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CNN'S PREDICTIVE STAGES OF BANANA RIPENESS

[1]Dr. G. JawaherlalNehru, [2]P.B.S. Aditya Kumar, D. Manasa, Ms. Maneesha

[1]Associate Professor, [2,3,4]Assistant Professor, Department of Computer Science and Engineering,

St. Martin's Engineering College, Secunderabad, Telangana, India

ABSTRACT

One of the most popular fruits in the world is the banana. A banana gives the body fullness and is a terrific source of energy. In all sports, bananas are a great source of energy. They are a nutritious source of potassium, fiber, vitamin B6, and vitamin C. There are numerous varieties and sizes, and they typically range in hue from green to yellow. It's among the cheapest fresh fruits. The market price and eating quality of banana fruit are typically impacted by its ripeness. The goal of this research is to forecast the ripening stages of bananas, including unripe, ripe, and overripe. Without the development of the convolutional neural network, banana categorization would not have been feasible with full accuracy and precision.

Keywords: Energy, Booster, Vitamin, Fiber, Types, Quality, Ripening, Dataset

I. INTRODUCTION

Agriculture assumes a basic job in the worldwide economy. Owing to the increase in human population, 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 for 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 Often, a farmer's crop selection is influenced with the minor considerations such as rapid growth of money, market demand, overestimating a soil's ability for the better yield.[1].

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 the logical area that allows machines to learn without being carefully customized, according to various definitions [2].

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 perception and investigation, it may be difficult or monotonous and repetitive [2]. This research aims to develop a software which can be used to identify if a fruit is unripe, ripe or spoilt. The recommended software is real time and end user friendly, it can detect the ripeness state of a fruit in real time video or pre-recorded footage. The researcher used 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.

II. LITERATURE REVIEW

This chapter includes rigorous literature survey on the existing ways to identify fruits and classify them, carried out during the last one decade. However, few existing methods are listed here for discussion. In 2017,"Deep Fruit Detection in Orchards “proposed by Suchet et al. 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 framework 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 than its precursors in terms of performance [3].

In 2019,"An Optimized method for Segmentation and classification of Apple diseases based on strong Correlation and Genetic algorithm-based feature selection" proposed by Muhammad attique khan. Three pipeline techniques are observed pre-processing, spot segmentation and features extraction. In this 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[4].

In 2020,"Using YOLO version3 algorithm pre- and post- processing for apple detection" proposed by Anna et al. In this method 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 recognize them effectively [5].

The efficiency of several techniques of dealing with fruit maturity in the past are compared. The amount of categories in the database, the extracted features, the color space used, the classifiers employed, and the accuracy achieved were all compared. The below table 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

Author	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

III. PROPOSED WORK AND MODULES IDENTIFIED

Theoretical Consideration

The presence of a natural product is one of the most important characteristics that demonstrates its preparation and quality. Natural products' color 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 [11] .

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

Data Flow and Identification

The ripeness of fruits can be detected by various manners such as the level of chemical content, color, texture and hardness. This research dwells in classifying a fruit as Ripe, Unripe or Spoilt based on its color once the fruit has been detected successfully by using YOLOv3 algorithm. The data flowchart for the Fruit Ripeness Assertion Using Deep Learning is given in figure 1. The following are the steps for prediction.

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

Use GOOGLE images to look for example images.

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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.

b) Data Set Labeller: - Labelling is a Python-based graphical annotation tool that makes use of quality for its Graphical Interface (GI). Annotations are stored in XML Files and supports YOLO format. Label the images and store the both the images and labels in the same file.

c) 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.

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

Dataset Collection

The dataset is gathered from Google pictures. It is a drawn-out and dreary strategy to download pictures exclusively from different locales and 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, manually cleaned 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 the application to identify different types of fruits and collected images of fruits such as Banana, orange and Mango as per the above-mentioned categories. The sample image of Ripe banana and Unrip banana given in Figure. 2 and Figure. 3.

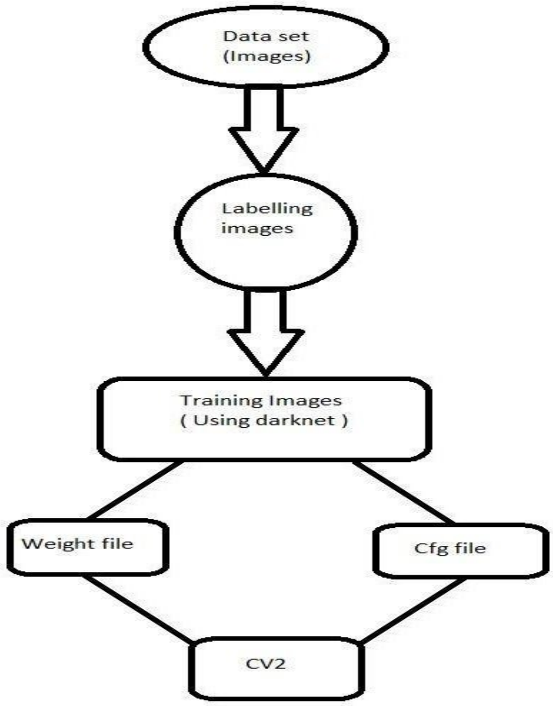

Fig. 1. Data Flowchart

Fig. 2. Sample Images Named Ripe Banana

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Fig. 3. Sample Images Named Unripe Banana

The framework of YOLO Network is given in figure 4, the framework is partitioned into two significant multi-scale segments: Feature Extractor and Detector. Image is given as input to the first segment the component extractor first with the goal that 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.

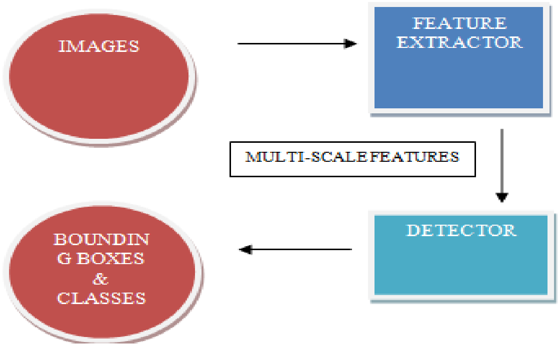

Fig. 4. YOLO Network

Training

The input for YOLO is an image. The algorithm separates the image input into a matrix 3X3 grid, for instance. The algorithm then previews boundary boxes for those objects found in those bounding boxes and its corresponding class probabilities. This is accomplished through the classification and positioning of the image, which is referred to as non-max Suppression. The NMS select the optimal bounding box while rejecting or deleting all other bounding boxes.

The steps below outline the utilization of NMS to discover the optimum bounding box. Step i: Choose the most objectively measured box

Step ii: Compare this box with other boxes (intersection over union) Step iii: Remove boundary boxes with more than 50 percent overlap Step iv: Choose the box with the highest objective value

Step v: Finally, repeat steps ii-iv.

Table. 2: Attributes in Yolo Files

y =	pc
	bx
	by
	bh
	bw
	c1
	c2
	c3

The researcher uses this algorithm and determined class probabilities to classify the fruits under their respective

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category - ripe, unripe or spoiled. It needs to pass the labeled data over the model in order to train it. Assume that the picture isolated into a matrix of size 3 X 3 and there is an aggregate of 3 classes which 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 in table -2.
Where 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.

IV. RESULTS

The estimated results of the fruit ripeness assertion system are 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 figure-5 shown Graph depicting the accuracy of the predicted ripening state.

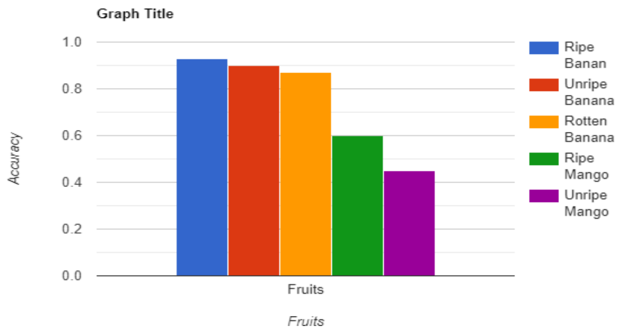

Fig. 5. Representation of accuracy of the predicted ripening state

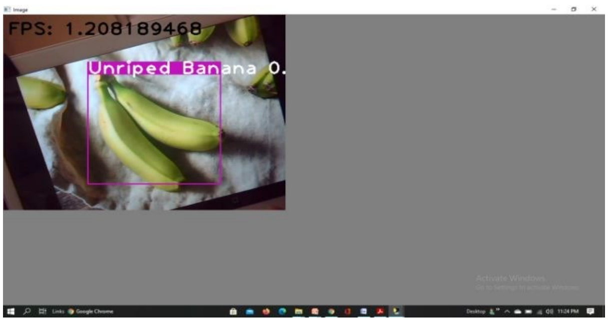

Fig. 6. Unripe Banana (Outcome 1)

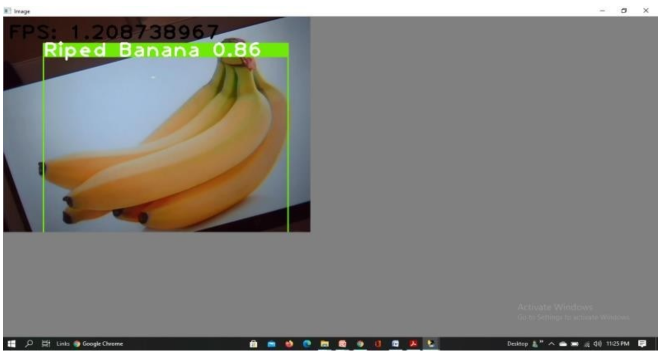

Fig. 7. Riped Banana (Outcome 2)

The Results observed were close to the estimated Output and hence concludes that the system was successful in

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classifying the fruit according to its ripeness state. The final outcome of the research is given below figure-6 for Unripe Banana,Figure-7 Riped Banana Figure-8 Rotten Banana Figure -9 Unripe mango Figure-10 Ripe Mango.

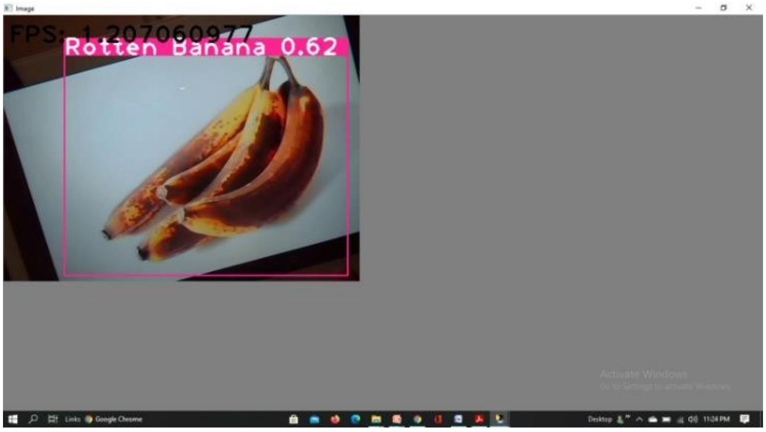

Fig. 8. Rotten Banana (Outcome 3)

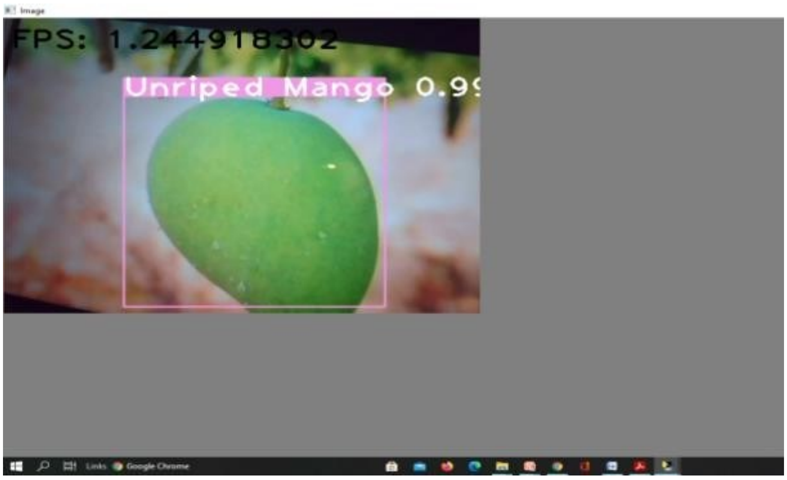

Fig. 9. Unripe mango (Outcome 4)

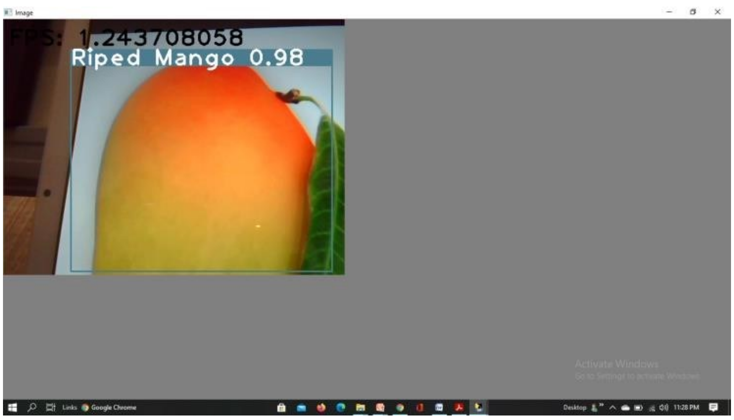

Fig.10 Ripe mango (Outcome 5)

V. CONCLUSIONS AND FUTURE WORK

The significant intention of this application is to predict ripeness level of fruit, classify and evaluate the fruits based on their physical characteristics like shape, color, and texture before the import to the market This ripening assessment is generally a human activity. In any case, late investigations prove that having physical attributes like shading, shape and surface as the main bases of value appraisal is inclined with human blunder because it requires consistency during the assessment. A few contemplates have proposed and introduced different strategies for more precise organic product discovery and characterization. This paper had the option to list probably the most broadly utilized and demonstrated successful techniques for example, profound learning, picture enlightenment, color detection, fruit identification etc. to determine the ripped state of fruits. In our future work, we may extend this idea and concentrate more on the yield mapping and estimation by implementing a model trained with large images related to fruit counting in orchards. This integrated output from Faster R-CNN with yield mapping and object association between adjacent frames excels.

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