A Low-Cost IIoT-Enabled Computer Vision-based System for Classifying Defect Types and Severity Levels in Industry 4.0

Panisara Kanjanarut[1] and Warut Pannakkong[2]
[1,2]School of Manufacturing Systems and Mechanical Engineering,
Sirindhorn International Institute of Technology, Thammasat University,
Pathum Thani, Thailand
E-mail: panpanisarakj@gmail.com, warut@siit.tu.ac.th

Received: June 11, 2022 / Revised: October 29, 2022 / Accepted: November 11, 2022

Abstract—**Industry 4.0 technologies such as the Industrial Internet of Things (IIoT) and Artificial Intelligence (AI) can assist in automating defect detection and classification processes which are crucial for quality control in the manufacturing industry. However, there is still a barrier to adopting the technologies in Small and Medium Enterprises (SMEs) because of their limited budget. This paper presents a low-cost defect detection and classification system and an interactive real-time dashboard monitoring IIoT data utilizing a single-board computer and mainly open-source software. In the system, workpieces will be classified into non-defective (OK) and defective (NG) workpieces. Then, the NG workpieces will be further classified into defective types and severity levels. The workpiece used in the case study is a sticker on a 4.4 cm diameter bottle cap. The defect types are Off-Color, Missing Details, and Scratches, then each type is divided further into four severity levels. From evaluation, the system can achieve 96% when classifying as OK/NG and 88% accuracy in classifying defective types and levels. The system's reliability is 100%. Based on experts' opinions, the proposed system is relatively low-cost, reliable, and accurate for practical uses. The proposed system can be implemented locally or globally via a cloud server.**

Index Terms—**Computer Vision, Defect Classification, Industrial Internet of Things, Industry 4.0**

I. Introduction

Industry 4.0 is a term coined by the German government project to encourage the 4th generation of manufacturing through the integration of Information and Communication Technologies (ICT), Internet of Things (IoT), Artificial Intelligence (AI), and web services with industrial machines, systems, and processes [1]. It also raises the term Industrial Internet of Things' or IoT. The cyber-physical infrastructure digitizes information and allows communication between relevant parties to improve efficiency [2]. Utilizing these technologies is beneficial for all-size enterprises, but Small and Medium-sized Enterprises (SMEs), whose processes are manual or semi-automated, are generally at an immense investment disadvantage [3]-[6]. Therefore, creating a low-cost technology and system to accompany SME development toward industry 4.0 that is compatible with the existing system becomes a necessary solution [7].

The common practice of Quality Control (QC) in manual or semi-automation processes is to perform an explicitly manual sampling inspection on the workpiece several times using different viewing angles and distances. When a new defective feature is found, it needs to be inspected by an expert and described manually [8]. These have proven to be a problem due to the sampling inspection strategy since not every workpiece will be inspected [9]. Defect Detection and Classification (DDC) using human operators is also labor-intensive, time-consuming, and tiresome. Leading to them losing concentration resulting in the accuracy of operation falling between 60-70% [10].

Recently, Computer Vision (CV) has become wildly adopted in automatic visual inspection for defect detection due to the availability of cheap cameras and the development of AI. CV is a subfield of AI that trains the computer to replicate human vision, allowing computers to accurately identify and classify objects the same way humans do. The advantages of CV are that camera installation does not interrupt the existing production line, and image taking can be done without a pause. In addition, the classification result from the AI model, along with the inspection timestamp, can be stored automatically, reducing the recording time for analysis.

Most existing literature is done with binary classification or defect/non-defect basis. However, there is more to be considered, such as the defect's type and severity. This information, combined with the date-time component, can prove vital for predictive maintenance [11]. Furthermore, detailed information provides ways to increase the efficiency and flexibility of the production system through real-time monitoring and high-speed reporting through the IIoT dashboard [12].

To develop SMEs toward 4.0, IIoT technology is essential. The main objective of IIoT is to connect a physical object to the Internet allowing remote access control and monitoring [13]. With IIoT devices' tremendous programming ability [14], business operations become more agile and transparent. The real-time dashboard will also support effective decision-making [15].

However, for existing literature, a low-cost DDCS that integrates IoT and real-time dashboards while also considering the type and severity level classification has not been developed.

This study aims to develop a low-cost DDCS and an interactive real-time dashboard monitoring IIoT data. An evaluation of the proposed system is also presented.

The rest of the paper is organized as follows, section II is Related Work of the existing literature. section III is Methodology. section IV is the Evaluation Result, and section V is Discussion. Lastly, section VI is the Conclusion and section VII is Future Work.

II. Related Work

The visual inspection process for defect detection and classification can be done in two ways, contact and contactless. For the contact approach, the operation is done manually by a human operator with an aided tool like magnifying glass or microscope [8], [16], [17]. The inspection task is performed by experienced inspectors who can be effect by fatigue and inattentiveness. Hence this method is unreliable and does not provide stable results due to the subjectiveness of the operator [12].

Also, a human could not operate in real-time, contradicting the Industry 4.0 concept [18], [19]. For the contactless approach, the inspection process is done through one or more cameras and CV software. It allows the operator to carry on without stopping the workpiece.

Many CV systems have been presented in literature within the last decade through the availability of cheap digital imaging devices and computational power development. Examples of industrial visual inspection applications in recent literature include mobile phone screen glass [20], steel surface [21], and leather [16]. Both image processing and deep learning approaches are used to obtain promising results. This technology gives digital data ready to be analyzed and stored locally and globally. However, accumulating data locally, for instance on a Programmable Logical Controller (PLC), is not preferable since the storage space is limited. The solution to this is globally stored on a cloud platform enabled by IIoT.

Researchers have recently focused more on integrated information and communication technology [22]. This Internetworking and connectivity of IoT allowed automation in various fields [11]. It also gave analysis measures that contribute towards strategical planning for SMEs. Moreover, knowing the process stability and quality gives the manufacturer time to reduce or control the defects during the process [9]. [23] stated that adopting IoT is one of the solutions to develop SMEs towards Industry 4.0.

From all the literature mentioned above, the algorithm is run on a Personal Computer (PC), which is not cost-effective for classifying and transmitting IoT data. A single-board computer is more practical than a PC for tasks like this. Raspberry Pi is a small yet powerful single-board computer introduced in 2012. Kurkovsky and Williams [24] stated that a Raspberry Pi has enough processing power to implement up to servicing layers needed to have a networked IoT device. Hou et al. [17] also use a Raspberry Pi 3B to run laser chip classification; They suggest that a better single-board computer needs to be considered. In June 2019, the Raspberry Pi 4B was released with a 1.5 GHz 64-bit quad-core ARM Cortex-A72 processor [25]. This improvement is promising

In conclusion, a low-cost IIoT-enables DDCS is proposed and evaluated. The system merges a low-cost non-contact visual inspection with IIoT to develop SMEs toward 4.0 requirements. This solution is important and quite challenging. The system also can be extended to other manufacturing processes.

III. Methodology

This section includes two main sections, the generalized concept of a proposed system and a case study.

A. Proposed System

Fig. 1 shows an overview of the proposed system for deployment in the production line. The camera captures the workpiece image and does image processing, then transmits measurement data to the classification model, database, and dashboard. Soon after, Statistics and a summary of the production line defect type and severity level are shown on the dashboard for monitoring. Such a system allows detailed evaluation and helps identify possible causes of faults.

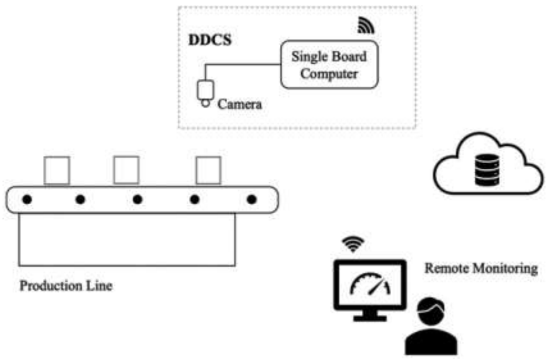


Fig. 1. The proposed system consisted of a camera, a single-board computer, and a remote monitoring system.

B. Case Study

In our case study, the proposed system is implemented in a demonstration set, as shown in Fig. 2. The camera used is a Mitsubishi Electric Vision Sensor (VS20). The single-board computer is a Raspberry Pi 4 Model B with 8 Gb RAM equipped with a 5V fan supply mounted on top powered by its own GPIO pin. The software used to develop a remote monitoring system is Node-Red, which is an open-source program. The database is Google Sheets. A green, yellow, and red LED will be connected to Raspberry Pi to act as a status indicator. Production Line is controlled by a Programmable Logic Controller (PLC). There are three photo sensors used as PLC's input in a ladder diagram. One at the starting of the conveyor is used to signal the conveyor. Another one locates before the camera is used to trigger the camera when the workpieces arrive. The last one is located after the camera signals the pusher to eject the defective workpiece.

1) Experiment Workpieces

The workpiece used in this experiment is a printed sticker on top of a twisted-off plastic cap with a clear glass bottle. For the quality characteristic, the sticker must have the correct color and clear printing with correct details. The types of defects are classified into three types: Off-color, missing details, and scratches, as shown in Fig. 3. Each type of defective workpiece consists of four severity levels (i.e., 1, 2, 3, and 4). The severity levels increase as the number goes up.

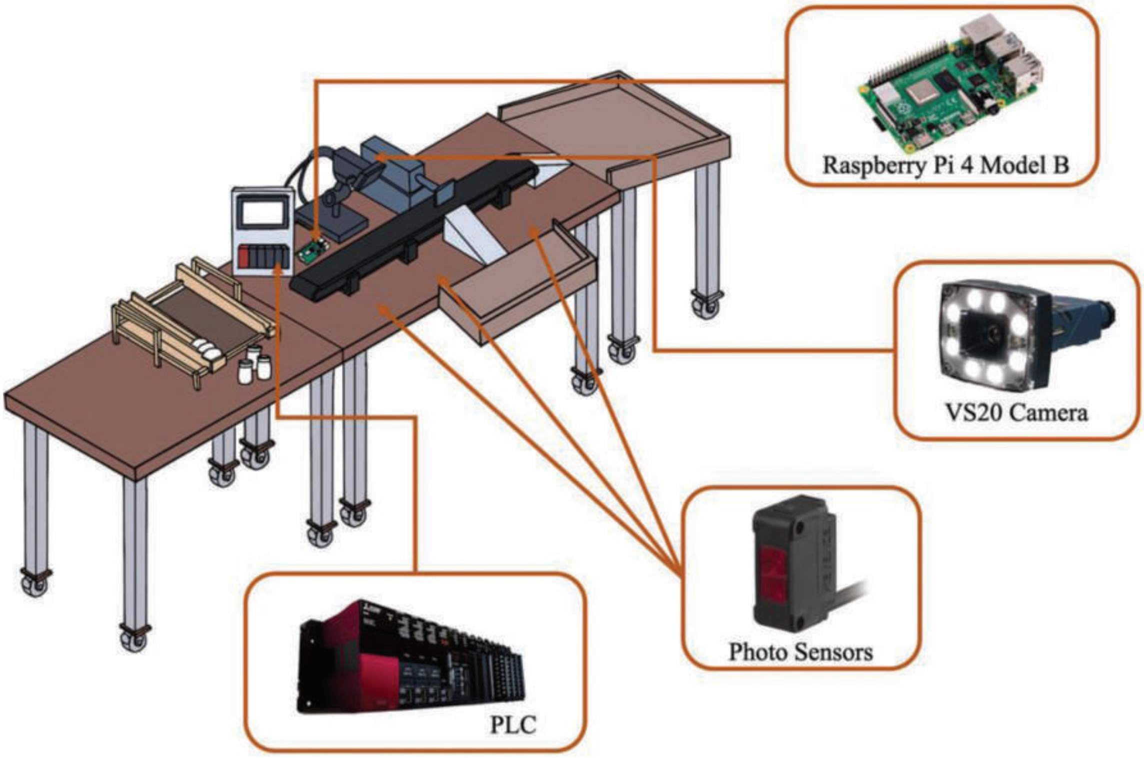


Fig. 2. Components of demonstration set [26]-[28]

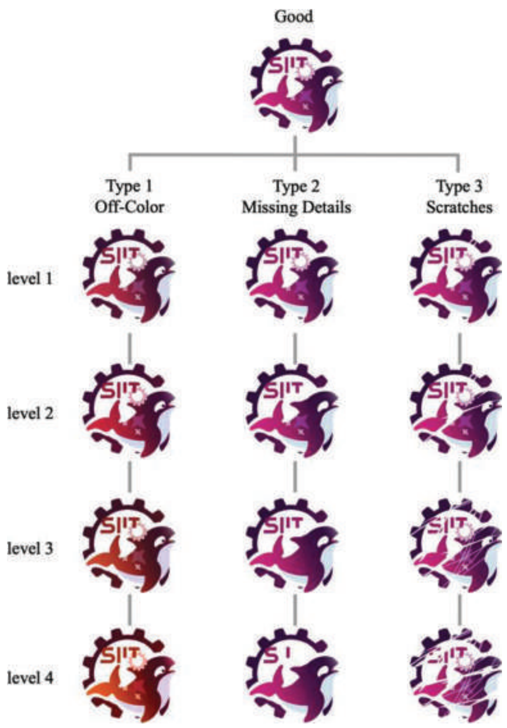


Fig. 3. 13 Types of stickers consisted of good and off-color type 1 to 4, missing details type 1 to 4, and scratches type 1 to 4.

For type 1 defect (off-color), the first two severity levels are less vibrant but are still purple, while the last two severity levels fade to the point that they appear brown. For type 2 defects (missing details), a severity level 1 is missing barely noticeable details like the eye. Severity level 2 is missing one component, while severity levels 3 and 4 lack most of the critical components. For type 3 defects (scratch), severity level 1 contains one or two small scratches. Severity level 2, the scratch is noticeable with minimal effort. Severity level 3, the scratches are evident. For severity level 4, the scratches almost erase the component's details.

Totally, there are 13 different stickers. One is for a good workpiece, and the remaining 12 are defective workpieces. However, severity level 1 is not significantly different from the original workpiece. Therefore, we assume that the user accepts the severity level 1 workpiece, and it can be classified as an OK workpiece along with Good stickers.

2) Vision System

In the demonstration set, the QC process is done using a Cognex Vision Sensor. The vision sensor is a specialized quality-control tool that combines a machine-vision camera with onboard intelligence.

There are three main used tools consisted of pattern, color pixel count, and logic tools. Each tool provides an output signal as pass or fail. The pattern tool determines whether a trained pattern is present or absent. The color pixel count tool determines whether a color feature is present or absent based on the number of matching color pixels in a searching region with the selected colors. Finally, the logic tool is an expression builder to create a logical formula combining the output signal from the other tools and generating a pass or fail signal. The list of tools used is shown in Fig. 4.

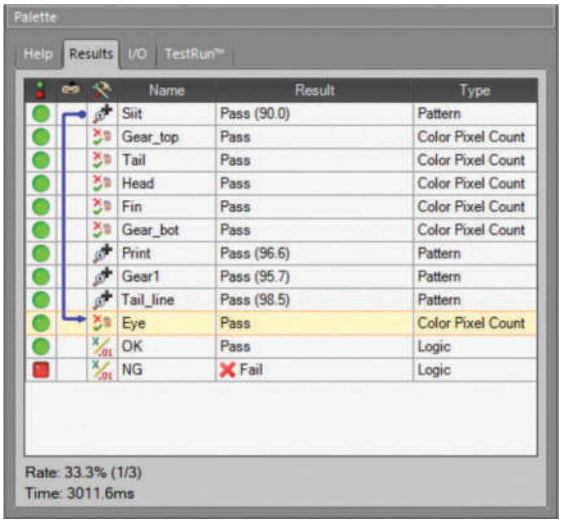


Fig. 4. Image processing tools used to extract information from the workpiece picture.

The output string from the vision system is encoded into UTF-8 format and then transferred to the Raspberry Pi through an ethernet cable. Finally, the output from each tool is selected to be used in the classification model, as shown in Fig. 5.

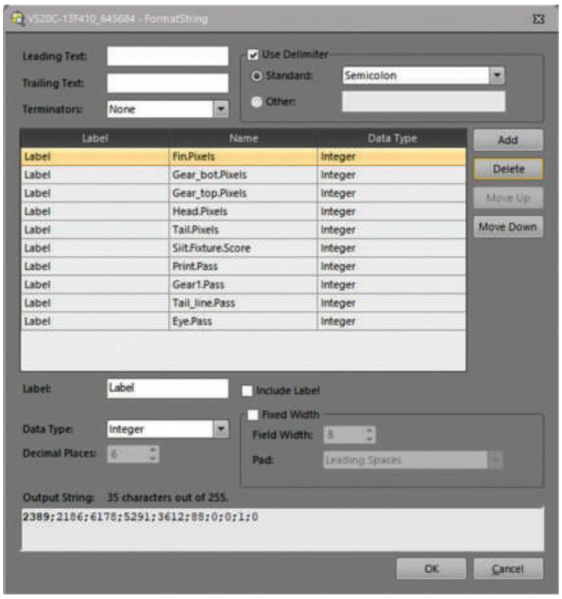


Fig. 5. Outputs from vision sensor to use as inputs for AI model

Outputs selected are the rawest possible outputs from each tool which are the number of pixels from the pixel count tool and the percent similarity score from the pattern tool. However, when the workpiece is missing details. Instead of giving the similarity score of 0, the pattern tool will give an error message and not send any output to the Raspberry Pi. The binary result (.pass) is used to resolve this issue.

3) Raspberry Pi

The communication between Raspberry Pi and VS20 is through a socket protocol coding in Python. The Raspberry Pi becomes a server waiting for a connection. When the data is received, it will go through a classification model and be uploaded to the database and dashboard.

The Raspberry Pi has a General Purpose Imput/Output (GPIO), which can be used to supply current to the output load. In this demonstration, the pin is connected to an LED. A green LED lights up when the connection with Node-RED has been established and will be off if the user calls emergency status from the dashboard, and a yellow LED will lighten up instead. The red LED lights up when the classification model predicts the workpiece is a defective product. A pseudocode for implementing Raspberry Pi is shown in Fig. 6.

```
set up socket server
set up MQTT to Node-RED
load classification model

while True:
    camera connect to Raspberry Pi
    green LED on

    while True:
        received data from the camera
        classification model predicts result
        get timestamp
        upload result and timestamp
        publish result to dashboard

        if result is defect:
            red LED on for 1 s

close the connection
```

Fig. 6. Psudo code

4) Classification Model

Random Forest (RF) is used to classify the workpiece (i.e., good or defect type and severity level) by using outputs from VS20 as its inputs. The training phase of the classification model is done outside using Google Colab, then used Pickle Python module, which is the standard way of serializing objects into a file for Python. Finally, the desterilized model is used to make a new prediction. Results from the classifier are transmitted to Node-RED over the Internet using the MQTT protocol.

In the RF model, there are three hyperparameters which are *n_estimator*, *criterior,* and *bootstrap*. The *n_estimator* specifies the number of trees in the forest. The *criterior* used is gini, which is a type of function to measure the quality of the tree split. The *bootstrap* is used when building the tree. If the *bootstrap* is False, then the whole dataset is used, otherwise, some samples in the dataset are used to train the model. Through a trial and error process, the best configurations of the hyperparameters are *n_estimator* = 500, *criterior* = gini, and *bootstrap* = False.

5) Monitoring

Node-RED is a flow-based development tool for visual programming. It was initially developed by IBM for wiring together hardware devices, APIs, and online services as part of the Internet of Things. AUI interface is then created using JavaScript. Fig. 7 below shows the proposed dashboard.

From the dashboard, detailed statistics related to production status can be monitored remotely. At a glance, it shows the summary of the production state. This information gives a clear summary of the production line and helps determine the progress when working on a specific order.

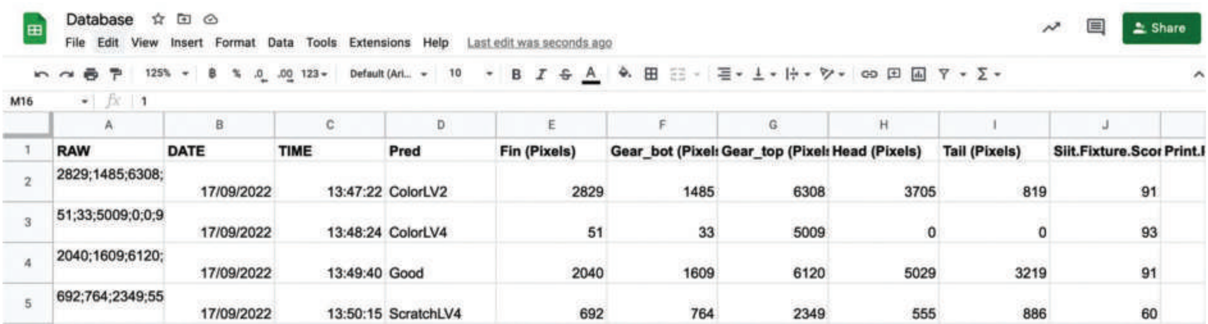
In the control panel section, the required user's input will be used to calculate the Overall Equipment Efficiency (OEE). It is a performance measurement tool that measures different types of production losses like quality loss, availability loss, and performance loss. The use of OEE can help identify areas for process improvement.

The Node-RED server can be hosted on the Raspberry Pi or the cloud server. Running the server locally will limit the user to be within the same network in order to access the dashboard, while the benefit of hosting on a cloud server is global access but will come with additional costs. Since Node-RED is IBM donated, lunching on the IBM cloud is more convenient.

6) Database

Using Google API, the classification results from the RF model, the date-time components, and the camera outputs can be uploaded to a Google Sheet for later use. The information included are raw data, date, time, and prediction result. The raw data is also split into individual columns as shown in Fig. 8.

Fig. 7. Dashboard of the case study



	A	B	C	D	E	F	G	H	I	J
1	RAW	DATE	TIME	Pred	Fin (Pixels)	Gear_bot (Pixel	Gear_top (Pixel	Head (Pixels)	Tail (Pixels)	Slit.Fixture.Scor
2	2829;1485;6308;	17/09/2022	13:47:22	ColorLV2	2829	1485	6308	3705	819	91
3	51;33;5009;0;0;9	17/09/2022	13:48:24	ColorLV4	51	33	5009	0	0	93
4	2040;1609;6120;	17/09/2022	13:49:40	Good	2040	1609	6120	5029	3219	91
5	692;764;2349;55	17/09/2022	13:50:15	ScratchLV4	692	764	2349	555	886	60

Fig. 8. Database Information

IV. Evaluation

For evaluating the performance of the demonstration set, reliability and accuracy have been tested.

A. Reliability Test

The ability to work over a long period is essential for equipment used in an industrial environment. Hence reliability is a concern.

To check the reliability, testing with an operating speed of 1000 units per hour over consecutive 8 hours has been performed under two ambient temperature conditions (i.e., an air-conditioned room (25) and a normal room (35)).

Over the 8 hours, we monitor the output generated from the Raspberry Pi, such as the classification result and dashboard statistics. As expected, the amount of output at the end of the testing is 8,000.

Moreover, the CPU and GPU temperatures in the Raspberry Pi are measured. The temperatures are shown in Fig. 9.

The temperature could reach a certain point until it throttles the processing capability. The time it takes the processor to calculate is also raised as an issue.

The average temperature is 42.4 on both processors for a normal room. For an air-conditioned room, the average temperature is 36.6 The temperatures are relatively steady around the averages. The testing result implies that the Raspberry Pi can pass this reliability test.

B. Accuracy Test

The accuracy is crucial. Without measuring accuracy, it is difficult to know whether the model is working as expected.

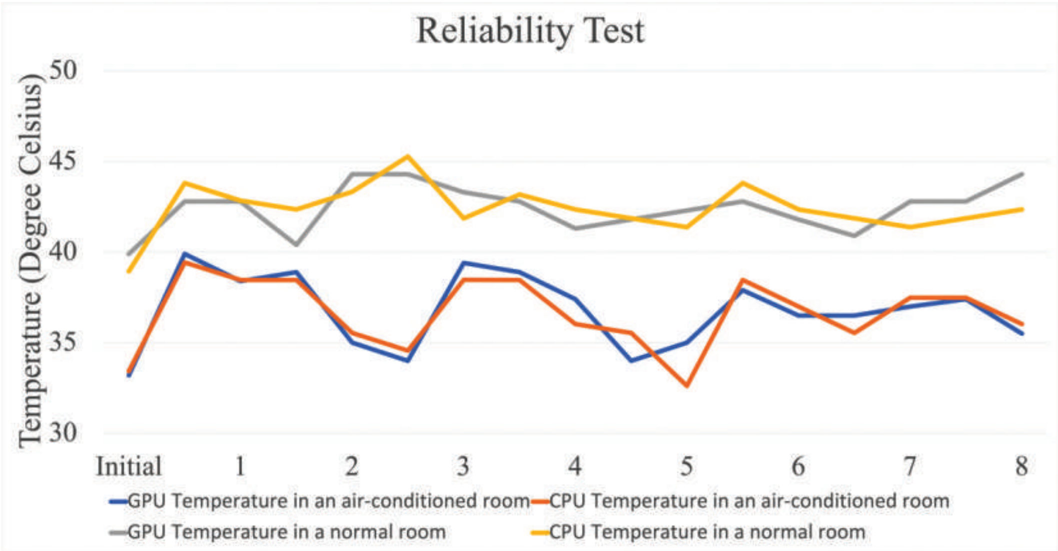


Fig. 9. CPU and GPU temperatures of Raspberry Pi over 8 hours

The test was conducted using 650 workpieces (50 workpieces of each 13 stickers) on the demonstration set. The bottle's placement is done manually at the starting position of the conveyor, and the sticker's rotation angle is random.

The performances measured are classification accuracy, precision, and recall. The results are shown in Fig. 10. The value lower than 80% is in red.

The model accuracy is 87.08%. When comparing precision and recall side by side, for most of the stickers, the results are satisfied. However, recall for Good, Missing Details level 1, and Scratches level 1 is alarming. For precision, Good, Scratches Level 1, and Scratches Level 2 are a concern.

		PREDICTED															
Type		Good	Off Color				Missing Details				Scratch						
	Level	-	1	2	3	4	1	2	3	4	1	2	3	4	Total	Recall	Precision
TRUE Good	-	32									16	2			50	64%	62%
Off Color	1		50												50	100%	100%
	2			50											50	100%	96%
	3			2	48										50	96%	100%
	4					50									50	100%	100%
Missing Details	1	15					17				12	5	1		50	34%	85%
	2							47	1		1	1			50	94%	92%
	3	1						1	44	2		2			50	88%	98%
	4									50					50	100%	96%
Scratch	1	4					2	3			31	10			50	62%	52%
	2						1					49			50	98%	70%
	3											1	49		50	98%	96%
	4												1	49	50	98%	100%

Accuracy	87.08%

Fig. 10. Camera and RF's model's accuracy test

The conclusion is that Good and Scratches level 1 is the main reason why the model is not as accurate. The model tends to predict Missing level 1 as another type and tends to predict other types as Scratches level 2.

Suppose we summarize the model result into OK/NG classification as shown in Fig. 11. The accuracy is significantly improved at 96.31% compared to the result from using the camera alone. The model gets almost 100% in rejecting defective workpieces and 90% accuracy in accepting a good workpiece. A 10% reject when actually a good workpiece is a concern but not as severe as a classified defective workpiece as OK.

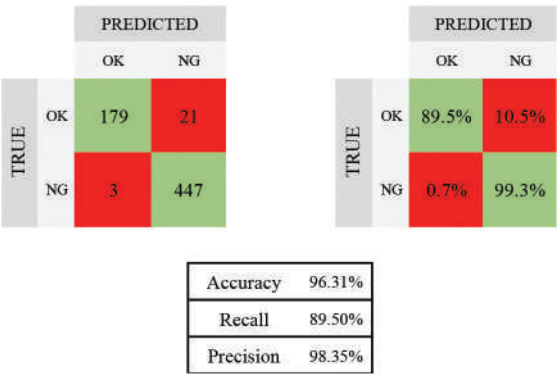


Fig. 11. Camera and RF's model's accuracy test as OK/NG

V. Discussion

To the best of our knowledge, cost is an aspect that has never been the main discussion for vision systems. The demonstration set presented in this paper solely utilized open-source programming tools. In a situation where the investor already has the camera, the cost of the system is approximately 6,000 THB. Nevertheless, without the VS20 camera, a webcam camera can be implemented without raising costs substantially. The current webcam price in the market is a few thousand. Assuming the webcam price is 5,000 THB, the total system cost becomes 11,000 THB. To hire an employee, would cost 15,000 THB/month. Therefore, the payback period is less than a month, which seems affordable for SMEs.

When compared to other low-cost IIoT applications from various fields, the price is highly dependent on the amount and the quality of sensors integrated into the system. The minimum price is 4,500 THB [30] and the maximum is 41,000 THB [31] while the median falls at 8,700 THB. This makes our application fall in the middle of the range. A box plot for comparing five applications [30]-[34] is shown in Fig.12.

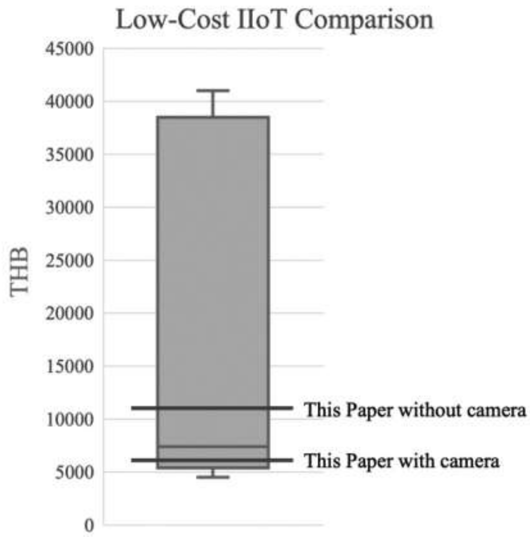


Fig. 12. Box plot of IIoT application cost

After obtaining the performance result, we conducted an initial survey with four people who have more than ten years of experience in the field of manufacturing and CV. The Participants are two Business Owners and two Vision System experts. Their opinion on the proposed system and performance is that pricing is cheaper than expected. If the breakeven point is lower than two years would definitely invest, but accuracy could be better.

From the reliability test, the developed system is highly reliable in both ambient environments. From the accuracy test, considering recall value, the RF model performs excellently except for Good, Missing Details level 1, and Scratches level 1. This is because the difference between these stickers is relatively small. The Missing Details level 1 does not have an eye of the orca, while Scratches level 1 has two minor scratches on the outer gear. A comparison between the three types of stickers is shown in Fig. 13.

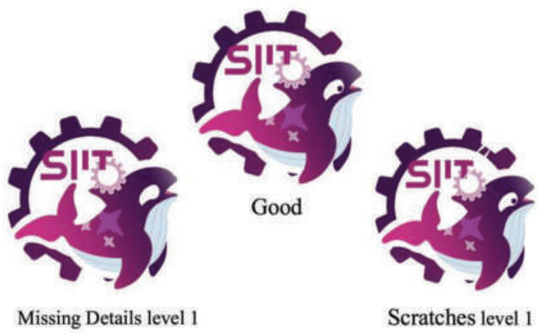


Fig. 13. Comparison between good, missing details level 1 and scratches level 1

The next point of concern is when a defective workpiece is classified as an OK even if the possibility is low at 0.7% (three samples from Fig. 11). The detailed information on the three samples is shown in Table I. The last four columns in Table I and further investigation by comparing the camera binary outputs to the ground truth shown in Table II imply the lack of repeatability since roughly 60% is correct.

TABLE I
GOOD WORKPIECE AS DEFECTIVE WORKPIECE OUTPUT

Predict	True	Print (Binary)	Small Gear (Binary)	Tail Line (Binary)	Eye (Binary)
Good	MissingLV3	0	0	0	1
ScratchLV1	MissingLV2	1	1	1	1
MissingLV1	ScratchLV2	1	1	0	0

TABLE II
GROUND TRUTH OF THE WORKPIECES

True	Print (Binary)	Small Gear (Binary)	Tail Line (Binary)	Eye (Binary)
MissingLV3	0	0	1	0
MissingLV2	1	0	1	0
ScratchLV2	1	1	0	1

VI. CONCLUSION

This study aims to develop a low-cost defect detection and classification system and an interactive real-time dashboard monitoring IoT data. An evaluation of the proposed system is also presented.

This paper proposed a low-cost defect detection and classification system with interactive real-time dashboard monitoring IoT data. The system utilizes 4.0 technology such as AI and IIoT to assist visual inspection process and automated data recording (i.e., date-time component, defective type, and severity level). Furthermore, the automated system allows every workpiece to be inspected, and the use of a single-board computer placed on the surface makes it compatible with the existing production line.

For the case study, the demonstration set has been evaluated. The reliability of Raspberry Pi is high in both 25 and 35 ambient temperatures. The accuracy is 96% on OK/NG classification and 87% on defective type and severity level. To deploy on an actual production line, the accuracy needs to be improved. If camera precision is improved, it should be possible to improve the overall accuracy, as shown when training AI with ground truth.

VII. FUTURE WORK

Another image processing program is also done manually and will need expert assistance when there is a new workpiece. A method to automate this process would be beneficial.

Subsequently, a long-term test should be conducted to determine the reliability and maintenance needed for hardware like the Raspberry Pi. Finding the most suitable machine learning algorithm is challenging and requires a trial-and-error process. Testing other algorithm performance over the same problem is highly interesting. Lastly, the classification should be redefined from multi-class to multi-label problems since defects can be more than one type at the same time.

ACKNOWLEDGMENTS

The authors wish to thank Mitsubishi Electric Thailand for providing us the industry knowledge and supporting us throughout this study. The authors also wish to thank Ms. Sureerat Phadungsakviriya and her team for in coordinating and supporting us to achieve this study. Lastly, the authors wish to thank Associate Professor Pisal Yenradee (D.Eng.) for his valuable guidance and advice.

REFERENCES

[1] Z. Shahbazi and Y. C. Byun, "Integration of Blockchain, IoT, and Machine Learning for Multistage Quality Control and Enhancing Security in Smart Manufacturing," *Sensors*, vol. 21, no. 4, p. 1467, Feb. 2021.

[2] U. Ullah, F. A. Bhatti, A. R. Maud et al., "IoT-Enabled Computer Vision-Based Parts Inspection System for SME 4.0," *Microprocessors and Microsystems*, vol. 87, p. 104354, Nov. 2021.

[3] P. Naruetharadhol, W. A. Srisathan, N. Gebsombut et al., "Industry 4.0 for Thai SMEs: Implementing Open Innovation as Innovation Capability Management," *International Journal of Technol*ogy, vol. 13, no. 1, pp. 48-57, Jan. 2022.

[4] E. Rauch, P. Dallasega, and M. Unterhofer, "Requirements and Barriers for Introducing Smart Manufacture Ring in Small and Medium-Sized Enterprises," *IEEE Engineering Management Review*, vol. 47, no. 3, pp. 87-94, Jul. 2019.

[5] H. Han and S. Trimi, "Towards a Data Science Platform for Improving SME Collaboration Through Industry 4.0 Technologies," *Technological Forecasting and Social Change,* vol. 174, p. 121242, Jan. 2022.

[6] H. Oliff and Y. Liu, "Towards Industry 4.0 Utilizing Data-Mining Techniques: A Case Study on Quality Improvement," in *Proc. CIRP*, 2017, pp. 167-172.

[7] M. Sony and S. Naik, "Critical Factors for the Successful Implementation of Industry 4.0: A Review and Future Research Direction," *Production Planning & Control*, vol. 31, no. 10, pp. 799-815.

[8] J. Villalba-Diez, D. Schmidt, R. Gevers et al., "Deep Learning for Industrial Computer Vision Quality Control in the Printing Industry 4.0," *Sensors*, vol. 19, no. 18, p. 3987, Nov. 2019.

[9] Z. Zhang, Z. Yang, W. Ren et al., "Random Forest-Based Real-Time Defect Detection of Al Alloy in Robotic Arc Welding Using Optical Spectrum," *Journal of Manufacturing Processes*, vol. 2, pp. 51-59, Jun. 2019.

[10] H. I. Çelik, L. C. Dülger, and M. Topalbekiroğlu, "Development of a Machine Vision System: Real-Time Fabric Defect Detection and Classification with Neural Networks," *The Journal of the Textile Institute*, vol. 105, no. 6, pp. 575-585, Jun. 2017.

[11] A. Kanawaday and A. Sane, "Machine Learning for Predictive Maintenance of Industrial Machines Using IoT Sensor Data," in *Proc. The 8th IEEE International Conference on Software Engineering and Service Science (ICSESS) 2017*, 2017, pp. 87-90.

[12] S. Mei, Y. Wang, and G. Wen, "Automatic Fabric Defect Detection with a Multi-Scale Convolutional Denoising Autoencoder Network Model," *Sensors*, vol. 18 no. 4, p. 1064, Apr. 2018.

[13] K. Shafique, B. A. Khawaja, and F. Sabir, "Internet of Things (Iot) for Next-Generation Smart Systems: A Review of Current Challenges, Future Trends and Prospects for Emerging 5G-IoT Scenarios," *IEEE Access*, vol. 8, pp. 23022-23040, Jan. 2020.

[14] D. Shah, J. Wang, and Q. P. He, "An Internet-of-Things Enabled Smart Manufacturing Testbed," *IFAC-Papers OnLine,* vol. 52, no. 1, pp. 562-567, Jan. 2019.

[15] G. Erboz, "How to Define Industry 4.0: Main Pillars of Industry 4.0," in *Proc. International Scientific Conference Managerial Trends in the Development of Enterprises in Globalization Era*, 2017, pp. 761-767.

[16] S. T. Liong, Y. S. Gan, Y. C. Huang et al., "Integrated Neural Network and Machine Vision Approach for Leather Defect Classification," *arXiv*, vol. 1, pp. 1-12, May. 2019.

[17] D. Hou, T. Liu, Y. T. Pan et al., "AI on Edge Device for Laser Chip Defect Detection," in *Proc. The 2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*, 2019. pp. 0247-0251.

[18] K. Židek, V. Modrák, J. Pitel et al., "The Digitization of Quality Control Operations with Cloud Platform Computing Technologies," *In Industry 4.0 for SMEs*, pp. 305-334, 2020.

[19] S. Groggert, M. Wenking, R.H. Schmitt et al., "Status Quo and Future Potential of Manufacturing Data Analytics—An Empirical Study," in *Proc. 2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 2017, pp. 779-783.

[20] C. Jian, J. Gao, and Y. Ao, "Automatic Surface Defect Detection for Mobile Phone Screen Glass Based on Machine Vision," *Applied Soft Computing*, vol. 52, pp. 348-358, Mar. 2017.

[21] Y. He, K. Song, H. Dong et al., "Semi-Supervised Defect Classification of Steel Surface Based on Multi-Training and Generative Adversarial Network," *Optics and Lasers in Engineering*, vol. 122, pp. 294-302, Nov. 2019.

[22] J. Harkonen, E. Mustonen, J. Koskinen et al., "Digitizing Company Analytics–Digitalization Concept for Valuable Insights." in *Proc. The 2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 2020, pp. 1012-1016.

[23] D. Grube, A. A. Malik, and A. Bilberg, "Generic Challenges and Automation Solution in Manufacturing SMEs," in *Proc. The 28th DAAAM International Symposium*, 2017, pp.1161-1169.

[24] S. A. Kurkovsky and C. Williams, "Raspberry Pi as a Platform for the Internet of Things Projects: Experiences and Lessons," in *Proc. The 2017 ACM Conference on Innovation and Technology in Computer Science Education*, 2017, pp. 64-69.

[25] Raspberry Pi. (2022, Mar. 8). *Raspberry Pi 4 Model B Specifications*. [Online]. Available: https://shorturl.asia/ichWb

[26] Newark. (2022, Mar. 8). *Single Board Computer, Raspberry Pi 4 Model B*. [Online]. Available: https://shorturl.asia/8FOWd

[27] Mitsubishi Electric (2022, Mar. 8). *Melsensor Vision Sensor*. [Online]. Available: https://www.mitsubishifa.co.th/files/dl/vs20_catalog_eng_rev.pdf

[28] Keyence. (2022, Mar. 8). *Square Retro-Reflective Cable Type.* [Online]. Available: https://shorturl.asia/a9TOQ

[29] Mitsubishi Electric. (2022, Mar. 8). *MELSEC iQ-R Series iQ Platform-compatible PAC*. [Online]. Available: https://shorturl.asia/dfJZx

[30] F. D. M. Marconcini, M. E. V. Segatto, and E. O. T. Salles, "A Low-Cost Smart Surveillance System Applied to Vehicle License Plate Tracking," *Journal of Microwaves, Optoelectronics and Electromagnetic Applications*, vol. 21, no. 1, pp.141-156, Mar. 2022.

[31] A. Arunachalam and H. Andreasson "RaspberryPi-Arduino (RPA) Powered Smart Mirrored and Reconfigurable Iot Facility for Plant Science Research," *Internet Technology Letters*, vol. 5, no. 1, p. e272, Jan. 2022.

[32] S. Komarizadehasl, M. Komary, A. Alahmad et al., "A Novel Wireless Low-Cost Inclinometer Made from Combining the Measurements of Multiple MEMS Gyroscopes and Accelerometers," *Sensors*, vol. 22, no. 15, p. 5605.

[33] T. Shaown, M. Shohrab Hossain, and T. M. Mukur, "Low-Cost Health Monitoring System: A Smart Technological Device for Elderly People," in *Proc. 6th International Congress on Information and Communication Technology*, pp. 851-860, 2021.

[34] J. S. Botero-Valencia, J. Valencia-Aguirre, D. Gonzalez-Montoya et al., "A Low-Cost System for Real-Time Measuring of the Sunlight Incident Angle Using IoT," *HardwareX*, vo1. 11, p. e00272, Apr. 2022.

Panisara Kanjanarut is currently a Master's student in the Artificial Intelligence and Internet of Things Program (AIoT) at Sirindhorn International Institute of Technology (SIIT), Thammasat University, Thailand. She received her B.Eng. in Industrial Engineering from SIIT. Her research interests are computer vision in industrial applications, the Industrial Internet of Things (IIoT), and machine learning.

Warut Pannakkong is an Assistant Professor at the School of Manufacturing Systems and Mechanical Engineering (MSME), Sirindhorn International Institute of Technology (SIIT), Thammasat University, Thailand. He received his B.Eng. in Industrial Engineering and M.Eng. in Logistics and Supply Chain Systems Engineering both from SIIT in 2010 and 2014, respectively. He earned his Ph.D. in Knowledge Science from the Japan Advanced Institute of Science and Technology (JAIST) in 2017. His research interests include time series forecasting, data mining, machine learning, computer vision in industrial applications, discrete event system simulation and optimization, production planning, and logistics and supply chain management.