International Journal of Computer (IJC)

ISSN 2307-4523 (Print & Online)

http://ijcjournal.org/

Recognition of West African Indigenous Fruits using a Convolutional Neural Network Model

Amarachi M. Udefi[a]*, Segun Aina[b], Samuel D. Okegbile[c], Aderonke R. Lawal[d], Adeniran I. Oluwaranti[e]

[a]Obafemi Awolowo University, Ile-Ife, osun state, 220282, Nigeria

[a]Email: amaraudefi@gmail.com

Abstract

The Fruit recognition involves the extraction and processing of relevant features from fruit images in order to deduce the categories of that fruit. Due to its importance to human health and sustainability, various systems exist for recognition of fruits, although none exist for recognition of west Africa's indigenous fruits. This research developed a fruit recognition system using a convolutional neural network (CNN) based model. Five west Africa indigenous fruits were selected, while images were directly used as input to CNN based model of (3 convolutional layers, 3 max pooling layers and 1 fully connected layer) for training and recognition without features extraction process. The study further presents a transfer learning on visual geometry group 16 and ResNet models for result comparison. Using the optimal training set, the proposed CNN based model produced a recognition rate of 96%.

Keywords: Convolution neural network (CNN); Fruit Recognition; ResNet; VGG 16.

1. Introduction

Pattern recognition is the branch of science whose aim is to classify objects into a number of classes or categories. Considering the type of pattern recognition application, these objects can be signal waveforms, images or any kind of magnitude that can be classified. Machine vision is the field that is very important to pattern recognition. A machine vision system captures pictures via a sensor or camera, analyze such pictures and output the illustration of what is obtained [1]. Owing to its ability to accurately represent images, machine vision is now being used in modelling fruit recognition systems.

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* Corresponding author.

Fruits are an essential part of humans lives and the environment. It is hence unsurprising that pomology – the science of fruit-growing, is important to the economic growth of any nation. Fruits are generally known to be vital sources of energy, fiber, minerals, vitamins, and other supplements and are an essential part of eating routine. Fruits can be classified as fleshy fruits (*e.g.* drupe, berries, citrus, pomes, *etc.*) and dry fruits (*e.g.* nut, legumes, capsules, samaras, caryopses, follicles, achenes, schizocarps, *etc*.). Drupe - the main focus of this research due to its importance in the western part of Africa, is an indehiscent class of fruit in which the outer fleshy part surrounds a single shell of hardened endocarp with a seed inside. Examples of drupe include cherry, African star apple, almond fruit, hog plum, monkey kola, ackee, dates, avocado, etc.

We provide brief information about the family of drupe considered in this paper:

- African star apple - African star apple is one of the indigenous fruits which are local to tropical African countries like Nigeria. It contains heaps of enhancements that are beneficial to human health [2].
- Hog plums - Hog plums are found in western Africa, majoring in Nigeria. It is traditionally called "*ebo"* or "*iyeye"*. The leaves act as germ-killers and these are utilized in making cleansers, treating sore throat, hack, jungle fever, *etc*. [3].
- Almonds - Almonds are famously called "fruit" in Nigeria. An almond contains certain minerals that are critical to human wellbeing. It fills in as cofactors for some important metabolic procedures in the body.
- Monkey Kola - Monkey Kola is the most significate kind of African indigenous fruit found in the southern parts of Nigeria, it is traditionally called "achicha", and contain substance, like vitamin C, riboflavin, and pro-vitamin.
- Ackee - Ackee is a fruit with red or yellow skin that contains no soaked fat or sterol. It is indigenous to West Africa and Guyana and is grown mostly in the western part of Nigeria and other parts of Africa.

Fruit recognition systems can be based on colour, shape or sizes of the fruit in question. The authors in [4] present an approach for a fruit recognition system, which incorporates three features analysis approach: colour-based, sized-based, and shape-based using the k-nearest neighbour classification algorithm. The authors in [5] on the other hand present a hybrid classification approach based on a fitness-scaled chaotic artificial bee colony algorithm and Feedforward Neural Network. A field-programmable gate array-based efficient fruit recognition system was proposed in [6] using a minimum distance classifier. These studies [4 – 6] combined feature extraction methods with classifier methods. In line with [4 – 6], we adopted a convolution neural network (CNN) model in order to develop the proposed fruit recognition system. The CNN was used as both feature extraction and classifier. A CNN is a deep learning algorithm that can lay hold of an input image, assign significant ('learnable' weight and 'biases') to the various entity in the image with the ability to separate one from other [7]. The outstanding classification accuracy and operational precision of CNN make it a good choice for handling image - processing problems. The pre-processing required in CNN seems much lower as compared to other classification algorithms. In most classification algorithms, filters (e.g. colour, size, coordinate, textures) are hand-engineered , with enough training while CNN has a capacity to learn these filters on its own. Furthermore, this study conducted a transfer learning on Visual geometry group (VGG) 16 and ResNet models. VGG 16 and ResNet are existing models of CNN.

2. Related Work

An automatic produced identity system called “Veggie-vision” for fruit recognition using texture, colour, and density was presented in [8]. This method was the first attempt at the fruit and vegetable recognition problem. It consists of a degree integrated scale and imaging system with a user-friendly interface. The reported accuracy was 95% when colour and texture features are combined. In [9], the authors proposed the shape variation analyzer for tomato and plant species such as butternut and banana. By combining the controlled vocabulary with the mathematic descriptors into a tomato analyzer, the objective measurement of the fruit shape trait was achieved. The approach produced an accuracy between 80 % and 85%. In a similar work, Seng and Mirisaee [4] developed a fruit recognition system which combines three features analysis methods: color-based, shape-based and size-based so as to increase the accuracy of the recognition. The system classifies and recognizes fruit images based on the obtained feature (attribute) values by using nearest neighbour’s classification. The recognition rate accuracy of 90% was obtained. Also, a fruit recognition approach based on the fusion of colour and texture features (attribute) was proposed in [10].

The recognition was achieved through the minimum distance classifier which was based upon the statistical and co-occurrence features derived from the wavelet transformed sub-bands. In [11], a comparative analysis of edge and colour-based segmentation for orange fruit Recognition was presented. The work uses an Edge-based and colour-based detection approach to segment images of orange fruits. MATLAB image processing toolbox was used for computation and comparison. Colour based algorithm was able to detect oranges with 85% accuracy . In [12], an automatic fruit classification was proposed using local texture descriptors and shape-size features. The local binary pattern and Weber local descriptor histogram were used to encode the texture pattern. Fruit classification was achieved in [5] using biogeography-based optimization and feedforward neural networks. A vegetable and fruit recognition system was proposed in [13] by utilizing CNN and image saliency. The system used image saliency in the area of image processing as well as VGG 16 as CNN model to classify the objects. The approach produced an accuracy of 96%. A machine vision-based classification system was presented in [14] to sort coffee fruits (cherries) with respect to their ripeness stage. Eight categories were defined and they included the entire coffee cherry ripeness process, from the initial stage (early green) to overripe and dry stages. A Bayesian classifier was implemented using a set of nine features which included colour, shape and texture enumerated on an image of the fruit.

In [15], an apple recognition technique was proposed to detect normal and infected apples. The approach classified and recognizes apple images based on obtained features values by using two-layer feed-forward network, with sigmoid hidden and output neurons. The toolbox supported feedforward networks, radial basis networks, dynamic networks, self-organizing maps, and other proven network paradigms . These studies adopted the method of feature extraction combined with classifiers. Instead, we propose a fruit recognition algorithm based on CNN. In this work, input images were directly straightened (fed) into the network for training and recognition without an initial feature extraction process. CNN also learned optimal features from images through the adaptation process .

3. Methodology

This section discusses the requirements and the design process for the formulation of the model. The proposed model is shown in Figure 1

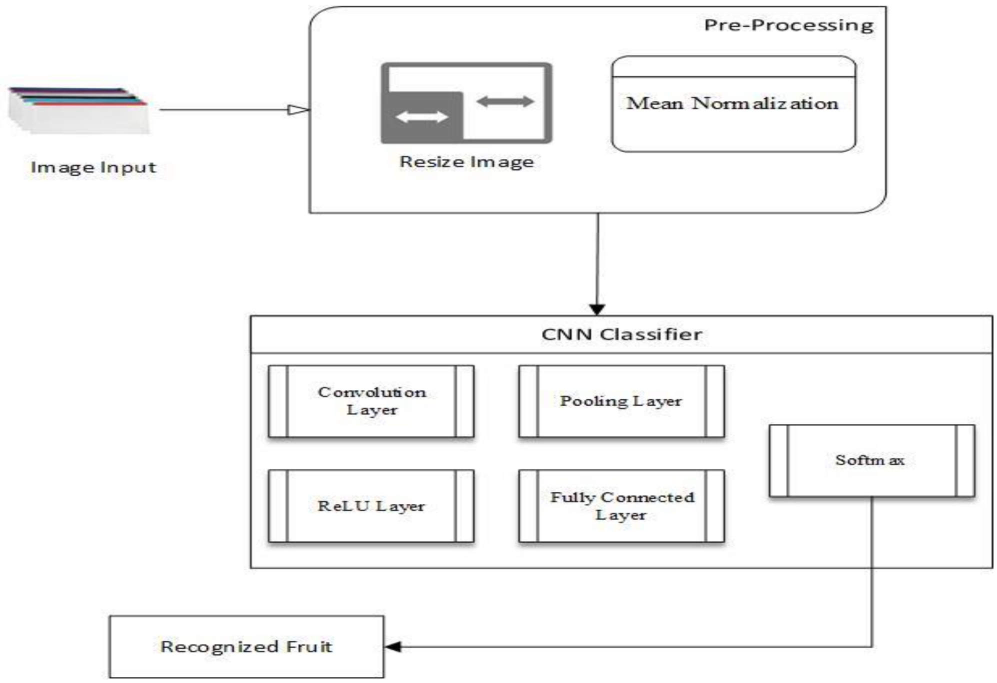

Figure 1: Proposed Model

3.1. Convolutional Neural Network

CNN is a class of deep neural networks that are most commonly applied to analyse visual imagery. The network structure is designed to extract relevant features from data. CNN is known to use relatively little pre-processing when compared to other image classification algorithms [16] and is used in this study for both training and recognition processes. CNN has four major building blocks (layers); Convolutional layers, pooling layers, fully connected layers, and loss layers.

- Convolutional layers. Convolutional layers are named after the convolution activity. Convolution is a procedure on two functions that creates a third function known as the convoluted version of the initial functions. A convolutional layer contains neurons that makeup kernels. These kernels are small in size though have the same depth as the input. Since it is inefficient to connect all neurons to all previous outputs when high dimensions' input is involved, the neurons are connected to the receptive field - the small area of the input. The kernels normally slide across the width and height of the input, extract high-level features and produce a 2-dimensional activation map. The stride at which a kernel slide is given is a parameter. The stride is a matrix for regulating the movement of various convolutional filters for pixel-wise operation across a given image space. The output volume spatial size is usually controlled through padding. The output of a convolutional layer is made by stacking the resulted activation maps which in turn is used to define the input of the next layer. The inputs to convolutional layers are called input channels, and the outputs are called output channels. The sample of convolution operation is given in Figure 2.

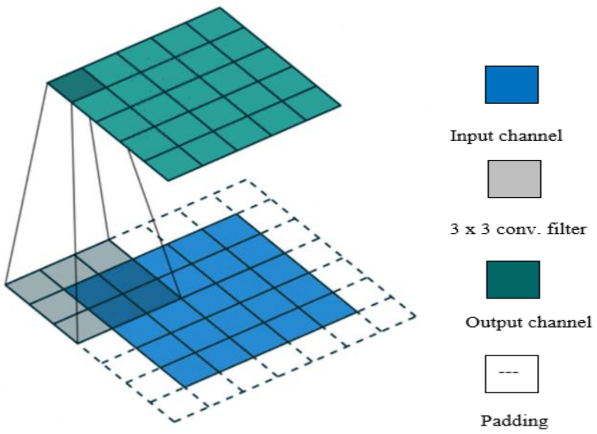

Figure 2: Sample of the convolution operation

The number of parameters of a convolutional layer is obtained as;

$$p_c = f(w_c * c + b_c) \quad (1)$$

where, $w_c = k^2 * N$, f is the applied nonlinear activation function, c denotes the number of channels of the input image, b_c is the number of bias of Convolutional layer, N denotes the number of the kernel, k is the size (width) of kernel used and w_c represents the number of weights of the convolutional layer.

- Pooling layer: Pooling layers are used to reduce the spatial dimensions of the representation and to reduce the amount of computation done in the network. The amount of data processing can be reduced while preserving useful information. The most used pooling layer has filters of size 2 x 2 with a stride of 2.
- Fully connected layer: Fully connected layers known as FC layer are layers from a regular neural network. Each neuron from a fully connected layer is linked to each output of the previous layer. The operations behind a convolutional layer are the same as in a fully connected layer. Thus, it is possible to convert between the two. There are two kinds of fully connected layers on CNN. The first FC layer is connected to the last convolutional layer, while later FC layers are connected to other FC layers. Considering each instance of fully connected layer separately, we have

Case 1: Number of parameters of a fully connected layer connected to a convolutional Layer – This is defined as;

$$\mathrm{p_{cf}} = \mathrm{f}(\mathrm{w_{cf}} * \mathrm{c} + \mathrm{b_{cf}}) \quad (2)$$

where, $w_{cf} = k^2 * N$, c denotes the number of neurons in the FC Layer, b_{cf} is the number of biases of FC Layer which is connected to a convolutional layer, N denotes the number of kernels in the previous convolutional layer, k is Size (width) of the output image of the previous convolutional layer and w_{cf} is the number of weights of FC Layer which is connected to a convolutional layer .

Case 2: Number of parameters of a fully connected lay connected to another FC Layer – This is defined as

$$p_{ff} = f(w_{ff} * F + b_{ff}) \qquad (3)$$

where, $w_{ff} = F_{-f} * F$, F is the number of biases of FC Layer which is connected to another FC Layer, F_{-f} is the number of neurons in the previous FC Layer and w_{ff} is the number of weights of FC Layer which is connected to another FC Layer .

- Loss layers: These are used to penalize the network for deviating from the expected output. This is normally the last layer of the network. Various loss function exists: SoftMax is used for predicting a class from multiple disjunct classes. The equation for SoftMax is given as;

$$S(X_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_i}} \qquad (4)$$

where, e^{x_i} is the exponential of a network output (x) and denominator is the summation of all the e^{x_i}. Example, if the output network of ackee, monkey kola, hog plum, Africa star apple, and almond is -1, 0, 2, 3, and 5 respectively. Ackee will have a numerator of 0.368 and a probability of 0.002, Monkey kola will have a numerator of 1 and a probability of 0.006, Hog plum will have a numerator of 7.389 and a probability of 0.041, Africa star apple will have a numerator of 20.09 and a probability of 0.118, Almond will have a numerator of 148.41 and a probability of 0.874. Therefore, the network will be 87.4% confident that the input image is Almond fruit image.

4. Implementation and Results

We now present the development of a CNN based model for west Africa indigenous fruits recognition. The model's performance is assessed and results are presented.

4.1. Data Description

Data were gathered through on-site capturing of images using a digital camera. Further images were obtained from online resources. Samples of the fruits' images used in this work are presented in Figure 3.

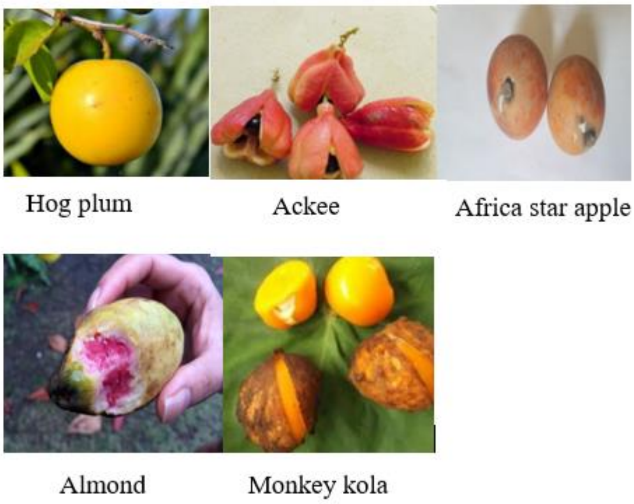

Figure 3: Sample images

The total data collected consisted of 800 images. Due to the small size of the training samples, over-fitting occurred. In order to avoid over-fitting, the data was supplemented using data augmentation techniques [17] so as to enable the model to learn from different image data variations. The dataset after augmentation consisted of 1000 images. The augmentation was carried out using the following expression;

$$\mathbf{h} = \mathbf{f}\phi + \mathbf{g}\psi \tag{5}$$

where ϕ and ψ are both random scalars between 0 and 1 with the two images f and g belonging to the same fruits class. A sample of the augmentation is presented as Figure 4.

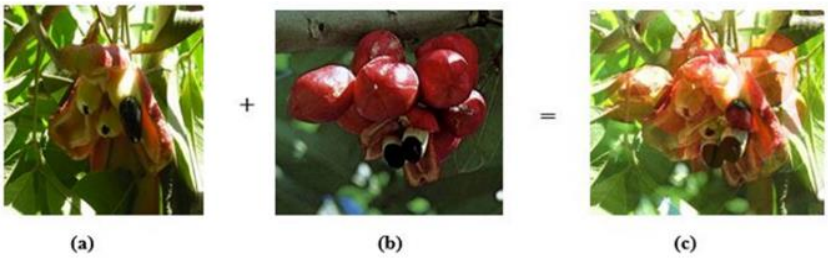

Figure 4: Two subject's images (a) and (b) from the ackee fruits class being combined to form a third image (c)

4.2. Modelling Method

The images were reshaped with the goal of obtaining size 224 x 224 x 3 and were fed it into the system as input. Three convolutional layers were adopted,

- 3 x 3 - 32 filters, to the first layer,
- 3 x 3 - 64 filters to the second layer, and
- 3 x 3 – 128 filters to the third layer.

Three max-pooling layers of size 2x2 and one fully connected layer

Convolution preserves the spatial relation between pixels by learning image features using small squares of input image. In this model we used 3×3 filter to compute convolved features. ReLU stand for rectified linear unit is a non-linear operation was also used. The purpose of ReLU is to introduce to non-linearity in our Convolutional Network because mostly Convolutional Network has to learn non-linear real-world data. ReLU trained the neural network much faster without a significant profusion to generalization accuracy. The first convolutional layer with Conv2D () was included. Next, we included the Leaky ReLU activation function, since there are five unique classes, (ackee, almond, Africa star apple, hog plum, and monkey kola), a non-direct decision limit is needed to isolate the five classes which are not clearly distinct. The ReLU function enables the activation to be thresholder at zero. Next, we include the max-pooling layer with MaxPooling2D. The last layer is a dense layer that has a SoftMax actuation work with 5 units, which is required for this class recognition problem. Adam optimizer was later used for the compilation of the model. Adam optimizer is one of the well-known optimization algorithms that can be used to refresh the network's weight. The model was trained with Keras' fit () function, with 20 epochs. Epoch is the total number of iterations, while batch size specifies the number of observations. The weight was updated and the model was trained on TensorFlow central processing unit (CPU) in an anaconda environment. During the process of training, some weights are learnt known as **parameters**. Learnable parameters in our model are gotten using the formula of convolution layer and fully connected layer as stated in equation 2 and 3 respectively. From equation 2, number of channels of input image c = 3 (because input image is an RGB), number of the kernel N = 32, number of bias of convolutional layer b_c = 32, The kernel size (width) k or filter = 3*3

p_c = 3 x 3 x 3 x 32 + 32 = 896

Therefore, learnable parameter in the first convolutional layer is 896.

Last convolutional layer, number of channels of input image c = 64, number of the kernel N = 128, number of bias of convolutional layer b_c = 128, The kernel size (width) k or filter = 3*3

p_c = 3 x 3 x 64 x 128 + 128 = 73,856

Learnable parameter in the last convolutional layer is 73856.

Learnable parameters in fully connected layer, using equation 3, number of fully connected layers of neurons, c = 128, number of fully connected layer biases, b_{cf} = 128, number of the previous Convolutional Layer Kernels N = 128, Size (width) of the previous Convolutional layer output image k = 28 x 28.

p_{cf} = 28 x 28 x 128 x 128 + 128 = 12,845,184

Learnable parameter in the first fully connected layer (FC) layer is 12,845,184, therefore, the summation of all the learnable parameters in the model is 12,939,077. All the parameters are shown in Table 2.

4.3. Results

The result is represented using the confusion matrix. The confusion matrix provides the output matrix and explains the model's full performance. The confusion matrix offers a better idea of what is going wrong with classification. In the confusion matrix, the X-axis is the predicted fruit labels and the Y-axis is the true labels. A confusion matrix is determined by true positive (TP); the cases in which we predicted yes and the actual output was yes, true negative (TN); The cases in which we predicted no and the actual output was no, false positive (FP); the cases in which we predicted yes and the actual output was no, false negative (FN); the cases in which we predicted no and the actual output was yes. The diagonal represents the correct results. The results in Figure 5 show that the majority of the fruit was correctly estimated.

Figure 5: Confusion matrix of the baseline model

4.4. Evaluation Method

The model was evaluated based on accuracy, precision, and sensitivity metrics. Accuracy gives the proportion of correct predictions out of all predictions made, i.e., it refers to the proportion of true results of fruits among the total number of fruits examined. It is given as

$$Accuracy = \frac{TP + TN}{P+N} \qquad (6)$$

where (TP + TN) is the total number of true predictions i.e., true positive + true negative and P + N is the total number of data set.

Sensitivity is known as a true positive rate, i.e., the proportion of fruits belonging to the same group that was correctly predicted , e.g. what proportion of ackee was predicted correctly? and can be obtained as

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \qquad (7)$$

where FN is a false negative.

Finally, precision gives us what proportion of a particular class of prediction that is actually correct, e.g., what proportion of those predicted as ackee is truly ackee, and can be obtained as

$$Precision = \frac{TN}{TN+FP} \quad (8)$$

where FP is False positive.

Based on (6) – (8), the proposed model produced accuracy, sensitivity, and precision of 96, 94, and 96% respectively. The outcomes are presented in Figure 6 and Figure 7.

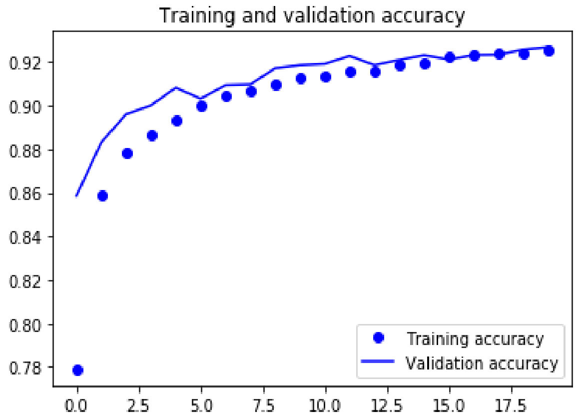

Figure 6: Plot of validation accuracy and training accuracy of baseline model

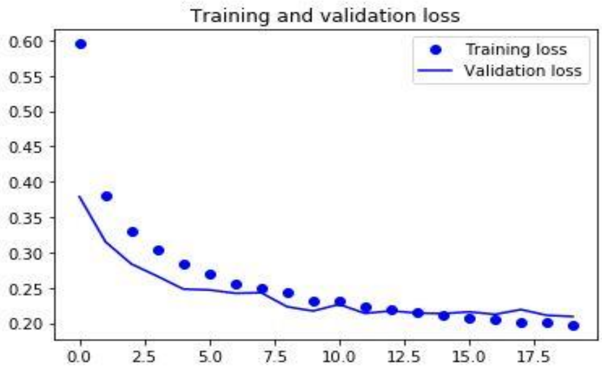

Figure 7: Plot of training loss and validation loss of baseline model

Although there are dozen or more top-performing models of CNN that can be downloaded and used as the basis for image recognition, VGG 16, ResNet and GoogleNet model are known to be among the best. We conducted transfer learning on VGG 16 and ResNet model. Transfer learning in deep learning is using the features learned for a source problem so that the same network can be optimized later through a fine-tuning process for a target problem [18]. VGG 16 and ResNet models are models that are pre-trained on the ImageNet dataset and are provided in the Keras library for use. VGG 16 was developed in [18], while ResNet was developed in [20]. The models were also trained on TensorFlow CPU in an anaconda for 20 epochs. Confusion matrix results of the VGG and ResNet model are shown in Figure 8 and Figure 9. It can be seen from the confusion matrix that VGG 16 model returns accuracy, sensitivity and precision of 91, 90 and 92% respectively, while ResNet model returns accuracy, sensitivity and precision of 84, 82 and 86% respectively. Table 1 shows a comparison analysis of the baseline model, VGG 16 and ResNet model.

Figure 8: Confusion matrix of VGG 16 model

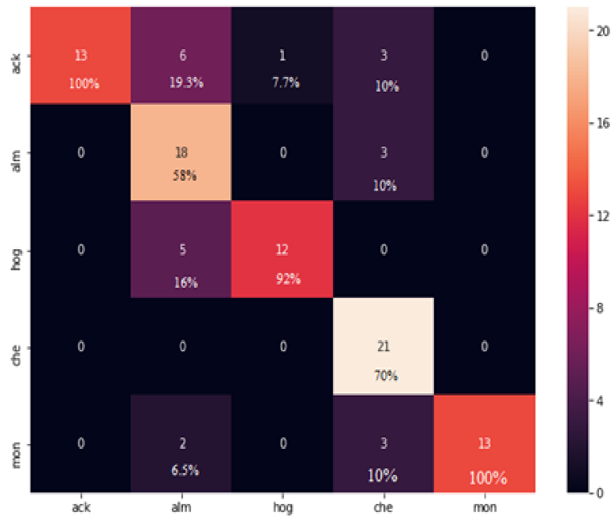

Figure 9: Confusion matrix of the ResNet model

The validation and training accuracy of the VGG 16 and ResNet model are presented in Fig.10 and Figure 11.

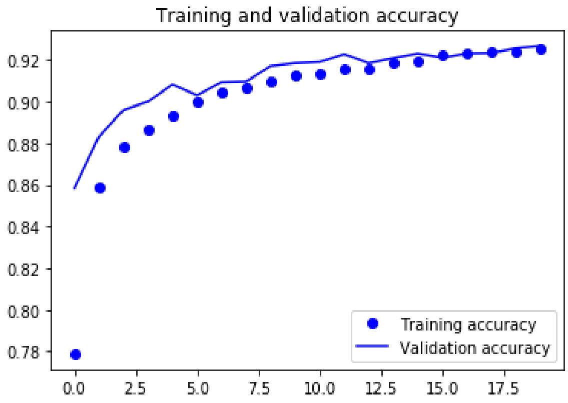

Figure 10: The plot of validation accuracy and training accuracy of VGG 16

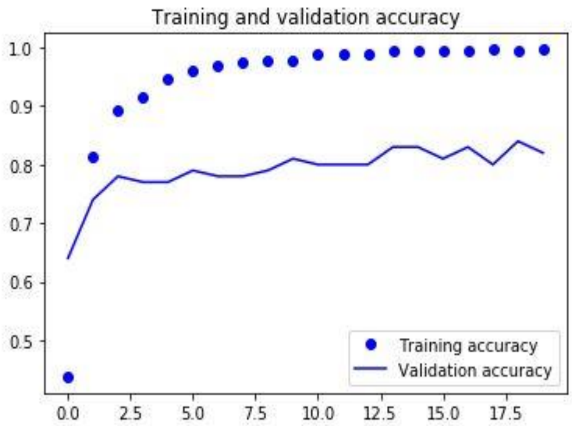

Figure 11: The plot of validation accuracy and training accuracy of ResNet model

5. Conclusion

In this study, a fruit recognition model based on convolution neural network (CNN) was proposed. The approach is composed of mainly two steps: the data pre-processing stage and the classification and recognition stage. CNN was used as a feature extraction and as a classifier. By comparing the proposed baseline model with the two existing models on which transfer learning was conducted, the recognition rate of the baseline model was shown to be higher than the VGG 16 and ResNet model as VGG 16, ResNet, and baseline model produced an accuracy of 91%, 84%, and 96% respectively. In future research, we plan to expand the dataset and investigate the performance of the system.

Table 1: Comparison analysis of the baseline model, VGG 16 and ResNet model

Models	Loss-(%)	Accuracy(%)	Val _ Loss(%)	Val-Accuracy(%)
		5 Epochs		
Baseline Model	0.0760	0.9789	0.1517	0.9600
VGG 16	0.1848	0.9124	0.2612	0.8980
ResNet	0.2151	0.9456	0.5110	0.7700
		10 Epochs		
Baseline Model	0.0226	0.9967	0.1288	0.9500
VGG 16	0.0873	0.9470	0.2712	0.9221
ResNet	0.1108	0.9789	0.4630	0.8100
		15 Epochs		
Baseline Model	0.1360	0.9989	0.1258	0.9600
VGG 16	0.0182	0.9648	0.2712	0.9065
ResNet	0.0136	0.9989	0.2712	0.9221
		20 Epochs		
Baseline Model	0.0102	0.9978	0.1214	0.9600
VGG 16	0.0182	0.9978	0.2554	0.9100
ResNet	0.0102	0.9978	0.4214	0.8200

Table 2: All Parameters

Layer	Output Shape	Number of Parameters
Conv3- 32	(224, 224, 32)	896
(LeakyReLU)	(224, 224, 32)	0
max_pooling2d	(112, 112, 32)	0
Conv3- 64	(112, 112, 64)	18496
(LeakyReLU)	(112, 112, 64)	0
max_pooling2d	(56, 56, 64)	0
conv3d_128	(56, 56, 128)	73856
(LeakyReLU)	(56, 56, 128)	0
max_pooling2d	(28, 28, 128)	0
flatten_17 (Flatten)	(2048)	0
dense_33 (Dense)	(128)	12,845,184
leaky_re_lu_60 (LeakyReLU)	(None, 128)	0
dense_34 (Dense)	(None, 5)	645

Total parameters: 12,939,077

Trainable parameters: 12,939,077

Non-trainable parameters: 0

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