A Study on the Application of Deep Learning Image Segmentation Techniques in Product Defect Analysis

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Abstract: ***This paper investigates the application of deep learning image segmentation algorithms in product defect detection. First, by analyzing the limitations of traditional methods in this domain, the key challenges faced by conventional approaches are identified. Subsequently, the advantages and specific applications of deep learning-based image segmentation techniques in product defect detection are examined in detail. The findings are intended to serve as a valuable reference for relevant researchers and practitioners in the field.***

Keywords: Deep learning; Image segmentation algorithm; Product defects; Application.

1. INTRODUCTION

Product defect detection is an important link in the production process, which is crucial for ensuring the quality and safety of products. Traditional product defect detection methods often rely on manual judgment and complex algorithm calculations, which suffer from subjectivity, low efficiency, and slow processing speed. To overcome these problems, deep learning image segmentation algorithms have gradually attracted widespread attention and application. The deep learning image segmentation algorithm utilizes deep neural networks for feature extraction and pattern recognition of product images, achieving automated classification and segmentation of product defects. This article will investigate the application of deep learning image segmentation algorithms in product defect detection and explore their advantages in improving detection accuracy and efficiency. In healthcare, Yi [1] designed a real-time fair-exposure ad allocation system for small and medium-sized businesses (SMBs) and underserved creators via contextual bandits-with-knapsacks. Tang et al. [2] focused on the design and optimization of shallow-angle grating couplers for vertical emission from indium phosphide devices. Sun [3] addressed designing inclusive interfaces, focusing on accessibility challenges and solutions in digital products. Long et al. [4] enhanced educational content matching using transformer models and InfoNCE loss. Tang and Zhao [5] investigated the relationship between aging population distribution and real estate market dynamics based on neural networks. Zhao et al. [6] researched labour market efficiency evaluation under the impact of media news using machine learning and the DMP model. Chen et al. [7] examined the green innovation effect of the digital economy. Yao [8] conducted research on the local head loss coefficient in short-tube hydraulic testing. Tian et al. [9] improved U-Net brain tumor image segmentation using a GSConv module and an ECA attention mechanism. Deng and Yang [10] proposed multi-layer defense strategies and privacy-preserving enhancements against membership reasoning attacks in a federated learning framework. Zhao et al. [11] optimized deep learning models for dynamic market behavior prediction. Yang et al. [12] developed a full-cycle intelligent risk control system for pre-loan, mid-loan, and post-loan lending, emphasizing AI-driven closed-loop management of online credit security. Shen et al. [13] applied the whale optimization algorithm to financial payment fraud detection. Ren [14] enhanced seq2seq models for role-oriented dialogue summary generation through adaptive feature weighting and dynamic statistical conditioning. Ximeng and Yiming [15] applied offline conservative reinforcement learning for transaction authorization to balance fraud risk and customer friction. Zhou [16] proposed a digital precision distribution strategy for social media content on private domain platforms in the automotive industry, employing a collaborative filtering model based on user behavior. Finally, Wensi [17] investigated AI-assisted marketing content generation for non-standard industrial automation solutions.

2. PROBLEMS IN THE APPLICATION OF TRADITIONAL METHODS IN PRODUCT DEFECT DETECTION

2.1 Dependence on manual judgment

(1) Subjectivity and subjective error:

Traditional methods rely on subjective judgments made by humans, and the results are often influenced by individual experience and subjective preferences, leading to inconsistencies and inaccuracies in the results. Different judgment personnel may have different judgment results for the same product, and this subjectivity makes the judgment results lack objectivity and replicability.

(2) Artificial fatigue and visual fatigue:

Long term visual or manual inspection can easily cause fatigue and visual fatigue among personnel, thereby affecting the accuracy and reliability of the judgment. When manual operators detect defects in a large number of products, it is inevitable that they will miss or misjudge due to fatigue, which will affect the quality control of the products.

(3) Difficult to deal with complex defects:

In some complex product defect detection, manual judgment methods often fail to meet the requirements. The complex defect morphology, texture differences, and subtle defect variations all make it difficult for traditional methods to accurately determine the existence and degree of defects [1].

2.2 High false alarm rate

False alarm rate refers to the proportion of detection tasks in which the detection system incorrectly identifies truly defect free samples as defective samples. Traditional methods commonly suffer from serious misjudgment of defects and noise, which means that some non defective information is also identified as defects, resulting in a high false alarm rate. For example, in an image, some ambiguous areas, areas with obvious gradient changes, etc. may be falsely reported as defect areas by traditional methods. The main reason for the high false alarm rate is that traditional methods use relatively simple feature extraction methods and classification algorithms, which have strong limitations. The traditional method usually first uses manually designed features to find defect areas, and then uses relevant classification algorithms to classify the defects. However, these manual feature extraction methods are often not accurate and effective enough to extract representative and discriminative feature information from complex images. Moreover, the decision boundaries of classifiers are usually rough, and the results are prone to misjudgment due to the limitations of the selected features.

2.3 Slow processing speed

Due to the manual design of feature extraction and classifier construction required by traditional methods, a large amount of computing resources and time are often needed, resulting in slow processing speed. Firstly, traditional methods of feature extraction are typically based on manually designed algorithms. Due to the fact that manually extracted features are usually relatively simple low-level features, it is often difficult to obtain effective high-level features and accurately express information such as the structure and shape of objects. This limitation is particularly significant when dealing with large-scale datasets, requiring a large amount of efficient computing resources for processing. Secondly, traditional methods often use simpler classifiers such as Support Vector Machines (SVM) and Random Forests (RF). When these classifiers perform classification, they need to consider the entire feature space, which requires a large amount of computation. At the same time, the decision boundary of the classifier is relatively rough, and the defect information detected is not accurate enough. Moreover, classifiers typically only detect a single defect type and cannot simultaneously detect multiple defect types, making it difficult to meet practical application requirements. In addition, traditional methods can usually only process a single image, making it difficult to achieve parallel processing. In practical applications, it is necessary to process a large number of image sequences simultaneously, which requires traditional methods to perform a lot of interactive operations, resulting in further reduced processing speed [2].

3. ADVANTAGES OF DEEP LEARNING IMAGE SEGMENTATION ALGORITHMS IN PRODUCT DEFECT DETECTION

3.1 Higher accuracy

Deep learning image segmentation algorithms have higher accuracy and can effectively locate and segment defect areas automatically. In contrast, traditional methods require manually designed features to extract defect areas and are prone to recognition errors due to limitations. Deep learning image segmentation algorithms can adaptively learn and extract features, reducing the occurrence of errors.

3.2 Better Scalability

The deep learning image segmentation algorithm is based on the framework of deep learning and has high scalability, which can be easily extended to new product types and datasets. In contrast, traditional methods require redesigning features and classifiers, which cannot quickly adapt to new datasets and tasks.

3.3 Faster calculation speed

Deep learning image segmentation algorithms can efficiently utilize computer GPUs for parallel computing, improving processing speed and efficiency. In contrast, traditional methods typically require a significant amount of image processing and computation, resulting in slower computational speeds.

4. APPLICATION OF DEEP LEARNING IMAGE SEGMENTATION ALGORITHM IN PRODUCT DEFECTS

4.1 Surface Defect Detection

Surface defects in products are a common issue that affects product quality and appearance. Traditional surface defect detection methods often rely on manual visual inspection, which is subjective, inefficient, and prone to missed and false detections. Deep learning image segmentation algorithms, through the training and optimization of deep neural networks, can achieve high-precision and automated surface defect detection. Firstly, deep learning image segmentation algorithms can perform pixel level segmentation on product images, thereby achieving accurate detection and localization of surface defects. Through the training of deep neural networks, image segmentation algorithms can learn the features and texture information of surface defects, and distinguish defect areas from normal areas in the image. For example, in the detection of surface defects on packaging boxes, deep learning image segmentation algorithms can accurately segment defects such as scratches and discoloration in the image, achieving precise detection and localization of defects. Secondly, deep learning image segmentation algorithms can automatically learn and adapt to the surface defect features of different products, and have strong generalization ability. Through training and repeated optimization on large-scale datasets, deep learning models can identify and extract feature patterns of surface defects, enabling them to cope with defects of different shapes, sizes, and types. This adaptability can significantly reduce the parameters and rules that need to be manually adjusted in traditional methods, improving the accuracy and stability of detection. For example, in surface defect detection of electronic products, deep learning image segmentation algorithms can automatically identify and segment defect areas for different types and specifications of electronic products, improving the efficiency and accuracy of defect detection [3].

4.2 Packaging Defect Detection

Packaging defect detection is one of the important aspects of product quality control, and deep learning image segmentation algorithms have been widely used in the field of packaging defect detection due to their powerful learning ability and accurate segmentation results.

Firstly, deep learning algorithms can achieve high-level semantic understanding of images, accurately segment packaging defect areas, and improve the accuracy and robustness of detection. Secondly, deep learning image segmentation algorithms can automatically learn features without the need for human design, greatly reducing the need for manual intervention. Meanwhile, deep learning image segmentation algorithms also have good universality and generalization ability, and can adapt to packaging defect detection tasks of different types and sizes. However, deep learning image segmentation algorithms also face some challenges in packaging defect detection.

Firstly, a large amount of annotated data is required to train deep learning models, and the acquisition and annotation costs of packaging defect datasets are relatively high. Secondly, for some complex packaging defects, current deep learning image segmentation algorithms still have certain limitations and need to be further improved to enhance the accuracy of detection. In addition, deep learning image segmentation algorithms also face certain pressures in terms of computational resources and time consumption, requiring higher performance hardware devices and optimized algorithms to meet the needs of real-time detection. To address the above challenges, future research can be conducted from the following aspects.

Firstly, further improve the deep learning image segmentation algorithm to enhance the accuracy and robustness of detecting complex packaging defects. Secondly, explore techniques such as few sample learning and transfer learning to reduce reliance on large amounts of annotated data. In addition, strengthen the research on the interpretability and interpretability of deep learning models to improve their credibility and reliability. It can also be combined with artificial intelligence assisted defect detection systems to improve detection efficiency and accuracy through human-machine collaboration. Finally, strengthen hardware optimization and algorithm acceleration of deep learning image segmentation algorithms to achieve real-time online detection.

4.3 Forming defect detection

Forming defects are one of the most common defects in manufacturing, typically caused by material and process issues during the production process. Traditional detection methods often rely on workers' experience and visual inspection, which results in certain human judgment bias and false detection rates. Deep learning image segmentation algorithms can effectively solve these problems and achieve automated detection of product forming defects.

Firstly, deep learning image segmentation algorithms can identify and separate different material regions, thereby eliminating the influence of material differences and achieving accurate detection of forming defects. Deep learning models can automatically perceive local features of products and extract the most prominent representations through learning from a large amount of sample data. If deep learning image segmentation algorithms are applied to defect detection in sheet metal forming, the sheet metal image can be segmented into normal areas and transition areas at corners, achieving recognition and judgment of important defects.

Secondly, deep learning image segmentation algorithms can quickly detect and determine the accurate location and area of forming defects, reducing manual intervention in the detection process. Compared to traditional defect detection methods, deep learning image segmentation methods greatly reduce the cost of defect detection. For example, in automobile body forming defect detection, deep learning algorithms can effectively and quickly detect defects while ensuring the accuracy and stability of the results.

Thirdly, deep learning image segmentation algorithms can be used to classify and sort defects. By learning from the sample library, deep learning models can accurately identify and classify various defects, further improving the accuracy and feasibility of defect localization. For example, applying deep learning to spline defect analysis in metal forming can more accurately classify images, automate detection, and standardize defects [4].

4.4 Quality Classification and Grading

The application of deep learning image segmentation algorithms in quality classification and grading can achieve automated classification and grading of different qualities through feature extraction and pattern recognition of product images. Firstly, deep learning image segmentation algorithms can extract key features from product images, such as color, texture, shape, etc., thereby achieving quality classification. Through training with a large number of samples, deep learning models can learn feature patterns of different qualities and segment key features in product images with corresponding qualities. For example, in textile manufacturing, deep learning image segmentation algorithms can segment textile texture, textile density, etc. in images to distinguish and classify different qualities. Secondly, deep learning image segmentation algorithms can segment defects in product images from normal areas, achieving grading of different qualities. By training the model, the deep learning model can learn features of different defect types and segment defect areas from normal areas in product images. For example, in electronic product manufacturing, deep learning image segmentation algorithms can segment display defects, color differences, etc. in images to achieve different levels of product quality.

4.5 Mixing detection

Mixing is one of the common defects in the production process, which refers to the mixing of different ingredients or batches of raw materials together during product manufacturing, resulting in a decrease or instability in product quality. The application of deep learning image segmentation algorithms in mixed material detection can effectively identify and separate mixed raw materials, thereby achieving automated detection of mixed material defects. Firstly, deep learning image segmentation algorithms can distinguish between different components or batches of raw materials, achieving region segmentation of mixed raw materials. Through training with a large number of samples, deep learning models can learn features such as morphology, color, and texture of different raw materials. For example, in food manufacturing, deep learning image segmentation algorithms can segment different color blocks in the image, thereby achieving localization and identification of mixed raw materials. Secondly, deep learning image segmentation algorithms can achieve defect detection of mixed raw materials through feature extraction and pattern recognition. Deep learning models can learn feature patterns from different raw materials and segment defects from normal regions in mixed raw materials. For example, in the production of plastic products, deep learning image segmentation algorithms can segment color differences, impurities, etc. in images, thereby achieving the detection of mixed material defects [5].

5. FUTURE DEVELOPMENT TRENDS OF DEEP LEARNING IMAGE SEGMENTATION ALGORITHMS IN PRODUCT DEFECT DETECTION

5.1 Multimodal Fusion

Future deep learning image segmentation algorithms may pay more attention to the fusion of multiple modal information. In addition to RGB images, other sensor data (such as infrared, radar, etc.) and textual information (such as product manuals) can be used as auxiliary information to improve the accuracy and robustness of defect detection. Related research may explore how to effectively integrate multiple modal information into deep learning models to improve the performance of defect detection.

5.2 Weakly Supervised Learning

Current deep learning image segmentation algorithms typically require a large amount of precise labeled data for training. However, obtaining annotated data is costly and time-consuming. Future research may focus on weakly supervised learning methods, by utilizing techniques such as weak labels, incomplete labels, or unsupervised/semi supervised learning to reduce dependence on annotated data and improve the practicality of the algorithm.

5.3 Real time and Efficiency

Real time and efficiency are of great significance for product defect detection. Future research may focus on improving the efficiency of deep learning image segmentation algorithms in terms of computational resources and time consumption to meet the needs of real-time detection. In response to the current issue of long training and inference times, more efficient algorithms and acceleration methods may be proposed.

6. CONCLUSION

Deep learning image segmentation algorithms can improve the effectiveness and accuracy of product defect detection. This article studies the application of deep learning image segmentation algorithms in product defect detection. At the same time, this article also analyzes the problems and challenges of deep learning image segmentation algorithms in product defect detection. Overall, deep learning image segmentation algorithms have broad application prospects and development potential in product defect detection, and further research can be strengthened in the future.

REFERENCES

[1] Yi, X. (2025, October). Real-Time Fair-Exposure Ad Allocation for SMBs and Underserved Creators via Contextual Bandits-with-Knapsacks. In Proceedings of the 2025 2nd International Conference on Digital Economy and Computer Science (pp. 1602-1607).

[2] Tang, Y., Kojima, K., Gotoda, M., Nishikawa, S., Hayashi, S., Koike-Akino, T., ... & Klamkin, J. (2020). Design and Optimization of Shallow-Angle Grating Coupler for Vertical Emission from Indium Phosphide Devices.

[3] Sun, Lingxin. "Designing Inclusive Interfaces: Accessibility Challenges and Solutions in Digital Products." Proceedings of the 2025 International Conference on Artificial Intelligence and Sustainable Development. 2025.

[4] Long, Y., Gu, D., Li, X., Lu, P., & Cao, J. (2024, September). Enhancing Educational Content Matching Using Transformer Models and InfoNCE Loss. In 2024 IEEE 7th International Conference on Information Systems and Computer Aided Education (ICISCAE) (pp. 11-15). IEEE.
[5] Tang, Y., & Zhao, S. (2025). Research on Relationship Between Aging Population Distribution and Real Estate Market Dynamics based on Neural Networks.
[6] Zhao, S., Lu, Y., Gong, C., & Xu, Q. (2025). Research on Labour Market Efficiency Evaluation Under Impact of Media News Based on Machine Learning and DMP Model.
[7] Chen, K., Zhao, S., Jiang, G., He, Y., & Li, H. (2025). The Green Innovation Effect of the Digital Economy. International Review of Economics & Finance, 103970.
[8] Yao, T. (2024, August). Research on the Local Head Loss Coefficient in Short-Tube Hydraulic Testing. In 2024 3rd International Conference on Applied Mechanics and Engineering Structures (AMES 2024) (pp. 89-97). Atlantis Press.
[9] Tian, Q., Wang, Z., & Cui, X. (2024). Improved Unet brain tumor image segmentation based on GSConv module and ECA attention mechanism. arXiv preprint arXiv:2409.13626.
[10] Deng, X., & Yang, J. (2025, August). Multi-Layer Defense Strategies and Privacy Preserving Enhancements for Membership Reasoning Attacks in a Federated Learning Framework. In 2025 5th International Conference on Computer Science and Blockchain (CCSB) (pp. 278-282). IEEE.
[11] Zhao, S., Lin, Y., Yang, X., Lu, Q., Xue, H., & Jiang, G. (2025). Optimization of Deep Learning Models for Dynamic Market Behavior Prediction. arXiv preprint arXiv:2511.19090.
[12] Yang, X., Xue, H., Hu, Q., & Zhang, Y. (2025, October). Design of a full-cycle intelligent risk control system for pre-loan, mid-loan, and post-loan lending: AI-driven closed-loop management of online credit security. In Proceedings of the 2025 2nd International Conference on Digital Economy and Computer Science (pp. 1022-1027).
[13] Shen, Zepeng, et al. "Research on Application of Whale Optimization Algorithm in Financial Payment Fraud Detection." 2025 4th International Conference on Artificial Intelligence, Internet and Digital Economy (ICAID). IEEE, 2025.
[14] Z. Ren, "Enhancing Seq2Seq Models for Role-Oriented Dialogue Summary Generation Through Adaptive Feature Weighting and Dynamic Statistical Conditioninge," 2024 6th International Conference on Communications, Information System and Computer Engineering (CISCE), Guangzhou, China, 2024, pp. 497-501, doi: 10.1109/CISCE62493.2024.10653360.
[15] Ximeng, Y., & Yiming, Z. (2026). Offline Conservative RL for Transaction Authorization: Smartly Balancing Fraud Risk and Customer Friction. Journal of Economic Theory and Business Management, 3(1), 1-9.
[16] Zhou, Z. (2025, November). Digital precision distribution strategy for social media content on private domain platforms in the automotive industry: a collaborative filtering model based on user behavior. In Proceedings of the 2025 International Conference on Digital Society and Intelligent Computing (pp. 516-521).
[17] Wensi, L. (2026). AI-Assisted Marketing Content Generation for Non-Standard Industrial Automation Solutions. Journal of Economic Theory and Business Management, 3(1), 18-25.