Fuzzy Systems and Soft Computing
ISSN : 1819-4362

A COMPREHENSIVE REVIEW OF ADVANCED TECHNIQUES IN FABRIC DEFECT DETECTION FOR QUALITY CONTROL

Mrs. C Kavitha Ph.D Research Scholar, Department of Computer Science, Erode Arts and Science College, Erode, Assistant Professor and Head,Department of Computer Science with Data Analytics, St.Joseph's College for Women, Tirupur
Dr.T.Ranganayaki Associate Professor, Department of Computer Science, Erode Arts and Science College, Erode.

Abstract
Fabric defect detection is crucial for quality control in textile manufacturing, requiring precise identification and classification of imperfections to ensure fabric quality. This paper offers a comprehensive review of recent advancements in fabric defect detection, emphasizing the latest techniques in pre-processing, segmentation, and feature extraction, along with recent developments in machine learning. Pre-processing methods, such as colour space conversion, noise reduction, and contrast enhancement, are vital for improving image quality and preparing it for analysis. Segmentation techniques are employed to accurately isolate defects, while advanced feature extraction methods capture relevant characteristics for defect classification. Recent innovations in machine and deep learning algorithms have significantly enhanced defect detection accuracy. This review underscores the importance of these advanced techniques in improving performance metrics, including accuracy, precision, and recall, within fabric defect detection systems.

Keywords: Fabric defect detection, image pre-processing, segmentation, feature extraction, classification, deep learning, machine learning.

Introduction
Fabric defect detection is a critical aspect of ensuring textile quality, as defects such as stains, tears, and irregularities can compromise both the appearance and functionality of fabrics. Traditionally, fabric inspection has relied on manual methods, which, despite their effectiveness, are labor-intensive and subject to human error. This has led to a growing reliance on automated systems designed to enhance accuracy and efficiency in defect detection [1].

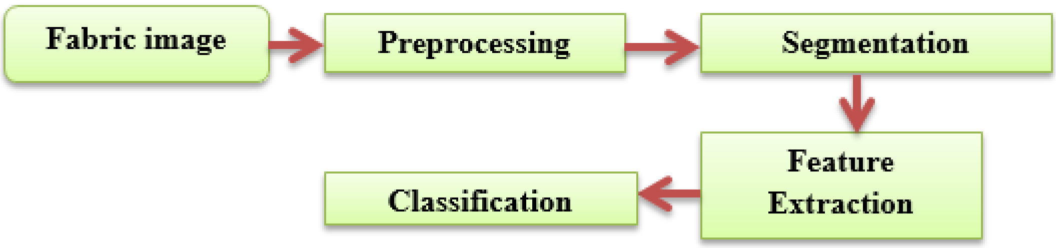

Fig.1. Image Processing Flow for Fabric Defect Detection

1. **Pre-processing:** Effective pre-processing techniques are essential for enhancing image quality and ensuring that defects are clearly visible. However, optimizing these techniques to avoid introducing artefacts remains a challenge.
2. **Segmentation:** Accurate segmentation is crucial for isolating defects from the background. Challenges persist due to the complexity of textures and variability in lighting conditions, which can affect segmentation accuracy.
3. **Feature Extraction:** Advanced feature extraction methods, particularly those involving deep learning, have shown promise in improving detection accuracy. However, these methods often require extensive data and substantial computational resources, presenting challenges in their implementation.

4. **Classification:** Recent innovations, such as deep learning models and multispectral imaging, offer significant improvements in defect detection accuracy. Despite their benefits, these technologies add layers of complexity to system integration and operation.

This paper reviews recent advancements in fabric defect detection, focusing on pre-processing, segmentation, and feature extraction, to provide insights into current technologies and future directions.

Literature survey

Advancements in fabric defect detection focus on preprocessing, segmentation, feature extraction, and classification models. Preprocessing includes color space conversion, noise filtering, and contrast enhancement. Segmentation isolates defects, while feature extraction uses statistical parameters and frequency-based analyses. ML and DL models significantly improve accuracy, precision, and recall. This section reviews these techniques and their recent developments.

2.1. Preprocessing:

In textile defect detection, image preprocessing is crucial to enhance input quality and consistency for detection algorithms. It begins with normalization to standardize pixel values, followed by resizing to ensure uniform dimensions. Augmentation techniques such as rotation and flipping create diverse training data, enhancing the model's ability to generalize. Methods like Gaussian blur for noise reduction and adjustments in color spaces improve image clarity and ensure consistent color representation. These steps optimize the performance and reliability of textile defect detection by emphasizing relevant features and reducing irrelevant variations. Below is a table listing various filters used in fabric defect identification, along with their respective functions [2].

Table: 1: Filters used in fabric defect detection

Filter Type	**Description**
Median Filter	A non-linear filter that replaces each pixel value with the median value of neighboring pixels, effective for reducing salt-and-pepper noise in fabric images
Gaussian Filter	Applies a Gaussian blur to an image to reduce noise and detail, smoothing out irregularities in fabric textures before further analysis.
Contrast Enhancement	Techniques such as histogram equalization or adaptive histogram equalization (CLAHE) to improve image contrast, enhancing the visibility of fabric defects.
Log Transformation	A mathematical operation that enhances the contrast of an image by compressing the dynamic range of pixel intensity values.
Fourier Transform	Converts an image into its frequency components to analyze texture patterns in fabric, useful for distinguishing defects from normal fabric patterns
Wavelet Transform	Decomposes an image into wavelet coefficients at different scales and orientations, allowing for multi-scale analysis of fabric textures and defects.
Morphological Operations	Erosion and dilation operations using structuring elements (e.g., cross-shaped or rectangular kernels) to refine image structures and enhance defect visibility

These preprocessing filters are essential for preparing fabric images by reducing noise, enhancing contrast, and extracting meaningful texture features, facilitating more accurate detection of defects during subsequent analysis stages.

The reviewed studies present various advanced methods for fabric defect detection, essential for enhancing quality control in textile manufacturing. Ouyang et al. (2019) focused on six types of fabric defects and applied data augmentation through horizontal and vertical flips to prevent overfitting, improving the robustness and accuracy of the Faster R-CNN model for defect detection. Similarly, Xie et al. (2020) introduced an image-processing algorithm specifically designed to detect scratches and stains on striped backgrounds. By preprocessing images and using a one-dimensional median filter, their approach achieved a 97.2% accuracy rate, despite challenges in distinguishing defects with similar grayscale values to the background. Khodier et al. (2022) developed novel defect detection models for jacquard fabrics, utilizing deep learning techniques like CNNs combined with multispectral imaging, which achieved nearly 99% accuracy, particularly with EfficientNet CNN, demonstrating effectiveness in complex-patterned fabrics. Another contribution by Xie et al. (2020) involved a fabric defect detection model based on Cascade R-CNN, incorporating innovative features such as block recognition and enhanced feature extraction layers, which showed significant potential for improving quality control in high-resolution fabric images. Li et al. (2023) proposed a refined approach using the improved RefineDet model, integrating attention mechanisms and advanced optimization techniques, proving effective in detecting defects across various fabric patterns. Lastly, Chong et al. (2022) introduced a defect detection model for periodic texture fabrics, employing saliency region identification and Gaussian filtering to enhance defect outline extraction and overall detection performance. Collectively, these studies underscore the importance of advanced image processing and deep learning techniques in streamlining fabric defect detection processes, thus enhancing the efficiency and reliability of manufacturing quality assurance.

2.2 Segmentation:

Segmentation in fabric defect detection divides images to pinpoint specific regions, like defects, crucial for accurate defect identification. Techniques include thresholding for basic tasks and deep learning-based semantic segmentation for intricate pattern recognition. Region-based methods, like watershed transformation, distinguish adjacent regions. Segmentation enhances defect localization precision, aiding quality control in textile manufacturing. Here's the table outlining segmentation techniques in fabric defect detection:

Table: 2: Segmentation technique used in fabric detection

Segmentation Technique	**Description**
Thresholding	Converts grayscale images into binary images by setting pixel values above or below a specified threshold, separating defects from background textures.
Canny Edge Detector	Detects edges in images by finding areas of high gradient, crucial for outlining boundaries and edges of fabric defects.
Morphological Operations	Erosion and dilation operations refine defect boundaries based on pixel structure, improving segmentation accuracy in fabric images.
Watershed Transform	Treats grayscale images as topographic maps, segmenting regions based on intensity gradients, useful for separating closely spaced fabric defects.
Region Growing	Groups pixels into regions based on similarity criteria, facilitating the identification of cohesive areas that may correspond to fabric defects.

The reviewed studies propose various methods for fabric defect detection, emphasizing segmentation and enhancing detection accuracy. Chong et al. (2022) introduced a segmentation method using projection location and super pixel techniques, achieving over 10.94% improvement in accuracy compared to alternatives like RPCA. Liu et al. (2022) combined canny edge detection with morphological processing, achieving a defect area correlation of over 85%, enhancing segmentation for fabric inspection. Huang et al. (2021) developed a CNN framework with minimal manual annotation, achieving real-time processing at 25 FPS, and outperforming eight state-of-the-art methods. Zhang et al. (2021) addressed uneven illumination with multi-scale filtering, local contrast enhancement, and quaternion image processing, improving recall and precision in defect detection.

Another contribution by Chong et al. (2022) employed an enhanced GAN with MLP layers for fabric defect segmentation, demonstrating significant improvements in precision, recall, and F1-score. Li et al. (2023) introduced an efficient segmentation algorithm using Gabor filters and a U-shaped architecture, achieving 90.03% accuracy and outperforming transformer-based models by nearly 10%. Lastly, Di et al. (2020) proposed an automatic thresholding method based on entropy, with the Renyi entropy method showing superior defect detection performance, highlighting its efficiency for real-time industrial applications. These methods collectively demonstrate advancements in fabric defect detection, improving segmentation accuracy and processing efficiency across diverse fabric types.

2.3 Feature Extraction:
Feature extraction in fabric defect detection refers to the process of identifying and quantifying distinctive characteristics or patterns from fabric images that are indicative of defects. This involves using algorithms to extract relevant information such as texture, color, gradients, and other visual cues that differentiate normal fabric patterns from abnormal ones. These extracted features serve as input to defect detection algorithms, enabling automated systems to accurately identify and classify defects, thereby improving quality control in manufacturing processes. Mengqi Chen et al. (2021) introduced a novel feature extraction method for fabric defect detection, using intertwined frames within a matrix window to enhance speed and accuracy. This approach generates distinctive features from vector functions between the center pixel and frame centroids, resulting in a 55% faster processing speed and at least 1.8% higher accuracy compared to traditional methods on the AITEX dataset, making it suitable for real-time applications on resource-constrained devices. Ahmet Çağdaş et al. (2021) developed completed local quartet patterns (CLQP), a refined local binary pattern (LBP) method that uses autocorrelation for detecting repetitive fabric patterns. It achieves a 97.66% detection rate on benchmark datasets, offering simplicity, rotation, and gray-scale invariance, and is applicable beyond fabric defect detection. Boshan Shi et al. (2021) proposed a method integrating low-rank decomposition of gradient information with a structured graph algorithm, enhancing defect detection by partitioning images into defect-free and defect-containing regions. Adaptive thresholding and defect prior information aid in accurate detection, achieving an 87.3% true positive rate and 1.21% false positive rate across various patterns. Di et al. (2020) presented a deep learning approach using autoencoders and One Class Classification (OCC) for defect detection without defect samples during training. By leveraging augmented defect-free samples, the model generates descriptors for automatic defect detection, proving more effective and flexible than traditional methods like SIFT, and enhancing quality control in manufacturing.

3. Fabric Defects:
Fabric defects refer to imperfections or flaws in textiles that can affect their quality and usability. These defects can arise during manufacturing and are categorized based on their impact. Critical defects are severe and render the fabric unusable or hazardous, major defects significantly affect the fabric's function or appearance, and minor defects are small cosmetic issues that don't impact overall usability. Identifying and addressing these defects through rigorous inspection processes are essential to ensure the fabric meets quality standards and avoids financial losses or customer dissatisfaction [17].

3.1. Fabric inspection:
Fabric inspection is crucial for identifying defects and ensuring quality during manufacturing. It involves two main types: manual inspection, performed by human inspectors, and automated inspection, which uses computer systems for detection. Effective inspection helps to address errors and adjust parameters as needed to maintain high manufacturing standards.

3.2. Manual fabric inspection:
Manual fabric inspection involves trained inspectors checking fabric for defects using illuminated horizontal or slanted tables. In basic setups, fabric is manually pulled over the table and inspected for flaws, while more advanced systems use power-driven machines to unroll fabric at speeds of 8-20

meters per minute. Inspectors pause the machine to record defects and then restart it, with defect rates calculated per meter and production alerted if defects are high.

3.3. Drawbacks of Manual Fabric Inspection:
- **Training Time**: Inspectors require extensive training; even the best can be fallible.
- **Human Limitations**: Human perception speed is slower than machines, and attention can wane due to boredom and fatigue.
- **Inspection Speed**: Inspectors can cover only 1.6-2 meters width at a maximum speed of 20 meters per minute.
- **Accuracy**: Manual inspection rarely achieves 100% accuracy, with decision efficiency around 70-80%. It is subjective, and quality control speed is slow, affecting overall production speed.

Due to these limitations, many industries are shifting towards automated inspection systems, which use cameras and imaging technology for more reliable and efficient quality control [18].

3.4. Computer Vision-Enhanced Fabric Defect Analysis:
Automated fabric inspection surpasses manual methods by offering continuous, precise defect detection without human error. It improves accuracy, speed, and efficiency, detecting defects as small as 0.1 mm at high speeds (up to 1,000 meters per minute). Automated systems reduce labor costs, eliminate subjective judgment, and provide real-time monitoring and detailed defect documentation, ensuring better quality control and consistent performance throughout the manufacturing process.

Table: 3: Types of textile defects

Type of Defect	**Description**	**Examples**
Vertical Lines	Defects appearing as lines running vertically across the fabric, often due to weaving or knitting inconsistencies.	Uneven yarn tension, misalignment in the loom.
Horizontal Lines	Defects manifesting as lines running horizontally, typically resulting from similar issues as vertical lines but oriented differently.	Faults in the dyeing process, variations in yarn density.
Isolated Defects	Single, sporadic flaws that occur at specific locations rather than being widespread.	A single missed stitch, localized discoloration.
Pattern Defects	Errors affecting the design or pattern of the fabric, impacting its visual appeal.	Misaligned prints, incorrect pattern repeats.
Finishing Defects	Issues occurring during the final processing stages, affecting the fabric's final appearance and feel.	Inadequate finishing treatments leading to poor texture or shine.
Printing Defects	Problems arising from the printing process, affecting the fabric have printed designs.	Smudged prints, colour bleeding, incomplete images.

The above table describes the lists types of textile defects with brief descriptions and examples

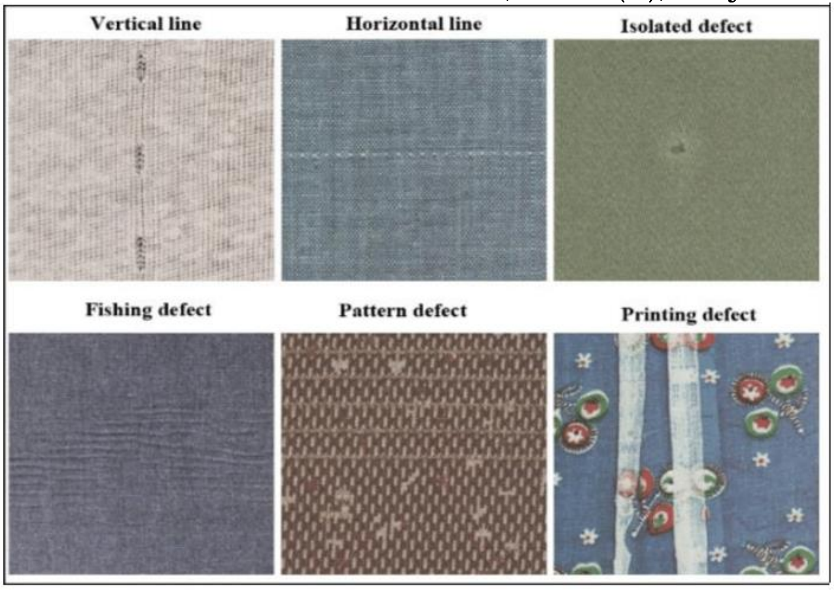

Fig: 1 Types of defects

The above diagram showcases examples of six types of textile defects: Vertical Line, Horizontal Line, Isolated Defect, Finishing Defect, Pattern Defect, and Printing Defect, each illustrated with a corresponding fabric image.

Fig: 2 Samples of defects

The numerous samples of the cloth that have defects are depicted in the figure that can be found above.

4. Methodology:

4.1. Image pre-processing:

In fabric defect detection, image preprocessing is crucial for optimizing image quality before applying defect detection algorithms. Techniques include noise reduction like Gaussian filtering, enhancing contrast for better texture visibility, standardizing color representation across images, resizing for uniform processing, and isolating regions of interest. These steps collectively enhance the accuracy and reliability of automated defect detection systems by preparing images effectively for analysis [19].

Image Capture

A digital camera with a resolution of 320x420 pixels captures the faulty image. Various input devices, such as digital cameras and scanners, can generate digital images. The acquired image may contain noise, requiring noise reduction techniques for prior processing.

Grayscale Conversion

Converting an image to grayscale is essential for continuous processing. An RGB image has three layers (red, blue, green), while a grayscale image has one layer with pixel intensity values from 0 to 255. The "RGB2GRAY()" function can be used for this conversion.

Noise Removal and Filtering

Noise during image capture or transmission causes pixel intensities to differ from true values. Noise removal algorithms reduce or eliminate this noise in the transformed image.

Thresholding and Histogram Equalization

Image histograms show pixel intensity values. Histogram equalization enhances contrast by distributing common intensity values, extending the intensity range, and improving visibility in low-contrast regions [20].

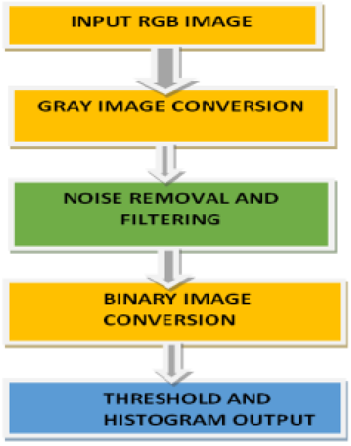

Fig: 3. The flow system of image pre-processing

4.2. Image Segmentation in Fabric Defect Detection

Image segmentation enhances object recognition by distinguishing local features from the background. It involves classifying each pixel as belonging to an object (value of 1) or the background (value of 0), forming a binary image. This process bridges low-level image processing and analysis by identifying object boundaries. Segmentation is essential for image classification but often relies on manual or semi-supervised methods, leading to inconsistencies and inefficiencies, especially in clinical applications. Therefore, automated segmentation tools are needed [21].

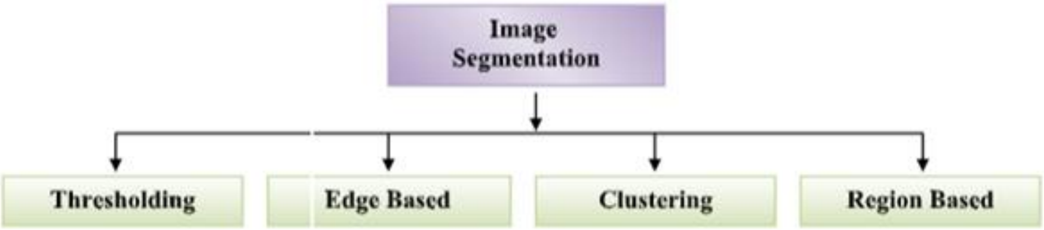

Fig: 4. Types of image segmentation

Automated segmentation techniques are categorized into four main types:

- **Thresholding:** Creates a binary image by assigning 1 to object pixels and 0 to background pixels.
- **Edge-Based Segmentation:** Focuses on detecting edges to identify object boundaries.
- **Clustering:** Groups similar pixels to reduce data complexity and identify regions of interest.
- **Region-Based Segmentation:** Includes methods like Region Growing and Contour Models to extract connected image regions.

The below table outlines four types of image segmentation algorithms: Thresholding, Edge-Based, Clustering, and Region-Based—each with specific techniques and examples for segmenting and simplifying images based on pixel values, edges, clusters, or connected regions.

Table: 4: Types of segmentation algorithms

Segmentation Type	Description	Examples
Thresholding	Converts an image into a binary format by assigning pixel values of 1 for objects and 0 for the background.	Otsu's Method, Simple Thresholding
Edge-Based	Detects edges in an image to identify object boundaries, utilizing techniques like the Sobel or Canny edge detectors.	Canny Edge Detection, Sobel Filter
Clustering	Groups pixels into homogenous clusters to simplify the image, commonly using algorithms like K-means or Mean Shift.	K-means Clustering, Mean Shift
Region-Based	Extracts connected regions within an image, encompassing methods such as Region Growing and Contour Models.	Region Growing, Active Contours (Snakes)

4.3. Feature Extraction for Fabric Defect Detection:

Feature extraction analyses image texture, enhancing understanding of texture and object shapes. It reduces input data dimensions for easier handling by converting images into a standardized set of features. In this study, feature extraction was applied to fundus images from normal and glaucoma categories, converting grouped pixels into numerical data. The key features used include [22]:

- **Gray Level Co-occurrence Matrix (GLCM):** Analyses pixel relationships to extract statistical features.
- **Gray-Level Run-Length Matrix (GLRM):** Captures lengths of consecutive pixels with the same intensity.
- **Gray Level Difference Matrix (GLDM):** Measures probability densities of gray level differences.
- **Local Binary Patterns (LBP):** Encodes texture by comparing each pixel with its neighbours.
- **Histogram of Oriented Gradients (HOG):** Describes gradient orientations in localized image regions.

Table 5: Types of Feature Extraction algorithms

Feature Extraction Algorithm	Description	Examples of Extracted Features
Gray Level Co-occurrence Matrix (GLCM)	Analyses the spatial relationship between pixels to extract statistical features.	Contrast, Correlation, Energy, Homogeneity
Gray-Level Run-Length Matrix (GLRM)	Captures the length of consecutive pixels with the same intensity in specific directions.	Run Length, Short Run Emphasis, Long Run Emphasis
Gray Level Difference Matrix (GLDM)	Measures the probability density functions of gray level differences between pixels.	Contrast, Energy, Entropy
Local Binary Patterns (LBP)	Encodes local texture by comparing each pixel with its neighbours, generating binary patterns.	LBP Histogram, Uniform LBP

Histogram of Oriented Gradients (HOG)	Describes the distribution of gradient orientations in localized portions of an image.	HOG Features, Edge Orientation

.

Conclusion

This review highlights the transformative impact of recent advancements in fabric defect detection on quality control within textile manufacturing. Key techniques in pre-processing, segmentation, and feature extraction have significantly improved detection accuracy and reliability. Advanced pre-processing methods enhance image quality, while sophisticated segmentation techniques ensure precise defect localization. Feature extraction methods effectively capture vital characteristics essential for identifying defects, contributing to overall system performance. These innovations collectively optimize fabric defect detection systems, ensuring higher efficiency and reliability in maintaining fabric quality. Continued research and development in these areas are crucial for advancing the capabilities of fabric defect detection technologies, offering substantial benefits for the textile industry.

Reference

1. W. Ouyang, B. Xu, J. Hou and X. Yuan, "Fabric Defect Detection Using Activation Layer Embedded Convolutional Neural Network," in IEEE Access, vol. 7, pp. 70130-70140, 2019.
2. M. M. Khodier, S. M. Ahmed and M. S. Sayed, "Complex Pattern Jacquard Fabrics Defect Detection Using Convolutional Neural Networks and Multispectral Imaging," in IEEE Access, vol. 10, pp. 10653-10660, 2022.
3. Xie, H.; Wu, Z. A Robust Fabric Defect Detection Method Based on Improved RefineDet. Sensors 2020, 20, 4260.
4. Li, W.; Zhang, Z.; Wang, M.; Chen, H. Fabric Defect Detection Algorithm Based on Image Saliency Region and Similarity Location. Electronics 2023, 12, 1392.
5. W. Chong, W. Jinghua, W. Jing and D. Huan, "Fabric Defect Detection Method Based on Projection Location and Superpixel Segmentation," 2022 4th International Conference on Natural Language Processing (ICNLP), Xi'an, China, 2022, pp. 20-25.
6. M. Liu, W. Xu, Z. Lin and Y. Dai, "Fabric Defect Image Segmentation Method Based on The Combination of Canny and Morphology," 2022 34th Chinese Control and Decision Conference (CCDC), Hefei, China, 2022, pp. 654-658.
7. Y. Huang, J. Jing and Z. Wang, "Fabric Defect Segmentation Method Based on Deep Learning," in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-15, 2021, Art no. 5005715.
8. Z. Zhang, X. Wan, L. Li and J. Wang, "An Improved DCGAN for Fabric Defect Detection," 2021 IEEE 4th International Conference on Electronics and Communication Engineering (ICECE), Xi'an, China, 2021, pp. 72-76.
9. Xu, H.; Liu, C.; Duan, S.; Ren, L.; Cheng, G.; Hao, B. A Fabric Defect Segmentation Model Based on Improved Swin-Unet with Gabor Filter. Appl. Sci. 2023, 13, 11386.
10. Li, L.; Li, Q.; Liu, Z.; Xue, L. Effective Fabric Defect Detection Model for High-Resolution Images. Appl. Sci. 2023, 13, 10500.
11. Di, L.; Long, H.; Liang, J. Fabric Defect Detection Based on Illumination Correction and Visual Salient Features. Sensors 2020, 20, 5147.
12. Ahmet Çağdaş Seçkin, Mine Seçkin, Detection of fabric defects with intertwined frame vector feature extraction,Alexandria Engineering Journal,Volume 61, Issue 4,2022,Pages 2887-2898,ISSN 1110-0168.
13. Boshan Shi, Jiuzhen Liang, Lan Di, Chen Chen, Zhenjie Hou,Fabric defect detection via low-rank decomposition with gradient information and structured graph algorithm,Information Sciences,Volume 546,2021,Pages 608-626,ISSN 0020-0255.
14. K. Ramakrishnan, P. G. Jayakumar, P. Saravanan and P. Sivakumar, "A Novel Fabric Defect Detection Network in textile fabrics based on DLT," 2023 International Conference on Artificial

Intelligence and Knowledge Discovery in Concurrent Engineering (ICECONF), Chennai, India, 2023, pp. 1-8.

15. K. H. Liu, S. J. Chen and T. -J. Liu, "Unsupervised UNet for Fabric Defect Detection," 2022 IEEE International Conference on Consumer Electronics - Taiwan, Taipei, Taiwan, 2022, pp. 205-206.
16. N. Sajitha and S. P. Priya, "Artificial Intelligence based Optimization with Extreme Gradient Boosting for Fabric Defect Detection and Classification Model," 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2023, pp. 509-515.
17. Mengqi Chen, Lingjie Yu, Chao Zhi, Runjun Sun, Shuangwu Zhu, Zhongyuan Gao, Zhenxia Ke, Mengqiu Zhu, Yuming Zhang,Improved faster R-CNN for fabric defect detection based on Gabor filter with Genetic Algorithm optimization, Computers in Industry, Volume 134, 2022,103551,ISSN 0166-3615,
18. Q. Liu, C. Wang, Y. Li, M. Gao and J. Li, "A Fabric Defect Detection Method Based on Deep Learning," in *IEEE Access*, vol. 10, pp. 4284-4296, 2022.
19. A. Durmuşoğlu and Y. Kahraman, "Detection of Fabric Defects Using Convolutional Networks," *2021 Innovations in Intelligent Systems and Applications Conference (ASYU)*, Elazig, Turkey, 2021, pp. 1-5.
20. G. Vladimir, I. Evgen and N. L. Aung, "Automatic Detection and Classification of Weaving Fabric Defects Based on Digital Image Processing," *2019 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus)*, Saint Petersburg and Moscow, Russia, 2019, pp. 2218-2221.
21. H. w. Zhang, Q. -l. Tan, S. Lu, Z. -q. Ge and D. Gu, "Yarn-dyed Fabric Defect Detection using U-shaped De-noising Convolutional Auto-Encoder," *2020 IEEE 9th Data Driven Control and Learning Systems Conference (DDCLS)*, Liuzhou, China, 2020, pp. 18-24.
22. N. Toradmal, V. Bairagi and D. Jadhav, "Feature Extraction of Unprinted Fabric for Defect Detection Using Gabor Filter, HOG and SVM," *2024 International Conference on Emerging Smart Computing and Informatics (ESCI)*, Pune, India, 2024, pp. 1-5.