YOLOv5: an improved algorithm for real-time detection of industrial defective pieces

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Article Info

Article history:

Received Apr 22, 2025
Revised Nov 24, 2025
Accepted Dec 15, 2025

Keywords:

Artificial intelligence
Defect detection
Industrial internet of things
Smart vision
YOLOv5

ABSTRACT

The rapid advancement of communication technologies and the growing demand for artificial intelligence are transforming traditional manufacturing into smart industries. Robotic arms and smart vision cameras are widely adopted to support industrial internet of things (IIoT) applications. Beyond enhancing production efficiency and quality, these technologies play a crucial role in cost reduction, energy savings, and improving operator safety. In this article, we propose an intelligent industrial system using an improved version of the you only look once (YOLO) algorithm for defect detection on production lines. The system integrates robots and cameras to automate defect inspection and classification of manufactured pieces. An updated YOLOv5 model is designed as an end-to-end solution for detecting surface defects in three specific regions. We trained and evaluated the model using custom data tailored to the inspected pieces. The system achieved a 99% mean average precision (mAP) and an 80% recall rate. Additionally, it delivers a 99% detection rate at high speed, enabling real-time surface defect detection. This method not only accurately predicts defective locations but also provides size information, which is critical for assessing the quality of newly produced pieces.

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1. INTRODUCTION

Industrial defect detection has been studied for decades, particularly in traditional machining processes. Most of the previous research has concentrated on methods for detecting defects in post-processed parts. In the composite's community, for example, researchers have used different traditional methods such as ultrasonic testing to detect damaged surfaces in carbon fiber-reinforced plastics [1], osmosis testing [2], X-ray testing [3], and traditional machine vision detection [4]. Therefore, several methods have been used in industry for defect detection that proceed in two stages: feature extraction and defect identification. From surface defect detection, feature extraction, identification, and perspectives, they can be categorized mainly into statistical methods, spectral methods, model-based methods, and learning-based methods. Despite their robustness and accuracy, ease of use, and integration, these methods cannot be implemented, for example for online tasks or making robotic automation an open-loop process. Besides, learning-based methods have shown much interest recently as they have shown interesting performance for both simulations and real applications. Genetic algorithms in support vector machine (SVM) [5], artificial neural network (ANN) [6], k-nearest neighbor (K-NN) [7], random forest [8], genetic algorithms [9], and clustering methods [10], are applied frequently for defection detection and classification for modern industrial applications. Furthermore, using only the necessary number of training images, data-driven, and machine-learning approaches can be quickly adapted to new types of products and surface defects.

Nowadays, industry is experiencing a massive revolution due to the impressive evolution and the adoption of new technologies and materials on the one hand and the fast market requirements on the other hand. All this is to improve the manufacturers' business and respond to customs needs. Many industries are now using diverse high-level devices that are connected to the internet like sensors, cameras, and robots that generate huge amounts of data which can be exploited to make the industrial application more intelligent and reduce human interventions. The industrial internet of things (IIoT) is making significant changes as it provides smart solutions exploiting the interactive data between machines, sensors, and actuation relying on emerging machine learning methods [11]. Generally, deep learning methods can achieve excellent results when applied to the problem of surface-quality control. When compared to traditional machine-vision methods, deep learning can directly learn features from low-level data and has a greater capacity to represent complex structures. This leads to replacing some human operators' monitored tasks with automated learning ones. Deep learning-based methods have become very suitable for newly emerged Industry 4.0 applications. Many researchers have adopted machine learning methods to remedy some issues in different case scenarios.

Recent advancements in deep learning have led to significant improvements across various fields. The "DualVitOA" model utilizes dual vision transformers to accurately grade knee osteoarthritis from X-ray images, achieving 78.4% accuracy and reducing diagnostic subjectivity [12]. In smart cities, you only look once (YOLO) has been employed for real-time detection of lethal weapons, achieving 89.56% accuracy [13]. Precision agriculture benefits from a hybrid approach integrating YOLO with a rice field sidewalk detection algorithm, ensuring high accuracy in object detection and distance measurement [14]. Additionally, deep learning models have been integrated for video enhancement, compression, and restoration, resulting in notable improvements in video clarity and bitrate reduction [15].

Convolutional neural networks (CNNs) have fueled significant advances in this field of computer vision, resulting in significant breakthroughs in image classification [16] and object detection [17]. Many researchers have applied CNNs to industrial inspection systems to increase their practical value, particularly in defect detection. They have begun to incorporate industrial production with object detection algorithms to directly obtain the locations and types of defects. To segment and localize defects on a metallic surface. For instance, Tao *et al.* [18] proposed a novel cascaded auto-encoder architecture. This method, however, cannot differentiate between different individuals of the identical type, and the background of the objects being detected. Faster region-based convolutional neural network (Faster-RCNN) [19] has been adopted for defect detection on a steel surface [20], [21]. Even though Faster-RCNN is a two-stage model, it is constrained in terms of the processing speed of images which severely limits its application in real-time industrial inspection. Piao *et al.* [22] proposed a decision tree ensemble learning-based method for detecting wafer map failures.

Since it has been introduced, the YOLO algorithm with its ameliorated versions has gained high interest as it saves time at the expense of a slight loss of accuracy when compared to the two-stage method. For example, the YOLOv3 [23] has been used to detect defects in rail surfaces and achieved a 97% recognition rate. Li *et al.* [24] have presented an automatic defect detection solution based on YOLOv4, that achieved both fast and accurate defect detection for wire and arc additive manufacturing (WAAM). In addition, a YOLOv5 was used on arm robot to effectively detect defect detection on custom industrial application [25].

The model YOLO has shown accurate enhancement on three existing object detection models: channel-wise attention, multiple spatial pyramid pooling, and exponential moving average [26]. In addition to its ease of adoption and simplicity, YOLOv5 provides high quality in terms of prediction and processing speed which is highly required in several emerging industrial applications compared to state-of-the-art methods. For these two reasons, we have selected to use YOLOv5 in concrete industrial tasks to improve the production rate and reduce human interventions in the process of specific electronic circuit cards manufacturing.

Motivated by the impressive reputation of deep learning implementation in diverse domains and their high performance in diverse fields like industrial supervision, drones, robotics [27]. Besides the outperformance of data-driven-based applications on classic machine vision methods in terms of accuracy, reliability, flexibility, and latency. In this paper, we provide an improved version of a machine learning method for detecting visual surface defects. It emphasizes the use of the YOLO algorithm, which has gained a lot of interest in computer vision in recent years. More precisely, we provide an intelligent industrial application method that detects anomalies from produced electronic pieces for the purpose of quality augmentation before the market. We provide a concrete smart industrial application that enables both a smart vision system for quality classification and an arm robot for the process of reducing human intervention, for example in industrial environments. The computer vision system relies on the intelligence of the YOLO algorithm to improve the inspection rate as it provides high performance and accurate latency. The system checks the quality of newly manufactured pieces intelligently in the absence of humans.

The collaboration between the camera and arm robot serves to monitor the surface of the concerted pieces. The piece may contain anomalies in three distinct areas, for this aim, we have collected data on different possible defect cases to train our model. The defect may be presented in one area, two, or three. To gain time if the system detects only one area as defective the system declares the piece as non-valid and should be removed from the production line. The rest of this paper is structured as follows. Section 2 provides the proposed system model. Sections 3 present respectively the found results and discussions. Finally, section 4 provides a conclusion.

2. SYSTEM MODEL

Visual inspection is one of the important pillars to improve the speed, quality, and flexibility in Industrial 4.0, especially for defect recognition on production lines. In the present work, we propose an ameliorated system that aims to improve the quality and automate visual inspection in a specific industrial application. The proposed system includes a collaborative robot, camera, and data processing unit that relies on the effectiveness of the artificial intelligence method to make reliable, efficient, and automatic inspection decisions. An ameliorated version of the YOLO algorithm is used to classify newly produced electronic pieces into defective (non-OK) or valid (OK) ones. The monitored pieces can carry defects on the surface in three distinct areas. The system classifies the pieces as defective if at least one area is invalid. Besides, an arm robot is linked to the vision inspection system and network communication collaborates intelligently to decide the quality of the produced piece (i.e., Part). Figure 1 shows the provided overall system functioning cycle. Firstly, the newly produced pieces mentioned as Part move on the conveyor with a specific distance separation.

Then a sensor detects the presence of the piece under the robot. After that an order is sent, and the robot retrieves the part and moves to the camera to take pictures of each side of the part. Finally, the artificial intelligence technique intervenes to make an adequate decision about the state of the picked piece. If the piece is classified as defective, it is removed from the conveyor. Table 1 presents the used hardware elements of the proposed system.

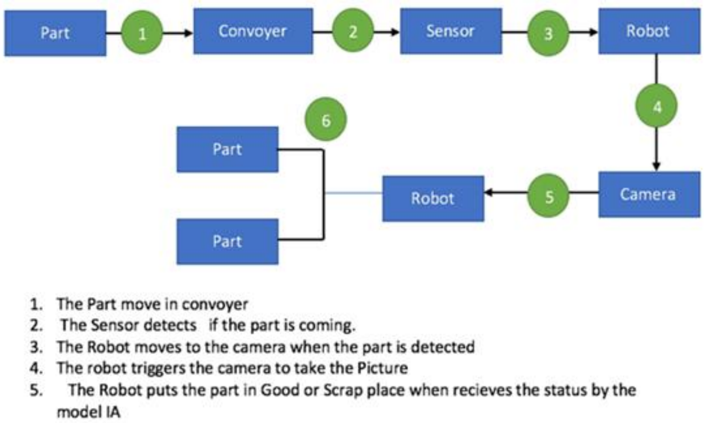

Figure 1. The proposed system flowchart

Table 1. The hardware of the proposed system

Component	Description
Robot	The robot has three functions; the first one is to retrieve the piece when receiving a signal from the sensor (indicate that the part is coming). The second one is to trigger the camera to take pictures (send to 24 V to the camera in the trigger line). The third function is receiving the status from the PC as input.
PC	The computer contains the vision system and when the artificial intelligence model sends the status of the part (OK or non-OK). The PC sends the status to the robot
Camera	The IP camera contains two lines; one is used for powering and the second one for triggering the camera to take the pictures.
Sensor	The used sensor is an ultrasonic one that works on the principle of emitting short high-frequency sound pulses on the concept of equal interval. When these pulses encounter an obstacle, they are echoed and reflected to the sensor as a reflection. This is what makes it possible to calculate the distance between the sensor and the object.

2.1. Dataset

The dataset is collected from a real production line; it contains 400 images. The images are labeled using label studio tools. The defect may appear on the piece's surface in three distinct areas. The dataset is divided into 30% for the test and 70% for the train. As the studied piece is confidential, we show in Figure 2 its approximation illustration. As shown, the objective of using the computer vision methods is to check the validity of the piece, in other words, it controls if the three areas illustrated do not carry any defect. The piece is considered non-valid if at least one area is defective.

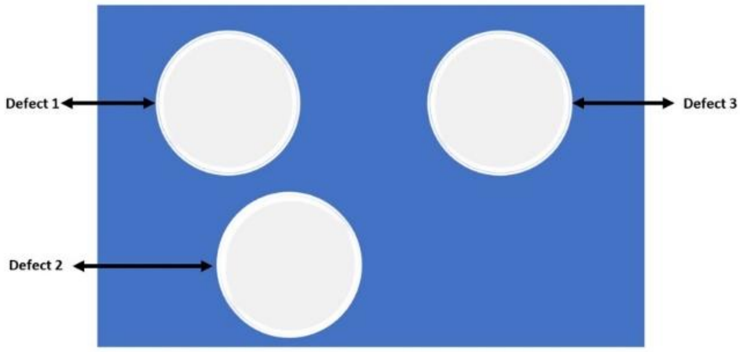

Figure 2. The piece illustration

2.2. Machine learning metrics

This section describes the evaluation metrics adopted to assess the performance of the proposed method. These metrics rely on the analysis of true and false prediction outcomes to determine the effectiveness of the model. Specifically, the evaluation is based on four fundamental quantities: true negative (TN), true positive (TP), false negative (FN), and false positive (FP). TN corresponds to negative samples correctly classified as negative, TP refers to positive samples correctly identified as positive, FN represents positive samples incorrectly classified as negative, and FP denotes negative samples incorrectly predicted as positive.

Precision is the first evaluation metric and measures the proportion of correctly predicted positive instances among all samples classified as positive. It is computed as (1).

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

Recall is the second metric and evaluates the model's ability to correctly identify positive samples. It represents the ratio of correctly detected positive instances to the total number of actual positive samples and is defined as (2).

$$Recall = \frac{TP}{TP+TN} \tag{2}$$

Accuracy is the third metric used to evaluate the overall performance of the classification model. It indicates the fraction of correctly classified samples among all evaluated instances and is formally expressed as (3).

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \tag{3}$$

The final metric measures the mean average precision (mAP) rate of the object detection algorithms including fast current neural networks and faster coroner networks. The YOLO algorithm solves two major problems: classification and localization [28]. The classification identifies if the object and its class are on the image. The localization predicts the coordinates of the bounding box around. Furthermore, the concept of intersection over union (IoU) is used by the YOLO algorithm to denote how much the predicted boundary overlaps the bounding box. The IoU is calculated by (4).

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \tag{4}$$

The IoU metric follows certain conditions. If IoU is superior to or equal to 0.5, the object detection is classified as TP. Else, then it is considered as a wrong detection and classified as FP. Furthermore, the mAP is calculated using (5).

$$mAP = \frac{1}{N}\sum_{c=1}^{N} AP_c \quad (5)$$

Where AP_c is the finding average precision of each class.

2.3. YOLO model

The aim of using the YOLOv5 algorithm is to detect the defect on the piece. Three defects are divided into 6 objects, where two objects can appear in each area, and two objects can appear in the first, second, and third area. The first and second object can appear in the first area, where the first object is OK and the second is non-OK, which is similarly applied to the rest areas. To train the YOLO algorithm, we dived the image into 3×3 bounding boxes. The target Y is defined as described in (6).

$$\begin{pmatrix} Pc \\ Bx \\ By \\ Bh \\ Bw \\ C1 \\ C2 \\ C3 \\ C4 \\ C5 \\ C6 \end{pmatrix} \quad (6)$$

Where P_C indicates if the object exists in the bounding box or not, if it is the case, it gets 1 else 0. B_X and B_y indicate the coordinates of the object. C_1, C_2, C_3, C_4, C_5, and C_6 present the possible classes of the object.

2.4. EfficientNet model

EfficientNet is CNN architecture and scaling method [29]. The aims of this architecture are to increase the dimension of the depth/width/resolution. The depth is to add more layers, the width is to increase the number of features, and the resolution means to increase the resolution of the images. Figure 3 shows the accuracy according to the numbers of the parameters. The figure indicates that EfficientNetB7 reaches 84.3% with 66 M parameters. In this proposed approach, we use EfficientNetB0.

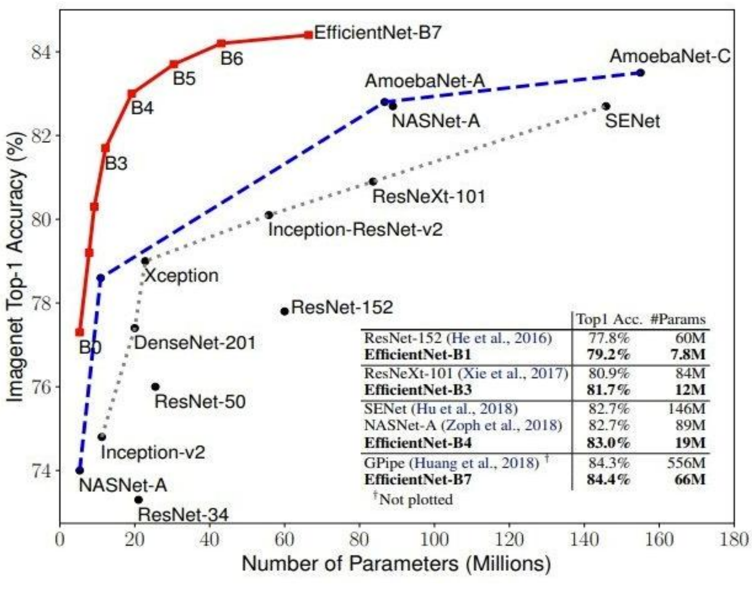

Figure 3. EfficientB0 To B7

3. RESULTS AND DISCUSSION

All experiments held in this paper were carried out using the coding language Python and the Pytorch deep learning framework. In addition to xARM 6 Robot, the hardware includes an Intel (R) Core (TM) i7-10750H CPU running at 2.60 GHz, 16 GB of RAM, an NVIDIA GeForce GTX 1650Ti (4 GB) GPU, and Windows 10 (64-bit). In our simulation, we utilized the categorical cross-entropy loss function to train the EfficientB0 algorithm using a specific dataset. The loss function measures the dissimilarity between the predicted probabilities and the true labels for each class in a multi-class classification problem. Table 2 summarizes the primary training parameters.

Table 2. Simulation settings and their values

Variable	Speed (rpm)
Initial learning rate	lr0=0.01
final OneCycleLR learning rate	lrf: 0.1
momentum	0.937
weight_decay	0.0005
Warmup epochs	3.0
warmup_momentum	0.8
warmup_bias_lr	0.1
box	0.05
cls	0.3
cls_pw	1.0
cls_pw	0.7
obj_pw	1.0
iou_t	0.20
anchor_t	4.0
fl_gamma	0.0
hsv_h	0.015
hsv_s	0.7

3.1. Model performance evaluation

Figure 4 shows the confusion matrix, which evaluates the quality of the classifier's output on the given data set. The diagonal elements reflect the number of points for which the predicted label equals the real label, and off-diagonal elements are those for which the classifier mislabeled. The greater the diagonal values of the confusion matrix, the righter predictions there are. This type of presentation can be useful for providing a more visual view of which classes are being misclassified. From this figure, we get the results shown in Table 3. From this table, we notice that the sensitivity reaches, a recall of 0.98, a specificity of 0.99, a precision of 0.98, and an F1-score of 0.98. These performances show positive feedback about the visual interpretation of the approach that the classes are being well classified.

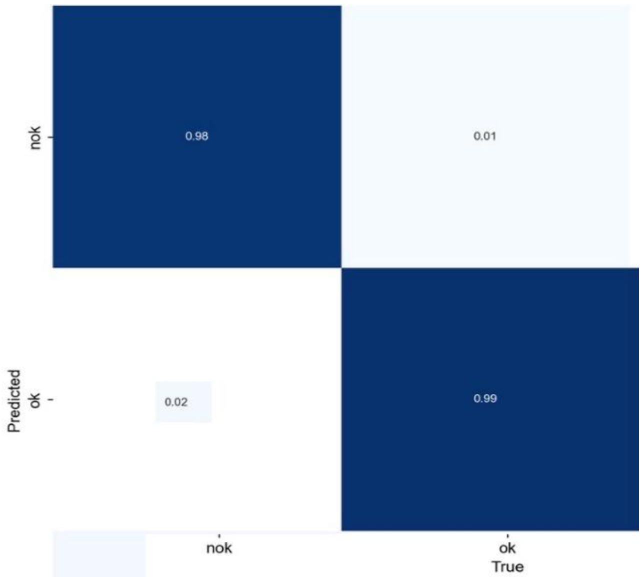

Figure 4. Confusion matrix performance representation

Table 3. Confusion matrix outputs measurements

Measure	Speed (rpm)
Recall	0.98
Specification	0.99
Precision	0.9899
Negative predictive value	0.9802
False positive rate	0.01
False discovery rate	0.01
False negative rate	0.02
Accuracy	0.9850
F1-score	0.9849

The balance between accuracy and recall may be illustrated using the F1-score curve, and a design point can be established using Figure 5. The confidence value that improves accuracy and recall is 0.321, as illustrated in the F1-score curve. Greater confidence value is preferred in many circumstances. In the case of this model, a confidence of 0.4 may be appropriate because the F1-score value looks to be about 0.63, which remains close to the maximum value of 0.90. Observing the accuracy and recall numbers at a confidence level of 0.4 suggests that this might be a good design point. The recall value begins to degrade around 0.4, although the accuracy value remains constant.

Figures 6 and 7 both show the performance of the EfficientB0 algorithm in terms of accuracy throughout the validation process. Figure 6 presents the loss performance of the algorithm for testing reaches zero after about 27 epochs. In other side, Figure 7 shows that after the 21st epoch, the accuracy of the algorithm on the dataset reaches 74%. This accuracy value indicates the percentage of correctly classified samples from the total number of samples in the dataset. Reaching a 74% accuracy after epoch 21 suggests that the algorithm has undergone several training iterations and has learned to make accurate predictions on the given dataset.

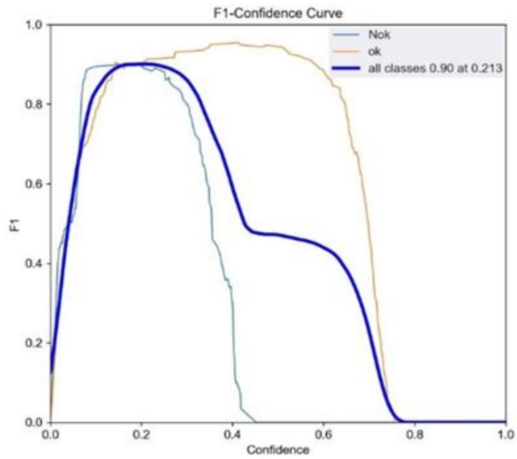

Figure 5. F1-score curve representation

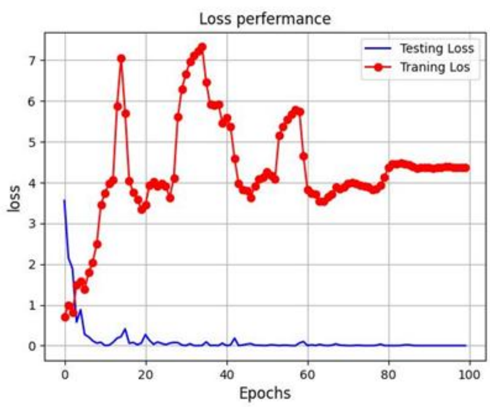

Figure 6. Loss performance of train and test over epochs

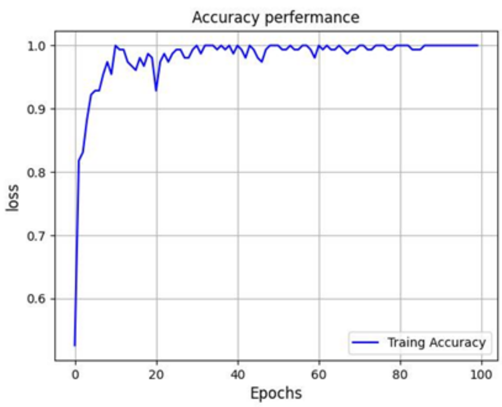

Figure 7. Accuracy of train over epochs

Figure 8 illustrates the recall metric, styled by the first metric, increasing gradually over the first 40 epochs, remaining under 0.8. After epoch 40, the recall metric experiences a significant rise, ultimately reaching 0.99. This suggests that the model improves its ability to identify relevant instances as training progresses. Figure 9 presents the loss values for box loss, object loss, and classification loss, which converge to 0.04, 0.01, and 0.00375, respectively. These results indicate that as the training advances, the model effectively learns to extract features and accurately localize objects within the inspected images. A lower loss signifies better generalization, meaning the model successfully minimizes errors in detecting defects.

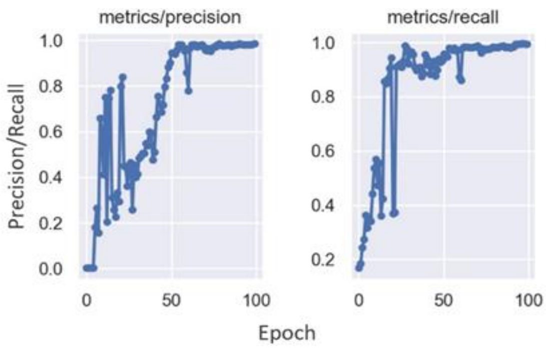

Figure 8. Precision and recall metrics

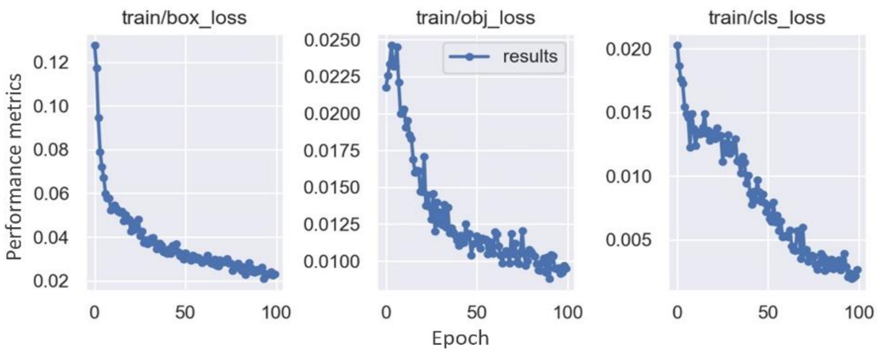

Figure 9. Validation loss performance versus each epoch

Figure 10 illustrates that the errors for box, object, and classification increase to 0.02, 0.016, and 0.0027, respectively. Additionally, it confirms that our proposed approach effectively detects both the box and the object in the inspected image. In this experiment, we set two IoU thresholds: 0.5 and 0.5-0.95. When IoU is 0.5, the mAP reaches 0.55, whereas it drops to 0.25 for an IoU range of 0.5-0.95. Figure 11 displays the simulation batches of the inspected pieces, where defective areas are highlighted with a bounding box labeled 'N-OK' and non-defective ones with 'OK'. This visualization represents a randomly shuffled sample of the trained dataset, categorized into two classes. As shown, the algorithm demonstrates high precision in distinguishing defective regions from non-defective ones.

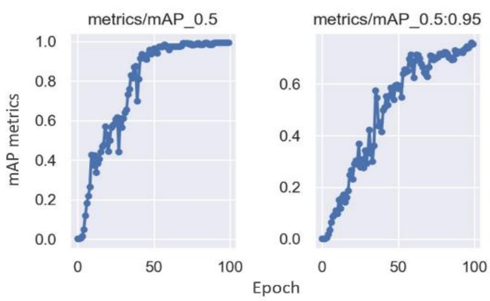

Figure 10. The mAP metrics performance evaluation

Figure 11. The simulation batches of studied pieces

3.2. Discussions

Many scientific papers have treated visual inspection using machine learning. In addition, automated defect detection using computer vision and machine learning has become a promising research area with a high and direct impact on the fields of visual inspection. Ismail and Malik [30] compare the performance of machine learning algorithms, including ResNet, DenseNet, MobileNetV2, NASNet, and EfficientNet, in which visual inspection is applied in the fields of agriculture. The revealing results of this work show that the accuracy reaches 99.2 and 98.6% using the EfficientNet model. In [31], deep learning is proposed for the quantitative assessment of visual detectability of different types of in- service defects in laminated composite structures. The results show that employing AlexNet network, using the relatively small image dataset, provided the highest accuracy level (87-96%) for identifying the damage severity and types in a reasonable computational time. Instead of using the mentioned data set, in our proposed approach we have used custom data that targets the improvement of smart Industrial 4.0 applications that concerns the real production lines.

The proposed method’s performance was achieved by learning from two sets of images of defective and non-defective samples. Furthermore, using only half of the defective samples demonstrated that good performance could still be achieved, whereas related methods produced worse results in this case. This indicates that the YOLO approach used is appropriate for the investigated industrial application, despite the limited number of defective samples available. Furthermore, three important characteristics were evaluated to further consider applications for the industrial environment: the performance to achieve a 100% detection rate, annotation details, and computational time. The YOLOv5 algorithm has been used to find the localization of the object and its class in the image to detect defective parts. The results show precision and recall reach respectively 99 and 80% and tan image results indicate that one algorithm can identify and localize the object in the image. In addition to the high provided performance of the used YOLO version in terms of precision and recall, this algorithm is very smooth and fast which is mandatory to deal with a high amount of data and latency. Therefore, our real demonstration by the robot system has shown interesting reactions in terms of time to detection and reaction.

4. CONCLUSION

Visual inspection, automation, and artificial intelligence are increasingly being used to enhance product quality and automate various tasks in the industry. In this paper, we propose an intelligent system that integrates robotics, network communication, and artificial intelligence to establish an Industry 4.0 solution for defect inspection. The findings of this study demonstrate that the modified version of the YOLOv5 algorithm delivers promising performance in defect classification and localization within inspected images. Furthermore, the system achieves a precision of 99% and a recall of 80%, effectively detecting defective pieces on the production line. The synergy between the accuracy of YOLOv5 and the flexibility and speed of the xARM-6 robot contributes to an accelerated production rate and improved quality of newly manufactured pieces. As a future perspective, we aim to explore enhanced versions of YOLO for another case study, particularly to analyze its performance in detecting complex defects that pose challenges for human operators. Additionally, we plan to incorporate edge computing and cloud computing platforms to optimize latency and accuracy.

FUNDING INFORMATION

This work was not supported by any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The study was carried out with the support of the authors' institutions, including ENSA Tétouan, Universidad Politécnica de Cartagena, and the Laboratory of Mathematics and Intelligent Systems, ENSA Tangier.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no known financial or non-financial competing interests that could have influenced the work reported in this paper. The authors state no conflict of interest.

DATA AVAILABILITY

The data is collected in real industry production. The data that support the findings of this study will be available in GitHub at https://github.com/abdel-az following a 3-month from the date of publication.

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