Manufacture Quality Assurance Using CV

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I. Introduction

In the era of Industry 4.0, the integration of advanced technologies such as Artificial Intelligence (AI) and Computer Vision (CV) into manufacturing processes is increasingly essential to maintain competitive advantages. Automation in quality control is a crucial aspect of this technological shift, as it significantly enhances the efficiency, precision, and consistency of defect detection on production lines. According to a report by McKinsey [6], implementing AI in manufacturing can increase productivity by up to 20% and reduce defects by up to 90%. Traditional manual inspection methods are labor-intensive and prone to human error, which can lead to suboptimal product quality and increased costs. The cost of poor quality in manufacturing, including rework, scrap, and warranty claims, can amount to 15-20% of sales revenue, underscoring the need for more reliable and efficient quality control systems [3]. Bangladesh's rapidly growing manufacturing sector, particularly in the textiles and automotive industries, faces significant challenges in implementing effective quality control systems. The textile industry alone accounts for over 80% of the country's export earnings, employing approximately 4.5 million people [4]. Despite this, the industry suffers from a defect rate of around 10-20%, significantly higher than the global average of 5-10%. The annual cost of defects in the Bangladeshi textile industry is around $2 billion [9].

Similarly, the automotive sector, which has been expanding with an annual growth rate of around 8%, also faces quality control issues [1]. The defect rates in automotive manufacturing contribute to increased production costs and reduce competitiveness in local and international markets. The lack of automation in these industries results in frequent defects and quality issues, undermining productivity and global competitiveness. Leveraging computer vision for automated defect detection offers a promising solution to these challenges by providing a scalable, efficient, and precise method for quality assurance. This paper presents a framework for implementing computer vision-based automated quality control in manufacturing, focusing on defect detection in the textile and automotive industries. By utilizing advanced deep learning models such as YOLOv9 and Detectron2/Faster-RCNN, we aim to demonstrate the feasibility and effectiveness of these technologies in identifying and categorizing defects. In our work, based on the Car dataset with a high precision of 0.86 and a mean Average Precision (mAP) of 0.58, we struggled on the Textile dataset with low precision of 0.0004 and mAP of just 0.001. On the other hand, Detectron2-Faster-RCNN performed consistently well, achieving high accuracy of up to 98% and maintaining a low false-negative rate below 0.41 across both datasets. Our paper tries to make several key contributions to the field of the manufacturing sector:

- We are building a system using computer vision ability to detect manufacturing product errors quickly and efficiently.
- Then, we create a QC checklist where, based on the defective product, we can generate a report where information can be shown.

II. literature Review

Computer Vision is an excellent option for object detection problems, and problems like the lack of automation in Bangladesh, especially in the manufacturing sector, are much needed. In [5],they are using traditional models like GAN, RNN, and CNN to create a manufacturing system for fault detection. In [8], the author introduces a system dealing with the additive manufacturing field, which is similar to ours. In [7], the author proposes a transfer learning approach to correctly identify defects on a dataset of source objects and extend its application to new unseen target objects. It can identify defects in finished products before they are shipped, which is crucial for quality assurance. In [2], the author used an old version of the Yolov5-based textile defect detection method. In [12], it designs an image acquisition process system. Then, it proposes a novel approach to addressing logistics packaging box defect detection (LPDD) on the basis of a support vector machine (SVM).

III. Proposed Solution

Computer Vision deals with images that help to detect defaults or errors. We have leveraged our computer vision ability to find an optimal framework to find defaults in the product. We have done some work to make this framework one by one. The framework workflow consists of a dataset, model, results, and inference.

A. Dataset

The first thing we need for our solution is a manufacturer-level dataset. As we do not have direct access to manufacturer data sets, we tried to find different ways to collect data from sites like Kaggle,roboflow, and DatsetNinja.

1) Textile

For the Textile part, we have mainly tried to find four types (holes, cut, stain, and thread errors) of defects in the manufacturer's cloth. We found a dataset that had enough images to work on. The four classes have different amounts of images, with the highest number of images in the thread error class. The cut and hole classes have similar numbers of images, but the stain class has the fewest images.

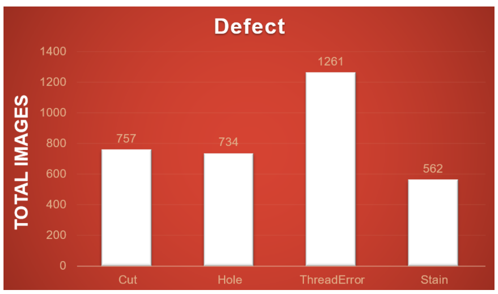

Fig. 1. The Textile Dataset Details. The highest number of images is in the thread error class, and the lowest is in the stain class.

2) Car

For the Car Dataset, we have mainly tried to find four types (scratch, dent, glass break, and color) of errors/defects in the manufacturer's car. Unfortunately, we have incorporated a dataset with only scratches, dents, glass breaks, and accidents. However, we will not use this accident class in our primary datasets.

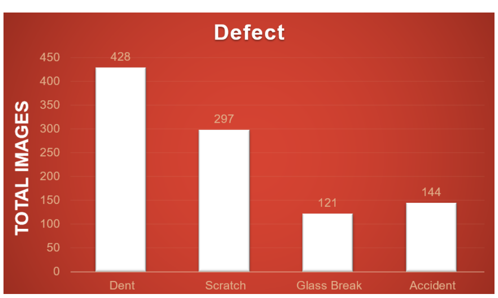

Fig. 2. The Car Dataset Details. The highest number of images are in the scratch class, and the lowest in the accident class.

B. Model

Models help us to predict the desired output according to the input. So, choosing models for our system is crucial. So, we have researched which models could be best for our system. We find that the yolov9 and Detectron2/FasterR-CNN models would give the desired output.

1) Yolov9

YOLOv9 is the latest iteration in the YOLO (You Only Look Once) series of real-time object detection systems. It builds upon previous versions, incorporating advancements in deep learning techniques and architectural design to achieve superior performance in object detection tasks. Developed by combining the Programmable Gradient Information (PGI) concept with the Generalized ELAN (GELAN) architecture, YOLOv9 represents a significant leap forward in terms of accuracy, speed, and efficiency. [10]

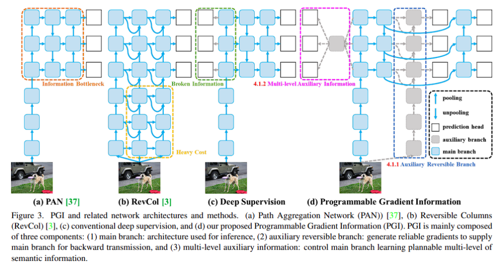

Fig. 3. Yolov9 Architecture.

2) Detectron2-Faster-RCNN

Detectron2 was developed by Facebook research. Detectron2 has several pre-trained models. One of them is Faster R-CNN. It is a deep convolutional network used for image object detection. It is quicker than Fast R-CNN and extends it by adding a region proposal network (RPN). Faster R-CNN algorithm to detect objects in an image by taking an input image and passing it to the ConvNet, which returns feature maps for the image. Then, it applies a Region Proposal Network (RPN) on these feature maps and gets object proposals. Then, it Applies the ROI pooling layer to bring down all the proposals to the same size. Finally, these proposals are passed to a fully connected layer to classify and predict the bounding boxes for the image. [11]

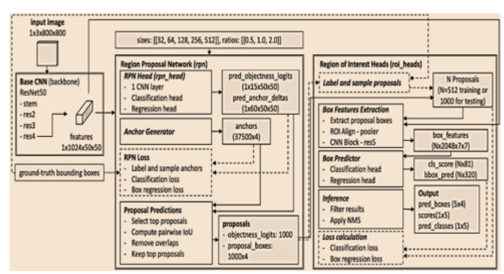

Fig. 4. Detectron2 Faster RCNN Architecture.

IV. Implementation Result

From the model, we have obtained some feasible results. For two datasets, we found two types of results for two models.

A. Defect Detection

We applied these two models to two datasets (Textile and Car). From there, we observed how the models provided outputs based on the input images. While there is still room for improvement in predictions, the models provided outputs that were largely positive.

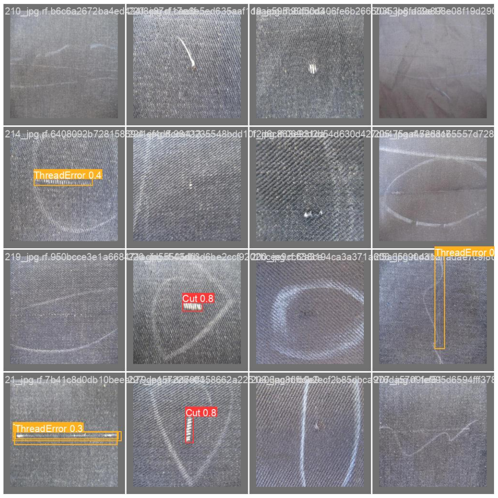

Fig. 5. YOLOv9 Textile Dataset Image.

Fig. 6. YOLOv9 Car Dataset Image.

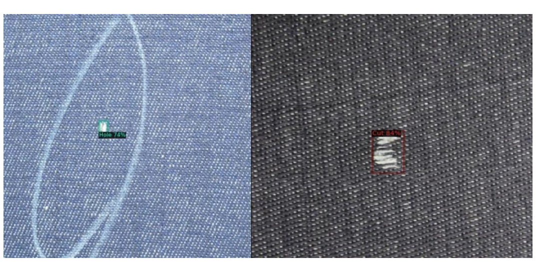

Fig. 7. Detectron2 Textile Dataset Result.

Fig. 8. Detectron2 Car Dataset Result.

B. Performance of the Model

1) YOLOv9

TABLE I
YOLOV9 PREDICTED RESULTS ON TEXTILE DATASET

Epochs	Training Loss		Performance Metrics		
	Box Loss	Cls Loss	Precision	Recall	mAP @ 0.5 IoU
24	3.8051	6.7232	0.0004	0.055	0.0009
25	3.8063	6.7176	0.0010	0.068	0.0017

TABLE II
YOLOV9 PREDICTED RESULTS ON CAR DATASET

Epochs	Training Loss		Performance Metrics		
	Box Loss	Cls Loss	Precision	Recall	mAP @ 0.5 IoU
24	1.4152	1.2151	0.76468	0.52177	0.53732
25	1.3852	1.179	0.86277	0.49577	0.57697

2) Detectron2-Faster-RCNN

TABLE III
D2-FASTERRCNN PREDICTED RESULTS ON TEXTILE DATASET

Iteration	Cls_Accuracy	False_Negative	Total_Loss
2979	0.97	0.38	0.23
3000	0.98	0.41	0.16

TABLE IV
D2-FASTERRCNN PREDICTED RESULTS ON CAR DATASET

Iteration	Cls_Accuracy	False_Negative	Total_Loss
2979	0.98	0.20	0.17
3000	0.97	0.20	0.20

V. FUTURE WORK

We have only collected from online, which is needed for the model to recognize the default. So we need to have to collect more data. If we can collect data from the manufacturing industry, we can get better results. So, we are working on gathering more data. After collection, our target is to label all the data we have collected manually, which might be from industry or car workshops for the particular car datasets. Till now, we have only fed the dataset to the model without any preprocessing technique. After labeling the data, our target will be to use different preprocessing techniques to help the model perform better. Lastly, we will apply augmentation and balancing techniques to process the image. In the model part, we have not yet done any fine-tuning. So, our observation in the next task for the model is to determine which way we can get the best results. According to the fine-tuning then, we will apply it to our final model.

Our last work only observed how models behaved about the dataset. We didn't have enough time to create a standard quality checklist for the product. So, we are working on creating a QC checklist based on the Input Image.

Lastly, these are our ideas for getting the best output from the input. We might have to change a lot of things according to the situation.

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