Fruit Quality Classification using Convolutional Neural Network

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Submission date: 27-Sep-2022 04:00PM (UTC+0700)
Submission ID: 1910269279
File name: it_Quality_Classification_using_Convolutional_Neural_Network.pdf (738.52K)
Word count: 1887
Character count: 10175

Fruit Quality Classification using Convolutional Neural Network

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Abstract. Fruit quality identification is very important in the food industry for maintaining product quality. The quality control in the food industry commonly conducted by human senses which is lack of objectivity and takes long time for real-time mass production quality control. The quality of the fruit can be identified through its color, smell, and texture. This study uses fruit image to classify the quality of the fruit. We trained artificial neural networks for classifying fruit quality from Indian Fruit Dataset with Quality (FruitNet). The dataset contains six classes of fruits with three categorical qualities (Good, Bad, and Mixed). The dataset features were extracted using several pre-trained deep learning networks trained on the ImageNet dataset. The convolutional networks for feature extraction used in this study are VGG16, MobileNetV2, EfficientNetB0, and ResNet50. The extracted features are forwarded to neural network for training the dataset. The result shown that f1-score for testing dataset reaches more than 90% except for MobileNetV2. The highest f1-score is obtained from ResNet50 feature extraction which is 95.7%.

1. Introduction

Fruit quality identification is an interesting process for supporting the food and beverage supply chain. Quality identification automation can speed up the production process, help the industry grow, and protect the customer. This problem has also become very important in agriculture for sorting fruit harvesting and monitoring the crops from disease. The alteration of its color can identify the disease of a fruit. Therefore, identification based on color analysis using certain technology can be used for providing rapid detection of fruit quality. This technology will help farmers improve their profit and land productivity[1].

Computer vision can be used for analyzing an image, specifically identifying the quality of the fruit [2–4]. Instead of using human eyes to observe the fruit color, the computer can process an image and classify fruit quality by using certain algorithms. The algorithm for image classification has been developed by the researcher and applied in several fields for a specific case. There are two major techniques for performing image classification: machine learning algorithms and deep learning methods. Bhavini et al classify apple quality by extracting fruit features using color coherence vector (CCV) and global color histogram (GCH). The extracted feature from the fruit was classified using random forest algorithm [5]. Abdelsalami et al create orange fruit defect identification captured with CCD camera and detect the defect using several algorithms. They segmented the fruit image and performed threshold to obtain the feature. The classification calculation is performed through a voting algorithm based on the selected color on the image, and they obtain an accuracy around 95% [6]. Patel et al built a system for identifying orange fruit quality using SVM Classifier with GCH, CCV, and color moment used as feature extraction methods. The result show that the accuracy in orange fruit quality classification around 67.74% [7].

Another approach which is more powerful than machine learning algorithm is by using deep learning [8–10]. But, it needs more computational resources depending on how deep the network is. This method can perform feature extraction integrated with the classification training process. In the network, there are two separate type of network which are convolutional network and fully connected layer. The convolutional network performs the task for feature extraction which encodes the image into vector with certain size. The extracted features were forwarded into fully connected layer to perform classification. Both network of feature extraction and classification are integrated therefore can be trained simultaneously. Albarrak et al proposed a deep learning model for date fruit classification and achieved 99% model accuracy [11]. Shahi et al built a system based on MobileNetV2 and attention module for fruit classification. The image prepared into 244 x 244 size RGB and trained on their proposed network. The result showed that proposed model can achieve 96.71% accuracy on testing data of fruit360 dataset [12].

In our study, we create a deep learning model for fruit classification using several pre-trained feature extraction models. The extracted features were trained on our fully connected layer for image classification. We used 1 hidden layer of fully connected layer with 1024 nodes to compare the accuracy of several pre-trained model for feature extractions.

2. Method

The research is implemented in Python using TensorFlow library. The pre-trained model trained on ImageNet dataset have been included in the library. We use this network for performing feature extraction. Moreover, the network connected to 1 hidden layer with 1024 nodes and connected to 18 nodes of fully connected layer at the top layer (Figure 1). The network trained with 18 class of fruit with quality which is 200 images for each class and augmented using horizontal flip, rotation, width shift, height shift, and zooming. The convolutional network was frozen with parameter from ImageNet training, which could not be trained during fruit quality training. In this research, we only train the fully connected layer using Adam optimizer with 0.001 learning rate and 10 epochs. We observe the performance of network with selecting different convolutional network MobileNetV2, EfficientNetB0, ResNet50, and VGG16 [13–16].

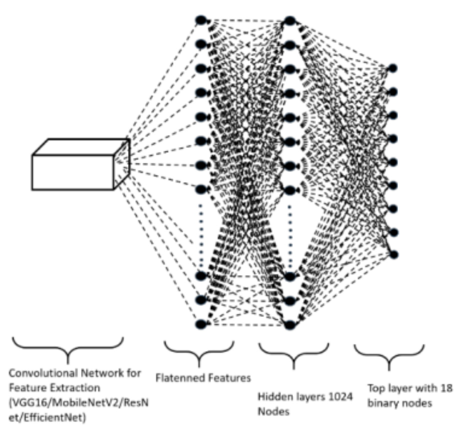

Figure 1. Convolutional network for feature extraction with fully connected layer for classification.

We use public dataset from FruitNet which consist of more than 14700 high quality images of six different class of fruit. The fruit divided into three categories as following good, mixed, and bad. The dataset has different number of images in each class, therefore it is not balance. For balancing the images, the data augmentation was carried out for increasing number of images in dataset. We use 3600 images for data training, 977 images for validation, and 976 images for testing.

3. Result and Discussion

The several original datasets were shown as in Figure 2a which are contains of 18 class of fruit. There are 3 class for quality of each fruit good, bad, and mix. The appearance of images show an obvious difference between each quality which is represented from the color and texture. Fruit with good quality have very low dark color on its skin, if the fruit quality undergoes degradation, then the fruit color turn become darker with several dark spot on its skin. For data training we select 200 images from each class and augmenting images of fruit class with number lower than 200. The result of augmented images is shown in Figure 2b.

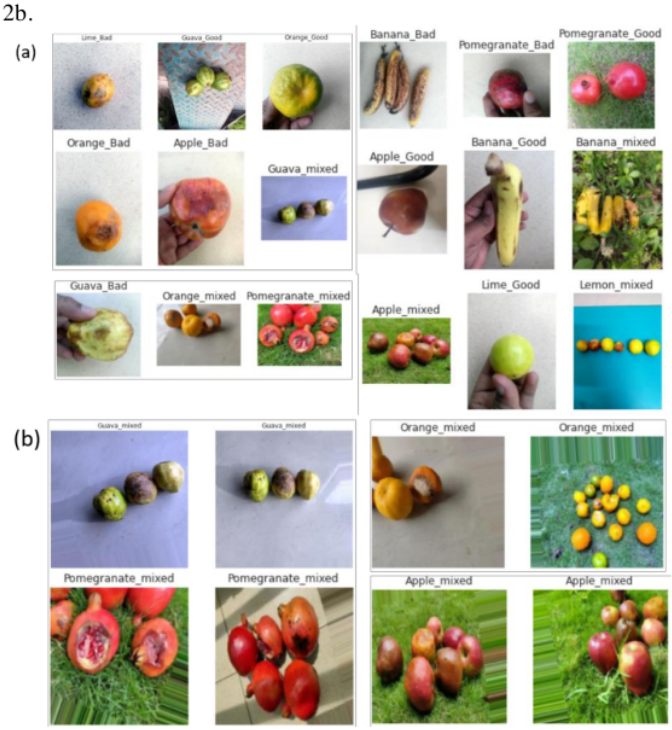

Figure 2. (a) Original FruitNet dataset (b) Augmented dataset for data balancing

In the next step the network was trained using our convolutional network and fully connected layers which is the fully connected layer set to be trainable. The training run for 10 epochs with 20 batch size. The result of training on model performance can be represented from its learning curve (Figure 3). During the training process, the training data and validation data was used. The training data for tuning network parameter and validation data for monitoring network performance during training. The result showed that the model reached the convergence state in 10 epochs, indicating constant change in loss function. To obtain the model performance after training, we test the model with the testing dataset which never used in training. The model accuracy on testing dataset is shown in Table 1.

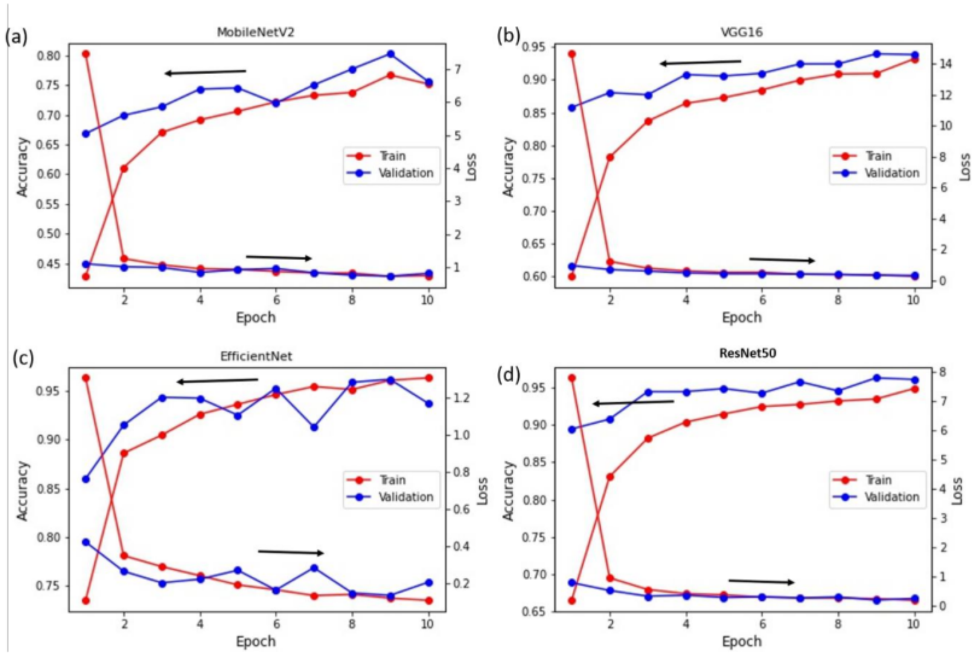

Figure 3. Learning curve of trained neural network model (a) MobileNetV2 (b) VGG16 (c) EfficientNet (d) ResNet50

Table 1. Model performance convolutional network on fruit quality classification

Network model	Accuracy	Number of network parameter	Number of features extracted
MobileNetV2	0.7623	2.257.984	62720
VGG16	0.9314	14.714.688	25088
ResNet50	0.9570	23.587.712	100352
EfficientNet B0	0.9488	4.049.571	1280

Table 1 show the best model performance for fruit classification is ResNet50 which has 0.95 accuracy. But the ResNet50 model has the highest number of parameters among other model which causes the model needs higher computational resources for deployment. The lowest parameter number own in MobileNetV2 architecture, but it has very low accuracy on testing data. Therefore, for the purpose of deployment on limited computational resource and obtaining high accuracy the EfficientNetB0 is more preferable. For more detail about model performance on predicting each fruit class can be represented using confusion matrix (Figure 4). This matrix obtained from conducting prediction on testing dataset and arrange the result into the matrix. For more detail about model performance on predicting each fruit class can be represented using confusion matrix (Figure 4). This matrix obtained from conducting prediction on testing dataset and arrange the result into the matrix.

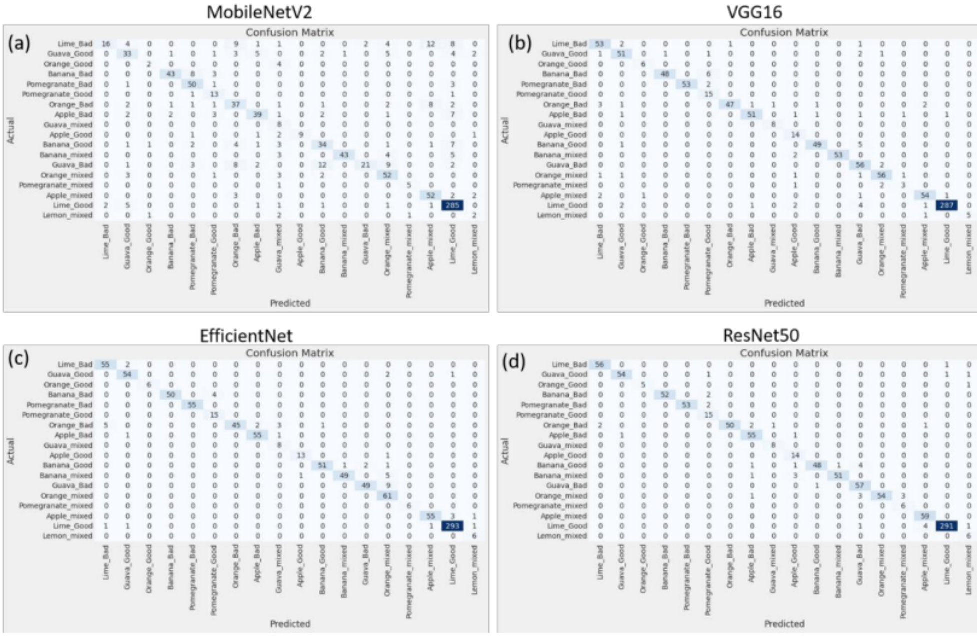

Figure 4. Confusion matrix of model performance (a) MobileNetV2 (b) VGG16 (c) EfficientNet (d) ResNet50

In addition, we used the feature generated from each convolutional network for visualizing the image in low dimensional plot. We select one fruit class, in this case apple, for visualizing data distribution in low dimension. We perform principal component analysis on the extracted features and plot the data in their PC1 and PC2 axis (Figure 5).

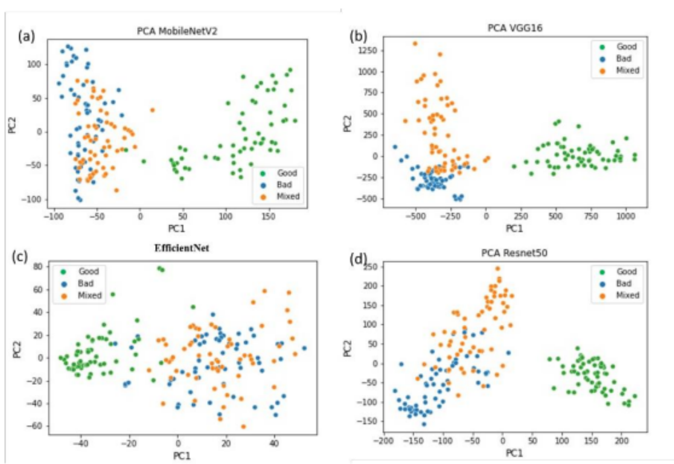

Figure 5. PCA plot of selected apple class for visualizing extracted feature in 2D (a) MobileNetV2 (b) VGG16 (c) EffientNet (d) ResNet50

The result showed that the dataset between fruit quality separated clearly. The good quality separated from bad and mix quality for all convolution network, meanwhile bad and mixed quality nearly blended in PCA distribution plot. This is due to the feature of bad and mixed quality almost similar which is indicated by dark spot on the fruit skin. Even though the bad and mixed quality in 2D plot are blended, but the fully connected layer can classify high dimension features with high accuracy.

4. Conclusion

In this study we have developed a convolutional neural network model for classifying fruit quality from FruitNet dataset. Several CNN models were employed for feature extraction and trained on fully connected layer. We compare model performance from several different CNN model, which obtained that ResNet50 provide the best accuracy until more than 0.95%.

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