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A YOLO-based Real-time Packaging Defect Detection System

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Abstract

Managing the quality of products is one of the primary concerns in manufacturing production to obtain better operational efficiency in factories. In recent years, there have been numerous different approaches for improving product quality management in manufacturing. Each method has certain advantages and limitations, and the common goal is to bring the best efficiency in managing product quality before delivering them to consumers. In this paper, we introduce an approach to creating a real-time packaging defect detection system based on deep learning techniques intending to automatically detect defective packaged products in industrial quality control of packages. To be more precise, we present a real-time defect detection system to help classify product quality automatically based on the YOLO (You only look once) algorithm. The system can be integrated into factories and production lines, helping to optimize efficiency and save operating costs.

Keywords: Product defect detection; Deep learning-based system; YOLO-based system; Quality control in manufacturing; Industrial quality control.

1. Introduction

In recent decades, many emerging technologies have been introduced and applied to enhance production line productivity and product quality in manufacturing. If workers had to participate in many stages in the production process of products in the past, those positions are gradually replaced by automatic machines and software today.

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Along with that replacement is the assurance of product quality throughout the production process. Consequently, the destination of producing products without defects is always of significant concern to managers in factories and manufacturing plants. ZDM (Zero defect manufacturing) is a manufacturer's attempt to remove defects and faults from products before delivering them to consumers. Manufacturing defects are inevitable due to different causalities, such as input materials and product processing. Hence, in order to control product quality, keeping defective products in the factory, and distributing only intact products to consumers are vital activities for manufacturing plants [1][2].

Artificial intelligence and deep learning algorithms have brought great efficiency in product creation in the era of the fourth industrial revolution [3][4][5][6]. In the factory, the production operation is synchronized from the management of input materials to creating the final product and its quality monitoring. Minimizing the involvement of employees in the production process will save costs and improve product quality. However, the efficiency of mechanization is a challenge for factories in replacing workers with machines [7][8]. The construction of a new manufacturing plant with modern equipment and technology is often expensive but not feasible for small and medium enterprises (SMEs) [9][10][11]. How to take advantage of using the existing infrastructure and applying new technologies in the production process is a concern for SMEs.

With the development of AI and deep learning algorithms, many studies and proposals have been presented for application in predicting the quality of products, such as using the long-short term memory models for predicting product status [12][13][14][15], using the deep neural network [16][17][18], classification methods for predicting quality in manufacturing [19][20][21][22][23], etc.

This paper introduces a deep learning-based approach for creating a real-time product defect detection system in factories. In particular, we present an architecture to create a system to predict the quality of boxes packed in the production line in real-time. Based on the YOLO algorithm [24], we trained a model to predict damaged and intact packages during product packaging in the factory [25]. Later on, with the trained model, we built a system to detect defective products (damaged boxes) in real-time. The system can be readily installed and deployed at factories with existing infrastructure (CCTV cameras and connected computers). Operating this system will benefit production lines and save human resources involved in the procedure, thereby enhancing system operating efficiency and saving production costs.

In the rest of this paper, we organize the content as follows. Section 2 discusses related works about zero defect in manufacturing, using deep learning algorithms and applying them to predict quality and detect defects of products. Section 3 presents an overview of the YOLO algorithm, how it works, and its application in different prediction models. Section 4 describes our proposed architecture and components for building a system to detect defects of packaging in real-time. Section 5 presents the experimental results of the approach applied to packaging images from a real factory. Finally, Section 6 discusses some conclusions and future works for development.

2. Related Works

In this section, we discuss some recent studies related to zero defect in manufacturing, product defect detection approaches, and using deep learning algorithms to detect defects of products.

Psarommatis *et al.* surveyed studies published from 1987 to the present on defect elimination in factory production lines - zero defect manufacturing [1]. They pointed out four zero defect manufacturing (ZDM) strategies: detection, repair, prediction, and prevention. ZDM is about reducing faults in the product, part of the product, and the production energy consumption, among several different indicators. Detection is the most used in the above strategies, and the product quality inspection takes place after the product's manufacturing is completed.

Yang *et al.* introduced a method using SVM (support vector machine) to detect defects in logistics packaging boxes [26]. This study designed an image acquisition process and proposed an approach to address packaging box defect detection in logistics. In the beginning, they described a mean denoising template and Laplace sharpening to enhance the image quality of packaging boxes. After that, an improved morphological method and a gray morphological edge detection algorithm were introduced to remove noises from images of boxes. Finally, the features of packaging boxes were extracted and transformed using the scale-invariant feature transform algorithm and SVM classifiers to classify the package quality. The results showed that their approach could detect two common types of defects in logistics packaging boxes (surface and edge defect) with correct detection probability archived at 91.2%.

Li *et al.* presented a method to detect the Steel strip surface defects in real-time based on the YOLO algorithm [27]. In the approach, they described a method to improve the YOLO network and made it all convolutional. Their method provided an end-to-end solution for detecting the surface defects of steel strips. The network achieved a detection rate of 99% at a speed of 83 FPS. Besides, the method could also predict the location and the size information of defect regions. To improve the YOLO network, they constructed all convolutional in YOLO with 27 convolutional layers. The first 25 layers are used to extract information about surface defect features on the steel strip, and the last two layers are used to predict the category of defects and their bounding boxes.

Aein *et al.* presented a system for inspecting the metal surface [28]. In the study, they used the YOLO object detection network as a model for examining metal surface defects. A metal surface inspection system that can distinguish the types of defects and encounter the defect was also introduced and implemented on a Jetson Nano board to detect surfaces on a dataset provided by Northeastern University. The result of mAP, 71% was achieved with six types of defect, and the processing time was about 29 FPS.

Xu *et al.* presented an approach to modifying the YOLO network to improve metal surface defect detection [29]. The approach generated a new scale feature layer to extract more features of minor defects from the metal surface. To do that, they combined the features of the 11th layer in the Darknet-53 with the in-depth features of the neural network. Consequently, the K-Means++ algorithm was used to decrease the sensitivity of the initial cluster. Their study reached an average result of 75.1% and the processing time was about 83 FPS.

Yang *et al.* proposed a real-time tiny part defect detection system in manufacturing using the single short detector (SSD) network and deep learning [30]. In the study, they presented a method to detect some tiny parts of defects by dividing the procedure into three steps. In the first step, they considered the important influences of properties of tiny parts and the environmental parameters on their stability. After that, by establishing a correlation model between the detection capability coefficient and the moving speed of the conveyor. Finally, they presented an algorithm and platform working with the SSD network for detecting tiny part defects. Their system predicted tiny parts of 0.8cm darning needle defects with high accuracy (98%, 99%, 97.8%, and 79.4% with different defects).

The application of deep learning algorithms to predict the quality and defects of products in the production lines is feasible and is being improved by researchers to bring better results. Through the studies we have just discussed, it can be seen that, in recent years, researchers have been focusing on understanding and studying different solutions for the purpose of supporting the operation of production lines in automated factories by predicting product quality results and detecting defects. With the same objectives, in this paper, we propose a solution to detect defects of packaging in real-time with the YOLO network and describe how to build the system and integrate it into existing facilities in a factory. In addition, we introduce the architecture and systems to integrate and operate defect detection in the production lines in real-time. The next section describes the YOLO network and its applications.

3. YOLO Network

The first version of YOLO network was introduced by Redmon and his colleagues in [24]. YOLO is a new approach to detecting objects in images/frames. The main idea of the algorithm is that object detection is considered as a regression problem to separate bounding boxes of objects and associate each bounding box with a class probability. The method uses a single neural network to predict bounding boxes and class probabilities directly in images/frames in one pass. Figure 1 illustrates the strategy of the YOLO algorithm, its architecture yields prediction extremely fast compared to the other object detection methods while maintaining high mAP prediction results. The YOLO algorithm detects objects in three main steps [24].

- Step 1. Resizes the input image to 448x448.
- Step 2. Runs a single convolutional neural network on the image to predict multiple bounding boxes and class probabilities.
- Step 3. Thresholds of the resulting detections by the model's confidence.

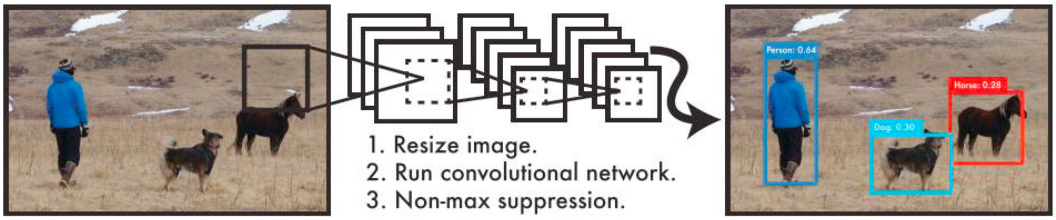


Fig. 1. The YOLO detection system (Reprinted from [24])

Although introduced in the recent six years, the YOLO algorithm has dramatically impacted the field of object detection and computer vision in general. Researchers have improved various versions of YOLO to make it work even better. Various problems and applications have used YOLO to support object prediction, such as early detection and diagnosis of cancer [31][32][33], automation in production lines [34][35], robots and self-propelled devices [36][37].

4. Real-time Packaging Defect Detection System

4.1. The proposed system for detecting packaging defects in real-time

In this section, we present the architecture, components, and functions of the YOLO-based real-time packaging defect detection system. The architecture consists of four main components and as shown in Figure 2. The functions of these components in the architecture are as follows.

- **YOLO Network.** First of all, the outside images of the packaging boxes collected from the cameras will be labeled and classified as defective/non-defective or damaged/intact through external appearance assessment. Then this module builds the YOLO network as described in [24] and trains the network with annotated images to produce the trained model. After that, the model will be put into the packaging defect detection system for detecting defects of boxes from the conveyor belts.
- **Real-time video receiving.** This module collects data from the cameras mounted on the conveyor belts and transmits frames of packages in real-time to the server. We utilize FFmpeg [38], a popular open-source, cross-platform solution used in video processing and streaming to support real-time frame processing.
- **Packaging defect detection.** This module manages frames sent from the Real-time video receiving module in a queue. Each frame in this queue will be resized and then put into the trained model to predict the probability values of which class the packaging boxes belong to. Finally, the prediction results of this frame are transmitted to the Automatic classifier module.
- **Automatic classifier.** Based on the probability values received from the Package defect detection module with a given threshold, this module will automatically process the classification of packages, giving the decision whether a package is defective or not. After that, information of defect package is sent to the robot arm to move the damaged package out of the conveyor belt.

With this architecture, we can proceed to install the system in production lines to support packaging quality detection. Of course, each specific production line will have its characteristics, and the architecture may be differentiated according to different manufacturing.

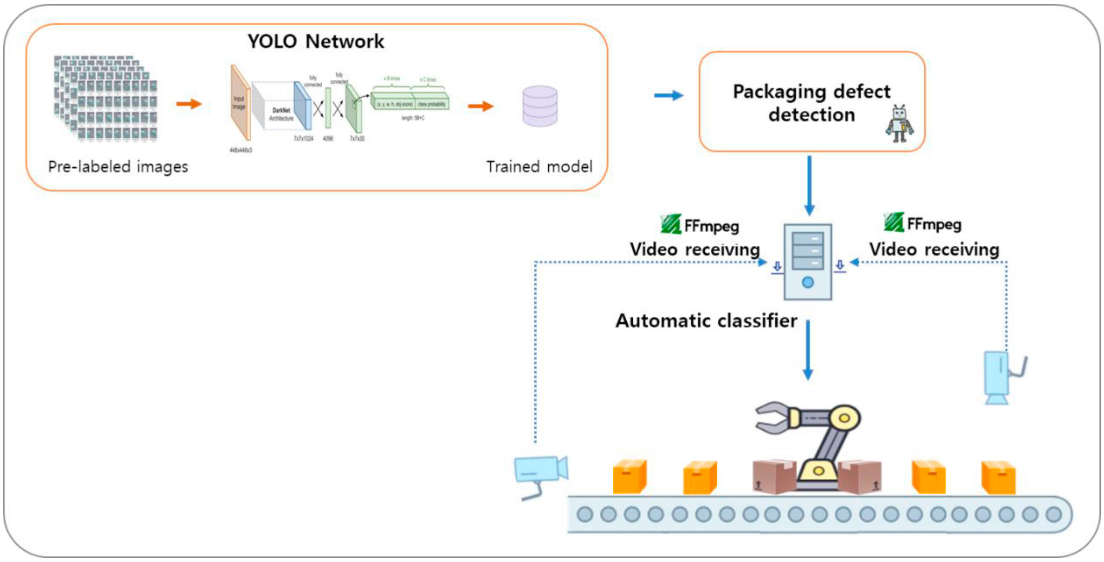


Fig. 2. The architecture of the proposed system for detecting packaging defects in real-time.

4.2. Measuring method

For measuring the accuracy of predicting which class the package belongs to (intact or damaged package), the mAP (mean average precision) and Precision metrics were used and calculated as follows.

$$(1)\ Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \qquad (2)\ Precision = \frac{TP}{TP + FP}$$

$$(3)\ mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i$$

Where: TP: True positive; TN: True negative; FP: False positive; FN: False negative.

We choose the prediction confidence threshold in YOLO to be 0.6 to calculate the mAP value as this value is larger than average (0.5) and acceptable. In future studies, we will further analyze the selection of a suitable threshold along with the threshold adjustment during system operation.

5. Experimental Results

In this section, we conduct the experiment on the proposed architecture with data from real manufacturing and provided by [25] through the Kaggle platform. The dataset contains images of packages from a production line classified into two classes:

- Damaged boxes: This class includes 200 image files of damaged boxes.
- Intact boxes: This class contains 200 image files of intact boxes.

Two cameras are used for capturing package images. One image is from the above camera, the other from the side camera, as shown in Figure 3. Each package is determined by a unique serial number (SN) visible on the side-view of the package. This number is used for naming the files in the dataset ({sn}side.png and {sn}top.png). We use 70% of images in the dataset for training, 20% for validating, and 10% for testing.

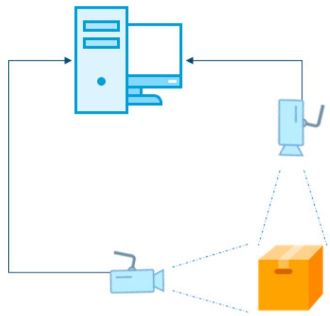


Fig. 3. Capturing method for collecting input images.

Using the YOLOv5s with default parameters [39], we trained the model through 150 epochs and got the training results of mAP, precision, and loss values, as shown in the charts in Figure 4.

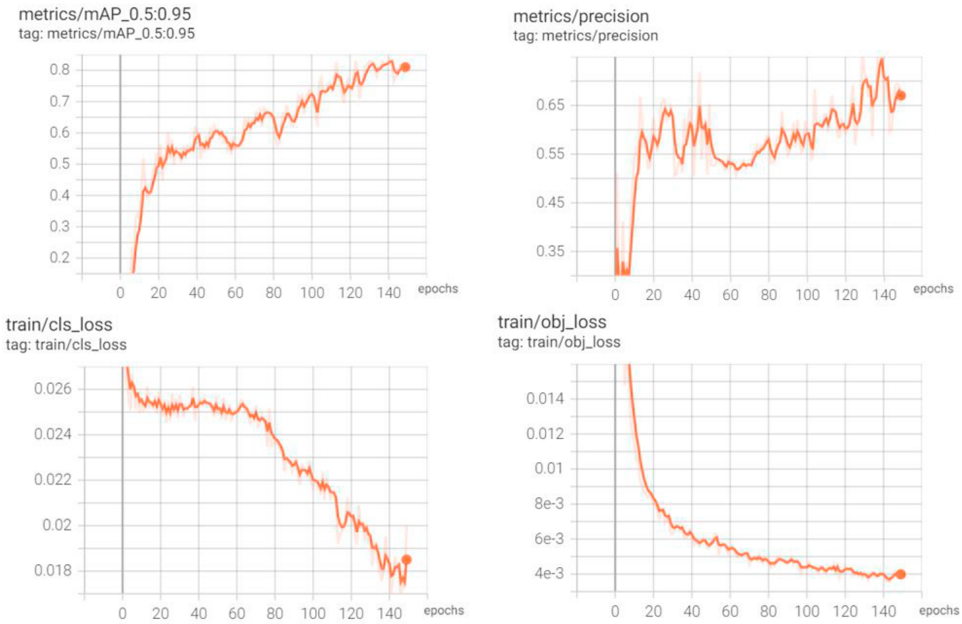
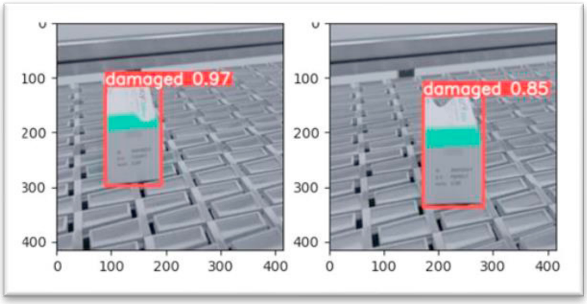


Fig. 4. Training results with the dataset

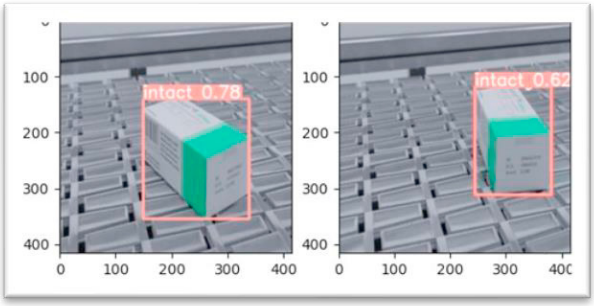
Figure 5 illustrates image results of detected damaged and intact boxes classified into TP, TN, FP, and FN groups. The top-left and top-right subfigures contain images of damaged and intact boxes detected from the system correctly. The bottom-left and bottom-right subfigures have images of boxes detected fail from the system. In this experiment, to simulate the real-time camera capturing packages on the conveyor, we proceed to combine the images in the original dataset to form a 30 FPS video. Each image of the packaging is displayed in the video in 3 seconds to simulate that the boxes pass the camera in 3 seconds. This duration is convenient for comparing the detecting defect results with our eye's vision. As a result, the values obtained are as follows in detecting the quality of 40 packages.

Precision: 81.8%, Accuracy: 82.5%, and mAP: 78.6%.

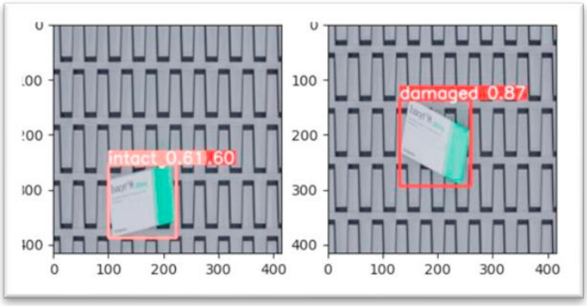
The instructions for using the system, how to create the component modules, and the results of all detected images are described in the *Repository section*.



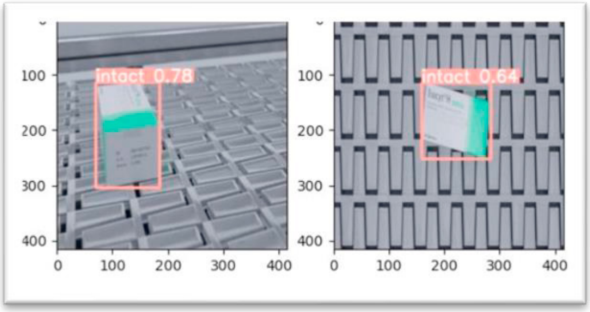
(a) Detected true positive (TP) boxes



(b) Detected true negative (TN) boxes



(c) Detected false positive (FP) boxes



(d) Detected false negative (FN) boxes

Fig. 5. Detected boxes from the system.

6. Conclusions and Discussions

Over the last few years, deep learning has significantly reduced human involvement in production lines and supported product defect detection before distribution to consumers. Using a deep learning system, manufacturing factories save costs and improve product quality, ensuring stable development. In this paper, we have introduced a real-time packaging defect detection system based on the YOLO algorithm for detecting defects on boxes from the conveyor belt. To be more precise, we:

- summarize the recent studies about using deep learning techniques for applying in manufacturing to detect defects of products;
- propose an architecture for creating a real-time system to detect defect boxes from the conveyor in manufacturing;
- create the YOLO-based real-time packaging defect detection system and apply the system to a dataset provided by a real company through the Kaggle platform.

Besides the obtained results, there are still some limitations and problems related to packaging defect detection that the paper has not yet solved and need to be discussed to solve in future studies:

- How to select a suitable threshold value to decide whether the packaging is damaged or intact. Different sides of each packaging will lead to different decision results, which sometimes leads to inaccurate prediction results. Also, different types of defects on packaging have not been classified.
- Two cameras are insufficient to conclude that the packaging is not a defective product. Sometimes the defective side of the product is hidden or located at the bottom. As a result, the defective image is not recorded, and the system can not detect it.
- The system is not flexible. If the manufacturing factory changes the product packaging design or product style, we must conduct labeling and train the new model.

- The system has not tracked the package on the conveyor belt. If the conveyor belt's speed is increased or multiple packages are lined up simultaneously passing through the cameras, the system cannot locate the defective product. Adding product tracking algorithms on the conveyor belt or integrating the packaging identification function through barcodes is necessary.

In future studies, we will try to deal with these outstanding issues and improve system performance. At the same time, we will collaborate with some manufacturing companies to put the system into practice.

7. Repository

All the source code, programs, and libraries for producing experimental results in this paper can be downloaded at https://github.com/vuthithuhuyen/A-YOLO-based-Real-time-Packaging-Defect-Detection-System

8. Acknowledgment

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