Application of Improved Yolov3 for Pill Manufacturing System ★

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Abstract: Pill defects encountered during the manufacturing process may cause in low quality product and high timeline delays, and costs. In this paper, an improved convolutional neural network is proposed for automatic pill defects detection during pill manufacturing. In the first step, Gauss filtering and smoothing techniques is implemented for complex background-weakening purpose. Then, Hog feature extraction is executed to simplify the representation of the image that contains only the most important information about the image. The aim of this sub-process is to reduce the computation burden. Lastly, an improved YOLO model is proposed for online detection of pill defects and it was validated on our experiment platform in the laboratory for online pill defect detection. The proposed approach obtains robust quantification of internal pill cracks. This proposed approach is effective tool implemented into the industrial pill manufacturing system.

Keywords: Quality Inspection, improved YOLOv3, Deep learning, detect defection, image processing.

1. INTRODUCTION

The pills manufacture is a complex operation to guarantee the sufficient quality for patient use. In the manufacturing chain, pills may encounter some factors which can cause defections such as crack or contamination. These defections are issued by failure in the quality inspection process. As consequence, inequality pills may cause therapeutic problem or decreasing patients' acquiescence. Accordingly, the pills quality control is an requisite aspect to advance the level of the pills manufacturing line.

Various studies have been investigated for pill defect detection based on computer vision techniques. The visual features such as shape, color, imprints and scoring are used to identify pills . A pill recognition techniques are developed by the United States National Library of Medicine, named "Pill Box" (Z. Yaniv et al. (2016)). Besides, (D. Ushizima et al. (2015)) study pill recognition methodologies on a new pill image data set and data planning. A three-stage approach included bar code recognition, text recognition, and feature matching) is proposed in (L. Magalhaes et al. (2017)). The system consists of a camera mounted on a device with Android system to provide the related medication packaging information for the users. The recognition accuracy is 80%. In (J. J. Caban et al. (2012)), pill features (shape, imprint and color) are implemented for a pill recognition with augmented images process. The augmented process is generated by random perturbation of the reference images. In (Ling, S. (2020)), authors provide a new pill image database with more varied imaging conditions and instances for each pill category, namely CURE. Normally, the vision-based methods heavily relies on the lighting conditions. As consequence, detection accuracy is not very robust.

Recently, deep learning techniques are applied for in daily life (J. Yang et al. (2018); G. Yang et al. (2018); J. Yang et al. (2018)) and industrial fields (Y. Xu et al. (2018); M. Trobe and M. D. Burke (2018)) in general and detecting part defects (J. Yang et al. (2018)) in particular. Deep learning techniques have become a promising research domain toward visual inspection. To obtain the better results of real-time defect detection, the essential requirement are fast detection processing and high classification accuracy. The most popular deep learning approaches are You Only Look Once (YOLOv3) (J. Redmon and A. Farhadi (2018)), FAST-RCNN (R. Girshick (2015)), DCN (Deep Convolutional Network) (A. H. Sabri et al., (2018)) and FPN (T. Lin et al. (2017)) In which, YOLOv3 uses an end-to-end method to regress features to reduce computational burden. Several studies indicate that YOLOv3 is more advantage than other approaches. Compare to SSD, FPN and other target recognition networks , YOLOv3 requires lower computation burden.

In this paper we present an improved Yolov3 to detect internal crack/contamination pills in the intelligent manufacturing system. In the first stage, Canny and Gauss filtering are implemented for pill detection. Then, Hog feature extraction is used to simplify representation of the image. In the final stage, improved YOLO is proposed for online detection of pill defects process. The proposed approach produces reference for the pills manufacturing industry to enhance production efficiency, product quality, and reduce laborious.

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This paper is organized as follows. In section 2, we explain the system design in subsection 2.1. In addition, the improved Yolo structure is introduced in subsection 2.2. In section 3, we give a description of experiment results and discussions. Finally, conclusion and future work are provided in section 4.

2. SETUP SYSTEM AND METHODOLOGY

The system is designed in lab-scale as shown in Fig.1 which includes main components: computer (PC), camera, two conveyors, rotary indexing table, feeding system, two cylinders and others. The pills defect detection systems uses camera to take driven pills' images on the belt conveyor. The workstation of Intel core i7-66600U CPU is used for data analysis. The workstation is used for data analysis. Based on the pill defect detection using the proposed deep learning, the PLC sends the different control signals to the whole system. If the pills are defective, they are excluded in the system. Otherwise, the qualified pills are pushed into the bottle at a packaged module as shown in Fig. 6. Based on the results, the PLC S7-1200 (programmable logic controller) sends the control signals to the real system. If the pills are defective, they are excluded in the system by cylinder 1. Otherwise, the qualified pills are pushed into the bottle at a packaged module.

In this study, we proposed the improved construction and training of YOLOv3 network for pill defect detection in the manufacturing system. Our system includes two phases: training phase and validation phase. In the training phase, raw inputs are pill image taken by camera. In the training phase, a total of includes 2500 images in which 900 quality tablet images and 1600 inequality images. Then Gauss and Canny algorithms are used for detection. The Hog extracted Feature is implemented to obtain the main feature of the pills. Lastly, the modified Yolo is developed for pill defect detection. The segmented image is then validated by the system to classify to good quality or crack or contamination as shown in Fig.2. After, the training process, the validation process is used to verify the proposed algorithm. We sued Snap7 client (64 bit) to communicate between PLC and the image processing through Ethernet cable, as depicted in Fig. 3. For the industrial manufacturing system, Tia Portal is implemented with PLC programming, simulator and WinCC for human - machine interface purpose (HMI) as shown in Fig. 4 and Fig.5.

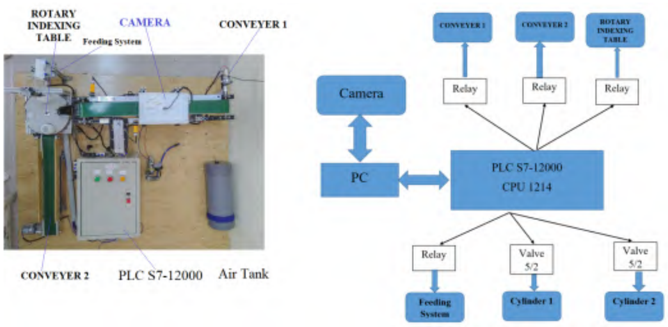

Fig. 1. The system setup and its components

3. IMPROVED CONSTRUCTION AND TRAINING OF YOLOV3 NETWORK

In order to solve the deep learning-based image classification for automated pill manufacturing system, a proposed model construction and training are introduced in this section. First, characteristics of YOLOv3 network structure is presented in section 3.1. Then, the improved version is introduced in section 3.2.

3.1 Characteristics of YOLOv3 Network Structure.

The YOLOv3 network model uses an end-to-end network architecture implemented in a CNN (J. Redmon and A. Farhadi (2018)). It is an object detector proposed by Joseph et al., and it takes the detection procedure as a regression task. The aim is to increase detection speed and accept different sizes of input images. YOLOv3 use Darknet-53 (J. Redmon and A. Farhadi (2018)) for performing feature extraction. Darknet-53 (J. Redmon and A. Farhadi (2018)) is much more powerful than Darknet-19 (J. Redmon et al., (2016)) but still more efficient than ResNet-101or ResNet-152 (K. He et al., (2016)). Its structure is basically presented in Fig. 6. As YOLOv3 uses multi-scale prediction, its accuracy is much improved.

Its network first divides the input image into S x S grids and the image by clustering. If the center point of an object in the image falls in the YOLO-divided grid, then the grid is responsible for predicting the object. Each grid is responsible for predicting B bounding boxes and the confidence of the bounding boxes (Liya Yu et al., (2019)). The confidence reflects the probability of containing objects in the bounding box predicted by the network model and the accuracy of the predicted position of the bounding box, which can be expressed as the following formula:

$$Confidence = Pr(Object) * IOU\frac{truth}{pred} \tag{1}$$

where IOU (Intersection over Union) represents the intersection ratio of the real target bounding box and the predicted target bounding box, which can be represented by Fig. 7. If an object exists in the grid, Pr(Object) = 1, then

$$Confidence = IOU\frac{truth}{pred} \tag{2}$$

Otherwise, Pr(Object) = 0, that is,

$$Confidence = 0 \tag{3}$$

Please refer (J. Redmon and A. Farhadi (2018)) for more detail.

3.2 Improved Construction and Training of YOLOv3 Network

The improved YOLO structure is presented in Fig. 7. Combining the types and characteristics of defects during actual pills manufacturing and the complex background of image acquisition on the factory production line, an

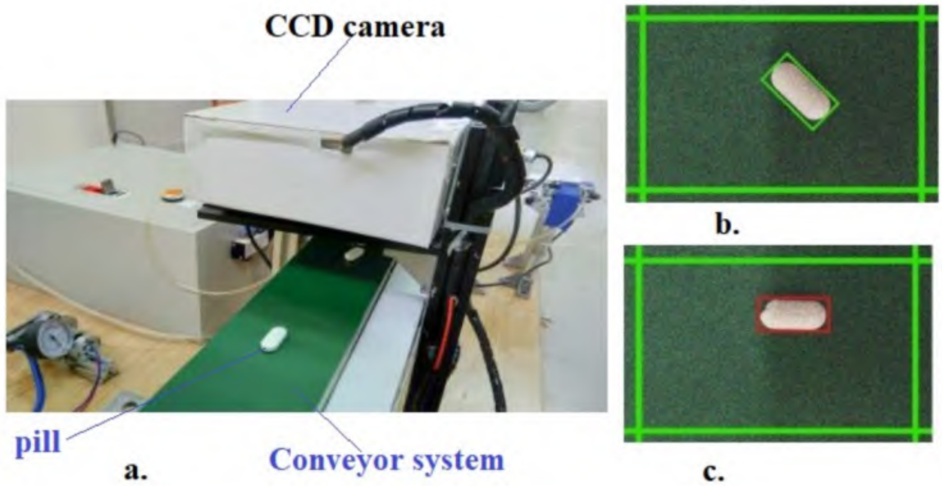

Fig. 2. Flowchart of the experimental platform.

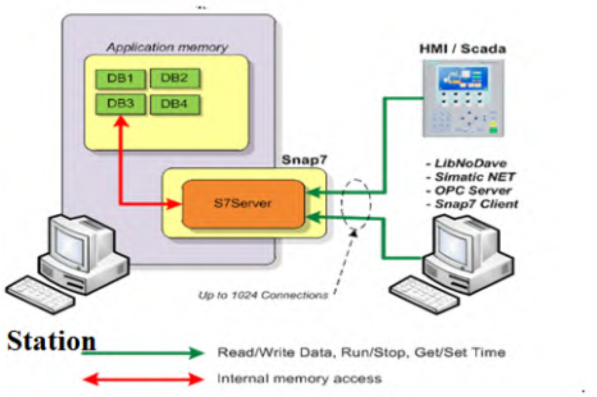

Fig. 3. Snap7 communication mode (64 bit).

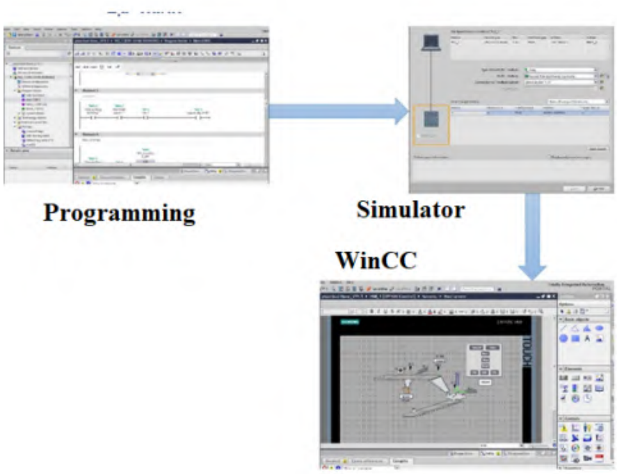

Fig. 4. Programming on TIA Portal V15.1.

improved online defect detection network for YOLOv3 pill is proposed. In this network structure, the end-to-end Darknet-53 convolutional network formed in YOLOv3 is maintained. In the smoothing layer, an Canny filter is used for edge detection. Then, a Gaussian filter with a pixel of 3 x 3 is then used for the secondary smoothing of the image. This filter mainly reduces the high-frequency noise in the collected image and further reduces the dust particles, and other impurities in the pills production system.

Fig. 8 and Fig. 9 show samples of input training images (with a total of 2500 images) for acceptable and unacceptable pill samples, respectively. The training samples are 80% total images. The rest is used for validation process.

Fig.10 shows the loss function of the training and validation processes. It can be seen that after 100 epochs of training and validation, the loss is decreased to an approximated zero values.

4. CONCLUSION

In this paper, the manufacturing defects in the pills manufacturing process were analyzed and studied. In addition, an analysis program that incorporates deep learning constitutional neural networks to fully automate the image analysis of pills for internal crack detection is investigated. The deep learning tool based on image processing is effectively implemented into the designed workflow system. Firstly, we first analyzed Canny algorithm and Gauss filtering for pill detection. Secondly, Hog feature extraction is implemented to simplify representation of the image. Lastly, improved YOLOv3 is proposed for online detection of pill defects. The proposed approach obtains robust quantification of internal pill cracks with proper loss function values.

Regarding future work, the proposed approach will be investigated in a large-scale pill manufacturing inspection, which brings the advantages of the production time and production cost reduction.

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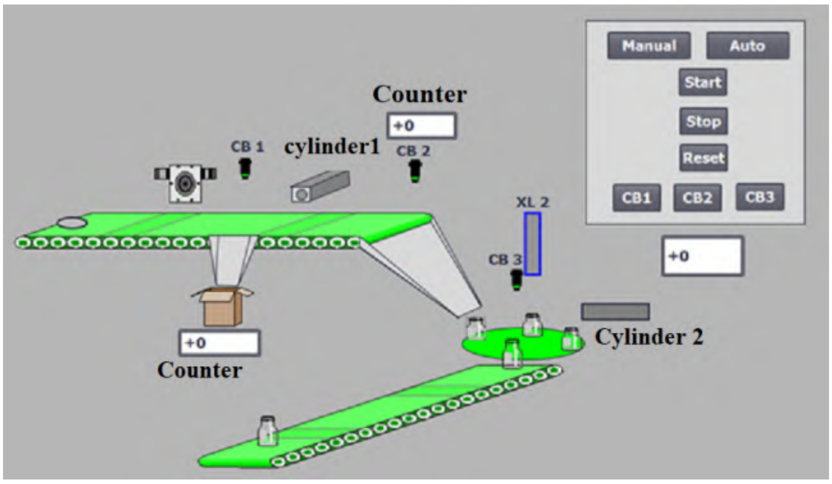

Fig. 5. HMI design in WinCC.

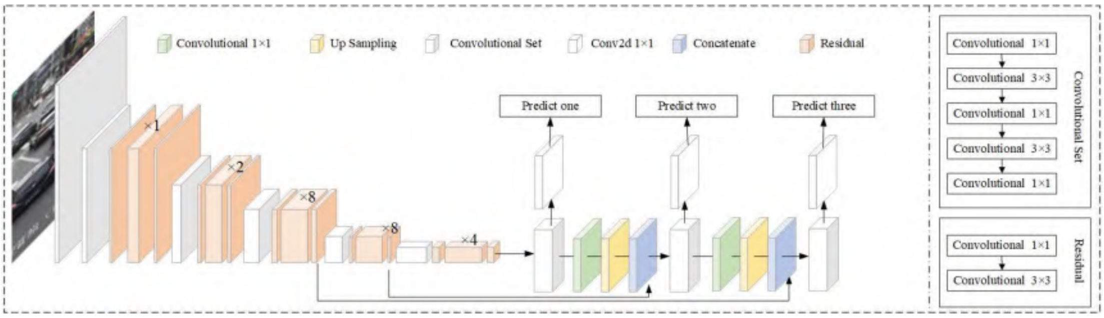

Fig. 6. YOLOv3 basic network Darknet-53 (Q. -C. Mao et al., (2019))

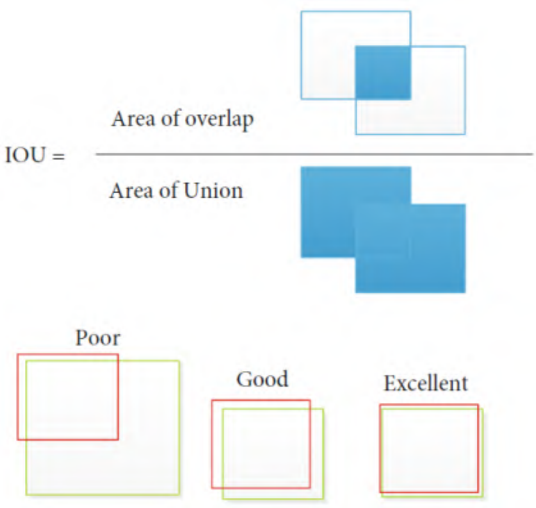

Fig. 7. IOU evaluation diagram.

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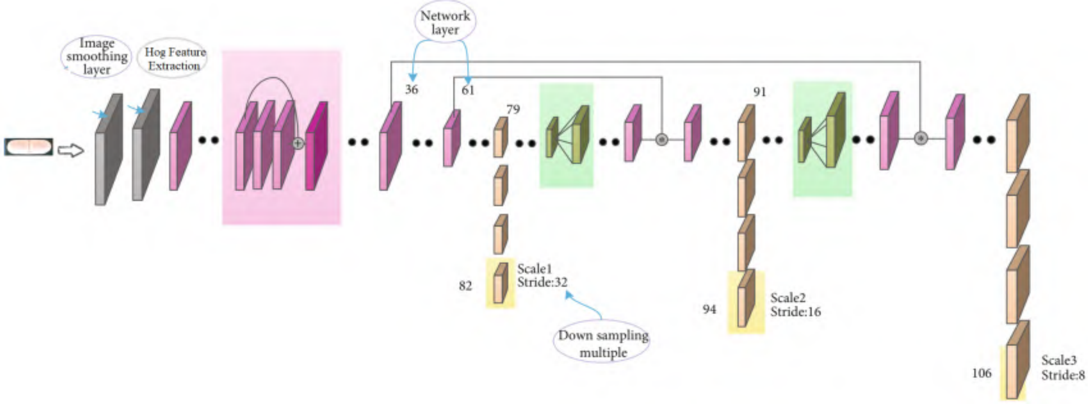

Fig. 8. Modified Yolo detection structure.

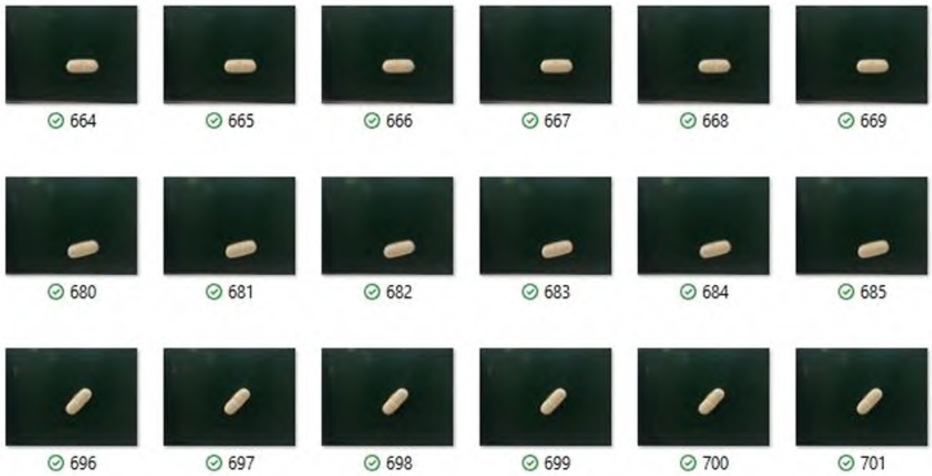

Fig. 9. Some input training images for acceptable pill samples in different angles.

Fig. 10. Some input training images for unacceptable pill samples in different angles.

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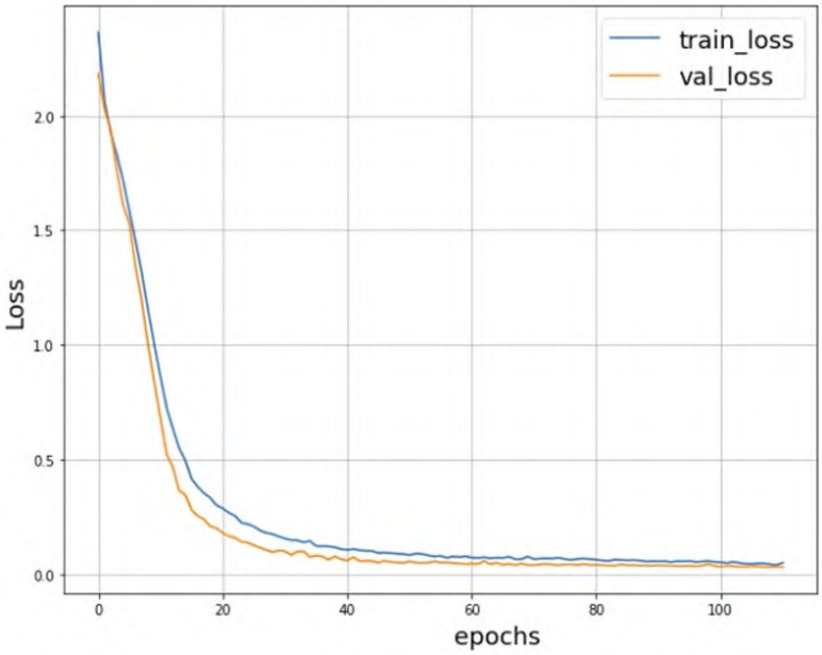

Fig. 11. Loss function of tranining àd validation process.

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