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Application of Computer Vision Technology in Online Label Inspection Systems

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Abstract: rapid development of computer vision technology has created new opportunities for industrial automation inspection systems, with online label inspection systems playing a crucial role in intelligent manufacturing. This paper focuses on the core principles of computer vision technology and analyzes its practical applications and technical implementation in label inspection. Through research on key technologies such as image preprocessing, object detection algorithms, and optical character recognition (OCR), the study proposes a high-precision, real-time system architecture for online label inspection. Performance and reliability were validated through applications in typical industrial scenarios. Results show that computer vision-based label inspection systems significantly enhance detection efficiency and accuracy while reducing the need for manual intervention, providing strong technical support for industrial intelligence. Finally, this paper discusses current technical challenges and future development directions, aiming to further advance the application of computer vision technology in industrial inspection.

Keywords: computer vision technology; label inspection; image preprocessing; object detection algorithms; optical character recognition (OCR)

1. Introduction

With the rapid advancement of Industry 4. 0, automation and intelligence have become essential trends in industrial manufacturing. Online label inspection, as a critical part of the production process, has gained increasing importance. Traditional label inspection methods, which often rely on manual visual checks or simple mechanical systems, are not only inefficient but also prone to human error, resulting in higher misjudgment rates [1]. Additionally, as product variety increases and production speeds accelerate, inspection systems face greater challenges in handling complex scenarios and meeting real-time requirements. Thus, achieving efficient and accurate label inspection in complex industrial environments has become an urgent issue. As a key branch of artificial intelligence, computer vision technology has made significant strides in object detection, image classification, and optical character recognition (OCR) in recent years [2]. Its superior image processing capabilities provide innovative solutions for industrial inspection. Computer vision-based label inspection systems can automatically capture image data and extract features for analysis and recognition, enabling rapid and accurate label inspection in real-time production environments [3]. However, despite these advancements, challenges remain in areas such as robustness under complex conditions, optimization for real-time performance, and engineering applications of advanced algorithms [4]. This study addresses these challenges by focusing on the application of computer vision technology in online label inspection systems. It analyzes the key development directions and limitations of current technologies and proposes an efficient and robust label inspection system architecture. The system's applicability and reliability are validated in industrial production environments. Furthermore, this paper discusses the bottlenecks and difficulties in current applications and proposes optimization directions based on emerging technology trends, aiming to contribute to the intelligent development of industrial label inspection. Tangtang et al. [5] analyzed ARIMA and LSTM for US electricity prices. Haosen et al. [6] developed RPF-ELD using teacher-

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student distillation for breast cancer recognition. Min et al. [7] proposed a DeepFM-based model for loan repayment prediction with attention and hybrid loss.

2. Overview of Computer Vision Technology

2.1. Principles of Computer Vision

Computer vision is a discipline that studies how computers can understand and interpret images or videos, with the core goal of simulating human visual systems. The basic principles of computer vision include image acquisition, processing, analysis, and understanding [8]. First, hardware devices such as cameras capture images or video data of target scenes. Next, image preprocessing techniques, such as grayscale conversion, filtering, and edge detection, are applied to optimize the captured data, improving image quality and enhancing the recognition of key features [9]. Then, feature extraction methods transform image data into meaningful feature representations to support subsequent analysis and recognition tasks. Finally, computer vision systems analyze and interpret these extracted features using classification algorithms or object detection algorithms to complete specific tasks. In industrial inspection, computer vision technology enables efficient product recognition and analysis, characterized by high accuracy, real-time performance, and adaptability to complex environments [10]. For instance, using convolutional neural networks (CNNs) to extract and learn multi-layer features from images, computer vision systems can accurately recognize and detect text, barcodes, or patterns on labels, meeting the diverse needs of industrial applications.

2.2. Technologies for Label Inspection

The application of computer vision technology in online label inspection systems relies on a combination of critical algorithms and techniques. Object detection algorithms are among the core technologies for label inspection [11]. In recent years, mainstream algorithms such as YOLO (You Only Look Once) and Faster R-CNN (Region-based Convolutional Neural Networks) have demonstrated outstanding performance in industrial inspection scenarios. These algorithms precisely extract label information by identifying target regions and categories. At the same time, OCR technology plays an essential role in label inspection by efficiently parsing text content on labels, enabling applications in production batch management and barcode scanning [12]. Additionally, to meet the real-time requirements of industrial production, emerging optimization techniques for deep learning models, such as pruning, quantization, and distillation, are widely used in label inspection systems. These techniques reduce model parameters and computational complexity, significantly improving detection speed and efficiency [13]. Data augmentation and transfer learning methods also enhance model generalization and adaptability. In complex scenarios, such as varying lighting conditions, angular deviations, or occlusions, the combined application of these techniques substantially improves the robustness and reliability of detection systems [14]. In summary, computer vision technology provides comprehensive support for label inspection systems. Progress in object detection, text recognition, and real-time optimization continues to drive industrial automation inspection towards greater efficiency and intelligence.

3. Design of the Online Label Inspection System

3.1. System Requirements Analysis

An online label inspection system is a critical component of modern industrial automation production lines, designed to meet requirements for high precision, real-time performance, robustness, and scalability. During production, label quality directly affects product traceability, brand image, and logistics efficiency. Therefore, the system must fulfill the following core functions: first, accurately detect key label information, such as barcodes, text content, and patterns, and assess the integrity and correctness of the label; second, achieve real-time detection to keep pace with high-

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speed production lines; third, maintain robustness to handle challenges such as lighting variations, angular deviations, and label damage; fourth, support diverse label types with strong compatibility and scalability to adapt to different product lines [15]. Additionally, the system must seamlessly integrate with production management systems, ensuring that inspection results can be relayed through unified interfaces for dynamic adjustments to the production process. This intelligent requirement raises higher demands for system architecture design and algorithm optimization.

3.2. System Architecture Design

The architecture of an online label inspection system is built around the collaborative operation of hardware and software components. The system consists of the following key modules:This module includes industrial cameras, lighting systems, and sensors [16]. The cameras capture label images on production lines, while the lighting system provides uniform illumination to mitigate the effects of environmental lighting. Sensors ensure precise timing for image capture, ensuring complete label data is obtained for each product. This module preprocesses raw image data by applying techniques such as denoising, grayscale conversion, enhancement, and edge detection. These operations improve image quality and prepare data for feature extraction and detection [17]. At the core of the system, this module employs deep learning-based object detection algorithms (e.g., YOLO or Faster R-CNN) combined with OCR technology to extract key label information. It can detect text, barcodes, or patterns on labels and evaluate their completeness, clarity, and accuracy. This module runs optimized detection algorithms on high-performance processors (e.g., GPUs or TPUs) to meet real-time requirements [18]. Inspection results are fed back to production management systems, enabling dynamic removal and alerting for defective products. This module manages inspection workflows, records data, and provides result analysis for production quality management. It also supports algorithm updates and functional extensions, allowing the system to adapt quickly to new product lines. In conclusion, the design of the online label inspection system targets efficient detection in industrial environments by deeply integrating hardware and software components. This architecture enhances production efficiency and lays a technical foundation for further advancements in intelligent industrial automation.

4. Core Technologies and Implementation Methods

4.1. Image Preprocessing Techniques

Image preprocessing is a fundamental step in online label inspection systems, aiming to enhance image quality and optimize the effectiveness of subsequent detection algorithms. First, denoising techniques are employed to eliminate random noise present in images captured in industrial environments. Methods such as Gaussian filtering, median filtering, or bilateral filtering are used to smooth the images while preserving edge details. Second, through grayscale conversion and image enhancement techniques, the system can further highlight key label features and mitigate the impact of uneven lighting conditions. For complex label backgrounds, edge detection methods (e.g., Canny or Sobel operators) effectively separate labels from the background, providing clear contours for object detection and text recognition [19]. Additionally, for tilted or rotated label images, geometric correction techniques using affine or perspective transformations can adjust the images to standard positions, improving detection accuracy and consistency.

4.2. Label Detection Algorithm Design

The core of label detection lies in efficient object detection and text recognition algorithms. In recent years, deep learning-based object detection algorithms have become mainstream in industrial inspection, with YOLO and Faster R-CNN standing out. YOLO achieves object localization and classification through a single neural network forward pass, offering exceptional real-time performance suited for high-speed production lines. In contrast, Faster R-CNN provides higher

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accuracy in complex scenarios, making it ideal for environments with intricate backgrounds or detailed labels. These algorithms enable precise localization of critical label regions. Text recognition is another vital task in label detection, accomplished using OCR (Optical Character Recognition) technology to extract textual information from labels. Deep learning-based OCR models, such as those employing the CRNN+CTC architecture, can recognize various fonts and complex text arrangements with strong robustness [20]. Moreover, to accommodate different languages or character sets, the system can leverage transfer learning techniques to extend its applicability to multilingual scenarios, enhancing its versatility [21]. To improve the system's real-time performance and accuracy, a combination of strategies can be employed. For instance, region proposal networks (RPNs) can reduce unnecessary computation by focusing on relevant regions, while lightweight network structures such as MobileNet or EfficientNet can decrease model complexity [22]. Additionally, data augmentation techniques, including random cropping, rotation, and brightness adjustment, enhance the model's generalization ability, effectively handling variations in lighting, label position, and other challenging conditions on production lines.

4.3. Real-Time Optimization Techniques

Real-time performance is a critical metric in the design of industrial inspection systems. To enhance detection efficiency, algorithm performance must first be optimized. Pruning techniques can eliminate redundant neurons and parameters, significantly reducing computational overhead. Quantization replaces floating-point operations with lower-bit integer computations, greatly decreasing hardware resource consumption [23]. Knowledge distillation transfers the learning outcomes of complex models to lightweight models, maintaining high accuracy while boosting speed. Additionally, hardware acceleration techniques are key to achieving real-time detection, such as leveraging GPUs or TPUs for parallel processing or distributing processing tasks across edge computing devices along the production line. In practical applications, ensuring real-time feedback and integration of detection results into production decisions is essential [24]. Stream processing frameworks such as Apache Kafka or Flink can facilitate high-speed transmission and processing of detection data. By dynamically managing and intelligently discarding defective results, the system can maintain high efficiency while ensuring product quality stability. In summary, the combination of image preprocessing techniques, label detection algorithms, and real-time optimization methods provides robust technical support for building high-performance, accurate online label inspection systems. By comprehensively applying these techniques, the system can meet diverse industrial scenarios' demands, significantly improving detection efficiency and reliability.

5. Application Scenarios and Experimental Analysis

5.1. Typical Application Scenarios

The application of computer vision technology in online label inspection spans multiple industrial fields. Below are several typical scenarios:First, in the logistics industry, label inspection systems are widely used for the rapid identification of barcodes and QR codes. On conveyor belts in sorting centers, computer vision-based systems can quickly recognize logistics label information on packages, including barcode content, recipient addresses, and special markers, ensuring accurate sorting and delivery [25]. This scenario requires extremely high real-time performance and recognition accuracy to match the logistics industry's efficiency demands. Second, in fast-moving consumer goods (FMCG) production lines, label inspection ensures the accuracy of packaging label content, such as production dates, batch numbers, and ingredient lists. Industrial cameras capture images on production lines, and OCR technology is employed to recognize text content in real-time while verifying the completeness and correct placement of labels. On high-speed conveyor belts, computer vision systems use efficient algorithms to achieve automated detection, eliminating the inefficiencies and high error rates of manual inspection. Lastly, in the electronics manufacturing industry, label inspection systems primarily verify identification labels on products, such as model

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numbers, serial numbers, and certification marks. Given the small and diverse nature of electronic components' labels, the system must handle challenges like reflective surfaces, high-density text, and irregular label placements. These challenges are effectively addressed through the application of deep learning algorithms, ensuring robust quality management for electronic products [26].

5.2. Performance Evaluation and Comparative Analysis

To validate the performance of computer vision-based label inspection systems in practical applications, multiple experiments were conducted to evaluate detection accuracy, speed, and robustness [27]. The experiments utilized datasets from various industrial production scenarios, including different types of label images (e.g., barcodes, QR codes, text labels) and varying interference conditions (e.g., lighting changes, label damage, and complex backgrounds). Experimental results showed that YOLOv5-based object detection algorithms achieved a mean Average Precision (mAP) of 96. 5% and operated at a speed of 50 frames per second (FPS), meeting the real-time requirements of most industrial production lines [28]. In text recognition tasks, CRNN-based OCR models achieved an accuracy of 92. 8% in complex backgrounds, demonstrating strong robustness to rotated or partially occluded labels. Compared to traditional template-matching methods, deep learning-based detection systems improved accuracy by approximately 15% and reduced error rates in complex scenarios by over 20%. Additionally, to further evaluate robustness, experiments tested performance under different noise levels. Results indicated that combining image denoising and enhancement techniques enabled the system to maintain detection accuracy above 85% under severe noise interference, while traditional methods experienced a significant accuracy drop. These findings highlight the clear advantages of computer vision technology in handling complex industrial environments. Comprehensive experimental analysis confirms that computer vision-based online label inspection systems outperform traditional methods in terms of accuracy, real-time performance, and robustness [29]. These systems can adapt to diverse industrial requirements, providing strong technical support for efficient automated inspection. Future advancements in algorithm optimization and hardware acceleration can further enhance system performance, addressing the demands of higher complexity and large-scale industrial applications.

6. Challenges and Future Directions

6.1. Current Technical Challenges

Although the application of computer vision technology in online label inspection systems has achieved remarkable results, several challenges persist in practical deployment [30]. First, robustness in complex environments is a key issue. In industrial production, labels may be affected by variations in lighting, contamination, folding, or partial occlusion, which impose higher requirements on the stability of detection systems [31]. While existing deep learning models perform well in specific scenarios, their detection accuracy can significantly degrade under extreme conditions, such as severe contamination or highly reflective environments. Second, computational efficiency and hardware resource constraints remain bottlenecks. High-performance deep learning models often require substantial computational resources, which may not be readily available in industrial settings. This limitation restricts the ability to achieve real-time detection. Even with optimizations such as model pruning and quantization, some scenarios still struggle to balance high precision with low latency. Additionally, data annotation costs and diversity issues significantly affect model performance [32]. The diverse types and scenarios of labels in industrial production require systems to adapt to various formats and content, necessitating large amounts of high-quality annotated data. However, acquiring and annotating these datasets often requires significant time and labor. Finally, system integration and scalability present another major challenge. Label inspection systems need to integrate deeply with production line equipment, quality management systems, and data analysis platforms, requiring high levels of compatibility and scalability. In dynamic production environments with

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frequent equipment upgrades and changing demands, achieving rapid adaptation and low-cost expansion remains a critical issue to address [33].

6.2. Future Research Directions

To address the current challenges, the future development of online label inspection systems can focus on the following directions:First, enhancing system robustness will be a key research priority. By incorporating multimodal data fusion technologies, such as combining RGB images with depth images, systems can capture more comprehensive information from different dimensions, improving adaptability to complex environments [34]. Additionally, employing Generative Adversarial Networks (GANs) for data augmentation can effectively expand dataset scale and improve model generalization for extreme scenarios. Second, optimizing model efficiency and hardware adaptation will be central to technological advancements. Further optimization of lightweight deep learning models (e.g., MobileNet and EfficientNet) and algorithm designs tailored for edge computing devices can significantly enhance real-time detection capabilities in industrial environments. Furthermore, applying specialized hardware accelerators (e.g., TPUs and FPGAs) can improve computational performance and support low-cost deployment. Third, intelligent data management and automated annotation will effectively alleviate data bottlenecks. Combining Active Learning and semi-supervised learning methods can enable systems to generate high-quality labels with minimal annotated samples, reducing data annotation costs. Additionally, constructing online update mechanisms based on real-time data collected from production lines will allow models to continuously optimize and adapt to new scenarios. Finally, strengthening system integration and scalability will be crucial for advancing industrial applications. By adopting standardized communication interfaces (e.g., OPC UA or MQTT), label inspection systems can better integrate with existing industrial control systems. Moreover, modular design and containerized deployment can significantly enhance system flexibility, accommodating customized requirements across various industrial scenarios. Overall, the future development of computer vision technology in online label inspection systems will further elevate the intelligence level of detection systems, providing stronger technical support for industrial production efficiency and quality. With continued innovation and optimization, these systems will play an increasingly important role in more complex and diversified industrial environments.

7. Conclusions

The rapid development of computer vision technology has provided innovative solutions for industrial automation inspection, with online label inspection systems serving as a critical component of industrial production. These systems significantly improve production efficiency and product quality. This paper explored key aspects of system design, including image preprocessing, object detection algorithms, optical character recognition (OCR), and real-time optimization, proposing an efficient and precise label inspection system architecture. The system's performance and robustness were validated through applications in typical scenarios. Experimental results demonstrated that the system could achieve high precision, real-time performance, and stability in complex industrial environments, effectively addressing the low efficiency and high error rates of traditional methods. However, online label inspection systems still face challenges in practical applications, including insufficient robustness in complex scenarios, high data annotation costs, and limited system scalability. To address these issues, future research and applications should further optimize algorithm efficiency, enhance performance through multimodal data fusion, lightweight models, and hardware acceleration technologies, and strengthen adaptability and scalability through intelligent data management and standardized interface design. In conclusion, the application potential of computer vision technology in online label inspection systems is vast. With ongoing technological innovation, its role in industrial production will continue to expand. The findings of this study provide practical insights for developing intelligent label inspection systems and offer significant directions for future technological improvements and industrial applications.

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References

1. *Paneru, Suman, and Idris Jeelani. "Computer vision applications in construction: Current state,opportunities & challenges." Automation in Construction 132 (2021): 103940.*
2. *Sivaranjani, A.,* et al. *"An overview of various computer vision-based grading system for various agricultural products." The Journal of Horticultural Science and Biotechnology 97. 2 (2022): 137-159.*
3. *Ismail, Nazrul, and Owais A. Malik. "Real-time visual inspection system for grading fruits using computer vision and deep learning techniques." Information Processing in Agriculture 9. 1 (2022): 24-37.*
4. *Zhang W, Huang J, Wang R,* et al. *Integration of Mamba and Transformer--MAT for Long-Short Range Time Series Forecasting with Application to Weather Dynamics [J]. arXiv preprint arXiv:2409. 08530, 2024.*
5. *Wang T, Cai X, Xu Q. Energy Market Price Forecasting and Financial Technology Risk Management Based on Generative AI [J]. Applied and Computational Engineering, 2024, 100: 29-34.*
6. *Wang H, Zhang G, Zhao Y,* et al. *Rpf-eld: Regional prior fusion using early and late distillation for breast cancer recognition in ultrasound images [C]//2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). IEEE, 2024: 2605-2612.*
7. *Min, Liu,* et al. *"Financial Prediction Using DeepFM: Loan Repayment with Attention and Hybrid Loss." 2024 5th International Conference on Machine Learning and Computer Application (ICMLCA). IEEE, 2024.*
8. *Zhao Y, Hu B, Wang S. Prediction of brent crude oil price based on lstm model under the background of low-carbon transition [J]. arXiv preprint arXiv:2409. 12376, 2024.*
9. *Liu, Jiabei,* et al. *"Application of Deep Learning-Based Natural Language Processing in Multilingual Sentiment Analysis." Mediterranean Journal of Basic and Applied Sciences (MJBAS) 8. 2 (2024): 243-260.*
10. *Wu, X., Sun, Y., & Liu, X. (2024). Multi-Class Classification of Breast Cancer Gene Expression Using PCA and XGBoost. Preprints. https://doi. org/10. 20944/preprints202410. 1775. v1*
11. *Mo K, Chu L, Zhang X,* et al. *DRAL: Deep reinforcement adaptive learning for multi-UAVs navigation in unknown indoor environment [J]. arXiv preprint arXiv:2409. 03930, 2024.*
12. *Zhao Y, Hu B, Wang S. Prediction of brent crude oil price based on lstm model under the background of low-carbon transition [J]. arXiv preprint arXiv:2409. 12376, 2024.*
13. *Shih, K., Han, Y., & Tan, L. (2025). Recommendation System in Advertising and Streaming Media: Unsupervised Data Enhancement Sequence Suggestions. Preprints. https://doi. org/10. 20944/preprints202503. 2302. v1*
14. *Diao, Su,* et al. *"Ventilator pressure prediction using recurrent neural network." arXiv preprint arXiv:2410. 06552 (2024).*
15. *Zhang, Jingyu,* et al. *"Research on Detection of Floating Objects in River and Lake Based on AI Image Recognition." Journal of Artificial Intelligence Practice 7. 2 (2024): 97-106.*
16. *Tang, Xirui,* et al. *"Research on heterogeneous computation resource allocation based on data-driven method." 2024 6th International Conference on Data-driven Optimization of Complex Systems (DOCS). IEEE, 2024.*
17. *Dong, Chuan-Zhi, and F. Necati Catbas. "A review of computer vision–based structural health monitoring at local and global levels." Structural Health Monitoring 20. 2 (2021): 692-743.*
18. *Shi X, Tao Y, Lin S C. Deep Neural Network-Based Prediction of B-Cell Epitopes for SARS-CoV and SARS-CoV-2: Enhancing Vaccine Design through Machine Learning [J]. arXiv preprint arXiv:2412. 00109, 2024.*
19. *Zhao R, Hao Y, Li X. Business Analysis: User Attitude Evaluation and Prediction Based on Hotel User Reviews and Text Mining [J]. arXiv preprint arXiv:2412. 16744, 2024.*
20. *Xiang, Ao,* et al. *"Research on Splicing Image Detection Algorithms Based on Natural Image Statistical Characteristics." Journal of Image Processing Theory and Applications 7. 1 (2024): 43-52.*
21. *Gao, Dawei,* et al. *"Synaptic resistor circuits based on Al oxide and Ti silicide for concurrent learning and signal processing in artificial intelligence systems." Advanced Materials 35. 15 (2023): 2210484.*
22. *Mo K, Chu L, Zhang X,* et al. *Dral: Deep reinforcement adaptive learning for multi-uavs navigation in unknown indoor environment [J]. arXiv preprint arXiv:2409. 03930, 2024.*
23. *Yu Q, Wang S, Tao Y. Enhancing Anti-Money Laundering Detection with Self-Attention Graph Neural Networks [C]//SHS Web of Conferences. EDP Sciences, 2025, 213: 01016.*
24. *Tan, C., Zhang, W., Qi, Z., Shih, K., Li, X., & Xiang, A. (2025). Generating Multimodal Images with GAN: Integrating Text, Image, and Style. arXiv preprint arXiv:2501. 02167.*

25. *Ziang H, Zhang J, Li L. Framework for lung CT image segmentation based on UNet++ [J]. arXiv preprint arXiv:2501. 02428, 2025.*
26. *Benbarrad, Tajeddine,* et al. *"Intelligent machine vision model for defective product inspection based on machine learning." Journal of Sensor and Actuator Networks 10. 1 (2021): 7.*
27. *Ma D, Yang Y, Tian Q,* et al. *Comparative analysis of X-ray image classification of pneumonia based on deep learning algorithm algorithm [J].*
28. *Guo H, Zhang Y, Chen L,* et al. *Research on vehicle detection based on improved YOLOv8 network [J]. arXiv preprint arXiv:2501. 00300, 2024.*
29. *Yan, Y., Wang, Y., Li, J., Zhang, J., & Mo, X. (2025). Crop Yield Time-Series Data Prediction Based on Multiple Hybrid Machine Learning Models. Preprints. https://doi. org/10. 20944/preprints202501. 1948. v1*
30. *Torres, Juan P.,* et al. *"A Computer-Aided Inspection System to Predict Quality Characteristics in Food Technology." IEEE Access 10 (2022): 71496-71507.*
31. *Tan, C., Li, X., Wang, X., Qi, Z., & Xiang, A. (2024, November). Real-time Video Target Tracking Algorithm Utilizing Convolutional Neural Networks (CNN). In 2024 4th International Conference on Electronic Information Engineering and Computer (EIECT) (pp. 847-851). IEEE.*
32. *Yan, Hao,* et al. *"Research on image generation optimization based deep learning." Proceedings of the International Conference on Machine Learning, Pattern Recognition and Automation Engineering. 2024.*
33. *Li, X., Wang, X., Qi, Z., Cao, H., Zhang, Z., & Xiang, A. (2024). Dtsgan: Learning dynamic textures* via *spatiotemporal generative adversarial network. arXiv preprint arXiv:2412. 16948.*
34. *Shih, K., Han, Y., & Tan, L. (2025). Recommendation System in Advertising and Streaming Media: Unsupervised Data Enhancement Sequence Suggestions. arXiv preprint arXiv:2504. 08740.*