

An Electronic System for Woven Fabric Quality Control Based on Image Processing

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ABSTRACT

This paper proposes the development of an electronic device that integrates image processing algorithms for quality control of woven fabrics by detecting three defects: holes, bumps, and stains. Although classic and deep learning-based image processing methodologies for detecting fabric defects exist in the literature, these proposals lack hardware integration with the software. The proposed device overcomes this limitation by integrating digital image processing algorithms implemented in Python on a single-board computer, along with control devices for the camera, lighting, and motor, to enable real-time fabric quality control. This adaptable architecture meets the needs of the textile industry and reduces the risks associated with manual inspection. The device was validated with 100 fabric samples evaluated by a textile engineering specialist, yielding a Cohen's Kappa index of 0.959 for light-colored fabrics and 0.869 for dark-colored fabrics, as well as an average inspection speed of 15.68 m/min.

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1. INTRODUCTION

Fabric quality is a crucial aspect of textile production, as it directly impacts customer acceptance of the product and the costs associated with returns and rework. This paper analyzes the early detection of defects during the inspection process, aiming to reduce these losses and maintain compliance with quality and environmental management standards, such as ISO 9001 [1] and ISO 14001 [2]. In many factories, quality control is still performed visually, with operators inspecting rolls of fabric, stopping the machine, and marking defective areas. However, manual quality control relies entirely on operators, and its results can be affected by fatigue, inter-operator subjectivity, and lengthy visual inspection times. It also becomes more complicated if the fabric defects are small. For this reason, automated inspection through image processing of the fabric is being sought to minimize dependence on visual inspection.

In the state of the art, textile defect detection has been addressed using conventional image processing techniques and deep learning models. For example, Lu et al. [3] developed a method for inspecting lace fabrics using videos on the production line. Their procedure involved video preprocessing, pixel reconstruction and fabric defect classification. This method was designed to detect the complex texture patterns of lace. However, this work specifically evaluated this type of fabric and did not describe the integration of the detection method into a complete control system for the inspection process.

Chakraborty et al. [4] investigated defect detection in printed tissues using convolutional neural networks (CNNs) and evaluated various network configurations by varying the number of layers, activation functions, and learning rates. They obtained validation accuracy between 48.5% and 73%, indicating that performance depended considerably on the selected configuration. However, their research was limited to the computational model without considering the hardware required for image acquisition, tissue transport and process control.

Nasim et al. [5] applied deep learning to detect defects in fabrics under real production conditions by training the nano version of YOLOv8 with a dataset collected at Chenab Textiles. They obtained a precision of 0.818 and a recall of 0.838; however, this study only evaluated the model in an industrial environment and did not integrate the detection stage with the mechanisms used to transport, stop, or unwind the fabric.

Oh et al. [6] presented a segmentation method for the visual inspection of fabrics with checkered and striped patterns. Their method, compared to conventional techniques, improved the identification and delimitation of irregular regions in these fabric designs. However, the work focused on the segmentation procedure and did not propose its implementation as part of an automated inspection system on a production line.

Wang et al. [7] proposed a sequential method for defect detection in printed fabrics by combining adaptive image segmentation with defect localization using LBP-GLCM feature matching. They obtained an accuracy greater than 98%, however, the proposed method requires manual adjustment of segmentation thresholds and does not include an automated image acquisition mechanism.

Kim and Kim [8] presented a textile image processing algorithm based on histogram equalization and pixel filtering. This algorithm achieved an accuracy of over 85% on a dataset of 22 images. However, its operation depends on fixed thresholds and may reduce its ability to handle variations in fabric color and lighting. Furthermore, the coordination of image analysis with a fabric transport or unwinding mechanism was not considered.

Navarro et al. [9] presented a combination of wavelet transform, multiresolution analysis, and image segmentation to characterize fabric texture and locate defective regions. They also observed that Fourier analysis has limitations in detecting localized irregularities and used a defect-free image as a reference for the inspection process. However, their validation was performed only in a computational environment without an integrated image acquisition or electromechanical control system.

Ma et al. [10] proposed a lightweight and accurate algorithm for automatic tissue defect detection using an optimized YOLOv8 architecture that combines structural efficiency (GhostConv), intelligent attention (SimAM), and a lightweight, shared detection head (LSCDH). However, the proposed algorithm was not implemented on actual industrial hardware.

Zhou et al. [11] developed an improved version of YOLOv8n that incorporates dynamic convolutions and efficient attention mechanisms called DCFE-YOLO. This model was designed to improve hole and stain detection while limiting the increase in computational cost. They achieved a precision of 87.3% and a recall of 83.7%; however, the computational requirements may still limit its implementation on resource-constrained platforms, and the study did not report a dedicated hardware implementation or its integration with the image acquisition and tissue control stages of an inspection system.

Biradar et al. [12] evaluated a three-layer deep convolutional neural network combined with a support vector machine and reported accuracies between 98.7% and 99.0% for hole detection and up to 98.3% for stain detection in unpatterned fabrics. However, for patterned fabrics, the reported accuracy decreased to approximately 87.3%. The method performed well, but its training process relies on labeled samples and computational resources that can be difficult to provide on low-cost embedded platforms.

Xu et al. [13] proposed a fabric defect segmentation model based on an enhanced Swin-Unet architecture, combining Gabor filter preprocessing, Transformer-based feature extraction, and multi-stage result fusion. They obtained intersection-on-join values of 0.5493 for the AITEX cropped dataset and 0.6323 for the Colored Fabric dataset. They also noted that Transformer-based models can struggle to represent repetitive textile textures. Furthermore, they did not consider implementing the model on a device for fabric defect detection.

Yang et al. [14] introduced ACCTNet, which combines adjacent context coordination with Transformer modules to extract local features while preserving global contextual information. This model has 26.72 million parameters and achieved E-measure scores of 0.7849 for plain fabrics and 0.9719 for patterned fabrics at 27 frames per second on a single GPU. While these results indicate that the model can process images at a practical speed on GPU-based hardware, its training requires a considerable number of labeled defective samples, which are difficult to obtain in the textile industry compared to defect-free samples.

Machado et al. [15] implemented YOLOv11 on an NVIDIA Jetson Orin Nano for the detection of holes in fabrics. The authors reported a precision of 89% and a recall of 76%. Their prototype was designed to be incorporated into existing textile production lines without requiring changes to the industrial machinery. Nevertheless, the experimental validation was limited to monochromatic fabrics, and the study did not evaluate stains, surface bumps, or fabrics with a broader range of colors.

Previous studies have therefore examined fabric defect detection using conventional image processing, convolutional neural networks, lightweight YOLO architectures, and Transformer-based segmentation models. These methods have achieved relevant results in classification, localization, and segmentation. Nevertheless, many depend on supervised training, annotated datasets, and GPU or high-

performance processing hardware. In addition, most studies evaluate the detection algorithm separately from the remaining elements required for continuous inspection, such as illumination control, image acquisition, fabric transport, user interaction, and embedded processing.

The present work addresses this integration problem through an electronic system for woven fabric quality control. The prototype combines a mechanical unwinding mechanism, an enclosed image acquisition area with adjustable illumination, a camera, and a Raspberry Pi for local processing. Instead of using a trained classification or segmentation model, the proposed method processes images in the CIE Lab color space under controlled acquisition conditions. This configuration was designed to detect holes, bumps, and stains for light and dark fabrics. Likewise, to maintain low computational requirements. The detection results are presented through a touch interface for the operator and shows the number of defects and their location on the inspected fabric.

2. PROPOSED SYSTEM

Table 1 shows the main hardware and software elements used in the proposed system.

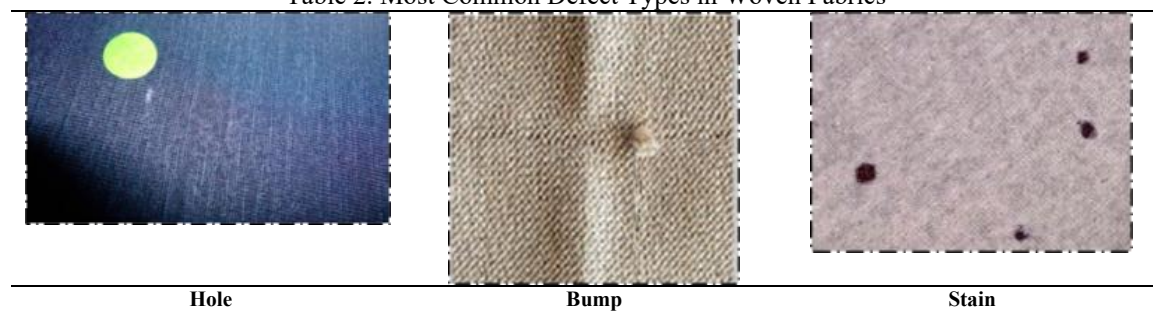
Table 1. Hardware and Software for Fabric Quality Control

Component / Category	Specification / Model	Purpose / Rationale
Single board Computer (SBC)	Raspberry Pi 4B 8GB	Runs image processing and system control.
Programming Language	Python	Implements processing and control routines.
Power Supply	12V 5A	Powers the system components.
Fabric Unwinding System	Motor 12V 300 RPM / Encoder 64 PPR	Moves the fabric and measures rotation.
Camera	Logitech Brio Ultra HD Pro	Captures images of the fabric surface.
User Interface	Touchscreen 7" TFT Raspberry	Displays results and system controls.
Illumination System	LED Ultra White, 10mm, 12V 20mA	Provides controlled lighting for image capture.
Enclosure Material	Metallic structure	Supports and protects the system components.
Enclosure Dimensions (H x W x D)	170cm x 50cm x 50cm	Accommodates the fabric and inspection mechanism.

2.1. Defects Present in the Fabric

The system was designed to detect three defects commonly found in woven fabrics: holes, stains, and bumps [16]. Holes and bumps may appear with different sizes and shapes, whereas the stains considered in this study generally show a bluish tone. Table 2 presents the defects included in the inspection process.

Table 2. Most Common Defect Types in Woven Fabrics



2.2. Acquisition Enclosure

The acquisition enclosure was designed to be lightweight and portable so that it could be moved without requiring additional equipment. Likewise, its structure was built with rectangular metal profiles measuring $1\frac{1}{2}$ " x $\frac{3}{4}$ ", $\frac{3}{4}$ " x $\frac{3}{4}$ ", and $\frac{1}{2}$ " hollow circular tubes.

Figure 1 shows the finished structure and it can be seen that the frame was covered with corduroy fabric to reduce the influence of external light and maintain more stable conditions during the image acquisition of the fabrics.



Figure 1. Side and Front View of the developed electronic system

2.2.1. Fabric Displacement System

The fabric displacement system moves the roll through the inspection area at a controlled speed using a 12 V DC motor connected to a gearbox with a 1:33 reduction ratio. This configuration reduces the motor speed and provides the torque necessary to move the fabric roll. Likewise, an encoder was installed to measure the rotation of the mechanism as seen in Figure 2.

Figure 3 shows the adjustable support used to install and remove the fabric rolls. On the other hand, during testing, the inspection was carried out in 0.4 m sections until reaching a total length of 5 m. This procedure can be applied to longer rolls by repeating the inspection sequence. Figures 4 and 5 show the front and rear views of the complete displacement mechanism.

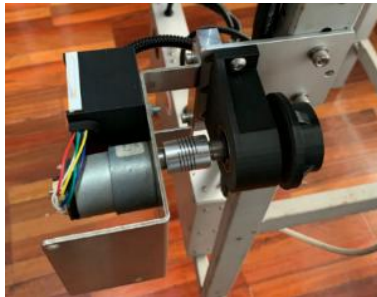


Figure 2. DC Motor and Encoder



Figure 3. Holding Lever

2.2.2. Illumination System

The illumination system combines backlighting and side lighting in such a way that the backlight is placed behind the fabric and is mainly used to reveal holes and discontinuities through transmitted light. On the other hand, the side lights illuminate the surface of the fabric and make bumps and other relief variations more visible.



Figure 4. Fabric roll displacement system, front view



Figure 5. Fabric roll displacement system, rear view

The backlight is installed at the base of the fabric support and contains eighty-four high-intensity LEDs distributed throughout the inspection area and its arrangement can be seen in Figure 6. On the other hand, for side lighting, seven high-intensity LEDs were placed on each side of the housing as seen in Figure 7.



Figure 6. LEDs distribution for Back Light Illumination

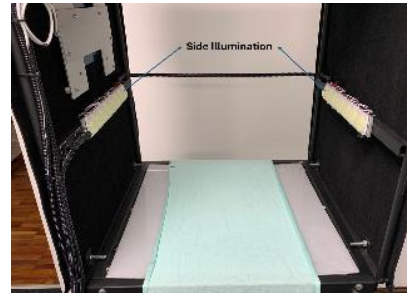


Figure 7. LEDs distribution for Side Illumination

2.3. Visual Interface

The interface of the proposed system is shown on a 7-inch Raspberry Pi touch screen located at the upper front part of the housing. Likewise, through this interface, the operator can access inspection controls and view detection results. Figure 8 shows the interface's home screen.

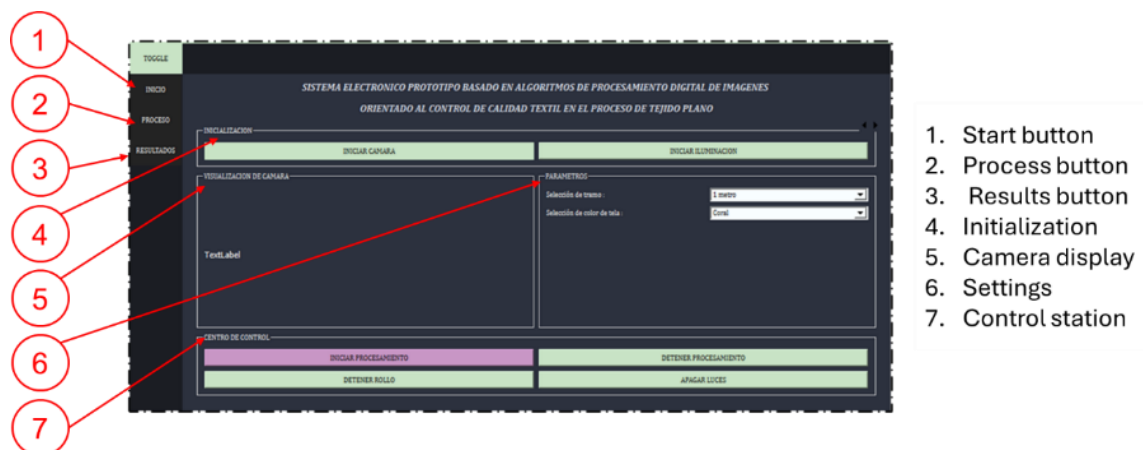


Figure 8. Visual Interface

2.4. Image Processing and Defect Detection

The proposed inspection procedure processes fabric images to identify hole, bump, and stain-type defects. This procedure has four stages as seen in Figure 9, which are: (i) image acquisition, (ii) parameter configuration, (iii) defect detection, and (iv) counting of detected defects.

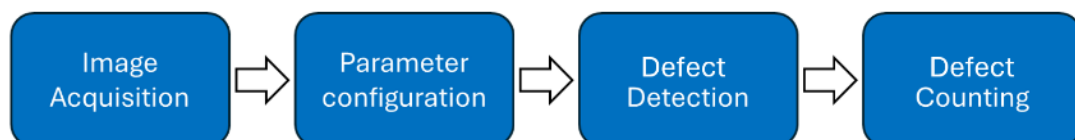


Figure 9. Block diagram of the defect detection algorithm

2.4.1. Image Acquisition

The images were captured with a Logitech Brio Pro webcam at a resolution of 1080p and 60 frames per second. Likewise, the camera's automatic settings were disabled to prevent exposure, focus, and white balance from changing between captures. This helped to maintain similar acquisition conditions throughout the inspection.

The images were recorded in RGB format. Each frame covered a fabric area measuring 400 mm in length and 300 mm in width. The camera was mounted 600 mm above the fabric surface, as illustrated in Figure 10. This position was selected according to the camera field of view and the dimensions of the inspection area. Figure 11 presents the resulting field of view and spatial resolution.

2.4.2. Parameter Configuration

The parameter configuration is performed through the following steps:

Step 1: The operator places the fabric roll onto the displacement system, leaving the fabric extended over the base of the enclosure, as shown in Figure 12.

Step 2: The meters of fabric to be processed and the fabric color must be selected. This is important because the length of the fabric to be processed determines the number of iterations the motor must perform, considering that the motor advances 40 cm of fabric in each segment. This is because each image acquisition captures fabric dimensions of 40 cm in length and 30 cm in width. On the other hand, the selection of the fabric color determines the illumination system configuration (Back Light and side illumination). Both light and dark fabrics can be processed.

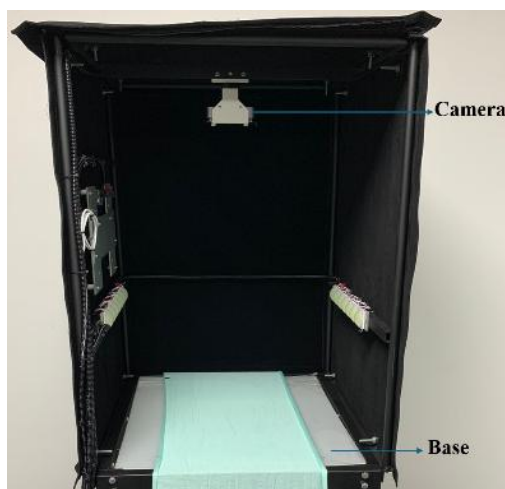


Figure 10. Camera Positioning in the Enclosure

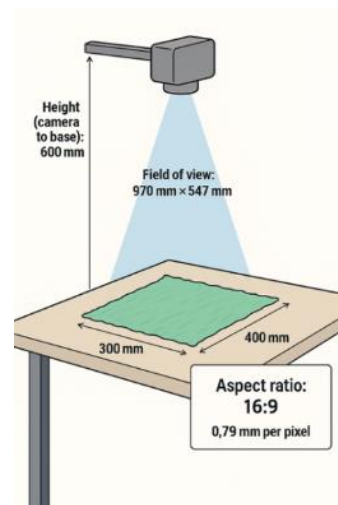


Figure 11. Camera's Field of View

2.4.3. Defect Detection

The fabric defect detection process depends on the type of defect to be detected. For all defect types, components of the $L^*a^*b^*$ color space [17] are used. This is because the fabric, in this color model, offers a clearer separation between lightness and color than the RGB color space, which is the default format of the chosen camera, therefore, Equation (1) was first used, in which $I_R(x, y)$, $I_G(x, y)$, $I_B(x, y)$ represent the intensities of the red, green, and blue channels of the RGB format. Likewise, $I_X(x, y)$, $I_Y(x, y)$, $I_Z(x, y)$ are the resulting components in the CIE-XYZ color space [18].



Figure 12. Placement of the fabric on the enclosure base

$$\begin{bmatrix} I_X(x, y) \\ I_Y(x, y) \\ I_Z(x, y) \end{bmatrix} = \begin{bmatrix} 0.4125 & 0.3576 & 0.1804 \\ 0.2127 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9502 \end{bmatrix} \times \begin{bmatrix} I_R(x, y) \\ I_G(x, y) \\ I_B(x, y) \end{bmatrix} \quad (1)$$

Equations (2), (3), and (4) were then used to convert from the CIE-XYZ color space to the L*a*b* color space, where X_n , Y_n y Z_n (Equation 5) are the coordinates of the D65 white point used as a reference. The $L(x, y)$, $a(x, y)$ and $b(x, y)$ components correspond respectively to the lightness, the green-red component, and the blue-yellow component of the L*a*b* color space.

$$L(x, y) = \begin{cases} 116 \times \sqrt[3]{\frac{I_Y(x, y)}{Y_n}} - 16, & \frac{I_Y(x, y)}{Y_n} > 0.008856 \\ 903.3 \times \frac{I_Y(x, y)}{Y_n}, & \frac{I_Y(x, y)}{Y_n} \leq 0.008856 \end{cases} \quad (2)$$

$$f(t) = \begin{cases} \sqrt[3]{t}, & t > 0.008856 \\ 7.787 \times t + \frac{16}{116}, & t \leq 0.008856 \end{cases}$$

$$a(x, y) = 500 \times \left[f\left(\frac{I_X(x, y)}{X_n}\right) - f\left(\frac{I_Y(x, y)}{Y_n}\right) \right] \quad (3)$$

$$b(x, y) = 200 \times \left[f\left(\frac{I_Y(x, y)}{Y_n}\right) - f\left(\frac{I_Z(x, y)}{Z_n}\right) \right] \quad (4)$$

$$X_n = 95.047, Y_n = 100, Z_n = 108.883 \quad (5)$$

2.4.3.1 Hole Defect Detection

Figure 13 shows the steps required for hole defect detection for both dark-colored and light-colored fabric. It is noted that for dark fabric, both illumination techniques are applied to obtain a sharp contrast for the holes in the fabric. In both cases, the Lightness (L^*) component of the L*a*b* color space is used.

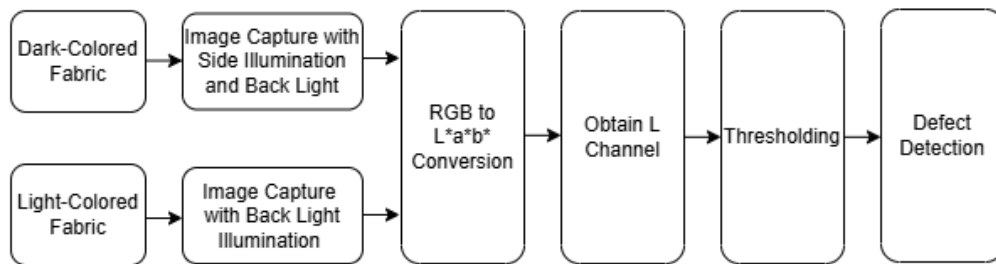


Figure 13. Hole Defect Detection Procedure

Figure 14 shows an example of the acquired image in RGB format and its $L(x, y)$ lightness component from the L*a*b* color space. In this component, the holes in the fabric appear white relative to the rest of the fabric, as the back light illumination passes through them.

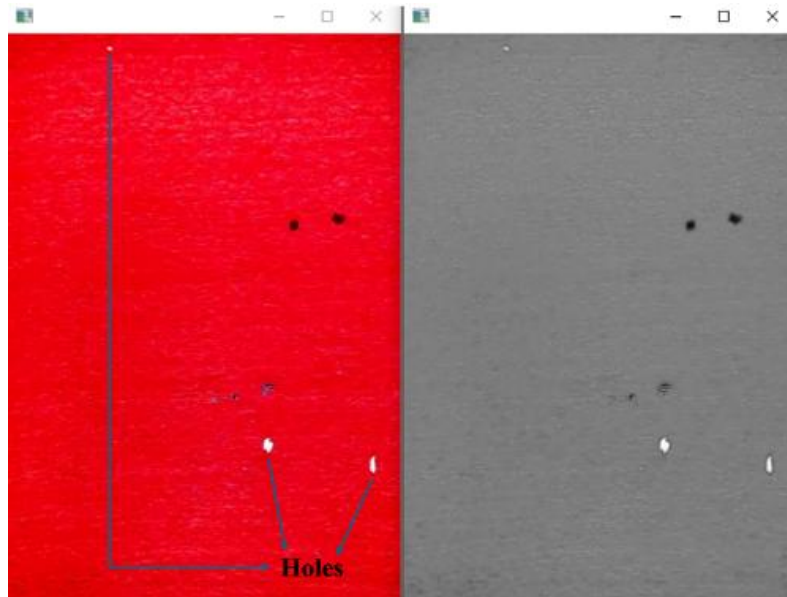


Figure 14. On the left is the original image in the RGB model and on the right is $L(x,y)$, the L component of the $L^*a^*b^*$ color space.

Afterward, threshold segmentation was used for hole detection. To determine the thresholds, histograms were analyzed for each fabric shade.

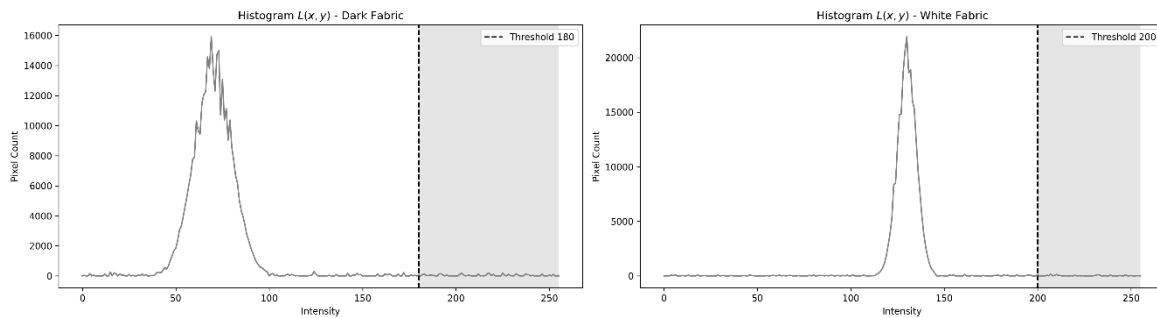


Figure 15. Histograms of the $L(x,y)$ component: Dark Fabric (left) and Light Fabric (right).

Finally, based on the histograms in Figure 15, a threshold T was defined according to the fabric shade. The binarized image containing the hole defects, $Z_1(x,y)$, is obtained using Equation (6). For dark-colored fabric, the threshold is $T = 180$, and for light-colored fabric, the threshold is $T = 200$.

$$Z_1(x,y) = \begin{cases} 255, & \text{if } L(x,y) \geq T \\ 0, & \text{if } L(x,y) < T \end{cases} \quad (6)$$

In Figure 16, the original image is shown on the left, and the binarized image after the threshold segmentation process is shown on the right. In the latter, the white pixels represent the holes present in the fabric.

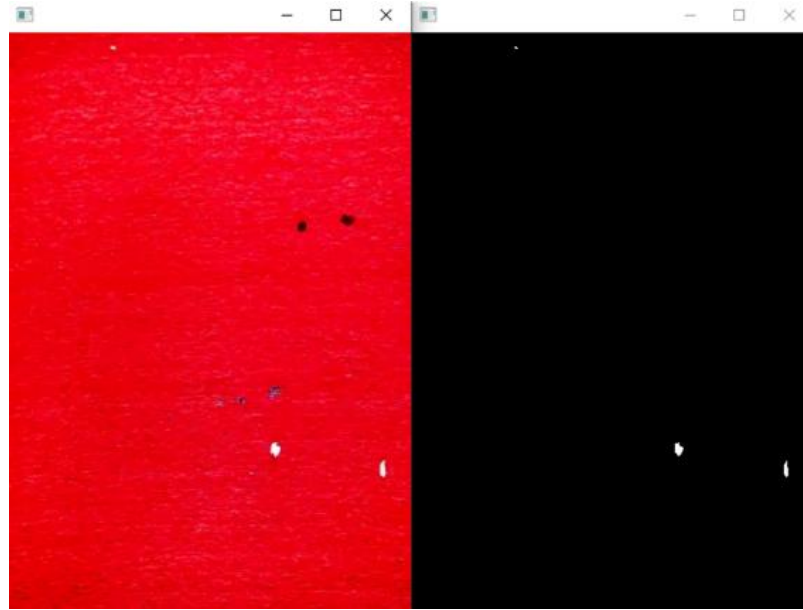


Figure 16. Left: Original Image. Right: Binarized Image for Hole-type Defect

2.4.3.2 Bump Defect Detection

Figure 17 shows the steps required for bump defect detection, for processing both dark-colored fabric and light-colored fabric. For the detection of the bump-type defect, a non-linear median filter with a 5x5 mask size [19] was used to reduce the noise generated by the back light illumination, as the bump-type defect could be confused with the hole-type defect.

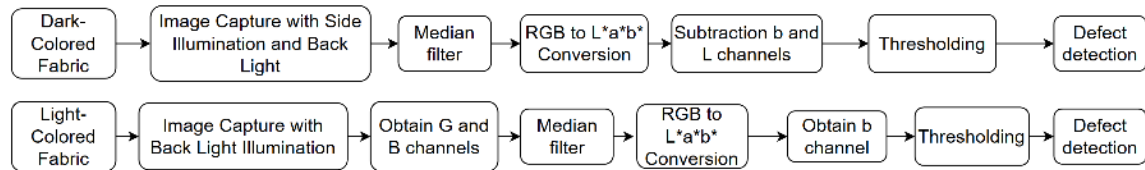


Figure 17. Bump Defect Detection Procedure

For dark-colored fabric, let $I_{bk1}(x, y)$ be the image captured under side illumination and back light, which is filtered with a 5x5 median filter [20], yielding $I_{med1}(x, y)$ as shown in Equation (7).

$$I_{med1}(x, y) = median_{5 \times 5}\{I_{bk1}(x, y)\} \quad (7)$$

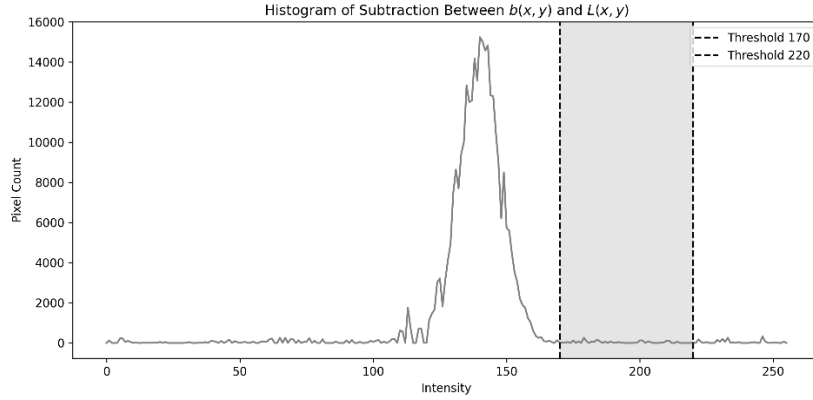
Furthermore, the resulting image $I_{med1}(x, y)$ is converted to the $L^*a^*b^*$ color model, whose resulting components are $I_{L1}(x, y)$, $I_{a1}(x, y)$ and $I_{b1}(x, y)$. Using these components, Equation (8) is applied, yielding $I_1(x, y)$.

$$I_1(x, y) = I_{b1}(x, y) - I_{L1}(x, y) \quad (8)$$

In the case of dark-colored fabrics, the histogram of $I_1(x, y)$ was obtained, and the threshold was calculated, as shown in Figure 18.

A threshold range between 170 and 220 was chosen for obtaining the binary image $Z_2(x, y)$ containing the bump-type defects in dark-colored fabrics, as shown in Equation (9).

$$Z_2(x, y) = \begin{cases} 255, & 170 \leq I_1(x, y) \leq 220 \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

Figure 18. Histogram of $I_1(x, y)$

In Figure 19, an image of dark-colored fabric is shown on the left, and on the right is the binarized image $Z_2(x, y)$ showing the detection of bumps.



Figure 19. Left: Original Image. Right: Binarized image for bumps in dark fabric.

For light-colored fabric, let $I_{bk2}(x, y)$ be the image obtained under side and back light illumination. From this RGB format image, $IG_{bk2}(x, y)$ and $IB_{bk2}(x, y)$ are obtained, which are the G and B components, respectively. The image $I_{bk2}(x, y)$ is filtered with a 5x5 median filter, yielding $I_{med2}(x, y)$ as shown in Equation (10).

$$I_{med2}(x, y) = \text{median}_{5 \times 5}\{I_{bk2}(x, y)\} \quad (10)$$

Furthermore, the resulting image $I_{med2}(x, y)$ is converted to the L*a*b* color model, obtaining $I_{L2}(x, y)$, $I_{a2}(x, y)$ and $I_{b2}(x, y)$, which correspond to the L, a, and b components, respectively. Finally, to segment and detect bump-type defects present in light-colored fabric via thresholding, Equation (11) is applied.

$$Z_3(x, y) = \begin{cases} 255, & IB_{bk2}(x, y) < 150 \cup IG_{bk2}(x, y) < 150 \cup 90 \leq I_{b2}(x, y) \leq 125 \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

Figure 20 shows the histograms of $IG_{bk2}(x, y)$, $IB_{bk2}(x, y)$ and $I_{b2}(x, y)$, where the respective threshold ranges for detecting bump-type defects in light-colored fabrics can be observed.

Finally, in Figure 21, the acquired image of a light-colored fabric is shown on the left, and the resulting binarized image $Z_3(x, y)$ with the detection of bumps present in the fabric is shown on the right.

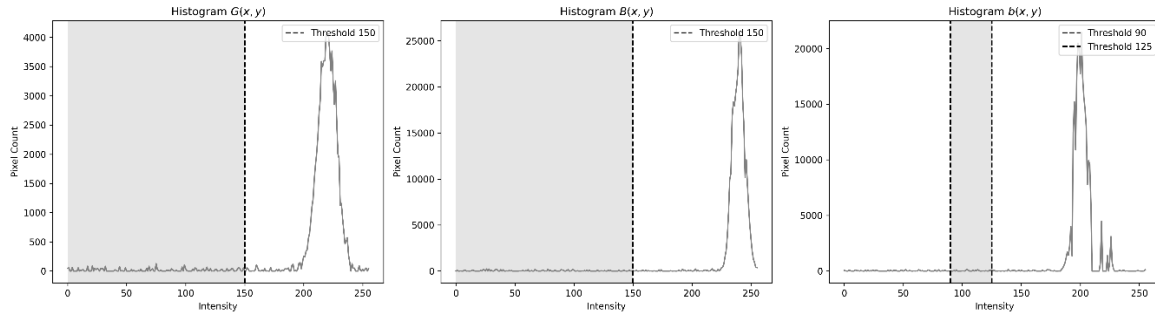


Figure 20. Histogram of components $IG_{bk2}(x, y)$, $IB_{bk2}(x, y)$ and $I_{b2}(x, y)$



Figure 21. Left: Original Image. Right: Binarized image for bumps in light fabric

2.4.3.3 Stain Defect Detection

In Figure 22 shows the steps required for stain-type defect detection for both dark and light-colored fabric cases.

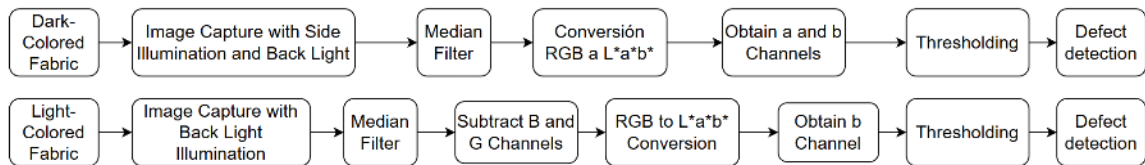


Figure 22. Stain Defect Detection Procedure

For dark-colored fabric, let $I_{bk3}(x, y)$ be the image captured under side and back light illumination, which is filtered with a 5×5 median filter, yielding $I_{med3}(x, y)$ as shown in Equation (12).

$$I_{med3}(x, y) = \text{median}_{5 \times 5} \{I_{bk3}(x, y)\} \quad (12)$$

Furthermore, the resulting image $I_{med3}(x, y)$ is converted to the $L^*a^*b^*$ color model, obtaining $I_{L3}(x, y)$, $I_{a3}(x, y)$ and $I_{b3}(x, y)$, which are the L, a, and b components, respectively. Finally, to segment and detect stain-type defects present in a dark-colored fabric via thresholding, Equation (13) is applied.

$$Z_4(x, y) = \begin{cases} 255, & 105 \leq I_{b3}(x, y) < 125 \cup I_{a3}(x, y) \geq 160 \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

Figure 23 shows the histograms of $I_{a3}(x, y)$ and $I_{b3}(x, y)$, where it can be observed how the respective threshold ranges were chosen to detect stain-type defects in dark-colored fabrics.

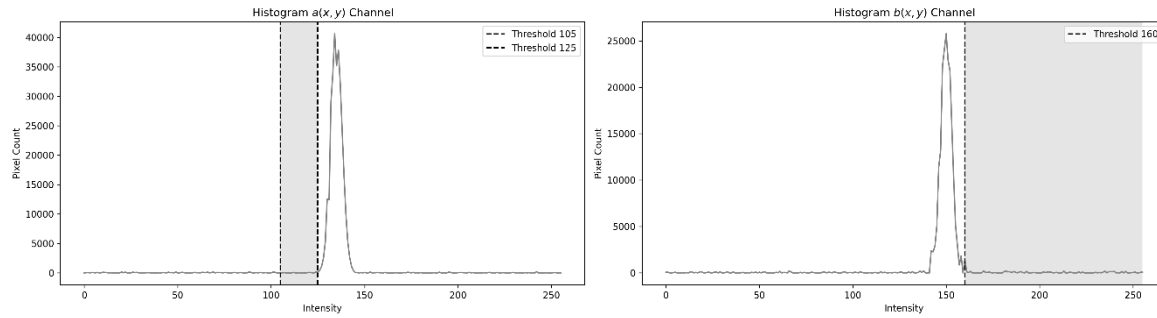


Figure 23. Histogram of $I_{a3}(x, y)$ and $I_{b3}(x, y)$

In Figure 24, the acquired image of a dark-colored fabric is shown on the left, and the obtained binarized image $Z_4(x, y)$ with the detection of stains present in the fabric is shown on the right.



Figure 24. Left: Original Image. Right: Binarized image for stains in dark fabric

For light-colored fabric, let $I_{bk4}(x, y)$ be the image obtained under side and back light illumination, which is filtered with a 5x5 median filter, yielding $I_{med4}(x, y)$ shown in Equation (14).

$$I_{med4}(x, y) = median_{5 \times 5}\{I_{bk4}(x, y)\} \quad (14)$$

Furthermore, from the obtained image $I_{med4}(x, y)$, $IB_4(x, y)$ and $IG_4(x, y)$ are obtained, which are the G and B color components, respectively. Using the obtained components, Equation (15) is applied, yielding $I_{GB}(x, y)$.

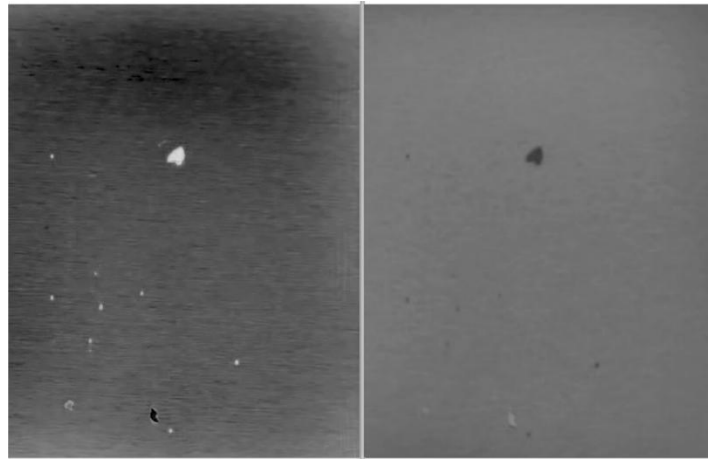
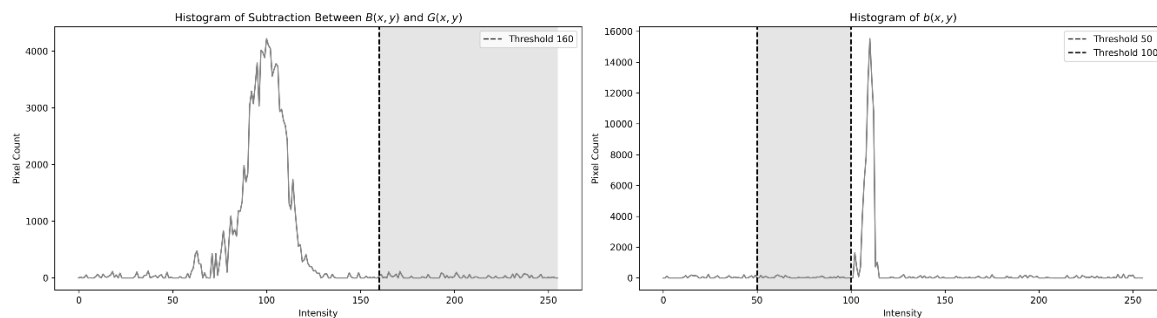
$$I_{GB}(x, y) = IB_4(x, y) - IG_4(x, y) \quad (15)$$

The obtained image $I_{GB}(x, y)$ is converted to the $L^*a^*b^*$ color model, obtaining $I_{b4}(x, y)$, which is the b component. Finally, to segment and detect stain-type defects present in a light-colored fabric via thresholding, Equation (16) is applied.

$$Z_5(x, y) = \begin{cases} 255, & I_{GB}(x, y) \geq 160 \cup 50 \leq I_{b4}(x, y) \leq 100 \\ 0, & otherwise \end{cases} \quad (16)$$

In Figure 25, $I_{GB}(x, y)$ is shown on the left side, and $I_{b4}(x, y)$ is shown on the right side.

In Figure 26, the histograms of $I_{GB}(x, y)$ and $I_{b4}(x, y)$ are shown, where it can be observed that the shaded region represents the respective threshold ranges for detecting stain-type defects in light-colored fabrics.

Figure 25. Left: $I_{GB}(x, y)$. Right: $I_{b4}(x, y)$ Figure 26. Left: Histogram of $I_{GB}(x, y)$. Right: Histogram of $I_{b4}(x, y)$

2.4.4. Quantification and Localization of Fabric Defects

The labeling algorithm [20] is applied to each of the binarized images obtained in the defect detection process to extract each white object corresponding to each defect type detection and to perform a count for each of them.

Furthermore, for each detected defect represented by a white object, its centroid [20] was calculated and located within each section of the fabric roll being processed. This pixel centroid was transformed into length using the image's spatial resolution; in this way, the defect's location within the processed fabric roll was obtained. Figure 27 shows the visual interface displaying the count of detected defects and their respective locations.

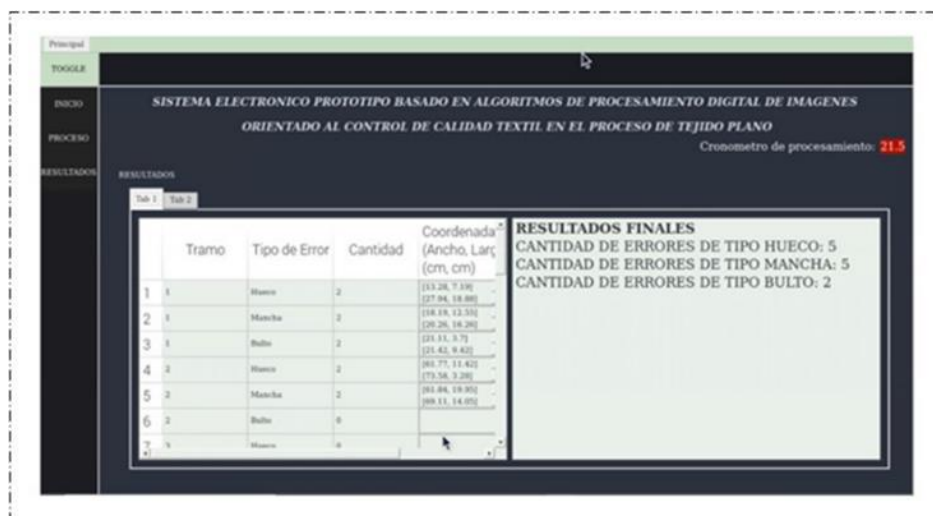


Figure 27. Results of detected defects and their respective localization on the processed fabric roll

3. RESULTS AND DISCUSSION

The performance results of the developed electronic system were validated using metrics based on the confusion matrix [21] and Cohen's Kappa index [22]. It should be noted that, for the determination of Cohen's Kappa index, the agreement between observations made via manual visual inspection by a textile quality control specialist and those provided by the implemented electronic system was taken as a reference. The index value varies between 0 and 1, and its degree is assigned according to Table 3.

Table 3. Degree of Agreement Function based on Kappa Value

Kappa	Degree of agreement
0	Poor
0.0-0.2	Slight
0.2-0.4	Fair
0.4-0.6	Moderate
0.6-0.8	Substantial
0.81-1	Almost Perfect

The evaluation was conducted through experimental tests in two scenarios with fabrics. The experimental validation was performed using rayon fabric with an approximate basis weight of 120 g/m². Therefore, the reported results correspond to this specific material condition. In this regard, the same detection performance cannot be assumed for fabrics with different GSM values, since variations in fabric weight may affect optical properties such as light transmittance and defect contrast under the controlled illumination conditions of the proposed system. In the first scenario, 50 samples of light-colored fabrics (aqua green and coral) were used, and in the second scenario, 50 samples of dark-colored fabrics (dark green and burgundy) were used. Regarding the first scenario, Table 4 shows an example of a sample evaluation.

For light-colored fabrics, the agreement between the proposed system and the textile specialist yielded a Cohen's kappa value of 0.959. According to the interpretation criterion shown in Table 3, this value corresponds to an "almost perfect" level of agreement. Figure 28 presents the confusion matrix for this scenario and Table 5 shows the classification metrics obtained.

The results show similar performance across the three defect categories. The F1 score was 0.969 for holes, 0.968 for bumps, and 0.987 for stains. On the other hand, the corresponding precision values were 0.959, 0.968, and 0.991. Stains obtained the highest scores, while holes and bumps showed similar results. Likewise, the confusion matrix in Figure 28 shows that only a small number of samples were assigned to an incorrect class.

Table 4. Reference Image Table for Cohen's Kappa Calculation

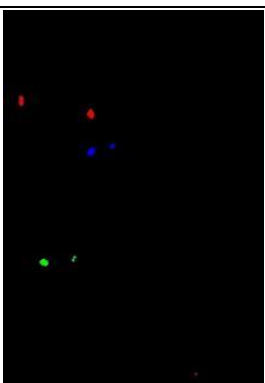
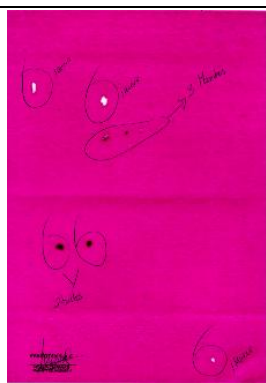
Original image captured in the developed system	Image processed by the electronic system	Image validated by the Specialist Engineer	Total errors per segment
			Defects detected by the System: Hole-type defects: 2 Bump-type defects: 2 Stain-type defects: 2 Defects detected by the Specialist: Hole-type defects: 2 Bump-type defects: 2 Stain-type defects: 3

Table 5. Classification Metrics for Defect Detection in Light-Colored Fabrics, by Defect Type

Defect Type	Accuracy	Precision	Recall	F1-score	Number of Samples
Holes	0.979	0.959	0.979	0.969	48
Bumps	0.968	0.968	0.968	0.968	31
Stains	0.983	0.991	0.983	0.987	115

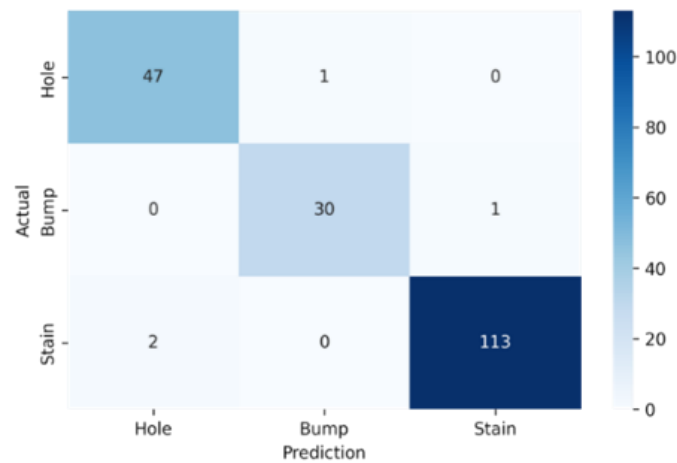


Figure 28. Confusion matrix for light-colored fabric type

For dark-colored fabrics, Cohen's kappa decreased to 0.869, which still corresponds to an "almost perfect" level of agreement under the same interpretation criterion. The confusion matrix is presented in Figure 29, and the corresponding metrics are summarized in Table 6.

In this second scenario, the F1-score values were 0.864 for holes, 0.846 for bumps, and 0.889 for stains. Precision reached 0.864, 0.846, and 0.889 for the same defect categories, respectively. Although the system continued to identify the three defects, its performance was lower than that obtained with light-colored fabrics. This is evidenced in Figure 29, where more samples were assigned to incorrect categories.

Table 6. Classification Metrics for Defect Detection in Dark-Colored Fabrics, by Defect Type

Defect Type	Accuracy	Precision	Recall	F1-score	Number of Samples
Holes	0.896	0.864	0.864	0.864	44
Bumps	0.93	0.846	0.846	0.846	26
Stains	0.913	0.889	0.889	0.889	45

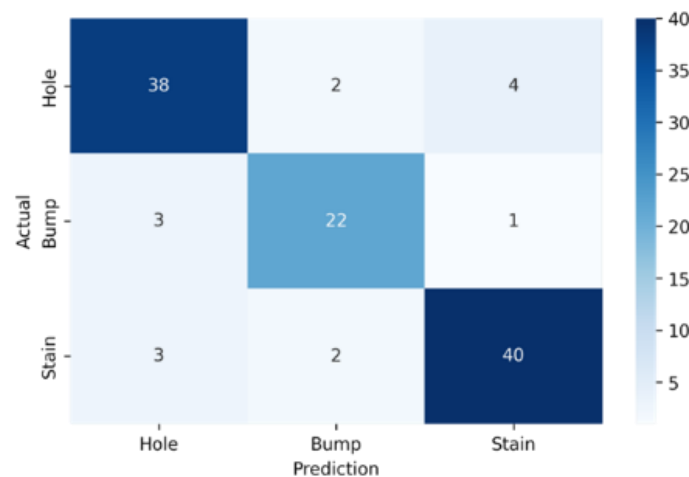


Figure 29. Confusion matrix for dark-colored fabric type

The reduction in performance for dark fabrics is associated with the lower contrast observed between the fabric surface and the defects under the implemented lighting conditions. Dark surfaces reflect less incident light, which makes it difficult to distinguish the boundaries of some defects during segmentation. This effect is relevant, as the proposed method uses color space transformation, histogram analysis, and threshold selection to separate the defective region from the background.

When the contrast decreases, the selected thresholds become more sensitive to small variations in lighting and fabric tone. Holes, bumps, and stains can generate overlapping intensity ranges, and the possibility

of confusion between defect categories could increase. This is the reason why the reduction was observed in all three classes and not just in one type of defect.

The processing sequence of the proposed prototype was intentionally based on operations with low computational requirements so that it can be executed on a Raspberry Pi without the need for a dedicated graphics processing unit or a model training stage. However, the method depends on controlled acquisition conditions such as camera position and lighting.

The validation performed in this study was limited to monochromatic fabrics divided into light and dark color groups; therefore, the presented results should not be directly extrapolated to striped, plaid, or other patterned fabrics. For these cases, additional image processing stages or machine learning-based methods might be necessary.

Table 7 compares the proposed method with approaches described in state-of-the-art literature. Most of the reviewed methods use supervised learning and require annotated images during training. In contrast, the proposed system uses controlled lighting, transformation to the CIE Lab color space, and threshold-based segmentation without training a classification or segmentation model.

Table 7. Comparison of results with the state of the art

Reference	Model	Defect Type	Performance		Training required
Zhou et al. [11]	DCFY-YOLO	Hole / Stain	Precision of 87.3%	Recall of 83.7%	Yes
Machado et al. [15]	YOLOv11	Hole	Precision of 89%	Recall of 76%	Yes
Nasim et al. [5]	YOLOv8-nano	Stain	Precision of 81.8%	Recall of 83.8%	Yes
Biradar et al. [12]	DCNN with SVM	Hole	Precision of 99.0 %		Yes
Biradar et al. [12]	DCNN with SVM	Stain	Precision of 98.3%		Yes
Our Work	Image Processing	Hole / Bump/ Stain	Precision of 92.58%		No

Under the evaluated conditions, the proposed method obtained an average precision of 92.58% for hole and stain detection. This value provides a general reference for comparing the system with previous studies, but it should not be treated as a direct benchmark. The datasets, fabric types, defect definitions, image-acquisition conditions, and evaluation procedures differ among the reviewed works.

Metrics such as the number of trainable parameters, floating-point operations, and model memory were not included because they are intended mainly for trainable neural network architectures. Since the proposed method is based on deterministic image-processing operations, its computational requirements are more appropriately described through its processing speed and its implementation on the Raspberry Pi platform.

On the other hand, a comparison of the average time spent on fabric evaluation by the proposed system versus the specialist's visual inspection was also performed. The results indicated that the electronic system presents an average processing speed of 15.68 meters of fabric per minute, while the specialist's manual evaluation is 2.44 meters of fabric per minute. This difference in results shows that the proposed system allows for faster fabric processing and improves performance in the defect detection stage.

4. CONCLUSION

This study presented an electronic system for the automatic detection of holes, bumps, and stains in woven fabrics. The prototype combines image acquisition, controlled illumination, fabric transport, embedded processing, and a touchscreen interface in a single platform. The detection procedure was implemented in Python and adapted to light- and dark-colored fabrics through image segmentation in the CIE Lab color space.

The combined use of backlighting and side lighting helped reveal different defect characteristics. Backlighting made holes and discontinuities more visible, whereas side lighting improved the visibility of bumps and surface variations. The illumination arrangement also reduced the influence of external light during image acquisition.

The best results were obtained with light-colored fabrics. Cohen's kappa reached 0.959, while the F1-score was 0.969 for holes, 0.968 for bumps, and 0.987 for stains. For dark-colored fabrics, Cohen's kappa was 0.869, and the F1-score ranged from 0.846 to 0.889. The lower values obtained in this group were mainly associated with the reduced contrast between the fabric surface and the defects.

For the detection of holes and stains, the proposed system obtained an average precision of 92.58% in the two fabric groups. Likewise, the studies reported in [5], [11], and [15] reached precision values of 81.8%, 87.3%, and 89%, respectively. These values evidence that the proposed system had a better performance in fabric defect detection, although the comparison is not strictly equivalent, as each study used different datasets, acquisition conditions, fabric types, and evaluation procedures.

The proposed prototype was evaluated under controlled conditions and with a single inspection module. Therefore, it should be considered as a laboratory-scale system. Its current mechanical structure does

not cover standard fabric widths such as 58 inches. For this, a wider transport mechanism and several coordinated cameras would be needed.

A multi-camera version would also require a common position reference, synchronized acquisition, geometric calibration, and uniform lighting across the entire inspection area. These elements would be necessary to avoid gaps, overlaps, and differences in the fabric image response between modules.

Future work should include striped, plaid, and other patterned fabrics, for which additional image processing stages would be needed for defect segmentation in those types of fabric. Likewise, it is necessary to evaluate fabrics with different grammage, composition, thickness, and light transmission properties, as these characteristics can affect defect contrast.

Finally, a full industrial assessment should consider inspection reliability during continuous operation, maintenance requirements, implementation cost, scalability, and return on investment. These aspects were outside the scope of the present work but are necessary before deployment on an industrial textile line.

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