# Fruits Recognition using Deep Learning Techniques

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# Abstract

Computer vision is a mathematical method of analyzing, processing, and understanding the details of images. The interest in computer vision fruit and vegetable recognition is divertingly increasing as it is considered efficient tools of reducing human workload and still it is challenging to implement it in the agriculture industry. It can be helpful for disease detection, fruit harvesting, point of sale system, and educational system to enhance the learning of children and down syndrome patients. A lot of researches are carried out on fruit recognition but still there are many challenges in current methodologies that needed to be addressed to design an efficient fruit recognition system, thus, this research focuses on developing a fruit recognition system using a machine learning algorithm. This study performs the classification of cherry, strawberry, and tomato using convolutional neural networks. The methodology includes background exploration, dataset exploration and analysis, model training, and testing. The model score accuracy rate of 71%.

# Introduction

Numerous real-life applications, for example, recognition of objects, object recognition, robotics, and autonomous vehicles mimic the functioning of the human brain to understand and analyze images. The food industry majorly relies on object recognition for the classification of freshly produced fruits and vegetables. In the conventional approach, a trained person is required for visual inspection of fruits and vegetables for assessment of production quality. There are some human-related constrain in the case of conventional inspection approaches such as the person need to acquire detailed information about the characteristics of fruit and vegetables (Hameed et al., 2018). The conventional approach needs to have a continual and consistent aspect recognition technique to maintain consistency. With the advancement in technology, the agriculture industry is now moving towards mechanized classification for the harvesting of crops, which is based on computer vision (Bhargava and Bansal, 2018). Computer vision is a mathematical method of analyzing, processing, and understanding the details of images. The interest in computer vision fruit and vegetable recognition is divertingly increasing as it is considered efficient tools of reducing human workload and still it is challenging to implement it in the agriculture industry (Bhargava and Bansal, 2018). It can be helpful for pest management (Pandey et al., 2013), insects detection (Koumpouros et al., 2004), disease detection (such as fungus) (Gulhane and Gurjar, 2011), fruit harvesting, plant nitrogen estimation (Tewari et al., 2013), and tracking of an object in real-time (Ozyildiz et al., 2002). The fruit and vegetables recognition technology can also be implemented point of sale system (Dubey and Jalal, 2015) and educational system to enhance the learning of children and down syndrome patients (Sahin, 1997).

Recent state-of-the-art of recognizing fruits and vegetables combined machine learning algorithm and features description. A lot of researches are carried out on fruit recognition but still, there are many challenges in current methodologies that needed to be addressed to design an efficient fruit recognition system. Thus, this research focuses on developing a fruit recognition system using a machine learning algorithm. This report mainly aims at the classification of cherry, strawberry, and tomato using convolutional neural networks. Some objectives have been set to achieve this aim. These objectives include in-depth Background exploration of this research and finding new computer vision techniques, detailed exploration of related baseline methodologies, dataset exploration and preprocessing, training and testing the model, and overcome the challenges faced in the previous studies.

# Problem investigation and Background

To deeply understand the problem, it is needed to first explore the background of problem. Related work with their limitation in stated in table below.

Table 1: Related Methodologies

|  |  |  |  |
| --- | --- | --- | --- |
| **Sr.no** | **Ref.** | **Method/Algo** | **Limitations** |
| 1. | (Vogl et al., 2014) | Formatting of field Code | Fruits recognition was based on color, texture, and shape of the fruit image. The system for more efficient for just cell phones.  . |
| 2. | (Meng and Wang, 2015) | Boundary Curvature | This research lack detection of overlapping fruits. |
| 3. | (Agushinta et al., 2017) | Augmented Reality | This study was failed to detect fruits without the internet and it was fully dependent on servers. |
| 4. | (Rachmawati et al., 2017) | “Hierarchal Multi-model Classifier” | The hybrid feature approach used in this paper is difficult to implement. |
| 5. | (Buzzelli et al., 2018) | Neural baseline Architecture | This study presents a fruit recognition fridge that is not suitable for a larger area. |
| 6. | (Othman et al., 2016) | RGB sensor and Fuzzy Logic | The research only considers one type of fruit. |
| 7. | (Moallem et al., 2017) | SVM and KNN | The only direction of apple was considered in this research. |

# EDA

For the exploratory data analysis, we look at the image of each fruits category and analyzed that there are the following issues in the images:

* Zoom in images of fruits
* Zoom out images of fruits
* Images with only fruits
* Fruits with background of other things
* Combination of fruits same time in the image

# Data pre-processing

According to the mentioned problems in the dataset, we load the dataset and tried to pre-process the data with different techniques. First of all we loaded the images of each category and labelled them as follow:

* Cherry as label 0
* Strawberry as label 1
* Tomato as label 2

After that we finalized the 27000 pixels for each image as we can get the exact photo of the fruit and can ignore the background. So in the way, we reshaped the images into 300 pixels as width and 300 pixels as height.

# Methodology

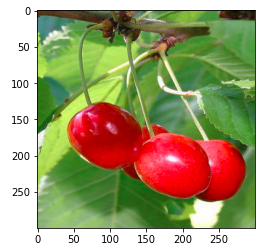
The methodology of this research is divided into different steps. These steps are as following:

* Dataset Exploration
* Dataset Preprocessing
* Simple Model
* Building CNN model
* Tuning and Training model
* Investigation of loss functions
* Applied different activation functions and optimizer

## Dataset Exploration

We used the Kaggle (Fruits 360) dataset. The dataset is divided into three classes. Each class contains a total count of 1500. This research utilizes 4500 images from the dataset. These classes are named as tomato, cherry, and strawberry. The images of the dataset include some noisy images that needed to be carefully handled.

In the First step, the images of the dataset are explored. There are a total of 3 types of fruits that are displayed. The following images show the image of cherry, strawberry, and tomato.

After that, the total count of is dataset is calculated. The following piece of code calculates the count of the dataset which is 4500.

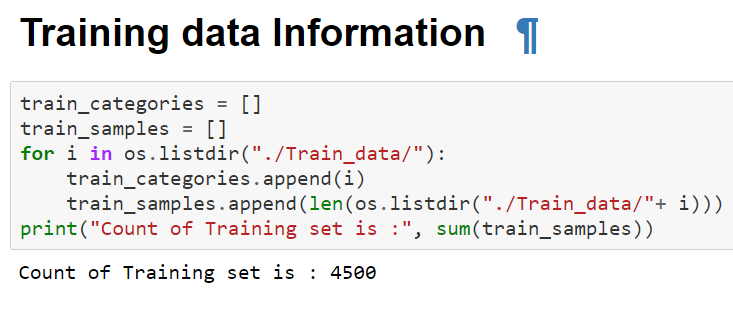


Figure 1: Training Data Information

After calculating the total count of the dataset, the frequency distribution is displayed. The dataset contains three classes. The x-axis represented classes of the dataset and the y-axis represents the number of image counts. Each class contains 1500 images.

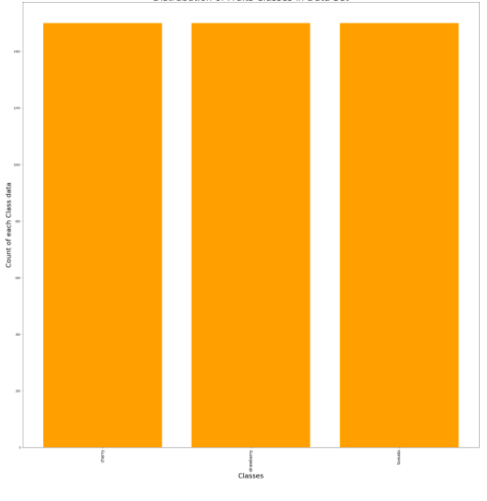


Figure 2: Distribution of Classes in Dataset

## Dataset Preprocessing

The second step of the methodology includes the preprocessing of the dataset. First of all, data is extracted from folders. There are mainly three folders i.e. “cherry”, “Strawberry", and tomato. After extraction of folders, the dataset images more than the size of 27000 are discarded. After that resizing is performed by giving each image the same dimension and size i.e. 300 x 300. Each image is saved into an array of numbers. Each class has assigned a label. 0 is assigned to cherry, 1 is assigned to strawberry, and 3 is assigned to tomato.



Figure 3: Dataset Preprocessing

## Simple Model

In this function crossEntrpyR2, forward, back, updater, and MPL are defined. Cross-Entropy Function is used as a loss function while performing optimization for the neural network. It calculates classification model performance whose output is a probability value between 0 and 1.  The forward pass function calculates the values output layer from input data. It navigates from the first to the last layer. The back pass function counts the weight change by utilizing a “gradient descent algorithm”. It moves from the last layer to the first layer. Multi-Layer Perceptron (MLP) is used to deal with multi classes

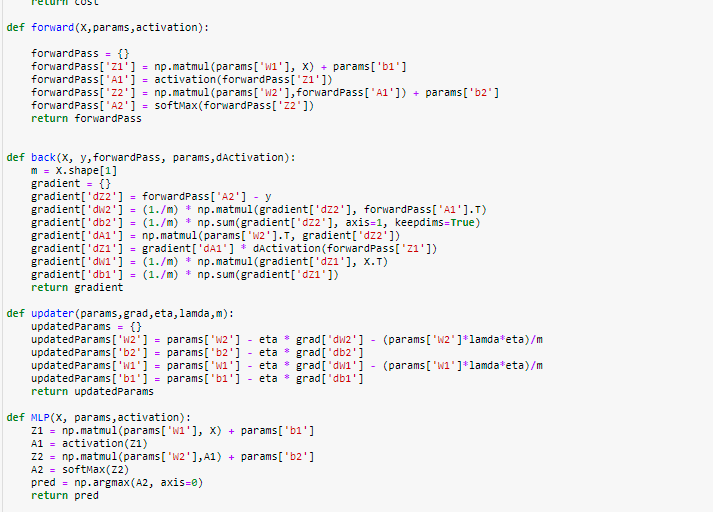


Figure 4: Simple Model

## Building CNN model

The sequential model is implemented in this study. The sequential model allows the handling of neural network sequentially. There is a total of 4 layers of CNN is used. First, ***conv2D*** is applied with 16 filters, 2 kernels size of 2, and input shape with size 300 x 300, where height is 300, and the width is 300. No padding is applied. After that, the ***Activation*** function performed the calculation of layers. ***MaxPooling2D*** reduces the dimensions in order to extract more interesting features of an image. The conv2D is applied with increasing filter from16 to 32, then from 32 to 64 and at last from 64 to 128. After that, dropout is performed on nodes, and flatten is applied to convert matrix in 1d array. At the end, dense function has applied that filter 3 predictions. 

Figure 5: Build the CNN model

## Tuning and Training model

After Building the CNN model tuning and training of the model is performed. The batch size is set to 32. All the images are grouped into 32 bathes and 1 batch is processed at a time. A total of 30 epochs is used for model training. The loss function value is set to ***Categorical\_crossentropy*** that is used for multiclass classification and an ***adam*** optimizer is used. The model complies with these parameters.

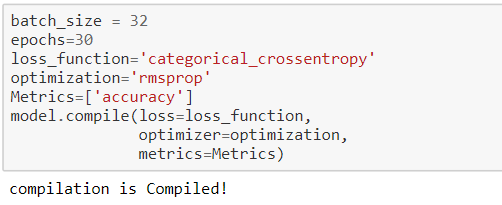


Figure 6: Tuning and Training model

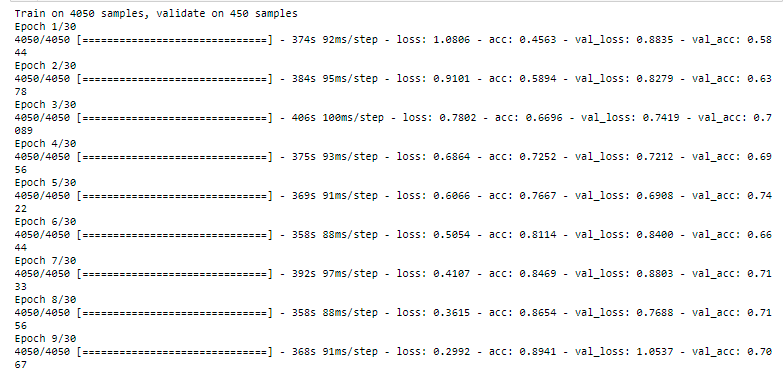
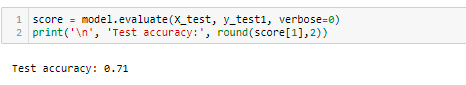


Figure 7: Model training on epochs

The model is saved as model.h5 so that it can be used in the future.

# Results & Discussion

The Trained model is tested on the testing dataset. The test result shows an accuracy rate of up to 71% which is quite low and not impressive at all.



The following confusion matrix shows the results of testing. The x-axis represents prediction labels and the y-axis represents true labels.

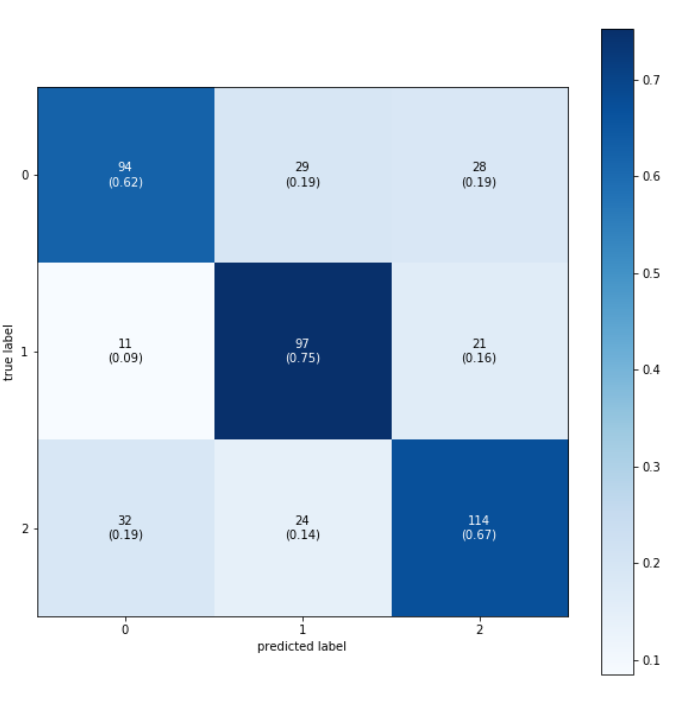


Figure 8: Confusion Matrix

The above figure shows the confusion matrix of the model. 0 represents cherry class, 1 represents strawberry class, and 3 represents tomato class. For cherry class, from 151 examples 94 are predicted correctly, 29 are predicted strawberry, and 28 are predicted as tomatoes. For strawberry class, from 129 examples 97 are predicted correctly, 11 are predicted cherry, and 21 are predicted as tomatoes. For tomatoes class, from 170 examples 114 are predicted correctly, 24 are predicted strawberry, and 32 are predicted as cherry.

The performance of the model was lowest on class cherry with a true positive rate of 0.62. The model performance was high on the tomato class with a true positive rate of 0.71. The overall accuracy of the model was quite low. We have done the experiments on the Jupyter Notebook. After completing all the experiments, we have saved these python files:

* Code.py
* Train.py
* Test.py
* Model.h5
* Traindata

# Conclusions and Future work

The interest in computer vision fruit and vegetable recognition is divertingly increasing as it is considered efficient tools of reducing human workload and still it is challenging to implement it in the agriculture industry. It can be helpful for disease detection, fruit harvesting, point of sale system, and educational system to enhance the learning of children and down-syndrome patients. A lot of researches are carried out on fruit recognition but still, there are many challenges in current methodologies that needed to be addressed to design an efficient fruit recognition system. Thus, this research focuses on developing a fruit recognition system using a machine learning algorithm. This study performs the classification of cherry, strawberry, and tomato using convolutional neural networks. The methodology includes background exploration, dataset exploration and analysis, model training, and testing. We achieved the 71% accuracy by splitting the training data further into train set and test set. We got low accuracy on MLP model with 55% accuracy but if we compare the training time, then CNN model took more time than MLP model. CNN model took almost 7 minutes on each epoch and MLP took 3 minutes which is huge difference. Training time is also important but the primary goal is to get the accuracy. The result of the fruit recognition system shows that the performance of CNN was best for class tomatoes class and lowest in the cherry class. There is a need to improve the model performance by considering more features of images. The study aims to consider more features in a study in order to improve more accuracy moreover the research can be carried out on more fruits types and can add other machine learning models to achieve higher accuracy. Transfer learning and ensemble learning can be a good option to improve the results.

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