

Deep Learning For Automated Fabric Defect Detection

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Introduction

The field of automated fabric defect detection has seen significant advancements, driven by the increasing demand for high-quality textiles and efficient manufacturing processes. Machine vision, particularly when integrated with deep learning techniques, has emerged as a powerful tool for identifying various flaws in fabrics. Convolutional neural networks (CNNs) have demonstrated remarkable capabilities in achieving high accuracy for defect identification, encompassing issues such as holes, stains, and yarn defects. However, challenges remain, including the sensitivity of these systems to lighting variations and the critical need for extensive, well-labeled datasets. Researchers are actively proposing solutions like data augmentation and transfer learning to overcome these hurdles, paving the way for more robust and adaptable detection systems [1].

A parallel development in this domain involves the creation of real-time fabric defect detection systems. The utilization of object detection models, such as YOLOv5, has enabled high detection speeds and accuracy for common textile flaws. These systems are carefully detailed from dataset creation and model training to performance evaluation, underscoring their suitability for practical industrial applications where immediate feedback is crucial [2].

Addressing the scarcity of labeled data, Generative Adversarial Networks (GANs) are being explored for augmenting fabric defect datasets. By synthesizing realistic defect images, GANs can significantly enhance the robustness and accuracy of deep learning models, especially for identifying rare defect types. The validation of this approach demonstrates its effectiveness in improving detection performance on limited datasets [3].

Furthermore, the push for efficiency in fabric defect detection has led to the development of lightweight deep learning models. These models are specifically designed for deployment on edge devices, aiming to strike a balance between detection accuracy and computational cost. The integration of attention mechanisms and efficient network architectures allows for real-time performance while minimizing resource requirements, making them ideal for constrained environments [4].

Beyond supervised learning, anomaly detection techniques are proving valuable for fabric defect identification, particularly when dealing with diverse or previously unseen defect types. Autoencoders are employed to learn normal fabric patterns, with deviations from these learned patterns being flagged as defects. This method is especially beneficial in scenarios where obtaining labeled data for all possible defects is impractical [5].

The inherent variability in manufacturing environments, especially concerning illumination conditions, poses a significant challenge to consistent defect detection. Researchers are developing strategies to enhance the robustness of fabric defect detection against such variations. This often involves combining pre-processing techniques with deep learning models to ensure stable and accurate performance

across different lighting scenarios [6].

A hybrid approach, merging traditional image processing techniques with deep learning, offers a promising avenue for fabric defect detection. This strategy aims to harness the strengths of both paradigms, using traditional methods for initial feature extraction and deep learning for subsequent classification. Such a combination can lead to improved accuracy and enhanced interpretability of the detection results [7].

To address the detection of fabric defects that vary in size, multi-scale attention networks are being developed. These networks incorporate attention mechanisms at different levels of scale, enabling the model to effectively capture both subtle and prominent defects. This is crucial for accurate detection on complex fabric surfaces where defect sizes can differ significantly [8].

Efficiency in deep learning models is further addressed through knowledge distillation. This technique involves training a smaller, faster student model using a larger, more capable teacher model. The goal is to achieve comparable accuracy with substantially reduced computational demands, making the models suitable for real-time industrial deployment without compromising performance [9].

Finally, the impact of data augmentation strategies on deep learning-based fabric defect detection models is a subject of ongoing research. Techniques such as rotation, scaling, and color jittering are applied to increase the diversity of training data. This diversification aims to improve the model's generalization capabilities and its robustness against defects not explicitly encountered during training [10].

Description

The application of machine vision for automated fabric defect detection is a rapidly evolving area, with a significant focus on deep learning methodologies. Convolutional neural networks (CNNs) are at the forefront, exhibiting high accuracy in identifying a wide spectrum of fabric flaws, including but not limited to holes, stains, and yarn defects. A key challenge identified is the inherent sensitivity of these systems to environmental factors like lighting variations, alongside the substantial requirement for large volumes of meticulously labeled datasets. To counter these obstacles, researchers are actively exploring and implementing strategies such as data augmentation and transfer learning, which are crucial for building more resilient and adaptable defect detection frameworks [1].

The pursuit of real-time capabilities in fabric defect detection has led to the successful implementation of object detection models like YOLOv5. This approach prioritizes achieving high detection speed concurrently with robust accuracy for identifying common textile imperfections. The research meticulously details the entire pipeline, from the creation of specialized datasets and the intricate process of model training to comprehensive performance evaluation, thereby confirming

the system's viability for demanding industrial settings [2].

In scenarios where labeled data for fabric defects is limited, Generative Adversarial Networks (GANs) offer a compelling solution for data augmentation. By generating highly realistic synthetic defect images, GANs play a pivotal role in bolstering the robustness and accuracy of deep learning models, particularly when dealing with less frequent or rare types of defects. The validation of this methodology consistently shows an improvement in overall detection performance [3].

Efficiency in computational resources is a critical consideration, especially for deployment in resource-constrained environments. The development of lightweight deep learning models addresses this need for fabric defect detection. These models are engineered to balance high detection accuracy with minimal computational overhead, often employing innovative network architectures and attention mechanisms to achieve real-time performance on edge devices with reduced power and processing capabilities [4].

Anomaly detection techniques present an alternative and effective paradigm for fabric defect identification, particularly suited for situations characterized by a wide diversity of defect types or when encountering unknown defects. The use of autoencoders allows for the learning of normal fabric patterns, with any significant deviation from these learned norms being classified as a defect. This methodology proves particularly advantageous in applications where acquiring comprehensive labeled datasets for all potential defect types is unfeasible [5].

Ensuring the consistent performance of fabric defect detection systems under varying environmental conditions, specifically fluctuating illumination, is a significant engineering challenge. Solutions often involve a combination of intelligent pre-processing techniques and sophisticated deep learning models. This integrated approach aims to standardize the input data and enhance the model's ability to maintain high accuracy and stability across a broad spectrum of lighting environments [6].

A hybrid methodology, which synergistically combines traditional image processing algorithms with advanced deep learning techniques, is being explored to enhance fabric defect detection. This integrated approach seeks to leverage the strengths of both domains: traditional methods for efficient initial feature extraction and deep learning for powerful pattern recognition and classification. The outcome is often an improvement in both detection accuracy and the interpretability of the system's decisions [7].

To effectively detect fabric defects that can manifest at various scales, from minute imperfections to larger flaws, multi-scale attention networks have been proposed. These networks strategically integrate attention mechanisms across different resolution levels. This allows the model to concurrently focus on and identify defects of diverse sizes, leading to more comprehensive and accurate detection on complex fabric surfaces [8].

Knowledge distillation is another important technique employed to enhance the efficiency of fabric defect detection models. This process involves leveraging a larger, high-performing 'teacher' model to train a more compact and computationally efficient 'student' model. The objective is to achieve performance levels comparable to the teacher model but with significantly reduced resource requirements, facilitating seamless integration into real-time industrial applications [9].

Furthermore, the impact and efficacy of various data augmentation strategies are under continuous investigation to optimize deep learning-based fabric defect detection. Techniques such as geometric transformations (rotation, scaling) and color space manipulations (color jittering) are employed to enrich the training dataset. This augmentation aims to improve the model's ability to generalize well to unseen data and enhance its overall resilience against variations in fabric appearance and defect presentation [10].

Conclusion

This collection of research focuses on advancing automated fabric defect detection using machine vision and deep learning. Convolutional Neural Networks (CNNs) and object detection models like YOLOv5 are highlighted for their high accuracy and real-time capabilities. Challenges such as lighting variations and limited labeled data are addressed through techniques like data augmentation, Generative Adversarial Networks (GANs), and anomaly detection using autoencoders. The development of lightweight models for edge devices and hybrid approaches combining traditional image processing with deep learning are also discussed. Multi-scale attention networks are employed to detect defects of varying sizes, while knowledge distillation aims to improve model efficiency. The impact of data augmentation strategies on model robustness and generalization is also a key area of investigation.

Acknowledgement

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Conflict of Interest

None.

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