Smart Detector For A Juice Vending Machine

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Abstract- *Image processing is a method of converting a physical image into a digital image in order to improve it or extract useful information from it. The detection of flaws on the fruit peel aids in the classification or grading of fruit quality. Because there is such a strong demand for high-quality fruits on the market, fruit defect detection is a critical responsibility in the agricultural industry. Human flaw identification, on the other hand, is time-consuming and labor-intensive. The proposed methodology can be used in supermarkets to sort fruits automatically from a variety of various types. This system reduces processing time and decreases errors. The goal of this project is to present fruit faults using the YOLOv3 object identification technique. To categorize the fruit as defective or fresh, the suggested technique uses the yolov3 algorithm, up sampling layer, detecting layer, and code written in Python on a Raspberry Pi.*

Keywords- Image Processing, Raspberry Pi, YOLO v3 algorithm, Conventional Neural Network, Up sampling Layer

I. INTRODUCTION

In image processing, an input image is provided, and the output image is an image or image features. Image processing can be used for a variety of purposes, including image recognition, pattern recognition, image sharpening, and image retrieval. The object detector YOLO is well-known. YOLOv3 is only considerably better than YOLOv2. For example, a better feature extractor, darknet-53 with shortcut connections, and a better object detector with up sampling and concatenation of convolution layers.

Fruit uniformity in size, shape, and other quality characteristics are required for determining the overall recognition quality for customers. Due to labor shortages and a lack of overall consistency in the process, automated alternatives were considered. Color, size, and number of flaws are all key factors to consider while inspecting fresh fruits. Various variables, such as rotting, crushing, peeling, fungi development, injury, disease, and so on, cause defects or damage in fruits. After the fruits have been harvested, proper care needs to be taken. To avoid cross-contamination and lower subsequent processing costs, these faults must be addressed.

In most cases, human professionals verify the quality of fruits. Manual sorting by visual inspection is time-consuming and labor-intensive. It suffers from inconsistency and random error in human judgement. Automation of the defect identification process is projected to minimize labor costs and enhance sorting efficiency with the arrival of rapid and high precision technology. Diverse image processing algorithms can be used to assess the quality of fruits.

The main goal of this project is to create an algorithm that uses digital image analysis to find defects and classify fruits.

The first section provides an overview of the technique for identifying faults in fruits. In Section II contains some technical information. Object detection is one of the most challenging tasks in the computer vision field. While there are a handful of different object detection algorithms. We are going to use yolov3(you look only once) algorithm.

You Only Look Once, Version 3 (YOLOv3) is a real-time object detection system that recognizes specific items in films, live feeds, or photos. To detect an object, YOLO employs features learnt by a deep convolutional neural network. YOLO versions 1-3 were created by Joseph Redmon and Ali Farhadi. YOLOv3 is an improved version of YOLO and YOLOv2.[2]

Artificial Intelligence (AI) algorithms employ object categorization systems to recognize certain items in a class as subjects of interest. The systems sort objects in images into groups where objects with similar characteristics are placed together, while others are neglected unless programmed to do otherwise. [11]

YOLO is named “you only look once” because its prediction uses 1×1 convolutions; the size of the prediction map is exactly the size of the feature map before it. YOLO is a Convolutional Neural Network (CNN) as shown in the Fig 6, for performing object detection in real-time. CNNs are classifier-based systems that can interpret incoming pictures as organized arrays of data and recognize patterns. Multi-scale prediction is used by YOLOv3, which implies it is identified on several size feature maps. YOLOv3 has the advantage of being much faster than other networks and still maintains accuracy.

It allows the model to examine the entire image at test time, allowing it to make predictions based on the image's overall context. [2], [7], YOLO and other convolutional neural network algorithms "score" areas based on their similarity to specified classes.[2] [7]

II. PROPOSED SYSTEM

A design of an image processing-based detector fixed in an automatic juice vending machine to detect the decayed and fresh fruits and separate them inside with a pneumatic piston connected to the servo motor separating material working according to the programmed using python supported by Rasperry Pi 4 with a high-resolution camera in its port.

III. OPERATION PRINCIPLE

1. **BOUNDING BOX PREDICTION**

YoloV3.tx, ty, tw, and th are anticipated in the same way. The total of squared error loss is employed during training. And logistic regression is used to predict the objectness score. If a bounding box prior overlaps a ground truth object more than any other bounding box prior, the value is 1. As demonstrated in Figure 2, each ground truth object has just one bounding box before [2], [4].

As offsets from cluster centroids, we anticipate the box's width and height. Using a sigmoid function, we forecast the centre coordinates of the box in relation to the filter application position. This self-plagiarized figure isn't the best, but it does overlap a ground truth object by more than a threshold. Unlike our approach, which only allocates one bounding box prior to each ground truth item, we utilise a threshold of 0.5. There is no loss in coordinate or class predictions if a bounding box prior is not assigned to a ground truth object; only objectness is lost. [1], [3], [11].

2. CLASS PREDICTION

Using multilabel classification, each box predicts which classes the bounding box may contain. We don't use a softmax because we've discovered that it's not necessary for good performance; instead, we use independent logistic classifiers. For class predictions, we use binary cross-entropy loss during training [2], [11].

When working with more complex domains, such as the Open Images Dataset [7], this formulation comes in handy. There are many overlapping labels in this dataset. When you use a softmax, you have to assume that each box has exactly one class, which isn't always the case. A multilabel approach to data modelling is more accurate. [2, 7,]

3. PREDICTION ACROSS SCALES

At three different scales, YOLOv3 predicts boxes. Using a concept similar to feature pyramid networks [8, our system extracts feature from those scales. We add several convolutional layers to our base feature extractor. Last, a 3-d tensor encoding bounding box, objectness, and class predictions are predicted. We predict three boxes at each scale in our COCO [10] experiments, so the tensor is N N [3 (4 + 1 + 80)] for the four bounding box offsets, one objectness prediction, and 80 class predictions. The feature map from the two previous layers is then upsampled by two. We also use concatenation to combine a feature map from earlier in the network with our upsampled features. The upsampled features provide more meaningful semantic information, while the earlier feature map provides finer-grained information. To process this combined feature map, we add a few more convolutional layers and predict a tensor that is similar but twice the size. We repeat the process in order to predict boxes for the final scale. As a result, all of the prior computation as well as fine-grained features from early in the network benefit our predictions for the third scale. Our bounding box priors are still determined using k-means clustering. We just picked nine clusters and three scales at random, then divided the clusters evenly across the scales. The COCO dataset had nine clusters: (10×13), (16×30), (33×23), (30×61), (62×45), (59×119), (116× 90), (156 × 198), (373 × 326). [2], [3], [5], [21]

3. FEATURE EXTRACTOR: DARKNET 53

For feature extraction, we employ a new network. Our new network is a cross between the YOLOv2 network, Darknet-19, and the newfangled residual network stuff. Our network employs a series of 3 3 and 1 1 convolutional layer, but it now includes shortcut connections and is significantly larger. As shown in Table 1, it has 53 convolutional layers. Darknet-53! [2], [21], [22].

This new network is significantly more powerful than Darknet-19, but it is still more efficient than ResNet-101 or ResNet-152. Table 2 displays some ImageNet results.[2], [11] [21], [22].

Each network is trained with the same settings and tested at a single crop accuracy of 256256. On a Titan X, run times were measured at 256 256. As a result, Darknet-53 outperforms state-of-the-art classifiers while using fewer floating-point operations and running faster. Darknet-53 is 1.5 times faster than ResNet-101. Darknet-53 performs similarly to ResNet-152 but is two times faster. In addition, Darknet-53 has the fastest measured floating-point operations per second. This means the network structure makes better use of the GPU, making evaluation more efficient and thus faster. This is due to the fact that ResNets have far too many layers and are inefficient. [2], [21], [22].

IV. FIGURES AND TABLES

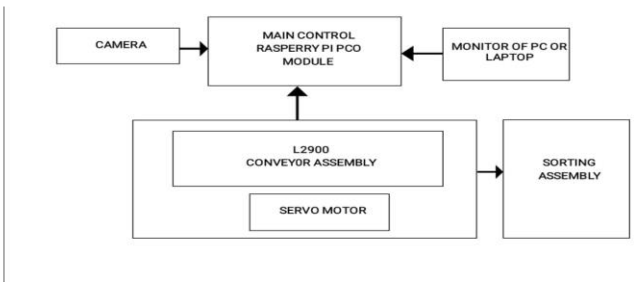

Fig 1: Real time setup block diagram

The above fig 1 shows the real time block diagram of assembly of our project.

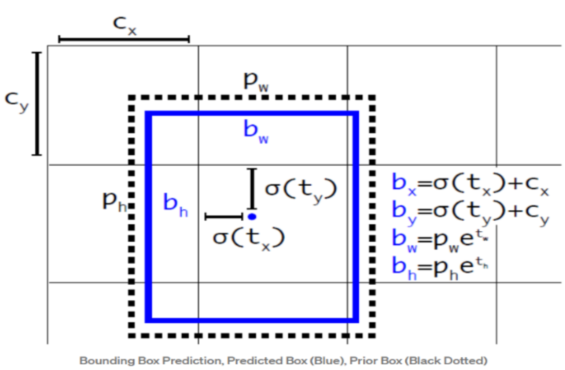

Fig 2. Bounding boxes with dimension priors and location prediction

The above figure shows the bounding boxes with dimension priors and location prediction correctly and formulas of object finding.

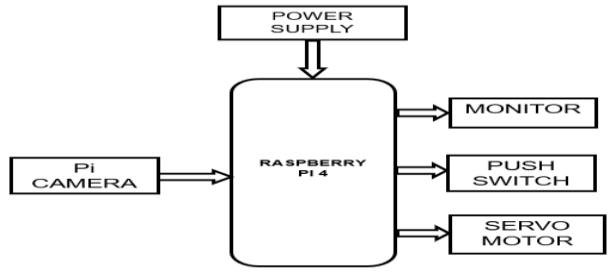

Fig 3: Proposed System Block Diagram

The above figure shows the proposed system prototype of automatic fruit detection.

Fig 4:Training images for damaged apples detection

The above figure shows the training images for the damaged apples to fruit detection.

Fig 5. Training images for fresh apples detection

The above figure shows the training in ages for the good apples to fruit detection

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Table 1. Darnet-53

The above figure shows the convolutional size and filters and output.[24], [25].

Backbone	Top-1	Top-5	Bn Ops	BFLOP/s	FPS
Darknet-19 [15]	74.1	91.8	7.29	1246	**171**
ResNet-101[5]	77.1	93.7	19.7	1039	53
ResNet-152 [5]	**77.6**	**93.8**	29.4	1090	37
Darknet-53	77.2	**93.8**	18.7	**1457**	78

Table 2.Comparison of backbones. Accuracy, billions of operations, billion floating point operations per second, and FPS for various networks.

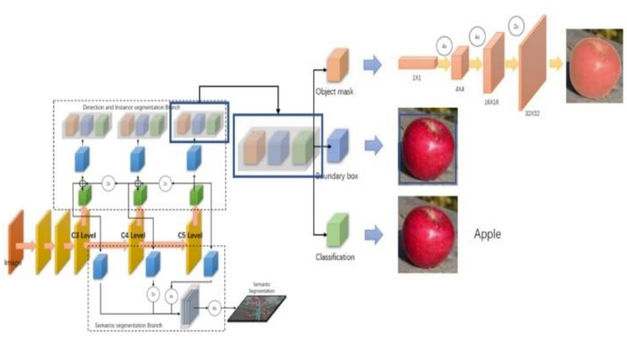

Fig 6. Architecture of Yolov3 Algorithm

The above figure shows the Architecture of Yolov3 Algorithm whichs shows the concatenation ,upsampling layers and so on [14], [15], [16] ,[20].

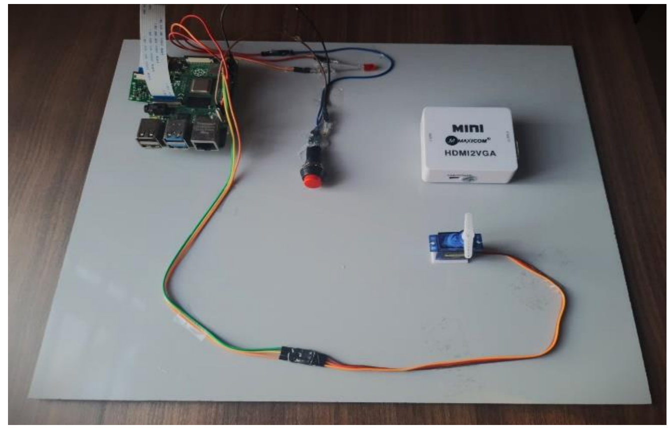

Fig 7. Proposed System Prototype

The above figure shows the our hand made proposed project prototype for automatic juice vending machine

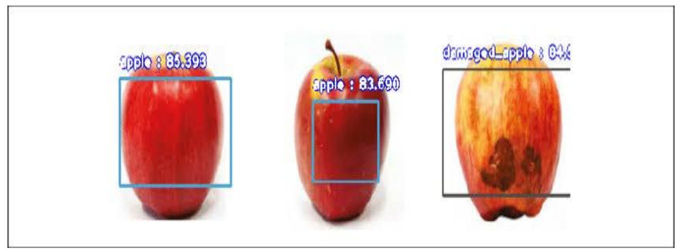

Fig 8. Output and result

The above shows the final output and result of our project

Examine the data. Apple You Only Look Once, Version 3 is incredibly fast, processing 45 frames per second thanks to the YOLO object detection algorithm. Generalized object representation is also understood by YOLO. The hardware is given control based on the classification of healthy and abnormal Apple. As a result, it can identify whether or not the Apple is affected. They are normal healthy Apples if they are not affected. It's abnormal Apple if they're affected. The classification of Apple is based on the output from the previous step. The signal is sent to the RASPBERRY PI microprocessor after taking a picture of Apple, as shown in Fig 4 for the Yolov3 Algorithm process. If the Apple is found to be abnormal, it is displayed on the LCD and an alarm is triggered. The servomotor then separates the normal and abnormal Apples [2], [3], [7], [17], [18].

V. RESULT AND DISCUSSION

High demand is one of the most important and difficult issues in the supply of fresh fruits. We are using this system to try to solve the problem. This is where fruit freshness is predicted. To protect our health from the chemicals used in the grocery store, we created a system that employs specific processes and algorithms. The goal of this project is to develop a new and efficient system. From images, the system will determine the type of fruit and its freshness.

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