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Journal of Advanced Research Design

Journal homepage:
https://akademiabaru.com/submit/index.php/ard
ISSN: 2289-7984

Part Detection Model for Aerospace Manufacturing Quality Control using Convolutional Neural Networks

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ARTICLE INFO

Article history:
Received 10 January 2025
Received in revised form 14 February 2025
Accepted 23 May 2025
Available online 2 June 2025

Keywords:
Part detection; convolutional neural networks; deep learning; quality control

ABSTRACT

Ensuring the precision and efficiency of quality control processes in the aerospace manufacturing industry is critical to remain competitive. This paper presents an advanced approach to address the challenge of identifying and categorising similar aerospace components quality effectively using Artificial Intelligence's computer vision and convolutional neural network's deep learning technique to resolve the issue of parts misclassification. Specifically, in the development of a comprehensive database for object detection using Phyton programming and tailored to the unique requirements of the aerospace industry under study. The methodology involved collecting a diverse dataset comprising 50 images per class, annotated with bounding boxes and class labels, covering a pilot of D232B and D233B machining parts. The dataset is partitioned into training, validation, and test sets to facilitate the model training and evaluation. Furthermore, tools for managing and accessing the dataset were introduced, including the interface for image labelling. Leveraging on TensorFlow, the effectiveness of this approach was able to be tested in training the part detection model with 94% accuracy for part D233B and 97% accuracy for part D232B, showcasing its suitability for real-world aerospace manufacturing quality inspection applications. Overall, this project represents a significant advancement in improving quality inspection process in the aerospace industry, offering a valuable approach for enhancing efficiency and accuracy in component identification.

1. Introduction

The manufacturing industry has experienced significant evolution throughout the last century. The Six Sigma, Lean, and Agile manufacturing approaches have been instrumental in driving increased productivity and cost reduction. Paradigms like Industry 4.0 (IR 4.0), Cyber-Physical Systems, and Smart Manufacturing (SM) have more recently ushered in an era of interconnected shop floor environments, leveraging advancements in robotics and automation. Thus, these manufacturing

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https://doi.org/10.37934/ard.133.1.110

businesses are forced to rethink, re-examine, and re-evaluate their current operations and future strategic directions in the new era of SM and IR 4.0 [1]. SM is a technologically advanced method that makes use of new hardware designs and Internet-connected machinery to monitor production processes, increase flexibility, and assist employees in their day-to-day tasks through creative human-computer interaction [2]. SM uses IR 4.0 technologies such as collaborative robots, internet of things (IoT), data analytics, augmented reality and artificial intelligence (AI). Helu *et al.,* [3] described the concept of SM to encompass manufacturing systems that integrate advanced manufacturing capabilities and digital technologies across the entire product lifecycle which exhibit enhancements in various aspects, i.e. Inter-system communication *via* network connectivity, gathering and utilisation of operational data, facilitation of decision-making processes, and enhanced adaptability to accommodate the use of advanced materials.

In the aerospace manufacturing industry, there is a challenge related to the identification and sorting of aircraft components, specifically the wing parts. The manufacturing process involves the creation of parts based on provided drawings. However, since the parts consist of both left and right sides that have similar appearances but different shapes, it becomes essential to label them correctly to avoid mistakes. As a result, the quality control team must refer back to the drawings to find the part numbers and analyze each part to determine its correct side. This process is time-consuming and prone to errors. Failing to address this problem can lead to incorrect parts being released to customers, compromising the overall quality and reliability of the aerospace products. Therefore, the aim of this project is to create a model for effectively identifying and classifying similar aerospace components' quality. This will be achieved through the utilization of artificial intelligence's computer vision and deep learning techniques, specifically convolutional neural networks. Hence, the efficiency and accuracy in part recognition and quality control processes for the aerospace manufacturing under study will be enhanced by leveraging computer vision technology and machine learning algorithms.

2. Convolutional Neural Networks

AI has shown tremendous promise in recent years, particularly in machine learning (ML), Pattern Recognition (PR) and Deep Learning (DL) to revolutionise the manufacturing industries by providing sophisticated analytics tools to handle the massive volumes of manufacturing data generated, or "Big Data."[4]. Balamurugan *et al.,* [5] evaluated the AI applications in various industries and discovered AI technologies including sensors, robots, and machine learnings contribute to enhancing both product quality and production flexibility. This data-driven approach is increasingly popular to replace the manual visual inspection task. The goal of PR is to identify and extract patterns from the input data in order to find recognisable patterns of the data. As such, sensors are used to gather huge amount of data for PR system to analyse and used to accomplish certain tasks [6]. ML uses two different PR approaches; the pixel-based using the pixel values of an image and feature-based where only a certain relevant characteristic of the image is extracted to design and train the inspection machine [7].

A more advanced PR technique is the DL which allows the machine to learn abstract features of an image automatically through various technologies such as convolutional neural network (CNN). The CNN is a type of neural network that can find important details in information using special patterns called convolutions. Unlike ML's feature extraction method, CNN uses visual perception which provides advantages such as effectiveness in focusing just on the important image parameters, which reduces the amount of data retention [8,9]. Hafizh *et al.,* [10] summarized various studies regarding the wide applications of CNN for the inspection of manufacturing parts with high classification and accuracy rates making CNN a popular computer vision method used for image classification and defect detection. Such CNN applications include inspection of metal additives manufacturing parts [11], metal casting parts for defect inspection [12] and aluminium part inspection for robotic arc welding [13]. Further, a most recent study using CNN was conducted by Elvitaria *et al.,* [14] for the batik industry on pattern classification.

In the manufacturing system, the inspection process is a crucial decision-making process where the operator, or decision maker, uses probabilistic reasoning involving precision, validity, reliability, versatility and rapidity to decide whether to accept or reject the product at each stage [15]. Visual inspection is a crucial kind of quality control in manufacturing where the inspector performs an evaluation on the product by sight at various stages to determine if it is ready to proceed to the next step. Wang and Drury [16] broke down the visual inspection process into distinct sequential tasks, which include positioning of the item, scrutinizing the item, identifying defect, categorizing the defect, decision making on the item, releasing the item and documenting pertinent information regarding the item. Therefore, the process of inspection requires significant human intelligence through cognitive effort, meticulous attention to detail, swift decision making, effective communication, and utilization of both short-term and long-term memory [17]. Image-based quality inspection techniques for defect detection in manufactured goods have been used in a number of works. As an example, Sundaram and Zeid [18] used the term smart quality inspection by applying AI through DL to replace the manual visual inspection of a casting manufacturing process with 99.86% model accuracy.

Despite the transformative potential of these approaches, smaller enterprises, particularly Small and Medium-sized Enterprises (SMEs), often encounter obstacles to adopt these technologies to their Quality Management System (QMS). SMEs struggle with implementing comprehensive QMS due to several factors: insufficient awareness regarding the significance of QM, limited resources, and a lack of tailored standards for SMEs [19]. In addition, many companies are still unwilling to make the move as they are concerned about the high cost and unclear benefits. The aerospace manufacturing industry in this case study is in the central region in Malaysia and plays a significant role in the global market due to the increasing demand for airplane parts. However, the industry still relies on traditional processes, lagging from the global trend of IR 4.0 including the labor-dependent quality inspection task. The current manual quality inspection process of similar machining parts causes misclassification issues resulting with customer complaints and returned parts. While prior studies have employed the CNN models to identify flaws in industrial products [20], less focus is being given on the recognition of similar machining parts. Hence, this study employs the CNN approach to be used on the quality inspection of similar machining parts for automatic part recognition.

3. Methodology

For effective implementation, a comprehensive database is required for the CNN model training, enabling it to recognize and analyze parts accurately [21,22]. Hence, to develop a CNN model for this study requires the use of industrial camera, Python programming language and TensorFlow, the open-source machine learning framework as the fundamental for the object detection system. Python, being a versatile and widely used programming language, serves as the primary platform for writing code for CNNs. Its simplicity and extensive libraries make it an ideal choice for prototyping and implementing neural network architectures like CNNs. Python's intuitive syntax facilitates easier development and debugging processes, allowing researchers and developers to focus more on the design and experimentation of CNN models rather than wrestling with complex programming constructs.

Meanwhile, TensorFlow is an open-source machine learning framework developed by Google, plays a pivotal role in the practical application and training of CNNs. TensorFlow provides a rich set of tools and functionalities specifically tailored for building and training deep learning models, including CNN. Thus, it can simplify the process of constructing convolutional layers, defining network architectures, and training models efficiently. Additionally, TensorFlow offers seamless integration and enables faster computation and scaling of CNN models to handle large datasets and complex tasks. The combination of Python's ease of use and TensorFlow's powerful capabilities empowers researchers and practitioners to harness the potential of CNN for a wide range of applications, from image recognition and natural language processing. Furthermore, Google Colab GPU is used for the model training. Thus, this set-up offers a promising solution for defect detection, allowing for quicker identification and rework of faulty parts. Figure 1 provides the flow of the methodology employed in the development of the smart quality inspection system for the defect detection of similar industrial machining parts.

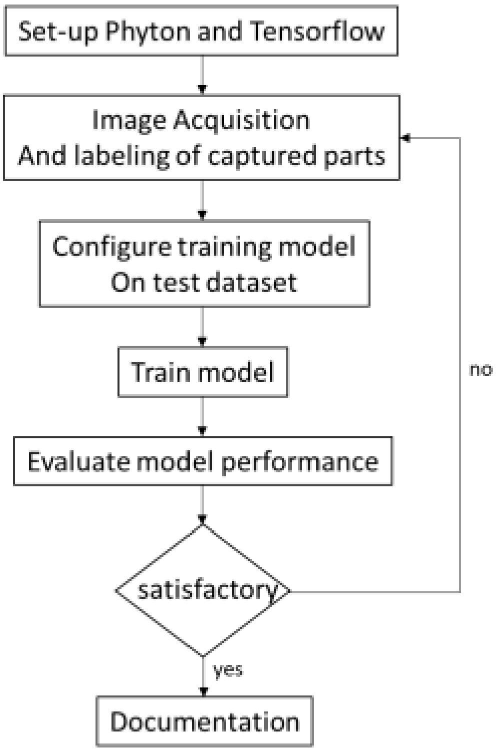


Fig. 1. Process flow for the development of the defect detection system

3.1 The Data Set

A total of 10 pairs of products were provided by the aerospace company to be used to train the system. These products consist of symmetrical parts having similar characteristics but used in the different sides of the aerospace manufacturing. Thus, the focus is to train the system to be able to accurately recognize these similar parts and detect any defects during the quality inspection. Figure 2 shows an example of a pair of parts; D232B and D233B, demonstrating how similar these parts appeared to be to the untrained eyes.

Fig. 2. The similarities between Part D232B and Part D233B

3.2 Phyton Coding

Phyton programming language is used to create the new virtual environment for the object imaging. A clone code was obtained from GitHub, a model training site used as a collaborative platform for software developers. This cloned code was then isolated using Phyton coding to avoid any conflicts with other libraries. Figure 3 shows an example of the Phyton cloning code.

```
(base) E:\project\1>git clone https://github.com/nicknochnack/TFODCourse
Cloning into 'TFODCourse'...
remote: Enumerating objects: 89, done.
remote: Counting objects: 100% (5/5), done.
remote: Compressing objects: 100% (2/2), done.
remote: Total 89 (delta 3), reused 3 (delta 3), pack-reused 84
Receiving objects: 100% (89/89), 30.02 MiB | 491.00 KiB/s, done.
Resolving deltas: 100% (34/34), done.
```

Fig. 3. The phyton programming language cloning code

Next, a Phyton code was created to activate the virtual environment. Further, an OpenCV, which is an open-sourced computer vision and machine learning software library was installed to provide a common infrastructure for the computer vision applications and to accelerate the use of machine vision. Figure 4 provides some of the code for the OpenCV installation.

```
(tfod) (base) E:\project\1\TFODCourse>pip install opencv-python
Collecting opencv-python
  Using cached opencv_python-4.6.0.66-cp36-abi3-win_amd64.whl (35.6 MB)
Collecting numpy>=1.17.3
  Using cached numpy-1.23.5-cp39-cp39-win_amd64.whl (14.7 MB)
Installing collected packages: numpy, opencv-python
Successfully installed numpy-1.23.5 opencv-python-4.6.0.66
```

Fig. 4. The OpenCV software library Installation

3.3 Image Labelling and Training

Further, image labelling was done using a cloned code from GitHub link. Image labelling is required to limit the image processing and guide the system to only to focus on the important parameters. Figure 5 shows the excerpt of the code to clone the image labelling.

```
(tfod) (base) E:\project\1\TFODCourse>git clone https://github.com/tzutalin/labelImg {LABEL
IMG_PATH}
Cloning into '{LABELIMG_PATH}'...
remote: Enumerating objects: 2097, done.
remote: Counting objects: 100% (7/7), done.
remote: Compressing objects: 100% (7/7), done.
remote: Total 2097 (delta 0), reused 4 (delta 0), pack-reused 2090
Receiving objects: 100% (2097/2097), 237.14 MiB | 531.00 KiB/s, done.
Resolving deltas: 100% (1245/1245), done.
```

Fig. 5. The code for cloning image labelling

All the images captured were coded and listed at the save file location. All the files were then tested on the functionality of the labelling window. Next, a rectangle box was drawn on every image for the purpose of the training system to focus only on the image inside the rectangle box when the system was initiated. It is also important to limit the system to learn and differentiate the part's image from the background and the environment. Figure 6 shows the labelling set-up for the D233B model.

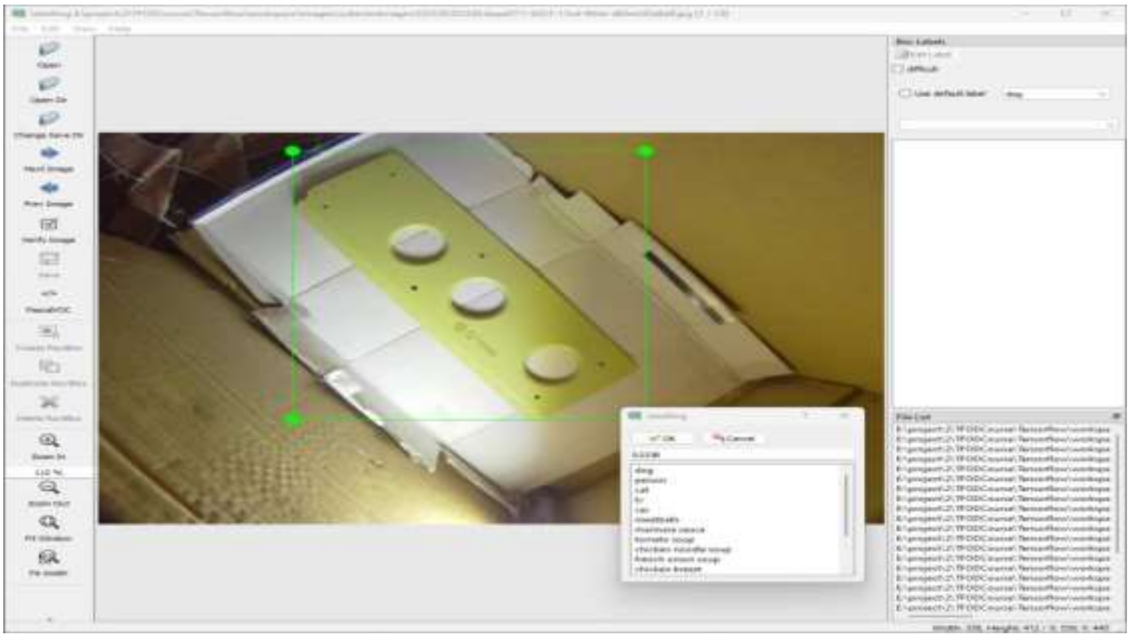


Fig. 6. The labelling and training for Part D233B

3.4 Object Detection Model

TensorFlow is an open-source machine learning framework developed by Google. It includes the Object Detection API, which allows you to train your own object detection models using a variety of techniques (such as transfer learning) and architectures (such as SSD and Faster R-CNN). The second-generation Google Brain system is called TensorFlow. The 1.0.0 version was made available on February 11, 2017. TensorFlow can run on several CPUs and GPUs, unlike the reference implementation, which only utilises a single device (with optional CUDA and SYCL extensions for general-purpose computing on graphics processing units). On 64-bit Linux, macOS, Windows, and mobile operating systems like Android and iOS, TensorFlow is accessible. Because of its adaptable design, computing is easily deployed across a range of platforms (CPUs, GPUs and TPUs), from desktop computers to server clusters to mobile and edge devices.

Stateful dataflow graphs are used to represent TensorFlow calculations. The actions that these neural networks carry out on multidimensional data arrays, known as tensors, are where the term TensorFlow originates.

4. Results and Discussion

The bounding box allows the system to focus on the object to be detected for the purpose of making an analysis and decision making. To assess the model's performance on a test set of photos, measures like average precision and mean average precision may be used [23]. These metrics assess the model's object detection precision and may be used to assess how well various models perform. As presented in Figure 7, in the case of the similar machining parts quality inspection, the system is now trained to differentiate between part D233B and D232B with 94% and 97% accuracy, respectively.

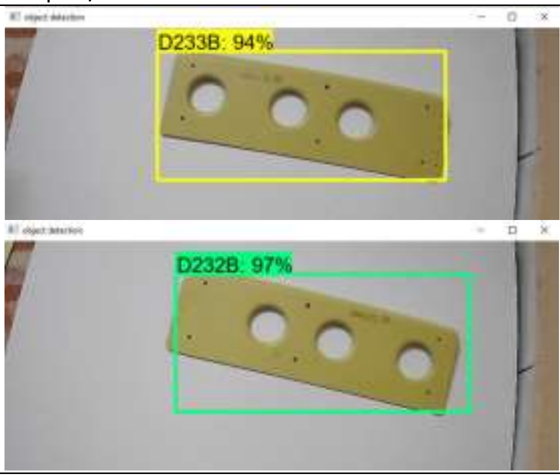
Objectives / Criteria	Output / Results
To detect the difference between the following almost similar parts: • D232B • D233B Background colour: **WHITE**	

Fig. 7. The results of the trained D233B and D232B Parts

When the system fails to identify the similarity of the datasets, it will be counted as a loss. The loss functions can be categorized into the classification loss and localization loss. The former is applied to train the classify and determine the type of target object, and the latter is used to train and regress the rectangular box to locate the target object. Classification loss occurs when the system is not able to detect and classify the object into the correct dataset. Localization loss occurs when the system fails to detect the object due to a certain confusion factor. The confusion factor matrix is shown in Table 1.

Table 1
Localization loss confusion matrix

True Positive Object is in the box System detects object Label and bounding box appeared on object	False Positive Object is not in the box System detects object Label and bounding box appeared even without object
True Negative Object not in the box System fails to detect object Label and bounding box do not appear	False Negative Object is in the box System fails to detects object Label and bounding box do not appear

Total loss is the sum of classification loss and localization loss. Figure 8a, 8b and 8c shows the classification loss, localization loss and total loss when performing object detection using the TensorFlow system.

(a) (b) (c)

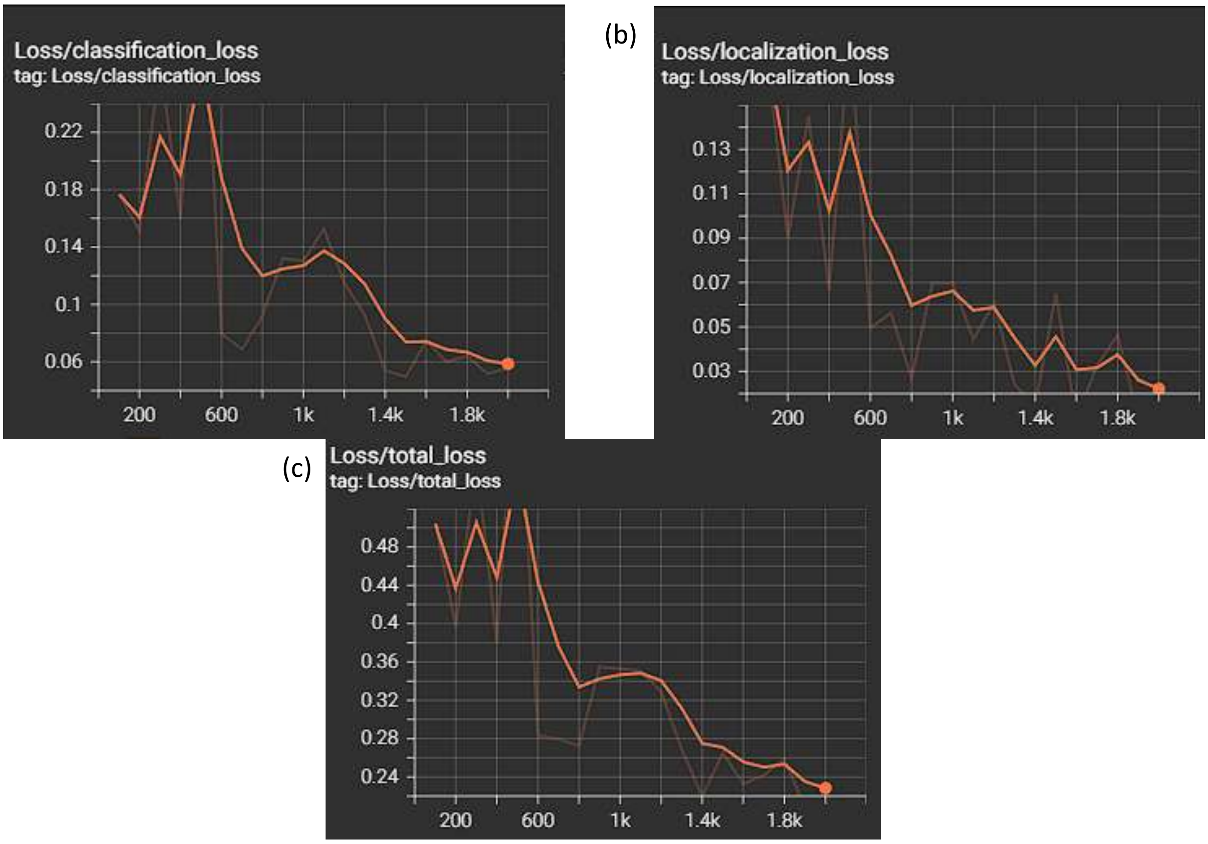


Fig. 8. (a) Classification Loss (b) Localization Loss (c) Total Loss

The TensorFlow results in Figure 8a show a peak at the 600 training steps and lowering down at 1.8K training steps to stabilize at the 0.06% classification loss. As for the localization loss in Figure 8b, TensorFlow's highest peak is at 500 training steps. However, the loss occurrence is nearly 0% after reaching 1.8K training steps. Thus, TensorFlow system can show the true positive and true negative localization loss. In addition, the total loss for the system approaches 0% at 1.8K training steps.

5. Conclusions

This paper proposes a method to develop a manufacturing database for similar aerospace part recognition in an automated quality inspection process. The CNN model which is one of AI deep learning architecture with Phyton as the programming language and TensorFlow as the CNN's framework has proven to be able to provide a very high accuracy detection for similar parts D233B at 94% accuracy and part D232B at 97% accuracy. Moreover, the classification loss and the localization loss were able to be reduced to 0.06% and 0%, respectively at 1.8K training steps. With the use of AI, the quality control team of the company are now able to improve the effectiveness of the quality inspection tasks and resolve the issues with human error due to parts misclassification of parts. To further improve the detection accuracy in the real setting, the current issue with the luminous element will have to be further improved by designing an enclosure box to place the part to be inspected and ensure a controlled lighting environment. In addition, a user-friendly interface will also need to be designed for the quality control inspector's ease-of-use.

Acknowledgement
The authors would like to extend their gratitude to Universiti Teknikal Malaysia Melaka for funding this project under a short-term grant (PJP/2022/FTKMP/S01889) and the aerospace component manufacturing company participating in this project.

References
[1] Monostori, László, Botond Kádár, Thomas Bauernhansl, Shinsuke Kondoh, Soundar Kumara, Gunther Reinhart, Olaf Sauer, Gunther Schuh, Wilfried Sihn, and Kenichi Ueda. "Cyber-physical systems in manufacturing." *Cirp Annals* 65, no. 2 (2016): 621-641. https://doi.org/10.1016/j.cirp.2016.06.005
[2] Zenisek, Jan, Norbert Wild, and Josef Wolfartsberger. "Investigating the Potential of Smart Manufacturing Technologies." *Procedia Computer Science* 180 (2021): 507-516. https://doi.org/10.1016/j.procs.2021.01.269
[3] Helu, Moneer, Don Libes, Joshua Lubell, Kevin Lyons, and Katherine C. Morris. "Enabling smart manufacturing technologies for decision-making support." In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, vol. 50084, p. V01BT02A035. American Society of Mechanical Engineers, 2016. https://doi.org/10.1115/DETC2016-59721
[4] Arinez, Jorge F., Qing Chang, Robert X. Gao, Chengying Xu, and Jianjing Zhang. "Artificial intelligence in advanced manufacturing: Current status and future outlook." *Journal of Manufacturing Science and Engineering* 142, no. 11 (2020): 110804. https://doi.org/10.1115/1.4047855
[5] Balamurugan, E., Laith R. Flaih, D. Yuvaraj, K. Sangeetha, A. Jayanthiladevi, and T. Senthil Kumar. "Use case of artificial intelligence in machine learning manufacturing 4.0." In *2019 International conference on computational intelligence and knowledge economy (ICCIKE)*, pp. 656-659. IEEE, 2019. https://doi.org/10.1109/ICCIKE47802.2019.9004327
[6] Bhamare, Devyani, and Poonam Suryawanshi. "Review on reliable pattern recognition with machine learning techniques." *Fuzzy Information and Engineering* 10, no. 3 (2018): 362-377. https://doi.org/10.1080/16168658.2019.1611030
[7] Ravikumar, S., K. I. Ramachandran, and V. Sugumaran. "Machine learning approach for automated visual inspection of machine components." *Expert systems with applications* 38, no. 4 (2011): 3260-3266. https://doi.org/10.1016/j.eswa.2010.09.012
[8] Dhillon, Anamika, and Gyanendra K. Verma. "Convolutional neural network: a review of models, methodologies and applications to object detection." *Progress in Artificial Intelligence* 9, no. 2 (2020): 85-112. https://doi.org/10.1007/s13748-019-00203-0
[9] Ajmal, Hina, Saad Rehman, Umar Farooq, Qurrat U. Ain, Farhan Riaz, and Ali Hassan. "Convolutional neural network based image segmentation: a review." *Pattern Recognition and Tracking XXIX* 10649 (2018): 191-203. https://doi.org/10.1117/12.2304711

[10] Hafizh, Hadyan, Amir Hamzah Abdul Rasib, Rohana Abdullah, Mohd Hadzley Abu Bakar, and Anuar Mohamed Kassim. "Application of convolutional neural networks for binary recognition task of two similar industrial machining parts." *International Journal of Advanced Computer Science and Applications* 12, no. 9 (2021). https://doi.org/10.14569/IJACSA.2021.0120946

[11] Ma, Guohong, Lesheng Yu, Haitao Yuan, Wenbo Xiao, and Yinshui He. "A vision-based method for lap weld defects monitoring of galvanized steel sheets using convolutional neural network." *Journal of Manufacturing Processes* 64 (2021): 130-139. https://doi.org/10.1016/j.jmapro.2020.12.067

[12] Yang, Yatao, Runze Yang, Longhui Pan, Junxian Ma, Yishuang Zhu, Tao Diao, and Li Zhang. "A lightweight deep learning algorithm for inspection of laser welding defects on safety vent of power battery." *Computers in industry* 123 (2020): 103306. https://doi.org/10.1016/j.compind.2020.103306

[13] Zhang, Zhifen, Guangrui Wen, and Shanben Chen. "Weld image deep learning-based on-line defects detection using convolutional neural networks for Al alloy in robotic arc welding." *Journal of Manufacturing Processes* 45 (2019): 208-216. https://doi.org/10.1016/j.jmapro.2019.06.023

[14] Elvitaria, Luluk, Ezak Fadzrin Ahmad Shaubari, Noor Azah Samsudin, Shamsul Kamal Ahmad Khalid, Salamun Salamun, Ira Puspita Sari, Zul Indra, and Rudiansyah Rudiansyah. 2024. “A Data-Driven Approach for Batik Pattern Classification Using Convolutional Neural Networks (CNN)”. *Semarak International Journal of Electronic System Engineering* 4 (1):22-30. https://doi.org/10.37934/sijese.4.1.2230

[15] See, Judi E., Colin G. Drury, Ann Speed, Allison Williams, and Negar Khalandi. "The role of visual inspection in the 21st century." In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 61, no. 1, pp. 262-266. Sage CA: Los Angeles, CA: SAGE Publications, 2017. https://doi.org/10.1177/1541931213601548

[16] Wang, M. J., and C. G. Drury. "A method of evaluating inspector's performance differences and job requirements." *Applied Ergonomics* 20, no. 3 (1989): 181-190. https://doi.org/10.1016/0003-6870(89)90075-6

[17] Gallwey, T. J. "Selection tests for visual inspection on a multiple fault type task." *Ergonomics* 25, no. 11 (1982): 1077-1092.

[18] Sundaram, Sarvesh, and Abe Zeid. "Artificial intelligence-based smart quality inspection for manufacturing." *Micromachines* 14, no. 3 (2023): 570. https://doi.org/10.3390/mi14030570

[19] Li, Xiang, Xiaodong Jia, Qibo Yang, and Jay Lee. "Quality analysis in metal additive manufacturing with deep learning." *Journal of Intelligent Manufacturing* 31, no. 8 (2020): 2003-2017. https://doi.org/10.1007/s10845-020-01549-2

[20] Dhillon, Anamika, and Gyanendra K. Verma. "Convolutional neural network: a review of models, methodologies and applications to object detection." *Progress in Artificial Intelligence* 9, no. 2 (2020): 85-112. https://doi.org/10.1007/s13748-019-00203-0

[21] Bhanumathy, Y. R., M. P. James, Shivangi Jha, and Sudeesh Balan. "Defect detection in PCBs using convolutional neural network." In *2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT)*, pp. 382-386. IEEE, 2021. https://doi.org/10.1109/RTEICT52294.2021.9573776

[22] Lei, Ruoshan, Dongpeng Yan, Hongjin Wu, and Yibing Peng. "A precise convolutional neural network-based classification and pose prediction method for PCB component quality control." In *2022 14th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, pp. 1-6. IEEE, 2022. https://doi.org/10.1109/ECAI

[23] Ram, G. Challa, M. Venkata Subbarao, D. Ramesh Varma, and A. Sri Krishna. "Enhanced Deep Convolutional Neural Network for Identifying and Classification of Silicon Wafer Faults in IC Fabrication Industries." In *2023 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET)*, pp. 1-6. IEEE, 2023. https://doi.org/10.1109/WISPNET57748.2023.101339