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Identifying Mango and Its Ripeness Using Image Processing and Machine Learning Approach

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Abstract
Fruit market is a subject of choice, thereby, a dealer needs to grade the fruit. Fruit grading commercially available systems are very expensive, and manual fruit grading systems used in small businesses and dealers are prone to human error and inaccuracy. This paper proposes a system for identifying and grading Mango which will bebeneficial if we consider Industry 4.0. A Faster Region-based Convolutional Neural Network (Faster R-CNN) object detection algorithm using Tensor Flow has been implemented for identifying the fruit and by Image processing the probable percentage of ripeness can be determined. Thereby categorizing the fruit into classes. The results show that the proposed methods are efficient and cost-effective for determining and detecting the ripeness of fruits. The same system, when trained effectively can be used for multiple fruits.
Keywords: Ripeness, Machine Learning, Image Processing

Introduction
Agriculture is a key player in any national economic stability. Agriculture employs the two-third population in India. Compared to the development that is occurring in the technology sector this is way faster than in agriculture. Also, numerous applications have been created under Industry 4.0 development.Hence, it is important to move up the impact of technology in agricultural development. Fruits market is a subject of choice. Thus, a dealer needs to grade the fruit. There are commercially available systems available in the market, which are very expensive. Right now, human experts manually grade the fruit based on their expertise but are prone to human error and inaccuracy. It is a human tendency to get tired of any redundant task, thus it concludes into human errors. Thus, introducing this very system will ensure efficient results, making it time effective and provide a support to growing economy. The demand in the fruit market is all dependent upon the demand/supply chain. In figure 1, it can be seen that the demand for a consumer increases as the fruit quality of the desired product increases. Hence, itdirectly reflects on the fruit inspect as it can assure the quality.

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Fruit inspection can be done depending on couple of factors viz. Its ripeness, shape, and size. The main factor we concentrate on is its ripeness, as the majority of the market relies on fruit ripeness, which eventually results in the sweetening of the fruit. Fruit ripening is a result of chemical changes or physical changes.The fruit colorisused to determine the ripening stage, as itis main factor thatconsumersrely on, whenchoosing a fruit. Mango in Indiaisconsidered the king of all fruits due to its taste. Thus, itishighlynecessary to create a system thatwillidentify and determine the better-quality fruit which has sustained no damage. Machine Learning isadvantageouslyutilized for the identification of trends and patterns, continuousimprovement, and canbeused to handlea large amount of data. Researchers developed machine learning for farmers as stated by fadillah et al. [1]. There are some drawbacks to the current system such as inefficiency, more cost, and sluggish performance. Color, shape, and fruit size are the main factors on which the human experts distinguish good quality fruits frombad fruits. But, humans tend to gettired of a redundant job whichresults in inefficiency, inaccuracy of the job. This creates the need of creating a superfast and efficient system. Then, the job willbe efficient and error-free. Multiple Machine Learning algorithmscanbeusedresolvetheseproblems as stated by Ranjit et. al [2] and Jang et. al. [3].

Literature Survey

The maturity of Mango isdefined by how it changes itscolorfrom green to yellow (In some cases, red). In a case study for ripeness of a tomato, Jaramillo et al. [4] describedmaturityin 6 stages, as shown in the below table.

Table 1 Stage, maturity, Range Comparision

Stage	Color/Maturity	Range
1	Green	>90%
2	Breaking	90% Green color; <10% otherthan Green
3	Turning	10%-30% Yellow
4	Pink	30% - 60% Yellow or Redcolor
5	Light Red	60% - 90%
6	Red	90% - 100%

Detection methods using artificial intelligence are widely practiced, this can be seen in the segmentation depending on the edge as states by Jana et al. [5]. The techniques used are image pooling, pre-processing, segmenting images, feature extraction, and detection using Support Vector Machine(SVM). Nandi et al.[6] conducted the same technique. It onlydiffered in capturing video using a Charge Coupled Device on the convey or with a Mango on it. Susnjak

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et al. [7] studied a setup enhancing the colors. In thispeculiarstudy, measuring the qualitywith the help of color segmentation abiding by the region of interes and pixel blob is animportant measure to check for a defective fruit. One more paperwaswritten on the study of tomato by Fojlaleyet al. [8]. He does the feature extraction dependingon R and G color, the shape of the fruit, and classifying the mangoesbased on the first, second, and the third moment.

Rismayatiet al. [9] studieddeeplearningusing CNN for salak fruitssorting. They are usingregion of interest of salak image and CNN classification method. They use 6filterlayerswith3x5x5 in 1stlayer, the 2nd layer makes 18 filtersof the size of 6x3x3. The detectionaccuracyattainedis81.45%. They chose thismethodbecause of itshigheraccuracy. Renet al. [10] provide a promisingresult on variousobjectdetectionmeasurements.

The aboveresearchinspired us to search the new frameworks of Tensorflow and MobileNet whichwaseventuallyused to implement the Faster R-CNN. In the said case, the convolutionalmodule isused to prepareproposalscalled the RegionProposal Networks and sigmoidfunctions to improve the speed of the system. Thisparadigm, betteraccuracy and efficiencyisexpectedwithimproved performance whichwillbe the key part of thisexperiment.

Proposed Method

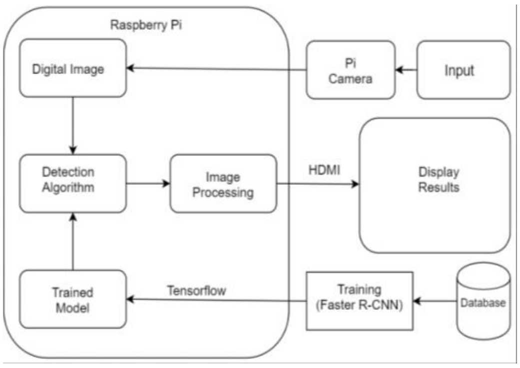

Fig. 2 Proposed Block Diagram

In our case study, we have present a system that inputs an image via a pi camera attached to the Raspberry pi, and then it runs through the model that was trained for fruit identification by a faster R-CNN algorithm. Then this detected image is processed to determine the ripeness and display the results on a display.

Tensorflow’s faster R-CNN algorithm uses deep learning as its prime objective that can be used to identify the traits of the fruit, which will eventually distinguish the fruit from all the other objects, thus categorizing the fruit we are going to detect. The listed technique is perfect for real-time identification of the fruit, which is Mango in our case. The developed software will be used to detect the fruit and its ripeness. Here, we will grade the fruit into three categories viz.

Class 1: High Ripeness
Class 2: Medium Ripeness

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Class 3: Low Ripeness

Raspberry Pi version 3 B+ model is used for the project. It has inbuilt 512MB SDRAM. Raspbian operating system is burnt in the SD card which works efficiently with the Raspberry and is a variant of Linux. Any HDMI monitor or TV can be interfaces as a display. The Raspberry Pi 3 B+ is shown in figure 3 [11].

Fig. 3 Raspberry Pi [11]

A highly-ripened Mango is used as an example to describe the working of the application. Thus, the algorithm can detect the Mango and its ripened state.

This system detects Mango and determines its ripeness category. Then we create and exchange the softmax classifier. Data is all the images that were collected either by capturing manually or downloading through Google. The data contains a total of 458 images including the 346 train images and remaining 112 to test. The steps that we follow are explained below.

A. Faster R-CNN Object Detection:

Figure 4 is the working model of the Faster R-CNN model. The feature maps are calculated with the convolution layer with the data that was shared via. the input layer.

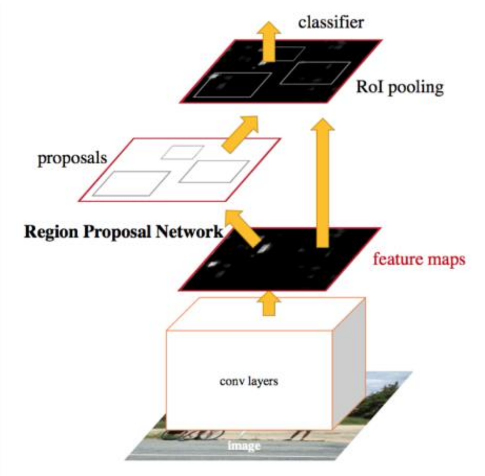

Fig. 4 Architecture of proposedFaster R-CNN model

The convolutionisachieved in the convolution layer as statedby [12]. RPNchecks for the images for predicting the group of object and object-ness by featuremaps. A certain part of

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eachwillbeevaluated by RoIduringeachproposal by the featuremap. Thisfeaturevectorispenetratedinsidea fullyconnectedlayerwhichthen has 2 output layers. The proposed system will check if the fruit ispresent or not. Finally, the four real figures willbeproduced by the regressor for constructing the location of the proposal.

B.Region of InterestPooling :(ROI) Pooling

The image poolingisusedto convert thetrainedfeatures, for thatwewill have featureselection. ToachieveRegion of Interest, they have been labeled all the images one by one by the application called**LabelImg**. The application in action isshown in figure 5.

Fig.5 Labeling Image

The xml file for each and the respective images are saved in the rootfolder, storing the height and width of each label. The csv file has fixedlengthdisplacement information for H by W eachHeight and Width are layeredvariables of all the images respectively. To process the data in a faster and efficient format, we have converted all the data in .csv format, as shown in figure 6:

filename	width	height	class	xmin	ymin	xmax	ymax
Mango1.jpg	275	183	Mango	15	15	140	134
Mango2.jpg	275	183	Mango	127	42	266	154
Mango3.jpg	216	233	Mango	51	66	158	173
Mango4.jpg	59	50	Mango	1	1	58	50
Mango5.jpg	75	50	Mango	12	8	50	27

Fig. 6Labeled image csv format

C.Binary Classification

Faster R-CNN ismainlydividedintotwocategories,fullyconvolutional network module and the detector module. Detector module usedis Softmax. Softmax estimatorprobability for object class is:

$$\boldsymbol{\sigma_i(m) = \frac{\exp(m_i)}{\sum_j^z \exp(m_j)}, i = 1, \dots, z}$$

$$\boldsymbol{Where}:$$
$$\boldsymbol{m = input\ vector}$$
$$\boldsymbol{m_i = elements\ of\ the\ input\ vector}$$
$$\boldsymbol{j = \ normalization\ term}$$
$$\boldsymbol{z = number\ of\ classes}$$

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We are using a two-class Softmax binary classification for fruit detection. Wealsoapplysigmoid function thuscreating an efficient model. The sigmoidfunction helps inclassifyingbinary and probability. Thus, the formula is as below:

$$\boldsymbol{\sigma_i(m) = \frac{1}{1+e^{-m}}}$$

We are usinga multi-taskloss to drive the training process, the multi-tasklossis

$$\boldsymbol{ML = ML_{cls} + ML_{reg}}$$

Where, $\boldsymbol{ML_{cls}}$is a classification lossislogged over 2 losses and$\boldsymbol{ML_{reg}}$is a Regressionloss over the regressor targetisdevised, it traverses over each pixel predictingits location. For $\boldsymbol{ML_{cls}}$, we have usedsigmoidentropyratherthanthat of softmax or multinomial entropy, Thereafter, we use a sigmoid function to detect if the objectcontains fruit or not. When the training data is not sufficientwethink, thisis the best methodthatwecanapply for the classification of fruits.

D.Implementation

Wehavetrained and tested the approach on an Intel's i7 processor, and NVIDIA'sQuadro P1000 GPU and itscuDNNusing32GB RAM. The model used for training is ssd_mobilenet_v1_coco. The images are chosenarbitrarily and processed in batches. The image isconvertedinto an 800x1200 pixel image by the training model, and thenweexecutedafaster R-CNN algorithm. Eachstep of training reports the loss. It willstartathigh classification loss and willgetlower as the training progresses. It startedat about 2 and drops below 0.1. Weran the model to train until the lossconsistently drops below 0.05, whichtook about 70,000 steps, round about 24 hours. As shown in below figure 7.

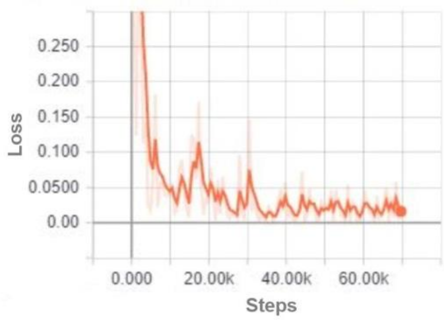

Fig. 7 Classification loss

Testing

Our model isready for Mango detection and weran the objectdetection code using python.

A. Input

Usingfaster R-CNN we have created an identification model on Mango data-set. Around 500 images provided as input to the model. The demonstrationisbased on a sample fruit image.

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Modelingiscreated on the MobileNet using python, Howard et al. [13] with TensorFlow library, Goldsborough et al. [14].

B. Training

Images provided in the train and test folder are used as the input to the model we chose in the prior section. Withlabeled images in thesefolders, westart training the model whichwilleventuallytakesomeamount of time to provide an inference graph. Whichwillbeeventuallyused by the python code to detect the RoI image.

C. Result

Total of 80% of images are trained and 20% are then tested. Thereby, the training process resultsin 99% accuracy, thisis a very idleresult, this is going to differ for other input images because of the arbitrary training process. If the labeling process isdone right and accuratelywecanobtainhighaccuracy as specified in, He et al. [15].

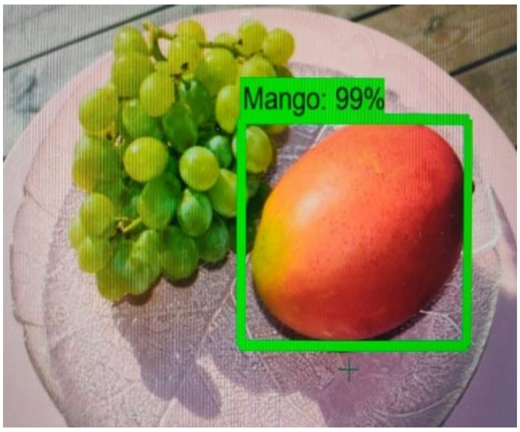

Fig. 8 Training result

Ripeness Determination :

After completing the detection process, the next step is ripeness determination using image processing.

The ripeness determination process is done by mainly following three stages namely, preprocessing, feature extraction, and classification, as shown below in figure 9.

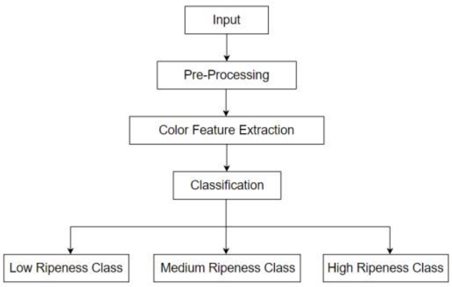

Fig. 9 Flowchart for ripeness detection

Algorithm is as follows:

1. Start
2. Input image from the last sections output.

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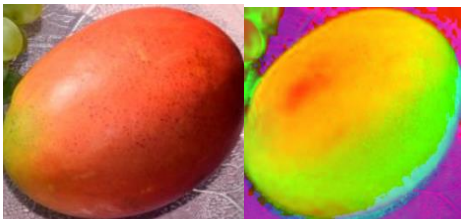
3. Transforming image into HSV image.
4. Thresholding hue for R, G and B color.
5. Defining saturation values as 0 and 255.
6. Getting blobs.
7. Create redness, yellowness and greenness mask.
8. Calculate which color is maximum.
9. Compute and show ripeness
10. End

Result Analysis

Now we proceed with the implementation of ripeness detection of the fruit. This analysis is done on the input image that was inputted by our last section's output. The below images show the RGB image and its corresponding HSV, which is used to create masks.



(a) (b)

Fig. 10 (a) RGB and (b) HSV Image

Once the HSV Image is obtained from the original image, it is thenused to create the redness mask, yellowness mask, and greenness mask for determining the maturity of Mango by counting the number of pixels of respective color. This has been done by giving the minimum and maximum values of their respective thresholds (RYG). The purpose of these masks, is to change a specific color to a different color. In our paradigm, the rednessmask image, as shown below in fig 11(a), changed the area containing the redcolor to white. Depending on the threshold, the non-red pixels willbeconverted to black. Thus, counting the white pixels for red-ness mask will give the exact number of red pixels present in the image. More number of pixels indicate the category of the maturity of Mango. Below images show how the HSV image will look whenitisfiltered through the green, red and yellow masks.

(a) **(b)**

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(c)

Fig. 11 (a) Red-ness, (b) Yellow-ness, (c) Green-ness Mask

The purpose of HSV conversion and masking is to determine the ripeness of Mango. This can be done by counting the number of pixels of the respective color.

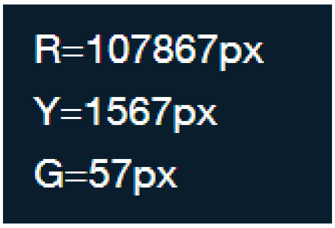

Fig. 12 Pixel count

In figure 12 it shows that the red color is prominent than others. The Mango fruit depending on their category, can be categorized as highly-ripened, when, either a Red color or Yellow color is prominent. Thus, in the application it shows that it belongs to Class 1.

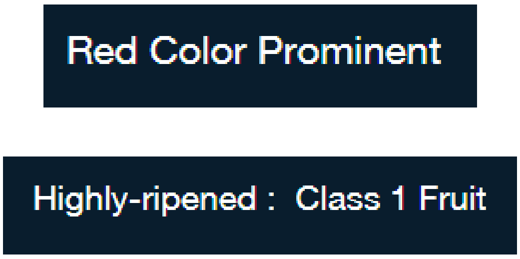

Fig.13 Result

Conclusion :

This case study is a demonstration of detection and determination of fruit and its associated ripeness using machine learning and image processing technique and will have high impact on Industry 4.0. We used Google's model architecture to classify the fruit, using Mobile Net convolutional network. This experiment takes advantage of the novel technique of determining the quality of fruit by analyzing its ripeness. This case study classifies the fruit into 3 classes on basis of color, thus verifying the good quality of fruit is distinguished from the bad one. Very well prediction of the class in which the quality of fruit falls is done with the help of image processing for e.g Class 1 fruit was taken in the experiment. There is a clear indication

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that faster R-CNN is better to build a faster, efficient model. We derived that with a large number of dataset and with good quality of images the model can be trained further efficiently. The same system, when trained effectively can be used for multiple fruits.

Future scope

In future, we would like to try our proposed system on various types of regional and imported fruits

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