Detection of Paper Bag Quality Production by Image Processing using Deep Learning Method

Dr.K.Venkatasalam[1]*, Mr.T.Nandhakumar[2], Mrs.C.Priyatharsini[3] and Mr.R.Rajesh[4]

[1] Associate Professor, Department of Computer Science and Engineering, Mahendra Engineering College (Autonomous), Namakkal. E mail: venkatasalamk@mahendra.info

[2,3,4] Assistant Professors, Department of Computer Science and Engineering, Mahendra Engineering College (Autonomous), Namakkal.

Article History

Received: **08.04.2024**

Revised and Accepted: **10.05.2024**

Published: **15.06.2024**

https://doi.org/10.56343/STET.116.017.004.004

www.stetjournals.com

ABSTRACT

Ensuring product quality and reliability is essential in the dynamic environment of industrial manufacturing. Detecting defects during production is critical to prevent the delivery of faulty products to customers. Traditional quality control methods, while effective in certain cases, often lack the efficiency, precision, and adaptability required for modern high-speed manufacturing. Manual inspection, in particular, is prone to errors and reduced accuracy. Recent advancements in Deep Learning (DL) and Computer Vision (CV) offer promising opportunities for automated defect detection, with the potential to transform quality control processes. This study focuses on implementing a VGG19-based Convolutional Neural Network (CNN) for automatic quality assessment of paper bags using image processing, replacing manual inspection methods. The proposed system was trained and tested on a dataset of 1,729 images, classified into “OK” and “NOT OK” categories based on defect presence. The model achieved an accuracy of 95.26%, significantly outperforming skilled human inspectors, whose accuracy typically ranges from 72–80%. These results demonstrate the effectiveness of DL and CV in enhancing manufacturing quality control by delivering higher accuracy and consistency than traditional manual inspection.

Keywords: Convolutional Neural Networks (CNN), defective product detection, deep learning (DL), industrial quality inspection, image-based defect detection, paper bag manufacturing, quality control automation

Dr. K. Venkatasalam

Associate Professor, Department of Computer Science and Engineering, Mahendra Engineering College (Autonomous), Namakkal.

E mail: venkatasalamk@mahendra.info

P-ISSN 0973-9157

E-ISSN 2393-9249

INTRODUCTION

Quality control remains a cornerstone of manufacturing, ensuring that products meet stringent reliability and performance standards. Traditional quality control methods—primarily manual inspections and basic automated systems—are often time-consuming, prone to human error, and insufficient for detecting subtle or complex defects (Alkhudary et al., 2020). Quality control in manufacturing encompasses procedures that guarantee products meet defined quality specifications and satisfy customer expectations. This step is critical in the production process, as it directly impacts both product performance and customer satisfaction.

While traditional quality control methods such as human visual inspections and rudimentary computerized systems have historically played an important role in maintaining standards, they frequently prove inadequate in modern, complex manufacturing environments. The diversity of products and the intricacies of defect types necessitate more advanced detection systems. Screening and removal of defective items is essential for most manufacturing organisations, with specialist inspectors comparing multiple product attributes to manufacturer specifications. However, such processes are labour-intensive, subjective, and often struggle to detect subtle or intricate flaws, highlighting the need for more sophisticated, dependable alternatives.

Producing defect-free products requires more than manufacturing excellence; effective defect management must be implemented throughout the entire production lifecycle. The Defect Management Technique (DMT) involves five sequential stages: discovery, analysis, prioritisation, removal, and verification. As shown in Figure 1, DMT begins with identifying a defect, using methods such as alpha or beta testing. Once a defect is detected, it is analysed to determine its nature and cause, prioritised according to severity and potential impact, and then removed using appropriate corrective measures. The final stage involves verifying that the defect has been successfully resolved, a task undertaken by technical experts or end-users.

Figure 1 Roadmap for DMT

These DMT procedures should be integrated into every phase of product development to improve system quality and reduce problems during implementation. Advanced defect management enhances detection tools and ensures timely, cost-effective product delivery.

Although conventional defect detection methods have strengths, they are often limited in scope. For example, osmosis testing is well-suited for identifying defects in highly permeable or impermeable materials, yet still relies on human intervention, requires device calibration, and incurs high equipment costs (Habib et al., 2020). Such limitations restrict adaptability and manufacturing accuracy.

In recent years, innovative defect detection approaches—particularly Computer Vision (CV) and Deep Learning (DL) techniques—have gained prominence as key technologies for automating quality inspection. These methods offer greater adaptability, reduced human involvement, and improved cost efficiency, while also enabling learning from new data and handling complex defect patterns (Zheng et al., 2021; Zhou et al., 2023). DL, a subset of machine learning, uses multi-layered neural networks to learn from large datasets, enabling highly accurate defect detection and classification (Dong et al., 2021). CV enables machines to process and interpret visual information, facilitating defect identification, localisation, and classification in manufactured products using images or videos (Szeliski, 2022).

Integrating DL and CV into industrial applications has advanced automated defect detection capabilities, overcoming many limitations of traditional methods. These technologies have achieved notable success in diverse applications such as object detection, intelligent robotics (Khan et al., 2020), acoustic event detection for smart city safety (Ciaburro, 2020; Ciaburro and Iannace, 2020), and UAV blade failure diagnostics (Costa et al., 2020). By combining low-level feature extraction with high-level feature representation, DL models—especially Convolutional Neural Networks (CNNs)—can significantly enhance defect detection accuracy.

This study investigates the application of a VGG19-based CNN architecture for real-world industrial defect detection in the manufacturing of paper bags. The case study focuses on a Swedish manufacturer producing high-quality paper bags for diverse applications, including packaging dry goods, waste, and animal feed. Customers demand products that preserve their contents in optimal condition (Tabernik et al., 2023). The proposed approach aims to replace manual inspection with a fully automated image-based quality control system, thereby increasing detection accuracy, reducing labour costs, and ensuring consistent product quality.

LITERATURE REVIEW

Tabernik et al. (2023) developed SegDecNet++, a novel deep learning (DL) architecture designed for concrete crack detection that combines pixel-wise segmentation with image-level classification for comprehensive analysis. In the steel industry, DL models have demonstrated strong performance in identifying surface defects and irregularities that compromise structural integrity. Li et al. (2024) proposed a DL model for steel surface defect detection incorporating a Multiscale Feature Extraction (MSFE) subsystem, which employs varied convolutional kernel parameters to improve feature extraction across multiple scales. Similarly, Demir et al. (2023) introduced PAR-CNN, an approach combining identical residual block learning with attention mechanisms to enhance the classification of steel surface defects.

Computer Vision (CV) techniques have also been widely applied in wood manufacturing for detecting defects such as knots and splits, which affect both visual quality and structural stability. Lim et al. (2023) proposed a compact and efficient CNN model capable of near real-time wood defect detection, optimised for embedded systems. Cui et al. (2024) developed CCG-YOLOv7, an improved YOLOv7-based model incorporating features such as Center Efficient Layer Aggregation Networks (C-ELAN) and Cascade Center of Gravity Batch Normalisation (CCG-BN) to enhance small-target detection in wood flooring.

Zhu et al. (2019) explored defect detection in emulsion pump manufacturing using an improved CNN to replace manual inspection. A key challenge in their work was the limited availability of defective product images, which made acquiring high-quality sample images critical. The authors applied slant correction as a pre-processing step to enhance image quality. Their CNN achieved 97% accuracy with an average detection time of 0.18 seconds on unseen images. In the textile industry, Jing et al. (2019) developed a CNN-based system to detect six common fabric defects using a dataset comprising various colours and repeating patterns. By automatically estimating patch sizes, their system improved defect visibility and achieved an average accuracy of 97%.

In pharmaceutical manufacturing, Rački et al. (2022) proposed a CNN-based surface defect detection method for solid oral dosage forms, employing ReLU activation and batch normalisation after each convolutional layer to improve training efficiency and model stability. Ouyang et al. (2019) suggested a CNN-based fabric defect detection approach with a customised activation layer optimised for fine texture segmentation, utilising batch normalisation to increase model stability and operational efficiency.

Several studies have also explored transfer learning (TL) for industrial defect detection. Yang et al. (2020) applied an optimised VGG model with TL to inspect laser welding, pre-training the model on a large-scale image dataset. He et al. (2020) used CNN for pixel-level defect detection on item surfaces, while Yun et al. (2020) proposed a convolutional variational autoencoder for multi-class metal surface defect recognition. Sassi et al. (2019) employed TL for welding defect detection, achieving competitive results on a small dataset. Oborski and Wysocki (2022) implemented a CNN-based visual quality control system within a holonic shop-floor environment for casting inspection. Lee et al. (2021) utilised a VGG16-based model for welded nut defect detection, experimenting with various CNN architectures before achieving optimal performance with VGG16.

RESEARCH METHODOLOGY

Jonsac's e-commerce paper bag product range varies frequently, serving customers with diverse requirements in terms of quantity, delivery intervals, colours, and customised prints for each bag section. Variations in bag structure, such as size, are common, while market dynamics—such as gaining new customers, losing existing ones, or adapting to changing preferences—further complicate quality control. These factors make it impractical to collect complete datasets for every product variation when training a deep learning (DL) model. Although sufficient images were available for the current product lines, the proposed VGG19-based Convolutional Neural Network (CNN) requires updated training with new image data whenever a new product variant is introduced.

A specific challenge arises when distinguishing between visually similar variants—for example, when a defect such as a colour or print anomaly in Variant X is visually identical to the intended design of Variant Y. In this study, the focus is on bag dimensions, which are largely identical across variants except for length. Many existing DL-based quality control systems overlook defects related to colour, print, and other aesthetic attributes; however, in this work, these factors are considered alongside geometric consistency. The dataset consists of 1,729 images across six product variants, with differentiation based on print, colour, and length. Structurally, all variants share identical geometry and folding lines except for two variants.

Based on these considerations, the study concentrates on inspecting only the **bottom section** of the bag, as this is the critical area for detecting most structural defects. The bottom section images were used for training the automated defect detection model. Images were manually classified into two categories: "OK" (no defect) and "NOT OK" (defective), with the latter representing deviations from the customer-approved geometry.

Figure 2 A instance of the defect product image from defect image database

The manual classification process involved experienced human inspectors, who determined defect categories based on visual assessment. The proposed CNN model was trained to not only classify defective images but also identify the specific defect region and its cause. Five distinct defect categories were defined:

1. Crushed side
2. Offset bottom
3. Tearing
4. Right-side skewed
5. Left-side skewed

Training using VGG19 based CNN

The Adam optimiser was used for training, with a batch size of 256, momentum set to 0.9, and an input pixel value range of 0–255. The L2 weight regularisation penalty was set to 5×10−45 \times 10^{-4}. Hyperparameters were tuned in Python using the Keras framework to reduce overfitting. A dropout rate of 0.5 was applied to the first and second fully connected (FC) layers. The learning rate was initially set at 0.01, and reduced by a factor of 10 when validation accuracy plateaued, leading to convergence after 49 epochs.

To address potential gradient instability in deep networks, weights were initialised using a random normal distribution (mean = 0, variance = 0.01) with zero bias. The VGG19 architecture consists of five convolutional blocks followed by max-pooling layers, and three FC layers. The input consists of RGB images resized to 224×224224 \times 224 pixels, with preprocessing involving mean RGB subtraction from each pixel.

Max-pooling was applied using a 2×22 \times 2 window with a stride of 2, and spatial padding of one pixel. The first two FC layers each contained 4,096 channels (1×1×40961 \times 1 \times 4096), while the final FC layer contained 1,000 channels for ImageNet classification, followed by a softmax output layer. Although the architecture is pre-trained, its layers were fine-tuned for this specific defect detection task to improve adaptability and performance.

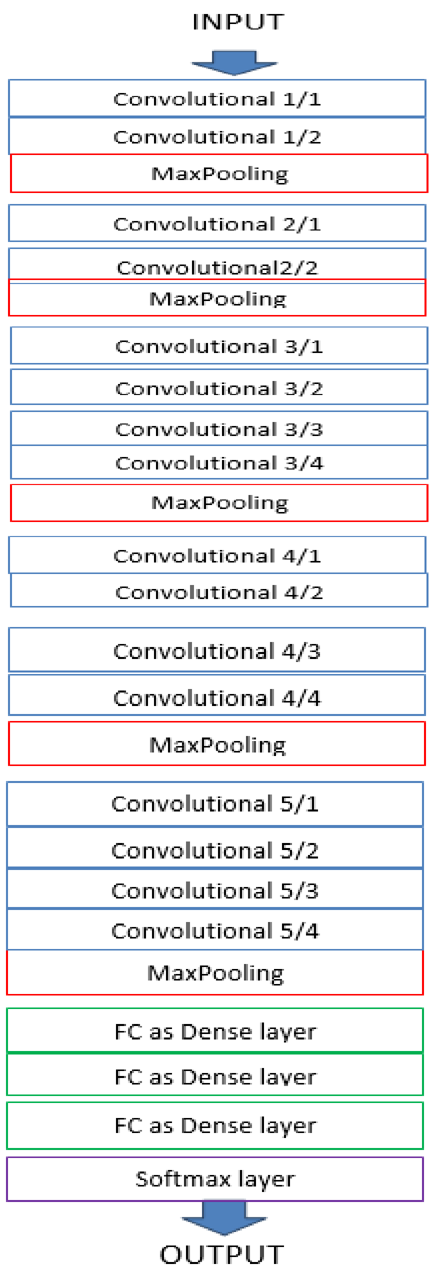

Figure 3 VGG19 architecture with CNN model

RESULT AND DISCUSSION

The experimental setup employed a VGG19-based Convolutional Neural Network (CNN) consisting of 16 convolutional layers, five max-pooling layers, and three fully connected layers for feature extraction and classification. The dataset of 1,729 images was split into 80% for training (1,383 images) and 20% for testing (346 images). The training set contained an equal proportion of "OK" and "NOT OK" samples, allowing the model to learn defect detection with balanced class representation.

Once trained, the model was evaluated on previously unseen data. The VGG19-based CNN demonstrated a strong ability to correctly classify both defective and non-defective samples. Annotations were automatically generated during classification, allowing for iterative refinement of the training dataset. This process improved model robustness by eliminating excessive or incorrect annotations and ensuring better fit to the paper bag product specifications.

The confusion matrix (Figure 4) summarises classification performance:

- **True Positives (TP):** Correctly identified defective bags
- **True Negatives (TN):** Correctly identified non-defective bags
- **False Positives (FP):** Incorrectly identified bags as defective
- **False Negatives (FN):** Incorrectly identified defective bags as non-defective

While occasional duplicate annotations were generated, these did not adversely affect the inspection process, as the defect verification steps remained consistent. Missed annotations (false negatives) were rare, and in such cases, the affected samples were still classified as "OK," reducing the risk of defective products being approved.

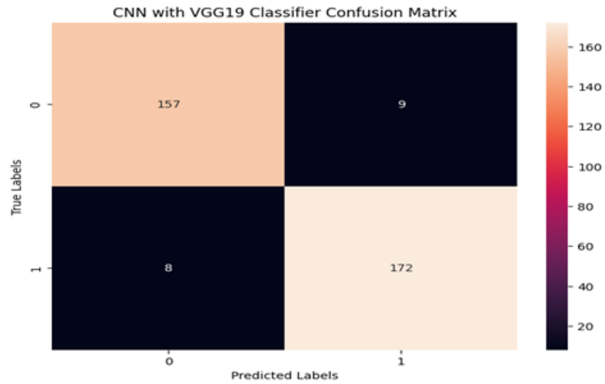

Figure 4 confusion matrix of CNN with VGG19 in predicting defect in paper bag product

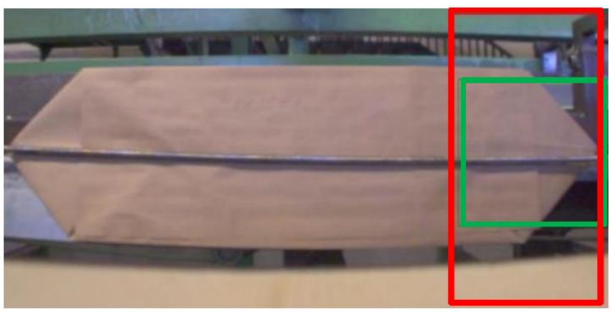

Figure 5 Defect identified by CNN with VGG19 from approved of existing technique

Figure 5 illustrates the successful identification of defects by the CNN model compared to products verified through human inspection. This comparison demonstrates the model's capacity to detect subtle anomalies that may be overlooked by human inspectors, such as slight geometric deviations or minor skewing.

Classification Method	Accuracy	Recall	Precision	Sensitivity	Specificity
CNN with VGG19	95.26	95.78	95.14	0.958	0.947
CNN with VGG16	94.51	94.88	94.56	0.949	0.941
CNN	93.00	93.69	92.97	0.937	0.922

Table 1 Performance metrics of CNN with VGG19 and other existing CNN techniques

Table 1 compares the performance metrics of the proposed VGG19-based CNN against other CNN variants. The proposed model achieved the highest accuracy (95.26%), with recall, precision, sensitivity, and specificity also outperforming the CNN with VGG16 and a baseline CNN model

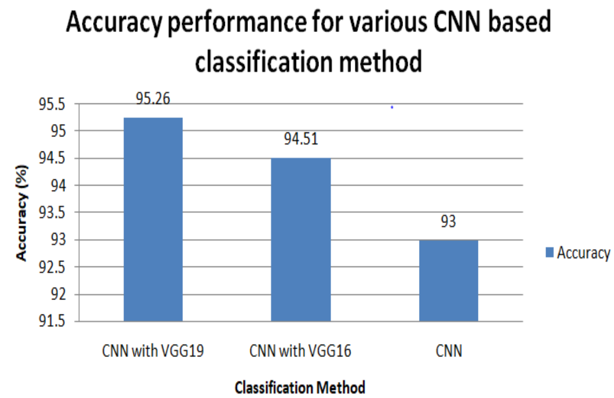

Figure 6 comparison of accuracy performance for various CNN based classification method

Figure 6 presents the accuracy comparison, confirming that the VGG19-based CNN outperformed the CNN with VGG16 (94.51%) and the baseline CNN (93.00%). The results indicate that VGG19's deeper architecture and fine-tuned parameters contribute to improved defect detection capability.

The high classification accuracy (95.26%) highlights the model's effectiveness in distinguishing between "OK" and "NOT OK" paper bags. This level of performance surpasses that of experienced human inspectors, whose accuracy typically ranges between 72–80% in similar industrial inspection settings. The superior performance of the VGG19-based CNN can be attributed to:

1. **Enhanced feature extraction** from deeper convolutional layers.
2. **Balanced dataset training**, ensuring robustness across defect types.
3. **Automated annotation refinement**, reducing noise in training data.

These findings align with prior research indicating that deep learning methods, when properly trained and fine-tuned, can outperform manual inspection in accuracy, speed, and consistency

CONCLUSION

This study investigated the application of deep learning (DL) and image processing for automated quality inspection in paper bag manufacturing, replacing the existing manual inspection process. Using a VGG19-based Convolutional Neural Network (CNN), the proposed system achieved an accuracy of **95.26%**, significantly surpassing the accuracy of experienced human inspectors, typically ranging from 72–80%.

The findings demonstrate that DL and Computer Vision (CV) technologies can effectively detect subtle and complex defects that are often overlooked in manual inspection. By focusing on the bottom section of the bag—where most structural defects occur—the system efficiently identified defects across five main categories: crushed side, offset bottom, tearing, right-side skewed, and left-side skewed.

The superior performance of the VGG19-based CNN can be attributed to its deep architecture, optimised hyperparameters, and balanced dataset training, which collectively enhanced feature extraction and classification accuracy. Additionally, the automated annotation refinement process reduced training noise and improved model robustness.

From an industrial perspective, implementing such a DL-based automated inspection system offers multiple advantages:

- **Higher detection accuracy** compared to human inspection.
- **Consistency and reliability** in defect identification, reducing variability due to human judgment.
- **Increased inspection speed** to match modern high-throughput manufacturing lines.
- **Scalability** to adapt to new product variants with minimal reconfiguration.

Overall, this research confirms that VGG19-based CNN architectures have significant potential to enhance quality control in manufacturing, particularly in applications requiring precision, speed, and adaptability. Future work could explore transfer learning approaches, integration with real-time production systems, and multi-modal defect detection combining visual and sensor-based inputs.

REFERENCE

Alkhudary, R., Mousavi, A. and Ebayyeh, A.R.M.A., 2020. A review and analysis of automatic optical inspection and quality monitoring methods in electronics industry. *IEEE Access*, 8, pp.183192–183227. https://doi.org/10.1109/ACCESS.2020.3024994

Chaffey, D. and Smith, P.R., 2013. *eMarketing eXcellence: Planning and Optimizing your Digital Marketing*. 4th ed. London: Routledge.

Ciaburro, G., 2020. Sound event detection in underground parking garages using convolutional neural networks. *Big Data and Cognitive Computing*, 4(2), p.20. https://doi.org/10.3390/bdcc4020020

Ciaburro, G. and Iannace, G., 2020. Improving smart cities safety using sound events detection based on deep neural network algorithms. *Informatics*, 7(2), p.23. https://doi.org/10.3390/informatics7020023

Costa, D.G., Vasques, F., Portugal, P. and Ana, A., 2020. A distributed multi-tier emergency alerting system exploiting sensors-based event detection to support smart city applications. *Sensors*, 20(1), p.170. https://doi.org/10.3390/s20010170

Cui, W., Li, Z., Duanmu, A., Xue, S., Guo, Y., Ni, C., Zhu, T. and Zhang, Y., 2024. CCG-YOLOv7: A wood defect detection model for small targets using improved YOLOv7. *IEEE Access*, 12, pp.10575–10585. https://doi.org/10.1109/ACCESS.2024.3340173

Demir, K., Ay, M., Cavas, M. and Demir, F., 2023. Automated steel surface defect detection and classification using a new deep learning-based approach. *Neural Computing and Applications*, 35(11), pp.8389–8406. https://doi.org/10.1007/s00521-023-08184-y

Dong, S., Wang, P. and Abbas, K., 2021. A survey on deep learning and its applications. *Computer Science Review*, 40, p.100379. https://doi.org/10.1016/j.cosrev.2021.100379

Habib, M.A., Kim, C.H. and Kim, J., 2020. A crack characterization method for reinforced concrete beams using an acoustic emission technique. *Applied Sciences*, 10(21), p.7918. https://doi.org/10.3390/app10217918

He, Y., Song, K., Meng, Q. and Yan, Y., 2020. An end-to-end steel surface defect detection approach via fusing multiple hierarchical features. *IEEE Transactions on Instrumentation and Measurement*, 69(4), pp.1493–1504. https://doi.org/10.1109/TIM.2019.2918718

Jing, J.F., Ma, H. and Zhang, H.H., 2019. Automatic fabric defect detection using a deep convolutional neural network. *Coloration Technology*, 135(3), pp.213–223. https://doi.org/10.1111/cote.12425

Khan, F., Salahuddin, S. and Javidnia, H., 2020. Deep learning-based monocular depth estimation methods—A state-of-the-art review. *Sensors*, 20(8), p.2272. https://doi.org/10.3390/s20082272

Lee, K.J., Kwon, J.W., Min, S. and Yoon, J., 2021. Deploying an artificial intelligence-based defect finder for manufacturing quality management. *AI Magazine*, 42(3), pp.5–18. https://doi.org/10.1609/aimag.v42i3.18177

Li, Z., Wei, X., Hassaballah, M., Li, Y. and Jiang, X., 2024. A deep learning model for steel surface defect detection. *Complex & Intelligent Systems*, 10(1), pp.885–897. https://doi.org/10.1007/s40747-023-00987-0

Lim, W.H., Bonab, M.B. and Chua, K.H., 2023. An aggressively pruned CNN model with visual attention for near real-time wood defects detection on embedded processors. *IEEE Access*, 11, pp.36834–36848. https://doi.org/10.1109/ACCESS.2023.3258691

Oborski, P. and Wysocki, P., 2022. Intelligent visual quality control system based on convolutional neural networks for holonic shop floor control of Industry 4.0 manufacturing systems. *Advances in Science and Technology Research Journal*, 16(3), pp.89–98. https://doi.org/10.12913/22998624/150483

Ouyang, W., Xu, B., Hou, J. and Yuan, X., 2019. Fabric defect detection using activation layer embedded convolutional neural network. *IEEE Access*, 7, pp.70130–70140. https://doi.org/10.1109/ACCESS.2019.2919467

Rački, D., Tomaževič, D. and Skočaj, D., 2022. Detection of surface defects on pharmaceutical solid oral dosage forms with convolutional neural networks. *Neural Computing and Applications*, 34(1), pp.631–650. https://doi.org/10.1007/s00521-020-05510-y

Sassi, P., Tripicchio, P. and Avizzano, C.A., 2019. A smart monitoring system for automatic welding defect detection. *IEEE Transactions on Industrial Electronics*, 66(12), pp.9641–9650. https://doi.org/10.1109/TIE.2019.2898622

Szeliski, R., 2022. *Computer Vision: Algorithms and Applications*. Cham: Springer. https://doi.org/10.1007/978-3-030-34372-9

Tabernik, D., Šuc, M. and Skočaj, D., 2023. Automated detection and segmentation of cracks in concrete surfaces using joined segmentation and classification deep neural networks. *Construction and Building Materials*, 408, p.133582. https://doi.org/10.1016/j.conbuildmat.2023.133582

Yang, Y., Pan, L., Ma, J., Yang, R., Zhu, Y., Yang, Y. and Zhang, L., 2020. A high-performance deep learning algorithm for the automated optical inspection of laser welding. *Applied Sciences*, 10(3), p.933. https://doi.org/10.3390/app10030933

Yun, J.P., Shin, W.C., Koo, G., Kim, M.S., Lee, C. and Lee, S.J., 2020. Automated defect inspection system for metal surfaces based on deep learning and data augmentation. *Journal of Manufacturing Systems*, 55, pp.317–324. https://doi.org/10.1016/j.jmsy.2020.03.002

Zheng, X., Zheng, S., Kong, Y. and Chen, J., 2021. Recent advances in surface defect inspection of industrial products using deep learning techniques. *International Journal of Advanced Manufacturing Technology*, 113(1–2), pp.35–58. https://doi.org/10.1007/s00170-021-06636-0

Zhou, L., Zhang, L. and Konz, N., 2023. Computer vision techniques in manufacturing. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 53(1), pp.105–117. https://doi.org/10.1109/TSMC.2021.3103732

Zhu, C., Zhou, W., Yu, H. and Xiao, S., 2019. Defect detection of emulsion pump body based on improved convolutional neural network. In: *Proceedings of the 2019 International Conference on Advanced Mechatronic Systems*, Kusatsu, Japan, 26–28 August 2019. pp.349–352. https://doi.org/10.1109/ICAMechS.2019.8861677