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Defect Detection in Manufacturing

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Abstract- The detection of quality defects is crucial in quality control in industrial production. An enhanced manufacturing defect detection method based on the You Only Look Once (YOLO) model is proposed in order to address the issues of ineffective detection brought on by conventional human inspection and indistinct features in industrial defect detection. Due to their complexity and distinctive characteristics, flaws might be difficult to detect in produced parts traveling on conveyor belts. These flaws are unique to each production line and can be found on many of them. YOLOV7 is real-time object detection technique, which internally utilizes convolutional neural network (CNN), is utilized to detect these inaccuracies. Despite the tiny dataset and minimal network adjustments, YOLOV7 can obtain a mean average precision (mAP) of above 70%. The network can get the bounding box coordinates that are detected and that correspond to one of the classes in the annotated data.

Indexed Terms- YOLO, SSD, Convolutional Neural Network, Object Detection.

I. INTRODUCTION

In every factory, mistakes in design and machine production equipment, as well as poor working conditions, can result in faults on items that are being delivered at the end of the conveyor line. Due to daily use, products may also corrode readily and become fatigued. These flaws significantly impair people and their safety while raising the expenses spent by businesses, reducing the useful life of manufactured goods, and wasting a great deal of resources. Determining flaws is therefore a vital ability that businesses should have if they want to raise the quality of their manufactured goods without harming productivity. The defect detector must be precise and quick in order to meet the demands of the production lines. Today's factories have advanced significantly and operate at a high rate, producing hundreds of items every hour. Additionally, the detector must be able to distinguish between interference from defects and interference from non-defects, such as discoloration marks. In the past, inspection and quality assessment were carried out manually by people, who might be slower than machines and are prone to becoming exhausted. In several industries, computer vision is replacing human labor and assisting with visual inspection. The greatest option for computer vision tasks is CNNs. Applications like picture segmentation and object classification have made significant strides because of CNNs. CNNs have also been employed in commercial settings. Additionally, CNNs include convolution layers for feature extraction, are resistant to shifts and image distortions, need less memory, and are better and faster due to the fewer parameters. CNNs also contain convolution layers for feature extraction. The YOLO network is utilized in this study to identify and categorize various flaws on finished product. The network can also extract the coordinates of the bounding boxes, which provides information about the position and size of each defect that is found.

II. OBJECTIVE

To assure the quality of the final product, defect detection during production processes is essential. Reducing operational and quality-related expenses requires prompt fault or defect detection and proper remediation. Using an automated system to increase the efficiency of the process of measuring quality as minimal human intervention will be required.

III. SCOPE

Majority of Industries need a system to duality control and defect detection. Research in multiple domains of Computer Vision techniques to build this system.

IV. RELATED WORK

The Working of a System -

YOLO is two-stage detectors like R-CNN use region-proposal to first generate potential bounding boxes and then run a classifier on these proposed boxes.

After classification, post-processing is used to refine the bounding boxes, eliminate duplicate detections, and rescore the boxes based on other objects in the scene. These complex pipelines are slow and hard to optimize because each individual component must be trained separately. YOLO is a real-time single-stage object detector which tackles object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. A single convolutional network simultaneously predicts multiple bounding boxes and class probabilities for those boxes.[1]

Yolov7 is the fastest real-time object detectors till date. Researcher claimed that YOLOv7 outperforms all known

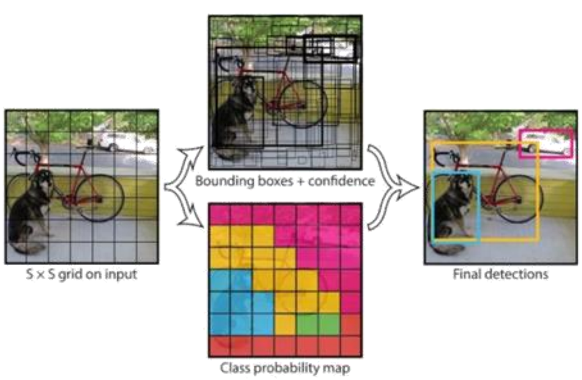

Fig. 1. Single stage detection [1]

object detectors in both speed and accuracy and has the highest accuracy 56.8% AP among all known real-time object detectors. The significant increase in the performance of the architecture is due to model re-parameterization. By combining numerous computational modules into one at the inference step, the model re-parameterization technique increases inference throughput. It can be categorized into two groups: module-level ensemble and model-level ensemble, and it can be thought of as an ensemble approach.[2]

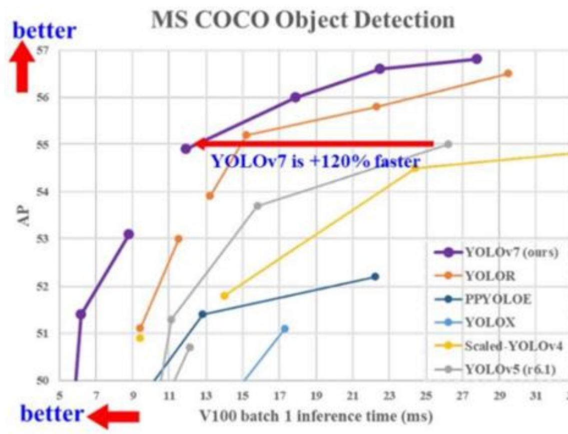

Fig. 2. Comparison between models [2]

There are two approaches to reparameterization models. One is to average the weights of all the models after training several identical models with various training sets. The weights of the models at various iterations are averaged out in the second method. The Module-level Method, on the other hand, divides a module during training into numerous identical or distinct module branches and then combines the branched modules into one during inference.

Some minor modifications in the network which yielded better results. Some parameters such as IOU (Intersection over union), confidence score and batch size were changed to observe the change in the results. Loss function in 2 convolutional layers were calculated using categorical cross-entropy.

As a result, the model was able to achieve a mAP of 70.66%. These changes are very subjective and vary with requirement, as the type of detection can have a lot of variation. Trial and error is the way to find the most suitable parameter value which suits our requirement.[3]

This paper incorporates some changes in the existing YOLO model. YOLO is not sensitive to small target detection; hence these changes are needed to increase accuracy for such detections. First change is adding a new feature layer to the network. After twice of up sampling, a feature layer that is suitable for the detection of small targets is combined with the neural network's deeper features.

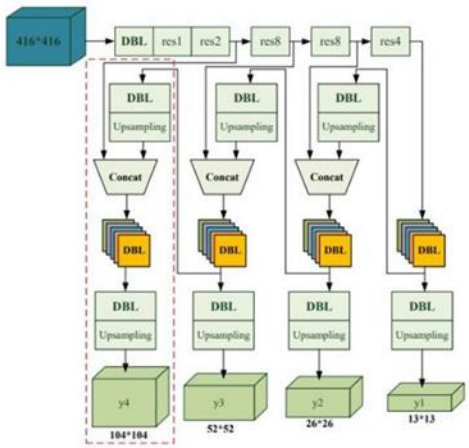

Fig. 3. Modified model [4]

The network is then made more capable of extracting features by creating a new feature layer through a convolutional layer with a convolution kernel size of 1x1. The input image is divided into smaller 4x4 grids, making a total of 104x104 grids. The size of the newly added feature layer is 1/4 the size of the original image. The network is more sensitive to small targets when the grid is smaller. In order to improve the model's capacity for extracting minute target features, it not only inherits the network's deep features but also fully utilizes its shallow features.[4][5]

The types and locations of surface defects are identified by using the method for surface defect detection that is proposed in this study, which is based on the MobileNet-SSD network. A regional planning strategy was proposed to eliminate the bulk of the defect, decrease redundant parameters, and increase the speed and accuracy of detection during the pre-processing stage. Meanwhile, data improvement increased the algorithm's robustness. To improve the detection accuracy, lighten the burden on the computer, and speed up the training of this algorithm, the MobileNet philosophy, a lightweight network, was introduced. In order for the suggested method to distinguish between small defects and the background, the MobileNet and SSD were modified to detect the surface flaws. Defect detection for the proposed approach was used to confirm its viability.[6]

V. INDUSTRIAL SETUP

There will be three industrial-grade, high-quality cameras mounted on a continuously moving conveyor belt to capture the top, right, and left views of the goal. A micro- controller embedded system is triggered when an object approaches the cameras by an IR sensor that will be placed right in front of those cameras. The system takes a frame from each camera after the trigger. The embedded system will use a deep learning model for defect detection, which will output the result as "OK" or "NOT OK" depending on the detection. The actuator and flap on the conveyor belt that separate defective products from non-defective products receive these results and relay them back.

VI. DATA DESCRIPTION

All the images are clicked from an industrial camera which contains 3 different views of a metal part. Types of defects vary for each view. For the top view, we just need to check the presence of a single nut, whether it is present or missing. The left and the right views need to be checked for the spot weld, whether they are correct or not.

To ensure that the faults to be recognized in the photographs are not too small but rather more in line with defects in the images and videos produced by cameras in factories, it is essential to start off with a reasonably large image while training with YOLO. Since YOLO requires five values to generate the bounding boxes, the labels are also changed to meet the YOLO format. Data augmentation might not be needed as the detects are fairly standard.

YOLO is pre-trained on the COCO (Common objects in in context) dataset, which contains 91 classes of some everyday common objects, hence transfer learning can be applied by downloading the pre-trained weights instead of training our model using some randomly initialized weights, which helps us save a lot of time and computation.

All images have fairly standard orientation and dimensions, we do not face much trouble in training as there is little to no significant variation in the images.

In order to determine the size and location of the flaws, the network also collects the coordinates of the bounding boxes that are generated. This is crucial for enhancing the production process and the caliber of goods leaving manufacturers. It is crucial to remember that YOLO can be used and trained on numerous industrial products even though it was developed for a particular product.

To be specific in the preprocessing steps, data have been cleaned for processing and augmented. Various features have been collected and later sent for classification step in the processing phase.

CONCLUSION

A modified YOLOV7 detector is trained on a dataset with four different class types for three different viewpoints. The labels are set up to fit the YOLO format, and the dataset is ready. YOLO is able to attain a mAP of above 70% coupled with high precision and recall following numerous tests and adjustments to the hyperparameters, such as batch size and network size. In order to determine the size and location of the flaws, the network also collects the coordinates of the bounding boxes that are generated. This is crucial for enhancing the production process and the caliber of goods leaving manufacturers. It is crucial to remember that YOLO can be used and trained on numerous industrial products even though it was developed for a particular product.

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