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Fabric Defect Identification based on KNN and PCA Algorithms

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Abstract
In this study, a K-Nearest Neighbor (KNN) classifier is employed for fabric defect identification. First, directional Grey-Level Co-occurrence Matrix (GLCM) of the fabric image is computed in , and 90° directions. Six intensity-based features are then extracted from these directional GLCMs. In addition, the minimum, maximum, median, and mean grey levels of the fabric image are computed. These sixteen features are combined into a single feature vector representing the fabric image. Next, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the feature vector. The reduced features are then classified using the KNN classifier, categorizing each fabric image as either defective or defect-free based on training data. To localize defects, patches containing defects are segmented from the original fabric image. Features of these defect patches are extracted, reduced via PCA, and classified using KNN. Finally, each defect class is identified, and defect locations are visualized using morphological operations. The proposed method is evaluated on the comprehensive TILDA dataset, which contains 3,200) fabric images (both defective and defect-free). Experimental results demonstrate a mean average accuracy of 95.65% for fabric defect identification across classes C_1, C_2, and C_3.

Keywords: Fabric Defect Identification; Feature Extraction; KNN Classifier; PCA Algorithm.

1- Introduction

A fabric defect refers to a flaw on the surface of a fabric caused by issues in the manufacturing process. In textile quality control, fabric defect identification is crucial for maintaining product standards [1]. To date, over 70 types of fabric defects have been documented in textile manufacturing [2]. The presence of defects can reduce fabric value by 45-65% [2].
Traditionally, defect identification has relied on human visual inspection [2], which suffers from limited accuracy; typically ranging between 60-75% [3]. As a result, manual inspection is inefficient and unreliable for long-term use [1]. Therefore, automatic fabric defect identification based on computer vision techniques is increasingly important for quality control in textile production [4].
Compared to manual methods, automatic fabric defect identification offers higher accuracy, reduced costs, and increased robustness in production lines [3]. However, due to the wide variety of defect types, accurately classifying fabric defects remains a challenging task [4].
Recently, deep learning-based approaches have achieved promising results in fabric defect identification. However, their performance heavily depends on large volume of labelled data [5]. Since labelling fabric defects is time-consuming and expensive for textile factories, using supervised learning methods that do not rely on deep learning can reduce this burden. Thus, developing efficient, accurate, and lightweight methods remains a key research goal [6].
In this study, we propose an automatic method based on the K-Nearest Neighbor (KNN) classifier to identify defects in both plain and patterned fabrics. First, the directional Grey-Level Co-occurrence Matrix (GLCM) of the fabric image is computed in 0°, and 90° orientations. From these GLCMs, six intensity features are extracted. Additionally, the minimum, maximum, median, and mean grey levels of the image are calculated. These sixteen features are concatenated into a single feature vector of size of 1×16. Principal Component Analysis (PCA) is then applied to reduce the dimensionality of the feature vector. The reduced features are subsequently classified using the KNN algorithm to categorize the image as either defective or defect-free.
To localize defects within defective images, defect patches are first segmented. Features from these patches are extracted, reduced using PCA, and classified via KNN.

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Finally, the type and position of each defect are determined and visualized using morphological operations. The proposed method is evaluated on the comprehensive TILDA dataset, which includes 3,200 fabric images (defective and defect-free). Experimental results show a mean average accuracy of 95.65% for defect identification across 1,390 images in classes C_1, C_2, and C_3 of the dataset.

The main innovation of the proposed method lies in achieving high classification accuracy; 95.65%, on the TILDA dataset using only PCA and KNN, without relying on any deep or non-deep neural network models. As a result, the proposed method is suitable for real world applications in fabric defect inspection. However, it is not effective for detecting defects in a randomly patterned fabrics, as demonstrated by lower performance in such cases within the TILDA dataset.

The remainder of this paper is organized as follows: Section 2 reviews related work in fabric defect identification. Section 3 presents the proposed methodology. Section 4 reports experimental results and comparisons with existing methods. Finally, Section 5 concludes the study.

2- Past Methods

Several methods have been proposed for fabric defect identification, ranging from traditional image processing to deep learning techniques. This section reviews a selection of these approaches and their reported performance.

An unsupervised learning method [1] identified fabric defects by reconstructing image patches at multiple levels of a Gaussian pyramid. The reconstruction residuals were used for defect prediction, yielding a maximum identification accuracy of 85.20% on 128 fabric images. However, the dataset did not include all defect types. A patch-based method [2] extracted local fabric image patches, which were then labelled and fed into a pre-trained deep convolutional neural network. Defects were localized by scanning the image with the trained model. This method achieved an accuracy of 97.20% on 300 non-randomly patterned fabric images from the TILDA dataset. A comprehensive survey [3] reviewed existing fabric defect identification algorithms and datasets, comparing identification accuracy and real-time performance. Auto-encoder networks [4] were trained using a loss function on Structural Similarity Index Measurement (SSIM). Defect identification was performed using SSIM residual maps. Identification accuracies of 92.70%, 79.80%, and 93.10% were reported for classes C_1, C_2, and C_3 of the TILDA dataset, with no results provided for class C_4. A multi-task mean teacher approach [5] was presented to simultaneously identify the defect area, contour, and distance map. Supervised and consistency losses were applied to labeled and unlabeled data, respectively, resulting in a mean accuracy of 87.77% on TILDA fabric images. A weighted double low-rank decomposition technique [6] located defects by identifying homogeneous regions with high correlation. This method achieved a mean accuracy of 90.66% on 250 plain fabric images from the TILDA dataset. A method based on Elliptical Gabor filter (EGF) [7] used a particle swarm optimization algorithm to determine EGF parameters from a defect-free template image. Defect identification was performed by convolving the sample image with the EGF, achieving 96.30% accuracy on 195 images from the Standard Fabric Defect Glossary dataset. Another approach [8] targeted defect identification in patterned fabrics. Defective blocks were segmented using pattern periodic distance, and compared to a dictionary of features from defect-free blocks. Distance metrics and thresholding were used to identify defects, with accuracy exceeding 95%. An enhanced YOLOv4 architecture [9] incorporated the Soft-Pool layer within the Spatial Pyramid Pooling (SPP) structure. Adaptive histogram equalization was also applied to enhance image quality. Using a dataset that combined Aliyun-FD-10500, Kaggle images, and real photographs, the method achieved a mean accuracy of 86.44%, an improvement of 6% over standard YOLOv4. A DenseNet-based edge detection algorithm [10] used an optimized cross-entropy loss and six enhancement designs to improve feature representation. The method outperformed conventional CNNs, improving the area under the curve (AUC) by 18% across 11 defect types. A method using direction templates and image pyramids [11] was presented for identifying defects in color and periodically patterned fabrics. A stacked de-noising auto-encoder reconstructed the image from blocks sampled in the pyramid representation. Defective blocks were identified using SSIM, resulting in a mean accuracy of 69.68% on TILDA fabric images. Two CNN-based structures [12] were presented for jacquard-patterned fabrics. One used CNNs for defect identification on isolated patterns, while the other applied integrated state-of-the-art CNNs to the entire dataset. The multispectral dataset included RGB and near-infrared images, which were preprocessed using adaptive histogram equalization. A saliency-based method [13] identified defects by estimating the membership degree of each defect region. Iterative thresholding and morphological operations were used, achieving a mean identification accuracy of 95.48% on various experimental images. A CNN model [14] was designed to learn defect features from only 50 labeled samples. Initially, the model was applied without training to generate raw outputs, which were later used for supervised learning. Experiments on four fabric datasets with different textures achieved a mean accuracy of

95.89%. A dictionary learning-based method [15] first segmented a defect-free fabric image to build a joint matrix, from which a random dictionary was created. Orthogonal matching pursuit and k-SVD (k singular value decomposition) were applied to learn sparse representations. Defect identification was based on reconstruction error and adaptive thresholding, achieving 93.63% mean accuracy on TILDA classes C_1, C_2, and C_3. A method for nonwoven fabric defect identification [16] was presented using the LL-YOLOv5 network, which incorporated the LSK and Light-RepGFPN modules. These modules enhanced small defect identification and feature fusion. The model achieved a mean accuracy of 90.30% on a hyperspectral nonwoven fabric dataset, outperforming standard YOLOv5 by 2.2%. A Color Conversion Network (CCN) [17] converted RGB images into an optimized color space to better distinguish defects from normal patterns. A contrastive loss function maximized the separation between defect and non-defect features. A complementary adversarial structure, CASDD [18], combined an encoder–decoder module with dual discriminators for identifying texture defects. Edge detection blocks were integrated into convolutional layers, while two discriminators focused on key features and edge differences to improve boundary identification. A YOLO-SCD network [19] used an attention mechanism to enhance feature representation in the neck of the model. It achieved a mean accuracy of 82.92%, improving YOLOv4 performance by 8.49%. Finally, a network incorporating a parallel dilated attention module [20] and a feature pyramid network was introduced to capture multiscale contextual information. Alpha-GIoU loss was used to refine bounding box regression. Additionally, a dual attention module, self-enhanced (SE) and cross-enhanced (SE), was developed [21] to enrich contextual and inter-layer feature representations for improved prediction accuracy.

3- Proposed Method

The steps of the proposed method are illustrated in Fig. 1. Each fabric image is selected from the TILDA dataset and has a resolution of 400×400 pixels. First, the GLCM of the input image is calculated in 0° and 90° orientations. From each matrix, six features are extracted using Equations (1) to (6). The feature defined in Equation (1) captures the scattering of grey levels around the mean intensity.

$$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i-\mu)^2 C(i,j) \quad (1)$$

Where μ, $C(i,j)$, and N_g are respectively mean, GLCM member at (i,j), and a number of grey levels of the image.

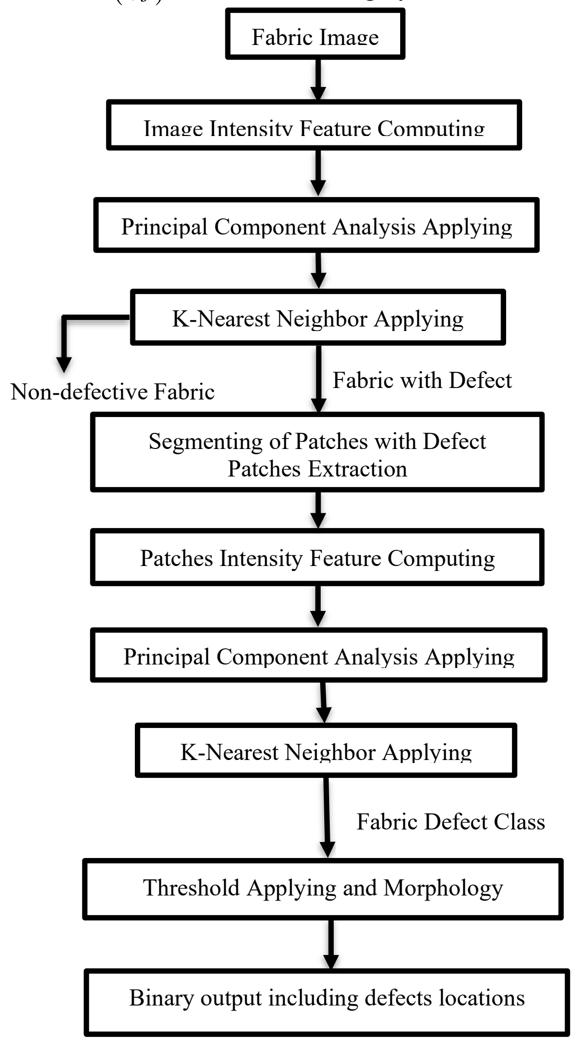

Fig. 1 Flowchart of the proposed method

The feature defined in Equation (2) shows the spreading of sum of grey levels around the mean intensity.

$$C_x(i)=\sum_{j=0}^{N_g-1} C(i,j)$$

$$C_y(i)=\sum_{i=0}^{N_g-1} C(i,j)$$

$$\sum_{i=2}^{2N_g}\left(i-\left[\sum_{i=2}^{2N_g} iC_{x+y}(i)\right]\right)^2 \quad (2)$$

The feature defined in Equation (3) shows the mean distribution of the sum of grey levels.

$$\sum_{i=o}^{2N_g-2} iC_{x+y}(i,j) \quad (3)$$

The feature defined in Equation (4) shows the irregularity of difference distribution of the image intensities.

$$-\sum_{i=0}^{N_g-1} C_{x-y}(i)\log\left(C_{x-y}(i)\right) \quad (4)$$

The feature defined in Equation (5) shows the maximum of the GLCM members.

$$Max_{i,j}\, C(i,j) \quad (5)$$

The feature defined in Equation (6) shows the homogeneity of the grey levels distribution.

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{C(i,j)}{1+(i-j)^2} \quad (6)$$

In addition to GLCM features, four statistical intensity features, minimum, maximum, median, and mean are computed from the original image.

4- Results and Comparisons

4-1- TILDA Database

TILDA database [27] is a comprehensive database commonly used for evaluating fabric defect identification algorithms. It contains 3,200 images across four classes, including various types of simple and patterned designs. The proposed method was implemented and tested on this dataset. The C_1 class has simple fabrics with a narrow structure. The C_2 class has simple fabrics with a random structure. The C_3 class has periodical structured fabrics. The C_4 class has fabrics with randomly patterns.

4-2- Evaluation Criteria

Four standard evaluation metrics, defined by Equations (7) to (10) [27], are used to assess the performance of the proposed method.

$$Sensitivity\,(Sens.) = \frac{TP}{TP+FN} \quad (7)$$

$$Specificity\,(Spec.) = \frac{TN}{TN+FP} \quad (8)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$False\,Rate\,(FR) = \frac{FP+FN}{TP+TN+FP+FN} \quad (10)$$

Where TP shows true defect identification, which indicates only the pixels with defect are white in the identification result. Both TN and FP show no white pixels in the identification result of the free defect image. FN shows no white pixels in the identification result of the defective image.

4-3- Validation

The simulation of the proposed method is done by *MATLAB* 2019 with 64 bit and operating system of the Windows 7. It is implemented on a system based on the Intel(R) core (TM) i3-2350 CPU @2.3 GHz, 4GB RAM.

Several results for C_1 are shown in Table 1. Two groups of designs in C_1 are C_1r_1 and C_1r_3 . 200 images of C_1r_1 are defective and 50 images are non-defective. 160 images of C_1r_3 are defective and 50 images are non-defective. The results in Table 1 report the high mean accuracy of the proposed method for defect identification in C_1 .

Table 1: Defect identification results of the proposed method for C_1

Class	*Sens.*	*Spec.*	*Accuracy*	*FR*
C_1r_1	90.14%	91%	92.10%	7.90%
C_1r_3	87.94%	100%	91.72%	8.28%

Several results for C_2 are shown in Table 2. Two groups designs in C_2 are C_2r_2 and C_2r_3 . 200 images of C_2r_2 are defective and 50 images are non-defective. 200 images of C_2r_3 are defective and 50 images are non-defective. It has to be noticed that black holes are randomly placed in the images background of C_2 , that should not be identified as the defects. The results in Table 2 report the high mean accuracy of the proposed method for defect identification in C_2 .

Table 2: Defect identification results of the proposed method for C_2

Class	*Sens.*	*Spec.*	*Accuracy*	*FR*
C_2r_2	100%	100%	100%	0%
C_2r_3	97.60%	100%	98.89%	1.11%

Several results for C_3 are shown in Table 3. Two groups designs in C_3 are C_3r_1 and C_3r_3 . 170 images of C_3r_1 are defective and 50 images are non-defective. 160 images of C_3r_3 are defective and 50 images are non-defective. The results in Table 3 illustrate that the defect identification in C_3 is more difficult than that on C_2 , because of various grey levels in the background of the patterned fabric images in C_3 .

Table 3: Defect identification results of the proposed method for C_3

Class	*Sens.*	*Spec.*	*Accuracy*	*FR*
C_3r_1	94.79%	100%	96.53%	3.47%
C_3r_3	93.42%	100%	94.67%	5.33%

4-4- Visual Results

The proposed method several visual results for C_1, C_2, and C_3 are respectively shown in Fig. 2, 3, and 4. In Fig. 2, images in rows 1 to 2 are from C_1r_1, and images in rows 3 to 4 are from C_1r_3. In Fig. 3, images in rows 1 to 2 are from C_2r_2, and images in rows 3 to 4 are from C_2r_3. In Fig. 4, images in rows 1 to 2 are from C_3r_1, and images in rows 3 to 4 are from C_3r_3.

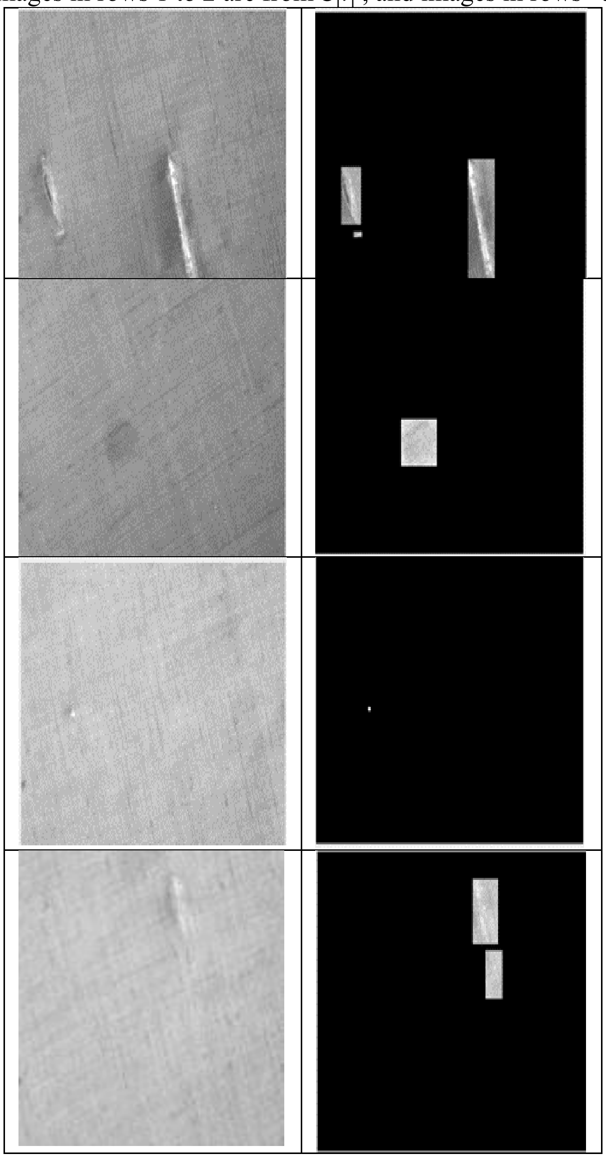

Fig. 2 Several fabric defect identification results for C_1r_1 (rows 1 to 2) and C_1r_3 (rows 3 to 4) by the proposed method

In some images, defects are highly camouflaged within the fabric background, leading to misidentification. Examples of such cases are shown in Fig. 5. Additionally, no results are reported for fabrics with random patterns, as the proposed method performs poorly on this category.

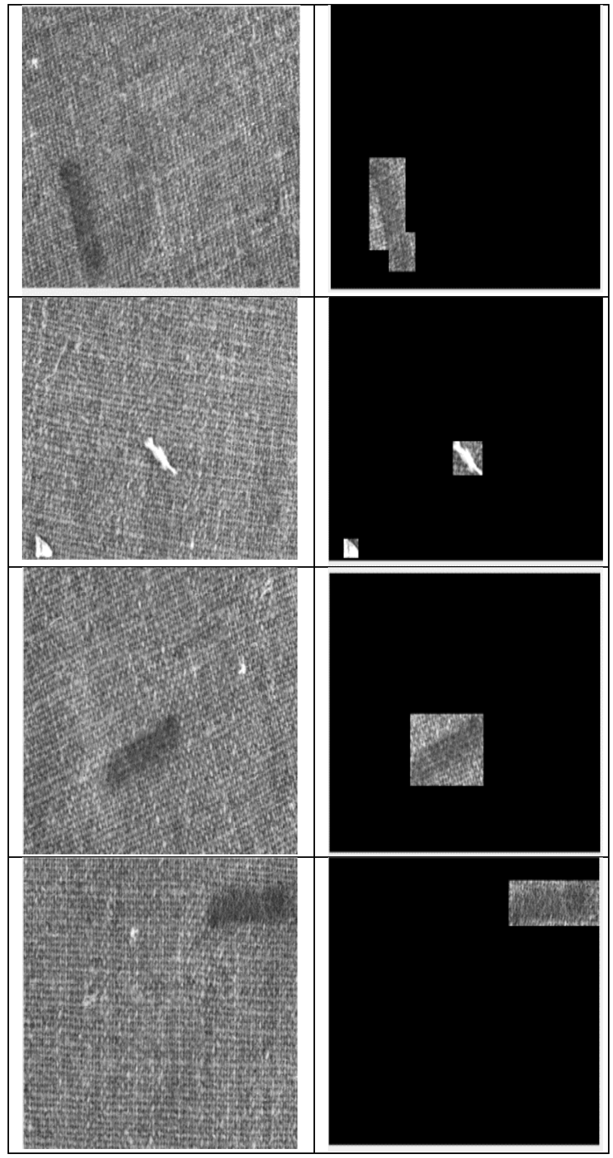

Fig. 3 Several fabric defect identification results for C_2r_2 (rows 1 to 2) and C_2r_3 (rows 3 to 4) by the proposed method

4-5- Comparisons

Several state-of-the-art methods were implemented and evaluated on the TILDA dataset for comparison. Table 4 summarizes the mean defect identification accuracy of each method. While some advanced models achieve slightly higher accuracy, they often rely on deep learning and require complex architectures or large amount of labeled data. In contrast, the proposed method is simple, interpretable, and easy to implement, yet achieves high accuracy for most fabric types, expect randomly patterned fabrics.

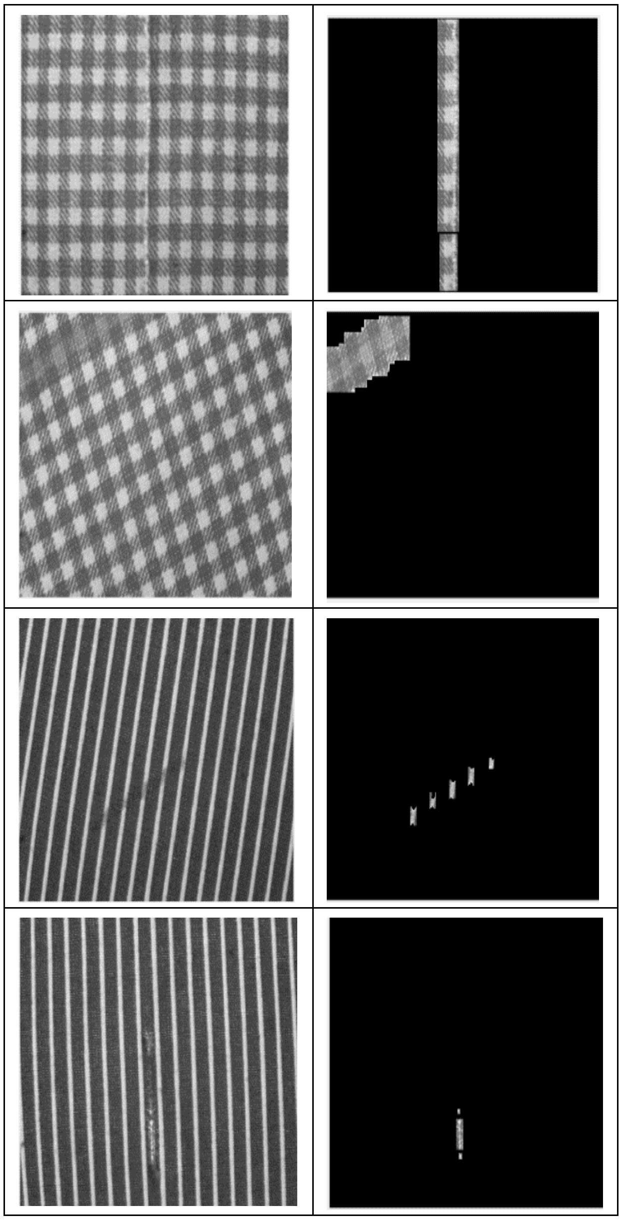

Fig. 4 Several fabric identification results for C_3r_1 (rows 1 to 2) and C_3r_3 (rows 3 to 4) by the proposed method

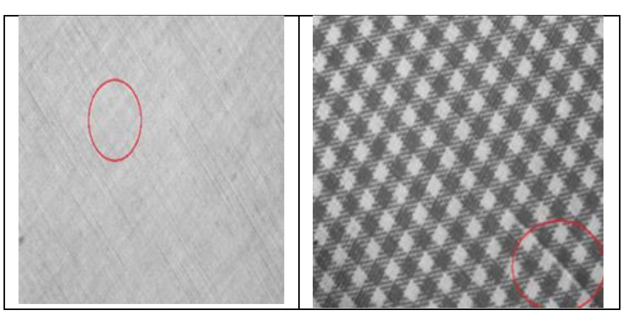

Fig. 5 Two samples of defects fade into the fabric background, leading to misidentification

Table 4: Defect identification mean accuracy of the proposed method compared with a several state-of-the-art methods on the TILDA

Method	Mean Accuracy
[2]	93.70%
[4]	94.95%
[5]	90.62%
[6]	89.86%
[7]	93.84%
[9]	94.37%
[8]	95.75%
[11]	95.25%
[13]	95.68%
[14]	95.30%
[19]	91.97%
Proposed	95.65%

5- Conclusions

This study introduced a simple, supervised method for accurate and reliable fabric defect identification using the KNN classifier and PCA. By reducing the dimensionality of the feature vectors. The proposed method achieves lower memory usage and computational cost, making it suitable for real-time applications.

Extensive experiments on the comprehensive TILDA dataset (3,200 images across four classes) demonstrated the effectiveness of the approach. While the method was not evaluated on fabrics with random patterns, it achieved high identification accuracy on simple and non-random patterned fabrics.

Specifically, the proposed method achieved mean identification accuracies of 91.91% for class C_1, 99.44% for class C_2, and 95.60% for class C_3. The lower performance in class C_1 is attributed to the narrow and less distinguishable textures in simple fabrics. The overall average accuracy across classes C_1 to C_3 is 95.65%.

The key innovation of this work is achieving competitive accuracy without using any deep or non-deep neural network models, relying solely on classical machine learning techniques (PCA and KNN). As a result, the method is well-suited for real-world applications where simplicity, interpretability, and resource efficiency are critical. However, the current method is not applicable to fabrics with random patterns, as the identification accuracy is insufficient for practical use in such cases.

Given its performance on the TILDA dataset, the method is expected to generalize well to other fabric datasets, provided the fabrics have simple or regular patterns. Future work will focus on extending the method to handle random patterns and more complex fabric structures.

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