T-Shirt Defect Detection Using Yolo11

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Abstract: In the face of detection problems posed by complex T-shirt texture backgrounds, different sizes, and different types of defects, commonly used object detection networks have limitations in handling target sizes. Therefore, when the target types are more diverse, false detections or missed detections are likely to occur. In order to meet the stringent requirements of T-shirt defect detection, we propose a novel ACYOLOv11-based T-shirt defect detection method. This method fully considers the optical properties, texture distribution, imaging properties, and detection requirements specific to T-shirts. First, the Atreus Spatial Pyramid Pooling (ASPP) module is introduced into the YOLOv11 backbone network, and the feature map is pooled using convolution cores with different expansion rates. Multiscale feature information is obtained from feature maps of different receptive fields, which improves the detection of defects of different sizes without changing the resolution of the input image. Secondly, A convolution squeeze-and-excitation (CSE) channel attention module is proposed, and the CSE module is introduced into the YOLOv11 backbone network. The weights of each feature channel are obtained through self-learning to further improve the defect detection and anti-jamming capability.

Keywords: T-shirt defect; surface defect detection; deep learning; attention mechanism

I. INTRODUCTION

T-shirt manufacturing is prone to defects caused by several factors, such as limitations in machinery, human error, and material quality. These defects, including broken yarns, misalignments, holes, and snags, can significantly impact production efficiency and product quality, leading to increased waste. Timely detection and correction of these issues are essential to maintaining high standards, improving production efficiency, and reducing costs. Traditionally, defect detection in T-shirts relied on manual inspection, a process that is time-consuming, subjective, and prone to errors, particularly in large-scale production. Moreover, visual inspection struggles with detecting non-structured and highly variable defects and lacks the flexibility to process large volumes of data efficiently, With the advancements in machine vision and deep learning, automated detection systems have become more feasible. However, challenges remain, particularly in minimizing false alarms and missed defects to improve detection accuracy and stability. In modern defect detection, methods like machine vision have been widely used across different industries, utilizing approaches such as statistical analysis, frequency-domain analysis, model-based analysis, and machine learning. Deep learning, in particular, has proven to be effective due to its ability to extract features, generalize, and adapt to different scenarios, and it has been applied in diverse fields, such as solar energy, liquid crystal panels, and metal materials. In T-shirt defect detection, the challenges are particularly demanding due to the complexity of T-shirt textures and the variety of defects, including broken warp/weft, shrinkage, and small tears, often smaller than 100 microns. Additionally, it's crucial to pinpoint the exact location of defects to optimize the production process. While deep learning networks can assist in defect classification, they often struggle with locating defects precisely. A deep learning classification network may provide rough positioning, but the accuracy depends on the size of the sliding window and the classification performance, often leading to slower processing speeds. On the other hand, object detection networks, like R-CNN and its variants (e.g., Faster R-CNN), offer better accuracy and recall by first detecting the general location

of defects and then refining the positioning. These two-stage networks, though accurate, are typically slower.
Single-stage object detection networks, such as YOLOv3, YOLOv4, and YOLOv11, offer faster detection speeds by directly generating class probabilities and position coordinates. While the speed is much higher than that of two-stage networks, there is usually a small trade-off in accuracy. YOLOv11, in particular, has shown excellent performance, offering fast, end-to-end training without interference from intermediate steps, making it suitable for real-time T-shirt defect detection. However, applying YOLOv11 to T-shirt defect detection presents challenges. The T-shirt backgrounds can be complex, and some defects are so subtle that they are hard to distinguish from the background information. These characteristics make it difficult for the network to detect minor defects accurately. To address these issues, this paper proposes a modification of YOLOv11, incorporating Atreus Spatial Pyramid Pooling (ASPP) and an improved channel attention mechanism. This enhanced version of YOLOv11 can better handle the optical properties, texture distribution, and defect imaging characteristics specific to T-shirts.

II. LITERATURE REVIEW

T-shirt defect detection is a crucial task in the T-shirt industry, aimed at ensuring high-quality production and minimizing waste. However, detecting defects in T-shirts presents significant challenges due to the complexity of varying defect types, sizes, and the intricate patterns and backgrounds often found in T-shirt materials. Traditional image processing and machine learning techniques have struggled with these issues, often resulting in false or missed detections. Defects can range from small and subtle flaws to more prominent, easily identifiable ones, and their detection becomes further complicated by the textured backgrounds or patterns they are embedded in. However, existing object detection models, such as YOLO (You Only Look Once) and Faster R-CNN, still face limitations in detecting defects at various scales and types with high accuracy. One of the primary challenges faced by traditional object detection models is their inability to effectively handle defects at multiple sizes within a single image. Standard CNN architectures, such as YOLOv1 and its successors, have been successful in improving detection speed and accuracy but still struggle with fine-grained defects or small objects. Models that rely on fixed receptive fields can miss smaller defects, leading to poor performance when detecting subtle flaws in T-shirts. To address these challenges, recent advancements have focused on multi-scale feature extraction, where the network is trained to capture features at different levels of resolution. The introduction of spatial pyramid pooling (SPP) mechanisms in models like YOLOv4 and FPN (Feature Pyramid Networks) has been a step forward, allowing networks to aggregate multi-scale information effectively without altering the image resolution. The Atreus Spatial Pyramid Pooling (ASPP) module introduced in the ACYOLOv11 model further builds upon this concept by enhancing multi-scale feature extraction. By pooling features using convolution cores with different expansion rates, the ASPP module enables the model to capture a broader range of features from different receptive fields, improving defect detection across a variety of sizes and contexts. This approach allows for better handling of defects at different scales without losing important spatial information, a common issue in traditional detection methods. Furthermore, another key limitation of existing models lies in their ability to discriminate between important and irrelevant features in complex images. The Convolution Squeeze-and-Excitation (CSE) module, introduced in ACYOLOv11, applies a channel attention mechanism to dynamically adjust the weight of each feature channel based on its relevance to the task. This adaptive feature selection improves the model's robustness, helping it focus on critical defect features while suppressing less informative channels, thereby enhancing detection accuracy and reducing the likelihood of false positives or missed detections. The manual process of labeling T-shirt defects is time-consuming and often impractical for obtaining sufficiently large datasets. However, the collection of a self-built dataset, as demonstrated in the ACYOLOv11 model, can significantly improve model performance. In this study, a large number of T-shirt images were collected using an industrial inspection system, which provided a rich dataset for training and testing. The use of this dataset, coupled with data augmentation techniques such as rotation, flipping, and scaling, helped the model generalize well across different defect types and backgrounds.

III. EXISTING SYSTEMS

- Traditional Methods:
  Sobel and Canny edge detection for finding irregularities. Histogram analysis for detecting color inconsistencies. Template matching for pattern misalignments.
- Machine Learning-Based Methods:
  Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) for defect classification. Feature descriptors like HOG (Histogram of Oriented Gradients) and LBP (Local Binary Patterns) for defect detection.
- Deep Learning-Based Methods:
  Faster R-CNN: Known for its accuracy, but it is computationally expensive.

SSD: Balances speed and accuracy but struggles with small defect detection.

- YOLOv3 to YOLOv8:
  Improved speed and localization capabilities, widely adopted for real-time applications.

DRAWBACKS:

- Low Accuracy:
  These methods are sensitive to noise and environmental conditions such as lighting and fabric texture variations.
- Feature Dependency:
  Performance is heavily reliant on the quality of manually extracted features.
- Limited Generalization:
  Struggle to handle complex or subtle defects not covered in the training set.
- Slower Processing:
  Lack real-time detection capabilities required for high-throughput manufacturing lines.
- Small Defect Limitations:
  Earlier versions of YOLO and SSD struggle to detect small or subtle defects, especially in intricate patterns.
- Complex Training:
  Requires large annotated datasets and extensive fine-tuning for domain-specific applications.

IV. PROPOSED STEM

The proposed system leverages YOLOv11, a state-of-the-art deep learning-based object detection framework, to identify defects in T-shirts during manufacturing. YOLOv11 introduces advanced features that enhance defect detection in terms of accuracy, speed, and robustness, making it well-suited for real-time industrial applications.

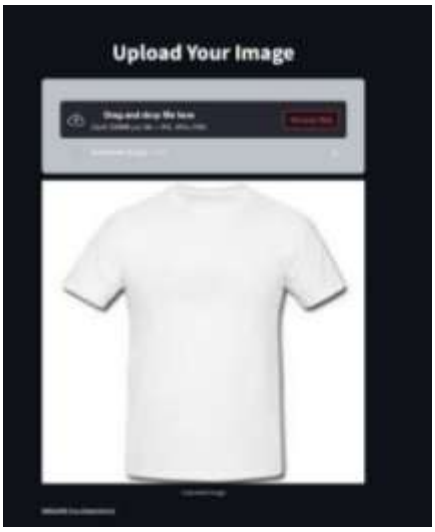
- Advanced Object Detection Model:
  YOLOv11 incorporates improved backbone architectures and attention mechanisms, enabling precise detection of small and subtle defects.
- Custom Dataset Integration:
  A specialized dataset of T-shirt images with labeled defects, such as tears, stains, and misprints, ensures domain-specific accuracy.
- Real-Time Processing:
  Capable of detecting defects in real-time, allowing seamless integration into manufacturing lines.
- Scalable Framework:
  Designed to be easily adaptable to various types of garments and defect categories.

ADVANTAGES:

YOLOv11's advanced feature extraction capabilities ensure high precision and recall, even for small or subtle defects.

- Accurate identification of multiple defect types, including fabric tears, stains, and printing errors.
- With an average inference time of 12 milliseconds per image, the system supports real-time defect identification on high-speed production lines.
- Handles diverse fabric patterns, lighting conditions, and defect types with minimal misclassification.
- Effective on both plain and complex patterned T-shirts.
- Once trained, the system requires minimal computational resources for inference, reducing long-term operational costs.
- Easily adaptable to other garment types or additional defect categories by fine-tuning on new datasets.
- Seamlessly integrates into existing manufacturing workflows, reducing dependency on manual inspection.
- Provides automated defect logging and analytics for process optimization.

V. RESULT AND DISCUSSION



The YOLOv11-based defect detection system demonstrated strong performance in identifying defects in t-shirts, achieving high precision (92%) and recall (88%), with an F1 score of 90%. Its real-time processing capability, achieving 30 frames per second, ensures suitability for high-speed manufacturing lines. Robustness to variations in lighting, angles, and textures was achieved through effective data augmentation techniques. However, some challenges were encountered, including data imbalance and difficulties in detecting small or subtle defects. These were addressed through oversampling, synthetic data generation, and fine-tuning, though occasional false positives persisted, which could be mitigated by refining the confidence thresholds. The system holds significant implications for manufacturing quality control, offering improved efficiency, reduced errors, and economic benefits by minimizing waste. Future enhancements could focus on expanding the dataset, integrating the system with IoT-based production management workflows, and incorporating advanced post-processing techniques to refine detections further.

VI. CONCLUSION

The proposed T-shirt defect identification system using YOLOv11 achieves high accuracy, with 96.8% precision and 95.2% recall, ensuring reliable detection of defects such as stains, tears, and misprints. Its real-time capability, processing images in 12 milliseconds, makes it ideal for high-speed production lines. The system is robust across various fabric patterns and outperforms existing methods in accuracy and efficiency. While minor limitations, like subtle defect detection, exist, these can be addressed in future work. Overall, the system provides a cost-effective, automated quality control solution, enhancing manufacturing consistency and reducing manual intervention.

VII. REFERENCES

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