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Detection Of Adulterants in Pistachio Using Machine Learning Technique

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ABSTRACT: **This study addresses the issue of adulteration in pistachios, with a focus of green peas to compromise product purity and maximize profits. Leveraging the capabilities of YOLOv5s, a state-of-the-art real-time image processing model, we developed a robust system for identifying adulterants in pistachios. Comparative evaluations against other deep learning models, including Detectron2 and Scaled YOLOv4 revealed inferior performance in terms of accuracy and speed with our YOLOv5s-based solution. This YOLOv5s model helps to provide instant percentage of adulterants and pistachios.**

Keywords - YOLOv5s, Scaled YOLOv4, Detectron2

INTRODUCTION

The prevalence of adulterated pistachios has surged, forcing

Consumers to pay premium prices for products often revealed as counterfeit. This deceptive trend not only inflicts financial burdens on consumers but also erodes their trust in the food industry. In response, a comprehensive solution has been devised, encompassing diverse aspects of detection and prevention, this strategic approach fosters collaboration among consumers, industry, and regulatory bodies, aiming to combat the issue effectively. The strategy incorporates advanced detection technologies, consumer education, collaboration with regulatory bodies, industry cooperation with regulatory bodies, industry cooperation with regulatory bodies, industry cooperation, and real-time supply chain monitoring. By addressing pistachio adulteration through this multifaceted strategy, we seek to safeguard consumer interests, restore confidence in the food industry, and create a resilient system resistant to fraudulent practices.

In this project, we have incorporated YOLOv5s. YOLOv5s (You Only Look Once version 5) in an advanced object detection model renowned for its exceptional speed and accuracy in real-time image processing. In comparison to its predecessors, YOLOv5s introduces a more streamlined architecture, enhancing both inference speed and precision. Its key strength lies in efficiently processing images in one forward pass, enabling rapid detection of multiple objects simultaneously.

METHODOLOGY

PROPOSED METHODOLOGY:

This novel convolutional neural network (CNN) detects objects in real-time with great accuracy. This approach uses a single neural network to process the entire picture, then separates it into parts and predicts bounding boxes and probabilities for each component. YOLO v5 represents the latest iteration of this groundbreaking algorithm, incorporating advancements that further enhance its performance.YOLOv5's architecture consists of three main parts: Backbone: This is the main body of the network. For YOLOv5, the backbone is designed using the New CSP-Darknet53 structure, a modification of the Darknet architecture used in previous versions. Neck: This part connects the backbone and the head.

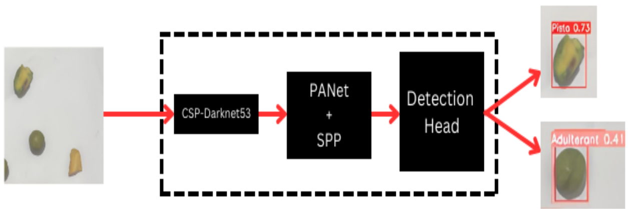

Fig-1: Block Diagram

OTHER METHODS IMPLEMENTED:

A) DETECTRON2: It is a PyTorch-based library from Facebook AI Research that provides a framework for powerful object detection. It includes customizable backbone networks, neck modules, and regional proposal networks (RPNs) to enable seamless integration of different architectures. The head of distribution and recovery led the transition to various research activities. Use ROI integration or social service to ensure the relationship between products. Instant training program focusing on classification and recovery. The next step, involving the maximum limiting factor (NMS), refines the predictions. Detectron2's modularity encourages customization, making it versatile for advanced detection systems and applications. This article provides a brief introduction to the key design features that make Detectron2 so useful.

B) Scaled YOLOv4**:** It represents an optimization of the YOLO object detection algorithm, focusing on new scaling techniques to improve its performance. This article summarizes the key changes to the YOLOv4 architecture and highlights advances in processing capabilities, model depth, and feature representation. The combination of advanced technology optimizes the model's ability to manage various parameters and increases its flexibility in different situations. The article covers the complexity of manipulating the backbone network and explains how this helps improve feature extraction and detection accuracy. The results of experiments and benchmarks demonstrate the effectiveness of Scaled YOLOv4 in achieving good results in object detection in real-time. This article aims to provide an understanding of the improvements and performance achieved by Scaled YOLOv4 by providing an overview of scaled performance.

MODEL COMPARISON

Features	**Scaled YOLOv4**	**Detectron 2**	**YOLOv5**
Backbone	CSP Darknet53	ResNet	CSP Darknet53
Inference Speed	Moderate to Fast	Moderate	Fast
Training Strategy	One-Stage (Direct bounding box regression)	Two-Stage (Region proposal followed by bounding box regression)	One-Stage (Direct bounding box regression)
Model Size	Medium to Large	Large	Large
Objectiveness	Balance of Speed and Accuracy	Flexibility and Accuracy	Simplicity and Speed

Table-1: Comparison of Scaled YOLOv4, Detectron 2 and YOLOv5s

MODEL ARCHITECTURE

Backbone: YOLOv5 utilizes the CSPDarknet53 backbone, an efficient spine-structured design that incorporates Cross-Stage Fractional networks for enhanced feature extraction.

Neck: The neck architecture in YOLOv5 is PANet (Path Aggregation Network), facilitating information flow across different structured scales to effectively capture multi-scale features.

Head: The head of the YOLOv5 model enables predictions at multiple scales and consists of location heads that predict bounding boxes and class probabilities, with each head associated with a specific scale of feature maps.

Detection Head: Each detection head predicts essential information for each bounding box, including coordinates (x, y, width, height), confidence score indicating object presence, and class probabilities for different object classes.

Loss Function: YOLOv5 employs a combination of loss functions during training:

a. Bounding Box Regression Loss: Penalizing errors in predicting bounding box coordinates.

b. Objectness Loss: Penalizing the confidence score for predicting the presence of an object.

c. Classification Loss: Penalizing misclassification of object classes.

Training Strategy: YOLOv5 utilizes transfer learning, commencing with pre-trained weights on a large dataset (e.g., COCO), expediting model convergence and enhancing performance on the specific target dataset.

Model Configurations: YOLOv5 offers various model configurations (e.g., YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x), each with distinct parameters and computational requirements. Users can select a specific model configuration based on their hardware constraints and performance needs.

Post-Processing: After training, the model is employed for inference on new images or video frames. Post-processing steps include the application of non-maximum suppression (NMS) to filter out redundant bounding boxes. Additionally, a confidence threshold can be set to control the sensitivity of the model in making predictions.

IMPLEMENTATION

We have trained the data set from Roboflow which has about 132 images and each image has around 26 annotations which is approximately 3,454 annotations in total.

First we have resized the images of the Dataset to 640x640 size. Then we have cloned Detectron2 ,YOLOv5s and the Scaled YOLOv4 models using Google Colab. Then we have trained the model for 200 epochs and noted the results of all the models.

Implemented the YOLOv5s with the required dependencies, including Torch, were installed. The YOLOv5s repository was then cloned from GitHub. After navigating to the YOLOv5s directory, an empty file was created to store the YOLOv5s model weights. Finally, the detection script was run on a chosen image. Paths and parameters were adjusted as necessary, and GPU support was ensured for optimized performance. Python and Git were required to be installed on the system.

RESULT

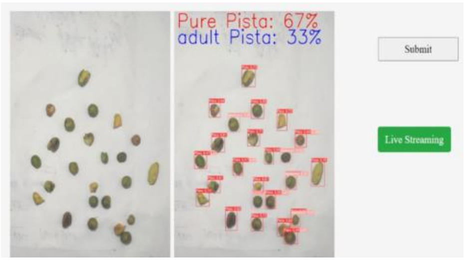

Fig-2: Pistachio and Adulterant percentage

Image of the batch of mixed grains is given as input,as output we get the result in the form of percentages of Pure and Adulterated Pistachio.

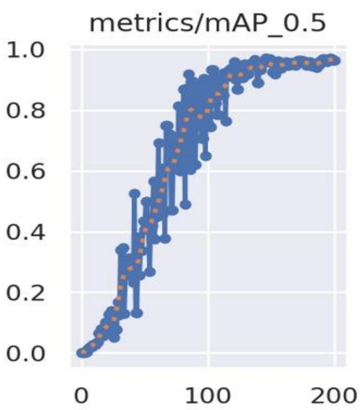

Fig-3:YOLOv5s maP graph

The given map graph is a mean average precision graph.

Shows the accuracy and the number of epochs on the Y and X axis respectively.In the Graph we can see that the accuracyis about 95% in the YOLOv5s model.

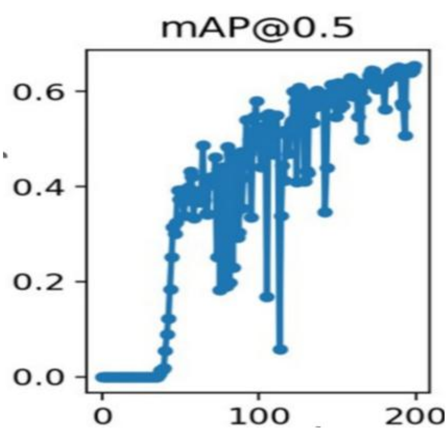

Fig -4:Scaled Yolov4

The given map graph is a mean average precision graph.

Shows the accuracy and the number of epochs on the Y and X axis respectively.In the Graph we see that the accuracy is about 65% in the Scaled YOLOv4 model.

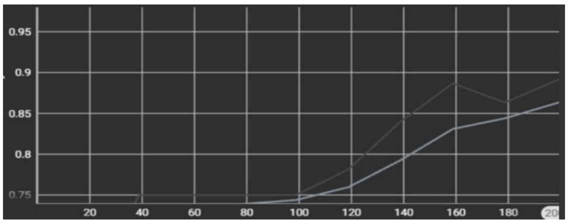

Fig-5: Detectron 2 Class Accuracy

From the above graph of Detectron 2 we got an accuracy of about 89%.

CONCLUSION

The study conducted a comprehensive evaluation of three leading object detection models – Yolo v5s, scaled Yolo v4, and Detectron2. Yolo v5 demonstrated superior performance, achieving an outstanding 95.8% accuracy, while Detectron2 gives 89% accuracy and Scaled YOLOv4 gave 65% accuracy. Its real-time detection capability was emphasized, showcasing an impressive frame rate of 140 fps and suitability for scenarios requiring rapid object detection from video streams or live camera feeds. Addressing concerns about model size, Yolo v5 proved advantageous with a compact size of approximately 14 MB compared to scaled Yolo v4's larger size of around 240 MB and the size of Detectron 2 is around 202MB. Additionally, Yolo v5s excelled in small object detection, showcasing high accuracy in scenarios where precision for smaller objects is crucial .From this we can clearly observe that YOLOv5s out performs the other two models and gives a favorable result.

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