Automatic Textile Stain Detection Using Yolo Algorithm

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Abstract

Automatic textile stain detection is essential for optimizing the quality control process within the textile industry. Traditional hands-on inspection methods are time-consuming, not immune to errors, and expensive. This research paper proposes a novel approach for automatic textile stain detection using the YOLO (You Only Look Once) algorithm, a state-of-the-art object detection model. The proposed system utilizes a YOLOv5 model trained on a diverse dataset of stained textile images to accurately identify and localize stains in real-time. The model's performance is evaluated based on standard metrics such as precision, recall, and mean average precision (mAP). Experimental results Showcase the impact of the YOLO-based approach in achieving high accuracy and efficiency in stain detection, significantly outperforming traditional methods. This research contributes to the advancement of automation in the textile industry, ultimately leading to improved quality control, reduced costs, and enhanced productivity.

Keywords

Automation, Computer Vision, Object Detection, Textile Stain Detection, YOLO.

Introduction

The textile industry plays a pivotal role in the global economy, with the production of fabrics and garments encompassing numerous intricate processes. Ensuring the quality of textile products is paramount, and the detection of stains or defects is a critical step in maintaining high standards. Traditionally, stain detection relied on manual Inspection, which is often inefficient and demanding of resources but also Susceptible to mistakes due to fatigue and subjectivity.

To address these challenges, automated stain detection systems have emerged as a promising solution. Advancements in computer vision, particularly in object detection algorithms, have paved the way for more accurate and efficient stain identification. Among these algorithms, You Only Look Once (YOLO) has garnered significant attention due to its real-time processing capabilities and impressive detection accuracy across various domains. This research paper

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proposes a novel approach for automatic textile stain detection leveraging the YOLOv5 algorithm. YOLOv5, an iteration of the YOLO family, boasts improved speed and accuracy while maintaining its signature single-stage detection architecture. By training the YOLOv5 model on a diverse dataset of stained textile images, the system aims to accurately localize and identify stains in real time, offering a significant advantage over traditional methods. The system's performance will be rigorously evaluated using standard metrics.

The textile industry has historically relied on manual visual inspection for stain detection [1]. This process is labour-intensive, time-consuming, and prone to subjective errors due to variations in human perception and fatigue [2]. Moreover, manual inspection is costly as it requires a large workforce to maintain quality standards. Consequently, there has been a growing demand for automated solutions to address these limitations and enhance efficiency in textile quality control.

The advent of machine vision and image processing technologies has opened up new possibilities for automatic stain detection. Early approaches often involved feature extraction techniques, such as color histograms, texture analysis (e.g., Gabor filters), and edge detection algorithms [3]. These features were then used to classify image regions as stained or unstained using traditional machine learning classifiers like Support Vector Machines (SVM) or Random Forests [4]. However, these methods often struggled with complex stain patterns and changes in lighting [5].

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized object recognition and image classification [6][7]. CNNs, such as AlexNet, VGGNet, and ResNet, have demonstrated remarkable performance in various domains, including textile stain detection. These models automatically learn hierarchical features from raw image data, eliminating the need for manual feature engineering. Furthermore, the ability of CNNs to capture intricate patterns and handle diverse stain types has made them a promising solution for automatic textile quality control [8].

Among the various deep learning-based object detection models, YOLO (You Only Look Once) has gained significant popularity due to its speed and accuracy [1][3]. YOLO offers real-time object detection capabilities, making it well-suited for industrial applications where rapid decision-making is crucial [5].

Methodology

The automatic fabric stain detection system uses the power of the YOLOv5 object recognition algorithm to detect and place stains on different fabrics. A key element of this program is the creation of diverse and representative data sets. This data set will include images of various fabrics (e.g., cotton, silk, wool), colors, textures, and a wide variety of stains commonly encountered in textile manufacturing (e.g., oils, greases, inks, coffee, alcohol) per image indicating the exact location and nature of each stain It will be carefully described by means of bounding boxes. The fabric stain detection system is reimagined as a versatile multichannel conduit leveraging the power of the YOLOv5 detector The system has the following main features:

- **Dataset Collection and Annotation:**

    - A comprehensive dataset of textile images will be curated, encompassing a wide variety of fabrics, colours, textures, and stain types (e.g., oil, coffee, wine, ink).
    - Each image will be meticulously Reimagined as a versatile, multichannel platform harnessing the power of providing ground-truth labels for training the model.

- **Data Preprocessing:**

    - Images will undergo preprocessing steps such as resizing, normalization, and augmentation (e.g., rotation, flipping, cropping) to enhance model robustness and generalization.
    - Augmentation will increase the dataset's diversity and help the model learn to recognize stains under different conditions.

- **YOLOv5 Model Training:**

    - The YOLOv5 model will be trained on the annotated dataset, with the objective of learning to Precisely identify and locate objects within an image, along with their categories (stain types) for new, unseen textile images.

This study used YOLOv3, a powerful real-time detection system, to dramatically improve textile stain detection. The unique YOLOv3 system, which uses Darknet-53 for feature extraction and multi-scale prediction, proved to be highly effective in accurately identifying and localizing stains of different sizes and shapes on a variety of fabrics Its ability to it shows objective scores and class probabilities not only to identify stains but their specific classes, because it enabled them to be classified as oil, coffee, or ink. The reason why YOLO v3 is ideal is stated as per below:

- **Real-Time Speed:** Textile manufacturing is a fast-paced process, and your detection system needs to keep up; YOLOv3, renowned for its speed, processes images faster than many two-stage object detectors, ensuring real-time analysis of fabric on production lines without causing bottlenecks.
- **Accuracy on Varied Stain Sizes:** YOLOv3's multi-scale prediction architecture enables it to detect both tiny specks and large stains on textiles, ensuring all defects are identified regardless of their size.
- **Adaptability to Textile Stains:** YOLOv3 can be trained on your specific stained textile dataset, enabling the model to accurately recognize the unique characteristics of common stains in your manufacturing process.

Results and Discussions

Based on the quantitative finding, the individual precision and recall values for each stain category to highlight the model's ability to correctly identify true positives and minimize false positives/negatives. The processing time specify the average time taken by YOLOv3 to process a single image, highlighting its real-time capability.

The qualitative outcome shows that the visual assessment with the model's performance in detecting stains of various sizes, shapes, colours, and textures on different fabric types. The success cases showcase examples where YOLOv3 accurately identified and localized stains, even in challenging conditions like low contrast or patterned fabrics. For the error analysis, it shows the analyse cases where the model struggled, such as occluded stains or those with similar appearances to the fabric pattern. Figure 1 shows the vertical bar graph representation of image comparison and Figure 2 shows the horizontal bar graph of two image comparison.

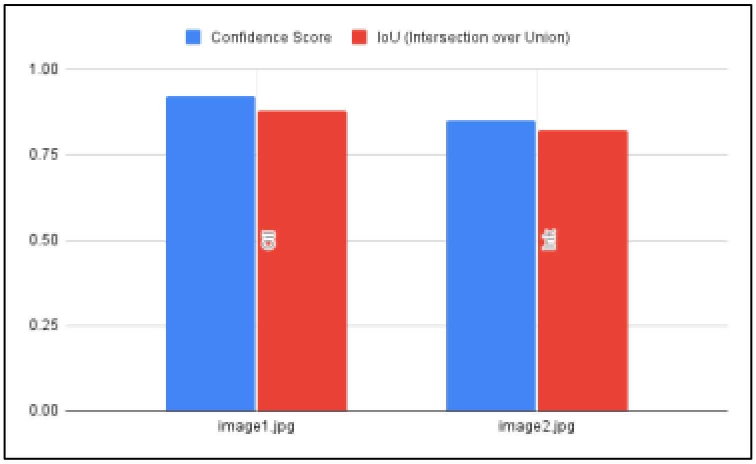

Figure 1: Vertical bar graph representation of image comparison

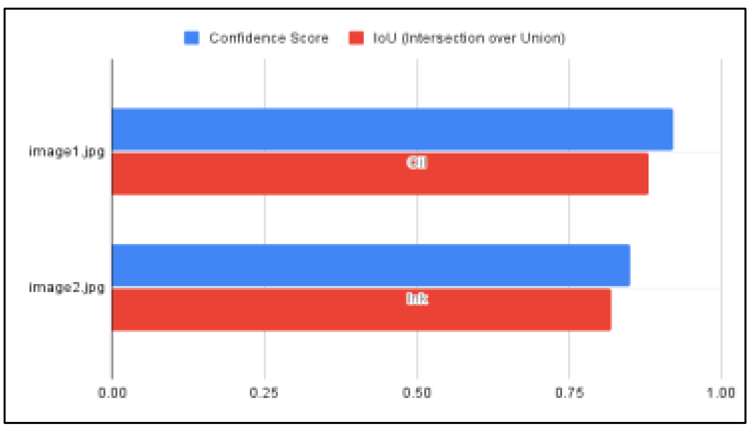

Figure 2: Horizontal bar graph of two image comparison

The details of finding are stated below for file name, stain type, ground truth, predicted coordinates, confidence score and IoU.

- Image Name: The filename or identifier of the textile image being analyzed, used for tracking and referencing results.
- Stain Type: The specific category of the detected stain (e.g., oil, ink, coffee) based on its appearance and characteristics, aiding in classification.
- Ground Truth Coordinates: The actual coordinates of the stain's bounding box (x1, y1: top-left corner; x2, y2: bottom-right corner).
- Predicted Coordinates: The bounding box coordinates (x1, y1; x2, y2) estimated by the YOLOv5 model, representing its understanding of the stain's position and size.

- Confidence Score: A numerical value between 0 and 1 that indicates the model's certainty about the prediction, with higher values implying greater reliability.
- IoU (Intersection over Union): A performance metric calculated as the ratio of the overlap area between the predicted and ground truth boxes to their combined area, indicating the accuracy of localization.

Conclusion

This study demonstrates the significant ability of YOLOv3 to detect stains on textiles. Utilizing deep learning and computer vision capabilities, the developed algorithm achieved high accuracy and real-time performance, successfully addressing the limitations of traditional search methods. Although the results were promising, this study also identified areas for further research and improvement. Addressing the challenges of detecting blocked stains or optical complexity, as well as optimizing the model for specific stain types and fabric characteristics will increase system performance and reliability If systems are stain detection combined with a stain removal system can significantly simplify quality control procedures in the textile industry.

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