International Journal of Advanced Science and Technology
Vol. 29, No. 12s, (2020), pp. 2766-2772

Development of an effective system to Identify Fruit ripening Stage for Apple, Banana and Mango

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Abstract

Ripeness is one of the main indicator of fruit quality, Subsequently the assurance of fruit ripeness stages could be a essential mechanical as well as agrarian concern in arrange to urge tall quality item. Ripeness assessment of natural product is an basic inquire about subject because it may prove benefits in guaranteeing ideal abdicate of tall quality item, this will increment the salary since natural product is one of the foremost imperative crops around the world.. Detecting Fruit ripening stage plays an essential role in many of the food processing industries like fruit juice companies, fruit jam companies, natural fruit flavors producing companies, etc. Also, knowing the fruit ripening stage would help farmers to harvest fruits at an appropriate time to improve productivity and help prevent crop failure. A number of techniques are available for detecting fruit ripening stage like Internet of Things(IoT), spectrometry, chromatography, Image processing, Machine Learning but, most of them turn out to be time consuming and hence are not effective. Also, some techniques require destructive detection approach which makes the fruit unfit for consumption. Using machine learning fruit ripening stage can be detected with minimal human effort and minimal time consumption also, the approach is non-destructive as only fruit images are used in this approach. This paper presents a non-destructive approach using Convolutional Neural Network(CNN) classifier to identify fruit ripening stage.

Keywords— Ripeness, CNN, Machine Learning, RoI, Faster R-CNN, Classification

1. Introduction

Fruit Ripening

The process of fruit ripening is intimately associated with the level of ethylene content in the fruit. As the fruit ripens the level of ethylene content gradually increases inside the fruit. The increased level of ethylene affects the fruit in a way that induces a change in colour, smell and taste of the fruit. These changes in physical and chemical properties of the fruit can be used to identify whether the fruit is ripened or not. The physical changes may be change in color, change in size, change in texture, change in shape etc. Identifying ripening stage using changes in chemical properties requires use of destructive methods of measurement but give more accurate results whereas, using changes in physical properties can be measured using non-destructive methods. But the drawback using changes in physical properties is that it gives less accurate measurement compared to that of changes in chemical properties. But the advantage is that measuring changes in physical properties is easy and time efficient as compared to chemical properties.

Machine Learning

One of the branch of Artificial Intelligence is Machine learning (ML). Machine Learning tries to give machines the capability to think on its own for a particular type of problems for which is trained for. A trained machine tries to emulate a real human to solve a particular problem. Broadly, there are two types of machine learning models, those are:- 1)Supervised Learning, 2)Unsupervised Learning. Machine learning is a promising field that helps to solve problems without human intervention that would otherwise take years to solve. Machine learning has several types of algorithms like Regression, Classification, Association, Clustering, etc which can be used depending the field of application.

Image Processing

Image processing is a field in which we manipulate and analyze an image with the intent of performing an operation and extracting useful information from the image. In Image Processing we manipulate image using various tools and techniques which gives meaningful information which can be further used for other applications like detecting a car in a video.

Convolutional Neural Network(CNN)

Deep learning has a branch named as Convolutional Neural Network which is now most prominently used in applications related to images. It consists of multiple layers each of which has it's own specific function. Different architectures with different number of hidden layers can be designed to serve the required purpose. CNN consist of multiple layers.

2. MOTIVATION

Fruits are an essential part of human diet as they are rich in several vitamins and proteins, but for a fruit to be fit for consumption it should have appropriate ripeness percentage. If fruit is raw it's taste isn't good and lacks certain vitamins and if fruit is over-ripened it might give foul smell and become unfit for consumption. Also, harvesting fruits at an inappropriate time may lead to heavy losses for farmers. In current scenario fruits need to be manually checked by farmers to identify ripened fruits and harvest them. But, this process is very time consuming and requires a lot of energy to survey all the fruit plantation. Hence, the idea is to develop a system to identify fruit ripening stage to help the farmers as well as industries identify whether the fruits have reached the required ripeness level or not and are ready for further process or not.

3. LITERATURE SURVEY

Method for classification of mango and pitaya fruit proposed for identifying and classifying fruits.

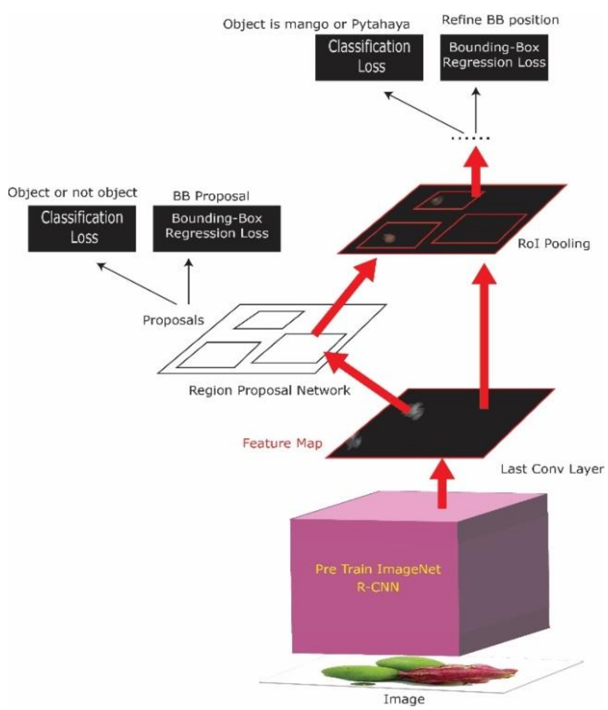

Fig 1: The architecture of the faster RCNN method [1].

A. Process stage to detect object on faster CNN

Figure 1 [1]. Shows the working of faster RCNN method . Input layer will be shared with the

Conv layer.conv layer will calculate the feature maps region of interest is use to fix length for each sub sequent feature.conv layer is the process of maping each slideing window it should be done to produce lower dinmation feature.

B. RoI(Region of Interest) Pooling Layer

Max pooling is utilized to change over the highlights that will be preparing within the range we need to have small feature determination scope. To urge the RoI application instruments named labelimg is utilized and checking the locale to be select and labeling the picture one by one to supply data related pictures. The frame of labeling can be seen within the picture;

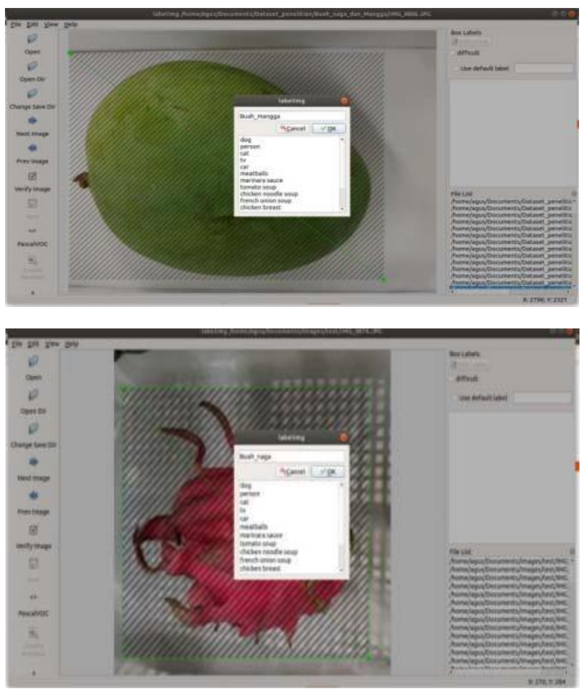

Fig 2: Label Image tool [1].

For the problem we have a expression which is as follow.

$$\sigma_i(z) = \frac{\exp(zi)}{\sum_j^m \exp(zj)}, \ i = 1,\ldots,m, \qquad (1)$$

Where:
= Output Fully Connected layer.
z_i= corresponds i-th
i = i-th
m = number of classes

A two-class softmax is utilized for offer assistance in natural products location employing a double classification issue. In any case in this extend, a sigmoid function is appended to induce distant and stronger result. The sigmoid can unravel the issue classification double and likelihood. The equation for calculating the likelihood of a parallel esteem takes after [1]:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

4. Proposed Methodology

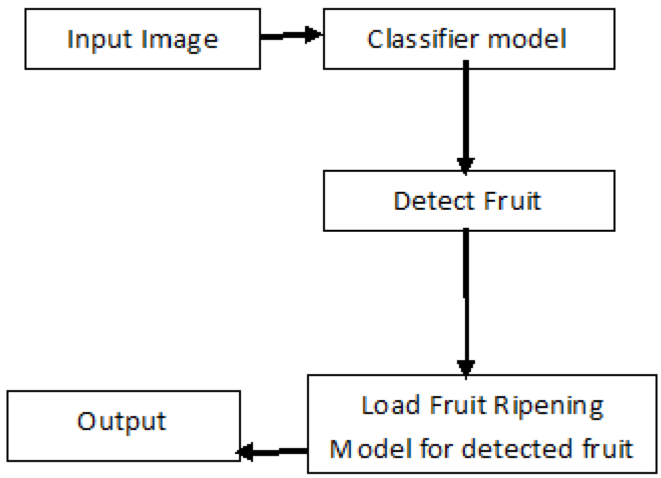

Fig 3: Flow of Proposed Methodology

The proposed method makes use of Convolutional Neural Networks(CNN) to classify fruits. The VGG16 architecture is used to train the model for fruit classification and fruit ripening detection. The VGG16 is a CNN architecture which consists of convolution layers having filters of 3x3 size and stride of 1and. Number 16 in VGG specifies the number of layers in the architecture.

First of all model is trained for fruit classification and for each fruit, fruit ripening detection model is trained to tell whether fruit is raw or ripened. The input image of fruit to be identified as raw or ripened is fed to the application. After the image is fed to the application it tries to classify the fruit according to the trained model. After the fruit in the image is identified the appropriate model for the fruit identified in the image is loaded and the image is then fed to that model. The model then tries to classify the fruit as raw or ripened. The steps performed in the application are as follows:-

1. Train the classifier model for the required fruits.
2. Train the fruit ripening model for all the respective fruits.
3. Load the appropriate model depending on the fruit identified by the classifier at the first stage.
4. Use the model to classify the fruit in the image as ripe or raw.

5. EXPERIMENTAL RESULTS

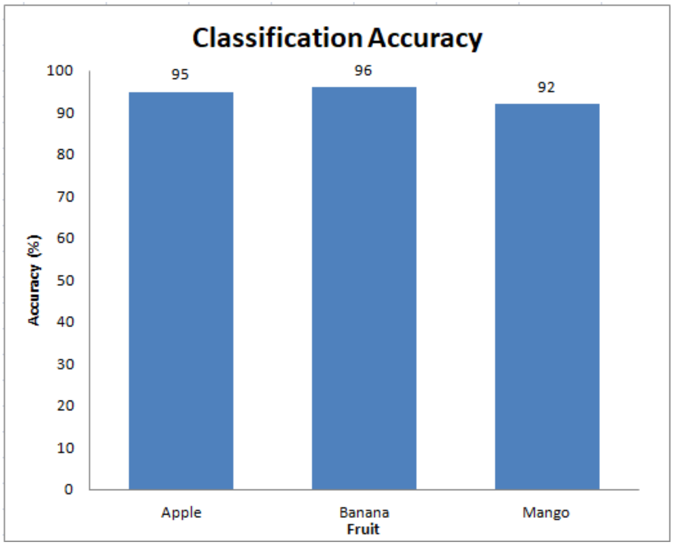

Fig 4: Fruit classification Accuracy

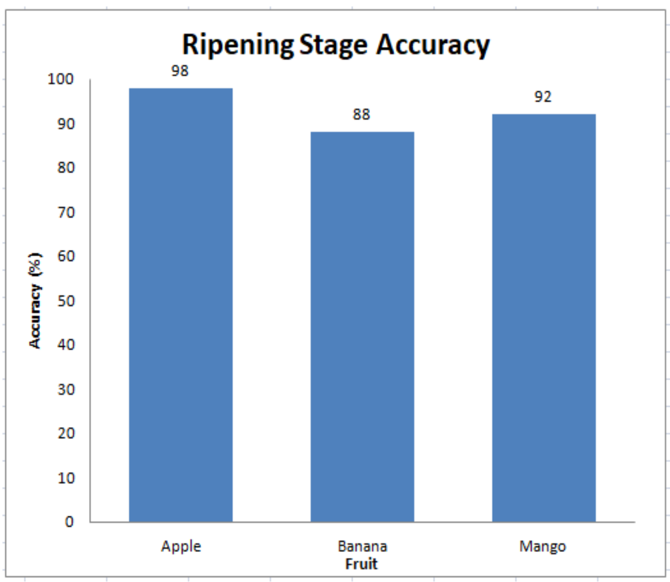

Fig 5: Fruit Ripening Accuracy

The fruit classification model was trained on the fruit 360 dataset from kaggle. VGG16 architecture was used for training the model for fruit classification. The model was trained for three fruits Apple, Banana and Mango and the obtained results are shown above. The model was trained on system with 8GB RAM and Intel i5 8^{th} generation processor and the software used for training the model was spyder IDE.

The training of the CNN is a resource consuming process hence requiring high performance GPU's. When trained on CPU it is very time consuming. Hence the lack of high performance GPU was a problem faced during the implementation of the project.

6. CONCLUSION

Through above discussion it was identified that over-ripened or under-ripened fruits are unfit for human consumption. The proposed system was used to classify and then identify fruit ripening stage using CNN. Three fruits i.e. Mango, Apple and Banana were classified and their corresponding ripening stage was identified. The advantage of this system is that it was generalized for three fruits, but it also poses the disadvantage that other fruits which show no physical changes on ripening cannot be used in this system. Also, the system poses disadvantage that it can be used only for 3 fruits.

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