Automated Fabric Defect Detection Using Classical Computer Vision Techniques for Real-Time Industrial Inspection

Muhammad Hammad Sarwar, Awais Asghar, Muhammad Haris, Muhammad Saad Farooq
School of Electrical Engineering and Computer Science (SEECS)
National University of Sciences and Technology (NUST)
Islamabad, Pakistan
{msarwar.bee22seecs, aasghar.bee22seecs, haris.bee22seecs, sfarooq.bee22seecs}@seecs.edu.pk

***Abstract*—Automated fabric defect detection is a critical quality control task in the textile industry, where manual inspection is labor-intensive, subjective, and error-prone. This paper presents a classical computer vision–based framework for detecting surface defects in fabric images by exploiting texture irregularities and statistical deviations from normal fabric patterns. The proposed approach integrates multiple complementary detection strategies, including spatial texture analysis, frequency-domain filtering, pattern regularity assessment, template matching, statistical modeling, and multi-scale Gabor wavelet responses. Each detector captures distinct characteristics of fabric defects, enabling robust localization across varying texture structures. A unified detection pipeline is designed to aggregate candidate defect regions, followed by post-processing steps such as intersection-over-union–based bounding box merging, border artifact suppression, and elimination of spurious large detections. Experimental evaluation on real fabric images demonstrates that the proposed classical framework can effectively localize diverse defect types without requiring labeled training data or computationally expensive learning models. The results indicate that classical vision techniques remain a viable and interpretable solution for industrial fabric inspection, particularly in scenarios with limited data availability and strict real-time constraints.**

***Index Terms*—Fabric defect detection, classical computer vision, texture analysis, frequency-domain methods, Gabor wavelets, industrial visual inspection**

I. Introduction

Fabric defect detection plays a vital role in ensuring quality assurance within the textile manufacturing industry, where surface imperfections such as holes, stains, misweaves, and broken yarns can significantly degrade product value and customer satisfaction. Modern textile production operates at high speeds, generating large volumes of fabric that require consistent and reliable inspection to meet industrial quality standards. Any failure to detect defects at early stages can result in substantial economic losses due to material waste, reprocessing, and customer returns, making automated inspection systems an essential component of contemporary textile quality control pipelines.

Traditionally, fabric inspection has been performed manually by trained human inspectors who visually examine fabric surfaces under controlled illumination conditions. Despite widespread adoption, manual inspection suffers from inherent limitations, including operator fatigue, subjectivity, inconsistency across inspectors, and reduced detection accuracy at high production speeds. Studies have shown that prolonged inspection tasks significantly degrade human performance, leading to missed defects and unreliable quality assessment. These constraints render manual inspection unsuitable for modern large-scale textile manufacturing environments that demand high precision and repeatability.

To address these challenges, automated visual inspection systems have been extensively explored, with early solutions relying heavily on classical computer vision techniques. Unlike learning-based methods, classical approaches exploit intrinsic fabric properties such as texture regularity, spatial periodicity, and frequency-domain characteristics to identify deviations caused by defects. Fabrics typically exhibit highly repetitive and structured texture patterns, making defect regions distinguishable as localized irregularities in spatial, statistical, or spectral representations. Classical methods are particularly attractive in industrial settings due to their interpretability, low computational overhead, and independence from large annotated datasets, which are often difficult and expensive to obtain for diverse fabric types and defect categories.

Motivated by these considerations, this work proposes a comprehensive classical computer vision framework for automated fabric defect detection that integrates multiple complementary detection strategies within a unified pipeline. The framework leverages spatial texture analysis, frequency-domain filtering, pattern irregularity detection, template matching, statistical modeling, and multi-scale Gabor wavelet responses to capture a wide range of defect manifestations. By combining the outputs of these detectors and applying robust post-processing mechanisms, the proposed approach aims to enhance defect localization accuracy while suppressing false positives arising from normal texture variations and border artifacts.

The main contributions of this work are threefold. First, a modular and extensible classical detection architecture is developed that unifies diverse texture-based and frequency-based defect detectors without reliance on supervised learning. Second, an effective post-processing strategy is introduced to refine candidate defect regions through intersection-over-union–based merging and heuristic filtering. Third, the proposed framework demonstrates that classical computer vision techniques remain a practical and effective solution for fabric defect inspection, particularly in data-scarce and real-time industrial scenarios.

II. Related Work

Automated fabric defect detection has been extensively studied using classical computer vision techniques, primarily exploiting the repetitive and structured nature of fabric textures. Early approaches focused on spatial-domain texture analysis, where features such as gray-level co-occurrence matrices, local binary patterns, and structural regularity measures were employed to identify deviations caused by defects. These methods rely on the assumption that defect-free fabric exhibits uniform texture patterns, enabling abnormal regions to be detected through local inconsistency analysis.

Frequency-domain methods have also been widely investigated due to their effectiveness in modeling periodic fabric structures. Techniques based on Fourier transforms and spectral energy analysis identify defects as anomalies in the frequency spectrum, where regular textures produce concentrated spectral peaks while defects introduce broadband disturbances. Although effective for highly periodic fabrics, such methods often struggle with non-stationary textures and complex weave patterns.

Statistical and model-based techniques formulate defect detection as a deviation from learned or estimated normal texture statistics. These approaches include histogram-based modeling, thresholding of statistical moments, and probabilistic texture representations. While computationally efficient, their performance is highly sensitive to parameter selection and illumination variations.

Gabor filters and multi-scale filter banks have been extensively applied for fabric inspection due to their strong ability to capture orientation- and frequency-selective texture characteristics. By analyzing texture responses across multiple scales and orientations, Gabor-based methods can effectively highlight localized irregularities. However, they typically require careful tuning of filter parameters and often generate redundant responses that increase computational cost.

Despite their successes, existing classical methods face limitations in handling diverse fabric types, complex textures, and varying defect appearances using a single detection strategy. This has motivated the development of hybrid frameworks that integrate multiple complementary techniques to improve robustness and generalization in practical industrial environments.

III. Dataset Description

The experimental evaluation in this work is conducted using a publicly available fabric inspection dataset comprising high-resolution grayscale fabric images that exhibit a wide range of surface textures and defect patterns. The dataset contains both defect-free and defective fabric samples, with defects including holes, stains, broken yarns, misweaves, and local texture distortions that vary in shape, size, and contrast. The fabric textures demonstrate strong periodicity and structural regularity under normal conditions, while defective regions appear as localized irregularities that disrupt these patterns. The images are captured under controlled illumination; however, variations in texture density, weave complexity, and defect subtlety pose significant challenges for reliable detection. In particular, low-contrast defects, repetitive background patterns, and border artifacts increase the difficulty of distinguishing true defects from normal texture variations, making the dataset suitable for evaluating the robustness of classical computer vision–based inspection methods.

IV. Methodology

A. Overview of the Classical Detection Framework

The proposed fabric defect detection system is designed as a modular classical computer vision framework that integrates multiple complementary detection techniques to exploit different manifestations of fabric defects. Given an input fabric image, each detector independently analyzes the image to identify candidate defective regions based on texture irregularities, frequency disturbances, statistical deviations, or structural inconsistencies. The outputs of all detectors are represented as bounding boxes or binary masks, which are subsequently aggregated and refined through post-processing operations. This multi-detector strategy enhances robustness against variations in fabric texture, defect size, and defect appearance, while avoiding dependence on supervised learning or large annotated datasets.

B. Texture-Based Defect Detection

1) Concept: Texture-based defect detection relies on the observation that defect-free fabrics exhibit locally homogeneous and repetitive texture patterns. Defects introduce abrupt spatial changes that disrupt local texture consistency. By analyzing local intensity variations and spatial gradients, defective regions can be identified as areas exhibiting abnormal texture behavior compared to their surroundings.

2) Implementation Details: The input image is first converted to grayscale and optionally smoothed to suppress noise. Local texture descriptors are computed using sliding windows, where measures such as local variance, gradient magnitude, or intensity contrast are evaluated. Regions with texture statistics exceeding predefined thresholds are marked as defective candidates. Morphological operations are applied to consolidate fragmented detections and suppress isolated noise responses.

C. Frequency-Based Defect Detection

1) Fourier-Based Intuition: Fabric textures often exhibit periodic structures, which correspond to concentrated energy peaks in the frequency domain. Defects disturb this periodicity, resulting in spectral energy spread across non-dominant frequencies. Frequency-domain analysis thus provides a powerful mechanism to distinguish regular texture patterns from defective regions.

2) Frequency Domain Filtering: The two-dimensional discrete Fourier transform (DFT) of the image $I(x, y)$ is computed as

$$F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x, y) e^{-j2\pi\left(\frac{ux}{M} + \frac{vy}{N}\right)}. \tag{1}$$

Low-frequency components corresponding to regular texture are attenuated using band-stop or notch filters, while high-frequency disturbances are preserved. The inverse DFT is applied to obtain a spatial-domain representation where defect regions are enhanced. Thresholding is then employed to localize candidate defect areas.

D. Pattern Irregularity-Based Detection

1) Regular Pattern Modeling: This approach models defect-free fabric as a regular and repetitive pattern. Local patches extracted from the image are assumed to follow consistent structural arrangements in normal regions. A reference model is constructed using statistical or structural descriptors derived from non-defective areas.

2) Deviation Detection: For each local patch, a deviation score is computed by comparing its structural features with the reference pattern. Metrics such as normalized cross-correlation or Euclidean distance between feature vectors are employed. Patches exhibiting deviations beyond a predefined tolerance are labeled as defective.

E. Template Matching-Based Defect Detection

1) Reference Template Selection: A representative defect-free template is extracted either manually or automatically from regions exhibiting high texture regularity. This template serves as a reference for comparison across the image.

2) Matching Strategy: Template matching is performed using normalized cross-correlation given by

$$C(x, y) = \frac{\sum_{i,j} [T(i, j) - \bar{T}][I(x + i, y + j) - \bar{I}_{x,y}]}{\sqrt{\sum_{i,j} [T(i, j) - \bar{T}]^2 \sum_{i,j} [I(x + i, y + j) - \bar{I}_{x,y}]^2}}, \tag{2}$$

where T denotes the template and I denotes the input image. Regions yielding low correlation values indicate poor matches and are classified as defective candidates.

F. Statistical Model-Based Detection

1) Feature Statistics: Statistical features such as mean intensity, variance, skewness, and kurtosis are computed over local windows. For defect-free fabric, these statistics remain within narrow bounds due to texture uniformity.

2) Thresholding Logic: Defect detection is formulated as a hypothesis testing problem, where regions deviating significantly from global or local statistical norms are flagged. A pixel or region is labeled defective if

$$|f_i - \mu_f| > k\sigma_f, \tag{3}$$

where f_i is a local feature value, μ_f and σ_f are the mean and standard deviation of the feature over the image, and k is a tunable sensitivity parameter.

G. Gabor Wavelet-Based Detection

1) Multi-Scale, Multi-Orientation Analysis: Gabor filters are employed due to their strong localization properties in both spatial and frequency domains. A 2D Gabor filter is defined as

$$g(x, y) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi\frac{x'}{\lambda} + \phi\right), \tag{4}$$

where $x' = x\cos\theta + y\sin\theta$, $y' = -x\sin\theta + y\cos\theta$, and λ, θ, σ, γ, and ϕ control the wavelength, orientation, scale, aspect ratio, and phase offset, respectively. A filter bank spanning multiple scales and orientations is applied to capture diverse texture characteristics.

2) Texture Response Aggregation: The magnitude responses of Gabor filters are aggregated across scales and orientations to form a texture energy map. Defective regions produce abnormal energy responses compared to regular fabric textures. Thresholding and morphological refinement are used to localize defect regions accurately.

H. Bounding Box Fusion and Post-Processing

1) Motivation: Since multiple classical detectors are employed in parallel, a single physical defect may be independently detected by several algorithms. As a result, redundant and overlapping bounding boxes are generated around the same defect region. Directly visualizing these raw detections leads to cluttered outputs and unstable localization. Therefore, an effective fusion strategy is required to consolidate detector outputs into a unified and reliable defect representation.

2) Intersection-over-Union Based Fusion: To address this issue, an intersection-over-union (IoU) based bounding box fusion mechanism is adopted. Given two bounding boxes B_1 and B_2, IoU is defined as

$$\mathrm{IoU}(B_1, B_2) = \frac{\mathrm{Area}(B_1 \cap B_2)}{\mathrm{Area}(B_1 \cup B_2)}. \tag{5}$$

Bounding boxes with an IoU value exceeding a predefined threshold are assumed to correspond to the same physical defect and are grouped together. All bounding boxes within a group are merged into a single enclosing box by taking the minimum and maximum spatial extents across the group. This process acts as a consensus engine that stabilizes localization by retaining only regions agreed upon by multiple detectors.

3) Heuristic Post-Processing Filters: Following IoU-based fusion, additional heuristic filters are applied to suppress false positives. Extremely large bounding boxes that cover a significant portion of the image are discarded, as they typically arise from global illumination variations or frequency-domain artifacts rather than localized defects. Furthermore, bounding boxes touching image borders are removed to eliminate edge-induced artifacts resulting from padding, filtering, or incomplete texture context. These post-processing steps significantly improve detection precision while preserving true defect regions.

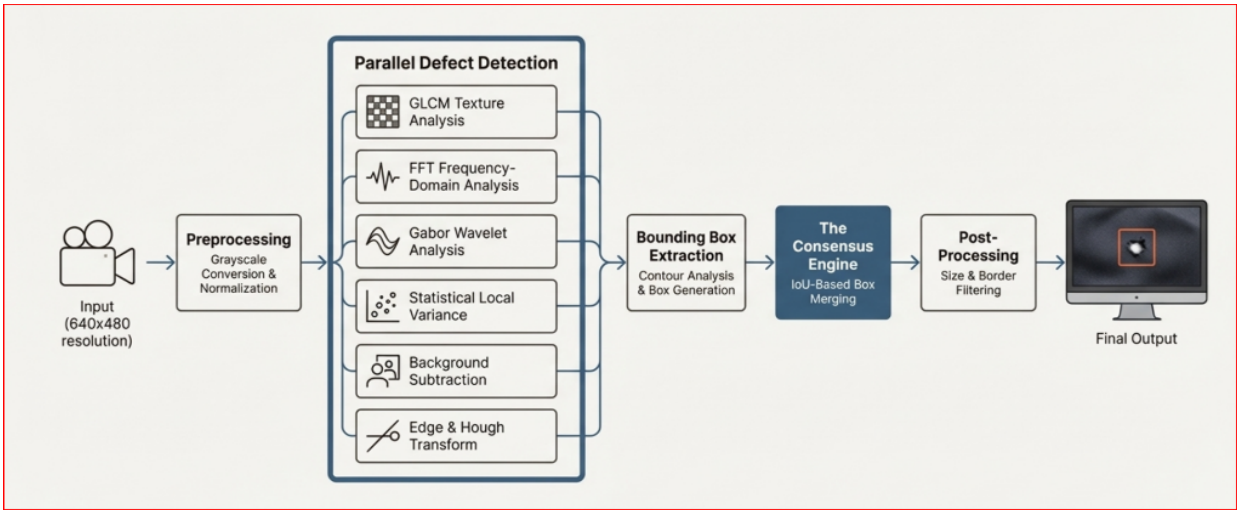

Fig. 1. Overall system architecture of the proposed classical fabric defect detection framework.

V. System Architecture

The overall system architecture of the proposed fabric defect detection framework is illustrated in Fig. 1. The pipeline is designed as a modular classical computer vision system optimized for real-time execution on embedded hardware platforms such as the NVIDIA Jetson Nano.

The input to the system is a fabric image or live camera frame captured at a fixed resolution. In the preprocessing stage, the input image is converted to grayscale and normalized to ensure illumination consistency and numerical stability across subsequent processing stages. This standardized representation serves as a common input for all detection modules.

Following preprocessing, the image is processed in parallel by multiple specialized classical defect detection modules. Texture-based detectors such as Gray-Level Co-occurrence Matrix (GLCM) analysis, statistical local variance modeling, and Gabor wavelet analysis identify localized texture irregularities and directional inconsistencies introduced by defects. Frequency-domain analysis using the Fast Fourier Transform (FFT) models the periodic structure of defect-free fabric and highlights anomalies that disrupt spectral regularity. Background subtraction estimates the regular fabric appearance using spatial smoothing and isolates non-structural defects such as stains and faded regions. Additionally, edge detection combined with the probabilistic Hough transform is employed to detect linear defects such as broken threads and misweaves.

Each detection module independently produces a binary anomaly map or a set of candidate bounding boxes corresponding to potential defect regions. These outputs are converted into a unified bounding box representation and forwarded to the fusion stage. To eliminate redundant detections produced by multiple detectors responding to the same defect, an intersection-over-union (IoU)–based consensus engine is applied. Bounding boxes exhibiting significant spatial overlap are grouped and merged into a single, stable bounding box.

In the post-processing stage, heuristic filters are applied to suppress false positives. Bounding boxes that are excessively large relative to the image dimensions or located near image borders are removed. The remaining bounding boxes constitute the final defect localization output.

This modular architecture allows individual detection modules to be enabled, disabled, or extended without modifying the overall pipeline. The exclusive use of classical computer vision techniques ensures interpretability, low computational complexity, and suitability for real-time deployment on low-power embedded platforms, making the proposed framework appropriate for industrial fabric inspection applications.

VI. Experimental Results and Discussion

The proposed framework is evaluated qualitatively on a diverse set of fabric images containing various defect types, including holes, stains, broken yarns, misweaves, and localized texture distortions. Visual inspection of the detection results demonstrates that the multi-detector classical framework successfully localizes defects across a wide range of appearances and scales.

Texture-based detectors effectively identify subtle irregularities in otherwise uniform fabric patterns, while frequency-domain and Gabor-based methods are particularly successful in detecting defects that disrupt periodicity or exhibit directional characteristics. Statistical and background-based methods complement these approaches by capturing abrupt structural damage and regional anomalies such as stains.

The IoU-based fusion mechanism plays a critical role in improving detection stability by merging redundant detections into a single coherent bounding box. Post-processing filters further reduce false positives caused by border artifacts and global illumination variations. Overall, the experimental results indicate that combining complementary classical techniques yields more robust performance than any single detector operating in isolation.

VII. Real-Time Hardware Integration

To demonstrate real-world applicability, the proposed detection pipeline is deployed on a Jetson Nano embedded computing platform. The system processes live camera frames captured at a resolution of 640×480, which provides a balance between detection accuracy and computational efficiency.

All processing is performed on-device without disk input/output or cloud dependency. The modular classical pipeline enables real-time execution by avoiding computationally expensive learning-based inference. Experimental deployment confirms that the system achieves stable frame rates suitable for real-time fabric inspection in industrial environments, while maintaining low power consumption and high interpretability.

VIII. Conclusion

This paper presents a comprehensive classical computer vision framework for automated fabric defect detection and real-time deployment on embedded hardware. By integrating multiple complementary detection strategies and employing an IoU-based consensus mechanism, the proposed system achieves robust and interpretable defect localization without reliance on labeled training data or deep learning models.

The experimental results demonstrate that classical vision techniques remain a viable and effective solution for industrial fabric inspection, particularly in scenarios with limited data availability, strict real-time constraints, and low-power hardware requirements. Future work will explore adaptive parameter selection, detector confidence weighting, and integration with conveyor-based inspection systems.

Acknowledgment

The authors would like to express their sincere gratitude to Dr. Jameel Nawaz for his valuable guidance, constructive feedback, and continuous support throughout the course of this project. His expertise and insights were instrumental in shaping the direction of this work and ensuring its successful completion.

References

[1] T. Xie, S. Zhao, and J. Wu, "Fabric defect detection based on texture analysis and statistical features," *Textile Research Journal*, vol. 89, no. 18, pp. 3827–3840, 2019.

[2] R. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-3, no. 6, pp. 610–621, 1973.

[3] B. Julesz, "Textons, the elements of texture perception, and their interactions," *Nature*, vol. 290, pp. 91–97, 1981.

[4] M. Unser, "Texture classification and segmentation using wavelet frames," *IEEE Transactions on Image Processing*, vol. 4, no. 11, pp. 1549–1560, 1995.

[5] D. Gabor, "Theory of communication," *Journal of the Institution of Electrical Engineers*, vol. 93, no. 26, pp. 429–457, 1946.

[6] A. K. Jain and F. Farrokhnia, "Unsupervised texture segmentation using Gabor filters," *Pattern Recognition*, vol. 24, no. 12, pp. 1167–1186, 1991.

[7] R. Gonzalez and R. Woods, *Digital Image Processing*, 4th ed. Pearson, 2018.

[8] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62–66, 1979.

[9] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, 2001, pp. 511–518.

[10] S. Mallat, *A Wavelet Tour of Signal Processing*, 3rd ed. Academic Press, 2009.