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REAL-TIME DETECTION OF PRINTING DEFECTS WITH YOLOV5 MODELS

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Abstract. *This study applies the method of using YOLOv5 to designing a real-time inspection system for the printing process of plastic injection molded products. During the process of printing and transferring markings on plastic products after the injection molding process, defects such as scratches can occur. A computer vision system based on deep learning techniques develops to improve the process of visually inspecting and determining the quality of the markings. This system applies deep learning algorithms to automating the inspection process. The YOLO model is selected as the deep learning model due to its fast detection speed and relatively high accuracy. A dataset is constructed using actual products, and the YOLOv5 model is trained on this dataset. Three different versions of YOLOv5 are compared to find the optimal model. The accuracy of YOLOv5s, based on the F1-Score, measures 0.9995, with an mAP@0.5:0.95 of 0.9206 and an FPS (frames per second) of 20.8. These results are expected to provide assistance in detecting defects and managing the quality of products in manufacturing processes.*
Keywords: Object detection, YOLOv5, Defect detection, Printing process

1. **Introduction.** Product defect inspection is an important process related to product quality in the production process [1]. Automated inspection systems using computer vision technology have gained significant importance in improving product quality and productivity in various industries. In the specific context of the printing process of plastic injection molded products, operator visual inspection is commonly used but can be costly, time-consuming, and prone to errors. To overcome these limitations, this study aims to introduce automated inspection systems to small and medium-sized manufacturing enterprises.

In addition, there is a wide range of related research and practical industrial applications [2]. Deep learning algorithms are widely used to detect defects in products, and this paper uses the YOLO (You Only Look Once) algorithm in consideration of the current production site, product characteristics, and partial detection of certain defects. Compared to other deep learning object detection algorithms, YOLO has a fast processing speed and relatively high accuracy [3]. The selected performance evaluation metrics are compared among various versions of YOLO, and the YOLOv5 model is chosen and compared. Based on the measurement results, application of the YOLOv5 model enables real-time detection of printing defects on plastic products. This paper presented an inspection system based on an artificial intelligence-based automatic defect detecting method for small and medium-sized manufacturing enterprises, which aims to improve the product quality and productivity.

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In the rest of this paper, we organize the content of this paper as follows. Section 2 discusses the related works and Section 3 explains the research process. After describing the results of the research in Section 4, Section 5 concludes the content of this paper.

2. **Related Works.** Detecting defects in products during the printing process is a crucial step before putting them on the market. In recent years, many research groups have paid attention to improving defect detection accuracy using several different approaches, especially deep learning algorithms. In this section, we discuss some recent studies that have applied deep learning methods and other advanced techniques to detecting defects in products during the printing process.

Shankar and his colleagues introduced an approach for creating a real-time defect detection for web offset printing [4]. They deployed a system for detecting and locating non-uniformities in a web offset printing machine. The system could monitor high-speed web offset printing in real time and alert the operator of any detected faults. The approach involved comparing two images during the fault identification process: a "golden master" or reference image and an actual print image. To validate the proposed system, they used a dataset consisting of 94 images of streak defects, 95 hazing defects, 73 structural defects, and 86 images of color splashes. The system achieved a correct average detection rate of 95.5%. The advantage of this study is that the authors proposed a potential solution to detect defects on the surface of printed products in real time. However, the authors had not yet given the real-time defect detection processing speed. Furthermore, to detect defects in the image, they had to use a reference image for comparison, and some images needed to be put in the same position as the checking image during the comparison. This activity led to time-consuming during the defect detection process.

Detecting defects in 3D printing using deep learning methods, in [5], Khan et al. introduced an approach for detecting defects in 3D printing using machine learning. The approach used a convolutional neural network (CNN) and extracted features of geometrical anomalies that occur in infill patterns to detect malicious defects in 3D printing. For training the model, they created a neural network with three convolution layers, three fully collected layers, and one dropout layer to prevent overfitting. For training the model, 1695 images (1454 defected and 241 without defects) were used with the infill pattern of honeycomb, linear, and grid. The authors' model achieved an accuracy of 84% with 50 epochs.

Computer vision techniques have seen significant advancements since the introduction of deep learning. Tasks in computer vision, including image classification and object detection, previously required manual specification of image features or model rules by users. However, since the development of deep learning, neural network models can autonomously derive features and rules from objects in the image, leading to improvements inconvenience and performance in computer vision. CNNs have played a particularly important role in advancing computer vision [6].

Using CARL-YOLOF [7], Wu et al. proposed the classification-aware regression loss (CARL) method embedded into YOLOF [8] to correlate the classification and localization tasks. The implementation of the proposed model has been trained and evaluated using a digital printing fabric dataset. Experimental results in the study indicated that their approach achieved 0.54 AP on COCO metrics, against 0.04 compared with YOLOF, and maintained the speed advantage of YOLOF, which reaches 42 FPS. For training the CARL-YOLOF model, they divided it into two parts: 1) The YOLOF and 2) The CARL module. In the CARL module, there are two processes, i.e., establish the loss functions and represent the definition of the positive and negative anchor using the Uniform-Match strategy. In this study, the authors introduced a fantastic solution, improving YOLOF to help detect defects from images with very high processing speed (42FPS) while achieving good inference accuracy (AP50 0.73).

In [9], Baumgartl et al. introduced a deep-learning model for detecting defects in the laser-powder bed fusion process using in-situ thermographic monitoring. In this study, the authors used a combination of thermographic off-axis imaging (data source) and deep learning-based neural network architectures to detect printing defects. The architecture of the method consisted of three blocks of convolutional and batch-normalization layers and was mainly based on the depthwise-separable convolutions described in [10]. With the proposed method, delamination and splatter defects in the laser-powder bed fusion process can be detected with an accuracy of 96.80%, as shown in the results of the study. However, the disadvantage of this method is that it is expensive to implement this method in real life due to the installation of cost temperature-measuring devices. Besides, it is difficult to apply this method to different types of products.

The studies mentioned here are among many other methods that use deep learning and machine learning for defect classification in the printing process. The following section describes in detail our proposed approach to building a model for creating a real-time inspection system in the printing process with the YOLOv5 model.

3. Research Process.

3.1. Definition of the problem. This study focuses on the printing process of a small-sized manufacturing company engaged in the production of plastic injection molding products. The company utilizes extrusion and injection machines to manufacture a wide range of plastic products, including plastic cores, office supplies, cleaning products, and packaging materials. During this process, the products are printed with barcodes, symbols, company names, and other relevant information as per customer requirements. However, the presence of defects in the printed products is a common occurrence, and currently, these defects are inspected visually by an operator.

Accurate identification and assessment of defects are crucial for addressing and preventing various issues related to product reliability, quality, and cost. Failing to evaluate the presence and severity of defects can have direct implications on product quality and cost, making it a matter of utmost importance. The current approach of relying on operator inspection for defect detection is associated with high costs and is prone to errors caused by subjective judgment [11,12]. Therefore, the objective of this study is to propose the implementation of a real-time inspection system that leverages computer vision techniques to address these challenges in the printing process.

3.2. Selection of deep learning model. After reviewing relevant research papers on the history of object detection, deep learning models from computer vision technology were identified as suitable for the task at hand. There are several approaches to object detection, including one-stage detector methods such as YOLO and SSD (Single Shot MultiBox Detector), as well as two-stage detector methods such as RCNN (Regions with CNN). Considering the requirement for faster real-time detection, particularly during the product's passage through the printing process, the YOLO model was chosen as the object detection model. It performs classification and region proposal simultaneously. It demonstrates fast detection speed and relatively high accuracy, making it well-suited for the objective of detecting defects quickly and in real time, as stated in Section 3.1.

3.3. Data definition. The dataset used in this study consists of real product images obtained from the plastics manufacturing process. To train the model for defect detection in the printed parts, the images were carefully examined and labeled with the respective states of the printed parts. To accomplish this, a free and open-source tool called labelImg was utilized, which allowed for the annotation of the regions of interest (ROIs) within the images. Bounding boxes were placed around the relevant objects, and the coordinates of these boxes were recorded in a txt file, containing the necessary information for the bounding boxes.

In terms of the product quality classification, the dataset includes two classes: "OK" for products without defects and "NG" for products with defects. Within the "NG" class, there are two sub-classes: "NG_Blur" for products with blurry prints in the detected area, and "NG_Scratch" for products with scratches. It is important to note that scratches occur three times more frequently than blurriness in the dataset. Table 1 provides the ratio and number of data samples for each class, taking this imbalance into consideration.

TABLE 1. Number of images for model training

Quality	**Class**	**Number of images**
OK	OK	400
NG	NG_Blur	100
	NG_Scratch	300
Total		800

To enhance the model's accuracy, additional images were generated by altering the position and angle of the ROIs. This augmentation technique helps to increase the diversity and robustness of the training data, improving the model's ability to generalize to new examples. Figure 1 provides a visual representation of the labeled data, illustrating the bounding boxes and the different classes of defects.

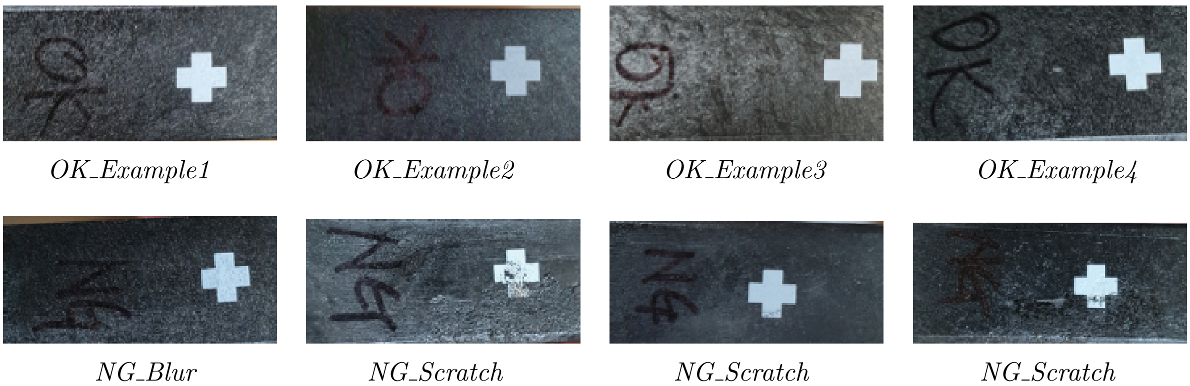


FIGURE 1. Example of label image of the printed product

3.4. **Application of YOLO model.** The YOLO model has several versions, with YOLOv5 being particularly notable for its fast detection speed and relatively high accuracy. Each version of YOLO has distinct model architectures and sizes. When comparing YOLOv5 small, YOLOv5 medium, and YOLOv5 large, it is observed that accuracy increases from small to large, but at the cost of reduced detection speed.

The performance metrics of the model include mean average precision (mAP), recall, precision, and F1-Score. Given the potential ambiguity in manually created bounding boxes, both object detection evaluation metrics and classification model performance metrics are considered. As a defect detection model, the detection of false positives, where non-defective items are incorrectly identified as defective, is considered more sensitive. Therefore, precision is given priority in making judgments. The evaluation of the model in this context focuses on precision, given its higher sensitivity towards false positive cases where non-defective items are mistakenly identified as defective. mAP is calculated by multiplying the Intersection over Union (IoU) with average precision. IoU is a metric that predicts the bounding box in object detection, with values ranging from 0 to 1. The average of the values multiplied by the respective average precision values with increasing

IoU thresholds from 0.5 to 0.95 is the value mAP@0.5:0.95, which is used for the evaluation of this study [13].

$$\text{F1-Score} = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{1}$$

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union} \tag{2}$$

The performance of a system can be evaluated using the number of frames per second (FPS), which represents the speed at which frames are processed in a video. A higher FPS value indicates smoother and more natural motion, as well as faster detection capabilities. Therefore, FPS is used as a metric to assess the performance of a system, with a higher FPS indicating better performance in terms of speed and efficiency [14].

We trained YOLOv5 models on the collected data. The models detect defects by taking pictures with a webcam as the product moves on the conveyor belt. This process enables real-time product quality inspection. Training environment is set on a GPU with 24GB RTX 3090, an Intel i9-12900KF CPU, and 128GB of Ram, and parameters are set to an image size of 640, a batch size of 16, and 300 epochs for all models.

4. **Results.** To detect the printing defects of the product, a dataset of defective parts was created, and a detection method was applied by training a YOLOv5 model. Table 2 shows a comparison of the performance evaluation for YOLOv5's small (s), medium (m), and large (l) versions.

TABLE 2. YOLOv5 model comparison

Model	Precision	Recall	F1-Score	mAP@0.5:0.95	Hour	File size	FPS
YOLOv5s	0.9995	1.0000	0.9995	0.9206	1.0	14 MB	20.8
YOLOv5m	0.9996	1.0000	0.9996	0.9449	1.4	41 MB	15.9
YOLOv5l	0.9996	1.0000	0.9996	0.9524	2.3	90 MB	12.7

When checking the performance by metric from YOLOv5s to l, YOLOv5s has the lowest accuracy, but it also has the lowest training time, smallest file size, and highest FPS. However, YOLOv5l shows the highest accuracy, but it has a long training time and a large file size. It also has the lowest FPS.

As shown in Figure 2, accuracy differences between the models in YOLOv5 can be seen, and all three models show relatively high accuracy.

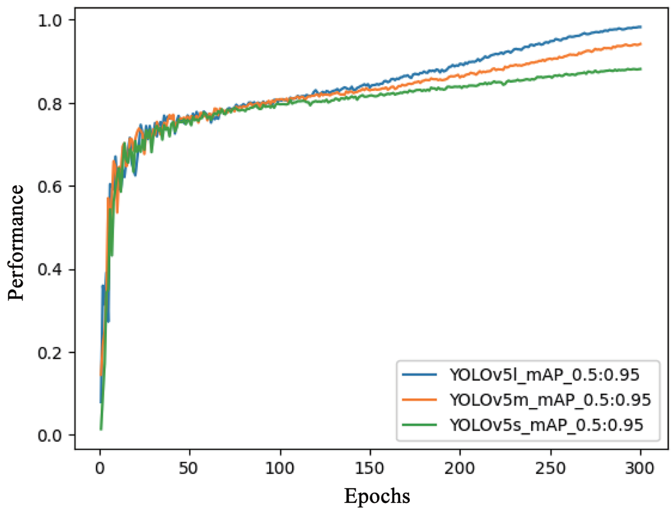
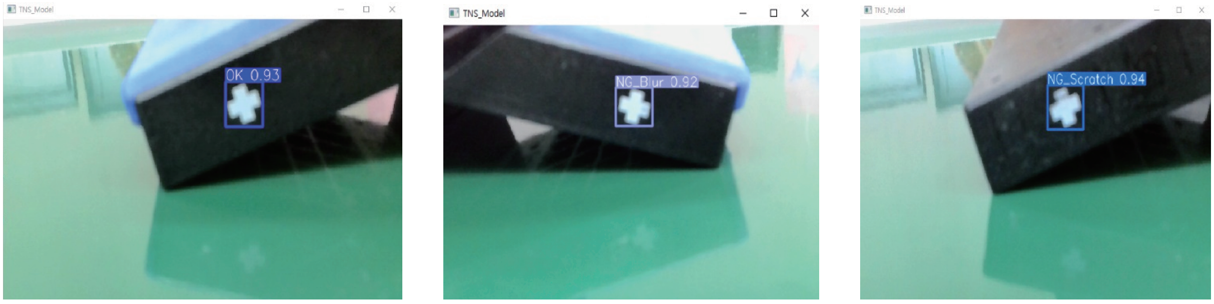


FIGURE 2. mAP comparison of three YOLOv5 models

The model utilized in this study is based on YOLOv5s, taking account of the aforementioned performance metrics. Figure 3 displays the detection results for defective parts of the product. The figure demonstrates accurate and real-time detection of the defined labels when identifying defects in the product. These results affirm that the model can effectively detect defects in products with a high level of inspection accuracy and speed within this process.



OK Detection NG_Blur Detection NG_Scratch Detection

FIGURE 3. Test screens using a webcam

In addition, we considered the possibility of replacing the network layer of YOLOv5 in our defect detection model to further improve accuracy, given a study of [15]. We also explored the possibility of addressing the impact of external factors such as environment and illumination on defect detection and increasing the robustness of our model [16]. This suggests that our model can contribute to improving reliability and performance in real-world industrial environments.

5. **Conclusions.** The primary objective of this research is to leverage deep learning-based computer vision techniques to develop an automated system that can detect defective parts of products and assess their performance. By utilizing the YOLOv5 model, defects in the printed parts of products within the plastic manufacturing process can be effectively detected, thereby enhancing the visual inspection process and increasing productivity in industrial settings. To train the YOLOv5 model, a dataset was curated by capturing product images using a webcam and labeling them with the assistance of labelImg. A total of 800 images were used, encompassing three classes: normal (OK), blurred (NG_Blur), and scratched (NG_Scratch). Data augmentation techniques were employed to generate additional images by varying the positions and angles based on the ROI. The performance of the model was evaluated using the mAP value and FPS value for object detection for the classification model. Based on the evaluation, the YOLOv5s model demonstrated impressive performance, achieving an F1-Score of 0.9995, an mAP@0.5:0.95 of 0.9206, and an FPS of 20.8.

By replacing the operator's visual inspection process following plastic injection molding and printing with the YOLOv5's trained models, it is possible to automatically detect product defects, leading to cost reduction and process productivity improvement.

In the future, there is potential to expand the application to identify printing errors on both sides of the product and transmit the results to a database for real-time production monitoring. The stored data can be utilized to generate lot-level summary files and control charts, enabling the identification of process anomalies during inspection. Additionally, the operating characteristic curve can be leveraged to determine the acceptability of a process. By incorporating statistical quality control techniques, the overall process can be further improved, enabling prompt action to be taken in response to any detected anomalies.

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