N size which sweeps the original image and converts the original data into a different shapes and adding then all the resulting components (13).

- **Convolution layer**

The convolution layer is a fundamental component of the CNN architecture that extracts features, that is usually consists of a mixture of linear and nonlinear operations, i.e. the purpose of convolution and activation (14).

The convolution layer contains multiple convolution kernels used to measure various feature maps. In the previous layer, such a neighborhood is referred to as the receptive field of the neuron. By first converting the input with a learned kernel and then applying an element-wise nonlinear activation function on the converted output, the new feature map can be obtained (15).

- **Max-Pooling Layer**

The maximum activation over kernel regions gives the output of the max-pooling layer which leads to a faster convergence rate by choosing superior invariant that increase the efficiency of generalization of the model (16). In general, max-pooling shows a higher performance than attentive pooling and average-pooling (17).

- **Fully Connected Layers**

Every neuron in one layer is connected to every neuron in another layer by Fully Connected (FC) layers. That is the same as the conventional multi-layer perceptron neural network (18).

For better performance, in shallow CNNs more nodes required in FC layers. However, in more deep CNNs less number of neurons is required regardless of type of the dataset (19).

Usually, the final layer has the same number of output nodes as the number of classes and a nonlinear function follows each fully connected layer (12).

- **Receptive Field**

The size of the receptive field is a significant matter in FC CNN layers, as the output must respond to large enough areas in the image to collect information about large items, where the value of each unit depends on the entire network input (20).

There is a logarithmic correlation between the accuracy of classification and the size of the receptive field, indicating that large receptive fields are essential for high-level recognition tasks. (21).

- **Weights**

In convolutional layers, the weights are represented as the multiplicative factor of the filters of particular shape represented by vector of weights and the bias (22). Each neuron calculates an output value in a neural network by applying a function to input values from the receptive field from the previous layer (21). In our model, weights from "ImageNet" has been used in the convolutional base.

5. WORKFLOW AND MODEL IMPLEMENTATION USING PYTHON AND GOOGLE COLAB

The model involves processing input images to extract features including:

- **Features extraction:**

The feature extraction part consists of 5 blocks each contains multiple Conv2D layer followed by multiple MaxPooling2D layer.

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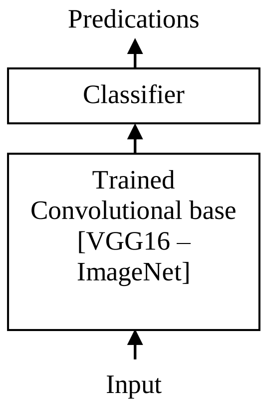

Figure 4 *Convolutional Base and Classifier*

VGG16 as convolutional base trained on ImageNet has been used to extract features as shown in Figure 4

Flatten layer:

Contains two dense layers and the last layer has Softmax activation function representing 4 outputs classes.

The workflow of development, training, validating and testing the model was achieved through the steps as shown in Figure *5*.

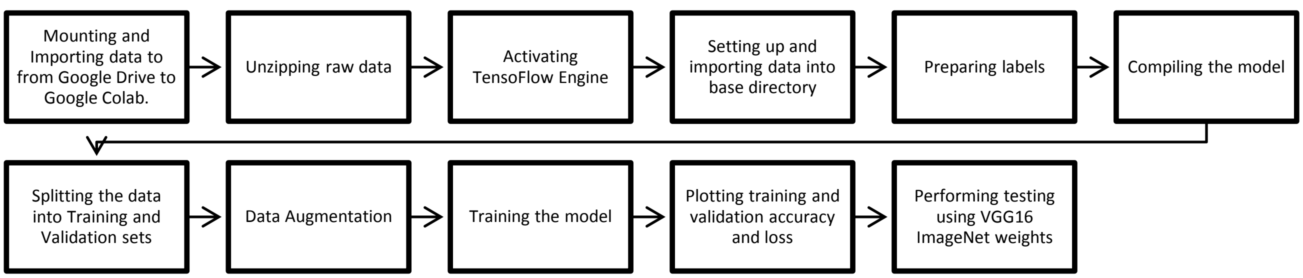

Figure 5 *Python Development Workflow using Google Colab*

Features extraction part and flatten layer are shown in Table *1* for including blocks, layers, output shapes and model parameters.

Table 1 *Model Parameters*

Layer (type)	**Output Shape**	**Param #**
input_1 (InputLayer)	(None, 256, 256, 3)	0
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1792
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36928
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73856
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147584
block2_pool (MaxPooling2D)	(None, 64, 64, 128)	0
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295168
block3_conv2 (Conv2D)	(None, 64, 64, 256)	590080
block3_conv3 (Conv2D)	(None, 64, 64, 256)	590080
block3_pool (MaxPooling2D)	(None, 32, 32, 256)	0
block4_conv1 (Conv2D)	(None, 32, 32, 512)	1180160
block4_conv2 (Conv2D)	(None, 32, 32, 512)	2359808
block4_conv3 (Conv2D)	(None, 32, 32, 512)	2359808
block4_pool (MaxPooling2D)	(None, 16, 16, 512)	0
block5_conv1 (Conv2D)	(None, 16, 16, 512)	2359808
block5_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block5_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block5_pool (MaxPooling2D)	(None, 8, 8, 512)	0
global_max_pooling2d_1 (Glob	(None, 512)	0
dense_1 (Dense)	(None, 4)	2052

Total params: 14,716,740
Trainable params: 14,716,740
Non-trainable params: 0

6. DATA REPRESENTATION

To see how the model works and what exactly learns, we chose to represent Training and Validation Accuracy and Loss. as shown on Figure *6* and Figure *7*

Figure *8* and Figure *9* shows that our model has been training and validated to reach an accuracy of 100% performed on the testing images

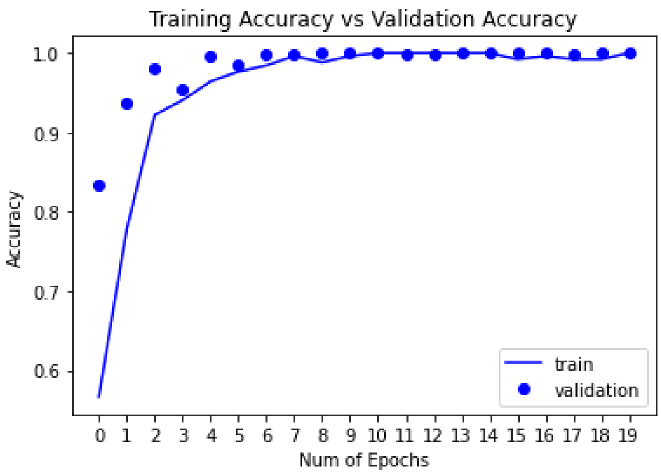

Figure 6 *Training and Validation Accuracy*

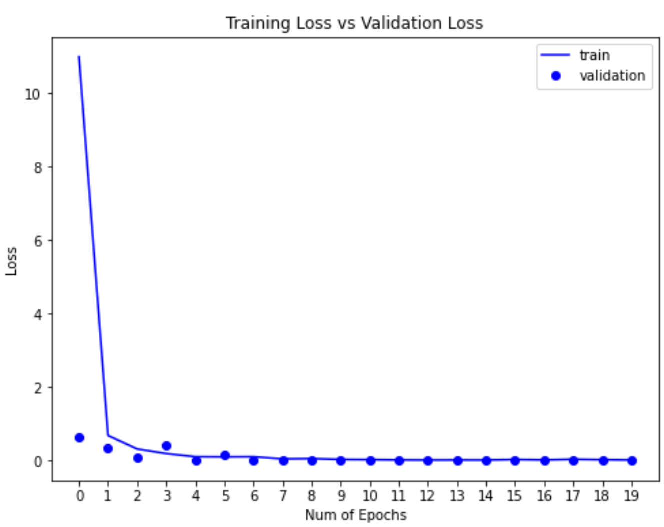

Figure 7 *Training and Validation Loss*

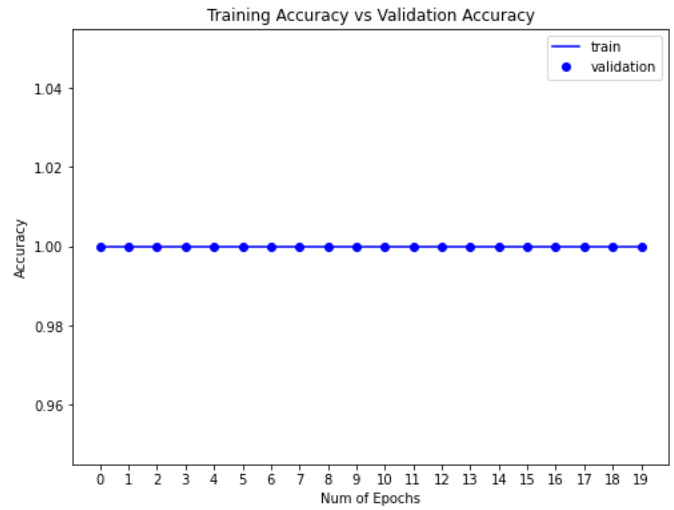

Figure 8 *Training and Validation Accuracy on Test Dataset*

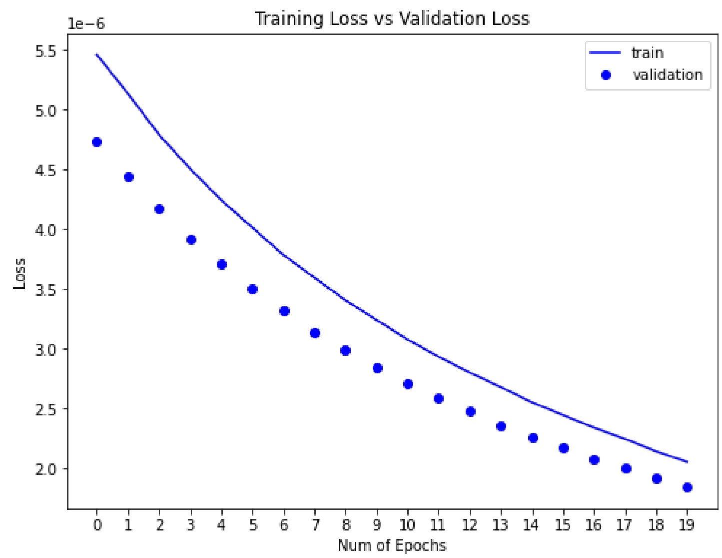

Figure 9 *Training and Validation Loss on Test Dataset*

7. CONCLUSION

DL techniques using CNNs for detecting types using images dataset is presented in this paper using Python and Google "Colab" Platform. The results have shown that the accuracyof 100% reached on test dataset which can be considered as representation of viable approach in detection and classifications applications.

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