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# A Design of Deep Learning Experimentation for Fruit Freshness Detection

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**Abstract.** Indonesia is a country with a tropical climate so that fruit and vegetable plants can grow easily in Indonesia. Fruits have many good nutrients such as vitamins, proteins and others. But the fruit also has a period where the fruit is said to be fresh fruit. During this time there are still many fruit supplier companies that send fruit unfit for consumption due to lack of accuracy in the process of sorting the fruit when the fruit is taken from the plantation and the entry of other fruit into an improper packaging. Thus, it makes detecting food spoilage from the production stage to consumption is very important. We propose a design of computer vision-based technique using deep learning with the Convolutional Neural Network (CNN) model to detect fruit freshness. The specially designed CNN model is then evaluated with public datasets of fruits fresh and rotten for classification derived from Kaggle.

**Keywords:** Fruit, Freshness, Detection, Image Classification, Deep Learning

## 1. Introduction

Indonesia is a country located between 6° 04' 30" north latitude and 11° 00' 36" south latitude and between 94° 58' 21" and 141° 01' 10" east longitude and crossed by the equator which is located at 0° latitude which makes Indonesia a country with a tropical climate according to the Central Statistics Agency [1]. Therefore, Indonesia is a country with a tropical climate that makes plants easy to grow in the territory of Indonesia. Especially fruit plants. Based on data compiled by the Central Statistics Agency [2] stated that the production of fruit plants in 2018 had increased compared to 2017. Not only local fruits that circulated in the Indonesian market, but also imported fruits from other countries.

Therefore, the fruit becomes one of the foods consumed by us everyday because the fruit has many good nutrients such as vitamins and proteins. But the fruit also has a period where the fruit is worth consuming. Fruit that is included in the category of rotten fruit is usually the content contained in the fruit will be reduced and can cause bacteria that are not good for the human body.

So far there are still many fruit supplier companies that send unsuitable fruit consumption due to lack of accuracy in carrying out the fruit sorting process carried out by their employees when the fruit is taken from the plantation and the entry of other fruit into an improper packaging.



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Based on the problems that have been described above makes detecting food spoilage from the production stage to consumption becomes very important. There is indeed an urgent need for a fast and accurate system, while conventional decay detection techniques are slow and time-consuming processes.

As a result, computer vision-based techniques and algorithmic approaches have been widely proposed in recent decades. As a fruit classification system with the use of computer vision in agriculture and plantations carried out by Kausar et al.[3] which uses the Convolutional Neural Network (CNN) to classify fruit into 81 classes. Meanwhile, research related to fruit freshness has been done by SinghandSingh [4] and also Karakaya et al.[5].

Computer vision-based techniques and algorithmic approaches are not proposed by themselves. The technique was proposed because of the success of the Machine Learning algorithm in making computers to learn independently until finally there emerged a trend of independent learning known as deep learning at this time.

Deep learning [6] is a sub-field of Machine Learning that deals with algorithms that are inspired by the structure and function of the brain. In other words, it reflects the functioning of our brain. The deep learning algorithm is similar to how the nervous system is structured where each neuron is interconnected and conveys information. So that deep learning makes it possible to study data representations with various levels of abstraction. In deep learning there are 3 types of Neural Networks, they are ANN (Artificial Neural Network), RNN (Recurrent Neural Network), and CNN. This method has dramatically improved the state-of-the-art models in speech recognition, visual object recognition, object detection, and much more. The purpose of this study is to design an appropriate experimentation plan to develop a CNN model to detect the freshness of the fruit evaluated by the public dataset Fruits fresh and rotten for classification[7].

## 2. Related Works

### 2.1. Deep Learning

Deep learning is one of the latest trends in Machine Learning and Artificial Intelligence research[8]. Many significant breakthroughs have been made in this field throughout the world. In the field of agriculture, deep learning was applied to classify the maturity of oil palm fruit[9] which is then developed to automate the palm fruit picking machine that can harvest palm fruit according to its level of maturity[10]. Other studies showed that deep learning can be used as an automatic system for plant counting [11,12].

Deep learning is also useful for various domains. For instance, in medical diagnostic imaging, it can reduce delays in diagnosis and provide a better level of accuracy than other analytical techniques[13], classify videos on knowledge management systems in an organization[14], for batik pattern recognition[15], remote sensing [16], and even for protein modeling [17]. This superior performance of deep learning is obtained from its capability to automate feature discovery, which differs from the classical image processing that needs handcrafted features [18,19]. However, this excellent performance comes at a cost of requiring a huge amount of data to train the model [20–22].

### 2.2. Convolutional Neural Network

In deep learning, Convolutional Neural Network is a class on deep neural networks that is most commonly applied to analyze visual images. It is used to perform image recognition, image classification, object detection, and face recognition. CNN consists of neurons that have weights and biases that can be learned. Each neuron can receive several inputs, by producing a point as a product and optionally following it with non-linearity. The whole network still expresses a single score function that can be distinguished from raw image pixels at one point to class scores at the other end.

In the algorithm, CNN is a deep learning model that can take pictures as input, by determining the value of weights and biases that can be learned from various aspects/objects in the image and can distinguish one from another. Pre-processing required by CNN is far more economical compared to

other classification algorithms. While in the previous method the filter was manually engineered, while CNN with sufficient training, was able to learn the filters/characteristics of an object. CNN has the advantage of computational efficiency which uses convolution operations, spatial integration, and uses parameter sharing. Thus, it allows CNN models to run on any device including mobile devices. In the history of the development of the first CNN is LeNet[23] then followed by AlexNet[24], GoogLeNet[25], VGGNet[26], Inception-V3[27], Inception-V4[28], ResNet-50[29], MobileNet[30], MnasNet[31], and many more.

### 3. Data and Methodology

#### 3.1. Datasets

The data used in this research is Fruits Fresh and Rotten for classification dataset which is derived from Kaggle and has been engineered by collecting, separating, and then labelled. This dataset includes 10,901 images of 3 types of fruit with 6 classes of fresh fruit and rotten fruit. In this study, separating the images by making labels into 6 classes as can be seen in Table 1 and Figure 1. The fruits in this dataset are not specifically Indonesian fruits, hence the model trained on this dataset is not guaranteed to perform well for Indonesian fruits. Despite the limitation, the developed model can be used as a pre-trained model for the Indonesian fruits dataset to improve the performance.

**Table 1.** Fruits Fresh and Rotten for Classification Datasets.

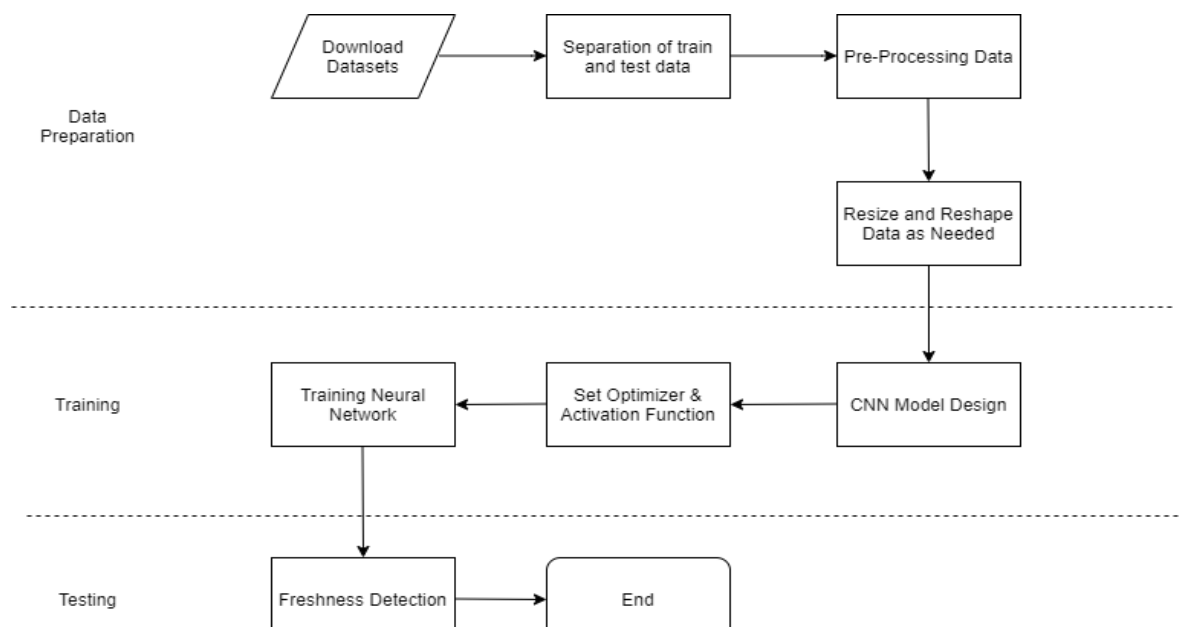
	Image	Train	Test
1	Fresh Apples	1693	395
2	Fresh Banana	1581	381
3	Fresh Oranges	1466	388
4	Rotten Apples	2342	601
5	Rotten Banana	2224	530
6	Rotten Oranges	1595	403



**Figure 1.** Examples of Fruit Classes in the Datasets Fruits Fresh and Rotten for Classification.

### 3.2. System Design Plan

The system design planned in this study can be seen in Figure 2. In preparing the data, the public dataset Fresh and rotten fruit for classification has been collected and the dataset has been divided into two parts, namely training data and testing data. The next process is pre-processing data by cropping, resizing the data as needed. The next process is training by designing a model that is planned to be used and a list of specified parameters such as the level of learning and the number of training epochs. In this process, accuracy is calculated using the loss function. The limitation for training data is limited to fresh apples, fresh oranges, fresh bananas, rotten apples, rotten oranges and rotten bananas so that the planned model can only predict these 6 classes. For the training process of CNN design, this study uses the open source Tensorflow framework, Python 3.6, and uses a PC with specifications as in Table 2.

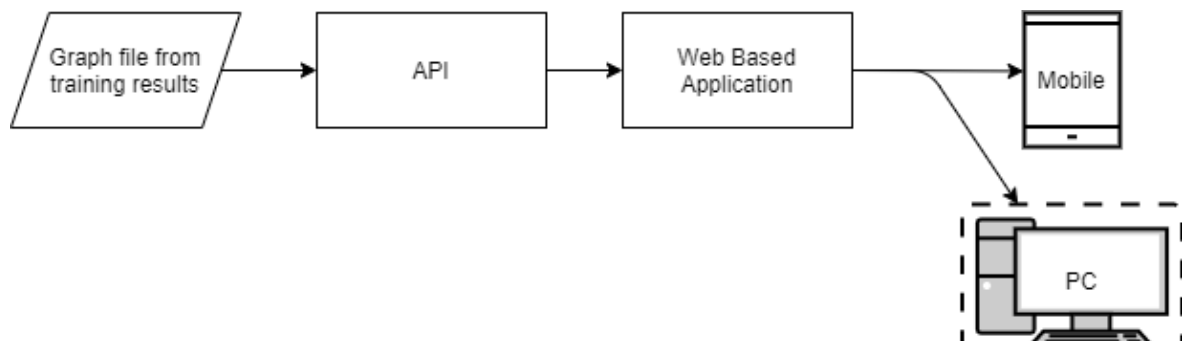


**Figure2.**Flow Chart Design.

**Table 2.**Computer Specifications for the Training Process.

Hardware & Software	Specification
Memory	32GB
CPU	Intel Core i5-9400F CPU @ 2.90 GHz x6
GPU	GeForce RTX 2080Ti 11GB
Operating System	Ubuntu 18.04 64 bits

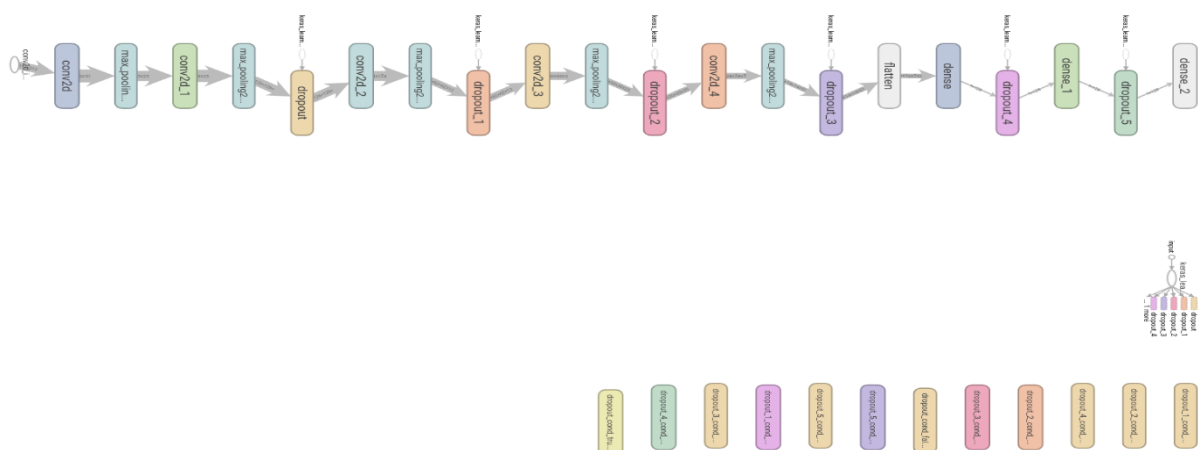
In testing, the data that has been trained with the CNN model which is designed is saved into a graph with the format (.h5) then the graph is made into an API so that the application can access the graph. The application for testing is a web-based application built with Python Flask. Web-based application was chosen because it can be accessed via mobile phone or PC with the help of a browser. To do classification is done by opening the application and inserting the image. After the image is entered, the application will respond in the form of the results of the predictions. This explanation can be seen in Figure 3.



**Figure3.Detailed Testing Stages.**

### 3.3. CNN Model Design

The design model of the planned CNN can be seen in Figure 4. Figure 4 illustrates the design of the planned CNN model. The designed model has a batch size of 32, MaxPooling2D with a pool size (2,2), Six Dropouts of 0.25, Conv2D of 32, 64, 128, 256 and 512. The model uses Rectified Linear Units (ReLU) as Activation Function and Adam as Optimizer. For a summary of this model can be seen in Figure 5.



**Figure4.CNN Model Design.**

#### 4. Conclusion

With the vital role of fruits in Indonesia and the significant breakthroughs made by Deep Learning, it is beneficial to develop a deep learning model for fruit freshness detection. Therefore, we designed an experimentation plan to develop a deep learning model for fruit freshness detection. Once the experimentation is completed, the performance evaluation of the developed deep learning model is to be followed.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 510, 510, 32)	896
max_pooling2d (MaxPooling2D)	(None, 255, 255, 32)	0
conv2d_1 (Conv2D)	(None, 253, 253, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 126, 126, 64)	0
dropout (Dropout)	(None, 126, 126, 64)	0
conv2d_2 (Conv2D)	(None, 124, 124, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 62, 62, 128)	0
dropout_1 (Dropout)	(None, 62, 62, 128)	0
conv2d_3 (Conv2D)	(None, 60, 60, 256)	295168
max_pooling2d_3 (MaxPooling2D)	(None, 30, 30, 256)	0
dropout_2 (Dropout)	(None, 30, 30, 256)	0
conv2d_4 (Conv2D)	(None, 28, 28, 512)	1180160
max_pooling2d_4 (MaxPooling2D)	(None, 14, 14, 512)	0
dropout_3 (Dropout)	(None, 14, 14, 512)	0
flatten (Flatten)	(None, 100352)	0
dense (Dense)	(None, 128)	12845184
dropout_4 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 128)	16512
dropout_5 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 6)	774

Total params: 14,431,046  
 Trainable params: 14,431,046  
 Non-trainable params: 0

**Figure5.**Summary CNN Model Design.

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