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Original Article

Research on Designing a Fabric Surface Defect Detection System Using YOLO in Vietnam

Huong Dinh Mai[1], Nam Pham Van[1], Huong Pham Thi Quynh[1], Hung Pham Van[1,2*]

[1]*Hanoi University of Industry, Ha Noi, Viet Nam.*
[2]*Hanoi University of Science and Technology, Ha Noi, Viet Nam.*

[*] *Corresponding Author : phamvanhung@haui.edu.vn*

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Abstract - *In the textile industry, detecting and classifying fabric defects is essential for maintaining product quality, improving production efficiency, and reducing manufacturing costs. This study presents a defect detection system based on YOLOv11, trained with a dataset that includes common defects such as yarn defects and stains. The system was tested on an experimental setup designed to match real production conditions. Results show that, at a fabric speed of 3 m/min, the model achieved over 95% accuracy for stain defects and up to 90% accuracy for yarn defects, meeting real-time inspection requirements. The system reduces dependence on manual inspection, lowers error rates, and improves reliability in fabric quality control. The results show that deep learning and Industry 4.0 work well for textile inspection and could also be applied in other industries.*

Keywords - *Image processing, YOLO, Machine Learning, Fabric surface defects, Textile industry.*

1. Introduction

The textile industry is a major part of Vietnam's economy and contributes strongly to export income. Fabric defects, such as stains or yarn breaks, lower product quality and often cause waste or extra processing costs. In many factories, inspection still depends on manual checking, which is slow and often inaccurate. As production lines run faster, these methods are no longer practical. To deal with this, automated inspection using computer vision and machine learning has been developed for textile production. Previously, fabric defect detection was primarily conducted through fundamental image processing approaches, including filtering, segmentation, and feature extraction. However, these approaches were limited to handling only easily recognizable defects and often required human intervention for classification. The authors in [1] employed traditional image processing methods, including binary image conversion, smoothing, and contrast enhancement, to make fabric defect features more distinguishable. The system identifies defect areas such as dirt spots, scratches, or holes based on processed features. In another study [2], a fabric defect detection method using Fourier analysis was introduced. Fourier analysis transforms images into the frequency domain, employing the 2D Fourier transform to represent fabric images in the frequency domain. Fabric defects like dirt spots, scratches, or holes cause changes in the image's frequency. Each type of defect has its characteristic frequency, with small defects often exhibiting high frequencies and large defects at low frequencies. After the Fourier analysis, the frequency features help identify defect regions by comparing them with standard patterns, thereby automating defect detection. Both approaches struggle with small or irregular defects, require high computation, and perform poorly on complex patterns. These limits reduce accuracy and speed in some cases.

As production lines require higher accuracy, AI and machine learning help detect defects that basic image processing often misses. In [3], an automatic fabric defect identification system was developed by integrating computer vision and artificial neural networks. This breakthrough improves the ability to classify defects automatically and accurately compared with traditional methods. Although traditional methods using Fourier analysis have demonstrated the ability to detect fabric defects in complex situations, when the input data is diverse and the defects become more difficult to identify, deep learning becomes the optimal choice. Fabric defect detection research is increasingly diverse, incorporating new technologies to improve the accuracy and efficiency of fabric defect detection. Models such as Faster R-CNN [4-7] or the study of Huang and Chen [8] have introduced a method that combines neural networks and fuzzy logic. This method is designed to classify various fabric defects, handle complex situations, and improve the accuracy of identifying and classifying fabric defects that previous techniques cannot handle well. This method improves classification and allows the model to deal with unclear defect features in real fabrics. Meanwhile, the study [9] provides an overview of computer vision-based fabric defect detection methods, and the study of

Kumar and Shen [10] uses neural networks and SVM techniques to inspect fabric structures and detect defects in fabric images, expanding the use of machine learning for identifying subtle defects. Real-time methods are also studied in [11], which introduces a real-time intelligent fabric defect detection system that meets the high production requirements for speed and accuracy.

Finally, [12] proposes to combine the wavelet transform and a neural network to detect fabric defects, which is highly effective in analyzing and identifying defects with complex structures. These studies show that machine learning and computer vision improve defect detection, leading to better product quality and higher production efficiency. These deep learning models can not only easily identify and classify common defects, but also detect difficult defects and small errors that are difficult to detect by traditional methods. In these studies, the authors used different datasets with fabrics containing 1 to 9 different types of defects, achieving accuracy from 67% to 96%. This confirms that deep learning models are effective for recognition and classification, with higher accuracy than traditional methods.

Currently, deep learning models such as YOLO [13-15] are used in agriculture and industry, bringing clear improvements in performance. In the textile domain, YOLO has also been applied to fabric defect classification using machine vision. Studies [16-18] indicate that while YOLO generally achieves a higher processing speed compared to Faster R-CNN, its accuracy may be relatively lower. The distinction stems from YOLO's single-stage detection paradigm, where class probabilities and bounding boxes are predicted in one unified step, in contrast to R-CNN and its derivatives, which follow a two-stage architecture that first produces region proposals and then performs classification and bounding box adjustment. For instance, a prevouis study improved YOLOv3 to enable fast and accurate object detection, suitable for high-speed industrial systems. Author Lin et al. [14] introduced the FPN method to enhance object detection capabilities in deep learning models, especially in tasks involving object detection at various sizes, which can support YOLO in identifying fabric defects at multiple levels of detail, especially when dealing with low-resolution images or complex patterns.

Additionally, research utilizing enhanced neural networks like YOLOv5 in the study by Guo et al. [15] has expanded the capability to identify fabric defects, particularly in dynamic production environments where defects may appear in difficult-to-detect forms. This method enhances fabric defect detection based on YOLOv5 to handle complex structures and diverse fabric defects. Experimental results showed that the method achieved 99.1% accuracy for easily recognizable defects, such as yarn breakages and tears, but had lower accuracy for challenging defects like dirt on the fabric surface. These studies have demonstrated the great potential of deep learning methods in fabric defect detection. However, in Vietnam, the application of these methods in actual fabric production is still limited. At present, most textile enterprises mainly rely on manual fabric inspection, in which workers visually inspect fabrics for defects. This approach is not only time-consuming but also prone to subjective errors, slow detection rates, and high costs, particularly in large-scale production environments. The adoption of advanced technologies, such as AI and deep learning, faces several challenges in the Vietnamese textile industry. Financial constraints are a significant barrier, as these technologies require substantial investment in both infrastructure and training.

Furthermore, integrating AI into existing production processes can be complex, as traditional manufacturing workflows may not easily adapt to these advanced systems. Finally, the willingness of companies and workers to embrace new technologies and adjust to changes in their workflows also impacts the speed of adoption. Therefore, a new defect detection method with high accuracy and detection speed is needed to replace the current manual processes. With the advent of Convolutional Neural Networks (CNNs) and the progress in deep learning and computer vision, numerous detection methods that leverage the strengths of these technologies [19] have been developed and applied, replacing traditional manual approaches.

This paper presents an automatic fabric defect detection system using YOLOv11 to improve efficiency and quality in Vietnam's textile production. The system is designed to quickly and accurately detect fabric defects, reduce inspection costs and time, while meeting the real-time quality inspection needs of the textile industry in Vietnam. The research focuses on fine-tuning the YOLOv11 model for the detection of common fabric defects and evaluating its performance using a custom-built, diverse dataset created through image generation and data augmentation techniques. In addition, an optical system is designed to ensure comprehensive coverage of the fabric surface, effectively reducing hardware design expenses.

A monitoring interface is also developed to track the fabric inspection process in real-time, providing an interactive way to monitor defects and performance. By utilizing a pre-trained model, the study enhances detection accuracy and operational efficiency, with results demonstrating high classification accuracy and suitability for real-time industrial applications. The findings confirm that AI tools improve fabric quality inspection by increasing accuracy and efficiency for manufacturers.Following the general introduction, the paper describes the core components of the proposed Fabric Surface Defect Detection System in Part 2. Part 3 outlines the process of building the Fabric Defect Identification software. Part 4 presents results on the experimental model in Vietnam. Finally, Part 5 provides the conclusion.

2. Fabric Surface Defect Detection System

This study builds a fabric defect detection system using computer vision technology. The system is illustrated in Figure 1, including main components such as an industrial camera cluster, lighting system, computer, and automatic fabric winding system. The system is capable of processing fabric at a speed of up to 3m/min, meeting the real-time requirements in industrial production environments. With an accuracy exceeding 90%, the system helps to minimize errors in defect detection and reduces dependence on employees' manual assessment. Consequently, it contributes to improving the production process and enhancing product quality and efficiency.

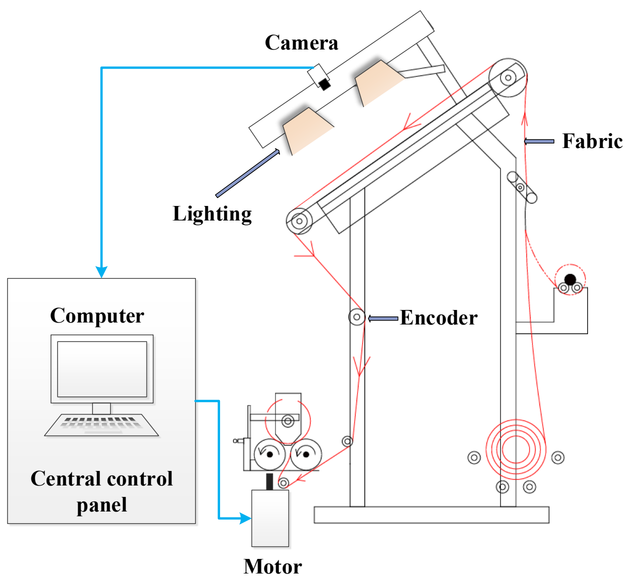

Fig. 1 Block diagram of the fabric surface defect detection system

Fig. 2 Cognex IS-5110 camera

Among the available industrial vision devices, the Cognex In-Sight 5110 camera was selected due to its cost-effectiveness and availability within the laboratory environment. The camera is mounted on the top, tilted at a suitable angle to capture images of the fabric surface as it moves. It serves as a high-resolution industrial vision system capable of detecting small details on the fabric. This device features a 1/3-inch CCD sensor with a maximum resolution of 640 × 480 pixels, supporting frame rates of up to 60 frames per second, and allows exposure times adjustable from 16 µs to 1000 ms to adapt to varying lighting conditions. The Cognex IS-5110 camera selection device, as shown in Figure 2, has specifications detailed in Table 1.

Table 1. IS-5110 camera specifications

Connection Port	Industrial M12 connection port
Lens Type	C-mount
Frame Rate (FPS)	60
Resolution (pixels)	640 x 480
Power Supply	24VDC

2.1. Lighting System

The lighting system is designed with 20-watt tube LED lights, 1.2 meters in length, installed under the fabric's moving surface. The lights provide stable and uniform intensity, enhancing contrast and highlighting defects such as scratches, holes, or small stains on the fabric. High-quality lighting is crucial for accurate detection of surface fabric defects.

2.2. Fabric Roll System

The fabric rolling system controls the fabric movement speed to ensure that the fabric moves steadily at a single speed. During system operation, the fabric is fed into the rolling system and moves through the inspection area. The camera continuously captures images under standard lighting conditions, ensuring clear image data. These images are transmitted to the central processor, where AI models analyze and detect defects on the fabric surface.

3. Software for the Detection and Classification of Fabric Defects

3.1. Fabric Defect Identification System Process

Based on practical requirements and the need for quality improvement in product inspection, this paper proposes a comprehensive solution for detecting and classifying surface defects in products, with a process outlined in the steps as depicted in Figure 3.

3.1.1. Step 1 (Fabric Image Collection)

The fabric is moved through the system using fabric rolls, uniformly illuminated by the lighting system. An industrial camera is positioned above the fabric surface and tasked with capturing images of the fabric during movement. The system ensures that fabric images are captured with high resolution and under standard lighting conditions.

3.1.2. Step 2 (Image preprocessing)

At this stage, the fabric image is normalized to improve quality, such as sharpening, filtering, and brightness adjustment to enhance image clarity for easy defect identification, supporting the YOLOv11 model to detect defects seamlessly.

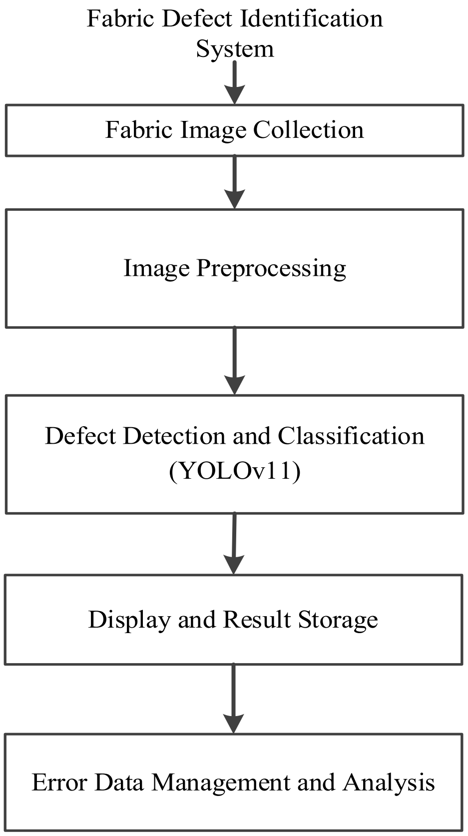

Fig. 3 Fabric defect identification system process

3.1.3. Step 3 (Defect Detection and Classification)

Following processing, images are fed into the YOLOv11 model. This model is trained to recognize and classify common fabric defects, such as yarn defects and stains. The YOLOv11 model utilizes Convolutional Neural Network layers to detect features in images and pinpoint defect areas.

3.1.4. Step 4 (Display and Storage)

Data on fabric defects is stored for analysis and production process enhancement. The classified defect results are displayed on the computer. Various types of defects are marked on the images for operators to monitor and address if necessary. Defect data is stored for analysis, aiding in production process improvement and quality inspection.

3.1.5. Step 5 (Data Analysis)

The defective fabric data is stored in the system. This information can be analyzed to determine the cause of the fabric defect, facilitate production process improvement, and optimize quality inspection steps. Furthermore, it helps reduce dependence on manual inspection.

3.2. Building the Dataset

The fabric defect dataset used in this study was created by directly collecting images from real production lines. Industrial cameras were employed to capture clear and detailed images suitable for supporting AI-driven defect detection. The data was gathered in a sewing training room at the Hanoi University of Industry practice laboratory, ensuring controlled conditions for consistent quality. After collection, the images were processed using cropping and resizing methods to a standard resolution of 640 × 640 pixels. This resolution is suitable for modern object detection models such as YOLO. The total dataset includes 3800 images, classified and labeled through the Roboflow platform – a powerful online tool for labeling and organizing image data for deep learning applications. The dataset focuses on two common types of defects often encountered in the fabric production process (surface defects): yarn defect (E1) and stains (E2). This study aims to enhance the efficiency of textile product quality inspection by detecting these external defects on the fabric's surface.

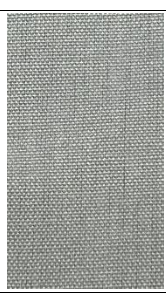	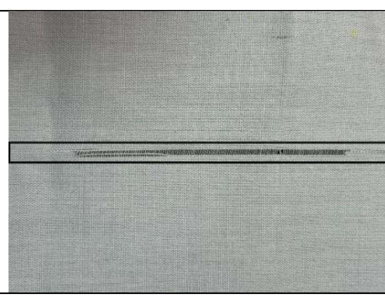	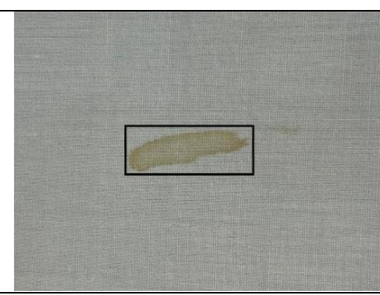
Normal (N)	**Yarn defects (E1)**	**Stain defects (E2)**

Fig. 4 Dual-sided external defects of the product

Specifically, the defects under investigation are illustrated in Figure 4 and include yarn defects and stains. Yarn defects, such as weak or broken threads, can lead to tears or holes larger than 2 mm, which significantly affect the product's quality. These defects often occur during production or transportation, and can arise during the weaving process or subsequent stages of processing. Early detection of these yarn defects is crucial, as it helps prevent the production of uneven and low-quality fabric. Stains, on the other hand, refer to contamination on the fabric surface caused by foreign substances such as preservatives, dust, debris, or other impurities. They may appear during weaving, processing, or transportation, and timely detection is essential to ensure the fabric maintains a clean and high-quality surface finish. Due to the complexity of identifying various types of defects, the number of images allocated for each defect type is uneven.

Specifically, the stain-related defects are easier to detect due to clear characteristics in shape, size, and differentiation from the fabric background, accounting for 800 images in the entire dataset. In contrast, yarn defects are more difficult to detect because they often blend with the background structure of the fabric. The sample set has a total of 1000 images. The dataset in this study includes training, validation, and testing sets. Each image and defect label type is divided into 70%, 15%, and 15%, serving the training and testing processes as shown in Table 2.

Table 2. Database set

No.	Sample Type	Total Quantity	Training Set	Validation Set	Testing Set
1	N	2000	1400	300	300
2	E1	800	560	120	120
3	E2	1000	700	150	150

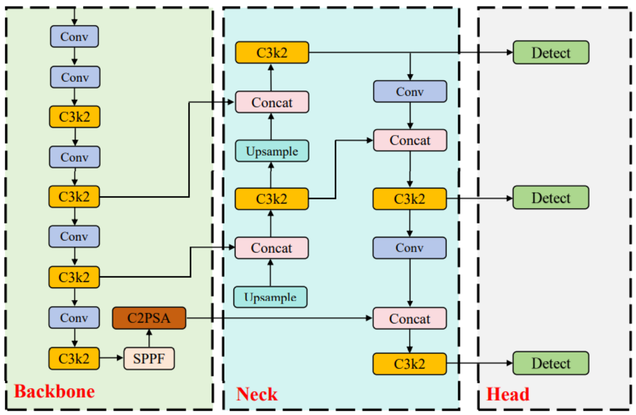

Fig. 5 General architecture of the YOLOv11 network

3.3. Model Training

The model used in this study is a fine-tuned pretrained YOLOv11 model trained with data to detect and classify fabric defects. YOLO is an advanced object detection algorithm known for its efficiency and simplicity. Through successive updates, newer versions of YOLO have achieved significant improvements in accuracy while maintaining fast processing speeds. Notably, the YOLOv11 model strikes a balance between speed and accuracy. This makes YOLOv11 highly efficient in object detection, providing the necessary accuracy and performance for modern applications. The YOLO framework [20], as depicted in Figure 5, comprises various components, including image preprocessing, model training on object detection training datasets, and result verification using test datasets. YOLOv11 employs an enhanced feature extraction strategy that integrates several key modules to improve both speed and accuracy. The C3k2 block reduces image resolution while increasing channel depth, cutting computation cost but preserving important information. The C2SPA module then applies spatial attention, enabling the network to focus on the most relevant regions for defect detection. Finally, the SPPF module (Spatial Pyramid Pooling – Fast) expands the receptive field.

Through multi-scale pooling, the model captures both fine details and broader context. Together, these components generate rich feature maps that provide a solid foundation for accurate and reliable fabric defect detection under diverse conditions.

Training was performed on an NVIDIA RTX 3050 GPU; the parameters were optimized as shown in Table 3.

Table 3. Training parameters

Training Parameter	Value
Batch size	1
Learning rate	0.01
Data augmentations	1
Input image size	640 x 640

4. The Simulation Results

4.1. Testing on the Test Dataset

As shown in Table 4, the model reached Recall and Precision values of 0.975, which indicates that most defects were detected correctly and false positives were very low. The F1-score was also 0.975, while the mAP@0.5 reached 0.935, demonstrating stable detection performance for both stain and yarn defects. The trained network is compact, only 22.5 MB, and processes each image in 21.1 ms. These characteristics make it practical for real-time use, even on devices with limited hardware resources.

Table 4. Mean performance metrics on the test set

Recall	Precision	mAP @0.5	F1-score	Model Size (MB)	Speed detection
0.975	0.975	0.935	0.975	22.5	21.1ms/ image

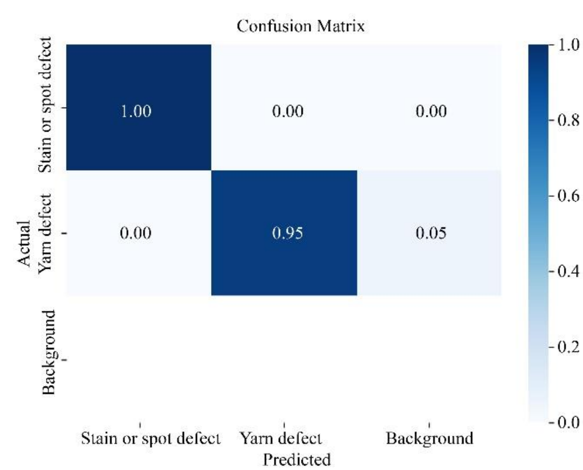

Fig. 6 Normalized result matrix

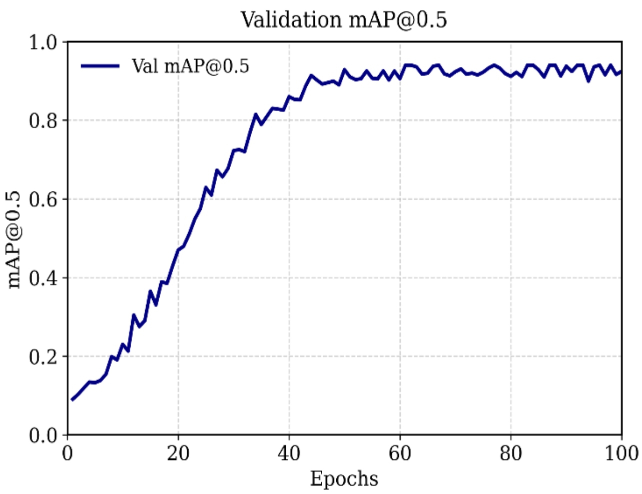

Fig. 7 mAP50 chart illustrating YOLOv11 model performance

The results on the test set, as shown in Figure 6, demonstrate that the model achieves very high accuracy in classifying defects. Specifically, the stain or speck defect class achieves 100% accuracy, with no classification errors. In contrast, the fiber defect class achieves 95% accuracy, with 5% of the errors being misclassified as background defects. The overall accuracy exceeded 97%, indicating the model performs very well in defect classification.

The mAP50 graph, shown in Figure 7, illustrates the performance of the YOLOv11 model during training. Initially, the accuracy increases rapidly from the early epochs but fluctuates significantly in the middle stages. From epoch 100 onwards, the mAP curve stabilizes and reaches a value of around 0.92 - 0.95, indicating the convergence and good error detection ability of the model. This result confirms the high accuracy of the model when trained on the current dataset.

4.2. Experimental Results on the Experimental Model

Based on the proposed fabric defect detection system as shown in Figure 1, an experimental model was constructed and tailored to meet real-world requirements, as illustrated in Figure 8. The test results of the fabric defect detection system using the YOLOv11 model, as shown in Figure 9, demonstrate over 95% accuracy for stain defects and up to 90% for yarn defects at a fabric speed of 3 m/min. This highlights the model's precise and reliable defect identification capabilities. With a processing speed of 3 meters per minute, the system not only meets real-time requirements but also fits industrial environments where speed and efficiency are crucial factors.

Fig. 8 Image of the experimental model

The system enhances defect detection accuracy and decreases reliance on manual inspection, leading to fewer human errors, higher production efficiency, and lower operating costs. Automation in the quality inspection process saves time and ensures that all defects, no matter how small, are detected and addressed promptly. The defect samples illustrate the model's ability to localize and classify flaws on fabric surfaces with high confidence scores. The experiments were carried out in an environment with stable lighting, ensuring consistent conditions for data acquisition. Under these settings, the detection results demonstrate reliable performance, unaffected by illumination variability, highlighting the system's potential as a dependable tool for quality inspection in controlled production environments. A monitoring interface, as shown in Figure 10, was developed to visualize real-time fabric defect detection results and issue alerts when defects are identified. These alerts allow operators to intervene immediately, preventing defective fabric from advancing along the production line and supporting more reliable quality control.

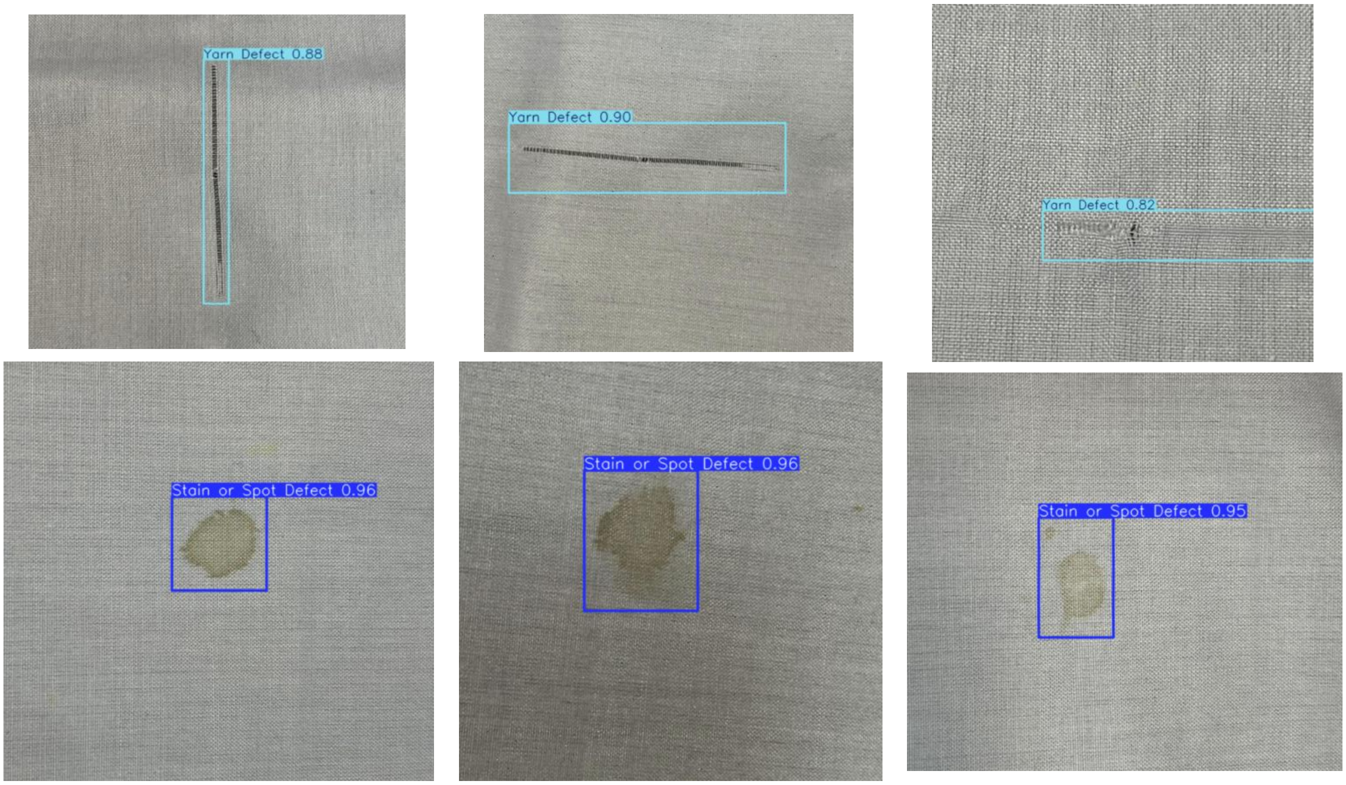

Fig. 9 Some identified defect recognition results on the experimental mode

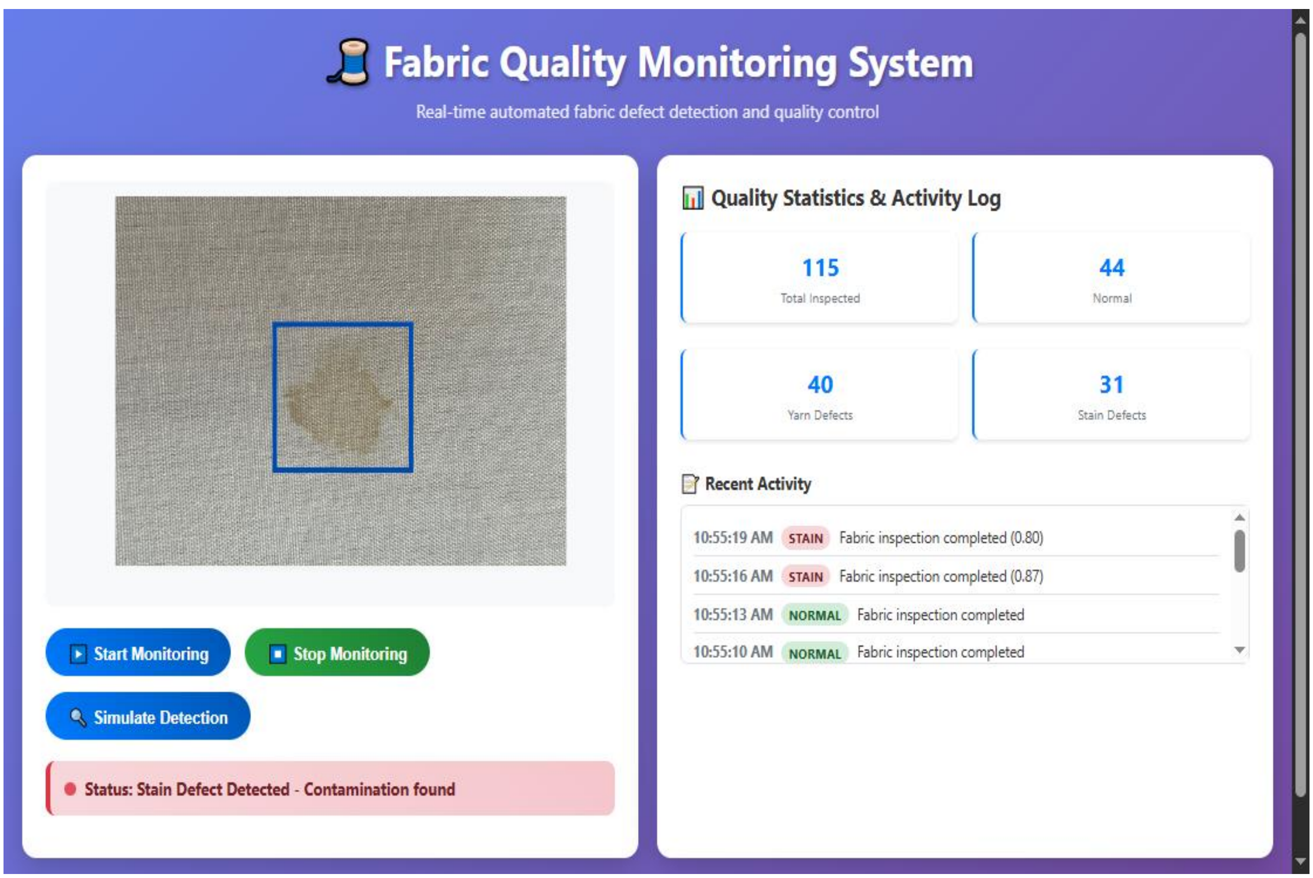

Fig. 10 Monitoring dashboard for fabric defect inspection

5. Conclusion

This study presents a fabric defect detection system that combines image processing with the YOLOv11 model. In real tests at a fabric speed of 3 m/min, the system achieved over 95% accuracy for stain defects and up to 90% accuracy for yarn defects, confirming its suitability for real-time inspection. It reduces manual inspection, lowers error rates, and improves efficiency in textile production. The approach can also be applied in other fields such as food processing, electronics, and consumer goods, supporting the adoption of Industry 4.0 technologies in Vietnam and worldwide.

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