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RESEARCH ARTICLE

Automated system for defect classification of images from 3D-printed additive-manufactured products

Nur Najiha Kamarulzaman[1], Nor Salwa Damanhuri [2]*, Nuraina Husna Mohamad Asri[1], Nor Azlan Othman[2], Noor Azlina Mohd Salleh[2], Belinda Chong Chiew Meng[1], Anik Nur Handayani[3], Tomonori Kato[4]

[1]Faculty of Electrical Engineering, Universiti Teknologi MARA, Cawangan Pulau Pinang, Pulau Pinang, Malaysia
[2]Faculty of Mechanical Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia
[3]Department of Electrical Engineering and Informatic, Universitas Negeri Malang, Malang, Indonesia
[4]Faculty of Science and Engineering Department of Mechanical Engineering, Hosei University, Tokyo, Japan

Abstract - Manual inspection of additive manufacturing is time-consuming and error-prone, making it unsuitable for high-speed production. Real-time automated systems should ensure precision and consistency of defect detection. Hence, this paper presents the development and evaluation of an automated defect classification system for additive manufacturing (AM) products using You Only Look Once version 8 (YOLOv8) and LabVIEW. This study utilized a dataset of 1200 images of AM products from the Malaysia Automotive Robotics & IoT Institute (MARii). YOLOv8, a state-of-the-art object detection technique, was used to develop a defect classification model. Following the development of the classification model, it was implemented on the Karakuri machine by interfacing the hardware with National Instruments' myRIO and LabVIEW. An infra-red sensor triggers image capturing via a USB camera system, while the real-time classification system activates the servo-based sorting mechanisms. Data augmentation techniques were deliberately applied to improve robustness during model training. The system achieved an average accuracy of 93.39% and demonstrated satisfactory performance across all evaluation criteria: precision, recall, and F1-score; thereby confirming its effectiveness in classifying defect and non-defect products. In conclusion, the results validate the designed system as a practically feasible and efficient approach toward automating quality control in additive manufacturing, reducing dependence on manual inspection while improving consistency and operational efficiency.

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1. Introduction

Additive manufacturing (AM), a general term used to describe 3D printing, has brought about a significant shift in production schemes by enabling the fabrication of intricate geometries with reduced material wastage. AM processes offer substantial advantages across multiple aspects of the manufacturing workflow through the utilization of sensors, data analytics, automation, artificial intelligence, and connectivity, thereby improving efficiency and productivity [1]. As AM technologies continue to advance, the demand for uniformity on print outputs has increased, however defects, such as cracks, voids, and surface irregularities that occur during, and occasionally after printing, and finishing, remain detrimental to structural integrity and functional performance of the manufactired products [2]. Hence, producing a good product with guaranteed high-quality products in AM production demands an inspection method that is accurate and reliable while under real-time industrial conditions. Quality inspection systems are vital for the detection and classification of defects in a manufacturing environment. However, traditional inspection methods are largely manual, limiting their effectiveness, precision, and suitability for high-speed production lines [3]. Detection of minor surface flaws like micro-cracks, layer delamination or missing structural parts is usually compromised, and accuracy of inspection degrades with time when the volume of production is high [4, 5]. Manual inspection is also tedious, labour intensive, time-consuming and unsuitable for large-scale production [6], while the availability of sufficient human resources to perform quality inspection may also be a limiting factor [7]. As manufacturing facilities transition toward Industry 4.0 models, there is a need to provide intelligent, scalable quality control solutions that would guarantee the precision and timely quality control without the risks of human error and inefficiency [2, 3].

To address these challenges, the implementation of automated defect classification systems using machine vision and deep learning has emerged as a highly effective alternative and has become vital in modern industrial inspection systems. For example, a study by Razak et al. utilized deep learning together with Raspberry Pi 4B and a USB webcam to detect, classify and track both moving and stationary vehicles in different lighting conditions, achieving an accuracy up to 80.00% [8]. Another study by Yang has combined the Convolutional Long Short-Term Memory (ConvLSTM) network and the Attention Mechanism (AM) to construct the wear prediction model (ConvLSTM-AM) [9]. The proposed model achieved an average classification accuracy in which the SVM-WOA for the four types of wear exceeded 97%, and the classification time of only 1.15 seconds. Both of these studies indicate that the utilization of deep learning is effective for performing detection and classification in real-time applications. In addition, a study by Abdelati et al. implemented deep learning, specifically artificial neural networks (ANN) to classify engine misfires using vibration signals, achieving an accuracy of 82.36% [10]. Furthermore, CNNs were successfully used to identify printed circuit board (PCB) flaws, with classification accuracies exceeding 90% [11]. Jain and Mittal stated that deep learning and ensemble learning models for

***CORRESPONDING AUTHOR | N.S. Damanhuri** | ✉ norsalwa071@uitm.edu.my

modelling eco-safe driving behavior showed that utilizing Recurrent Convolutional Networks (RCN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) and Decision Tree (DT) achieved impressive accuracies surpassing 99%, followed by Neural Networks (NN), Support Vector Machines (SVM) and Random Forest (RF) with accuracies ranging from 91% to 96% [12].

Recent advancements have improved deep learning models, such as YOLO (You Only Look Once), which combines the speed of object detection architectures with the feature-learning capabilities of CNNs, in order to overcome these restrictions. The YOLO family, especially the most recent YOLOv8 variant, uses a single-stage detection technique that carries out object localization and classification simultaneously. It offers sufficient processing speed and accuracy rates for real-time detection, is easy to deploy on edge devices and can yield satisfactory results even with small datasets [13]. For example, a study by Beg et al. utilized YOLOv8 integrated with infrared thermal camera sensor to detect objects like cars, motorcycles, and traffic lights on the roadways in real-time [14]. The study demonstrated the capability to process images in 3.6 milliseconds and make decisions in 8.5 milliseconds.

In this study, the classification process for defects depends on analysing the retrieved properties of AM products, which include texture patterns, edge shapes and color variations. LabVIEW is used to performs real-time analysis of these characteristics, ensuring efficient and accurate classification of defects. After characteristics retrieval, the decision-making algorithms utilize these features to determine the appropriate class. The combination of real-time decision-making capabilities within graphical programming through LabVIEW enhances process efficiency by enabling faster classification. Manufacturers who implement LabVIEW for defect classification can establish dependable, scalable systems that achieve faster and more accurate results than previous human-operated approaches. The image processing functionality in LabVIEW acts as a fundamental element for industrial automation since it enhances defect classification accuracy and efficiency. Manufacturers benefit from NI-IMAQdx and Vision Assistant integration as this enables automated object detection and classification according to factors including colour and shape and texture, and size attributes [15]. The integration of LabVIEW in conveyor roller systems supports consistant defect recognition through pattern-matching algorithms by comparing against reference models in real time [16]. Through the HSL image conversion process and its normalized cross-correlation analysis, the system can effectively detect surface defects and achieve stable discrimination under varying environmental situations [16].

The collaboration between machine vision and artificial intelligence brings superior accuracy in defect classification capabilities, according to the research in [17]. Historical defect data is fed into LabVIEW through machine learning algorithms, which continuously use this data to improve classification results. The system enables real-time operational automation across numerous industries, including aquaculture, where the tool provides automated water quality monitoring for the prawn industry. The system is operated via IoT-enabled remote monitoring which manages pH and temperature settings to showcase LabVIEW's industrial flexibility [18]. Defect classification utilizing the LabVIEW platform enables manufacturers to reach both higher levels of efficiency and consistency [19]. Systems that automatically sort products using servo motors achieve accuracies exceeding 95% by removing human errors from while simultaneously increasing production throughput [17]. The versatility of LabVIEW for live monitoring and automation makes it effective across a wide range of industrial applications [18]. The model, trained using labelled images under consistent lighting conditions, performs real-time classification within LabVIEW, similar to CNN-based plant classification approaches [20].

This study proposes a solution using a deep learning model (YOLOv8) with LabVIEW and myRIO hardware to automate defect classification and sorting in real time. The myRIO is increasingly being used to optimize the defect classification of 3D-printed products [21]. It is appropriate for such applications due to its LabVIEW software interconnectivity to the FPGA acceleration and real-time processing properties. Furthermore, the capability of MyRIO to be integrated with cameras, sensors, and other devices enables comprehensive monitoring and immediate response to production issues. Being compact and reliable, it can be easily applied in different industrial environments, enhancing operational efficiency and product quality. With the manufacturing environment constantly changing, MyRIO represents future-proof solution for advanced automated quality control system. This study uses YOLOv8 with LabVIEW and myRIO to provide a hardware-integrated real-time detection system with automated sorting, overcoming some of the shortcomings of previous inspection systems and providing improved inspection capabilities [22].This study aims to develop an automated system for surface defect classification of 3D printed parts. The two objectives of this study are as follows: (1) to establish an automated defect classification system using YOLOv8 and LabVIEW to enable accurate defect classification of 3D printed products, and (2) to evaluate the performance of the system in terms of accuracy, reliability, and efficiency of defect classification in a 3D printing scenario. These goals align with the requirement for automated and scalable inspection systems that can operate effectively in fast-paced, high-volume production scenarios [3].

2. Materials and Methods

The block diagram in Figure 1 illustrates the complete workflow of the proposed automated defect classification system, which integrates image acquisition, deep learning classification, and real-time actuation. The process begins with the input phase, where additive manufacturing (AM) product images are collected and uploaded into Roboflow for annotation. These annotated images are then used to train the YOLOv8 model during the Classification Model Phase. In the Automation Phase, the National Instruments myRIO device receives signals from an infrared (IR) sensor and a USB camera to capture real-time images of AM products. These images are processed through LabVIEW, where the YOLOv8 model is executed via a compiled .exe file, allowing seamless integration of the Python-based detection into the LabVIEW environment. The classification result is output as a binary value 1 for defect, 0 for non-defect, which is saved to a text file for tracking and decision-making. Based on this output, LabVIEW triggers the servo motor to sort the items into either the "Defect Bin" or "Non-defect Bin" container. The entire system is designed to operate autonomously with minimal human intervention, making it suitable for high-speed industrial inspection applications.

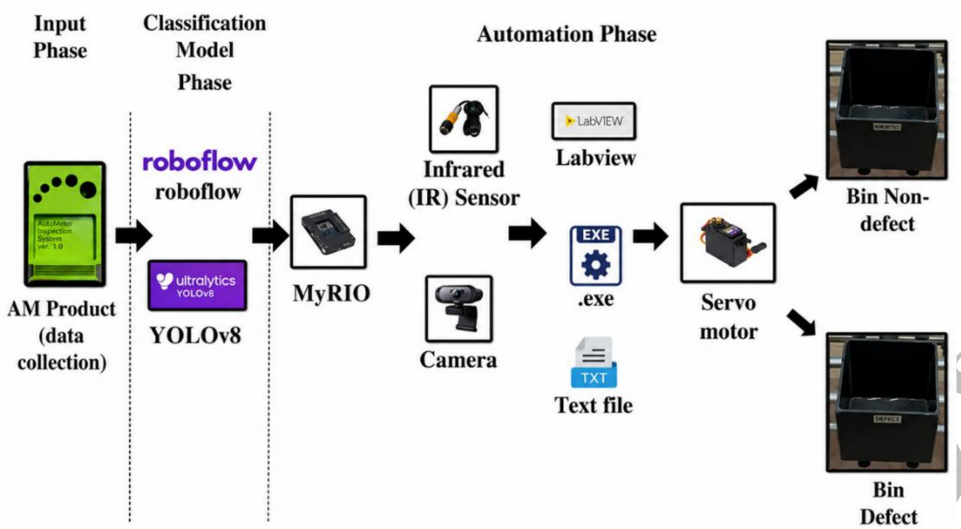


Figure 1. The block diagram of developed automated system consists of input phase, classification model phase and automation phase

2.1 Input phase

The dataset utilized in this study consists of 1200 AM images collected from Malaysia Automotive Robotics & IoT Institute (MARii). The dataset contained both defect and non-defect products, with balanced representations of non-defect and visible defect products. Visible defects include cracks, missing features, and irregularities on the surface. All images were subsequently pre-processed by cropping and resizing to a fixed size of 256 x 256 pixels and saved as PNG. This uniform input size reduces the computational burden during neural network training. To enhance the generalizability of the model and minimize overfitting, a previous study [23] examined various training, validation and testing data split ratios, as tabulated in Table 1. The proportion of 70% training, 20% validation and 10% testing was selected as this ratio showed the best performance by ensuring that the model learns efficiently while still being evaluated on enough unknown data to confirm its performance by striking the ideal balance between training accuracy and evaluation robustness. In machine learning applications, the 70:20:10 split is well recognized for providing a workable balance between model generalization and learning capability. Examples of images are shown in Figure 2. Figure 2(a) depicts a non-defect product, featuring a smooth, regular structure, and Figure 2(b) presents a defect product with cracks, surface imperfections, and missing structural features that are essential for training the deep learning model.

Table 1. Dataset distribution for training and testing.

Training (%)	No. of images	Validation (%)	No. of images	Testing (%)	No of images
70	839	20	240	10	121

(a) (b)

Figure 2. The example of AM product where (a) non-defect product; and (b) defect product

Although the printed products may have different colours, this does not affect the performance of YOLOv8 in performing defect classification. The defect classification process relies on features like edges, textures, and irregularities extracted from the input image. These features are not affected by the color variation, as they appear in the spatial distribution of pixels, rather than in the hue itself. Therefore, the color differences between the input image do not affect the training process of the deep learning model, specifically YOLOv8, used in this study.

2.2 Classification model phase

This study presents an approach to detect manufacturing defects in real-time by using YOLOv8 technology. Roboflow enhances the efficiency of YOLOv8-based classification by providing image dataset annotation services. The YOLOv8 architecture contains three main components, which include the backbone, neck and the head section. These three component sections coordinate their functions to process images into refined information before executing classification tasks.

2.2.1 Roboflow

The image dataset utilized in the current research consists of both defect and non-defect 3D-printed products, which were classified according to pre-established visual criteria based on the surface conditions, cracks, missing parts, or deformed structure. The annotation of the corresponding images was performed using the Roboflow platform which provides a user-friendly interface for object labelling and dataset management. During annotation, contrast and brightness modification of the image was applied to ensure that the defects were visible and distinguishable. The image dataset was kept in RGB format during annotation without conversion to grayscale. The annotation process only involved labelling the image as either defect or non-defect classes, where no color channel was altered. It is worth noting that the use of different colors did not bias YOLOv8 in extracting features since it learns structural features and does not rely on hue of the input image. The process of labelling using Roboflow was made more precise and reliable, which is essential during the training of the object detection model. Roboflow automatically generated a well-organized folder structure that was fully compliant with the YOLOv8 classification model once all the images had been successfully annotated. This format contained the annotated images, the label files in the desired format and a configuration file that provided the class labels and file paths. The Roboflow integration significantly reduced preprocessing time by automating the process of augmenting, scaling, and formatting images and ensuring that they were ready to for training and deployment in the automated defect classification system.

2.2.2 YOLOv8 model

In this study, the YOLOv8 model was adopted from the study by Kamarulzaman et al. [23]. YOLOv8 serves as the core model of the defect classification system for performing real-time object recognition and categorization efficiently. At the backbone stage, the system performs its initial operation to extract features from incoming images as depicted in Figure 3. The backbone processes these images to detect significant attributes such as shapes, textures and patterns. Progressive reduction of image resolution provides the system with essential information while enhancing processing efficiency. The retrieved characteristics are then directed to the neck section which performs mixing operations that aggregate information across different backbone levels. This component enhances the network by merging fine-grained details with broader contextual patterns, enabling multi-scale categorization across multiple feature levels. In this way,the neck component enhances the system's identification capability to identify minor defects through its ability to consolidate information at different levels.

Upon receiving all features from the neck component, the head section classifies images into "defect" and "non-defect" categories. Accurate predictions from the head section involve functional blocks consisting of convolutional (CONV) and detection blocks. The bounding box predictions within these blocks help to to localize objects and identify precise defect locations. The great performance of YOLOv8 results from its advanced block pattern across every component. The Conv2d, BatchNorm2d, and result activation function combination within the convolutional block enables the extraction of important image data while reducing the resolution to improve processing efficiency. The C2F block includes conv, split, bottleneck, and concat layers to reduce input dimensions, enhance network optimization and minimize overfitting. The SPPF block uses Spatial Pyramid Pooling Fast technology to obtain and display object features across multiple pixel scales at full resolution for maintaining vital information. The detect block at the head section performs two main tasks: it finds bounding areas that pinpoint objects while classifying their identified flaws for precise and dependable results.The overall design framework of YOLOv8 balances computational speed with reliable accuracy, which qualifies it as an ideal real-time defect categorization solution.

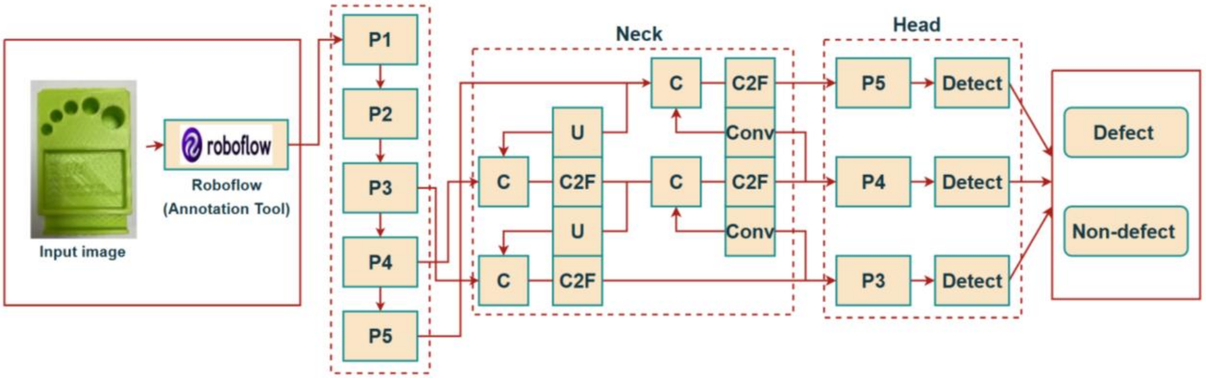


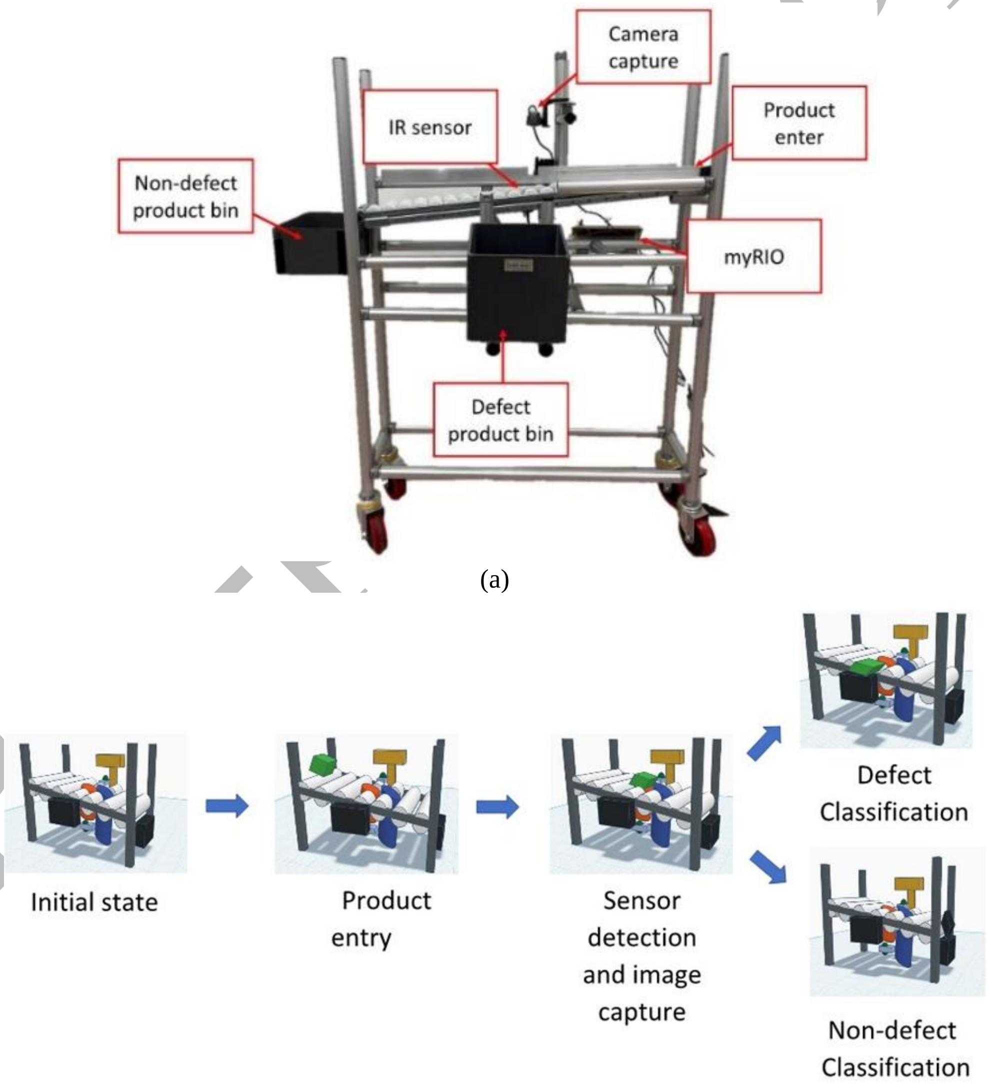
Figure 3. The YOLOv8 structure where the input image going through the backbone, neck and head to get the output either defect or non-defect class

The effective processing of characteristics combined with optimization and analytical capabilities, enables the system to control numerous defect conditions with precise identification, thereby providing robust quality control in manufacturing processes.The Google Colab serves as the training environment for the model after its implementation while users optimize performance through adjustments of learning rate along with batch size and epoch count parameters.

2.3 Automation phase

This study focuses on the development and application of a real-time automated defect classification and sorting system for 3D-printed additive-manufactured products. This system was created using National Instruments' myRIO embedded hardware and LabVIEW software to create a closed-loop control environment that responds to real-time conditions. The combination enables the coordinated performance of major functions such as object detection, deep learning classification, and mechanical sorting. This helps to minimize the use of manual inspection and enables more accurate and scalable quality control in an industrial environment.

The proposed system automates the inspection and sorting of 3D-printed AM products using a LabVIEW-based setup on the Karakuri machine. Based on the components's setup illustrated in Figure 4(a), an infrared (IR) sensor detects the presence of a product upon its arrival at the inspection station and notifies the myRIO controller. The USB camera captures an image of the product, which is then analysed in the LabVIEW environment using the VDM. The image goes through a Python node, which executes the trained YOLOv8 model to determine whether the product is defect or non-defect. The result is encoded as 1, which represents a defect, and 0, which represents a non-defect, and is saved to a text file. The LabVIEW software reads this file and controls a servo motor to either reject the defective product into a defect bin or allow non-defective products to proceed. Overall, the defect classification process is visualized in Figure 4(b) which illustrates the fast and dependable sorting with reduced inspection time and human error.



(a)

(b)

Figure 4. The automated defect classification AM product on the Karakuri machine with (a) the components on the Karakuri machine; and (b) the workflow of the classification process

2.3.1 TCP Protocol

The Transmission Control Protocol (TCP) is utilized as the primary means of communication between the myRIO controller and the computer with the YOLOv8 image classification model installed in this study. TCP provides reliability, ordered transmission, and lossless data exchange between these two devices [24]. This is significant in automated systems, whereby any delays or wrong messages may result in sorting errors. When the IR sensor identifies a product on the inspection line, myRIO sends a TCP request to the PC and commands it to capture an image of the product and process it. The YOLOv8 model processes the image and decides whether the product is defective or non-defective. When the result is available, the PC communicates the classification to myRIO via TCP. According to the information that is received, myRIO will instantly power the servo motor to place the product in the corresponding category. All of this is performed in real time, ensuring smooth, accurate, and synchronized operation between the software and the hardware. LabVIEW facilitates this with its built-in TCP/IP capabilities, including TCP Open, TCP Read, and TCP Write to help simplify the development of client-server communication in automation systems [25].

2.3.2 Schematic diagram of MyRio connection

The schematic diagram illustrates the hardware interconnections among the IR sensor with servo motors and the myRIO controller required to realize a functional defect classification system. As shown in Figure 5, this setup depicts the routing of sensor signals and actuator commands through myRIO for real-time processing. Proper hardware integration and mechanical stability are essential for the smooth operation of the automated inspection system. The first step focuses on hardware integration through which the IR sensor and servomotors are connected to the myRIO controller via configured ports. The established connections ensure the correct transmission of signals between device components. The hardware is powered through the myRIO MXP port, which supplies a constant +5V and GND to the IR sensor and servomotors. Accurate signal transmission is essential for correct system operation. The IR sensor activates myRIO controller through signal transmission when it detects a product, allowing the system to initiate its analysis process. The system activates the appropriate servomotor after performing analysis assessments. When a a defective product is identified, the ejector motor activates to direct the item into the designated rejection bin. The stopper motor remains inactive when handling non-defect products, thus allowing items to move onto the conveyor belt.

The real-time operations are managed through LabVIEW programming. Real-time control and monitoring become possible with this code because it connects outputs from servomotors to inputs from the IR sensor. The programmed commands enable immediate detection and accurate classification of products while executing the corresponding mechanical operations. This integrated design and implementation approach ensures seamless compatibility between hardware and software components, resulting in a dependable system for classifying product defects in current industrial settings.

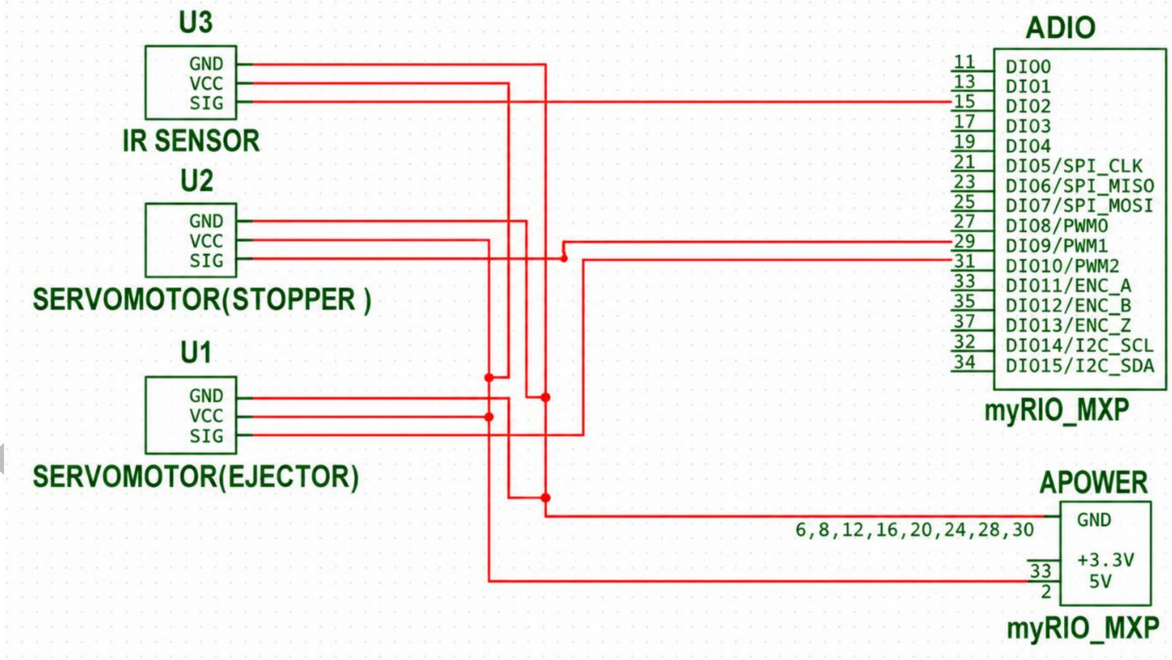


Figure 5. The schematic diagram of myRIO connection with the IR sensor and two servo motors for the AM defect classification process

2.4 Performance analysis and evaluation

The performance of the YOLOv8 model in classifying the 3D-printed AM products into defective and non-defective categories is assessed using a confusion matrix, as depicted in Figure 6. It comprises four outcomes which are True Positive (TP) or the successful identification of defective products, True Negative (TN) or the successful identification of non-defective products, False Positive (FP) or the erroneous labelling of a product as defective, and False Negative

(FN) or the erroneous passing of a defective product as good. These results can be used to determine the accuracy, sensitivity, and reliability of the model, thereby demonstrating that it is effective in automated quality inspection.

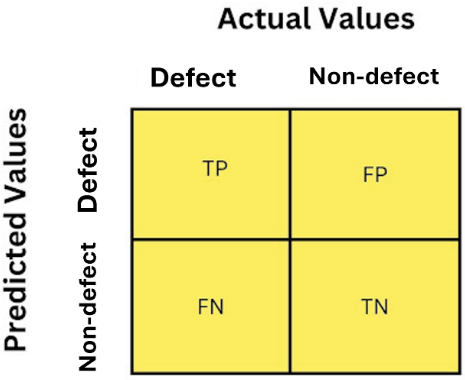


Figure 6. The confusion matrix of the developed YOLOv8 model

To evaluate performance, four performance metrics were used: accuracy, precision, recall, and F1-score. Accuracy is defined as the percentage of accurately predicted instances among all predictions and it was determined using Eq. 1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where TP, TN, FP, and FN represent the number of true positives, true negatives, false positives, and false negatives, respectively. However, because it places greater emphasis on learning the majority classes than the minority classes, the accuracy result can be highly deceptive when dealing with unbalanced data. Therefore, when object detection comprises multiple classes, accuracy is not usually used to assess performance.

Precision, also known as positive predictive value, quantifies the proportion of right predictions based on the chance that the predicted product would match the actual ground truth product, as calculated in Eq. 2.

$$Precision = \frac{TP}{TP + \mathrm{FP}} \tag{2}$$

Additionally, the true positive rate, or also referred to as recall or sensitivity, measures the likelihood that ground truth objects would be accurately recognized, with FN denoting false negative, as calculated in Eq. 3.

$$Recall = \frac{TP}{TP + \mathrm{FN}} \tag{3}$$

Meanwhile, the balance between recall and precision was assessed using the F1-score, particularly in cases where the distribution of classes is not uniform. It can be calculated using Eq. 4.

$$F1 - score = \frac{2 * Recall * Precision}{Recall + Precision} \tag{4}$$

3. Result and discussion

The main purpose of this study was to develop an automated system that is able to automatically classify the defects and non-defects in AM products. The confusion matrix is depicted in Figure 7 and the performance of the defect classification system using YOLOv8 is depicted in Table 2. The system achieved an accuracy of 93.39%, a precision of 91.30%, and a recall of 100%, with the latter indicating that the model successfully identified all actual defect instances. The F1-score of 95.45% reflects a strong balance between precision and recall. These findings align with the study by Cao et al., where YOLOv8 demonstrated the best performance in classifying AM defects [26]. In addition, a study by Zubayer et al. proved that YOLOv8 demonstrated remarkable defect classification accuracy of metal AM, outperforming CNN, SSD, Faster R-CNN, and YOLOv5 models [27].The recommended 70:20:10 split is well-known due to the ability to provide adequate training data while retaining sufficient unseen data for validation, thereby preventing overfitting and ensuring reliable generalization[16]. This makes it well suited for real-time defect classification of 3D-printed AM products.

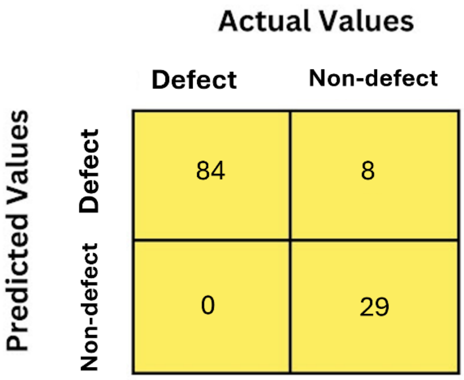


Figure 7. The confusion matrix obtained from the testing images for both non-defect and defect classes

Table 2. The performance analysis for accuracy, precision, recall and F1-score

Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
93.39	91.30	100	95.45

3.1 Graphical user interface (GUI)

The graphical user interface (GUI) of LabVIEW, as illustrated in Figure 8, was successfully linked with the YOLOv8 defect classification model, enabling real-time monitoring and feedback on the condition of 3D-printed products. This interface effectively connects the YOLOv8 classification model to the hardware components, allowing the operator to control and observe the inspection process. The infrared (IR) sensor is triggered when a 3D-printed additive manufacturing (AM) product reaches the inspection zone and it alerts the system to start analysis. The camera module is then used to capture a live image of the product which is instantly shown in the image display section of the GUI so that the user refers to it.

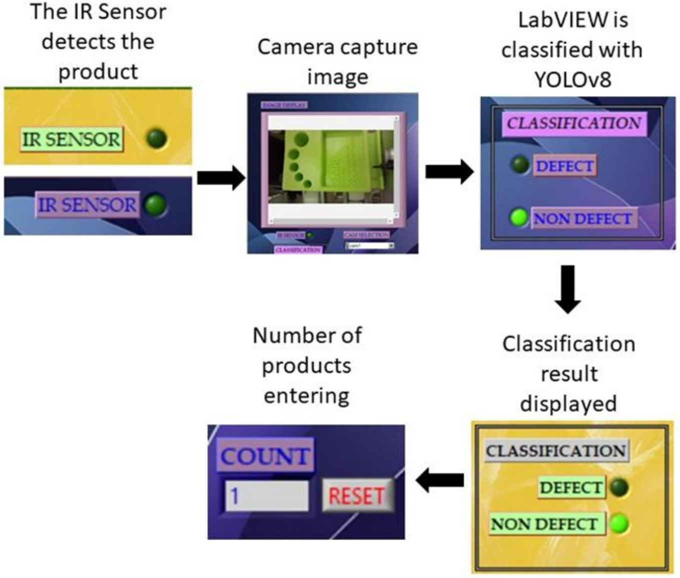


Figure 8. The GUI of the defect classification system displays the defect or non-defect result of the AM product

The key component of the GUI comprised buttons labelled “defect” and “non-defect” to show the classification result. When an object moves through the inspection point, an IR sensor was triggered. In addition, an image display window was incorporated into the interface, which showed the captured images used for defect detection by YOLOv8. This allowed the operators to visually confirm the classification outcome of each product under analysis. This GUI provided the operators with real-time classification results. It also facilitated a smooth transition between automated processing and manual intervention when necessary. The LabVIEW interface enhanced the usability and transparency of the system, enabling operators to interact with the defect classification process more effectively and respond to detection results promptly.

In the updated GUI, a product counter was integrated to automatically track the total number of items that pass through the inspection system. Whenever the infrared (IR) sensor detects a product entering the inspection area, the counter is incremented by one. This count is shown in a numerical indicator, labelled “COUNT”, which provides real-time feedback to the operator. A “RESET” button is also available, through which the operators can reset the count to zero manually at any point in time when tracking or testing batches. This aspect improves the traceability of inspection activities and accurate tracking of throughput in the production setting.

3.2 Result interpretation of defect and non-defect

To assess the performance of the system, an series of images of 3D-printed AM products were tested using the trained YOLOv8 model. The system classified the products into the defect and non-defect categories. An AM product consisting of visible surface defect such as cracks, deformation, or missing features, were generally classified as defective products can be detected using this model. As shown in Figure 9(a), the model clearly identified the non-defect product and correctly classified it as non-defective, while Figure 9(b) demonstrates the correct classification of a defect product as defective, with the model accurately highlighting the primary defect areas. The non-defect products were classified accurately with low false-positive rates, without unnecessarily flagging non-defective regions. Products with consistent, smooth structures were classified as non-defect without issues of precision. This indicates that the model is able to support rapid and accurate inspection in real-time, on-line production environments.The classification results successfully demonstrated the system's ability to distinguish between defective and non-defective products, making it an advantageous option for integration into automated inspection systems across manufacturing settings.

(a) (b)

Figure 9. Result for (a) no defect product; and (b) defect product

In this study, YOLOv8, National Instruments' myRIO and LabVIEW software were used to create a closed-loop control environment that performs real-time object detection, deep learning classification, and mechanical sorting of AM products. The proposed framework is effective in minimizing manual inspection while enabling more accurate and scalable quality control in an industrial environment. Although the proposed method is effectiveit currently focuses on classifying and sorting between defective and non-defective AM products. The proposed framework can be extended to handle any specific types of AM defects such as stringing and layer shifting as well as defect arising from any types of materials used for 3d-printing including metal and ceramics.

4. Conclusion

This study accomplished its primary objective of developing a real-time automated defect classification system and sorting system for additive manufacturing products by coupling the YOLOv8 object detection model with LabVIEW software and myRIO embedded hardware. The YOLOv8 model achieved an accuracy of 93.39%, a precision of 91.30%, a recall of 100%, and an F1-score of 95.45%. LabVIEW successfully integrated the YOLOv8 model with the hardware components, including the USB camera and infrared sensor. The proposed framework is capable of automatically ejecting defective products or allowing non-defective products to continue along the Karakuri conveyor. The classification results are also simultaneously displayed on the GUI in real time. The synchronization of the hardware parts, such as an infrared sensor, USB camera, and servo motor, with the LabVIEW graphical interface allowed the inspection process to be smooth and with minimal human interaction. The interface also increased the usability of the system through real-time monitoring and efficient interaction during use. For future development, the system can be enhanced to identify certain types of defects instead of poerforming binary classification. This would provide more detailed information during inspection. Furthermore, the system's accuracy and flexibility across different production settings might be enhanced by the inclusion of several cameras and variable lighting systems. Further refinement of the existing model through the adoption of more advanced deep learning algorithms can also enable detection of smaller or concealed defects. Overall, the project presents a feasible, sound, and adaptable method of enhancing quality control within the additive manufacturing practice through intelligent automation.

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Declaration of Competing Interest
The authors declared that there are no conflicts of interest.

CRediT Authorship Contribution Statement
N.N. Kamarulzaman (Writing - review & editing; Methodology; Software)
N.S. Damanhuri (Writing - review & editing; Supervision; Methodology; Conceptualization)
N.H.M. Asri (Writing - original draft; Validation; Software; Methodology; Investigation; Formal analysis)
N.A. Othman (Writing - review & editing; Formal analysis)
B.C.C. Meng (Writing - review & editing)
T. Kato (Writing - review & editing)

Availability of Data and Materials
The data of this study's findings are available upon request from the corresponding author.

Ethics Statement
This study did not involve human participant or animals. Ethical approval was therefore not required.

Generative Artificial Intelligence Declarations
The authors claim that artificially intelligent-assisted technologies, such as generative AI, were not used to generate content, ideas, or theories. We have just utilised AI to enhance readability and refine the language. This was used with extreme human control and oversight. The authors take full responsibility for reviewing and approving the content.

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