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Fruit Ripeness Assertion Using Deep Learning

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Abstract

The agricultural industry is one of the most important sectors in any country because it contributes to so many different areas. In comparison to other emerging countries, however, farmers and agriculture fields in some countries have limited technology and reach. Agricultural and allied sector operations employ 54.6 percent of the total workforce and contribute for 17.1 percent of the country's Gross Value Added (GVA) in 2017-18, according to India Census 2011. However, Agriculture's contribution to GVA continues decline.[7] This agricultural field is obviously a challenging field to the digital technology and this "smart fruit ripening assertion" model considerably gives the high-quality and accurate results by utilizing the deep learning techniques such as YoloV3 which is a deep Convolutional Neural Network (CNN). This model's main focus is on the design and implementation of practical tasks, such as predicting the ripening stages of various types of fruits based on form, colour, and texture by combining and comparing various ML methods, OpenCV, and Internet of Things (IoT), thereby providing accurate prediction of ripening stages of fruits with the aid of a computer application which results introduction of large-scale manpower and saves time.

Keywords: *Deep Learning, YoloV3, Convolutional Neural Network, OpenCV, IoT*

1. Introduction

Agriculture assumes a basic job in the worldwide economy. Owing to the increase in human populace, weight on the horticultural framework is gaining with each passing day. The information produced in current ,a wide range of sensors are used in farming activities to enable a better understanding of the operational condition (a communication of dynamic yield, soil, and climate conditions) as well as the activity itself (hardware information), resulting in increasingly precise and faster dynamic In most circumstances, a farmer's choice of crop is influenced by his intuition as well as other minor considerations such as generating quick money, being unaware of market demand, overestimating a soil's ability to sustain a given crop, and so on.[10] Machine Learning has developed alongside tremendous knowledge advances with the advent of science and technology, offering new opportunities to unwind, analyze, and comprehend information escalated types in rural operating conditions. ML is defined as the logical field that allows machines to learn without being carefully customized, according to various definitions.

Order of different sorts of products of soil vegetables and their current ripened state is not a straightforward assignment because of a few similarity parameters such as size, and shading. Regularly, natural products, vegetables, and harvests, prior to being collected and discharged to the market, are inspected by a master or prepared workforce. A few elements considered by these individuals in the quality evaluation are the shading and surface of the items. Be that as it may, manual checking and grouping offer ascent to a few potential human blunders. For a gathering to be fruitful, anyone preparing to inspect the objects must have accurate recognition and investigation, which may be difficult or monotonous as it becomes repetitive. In this project we aim to develop a software which can be used to identify if a fruit is unripe, ripe or spoilt. The proposed software can be used in real time by the end user since it can detect the ripeness state of a fruit in real time video or pre-recorded footage. We use a large number of images as data sets labeled ripe and unripe to train the model to recognize & classify the fruit and its condition based on its colour, shape and texture.

Literature Review

In this segment we performed rigorous literature survey on the existing ways to identify fruits and classify them, carried out during the last one decade. However, we listed here very few for discussion. In 2017,"Deep Fruit Detection in Orchards"[1]was published by Suchet Bargotiand James Underwood. This paper aims to present the use of a state-of-the-art object detection framework, Faster R-CNN, for detecting fruits in orchards, including mangoes, almonds and apples. A tiling approach was introduced for the Faster R-CNN frame work in order to processor char data containing 50-500 fruits per an image. With an F1-score of greater than 0.9 achieved for apples and mangoes, the study fared better then its precursors in terms of performance. Conversely, in the study put forward by Selman UluiŞik, et. al[7], high-resolution digital cameras had been used to capture five different photographs of a tomato and the volume of the fruit is measured by determining the horizontal and vertical distance between the captured images. In this paper, we specialize in an equivalent original Faster R-CNN network, which is within an family of deep learning based detectors, because of its easy-to-use open-source implementation.

In 2019,"An Optimized method for Segmentation and classification of Apple diseases based on strong Correlation and Genetic algorithm based feature selection" [2] was published by Muhammad attique khan. Three pipeline techniques is observed pre-processing, spot segmentation and features extraction. The proposed method is being evaluated on four different apple disease types, as well as safe leaves, including Blackrot, Rust, and Scab. For the results, ninety pictures of diseased leaves were chosen from a cluster of disease types: powdery mould, mosaic, and rust, with a ninety percent category rate. The foremost gain of SVR set of rules is to decrease the error charge and increase the class accuracy. The extracted capabilities are reduced through PCA and fed to SVM for category, which resulted into an accuracy of 99%.A genetic algorithm is implemented to pick out the first-class capabilities which can be later used by M-SVM for category.

In 2020,"Using YOLO version3 algorithm pre- and post- processing for apple detection"[3] was published by Anna kuznetsova,Tatiana maleva and vladimir soloviev. The proposed pre-and post-handling procedures made it possible to adapt the YOLOv3 calculation for use in an apple-reaping robot machine vision system, resulting in an average apple position time of 19 ms, with a percentage of things mistaken with apples of 7.8% and a percentage of ignored apples of 9.2%. Other modern measurements are compared to the pre- and post-handling schemes (YOLOv3-Dense, DaSNet-v2, Faster-RCNN, LedNet). Since shading recognition is highly dependent on lighting conditions, shading spaces other than RGB are frequently used, including HIS, CIE L*a*b, LCD, and their combinations. This approach showed a 90% portion of accurately perceived apples, this methodology showed a 95% portion of effectively perceived apples. Applying KNN classifier to shading and surface information permitted discovering 85% of green apples in crude pictures and 95% close by prepared pictures. To interpret green citrus natural goods, a faster R-CNN was used; 95.5 percent exactness and 90.4 percent review were achieved. Since YOLOv3 was not trained on tomatoes, it will need to be retrained on these vegetables in order to recognise them effectively.

In 2020,"Ripe fruit detection and classification using ML"[4]was distributed by Aaron m.Africa, et al. Modern advancements reveal that the present ethylene in organic fruits can be used to assert their fruition. Employing methods such as DL, Regional- CNN along with the assistance of a chromatic configuration in distinguishing ethylene gas, an accuracy of around 95% was achieved with the only limitation being that the dataset used for testing were pre-recorded and not real-time. On the contrary, H. Kinja, et al. had put forward a study wherein an odor sensor can be used to obtain smell data consisting of a dead time and a step response of a lag element of the first order. They focused on the first order lag element which gives out a curve in its graphical form that rises exponentially to a constant value.[8]

Comparison and Existing Work

We compared the efficiency of several techniques of dealing with fruit maturity in the past. The amount of categories in the database, the extracted features, the colour space used, the classifiers employed, and the accuracy achieved were all compared. The below table we have shown the different existing methods and how they differ in terms of accuracy, methods used and the features that can be shown using the proposed method.

Table 1: Existing Work And Their Comparison

Reference	Features	Color training space	Evaluation criteria
Dubey and Jalal	ISADH	HSV	Accuracy
Faria et al.	Color, texture and shape	HSV	Accuracy
Rocha et al.	GCH+CCV +BIC+Unser (Fusion)	HSV	Average error
Chowdhury et al.	Color histogram +Texture	HSV	Accuracy
Danti et al.	Mean and range of Hue and saturation	HSV	Accuracy
Suresha et al.	Texture features	RGB	Accuracy

Proposed work and Modules Identified

A. Theoretical Consideration

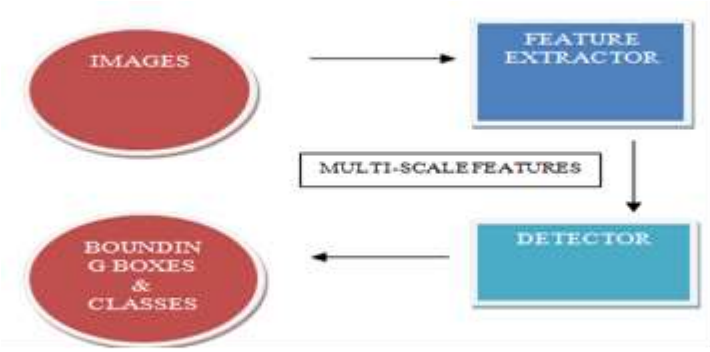
The presence of a natural product is one of the most important characteristics that demonstrates its preparation and quality. Natural products' colour and texture shift as they age. Even with qualified staff, however, discrepancies and human error might occur while analyzing and testing these variables. AI's use in detecting and arranging objects is currently being investigated.

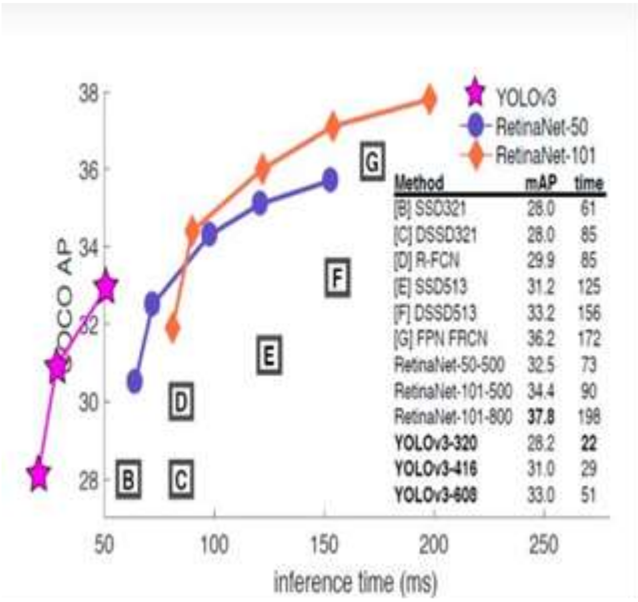
The ripeness of fruits can be detected by various manners such as the level of chemical content , color, texture and hardness. Our project dwells in classifying a fruit as Ripe , Unripe or Spoilt on the basis of its color once the fruit has been detected successfully by using YOLOv3 algorithm . The efficiency of collecting fruit robots are fundamentally dictated calculations utilized to identify organic products in pictures. In different models of such robots, different acknowledgment procedures based on at least one elements were used. The evident benefit of natural products identification by shape and color is the simplicity of implementation .

B. YOLO v3 Algorithm

You Only Look Once (YOLOv3) Version 3 is a real-time object recognizing alg. that detects objects in videos, live streams, and photographs in real time. look YOLO is a cutting-edge, always-on item recognition system. On COCO test-dev, it tests pictures at 30 frames per second and has a mAP of 57.9% on a Pascal Titan X. YOLO is a Convolutional Neural Network (CNN) that can identify protests. CNNs are classifier-based frameworks that can compute input images as ordered types of information and recognise patterns between them using classifiers. YOLO has the advantage of being much faster than other companies while still maintaining precision.

The entire framework can be partitioned into two significant segments: Feature Extractor and Detector; both are multi-scale. At the point when another picture comes in, it goes through the component extractor first with the goal that we can get include embeddings (at least three) distinct scales. At that point, these highlights are feed into (at least three) parts of the identifier to get bounding boxes and class data.





A. Dataset Collection

We gather the dataset from Google pictures. Since it is a drawn-out and dreary strategy to download pictures exclusively from different locales, we utilize a web scrapping procedure to download countless pictures without a moment's delay. In any case, Google pictures contain many garbage pictures that are not identified with what is being looked. Consequently, we manually clean the dataset by erasing irrelevant pictures.

The Dataset is largely divided into three main categories as Ripe, Unripe and Spoilt where each category has a minimum of 400 images to train the model in order to accurately identify the fruits and classify them accordingly. To enable our application to identify different types of fruits we collected images of fruits such as Banana, orange and Mango as per the above mentioned categories.

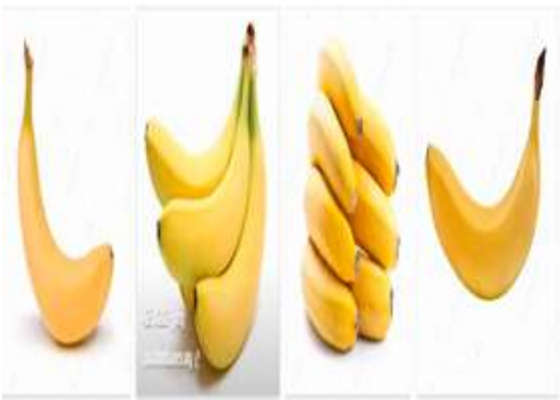


Fig 3: Sample Images Named Ripe Banana

Fig 4: Sample Images Named Unripe Banana

A. Modules Identified

1) Data Set Collector :- We first intend to collect the large number of images from the internet in order to train our ML model.

- Use GOOGLE images to look for example images.

- Grab the URL's of images using a little JavaScript and store them in a txt file.

- Download the images using Python and request Libraries.

2) Data Set Labeler :- LabelImg is a Python-based graphical annotation tool that makes use of Qt for its Graphical Interface(GI). Annotations are stored in XML Files and also supports YOLO format. We label the images and store the both the images and labels in the same file.

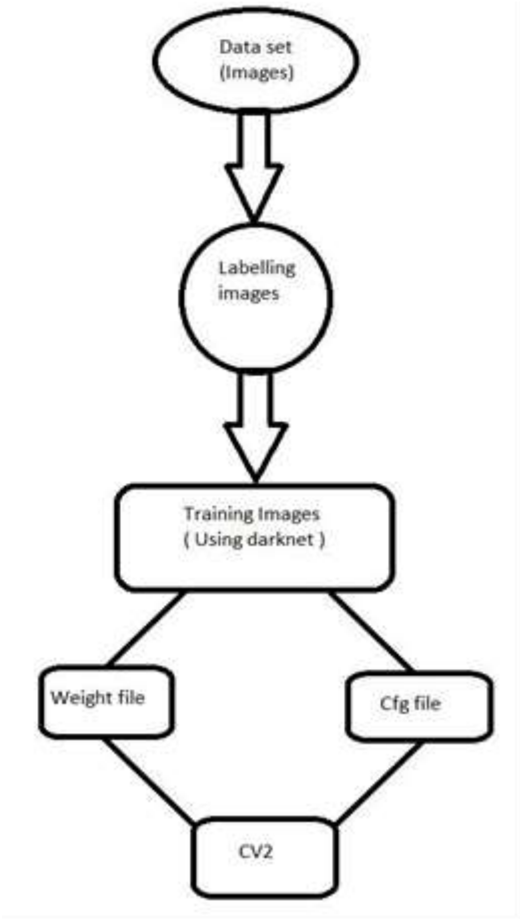
3) Training Module :- The dataset for training a detector with YOLOv3 consists of two parts. They are: Images and Labels. Each image will have a label file usually a text file that uses the a code syntax to specify the object type and coordinates of every object in the picture .Then, in order to train.!./darknet detector train "route" – don't show, we set up our Collab Environment and load the image files.

4) Making predictions Using OpenCV with YOLOv3:- You can use OpenCV to load YOLOv3 architecture and utilise this weight to detect their objects and extract their characteristics after acquiring our training weight and deliver the required prediction which is if a fruit is ripe or not in our situation

OpenCV for YOLO

Here are some reasons why we chose to go with Open CV in our project . Firstly, Simple incorporation with an OpenCV application: If your application as of now utilizes OpenCV and you essentially need to utilize YOLOv3, you don't need to stress over arranging and building the extra Darknet code. Next, OpenCV CPU variant is 9x quicker: OpenCV's CPU execution of the DNN module is amazingly quick. For instance, Darknet when utilized with Open MP requires around 2 seconds on a CPU for surmising on a solitary picture. Interestingly, OpenCV's execution runs in a simple 0.22 seconds! Look at table beneath. Python support: Darknet is written in C, and it doesn't formally uphold Python. Interestingly, OpenCV does. There are python ports accessible for Darknet though.

B. Data Flow and Identification



Step iv: Choose the box with the highest objective value

Step v: Finally, repeat steps ii-iv.

Now, our model uses this algorithm and uses the determined class probabilities to classify the fruits under their respective category - ripe, unripe or spoiled. We need to pass the labeled data over the model in order to train it. Assume we have isolated the picture into a matrix of size 3 X 3 and there are an aggregate of 3 classes which we need the items to be characterized into. Suppose the classes are ripe, unripe and spoilt separately. So for every grid cell, a vector of 8 dimensions will be declared with the following attributes.

$$y = \begin{bmatrix} pc \\ bx \\ by \\ bh \\ bw \\ c1 \\ c2 \\ c3 \end{bmatrix}$$

Fig 6: Attributes in Yolo Files

pc - Probability of the presence of the object in the grid .bx, by, bh, bw - Specifications of the bounding box, if any, object is present. c1, c2, c3 represent the classes. If the object is a ripe fruit, c1 is set to 1 and the other parameters are set to 0 and likewise for the other classes. c2 will be set to 1 (indicating it's an unripe fruit) and the others to 0 if the object is an unripe fruit.

3. Results and Discussion

The estimated results of the fruit ripeness assertion system is shown in the given figures where bananas are being classified as they are fed as in input to the application via live video feed. The Results observed were close to the estimated Output and hence concludes that the system was successful in classifying the fruit according to its ripeness state.

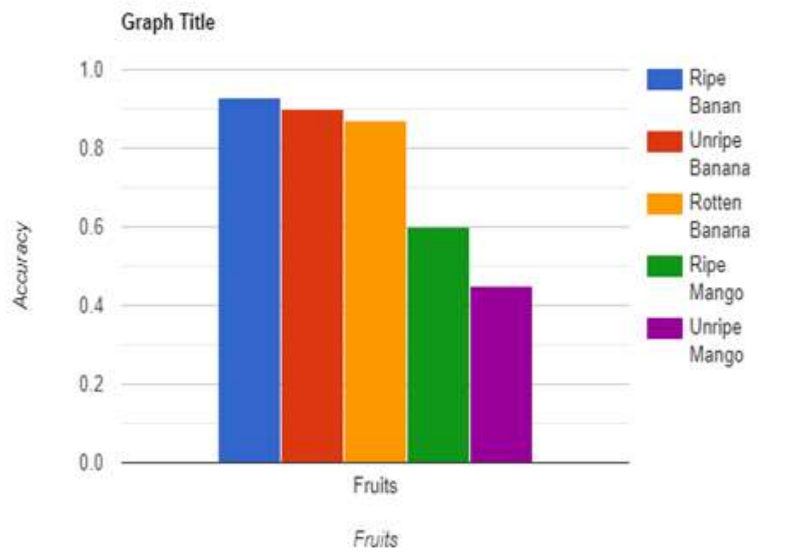


Fig 7: Graph depicting the accuracy of the predicted ripening state

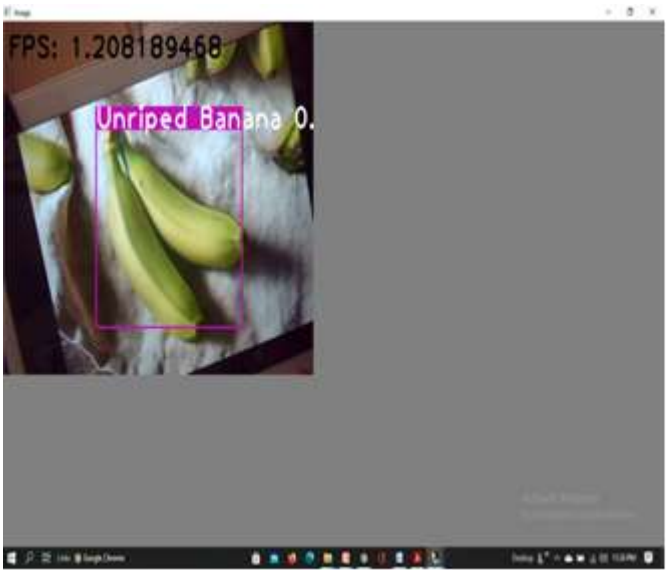


Fig 8: Final Outcome 1

Fig 9: Final Outcome 2

Fig 10: Final Outcome 3

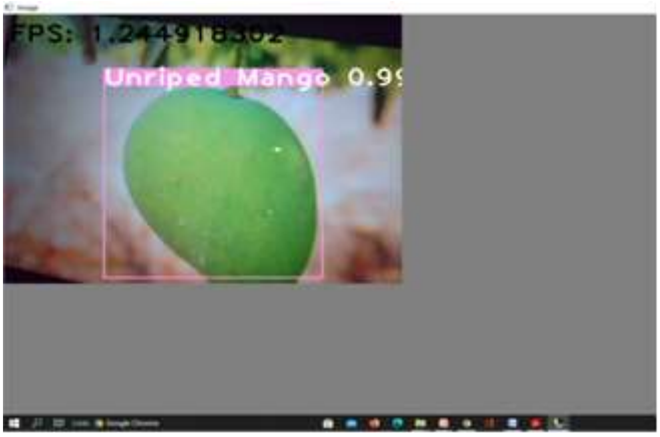


Fig 11: Final Outcome 4

4. Conclusion

The main purpose of this application is to determine ripeness level of fruits, classify fruits, and assess their quality, based on physical characteristics, such as form, colour and texture, before they are released into the market. The grouping of ripe fruits is generally determined by a designated master. In all instances, investigations indicate that the key basis for evaluation of value is physical attributes such as form, colouring and texture since these aspects require coherence. Some contemplates suggested and implemented various methods for the more accurate discovery and characterization of organic products. This paper had a possibility to list, for example, depth of learning, image enlightenment, colour recognition, identifying fruits, etc., which were most widely used and demonstrated in order to determine the rip state of fruits. Crop growth and yield must be monitored in order to fully understand how the crop reacts to the environment and farming techniques, and to establish successful fieldworks [9-16]. By adopting an educated model over big photos, which are required in orchards for fruit counting, we may widen the concept and focus more on the mapping and estimation of fruit in our future work. This combines the detection performance of the Faster R-CNN with yield mapping, resulting in an object relationship between adjacent frames.

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